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Designing functional macromolecules

by

Kale Kundert

DISSERTATION

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Kale Kundert

Think it possible that you may be
mistaken.

Oliver Cromwell

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Designing functional macromolecules

Kale Kundert

Biology is driven by functional macromolecules, most notably proteins and non-coding RNAs. Learning how to design similarly functional macromolecules is a natural goal. Success will not only bring the ability to create new biological systems, but also the ability to more finely study and manipulate existing biological systems. In this thesis, I will describe two design projects that I pursued over the course of my PhD. The first is a project to remodel the backbone of a protein for the purpose of accurately positioning a catalytic sidechain. The second is a project to ligand-sensitive guide RNAs for the CRISPR-Cas9 system. There is of course much more to be done before we can say that we are able to design functional macromolecules, but the projects described herein move us closer to that goal.

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Chapter 1

Computational design of structured protein loops

Structured loops are an element of protein structure with special importance for functional proteins. Unlike the canonical elements of protein structure — α -helices and β -sheets — loops can adopt a broad range of conformations because they are not defined by regular geometries or patterns of H-bonds between the polar atoms of the peptide backbone. Similarly, loops can be either rigid or flexible (or rigid in some parts and flexible in others) depending on the interactions they make with themselves and their environments. This conformational and dynamical breadth makes loops well-suited for functionally important tasks like positioning active site residues, forming interfaces, and reacting to signals.

The routine design of functional proteins has been a longstanding goal in the field of protein design. Given the prominent and unique ways in which loops can contribute to function, achieving this goal will inevitably require the ability to rationally design loops. But the same conformational and dynamical breadth that make loops functionally useful also makes them challenging to design: each sequence could adopt a vast number of conformations, each mutation could affect the conformation of every other position in the loop, and each residue could be flexible when it should be rigid, or rigid when it should be flexible.

This perspective will cover the progress that has been made in the field of loop design. I will begin by discussing some examples of functional loops found in nature, to illustrate the applications

that loop design aims to enable. I will then continue by reviewing the various efforts that have been made to design loops to date, before concluding by discussing some promising ways for the field to continue moving forward. I believe that the field of loop design is on the verge of significant achievement, and hope that the ideas shared in this perspective can contribute in some way to that achievement.

1.1 Functional loops in nature

Many examples of functional loops can be found in enzymes. In fact, loops are much more common in active sites (50% of residues) than they are in general (30% of residues) [1]. This observation draws attention to the number of ways in which loops can contribute to catalysis. One way is simply by positioning the necessary functional groups. An example of this is the diffusion-limited enzyme ketosteroid isomerase (KSI), in which a catalytic general base (Asp38) positioned by a structured loop isomerizes a double bond. Double mutant cycles have been used to estimate that the positioning provided by the loop has a 1700x effect on k_{cat} [2]. As the loop contains both a cis-proline and a glycine in “right-handed” Ramachandran space, it is unlikely that the same positioning could have been provided by a conventional secondary structure element [2]. Another way that loops can contribute to catalysis is by acting as a lid for the active site. A prototypical example of this is triose phosphate isomerase (TIM). Upon substrate binding, an active site loop moves over 7Å to surround the substrate and hydrogen-bond (H-bond) with the substrate’s phosphate group. This dramatic movement excludes solvent from the reaction and prevents reactive intermediates from escaping the active site [3]. It also limits the rate of product release, highlighting a carefully balanced trade-off between creating an isolated active site and allowing the product to leave. The active site loop is mostly pre-structured, moving only in a hinge region, suggesting that it has been optimized to reduce the entropy penalty of closing [4]. Rationally designing similar systems will require exquisite finesse.

Structured loops also play an important role in protein-protein interactions. Perhaps the most prominent examples of this are antibodies, which use six structured loops — each called a complementarity determining region (CDR) — to bind an astonishing breadth of targets with high affinity and specificity. An examination of these interfaces reveals how loops can contribute to binding.

First is through shape-complementarity. As antibody CDRs mature, they become more complementary to their antigen, which allows for more favorable van der Waals and H-bonding interactions [5, 6]. Second is through pre-organization, which reduces the conformational entropy penalty of antigen binding [7, 8, 9]. However, pre-organization is not a universal feature of high-affinity antibodies [10]. Antibodies with less organized CDRs may benefit from more favorable enthalpic interactions or the ability to bind their antigen in multiple modes [11, 12]. The challenge for rational design will be to create loops that can similarly adopt the surfaces and motions necessary for tight binding.

More examples of functional loops can be found in proteins that react to their environment. One example of this is the bacterial outer membrane protein G (OmpG) which forms a pH-gated pore in the membrane. The gating is mediated by an extracellular loop containing two histidine residues [13, 14]. At basic pH, the histidines are neutral and cohabit adjacent strands of the β -barrel that forms the pore. At acidic pH, the histidines become charged and their strands unzip separate the charge. This results in the loop becoming longer and adopting a conformation which covers the pore. Another prominent example is the activation loop present in protein kinases. When phosphorylated, this loop forms contacts that stabilize the active site and contribute to catalysis. When unphosphorylated, the loop is disordered and catalysis is impaired [15]. These examples illustrate the utility of being able to design and balance multiple functional loop conformations.

1.2 Loop design: The state of the art

In spite of the numerous applications for loop design, there are precious few reports of loops being redesigned. The first such report that I am aware of was an effort to improve a monomeric variant of TIM by restabilizing an 8-residue active site loop that, in wildtype TIM, participated in the dimer interface [16]. The defining feature of this report is that the mutations were chosen manually. In four iterations, computational models of the loop were predicted using Monte Carlo simulations, then mutations were manually proposed to fix various defects in the models. The final result was a 7-residue loop that improved the activity of monomeric TIM. Furthermore, a crystal structure of the designed protein agreed well with the predicted loop conformation well (0.5\AA C/C α /N/O RMSD). This report established very early on that loop design is both achievable and useful.

Another report of manual loop design was made more recently. In this case, players of FoldIt [17] were asked to improve a computationally designed Diels-Alderase [18] by designing an active site loop that would better desolvate the substrate [19]. In the first round of design, the players were allowed to make 5-residue insertions into any of the four active site loops. The authors experimentally tested the 4 best designs (as judged by score and by eye) and over 500 variants. In the second round of design, the players were instructed to stabilize the best first-round design through the creation of a helix-turn-helix motif. This time, the authors tested the 2 best designs and over 400 variants. The result was a variant with a 13-residue insertion that improved catalysis by 150x. A model of the final variant was also created by the players, and was similar to the crystal structure except for a rotation in one of the helices (3.1Å C/Cα/N/O RMSD). Although the design process required testing hundreds of variants, it clearly demonstrated that human intuition can guide the design of long and functional loops. Ultimately, though, in order for loop design to become a scalable and routine technique, the actual design aspect must be done computationally.

The first report to attempt automated loop design was an effort to graft a loop from an unrelated protein into the fibronectin type III (FN3) domain [20]. This domain had already been established as a non-antibody scaffold for evolving loop-based binding interfaces, and like an antibody, it has a β-sandwich fold that presents 3 mutation-tolerant loops. The aforementioned report redesigned the first of these loops by searching for 12-residue fragments in the protein data bank (PDB) with similar take-off and landing points (within 3Å), grafting each of those loops into the FN3 scaffold, repairing the resulting (small) discontinuities in the backbone, then optimizing the sequence of the new loop while allowing very slight backbone movement (≈0.3Å C/Cα/N/O RMSD, i.e. similar to the average coordinate error in a typical crystal structure). Three designs were purified and two were successfully crystallized. One had the intended loop conformation (0.46Å RMSD), but was in almost the same conformation as the original loop (0.77Å RMSD). The other was missing density for the loop, presumably indicating the lack of defined structure. The significance of this report is that it demonstrated for the first time that a structured loop could be computationally designed. However, this report is also limited: Only 1 of the 3 loops in the scaffold was redesigned, the coordinates of the new loops were taken directly from existing proteins, and the only successful design was in nearly the same conformation as the wildtype loop.

Some of these limitations were addressed by another report in which *de novo* loops were com-

putationally designed in a *de novo* scaffold assembled from 24 repeats of a 5-residue motif [21]. The loops were designed by inserting residues in the middle of the scaffold, sampling them with a coarse-grained and sequence-independent algorithm, then reconstructing them in full-atom detail and performing fixed-backbone sequence optimization. This produced 4000 loop designs. The conformations represented by these designs (which remained sequence-independent) were assumed to approximate the ensemble of states accessible to an 8-residue loop, so the pseudo-probability that each design would fold into its intended conformation was calculated by threading the design sequence onto each design model and comparing the resulting Boltzmann-weighted scores. The 10 designs that were most predicted to fold correctly were tested. Of these, 5 could be purified and 4 could be crystallized. All of the crystal structures were low-resolution ($>3.5\text{\AA}$), but two were consistent with their design models, 1 was inconsistent with its model, and 1 was missing density for the loop. This report showed that it's possible to design loops with fully *de novo* conformations, but important limitations remain: the loops were not designed to achieve any particular structure or function, and only a small fraction of the tested designs could be shown to adopt the intended loop conformation.

The effort to change the substrate specificity of human guanine deaminase (hGDA) from guanine to ammelide was the first report of computational loop design being used to achieve a desired function [22]. The ultimate goal was to change the substrate specificity of hGDA from guanine to cytosine, but ammelide was chosen as an intermediate step because it resembles guanine on one face and cytosine of the other. Where hGDA binds guanine using arginine (Arg) and phenylalanine (Phe), it would need either an asparagine (Asn) or glutamine (Gln) to bind ammelide instead. Consequently, the design goal was to remodel the Arg/Phe loop in hGDA to instead position Asn or Gln with the right geometry to bind the cytosine-resembling face of ammelide*. The loop was remodeled by positioning the ends of the Asn and Gln sidechains ideally with respect to ammelide, rotating the sidechain χ angles to generate backbone conformations capable of supporting that ideal positioning, superimposing segments from the scaffold on those backbones, randomly adding or removing residues from either end of those segments, and repairing the backbone with Rosetta. Designs were then made by performing fixed-backbone sequence optimization on the

*Interestingly, in cytosine deaminases the Asn/Glu is positioned by a different active site loop, so this project is really attempting to build a novel active site architecture.

lowest-scoring backbone model (which featured Asn and two deletions). A single design (GNGV) was chosen for experimental characterization, based on visual inspection and the results of an unrestrained loop modeling simulation. The chosen design effected a 100x increase in ammelide deaminase activity, along with a 25,000x decrease in guanine deaminase activity. A crystal structure revealed that the loop was close to its model (1.0Å C α RMSD), but that the designed Asn was not pre-organized. This report is significant because it showed that loops can be designed for function, and because the authors remarkably needed to test a only single design (giving hope that loop design can eventually become routine). But there is still clear room for improvement. The designed loop was short and its conformation was only slightly different than wildtype. If we are to employ loops to their full effect, we must learn how to design larger loops and more dramatic conformational changes.

Loop design has also been applied to the very difficult problem of designing antibody CDRs to bind particular targets of interest. This is an especially challenging problem for a number of reasons: (i) there are 6 CDRs, which interact with each other to form a single interface, (ii) some of the CDRs, most notably H3, are very long, and (iii) the position of the antigen is not fixed, and must be optimized in concert with the CDRs. However, there is also an exceptional amount of sequence and structural data available for antibodies, and two groups have reported leveraging this data to rationally design antibody binding interfaces [23, 24]. The first report is based on the idea that each CDR (except H3) can be assigned to a small number of conformational clusters [25]. By combining loops from every possible cluster, 4500 models are created. The epitope is then docked against each model, and the models are designed subject to sequence restraints derived from the natural sequence profiles for each cluster. Each loop is then optimized by iteratively installing different conformations from the same cluster, repacking the sidechains, and minimizing [23]. With the benefit of manual design and directed evolution, this algorithm produced antibodies for two different targets, both with mid-nanomolar affinities. One of these antibodies was crystallized and showed atomic-level accuracy in 4 of the 6 CDRs (backbone and sidechain), with the only errors being in H1 and the notoriously difficult H3 [26]. The second report is based on mimicking the natural process by which low-affinity germline antibodies undergo mutation and mature into high-affinity binders [24]. The epitope is first placed in various positions relative to the antibody framework, then CDRs from a database are grafted in to create binding interfaces. These interfaces are relaxed in

100 ns molecular dynamics (MD) simulations. If the epitope stays in the binding pocket designed for it, the interface considered analogous to a low-affinity germline antibody and is matured via *in silico* design. This approach produced produced low-nanomolar binders for a dodecapeptide, but the accuracy of the design models cannot be judged since no crystal structure was solved. Together, these methods suggest that it is possible to design large loops, even while also optimizing other degrees of freedom (e.g. epitope docking). They also offer another glimpse of the potential that loops have to provide valuable functionality. The drawback to these methods is that they are dependent upon the vast amount of information available for the antibody scaffold. It is possible that other common scaffolds, e.g. TIM-barrels, might also be amenable to this kind of design, but there remains a need for methods that can be applied to any scaffold.

Having discussed what loop design is, let us briefly discuss some related fields that I consider to be distinct and outside the scope of this review. First is flexible backbone design. While it is well-known that small amounts of backbone motion can dramatically improve sidechain packing [27], this small amount of motion does not seek to move the backbone into a functionally different conformation. In contrast, loop design does seek to move the backbone into functionally different conformations. Second is loop grafting. The goal in loop grafting is to present a fragment of one protein, in its native conformation, on the scaffold of another [refs]. Most often this is done to create an epitope, so that antibodies can be raised against an otherwise recalcitrant antigen. While loop grafting, like loop design, aims to create loops in a particular conformation, it is distinct from loop design because the conformation in question has a known and immutable sequence and structure. This takes the focus off the loop itself and puts it on finding a good scaffold and creating a compatible environment. Third is turn design. An important part of designing *de novo* folds is designing good turns to connect secondary structural elements [28]. This is distinct from loop design because the conformation of the loop doesn't matter so long as it connects the secondary structural elements in question and folds efficiently. Turn design is also a problem that is well-addressed by simple database searches, since small turns have only a limited number of favorable conformations [29].

1.3 What can we learn from loop modeling?

With the current state of rational loop design in mind, it's interesting and worthwhile to consider how the field might progress in the near future. One way to do this is to examine the related — but much more mature — field of loop modeling. Loop modeling is the problem of trying to predict the structure of a loop from its sequence. This is the inverse of the loop design problem, which could be framed as trying to predict sequences that will adopt a particular loop structure. More generally, loop design can be framed as trying to predict sequences that will satisfy certain functional restraints, e.g. positioning one or more sidechains, adopting a particular conformation, changing conformation in the presence of a ligand, etc. By carefully considering the similarities and differences between these two related problems, we will see how previous advances in loop modeling can illuminate the way forward in loop design.

The basic structure of a loop modeling algorithm is as follows: The inputs are (i) the sequences of one or more loops and (ii) the atomic coordinates for the rest of the protein. For example, these coordinates might come from homology models or experimental structures with missing atoms. The outputs are the atomic coordinates for loops in question. To produce these coordinates, a loop modeling algorithm needs four components: a way to represent the atoms in question, a way to sample new loop conformations, a way to keep the backbone closed, and a way to score different loop conformations. I will discuss each of these components, and how they might be applied to the loop design problem, below.

1.3.1 Representation

Almost every loop modeling algorithm makes use of two representations: one that's coarse-grained and another that's full-atom. A coarse-grained representation is one that strips away some atomic detail in the interest of simplicity. This could mean replacing the sidechain atoms with a single large sphere, or removing the sidechain atoms altogether, or removing everything except the α -carbons. In contrast, a full atom representation includes every backbone and sidechain atom, although most still exclude solvent atoms. The advantage of coarse-grained representations is that they create smaller and smoother energy landscapes which can be thoroughly explored, while the advantage of full-atom representations is that they allow for important physical interactions, like hydrophobic

packing and H-bonding, to be modeled. For this reason, most loop modeling methods begin by searching for reasonable loop conformations in a coarse-grained representation, then switch to a full-atom representation to winnow and refine those conformations [30, 31, 32, 33, 34, 35]. An interesting exception is an algorithm that uses only a full-atom representation [36, 37]. It is based on the premise that the best loop conformation will comprise the best residue conformations, so it build loops by sampling each residue in full-atom detail, one-at-a-time, until the whole loop has been assembled.

The clear consensus from the loop modeling literature is that it's best to use both coarse-grained and full-atom representations. However, the variety of coarse-grained representations that can be used for loop design is limited by the need to represent sequence. Loop design is fundamentally a search for sequences, so in order to perform a coarse-grained version of this search, the representation must encode sequence. Even defining the objective of a loop design effort can depend on the sidechains being represented. For example, if the goal is to position the functional group of an active site residue, solutions will need to take into account the size and geometry of that residue's sidechain, even at a coarse-grained level. In short, coarse-grained representations that ignore the sidechains altogether will be less appropriate for loop design. The coarse-grained representation in Rosetta (termed "centroid-mode") may be a good candidate moving forward, as it represents different sidechains as spheres with different sizes and polar properties [38]. It may also be worthwhile to develop new representations specifically for the loop design problem.

1.3.2 Sampling

The easiest way to distinguish two loop modeling algorithms is by how they sample different conformations. Algorithms are traditionally categorized as either "template-based" or "template-free" [39, 40, 41], where the former query databases of known structures to sample loop conformations, and the latter don't. However, most algorithms lie on a continuum between the two. On one side of this continuum are the algorithms that make no direct use of structural data. One way to do this is to randomly place atoms and subsequently refine them to satisfy certain physical or experimental restraints [30, 42, 43]. Another way is to make small perturbations to the backbone coordinates, in either Monte Carlo [44, 45] or molecular dynamics (MD) [46, 47, 48, 49] simulations. The first step

along the continuum is to sample backbone torsions from the Ramachandran distribution, which is derived from the frequencies of different combinations of the ϕ and ψ backbone torsions in high-resolution protein structures. This is perhaps the most popular strategy [32, 34, 50, 51, 52, 53, 54, 55, 56], and has even been extended to two-residue [57] and three-residue [58] versions of the Ramachandran distribution. Next are the algorithms that sample new loop conformations by stitching together fragments (usually of about 3–9 residues) from known structures [33, 35, 59]. This fragment-based approach posits that all relevant local conformations are present in the PDB, and is widely recognized for its successful application to the *ab initio* prediction of protein tertiary structures [60]. Finally, on the far side of the continuum are the fully template-based algorithms. These algorithms query structural databases for loops of the right length that roughly match the takeoff and landing points of the loop in the input structure [61, 62, 63, 64, 65, 66, 67, 68, 69]. Matching loops are usually ranked by how well they fit the gap and align with the input sequence, and can be subsequently relaxed using a full-atom score function.

In terms of sampling, the clearest difference loop modeling and design is that the former only needs to sample conformation-space, while the latter needs to simultaneously sample conformation- and sequence-space. I will put aside the issue of sampling sequence-space, as it is not informed by the aforementioned literature, and focus instead on the issue of sampling conformation-space.

Due to the lack of fair and comprehensive benchmarks between loop modeling methods [40], I can't judge which has been the most successful for loop modeling. However, I can speculate that the template- and fragment-based algorithms will be the most successful for loop design [22, 23, 70]. The reason is that these algorithms offer a solution to the “designability” problem [71]: Given a desired conformation, is it possible for some sequence (in some environmental context) to adopt that conformation? If the desired conformation came from a structural database, the answer is yes. There are two challenges in applying purely template-based algorithms to the problem of loop design. The first is ensuring that the loop will still adopt the desired conformation in its new context. The second is that there will be extra geometrical constraints on the loop. For example, to design a loop that positions an active site residue, a database query would have to find loops that not only start and stop in the right place, but also are capable of positioning the residue in question. This challenge only gets worse as more residues are included in the design. For example, an interface design project might require that *every* residue in the loop contributes to binding! That

said, loop design also makes the database query easier in other ways — the algorithm can pick its takeoff and landing points, and the loop can be of any length or sequence — so it's not clear *a priori* how difficult it will be to apply template-based algorithms this new problem. Either way, the fragment-based algorithms are another promising choice. They offer similar advantages to the template-based algorithms in terms of designability, but can also easily accommodate restraints imposed by the design goal, e.g. with extra score terms.

Another aspect of sampling is the question of how large barriers are traversed. The most common answer to this question is simulated annealing, whereby the temperature of the simulation is gradually increased and decreased over the course of the simulation [30, 33, 34, 44, 45, 46, 54, 55, 59]. A closely related alternative is parallel tempering, whereby simulations at different temperatures are run simultaneously and occasionally swap coordinates [48, 72]. The advantage of this technique is that it produces ensembles with defined temperatures, but the proper treatment of thermodynamic ensembles has not been a priority for the field. Genetic algorithms have also been used to enhance sampling [43, 73, 74]. While genetic algorithms can traverse barriers very efficiently, they also have to confront the fact that crossover operations involving backbone torsions are likely to produce large clashes[75]. Lastly, a handful of methods have attempted to exhaustively sample conformational space, subject to some binning [32, 36, 37, 53].

Any of these barrier traversal strategies could be effectively applied to the part of a loop design protocol that involves searching for sequences and conformations that satisfy the design criteria. But once that that part of the protocol produces some candidate sequences, the next part needs to assess which sequences will really adopt the intended conformation. This validation step is similar to a loop modeling simulation, but it's simplified in one way: It's testing the hypothesis that the intended conformation is the global energy minimum, so it can stop as soon as it finds evidence to the contrary. If a small number of plausible off-target states could be identified (or perhaps even recalled from the simulations that produced the candidate in question), the validation problem could be recast as a comparison between those states, rather than as a global search for the energy minimum. In turn, this may justify the use of enhanced sampling techniques like umbrella sampling [76] or the adaptive biasing force method [77].

1.3.3 Closure

A unique feature of loop modeling algorithms is that they must sample new loop conformations without creating breaks in the protein backbone. This is referred to as the closure problem. The simplest solution is to simply start building the loop from both ends, and to keep models that happen to meet in the middle [32, 36, 52]. This is a common approach for sampling algorithms that are enumerative in some way. Another solution is to define some kind of score term that favors a closed backbone (e.g. a harmonic restraint across the break) and to let the sampling algorithm (or a gradient minimizer) find ways to satisfy that term [30, 42, 43, 44, 45, 53, 54, 56, 59, 78]. However, this solution may require spending a significant amount of time sampling conformations that aren't even closed, which is inefficient. An alternative is to use inverse kinematics algorithms borrowed from the field of robotics. These algorithms seek to solve the following problem: If you have a robot arm with multiple joints, and you want the end of the arm at some given position and orientation, to what angle should you set each joint? In the context of loop modeling, such algorithms can be used after sampling to adjust the backbone torsions in the loop such that its ends remain connected to the rest of the protein. There are many inverse kinematics algorithms, but they can be broadly categorized as either iterative or analytical. Iterative algorithms converge on a closed backbone over a series of steps, as exemplified by cyclic coordinate descent (CCD) [79]. These algorithms are conceptually simple and have been applied in many protocols [33, 51, 55, 68, 73, 80, 81]. Analytical algorithms calculate exact solutions to the closure problem, as exemplified by kinematic closure (KIC) [82]. Since the end of the "robot arm" has 6 degrees-of-freedom (3 positional and 3 orientational), these algorithms must set 6 backbone torsions to achieve closure. Any other torsions are unaffected, no matter how long the loop is. These algorithms are more complicated, but have the nice properties of perturbing the minimum number of torsions and indicating immediately if closure is possible. They have also been used in many protocols [34, 35, 37, 74, 83].

Loop design will require efficient sampling in sequence- and conformation-space. For this reason I believe that the efficiency of the inverse kinematics methods, especially the analytical ones, will make them the best choices for maintaining closed loops.

1.3.4 Scoring

The last component of a loop modeling algorithm is the score function used to evaluate which conformations are the most realistic. As with sampling, loop modeling algorithms lie on a continuum based on the score function they employ and how much structural data it makes use of. On one side of the continuum are the algorithms that use physical score functions like AMBER [46, 49], CHARMM [48, 53, 72], and OPLS [32]. Some algorithms also use a “colony” score term that tries to capture the idea of entropy by favoring the models with the most conformationally similar neighbors [51, 84]. These score functions attempt to apply our understanding of physics, in a simplified way, to discriminate between loop models. On the other side of the continuum are algorithms that use statistical score functions like DFIRE [35, 37, 66, 85], DOPE [54], SOAP-Loop [68], and others [45, 50, 86]. These score functions attempt to create rules from the distributions of atoms and residues observed in high-resolution structures, and can be good at implicitly capturing complex effects like secondary structure, sidechain-sidechain interactions (e.g. salt-bridging, π -stacking), and packing defects. However, by far the greatest share of loop modeling algorithms fall in the middle of the continuum and use hybrid score functions, or score functions which include both physical and statistical terms [30, 31, 33, 34, 43, 55, 59, 73, 74]. Hybrid score functions typically include a complete set of physical terms, plus statistical terms that favor common backbone torsions, sidechain torsion, and H-bonding geometries. It’s also common for methods to use a statistical score function for coarse-grained sampling and a physical score function for the full-atom sampling.

What considerations are relevant to loop design? Hybrid score functions are a clear consensus, especially among the most recent methods, so I expect their use to continue. A more significant consideration is the need for a score term that allows for the fair evaluation of mutations. For example, imagine that you were to attempt to mutate an alanine to an arginine. Absent any correction, arginine would artificially score better than alanine simply because it has more atoms, and thus more opportunities to make favorable contacts. A score term is needed to counteract this bias. While in principle such a term could be added to any of the score functions used for loop modeling, the Rosetta score function is the only one of those that already has one (called the “reference energy”). This means that for now, the Rosetta score function is the best candidate for applications in loop design. In keeping with this idea, four of the five computational loop design

methods reviewed above used the Rosetta score function (the other ignored this consideration).

Another consideration for loop design is the solvent model. While every loop modeling method that I am aware of uses an implicit solvent model (or doesn't consider the solvent at all), it may be possible to apply explicit solvent models in the context of loop design. As mentioned in the paragraphs on barrier traversal, the validation step of a loop design protocol may be able to devote more time towards a small number of structures, allowing the use of more resource-intensive techniques. As loops are typically solvent exposed, an explicit treatment of the solvent may yield worthwhile improvements in accuracy.

1.4 What problems are unique to loop design?

Having discussed loop design in the context of loop modeling, let us now focus on some problems that are specific to the loop design problem. The first of these is: how many residues should be in the designed loop? It must be long enough to fulfill the design goal (e.g. if the goal is to position a residue, the loop must be able to reach that residue), but ideally as short as possible. Not only are shorter loops less likely to be conformationally heterogeneous, but they are also easier to accurately model. The most naive approach to designing loop length is to simply try several different lengths, but this is inefficient. Loop design already has to grapple with the enormous task of sampling both sequence- and conformation-space. It would be wasteful to sample unnecessary loop lengths on top of that, especially for problems where the loop length may not be well constrained. Two more thoughtful approaches have already been explored. Murphy et al. randomly added and removed residues from the loop during design, and validated their approach with a loop length recovery benchmark [22]. Lapidotoh et al. sampled loop sequences and conformations from a database, which included loops of different lengths [23]. However, neither of these approaches used a score function that was capable of fairly comparing loops of different lengths. Just as score functions will naturally prefer large amino acids over short ones (as described above), so too will they prefer long loops over short ones. While this bias did not prevent either group from creating successful designs, it is a shortcoming that should be addressed as the field matures.

The second problem that loop design must confront is: how can the rigidity of a loop be designed? Although it is well known that proteins are best thought of as occupying an ensemble of

states at equilibrium, only a handful of loop modeling methods have tried to account for the possibility that a loop might not have a single defined conformation [87, 88, 89]. This may be a niche consideration for loop modeling, where the sequences being predicted have been optimized by evolution and are often well-structured, but it is of immediate importance to loop design, where the sequences being predicted were created *in silico* and disorder could be a common mode of failure. Making a loop more flexible or rigid may also be a design goal. Predicting protein flexibility is an established field, although to my knowledge it had never been applied to loop design. There are two basic approaches. The first is to generate an ensemble of possible conformations, then to calculate Boltzmann-averaged quantities (like RMSD) over that ensemble [87, 88, 90, 91]. The challenge with this approach is the expense of computing the ensembles and the impossibility of knowing whether all of the relevant states have been sampled. The ensembles must also be generated by a method that obeys detailed balance, which adds complexity. The second approach is to represent the protein as a graph and to infer rigidity from the connectivity of that graph [92, 93, 94, 95, 96]. Usually the nodes represent atoms or residues, and the edges represent the covalent and non-covalent interactions between those nodes. The challenge with this approach is that it abstracts the details of protein structure and is often more focused on motions at the domain level than at the individual residue level. It is still an open question which of these two approaches will work best for loop design.

1.5 Closing remarks

In conclusion, I have reviewed the current state of the loop design field and highlighted several promising avenues for progress in the near future. The field has had success designing small loops and antibodies, and can continue making progress by repurposing existing loop modeling algorithms. Questions like how long to make a loop, and how to make a loop either rigid or flexible, still need to be grappled with. That said, I believe that the technologies enabling the next steps forward are largely in place. My hope is these steps will lead to methods capable of routinely and accurately designing structured loops. As loops are an integral feature of many functional proteins — including enzymes, binders, and switches — such methods will be a boon to the broader and ongoing effort to design functional proteins.

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Chapter 2

Remodeling the protein backbone to position a catalytic residue

Natural proteins often use highly structured loops to position key functional residues. Mimicking this approach in rationally designed proteins is an important step towards the routine design of functional proteins. But even though it is now often possible to predict loop structures with sub-angstrom accuracy, designing structured loops to position functional residues with similar accuracy remains an unsolved problem. We are approaching this problem by developing a protocol called Pull Into Place (PIP) that iterates between flexible-backbone design and state-of-the-art loop structure prediction. The first step of our protocol searches for backbones that support the desired sidechain geometry by using loop modeling simulations with gentle restraints to hold the sidechains in place. The second step finds sequences that stabilize the backbone models found in the first step. The third step uses unrestrained loop modeling simulations to eliminate designs for which the desired structure is not the lowest in energy. Good models from the third step are then fed back into the second step for further optimization. We are testing our protocol by attempting to rescue the Asp-to-Glu mutation of the catalytic residue in bacterial ketosteroid-isomerase (KSI), which moves the catalytic carboxylate by 1.8Å RMSD and causes a 240-fold decrease in k_{cat} . Although we have successfully rescued the positioning of the catalytic carboxylate, we have not yet been able to rescue the enzyme's catalytic activity. Our hope is that further development of this pipeline will yield significant progress towards the design of functional proteins.

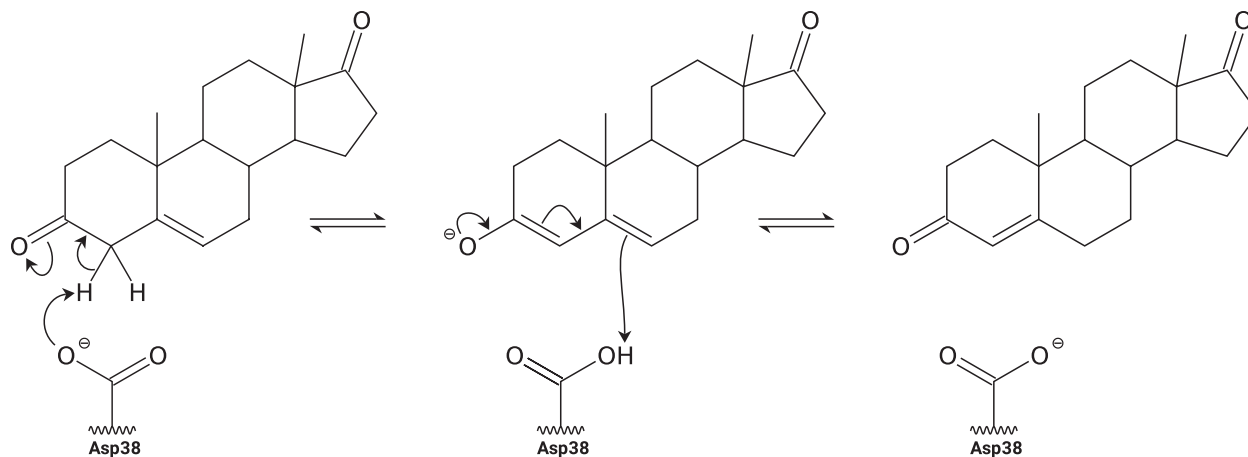


Figure 2.1: Mechanism of the isomerization catalyzed by KSI.

