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Using Developmental Modeling to Specify Learning and Representation of the Passive in English Children

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1 Introduction

The acquisition of the verbal *be*-passive in English (e.g., *Matthew was hugged by Diana*) is delayed in children compared to other constructions that involve object-movement (e.g., object *wh*-questions and unaccusatives). Interestingly, there's also variation across English verbs with respect to the passive: the passive of some verbs (like *love*) seems to be available later than other verbs (like *hug*) (Bever, 1970; de Villiers and de Villiers, 1973; Horgan, 1978; Maratsos et al., 1985). There have been several proposals about the causes of this developmental variation, including effects of input frequency. Nguyen and Pearl (2018) demonstrated that the input frequency of individual verbs doesn't correlate with the developmental trajectory derived from a collection of child behavioral studies; however, lexical semantic features correlate quite well. More specifically, verbs with specific sets of lexical features (which Nguyen and Pearl (2018) called lexical *profiles*) have their passive use acquired before verbs with other profiles. Nguyen and Pearl (2018) suggested that input frequency of lexical features might explain the observed developmental trajectory of the English passive across different verbs.

Taking this as a starting point, we attempt to capture five-year-old English passivization behavior via a probabilistic learning strategy that relies on the frequencies of features associated with individual verbs in children's input. We implement this with a Bayesian developmental model, where children's prior beliefs and abilities associated with the passive structure also impact their observed passivization behavior.

We first review potential sources of information that children could use to determine whether a verb is passivizable, including lexical and syntactic features available in their input. We then discuss the empirical data on English children's passive acquisition, in particular the behavioral output we use as a target for our developmental model and the child-directed speech we use as input for our developmental model. We then describe the developmental model itself, which combines the available information sources from children's input with their prior beliefs and abilities to produce their output knowledge. Using this model, we discover that it's unlikely children attend to all the features we considered when generating the passivization behavior they do at five years old. So, we then

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describe how our developmental model can include considerations of selective attention, sometimes known as input filtering (Pearl and Weinberg, 2007; Lidz and Gagliardi, 2015; Gagliardi et al., 2017). Taken together, we (i) identify how English children may be integrating lexical feature frequency information when learning which verbs are passivizable by age five, and (ii) find that children may not be harnessing all of the information available to them in the input. Our results suggest that, if children do indeed learn to passivize this way, five-year-olds may not perceive the passive structure as very costly *a priori*. We conclude with discussion of the implications for language development, and future computational and experimental directions.

2 Sources of information

Lexical profiles that are comprised of seven lexical semantic features (Table 1) are strongly correlated with the observed age of acquisition (**AoA**) for the verbal *be*-passive (Nguyen and Pearl, 2018). Nguyen and Pearl (2018) noted that these were descriptive features proposed by experimenters to explain specific experimental results rather than theoretically-motivated features that were intended to be mutually exclusive (Maratsos et al., 1985; Pinker et al., 1987; Messenger et al., 2012; Liter et al., 2015).[1]

Table 1: Descriptive features derived from prior experimental studies, including example verbs with (1) and without (0) that feature.

Feature	Signal	+	-
ACTIONAL	Observable	*eat*	*scare*
STATIVE	Simple present tense acceptable in an "out of the blue" context	*scare*	*eat*
VOLITIONAL	"deliberately *VERB*" is acceptable	*annoy*	*see*
AFFECTED	X affects Y	*annoy*	*like*
OBJ-EXP	-ACTIONAL where object is Experiencer	*frighten*	*chase*
SUBJ-EXP	-ACTIONAL where subject is Experiencer	*like*	*annoy*
AGT-PAT	+ACTIONAL where θ-roles = Agent, Patient	*eat*	*whisper*
TRANS	Allows an object to follow	*scare*	*fall*

We now briefly review these features. Actionality (ACTIONAL) intuitively

[1]However, we note that these features are distinct with respect to the verbs in the input sample described in section 3 – that is, for every feature in Table 1, the set of verbs that have that feature (e.g., +ACTIONAL) is not identical to the set of verbs that have any other feature (e.g., +AGT-PAT). So, these features are not obviously notational variants of each other.

