

# COMPARING SOLUTIONS TO THE LINKING PROBLEM USING AN INTEGRATED QUANTITATIVE FRAMEWORK OF LANGUAGE ACQUISITION

LISA S. PEARL

JON SPROUSE

*University of California, Irvine*

*University of Connecticut, Storrs*

To successfully learn language—and more specifically how to use verbs correctly—children must solve the linking problem: they must learn the mapping between the thematic roles specified by a verb’s lexical semantics and the syntactic argument positions specified by a verb’s syntactic frame. We use an empirically grounded and integrated quantitative framework involving corpus analysis, experimental meta-analysis, and computational modeling to implement minimally distinct versions of mapping approaches that (i) either are specified a priori or develop during language acquisition, and (ii) rely on either an absolute or a relative thematic role system. Using successful verb class learning as an evaluation metric, we embed each approach within a concrete model of the acquisition process and see which learning assumptions are able to match children’s verb-learning behavior at three, four, and five years old. Our current results support a trajectory where children (i) may not have prior expectations about linking patterns between ages three and five, and (ii) begin with a relative thematic system, progressing toward optionality between a relative and an absolute system. We discuss implications of our results for both theories of syntactic representation and theories of how those representations are acquired. We also discuss the broader contribution of this study as a concrete modeling framework that can be updated with new linking theories, corpora, and experimental results.\*

*Keywords:* computational modeling, derived mapping, innate mapping, linking problem, UTAH, rUTAH, verb classes

**1. INTRODUCTION.** To successfully learn how to use a verb, children must learn (at least) three pieces of information: (i) the syntactic properties of the verb, such as the syntactic frames it can appear in, (ii) the lexical semantics of the verb, including the thematic roles assigned by the verb, and (iii) a mapping between the thematic roles specified by the verb’s lexical semantics and the syntactic argument positions specified by the verb’s syntactic frame(s). The learning of this third component is often called the LINKING PROBLEM.

At the level of individual verbs and individual syntactic frames, the linking problem does not appear to be much of a problem. We might imagine that children simply learn the mappings between thematic roles and syntactic positions for each combination of a verb and syntactic frame one at a time. However, this does not account for children’s ability to generalize their knowledge to new verbs. That is, if the linking between thematic roles and syntactic positions is only ever learned on a verb-by-verb basis, how could children use a new verb appropriately without hearing all of its possible uses? It seems children must be learning linking patterns at a more abstract level because they are capable of generalizing linking patterns from one verb to another (sometimes incorrectly during the course of development): see, for example, Gropen et al. 1989, Naigles 1990, Naigles & Kako 1993, Gelman & Koenig 2001, Bungler & Lidz 2004, 2008, Huttenlocher, Vasilyeva, & Shimpi 2004, Kidd, Lieven, & Tomasello 2006, 2010, Conwell & Demuth 2007, Papafragou, Cassidy, & Gleitman 2007, Thothathiri & Snedeker 2008,

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Scott & Fisher 2009, Yuan & Fisher 2009, Becker 2014, and Hartshorne, Pogue, & Snedeker 2015.

The additional complexity of the linking problem becomes apparent when we consider the broader linking patterns that we see crosslinguistically. Two core linking patterns emerge:<sup>1</sup>

- (i) For the vast majority of verbs in accusative languages, Agent-like thematic roles tend to appear in syntactic subject position, Patient-like thematic roles tend to appear in syntactic object position, and Instrument/Source/Goal-like roles tend to appear in oblique syntactic positions such as indirect object or object of PP.
- (ii) Exceptions to this pattern tend to be contained within very specific semantic classes of verbs (see §2 for examples).

How and why does this regularity in linking patterns emerge? There are currently two general approaches. The first is that the linking patterns could result from children possessing explicit innate knowledge of the linking patterns themselves, such that the linking pattern does not need to be learned during development. We call these *INNATE-MAPPING* approaches. We note that innate-mapping approaches may be coupled with either early maturation or late maturation of the innate linking knowledge, in terms of the predicted developmental trajectory. Early maturation predicts the knowledge to be present as young as we can test, while late maturation predicts the knowledge to be present only in older children. The second possibility is that the linking patterns could derive from the interplay between the input that children receive and the learning mechanisms underlying verb learning. We call these *DERIVED-MAPPING* approaches. Derived-mapping approaches would predict that the linking knowledge will take time to develop, so it would be less likely to be present in younger children.

To empirically compare these approaches, we must create a framework that meets two criteria: it must be possible to (i) systematically manipulate the presence or absence of prior knowledge of linking patterns, and (ii) evaluate both approaches on a neutral metric of success. We note that achieving knowledge of the linking pattern itself cannot be the metric of success because the innate-mapping approach builds that pattern into the learner explicitly, and thus would automatically ‘win’ under such a metric. With this in mind, we propose to measure success by assessing one prominent type of acquired knowledge that relies on learning linking patterns: whether developmentally attested verb classes can be learned from the data children encounter, given a computationally modeled child who either explicitly has or does not have prior linking knowledge. In other words, we use an argument from acquisition to evaluate theories of knowledge representation (Pearl, Ho, & Detrano 2016, Pearl 2017) for linking patterns.

Though the verb-class-learning literature and the linking-pattern literature do not always intersect (presumably because the verb-class-learning literature focuses on development, and the linking-pattern literature focuses on adult end states), we believe that verb class learning is a useful common denominator for evaluating the two major approaches. This is because the linking pattern is defined over verb classes (see §2). More specifically, because innate-mapping approaches predict linking knowledge to also be operative during language learning, it is reasonable to expect modeled learners that incorporate this innate linking knowledge to better match the observed developmental tra-

<sup>1</sup> We use initial uppercase letters to indicate thematic roles (e.g. Agent). We also abstract away from the details of syntactic structure, which may vary crosslinguistically, by referring to positions using grammatical labels (e.g. *subject*) rather than phrase structure labels (e.g. *spec-TP*).

jectory of human children. An empirical question is exactly how much prior linking knowledge aids a modeled learner in achieving children's observed verb-class-learning behavior—this is a question we investigate here using our integrated quantitative framework of the acquisition process.

For this study, we explore two of the most prominent innate-mapping approaches in the literature that are built on cognitively plausible assumptions about the thematic role systems available to children during development: (i) the UNIFORMITY OF THETA ASSIGNMENT HYPOTHESIS (UTAH; Baker 1988, building on Perlmutter & Postal 1984), which uses an absolute thematic system, and (ii) the RELATIVIZED UNIFORMITY OF THETA ASSIGNMENT HYPOTHESIS (rUTAH; Grimshaw 1990, Larson 1990, Speas 1990), which uses a relative thematic system. We contrast these with derived-mapping versions that use the same thematic systems, but that do not build in knowledge of how to map to syntactic positions. In this way, these two derived-mapping approaches are minimally different from UTAH and rUTAH, leveraging those approaches to thematic systems, but without the added assumption of innate linking patterns. Our modeling framework can therefore contribute to two sets of debates: the debate between innate-mapping and derived-mapping approaches, and the debate about the details of the thematic role system.

Within our integrated quantitative framework, we create computationally modeled learners that rely on different combinations of assumptions (e.g. innate mapping vs. derived mapping, absolute vs. relative thematic systems). The framework uses existing child-directed corpus data to determine the input for each modeled learner and existing child behavioral evidence to determine the target output knowledge that modeled learners should achieve. The modeled learners use hierarchical Bayesian inference to infer verb classes from realistic input distributions, and these inferred verb classes are compared against the target verb classes at different ages. The modeled learner whose output best matches the target verb classes known by children can be considered the modeled learner that is most likely to encode the learning assumptions children actually use.

The rest of this article is organized as follows. We first discuss the linking problem in more detail, along with the theoretically motivated solutions mentioned above: the innate-mapping UTAH and rUTAH, and their derived-mapping equivalents. We then discuss our use of verb class learning as a neutral evaluation for comparing different approaches. We also present the verb classes that children have acquired by ages three, four, and five, as derived from a review of thirty-eight studies from the experimental acquisition literature; we additionally review the VERB BEHAVIORS examined in those studies, where 'verb behavior' refers to which syntactic frames a verb can appear in, as well as the thematic role information of its arguments within each frame. We subsequently introduce our acquisition-modeling framework, highlighting (i) the components necessary to implement a modeled learner that attempts to learn verb classes, and (ii) how different learning assumptions impact a modeled learner. This includes discussion of how a modeled learner interprets the syntactic and conceptual information available in the input, as well as the empirical data from the CHILDES Treebank (Pearl & Sprouse 2013a) on which the modeled learner's input is based. We also discuss the hierarchical Bayesian inference process that allows the modeled learner to use the available input to infer verb classes.

Our first key finding is that there is always at least one modeled learner at every age who performs relatively well, which affirms that verb classes can be probabilistically learned from relatively sparse linguistic and conceptual information, as opposed to requiring richer information. Our second key finding is that the modeled learner (and

therefore the specific learning-assumption combination) that best matches children's verb class knowledge can change over time. Here, we assume that the progression of learning assumptions that best matches children's verb class knowledge is a reasonable reflection of children's true learning assumptions. With this as a working hypothesis about children's underlying knowledge, our results support a developmental trajectory that begins at three years old with a relative thematic system; it then progresses toward optionality between absolute and relative thematic systems. Interestingly, our results also support either innate-mapping or derived-mapping approaches to linking, depending on the other learning assumptions active in three-, four-, and five-year-olds. We discuss the implications of our current results for syntactic theory, acquisition theory, and future experimental and computational studies of verb learning. Finally, at the broadest level, we discuss the value of explicit, integrated quantitative frameworks like the one here for exploring fundamental questions in syntactic theory and language acquisition, and how the framework we develop here can be extended with additional empirical data and additional theoretical proposals.

