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2 **Lifecycle of a probabilistic construction**

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8 **1 Introduction**

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10 A comprehensive theory of language must be evaluated not just as a system of
11 representing linguistic knowledge, but as an account of how humans acquire
12 and process this knowledge. Yet it is prevalent in the tradition of theoretical lin-
13 guistics to ignore the learning process and focus on the end product. Müller and
14 Wechsler (henceforth M&W) correctly remark that the construction-based view is
15 often affiliated with usage-based theories of human language, and strongly moti-
16 vated by observational and experimental findings on child language acquisition.
17 But M&W's review of the psycholinguistic evidence on human language acquisi-
18 tion and use is limited to isolated cases and does not depict a complete picture.
19 It is critical to assess the descriptive power of lexical vs. construction-based ap-
20 proaches for humans' behavioural patterns in various language tasks.

21 It is often difficult to evaluate the concrete predictions of a linguistic theory,
22 since many details about the representational framework and the learning and
23 processing mechanisms are inevitably left out or underspecified. The theoretical
24 literature on constructionist approaches offers a variety of strategies for acquiring
25 and applying constructions, but few provide a detailed account of a fully worked
26 out process. Many of the criticisms raised by M&W are due to this vagueness
27 which leads to a lack of understanding of how a fully constructional approach
28 works in practice. Recent attempts at modelling constructions in a computational
29 framework can help this discussion. Computational models are often simplistic
30 in the range of linguistic phenomena they investigate, but they provide insight
31 into the lifecycle of a construction from the moment of emergence into maturation,
32 and how it is used in various language comprehension and production
33 tasks. In this way, computational models allow us to simulate realistic scenarios
34 and make concrete predictions about linguistic behaviour of language users ac-
35 cording to a specific theory. Moreover, they can propose alternative interpreta-
36 tions of the theoretical devices.

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One of the strongest suggestions of the existing computational studies is that argument structure acquisition and processing might best be described as a probabilistic process. Linguistic constructions are often formalised as rigid schemas with fixed syntactic and semantic components and clearly defined constraints, but such an approach discards the gradual and flexible nature of language. Semantically similar predicate terms often differ in their degree of syntactic variability and in their frequency of usage in various constructions (Ambidge et al., 2008, 2012), and a construction's applicability is best described based on its probabilistic match with a particular situation. Probabilistic representations are equally useful in describing the degree of association between an abstract syntactic pattern and certain meaning elements (ranging from weak associations in transitive and intransitive to strong associations in ditransitive constructions), as opposed to searching for an ideal truth-conditional meaning for each construction.

In this commentary, I will first present a brief overview of the most relevant psycholinguistic evidence on language acquisition and processing. Next, I will lay out a probabilistic account of representing, learning and using constructions proposed by Alishahi and Stevenson (2008, 2010), and discuss how this model explains the experimental findings from human language learners. I conclude by comparing the predictions of the construction-based with that of a lexical approach.

2 Evidence from language acquisition

M&W posit the *Verb-island Hypothesis* (Tomasello, 2003) as the main argument for a pattern-based view on language acquisition (M&W, Section 9.1). Verb Island Hypothesis is one of a family of usage-based theories of language, motivated by experimental and observational studies on language comprehension and generation in young children. These studies show that children build their linguistic knowledge around individual items (Bowerman, 1982; Akhtar, 1999; Tomasello, 2000). Verb Island Hypothesis suggests that young children initially form lexical constructions which encapsulate the syntactic and semantic relationship between each individual verb and its arguments, on an item-by-item basis. Later, they apply domain-general techniques such as analogy, categorisation and structure mapping to gradually generalise the item-based constructions into more abstract form-meaning associations, which they use productively.

M&W correctly argue that lexical rules can also be learned in a bottom-up fashion, and the item-based nature of children's early linguistic knowledge does not rule out a lexical approach. However, their examination of the acquisition-

1 related evidence stops here. An important behavioural pattern that needs to be
2 explained is the conservative nature of early language use. For example, two-year
3 old children show little tendency to apply syntactic structures they have already
4 learned to new verbs, but rather conservatively use each verb in structures they
5 have heard it in before (Akhtar, 1999; Tomasello, 2000). According to a lexical
6 approach, the valence structure for each verb is stored individually, but the com-
7 bination patterns or lexical rules are verb-independent. Therefore, once a child
8 forms a lexical rule and starts using it productively for a subset of verbs, s/he
9 should be able to apply it to any new verb which satisfies the constraints of a rule.