captures action and is defined as any verb that's *not* a mental, psych, or perception verb (Maratsos et al., 1985). One signal of a +ACTIONAL verb is whether the event described by the verb is observable. So, *eat* would be +ACTIONAL because eating can be directly observed (e.g., *The penguin is eating a fish* – we can observe the penguin eating the fish). In contrast, a psych verb like *scare* would be -ACTIONAL because the internal state caused by scaring can't be directly observed (e.g., *Spiders scare Lisa* – we can't observe Lisa's internal state of mortal terror at arachnids because that psychological state is internal to Lisa).

Stativity (STATIVE) and Volitionality (VOLITIONAL) were proposed by Liter et al. (2015). +STATIVE verbs represent states and are acceptable in the simple present tense in an "out of the blue" context. For example, the +STATIVE verb *scare* is acceptable in the simple present tense without any special context: *Spiders scare me*. This contrasts with the -STATIVE verb *eat* because using the simple present tense in *The penguin eats a fish* sounds odd out of the blue, unless we're narrating an event in real time.

+VOLITIONAL verbs imply intentionality on the part of the subject and are acceptable following the adverb *deliberately*. For example, *annoy* is +VOLITIONAL because *Marcus deliberately annoyed Miriam* sounds acceptable, and describes an event where Marcus made a concerted effort to annoy Miriam. In contrast, *see* is -VOLITIONAL because *Marcus deliberately saw Miriam* sounds somewhat odd in its default interpretation, as it describes an event where Marcus has preternatural control over his visual perception and can choose whether to consciously perceive Miriam.

Affectedness (AFFECTED) (Pinker et al., 1987) applies to verbs where the subject affects the object. For example, *annoy* is +AFFECTED because in *Marcus annoyed Miriam*, Miriam is affected by Marcus – she is, in fact, annoyed by him. This contrasts with a -AFFECTED verb like *like*: in *Marcus liked Miriam*, Miriam isn't impacted by Marcus liking her.

Messenger et al. (2012) proposed that a verb's thematic role relations matter, and made three distinctions: Object-Experiencer (OBJ-EXP), Subject-Experiencer (SUBJ-EXP), and Agent-Patient (AGT-PAT).[2] When transitive verbs are -ACTIONAL, they often involve Experiencers which can either be the object or subject in an active sentence. An OBJ-EXP verb like *frighten* has the Experiencer as the object (e.g., *Marcus frightens Miriam* – Miriam is the Experiencer of the fright); a SUBJ-EXP verb like *like* has the Experiencer as the subject (e.g., *Marcus likes Miriam* – Marcus is the Experiencer of the liking).

In contrast, when transitive verbs are +ACTIONAL and the thematic roles are Agent (subject) and Patient (object), the verb is AGT-PAT. For example, a verb like *eat* is +AGT-PAT because a sentence like *The penguin is eating the fish* describes an event where the penguin is the Agent and the fish is the Patient. This contrasts with *whisper* (e.g., *Matthew whispered the secret*), which is +ACTIONAL but doesn't

[2]OBJ-EXP and SUBJ-EXP have also been referred to respectively as Stimulus-Experiencer and Experiencer-Stimulus verbs in the literature.

obviously involve Agent and Patient roles; therefore, it's -AGT-PAT.

Given the developmental correlation of these features with the AoA of the verbal *be*-passive in English, Nguyen and Pearl (2018) suggested that the frequency of these features in children's input may yield insight on the observed developmental differences across individual verbs. Still, because the lexical semantic features were empirically (rather than theoretically) motivated, it's unclear if all seven features are necessary. Nonetheless, just five verb profiles consisting of these seven binary features (out of the logically possible 128) accounted for all 30 verbs experimentally attested to have an AoA by age five, as observed across 12 studies in Nguyen and Pearl (2018)'s meta-analysis (Table 2).