We note also that our online supplementary materials provide all of the information required to reproduce the current study, and to extend our models as additional input corpora or child behavioral studies become available.<sup>2</sup> Section A of the supplement briefly reviews the thirty-eight child behavioral studies that we used to determine the verb classes that children know at different ages, and section B lists the verb classes derived from these child behavioral data, which serve as the target state of the modeled learner. A description of the modeled learner's inference process at the level of detail necessary to reproduce, alter, or extend the code is provided in section C, and section D lists the complete modeled learner's output verb classes for each learning assumption combination at each age (i.e. our raw results).

## 2. THE LINKING PROBLEM AND ITS POTENTIAL SOLUTIONS.

**2.1. A BRIEF INTRODUCTION TO THE LINKING PROBLEM.** As mentioned above, the linking problem is predicated on two observations. First, there seems to be a primary pattern robustly observed crosslinguistically (see Baker 1997 for a review), as shown in the English examples in 1. This pattern has Agent-like roles in the syntactic subject position, Patient-like roles in syntactic object position, and Instrument/Source/Goal-like roles in oblique syntactic positions.

### (1) The primary pattern

- a. Jack cut the pie with a knife.  
(subject = Agent, object = Patient, object of PP = Instrument)
- b. Jack stole the jewels from the store.  
(subject = Agent, object = Patient, object of PP = Source)
- c. Lily sent the letter to her parents.  
(subject = Agent, object = Patient, object of PP = Goal)

Second, verbs that are exceptions to this primary pattern tend to form well-defined semantic classes (again, see Baker 1997 for a brief review). For instance, in English, one example is the semantic class known as PSYCH-VERBS, which involve one of the verb arguments experiencing a psychological or mental state (see Postal 1971, Belletti & Rizzi 1988, and Dowty 1991, among many others). The psych-verb pair in 2 involves two verbs, *fear* and *frighten*, that have very similar lexical semantics but nonetheless yield two distinct linking patterns: the Experiencer of the psychological state and the

<sup>2</sup> Supplementary materials can be accessed online at <http://muse.jhu.edu/resolve/83>.

apparent Causer of the psychological state alternate syntactic positions. Interestingly, we do not tend to find this sort of alternation for verbs from other semantic classes.

(2) Psych-verb examples

- a. Lily fears spiders.  
(subject = Experiencer, object = Causer)
- b. Spiders frighten Lily.  
(subject = Causer, object = Experiencer)

A second example of exceptions connected to semantically defined verb classes involves SPLIT-INTRANSITIVITY, where intransitive verbs can be subdivided into two or more subclasses (sometimes called UNERGATIVE and UNACCUSATIVE) that are derived from the lexical semantics of the verbs (Perlmutter 1978, Burzio 1986, Levin & Rappaport Hovav 1995, Sorace 2000). In English, we can see this in the examples in 3: unergative *sneeze* maps an Agent to the subject position, while unaccusative *arrive* maps a Patient to the subject position.

(3) Split-intransitivity examples

- a. Jack sneezed during the meeting.  
(subject = Agent)
- b. The package arrived during the meeting.  
(subject = Patient)

The regularity of the primary pattern crosslinguistically and the semantic coherence of the exceptions to it have spurred theories of representation (e.g. explicit linking patterns like UTAH and rUTAH) that compactly encode this regularity. From a representational standpoint, this compact representation would allow easier storage and use of the relevant knowledge that links thematic roles to syntactic positions. From a developmental standpoint, this compact representation would helpfully constrain children's hypotheses and so enable them to solve the linking problem more quickly (Pearl et al. 2016, Pearl 2017).

As mentioned above, developmental approaches diverge on whether this linking-pattern representation is available innately as explicit knowledge (innate mapping) or is instead derived from language experience (derived mapping). For innate-mapping approaches, the primary pattern comes for free, and children learn exceptions (such as certain psych-verbs and split-intransitivity verbs) through language experience, drawing on learned knowledge of lexical semantics and specific grammatical mechanisms (e.g. the movement operation in syntactic theory). In contrast, for derived-mapping approaches, all linking patterns (both the primary one and any exceptions) are inferred from experience with particular verbs. General mechanisms of abstraction allow children to generalize across verbs and learn any linking patterns that exist, based on the input available.

To be clear, there can be significant variability among the theories within each type: innate-mapping theories can vary substantially in how they capture the exceptions to the mapping (Fillmore 1968, Perlmutter & Postal 1984, Jackendoff 1987, Larson 1988, Grimshaw 1990, Larson 1990, Speas 1990, Dowty 1991, Baker 1997), and derived-mapping theories can vary substantially in how they capture regularities (Bowerman 1988, Tomasello 1992, 2003, Braine & Brooks 1995, Goldberg 1995, 2006, 2013, Boyd & Goldberg 2011). Given this, we intend to compare modeled learners instantiating (i) approaches that assume or do not assume prior explicit linking knowledge, and (ii) more fine-grained differences within each approach. To that end, we have focused on two prominent innate-mapping solutions, UTAH and rUTAH, and their derived-mapping

counterparts; importantly from a cognitive standpoint, these approaches rest on plausible assumptions about the complexity of the thematic system available during development (discussed in §4.2) but differ in the thematic-system details.

**2.2. THE UNIFORMITY OF THETA ASSIGNMENT HYPOTHESIS (UTAH).** UTAH (Fillmore 1968, Perlmutter & Postal 1984, Jackendoff 1987, Baker 1988, Grimshaw 1990, Speas 1990, Dowty 1991, Baker 1997) has two components: (i) an inventory of thematic roles used for the calculation of syntactic position, and (ii) an expected mapping between each of the thematic roles and syntactic positions. Here, we assume the implementation from Baker (1997), which posits an inventory of three thematic macro- or proto-roles (Dowty 1991): proto-Agent, proto-Patient, and Other. This implementation is agnostic about the existence of finer-grained thematic roles at a semantic level. All it requires is that any finer-grained typology of thematic roles map to the three proto-roles necessary for the syntactic calculation. In this way, UTAH represents an absolute approach to the thematic system, where each proto-role is a fixed thematic category.

Under this implementation, thematic roles that tend to involve internal causation map to proto-Agent, roles that tend to involve external causation map to proto-Patient, and all other roles map to Other (Levin & Rappaport Hovav 1995). Example 4 lists thirteen common finer-grained thematic roles from the literature and how they would map to the three proto-roles in this implementation.

- (4) Example UTAH mapping with three fixed proto-roles
- a. proto-Agent: Agent, Causer, Experiencer (when internally caused), Possessor
  - b. proto-Patient: Patient, Theme, Experiencer (when externally caused), Subject matter
  - c. Other: Location, Source, Goal, Benefactor, Instrument

Baker's (1997) implementation assumes that the proto-Agent role maps to the syntactic subject position, the proto-Patient role maps to the syntactic object position, and the Other role maps to oblique object positions (such as object of PP).

To see this UTAH implementation in action, we can apply it to examples of primary and exceptional patterns. For primary-pattern sentences like *Jack cut the pie with a knife*, the subject is a proto-Agent, the direct object is a proto-Patient, and the oblique object is Other. For psych-verbs, this implementation of UTAH leverages the internal- vs. external-causation distinction: in *Lily fears spiders*, *Lily* is causing her own mental state and is thus a proto-Agent; in *Spiders frighten Lily*, *spiders* are causing Lily's mental state, and thus *Lily* is the proto-Patient. For the unergative *sneezed* in *Jack sneezed during the meeting*, *Jack* is the proto-Agent and is mapped to the subject. For the unaccusative *arrived* in *The package arrived during the meeting*, this implementation would claim that *the package* enters the syntactic derivation as the object of *arrive*, thus respecting UTAH. *The package* would then be moved to the subject position by an additional mechanism (such as the movement operation in syntactic theory).

**2.3. THE RELATIVIZED UNIFORMITY OF THETA ASSIGNMENT HYPOTHESIS (rUTAH).** rUTAH (Larson 1988, 1990, Grimshaw 1990, Speas 1990) also has two components: (i) a hierarchy of thematic roles used for the calculation of syntactic position, and (ii) an expected mapping between the relative position of thematic roles on the hierarchy and syntactic positions. The basic idea is that for any given utterance, the rUTAH calculation requires the learner to first determine an ordering relation among the utterance's thematic roles, based on a previously established thematic role hierarchy. This hierarchy is presumably based on some sort of relative salience of the different thematic roles, possibly even outside of the domain of language itself (though most rUTAH-



based analyses leave open the etiology of the thematic role hierarchy). The learner can then use that ordering relation of the utterance's roles to map each role to a syntactic position: the thematic role that is highest in the hierarchy will map to the (structurally) highest syntactic position, the next highest thematic role will map to the next highest syntactic position, and so on. Here, we created a thematic role hierarchy based on the hierarchies developed in Larson 1988, 1990, using the thirteen common thematic roles from the literature mentioned above. This hierarchy is given in 5. Note that some roles may not be strictly ordered with respect to each other in the hierarchy. For instance, Location and Source are equally salient in the hierarchy in 5. For this implementation, we assume that syntactic subjects are structurally higher than syntactic objects, which in turn are higher than oblique objects.

- (5) HIERARCHY: Agent > Causer > Experiencer > Possessor > Subject matter > Causee > Theme > Patient > (Location, Source, Goal, Benefactor, Instrument)

For primary-pattern sentences like *Jack cut the pie with a knife*, there are three thematic roles: Agent, Patient, and Instrument. The thematic hierarchy places them in that order (Agent > Patient > Instrument), so they map to subject, object, and oblique object positions, respectively. For psych-verbs like *fear* in *Lily fears spiders*, rUTAH would posit that *Lily* is an Experiencer, while *spiders* is a Subject matter. As such, *Lily* will map to the subject position, and *spiders* will map to the object position. In contrast, for psych-verbs like *frighten* in *Spiders frighten Lily*, rUTAH would posit that *spiders* is now a Causer, though *Lily* is still an Experiencer. Because Causer > Experiencer, *spiders* will map to the subject position, and *Lily* will map to the object position. Finally, for both unergative verbs like *sneezed* and unaccusative verbs like *arrived*, rUTAH assumes one syntactic position (subject). For unergatives, the single thematic role Agent is the highest in the hierarchy and therefore appears in subject position; for unaccusatives, the single thematic role Theme is the highest in the hierarchy and therefore appears in the subject position. (In this way, rUTAH follows other nonmovement frameworks in explaining split-intransitivity effects through the thematic differences in the arguments.)