10 The imitation phase (where the child only uses each verb in the constructions
11 s/he has heard them used before) is soon followed by a generalisation phase,
12 where abstract constructions are formed and used productively. Children seem to
13 possess some knowledge about the general regularities in the relationship be-
14 tween semantic roles such as Agent and Theme and syntactic functions such as
15 Subject and Direct Object as early as age three (MacWhinney, 1995; Demuth et al.,
16 2002). They use this knowledge to produce utterances they have never heard be-
17 fore, and to generalise the behaviour of verbs they have already learned to new
18 ones. This ability sometimes leads to overgeneralization, in which a verb is used
19 in a frequent construction that is not applicable to that particular verb, as in
20 **I said her no* or **don't you fall me down* (Bowerman, 1982, 1996). Crucially, over-
21 generalisation errors seem to be semantically motivated, for example in cases
22 where a typically intransitive verb is used in a transitive construction to empha-
23 sise the existence of a causal agent (e.g., **Adam fall toy*, Brown corpus, CHILDES,
24 MacWhinney, 1995).

25 Experimental data on language learning demonstrates consistent patterns
26 among children: for a given construction, few overgeneralization errors are made
27 at the very early steps of learning; the number of errors increases considerably as
28 the general constructions start to emerge, but after a while they decrease again
29 (Marcus, 1993). Studies on children's use of verb argument structure (Bowerman,
30 1982, 1990) confirm that overall, overgeneralization errors are relatively rare for
31 all the constructions in a language, and occur at a roughly constant low rate
32 from the age of two into the school-age years. Such errors gradually cease as
33 children get older, and by teenage years they acquire almost adult-like linguistic
34 competence (Demuth et al., 2002; Bowerman, 1996). The overgeneralization pat-
35 tern can be considered an important clue to the internal mechanisms of language
36 learning.

37 Various language comprehension studies have also shown that children are
38 aware of abstract form-meaning associations from a young age. Children's use
39 of the associations between syntactic positions in a sentence and the semantic
40 properties of the arguments has been tested in preferential looking experiments.

For example, Fisher (1996) introduces three and five-year-olds to novel transitive and intransitive verbs while playing unfamiliar Agent-Patient events (*Look, she is blicking her over there!* or *Look, she's blicking over there!*). When asked to choose the participant that appears in the Subject position (*Which one is blicking her over there?* vs. *Which one is blicking over there?*), children interpreted the verbs differently depending on their sentence structure. In each condition, children were more likely to choose causal agents as subjects of transitive than intransitive verbs. Other studies show that humans use their knowledge of form-meaning associations to guide word learning and reduce ambiguity, by using a familiar linguistic construction to infer the potential meaning of a novel word (e.g., Fisher et al., 2006; Gertner et al., 2006).

Accounting for these findings would be difficult without assuming the existence of abstract but meaningful phrasal constructions. M&W acknowledge this fact, but they argue that such constructions co-exist with lexical rules (or meaningless constructions): “While the ditransitive construction plausibly contributes meaning, no truth-conditional meaning has yet been discovered for either the intransitive or (mono)transitive constructions. Clearly the constructionist’s evidence for the meaningfulness of *certain* constructions such as the ditransitive does not constitute evidence that *all* phrasal constructions have meaning” (M&W, Section 5.1). Experiments of the type described above refute the claim that no meaning is associated with more general constructions such as transitive and intransitive. We will discuss this issue further in the next section.

3 Computational simulation of a construction-based approach

Various interpretations of a constructionist approach are simulated via computational modelling, and tested on child-directed data (Chang, 2004; Bergen and Chang, 2005; Alishahi and Stevenson, 2008, 2010; Perfors et al., 2010; Parisien and Stevenson, 2010). These models differ in their representation of constructions, the details of their underlying learning mechanisms, and the cognitive tasks they simulate. However, all share the basic definition of a construction as a pairing between syntactic form and semantic features. Chang (2004) and Bergen and Chang (2005) present a model for learning lexically specific multiword constructions from annotated child-directed transcript data, by learning associations between graph representations of form and meaning relations. Alishahi and Stevenson (2008, 2010) use a probabilistic framework for representing constructions and incrementally generalising them based on instances of language

1 use. Perfors et al. (2010) and Parisien and Stevenson (2010) expand this ap-
2 proach to model a hierarchy of constructions, and to simulate learning of verb
3 alternations.