2.1 Model system

Ketosteroid isomerase (KSI) is an enzyme that catalyzes the rearrangement of a double bond in steroid molecules. The mechanism is outlined in Figure 2.1. Briefly, the general base (D38) abstracts a proton to form an enolate intermediate, which then collapses to form the enone product. The reaction naturally progresses in the forward direction due to the increased conjugation of the enone compared to the isolated ketone and alkene groups. Note that the first step involves a carboxylate ($pK_a = 4.5$) [1] deprotonating an allylic carbon ($pK_a = 12.7$) [2], which would normally be prohibitively unfavorable. It occurs in the KSI active site due to the influence of the oxyanion hole (Figure 2.2).

The precise positioning of the D38 carboxylate group has a strong effect on catalysis. The D38E mutant, which moves the carboxylate by 1.8\AA RMSD^{*}, decreases k_{cat} by 240-fold [3]. Double-mutant cycle experiments have established which residues are most important for accurately positioning the carboxylate [3, 4]. The first these residues are F54 and F116: the two phenylalanines flanking D38 [3]. Although they seem to bury the carboxylate in a hydrophobic pocket, they are actually engaging it in two anion-aromatic interactions. Anion-aromatic interactions are driven by the fact that electron density is localized in the center of aromatic rings, creating a partial positive charge around the edge of the ring that attracts negatively charged residues[†]. The third residue

^{*}From superimposing 4L7K on 8CHO.

[†]This is the opposite of the cation- π interaction, where for the same reason positively charged residues are attracted to the face of aromatic rings.

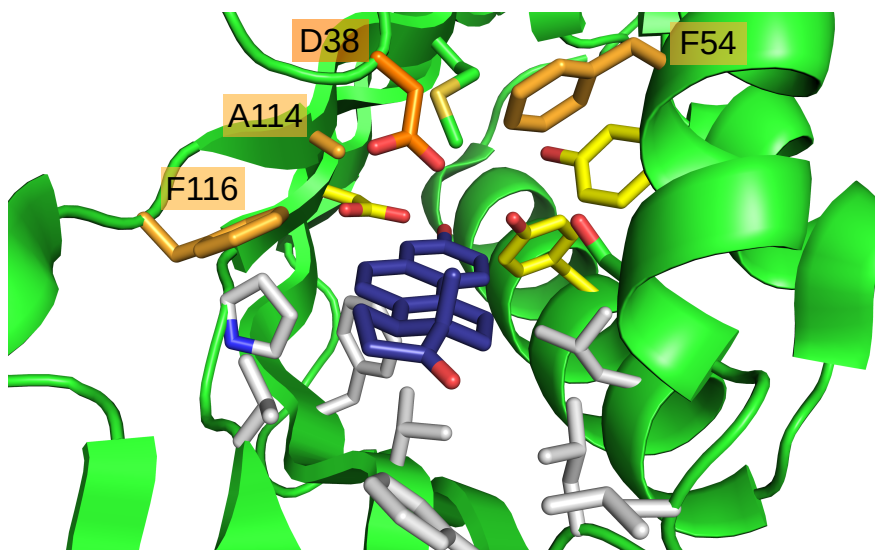


Figure 2.2: Important residues in the KSI active site. Purple: substrate analog equilenin. Orange: the general base (D38). Pale orange: residues that have been shown to contribute to the positioning of D38. Yellow: the oxyanion hole. White: the hydrophobic binding pocket.

important for positioning D38 is A114, simply because it packs against the D38 sidechain [4]. The rest of the residues (P39, V40, G41) make up the active site loop, and are collectively the most important contributors [4].

Our goal is to rescue the catalysis of the D38E mutant by redesigning the active site loop to position the E38 carboxylate in the same place as the wildtype D38 carboxylate (Figure 2.3). Our primary interest is to develop a method for very accurately remodeling structured loops, and there are a number of features that make KSI a good model system for such a project. First is that by starting from an enzyme that's highly functional in every way except the one we deliberately perturbed, we control for many of the challenges associated with enzyme design in general and focus on the challenges associated with remodeling the backbone. Second is that KSI has been well studied. In addition to the double mutant cycles described above, there is a wealth of information available on how catalysis is affected by the oxyanion hole [5] and the electrostatic field created by the enzyme [6]. Third is that KSI is a small and soluble protein. Fourth is that the active site loop is tolerant to mutation. It has been shown that the entire loop can be mutated (to glycine) with no apparent effect on K_M , suggesting that the active site loop is not involved in either binding the substrate or stabilizing the protein fold [4]. Fifth is that k_{cat} is very sensitive to small changes in carboxylate positioning, as evidenced by the 240-fold response to the 1.8Å perturbation made by

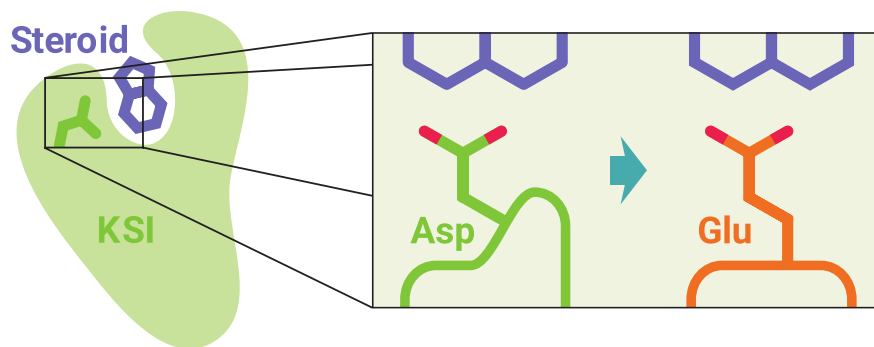


Figure 2.3: Our goal is the redesign the active site of KSI to use a glutamic acid for catalysis, rather than an aspartic acid.

the D38E mutation. This gives us a way to make sub-angstrom inferences about the position of the active site loop by just measuring k_{cat} , which we can do in higher throughput than we can solve crystal structures. The 240-fold effect on k_{cat} also gives us a large dynamic range in which to observe improvements made by our designs. Sixth is that established assays exist to measure KSI's catalytic activity, and seventh is that KSI has proven very amenable to structure determination via both x-ray crystallography and nuclear magnetic resonance (NMR), so we stand a good chance of being able to visualize our designs.

Despite all those positives, there are some drawbacks to using KSI as a model system. First is that the enzyme assay requires purified protein, which limits the number of designs we can test. Second is that enzymes are very sensitive, and there are a number of ways we could incidentally harm catalysis that are unrelated to the positioning of the carboxylate group. For example, we could alter electrostatic interactions (which are long-range, if not effectively shielded by solvent), or the pK_a of various residues, or solvent access to the active site, or the dynamics of the designed loop, or something else. Third is that the anion-aromatic interaction that helps stabilize the carboxylate is not explicitly modeled by the Rosetta score function. As a result, the energy of the desired conformation may be overestimated in our simulations.

2.2 Results

To address the challenge of remodeling a protein backbone to position one or more functionally important sidechains with sub-angstrom accuracy, we developed a new computational protocol

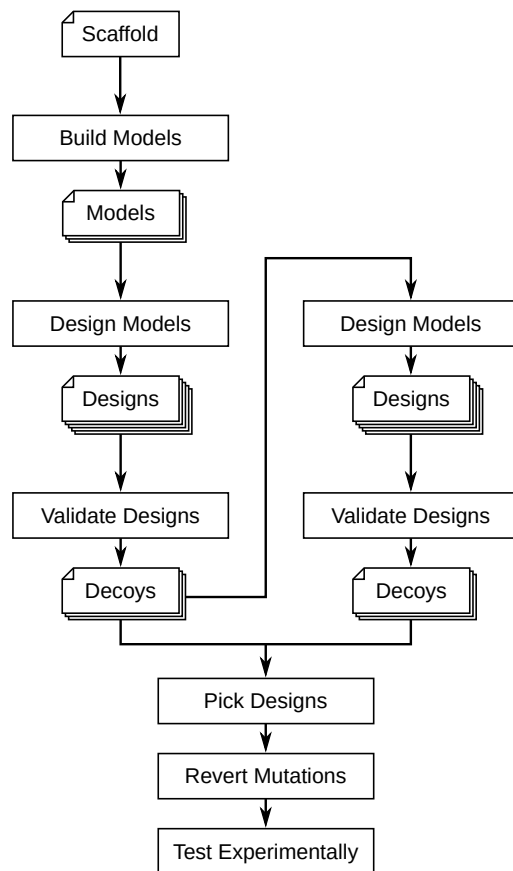


Figure 2.4: Schematic of the PIP protocol.

called Pull Into Place (PIP). PIP seeks to build on the the kinematic closure (KIC) algorithm, which is often successful at predicting sub-angstrom loop conformations [7, 8], in a three-step process (Figure 2.4). The first step (“build models”) is to use KIC to generate backbone conformations capable of satisfying the design goal, which in this case is to position the E38 sidechain where it can catalyze the reaction. The design goal is represented using harmonic restraints, so the simulation can simultaneously optimize for conformations that satisfy the restraints and are physically realistic. The second step (“design models”) is to design optimized sequences for each backbone, without sampling new backbone conformations. The third step (“validate designs”) is to use KIC again, this time without any restraints, to predict the preferred conformations of the designed sequences. Sequences that are predicted to prefer their designed conformation are candidates for experimental testing. The third step typically generates a number of models that satisfy the design goals well despite scoring poorly. These models are fed back into the second step, to see if their scores could be improved by another round of sequence optimization. In this way, the second and third steps can be iterated.

As a proof of concept, we applied the PIP protocol to the problem of remodeling the active site loop in KSI to rescue the D38E mutant. We independently created designs for two different loop lengths: the first the same length as the wildtype loop (13 residues), and the second with a one-residue deletion (12 residues). We began the protocol by creating 4,128 models that positioned the E38 such that all three carboxylate atoms were within 0.6Å of their intended positions (Table 2.1). From these models we designed 176,417 unique sequences to stabilize the remodeled backbone and E38 sidechain conformations (Table 2.2). We chose 200 of these sequences to validate computationally. For 41 of the designs, the predicted structure places all three of the E38 carboxylate atoms within 1.2Å of their intended positions (Table 2.3). These designs were said to “pass validation”. We also found 300 models (mostly with one deletion in the loop) that positioned the carboxylate atoms within 0.6Å of their intended positions. We used these to design 12,825 more unique (Table 2.2), of which 100 were validated and 70 passed (Table 2.3). Note that the fraction of designs that passed validation increased from 21% in the first round to 70% in the second round, suggesting that backbone models from unrestrained loop modeling simulations are good scaffolds for design. As described in the Methods, we visually inspected the 41+70=111 designs that passed validation and picked 14 to test experimentally (Table 2.6). We then attempted simplify

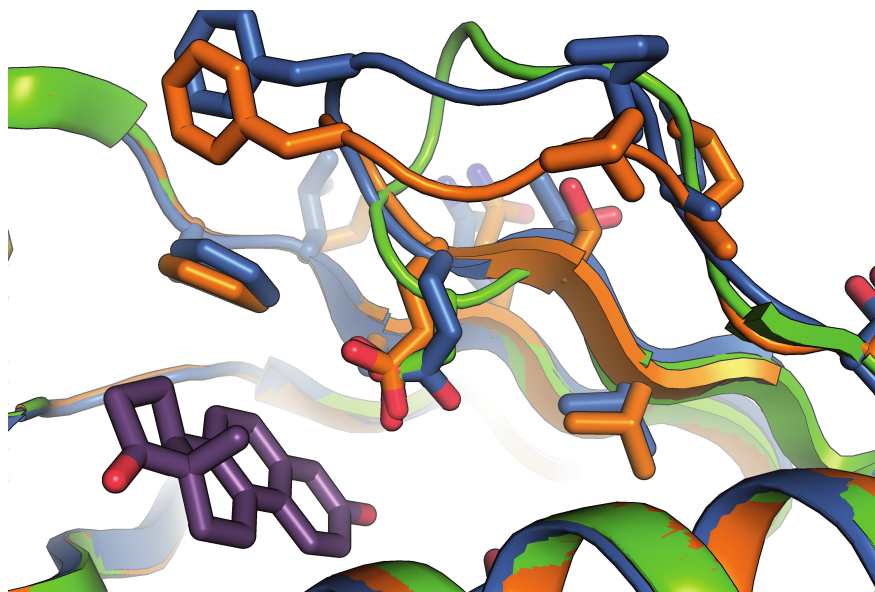


Figure 2.5: Comparison of wildtype KSI (green), the design L model (orange), and the design L crystal structure (blue). The crystal structure was solved by Lin Liu.

each designs by computationally validating different combinations of wildtype reversion mutations (Table 2.7).

Of the 14 designs we tested experimentally, 11 could be expressed. None were soluble, but 10 could be purified from inclusion bodies. Only 4 of these were stable, and 3 had detectable enzymatic activity in the assay described in [4] (Table 2.4). We calculated Michaelis-Menten parameters for design L (Table 2.5, Figure 2.6a). From this we can conclude that design L actually made catalysis worse than the D38E mutant alone, but did not affect substrate binding. Despite the poor activity, we solved the crystal structure for this design (Figure 2.5). Surprisingly, the geometry matched the design model fairly well. The carboxylate group in the crystal structure was offset 1.28\AA C/O/O RMSD from the model. The $C\alpha$ was even closer: just 0.61\AA from the model. The RMSD between the crystal structure and design model for the 12-residue remodeled loop was 1.41\AA , mostly due to small hinge motions in S39 and F44.

However, the crystal structure does not explain the loss in catalysis, since E38 is positioned better than in design L than in the D38E mutant. Instead, the loss in catalysis is better explained by the fact that the design is a monomer in solution (Figure 2.6b). The design is a dimer in the crystal structure, which suggests that our design might adopt a different conformation in solution that it does in the structure. Wildtype KSI is not active as a monomer, so being monomeric could

# Dels	Loop	# Models	<0.6Å
0	34–46	10340	1943
1	34–45	9998	2185

Table 2.1: Models capable of correctly positioning E38. # Dels: The number of deletions in the active site loop. Loop: The residues comprising the active site loop. # Models: The total number of backbone models that were generated. <0.6Å: The number of backbone models that positioned all three E38 carboxylate atoms within 0.6Å of their intended positions.

Round	# Dels	# Inputs	# Designs	# Unique
1	0	1943	96689	84853
1	1	2185	108929	91564
2	0	24	7150	4190
2	1	276	13754	8635

Table 2.2: Designs that stabilize the correct positioning of E38. Round: The first or second iteration of the design step. # Dels: The number of deletions in the active site loop. # Inputs: The number of backbone models that were used as the scaffold for fixed-backbone design. # Designs: The total number of designs that were for generated. # Unique: The number of unique designs that were generated.

Round	# Dels	# Designs	<1.2Å	# Picked
1	0	100	21	4
1	1	100	21	3
2	0	50	38	3
2	1	50	32	4

Table 2.3: Computationally validated designs. Round: The first or second iteration of the validation step. # Dels: The number of deletions in the active site loop. # Designs: The number of designs that were chosen for computational validation. <1.2Å: The number of designs for which the lowest scoring decoy (of 500) positioned all three atoms of the E38 carboxylate within 1.2Å of their intended positions. # Picked: The number of designs that were picked for experimental testing.

Name	Expressed	Soluble	Purified	Stable	Active
A	✓		✓	✓	
B	✓		✓		
C					
D	✓				
E	✓		✓		
F	✓		✓		
G	✓		✓		
H					
I	✓		✓		
J	✓		✓		
K	✓		✓	✓	✓
L	✓		✓	✓	✓
M	✓		✓	✓	✓
N					

Table 2.4: Experimental validation of the KSI designs. Name: The name of the design. Expressed: Whether or not the design was expressed, as indicated by its presence in either the soluble or insoluble fraction (determined by visual inspection of a Coomassie PAGE gel). Soluble: Whether or not the design was soluble, as indicated by its presence in the soluble fraction (determined as above). Purified: Whether or not the design could be purified. Designs that could be expressed but were not soluble were purified from inclusion bodies (see Methods). Stable: Whether or not the design remained soluble after being stored at 4°C for 1 day. Active: Whether or not the design catalyzed the isomerization of 5(10)-estrene-3,17-dione above the baseline rate (determined by the visual inspection of an absorbance vs. time plot for a single enzyme concentration). All data in this table was collected by Lin Liu.

Name	k_{cat} (s^{-1})	K_M (μM)
wildtype	36	50
D38E	0.15	35
design L	0.0027	38

Table 2.5: Michaelis-Menten parameters for design L. The data for design L was collected by Lin Liu. The data for wildtype KSI and the D38E mutant are reproduced from [4] for comparison.

explain the poor activity of the design. Changes in the quaternary structure of the scaffold were also not accounted for by our computational models. Initial efforts to restore the dimeric quaternary structure by making reversion mutations have so far been unsuccessful.

2.3 Discussion

The PIP protocol presented in this chapter is neither a beginning nor an end. Older versions incorporated ideas that we later thought better of, and newer versions have attempted to address the shortcomings of their predecessors. The most recent version of the protocol is available from: <http://pull-into-place.readthedocs.io/en/latest/>. In the interest of informing future efforts to develop PIP (or similar protocols), here we will discuss the reasoning behind both the ideas we moved away from, and the ideas we are moving toward.

2.3.1 Build models

Our first consideration was how to create backbone models capable of supporting desired sidechain geometries. Before we settled on using flexible backbone simulations with harmonic restraints, we experimented with using inverse rotamers instead. In hindsight, restraints are the better option for a number of reasons. The idea of inverse rotamers is to hold the end of a sidechain fixed in some desired position, then to rotate the sidechain torsions to create a library of rotamers that all have their backbone atoms in different positions. The challenge is then to connect the backbone for the rest of protein with the various inverse rotamers. We generated inverse rotamers that positioned the E38 carboxylate exactly as in wildtype KSI, then used KIC close the two resulting gaps in the backbone: one from the N-terminal edge of the loop to E38, and another from E38 to the C-terminal edge of the loop. In principle, closing a gap requires setting at least 6 torsions, or 3 residues (since each residue has ϕ and ψ torsions). In practice, there often aren't any solutions if only 3 residues can move, so at least 4 are needed. This brings us to the first problem with inverse rotamers: you have to move 4 residues on either side of each residue you have inverse rotamers for. This would make it impossible to design two residues that are separated by less than that[‡]. It also means

[‡]For example, the two residues responsible for recognizing the protospacer adjacent motif (PAM) in Cas9 are separated by only one residue, and thus could not be designed with this approach.

that a loop designed to position one residue can be no shorter than 9 residues long (4 on each side, and 1 for the residue itself), which is already a nontrivial length, although for KSI we chose to design more residues than that anyway. The second problem with inverse rotamers is that the resulting models, which have the sidechain positioned perfectly and the backbone fully connected, are not realistic. By forcing the sidechain into the perfect position, we also force the backbone into a relatively strained conformation. When the backbone is allowed to move freely, it often adopts a different conformation and doesn't position the sidechain correctly. Using restraints lets the simulation balance the strain between the sidechain and the backbone and favors the models that minimize that strain the most.

We are now attempting to apply more powerful backbone sampling methods to the model building step, specifically fragment KIC (fKIC) or loop hash KIC (lhKIC) (Listing 2.8). Both algorithms incorporate structural information from the protein data bank (PDB) in their sampling. fKIC compares the sequence of the region being sampled to structural motifs derived from the PDB, then samples backbone torsions from the motifs that are most similar in sequence. lhKIC instead searches for structural motifs from the PDB that nearly connect the ends of the region being sampled, then samples both backbone torsions and residue identities from those motifs. A significant advantage sampling from the PDB is the ability to design secondary structure. In the context of the KSI project, this means that both algorithms sometimes produce models that expand the β -sheet adjacent to the active site loop. For comparison, the designs described in this chapter were modeled with NGK, which samples backbone torsions from the two-body Ramachandran distribution. While this incorporates correlations between adjacent residues, it did not produce models with expanded secondary structure.

One factor that makes lhKIC (at present) more conceptually pleasing is that it also samples sequence. Although the primary focus of the model building step is to sample backbone conformations, we allow the sequence to change simultaneously because it doesn't make sense to sample new loop conformations exclusively in the context of the wildtype sequence. This is a problem for fKIC, which uses a static database of structural motifs selected based on their similarity to the wildtype sequence. As the simulation progresses and the sequence accumulates more and more mutations, that database gets more and more out-of-date. lhKIC avoids this problem by taking both sequence and structure from the motifs it finds. We note that fKIC could address this

problem by picking fragments from a dynamically updating database, but this feature does not yet exist.

We are also now attempting to remodel larger stretches of the backbone in the model building step (Listing 2.15,2.16). For example, we often strive to begin and end remodeling in secondary structural elements, where we expect the structure to be robust and reliable. To make this possible, we keep all the initial coordinates of the scaffold, instead of discarding the coordinates for the loop (Listing 2.8). This reduces the space of structures that needs to be searched, and immediately focuses on those loops that are most similar to the wildtype (and therefore the most plausible) while still fulfilling the design goals.

2.3.2 Design models

Depending on whether a KSI is considered successful based on its crystal structure or its enzymatic activity, we had either 1 or 0 successful designs in 14 tries. One probable reason for this low success rate is that we were far too liberal in both which positions we allowed to design and which amino acids we allowed those positions to design to (Listing 2.3,2.7). In 125- and 124-residue scaffolds (corresponding to the two loop lengths), we allowed 41 and 38 residues to mutate. Making this many mutations severely stresses a fundamental assumption in protein design, which is that the conformation of the scaffold won't significantly change. In our current efforts to remodel the active site loop in KSI, we have been more conservative about which positions are allowed to design. Not counting E38, we chose 15 positions to mutate by visually inspecting the structure . We also are using LayerDesign ConsensusLoopDesign to limit the allowed amino acid identities based on the burial, secondary structure, and turn geometry of each position (Listing 2.11) [9].

When subjected to computational validation, a surprising number of KSI designs were predicted to adopt the right backbone geometry but the wrong E38 rotamer. One way to address this issue and to increase the number of designs that pass validation is to consider both positive and negative conformations in the design step. Specifically, after iterating between design and validation a few times, we often have competitive off-target models for each design. Subsequent rounds of design could use one of the multi-state design paradigms in Rosetta [10, 11, 12] to selectively destabilize those off-target states.

We're also trying to improve the design models step by using flexible backbone design rather than fixed backbone design. The goal is to allow the backbone to move enough to accommodate all plausible sidechain rotamers, but not enough to significantly change conformation. The protocol we're currently using for this purpose is FastDesign (Listing 2.9), which works by iterating between sidechain rotamer optimization and gradient minimization while ramping the temperature between iterations [13]. The backbone moves slightly because we allow the torsions within the loop to minimize. We have also considered using CoupledMoves [14] as an alternative to FastDesign.

2.3.3 Validate designs

Because we can produce so many more designs ($\approx 200,000$) than we can computationally test (≈ 200), picking which designs to validate is an important task. For the designs described in this chapter, we approached this task in two ways. The first was to simply pick the designs with the lowest scores. This turned out to be inefficient because the lowest scoring designs tended to have very similar sequences (i.e. differing only in inconsequential positions). Repeatedly validating variants of one or two motifs was a waste of our computational resources. Our second approach was to pick designs with a probability proportional to their Boltzmann-weighted score. In other words, we sought to prefer designs with low scores, but not to the exclusion of designs with slightly higher scores. This gave us a better diversity of designs to test.

The drawback to both of the design-picking methods described above is that they only consider score. We are now scoring each design by a variety of metrics, including score, buried unsatisfied H-bonds, E38 rotamer probability, E38 interaction score, exposed hydrophobic surface area, predicted pK_a , and fragment quality (Listing 2.12). We then leverage the information in these metrics by picking the designs that are on the Pareto front. Simply put, a design is on the Pareto front if no other design scores better than it in every metric. This will include the designs that score the best in each individual metric, along with those that score generally well in multiple metrics. Since designs that score well for different reasons tend to have different sequences, this is an excellent way to pick a diverse set of designs to validate.

To get more accurate validation results, we have switched to using fKIC instead of NGK for these simulations (Listing 2.10). In addition to being a better algorithm for sampling secondary

structure, fKIC also substantially outperforms NGK on a difficult 16-residue loop modeling benchmark (Roland Pache & Xingjie Pan, personal communication). We are also experimenting with validating 10x more designs by performing 10x fewer fKIC simulations for each design. For loop modeling applications, it's necessary to run 500 simulations per loop in order to get accurate predictions for the most difficult loops in our benchmarks. However, other loops can be successfully predicted in just a handful of simulations. For design applications, it may be smarter to focus on the latter kind of loop. We're currently testing whether 50 simulations is enough to identify designs worth testing. Interestingly, with this few simulations, the fragment generation step required by fKIC becomes to be limiting in terms of both time and space. If we built a way to efficiently pick fragments on-the-fly, it might be worth testing as few as 10 fKIC simulations per design.

2.4 Conclusion

We have developed a computational protocol to automate the design of structured loops. Broadly speaking, the protocol has three steps: building models that satisfy the design goal, designing optimized sequences for those models, and computationally validating the designs via loop modeling. In the process of developing this protocol, we gained valuable practical experience on the topic of structured loop design. Although we have not yet executed a successful design, we have promising structural results suggesting that this protocol is capable of designing structured loops.

2.5 Methods

2.5.1 Computational design

Rosetta

The designs described in this chapter were generated using Rosetta version 10b6f2f8e20d70757e6b510def2ddcbeef172538 with the talaris2013 score function.

Input Files

There were two structures of KSI that we could have based our designs on: 8CHO [15] and 1QJG [16]. 8CHO has an empty binding pocket, while 1QJG is binding a substrate analog (equilenin) and has the D38N mutation. Both structures have the same resolution (2.3Å), R_{work} (0.205), and R_{free} (0.271). We chose to start from 1QJG, since we thought it would be valuable to have the ligand in the structure. Even though the active site loop doesn't interact with the ligand directly, we wanted to avoid creating designs that inadvertently occlude the ligand-binding pocket. We created parameters for the equilenin ligand using the `molfile_to_params.py` script distributed with Rosetta (Listing 2.1,2.2). KSI is an obligate dimer, so we included both monomers in our initial structure. To design two different loop lengths, we created two versions of the initial structure: one with a deletion and one without. Finally, we replaced N38 with E38 by hand and relaxed the resulting models in the `talaris2013` score function using FastRelax, with only sidechain degrees-of-freedom allowed to move.

The desired position of the E38 sidechain was expressed in a restraint file (Listing 2.5). Each atom in the E38 carboxylate group was restrained to the position of the corresponding atom in the N38 amide group in the structure we began from (1QJG). We visually confirmed that N38 in 1QJG has the same rotameric conformation as D38 in 8CHO.

The residues being remodeled were expressed in loop files (Listing 2.6,2.7). There are two loop files because we designed two different loop lengths. We chose which residues to remodel using our intuition. Our goals were to provide adequate room for remodeling on either side of E38, while minimizing loop length to improve the accuracy of loop modeling. The loops we chose were 13 and 12 residue long. For comparison, NGK has been shown to predict 12-residue loops with sub-angstrom accuracy [8].

The residues that were allowed to design and repack were specified in a resfile (Listing 2.3,2.4). There are two resfiles because we designed two different loop lengths, and changing the loop length changes the indices of all the other residues in the protein. Any residue that had a sidechain atom within 4Å or 6Å of any loop atom in any model generated in the "Build models" step was allowed to design or repack, respectively. F54, A114, and F116 were not allowed to design because they are known to be important for positioning the catalytic residue. Each designed residue was

allowed become any of the 20 canonical amino acids except cysteine (due to the potential for disulfide bonds) and histidine (due to the potential for pH-dependent behavior).

Note that the inputs described above are out-of-date. As we've continued to work on remodeling the KSI active site loop, we've changed which algorithms we use, which atom we restrain, which loops we remodel, which residues we design and repack, etc. The most recent input files are available from the following repository: https://github.com/Kortemme-Lab/ksi_inputs.git. Furthermore, the specific input files used in this chapter (including the PDB files) and listed in the appendix can be found in the 3967a341318008b2c614ba43164d5c82bc0f50b1 commit of this repository, in the subdirectories labeled "v1" (where relevant).

Build models

We created models satisfying the design goal by running 10,000 next generation KIC [8] simulations (Listing 2.17) with restraints as described above (Listing 2.5). Backbone remodeling was limited to the loop defined in the appropriate file (Listing 2.6,2.7) and design was allowed according to the appropriate resfile (Listing 2.3,2.4). The initial coordinates of the loop being remodeled were discarded and rebuilt from scratch. Only models that put all three restrained atoms within 0.6Å of their intended positions were carried on to the next step.

Design models

We used fixed-backbone design to stabilize models that correctly positioned E38. We ran 50 fixbb simulations per model, or more if there were relatively few models (Listing 2.18). Design was allowed according to the appropriate resfile (Listing 2.3,2.4). We picked 50–100 designs to validate with probability proportional to their Boltzmann-weighted talaris2013 scores (in REU).

Validate models

We computationally validated our designs by running 500 NGK simulations for each one (Listing 2.19). Backbone movement was limited to the loop defined in the appropriate file (Listing 2.6,2.7). The initial coordinates for that loop were discarded and rebuilt from scratch. Any design for which the lowest scoring decoy put all three carboxylate atoms within 1.2Å of their intended positions

was carried on to the manual screening step. Furthermore, any decoy at all (regardless of score) that put all three carboxylate atoms within 0.6Å of their intended positions was used as input for a second round of design simulations.

Manual screening

We picked designs to experimentally validate by comparing quality metrics and visually inspecting models. The quality metrics are described in Table 2.6. We paid particular attention to the score gap and the number of buried unsatisfied H-bonds. We also made an effort to pick designs from different clusters. We visually inspected the lowest scoring model for each design to eliminate those with unreasonable backbone or sidechain conformations.

Wildtype reversions

For each design selected for experimental validation, we reran the simulations described in the “Validate models” subsection for each individual wildtype reversion mutation. We then combined any reversions that had no apparent effect and reran the validation simulations again. In cases where the combination of all the individually acceptable reversions had a deleterious effect, we manually picked more conservative combinations of reversions to validate. If no acceptable combination of reversions could be found, no reversions were made (Table 2.7).

2.5.2 Experimental validation

The 14 design chosen for experimental validation were ordered from GenScript pre-cloned into the pET-21a expression vector. Unless otherwise noted, the following protocols are contributed by Lin Liu:

Expression

1. Start a 2 L LB broth culture from an overnight culture (1:100 dilution) with 50 µg/mL carbenicillin

2. Grow to an O.D. of 0.6 (~4 hours) at 37°C. Remove 1 mL aliquot of cells before induction for SDS-PAGE.
3. Induce with 0.5 mM IPTG (1 mL of 1 M IPTG in 2 L LB medium)
4. Grow another 3-4 hours, then remove 1 mL aliquot of cells for SDS-PAGE (post-induction sample).
5. Harvest cells by centrifugation (3500 rpm/20'/4°C)
6. Resuspend in 10-15 mL of lysis buffer: (40 mM Tris-HCl, 1 mM EDTA, 25% sucrose w/v, pH 8.5) Remove 100 µL aliquot for SDS-PAGE.
7. Freeze (unless using immediately)

Harvesting inclusion bodies

1. Thaw cells (if frozen above)
2. Lyse using emulsiflex (4–5 passes with air pressure knob set to 60–80)
3. Centrifuge at 20,000 rpm/20'/4°C in JA-20 rotor with Oakridge tubes.
4. Discard supernatant
5. Solubilize pellet in ~20-25 mL of 20 mM Tris-HCl, 1% sodium deoxycholate, 200 mM NaCl, 2 mM EGTA, pH 8.5 using a dounce. (Can try vortexing the pellet with buffer first before resorting to dounce)
6. Centrifuge at 8,000g/10'/4°C in JA-20 (Oakridge tubes) or conical tube centrifuge (with falcon tubes)
7. Remove 100 µL aliquot of supernatant for SDS-PAGE, then discard rest of supernatant
8. Solubilize pellet in 25 mL of 10 mM Tris-HCl, 0.25% sodium deoxycholate, pH 8.5
9. Centrifuge at 8,000g/5'/4°C.
10. Discard supernatant.