**2.4. UTAH vs. rUTAH.** To be clear, the implementations of UTAH and rUTAH that we adopt here are just two of many possible implementations of these theories. We do not believe there is anything special about the specific implementations that we chose (and future studies should investigate other implementations). What is critical for our purposes, because we intend to model the acquisition process, is that UTAH and rUTAH involve two distinct types of thematic systems that are developmentally plausible. That is, to map thematic roles onto syntactic positions, children are likely to either (i) make a small number of coarse intermediate categories of thematic roles corresponding to proto-roles or (ii) view some roles as more salient than others, and order roles accordingly. In each case, the critical step is limiting the number of thematic roles that children must attend to and track statistically, either in absolute or in relative terms. That said, we do believe that the implementations of UTAH and rUTAH that we have chosen for our models are relatively representative of the theory types as a whole, at least as far as the two theories are represented in the theoretical literature.

**2.5. DERIVED-MAPPING EQUIVALENTS OF UTAH AND rUTAH.** Derived-mapping approaches do not postulate any expected mapping between thematic roles and syntactic positions at the beginning of acquisition. Instead, some verbs and their linking patterns are first learned in isolation; then, over time, if enough verbs are learned with the same properties, a class is formed via general-purpose learning mechanisms that allows these linking patterns (and other verb behaviors) to generalize. In other words, over time, children will build verb classes that can be used to make predictions about novel verbs. In

this way, derived-mapping approaches can capture both the regularities and the exceptions we observe within and across languages. Both result from different verb classes derived in a bottom-up way from experience. More specifically, children learn patterns associated with individual verbs, create verb classes based off of those verbs, and then generalize to more abstract patterns (e.g. an expected linking pattern within a given verb class). So, children derive an expectation for linking-pattern mappings over time, rather than being innately equipped with this expectation. We note that derived-mapping approaches would need to identify another source of the primary linking pattern's cross-linguistic robustness. That is, because knowledge of the explicit linking pattern is not innate, the consistency of the primary linking pattern across languages must come from somewhere else under a derived-mapping approach. Moreover, we note that derived-mapping approaches clearly must assume some kinds of innate knowledge and abilities (e.g. the general-purpose learning mechanisms they rely on are typically considered to be innate). Derived-mapping approaches just do not assume that the explicit linking-pattern knowledge itself is innate, the way innate-mapping approaches do.

**2.6. EVALUATING THE EXPECTATION FOR A MAPPING.** To evaluate the role of expected mappings in acquisition, we begin with the thematic role systems from either UTAH (an absolute set of three proto-roles) or rUTAH (a relative hierarchy) and manipulate the presence or absence of an expected link between thematic roles and syntactic positions. To reiterate, we focus on UTAH and rUTAH because they are prominent innate-mapping approaches and can easily generate minimally different derived-mapping versions. Importantly, by manipulating whether a modeled learner has or does not have prior knowledge of a linking pattern between thematic roles and syntactic positions, we can evaluate whether having or not having this knowledge yields behavior that matches children's observable behavior with respect to verb classes. Any results can then be interpreted with respect to innate-mapping and derived-mapping approaches to solving the linking problem.

### 3. VERB CLASSES AS AN EVALUATION METRIC.

**3.1. VERB CLASSES DEFINED BY VERB BEHAVIORS.** To compare different approaches to solving the linking problem, we evaluate these approaches on a shared goal: the acquisition of developmentally observed verb classes. The predominant approach to defining verb classes in the literature (e.g. Levin 1993) is by verb behavior: which syntactic frames a verb can appear in, as well as the thematic role information of its arguments within each frame. For example, both *want* and *seem* can appear in the syntactic frame NP V IP<sub>-finite</sub> (e.g. *Jack wants/seems to laugh*). However, *want* gives the subject NP *Jack* an Experiencer role, while *seem* gives the subject NP no role (instead, that NP's role comes only from the embedded verb). We additionally include animacy information of a verb's arguments (e.g. *Jack* is +animate) as part of a verb's behavior. (See §4.2 for the developmental motivation to include animacy information.) Importantly for our purposes, a verb class can then be defined as a distribution over verb behavior, that is, the combination of syntactic frames, positional thematic roles, and animacy of arguments a verb appears with.<sup>3</sup> For example, one verb class during the course of development may consist of the verbs that, given current developmental evidence, are known only to be passivizable by a certain age (+passive): they appear with the syntactic frame

<sup>3</sup> We note that this definition of verb class differs from prior definitions, which might, for example, have an 'unaccusative' verb class; under those prior definitions, a verb class captures a single verb behavior (e.g. unaccusative constructions), and so a verb can belong to multiple verb classes, each involving a particular verb behavior. Here, a verb class captures a SET of verb behaviors—thus, a verb only ever belongs to one verb class, though it may shift from class to class over the course of development.



NP *be/get* V<sub>participle</sub> (e.g. *The cookie was/got eaten*), and in that frame, the subject NP is the Patient (and either +animate or -animate). Another verb class may consist of verbs known to be both passivizable and able to take a nonfinite *to* sentential complement (+passive, +nonfinite *to*): they exhibit the passive behavior noted above, and in addition allow the syntactic frame NP V IP<sub>-finite</sub>.

**3.2. TARGET STATES: VERB CLASSES KNOWN BY CHILDREN AT DIFFERENT AGES.** To evaluate the performance of our modeled learners, we need to establish a target knowledge state for them to reach. We are also interested in the developmental trajectory of verb class knowledge, and so want to assess a modeled learner’s ability to capture child knowledge at different ages. Importantly, English child verb classes may well differ from English adult verb classes, so we use the experimental acquisition literature on children’s comprehension and production of verbs as evidence of children’s knowledge of verb classes.

To derive those verb classes, we first did a meta-analysis of thirty-eight articles from the experimental acquisition literature. Based on this, we extracted (i) the set of verbs that children comprehend and/or produce at different ages, and (ii) the set of verb behaviors that are associated with these verbs at those ages. This meta-analysis yielded twelve verb behaviors (see Table 1) for eighty-six verbs that can be used to define child verb classes in English.<sup>4</sup>

VERB BEHAVIOR	EXAMPLE	DESCRIPTION
Unaccusative	The ice <i>melted</i> .	Intransitive (NP V) frame where subject is Patient.
Ditransitive	Jack <i>sent</i> Lily the apple.	Verb allows double object construction (NP V NP NP).
Passivizable	Jack <i>was tricked/laughed at</i> .	Verb allows passive frame (NP <i>be/get</i> V <sub>participle</sub> ) where subject is Patient of verb or verbal complex.
Control object	Lily <i>asked</i> him to escape.	Embedded subject is Goal of matrix verb and Agent of embedded verb in NP V NP IP <sub>-finite</sub> frame.
Raising object	Lily <i>wanted</i> him to escape.	Embedded subject is Agent of embedded verb only in NP V NP IP <sub>-finite</sub> frame.
Control subject	Jack <i>tried</i> to escape.	Subject is Agent of matrix verb and embedded verb in NP V IP <sub>-finite</sub> frame.
Raising subject	Jack <i>happened</i> to escape.	Subject is Agent of embedded verb only in NP V IP <sub>-finite</sub> frame.
Psych: Subject experiencer	Jack <i>loved</i> Lily.	Subject is Experiencer of verb in NP V NP frame.
Psych: Object experiencer	The giant <i>frightened</i> Jack.	Object is Experiencer of verb in NP V NP frame.
Nonfinite <i>to</i> -complement	I <i>want</i> (him) to go.	Verb allows a nonfinite <i>to</i> -complement, with or without an embedded subject (NP V (NP) IP <sub>-finite</sub> ).
<i>that</i> -complement	Lily <i>hoped</i> that Jack escaped.	Verb allows finite complement headed by <i>that</i> (NP V CP <sub>that</sub> ).
<i>whether/if</i> -complement	Lily <i>wondered</i> whether Jack escaped.	Verb allows finite complement headed by <i>whether</i> or <i>if</i> (NP V CP <sub>whether/if</sub> ).

TABLE 1. Verb behaviors associated with specific verbs from the child behavioral study meta-analysis.<sup>5</sup>

<sup>4</sup> We note that the earliest age documented in the experimental literature was used as the age of acquisition for the verb behavior associated with a specific verb.

<sup>5</sup> We note that the verb behavior of taking a nonfinite *to*-complement is a superset of the more specific behaviors of control vs. raising (subject or object). This is due to the distinctions made by the developmental researchers conducting the relevant developmental studies. In this particular case, production data are unable to

Because the input data available to our modeled learners from the CHILDES Treebank (Pearl & Sprouse 2013b) range up to five years old, we focused on the verb classes children seem to know by ages three, four, and five. (These corpus data are discussed in more detail in §4.2.) We additionally restricted these classes to verbs appearing five or more times in the age-appropriate input sets for three-, four-, and five-year-olds, with the idea that a modeled learner could infer something from the distribution of verbs appearing at least this often. This process resulted in the verbs and derived verb classes characterized by different verb behaviors that are summarized in Table 2, for a total of fifteen to twenty-five verb classes comprising sixty to eighty-four verbs from ages three to five.

