

## **UC Merced**

### **Proceedings of the Annual Meeting of the Cognitive Science Society**

#### **Title**

The Role of Conditional and Joint Probabilities in Segmentation of Dynamic Human Action

#### **Permalink**

<https://escholarship.org/uc/item/9029r9sc>

#### **Journal**

Proceedings of the Annual Meeting of the Cognitive Science Society, 30(30)

#### **ISSN**

1069-7977

#### **Authors**

Meyer, Meredith  
Baldwin, Dare

#### **Publication Date**

2008

Peer reviewed

# The Role of Conditional and Joint Probabilities in Segmentation of Dynamic Human Action

**Meredith Meyer (mmeyer2@uoregon.edu)**  
Department of Psychology, 1227 University of Oregon  
Eugene, OR 97403 USA

**Dare Baldwin (baldwin@uoregon.edu)**  
Department of Psychology, 1227 University of Oregon  
Eugene, OR 97403 USA

## Abstract

Segmentation of human action may be facilitated by sensitivity to statistical regularities in the action stream. We present two studies that examine the precise nature of adults' statistical learning of human action. Across two studies, adults were unable to reliably segment action based on conditional probability among small motion elements. However, they were robustly skilled at making use of joint probability information provided by co-occurrence frequency of these elements. These findings showcase possible differences in ways in which statistical learning mechanisms support segment discovery within human action as opposed to other domains, such as language.

**Keywords:** statistical learning; action processing

People consistently and easily redescribe the human action they observe into units that correspond with their judgment of the intentions underlying that action (Baldwin & Baird, 2001; Hard, Tversky, & Lang, 2006; Zacks, 2004). The ease with which we make these judgments, however, belies the complexity of the action itself and by extension our ability to analyze it. Careful consideration of human action suggests that it is, in fact, a remarkably complex stimulus. A person's action frequently lacks pauses or other clear markers of when a goal is completed and another initiated; instead human action unfolds in a fairly fluid manner (Newton & Enquist, 1976). The dynamic and continuous nature of action thus may pose a very real problem for segmentation necessary for later analysis in terms of underlying intentions and goals.

The ability to analyze human action in terms of intentions likely draws heavily from top-down inferences of people's desires and beliefs as well as knowledge of object affordances and one's own past experience with action. Top-down processes involved in action segmentation are unlikely to account for the entire story, however. Baldwin and colleagues (e.g., Baldwin et al., 2001; Saylor et al., 2007), for example, found that even infants parse dynamic human action in units corresponding to the completion and initiation of intentions, despite the fact that infants probably lack sophisticated theory of mind skills and knowledge of the intentions that motivate even ordinary, everyday adult activity.

Another possibility, then, is that action segmentation may be partially supported by bottom-up mechanisms. One likely

candidate for such a mechanism is sensitivity to statistical regularities among small motion elements. By way of example, imagine being asked to identify individual action units performed by a person cooking a meal. Even without extensive prior knowledge of cooking or food preparation, bottom-up processing of the action stream could enable detection of which elements tend to predict others. Elements that are likely to follow each other (e.g., grasping a knife and then cutting a potato) are probably parts of the same overall action, whereas elements that are less likely to follow each other (e.g., cutting a potato and then opening a refrigerator) are likely parts of different actions motivated by two different goals.

The fact that one element predicts another may link the two as parts of a larger unit, enabling segmentation without requiring top-down knowledge of intentions or goals. In the current study, we report on two experiments that investigated whether adults are able to compute one specific type of statistical information present in a motion stream, conditional probability. We further assessed whether they are sensitive to joint probability information provided by another statistical regularity in the action stream, namely co-occurrence frequency of the smaller motion units comprising an action.