11. Repeat steps 8-10 at least 2x, or until supernatant clear.
12. Solubilize in 25 mL of 20 mM Na-HEPES, 500 mM NaCl, 1 mM EDTA, pH 8.5 to remove detergent.
13. Centrifuge at 8,000g/5'/4°C.
14. Discard supernatant.
15. Repeat steps 12-14 at least 2x, or until supernatant clear.
16. Freeze purified inclusion bodies (unless using immediately)

Solubilizing and refolding inclusion bodies

1. Add 10 mL 8 M urea, 20 mM Na-HEPES, 500 mM NaCl, 1 mM EDTA, pH 8.5, 10 mM DTT (add fresh DTT). Incubate on shaker for 30' to dissolve, or use dounce.
2. Centrifuge at 20,000 rpm/20'/4°C in JA-20 (Oakridge), or 15,000 rpm/15'/4°C in conical tube centrifuge (falcon tubes)
3. Add supernatant to 200 mL 40 mM KPi, 1 mM EDTA, 2 mM DTT while stirring at 4°C. Continue stirring for 1 hour (0.4 M urea final)
4. Filter with 0.4 µm filter (can use 250 mL filter bottle, or syringes. May have to add filter paper on top of bottle attachment to prevent clogs).
5. Save 100 µL aliquot of refolded material for SDS-PAGE.

Purification

1. Pre-equilibrate 5-10 mL deoxycholate affinity column with 40 mM KPi, 1 mM EDTA, 2 mM DTT, pH 7.2
2. Apply filtered refolded enzyme to deoxycholate column by gravity at 4°C. Can use large funnel attached to falcon tube funnel, covered with saran wrap. Will take overnight or longer. Save 100 µL aliquot of flow-through for SDS-PAGE.

3. Wash with 100 mL 400 mM KPi, 1 mM EDTA, 2 mM DTT, pH 7.2 with vacuum manifold.
4. Wash with 50 mL 40 mM KPi, 1 mM EDTA, 2 mM DTT, pH 7.2 with vacuum manifold.
5. Elute with 25 mL 40 mM KPi, 1 mM EDTA, 50% EtOH, 2 mM DTT, pH 7.2. Collect 1 mL fractions, and check using mini-Bradford for protein.
6. Pool fractions that contain protein (If < 6 mL, adjust to 6 mL volume with 50% EtOH buffer).
7. Load on superose 12 size exclusion column:
 - (a) Isocratic 1 mL/min 40 mM KPi, 1 mM EDTA, 2 mM DTT
 - (b) 6 mL injection
 - (c) 128 mL total flow
 - (d) Collect 2 mL fractions after 40 min (so after 40 mL flow-through).
8. Pool fractions containing protein (by absorbance).
9. Concentrate in Amicon Ultra 10 kDa cutoff spin filter units at 3500 rpm/20'/4°C.
10. Store concentrated enzyme at 4°C.

Concentration determination

1. Determine protein concentration by recording (A₂₈₀ - A₃₂₀) for a series of dilutions in 40 mM KPi, 6 M GuHCl, pH 7, and using $\epsilon = 16860 \text{ M}^{-1}\text{cm}^{-1}$ for WT pKSI (use <http://www.basic.northwestern.edu/biotools/proteincalc.html> for other mutants).
2. Typical protocol:
 - (a) Goal is to get all absorbance values between 0.05–1 (preferably 0.1–1).
 - (b) Prepare 1:10 dilution of stock protein in 40 mM KPi.
 - (c) Prepare 0, 10, 20, 30, 40% dilutions of above stock in 40 mM KPi
 - (d) Take 25 μL of each dilution, and add 75 μL of 40 mM KPi, 8 M GuHCl, pH 7.
 - (e) Record absorbance spectra from 240 – 400 nm, blanking with 25 μL 40 mM KPi + 75 μL 40 mM KPi, 8 M GuHCl.

- (f) For an original stock concentration of 2.5 mM WT pKSI, this method will give A280 ~ 0.1 for the lowest protein sample (1:400 net dilution). If protein of interest has smaller ϵ or expected concentration, adjust dilutions accordingly to get A280 between 0.05–1.

Check purity

1. 5% Tris-glycine SDS-PAGE (37.5:1 acrylamide:bis-acrylamide)
2. Before loading, heat all samples (except the MW marker) at 95°C for 5 min.

Typical lanes:

1. Molecular weight (MW) marker
2. Pre-induction
 - (a) Centrifuge 1 mL cells aliquot at 14,000g/5'/4°C.
 - (b) Resuspend cells in 100 μ L of 5x SB, and heat at 95°C for 5 min
 - (c) Load 10 μ L of resuspended cells
3. Post-induction:
 - (a) Prepare as above.
 - (b) Load 10 μ L.
4. Lysate supernatant
 - (a) Centrifuge 100 μ L cell lysate at 14,000g/5'/4°C.
 - (b) Transfer 100 μ L of supernatant into fresh tube.
 - (c) Load 5 μ L of this supernatant + 5 μ L 5x SB.
5. Lysate pellet
 - (a) Resuspend pellet from part (d) above in 100 μ L of 20 mM NaPi, 7 M urea, pH 7.2 (or any high urea buffer)
 - (b) Load 5 μ L of this suspension + 5 μ L 5x SB.

6. 1% DOC wash:

(a) Load 5 μL of DOC wash + 5 μL 5x SB.

7. Refolded enzyme, before affinity step:

(a) Load 15 μL + 5 μL 5x SB (note large loading volume due to huge dilution here).

8. h. Affinity flow-through:

(a) Load 15 μL + 5 μL 5x SB (again note large loading volume).

9. Final protein

(a) If the concentration of the final protein is known, loading 10 μL of 50–100 μM pure protein solution (0.5–1 nmol) should be more than sufficient to see plenty of material by Coomassie without drastic overloading for a 10-lane gel. Adjust volume accordingly for higher concentrations.

(b) If the concentration is unknown, 1–5 mM pure protein solution after final concentration step is typical. Loading 1 μL of 1 mM solution should more than suffice, and loading 1 μL of 2 mM or greater solutions can result in noticeable overloading of lanes. For a publication quality gel, it is probably best to quantify amount of protein first

Activity assay

KSI activity was determined as in [4].

Crystallography

Crystallization buffer: 1.0M $(\text{NH}_4)_2\text{SO}_4$. 2 μL buffer, 2 μL protein (3.5 mg/mL). CRYST1 52.570 52.570 177.910 90.00 90.00 120.00 P 65 2 2. Resolution: 1.97 \AA . $R_{\text{work}} = 0.2658$. $R_{\text{free}} = 0.3159$.

2.6 Appendix

2.6.1 Input Files

Listing 2.1: Centroid-mode parameters for the equilenin ligand.

```

NAME EQU
IO_STRING EQU Z
TYPE LIGAND
AA UNK
ATOM  C10  CAbb  X  -0.09
ATOM  C4   CAbb  X  -0.09
ATOM  C3   CAbb  X  -0.09
ATOM  C2   CAbb  X  -0.09
ATOM  C1   CAbb  X  -0.09
ATOM  O1   OCbb  X  -0.63
ATOM  H1   HNbb  X  0.46
ATOM  C6   CAbb  X  -0.09
ATOM  C5   CAbb  X  -0.09
ATOM  C7   CAbb  X  -0.09
ATOM  C8   CAbb  X  -0.09
ATOM  C9   CAbb  X  -0.09
ATOM  C11  CAbb  X  -0.06
ATOM  C12  CAbb  X  -0.06
ATOM  C13  CAbb  X  -0.15
ATOM  C14  CAbb  X  -0.15
ATOM  C17  CAbb  X  0.65
ATOM  C16  CAbb  X  -0.15
ATOM  C15  CAbb  X  -0.15
ATOM  O2   OCbb  X  -0.73
ATOM  C18  CAbb  X  -0.24
BOND_TYPE  C1  O1  1
BOND_TYPE  C1  C2  4
BOND_TYPE  C1  C6  4
BOND_TYPE  O1  H1  1
BOND_TYPE  C2  C3  4
BOND_TYPE  C3  C4  4
BOND_TYPE  C3  C7  4

```

```

BOND_TYPE C4 C5 4
BOND_TYPE C4 C10 4
BOND_TYPE C5 C6 4
BOND_TYPE C7 C8 4
BOND_TYPE C8 C9 4
BOND_TYPE C9 C10 4
BOND_TYPE C9 C11 1
BOND_TYPE C10 C14 1
BOND_TYPE C11 C12 1
BOND_TYPE C11 C15 1
BOND_TYPE C12 C13 1
BOND_TYPE C12 C17 1
BOND_TYPE C12 C18 1
BOND_TYPE C13 C14 1
BOND_TYPE C15 C16 1
BOND_TYPE C16 C17 1
BOND_TYPE C17 O2 2
CHI 1 C2 C1 O1 H1
PROTON_CHI 1 SAMPLES 2 0 180 EXTRA 1 20
NBR_ATOM C10
NBR_RADIUS 6.457284
ICoor_INTERNAL C10 0.000000 0.000000 0.000000 C10 C4 C3
ICoor_INTERNAL C4 0.000000 180.000000 1.418226 C10 C4 C3
ICoor_INTERNAL C3 0.000000 60.891172 1.489702 C4 C10 C3
ICoor_INTERNAL C2 -179.653613 59.343553 1.418490 C3 C4 C10
ICoor_INTERNAL C1 0.206150 62.634983 1.387028 C2 C3 C4
ICoor_INTERNAL O1 179.723817 63.181116 1.286966 C1 C2 C3
ICoor_INTERNAL H1 0.131327 60.000772 0.936981 O1 C1 C2
ICoor_INTERNAL C6 -179.865025 58.144838 1.432274 C1 C2 O1
ICoor_INTERNAL C5 -0.054123 58.255220 1.379395 C6 C1 C2
ICoor_INTERNAL C7 179.848594 58.760349 1.444112 C3 C4 C2
ICoor_INTERNAL C8 -0.451279 61.728926 1.438722 C7 C3 C4
ICoor_INTERNAL C9 0.133493 59.739449 1.438572 C8 C7 C3

```


IC00R_INTERNAL	C11	-178.865124	61.637379	1.475424	C9	C8	C7
IC00R_INTERNAL	C12	-152.758365	67.129337	1.548286	C11	C9	C8
IC00R_INTERNAL	C13	-54.167776	68.113044	1.540645	C12	C11	C9
IC00R_INTERNAL	C14	52.841508	67.456988	1.555093	C13	C12	C11
IC00R_INTERNAL	C17	-124.747589	83.656618	1.511318	C12	C11	C13
IC00R_INTERNAL	C16	-31.441534	69.687007	1.576369	C17	C12	C11
IC00R_INTERNAL	C15	-0.413699	79.661791	1.576716	C16	C17	C12
IC00R_INTERNAL	O2	179.877290	56.474680	1.205589	C17	C12	C16
IC00R_INTERNAL	C18	-110.972689	67.126267	1.544635	C12	C11	C17

Listing 2.2: Fullatom-mode parameters for the equilenin ligand.

```

NAME EQU
IO_STRING EQU Z
TYPE LIGAND
AA UNK
ATOM C10 aroC X -0.09
ATOM C4 aroC X -0.09
ATOM C3 aroC X -0.09
ATOM C2 aroC X -0.09
ATOM C1 aroC X -0.09
ATOM O1 OH X -0.63
ATOM H1 Hpo1 X 0.46
ATOM C6 aroC X -0.09
ATOM C5 aroC X -0.09
ATOM H3 Haro X 0.14
ATOM H4 Haro X 0.14
ATOM H2 Haro X 0.14
ATOM C7 aroC X -0.09
ATOM C8 aroC X -0.09
ATOM C9 aroC X -0.09
ATOM C11 CH1 X -0.06
ATOM C12 CH1 X -0.06
ATOM C13 CH2 X -0.15

```

ATOM	C14	CH2	X	-0.15
ATOM	H10	Hapo	X	0.12
ATOM	H11	Hapo	X	0.12
ATOM	H8	Hapo	X	0.12
ATOM	H9	Hapo	X	0.12
ATOM	C17	C00	X	0.65
ATOM	C16	CH2	X	-0.15
ATOM	C15	CH2	X	-0.15
ATOM	H12	Hapo	X	0.12
ATOM	H13	Hapo	X	0.12
ATOM	H14	Hapo	X	0.12
ATOM	H15	Hapo	X	0.12
ATOM	O2	OOC	X	-0.73
ATOM	C18	CH3	X	-0.24
ATOM	H16	Hapo	X	0.12
ATOM	H17	Hapo	X	0.12
ATOM	H18	Hapo	X	0.12
ATOM	H7	Hapo	X	0.12
ATOM	H6	Haro	X	0.14
ATOM	H5	Haro	X	0.14
BOND_TYPE	C1	O1	1	
BOND_TYPE	C1	C2	4	
BOND_TYPE	C1	C6	4	
BOND_TYPE	O1	H1	1	
BOND_TYPE	C2	C3	4	
BOND_TYPE	C2	H2	1	
BOND_TYPE	C3	C4	4	
BOND_TYPE	C3	C7	4	
BOND_TYPE	C4	C5	4	
BOND_TYPE	C4	C10	4	
BOND_TYPE	C5	C6	4	
BOND_TYPE	C5	H3	1	
BOND_TYPE	C6	H4	1	

```

BOND_TYPE C7 C8 4
BOND_TYPE C7 H5 1
BOND_TYPE C8 C9 4
BOND_TYPE C8 H6 1
BOND_TYPE C9 C10 4
BOND_TYPE C9 C11 1
BOND_TYPE C10 C14 1
BOND_TYPE C11 C12 1
BOND_TYPE C11 C15 1
BOND_TYPE C11 H7 1
BOND_TYPE C12 C13 1
BOND_TYPE C12 C17 1
BOND_TYPE C12 C18 1
BOND_TYPE C13 C14 1
BOND_TYPE C13 H8 1
BOND_TYPE C13 H9 1
BOND_TYPE C14 H10 1
BOND_TYPE C14 H11 1
BOND_TYPE C15 C16 1
BOND_TYPE C15 H12 1
BOND_TYPE C15 H13 1
BOND_TYPE C16 C17 1
BOND_TYPE C16 H14 1
BOND_TYPE C16 H15 1
BOND_TYPE C17 O2 2
BOND_TYPE C18 H16 1
BOND_TYPE C18 H17 1
BOND_TYPE C18 H18 1
CHI 1 C2 C1 O1 H1
PROTON_CHI 1 SAMPLES 2 0 180 EXTRA 1 20
NBR_ATOM C10
NBR_RADIUS 6.457284
ICOR_INTERNAL C10 0.000000 0.000000 0.000000 C10 C4 C3

```

IC00R_INTERNAL	C4	0.000000	180.000000	1.418226	C10	C4	C3
IC00R_INTERNAL	C3	0.000000	60.891172	1.489702	C4	C10	C3
IC00R_INTERNAL	C2	-179.653613	59.343553	1.418490	C3	C4	C10
IC00R_INTERNAL	C1	0.206150	62.634983	1.387028	C2	C3	C4
IC00R_INTERNAL	O1	179.723817	63.181116	1.286966	C1	C2	C3
IC00R_INTERNAL	H1	0.131327	60.000772	0.936981	O1	C1	C2
IC00R_INTERNAL	C6	-179.865025	58.144838	1.432274	C1	C2	O1
IC00R_INTERNAL	C5	-0.054123	58.255220	1.379395	C6	C1	C2
IC00R_INTERNAL	H3	-179.816263	59.664315	1.031977	C5	C6	C1
IC00R_INTERNAL	H4	-179.999559	60.871901	1.032042	C6	C1	C5
IC00R_INTERNAL	H2	-179.997784	58.684437	1.031961	C2	C3	C1
IC00R_INTERNAL	C7	179.848594	58.760349	1.444112	C3	C4	C2
IC00R_INTERNAL	C8	-0.451279	61.728926	1.438722	C7	C3	C4
IC00R_INTERNAL	C9	0.133493	59.739449	1.438572	C8	C7	C3
IC00R_INTERNAL	C11	-178.865124	61.637379	1.475424	C9	C8	C7
IC00R_INTERNAL	C12	-152.758365	67.129337	1.548286	C11	C9	C8
IC00R_INTERNAL	C13	-54.167776	68.113044	1.540645	C12	C11	C9
IC00R_INTERNAL	C14	52.841508	67.456988	1.555093	C13	C12	C11
IC00R_INTERNAL	H10	94.989030	72.130472	1.070042	C14	C13	C12
IC00R_INTERNAL	H11	122.345167	74.240083	1.069964	C14	C13	H10
IC00R_INTERNAL	H8	-120.456750	71.300890	1.070002	C13	C12	C14
IC00R_INTERNAL	H9	-121.039781	72.329013	1.070015	C13	C12	H8
IC00R_INTERNAL	C17	-124.747589	83.656618	1.511318	C12	C11	C13
IC00R_INTERNAL	C16	-31.441534	69.687007	1.576369	C17	C12	C11
IC00R_INTERNAL	C15	-0.413699	79.661791	1.576716	C16	C17	C12
IC00R_INTERNAL	H12	150.943087	68.073569	1.069962	C15	C16	C17
IC00R_INTERNAL	H13	117.878279	64.756126	1.069995	C15	C16	H12
IC00R_INTERNAL	H14	118.503132	68.296876	1.070046	C16	C17	C15
IC00R_INTERNAL	H15	117.995988	65.280179	1.069947	C16	C17	H14
IC00R_INTERNAL	O2	179.877290	56.474680	1.205589	C17	C12	C16
IC00R_INTERNAL	C18	-110.972689	67.126267	1.544635	C12	C11	C17
IC00R_INTERNAL	H16	-75.495035	70.531520	1.070031	C18	C12	C11
IC00R_INTERNAL	H17	-120.001823	70.529126	1.069978	C18	C12	H16

IC00R_INTERNAL	H18	-119.999702	70.532272	1.069991	C18	C12	H17
IC00R_INTERNAL	H7	-123.199482	82.078338	1.069972	C11	C9	C12
IC00R_INTERNAL	H6	-179.999034	60.128775	1.031975	C8	C7	C9
IC00R_INTERNAL	H5	179.998938	59.135188	1.031969	C7	C3	C8

Listing 2.3: Resfile for the input model with no deletions.

NATRO

START

Design residues in the loop itself. Don't move the catalytic residue,
because we want to find designs which stabilize that rotamer.

34 - 37 A NOTAA HC

38 A NATRO

39 - 46 A NOTAA HC

Design any residue that has a sidechain atom within 4A of any loop atom in
any input model. Phe54, Ala114, and Phe116 are excluded because they are
known to be important for positioning the catalytic residue.

30 A NOTAA HC

31 A NOTAA HC

32 A NOTAA HC

33 A NOTAA HC

47 A NOTAA HC

48 A NOTAA HC

49 A NOTAA HC

50 A NOTAA HC

51 A NOTAA HC

52 A NOTAA HC

53 A NOTAA HC

55 A NOTAA HC

57 A NOTAA HC

58 A NOTAA HC
60 A NOTAA HC
109 A NOTAA HC
110 A NOTAA HC
111 A NOTAA HC
112 A NOTAA HC
113 A NOTAA HC
115 A NOTAA HC
117 A NOTAA HC
118 A NOTAA HC
121 A NOTAA HC
199 B NOTAA HC
200 B NOTAA HC
201 B NOTAA HC
202 B NOTAA HC

Repack any residue that has a sidechain atom within 6A of any loop atom in
any input model.

10 A NATAA
11 A NATAA
13 A NATAA
14 A NATAA
15 A NATAA
16 A NATAA
17 A NATAA
18 A NATAA
23 A NATAA
26 A NATAA
27 A NATAA
29 A NATAA
54 A NATAA
56 A NATAA

59	A NATAA
61	A NATAA
63	A NATAA
77	A NATAA
78	A NATAA
79	A NATAA
80	A NATAA
81	A NATAA
82	A NATAA
84	A NATAA
86	A NATAA
93	A NATAA
95	A NATAA
96	A NATAA
97	A NATAA
98	A NATAA
99	A NATAA
100	A NATAA
101	A NATAA
102	A NATAA
103	A NATAA
104	A NATAA
108	A NATAA
114	A NATAA
116	A NATAA
119	A NATAA
120	A NATAA
122	A NATAA
123	A NATAA
127	B NATAA
129	B NATAA
132	B NATAA
197	B NATAA

```
198      B NATAA
203      B NATAA
204      B NATAA
205      B NATAA
224      B NATAA
225      B NATAA
226      B NATAA
227      B NATAA
228      B NATAA
234      B NATAA
235      B NATAA
236      B NATAA
237      B NATAA
238      B NATAA
239      B NATAA
```

Listing 2.4: Resfile for the input model with one deletion.

```
NATRO
START
```

```
# Design residues in the loop itself.  Don't move the catalytic residue,
# because we want to find designs which stabilize that rotamer.
```

```
34 - 37    A NOTAA HC
38         A NATRO
39 - 45    A NOTAA HC
```

```
# Design any residue that has a sidechain atom within 4A of any loop atom in
# any input model.  Phe53, Ala113, and Phe115 are excluded because they are
# known to be important for positioning the catalytic residue.
```

```
29         A NOTAA HC
30         A NOTAA HC
```


31 A NOTAA HC
32 A NOTAA HC
33 A NOTAA HC
46 A NOTAA HC
48 A NOTAA HC
49 A NOTAA HC
50 A NOTAA HC
52 A NOTAA HC
54 A NOTAA HC
56 A NOTAA HC
57 A NOTAA HC
108 A NOTAA HC
109 A NOTAA HC
110 A NOTAA HC
111 A NOTAA HC
112 A NOTAA HC
114 A NOTAA HC
116 A NOTAA HC
117 A NOTAA HC
120 A NOTAA HC
198 B NOTAA HC
199 B NOTAA HC
200 B NOTAA HC
201 B NOTAA HC

Repack any residue that has a sidechain atom within 6A of any loop atom in
any input model.

10 A NATAA
11 A NATAA
13 A NATAA
14 A NATAA
15 A NATAA

16	A NATAA
17	A NATAA
18	A NATAA
23	A NATAA
26	A NATAA
27	A NATAA
28	A NATAA
47	A NATAA
51	A NATAA
53	A NATAA
55	A NATAA
58	A NATAA
59	A NATAA
60	A NATAA
62	A NATAA
76	A NATAA
77	A NATAA
78	A NATAA
79	A NATAA
80	A NATAA
81	A NATAA
83	A NATAA
85	A NATAA
92	A NATAA
94	A NATAA
95	A NATAA
96	A NATAA
97	A NATAA
98	A NATAA
99	A NATAA
100	A NATAA
101	A NATAA
102	A NATAA

103 A NATAA
107 A NATAA
113 A NATAA
115 A NATAA
118 A NATAA
119 A NATAA
121 A NATAA
122 A NATAA
126 B NATAA
128 B NATAA
131 B NATAA
196 B NATAA
197 B NATAA
202 B NATAA
203 B NATAA
204 B NATAA
223 B NATAA
224 B NATAA
225 B NATAA
226 B NATAA
227 B NATAA
233 B NATAA
234 B NATAA
235 B NATAA
236 B NATAA
237 B NATAA
238 B NATAA

Listing 2.5: Harmonic restraints reflecting the design goal

```
CoordinateConstraint OE1 38 CA 1 17.895 73.085 10.634 HARMONIC 0.0 1.0  
CoordinateConstraint OE2 38 CA 1 19.471 74.505 10.507 HARMONIC 0.0 1.0  
CoordinateConstraint CG 38 CA 1 20.090 72.256 10.794 HARMONIC 0.0 0.707
```

Listing 2.6: Loop positions for the input model with no deletions.

```
LOOP 34 46 46 0 1
```

Listing 2.7: Loop positions for the input model with one deletion.

```
LOOP 34 45 45 0 1
```

Listing 2.8: The most recent version of the "build models" step.

```
<ROSETTASCRIPTS>

  {% include "shared_defs.xml" %}

<TASKOPERATIONS>
  <RestrictToRepacking name="repackonly"/>
</TASKOPERATIONS>

<MOVERS>
  <LoopModeler name="modeler"
    config="loophash_kic"
    scorefxn_fa="scorefxn_cst"
    task_operations="resfile, repackonly, ex, aro, curr"
    loops_file="{{ w.loops_path }}"
    loophash_perturb_sequence="yes"
    loophash_seqposes_no_mutate="38"
    fast="{{ 'yes' if test_run else 'no' }}"
  />
</MOVERS>

<PROTOCOLS>
  <!-- Constraints read from command line -->
  <Add mover_name="modeler"/>
  <Add mover_name="writer"/>
</PROTOCOLS>

<OUTPUT scorefxn="scorefxn"/>
```

```
</ROSETTASCRIPTS>
```

Listing 2.9: The most recent version of the "design models" step.

```
<ROSETTASCRIPTS>
```

```
{% include "shared_defs.xml" %}
```

```
<RESIDUE_SELECTORS>
```

```
  <Index name="turn" resnums="199-200"/>
```

```
</RESIDUE_SELECTORS>
```

```
<TASKOPERATIONS>
```

```
  <LayerDesign name="layer"
```

```
    ignore_pikaa_natro="yes"/>
```

```
  <ConsensusLoopDesign name="abego"
```

```
    residue_selector="turn"
```

```
    include_adjacent_residues="no"/>
```

```
</TASKOPERATIONS>
```

```
<MOVERS>
```

```
  <AtomTree name="foldtree" fold_tree_file="{ { w.find_path('foldtree') } }"/>
```

```
  <AtomTree name="unfoldtree" simple_ft="yes"/>
```

```
  <AddChainBreak name="break_loop" resnum="39" change_foldtree="no"/>
```

```
  <AddChainBreak name="break_turn" resnum="199" change_foldtree="no"/>
```

```
  <FastDesign name="fastdesign"
```

```
    task_operations="resfile,layer,abego,ex,aro,curr"
```

```
    scorefxn="scorefxn_cst" >
```

```
  <MoveMap bb="no" chi="yes" jump="no">
```

```
    <Span begin="26" end="50" chi="yes" bb="yes"/>
```

```
    <Span begin="197" end="202" chi="yes" bb="yes"/>
```

```
  </MoveMap>
```

```
</FastDesign>
```

```
</MOVERS>
```

```
<PROTOCOLS>
```

```
<Add mover_name="nativebonus"/>
```

```
<Add mover_name="cst"/> <!-- Added via mover b/c command-line ignored. -->
```

```
<Add mover_name="foldtree"/>
```

```
<Add mover_name="break_loop"/>
```

```
<Add mover_name="break_turn"/>
```

```
<Add mover_name="fastdesign"/>
```

```
<Add mover_name="unfoldtree"/> <!-- Otherwise Foldability segfaults. -->
```

```
<Add mover_name="writer"/>
```

```
</PROTOCOLS>
```

```
<OUTPUT scorefxn="scorefxn"/>
```

```
</ROSETTASCRIPTS>
```

Listing 2.10: The most recent version of the "validate designs" step.

```
<ROSETTASCRIPTS>
```

```
{% include "shared_defs.xml" %}
```

```
<MOVERS>
```

```
<LoopModeler name="modeler"
```

```
  config="kic_with_fragments"
```

```
  scorefxn_fa="scorefxn"
```

```
  loops_file="{{ w.loops_path }}"
```

```
  fast="{{ 'yes' if test_run else 'no' }}">
```

```
    <Build skip="yes"/>
```

```
</LoopModeler>
```

```
</MOVERS>
```

```
<PROTOCOLS>
```

```

    <Add mover_name="modeler"/>
    <Add mover_name="writer"/>
</PROTOCOLS>

<OUTPUT scorefxn="scorefxn"/>

</ROSETTASCRIPTS>

```

Listing 2.11: Shared RosettaScript elements for the above steps.

```

{% include "filters.xml" %}

<SCOREFXNS>
  <ScoreFunction name="scorefxn" weights="{{ w.scorefxn_path }}" />
  <ScoreFunction name="scorefxn_cst" weights="{{ w.scorefxn_path }}" />
    <Reweight scoretype="coordinate_constraint" weight="1.0" />
    <Reweight scoretype="atom_pair_constraint" weight="1.0" />
    <Reweight scoretype="angle_constraint" weight="1.0" />
    <Reweight scoretype="dihedral_constraint" weight="1.0" />
    <Reweight scoretype="res_type_constraint" weight="1.0" />
    <Reweight scoretype="chainbreak" weight="100.0" />
  </ScoreFunction>
</SCOREFXNS>

<RESIDUE_SELECTORS>
  <Chain name="chA" chains="A" />
  <Index name="E38" resnums="38" />
</RESIDUE_SELECTORS>

<TASKOPERATIONS>
  <ReadResfile name="resfile" />
  <ExtraRotamersGeneric name="ex" ex1="yes" ex2="yes" extrachi_cutoff="0" />
  <LimitAromaChi2 name="aro" include_trp="yes" />
  <IncludeCurrent name="curr" />

```

```
</TASKOPERATIONS>
```

```
<MOVERS>
```

```
<FavorNativeResidue name="nativebonus" />
```

```
<ConstraintSetMover name="cst" cst_fa_file="{ w.restraints_path }"/>
```

```
<WriteFiltersToPose name="writer" prefix="EXTRA_METRIC "/>
```

```
</MOVERS>
```

Listing 2.12: Score metrics calculated in the above steps.

```
<FILTERS>
```

```
<PackStat
```

```
name="PackStat Score [+]"
```

```
threshold="0"
```

```
chain="0"
```

```
repeats="1"
```

```
/>
```

```
<ResidueIE
```

```
name="E38 Interaction Energy [-|REU]"
```

```
scorefxn="scorefxn_cst"
```

```
score_type="total_score"
```

```
energy_cutoff="-10"
```

```
restype3="GLU"
```

```
interface="0"
```

```
whole_pose="0"
```

```
selector="E38"
```

```
jump_number="1"
```

```
interface_distance_cutoff="8.0"
```

```
max_penalty="1000.0"
```

```
penalty_factor="1.0"
```

```
/>
```

```
<PreProline
```

```
name="Pre-Proline Potential [-]"
```

```
use_statistical_potential="true"
```



```

/>
<TotalSasa
  name="Total SASA [-|Å²]"
  threshold="0"
  upper_threshold="10000000000000000"
  hydrophobic="0"
  polar="0"
/>
<ExposedHydrophobics
  name="Exposed Hydrophobic Residue SASA [-|Å²]"
  sasa_cutoff="20"
  threshold="-1"
/>
<HbondsToResidue
  name="H-bonds to E38 [+|#]"
  scorefxn="scorefxn_cst"
  partners="0"
  energy_cutoff="-0.5"
  backbone="true"
  bb_bb="true"
  sidechain="true"
  residue="38"
  from_other_chains="true"
  from_same_chain="true"
/>
<HbondsToResidue
  name="H-bonds to E38 (Backbone) [+|#]"
  scorefxn="scorefxn_cst"
  partners="0"
  energy_cutoff="-0.5"
  backbone="true"
  bb_bb="true"
  sidechain="false"

```

```

    residue="38"
    from_other_chains="true"
    from_same_chain="true"
  />
  <HbondsToResidue
    name="H-bonds to E38 (Sidechain) [ +|#]"
    scorefxn="scorefxn_cst"
    partners="0"
    energy_cutoff="-0.5"
    backbone="false"
    bb_bb="false"
    sidechain="true"
    residue="38"
    from_other_chains="true"
    from_same_chain="true"
  />
  <BuriedUnsatHbonds
    name="Buried Unsatisfied H-Bonds [ -|#]"
    scorefxn="scorefxn"
    print_out_info_to_pdb="true"
    task_operations="resfile"
  />
  <OversaturatedHbondAcceptorFilter
    name="Oversaturated H-bonds [ -|#]"
    scorefxn="scorefxn_cst"
    max_allowed_oversaturated="0"
    hbond_energy_cutoff="-0.5"
    consider_mainchain_only="false"
  />
  <RepackWithoutLigand
    name="Repack Without Ligand  $\Delta$ [ -|REU]"
    scorefxn="scorefxn_cst"
    target_res="all_repacked"

```

```

    rms_threshold="100"
  />
{% if w.focus_name != 'validate_designs' %}
<Foldability
  name="Foldability (35-41) [+]"
  tries="60"
  start_res="35"
  end_res="41"
/>
<Foldability
  name="Foldability (37-44) [+]"
  tries="60"
  start_res="37"
  end_res="44"
/>
{% endif %}
<FragmentScoreFilter name="Max 9-Residue Fragment  $\alpha$ C RMSD [-|Å]"
  scoretype="FragmentCrmsd"
  sort_by="FragmentCrmsd"
  threshold="9999"
  direction="-"
  start_res="{{ w.largest_loop.start }}"
  end_res="{{ w.largest_loop.end }}"
  compute="maximum"
  outputs_folder="{{ w.seqprof_dir }}"
  outputs_name="%%job_id%%"
  csblast="/netapp/home/krivacic/software/csblast-2.2.3_linux64"
  blast_pgp="/netapp/home/klabqb3backrub/tools/blast-2.2.26/bin/blastpgp"
  placeholder_seqs="/netapp/home/xingjiepan/Databases/BLAST/placeholder/placeholder_seqs"
  psipred="/netapp/home/xingjiepan/Softwares/parametric_scaffold_design/dependencies/dep
  sparks-x="/netapp/home/klabqb3backrub/tools/sparks-x"
  sparks-x_query="/netapp/home/klabqb3backrub/tools/sparks-x/bin/buildinp_query.sh"
  frags_scoring_config="{{ w.fragment_weights_path }}"

```

```

    n_fragments="200"
    n_candidates="1000"
    fragment_size="9"
    vall_path="{{ w.rosetta_vall_path(test_run) }}"
  />
</FILTERS>

```

Listing 2.13: Most recent resfile, for the input model with no deletions.

```

NATRO
START

# Design positions
# =====
# This resfile simply encompasses the whole active site loop, the beta
# strand leading up to it, and the turn on the opposite monomer. Compared to
# our previous resfile, this one allows two more positions to design on each
# side of the active site loop, which we hope will lead to design models that
# better satisfy the constraints:
#
# Positions 35+37: Previously we excluded these positions because they're
# pointing into solvent and clearly not affecting the active site loop.
# Despite that, we now think that the more important thing is to create a more
# diverse set of backbones in the initial model building step. Allowing
# loophash to design the whole loop should help accomplish that. We'll use
# LayerDesign in the next step to make sure we still end up with greasy
# residues on the inside and polar one on the outside.
#
# Positions 45+46: Design the active site loop up to G47. We don't think it
# would be wise to include G47 in the design, since it seems to be responsible
# for breaking the  $\alpha$ -helix at position 48. Previously we stopped at position
# 44 in hopes of keeping its salt-bridge with E53, but Rosetta usually got rid
# of that interaction anyways.
#

```

```
# We'll be using LayerDesign and ConsensusLoopDesign to restrict which residues
# can go where, so the only thing we're specifying here is `NOTAA CH`. We
# never want cysteine because it can mess up the global fold by forming
# unexpected disulfides, and we never want histidine because it's behavior can
# be pH dependent.
```

```
34      A NOTAA CH
35      A NOTAA CH
36      A NOTAA CH
37      A NOTAA CH
38      A PIKAA E
39      A NOTAA CH
40      A NOTAA CH
41      A NOTAA CH
42      A NOTAA CH
43      A NOTAA CH
44      A NOTAA CH
45      A NOTAA CH
46      A NOTAA CH
199     B NOTAA CH
200     B NOTAA CH
201     B NOTAA CH
202     B NOTAA CH
```

```
# Repack positions
```

```
# =====
```

```
# The following repack positions were chosen by the clash-based repack
# shell creator (excluding the ligand).
```

```
14      A NATAA
30      A NATAA
50      A NATAA
51      A NATAA
```

54 A NATAA
55 A NATAA
95 A NATAA
109 A NATAA
111 A NATAA
112 A NATAA
113 A NATAA
114 A NATAA
115 A NATAA
116 A NATAA
121 A NATAA
127 B NATAA
204 B NATAA
225 B NATAA
227 B NATAA

The following repack positions were added after visual inspection of
clash-based repack shell.