AGE	# CLASSES	# VERBS	VERB BEHAVIORS
3 yrs	15	60	unaccusative, ditransitive, nonfinite <i>to</i> -complement, passivizable, <i>that</i> -complement
4 yrs	23	76	unaccusative, ditransitive, nonfinite <i>to</i> -complement, passivizable, <i>that</i> -complement, control object, control subject, psych object experiencer, psych subject experiencer, raising object, raising subject
5 yrs	25	84	unaccusative, ditransitive, nonfinite <i>to</i> -complement, passivizable, <i>that</i> -complement, control object, control subject, psych object experiencer, psych subject experiencer, raising object, raising subject, <i>whether/if</i> -complement

TABLE 2. Summary of verb classes derived from child behavioral data for three-, four-, and five-year-olds. This includes the number of derived verb classes, the number of verbs appearing five or more times in the data set captured by those classes, and the verb behaviors that define the derived verb classes.

One important property of the child verb classes serving as the modeled-learner target state is that a specific verb can change its verb class over time (based on child behavior with that verb); this therefore means the content of verb classes can change over time. For example, the class where verbs are known only to be passivizable ([+passive]) at age three contains twenty verbs, while the same class at age four contains twenty-six verbs (it adds six verbs over time). As another example, *see* belongs to the passivizable ([+passive]) class at age three, the passivizable class that also allows *that*-complements ([+passive, +*that*-complement]) at age four, and the passivizable class that allows both *that*- and *whether/if*-complements ([+passive, +*that*-complement, +*whether/if*-complement]) at age five. We note that because these verb classes are derived from existing behavioral data, the changes to a verb's class represent either (i) development of verb class knowledge or (ii) a (current) lack of empirical data about knowledge of verb behavior at younger ages. Under the working assumption that these are developmental changes to verb class knowledge over time, we test our modeled learners at three ages, determining which modeled learners (representing different learning-assumption combinations) can best match children's verb class knowledge development.

### 3.3. ASSESSING VERB CLASS LEARNING.

THE RAND INDEX. Each modeled learner outputs a set of inferred verb classes, with each class containing one or more verbs, and each verb belonging to only one class. We want to assess how well these inferred verb classes match the true verb classes derived from observed child behavior. Because the output is similar to that of a clustering task

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distinguish which interpretation children assigned to the arguments of the verb (which would indicate a raising vs. control interpretation), and instead simply noted if the verb was produced with a nonfinite *to*-complement.

(i.e. the modeled learner outputs clusters of verbs, which are the inferred verb classes), we consider evaluation metrics from the machine learning literature on clustering. For this study, we use the RAND INDEX (RI; Rand 1971) because it is a common measure in the clustering literature and it has an intuitive absolute interpretation.

The RI is a pairwise measure derived from signal detection theory. When considering a pair of verbs, there are two possible true states: the two verbs are clustered together into a single class in children's minds, or the two verbs are separated into two distinct classes. Similarly, there are two possible modeled-learner output states: the two verbs are clustered into a single class in the modeled learner, or the two verbs are separated into two distinct classes. Crossing the true-child and modeled-learner output states leads to four possible combinations, as shown in Table 3. When two verbs are the same kind in the true state ('True child state: Together'), they should be clustered together in the modeled-learner output. A true positive (TP) occurs when the modeled learner clusters these verbs together, while a false negative (FN) occurs when the modeled learner separates these verbs. When two verbs are not the same kind in the true child state ('True child state: Separate'), they should be separated by the modeled learner. A true negative (TN) occurs when the modeled learner does separate them, while a false positive (FP) occurs when the modeled learner clusters them together. The RI is the ratio of correct classifications (true positives and true negatives) to the total number of classifications made (true positives, true negatives, false positives, and false negatives):  $\frac{TP + TN}{TP + TN + FP + FN}$ . The intuitive appeal of this ratio is that credit is given both for correctly putting verbs together into the same class and for correctly keeping them separate. The RI ranges between 0 (no classifications are correct) and 1 (all classifications are correct):  $0 \leq RI \leq 1$ . The interpretation of the RI is intuitive in an absolute sense: an RI of 0.5 means that half of the classifications were correct; equivalently, for any randomly chosen verb pair, there is a probability of 0.5 that the modeled learner's output will agree with the true child state.

		MODELED LEARNER OUTPUT STATE	
		TOGETHER	SEPARATE
TRUE CHILD STATE	TOGETHER	true positive	false negative
	SEPARATE	false positive	true negative

TABLE 3. Signal detection theory distinctions relevant for the Rand index when applied to a verb pair.

EVALUATING AN RI SCORE RELATIVE TO CHANCE. One limitation of the RI is that the distribution of RI scores for any given number of classes is not known; therefore we cannot determine from the RI score alone if the RI score we obtain is particularly good or particularly bad. We might therefore want to perform some sort of test that compares the observed RI score to the distribution of RI scores expected by a null hypothesis (either chance or some other null expectation). One solution to this problem is to use a randomization test that randomizes the three types of information (i.e. the parameters) the modeled learners are inferring from their input: the number of verb classes, the size of each verb class, and the assignment of individual verbs to these classes. In particular, using the same generative process the modeled learners will use (described more fully in §4.3), we generate a random number of classes of random size, and randomly assign verbs to these classes. We can then calculate an RI score for this randomized set of classes, which is equivalent to an RI under the null hypothesis that the parameters are exchangeable. We can repeat this process some large number of times (e.g. 10,000) to estimate a distribution of RI scores under this null hypothesis. We can then calculate the

probability of obtaining our observed RI score (or one more extreme) under the null hypothesis using this distribution. We report the observed RI and the threshold for significance at  $p < 0.01$ .

#### 4. COMPUTATIONALLY MODELING THE ACQUISITION OF VERB CLASSES.

**4.1. THE ACQUISITION FRAMEWORK.** We follow the view that language acquisition is an information-processing task, where children use their available input to build an internal system of linguistic knowledge whose behavioral output we can observe (Lidz & Gagliardi 2015, Omaki & Lidz 2015, Pearl 2020). The framework of Pearl 2020, building on that of Lidz and Gagliardi (2015) and Omaki and Lidz (2015), articulates several crucial components of this task, underscoring how theories of representation and theories of the learning process work together to create a complete theory of acquisition.

For our purposes, there are three crucial pathways. First is the INPUT-INTAKE pathway, where the external signal, the INPUT, is encoded by the child into an internal mental representation we call the LINGUISTIC INTAKE.<sup>6</sup> The parts of the linguistic intake that are identified by the acquisition system as relevant for acquisition are called the ACQUISITIONAL INTAKE. For example, an input utterance of *What's she climbing over?* might be encoded by the child as containing certain pieces of syntactic and conceptual information—this is the linguistic intake, which serves as the child's representation of that utterance at this stage of development. This encoding process will depend on the child's ability to deploy her existing linguistic and extralinguistic knowledge in real time, given her developing cognitive abilities. The acquisitional intake is the portion of that representation relevant for the acquisition task at hand—for example, perhaps only syntactic structure may be relevant for learning about certain constraints on WH-dependencies (as in Pearl & Sprouse 2013a,b), but perhaps conceptual information may be relevant for learning about the verb argument structure of *climb*. The acquisitional intake is determined by the child's learning biases about what information is relevant in the linguistic intake. For verb class learning, this pathway will determine how the age-appropriate child-directed speech samples serving as input are transformed into different acquisitional intakes, depending on the modeled learner's learning assumptions.

The second pathway is the INTAKE-INFERENCE pathway, which takes the acquisitional intake and does inference on it to generate the most up-to-date hypotheses or generalizations about the linguistic system encoded by the developing grammar. The exact update procedures used will depend on the child's current learning biases. For example, a child might use purely statistical inference within a hypothesis space defined in terms of clusters of salient features, or a hypothesis-testing approach within a hypothesis space defined in terms of linguistic parameters. For verb class learning, this pathway will involve hierarchical Bayesian learning that generates the verb classes in the modeled learner's developing grammar (i.e. the learner's inferred classes), based on the syntactic, conceptual, and linking information in the acquisitional intake.

The third pathway is the GRAMMAR-BEHAVIOR pathway. This pathway describes how the child's internal representations (encoded by the linguistic intake of the moment and the developing grammar) are transformed into various types of external behavior that

<sup>6</sup> What we call the linguistic intake has been referred to in the framework mentioned above as 'perceptual intake' because it is what the child is capable of perceiving from the available input at that point in development; we choose 'linguistic' to highlight that this representation includes more than just perceptual information.

we can observe, such as utterance generation, truth-value judgments, or looking times. This depends on both the state of the child's internal representations and the production systems that operate on those representations to produce observable behavior. For example, an internal representation of *What's she climbing over?* that involves both syntactic and conceptual information might cause a child to generate the utterance *What's she dancing on?* using her developing grammar, because the new utterance has syntactic and conceptual properties similar to those of the sentence in the linguistic intake. For verb class learning, this pathway will involve how the verb classes in the modeled learner's developing grammar (i.e. the inferred classes in the learner's output) compare to the verb classes derived from observed child behavior at ages three, four, and five.

By using this framework—and, more specifically, these three pathways—we can make theories of acquisition (which involve both theories of representation and theories of the learning process) explicit and testable against available empirical data (Pearl 2014, 2017, 2020, Pearl & Sprouse 2015). Here, this means that we can evaluate different theories of how to solve the linking problem by how well they enable a modeled learner to learn verb classes the way children seem to. More specifically, each modeled learner implements a combination of learning assumptions that corresponds to different theoretical claims (e.g. an absolute vs. relative thematic system, prior knowledge of the mapping vs. no prior knowledge). By seeing if a given modeled learner can learn the verb classes children do at different ages, we can evaluate the utility of these assumptions for acquisition.

