The Acquisition Process

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Abstract

This chapter discusses the acquisition process, and how we build theories that explain how that marvelous process occurs in children. I review insights about the relevant factors in the acquisition process, and what we currently know about those factors, drawing on results from quantitative approaches to language acquisition that allow us to concretely articulate and evaluate potential acquisition theories. The insights gained from these approaches will hopefully allow us to construct a complete, elegant theory of syntactic language acquisition.

1 Explaining the marvelous process of language acquisition

A goal of this handbook is to identify key concepts that we need in order to create insightful, elegant theories of syntactic language acquisition. Why do we want to do this? Well, for one, language acquisition is something of a marvel that seems in need of explanation. The knowledge that children develop about their native language(s) is quite sophisticated, and children develop it more completely than adults typically can. The time children take to develop this sophisticated knowledge is relatively short, and in fact shorter than the time taken by many adults who try to develop proficiency in a non-native language. The cognitive capacities (like attention, memory, executive control, and so on) that children have available to deploy towards the development of this sophisticated knowledge are also limited, especially when compared to adult capacities.

Moreover, children are often doing other things at the same time as they're developing their linguistic knowledge: teasing a sibling, claiming a coveted space on a parent's lap, or learning to barter for a desired toy (among many other activities). Children aren't sitting down with laser focus to analyze their input for relevant linguistic information the way adults might do in structured educational settings. Yet, children achieve native proficiency while most adults don't. In other words, children succeed at language acquisition while most adults don't. This is a marvel. Importantly, the considerations I mentioned above (the nature of children's knowledge; their limited time, cognitive capacities, and focus) are only some of the factors that we need to keep in mind when coming up with an explanation for how this marvelous process occurs.

So, how *do* we come up with an explanation – that is, how do we come up with a theory about how the process of acquisition works? If we want to build a theory, we need to be precise about what we're trying to explain and how we're going to try to explain it. More specifically, for language acquisition, we're trying to explain the empirical data available about how language acquisition works (what children seem to have acquired when, and how they seem to do it). A theory is a useful abstraction of those empirical data (Dennett, 1990, Futrell & Mahowald, 2025) – that is, a theory is a way to "compress" the data so we can explain how those data were generated in a way that doesn't involve "cumbersomeness, lack of generality, and unwanted detail" (Dennett, 1990). If we think about theories this way, one key thing we're interested in is the set of relevant factors – the ones that are necessary, rather than unnecessary – for explaining the language acquisition process. So then, for building theories of language acquisition, what *are* all those relevant factors that we should keep in mind?

I'll begin by trying to answer this question about relevant factors, drawing on quantitative approaches to language acquisition that concretely articulate theories of acquisition: mathematical learnability and computational modeling. In particular, I'll review the factors that these approaches consider in their investigations of language acquisition. I'll then try to synthesize some of the results coming from these approaches, prefaced by cautions and caveats for how to interpret those results. For our purposes, the insights gained through careful interpretation of quantitative investigations are (hopefully) some pieces of a complete, elegant theory of syntactic language acquisition.

2 What are the relevant factors?

2.1 What mathematical learnability approaches have told us

Mathematical learnability investigations typically have idealized the language acquisition process in exactly the way I mentioned above for theory-building: trying to abstract away from unnecessary detail in order to gain insights that are as generally applicable as possible (e.g. Gold, 1967, Horning, 1969, Wharton, 1974, Angluin, 1980, Wexler & Culicover, 1980, Osherson et al., 1983, 1986, Valiant, 1984, Angluin, 1988b, Gibson & Wexler, 1994, Niyogi & Berwick, 1996, Osherson et al., 1997, Niyogi, 2006, Clark & Eyraud, 2007, Hsu & Chater, 2010, Hsu et al., 2011, 2013, Clark & Lappin, 2011, Chater et al., 2015, Heinz, 2016, Rawski, 2021, De Santo & Rawski, 2022, Heinz & Rawski, 2024). Along the way, there has been some consensus on some of the relevant factors for any language acquisition theory:

- the nature of the **input**
- the **hypothesis space** of the child
- the **learning period** during which acquisition occurs
- the way the child **updates** her hypotheses
- the nature of the **target state**