Conditional probability provides predictive information relating one event to another. In the example above, the probability that *grasp knife* predicts *cut potato* is higher than the probability that *cut potato* predicts *open refrigerator*. Thus the conditional probability between *grasp* and *cut* is higher than between *cut* and *open*. Joint probability is another distinct type of statistical information that is also present in naturalistic action. Joint probability reflects the frequency with which elements occur together; such statistics provide information about the likelihood that elements will co-occur across time. To expand the example above, one could easily predict that across time, the overall number of times a person sees *grasp/cut* in succession exceeds the number of times a person sees *cut/open* in succession.

## Statistical Learning in Other Domains

An analogous inquiry in the domain of speech has already established that people are sensitive to the conditional probabilities among syllabic units. Present even in infancy,

this skill is believed to be one source of information that helps infants segment the continuous speech stream into words. Saffran, Aslin, and Newport (1996) exposed infants to a series of syllables that occurred in word-like groups (“words”) of three. After listening to these syllables repeated in a continuous speech stream, infants were given the opportunity to listen to sequences whose average conditional probabilities were 1.0 (i.e., a word) or sequences whose average conditional probabilities were less than 1.0. Infants preferred to listen to the latter, suggesting that they deemed these sequences more novel than the words they had segmented during exposure. However, infants may also have been responding to another statistical regularity, namely co-occurrence frequency of syllables. Specifically, because each word was presented an equal number of times in the exposure corpus, words had not just overall higher conditional probabilities among the syllables that comprised them, but also occurred more frequently than any other trisyllabic sequence. Since frequency of co-occurrence for syllables comprising words was higher than other sequences, infants may have been responding to this difference in joint probability rather than computing conditional probabilities.

Aslin, Saffran, and Newport (1998) resolved this issue by controlling for the frequency with which test sequences were heard during exposure. They found that after exposure, infants again preferred to listen to the sequences with lower average conditional probabilities, replicating the original Saffran et al. (1996) findings. Crucially, however, the sequences that infants discriminated between had been presented the same number of times during exposure. This study thus unambiguously demonstrated that infants were able to compute conditional probabilities across a continuous speech stream and to discriminate sequences whose conditional probabilities differed.

Related work has demonstrated that adults are also capable of using statistical regularities to segment speech (Saffran, Newport, & Aslin, 1996), musical tones (Saffran, et al., 1999), visual patterns (Kirkham, Slemmer, & Johnson, 2002), and visuomotor sequences (Hunt & Aslin, 1998). Although these studies did not directly address whether adults were computing conditional probability, joint probability, or both, other research suggests that adults are indeed sensitive to conditional probability independent of co-occurrence frequency. Adults compute conditional probabilities both in spatial correlations of visual patterns (Fiser & Aslin, 2001) and in shape sequences (Fiser & Aslin, 2002a). Taken together with the infancy findings of Aslin and colleagues (1998; Fiser & Aslin, 2002b; also see Graf Estes et al., 2007 for replication in speech), research suggests that sensitivity to conditional probability is a robust mechanism that persists across development and can function in many modalities.

### Statistical Learning in Action

Work in the action domain has also demonstrated adult sensitivity to statistical regularity in human action. Baldwin

et al. (2008) investigated adults’ ability to segment a novel stream of action making use of a methodology similar to that already used in speech (e.g., Saffran et al., 1996). Because the current study employs very similar methodology, a more in-depth description of their stimuli is in order. They showed participants a sequence of continuous human object-directed action featuring 12 small motion elements (SMEs). SMEs were grouped into four actions, with each action consisting of three SMEs (e.g., Action 1 = *stack/poke/drink*; Action 2 = *blow/touch/rattle*). The conditional probability among SMEs within an action was 1.0 (e.g., for Action 1, *stack* always was followed by *poke*, which in turn always was followed by *drink*). However, when adjacent elements crossed action boundaries, creating a “part-action”, average conditional probability decreased (e.g., conditional probability among *rattle/stack/poke* was on average lower, as the probability of *rattle* followed by *stack* was <1.0). Actions were randomly ordered in a continuous fashion to construct the exposure corpus. During test, participants were shown action/part-action pairs and asked to determine which was more familiar. Participants selected actions as more familiar, suggesting that they had segmented the stream based on the statistical regularities inherent in the action stream.