#### 4.2. THE INPUT-INTAKE PATHWAY.

INPUT. Children's input signal can include both linguistic information (e.g. spoken or signed productions) and nonlinguistic information (e.g. contextual information about intended meaning). We take realistic samples of this input signal from the CHILDES Treebank (Pearl & Sprouse 2013b), which contains speech directed at children between one and five years old, annotated with linguistic and nonlinguistic information. In particular, around 180,000 child-directed speech utterances from the BrownEve, BrownAdam, and Valian corpora (Brown 1973, Valian 1991) have been annotated with syntactic, conceptual, and thematic information. First, these utterances are marked for syntactic phrase structure, based on an adapted version of the Penn Treebank annotation system. This annotation was done using a combination of automated and hand annotation (see Pearl & Sprouse 2013a and the included readme file at <http://www.socsci.uci.edu/~lpearl/CoLaLab/CHILDESTreebank/childestreebank.html> for details). Second, animacy for each NP argument was annotated by hand. We included animacy because a number of acquisition studies have demonstrated that animacy is a useful cue for learning verb classes (Becker 2009, 2014, 2015, Kirby 2009, 2010, Scott & Fisher 2009, Becker & Estigarribia 2013, Hartshorne et al. 2015). Third, thematic roles for the arguments of each verb (except the copula *be*) were annotated by hand using thirteen thematic role labels that are common in the literature (again, see the readme file mentioned above for details).

We divided these utterances into age ranges based on the age of the child the speech was directed at: less than three years of age, less than four years of age, and less than five years of age. We then constructed data sets representing the input to a child of a particular age. We note that the data sets used as input for models of older children (e.g. '< 4yrs', representing a four-year-old child) include the data directed at younger children (e.g. '< 3yrs' plus data directed at children between the ages of three and four). This is because we assume older children would learn from all of the data they have



DATA SET	SOURCES	# CHILDREN	AGES	# UTT	# WORDS	# VBS	# VBS > 5
< 3yrs	BrownEve, Valian	22	1;6–2;8	≈ 39.8K	≈ 197K	555	239
< 4yrs	BrownEve, Valian, BrownAdam3to4	23	1;6–4;0	≈ 50.7K	≈ 254K	617	267
< 5yrs	BrownEve, Valian, BrownAdam3to4, BrownAdam4up	23	1;6–4;10	≈ 56.5K	≈ 285K	651	285

TABLE 4. Child-directed speech data used as input to modeled three-year-old, four-year-old, and five-year-old learners. This includes the sources of these data in the CHILDES Treebank, the number and the age range of children the speech was directed at, the total number of utterances, words, and verb types, and the number of verb types appearing five or more times in the data set.

heard up until that point. Table 4 provides a detailed summary of the statistics for each input data set.

**LINGUISTIC INTAKE.** From the input signal, children extract their linguistic intake. The information they extract depends on what information is salient to them and what they can plausibly extract from the input in real time. We consider three types of information children could plausibly extract for learning about verb classes: one syntactic, one conceptual, and one linking conceptual and syntactic information.

Syntactic information seems plausible, as children are known to be adept at syntactic bootstrapping—that is, using the syntactic context—when learning about verbs (Lan-dau & Gleitman 1985, Gleitman 1990, Gillette et al. 1999, Fisher et al. 2010, Gutman et al. 2015, Harrigan, Hacquard, & Lidz 2016). One way to implement syntactic information is via phrase structure, with verb argument positions like ‘subject’ labeled, as shown in 6a below.

Another plausible information source is the concept of animacy (e.g. a penguin is animate, while an ice cube is not). Animacy is something young children are known to both be sensitive to as a general property and also use as a cue in experimental studies to predict how verbs will behave (Becker 2009, 2014, 2015, Kirby 2009, 2010, Scott & Fisher 2009, Hartshorne et al. 2015). Moreover, if children are able to harness animacy effectively in their input, it is possible to use the animacy of a verb’s arguments (in particular, whether the argument is INANIMATE) to distinguish verb behaviors such as those associated with subject raising, subject control, object raising, and object control (Kirby 2009, 2010, Becker & Estigarribia 2013, Becker 2014). One way to implement this conceptual information is for the verb’s NP arguments to be labeled as ±animate, as in 6b.

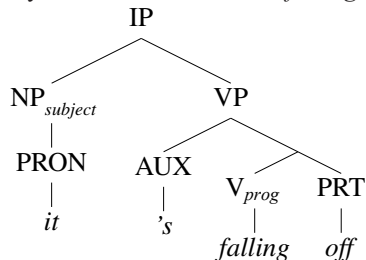
A third source of information corresponds directly to linking theories, as it concerns the link between conceptual information like thematic roles and syntactic position. More specifically, infants under a year old are sensitive to the presence of thematic roles (less than ten months: Gordon 2003; less than six months: Hamlin, Wynn, & Bloom 2007, Hamlin et al. 2011), making thematic roles a plausible information source for learning verb classes. UTAH and rUTAH assume a built-in mapping from the intermediate thematic representation (whether fixed proto-roles like UTAH or an ordered hierarchy like rUTAH) to syntactic positions like subject; derived-mapping approaches using the same thematic systems do not assume this mapping is present initially. Importantly, all approaches require the child to extract the syntactic positions of the verb’s arguments and to be aware of their thematic role, as shown in 6c.

Here, we make the simplifying assumption that the perceptual encoding process creating the linguistic intake is perfectly reliable (an assumption that can be relaxed in future work). Implementationally speaking, this means we assume that when given an input utterance like *it’s falling off* from the BrownEve corpus in the CHILDES Treebank (Pearl & Sprouse 2013a), we assume a linguistic intake that encodes syntactic and

conceptual information, such as 6, which is taken directly from the structural annotations in the CHILDES Treebank.

(6) Example linguistic intake for *it's falling off*

a. Syntactic information for *falling*:



b. Animacy information:

*it* (subject<sub>falling</sub>) = -animate

c. Thematic information:

*it* (subject<sub>falling</sub>) = Theme<sub>falling</sub>

THE ACQUISITIONAL INTAKE. From this linguistic intake, the modeled learners extract their acquisitional intake. The exact acquisitional intake depends on the learning assumptions the learner is using.

For the syntactic information, syntactic frames encoding surface argument structure can be derived from the phrase structure of the verb usage. For example, the utterance *it's falling off* might yield a frame for *fall* involving the NP subject and the particle, either with or without the progressive morphology that surfaces on the verb itself ( $\pm$ SURFACE-MORPHOLOGY), as in 7. Whether children heed the verbal surface morphology when encoding syntactic frames for their acquisitional intake is currently unknown, given available developmental data. Importantly, how the modeled learner deals with verbal morphology must be fixed before a modeled learner can be constructed. Since either option is plausible, we implement modeled learners of both kinds—that is, our modeled learners will also vary on whether they encode the verb's surface morphology in their syntactic frames.

(7) *fall* syntactic frame options for *it's falling off*

a. +surface-morphology: NP V<sub>+prog</sub> PRT

b. -surface-morphology: NP V PRT

Another key point of variation is whether the mapping from the intermediate thematic representation is present. This affects whether the modeled learner expects a mapping a priori (EXPECT-MAPPING). If the modeled learner expects a mapping (+expect-mapping), then it will be sensitive to violations of that expectation. Our modeled learners interpret these violations as instances of movement. That is, the learner will abstract away from the specific roles and positions, and instead take in only the fact that movement occurred, as shown in 8b. If instead the modeled learner does not yet expect a mapping (-expect-mapping), the learner will track the distribution of the intermediate thematic representation. That is, the learner will take in the details of which (proto-)role occurred in which position, as shown in 8c. In this way, the expectation of a mapping directly impacts the learner's acquisitional intake.

(8) Acquisitional intake for *The ice was melted by the girl*, using  $\pm$ expect-mapping

a. *the ice* = Patient = subject

*the girl* = Agent = object of PP

- b. +expect-mapping
- (i) absolute (UTAH): proto-Patient = subject, proto-Agent = object of PP  
Unexpected. Indicates +movement.  
**Acquisitional intake:** two instances of movement
  - (ii) relative (rUTAH): 2ND-HIGHEST = subject, HIGHEST = object of PP  
Unexpected. Indicates +movement.  
**Acquisitional intake:** two instances of movement
- c. -expect-mapping
- (i) absolute: proto-Patient = subject, proto-Agent = object of PP  
**Acquisitional intake:** one proto-Patient as subject, one proto-Agent as object of PP
  - (ii) relative: 2ND-HIGHEST = subject, HIGHEST = object of PP  
**Acquisitional intake:** one 2ND-HIGHEST as subject, one HIGHEST as object of PP

The different learning assumptions affecting the learner's acquisitional intake and their different combinations are shown in Table 5. Given the three binary choices ( $\pm$ surface-morphology, absolute/relative thematic system, and  $\pm$ expect-mapping), we implement eight modeled learners: a +surface-morphology and -surface-morphology variant for learners using one of the two thematic systems and either expecting or not expecting a mapping. Note that all modeled learners use the animacy of a verb's arguments, in addition to syntactic frame information and thematic role information. Where they differ is how exactly they use the information about syntactic frame and thematic role.

ABSOLUTE THEMATIC expected mapping	ABSOLUTE THEMATIC no expected mapping	RELATIVE THEMATIC expected mapping	RELATIVE THEMATIC no expected mapping
NP V( <i>prog</i> ) PRT	NP V( <i>prog</i> ) PRT	NP V( <i>prog</i> ) PRT	NP V( <i>prog</i> ) PRT
subject <sub>-anim</sub> = 1	subject <sub>-anim</sub> = 1	subject <sub>-anim</sub> = 1	subject <sub>-anim</sub> = 1
movement = 1	subject <sub>proto-Patient</sub> = 1	movement = 0	subject <sub>HIGHEST</sub> = 1

TABLE 5. Example of a child's linguistic intake from 6 (the utterance *it's falling off*) for the four modeled-learner types. To save space, surface morphology is in parentheses to indicate the two modeling options for each learner type.