10 A NATAA
13 A NATAA
17 A NATAA
25 A NATAA
52 A NATAA
53 A NATAA
56 A NATAA
57 A NATAA
58 A NATAA
108 A NATAA
110 A NATAA
117 A NATAA
118 A NATAA
126 B NATAA

```
128      B NATAA
228      B NATAA
```

Listing 2.14: Most recent resfile, for the input model with one deletion.

```
NATRO
START

# Design positions
# =====
# This resfile simply encompasses the whole active site loop, the beta
# strand leading up to it, and the turn on the opposite monomer. Compared to
# our previous resfile, this one allows two more positions to design on each
# side of the active site loop, which we hope will lead to design models that
# better satisfy the constraints:
#
# Positions 35+37: Previously we excluded these positions because they're
# pointing into solvent and clearly not affecting the active site loop.
# Despite that, we now think that the more important thing is to create a more
# diverse set of backbones in the initial model building step. Allowing
# loophash to design the whole loop should help accomplish that. We'll use
# LayerDesign in the next step to make sure we still end up with greasy
# residues on the inside and polar one on the outside.
#
# Positions 44+45: Design the active site loop up to G46. We don't think it
# would be wise to include G46 in the design, since it seems to be responsible
# for breaking the  $\alpha$ -helix at position 47. Previously we stopped at position
# 43 in hopes of keeping its salt-bridge with E52, but Rosetta usually got rid
# of that interaction anyways.
#
# We'll be using LayerDesign and ConsensusLoopDesign to restrict which residues
# can go where, so the only thing we're specifying here is `NOTAA CH`. We
# never want cysteine because it can mess up the global fold by forming
# unexpected disulfides, and we never want histidine because it's behavior can
```

be pH dependent.

34 A NOTAA CH
35 A NOTAA CH
36 A NOTAA CH
37 A NOTAA CH
38 A PIKAA E
39 A NOTAA CH
40 A NOTAA CH
41 A NOTAA CH
42 A NOTAA CH
43 A NOTAA CH
44 A NOTAA CH
45 A NOTAA CH
198 B NOTAA CH
199 B NOTAA CH
200 B NOTAA CH
201 B NOTAA CH

Repack positions

=====

The following repack positions were chosen by the clash-based repack
shell creator (excluding the ligand).

14 A NATAA
30 A NATAA
49 A NATAA
50 A NATAA
53 A NATAA
54 A NATAA
94 A NATAA
108 A NATAA
110 A NATAA


```
111    A NATAA
112    A NATAA
113    A NATAA
114    A NATAA
115    A NATAA
120    A NATAA
126    B NATAA
203    B NATAA
224    B NATAA
226    B NATAA
```

```
# The following repack positions were added after visual inspection of
# clash-based repack shell.
```

```
10     A NATAA
13     A NATAA
17     A NATAA
25     A NATAA
51     A NATAA
52     A NATAA
55     A NATAA
56     A NATAA
57     A NATAA
107    A NATAA
109    A NATAA
116    A NATAA
117    A NATAA
125    B NATAA
127    B NATAA
227    B NATAA
```

Listing 2.15: Most recent loop file, for the input model with no deletions.

```
LOOP 26 51 40 0 0
```

```
LOOP 198 203 200 0 0
```

Listing 2.16: Most recent loop file, for the input model with one deletion.

```
LOOP 26 50 40 0 0
```

```
LOOP 197 202 199 0 0
```

2.6.2 Command lines

Below are the command lines that were used at each step of the PIP protocol. The following variables are placeholders for different input paths and parameters:

\$ROSETTA Path to a Rosetta installation.

\$ROSETTA_BUILD OS, compiler, and options used to build Rosetta, e.g. `linuxclangrelease`

\$INPUT_PDB The input structure for the current step, e.g. an output structure from the previous step.

\$NATIVE_PDB The structure of KSI D38E, with the native active site loop geometry.

\$RESFILE The residues that are allowed to mutate.

\$RESTRAINT The target coordinates for the E38 carboxylate.

\$LOOP The region of backbone that was remodeled.

Listing 2.17: Command-line used for the build models step.

```
$ROSETTA/source/bin/loopmodel.$ROSETTA_BUILD \
  -in:file:s $INPUT_PDB \
  -in:file:native $NATIVE_PDB \
  -in:file:extra_res_fa "EQU.fa.params" \
  -in:file:extra_res_cen "EQU.cen.params" \
  -in:file:fullatom \
  -out:overwrite \
  -out:pdb_gz \
  -packing:ex1 \
  -packing:ex2 \
```

```

-packing:extrachi_cutoff 0 \
-packing:resfile $RESFILE \
-constraints:cst_fa_weight 1.0 \
-constraints:cst_fa_file $RESTRAINT \
-loops:loop_file $LOOP \
-loops:remodel "perturb_kic" \
-loops:refine "refine_kic" \
-loops:kic_rama2b \
-loops:kic_omega_sampling \
-loops:allow_omega_move "true" \
-loops:ramp_fa_rep \
-loops:ramp_rama \

```

Listing 2.18: Command-line used for the design models step.

```

$ROSETTA/source/bin/fixbb.$ROSETTA_BUILD \
-in:file:s $INPUT_PDB \
-in:file:extra_res_fa "EQU.fa.params" \
-in:file:extra_res_cen "EQU.cen.params" \
-out:overwrite \
-out:pdb_gz \
-packing:ex1 \
-packing:ex2 \
-packing:extrachi_cutoff 0 \
-packing:use_input_sc \
-packing:resfile $RESFILE \

```

Listing 2.19: Command-line used for the validate designs step.

```

$ROSETTA/source/bin/loopmodel.$ROSETTA_BUILD \
-in:file:s $INPUT_PDB \
-in:file:native $NATIVE_PDB \
-in:file:extra_res_fa "EQU.fa.params" \
-in:file:extra_res_cen "EQU.cen.params" \
-in:file:fullatom \

```

```
-out:pdb_gz \
-out:overwrite \
-packing:ex1 \
-packing:ex2 \
-packing:extrachi_cutoff 0 \
-loops:loop_file $LOOPS \
-loops:remodel "perturb_kic" \
-loops:refine "refine_kic" \
-loops:kic_rama2b \
-loops:kic_omega_sampling \
-loops:ramp_fa_rep \
-loops:ramp_rama \
```

2.6.3 Manual screening

Design	# Del	Round	Number	Loop Sequence	Loop Cluster	COOH Offset (Å)	Score Gap (REU)	% Sub-Å Offset	pKa	Δ Buried Unsat
	0	2	49	AKWEELLSVPIYP	1	0.75	-5.97	2.80	10.02	14
	0	1	68	AKWEELLDVPIYP	1	0.98	-3.55	0.80	9.82	14
	0	2	33	AEFKEQIPGQVGR	2	1.10	-6.09	2.20	7.81	6
	0	1	35	ARFEEQIPGQVGQ	2	0.51	-4.79	0.60	9.10	7
	0	2	32	AEFVEQIPGQIGR	2	1.09	-3.20	5.20	9.92	7
	0	1	29	ARFEEQIPGMVGQ	2	1.15	-0.15	1.60	7.68	10
D	0	1	87	AIRRERYAKANPR	3	0.67	-2.91	1.20	5.74	8
	0	1	83	AWTYEYIGPPGGN	4	1.18	-1.63	0.40	9.13	3
	0	2	30	A EVTETKYPEPRR	5	0.69	-3.47	5.20	9.17	1
E	0	2	1	AKVIETQYPEPRK	5	0.68	-6.56	6.60	9.11	2
	0	2	5	A EVIETQYPEPRR	5	0.70	-1.71	8.00	9.34	2
	0	2	10	A EVTETKYPEPRR	5	0.78	-4.09	4.80	9.14	2
	0	2	29	AKVTETKYPLPMK	5	0.87	-5.82	3.80	8.63	2
G	0	2	9	ARVEETKYPEDRK	5	0.94	-13.76	0.80	8.76	2
	0	2	6	A EVIETQYPEPRR	5	0.66	-10.14	7.00	9.07	3
	0	2	8	A EVIETQYPYPKR	5	0.68	-8.51	8.82	8.92	3
	0	2	22	AKVTETMYPEPRK	5	0.71	-7.68	6.60	9.15	3
	0	2	17	AKVTETKYPEPRK	5	0.77	-7.89	7.00	8.94	3
	0	1	22	AKVTETKYPEDRK	5	0.78	-6.87	2.61	9.05	3
	0	1	17	AKVTETKYPEDRK	5	0.81	-3.35	6.01	9.03	3
	0	2	27	A EVTETKYPEPRR	5	0.91	-6.50	2.61	8.79	3
	0	2	16	ASVTETKYPEDRT	5	0.99	-8.92	5.60	8.81	3
F	0	2	4	AKVIETQYPEPRK	5	0.66	-11.96	7.41	8.96	4
	0	2	0	A EVRETQYPEDRR	5	0.72	-10.74	5.40	8.94	4
	0	2	7	AKVIETQYPEPRK	5	0.82	-6.95	8.40	8.88	4
	0	2	12	AKVTETKYPEPRK	5	0.93	-7.47	5.80	8.72	4
	0	2	39	A EVTETQYPTNFR	5	0.65	-1.27	10.60	8.95	5
	0	2	15	AKVRETKYPEPRK	5	0.97	-10.38	4.40	8.79	5
	0	2	25	AKVIETQYPYDFQ	5	0.61	-5.44	13.20	9.32	6
	0	2	3	ARVEETQYPEDRK	5	0.64	-10.55	4.21	8.96	6
	0	2	44	AKVTETKYPTDFK	5	0.65	-2.39	8.40	9.08	6
	0	2	41	AKVTETKYPTDFK	5	0.81	-3.07	13.43	8.75	6
	0	2	2	A EVIETQYPEPRR	5	1.05	-9.11	9.22	8.70	6
	0	2	46	ASVIETKYPNDYT	5	0.64	-5.35	9.20	9.15	7
	0	2	28	AKVIETQYPYDFK	5	0.71	-2.52	13.20	9.29	7
	0	2	42	AKVIETKYPNDYK	5	0.83	-5.20	11.00	8.76	8
	0	2	24	AKVIETKYPYDFQ	5	0.79	-9.21	16.83	8.74	9
	0	2	34	AKVIETKYPYDFQ	5	0.81	-6.42	16.80	8.80	9
	0	2	36	AKVIETKYPNDYK	5	0.77	-5.35	12.25	8.81	11
A	0	1	6	AYVEESAGQPKYW	6	1.05	-0.32	0.60	7.68	4
	0	1	54	ARVWEGGLTQWYK	7	1.09	-0.13	1.80	8.58	10
	0	1	59	A QVVESFYRGWPP	8	0.91	-3.82	12.60	8.54	11
	0	2	21	AFWYELTDYPWYP	9	0.87	-7.69	18.18	8.85	9
	0	2	31	AFWYELTDYPWYP	9	0.77	-7.70	15.20	9.07	10
	0	2	26	AFYYELTDKPWYP	9	0.95	-10.72	10.40	6.88	10
	0	2	14	AFWYENTDKPWYP	9	0.77	-0.34	10.04	8.91	11
	0	1	44	ANYTESQNPDIRG	10	1.04	-3.42	1.20	7.33	8
B	0	1	25	AKVTEDAGLGGYQ	11	0.86	-1.64	7.41	8.66	2
	0	1	38	GWLEEQYGYWKYS	12	1.17	-5.27	1.60	9.82	10
	0	1	81	GYRREQNGFWKYT	12	0.87	-2.88	1.00	6.37	12
	0	1	37	GRREEQFGWENYS	12	1.01	-7.26	1.20	6.27	14
	0	2	38	A EWNEQFGWRGNP	13	0.53	-2.28	1.40	9.14	9
	0	1	10	AIWNEQYGWRGRP	13	0.61	-3.21	1.20	8.85	9
C	0	1	47	ARRNEIGGPPPLP	14	0.92	-1.30	3.20	6.76	6
	0	1	74	ARYNEPYFDRDEK	15	0.73	-3.46	3.60	8.65	9
	0	1	73	AFYYEYNWGTWRP	16	0.89	-6.29	0.60	7.13	15
	0	2	47	AFYYESNSGDWYP	17	1.18	-0.23	1.00	6.81	10
	0	1	91	A ELGEGEDTGIPR	18	1.13	-2.11	0.00	8.68	6
	0	1	56	ADSPEGGPWSSYR	19	0.71	-0.23	0.60	7.90	5

Design	# Del	Round	Number	Loop Sequence	Loop Cluster	COOH Offset (Å)	Score Gap (REU)	% Sub-Å Offset	pKa	Δ Buried Unsats
	1	1	82	GRADENGTGYK	1	0.74	-0.99	2.20	7.83	12
	1	1	86	AQFDEGDQGWPN	2	0.96	-0.34	1.20	8.65	6
	1	1	60	GYRDELKYPPLP	3	0.89	-3.95	2.00	6.29	8
	1	1	61	ARYEEQYPPKE	3	0.48	-1.37	1.81	7.71	9
	1	1	66	ARYEELYFPPLP	3	0.80	-0.85	3.40	7.41	9
	1	1	78	ARYEEQYFPPLS	3	0.46	-2.69	2.20	7.31	10
N	1	2	46	AQYNEIGFPGGS	4	0.58	-1.95	12.42	7.82	6
	1	2	44	AQYNEIGFRGDS	4	0.33	-4.30	17.80	7.75	7
	1	2	5	ARYIERGFNPQP	4	0.43	-2.88	20.64	7.43	7
	1	2	43	AKYIERGFNPPLP	4	0.56	-0.55	18.67	7.33	7
	1	2	23	AQYVEEGFPNLP	4	0.95	-2.22	23.80	9.84	7
	1	2	38	AQYVERGFNKP	4	0.30	-0.70	20.64	7.55	8
	1	1	67	AQYDEIGFRGDS	4	0.40	-4.78	12.40	7.30	8
	1	2	30	AQYNEIGFRGDS	4	0.38	-3.34	18.40	7.70	9
	1	2	11	AQYVERGFNPPLP	4	0.50	-1.24	22.24	7.43	9
	1	2	34	AQYDEIGFRGDP	4	0.66	-2.48	25.90	7.27	9
	1	2	40	ARYVEEGFPNLP	4	0.86	-1.12	22.24	9.61	9
	1	2	20	AQYVERGFNPNP	4	0.30	-0.17	21.80	7.54	10
	1	2	14	AQYVERGFNKP	4	0.38	-0.52	19.40	7.41	10
	1	2	35	ARYIERGFNPPLP	4	0.40	-1.81	18.91	7.56	10
	1	2	15	AQYDEIGFRGDP	4	0.41	-1.82	22.74	7.78	10
	1	2	28	AQYVERGFNPPLP	4	0.54	-0.62	23.20	8.80	10
	1	1	58	AQYDEIGFRGDS	4	0.64	-4.41	16.20	9.21	10
	1	2	6	ARYIERGFNPQP	4	0.27	-2.12	24.60	7.81	11
	1	2	24	AQYDEIGFRGDP	4	0.47	-3.31	26.60	8.89	11
	1	2	42	AQYVERGFNKP	4	0.61	-0.26	22.85	7.90	11
	1	2	26	AQYVEIGFPNLP	4	0.86	-3.04	36.40	9.57	11
	1	2	41	ARYVERGFNPNP	4	0.31	-1.02	24.05	7.77	12
	1	1	49	AQYVEIGFPNLP	4	0.91	-1.28	39.68	9.29	12
	1	2	29	AQYFEIGFRGDP	4	0.41	-2.47	26.25	7.75	13
	1	2	37	AQYVEIGFPNLP	4	0.78	-2.22	47.49	9.38	13
	1	2	32	ARYVEIGFPNLP	4	0.82	-2.50	38.96	9.52	13
	1	2	25	AQYVEIGFPNLP	4	0.83	-2.48	37.80	9.63	13
I	1	1	28	ARYDEIGFPDTG	5	0.38	-2.84	6.60	7.88	5
	1	1	34	ADAERGFPPPLT	5	0.60	-1.19	0.80	7.48	5
	1	2	45	AWVYEQGYPIGP	6	0.81	-4.05	4.21	8.86	5
	1	1	53	AWVYEQGYPIGP	6	0.61	-3.59	3.80	9.35	6
L	1	2	7	ATVRESFRPPFT	7	1.06	-3.46	10.20	8.75	0
	1	2	0	ATVRESFRPPFT	7	1.12	-3.57	9.02	8.88	0
M	1	2	21	ASVRESFRPPFT	7	0.75	-2.93	16.03	8.86	1
	1	2	3	AEVRESFRPPFR	7	0.97	-2.24	12.40	8.92	1
	1	2	1	ATVRESFRPPFT	7	1.10	-4.19	8.05	8.73	1
K	1	2	4	ATVRESFRPPFT	7	0.81	-4.75	17.80	8.94	2
	1	1	13	ATVREAFRPPFT	7	0.75	-3.66	21.80	8.84	3
	1	1	19	ATVTEAFRPPFT	7	0.74	-3.06	31.80	8.72	4
	1	2	13	AAVRESFRPPFK	7	0.77	-4.61	19.20	8.71	4
H	1	1	5	AIRYEQYYEGGK	8	0.64	-3.97	2.81	6.11	4
	1	1	0	AERFEQYYEGGR	8	0.74	-4.19	1.60	6.47	4
	1	1	7	AIRYEQYYEGGK	8	0.66	-2.17	2.20	6.20	5
	1	1	11	ATRYEQYYEGGT	8	0.70	-6.68	0.80	6.16	5
J	1	1	62	AQYDEIGFDGGS	9	0.46	-2.01	7.40	7.21	2
	1	1	64	GYRDEQFGWKWT	10	0.83	-6.28	2.80	6.29	11
	1	1	56	ARVEEWLGYGGQ	11	1.12	-1.40	0.60	7.70	3

Table 2.6: Quality metrics for the designs that were manually screened. Name: The names assigned to the designs that were picked for experimental validation. # Del: The number of deletions. Round: The round of computational design and validation that produced the design. Number: The number assigned to each design within its round. Loop Sequence: The residue identities for the positions where the backbone was remodeled. Loop Cluster: Designs were clustered according to the C/C α /N/O RMSD for the positions where the backbone was remodeled (Listings 2.6,2.7). Clusters were formed such that the RMSD between any two designs in the same cluster was no greater than 1.2Å. COOH Offset: The furthest distance between any of the atoms in the E38 carboxylate and their target positions, for the lowest scoring loop modeling decoy. Score Gap: The difference in score between the lowest scoring decoy that puts all of the atoms of the E38 carboxylate less than 1Å from their target positions, and the lowest scoring decoy that puts at least one atom of the E38 carboxylate more than 2Å from its target position. % Sub-Å Offset: The fraction of the loop modeling decoys that are predicted to position the all atoms of the Glu carboxylate less than 1Å from their target positions. pKa: The of E38 as predicted by PROPKA3.0 [17]. D38 in wildtype KSI has a pKa of 4.5 [1], but is predicted by PROPKA3.0 to be 6.2 (PDB: 8CHO). Δ Buried Unsats: The change in the number of buried unsatisfied H-bonds relative to wildtype KSI, as calculated by the BuriedUnsatFilter in Rosetta.

2.6.4 Experimental validation

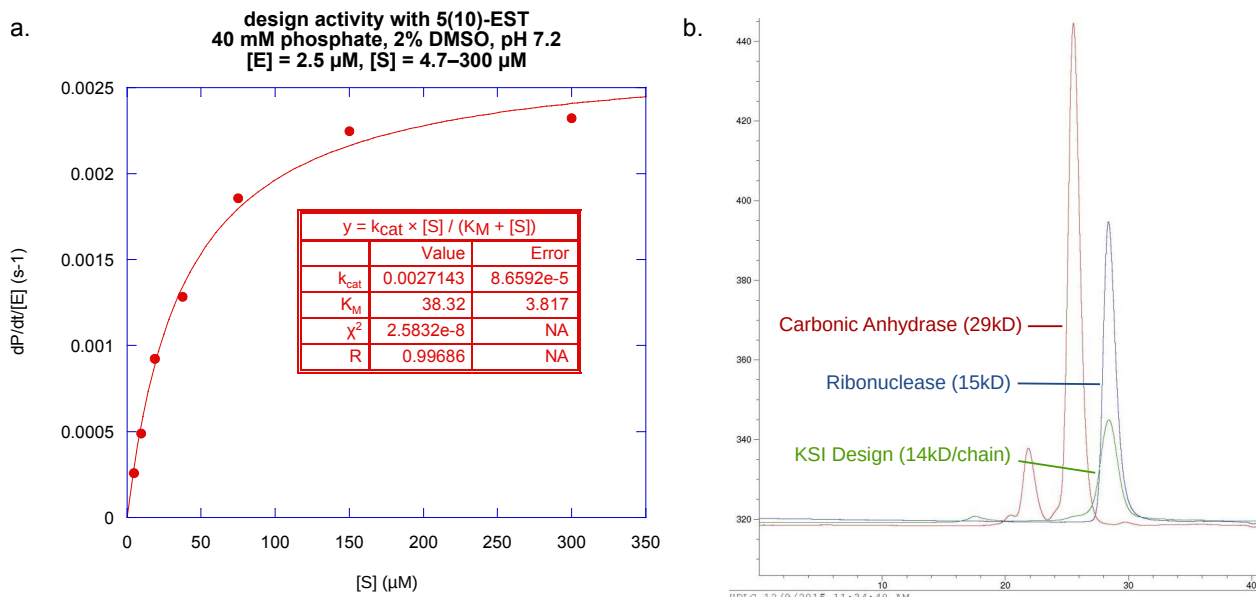


Figure 2.6: Experimental characterization of the most active KSI design. (a) Determination of k_{cat} and K_M . (b) Size exclusion chromatography traces, showing that the KSI design is a monomer in solution.

2.6.5 Sequences

Listing 2.20: Amino acid sequences for the designs that were experimentally validated.

>A

HMNTPEHMTAVVQRYVAALNAGDLGIVALFADNAYVEESAGQPKYWGTDAIRKFYANQLKLPLAVELTQEVRAANEAA
FAFIVSFEYQGRKTVVAPIDHFRFNGAGKVVSARAIKFGDKNIHAGA

>B

HMNTPEHMTAVVQRYVAALNAGDLGIVALFADDAKVTEDAGLGGYQGTAWIREFYANSLKLPLAVELTQEVANANEAA
FAFIVSFEYQGRKTVVAPIDHFRFNGAGKVSMRATFGEKNIHAGA

>C

HMNTPEHMTAVVQRYVAALNAGDLGIVALYDDTARRNEIGGPPPLPGRDNIRKFYAEDLALPLAVELTQEV RATNGEAA
FAFIVSFEYQGRKTVVAPIDHFRFNGAGKISYAQAVFGDKNIHAGA

>D

HMNTPEHMTAVVQRYVAALNAGDLGIVALYSPDAIRRERYAKANPRGRDAIRQFYAEDLALPLAVELTQEV RATNGEAA
FAFIVSFEYQGRKTVVAPIDHFRFNGAGKIAEAQAIKFGDKNIHAGA

>E

HMNTPEHMTAVVQRYVAALNAGDLGIVALYAPNAKVIETQYPEPRKGRDNIREFYAEALRLPLAVELTQEVRAANGEAA
FAFIVSFEYQGRKTVVAPIDHFRFNGAGKINYAQAQVFGPKNIHAGA

>F

HMNTPEHMTAVVQRYVAALNAGDLGIVALFADDAKVIETQYPEPRKGTAAIREFYANSLKLPLAVELTQEVRAAANEAA
FAFIVSFEYQGRKTVVAPIDHFRFNGAGKVV SARALFGEKNIHAGA

>G

HMNTPEHMTAVVQRYVAALNAGDLGIVALFADNARVEETKYPEDRKGTA AIREFYANQLALPLAVELTQEVRAAANEAA
FAFIVSFEYQGRKTVVAPIDHFRFNGAGKVVSAQALFGEKNIHAGA

>H

HMNTPEHMTAVVQRYVAALNAGDLGIVALYDSTAIRYEQYYEGGKGTDNIRKFYAMD LKLPLAVELTQEV RATNGEAAF
AFIVSFEYQGRKTVVAPIDHFRFNGAGKIAEARAIFGDKNIHAGA

>I

HMNTPEHMTAVVQRYVAALNAGDLGIVALYAPNARYDEIGFPDTGGTDNIRAFYAKQLKLPLAVELTQEV RATNGEAAF
AFIVSFEYQGRKTVVAPIDHFRFNGAGKIAEARAIFGDKNIHAGA

>J

HMNTPEHMTAVVQRYVAALNAGDLGIVALYDSTAQYDEIGFDGGSGTENIRRFYAKQLKLPLAVELTQEV RATNGEAAF
AFIVSFEYQGRKTVVAPIDHFRFNGAGKIAEARAIFGDKNIHAGA

>K

HMNTPEHMTAVVQRYVAALNAGDLGIVALFADDATVRESFRPPFTGTAAIREFYAN NLKLPLAVELTQEV RASNNEAAF
AFIVSFEYQGRKTVVAPIDHFRFNGAGKVVEA QALFGEKNIHAGA

>L

HMNTPEHMTAVVQRYVAALNAGDLGIVALYASDATVTESFRPPFTGTEAIREFYAN SLKLPLAVELTQEV RAANGEAAF
AFIVSFEYQGRKTVVAPIDHFRFNGAGKIVYA QALFGEKNIHAGA

>M

HMNTPEHMTAVVQRYVAALNAGDLGIVALFADDASVTESFRPPFTGTAAIREFYAN NLKLPLAVELTQEV RASNNEAAF
AFIVSFEYQGRKTVVAPIDHFRFNGAGKVV SARALFGEKNIHAGA

>N

HMNTPEHMTAVVQRYVAALNAGDLGIVALFADDAQYNEIGFRGDSGTAAIREFYAN QLKLPLAVELTQEV RAVNGEAAF
AFIVSFEYQGRKTVVAPIDHFRFNGAGKV VYARALFGEKNIHAGA

Listing 2.21: DNA sequences for the designs that were experimentally validated.

