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# Modeling Melodic Perception as Relational Learning Using a Symbolic-Connectionist Architecture (DORA)

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## Abstract

Like many other cognitive processes, the perception of music involves processes and structural considerations that are highly relational in nature. To date, no physiologically plausible model has been used to simulate and explain how infants perceive melodic content. Here we used DORA (*Discovery Of Relations by Analogy*; Doulas et al., 2008), a domain-general symbolic-connectionist model of relational learning, to simulate melodic perception and categorization by infants (Chang & Trehub, 1977; Trehub et al, 1984), and to provide an account of the mechanism for melodic processing in infants. Given four input semantic features for each note in the melodic stimuli sequence (two of which could be internally obtained from the other two via a comparator), DORA's performance matched the behavioral data from the infant studies. Furthermore, the ability of our model to simulate infants' behavior is evidence that structured representations of relational musical properties can be bootstrapped from unstructured feature representations.

**Keywords:** Melodic perception; relative pitch; relational learning; symbolic connectionist; DORA.

## Introduction

While there are many defining characteristics of music (e.g., harmony, rhythm, timbre, pitch, etc.), one of the most fundamental and salient aspects is the melody. Indeed, simple melodies were likely the earliest form of music to have been created and transmitted, and have been (and still are) prevalent in all documented cultures past and present (Sachs, 1943).

Simple melodies consist of discrete units or notes, with each note characterized by a pitch, or fundamental frequency. Importantly, there are several ways in which the pitch sequence of a melody can then be encoded and stored. The two most well documented forms of encoding are *absolute* or *relative* pitch. Absolute pitch encodes and stores a melody using the fundamental frequencies of each pitch, while relative pitch (or intervallic) encodes the melody in terms of the *relations* (or specific frequency differences) between each note. Notably, processing melodies in terms of the relative pitch information (or intervallic patterns) is considered to be the strategy most humans use to

characterize and store familiar melodies (Attneave & Olson, 1971). Another characteristic upon which melodies can be categorized, however, is according to the contour (general shape, or sequence of up and down movements in frequencies from note to note). Given the existence of these various characteristics, there has been considerable research and speculation on the extent to which these categorizations contribute to a listener's mental representation of a melody, and how they may interact.

## Relative pitch and melodic contour

The properties of relative pitch (or intervallic patterns) are most commonly used in long term musical storage and recall (Page, 1994). For example, when listening to the melody of a song, such as *Happy Birthday*, what makes the song immediately recognizable is the unique intervals between each of the notes in the song. That is, the song is recognizable whether it initially starts on a low or high note due to the unique intervallic pattern between all subsequent notes. There is much evidence on the use of relative pitch information in adults through both behavioral studies (Dowling, 1978, 1984, 1988) as well as neuroimaging studies (Fujioka, Trainor, Ross, Kakigi, & Pantev, 2004; Trainor, McDonald, & Alain, 2002).

It is worth noting that while a melody with an identical contour to *Happy Birthday*, but with a different intervallic sequence would sound like a completely different tune, it would still have the same general "shape", or up and down pattern. Although the intervallic pattern may be the most overtly salient feature of a melody, studies have shown that human adults are also sensitive to absolute pitch and melodic contour in the short term (Bartlett & Dowling, 1980; Dowling, 1978). And while there is evidence that infants may also be sensitive to intervallic information (Trehub, Bull, & Thorpe, 1984), numerous experiments with infants suggest that they may primarily encode melodies using contour information (for review, see Trehub, 2001; Trehub, Trainor, & Unyk, 1993).

Even though intervallic and contour properties may characteristically differ in the type of information they

carry, what is perhaps more important is the fact that the nature of the information they carry are both fundamentally relational in nature. That is, this information depends on the relationship (whether it is the precise intervallic distances or the general contour shape) between each pitch, and not on the actual pitch frequencies themselves. And it is within this capacity that melodic perception can be said to share a cornerstone property with many higher-level cognitive tasks (and arguably certain “lower” level processes such as pattern recognition as well).

### Relational processing

The ability to explicitly represent and reason about relational properties has been proposed as a fundamental mechanism underlying a wide range of cognitive phenomenon, including analogy-making (Gentner, 1983; Gick & Holyoak, 1980; Holyoak & Thagard, 1995), language (Kim, Pinker, Prince, & Prasada, 1991), detection of perceptual similarities (Medin, Goldstone, & Gentner, 1993), and the application of rules in novel situations (Lovett & Anderson, 2005). Given that melodic processing appears to require extracting relational information from melodies, it is reasonable to assume that the same mechanisms used in other relational tasks might also operate when processing musical information. That is, common to both of the main approaches used by adults and infants (intervallic and contour) to encode melodic information is that the underlying structure of the melody is represented as the relations between the individual notes. The strength of relational reasoning is in the ability to reason about the roles that objects play rather than the literal features of those objects (see Doumas, Hummel, & Sandhofer, 2008). Similarly, the ability to recognize a melody (or its shape) rests on appreciating the relationship between the pitches, and not the specific frequencies of each note. To evaluate the similarity between relational reasoning and music processing, we modeled melodic perception using a neurally plausible domain-general model of relational cognition.