As an example, let us consider the different acquisitional intakes for the utterance *it's falling off*, whose linguistic intake was shown in 6. All learners encode one instance of an inanimate argument in subject position (subject<sub>-anim</sub>). So, there is no difference in the acquisitional intake with respect to animacy. For those learners ignoring surface morphology on the verb, only the core verb frame would be extracted: NP V PRT. For learners heeding surface morphology, the fact that the verb is in the progressive would additionally be included: NP V<sub>prog</sub> PRT.

The exact thematic information extracted depends on the thematic system (absolute/relative): with an absolute thematic system, the thematic role of the subject (Theme) is mapped to proto-Patient; with a relative thematic system, the learner uses the thematic role hierarchy to map the thematic role of the subject (Theme) to the HIGHEST role because it is the only thematic role present. If there is no expectation of mapping, the learner encodes the distribution of thematic representations (here, proto-Patient or HIGHEST in subject position). If there is in fact an expectation of mapping, the learner encodes whether the observed mapping obeys or violates that expectation. For the absolute thematic representation with a mapping expectation (UTAH), a proto-Patient in subject position violates the expected mapping and so is interpreted as movement; in contrast, for the relative thematic representation with a mapping expectation (rUTAH),

the HIGHEST role in subject position obeys the expected mapping and so is interpreted as no movement.

**4.3. THE INTAKE-INFERENCE PATHWAY.** Each modeled learner uses the acquisitional intake defined by its respective learning-assumption combination to update its hypotheses about verb classes (i.e. its generalizations about which verbs behave alike in its developing grammar); a successful assumption combination will allow the learner to match children’s observable behavior for verb classes. We implement this update process using hierarchical Bayesian inference, where the learner assumes the generative process depicted in Figure 1 (the generative process is represented with standard plate-diagram notation for hierarchical Bayesian modeling). The observable verb data  $V$  in the acquisitional intake are generated by combining the available syntactic, animacy, and thematic information in the acquisitional intake, mediated by the latent representation of verb classes  $C$ . Below we provide high-level descriptions of the different components of the inference process shown in Fig. 1.

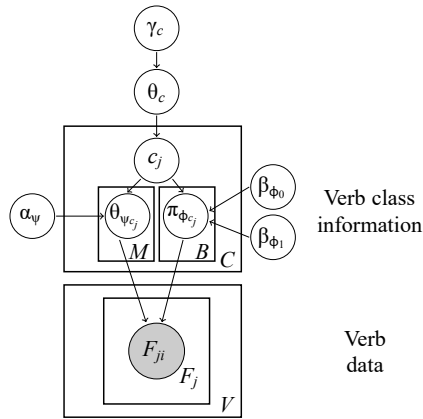


FIGURE 1. Plate diagram for a generative model of verb classes, based on syntactic, animacy, and thematic information from individual verbs in the input. Observable verb data  $V$  (and specifically verb frame instances  $F_{ji}$ ) are generated based on the underlying verb class information  $C$ , which involves different characteristics  $M$  and  $B$  tracked by modeled learners (specifically, multinomial characteristics  $\psi$ , like syntactic frame information, and binomial characteristics  $\phi$ , like argument animacy information).

Observable data are available for each verb  $v_j \in V$ , in the form of the frames  $F$  that verb is used in, which include the syntactic structure, the animacy of the arguments, and the thematic roles present. For example, the verb *fall* may appear multiple times, in instances such as *it’s falling off*, *she fell down*, *don’t fall!*, and *London Bridge is falling down*. Each frame instance  $F_j$  for a verb appears with some frequency  $F_{ji}$ —for example, *it’s falling off* might occur three times.

The objective of the modeled learner is to infer the set of verb classes  $C$  that generate the observable verb data. Each verb  $v_j$  belongs to its verb class  $c_j$ . The learner does not know beforehand how many verb classes there are, what size they are, or which verb belongs to which. However, via the verb class hyperparameters  $\theta_c$  and  $\gamma_c$ , the learner has a bias for classes distributed in a power law distribution, where a few classes have many verbs and the rest of the classes have few verbs.

Each verb class  $c_j$  has certain binomial characteristics  $B$  and multinomial characteristics  $M$  associated with it. Binary characteristics  $\phi \in B$  include whether the subject, ob-

ject, and oblique object are animate ( $\pm$ animate). If the modeled learner involves an expected mapping, then whether the mapping was violated (and so interpreted as movement) is also a binary characteristic. Each class will have some probability of preferring each option  $\pi_{\phi c_j}$ . For example, a class  $c_j$  might prefer inanimate to animate subjects, with  $\pi_{-animate_{subject}} = 0.70$  and  $\pi_{+animate_{subject}} = 0.30$ . During the course of learning, the learner infers these probabilities for each verb class. The hyperparameters ( $\beta_{\phi_0}, \beta_{\phi_1}$ ) implement an initial uniform probability over the possible binary options, thereby implementing no bias a priori.

Multinomial characteristics  $\psi \in M$  include which syntactic frame a verb appears in (e.g. NP V PRT for *it's falling down*). If the modeled learner does not assume a mapping between thematic roles and syntactic positions, then the syntactic position is also a multinomial property (e.g. if the proto-Agent appears in subject, object, or oblique object position). Each class will have some probability of preferring each option  $\theta_{\psi c_j}$ . For example, a class  $c_j$  might primarily prefer the NP V PRT and NP V syntactic frames, giving them higher probabilities, and disprefer the frame NP V IP ( $\theta_{NP V PRT} = 0.50, \theta_{NP V} = 0.40, \dots, \theta_{NP V IP} \approx 0.00$ ). During the course of learning, the learner infers these probabilities for each verb class. The hyperparameter  $\alpha_{\psi}$  implements an initial uniform probability over the possible multinomial options, thereby implementing no bias a priori.

Importantly, the learner infers different verb classes precisely because the characteristics of verb classes differ sufficiently. In particular, given the observed instances of verb usage, the learner uses Bayesian inference to infer (i) how many verb classes there are, (ii) what the characteristics of each verb class are, and (iii) which class each verb belongs to. The best hypothesis is the one that maximizes the probability of the observed data, balanced against the prior preference for classes distributed in a power law distribution.

This inference is accomplished via Gibbs sampling operating over the data as a single batch, which is guaranteed to converge on the optimal answer if given sufficient time to search the hypothesis space (i.e. Gibbs sampling is an optimal inference process). This is part of what makes the modeled learners IDEAL LEARNERS—the inference computation is implemented by an optimal inference process that is NOT intended to be realistically constrained. Instead, humans likely approximate this inference process to accomplish the same computation and execute inference incrementally as data are encountered.

A reasonable question is why we should use an ideal inference process rather than a realistically constrained process to model language acquisition. Typically, acquisition modelers will start with an optimal inference process in order to know if the mental computation specified by the model is a potential match to human behavior (here, child language acquisition behavior; Pearl 2020). If not, this is a signal that the learning assumptions encoded in the model are unlikely to be right. That is, if a modeled learner cannot get close to human behavior even when the mental computation is performed as perfectly as possible, then that computation is probably not the right one. This would mean the learning assumptions that circumscribe that mental computation (here: using syntactic, animacy, and thematic information in particular ways) are not useful.

In contrast, if a modeled learner using optimal inference can match human behavior, this suggests that the learning assumptions are plausible. Subsequent work could then explore how acquisition unfolds when inference is nonoptimal (e.g. subject to the cognitive constraints children have and the incremental nature of learning). In the meantime, the ideal learning model using optimal inference serves as a useful proof of concept in the search for learning assumptions that can potentially solve the acquisition problem under investigation. More generally, it is important to determine that learning



assumptions are potentially useful to children before investigating if they are usable by children. This is the approach we pursue here.

**4.4. THE GRAMMAR-BEHAVIOR PATHWAY.** This pathway determines how a modeled learner's output will be evaluated when the target is observed behavior. In §3.2, we described the verb classes derived from observed child behavior. It is reasonable to believe that such verb classes are a legitimate target state reflecting children's underlying knowledge because of how we think of the grammar-behavior pathway. In particular, we assume here that if children's comprehension and/or production indicate that they treat two verbs similarly with respect to some verb behavior (e.g. being passivizable), this transparently reflects children's developing grammars—that is, the two verbs in question are clustered together in children's minds with respect to that verb behavior. If children's verb comprehension and/or production indicate that two verbs are clustered together for all currently tested verb behaviors for those verbs, then we assume that the verbs are in the same class in children's developing grammars.

We take these verb classes, derived for children ages three, four, and five, as representative of the developing grammars of children of these ages. So, modeled-learner output is compared against them using the measures discussed in §3.3. The modeled learners whose inferred classes best match these child verb classes at particular ages can be thought to encode the learning assumptions that children have at those ages.

**5. MODELING RESULTS.** Recall that each of the eight modeled learners uses a different combination of learning assumptions, based on how linguistic and nonlinguistic information are used (Table 5). For each learner, we ran an ideal-learner implementation ten times over each age-based data set (< 3yrs, < 4yrs, and < 5yrs). The resulting ten sets of inferred verb clusterings were aggregated into a single set of verb classes, using a simple threshold: any verb pair together in more than 75% of the runs (i.e. more than seven of ten) was put together in the aggregate verb clustering; similarly, any verb that was in a class of its own (a SINGLETON) for more than 75% of the runs was put as a singleton in the aggregate verb clustering for that modeled learner. Figure 2 shows RI when compared to the child verb classes relevant for different ages of acquisition (i.e. verb classes learned by age three for the < 3yrs data set; verb classes learned by age four for the < 4yrs data set; verb classes learned by age five for the < 5yrs data set). For the RI randomization tests, we use a threshold of  $p < 0.01$  for significance (two-tailed). We indicated the threshold for the null hypothesis (randomizing all three parameters) with a solid horizontal line. We also added a single asterisk (\*) to models that are significant under this null hypothesis. The learners surpassing the  $p < 0.01$  threshold are summarized in Table 6.