Baldwin et al. (2008) provided a clear demonstration that people can use statistical learning to segment human action. Baldwin et al.’s design, however, like that of many other statistical learning studies, did not control for the frequency of co-occurrence of small motion elements comprising the actions vs. part-actions. Rather, sequences with higher conditional probabilities (actions) also occurred more frequently during exposure. It is thus ambiguous whether, in making judgments between actions and part-actions, adults were responding based on their computation of conditional probability among small motion elements, or rather to the higher co-occurrence frequency of the small motion elements comprising the actions.

## Experiment 1

Experiment 1 precisely examines the type of statistical information that adults can use in segmenting dynamic human action. In order to control for small motion element frequency, we created an exposure corpus that varied the frequency of actions. This enabled selection of action/part-action pairs that had occurred an equal number of times during exposure for use during test. This component of the design is similar to that of Aslin and colleagues’ frequency-balanced control study examining infant segmentation of speech (1998). An additional component of the current design also asked participants to compare other combinations of action/part-action pairs during test, allowing us to assess the effect of small motion element co-occurrence frequency; namely, test pairs also featured actions that had been 10, 5, and 2 times more frequent in the exposure corpus than their comparison part-action.

In light of past research suggesting humans’ sensitivity to conditional probabilities, our primary hypothesis was that adults would be able to compute conditional probabilities across exposure and to use this information to segment the action stream. This ability would be reflected in adults reporting actions as more familiar than their counterpart frequency-balanced part-actions. We also hypothesized that adults would show even greater learning on trials in which sequence frequency (i.e., co-occurrence frequency of the small motion elements) was higher for the actions in comparison to the part-actions. Prior findings suggest that across studies, learning is lower for frequency-balanced sequences, and it has been suggested that they are harder to learn than imbalanced sequences (Fiser & Aslin, 2002a; Graf Estes et al., 2007).

## Method

**Stimuli** Similar to the original studies of human action segmentation (Baldwin et al., 2008), we filmed 12 individual object-directed motions, dubbed *small motion elements* (SMEs). SMEs were grouped into four *actions* with each action consisting of three SMEs. In order to make the action stream appear more continuous, transitions among individual SMEs (both within and across actions) were smoothed using the Overlap transition in iMovie (v. 5.0.2). SMEs were also slightly sped using the FastForward effect in order to create a corpus length that was manageable by our participants. We then created a twenty-five minute exposure corpus within iMovie that contained 120 tokens each of Actions 1 and 2 and 60 tokens each of Actions 3 and 4 (See Table 1 and Figure 1). Actions were randomly ordered with the exception that no action could follow itself.

Table 1: Actions and Part-Actions for Corpus 1.

Actions	Frequency
Empty/Clean/Under	120
Feel/Blow/Look	120
Drink/Twirl/Read	60
Rattle/Slide/Poke	60
Part-Actions	Frequency
Clean/Under/Feel	60
Blow/Look/Empty	60
Read/Rattle/Slide	12
Poke/Drink/Twirl	12

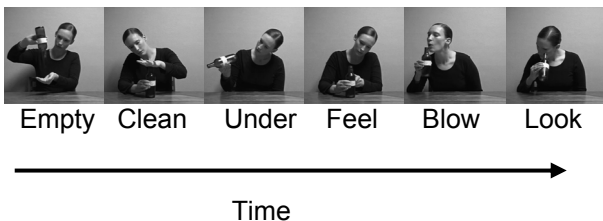


Figure 1: Still-Frames From Segment of Exposure Corpus. Actions shown are *empty/clean/under* and *feel/blow/look*; part-action *clean/under/feel* spans an action boundary.