### The LISA/DORA models

LISA (*Learning and Inference with Schemas and Analogies*; Hummel & Holyoak, 1997, 2003) is a symbolic-connectionist model of analogy and relational reasoning. DORA (*Discovery Of Relations by Analogy*; Doumas et al., 2008) is an extension of LISA that learns structured (i.e., symbolic) representations of relations from unstructured inputs. That is, DORA provides an account of how the structured relational representations LISA uses to perform relational reasoning can be learned from examples. At present, DORA accounts for over 30 phenomena from the literature on relational learning, and cognitive development, and as it learns representations of relations it develops into LISA and can simulate the additional 40+ phenomena in relational thinking for which LISA accounts for (e.g., Doumas et al., 2008). In the following, we provide a very brief description of the LISA/DORA models (for full details, see Hummel & Holyoak, 1997, 2003; Doumas et al., 2008).

**LISAese Representations** In LISA (and DORA *after* it has gone through learning), relational structures are represented by a hierarchy of distributed and localist codes (see Figure 1). At the bottom, “semantic” units (small circles in Figure 1) represent the features of objects and roles in a distributed fashion. At the next level, these distributed representations are connected to localist units (POs) representing individual predicates (or roles) and objects (triangles and larger circles in Figure 1). Localist role-binding units (RBs; rectangles in Figure 1) link object and role units into specific role-filler bindings. At the top of the hierarchy, localist P units (ovals in Figure 1) link RBs into whole relational propositions.

Relational structures (or propositions) are divided into two mutually exclusive sets: a driver and recipient(s). In LISA/DORA, the sequence of firing events is controlled by the driver. Specifically, one (or at most three) proposition(s) in the driver become(s) active (i.e., enter working memory). When a proposition enters working memory, role-filler bindings must be represented dynamically on the units that maintain role-filler independence (i.e., POs and semantic units) to allow for reusability of units and preservation of similarity across different bindings (Hummel & Holyoak, 1997). In LISA, binding information is carried by synchrony of firing (with roles firing simultaneously with their fillers). In DORA, binding information is carried by systematic asynchrony of firing, with bound role-filler pairs firing in direct sequence (for details, see Doumas et al., 2008).<sup>1</sup>

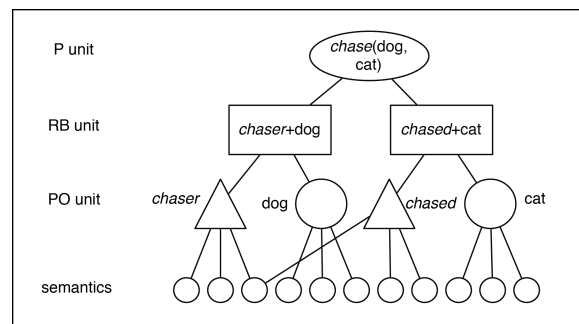


Figure 1. LISA/DORA representation of the proposition, *chase* (dog, cat).

**Relational Learning** In broadest strokes, DORA learns structured representations by comparing objects to isolate their shared properties and to represent these shared properties as explicit structures. More specifically, DORA starts with simple feature-vector representations of objects (i.e., a node connected to set of features describing that object; large and small circles from Figure 1). When DORA compares one object to another, corresponding elements (i.e., shared features) of the two representations fire simultaneously. Any semantic features common to both

<sup>1</sup> Asynchrony-based binding allows role and filler to be coded by the same pool of semantic units, which allows DORA to learn representations of relations from representations of objects (Doumas et al., 2008).

objects receive twice as much input and thus become roughly twice as active as features connected to one but not the other. By recruiting a new PO unit and learning connections between that unit and active semantics via Hebbian learning (wherein the strength of connections is a function of the units' activation), DORA learns stronger connections between the new PO unit and more active semantic units. The new PO thus becomes an explicit representation of the featural overlap of the compared objects and can act as a single place predicate, taking other object representations as arguments to form role-filler pairs (see Doumas et al., 2008). Applied iteratively, this process allows DORA to learn structured explicit single-place predicate representations of any properties compared objects may share. Comparison also allows DORA to learn representations of multi-place relations by linking sets of constituent role-filler pairs into relational structures (i.e., to learn the *chases* relation by linking together representations of the roles *chaser* and *chased*; see Doumas et al., 2008 for details).