Of course, the investigations mentioned above have naturally explored different implementations of these factors in order to see these factors' potential impact on language acquisition. For instance, when considering the child's input, is the child only learning from examples of what's in the language (direct positive evidence: Gold 1967, Angluin 1980, Valiant 1984, Angluin 1988b, Gibson & Wexler 1994, Niyogi & Berwick 1996, Niyogi 2006, Clark & Eyraud 2007, Hsu & Chater 2010, Hsu et al. 2011, 2013, Clark & Lappin 2011, Chater et al. 2015, Heinz 2016)? Or instead, is the child also getting feedback directly or indirectly about what isn't in the language (direct negative evidence: Gold 1967, Angluin 1980, Valiant 1984, Angluin 1988b, Heinz 2016; indirect negative evidence: Clark & Lappin 2011)? Is the child able to actively learn by asking specific questions about what she wants to know (targeted queries: Angluin 1988b, Heinz 2016)? What happens if the input is "messy", containing items (perhaps by accident) that aren't actually in the target language (noise in the input: Horning 1969, Clark & Lappin 2011, Heinz 2016)? What kind of information is available in the input signal anyway (e.g., semantic information along with syntactic structure for learning about syntax: Wexler & Culicover 1980)?

When thinking about the child's hypothesis space, what kind of prior knowledge is necessary to helpfully restrict that hypothesis space (Heinz & Rawski, 2024)? For the learning period, what happens if we simply translate the time during which the child learns directly into the quantity of input encountered during that time period, while factoring out how the child's absorption of the available information might change over time (Gold, 1967, Wharton, 1974, Angluin, 1980, Wexler & Culicover, 1980, Niyogi & Berwick, 1996, Clark & Eyraud, 2007, Clark & Lappin, 2011, Heinz, 2016)? When investigating how a child might update her internal state on the basis of the information in the input, do the "learning algorithms" that lead to acquisition success involve some element of randomness (e.g., guessing: Gold 1967; sampling: Niyogi & Berwick 1996)? Do successful algorithms involve sensitivity to errors when predicting the input (error-driven learning: Wexler & Culicover 1980, Gibson & Wexler 1994, Niyogi & Berwick 1996, Yang 2002, Heinz & Rawski 2024)?

For the child's acquisition target, does the correct knowledge concern the entire language system (e.g., grammar: Gold 1967, Horning 1969, Wexler & Culicover 1980, Gibson & Wexler 1994, Niyogi & Berwick 1996, Niyogi 2006, Heinz 2016, De Santo & Rawski 2022, Heinz & Rawski 2024) or instead certain key components of the language system (e.g., a transformational component: Wexler & Culicover 1980)? Does the internalized knowledge have to be exactly right, or instead "close enough" to satisfy some other objective (Wharton, 1974, Valiant, 1984, Clark & Lappin, 2011)?

Manipulating these factors in these ways (and others) and then seeing the result on what can (in principle) be learned has been the hallmark of mathematical learnability. As you can hopefully tell, there's quite a bit to investigate even when focusing just on these factors as the relevant ones. With that said, I do think there may be more potentially relevant factors when building a theory of language acquisition. I'll briefly review these other factors below.

2.2 Some additional factors that probably matter

The factors I want to focus on here come from theorists taking inspiration from behavioral data about both language development and general cognitive development in children. Figure 1 was a recent attempt I made (Pearl, 2023a) to highlight some factors that might be relevant from this perspective, organized into different types of factors (e.g., external vs. internal factors). As I go through these factors, I'll connect the terms in this figure to the relevant factors I discussed above that come from mathematical learnability investigations: **input**, **hypothesis space**, **learning period**, **update**, and **target state**.