>A

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT

CGTCGCGCTGTTTGCCGATAACGCCTATGTGGAAGAATCCGCGGGTCAGCCGAAATATTGGGGTACGGATGCGATTTCGTA
AGTTTTACGCCAACCAGCTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGGCCGCCAACGAAGCGGCC
TTCGCTTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTTCGCTTCAATGGCGC
CGGCAAGGTGGTGAAGCGCGCGCCATCTTTGGCGATAAGAATATTCACGCTGGCGCCTGAAGCTT

>B

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTTTGCCGATGACGCCAAGGTGACAGAAGACGCGGGTCTCGGGGGCTATCAGGGTACGGCTTGGATTTCGTG
AGTTTTACGCCAACCAGCTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGAACGCCAACGAAGCGGCC
TTCGCTTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTTCGCTTCAATGGCGC
CGGCAAGGTGGTGAAGCATGCGCGCCACGTTTGGCGAGAAGAATATTCACGCTGGCGCCTGAAGCTT

>C

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTATGACGATACCGCCAGGAGGAATGAAATCGGGGGTCCCCGCCCTGCCCGGTAGGGATAATATTCGTA
AGTTTTACGCCGAAGATCTCGCACTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGACCAACGGCGAAGCGGCC
TTCGCTTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTTCGCTTCAATGGCGC
CGGCAAGATCTCGTACGCGCAGGCCGTGTTTGGCGATAAGAATATTCACGCTGGCGCCTGAAGCTT

>D

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTATCCCCTGACGCCATCCGGCGAGAACGCTATGCTAAGGCGAACCCGCGCGGTAGGGATGCGATTTCGTC
AGTTTTACGCCGAAGATCTCGCACTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGACCAACGGCGAAGCGGCC
TTCGCTTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTTCGCTTCAATGGCGC
CGGCAAGATCGCGGAGGCGCAGGCCATCTTTGGCGATAAGAATATTCACGCTGGCGCCTGAAGCTT

>E

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTATGCCCTAACGCCAAGGTGATAGAAACCCAGTATCCCGAGCCCAGGAAGGGTAGGGATAACATTTCGTG
AGTTTTACGCCGAGGCGCTCAGACTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGGCCAACGGCGAAGCGGCC
TTCGCTTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTTCGCTTCAATGGCGC
CGGCAAGATCAATTACGCGCAGGCCGTGTTTGGCCCCAAGAATATTCACGCTGGCGCCTGAAGCTT

>F

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTTTGCCGATGACGCCAAGGTGATAGAAACCCAGTATCCCGAGCCCAGGAAGGGTAGGGCTGCGATTTCGTG
AGTTTTACGCCAACCAGCTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGGCCGCCAACGAAGCGGCC
TTCGCTTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTTCGCTTCAATGGCGC

CGGCAAGGTGGTGAGCGCGCGCCTTGTGGCGAGAAGAATATTCACGCTGGCGCCTGAAGCTT

>G

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTTTGCCGATAACGCCAGGGTGAAGAAACCAAGTATCCCGAGGACAGGAAGGGTACGGCTGCGATTCTGTG
AGTTTTACGCCAACAGCTCGCACTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGGCCGCCAACGAAGCGGCC
TTCGCTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTCGCTTCAATGGCGC
CGGCAAGGTGGTGAGCGCGCAGGCCTTGTGGCGAGAAGAATATTCACGCTGGCGCCTGAAGCTT

>H

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTATGACAGTACCGCCATCCGGTATGAACAGTATTACGAGGGCGGGAAGGGTACGGATAATATTCGTAAGT
TTTACGCCATGGATCTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGACCAACGGCGAAGCGGCCTTC
GCTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTCGCTTCAATGGCGCCGG
CAAGATCGCGGAGGCGCGGCCATCTTTGGCGATAAGAATATTCACGCTGGCGCCTGAAGCTT

>I

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTATGCCCCTAACGCCAGGTATGACGAAATCGGTTTCCCGGACACGGGCGGTACGGATAACATTCGTGCGT
TTTACGCCAAGCAGCTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGACCAACGGCGAAGCGGCCTTC
GCTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTCGCTTCAATGGCGCCGG
CAAGATCGCGGAGGCGCGGCCATCTTTGGCGATAAGAATATTCACGCTGGCGCCTGAAGCTT

>J

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTATGACAGTACCGCCAGTATGACGAAATCGGTTTCCGACGGCGGGTCCGGTACGGAAAATATTCGTGCGT
TTTACGCCAAGCAGCTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGACCAACGGCGAAGCGGCCTTC
GCTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTCGCTTCAATGGCGCCGG
CAAGATCGCGGAGGCGCGGCCATCTTTGGCGATAAGAATATTCACGCTGGCGCCTGAAGCTT

>K

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTTTGCCGATGACGCCACGGTGCAGAAATCGTTCGCCCCCCTTTACCGGTACGGCTGCGATTCTGTGAGT
TTTACGCCAACAACTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGAGCAACAACGAAGCGGCCTTC
GCTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTCGCTTCAATGGCGCCGG
CAAGGTGGTGGAGGCGCAGGCCTTGTGGCGAGAAGAATATTCACGCTGGCGCCTGAAGCTT

>L

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT

CGTCGCGCTGTATGCCAGTGACGCCACGGTGACAGAATCGTTTCGCCCGCCCTTTACCGGTACGGAAGCGATTTCGTGAGT
TTTACGCCAACTCGCTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGGCCAACGGCGAAGCGGCCTTC
GCTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTCGCTTCAATGGCGCCGG
CAAGATCGTGTACGCGCAGGCCTTGTTTGGCGAGAAGAATATTCACGCTGGCGCCTGAAGCTT

>M

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTTTGCCGATGACGCCTCGGTGACAGAATCGTTTCGCCCGCCCTTTACCGGTACGGCTGCGATTTCGTGAGT
TTTACGCCAACAACTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGAGCAACAACGAAGCGGCCTTC
GCTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTCGCTTCAATGGCGCCGG
CAAGGTGGTGAGCGCGCGCCTTGTTTGGCGAGAAGAATATTCACGCTGGCGCCTGAAGCTT

>N

CATATGAATACCCAGAACACATGACCGCCGTGGTACAGCGCTATGTGGCTGCGCTCAATGCCGGCGATCTGGACGGCAT
CGTCGCGCTGTTTGCCGATGACGCCAGTATAATGAAATCGGTTTCCGGGGCGACTCCGGTACGGCTGCGATTTCGTGAGT
TTTACGCCAACAGCTCAAACCTGCCTTTGGCGGTGGAGCTGACGCAGGAGGTACGCGCGGTCAACGGCGAAGCGGCCTTC
GCTTTCATCGTCAGCTTCGAGTATCAGGGCCGCAAGACCGTGGTTGCGCCCATCGATCACTTTCGCTTCAATGGCGCCGG
CAAGGTGGTGACGCGCGCGCCTTGTTTGGCGAGAAGAATATTCACGCTGGCGCCTGAAGCTT

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Chapter 3

Controlling CRISPR-Cas9 with ligand-activated and ligand-deactivated sgRNAs

This chapter is adapted from the bioRxiv preprint by Kale Kundert, James E Lucas, Kyle E Watters, Christof Fellmann, Andrew H Ng, Benjamin M Heineike, Christina M Fitzsimmons, Benjamin L Oakes, David F Savage, Hana El-Samad, Jennifer A Doudna, Tanja Kortemme entitled “Controlling CRISPR-Cas9 with ligand-activated and ligand-deactivated sgRNAs” Its contents are reproduced here under the Creative Commons Attribution (CC BY) License.

The CRISPR-Cas9 system provides the ability to edit, repress, activate, or mark any gene (or DNA element) by pairing of a programmable single guide RNA (sgRNA) with a complementary sequence on the DNA target. Here we present a new method for small-molecule control of CRISPR-Cas9 function through insertion of RNA aptamers into the sgRNA. We show that CRISPR-Cas9-based gene repression (CRISPRi) can be either activated or deactivated in a dose-dependent fashion over a >10-fold dynamic range in response to two different small-molecule ligands. Since our system acts directly on each target-specific sgRNA, it enables new applications that require differential and opposing temporal control of multiple genes.

3.1 Introduction

CRISPR-Cas9 has emerged as an immensely powerful system for engineering and studying biology due to its ability to target virtually any DNA sequence via complementary base pairing with a programmable single-guide RNA (sgRNA) [1]. This ability has been harnessed to edit genomes, repress [2] or activate [3, 4] gene expression, image DNA loci [5], generate targeted mutational diversity [6] and to modify epigenetic markers [7].

In addition to engineering CRISPR-Cas9 for diverse applications, there has also been broad interest in developing strategies to regulate CRISPR-Cas9 activity [8, 9]. Such strategies promise to mitigate off-target effects and allow the study of complex biological perturbations that require temporal or spatial resolution [9]. To date, most of the progress in this area has been focused on switching the activity of the Cas9 protein using chemical [10, 11, 12, 13, 14, 15, 16] or optical [17, 18, 19] inputs. A general issue with these approaches is that all target genes are regulated in the same manner, although this limitation can be addressed with orthogonal CRISPR-Cas9 systems [16, 20, 21].

An alternative but less explored strategy is to regulate the sgRNA instead of the Cas9 protein. Since the sgRNA is specific for each target sequence, controlling the sgRNA directly has the potential to independently regulate each target. This strategy has been approached using sgRNAs that sequester the 20 nucleotide target sequence (the spacer) only in the absence of an RNA-binding ligand [22, 23], ligand-dependent ribozymes that cause irreversible RNA cleavage [23, 24], ligand-dependent protein regulators recruited to the sgRNA to alter CRISPR function [12], and engineered antisense RNA to sequester and inactivate the sgRNA [25].

Here we describe a new method to engineer ligand-responsive sgRNAs by using RNA aptamers to directly affect functional interactions between the sgRNA, Cas9, and the DNA target (Figure 3.1a). In contrast to prior sgRNA-based methods, our approach can be used to both activate and deactivate CRISPR-Cas9 function in response to a small molecule. In addition, our approach requires only Cas9 and the designed sgRNAs. We further show that control of CRISPR-Cas9 function with our method is dose-dependent over a wide range of ligand concentrations and can be used to simultaneously execute different temporal programs for multiple genes within a single cell. We envision that this method will be broadly useful for regulating essentially all applications

of CRISPR-Cas9-mediated biological engineering.

3.2 Results and Discussion

We sought to insert an aptamer into the sgRNA such that ligand binding to the aptamer would either activate or deactivate CRISPR-Cas9 function. We envisioned that ligand binding could either stabilize or destabilize a functional sgRNA conformation — bound to Cas9 and the DNA target — over other competing states in the ensemble (Figure 3.1a). We chose the theophylline aptamer [27] as a starting point because it is well-characterized and has high affinity for its ligand, which is cell permeable and is not produced endogenously.

We first asked which sites in the sgRNA were most responsive to the insertion of the theophylline aptamer and which strategies for linking the aptamer to the sgRNA were most effective. We designed aptamer insertions at each of the sgRNA stem loops at sites that are solvent-exposed in the Cas9/sgRNA/DNA ternary complex and exhibit various levels of tolerance to mutation [26]. These insertion sites are denoted the upper stem, nexus, and hairpin (Figure 3.1b). We tested three linking strategies aimed at stabilizing a functional sgRNA conformation in the presence of the ligand: (i) replacing parts of each stem with the aptamer, (ii) splitting the sgRNA in half and using the aptamer to bring the halves together, and (iii) designing strand displacements (i.e. sequences that allow for alternative base pairing in the apo and holo states) (Figure 3.1c, Table 3.1).

To test the resulting 86 designed sgRNAs, we used an *in vitro* assay to measure differential Cas9-mediated DNA cleavage in the presence and absence of theophylline. We identified theophylline-responsive sgRNAs for all three insertion sites (Figure 3.1d), with the most successful designs derived from the strand displacement linking strategy (Table 3.1). We confirmed that the activity of our designs depended on the concentration of theophylline, as would be expected if the ligand affects function through binding the aptamer-containing designed sgRNA (Figure 3.1e). In total, 10 designs were responsive to theophylline *in vitro*. For nine of these responsive designs theophylline addition activated CRISPR-Cas9 function, while for one design (#61) theophylline unexpectedly deactivated function. Interestingly, all of the theophylline-activated designs had the aptamer inserted into either the upper stem or the hairpin, while the theophylline-deactivated design had the aptamer inserted into the nexus (Figure 3.1b,d, Table 3.1). These findings suggested

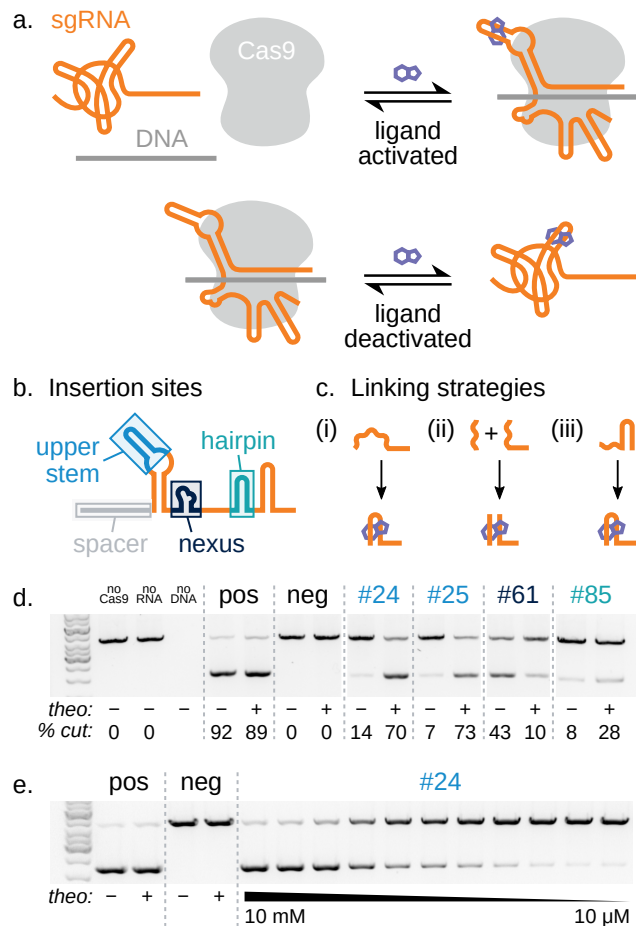


Figure 3.1: Design of ligand-controlled sgRNAs by inserting small molecule aptamers into the sgRNA. (a) Illustration of the design goal, where functional Cas9/sgRNA/target DNA complexes are stabilized either in the presence (top) or absence (bottom) of a small molecule ligand. (b) Aptamer insertion sites; sgRNA domains defined as in ref. [26]. (c) Strategies for linking the aptamer to the sgRNA: (i) stem replacement; (ii) induced dimerization; (iii) strand displacement (Table 3.1). (d) Efficiency of *in vitro* Cas9 cleavage of DNA in the presence and absence of 10 mM theophylline for controls and selected designs. Design numbers refer to Table 3.1 and are color-coded by aptamer insertion sites defined in (b). Percent cut values (bottom) are the average of at least two experiments. All data shown are from a single gel (some lanes are excluded for clarity). (e) Dose-dependence of cleavage efficiency in response to increasing concentrations of theophylline for a representative design (#24).

the exciting possibility of regulating CRISPR-Cas9 function with both ligand-activated and ligand-deactivated sgRNAs, depending on the aptamer insertion site.

We next sought to find designed sgRNAs that would function robustly in *E. coli*. To screen designed libraries using fluorescence-activated cell sorting (FACS), we changed to a cellular assay based on CRISPR-Cas9-mediated repression (CRISPRi) of super-folder green fluorescent protein (sfGFP) and monomeric red fluorescent protein (mRFP) (Figure 3.2a) [14]. The strongest rational designs exhibited only weak activity in the CRISPRi assay (Figure 3.4). Since the sequences linking the aptamer to the remainder of the sgRNA affected activity in our *in vitro* experiments, we designed libraries with randomized linkers of 4–12 nucleotides at all three insertion sites to broadly sample different aptamer contexts (Figure 3.2b, Table 3.2). To identify ligand-activated sgRNAs, we screened each library first for CRISPRi activity in the presence of theophylline, then second for lack of activity in the absence of theophylline. We then repeated that selection/counter-selection with a different spacer to avoid selecting sgRNA scaffold sequences that would be specific for a particular spacer (Figure 3.2c). To identify ligand-inhibited sgRNAs, we used an analogous four-step selection/counter-selection protocol that began by screening for activity in the absence of ligand. We validated the activity of the selected hits with a third spacer that was not used in any of the screens (Table 3.3). The most robust ligand-activated sgRNA variant (termed ligRNA⁺; i.e. sgRNA that is active in the + ligand state) and ligand-inactivated sgRNA (termed ligRNA⁻) showed 11x and 13x dynamic ranges that spanned 55% and 59% of the range achieved by the controls, with negligible overlap between the active and inactive populations (Figure 3.2d,e, Table 3.4).

The ligRNA⁺ construct derived from inserting the aptamer into the hairpin while randomizing the remainder of the hairpin, the 5 unpaired nucleotides at the apex of the nexus, and the region between the hairpin and the nexus. The hairpin became more GC-rich, but the base-pairing was conserved with the exception of a single mismatch. The apex of the nexus became complementary to the 5' region of the aptamer. The region between the hairpin and the nexus remained AU-rich and unpaired (Figure 3.5a). Secondary structure predictions of ligRNA⁺ using ViennaRNA [29] (Figure 3.5b) are consistent with our intended mechanism, where ligand binding to the aptamer leads to strand displacements stabilizing the active sgRNA conformation.

The ligRNA⁻ construct derived from inserting the aptamer into the nexus while randomizing the nexus stem. The nexus stem was extended from 2 to 5 bp, but remained base-paired and

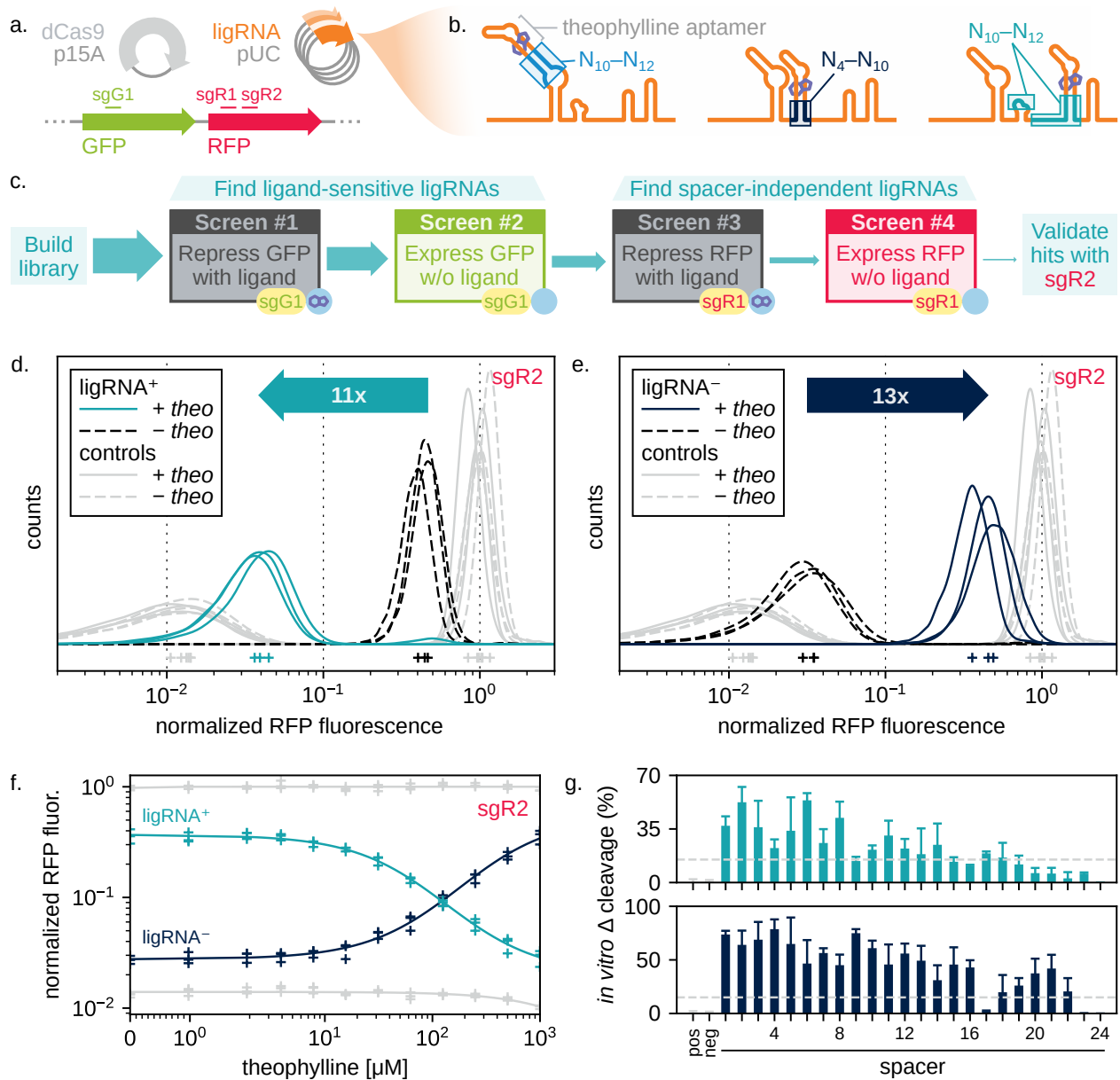


Figure 3.2: (caption on next page)

Figure 3.2: Identification of robust ligRNAs using CRISPRi-based gene repression in *E. coli*. (a) Components used in the CRISPRi assay. dCas9 and any ligRNAs were expressed from plasmids, while the fluorescent reporters (GFP and RFP) were chromosomally integrated. The DNA regions targeted by different spacers (sgG1, sgR1, sgR2) used to repress the fluorescent reporters are indicated. (b) Regions randomized in each ligRNA library. (c) Schematic of the screen used to isolate ligRNA⁺. sgG1, sgR1, and sgR2 refer to spacers targeting GFP and RFP, respectively (Table 3.4). (d,e) Single-cell RFP fluorescence distributions for ligRNA⁺ (teal, panel d) and ligRNA⁻ (navy, panel e) targeting RFP using the sgR2 spacer with (solid lines) and without (dashed lines) theophylline. Control distributions are in grey (positive control: optimized sgRNA scaffold [28]; negative control: G43C G44C [26]). The mode of each distribution is indicated with a plus sign. RFP fluorescence values for each cell are normalized by both GFP fluorescence for that cell and the modes of the un-repressed control populations (i.e. apo and holo) measured for that replicate. (f) Efficiency of CRISPRi repression with increasing theophylline concentrations for ligRNA⁺ (teal) and ligRNA⁻ (navy). Controls are in grey. The fluorescence axis is the same as in (d) and (e). The fits are to a two-state equilibrium model. (g) Change in the percentage of DNA cleaved *in vitro* in the presence and absence of theophylline for ligRNA⁺ and ligRNA⁻ in the context of 24 representative spacers. Each bar represents the mean of three or four measurements with a single spacer (except for spacer #24, where n=2, Table 3.5), and the error bars give the standard deviation. Pos and neg denote the positive and negative controls (Table 3.4), which are independent of theophylline.

GC-rich (Figure 3.5a). The mechanism underlying the ability of ligRNA⁻ to deactivate CRISPR-Cas9 function upon the addition of theophylline was unclear. ViennaRNA predictions of the lowest energy conformation for ligRNA⁻ were uninformative on the mechanism of ligand control, as they suggested that ligRNA⁻ adopts the same secondary structure in the presence and absence of theophylline (Figure 3.5c). However, we noticed that in the stem sequence selected in our screen, U95 in ligRNA⁻ (U59 in the crystal structure of the Cas9 ternary complex with DNA and RNA [30]) was conserved in 17 of the 20 isolated sequences (Table 3.3). This uracil makes specific hydrogen-bonding interactions with asparagine 77 in the ternary complex. In the sgRNA scaffold this uracil is always unpaired, but in ligRNA⁻ it is predicted to engage in a wobble base pair with G65 in the stem leading up to the aptamer (Figure 3.5c). These observations led us to hypothesize that ligand binding to the aptamer controls the extent to which U95 is unpaired, which in turn determines whether or not ligRNA⁻ interacts functionally with Cas9 and the target DNA. To test this hypothesis, we first designed strand-swapping mutations in the stem leading up to the aptamer (Figure 3.6). As expected, swapping U95 rendered ligRNA⁻ completely inactive, while swapping base pairs at the positions between U95 and the aptamer had only a mild effect (Figure 3.6d). We then modulated the strength of the base pairs between U95 and the aptamer. Consistent with the hypothesis that

ligand binding to the aptamer decreases access to U95, we found that weaker base pairs were more repressing while stronger base pairs were more activating (Figure 3.6e). These results provide a possible explanation for how ligRNA⁻ deactivates CRISPR-Cas9 function in the presence of the ligand and suggest additional ways for ligRNAs to be tuned for specific applications.

Next, we tested whether the ligRNAs responded to increasing concentrations of theophylline in a dose-dependent manner in the cellular CRISPRi assay. We observed that the activities of both ligRNA⁺ and ligRNA⁻ were smoothly titratable and exhibited a nearly linear response over a large range of ligand concentration (Figure 3.2f). We note that the apparent EC₅₀s of ligRNA⁺ and ligRNA⁻ (134.3±11.3 μM and 177.6±17.3 μM) are much higher than the K_D of the theophylline aptamer alone (320 nM) [31]. This discrepancy is common for RNA devices [32] and could be explained by the altered structural context of the aptamer embedded in an sgRNA sequence. Nevertheless, the linear concentration dependence of the ligRNAs demonstrates their utility for not only turning genes on or off, but also for precisely tuning their levels of expression.

Because RNA devices are known to be sensitive to sequence context [33], we tested ligRNA⁺ and ligRNA⁻ with 24 different spacers using the *in vitro* DNA cleavage assay (Figure 3.2g, Figure 3.7, Table 3.5). We found that both ligRNA⁺ and ligRNA⁻ respond to theophylline for the majority of the tested spacers (15 and 21 out of 24 spacers for ligRNA⁺ and ligRNA⁻, respectively). For the few spacers that did not function, we hypothesized that base-pairing of the spacer sequence with the aptamer might explain the lack of sensitivity to theophylline. To address this question, we predicted the affinity between each spacer and the aptamer (with its associated linker) for both ligRNAs using ViennaRNA [29] (Figure 3.8). For ligRNA⁺ constructs the correlation between the duplex free energy prediction and theophylline sensitivity was negligible. However, for ligRNA⁻ constructs increased predicted affinity of the spacer for the aptamer sequence correlated with a smaller change in Cas9-mediated DNA cleavage in response to theophylline. This analysis suggested that spacers with predicted affinity for the aptamer could interfere with switching of the ligRNA⁻ function, providing a useful design criterion for functional spacers. Taken together, these results suggest that ligRNAs should be capable of regulating most genes, especially those that can be targeted by multiple spacers.

To test how decreased expression levels would affect the ligRNAs, we replaced the strong constitutive promoter driving sgRNA expression (J23119) with a weak constitutive promoter (J23150)

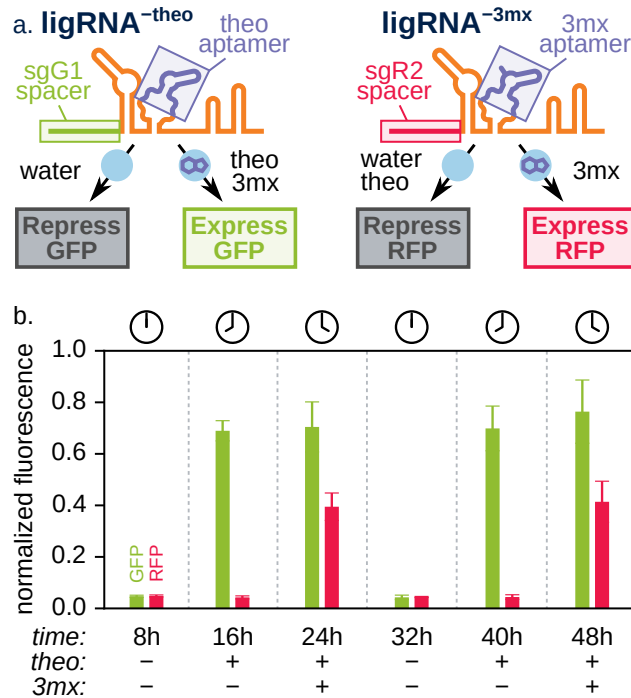


Figure 3.3: Multiplexed temporal control of two genes with two ligands. (a) Schematic illustrating the constructs and the expected consequences of adding theophylline (theo) and 3-methylxanthine (3mx) for each fluorescent reporter. (b) GFP and RFP fluorescence measured at indicated time points by flow cytometry. Presence of theo leads to GFP expression; addition of 3mx separately at a different time point also triggers RFP expression. Both effects are reversible (GFP and RFP are repressed when both ligands are absent) and expression can be triggered a second time with ligand addition. Bar heights and error bars represent the modes and standard deviations of the cell distributions, respectively. Unlike in Figure 3.2, fluorescence is normalized by side-scatter because both fluorescent channels are being manipulated.

and repeated the CRISPRi assay. Both ligRNAs remained functional with the weak promoter, albeit with a somewhat narrower dynamic ranges (from a 10.2 ± 0.7 -fold to a 5.9 ± 0.5 -fold change upon theophylline addition for ligRNA⁺ and from a 16.2 ± 1.0 -fold to a 11.6 ± 0.9 -fold change for ligRNA⁻, Figure 3.9). Notably, the weak promoter shifted the dynamic ranges of both ligRNAs in the direction of increased gene expression, to the point where nearly full gene activation was achieved in the non-repressing state. These results suggest that the ligRNAs are able to repress at low expression levels, and that tuning promoter strength is useful for applications that require full gene activation (alternatively, a collection of ligRNA variants that shift the dynamic range is shown in Figure 3.10).

A key advantage of regulating CRISPR-Cas9 using the sgRNA instead of the protein is the ability to independently control different genes with different ligands in the same Cas9 system. To test this idea, we replaced the theophylline (theo) aptamer in the ligRNAs with the 3-methylxanthine

(3mx) aptamer (the resulting sgRNA constructs were termed ligRNA^{±3mx}). While the theophylline aptamer is recognized by both ligands, the 3-methylxanthine aptamer is specific to its ligand [34]. Since the aptamers differ in only one position, the replacement of the theophylline aptamer with the 3-methylxanthine aptamer was straightforward and led to a 3-methylxanthine-sensitive ligRNA⁻ variant without further optimization. (ligRNA⁺ also remained functional with the 3-methylxanthine aptamer but exhibited an undesirable albeit small ~2-fold response to theophylline, Figure 3.11). We used the two ligRNA⁻ variants to construct a system that expresses GFP upon addition of theophylline and expresses GFP and RFP when both ligands are added (Figure 3.3a). We then performed a timecourse where we sequentially activated, deactivated, and reactivated both reporter genes using ligRNAs and observed the expected temporal expression program (Figure 3.3b).

Taken together, ligRNAs provide control of both gene repression and gene activation and can be multiplexed for differential control of genes in the same system (Figure 3.3). While ligRNAs function robustly in bacteria, transferring them to eukaryotic systems will require further optimization (Figure 3.12, Figure 3.13) which could be achieved using methods similar to our optimization (Figure 3.2) of the initial rational designs (Figure 3.1). Nevertheless, there are already many useful applications for ligRNAs in bacteria. For example, many species of bacteria do not have facile genetic controls available, and ligRNAs provide such controls with a minimal footprint. Moreover, temporally controlled gene expression programs are thought to be important for key biological processes in bacteria [35], and ligRNAs provide a way to conduct large-scale screens to probe these programs and their role in the interactions between bacteria and their environments [36].

The study of subtle effects in complex biological systems will increasingly require the ability not just to probe individual genes, or to knock down different sets of genes, but to tune the expression of many different genes with fine temporal precision. ligRNAs provide this capability by adding ligand- and dose-dependent control of individual sgRNAs to the already powerful CRISPR-Cas9 technology.

3.3 Future work

3.3.1 Orthogonal ligands

We attempted to create ligRNAs that were responsive to a number of small-molecules other than theophylline and 3-methylxanthine. We were most successful with thiamine pyrophosphate (TPP). Although TPP is a natural metabolite, its aptamer has been used to regulate access to ribosome binding sites (RBS) in *E. coli* grown in minimal media with or without thiamine [37]. It's notable that this system is responsive to small quantities of ligand: half-maximal and maximal response are seen at 0.6 μM and 2 μM , respectively. The K_D of the TPP aptamer is 0.1 μM [38], and although the total concentration of TPP in *E. coli* is as high as 3.9 μM [39], the concentration of free TPP (in the absence of exogenous thiamine) is presumably much lower.

To test the ability of the TPP aptamer to regulate sgRNA function, we created a variant of ligRNA⁻ containing the TPP aptamer with no further optimization. It exhibited a 1.5x response to 500 μM thiamine in our CRISPRi assay (Figure 3.14). Although this response was slight, it was enough to justify screening an entire library of TPP ligRNAs via the same four-screen process we used to find theophylline-sensitive ligRNAs. We ultimately found 11 unique TPP-activated ligRNAs, each with a roughly 5x response to TPP (Figure 3.15, Table 3.3). We did not pursue these ligRNAs any further, but future work could focus on improving their response to ligand, screening for TPP-deactivated ligRNAs, and testing the TPP ligRNAs with different spacers.

We also attempted to create ligRNAs that were responsive to adenine, guanine, and ammeline. These three molecules are closely related: adenine and guanine are both purines, ammeline is similarly an aromatic heterocycle, and the corresponding aptamers differ in only 3 positions [40]. However, we were not able to create responsive ligRNAs for any of these molecules. We abandoned adenine because it was toxic at concentrations as low as 8 μM (Figure 3.16). This toxicity results from a depletion of the cell's GTP pool, due to there being an excess of adenine relative to guanine [41]. We abandoned guanine because it was insoluble in water and DMSO. It is soluble to 5 mM in 20 mM NaOH, but precipitates when diluted into media to 500 μM . We were able to screen for ammeline-responsive ligRNAs, but we were not able to find any. We attribute this failure to the low affinity ($K_D= 1.2 \mu\text{M}$) of the ammeline aptamer for its ligand. This low affinity is the result of how the ammeline aptamer was created: the adenine aptamer was mutated in 3 positions such that it

had no detectable binding to adenine, then a panel of 80 heterocyclic compounds was screened to find those that bound the new aptamer, of which ammeline bound the strongest [40]. No further optimization was performed to improve affinity.