**Mapping** For the purpose of analogical mapping, LISA/DORA learns *mapping connections* between units coactive of the same type in the driver and recipient (e.g., between PO units in the driver and PO units in the recipient). These connections grow whenever corresponding units in the driver and recipient are active simultaneously. They permit LISA to learn the correspondences between matching structures in separate analogs. They also permit correspondences learned early in mapping to influence the correspondences learned later.

## Methods

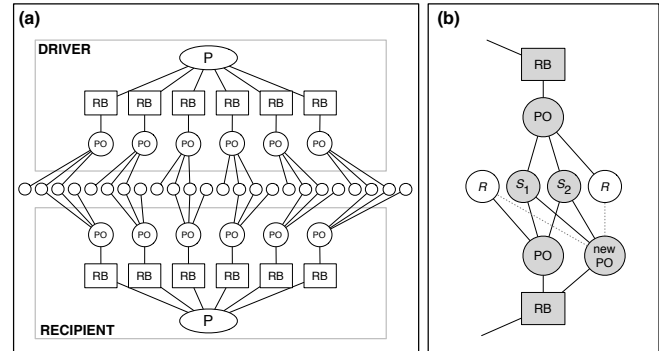
In this section we describe two infant studies (Chang & Trehub, 1977; Trehub et al., 1984), followed by the details and outcomes of DORA's simulation.

### Task 1 description

In an experiment by Chang and Trehub (1977), infants (4.5 to 6 months of age) were tested on their ability to recognize melodies based on either the absolute pitch frequencies or relational properties extracted from these pitches. This between-group experiment was conducted with a set of 15 habituating trials, followed by four novel dishabituation trials, while the infants' heart rates were monitored throughout to determine their expectation and recognition levels for the novel stimuli. The habituation stimuli consisted of randomly constructed six note melodic patterns. The dishabituation stimuli varied depending on which of two groups the infants were in.

Crucially, in the "transposed" group, the novel test stimulus consisted of the same melody transposed to a different key. The novel melody retained the relational information between the individual notes (intervallic sequence), but none of the featural information (specific frequencies) of the individual notes. In the control group, the novel melody was a scrambled version of the original melody. The individual notes' featural characteristics (pitch

frequencies) were retained, while the relational characteristics between the notes were not. Thus, comparing performance between the "transposed" and control groups would indicate whether infants were processing the melodies based on the individual frequencies, or extracting the relational information between notes.



Figures 2. a) The note sequences in the driver and recipient are compared with each other. b) After mapping notes in the sequence, DORA learns a new PO unit from the featural overlap of the mapped notes.  $S_n$  are semantic units, and  $R$  are random units (only two each are shown here).

### Simulation 1

To simulate the training portion of the study, we created a "melody" consisting of 6 object PO units—one PO for each note (see Figure 2a). Each note PO unit was attached to four random semantic units (chosen from a pool of 100 features), one semantic indicating the note's place in the stimuli sequence (1-6), one semantic describing the note's specific frequency (between f1 and f24), one semantic for whether the note was higher or lower than the previous note (the first PO in the sequence was not connected to such a semantic), and one semantic describing the note's distance (i.e., frequency difference) from the previous note. The information the semantic units carried was based on features which infants have been shown to be capable of extracting from melodies to greater or lesser extents. For instance, infants have been shown to be sensitive to sequential order (Thorpe & Trehub, 1989; Thorpe, Trehub, Morriongiello, & Bull, 1988), are sensitive to and can discriminate absolute pitch information under certain conditions (Lynch, Eilers, Oller, & Urbano, 1990; Trehub, Cohen, Thorpe, & Morriongiello, 1986), can process contour information (Trehub et al., 1984; Trehub et al., 1993), and are also sensitive to intervallic differences (Schellenberg & Trehub, 1996a, 1996b). Importantly, the semantic values specifying frequency direction and frequency difference can be generated from the raw frequency values using the comparator mechanism described in Doumas et al. (2008) and adopted from the JIM model of object recognition (Hummel & Biederman, 1992). Finally, each PO was attached to an RB unit, and all the RBs attached to a single P unit, representing that the notes all belonged to a single sequence.