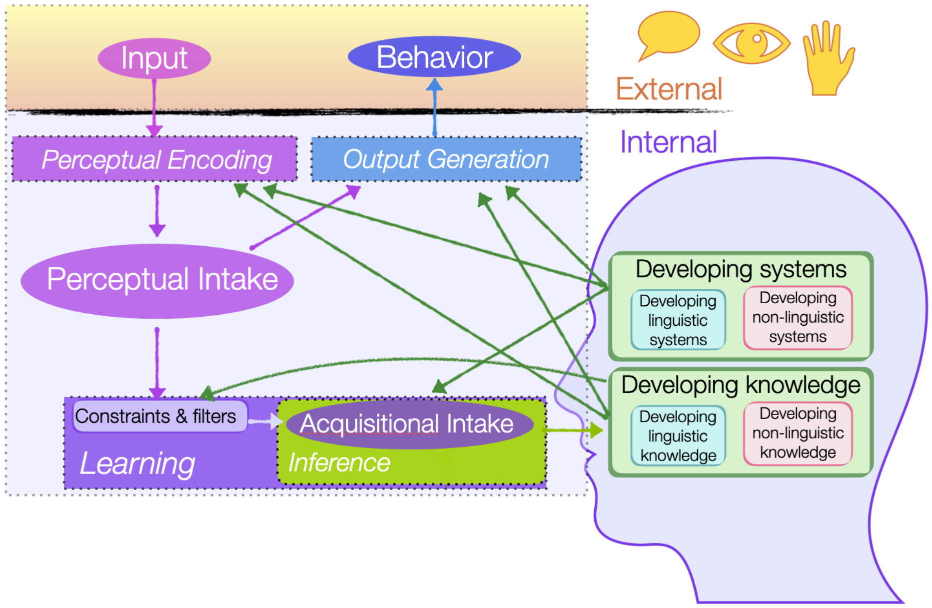

Figure 1: Some relevant parts of the acquisition process, as specified by Pearl (2023a). External components (input and behavior) are observable. Internal components aren't observable, and include perceptually encoding information from the input signal (yielding the perceptual intake), generating output from the encoded information (yielding observable behavior), and learning from the encoded information (using constraints & filters to yield the acquisitional intake, and doing inference over that intake). The developing systems and developing knowledge (both linguistic and non-linguistic) impact all internal components, while the learning component updates the developing knowledge.

Figure 1 is meant to capture a snapshot of how acquisition iteratively unfolds over time. So, in effect, the proposal in Figure 1 specifies what can go on during one "unit" of time of the child's **learning period**. The learning period itself could occur over days, months, or years, depending on the specific aspects of acquisition we focus on.

With that in mind, each moment of time involves both external and internal components. External components are observable. For instance, we can observe the **input** signal children encounter (e.g., the child language interactions they experience). The input signal is the physical signal in the world, such as auditory components like pitch and loudness of the utterance. For example, consider this utterance: "Why did you think it was a good idea to draw on the wall with permanent marker when Mommy wasn't paying attention?" This utterance might be said with a rising pitch contour and increasing volume. The input can also include other aspects of the environment, such as who said the utterance (e.g., an exasperated Mommy), where they said it (e.g., in the kitchen), when they said it (e.g., late morning), and what people or objects were in the environment at the time (e.g., Mommy, children, permanent markers, a marked-up wall, etc.). Notably, the "input" that mathematical learnability investigations have considered likely doesn't correspond to this physical, observable signal. Instead, that factor may be more like the internal factor of **acquisitional intake** in Figure 1, which is the information the child actually learns from in that moment.

The astute reader will notice that, according to the proposal in Figure 1, there are some steps in between the observable physical signal of the input and the acquisitional intake the child learns from. The first transformation is from external to internal: from the observable input to the unobservable **perceptual intake**, which is the information the child is able to perceive and extract from the input signal. This perception and extraction process is the **perceptual encoding** that generates the perceptual intake from the input. Perceptual encoding draws on the child's developing knowledge and systems to extract information.

For instance, in our example utterance, the child may be able to perceive syllables (e.g., /waj/, /dɪd/, /ju/, /θɪŋk/ etc.), words (e.g., *why*, *did*, *you*, *think*, etc.), and syntactic structure (e.g., [$_{CP}$ Why did [$_{IP}$ you [$_{VP}$ think $\_\_{why}$ ...]]]), as well as properties of the events described (thinking, drawing on the wall, paying attention), among many other types of information. Under this proposal, what children can perceive depends on several things. First, children's perceptual intake depends on what they currently know about their language, given their developing linguistic knowledge (e.g., *why*, *think*, and *draw* are words; *why* is understood in a position later than than the position it's uttered in, etc.). Second, children's perceptual intake depends on what they currently know about the world, given their developing non-linguistic knowledge (e.g., what event Mommy is probably asking why about, given that she's not at all pleased). Third, children's perceptual intake depends on how well they can extract information of different kinds, given their developing linguistic systems (e.g., speech segmentation, syntactic parsing, *wh*-dependency resolution) and their developing non-linguistic systems (e.g., memory, cognitive inhibition). Notably, extracting information from the input signal involves ignoring information present (e.g., where the utterance was spoken) and adding information not explicitly present (e.g., what the words are in the speech stream, how words group together to form constituents). What children ignore and add to generate their perceptual intake depends on their developing knowledge and developing systems.