4 In the rest of this paper, we will focus on the probabilistic model of Alishahi
5 and Stevenson (2008, 2010; henceforth A&S), and investigate various stages of
6 learning and using argument structure constructions. We will discuss the “true
7 nature” of a construction in this model; that is, the internal representation of the
8 syntactic and semantic characteristics that a construction encapsulates. We will
9 look at how constructions emerge from usage data and how they are entrenched
10 and generalised over time. Moreover, we will describe how these acquired con-
11 structions are used in various language comprehension and production tasks,
12 and how the model explains the behavioural trajectory of language users at dif-
13 ferent learning stages.

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16 3.1 Representation of constructions

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18 In the theoretical linguistics literature, constructions are defined as a rigid pair-
19 ing of a syntactic form, and a relational meaning between the participants of
20 the described event. But if argument structure constructions are in fact emerged
21 from instances of verb usage, their formation must be gradual and the syntax-
22 semantics associations they depict more blurred. In the A&S model, construc-
23 tions are viewed simply as a collection of similar verb usages. Each verb usage,
24 represented as a *frame*, is a collection of features which can be lexical (the head
25 word for the predicate and the arguments), syntactic (case marking, syntactic
26 pattern of the utterance) or semantic (lexical characteristics of the event and its
27 participants, thematic roles that the participants take on). A construction is noth-
28 ing more than a cluster of such frames.

29 As a result of this view, a construction is inherently probabilistic in nature:
30 each feature within a construction is represented as a probabilistic distribution
31 over the observed values of the member frames, and the construction as a whole
32 represents a probabilistic association between various lexical, syntactic and se-
33 mantic features. In other words, each construction makes predictions about the
34 likelihood of each aspect of its instances.

35 For example, English transitive construction ideally consists of a set of frames
36 representing usages such as *he baked a cake*, *daddy made a tree house*, and *Anne*
37 *kicked the ball*. This construction makes a very strong prediction that each of its
38 instances depicts a causal action, where the first argument is animate and the
39 initiator and the cause of the event, the second argument a physical object and
40 undergoing some change. It also makes a strong prediction about the order of

arguments in a sentence: the “agent-like” argument is most likely preceding the predicate term (or main verb, in this case), and the “theme-like” argument following it. However, such a construction can also make weaker predictions about the characteristics of the event (e.g., it depicting a change of state) or the arguments (e.g., the first argument being a human), reflecting the characteristics of the past events represented by frames already clustered in this construction. But predictions about a specific feature can be made more accurately if other features are known; for example, if a new transitive usage is known to describe a consumption event (such as *eat*), it is more likely that the second argument is edible and undergoes a physical change. Such associations are simply induced from the probabilistic representation of the observed events that are now grouped together to form a construction.¹

In such a representational framework, it is easy to see how item-specific constructions metamorphose to abstract ones over time. An item-specific construction contains a small set of frames which correspond to the same predicate term (e.g., *he drank water*, *kitty drank milk*). However, as similar usages of different predicates are encountered and grouped together over time, the corresponding construction abstracts away from the characteristics of the event described by the original predicate (or verb, or item), and represents a wider range of events with similar characteristics. That said, some item-specific constructions might persist due to their idiomatic nature, for instance *kick the bucket* might manifest itself as a group of frames which share some features with a typical transitive usage, but differ in the semantic properties of the event they describe and the lexical heads they take as the predicate and the second argument (*kick* and *bucket*).

A consequence of such a definition of a construction is that the association between feature values is changing every time a new instance of the construction is observed. This might sound undesirable, since the linguistic knowledge of language users within a community seems to stabilise and converge. However, A&S’s computational simulations of a range of constructions show that although the probabilistic distribution of each feature varies significantly across simulations at the early stages of learning (due to each simulation having a different stream of linguistic and perceptual input), once enough input has been received, the profile of the same construction formed in each simulation converges

¹ Alishahi and Stevenson (2008) uses single labels such as AGENT and THEME to represent the thematic role of an argument. Alishahi and Stevenson (2010) expand this model by using a distributional representation of thematic roles, using thematic role properties similar to the proto-roles proposed by Dowty (1991), and show that the model can learn to associate appropriate *thematic profiles* (i.e., probability distributions over the thematic role properties) to each grammatical position within a construction.

1 to that in other simulations, and does not change noticeably upon receiving new
2 usages. This corresponds to young children's idiosyncratic patterns of language
3 comprehension and generation (and distinct errors they make) due to the specific
4 input they receive during their early years, but such differences fade out though
5 adulthood.