We allowed DORA to compare each note sequence to the previously experienced note sequence, map the two sequences, and learn new predicate POs using the predication learning algorithm described above. The sequence of firing of the PO units in the driver was the same as the order of the notes in the melodic sequence (i.e., the first note in the sequence fired first, the second note second, and so on). More specifically, DORA represented the current note sequence in the driver and the previous note sequence in the recipient (see Figure 2a). Next DORA attempted to map the sequences. Finally, DORA learned new PO units using these mappings (Figure 2b). DORA stored the results of learning in memory.

In previous studies, DORA has successfully been used to simulate frontal lobe maturation by adjusting the level of lateral inhibition between units in the recipient (e.g., Dumas, Morrison, & Richland, 2009, 2010; Morrison, Dumas, & Richland, 2006, 2011). Reflecting the fact that we are simulating infants we used a highly reduced lateral inhibition parameter of 0.5.

After training, DORA's LTM consisted of the 15 sequences of notes it had learned during training. In addition, we created 50 additional sequences of between 2 and 8 notes to serve as distractors in memory (following the assumption that other melodic sequences may have been learned by the infant). In each distracter note sequence each PO from the same sequence was attached to a single RB unit with all RBs from the same sequence attached to a single P unit, indicating all the notes belonged to a single sequence (as with the training items). Each PO was attached to 4 random features as well as one semantic indicating the note and another semantic indicating the interval (frequency difference) from the previous note.

To simulate the test, we created two melodies, each consisting of 6 PO units, each representing a single note. Each note PO unit was attached to four random semantics, one semantic unit describing the note's place in the sequence (1-6), one semantic describing the frequency, one describing frequency difference from the previous note, and another describing the direction of the difference (just as for the melodies created in the training condition). Additionally, as originally conducted by Chang and Trehub (1977), we created a transposed melody that consisted of the same sequence of notes as the training melodies, but in a different key. The control melody consisted of the exact same POs used in training, but in a scrambled order.

We put the test melody (transposed or control) in the driver, and allowed DORA to attempt to retrieve an item from LTM, and attempt to map it to the melody in the driver. If DORA successfully mapped the new melody to one of the sequences it had learned during training, this implied that DORA recognized the new melody. Otherwise, DORA was taken to be surprised by the new melody.

We ran 200 simulations (100 transposed and 100 control), each consisting of 15 training and one test trial (the exact same number of training and test trials used in the original study). DORA's performance was a close qualitative match

to the data from Chang and Trehub's (1977) study. Just like infants in the transposed condition, when presented with transposed melodies, DORA was much more frequently unsurprised (77 of 100 trials). On the other hand, for control melodies, DORA was unsurprised much less frequently (31 of 100 trials). These results indicate, that DORA, like the infants in the original study, could detect and extract regularity in melodic sequences, and generalize that regularity to novel keys.

## Task 2 description

For the second simulation, we used a study by Trehub, Bull, and Thorpe (1984). This study was conducted on infants 8 to 11 months of age, and used a broader range of melodic stimuli to examine the extent to which infants process intervallic, contour, octave transpositions, and range information from melodies. Although the first task (Chang & Trehub, 1977) demonstrated that infants used relational information to categorize melodies, the design did not specifically differentiate between intervallic and contour relations (it is possible that infants could have used either strategy to categorize the melodies).

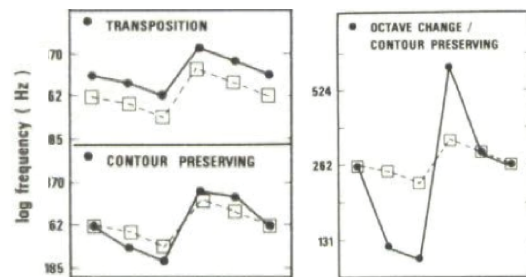


Figure 3. Three types of transformations applied to test melodies in Trehub, Bull, & Thorpe (1984).

Although a similar paradigm to Chang and Trehub's (1977) study was used by Trehub et al. (1984), the two studies differed in two important aspects. First, the training and testing methodology was different. Whereas the first experiment used a habituation/dishabituation training paradigm and monitored heart-rate during testing, the second experiment used a training procedure that habituated infants to a melodic pattern and also trained them to respond with head turns to melodies that differed in melodic contour and range. Infants were then tested for subsequent discriminations of novel stimuli by monitoring head turns. Secondly, although training and testing stimuli also consisted of six note melodic patterns, several additional melodic properties were examined Trehub et al.'s testing condition. In addition to the transposed melody (as used in Chang and Trehub, 1977), the testing conditions included *contour preserving* and *contour violating* conditions in order to test for octave and frequency range sensitivity. The *contour preserving* condition (see Figure 3) allowed the researchers to test whether infants categorize melodies based on intervallic or contour properties. That is, it was