To get to the acquisitional intake (again, what mathematical learnability investigations might term "input") – that is, the information that children actually learn from – there's an additional key transformation. The basic idea is that children don't learn from all the information they can perceive. So, for instance, even if they can perceive all the words in the utterance from before, it may be less relevant that individual words are present in the speech stream (e.g., *why*, *did*, *you*, *think*) if children are fairly confident about their speech segmentation. Instead, if children are still learning about the distribution of *wh*-dependency structures in their language, what may be more relevant are characteristics of the *wh*-dependency in that utterance, such as the structures the words are part of (e.g., CP, IP, VP, etc.) and where the *wh*-word *why* is interpreted (e.g., in the VP with *think* as opposed to the VP with *draw* or the VP with *paying attention*). This is where the **constraints & filters** of Figure 1 come in: focusing the child on the relevant information in the perceptual intake, given the current stage of acquisition.

Importantly, what's perceived as "relevant" depends on what children are trying to learn, and what hypotheses they're considering. That is, because the **hypothesis space** of the child specifies which hypotheses are under consideration, the hypothesis space helps focus the child on the relevant information in the perceptual intake. In terms of the proposal in Figure 1, constraints can help define what hypotheses are worth considering (that is, how the child's hypothesis space should be usefully restricted: Heinz & Rawski 2024). For instance, in our *wh*-question example, suppose the child is learning about the distribution of *wh*-dependencies. Perhaps her hypothesis space is then constrained to the set of possible *wh*-dependencies and their relative frequencies, characterized by the syntactic structures that comprise those dependencies. Then, given that hypothesis space, only certain aspects of the perceptual intake become relevant for the utterance above: specifically, where "why" is intended to be interpreted (in the VP with *think* as in [$_{CP}$ Why did [$_{IP}$ you [$_{VP}$ think $\_\_{why}$ ...]]]).

Filters may also focus the child's attention on a subset of the perceptual intake, irrespective of any hypothesis space restrictions. For example, an attentional filter might cause the child to mis-interpret the *why* because her attention is drawn to emotionally-charged components of the utterance (e.g., *draw on the wall...*). That is, she might mis-interpret *why* as being understood in the VP with *draw*, rather than in the VP with *think*, even though she perceived the VP with *think* as part of her perceptual intake. An interesting effect of mis-interpreting *why* (whatever the cause) is that the acquisitional intake in this case is actually a skewed version of what an adult would extract from the original input (i.e., a *wh*-dependency with *why* interpreted somewhere other than with the VP containing *think*). That is, what the child is learning from is different than what seems to be available in the input signal, at least according to adult perceptions.

This is not to say that the acquisitional intake is always skewed like this, compared to the "intended" input. It could be that the child in the example above would interpret *why* as an adult would despite any constraints or filters, and so her acquisitional intake would be similar to an adult's. Still, the simple fact that the available signal the child learns from might indeed be transformed is worth noting in any theory of the acquisition process because the child's acquisitional intake could, indeed, be different from an adult's. Whatever the resulting information in the acquisitional intake, that's the information the child uses to **update** her internal state (in this example: to update her hypotheses about *wh*-dependency distributions).

The process of updating on the basis of the acquisitional intake is captured in the "Learning" block of Figure 1, under **inference**. In particular, this internal piece concerns how the child's developing knowledge (both linguistic and non-linguistic) is updated over time. Inference typically involves non-linguistic abilities that themselves may be developing, like probabilistic inference, statistical learning, or hypothesis testing. The result of this inference can be used to update the developing knowledge – potentially both linguistic knowledge and non-linguistic knowledge. For instance, in our *wh*-dependency example, the child might update her hypotheses about how likely *why* is to be interpreted with *think* as a main verb (linguistic knowledge) and how likely adults like Mommy are to ask about why the child thought something was a good idea (non-linguistic knowledge).

Whatever the contents of the child's developing knowledge, that is what she uses to generate the observable **behavior** we see externally as output. The **target state** of mathematical learnability has traditionally corresponded to the internal **developing knowledge** of the child (e.g., which items might be more or less "grammatical" for a given target grammar). However, as noted, that's an internal component that we can't observe; instead, we can observe behavior like linguistic productions or behavior (naturalistic or coming from clever experimental designs that elicit those productions or behavior).