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8 **3.2 Learning abstract constructions from instances** 9 **of language use**

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11 A&S model the acquisition of constructions as an incremental clustering pro-
12 cess. Upon hearing a new utterance, the model extracts a frame including all
13 the available features from the utterance and its perceptual context. This frame
14 is then added to the most suitable construction, either an existing or a new one.
15 In selecting the best construction for a given frame, two factors are taken into
16 account:

- 17 – The prior probability of each construction: this factor shows how applicable
18 the construction is to any frame (without knowing the frame features), and
19 is estimated as a function of the relative size of the construction (or the ratio
20 of the number of frames it already contains to the total number of frames
21 observed so far). For example, if we do not know anything about a new verb,
22 it is more likely that it can be used in a transitive rather than ditransitive con-
23 struction, since transitive usages are much more common in English. In this
24 way, the prior probability of a construction encompasses its degree of *en-*
25 *trenchment* (Braine and Brooks, 1995; Goldberg, 1995).
- 26 – The conditional probability of the construction: this factor shows the similar-
27 ity between the new frame and the previous members of this construction. In
28 other words, the conditional probability of a frame given a construction tells
29 us how likely it is that a typical member of that construction displays the
30 feature values in the target frame. This factor can be simply estimated based
31 on the likelihood of each of the individual features in the target frame; that is,
32 by calculating the proportion of the member frames which share the same
33 value with the new frame on a given feature (for instance, the number of
34 frames with two arguments or with a manner of motion event). This factor
35 has been referred to as *competition* for syntactic features (MacWhinney, 1987)
36 and *cue construction* for semantic features (Bowerman, 1982; Pinker, 1984;
37 MacWhinney, 2004).

38

39 Simply put, larger constructions which contain frames similar to the new one
40 have a better chance of winning in this race.

Note that the number of constructions in a language is not predetermined, 1
 instead new constructions are added on demand. A new construction has a rela- 2
 tively low prior probability (since it only contains one potential frame), and a 3
 uniformly distributed conditional probability (since any feature value is equally 4
 likely to occur in a new construction). Therefore, if the new frame is similar to 5
 any of the usages processed in the past, the corresponding construction will 6
 most likely take in the new frame as well. But if the new frame is different from 7
 what the model has seen before, the conditional probability for all the exist- 8
 ing constructions will be very low (due to mismatch on some features), and it 9
 is more likely that a new construction is created. As the model receives more 10
 input, the prior probability of the new construction drops and it becomes less and 11
 less likely for a new construction to be created, just as it becomes less probable 12
 for a speaker of language to encounter an instance of a new construction as they 13
 age. 14

The interaction between the main two learning factors results in various 15
 learning stages: at first, all constructions are small and have a low prior probabili- 16
 ty, therefore those with a higher conditional probability easily win. These are 17
 often the ones which share the main predicate with the new frame, leading to 18
 conservative language use. As the constructions grow and become more general, 19
 the model applies them more readily to new frames, resulting in occasional over- 20
 generalisation mistakes. Once the model receives enough “acceptable” usages of 21
 an overgeneralised predicate, the conditional probabilities shift in favour of the 22
 appropriate constructions and the model recovers from making further mistakes. 23
 A careful examination and analysis of these learning phases is presented in the 24
 simulations of A&S. 25

3.3 Applying constructions in linguistic tasks 28

The main confusion over the mechanics of a constructionst approach seems to 30
 come from the applicability criterion, namely when a construction can or cannot 31
 be used for generating or interpreting a verb usage. The dominant strategy has 32
 been to define a clear set of constraints for each construction which limits its ap- 33
 plicability to appropriate cases, and rules out the inappropriate ones. In contrast, 34
 a probabilistic strategy reduces the question of applicability to that of choosing 35
 the best probabilistic match. 36

In A&S, any task that involves language use is modelled as a prediction 37
 problem, where the value of a missing feature in a partial frame must be selected 38
 based on the available features. In this approach, any language comprehension 39
 task is reduced to choosing the most probable semantic features (such as the the- 40

1 matic roles of the arguments or the characteristics of an event), whereas sentence
2 production is modelled as selecting the most probable syntactic pattern and/
3 or case marking. This strategy covers other scenarios as well, for example when
4 encountering a novel word in a sentential context, its semantic properties can
5 be estimated based on the structure of the sentence and the properties of other
6 words.

7 The most appropriate value for a missing feature in a frame is the one which
8 is assigned the highest probability according to a Bayesian prediction model. This
9 model collects probabilistic predictions made by each individual construction
10 and combines them, each weighted according to how well the construction
11 matches the frame (this matching weight is estimated just as in the learning
12 model, by looking at the prior and conditional probabilities of each construc-
13 tion). This means that the feature value suggested by a relevant construction has
14 higher weight, and depending on how entrenched the construction is and how
15 well it matches the target (partial) frame, it can determine the outcome.