The frequency difference between Actions 1 and 2 vs. Actions 3 and 4 allowed us to control for SME co-occurrence frequency during test by selecting actions and part-actions that had an equal frequency of occurrence during exposure. Specifically, part-actions consisting of elements from Actions 1 and 2 (e.g., *clean/under/feel*) were seen equally as frequently as Actions 3 and 4, i.e., 60 times each. Additional combinations of frequencies of actions and part-actions were also possible, and we included these comparisons during test in an attempt to discern the role of SME co-occurrence frequency in segmentation. We exhaustively paired every action with every part-action, resulting in a total of 16 test trials and 4 co-occurrence frequency differences (4 trials each for actions that were 10 times, 5 times, and 2 times more frequent than comparison part-actions, in addition to the four frequency-balanced pairs) (see Table 2).

Table 2: Small Motion Element Co-Occurrence Frequency Trial Types

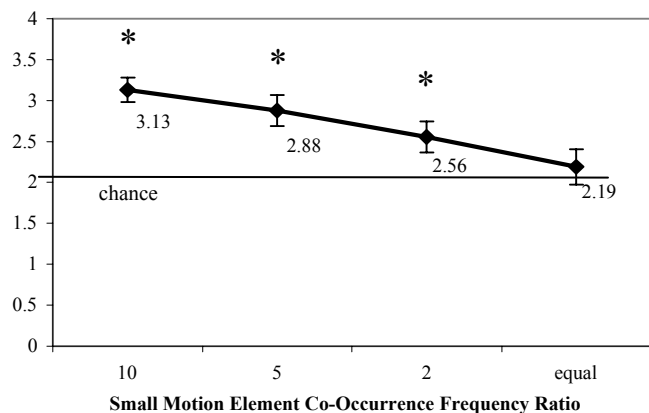
Co-occurrence ratio of action to part-action	10 x	5 x	2 x	equal
SME co-occurrence frequency for action	120	60	120	60
SME co-occurrence frequency for part-action	12	12	60	60

In order to avoid concerns that certain sequences were, just by chance, *a priori* more easily segmentable, we created three more exposure corpora. Actions from Corpus 1 served as part-actions in Corpus 2 and vice versa. We further counterbalanced which actions appeared highly frequently (120 times) and which appeared less frequently (60 times) such that highly frequent actions in Corpus 1 were less frequent in Corpus 3, and highly frequent actions in Corpus 2 were less frequent in Corpus 4. As well, it should be noted that while the small motion elements themselves had clear underlying intentions and were thus meaningful, the sequences themselves were arbitrary and provided no information that could be used by top-down mechanisms to aid in the segmentation process.

**Participants and Procedure** Participants were 32 university students (12 male, 20 female) receiving class credit for participation. Participants were randomly assigned to 1 of 4 exposure corpora and instructed to watch the corpus. They were told that they would be asked questions about what they saw after the exposure, but no further information was provided about the nature of the task. Upon finishing the exposure corpus, participants judged whether actions were more familiar than part-actions in a forced-choice test format. Order of presentation of the actions and part-actions within a trial was randomly determined, as was the order of the 16 trials.

**Results** Segmentation is demonstrated by greater-than-chance selection of actions as more familiar than part-actions. Across all 16 test trials, participants indeed were successful at discriminating actions from part-actions,  $M = 10.75$  ( $SD = 2.97$ ),  $t(31) = 5.23$ ,  $p < .001$ . In order to evaluate our primary hypothesis that adults could segment based on conditional probabilities, we next restricted analyses only to the four trials in which actions and part-actions were equally frequent during exposure. Here we did not find any evidence of segmentation; on the contrary, participants were unsystematic ( $M = 2.19$ ,  $SD = 1.26$ ;  $t(31) = .85$ ,  $p > .05$ ).