For instance, in our *wh*-dependency example, an immediate observable behavior might be the child's answer (answering why she thought it was a good idea vs. why she drew on the wall or why Mommy wasn't paying attention). A more abstract behavior might be elicited by asking the child's interpretation of potentially ambiguous *wh*-dependencies (de Villiers et al., 2008, Omaki et al., 2014) that aren't exactly like the one she heard (e.g., "Where did Lizzie say she was going to catch butterflies?"). By seeing how she interprets these other potentially ambiguous *wh*-dependencies (e.g., where the saying happened vs. where the butterfly-catching happened), we can observe which *wh*-dependency she thinks is more likely in context; her preferred *wh*-dependency in this context demonstrates her internalized knowledge about the distribution of *wh*-dependencies in her language.

Key to this relationship between the internal knowledge of the child and her observable behavior is the **output generation** of Figure 1. In particular, output generation depends both on the child's current perceptual intake, as well as her developing knowledge and developing systems. For example, suppose we're trying to elicit her knowledge about *wh*-dependencies, and ask for her preferred interpretation of "Where did Lizzie say she was going to catch butterflies?" (Omaki et al., 2014). Her perceptual intake is whatever information she can encode from that utterance, and then she draws on her developing knowledge (e.g., linguistic: about *wh*-dependency distributions in her language; non-linguistic: about where Lizzie is likely to do different actions) and her developing abilities (e.g., linguistic: utterance generation; non-linguistic: motor control, attention, and decision-making) to generate observable behavior. The behavior could be linguistic (e.g., answering where Lizzie did the saying vs. answering where Lizzie did the butterfly-catching) or non-linguistic (pointing at a picture of the location where Lizzie was speaking vs. a picture of the location where Lizzie was catching butterflies).

My goal in walking through the details of this proposal about the acquisition process was to highlight both (i) the factors that we should consider when building our acquisition theories, and (ii) how complicated it can get. One striking thing (to me) about Figure 1 is how connected everything is (i.e., there are a lot of arrows). We might reasonably wonder if we can make any progress at all on theorizing with this kind of interconnectivity present – that is, until we know for sure about factor X (e.g., developing systems), how can we possibly say anything sensible about factors Y and Z (e.g., perceptual encoding, inference) that depend on factor X?

In response to this question, I (currently) feel that we should hearken back to the idealizing spirit of mathematical learnability investigations. That is, we have to idealize somewhere to get anywhere – perhaps we ignore (for now) the impact of certain factors or we simplify the contributions of any particular factor. Still, I think it's useful to know what might be considered relevant factors, because there will (hopefully) come a time when we won't need to idealize so much. In the meantime, we can at least implement what we can of the factors we think are relevant, thereby implementing theories of the acquisition process that we can then evaluate against the available empirical data.

3 What we've learned so far from quantitative approaches

Now I'll review some of the insights we've gained from different quantitative approaches, like mathematical learnability and computational modeling. I'll begin first with some caveats about interpreting results from these approaches, and then survey results from quantitative approaches, keeping in mind how they help us build acquisition theories.

3.1 Caveats: What can they tell us anyway?

When interpreting the results of quantitative investigations, it's important to remember what it is they're actually investigating – in particular, which aspect(s) of the acquisition process they're implementing concretely and evaluating. Moreover, any acquisition theory implemented by a quantitative approach is a "(dis)proof of concept": the modeled child operating in the acquisition scenario formalized by that quantitative approach will behave in the predicted way (Pearl, 2021, 2023a,b, Portelance & Jasbi, 2024). Hopefully, that predicted way connects in some interpretable way to children's behavior, so that we can evaluate whether *that implementation of the acquisition theory* works (or doesn't). This is an important point: we can only interpret the results with respect to that acquisition theory, as implemented by the quantitative approach. If there are other theories (or other versions of the implemented theory), the results *don't* apply – they only apply to the implemented acquisition theory. This is why the assumptions about how relevant factors are implemented (or ignored) are so important: these are the assumptions that implement the acquisition theory being evaluated. It is only this acquisition theory that any results can then provide evidence for (or against).