Table 2: Profiles for example verbs (in *italics*) with an observed AoA by age five. Profiles are comprised of lexical semantic and syntactic features, with 1 indicating the verb is +*feature* and 0 indicating the verb is -*feature*.

	carry	*annoy*	*find*	*forget*	*hate*
Profile	**1**	**2**	**3**	**4**	**5**
ACTIONAL	1	0	1	0	0
STATIVE	0	1	0	0	1
VOLITIONAL	1	1	0	0	0
AFFECTED	1	1	0	0	0
OBJ-EXP	0	1	0	0	0
SUBJ-EXP	0	0	0	1	1
AGT-PAT	1	0	1	0	0
TRANS	1	1	1	1	1

Here, we add an additional profile feature: the syntactic feature of Transitivity (TRANS). We did this because passives are formally defined via transitivity in the theoretical literature (Levin, 1993)[3] and children are sensitive to transitivity very early (Naigles, 1990). Therefore, this seemed to be a reasonable feature that would be both useful and plausible for children to pay attention to in their input. +TRANS verbs allow an object to follow them (e.g., *The penguin is eating a fish* indicates *eat* is +TRANS, while **I laugh the joke* indicates *laugh* is -TRANS). All five verb classes that children are observed to passivize by age five are +TRANS. We note also that by the formal definition of passives, all passivizable verbs in English will be +TRANS. But the reverse is not the case: not all +TRANS verbs passivize in English. For example, highly stative transitive verbs such as *weigh* and possessive *have* are unacceptable in the passive (e.g. **Three pounds were weighed by the apples*, **Two buttons were had by the coat.)*. So, while TRANS is likely to be a useful feature, knowing a verb's transitivity is not the same as knowing if that verb is passivizable.

[3]This is what separates passives from pseudopassives like *laugh at* that can also have a passive form (e.g., *She was laughed at*).

3 Empirical data on children's passives

To empirically ground our developmental model of the English verbal *be*-passive, we need (i) clearly defined output behavior as the target of development, and (ii) a reasonable sample of input to learn from which the model, representing a modeled child, will use as input.

As the target output for our developmental model, we consider the 30 verbs English children have been experimentally attested to comprehend the passive use of by age five (Nguyen and Pearl, 2018): *carry, drop, eat, hold, hug, kick, kiss, push, shake, wash, annoy, chase, frighten, hit, pat, pull, scare, shock, squash, surprise, upset, find, fix, forget, paint, spot, hate, like, love, remember*. These 30 verbs fall under five profiles (recall Table 2). Importantly, Nguyen and Pearl (2018) defined successful comprehension as children performing significantly above chance in any of the 12 experimental studies reviewed in their meta-analysis. Given that chance is 50% (either the child does or doesn't understand the passive for the stimulus presented), we operationalize this as the modeled child deciding that verbs of those profiles can be passivized with a probability above 50%.

As a realistic input sample of a five-year-old's input, we extracted verbs from the same corpus that Nguyen and Pearl (2018) used for their corpus analysis: the Brown-Adam, Brown-Eve, Brown-Sarah (Brown, 1973), and Valian corpora (Valian, 1991) from the CHILDES Treebank (Pearl and Sprouse, 2013). This corpus collectively consists of 113,024 utterances (62,772 verb tokens, 742 verbs) of speech directed at children ages 1;06-5;01. The extracted verbs were then annotated for their profiles (as in Table 2);[4] verb frequencies (passive use and overall) were then calculated.[5] This allowed us to subsequently estimate the frequency of verb features in both the set of verbs that are observed to be passivizable ($+pass$) vs. not ($-pass$) in children's input.

4 Modeling passivization behavior

We model a child's decision about whether a verb from a specific profile should be passivized as a classification problem. In particular, given the lexical features comprising a particular profile and the child's prior beliefs and abilities associated with the passive, should that profile be part of the class of passivizable profiles (c_{+pass}) or not (c_{-pass})? The c_{pass} classification impacts children's predicted behavior in experiments involving the passive structure: if a verb is part of the c_{+pass} class, the child can (more easily) comprehend the passive form; if a verb is part of the c_{-pass} class, the child can't. So, a successful modeled child will classify all five verb profiles from Table 2 as $+pass$, because five-year-olds

[4] Annotations were done manually according to the native English judgments of the first author. These annotations can be found on the first author's personal website.