A possible future direction for this project would be to screen for fluoride-sensitive ligRNAs. The fluoride aptamer was suggested to us by Kyle Watters, our collaborator with expertise in RNA devices. Although the fluoride aptamer has low affinity (60 μM) for its ligand [42, 43], this is balanced by the ability to grow cells in high concentrations of fluoride (up to 1 mM) without causing toxicity [44].

3.3.2 Eukaryotic ligRNAs

None of the ligRNAs screened in bacteria were immediately transferable to either human (Figure 3.12) or yeast cells (Figure 3.13). To create ligRNAs were functional in such eukaryotic systems, we sought to screen for ligRNAs in those same systems. We focused on yeast since it was the more experimentally tractable option, and we hypothesized that ligRNAs identified in yeast could be transferable to other eukaryotic systems. However, it may also have been possible to conduct such screens in human cells, as sgRNA libraries with about 3×10^5 variants (1x coverage) can be transfected [45, 46, 47].

We created and screened theophylline-based libraries 36–45 (Table 3.2) as described in the Methods, but found no ligand-sensitive sgRNAs. The most likely explanation for this failure was that our library coverage was low because our transformation efficiency was poor. This could have been a consequence of our libraries being chromosomally integrated. Compared to being on a plasmid, this makes sgRNA expression more homogeneous across the population, but it may also impair transformation. Improving transformation efficiency and repeating this screen would be a promising direction for future work.

3.4 Methods

3.4.1 Constructs

All experiments used Cas9 from *S. pyogenes* (called Cas9 throughout), with mutations D10A and H840A for CRISPRi experiments (dCas9). Sequences of relevant ligRNAs, aptamers, spacers and controls are listed in Table 3.4.

3.4.2 *in vitro* DNA cleavage assay

sgRNA *in vitro* transcription: Linear, double-stranded template DNA was acquired either by ordering gBlocks® Gene Fragments from IDT (experiments in Figure 3.1d,e) or by cloning the desired sequence into a pUC vector and digesting it with EcoRI and HindIII (experiments in Figure 3.2g). Each construct contained a T7 promoter and a spacer that began with at least 3 Gs (Table 3.4). DNA template (10–50 ng) was transcribed using the HiScribe™ T7 High Yield RNA Synthesis Kit (NEB E2040S) and unincorporated ribonucleotides were removed with Zymo RNA Clean & Concentrator™-25 spin columns (Zymo R1018).

Target DNA: Target DNA was prepared using inverse PCR to clone the appropriate sequence into a modified pCR2.1 vector approximately 2.1 kb downstream of its XmnI site. The vector was then digested with XmnI (NEB R0194S) as follows: mix 43.5 µL ≈500 ng/µL miniprep pCR2.1 DNA, 5.0 µL 10X CutSmart buffer, and 1.5 µL 20 U/µL XmnI; incubate at 37°C until no uncleaved plasmid is detectable on a 1% agarose gel (usually 30–60 min); dilute to 30 nM in 10 mM Tris-Cl, pH 8.5; store at -20°C.

Cas9 reaction: We adapted the following protocol from ref. [26]: mix 5.0 µL water or 30 mM theophylline (in water) and 1.5 µL 1.5 µM sgRNA (in water); incubate at 95°C for 3 min, then at 4°C for 1 min; prepare Cas9 master mix for 40 reactions: 241.0 µL water, 66.0 µL 10x Cas9 buffer (NEB B0386A), and 1.0 µL 20 µM Cas9 (NEB M0386T); add 7.0 µL Cas9 master mix; incubate at room temperature for 10 min; add 1.5 µL 30 nM target DNA; pipet to mix; incubate at 37°C for 1 h; prepare quenching master mix: 4.68 µL 20 mg/mL RNase A (Sigma R6148), 4.68 µL 20 mg/mL Proteinase K (Denville CB3210-5), and 146.64 µL 6x Orange G loading dye via master mix; add 3 µL quenching master mix; incubate at 37°C for 20 min, then at 55°C for 20 min; run the entire

reaction (18 μ L) on a 1% agarose/TAE/GelRed gel at 4.5 V/cm for 70 min.

Gel quantification: Band intensities were quantified using Fiji (1.51r) [48]. The background was subtracted from each image using a 50 pixels rolling ball radius. The fraction of DNA cleaved in each lane (f) was calculated as follows ($\text{pixels}_{2\text{kb}}$ and $\text{pixels}_{4\text{kb}}$ are the intensities of the cleaved and uncleaved bands, respectively):

$$f = \frac{\text{pixels}_{2\text{kb}}}{\text{pixels}_{4\text{kb}} + \text{pixels}_{2\text{kb}}}$$

The change in cleavage due to ligand (Δf) was calculated as follows (f_{apo} and f_{holo} are the fractions of DNA cleaved in the reactions without and with theophylline, respectively):

$$\Delta f = f_{\text{theo}} - f_{\text{apo}}$$

3.4.3 CRISPR-Cas9-based repression (CRISPRi) assay in E. coli

Strain: The strain used for all CRISPRi experiments was E. coli MG1655 with dCas9 (containing the D10A and H840A mutations) and ChlorR on a p15A plasmid (pgRNA-bacteria, Addgene 44251), sgRNA and AmpR on a pUC plasmid (pdCas9-bacteria, Addgene 44249), and sfGFP [49], mRFP [50], and KanR chromosomally integrated at the *nsfA* locus. This strain was originally described in ref. [2].

Flow cytometry: Overnight cultures of the CRISPRi strain above were inoculated from freshly picked colonies in 1 mL Lysogeny Broth (LB) medium with 100 μ g/mL carbenicillin (100 mg/mL stock in 50% EtOH) and 35 μ g/mL chloramphenicol (35 mg/mL stock in EtOH). The next morning, fresh cultures were inoculated in 15 mL culture tubes or 24-well blocks by transferring 4 μ L of overnight culture into 1 mL EZ Rich Defined Medium (Teknova M2105) with 0.1% glucose, 1 μ g/mL anhydrotetracycline, 100 μ g/mL carbenicillin, 35 μ g/mL chloramphenicol, with or without 1 mM theophylline (added from a 30mM stock dissolved in water). These cultures were then grown for 8h at 37°C with shaking at 225 rpm before GFP (488 nm laser, 530/30 filter) and RFP (561 nm laser, 610/10 filter) fluorescence were measured using a BD LSRII flow cytometer. Approximately 10,000 events were recorded for each measurement. Biological replicates were performed on different days using different colonies from the same transformation.

Data analysis: Cell distributions were obtained by computing a Gaussian kernel density estimation (KDE) over the base-10 logarithms of the measured fluorescence values. The mode was considered to be the center of each distribution (e.g. for determining fold changes) and was obtained through the Broyden-Fletcher-Goldfarb-Shanno (BFGS) maximization of the KDE. Dose response curves were fit to the Hill equation (y is the normalized fluorescence, x is the theophylline concentration, EC_{50} is the inflection point, and y_{\min} and y_{\max} are the lower and upper asymptotes of the fit):

$$y = y_{\min} + \frac{y_{\max} - y_{\min}}{1 + EC_{50}/x}$$

3.4.4 Identification of functional ligRNAs in *E. coli* using FACS screens

Library generation: Randomized regions were inserted into the sgRNA using inverse polymerase chain reaction (PCR) with phosphate-modified and high-performance liquid chromatography (HPLC)-purified primers containing degenerate nucleotides.

Electrotransformation: Electrocompetent cells were prepared as follows: make "low-salt" Super Optimal Broth (SOB) medium: 20 g bacto-tryptone, 5 g bacto-yeast extract, 2 mL 5 M NaCl, 833.3 μ L 3 M KCl, water to 1L, pH to 7.0 with NaOH, autoclave 30 min at 121°C; pick a fresh colony and grow overnight in 1 mL SOB; in the morning, inoculate 1 L SOB with the entire overnight culture; grow at 37°C with shaking at 225 rpm until OD=0.4 (\approx 4 h); place cells in an ice bath for 10 min; wash with 400 mL pre-chilled water, then 200 mL pre-chilled water, then 200 mL pre-chilled 10% glycerol; resuspend in a total volume of 6 mL pre-chilled 10% glycerol; make 100 μ L aliquots; flash-freeze and store at -80°C. Electrocompetent cells were transformed as follows: thaw competent cells on ice for 10 min; pipet once to mix cells with 2 μ L \approx 250 ng/ μ L library plasmid; shock at 1.8 kV with a 5 ms decay time; immediately add 1 mL pre-warmed SOB with catabolite repression (SOC) medium; recover at 37°C for 1 h; dilute into selective liquid media and grow at 37°C with shaking at 225 rpm overnight. After PCR and ligation, libraries were first transformed into electrocompetent Top10 cells, then mira-prepped [51], sequenced, and combined to achieve approximately equal representation of variants based on library size and DNA concentration, then transformed again into electrocompetent MG1655 cells already harboring the dCas9 plasmid.

Cell sorting: Cells were grown as for the CRISPRi assay, but when starting new cultures, care was taken to subculture at least 10x more cells than the size of the library (often 200 μ L). Sorting was done using a BD FACSAria II cell sorter. Sorting was no slower than 1000 evt/s and no faster than 20,000 evt/s, with the slower speeds being more accurate and the faster speeds being necessary to sort large libraries. Gates were drawn based on the position of the control population if possible, and based on the most extreme library members otherwise. Typically the gates included between 1% and 5% of the population being sorted. All gates were drawn diagonally in GFP vs. RFP space. Sorted cells were collected in 1 mL SOC at room temperature and, after sorting, were diluted into selective media and grown at 37°C with shaking at 225 rpm overnight.

Screening for ligRNA⁺: Pool libraries 23–28 from Table 3.2. First screen: grow without ligand, gate for GFP expression, sort 10,000 evt/s for 3.5 h. Second screen: grow with ligand, gate for GFP repression, sort 1500 evt/s for 70 min. Third screen: grow without ligand, gate for GFP expression, sort 1700 evt/s for 10 min. Fourth screen: grow with ligand, gate for GFP repression, sort 1000 evt/s for 2 min. Fifth screen: grow without ligand, gate for GFP expression, sort 5000 evt. Plate cells and test 96 individual colonies using the CRISPRi assay. Miniprep and sequence the 20 selected designs with the largest response to theophylline. Only one unique sequence was identified, and it did not function with the sgR1 spacer (Table 3.3). Note that we did not change the spacer in between the second and third screens for this library. We then designed libraries 29–30 (Table 3.2) to keep the stem identified in the previous screen of libraries 23-28 and to randomize other regions of the sgRNA that might be participating in ligand-dependent base-pairing. First screen: grow with ligand, gate for GFP repression, sort 4000 evt/s for 2 h. Second screen: grow without ligand, gate for GFP expression, sort 1500 evt/s for 1 h. Change the spacer from sgG1 to sgR1 (Table 3.7) using inverse PCR. Third screen: grow with ligand, gate for RFP repression, sort 2000 evt/s for 10 min. Fourth screen: grow without ligand, gate for RFP expression, sort 10,000 evt. Plate cells and test 96 individual colonies using the CRISPRi assay. Miniprep and sequence the 15 selected designs with the largest response to theophylline, then test those designs with four different spacers (sgG1, sgR1, sgG2, sgR2). There was only 1 duplicate sequence, and 8 of the sequences had acquired unexpected mutations outside of the randomized region. The majority of these hits were tested with four different spacers (sgG1, sgR1, sgG2, and sgR2). ligRNA⁺ and ligRNA⁻ performed best (none of the hits performed well with the sgG2 spacer.) Details on all

library hits and validation with different spacers can be found in Table 3.3.

Screening for ligRNA⁻: Pool libraries 7–22 from Table 3.2. First screen: grow without ligand, gate for GFP repression, sort 18,000 evt/s for 1 h. Second screen: grow with ligand, gate for GRP expression, sort 1000 evt/s for 10 min. Third screen: grow without ligand, gate for GFP repression, sort 1000 evt/s for 10 min. Fourth screen: grow with ligand, gate for GRP expression, sort 1000 evt/s for 10 min. Fifth screen: grow without ligand, gate for GFP repression, sort 1500 evt/s for 7 min. Plate cells and test 96 individual colonies using the CRISPRi assay described above. Miniprep and sequence the 20 selected designs with the largest fold response to theophylline. In this group there were only 9 unique sequences. ligRNA⁻ appeared 5 times and had the largest response to theophylline (Table 3.3). Note ligRNA⁻ is functional with other spacers (Figure 3.2g) despite the fact that we did not change the spacer in between the second and third screens for this library.

3.4.5 Test of different spacers

The spacers for this assay were chosen by a script that generated uniformly random sequences, scored them using a previously published machine learning approach for designing functional sgRNAs [52], and kept only those that scored higher than 0.5 (the median). This approach was designed to produce spacers that were as unbiased as possible, while still being likely to function as expected in the positive (optimized sgRNA scaffold [28]) and negative (G43C G44C [26]) controls shown in Table 3.4. The average cleavage for the positive controls was 93%, and the lowest cleavage for any of the positive controls was 78% (Table 3.5).

3.4.6 RNA secondary structure predictions

Secondary structure predictions were performed using the RNAfold program from the ViennaRNA package (version 2.4.3). The structures reported here are minimum free energy (MFE) predictions, although centroid and maximum expected accuracy (MEA) structures from partition function calculations were nearly identical in every case. The holo state was simulated using soft constraints: a -9.21 kcal/mol bonus was granted for forming the base pair flanking the aptamer. This bonus corresponds to the 320 nM affinity of the theophylline aptamer for its ligand [31]. The command-lines used for the apo and holo states, respectively, are given below:

```
$ RNAfold --partfunc --MEA
$ RNAfold --partfunc --MEA --motif \
    "GAUACCAGCCGAAAGGCCCUUGGCAGC, (...(((((((.....))))))....)), -9.212741321099747"
```

Free energy predictions for Figure 3.5 were performed using the RNA duplex program from the ViennaRNA package (version 2.4.3):

```
$ RNA duplex
```

3.4.7 CRISPRi assay in *S. cerevisiae*

Yeast Strains: All yeast strains were constructed using the MoClo golden gate cloning framework and the Yeast Toolkit from [53]. The background strain was WCD230 (derived from BY4741 (MATa his3 Δ 1 leu2 Δ 0 met15 Δ 0 ura3 Δ 0) with a larger fraction of the his3 gene removed [54]. All yeast strains contained the dCas9-Mxi1 inhibitor, fluorescent reporters, and ligRNA or control sgRNA construct, respectively (Figure 3.13a). The inhibitor cassette was integrated into the Ura3 locus and contained pGal1-dCas9-Mxi1 and pRnr2-GEM constructs that allowed for estradiol-inducible expression of dCas9-Mxi1 [55]. The Mxi1 inhibition domain was derived from Addgene catalog number 46921 [3] with synonymous mutations made to the E68 and T69 codons to render the construct compatible with golden gate cloning. The fluorescent reporter cassette was integrated into the His3 locus and contained pCcw12-sfGFP and pTdh3-mRFP. The guide cassette was integrated into the Leu2 locus and contained (tRNAPhe)-HDV Ribozyme-sgRNA. The HDV Ribozyme cleaved the ligRNA or control sgRNA from the rest of the transcript to prevent unwanted interactions [56]. The sgRNA was either positive or negative control sgRNA, ligRNA⁺, ligRNA⁺₂, or ligRNA⁻.

Experimental protocol: Strains were plated from freezer stocks on SD-HIS (Yeast Nitrogen Base (YNB), Complete Synthetic Media (CSM) lacking histidine, 2% glucose) because the fluorescent reporter cassette integrated into the His3 locus caused a slight growth defect that was also present for an empty vector integrated in the same locus. After incubating at 30°C, single colonies were grown overnight in 0.5 mL YPD (yeast extract, peptone, 2% glucose) in 96 well plates with 2 mL/well maximum capacity, shaking at 900 RPM at 30°C in an Infors HT Multitron Pro shaker. Saturated cultures were diluted 1:100 into 1 mL SDC (YNB, CSM, 2% glucose) in a new 2 mL 96 well plate

and placed at 30°C shaking at 900RPM for 2 hours. Cells were then diluted 1:4 into 400 µL SDC with estradiol and either theophylline from a 30 mM stock or water in a new 2 mL 96 well plate. The final concentration of estradiol was 125 nM and the final concentration of theophylline when present was 2.5 mM. After 8 hours shaking at 900 rpm and 30°C, cells were diluted in 1X TE buffer and analyzed on a flow cytometer (BD LSR II).

3.4.8 Gene editing assay in mammalian cells

HEK293T (293FT; Thermo Fisher Scientific) cells, and derived cell lines, were grown in Dulbecco's Modified Eagle Medium (DMEM; Corning Cellgro, #10-013-CV) supplemented with 10% fetal bovine serum (FBS; Seradigm #1500-500), and 100 Units/mL penicillin and 100 µg/mL streptomycin (Pen-Strep; Life Technologies Gibco, #15140-122) at 37°C with 5% CO₂. HEK293T and HEK-RT1 cells were tested for absence of mycoplasma contamination (UC Berkeley Cell Culture facility) by fluorescence microscopy of methanol fixed and Hoechst 33258 (Polysciences #09460) stained samples.

HEK293T-based genome editing reporter cells, referred to as HEK-RT1, were established in a two-step procedure. In the first step, puromycin resistant monoclonal HEK-RT3-4 reporter cells were generated as previously described (Hui Liu et al., in revision). In brief, HEK293T human embryonic kidney cells were transduced at low-copy with the amphotropic pseudotyped retrovirus RT3GEPiR-sh.Ren.713 [57], comprising an all-in-one Tet-On system enabling doxycycline-controlled EGFP expression. After puromycin (2.0 µg/ml) selection of transduced HEK239Ts, 36 clones were isolated and individually assessed for i) growth characteristics, ii) homogeneous morphology, iii) sharp fluorescence peaks of doxycycline (1 µg/ml) inducible EGFP expression, iv) relatively low fluorescence intensity to favor clones with single-copy reporter integration, and v) high transfectability. HEK-RT3-4 cells are derived from the clone that performed best in these tests. In the second step, HEK-RT1 cells were derived by transient transfection of HEK-RT3-4 cells with vectors encoding Cas9 and sgRNAs targeting puromycin, followed by identification of monoclonal reporter cell lines that are puromycin sensitive.

A lentiviral vector, referred to as pCF204, expressing a U6 driven sgRNA and an EFS driven Cas9-P2A-Puro cassette was based on the lenti-CRISPR-V2 plasmid [58], by replacing the sgRNA

with an enhanced *Streptococcus pyogenes* Cas9 sgRNA scaffold [5]. All sgRNAs (sgRen71: TAG-GAATTATAATGCTTATC, sgGFP1: CCTCGAACTTCACCTCGGCG, sgGFP9: CCGGCAAGCT-GCCCGTGCCC) were designed with a G preceding the 20-nt guide for better expression, and cloned into the lentiviral vector using the BsmBI restriction sites. The lentiviral vectors expressing ligRNA⁺, ligRNA2⁺ and ligRNA⁻ (referred to as pCF441, pCF442 and pCF443, respectively) were all based on pCF204, by replacing the SpyCas9 sgRNA scaffold with the respective ligRNAs using custom oligonucleotides (IDT), gBlocks (IDT), standard cloning methods, and Gibson assembly techniques. Lentiviral particles were produced using HEK293T packaging cells; viral supernatants were filtered (0.45µm) and added to target cells. Transduced HEK-RT1 target cells were selected on puromycin (1.0 µg/ml).

GFP expression in HEK-RT1 reporter cells was induced using doxycycline (1 µg/ml; Sigma-Aldrich). Percentages of GFP-positive cells were assessed by flow cytometry (Attune NxT, Thermo Fisher Scientific), routinely acquiring 10,000-30,000 events per sample. Theophylline (Sigma-Aldrich, #T1633-50G) was used at the indicated concentrations, ranging from 0.1 mM to 10 mM. Note, theophylline concentrations of 5 mM and 10 mM resulted in considerable cellular toxicity in the HEK293T-based reporter cell line.

3.4.9 Screen for different ligands

TPP media: 1x MOPS (Teknova M2101), 1x K₂HPO₄ (Teknova M2102), 1x Supplement EZ (Teknova M2104), 0.4% glucose (Teknova G0520), 0.2% casamino acids, 500 µM thiamine.

Adenine/Guanine media: 1x MOPS (Teknova M2101), 1x K₂HPO₄ (Teknova M2102), 1x ACGU (Teknova M2103), 0.4% glucose (Teknova G0520), 8–2000 µM adenine/guanine.

3.4.10 FACS screen in *S. cerevisiae*

Libraries 36–45 were prepared as described for the bacterial screens, then were transformed into yeast by the method of Gietz and Schiestl [59]. The order of the screens and the gating strategies were as described for the bacterial screens. In between the second and third screen, the spacer was swapped via colony PCR and Golden Gate cloning. Colony PCR: mix 46.1 µL water, 3.3 µL OD≈10 library culture, 0.6 µL 5 U/µL zymolase; incubate for 30 min at 37°C, then for 10 min at

95°C; PCR amplify the sgRNA library using the zymolase reaction as the template and primers containing the second spacer sequence and BsaI sites on either side of the sgRNA. Golden Gate cloning: 1.0 µL Yeast Toolkit [53] destination vector, 25.0 µL PCR product, 3.1 µL 10 T4 ligase buffer (NEB), 1.0 µL T4 ligase (NEB), 1.0 µL BsaI-HF (NEB); incubate for 30 cycles of 42°C and 16°C for 5 min each; electrotransform into Top10 cells as described previously.

A different strategy was used to change the spacer in libraries 36–38. Since the randomized region in these libraries was located just 6 bp from the spacer, there was no room for an inverse PCR primer to bind without overlapping the spacer. We instead designed primers that overlapped the 6 bp before the randomized region plus 10 bp of the spacer, followed immediately by a BtgZI restriction site. BtgZI cleaves 10 bp away from where it recognizes, and thus removes the spacer information from the amplified sgRNA. The amplified sgRNA and a destination vector including the desired spacer preceding a complementary BtgZI site were separately digested, gel purified, ligated, and electrotransformed into Top10 cells.

3.5 Appendix

Table 3.1: Complete results of the *in vitro* screen of rational designs. #: Design number. Strategy: The mechanism by which the design was intended to work. "Stem Replacement" means a stem in the sgRNA was replaced by the aptamer (in some cases including a linker), with the expectation that ligand binding to the aptamer would stabilize the stem to adopt a functional sgRNA conformation. "Induced dimerization" means the sgRNA was split in half, with each half containing part of the aptamer, in the hope that the two halves would dimerize in the presence of ligand. "Strand displacement" means that strands were designed to base pair in two ways — one maintaining the wildtype sgRNA functional conformation and the other adopting an alternative conformation — and that ligand binding to the aptamer would stabilize the functional conformation. Domain: The domain in the sgRNA (as defined in Figure 3.1b in the main text) into which the aptamer was inserted. Cleavage: The percent of DNA that was cleaved by a design in the *in vitro* assay. The apo and holo columns refer to the cleavage with and without theophylline, respectively, Δ is the difference between these values, and σ is the standard deviation of the Δ values for designs with three or more replicates. All percentages are averages of any replicates and are rounded to the nearest integer. N: The number of replicates for each design. Active: We denote a design as "active" if it exhibited a $>15\%$ change in cleavage in response to ligand. Sequence: The sequence of the design, including the AAVS spacer used in this assay (Table 3.4). Sequences are aligned and color coded by sgRNA domain as in Figure 3.1b (grey: spacer; blue: upper stem; navy: nexus; teal: hairpin; purple: aptamer; orange: other regions).

Name	Library	Picks	Fold Change			Sequence
			sgG1	sgR2	sgR1	
* ligRNA ⁻	1-6	1/18	10.2 ⁺	—	1.0 [*]	GUUUUA--AAGGAUACAGCCGAAAGGCCCUIUUGCCAGCUUUUAGC- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	2/18	12.4 ⁺	—	1.2 [*]	GUUUUA-CCGGAUACCCAGCCGAAAGGCCCUIUUGCCAGCUUUCG- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	10.7 ⁺	—	1.4 [*]	GUUUUA--AUGGAUACAGCCGAAAGGCCCUIUUGCCAGCGGGUUJ- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	11.3 ⁺	—	1.1 [*]	GUUUUA--UAGGAUACAGCCGAAAGGCCCUIUUGCCAGCUUUCG- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	9.0 ⁺	—	1.1 [*]	GUUUUA-ACUUGAUACAGCCGAAAGGCCCUIUUGCCAGCUUGA- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	8.0 ⁺	—	1.0 [*]	GUUUUA-CCGGAUACAGCCGAAAGGCCCUIUUGCCAGCAGUCU- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	7.5 ⁺	—	1.4 [*]	GUUUUA--CCGGAUACAGCCGAAAGGCCCUIUUGCCAGCAGAGU- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	8.2 ⁺	—	1.3 [*]	GUUUUA-CCGGAUACAGCCGAAAGGCCCUIUUGCCAGCUAGG- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	7.7 ⁺	—	1.0 [*]	GUUUUA-CCGGAUACAGCCGAAAGGCCCUIUUGCCAGCUAGG- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	9.4 ⁺	—	1.1 [*]	GUUUUA--CGUGAUACAGCCGAAAGGCCCUIUUGCCAGCUUUCG- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	8.6 ⁺	—	1.0 [*]	GUUUUA--UCGUAUACAGCCGAAAGGCCCUIUUGCCAGCCUUG- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	6.0 ⁺	—	1.2 [*]	GUUUUA--CCAGAUACAGCCGAAAGGCCCUIUUGCCAGCUGCC- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	6.4 ⁺	—	1.3 [*]	GUUUUA--AUCGAUACAGCCGAAAGGCCCUIUUGCCAGCUGCUU- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	33.6 ⁺	—	1.3 [*]	GUUUUA--GCGGAUACAGCCGAAAGGCCCUIUUGCCAGCUGGCUU- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	17.9 ⁺	—	1.2 [*]	GUUUUA--ACGGAUACAGCCGAAAGGCCCUIUUGCCAGCUGGCUU- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/18	8.0 ⁺	—	1.2 [*]	GUUUUA--AUAGAUAACAGCCGAAAGGCCCUIUUGCCAGCAGC- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/21	6.6 ⁻	—	—	GUUUUAAGAGCUUACAGCCGAAAGGCCCUIUUGCCAGCUGCC- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
	1-6	1/21	6.0 ⁻	—	—	GUUUUA-CCCUAUAACAGCCGAAAGGCCCUIUUGCCAGUGGGUJ- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
1-6	10/21	6.9 ⁻	—	1.0 [*]	GUUUUAAGCGUGAUACAGCCGAAAGGCCCUIUUGCCAGCUGCC- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
1-6	1/21	3.9 ⁻	—	—	GUUUUAAGUUGAUACAGCCGAAAGGCCCUIUUGCCAGUAAGUJ- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
1-6	3/21	3.7 ⁻	—	—	GUUUUAACCUUGAUACAGCCGAAAGGCCCUIUUGCCAGCUAGUJ- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
1-6	2/21	7.1 ⁻	—	—	GUUUUA-ACUCUAUACAGCCGAAAGGCCCUIUUGCCAGUGGU- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
1-6	3/21	5.6 ⁻	—	—	GUUUUA-CCCCUAUACAGCCGAAAGGCCCUIUUGCCAGGGGGUJ- UAAAAUAAGGCUAGUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
7-22	4/20	8.6 ⁻	—	—	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
7-22	5/20	13.7 ⁻	—	—	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
7-22	4/20	10.2 ⁻	4.3 ⁻	5.5 [*]	10.2 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
7-22	1/20	13.2 ⁻	—	—	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
7-22	1/20	11.0 ⁻	—	—	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
7-22	1/20	—	—	—	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
7-22	2/20	5.6 ⁻	—	—	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
7-22	1/20	7.3 ⁻	—	—	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
7-22	1/20	—	—	—	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
23-28	6/6	14.1 ⁺	—	1.4 [*]	GUUUUAAGAGCUA----GAAA-----UAGCAAGUUAUUUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU	
29-30	1/15	9.7 ⁺	—	4.8 [*]	4.4 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	4.5 ⁺	1.3 ⁺	5.4 [*]	—	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	9.6 ⁺	1.7 ⁺	3.8 [*]	—	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	7.3 ⁺	1.3 ⁺	9.8 [*]	4.5 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	10.1 ⁺	1.3 ⁺	2.5 [*]	6.5 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	7.5 ⁺	1.4 ⁺	7.6 [*]	6.1 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	2/15	10.8 ⁺	—	3.4 [*]	—	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	10.8 ⁺	1.1 ⁺	5.0 [*]	6.8 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	7.7 ⁺	—	4.8 [*]	—	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	10.3 ⁺	1.4 ⁺	8.6 [*]	7.8 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	7.2 ⁺	—	3.8 [*]	3.8 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	7.2 ⁺	1.0 ⁺	15.3 [*]	10.8 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	7.2 ⁺	1.4 ⁺	10.3 [*]	—	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU
29-30	1/15	11.2 ⁺	1.2 ⁺	3.2 [*]	5.3 [*]	GUUUUCAGAGCUUUGCUUGAAACAGCAUAGCAAGUUGAAUAJ.GGGGAUAUCCAGCCGAAAGGCCCUIUUGCCAGUCCUCCGUUAUCAACUUGAAAAAGUGGCACCGAGUCGGUGCUUUUUUU

Table 3.3: Ligand-sensitive sgRNAs isolated from FACS screen. Name: Names of designs described in the main text. The asterisk (*) denotes the design that was the precursor to ligRNA⁻; we created ligRNA⁻ by transferring the nexus stem from this precursor into the optimized sgRNA scaffold described in ref. [1]. Library: Libraries (Table 3.2) from which each design was isolated. Picks: The number of times each design appeared (first number) out of the total number of colonies picked to sequence from each library (second number). Fold Change: The fold change in fluorescence in response to the addition of theophylline, measured by flow cytometry. All data in this table are single-replicate. The subcolumns (sgG1, sgG2, sgR1, sgR2) indicate the spacer used for each measurement. Superscripts indicate whether CRISPRi was activated (+) or inhibited (-) by theophylline. Dashes indicate spacers that were not tested. Note that the designs selected from libraries 1–6 appear to be spacer-dependent, i.e. they are functional with the sgG1 spacer that was used in the selection but not with the sgR1 spacer (which for these libraries was not used in the selection). We therefore did not pursue these designs further. In contrast, the designs from libraries 29–30 were selected using both the sgG1 and sgR1 spacers as described in Figure 3.2c, and in validation experiments also function with the sgR2 spacer (the sgG2 spacer is not functional with any of the designs). Sequence: The sequence of the isolated design, color coded as in Table 3.1. Note that the randomized regions on either side of the aptamer often form base-paired stems. Also note that for the nexus insertions (libraries 7–22), U95 and G63 (in ligRNA⁻ numbering, alternatively the third position from the 3' end of the nexus and the position at the 5' end of the nexus) are conserved in 17 and 20 of the 20 of the isolated sequences, respectively. This observation corroborates the importance of these positions in our mutagenesis experiments (Figure 3.6).