With these considerations in mind, an acquisition theory can try to provide an explanation at different levels in the sense of Marr (1982): computational, algorithmic, and implementational (Pearl, 2023b). In my experience, computational-level acquisition theories are committed to the specified mental computations being performed (e.g., Bayesian inference over a certain acquisitional intake), but not necessarily committed to actual children performing them the way the modeled child does. Ideal/rational learner models (e.g., Foraker et al., 2009, Hsu & Chater, 2010, Pearl, 2011, Perfors et al., 2011, Hsu et al., 2011, Feldman et al., 2013, Hsu et al., 2013, Orita et al., 2013, Abend et al., 2017, Pearl et al., 2017, Nguyen & Pearl, 2019, Pearl & Sprouse, 2019, 2021, Dickson et al., 2022, Pearl & Forsythe, 2022, Dickson et al., 2024) as well as investigations leveraging large language models (e.g., Wilcox et al., 2023, Yedetore et al., 2023, Lan et al., 2024) typically take this approach, and so explain what is (im)possible to do, given the acquisition scenario specified. Algorithmic-level acquisition theories are committed to the specified mental computations being performed using the specific steps the modeled child uses (e.g., a step-by-step approximation of Bayesian inference over a certain acquisitional intake received incrementally over time). Constrained/process learner models (e.g., Regier & Gahl, 2004, Yang, 2004, Pearl & Lidz, 2009, Pearl & Sprouse, 2013a, Pearl & Mis, 2016) typically take this approach, and so explain what is (im)possible for children to do, given the acquisition scenario specified. Implementational-level models are committed to the specified mental computations being performed using the specified steps within a specified medium (e.g., a collection of neurons organized a particular way in a brain). To my knowledge, we don't currently have acquisition theories of this kind, but if we did, they would explain what is (im)possible for children's brains to do, given the acquisition scenario specified.

Explanations targeting different levels naturally tend to focus on some of the available relevant factors, rather than others (e.g., a computational-level theory may not be concerned with the learning period and developing non-linguistic abilities that impact inference, while an algorithmic-level theory may well be). So, when we consider how to interpret the results of quantitative investigations, it's useful to be specific about which acquisition theory factors the result speaks to. With this in mind, I'll discuss factors we've gained insight about, and what those specific insights are, given the results from different quantitative approaches.

3.2 Intake, hypothesis space, and target knowledge

Interestingly (and perhaps unsurprisingly given the interconnectivity demonstrated in Figure 1), several insights involve the intake, hypothesis space, and target knowledge considered together. That is, if the intake is like $Intake_A$, then the hypothesis space needs to be like $HypothesisSpace_A$ and the target knowledge like $TargetKnowledge_A$. If instead, the intake is like $Intake_B$, then the hypothesis space should be like $HypothesisSpace_B$ and the target knowledge like $TargetKnowledge_B$.

From mathematical learnability investigations (Gold, 1967, Horning, 1969, Wiehagen, 1977, Angluin, 1988b, Heinz, 2016, De Santo & Rawski, 2022), we find that children's hypothesis space (and therefore the target knowledge children aim to develop) must be helpfully restricted for any chance of success, given plausible assumptions about children's intake and the nature of the acquisition task (e.g., children's limited learning period and their developing cognitive systems). In particular, a collection of investigations (Gold, 1967, Berwick, 1985, Angluin, 1988b, Heinz, 2007, Tîrnăucuă, 2008, Heinz, 2009, Clark & Lappin, 2011, Heinz, 2016) suggests that if children's intake is restricted to "positive evidence" (only examples of what's in the language, rather than also pointing out what's not), then human languages must be more restricted than we might otherwise expect in order for acquisition to succeed.

Recent investigations with large language models (**LLM**s) suggest some particular ways that human languages may need to be restricted. One way involves the idea of "information locality" (Kallini et al., 2024), where "elements that statistically predict each other are close to each other" (Futrell & Mahowald, 2025). In other words, the hypothesis space of human languages may be biased towards languages that have this information locality property. Another LLM-based finding is that human languages seem to have "low sensitivity" (Hahn et al., 2021, Bhattamishra et al., 2023, Abbe et al., 2024, Hahn & Rofin, 2024, Futrell & Mahowald, 2025), where small fluctuations (e.g., in word order) are allowed because these fluctuations don't disrupt the learning process of sufficiently powerful learners (like LLMs and potentially like humans). More generally, recent LLM-based investigations suggest that children's hypothesis spaces, while needing restrictions, may not need the specific restrictions traditionally proposed in the learnability literature (Yedetore et al., 2023). That is, the shape of the necessary restrictions may be different than we originally thought, though children do in fact need restrictions on their hypothesis space.