[5] We note that this sample includes verbs from 36 lexical profiles (with 116 verbs from 11 profiles passivized in children's input).

demonstrate successful comprehension of passives for verbs with these profiles.

The modeled child's reasoning process, which combines the probabilistic cues coming from the feature frequency in children's input with the child's prior about the passive, is implemented via Bayesian inference, as in (1). Bayesian inference is often used for cognitive development modeling, as it can capture human behavior very well (e.g., Perfors et al., 2011; Pearl and Mis, 2016). Here, to determine if a profile with a particular collection of feature values ($v_{f_1}...v_{f_8}$) for the 8 profile features ($f_1...f_8 \in F$) should be in the c_{+pass} class, the modeled learner calculates the **posterior** probability, $P(c_{+pass}|v_{f_1}\ldots v_{f_8})$.

(1) $$P(c_{+pass}|v_{f_1},\ldots v_{f_8}) \quad \propto \quad \prod_{f_i \in F} P(v_{f_i}|c_{+pass}) \quad \cdot \quad P(c_{+pass})$$

As (1) shows, this calculation depends on two parts. The first is the **likelihood** of the profile feature values, if the verb is part of the c_{+pass} class. This likelihood probability depends on the probability of a particular feature f_i having the value v_{f_i} (e.g., ACTIONAL=1), given that the verb is c_{+pass}; this is the likelihood of $v_{f_i}|c_{+pass}$, shown as $P(v_{f_i}|c_{+pass})$. The probabilities for all 8 profile features are multiplied together to calculate the collective likelihood of this feature profile, given c_{+pass} – this is shown as $\prod_{f_i \in F} P(v_{f_i}|c_{+pass})$.[6]

The second part of the posterior calculation is the **prior** probability of the verb being passivizable – i.e., $P(c_{+pass})$. This is meant to capture anything that the child brings to the passivization task, before incorporating feature frequencies from the input. Thus, it can include both the child's prior knowledge about which verbs are passivizable and the passive structure itself as well as the child's ability to deploy that passivization knowledge in real time during an experiment. So, this prior on the passive structure intuitively captures any inherent complexity of the passive structure, wherever that cost originates. For example, the passive may be costly because it's a more complex structure syntactically, or because it's a more complex structure to process in real time even when children have the knowledge (Stromswold et al., 2002; Collins, 2005; Hirotani et al., 2011; Huang et al., 2013; Mack et al., 2013; Feng et al., 2015; Ud Deen et al., 2018).

We can also do a similar posterior probability calculation to determine the probability that the verb belongs to the non-passivizable class (c_{-pass}):

(2) $$P(c_{-pass}|v_{f_1},\ldots v_{f_8}) \quad \propto \quad \prod_{f_i \in F} P(v_{f_i}|c_{-pass}) \quad \cdot \quad P(c_{-pass})$$

With these posterior probabilities in hand (that is $P(c_{+pass}|v_{f_1}\ldots v_{f_8})$ and $P(c_{-pass}|v_{f_1}\ldots v_{f_8})$), we can then normalize them as see if the probability of the verb being passivizable is greater than 0.50, as in (3). If so, the model predicts

[6]We note that this way of calculating likelihood assumes the feature values are independent of each other. This is what allows us to multiply the individual probabilities together. This is an assumption that can be relaxed in future work, and would yield a different likelihood calculation.

children will comprehend the passive form in an experiment. If not, the model predicts children won't comprehend the passive form.