Taken together, what stands out is that there are learners at each age who are doing better than chance, though the collection of learning assumptions that successful learners encode varies by age. Below we interpret these results with respect to the four linking-theory proposals: the innate-mapping UTAH and rUTAH, and their derived-mapping equivalents.

UTAH assumes an absolute thematic system and innate knowledge of the linking pattern. This set of assumptions (absolute, +expect-mapping) is not compatible with the assumptions of successful modeled learners at three years old, though it is at four and five years old. So, UTAH would need to be coupled with a late-maturation developmental theory, where the absolute thematic knowledge and innate linking knowledge become available only at age four or later. We note that if such knowledge emerges at four, children would also need to ignore verb surface morphology.

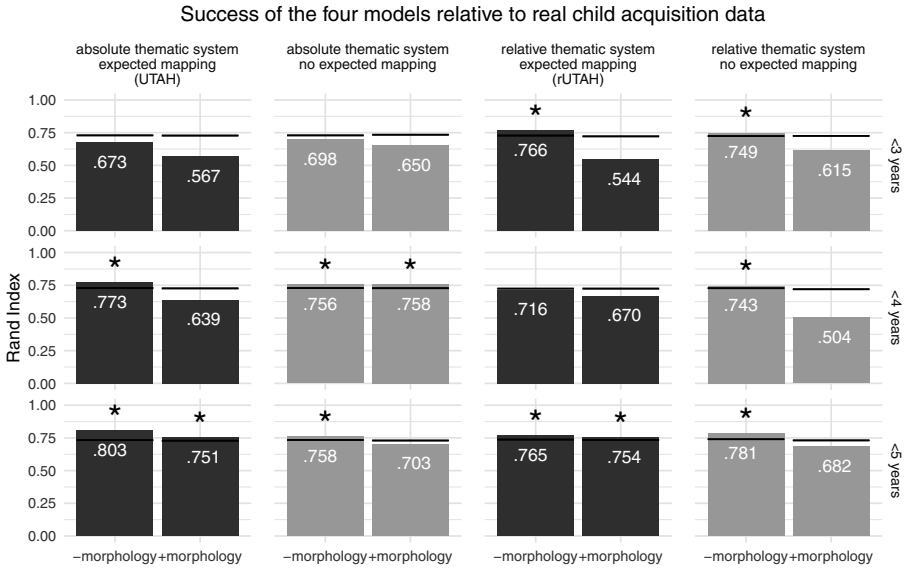


FIGURE 2. Rand index scores for all modeled learners. The four major modeled-learner types are organized into columns, with classic UTAH and rUTAH in black. Surface morphology is nested within each major modeled-learner type. The solid horizontal lines indicate the (upper)  $p < 0.01$  threshold for the (two-tailed) randomization tests randomizing across all three parameters in the model: number of classes, size of classes, and verb assignment to classes. An asterisk (\*) means the result was significant for the randomization test. The white numbers within each bar report the RI index value to three decimal places.

AGE	THEMATIC SYSTEM	EXPECT-MAPPING	SURFACE-MORPHOLOGY
< 3yrs	relative	±	–
< 4yrs	absolute	±	–
	absolute/relative	–	+
< 5yrs	absolute/relative	+	±
	absolute/relative	–	–

TABLE 6. Modeled learners by age passing the  $p < 0.01$  threshold, based on RI scores. The learning assumptions shown are which thematic system is used (absolute/relative), whether a mapping from thematic roles to syntactic positions is expected (expect-mapping), and whether surface morphology on verbs is heeded for verb syntactic frames (surface-morphology). Each row represents a set of modeled learners above threshold at matching children’s verb classes.

rUTAH assumes a relative thematic system and innate knowledge of the linking pattern. This set of assumptions (relative, +expect-mapping) is compatible with the assumptions of successful learners at three and five years old, but not at four years old. So, rUTAH would need to be coupled with a developmental theory where the innate linking knowledge is either (a) inaccessible at age four for some reason, or (b) is not actually accessible until age five, and so children at age three do not have access to the innate linking knowledge (relative, –expect-mapping). That is, rUTAH requires either a U-shaped developmental theory or a late-maturation developmental theory.

The derived-mapping variant of UTAH assumes an absolute thematic system and derived knowledge of the linking pattern. This set of assumptions (early: absolute, –expect-mapping; late: absolute, +expect-mapping) does not seem obviously compatible with the assumptions of successful learners at three years old. This is because all successful learners at this age rely on the relative thematic system. So, the child would

need to derive both the absolute thematic system and the linking pattern after this age. At four and five, however, there are successful learners relying on the absolute thematic system. So, a derived-mapping UTAH child could have derived both this thematic system and the linking-pattern knowledge at four or five. If linking knowledge is derived by four, the child would be ignoring surface morphology; if linking knowledge is derived by five, the child could heed or ignore surface morphology.

The derived-mapping variant of rUTAH assumes a relative thematic system and derived knowledge of the linking pattern. This set of assumptions (early: relative, -expect-mapping; late: relative, +expect-mapping) is compatible with the assumptions of successful learners at all ages. For example, at three, children relying on a relative thematic system would not expect a mapping (and would also ignore surface morphology); at four, they would not expect a mapping (but now would heed surface morphology); at five, they would have derived linking knowledge and expect a mapping (and either heed or ignore surface morphology).

Taken together, our results highlight the connection between theories of representation and theories of development. While our results are compatible with both innate-mapping approaches (UTAH, rUTAH) and their derived-mapping equivalents, they argue against an early-maturation innate theory of development. That is, neither of the innate-mapping linking-theory proposals seems immediately compatible with early-maturation innate knowledge. Instead, the linking knowledge (and sometimes the thematic knowledge) would need to develop later (late-maturation innate mapping); conversely, the linking knowledge (and sometimes the thematic knowledge) could be derived from language experience, as in the derived-mapping approaches. To choose among these linking-theory proposals, we therefore need more empirical data about the other learning assumptions (i.e. thematic systems and attention to surface morphology) that English children use at ages three, four, and five when creating verb classes. We return to this empirical need in the next section.

**6. DISCUSSION.** We believe that a significant contribution of this work is the integrated quantitative framework itself, which provides a concrete way for linking-theory proposals to both (i) generate developmental predictions and (ii) be evaluated on those developmental predictions. In particular, the framework implements an acquisition process that is both empirically grounded and theoretically motivated. Empirical data determine the modeled learner's input and desired output, and motivate the probabilistic learning mechanism used for inference; theoretical proposals determine the representations that control how the learner's input is transformed into the intake that drives learning. Below we discuss the results of using this framework for the particular linking proposals investigated here, and also how this framework can be used in the future as (i) more empirical data become available, or (ii) different theories of representation and/or development are proposed.

**6.1. IMPLICATIONS FOR THEORIES OF REPRESENTATION AND DEVELOPMENT.** Given the complexity of the learning problem, which involves creating dozens of verb classes, and given that the learning assumptions implemented in the modeled learners here involve only a subset of all the possible information children could be using to solve that problem, our first noteworthy result is that ANY of the learning-assumption combinations are successful. Though we started this project from the assumption that syntactic frames, thematic information, and animacy information from child-directed input would be sufficient to learn verb classes, there is no a priori reason to believe that this information would be sufficient. So, these results empirically support the common as-

sumption in the literature that these specific pieces of information are sufficient to learn verb classes the way children seem to.

From the perspective of theories of linguistic representation, these results have two implications. First, both UTAH and rUTAH are reasonably accurate at capturing children's representations at some point in development. This provides developmental support that they are plausible representational theories. Moreover, because they are compatible with the oldest children's verb behavior (at five years old), they are also plausible representational theories for adults.

However, one particularly notable finding is that not all of the options capture younger children's behavior equally (at three and four years old). The results here suggest three-year-olds are more likely to rely on a relative thematic system, while older children may not. This has real implications for what needs to be built in to yield the linguistic development we observe in children. Here, it seems that the conceptual categories corresponding to proto-roles are NOT required (which UTAH relies on); moreover, there may not need to be a built-in expectation of a specific mapping between thematic roles and syntactic positions (as early-maturation innate-mapping approaches would predict). Instead, both types of knowledge could potentially develop later (or be accessed later if children do not have sufficient cognitive resources to do so earlier in development).

Both innate-mapping and derived-mapping approaches are compatible with these results, but then require different promissory notes. For late-maturation innate-mapping approaches, a developmental account is needed either for (i) why the knowledge itself develops later, or (ii) why children's access to this knowledge develops later. Either avenue also requires evidence from developmental neurobiology. For derived-mapping approaches, the required knowledge would be derived from language experience, rather than being innately specified. Under this approach, it remains to be seen exactly how the conceptual categories of the absolute thematic system and the expectation of a mapping would be derived from children's input. That is, a viable derived-mapping approach should demonstrate what prior knowledge and abilities are needed in combination with children's input to derive both the appropriate conceptual categories and the appropriate mapping. Future computational modeling may be able to contribute to this investigation. Moreover, another future step would focus on the precise mechanisms that derived-mapping approaches can use to explain the distribution of linking patterns across languages. In particular, derived-mapping approaches would need to demonstrate how the linking patterns observed crosslinguistically can be derived from children's input in each language.

**6.2. OPEN QUESTIONS.** There are a number of open questions that the current results highlight, in terms of both the empirical foundations and the theories of representation and development. Here we classify these questions into three types: experimental, computational, and theoretical avenues of inquiry.