Investigations using computational cognitive modeling align with this idea that hypothesis space restrictions may be different from what acquisition theorists traditionally thought they were. More specifically, some restrictions may be more "general-purpose", targeting not just (the exclusion of) specific linguistic elements but instead targeting the shape of the allowed linguistic system more broadly. For instance, to learn certain restrictions on *wh*-dependencies in English (known as "syntactic islands"), children's hypothesis space doesn't need to be defined in terms of certain linguistic structures ("bounding nodes") that only arise when considering if a *wh*-dependency crosses a syntactic island (Chomsky, 1973, Rizzi, 1982, Huang, 1982, Lasnik & Saito, 1984, Torrego, 1984). Instead, children's hypothesis space can be defined more generally in terms of the structures that make up any *wh*-dependency (and indeed, any utterance) in the language (e.g., verb phrases and complementizer phrases) (Pearl & Sprouse, 2013a,b, Pearl, 2014, Pearl & Sprouse, 2015, Pearl, 2017, Bates & Pearl, 2019, Pearl & Bates, 2022, Dickson et al., 2022, 2024).

Still, mathematical learnability investigations also suggest that fewer restrictions on children's hypothesis space may be necessary if in fact children's intake is not simply the direct positive evidence. For instance, acquisition success in a less-restricted hypothesis space is possible if children also get negative evidence (i.e., signals about what's not in the language) (Gold, 1967, Angluin, 1988b, Tîrnăucuă, 2008, Clark & Lappin, 2011). On the flip side, computational cognitive modeling investigations have suggested that helpful restrictions on the intake (i.e., learning only from a subset of the direct positive evidence) can lead to acquisition success, even within a less-restricted hypothesis space, just as some mathematical learnability investigations speculated (but didn't test at the time) (Gold, 1967, Heinz, 2016).

More specifically, if children filter out information present in the input – that is, their acquisitional intake ignores some of the positive evidence available – they can succeed at acquisition for several types of linguistic knowledge, including basic word order (Pearl, 2007, Pearl & Weinberg, 2007, Maitra & Perkins, 2023, Perkins & Hunter, 2023), English anaphoric *one* (Pearl, 2007, Pearl & Lidz, 2009), restrictions on *wh*-dependencies (Pearl & Sprouse, 2013a,b, 2015), passives (Nguyen & Pearl, 2019, 2021), and pronoun interpretation (Frank et al., 2013). This kind of filtering is particularly useful in realistic learning situations where noise is present, and children might be led astray if they naively tried to learn from all the available direct positive evidence. Interestingly, recent computational cognitive modeling work has suggested how children might learn what to filter out of their acquisitional intake, rather than needing to know specifically what to filter out beforehand (Perkins et al., 2022, Maitra & Perkins, 2023, Perkins & Hunter, 2023, Perkins et al., 2024). A key assumption is that children have "general-purpose" knowledge that some of the input signal is noise – not how much noise there is or what items are noise, but simply that there *is* noise that needs to be filtered out.

On the other hand, some investigations also find fewer restrictions on children's hypothesis space necessary if children's intake expands to include a broader set of information, rather than contracting to a subset of direct positive evidence (Pearl, 2023a). Here are some highlights from recent computational cognitive modeling investigations:

- Including data from all utterances in the language when learning about English yes/no questions like "Was the penguin who was on the iceberg eating a fish?" (Reali & Christiansen, 2005, Perfors et al., 2011, Abend et al., 2017, Fitz & Chang, 2017)

- Including data from all *wh*-dependencies when learning about the acceptability of specific *wh*-dependencies (Pearl & Sprouse, 2013a,b, Pearl, 2014, Pearl & Sprouse, 2015, Pearl, 2017, Bates & Pearl, 2019, Pearl & Bates, 2022, Dickson et al., 2022, 2024)
- Including data from other pronouns besides *one* when learning about English anaphoric *one* (Pearl & Mis, 2011, 2016)
- Including lexical semantic information when learning about the syntax of the English passive (Nguyen & Pearl, 2018, 2019, 2021)
- Including discourse information when learning about the syntax of English pronouns (Orita et al., 2013)

3.3 Update

We also have some insights about how children update their internal knowledge on the basis of their acquisitional intake – that is, in some sense, how the heart of "learning" operates. Notably, two insights about the update are tied to other aspects of the acquisition process. The first insight, coming from mathematical learnability, ties update to hypothesis space restrictions: being able to leverage probability information during update doesn't help with acquisition unless there are also restrictions on children's hypothesis space (Angluin, 1988a, Heinz, 2016). That is, being able to navigate a hypothesis space in a more sophisticated way (by leveraging available probabilistic information) doesn't help much if the hypothesis space isn't helpfully restricted in the first place.