assumed that if infants recognized only the transposed condition and not the contour-preserving condition, then that would be taken as evidence that they processed the melodies based on intervals. On the other hand, if they recognized both, the most parsimonious explanation would be that they were processing the melodies based on contour alone. Additionally, the *octave change* conditions tested whether infants' were also sensitive to larger changes in intervallic patterns. Crucially, it was found that infants did not discriminate either the transposition or contour preserving melodies, but discriminated the *octave change* melodies.<sup>2</sup> In summary, Trehub et al. found that infants could categorize melodies by contour properties, but were also sensitive to the magnitude of the contour, and therefore could discriminate larger intervals (outside of the general original range) from the smaller intervals of melodies that occurred within the original melodic range.

## Simulation 2

Although there were methodological differences between Task 1 and 2, we simulated Trehub et al. (1984) using the same basic procedure as in Simulation 1. Fundamentally, Task 2 used the same approach by exposing infants to a standard melody and then subsequently observing how they would perceive and categorize novel test stimuli. Accordingly, we created a set of training patterns and trained the model as in Simulation 1.

To test the model, we created transposition melodies just as in Simulation 1. In addition, we created two kinds of contour preserving melodies. Close contour preserving melodies were similar to the training melodies, but with frequencies within 2 units of the training trials. So for example, if the first three notes of the training stimulus were: frequency2, frequency6, frequency8, the first three notes of the test pattern would be frequency2  $\pm$ 2, frequency6  $\pm$ 2, frequency8  $\pm$ 2 (under the constraint that the direction of the note was maintained across training and test patterns—e.g., if the second note of the training melody was higher than the first, the second note of the test melody was also higher than the first). Similarly, the far contour preserving melodies were created in exactly the same manner, but with each note  $\pm$ 6 from the original.

The results followed the same qualitative pattern observed in Trehub et al. (1984). As in the previous simulation, DORA successfully matched transposed melodies. Importantly, DORA also successfully matched close contour preserving melodies the majority of the time (74 of 100 trials), and was surprised on far contour preserving melodies more frequently (63 of 100 trials). In other words, like the infants in Trehub et al.'s study, DORA was sensitive to contour preservation, but under conditions when the contour was preserved but coupled with large changes in

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<sup>2</sup> There was no evidence that infants processed octave shifts as musical pitches with closely related harmonic properties (as adults generally do), but rather that they only processed them as large shifts in frequency (see Trehub et al., 1984).

frequency, DORA was more likely to categorize the melody as being different or produce a surprise reaction.

## Discussion

To our awareness, this is the first time a general model of relational cognition has been used to simulate melodic perception, and the results subsequently compared to existing behavioral data from infants.<sup>3</sup> We view these first steps as a very simple beginning, and hope to expand the complexity of the model and the range of future simulations.

The results of both simulations were a good match to their behavioral counterparts, and supported our hypothesis that relational processing might play an important role in music perception. In the first simulation, DORA performed similar to infants in extracting the relational properties of transposed melodies, and also in failing to recognize the scrambled melody. In the second simulation, both DORA and infants categorized the melodies based primarily on relational information of the melodic contours. Furthermore, DORA's ability to discriminate large contour distortions (far contour) in Simulation 2 suggests that infants may be sensitive to certain intervallic properties.

While these simulations provide insights into some of the mechanisms that infants may use when categorizing music, we hope to determine through future studies, when and how children begin to learn the more typically defining feature of melodies: the intervallic sequences, or relative pitch relations between notes. Crucially, this study corroborates existing evidence that infants as young as four months are sensitive to relational features of music and appear to reason about these relational features in a structure sensitive manner (i.e., generalizing relational properties to novel inputs). Another important question that future simulations and studies should attempt to answer is whether this widespread ability to discriminate intervallic sequences in adults is innate, or in fact a learned ability.

Lastly, DORA is currently the only model that learns complex structured relations and that can subsequently "grow up" to reason like an adult (Doumas & Hummel, 2005). Accordingly, we hope to determine through future simulations whether DORA can perhaps also grow up to "appreciate" (or even compose) music like an adult.

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<sup>3</sup> We also simulated Task 1 using an Elman neural network with similar inputs to what was given to DORA. With a hidden layer of 24 neurons, the network learned the training melody sequence to a MSE of .01 within 15 iterations, however, after training it failed to systematically generalize to contour preserving melodies even when the intervallic pattern was consistent (performing at chance when predicting the contour). Moreover, this failure occurred even while the Elman network was provided a clean input set (unlike DORA, which was "handicapped" with distractor sets in memory and a highly reduced lateral inhibition parameter).

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