**EXPERIMENTAL AVENUES.** One avenue for future experimental work is to increase the number of verbs and verb classes that are used in early acquisition studies. Though our corpus analysis yielded up to 285 verbs appearing five or more times (< 3yrs: 239, < 4yrs: 267, < 5yrs: 285) in the CHILDES Treebank, the available experimental data about specific verb behaviors yielded far fewer verbs to evaluate our simulations on (< 3yrs: sixty, < 4yrs: seventy-six, < 5yrs: eighty-four). This means there are nearly 200 verbs for each age group that we have model predictions for, but no behavioral data about (and therefore were not reported here). With more targeted child-language exper-

iments, we will have a broader empirical basis to evaluate our acquisition theories against. For example, at three years old, there are two modeled learners that best match what we currently know about three-year-old verb classes. These learners both rely on the relative thematic system and ignore surface morphology on verbs. The learner that does not expect a mapping puts together *keep* and *stop* in one class and *miss* and *say* in a separate class, while the learner that does expect a mapping groups all of these verbs together into the same class. Do three-year-olds expect different behaviors for these four verbs, or the same behaviors? Once we know, we can better choose between the two learning-assumption combinations that currently best fit three-year-old behavior.

This lack of behavioral data also applies to the verb behaviors we know about—here, there were twelve attested verb behaviors, but there are many more where we need knowledge of how specific verbs behave (e.g. intransitivity, monotransitivity, unergativity, verbs taking nonfinite complements with *-ing*, verbs taking small-clause complements, *wager*-class verbs). Again, with a broader child behavioral foundation, we will be better able to choose among the modeled-learner options and the learning assumptions they encode.

COMPUTATIONAL AVENUES. One avenue for computational work is complementary to the future experimental work with children. Each modeled learner here has generated a set of verb classes which is that learner's internal representation of which verbs behave like other verbs. Each verb class has a set of characteristics (involving syntactic and conceptual preferences) that can be used to generate precise predictions for any experimental set-up. For example, we can calculate the probability distribution over verbs that a modeled child will prefer to use with a particular utterance that has certain syntactic and conceptual characteristics (e.g. *She \_\_\_ to laugh* = subject<sub>+anim</sub>, NP V IP<sub>-finite</sub>, subject<sub>Experienter</sub>). This corresponds to what might be observed in child productions. We can also calculate the probability distribution over utterances that a modeled child will prefer to use for a particular verb (e.g. *want* might have a high probability for *She \_\_\_ to laugh*, while *make* has a low probability). This corresponds to both the productions a child might generate, and also the ease with which a child would comprehend a verb used in a particular utterance. Both of these are examples of the modeled learner generating concrete behavioral predictions that can be experimentally evaluated. When the predictions diverge and only one matches children's behavior, we then have additional empirical support for whichever modeled child (and therefore whichever specific combination of learning assumptions) was successful.

We can also make more sophisticated computational models that capture both the incremental nature of children's learning and children's cognitive constraints. Recall that the model implementations here were ideal learners; this means these modeled learners (i) learn from all of the data at once that children of a certain age would have seen (i.e. the modeled learners are not incremental), and (ii) are able to do inference optimally over these data (i.e. model inference is not constrained by cognitive limitations). As mentioned, this is a first step in understanding the mental computations that occur during acquisition. Future work can relax some of the idealized assumptions present in the ideal modeled learners used here. For example, one option is to make more realistic learners that (i) learn from data as they are encountered one utterance at a time (rather than as a batch) and (ii) use an inference approximation, rather than Gibbs sampling, to converge on the final set of verb classes (e.g. see the learning approaches of Fazly, Alishahi, & Stevenson 2010 and Barak, Fazly, & Stevenson 2014a,b). Unlike the ideal-learner model implementations, these more realistic modeled learners would be execut-



ing a potential inference algorithm that children could be capable of—this makes these future models algorithmic-level (rather than computational-level) in the sense of Marr (1982).

The utility of algorithmic-level implementations is to see if the learning assumptions that were useful for a computational-level learner are STILL useful when incremental learning and cognitive constraints are present (Pearl 2014, 2020, Phillips & Pearl 2015, Pearl & Phillips 2018). That is, algorithmic-level implementations can tell us if the learning assumptions that seem to be useful for ideal learners are actually USABLE by real children, who have various constraints on their acquisition computation. This is not always the case—it could turn out that certain learning assumptions are less helpful to a cognitively constrained learner while other assumptions are more helpful (Phillips & Pearl 2015, Pearl & Phillips 2018). That is, a learning assumption (e.g. relative thematic representations) may be useful to a modeled learner only if the learner is capable of either seeing all of the data at once or performing its inference optimally; when the modeled learner is constrained to learn incrementally or approximate optimal inference, that same learning assumption may turn out not to be as useful. In contrast, a different learning assumption (e.g. absolute thematic representations) may not seem as useful for an idealized learner, but a constrained learner may find that assumption more useful. So, for instance, a constrained learner might better match children's behavior when using an absolute thematic representation rather than when using a relative one.

Still, assuming that the developmental trajectory suggested by these results holds under future experimental and (incremental) modeling work, another open question that can be investigated via computational methods is how the primary linking pattern and the secondary exception patterns arise under a derived-mapping approach. That is, how could the expectation for the 'right' mapping between thematic representations and syntactic positions develop between ages three and five? Without a built-in expectation of specific mappings, these patterns are dependent on the content of the input in combination with whatever prior knowledge and abilities children have. If there are a sufficient number of primary-pattern verbs in the input (and/or verb classes) learned at early stages, then this will lead to the development of the primary-pattern expectation. Mathematical analyses of children's input that predict when children will make a generalization vs. not, such as the TOLERANCE PRINCIPLE (Yang 2005, Legate & Yang 2013, Schuler, Yang, & Newport 2016, Yang & Montrul 2017), can provide an answer. Such analyses can either support the ability of realistic input to help children derive the primary mapping or demonstrate the obstacles to be surmounted under the derived-mapping approach.

**THEORETICAL AVENUES.** From a theoretical perspective, there may be other solutions to the linking problem that we wish to investigate using this integrated quantitative framework. Here, we focused on two prominent options discussed in the theoretical literature (UTAH and rUTAH) that (i) take thematic roles as their basis, and (ii) involve either an absolute (UTAH) or relative (rUTAH) perception of these thematic roles. While these both seem plausible, other options are certainly available. For example, perhaps children abstract across thematic roles in different absolute or relative ways from the implementations explored here (more than three proto-roles, different definitions of proto-roles, different orderings in the role hierarchy, etc.). Relatedly, there could also be different thematic role distinctions at the basic conceptual level—the thirteen roles here were chosen to make the CHILDES Treebank as useful as possible to the widest range of users (Pearl & Sprouse 2013a). That said, there are a number of specific proposals for thematic role systems in the literature; the diversity of theories only in-

creases when we consider that children's thematic distinctions might differ from adults' in complex ways (especially very young children's). It could also be that children begin by not abstracting over thematic roles at all. Instead, they might track mappings from the individual thematic roles directly to syntactic positions. Finally, it is also possible that the source of the linking patterns we see lies outside of syntax (so, not in principles like UTAH or rUTAH) and is instead a consequence of a constraint on the types of semantic representations that language allows (Wood 2015, Kastner 2016, Myler 2016). This is still a type of innate knowledge; therefore, the quantitative framework developed here could be modified to compare modeled learners with knowledge of that constraint versus modeled learners without knowledge of that constraint.

Related to the idea of different underlying thematic systems and how they might change during development, there may also be a change to the information children are sensitive to in the input. For example, while younger children may rely on syntactic frames, older children may rely on additional and/or more abstract syntactic information. For example, when encountering the utterance *She seemed to laugh*, a younger child might extract the syntactic frame NP \_\_\_ IP<sub>-finite</sub> for *seem*. In contrast, an older child might also perceive the raising dependency, and so encode *seem*'s syntax as NP<sub>1</sub> [IP t<sub>1</sub> VP<sub>-finite</sub>]. Knowing exactly what information children of different ages are able to both extract from their input and use for learning depends on having precise theories of acquisition that combine developing representations with developing abilities to use those representations in real time.

Moreover, it is also important to reconcile any current and future findings with existing child behavioral data. For example, both the late-maturation innate-mapping and derived-mapping approaches supported by our results here will need to account for data suggesting that children do have some early mapping preferences (Naigles 1990, Naigles & Kako 1993, Bunker & Lidz 2004, 2008, Gertner, Fisher, & Eisengart 2006, Hartshorne et al. 2015). We leave this exciting theoretical work for the future.

**7. CONCLUSION.** To successfully learn language—and more specifically, how to use verbs correctly—children must solve the linking problem: they must learn the mapping between the thematic roles specified by a verb's lexical semantics and the syntactic argument positions specified by a verb's syntactic frame. Here, we have constructed an argument from acquisition for different theoretical approaches to solving the linking problem. In particular, we have used acquisition of verb classes as an evaluation metric for theories of solving the linking problem, with the idea that a good theory will be able to account for children's developing knowledge of verb classes over time. We made different theoretical options concrete within an integrated quantitative framework of the acquisition process that relies on corpus analysis, experimental meta-analysis, and computational modeling. More specifically, we compared different underlying thematic representations (absolute vs. relative) that are linked to syntactic positions; we also compared different options for when prior knowledge of a mapping is available (at three, four, or five years old).

Our results allowed us to specify for the first time a developmental trajectory of mental representations and learning assumptions children may have when learning verb classes. Importantly, this specification is compatible with both innate-mapping and derived-mapping approaches to solving the linking problem, in combination with other learning assumptions about the thematic system and attention to verbal surface morphology. However, our results argue against early-maturation innate theories of development for either UTAH or rUTAH. An advantage of innate-mapping approaches like UTAH and rUTAH is that they can easily explain the crosslinguistic regularity of link-

ing patterns. So, one fruitful avenue of future work for derived-mapping approaches is to understand how children derive the regularity we see in linking patterns from their input. Beyond this, our results support relative thematic representations in three-year-olds, with both absolute and relative thematic representations potentially available for four- and five-year-olds. More generally, our quantitative approach to language acquisition allows us to connect theories of linguistic representation and theories of the learning process, and so better understand both as part of an integrated theory of language.

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[lpearl@uci.edu]  
[jon.sprouse@uconn.edu]

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