Instead, selection of actions as more familiar only occurred for pairs where actions were seen more frequently than part-actions, i.e., sequences whose SME co-occurrence frequency was higher. When actions were seen 10 times more often than part-actions, mean selection of actions out of 4 trials was 3.13 ( $SD = .87$ ),  $t(31) = 7.31$ ,  $p < .001$ ; for actions that were 5 times more frequent, mean selection was 2.88 ( $SD = 1.07$ ),  $t(31) = 4.63$ ,  $p < .001$ ; and for actions that were 2 times more frequent, mean selection was 2.56 ( $SD = 1.08$ ),  $t(31) = 2.96$ ,  $p < .01$  (See Fig 2). A repeated-measures ANOVA revealed differences among action selection across the four frequency groups,  $F(3, 93) = 6.49$ ,  $p < .001$ . Within-subjects contrasts showed that a linear trend best characterized the data,  $F(1, 31) = 16.83$ ,  $p < .001$ ; no other trends were evident.<sup>1</sup>



\*=different from chance at  $p < .01$

Figure 2: Action Selection by Co-Occurrence Frequency Trial Type (Ratios refer to co-occurrence frequency of action SMEs in comparison to part-action SMEs.)

<sup>1</sup> Although test trials did not consistently feature comparison sequences equated in either the probability of appearance of each of the individual SMEs or in joint probabilities of two SMEs co-occurring (as opposed to a triplet), the pattern of data we obtained in Experiment 1 suggests that these sources of information were not used by our participants in making their judgments. Thus we do not report on how these statistics vary across test pairings.

## Discussion of Experiment 1

Results disconfirmed Hypothesis 1; contrary to our prediction, participants were not able to segment based on sensitivity to conditional probability. However, we did find clear evidence that adults are able to segment based on co-occurrence frequencies of small motion elements, suggesting that they are sensitive to joint probability. Participants readily selected actions as more familiar than part-actions as long as a particular action sequence had been seen more times in comparison to a part-action sequence. Further, the linear trend in performance suggests that as action frequency in comparison to part-action frequency decreases, the ability to differentiate action from part-action suffers. In light of prior findings that people are able to extract conditional probability information in other domains, we considered alternative interpretations of the findings from Experiment 1. A major concern was that our measure was simply not sensitive enough to capture learning. Action and part-action frequency were matched on only four test trials, leading to the possibility that analysis of such a low number of test trials might have missed a fragile but very real ability to segment action based on conditional probability. A second concern was that every participant made comparisons between every combination of action frequency to part-action frequency (i.e., participants made judgments between actions that were 10, 5, and 2 times more frequent than their comparison part-actions as well as the frequency-balanced pairs). If adults are sensitive to both overall frequency and conditional probability, participants may have been led (most likely unconsciously) to employ a “frequency-based” strategy in their responses, even on the frequency-balanced trials where this would not have helped. To address these two concerns, in Experiment 2 we only included frequency-balanced test trials. We further doubled the number of test trials from four to eight.

## Experiment 2

### Method

**Stimuli** Exposure corpora were identical to those used in Experiment 1. The number of test trials consisting of equally frequent actions and part-actions was doubled from Experiment 1 by reversing the action/part-action presentation order and including these trials. Other trials were not included; thus test trials in the current experiment consisted only of 8 frequency-balanced action/part-action pairs.

**Participants and Procedure** Participants were 16 university students (5 male, 11 female) receiving class credit for participation. They had not participated in Experiment 1. As in Experiment 1, participants were randomly assigned to one of four exposure corpora and instructed to watch the corpus. Upon finishing the exposure corpus, participants judged whether actions were more familiar than part-actions. Order of the 8 trials was randomly determined.

## Results

Segmentation based on conditional probability alone would be revealed by above-chance selection of actions in comparison to frequency-balanced part-actions. Similar to the results obtained in Experiment 1, we again did not find evidence for segmentation. Mean selection of actions in comparison to frequency-balanced part-actions was unsystematic,  $M = 3.94$ ,  $SD = 2.49$ ,  $t(15) = -1$ ,  $p > .05$ .

## General Discussion

Across two experiments, we demonstrated that adults were able to segment dynamic human action; however, they were only able to evidence this ability when co-occurrence frequency of small motion elements comprising actions was higher in comparison to elements comprising part-actions. We found a linear trend suggesting that as action frequency approached part-action frequency, learning declined. The fact that higher frequency of small motion element co-occurrence aided segmentation was consistent with our secondary hypothesis. Contrary to our primary hypothesis, however, adults did not demonstrate sensitivity to conditional probability among small motion elements, evidenced by their inability to use this statistic to differentiate actions from frequency-balanced part-actions.