A second insight comes from computational cognitive modeling work, and connects update to children's acquisitional intake. In particular, learning from data perceived as ambiguous is very helpful, rather than (waiting for and) only learning from data perceived as unambiguous (e.g., word order: Fodor 1998a,b, Sakas & Fodor 2001, Sakas & Nishimoto 2002, Yang 2002, 2004, Fodor & Sakas 2005, Fodor et al. 2007, Pearl 2007, Pearl & Weinberg 2007, Sakas & Fodor 2012, Yang 2012, Sakas 2016, Fodor 2017, Fodor & Sakas 2017; English anaphoric *one*: Pearl 2007, Foraker et al. 2009, Pearl 2009, Pearl & Mis 2011, 2016; optional infinitives: Legate & Yang 2007). To be sure, updating more confidently when the data are perceived as unambiguous is fine – but children likely also update even when the data are perceived as ambiguous, in order to learn what they do as quickly as they do. This seems especially true during the beginning of acquisition, when so much is uncertain and most data are likely perceived by children as ambiguous.

A third insight involves learning in the real world, where children's input naturally varies due to a variety of factors, including cultural background, birth order, family size, number of caretakers present, diversity of at-home vs. away-from-home experiences, and socioeconomic status, among many others. A recent finding from computational cognitive modeling suggests that at least some existing learning algorithms (which involve update on the basis of the acquisitional intake) are robust to naturalistic input variation (i.e., learning about constraints on *wh*-dependencies, given different socioeconomic status backgrounds: Bates & Pearl 2019, Pearl & Bates 2022).

3.4 Developing systems and knowledge

A final set of insights relates to children's developing cognitive systems and developing knowledge. Interestingly, a recent insight from LLM-based approaches is that there can be sudden leaps in internalized linguistic knowledge (as measured by performance on language tasks meant to assess internalized knowledge) *without* any internal systems overtly changing (Futrell & Mahowald, 2025). That is, learners who have very powerful learning mechanisms (the way LLMs do and children might) may show sudden improvements after plateauing for awhile. This sudden improvement is sometimes called "double descent" (Nakkiran et al., 2021) or "grokking" (Power et al., 2022), and occurs even though nothing internal has changed for the learner (i.e., increased memory, more accurate inference, etc.). Why this occurs is currently unclear, but the simple fact that it *can* occur suggests that children's cognitive systems supporting language acquisition may not need to change (e.g., a qualitative change due to maturation) in order for qualitative updates to occur in children's acquired knowledge. Instead, some internal magic happens after some crucial amount of data has been learned from, and this magic is not necessarily due to a change in the learner's developing linguistic and non-linguistic systems. Perhaps some internal reorganization of the linguistic or non-linguistic knowledge occurs that enables a sudden leap in acquisition performance – but we simply don't yet know what that change is and why it occurs. In short, the knowledge must develop, but the systems don't need to in order for that knowledge to develop.

On the flip side, sometimes it is in fact the internal systems that need to develop, and not the internal knowledge. More specifically, children's linguistic knowledge may already be the target knowledge (i.e., adult-like), but the systems that support children demonstrating that knowledge may still need to develop. Insights from computational cognitive modeling suggest that, in some cases, non-adult-like observable behavior is due to still-developing cognitive systems rather than still-developing linguistic knowledge (e.g., optional infinitives: Freudenthal et al. 2007, 2009, 2010, 2015, 2024; quantifier scope resolution: Savinelli et al. 2017, 2018, Scontras & Pearl 2021; pronoun interpretation: Forsythe & Pearl 2020, Pearl & Forsythe 2022)

4 Conclusion

To recap, our goal is to build an insightful, elegant theory of syntactic acquisition – that is, a useful abstraction that compactly explains the linguistic behavior we observe during acquisition. Such a theory will articulate the acquisition process by specifying the relevant factors and how they work together to generate the empirical data we have about language acquisition. Here I've tried to provide a sense of what we think those relevant factors might be and what we currently know about them, courtesy of formal approaches that use either mathematical learnability techniques or computational modeling techniques. These approaches allow us to precisely articulate a particular theory of the acquisition process (and especially the sometimes hidden assumptions that underlie a given theory). Of course, there seem to be quite a few factors that are relevant, and they interact with each other. Nonetheless, these approaches have yielded insights about the nature of (at least some of) these factors and their interactions, when it comes to explaining children's syntactic acquisition. By continuing to use these methods, we can hopefully gain more insights that allow us to build more complete theories of how children learn what they do as fast and as well as they do.

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