16 In A&S (2008, 2010), this prediction model is applied to a range of language
17 tasks and the performance of the model is compared to experimental findings on
18 children. We will review some of these results that are relevant for the promotion
19 of a construction approach.

20

21 **Comprehending novel verb usages in familiar constructions.** Central to the
22 construction-based approach is the idea that linguistic constructions encompass
23 information about the semantic properties of the described events and their par-
24 ticipants. As mentioned before, young children are aware of such associations
25 (Fisher, 1996); for instance, three-year-olds successfully identify the event partic-
26 ipant referred to in each grammatical position based on the structure of the sen-
27 tence (e.g., *Look! She is blicking her over there. Show who is blicking!*). In A&S
28 (2010), such a novel verb usage is represented as a partial frame which only con-
29 tains the number of arguments and the syntactic pattern of the sentence. The
30 model then predicts the semantic primitives of the event, and the thematic roles
31 of each argument based on this information. Simulation results show that once
32 the model has received enough input, it can predict an intuitive probability distri-
33 bution over the semantic features. For example, for a transitive usage of *blick*, the
34 model predicts the highest probability for “agent-like” thematic role properties
35 (such as INDEPENDENT and SENTIENT) for the first argument, and “theme-like”
36 properties for the second argument.

37 Some syntactic patterns might carry different meaning elements in different
38 circumstances. The transitive usages *I feel resistance* and *he saw a lion* share the
39 same number of arguments and the same word order, but the thematic roles that
40 the arguments take in each case are completely different (Theme and State versus

Experiencer and Stimulus). Interestingly, if the model is given additional information about the predicate (that is, if the partial frame contains the semantic primitives of the event), the predicted proto-role properties for the arguments become more specific. For example, for a CHANGEOfSTATE event (as in *I feel resistance*), the most probable predicted property for the second argument is STATE, whereas for a PERCEIVE event (as in *he saw a lion*) the most probable properties are INDEPENDENT and PERCEIVABLE.

Preferential looking studies. Preferential looking studies have shown that young children look longer at a scene which best matches the construction of an utterance they have just heard. For example, they look at a causal action scene when they hear a novel verb used in a transitive pattern, and at a manner of motion scene when the verb appears in an intransitive pattern. (e.g., Naigles, 1990). Such studies can be modelled as translating each interpretation into a separate frame, and selecting the one that matches the model's linguistic knowledge best. A "correct" interpretation of a transitive usage, for instance, is the frame which contains semantic primitive CAUSE for the event, and agent-like and patient-like thematic properties for the first and second arguments, respectively. Again, simulation results show that the behaviour of the model is compatible with that of young children performing the task, and it goes through the same learning trajectory as it receives more input.

Creative generalisation. Children eventually recover from making over-generalisation errors, but language users maintain their linguistic creativity through adulthood. Such creative usages have been discussed extensively in the construction-based literature. It has been argued that speakers of a language who hear an unusual usage of a familiar verb such as *the truck rumbled down the street*, combine the meaning of the verb with that indicated by the construction (Goldberg, 1995).

This combined interpretation happens naturally in the prediction model, where the semantic and thematic role properties of the event and its arguments are predicted based on not only the available head verb, but also the syntactic features of the utterance the verb is used in. The simulation results show that whereas for a typical usage of the intransitive verb *dance* the model predicts primitives such as ACT and MOVE, for a creative use of *dance* in *he danced her down the street* the predicted primitives change to CAUSE and MOVE. A similar trend can be observed in sentence production as well: if the semantic properties of a particular usage of a familiar verb are different from those in a typical usage of the same verb, the model picks an appropriate syntactic pattern for expressing that usage (even if such pattern has not been used for that verb before).

4 Conclusion

We have shown that a probabilistic version of the construction-based approach is cognitively plausible: it is compatible with the usage-based and bottom-up nature of language development, and it can provide a clear explanation for well-studied learning stages that young language learners go through, as well as for human performances in various language comprehension and production tasks.

To account for the fact that humans draw on abstract pairings of form and meaning in the absence of a familiar verb, even a lexicalist approach has to accommodate meaningful constructions in its grammar. Constructionists thus claim to offer a simpler and more elegant approach by using a single theoretical device. M&W repeatedly argue that a working construction-based approach is not simpler and more powerful than a lexical approach, because in both cases it is necessary to stipulate which verbs can appear in which construction/rule. The probabilistic account discussed in this paper suggests that such extra machinery is not necessary. In fact, establishing a hard link between verbs and their constructions restricts creative language use.

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