Ample research in both speech and vision has suggested that people are capable of learning conditional probabilities and using this information in the service of segmentation (e.g., Aslin et al., 1998; Fiser & Aslin, 2002a; 2002b; Graf Estes et al., 2007). What, then, can explain our findings? One possibility is that our stimuli were too complex, and participants did not have enough exposure time to learn the conditional probabilities. Motion elements such as the ones we used unfolded over a longer period of time (on average, 1.09 seconds) than the syllables used in investigations of speech (e.g., Saffran et al., 1996). Further, in naturalistic speech, the syllables that create words possess no semantic content themselves. Similarly, shapes used in studies of visual learning (e.g., Fiser & Aslin, 2002) were fairly simple and had no apparent function or name. However, this is *not* the case in action; individual small motion elements such as the ones we used have meaning in and of themselves; further, one can decompose these motions into yet-finer units corresponding to finer-grained goals (e.g., Zacks & Tversky, 2001). Perhaps the small motion elements in our research are less encodable as units than syllables or shapes used in other research, making the task of tracking their conditional probability more difficult and requiring more time during exposure.

While it is possible that adults were not able to discover conditional probabilities in our study due to an overly short exposure time, we do not favor this explanation. Knowing in advance that this task was potentially more complex than syllable- or shape-sequence learning due to the complexity of human action, we created exposure corpora that contained a number of actions that well exceeded the

number of words presented to infants in the frequency-balanced design examining speech segmentation of infants (Aslin et al., 1998) as well as the number of shape triplets presented to adults in examination of shape sequence learning (Fiser & Aslin, 2002a). As well, participants displayed strong learning for joint probability, suggesting they were able to extract at least one type of higher-order statistic from the stream. Despite our relatively lengthy exposure corpus, however, adults still did not display segmentation based on conditional probability.

We more seriously entertain two alternative possibilities. First, perhaps our stimuli invited learning in ways that are not representative of everyday action processing. Second, maybe statistical learning plays out differently in action processing than it does in other domains. To address the first possibility, we note one important difference between our stimuli and real-life action. Unlike naturalistic action, our sequences were arbitrary. We took great care to use sequences that appeared to have no *a priori* explanations that might link certain motion elements together and thus lead participants to segment them more readily. This was necessary in order to rule out top-down clues to segmentation, and thus successfully isolate statistical learning as the source of adults' segment discovery. This feature of our design was deliberately analogous to the arbitrary speech sequences in Saffran et al. (1996; 1999) and Aslin et al. (1998). In real life, however, small motion elements would usually be united by common underlying goals. Perhaps the ability to compute conditional probability in adulthood is only recruited when statistically predictive actions are also related, either through cause-effect associations or by common underlying intentions. Evidence from the causal learning literature (e.g., Gopnik & Schulz, 2004) suggests that young children are indeed capable of learning conditional probabilities relating cause-effect events. Because our stimuli were artificially arbitrary and unassociated, and participants had no reason to link actions with one another (either implicitly or explicitly), normal activation of learning based on conditional probability may have been muted.

Our second alternative explanation is that action segmentation truly does involve statistical learning mechanisms differently than other domains. Conway and Christiansen (2005) suggest that statistical learning is unlikely to rely on a single, domain-general mechanism. Based on different performance patterns across different modalities, they suggest instead that people possess multiple, modality-specific mechanisms that function somewhat differently from one another. While our data taken in the context of positive findings in other domains is consistent with this account, we believe that it is premature to argue for a domain-specific mechanism. Very little is known about the structural regularities present in intentional human action, and it is very likely that the nature of the input in this domain is different from other domains such as speech and vision. This would suggest the possibility for a domain-general statistical learning mechanism that is

activated differently depending on the nature of the input as well as the task demands. This latter interpretation suggests that modification of the task might invite access to conditional probability computation. Studies are currently underway to address this possibility by assessing segmentation through means other than requiring familiarity judgments.