(3)
$$\frac{P(c_{+pass}|v_{f_1}\ldots v_{f_8})}{P(c_{+pass}|v_{f_1}\ldots v_{f_8}) + P(c_{-pass}|v_{f_1}\ldots v_{f_8})} > 0.50.$$

Estimating likelihoods. To estimate the likelihood probabilities of individual features, we use the input frequencies from our corpus sample (Table 3). Table 4 further in this section shows an example likelihood calculation for the profile of the verb *annoy*.

Table 3: Likelihood probabilities for individual features, calculated from child-directed speech input.

	$P(v_{f_i}\|c_{+pass})$		$P(v_{f_i}\|c_{-pass})$	
v_{f_i}	1	0	1	0
ACTIONAL	0.923	0.076	0.889	0.110
STATIVE	0.067	0.932	0.092	0.907
VOLITIONAL	0.915	0.084	0.768	0.231
AFFECTED	0.847	0.152	0.528	0.471
OBJ-EXP	0.050	0.949	0.017	0.982
SUBJ-EXP	0.025	0.974	0.051	0.948
AGT-PAT	0.872	0.127	0.634	0.365
TRANS	0.940	0.059	0.710	0.289

Estimating priors. Importantly, while we can estimate likelihood probabilities from the input frequencies, it is unclear *a priori* what the prior on passivization should be. We use this as an opportunity to *define* what the prior would need to be in order for five-year-olds to passivize the verbs they do, assuming they were learning from the frequency of these lexical and syntactic features in their input. That is, because we have empirical estimates of the likelihood and the desired output behavior, we can attempt to converge on an estimate for the prior on passivization that generates the desired output behavior when that prior and the likelihood are combined. This can define how costly five-year-olds would view passivization to be as a linguistic structure, irrespective of which verbs it applies to.

To calculate the necessary c_{+pass} prior, we can compare the likelihoods of c_{+pass} and c_{-pass}, i.e., l_{+pass} and l_{-pass}. In particular, we can calculate the c_{+pass} prior ($P(c_{+pass})$) necessary to prefer passivization as in (4). The idea formalized here is that a posterior probability favoring c_{+pass} results when the posterior for c_{+pass} is greater than the posterior for c_{-pass}. This in turn results when c_{+pass}'s likelihood $\cdot$ prior is greater than c_{-pass}'s likelihood $\cdot$ prior. This in turn can be calculated based solely on the likelihoods associated with c_{+pass}

and c_{-pass} (l_{+pass} and l_{-pass}) as shown in (4), using the idea that the prior for c_{-pass} is (1 - the prior for c_{+pass}). We can therefore calculate the likelihood ratio at the bottom of (4) to determine the minimum the prior would need to be to allow passivization of the verb in question. We show a sample calculation of the minimum $P(c_{+pass})$ for the verb *annoy* in Table 4.

(4a) $$P(c_{+pass}|v_{f_1} \ldots v_{f_8}) > P(c_{-pass}|v_{f_1} \ldots v_{f_8})$$

(4b) $$l_{+pass} \cdot P(c_{+pass}) > l_{-pass} \cdot P(c_{-pass})$$

(4c) $$l_{+pass} \cdot P(c_{+pass}) > l_{-pass} \cdot (1 - P(c_{+pass}))$$

(4d) $$P(c_{+pass}) > \frac{l_{-pass}}{l_{+pass} + l_{-pass}}$$

Table 4: Calculation of the likelihood probability (l_{pass}) and the prior probability ($P(c_{+pass})$) for *annoy*, given the likelihood probabilities of its feature profile. The likelihood ratio indicates the minimum the c_{+pass} prior probability could be and still allow passivization for the profile of the verb *annoy*.