Name	Sequence
T7 promoter	TATAGTAATAATACGACTCACTATAG
AAV/S spacer	GGGGCCACTAGGGACAGGAT
sg1 spacer	CATCTAAATCAACAAGAAAT
sgR1 spacer	AACTTTCAGTTTAGCGGTCT
sgG2 spacer	AGTAGTGCAAAATAAAATTTAA
sgR2 spacer	TGGAACCGTACTGGAACCTGC
Theophylline aptamer	ATACCAGCCGAAAGGCCCTTTGGCAG
3-Methylxanthine aptamer	ATACCAGCCGAAAGGCCCTTTGGCAG
Positive control	GTTTTCAGAGCTATGCTGGAAACAGCATAGCAAGTTGAAATAAGGCTAGTCCGTTTATCAACTTGAAAAAGTGGCACCGAGTCGGTGCCTTTTTT
Negative control	GTTTTCAGAGCTATGCTGGAAACAGCATAGCAAGTTGAAATAAGGCTAGTCCGTTTATCAACTTGAAAAAGTGGCACCGAGTCGGTGCCTTTTTT
ligRNA ⁺	GTTTTCAGAGCTATGCTGGAAACAGCATAGCAAGTTGAAATAAGG66 - TGTCCCGTATAGCCGATACCAGCGAAAGGCCCTTGGCAGCGACGGCACCGAGTCGGTGCCTTTTTT
ligRNA ⁺ ₂	GTTTTCAGAGC - ATGCTGGAAACAGCATAGCAAGTTGAAATAAGGCTTCCCGCATCCCGCATACCAGCGAAAGGCCCTTGGCAGCGACGGCACCGAGTCGGTGCCTTTTTT
ligRNA ⁺ ₃	GTTTTCAGAGCTATGCTGGAAACAGCATAGCAAGTTGAAATAAGGC - TGTCCCGTATAGCCGATACCAGCGAAAGGCCCTTGGCAGCGACGGCACCGAGTCGGTGCCTTTTTT
ligRNA ⁺ ₄	GTTTTCAGAGCTATGCTGGAAACAGCATAGCAAGTTGAAATAAGCG - TGTCCCGTATAGCCGATACCAGCGAAAGGCCCTTGGCAGCGACGGCACCGAGTCGGTGCCTTTTTT
ligRNA ⁻	GTTTTCAGAGCTATGCTGGAAACAGCATAGCAAGTTGAAATAAGTGGGATACCAGCGAAAGGCCCTTGGCAGCCTACGTTATCAACTTGAAAAAGTGGCACCGAGTCGGTGCCTTTTTT
ligRNA ⁻ ₂	GTTTTCAGAGCTATGCTGGAAACAGCATAGCAAGTTGAAATAAGAGGGATACCAGCGAAAGGCCCTTGGCAGCCTTCGTTATCAACTTGAAAAAGTGGCACCGAGTCGGTGCCTTTTTT
ligRNA ⁻ ₃	GTTTTCAGAGCTATGCTGGAAACAGCATAGCAAGTTGAAATAAGTGGAAATACCAGCGAAAGGCCCTTGGCAGTCTACGTTATCAACTTGAAAAAGTGGCACCGAGTCGGTGCCTTTTTT

Table 3.4: DNA sequences of main constructs.

#	Spacer (with context)	Score	pos (% cut)			neg (% cut)			ligRNA ⁺ (% cut)			ligRNA ⁻ (% cut)							
			apo	holo	Δ σ	apo	holo	Δ σ	apo	holo	Δ σ	apo	holo	Δ σ					
1	gcagGGGAACCAAGAGCGGAGGGTggtca	0.622	91	90	-1	1	2	1	0	20	57	37	6	89	15	-74	3	3	
2	acgCGGCTTACCTTTAATAAGAGgggtc	0.523	94	94	0	2	3	2	-1	1	36	88	52	10	94	30	-64	13	3
3	cccGGGTATGCCTACGATGACCgggaat	0.582	95	95	-0	1	3	1	-2	2	43	79	36	17	93	24	-69	17	3
4	atcagGGTGAAGGATCGAGTGCaggctc	0.518	91	92	1	3	0	0	0	7	30	23	6	87	8	-79	9	3	
5	ctgtGGATAAGGAGTTCGTCGTGtagggc	0.568	—	—	—	—	0	1	0	47	81	34	22	95	30	-65	25	3	
6	gcagGGCTTGTATTGGTTCGAGTggata	0.605	90	89	-1	1	2	1	-1	1	27	81	54	5	90	44	-47	22	3
7	gaagGGAAAGAACTCATTCGTTggtgg	0.587	97	97	-0	0	3	2	-2	1	52	77	26	9	97	41	-56	4	3
8	cttGGCGGGTTGAATAGTCGTTggtga	0.505	91	92	1	4	0	0	-0	0	28	71	42	11	69	24	-45	10	3
9	tgaGGGCATGACCTAAACTCTATcgca	0.582	94	93	-1	1	4	2	-2	2	2	16	14	3	90	15	-75	4	3
10	taccGGTTGTATTGGTAACAGATggggg	0.563	96	95	-0	1	0	0	-0	1	44	66	21	3	87	26	-61	7	3
11	acaGGGACCATATAGTAGAACATggcca	0.702	93	93	-0	1	5	3	-2	2	28	59	31	10	93	47	-46	19	4
12	tctcGGGTCATCAGTATGAGTAAaggac	0.548	83	85	2	3	3	1	-2	2	35	58	22	6	89	33	-56	9	4
13	cgctGGGATAACAAATGACCATGcgtlct	0.728	97	97	-0	0	1	1	-1	1	46	64	19	17	71	22	-49	14	3
14	acgaGGAGCTCACTATTCAGGTCggtaa	0.688	94	94	-0	0	0	0	0	8	32	25	14	34	3	-31	14	3	
15	gagaGGTCAGAGGGGAAAGCCGgacgtat	0.627	89	89	0	2	0	0	0	2	15	14	3	71	25	-46	16	3	
16	gtacGGTTAACGGATCCAACACGaggacg	0.708	97	97	-0	0	0	0	0	4	15	11	1	45	2	-43	7	3	
17	ttagGGTGCCTTTCCACGAGTgggtag	0.515	96	95	-2	2	0	0	0	5	24	19	1	1	3	2	0	3	
18	ggccGGGAGGGCGTGAGAAATCGtgaa	0.522	90	90	1	1	0	0	-0	7	23	16	10	39	19	-20	16	3	
19	acatGGGGTATCCGACTTGACATggtgg	0.594	91	90	-0	0	0	0	-0	26	37	12	6	46	20	-26	7	3	
20	gcagGGAGTGGACAGGAGTACGTgggaa	0.525	92	90	-2	0	0	0	0	3	9	6	3	46	9	-37	14	3	
21	tatcGGTTGGACTCTTAACGATaggaaa	0.622	97	96	-1	1	0	0	0	12	18	6	4	50	8	-42	13	3	
22	caccGGCCAGCGTCGTCAAGCGgggtg	0.510	94	91	-3	4	0	0	0	0	3	3	4	22	1	-21	12	3	
23	gtgtGGGTTAGAGGCTGAGTCCagggtcc	0.534	95	94	-1	1	0	0	0	2	8	6	1	0	0	0	0	3	
24	tcaGGGCCCCGGAGCCTGgcaGTTggaag	0.527	96	95	-1	1	0	0	0	0	0	0	0	0	0	0	0	2	

Table 3.5: Detailed results for the *in vitro* DNA cleavage assay in the context of different spacers (Figure 3.2g in the main text). #: The spacer number in Figure 3.2g. Spacer (with context): In upper case is the 20 nt spacer sequence being tested. Note that each spacer begins with 3 Gs for facile transcription by T7 polymerase. In upper and lower case is the corresponding sequence present in the target DNA. This includes 10 bp of context and (to the right of the spacer) the NGS protospacer adjacent motif (PAM). These sequences were chosen as described in the Methods section. Score: The “Rule Set 2” score of the target sequence by the method of ref. [2], which predicts Cas9 cleavage efficiency for the target sequence. We only tested sequences with scores greater than 0.5 (approximately half of those generated). pos, neg, ligRNA⁺, ligRNA⁻: Cleavage data for the controls and indicated sgRNA. The apo, holo, Δ , σ , N columns are as in Table 3.1.

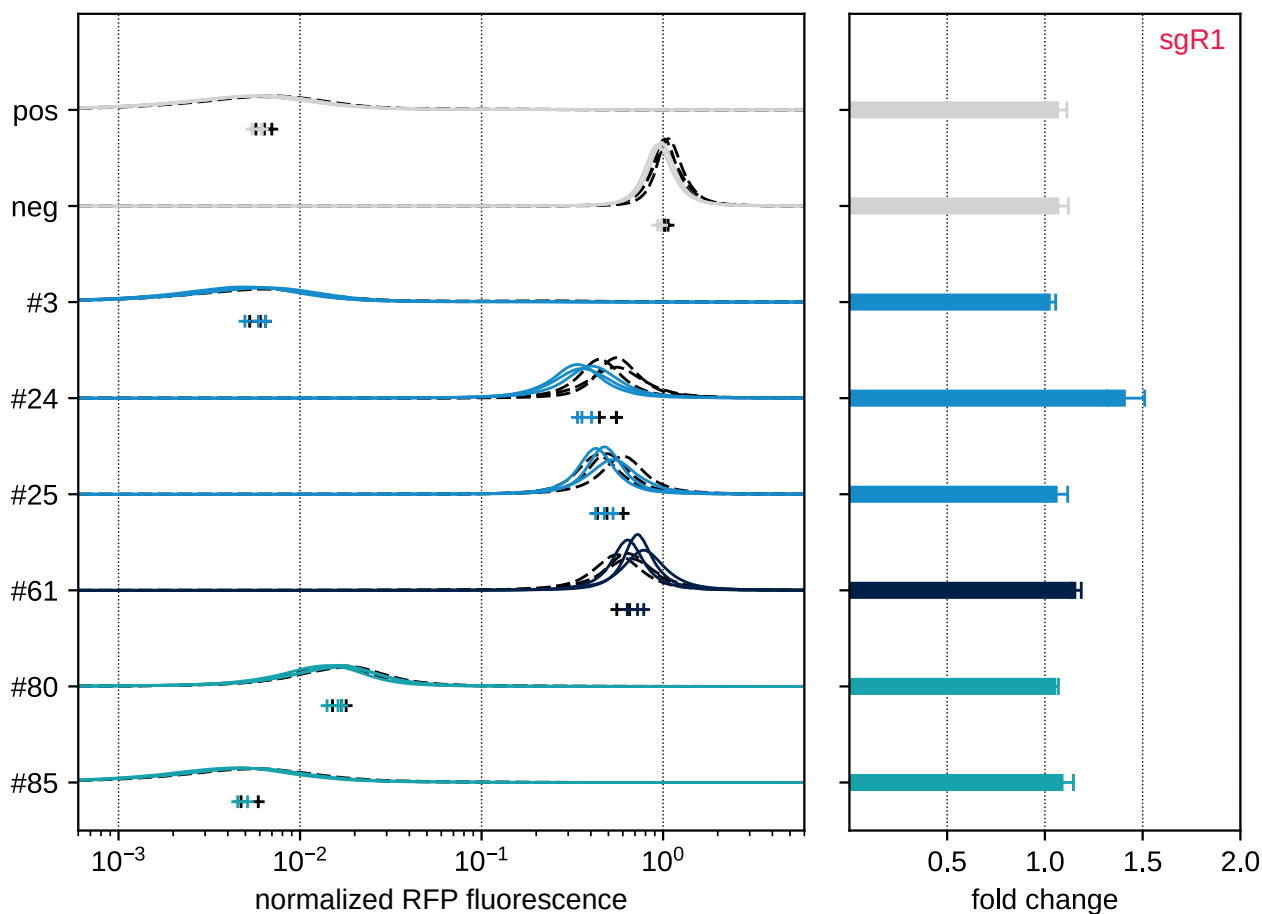


Figure 3.4: The strongest rational designs (determined by the *in vitro* cleavage assay, Table 3.1) have weak ligand-sensitivity in a CRISPRi-based assay in *E. coli*. Flow cytometry traces and fold changes for the rational designs that were tested in *E. coli*. The labels on the y-axis refer to Table 3.1. Traces are color-coded by aptamer insertion site (defined in Figure 3.1b). RFP fluorescence values for each cell are normalized by both GFP fluorescence for that cell and the modes of the un-repressed control populations (i.e. apo and holo) measured for that replicate. All other lines and symbols are as described in Figure 3.2. Data are from three experiments performed on the same day (for all other experiments reported in this paper, replicates were performed on different days). Designs #24 and #61 display a small ligand-dependency. For design #24 adding theophylline shifts the fluorescence distribution to the left (less fluorescence, indicating stabilization of the functional sgRNA conformation with ligand), whereas for design #61 the opposite is the case (shift to more fluorescence indicating destabilization of the functional sgRNA conformation with ligand). These changes are in the same direction as observed for these designs in the *in vitro* DNA cleavage assay (Table 3.1).

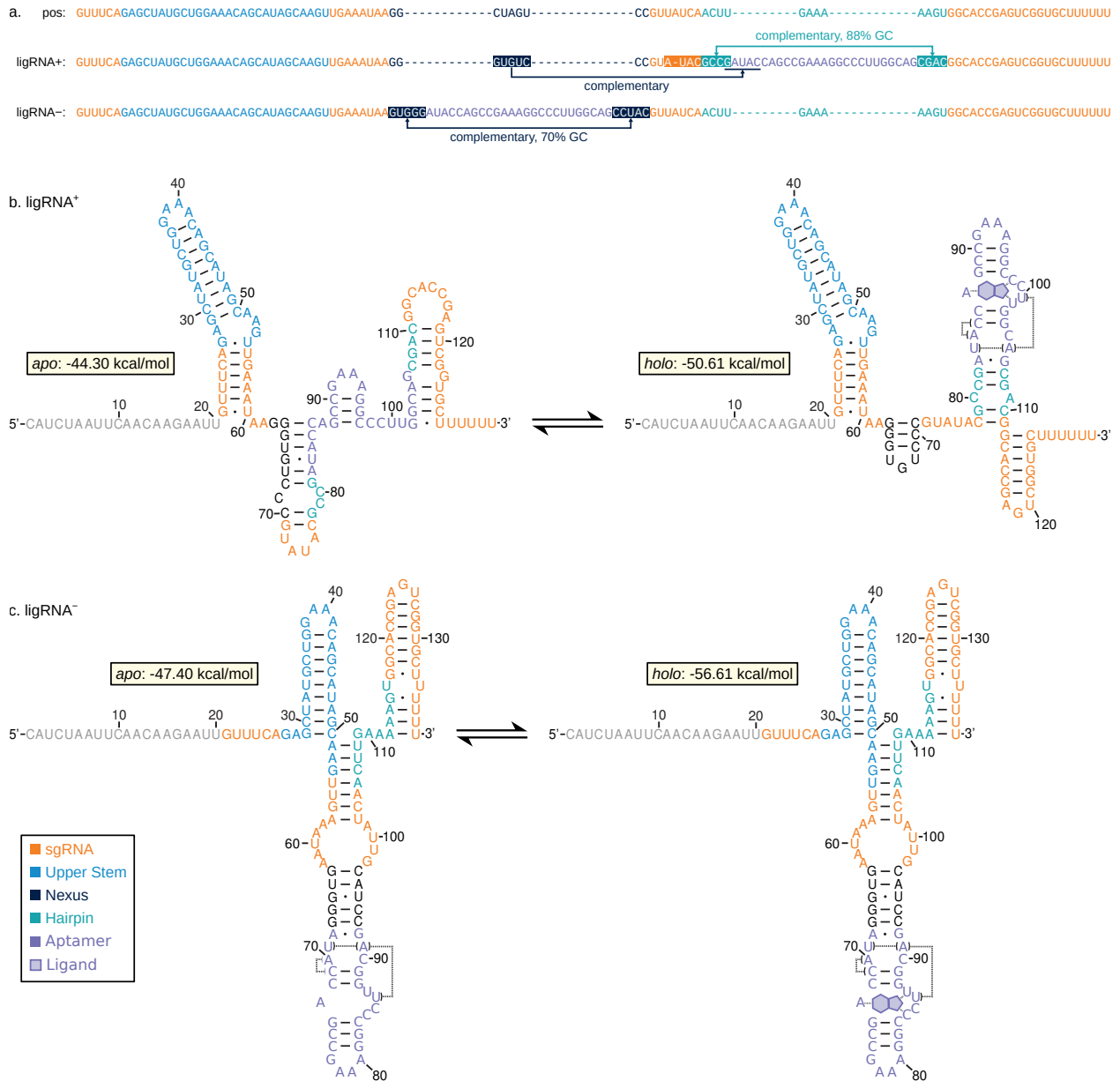


Figure 3.5: Secondary structure predictions suggest mechanisms of ligand sensitivity. (a) Sequence alignment of the positive control sgRNA, ligRNA⁺, and ligRNA⁻. Nucleotides are color-coded by domain, and randomized positions are shaded. Several sequence features of the selected ligRNAs are noted. (b,c) Secondary structure and free energy predictions for ligRNA⁺ (b) and ligRNA⁻ (b) in both the apo and holo states, calculated as described in the Methods section. Nucleotides are color-coded by domain. (b) In the apo state of ligRNA⁺, the nexus is predicted to base-pair with the aptamer, but in the holo state, the sgRNA is predicted to fold correctly. (c) The apo and holo states for ligRNA⁻ are predicted to have the same fold and neither prediction recapitulates the known sgRNA stems. This figure was drawn by Kyle Watters.

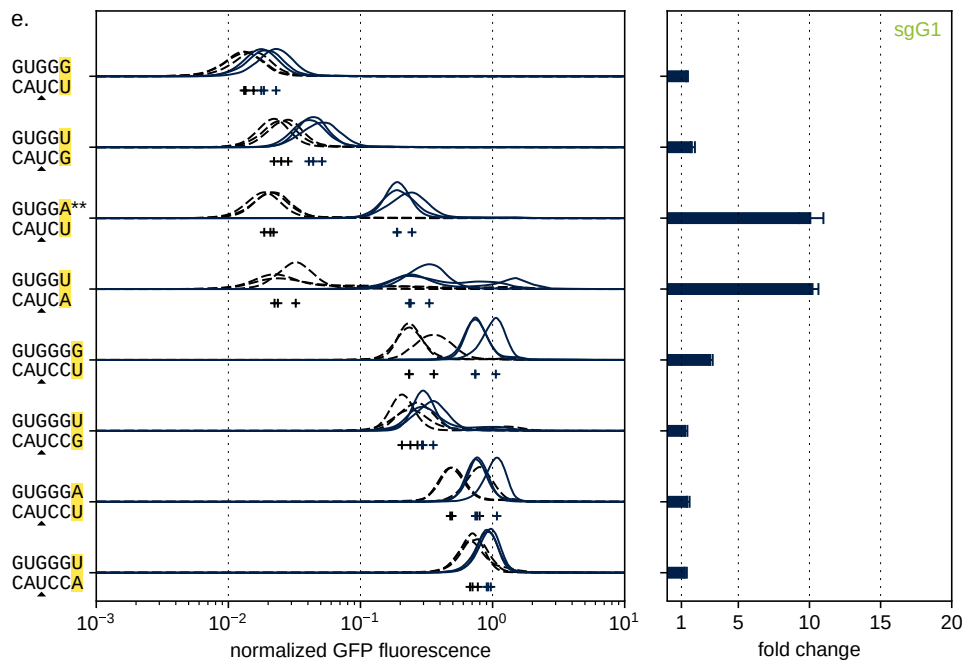
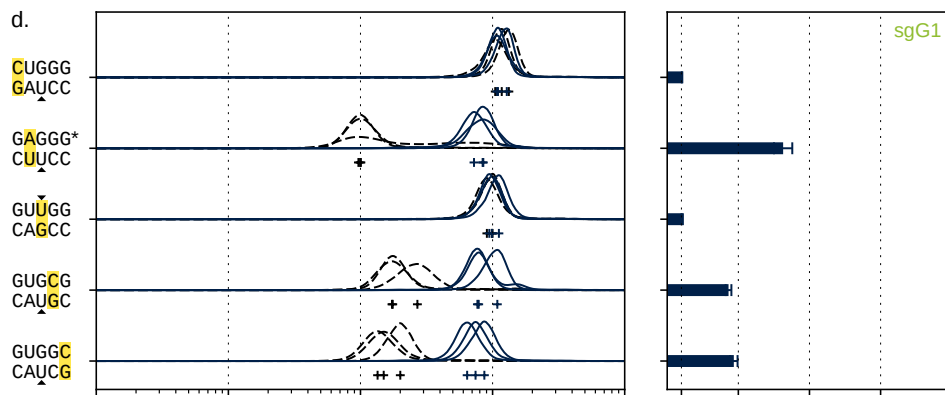
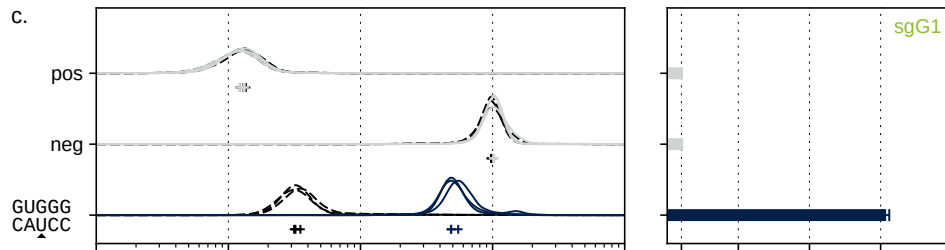
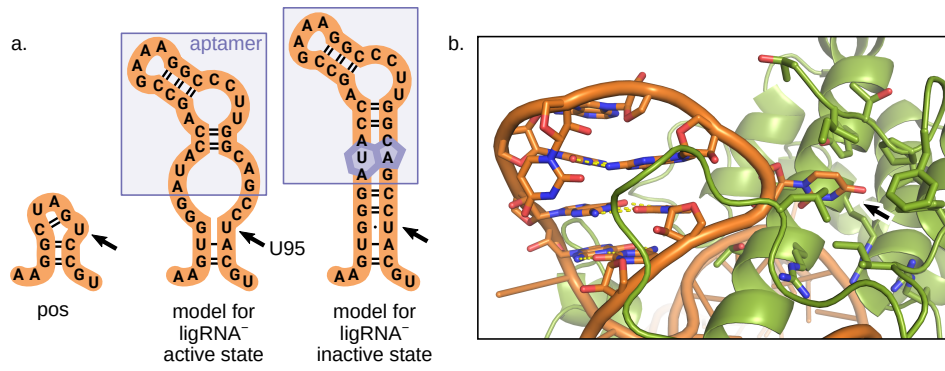


Figure 3.6: Mechanistic insights into ligRNA⁻ function. (a) Model of possible mechanism, where ligRNA⁻ functions by sequestering the indicated uracil (U95) in the presence of the ligand. U95 is unpaired in wildtype sgRNA (left). Our hypothesis is that in ligRNA⁻ U95 is unpaired to a larger extent in the apo state (center) than in the holo state (right). (b) A crystal structure of Cas9 in complex with an sgRNA [3] (PDB ID 4UN3) shows the indicated uracil flipped out (black arrow) and interacting with the Cas9 protein. (c-e) Flow cytometry traces and fold changes for different mutants of ligRNA⁻. The labels show the sequence of the particular mutant being tested. Mutations relative to ligRNA⁻ are highlighted in yellow. The uracil in question is indicated with a small triangle. The ligRNA⁻₂ and ligRNA⁻₃ variants (Table 3.4; Figure 3.10) are marked by * and **, respectively. GFP fluorescence values for each cell are normalized by both RFP fluorescence for that cell and the modes of the un-repressed control populations (i.e. apo and holo) measured for that replicate. All other lines and symbols are described in Figure 3.2. (c) Positive and negative controls, and ligRNA⁻. (d) Strand-swap mutations for each position along the nexus stem. None of the mutants are as functional as ligRNA⁻, but the design is tolerant to strand-swap mutation at positions 2, 4, and 5. As expected, position 3 containing the critical uracil is intolerant to mutation. The simple model in (a) does not explain the intolerance of position 1 however. (e) Modulating the strength of the base-pairs between the uracil and the aptamer has a predictable effect on function. From top to bottom, the mutants are arranged in the order of increasing base-pairing strength. Fluorescence distributions shifted to the left indicate stronger activation of the sgRNA (fluorescence is more effectively repressed). Our hypothesis (that ligRNA⁻ works by sequestering the uracil upon ligand binding) predicts that weakening or strengthening the base-pairs between the uracil and the aptamer should increase or decrease activation, respectively. The clear downward diagonal trend in the populations supports this hypothesis and demonstrates that we can tune the dynamic range of ligRNA⁻ to some extent. The third and fourth mutants (AU and UA) may be useful for applications where strong repression is desired because they show stronger repression than the original ligRNA⁻ design in the absence of the ligand, although their dynamic range (10x) is somewhat narrower than that of ligRNA⁻ (15x).

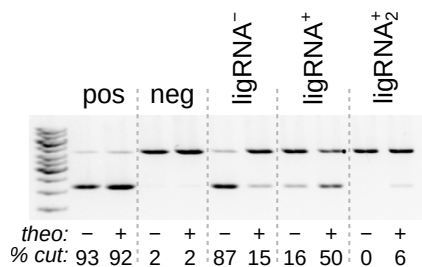


Figure 3.7: Representative gel from the *in vitro* spacer assay. Shown is a single replicate for spacer #1 (Figure 3.2g). The upper and lower bands are uncleaved and cleaved DNA, respectively. Each design was tested in the absence and presence of theophylline. The amount of DNA cleavage was quantified by gel densitometry and is reported as a percentage below each lane.

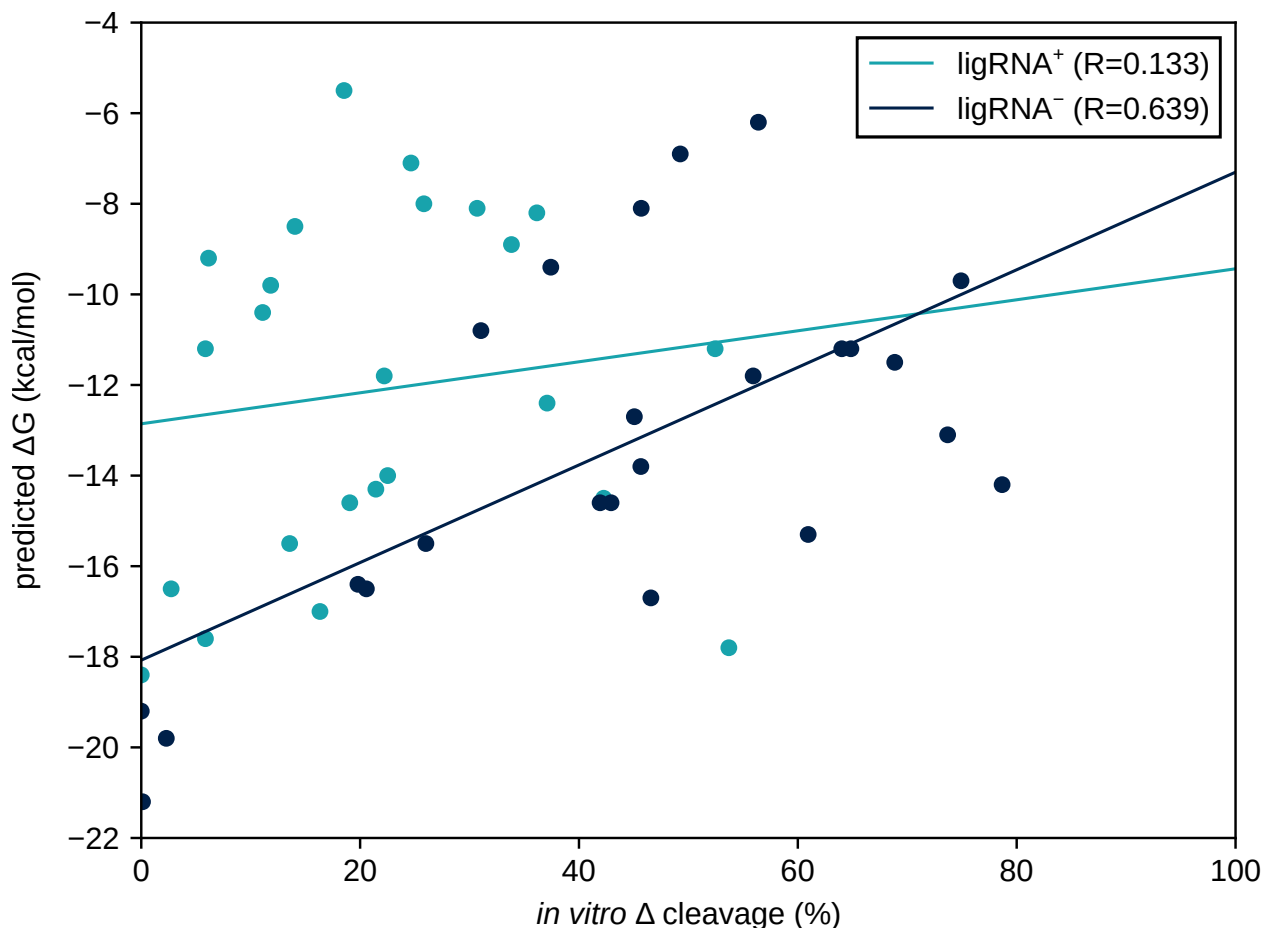


Figure 3.8: Correlation between ligRNA function and the predicted binding free energy of base-pairing between the spacer and the aptamer insert. Binding free energies (y-axis) were calculated using the duplexfold method from the python3 API of the ViennaRNA package (version 2.4.3). This method returns the minimum binding energy between two strands of RNA considering only inter-strand base pairs. For each calculation, the first strand was one of the 24 20 nt spacers used in the *in vitro* spacer assay (Table 3.5). The second strand was GCCGAUACCAGCCGAAAGGC-CCUUGGCAGCGAC for ligRNA⁺ or GUGGGAUACCAGCCGAAAGGCCCUUGGCAGCCUAC for ligRNA⁻. These sequences include both the aptamer and the randomized linker connecting the aptamer to the sgRNA scaffold. Percent cleavage values (x-axis) are the means of the replicates from the *in vitro* spacer assay (Figure 3.2g, Table 3.5). Linear regressions (solid lines) and R-values are shown.

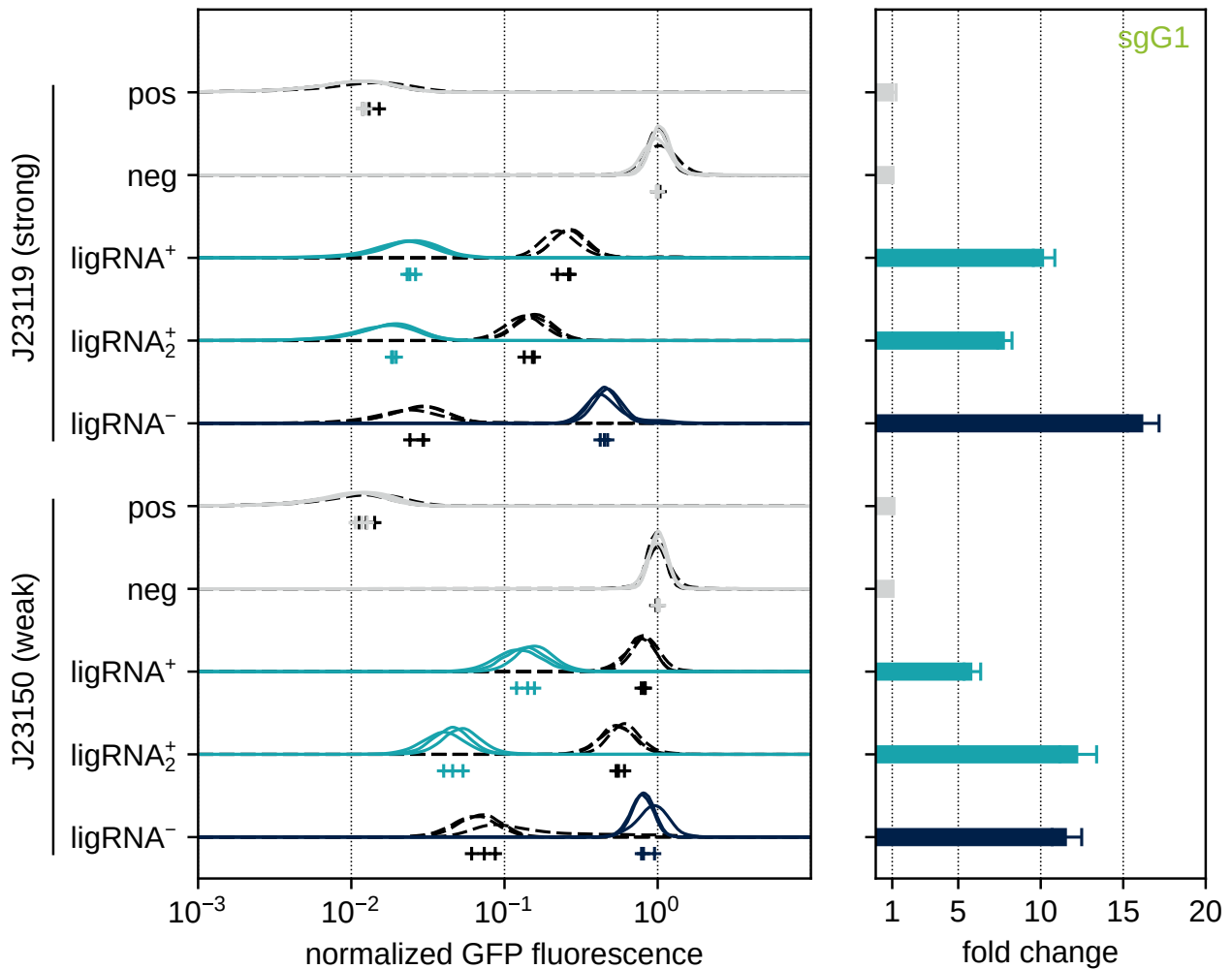


Figure 3.9: ligRNA activity with two promoter strengths. Flow cytometry traces and fold changes for three ligRNAs (ligRNA⁺ and ligRNA⁻ discussed in the main text and a third sequence termed ligRNA⁺₂ isolated from the same screen as ligRNA⁺, Table 3.3) in the context of a strong (J23119) and a weak (J23150) constitutive promoter. GFP fluorescence values for each cell are normalized by both RFP fluorescence for that cell and the modes of the un-repressed control populations (i.e. apo and holo) measured for that replicate. All lines and symbols are described in Figure 3.2. The alternate ligRNA⁺₂ has a larger dynamic range with the weaker promoter, and may be useful for applications where lower concentrations of ligRNA are anticipated. Moreover, in the context of the weak promoter, the fluorescence distributions of ligRNA⁺₂ in the absence of the ligand and the distributions of ligRNA⁻ in the presence of the ligand (inactive states) are close to the fluorescence distributions of the negative control, which may be useful when one of the desired states is full activation of gene expression.