In summary, our studies did not show any evidence of sensitivity to conditional probabilities in segmentation of human action, though it did reveal a robust sensitivity to joint probability information. Disentangling the reasons for differences we observed between statistical learning in action relative to other domains is an inviting focus for future investigations.

### Acknowledgements

We wish to thank Jenny Saffran for helpful comments throughout the research process. We additionally thank Baldwin Lab members Jeff Loucks, Eric Olofson, Lindsay Henson and Jason Dooley for their help in stimulus creation.

### References

- Aslin, R. N., Saffran, J. R., & Newport, E. L. (1998). Computation of conditional probability statistics by 8-month-old infants. *Psychological Science, 9*, 321-324.
- Baldwin, D., Andersson, A., Saffran, J., & Meyer, M. (2008). Segmenting dynamic human action via statistical structure. *Cognition, 106*, 1382-1407.
- Baldwin, D., & Baird, J. (2001). Discerning intentions in dynamic human action. *Trends in Cognitive Sciences, 5*, 171-178.
- Baldwin, D., Baird, J., Saylor, M., & Clark, A. (2001). Infants parse dynamic human action. *Child Development, 72*, 708-717.
- Conway, C. M., & Christiansen, M. H. (2005). Modality-constrained statistical learning of tactile, visual, and auditory sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31*, 24-39.
- Graf Estes, K., Alibali, M. W., Evans, J. L., & Saffran, J. R. (2007). Can infants map meaning to newly segmented words? Statistical segmentation and word learning. *Psychological Science, 18*, 254-260.
- Fiser, J., & Aslin, R. (2002a). Statistical learning of higher-order temporal structures from visual shape sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 28*, 458-467.
- Fiser, J., & Aslin, R. N. (2002b). Statistical learning of new visual feature combinations by infants. *Proceedings of the National Academy of Sciences, 99*, 15822-15826.
- Gopnik, A., & Schulz, L. (2004). Mechanisms of theory-formation in young children. *Trends in Cognitive Science, 8*, 8.
- Hard, B. A., Tversky, B., & Lang, D. (2006). Making sense of abstract events: Building event schemas. *Memory and Cognition, 34*, 1221-1235.
- Hunt, R.H. & Aslin, R.N. (1998). Statistical learning of visuomotor sequences: Implicit acquisition of sub-patterns. Proceedings of the twentieth annual conference of the Cognitive Science Society, Lawrence Erlbaum Associates, Hillsdale, NJ
- Kirkham, N.Z., Slemmer, J.A., & Johnson, S. P. (2002). Visual statistical learning in infancy: evidence of a domain general learning mechanism. *Cognition, 83*, B35-B42.
- Newton, D., & Enquist, G. (1976). The perceptual organization of ongoing behavior. *Journal of Experimental Social Psychology, 12*, 435-450.
- Saffran, J., Aslin, R., & Newport, E. (1996). Statistical learning by 8-month-old infants. *Science, 274*, 1926-1928.
- Saffran, J. R., Johnson, E., Aslin, R. N., & Newport, E. L. (1999). Statistical learning of tone sequences by human infants and adults. *Cognition, 70*, 27-52.
- Saffran, J. R., Newport, E. L., & Aslin, R. N. (1996). Word segmentation: The role of distributional cues. *Journal of Memory and Language, 35*, 606-621.
- Saylor, M. M., Baldwin, D., Baird, J. A., & LaBounty, J. (2007). Infants' on-line segmentation of dynamic human action. *Journal of Cognition and Development, 8*, 113-128.
- Zacks, J. (2004). Using movement and intentions to understand simple events. *Cognitive Science, 28*, 979-1008.
- Zacks, J., & Tversky, B. (2001). Event structure in perception and conception. *Psychological Bulletin, 127*, 3-21.