Profile Features	Profile of *annoy*	Likelihood $P(v_{f_i}\|c_{+pass})$	Likelihood $P(v_{f_i}\|c_{-pass})$
ACTIONAL	0	0.076	0.110
STATIVE	1	0.067	0.092
VOLITIONAL	1	0.915	0.768
AFFECTED	1	0.847	0.528
OBJ-EXP	1	0.050	0.017
SUBJ-EXP	0	0.974	0.948
AGT-PAT	0	0.127	0.365
TRANS	1	0.940	0.710
$\prod_{f_i \in F} P(v_{f_i}\|c_{pass})$ of *annoy*		l_{+pass}	l_{-pass}
		0.0000223071	**0.0000171389**
Prior minimum $\frac{l_{-pass}}{l_{+pass}+l_{-pass}}$		**0.434**	

Here, we assume that passivization is harder than not (i.e., more costly in whatever relevant sense than other structures that could be used), and so we look for a $+pass$ prior minimum <0.50. The feature input frequencies for *annoy* yield a passive prior minimum of 0.44. So, this model would predict that *annoy* should be passivized by five-year-old children, based on the lexical and syntactic feature frequencies considered here. To yield this behavior, five-year-olds would need to have a passive prior of at least 0.44 – so, the passive would be harder than not (as the probability is <0.50), but not much harder (as 0.44 isn't much lower than 0.50). We use this approach to evaluate the five verb profiles in Table 2. In particular, we look for all five verb profiles to be passivizable by five-year-olds with c_{+pass} prior minimum estimates <0.50.

5 Results

We begin with the assumption that children attend to all the features available in the input (ALL FEATURES). Table 5 shows the minimum c_{+pass} prior necessary for passivization of each of the five lexical profiles of interest.

Table 5: The minimum priors on the passive structure required to yield five-year-old passivization behavior for the five lexical profiles of interest, when all features are heeded. Priors below 0.50 are in bold.

	carry **1**	*annoy* **2**	*find* **3**	*forget* **4**	*hate* **5**
ALL FEATURES	**0.21**	**0.43**	0.81	0.98	0.99

Recall that if we take the idea seriously that the passive should be more costly than not, we should look for c_{+pass} priors <0.50 as a reasonable estimate. When all features are heeded, only verbs from profiles 1 and 2 have a prior like this (profiles 3-5 require a prior that significantly or nearly exclusively favors passivization: 0.81-0.99). This would mean that in order to passivize verbs from profiles 3-5, five-year-olds would need to find the passive very, very easy – this is what prior minimums that high indicate. Given experimental evidence to the contrary (e.g., Stromswold et al., 2002; Hirotani et al., 2011; Huang et al., 2013; Mack et al., 2013; Feng et al., 2015; Ud Deen et al., 2018), we conclude that if five-year-old children were attending to the input frequency of all these features, they would be unlikely to generate their observed passivization behavior for these five verb profiles. Therefore, we take this to mean they may not be attending to all these features. That is, five-year-olds may be selectively attending to the available information (Pearl and Weinberg, 2007; Gagliardi et al., 2012; Lidz and Gagliardi, 2015; Gagliardi et al., 2017), and applying an input filter that causes them to ignore information from some features that are available in their input.

We now explore this possibility. While there are many ways to implement selective attention, we adapt our modeled child to filter the input by selectively attending to one or more features in a categorical fashion. That is, when a feature's attended to, it's completely heeded (i.e., the child incorporates its information with a probability of 1); when it's not attended to, it's completely ignored (i.e., the child incorporates its information with a probability of 0)). No other weighting of features is used. This selective attention impacts the likelihood calculation, as shown in Table 5 for the verb *annoy* when only the features ACTIONAL and TRANS are heeded. The other six features are ignored in the calculation. From this example calculation, we can see that this input filter yields a passive prior minimum above 0.50 (though just barely), which indicates the child would need to slightly favor passivization. As this doesn't align with our assumption that children would find the passive harder than not, we would consider this input filter as not successful for yielding five-year-old passivization behavior.

With this in mind, we investigate if there's any subset of features from our set of eight capable of yielding five-year-old passivization behavior. There are 256

Table 6: Calculation of the likelihood probability (l_{pass}) and prior probability $P(c_{+pass})$ for the verb *annoy* if only the features ACTIONAL and TRANS were attended to. The likelihood ratio indicates the minimum the c_{+pass} prior probability could be and still allow passivization for the profile of the verb *annoy*.