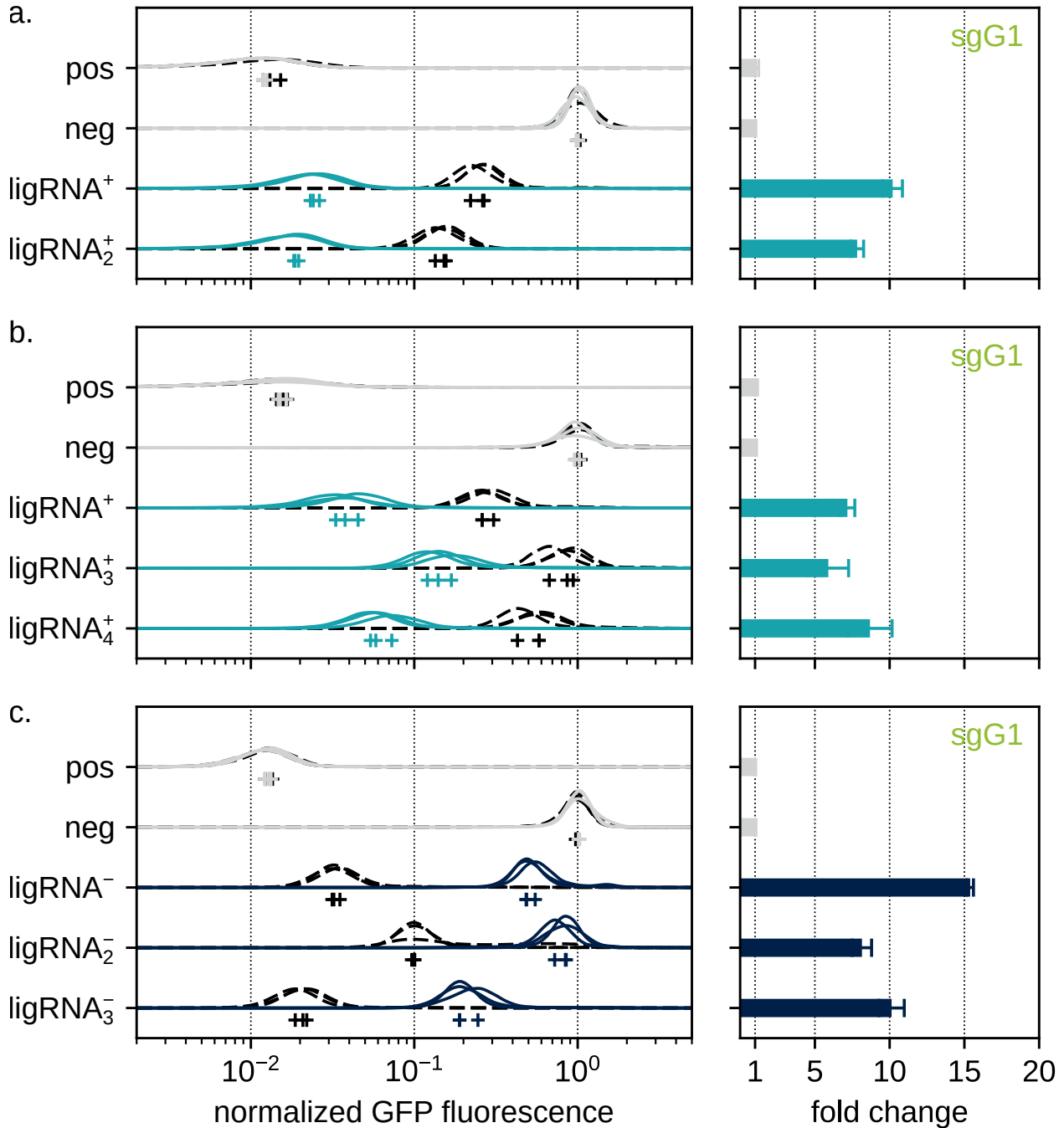


Figure 3.10: ligRNA variants with shifted dynamic ranges. Flow cytometry traces and fold changes for sequence variants of ligRNA⁺ (a,b) and ligRNA⁻ (c) that maintain significant sensitivity to theophylline, but shift the dynamic range either towards maximum expression (ligRNA⁺₃ and ligRNA⁺₄ in the absence of the ligand, panel b; ligRNA⁻₂ in the presence of the ligand, panel c) or maximum repression (ligRNA⁺₂ in the presence of the ligand, panel a; ligRNA⁻₃ in the absence of the ligand, panel c). See Table 3.4 for the sequences of these variants. GFP fluorescence values for each cell are normalized by both RFP fluorescence for that cell and the modes of the un-repressed control populations (i.e. apo and holo) measured for that replicate. All lines and symbols are described in Figure 3.2.

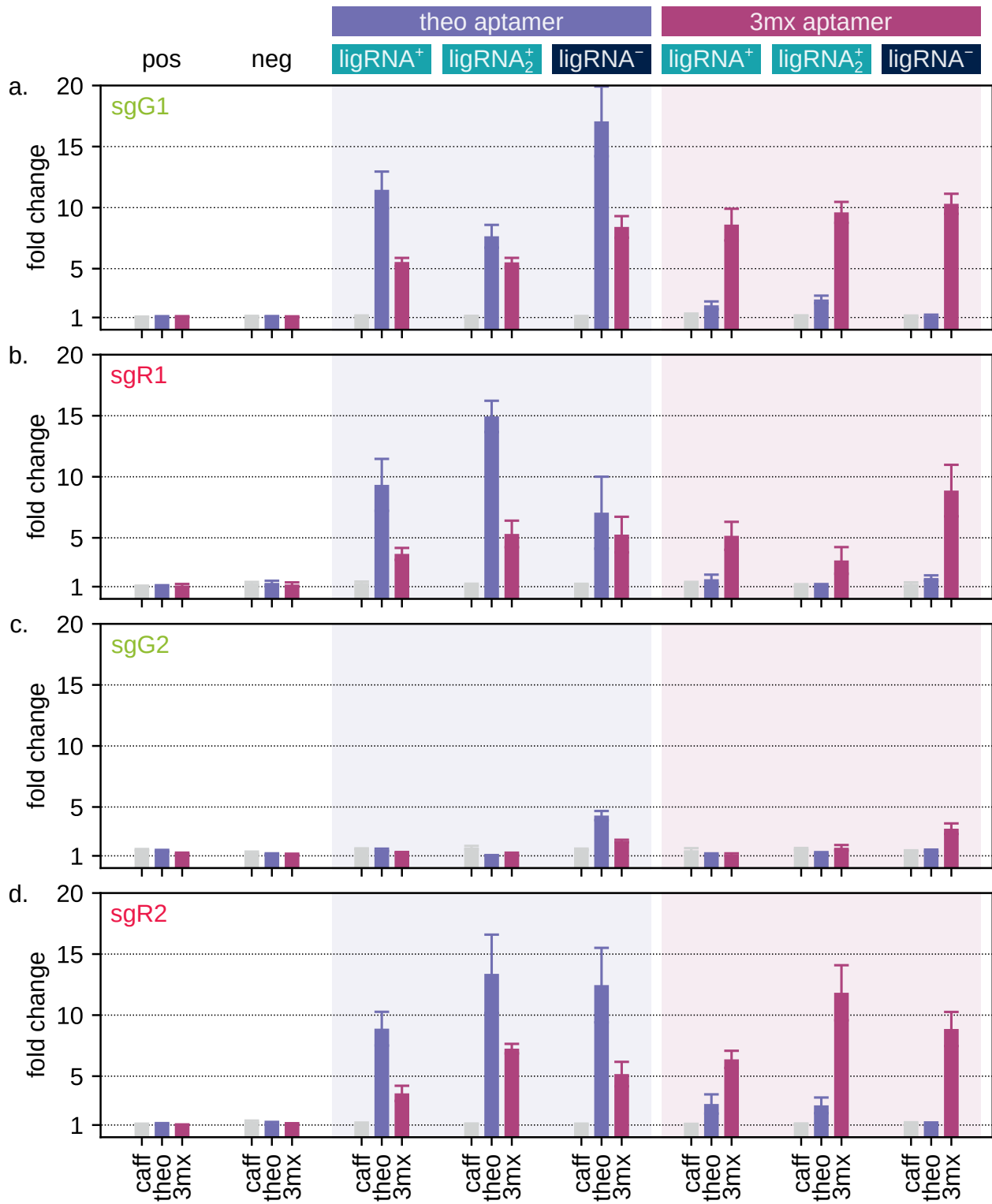


Figure 3.11: ligRNA function with two different aptamers, four different spacers and three different ligands. We built versions of each ligRNA with both the theophylline aptamer (purple heading) and the 3-methylxanthine aptamer (magenta heading) and then tested them with the three different ligands indicated at the bottom: caffeine (caff, grey bars), theophylline (theo, purple bars), and 3-methylxanthine (3mx, magenta bars). Caffeine is a negative control; it is chemically similar to theophylline and 3-methylxanthine, but is not expected to bind to either aptamer at the concentrations used. The reported fold changes are relative to treatment with no ligand and are calculated from the modes of fluorescence distributions measured by flow cytometry. Panels (a-d) show data for the sgG1, sgR1, sgG2, and sgR2 spacers (Table 3.4), respectively. Note that the theophylline aptamer (purple shading) is expected to be sensitive to both theophylline and 3-methylxanthine, but that the 3-methylxanthine aptamer (magenta shading) is expected to be specific to its ligand 3-methylxanthine with much reduced or no sensitivity to theophylline. The tested ligRNAs behave as expected with the different aptamers and ligands (note that none of the ligRNAs except ligRNA⁻ showed significant ligand sensitivity with the sgG2 spacer, which we expected based on our prior results shown in Table 3.3). This data was collected by James Lucas.

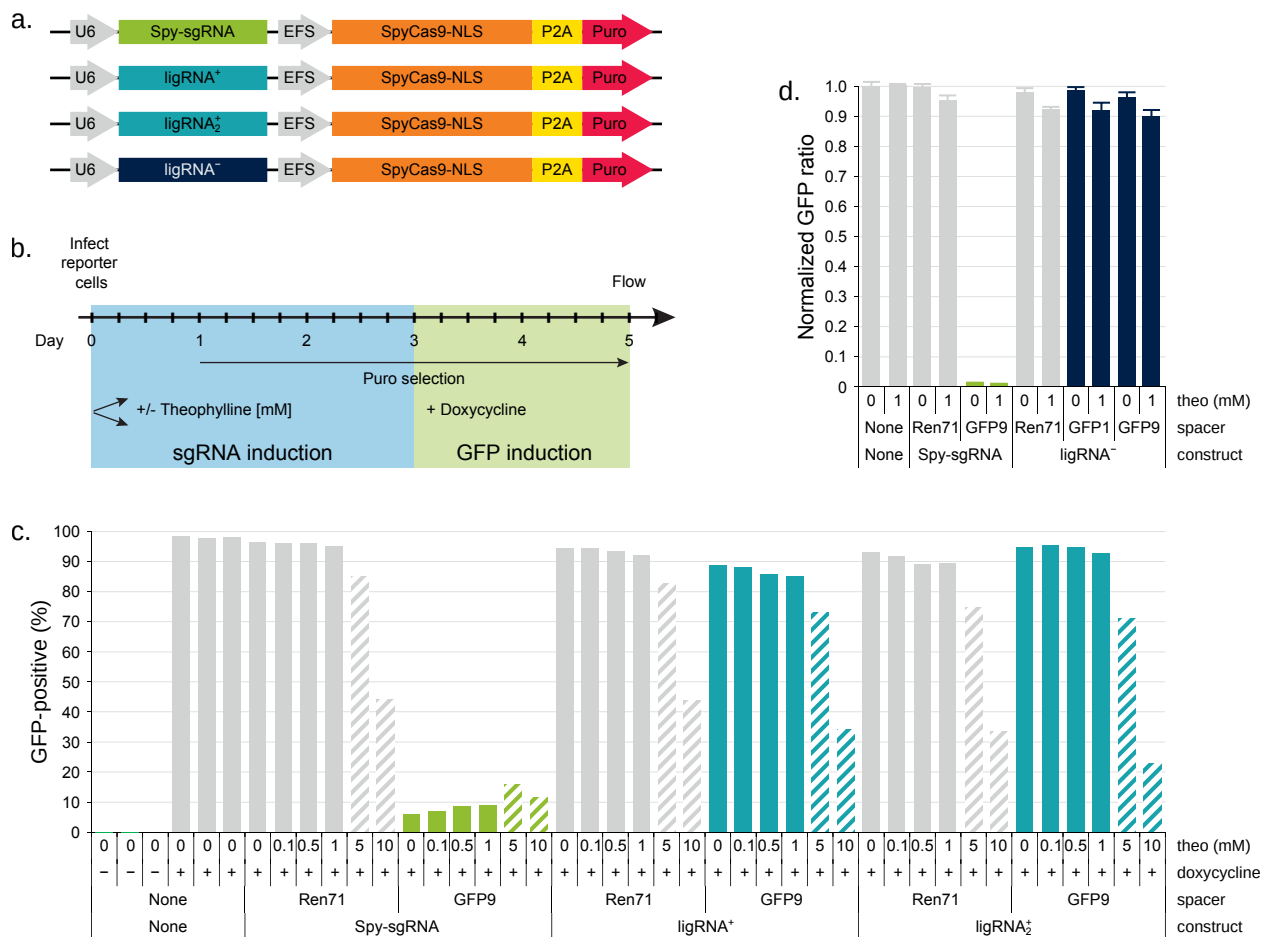


Figure 3.12: Test of ligRNA-mediated target editing in mammalian cell lines. (a) Vector maps of lentiviral constructs expressing Cas9 and either a standard sgRNA as control, or a ligRNA. (b) Schematic of the GFP knockout assay in a HEK293T-based reporter cell line with doxycycline-controlled GFP expression. (c) ligRNA⁺ does not exhibit theophylline-dependent editing in this assay. Theophylline concentrations from 0.1 to 10 mM were tested. Concentrations above 1 mM caused severe cell death (dashed bars). sgGFP9 targets the GFP of the reporter cell line. sgRen71 is a negative control sgRNA. Note, ligRNA⁺ resulted in a slight decrease of GFP-positive cells, but this trend began in absence of theophylline. (d) ligRNA⁻ does not exhibit theophylline-dependent editing in this assay. The slight differences between the 0 mM and 1 mM bars cannot be attributed to ligRNA⁻, because the Ren71 control has a similar difference; in addition, we would expect editing with ligRNA⁻ to be inhibited, not activated, by theophylline. This data was collected by Christof Fellman.

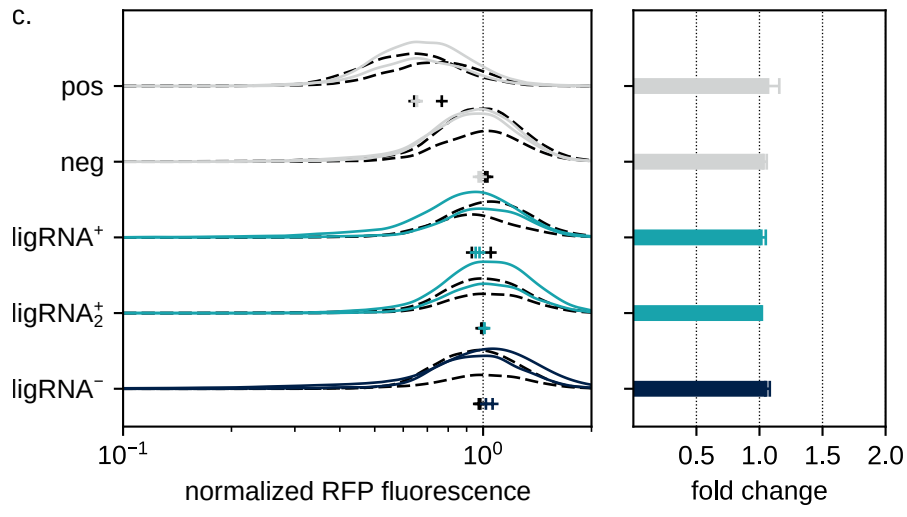
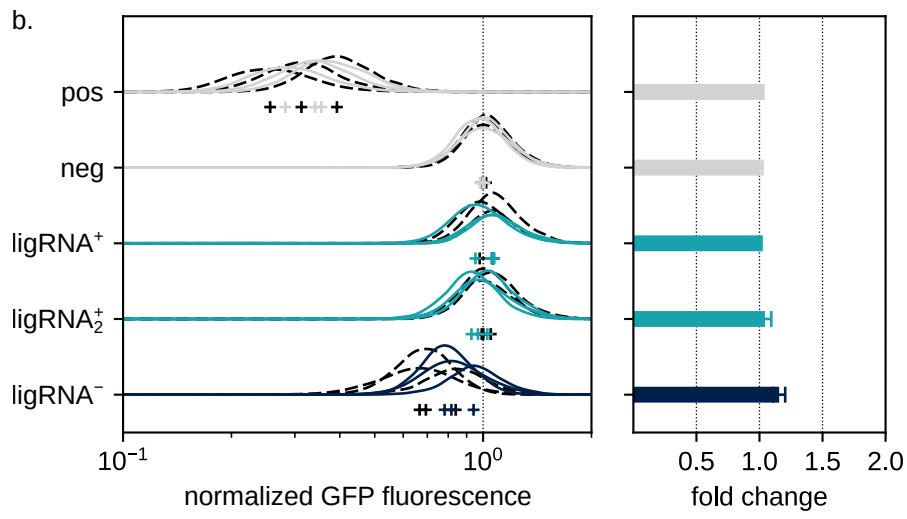
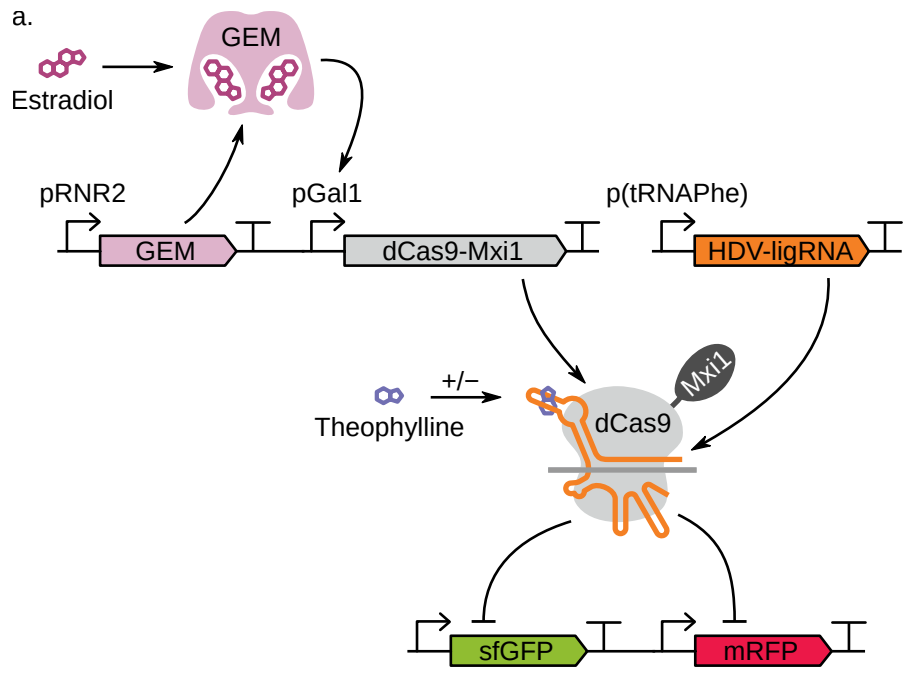


Figure 3.13: Test of ligRNA-mediated gene repression in yeast cells. Flow cytometry traces and fold changes for the ligRNAs and positive and negative controls in a CRISPRi assay in *S. cerevisiae*. (a) Schematic depicting the various constructs in the engineered yeast strains. (b) GFP repression with the sgG2 spacer. ligRNA^+ and ligRNA^+_{2} do not exhibit ligand-dependent activity in this assay. ligRNA^- exhibits a weak effect in the expected direction. (c) RFP repression with the sgR2 spacer does not show ligand dependence in this assay. The theophylline concentration in the plus ligand condition was 2.5 mM. The expression of dCas9-Mxi1 was induced with 125nM estradiol. Fluorescence values for each cell are normalized by side scatter (SSC) and the modes of the un-repressed control populations (i.e. apo and holo) measured for that replicate. All lines and symbols are described in Figure 3.2. This data was collected by Andrew Ng and Ben Heineike.

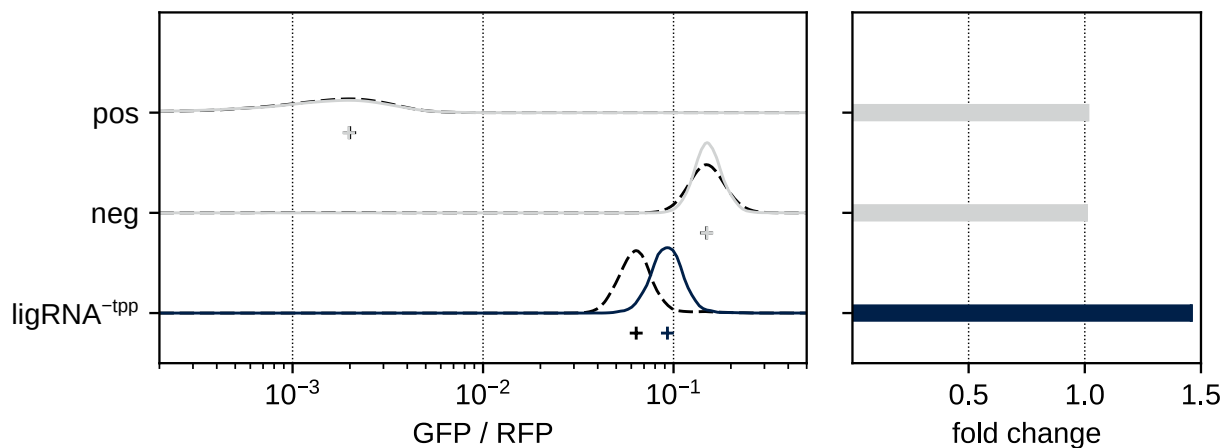


Figure 3.14: ligRNA^- exhibits a small response to thiamine. GFP fluorescence values for each cell are normalized by both RFP fluorescence for that cell and the modes of the un-repressed control populations (i.e. apo and holo) measured for that replicate. All lines and symbols are described in Figure 3.2.

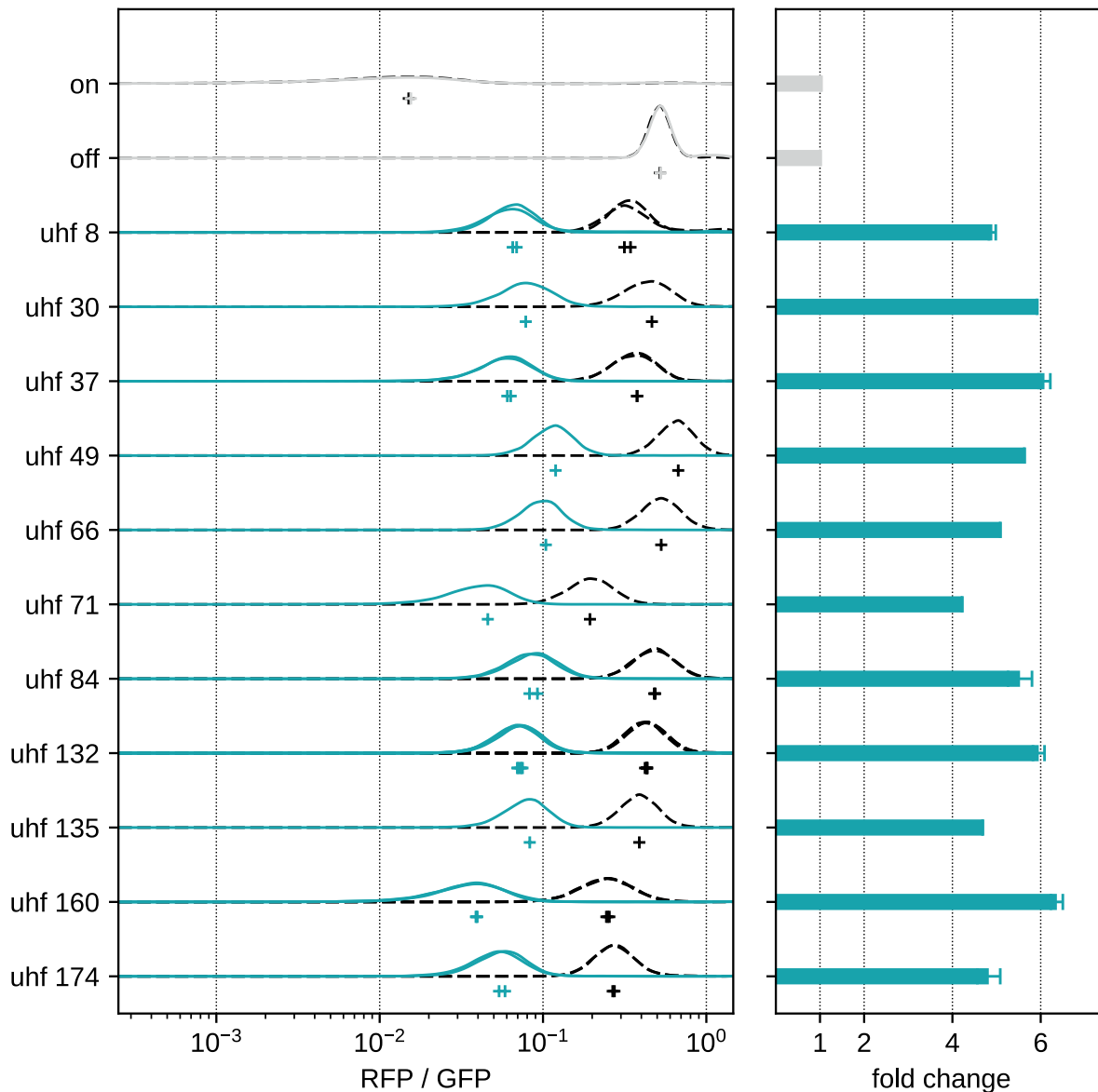


Figure 3.15: Flow cytometry traces for all 11 unique TPP-sensitive sgRNAs. RFP fluorescence values for each cell are normalized by both GFP fluorescence for that cell and the modes of the un-repressed control populations (i.e. apo and holo) measured for that replicate. All lines and symbols are described in Figure 3.2.

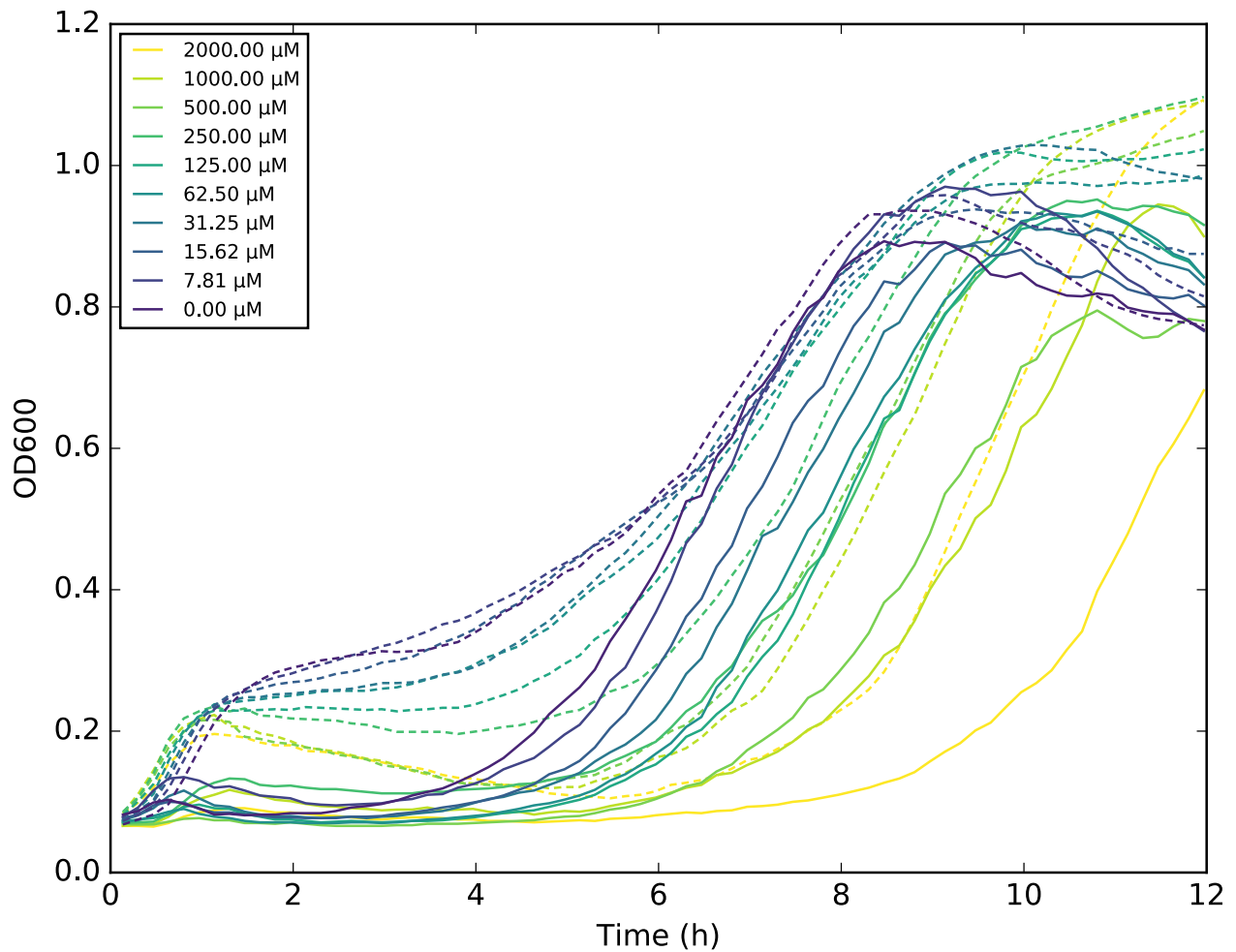


Figure 3.16: Exogenous adenine increases lag time at concentrations as low as 8 μM. Growth curves were recorded for the bacterial CRISPRi strain growing in 200 μL adenine media (see Methods) at 37°C for 12h. Dashed and solid lines represent two biological replicates.

3.6 References

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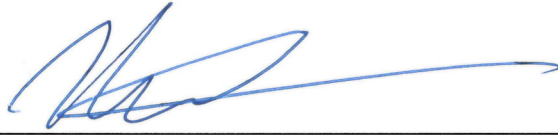
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