Profile Features	Profile of *annoy*	Likelihood $P(v_{f_i}\|c_{+pass})$	Likelihood $P(v_{f_i}\|c_{-pass})$
ACTIONAL	0	0.076	0.110
TRANS	1	0.940	0.710
$\prod_{f_i \in F} P(v_{f_i}\|c_{pass})$ of *annoy*		**0.0714**	**0.0781**
Prior minimum $\frac{l_{-pass}}{l_{+pass}+l_{-pass}}$		**0.522**	

possible filters, given that each of the 8 features can be heeded or not (2^8 = 256). Table 5 shows the successful filters capable of yielding passive prior minimums less than 0.50, of which there were only two. So, our model can generate the observed five-year-old passivization behavior as long as children either attend to the TRANS feature exclusively, or attend to both the TRANS and OBJ-EXP features. These are the only two cases where the minimum passivization prior is below 0.5 for all five verb profiles. So, this model would predict that five-year-olds can find the passive harder than not (a passivization prior <0.50) and passivize the verbs they've been observed to, as long as they attend to only the transitivity of the verbs in their input or the transitivity and object-experiencer feature.

Table 7: Successful input filters that yield minimum priors on passivization below 0.50 and still generate five-year-old passivization behavior for the five lexical profiles of interest, given different collections of features to selectively attend to.

	carry **1**	*annoy* **2**	*find* **3**	*forget* **4**	*hate* **5**
TRANS	0.43	0.43	0.43	0.43	0.43
TRANS+OBJ-EXP	0.44	0.21	0.44	0.44	0.44

6 Discussion

Using developmental modeling, we have provided empirical evidence for two ideas: (i) English children's passivization behavior can be explained by them selectively attending to the available lexical feature information in their input (i.e., filtering their input), and (ii) children view the passive structure as somewhat costly *a priori*, though not excessively so. We demonstrated this via an existence proof implemented in a Bayesian developmental model that was able to prefer passivization for the five verb profiles that five-year-old English children comprehend the passive for, when the model was given a realistic sample of English child-directed speech to learn from. Importantly, because the Bayesian model incorporates both likelihood and prior information, we were able to not only formalize how children harness the information available in their input but also to quantify how costly English five-year-olds would view the passive structure to be, in the form of a prior on passivization.

Interpreting the passivization prior. How exactly do we interpret the estimates on the passivization prior? We reiterate that this prior on the passive structure can include both the child's prior knowledge about which verbs are passivizable and the passive structure itself, as well as the child's ability to deploy that passivization knowledge in real time during an experiment. Given this, a plausible assumption could be that the perceived cost of the passive structure is fixed – that is, the *a priori* passive structure cost doesn't vary by verb or verb class.[7] With this in mind, we might view the highest minimum estimate as the perceived cost because that cost is the *least* it could be and still allow five-year-olds to generate the correct passivization behavior for all five profiles. Looking at the two successful models in Table 5, this would yield an estimate of 0.43-0.44. This is noticeably not much below 0.50, suggesting that by five years old, English children would not *a priori* view the passive as that expensive a structural option.

Future work. There are several open questions that our results raise. First, while the present model assumes that the verb features are independent from each other, it might be that these features are correlated to each other. We might then wonder how these correlations could impact our developmental model, as the likelihood calculation would change, on the basis of these correlations. In particular, if the features aren't independent, we wouldn't calculate the likelihood by multiplying their independent likelihoods (e.g., p(ACTIONAL=1$|c_{+pass}$)*p(AGT-PAT=1$|c_{+pass}$)). Instead, we would need to calculate joint likelihoods for correlated features (e.g. p(ACTIONAL=1,AGT-PAT=1 $|c_{+pass}$)).

Given our current results however, we think these correlations are unlikely to impact the qualitative results we found related to the features five-year-olds would need to attend to vs. ignore. In particular, we would predict that if features are in fact correlated, they should either both be attended to or both be ignored by children. We found only two filters that are predicted to lead to five-year-old passivization behavior: attending to TRANS only, or attending to TRANS and OBJ-EXP. Therefore, all the other features were ignored – so, if any of these other features are in fact correlated, they were all ignored. For the case where two features are attended to (TRANS+OBJ-EXP), it's possible that TRANS is correlated with OBJ-EXP; this seems less likely because TRANS is a syntactic feature while

[7]If however, we believed that the cost of the passive did vary by verb or verb class, perhaps because children's input experience strongly determined which verbs they even considered passivizable, then we might not make this assumption. Instead, we might allow multiple passive priors.

OBJ-EXP is a lexical feature. However, if these two features were in fact correlated, then perhaps it's not surprising that the only two successful filters involved TRANS and TRANS+OBJ-EXP.

A second open question relates to the target state we assumed in this study: the five verb profiles that five-year-olds are thought to be able to passivize, on the basis of the Nguyen and Pearl (2018) meta-analysis. To check whether these profiles actually *are* available to five-year-olds, we should evaluate five-year-old comprehension of other verbs in these profiles. If five-year-olds do understand other verbs in these five profiles, we have additional support that they represent the appropriate target knowledge in five-year-olds. Moreover, Nguyen and Pearl (2018) discovered that some profiles are predicted to be comprehended by three- and four-year-olds, while others aren't. So, younger children's passive comprehension can also be evaluated on verbs that are in the profiles predicted to be passivizable by that age. Knowing which verbs children of different ages can comprehend allows us to be more confident in the set of verb profiles that children can comprehend at each age. This then allows us to have the target knowledge for future developmental models aimed at capturing three- and four-year-old passivization behavior, and thereby provide a precise, quantified developmental trajectory for the passive in English children. To this end, the first author is currently developing a Truth Value Judgment task (Crain and McKee, 1985) to test passive comprehension of the same verbs across three-, four-, and five-year-olds.

With the verb profiles in hand that three-, four-, and five-year-olds are able to passivize, we can follow the same process we implemented here to determine which features and passivization priors would cause children to produce the behavior we observe them to have at these ages. That is, we can provide a quantified snapshot of the representations underlying the observed developmental behavior. Based on this, we can then make experimentally testable predictions about which other verbs and lexical profiles should be passivized at different ages in English children.

A third open question relates to the specific input filters discovered by our current developmental modeling results for English five-year-olds. In particular, our developmental model suggests that five-year-olds must attend to transitivity (TRANS) to understand the passives that they do, and they may also attend to Object-Experiencer (OBJ-EXP). This is a testable prediction for the features that five-year-olds should be sensitive to in a behavioral study involving verbs with and without these features. In particular, are five-year-olds particularly attentive to these features when deciding if a verb can be passivized? A novel verb learning task may be able to evaluate this. The first author is currently developing such a study, where five-year-old children are taught nonce verbs involving different combinations of the features Transitivity and Object-Experiencer. The children will then be asked to choose the scene (out of two) that's represented by the passive sentence containing that verb (e.g., after learning that *blick* is +TRANS, children hear *Diana was daxed by Matthew*, and choose between a picture that shows

Diana doing something to Matthew and a picture that shows Matthew doing something to Diana). The developmental model here allows us to make predictions about children's expected success for the different feature combinations (i.e., by calculating the posterior in (3)). We can compare these predictions against the behavioral results obtained from this experiment to see if either of the predicted input filters do indeed seem to be active in five-year-olds.

More generally, an important contribution of our developmental modeling approach is that it provides a way to be explicit about (i) how children use the input available to them when comprehending the passive, and (ii) how costly children perceive the passive structure to be. In particular, we can define what children's selective attention could look like and the cost that the passive structure could have for five-year-olds. This work underscores the utility of developmental modeling for researchers concerned with both representations and the acquisition process. Through an empirically grounded mathematical model of English children's acquisition of the passive, we have specified theories of both the learning process and the representations underlying that learning process, as well as provided promising future directions for a more complete understanding of the developmental trajectory.

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