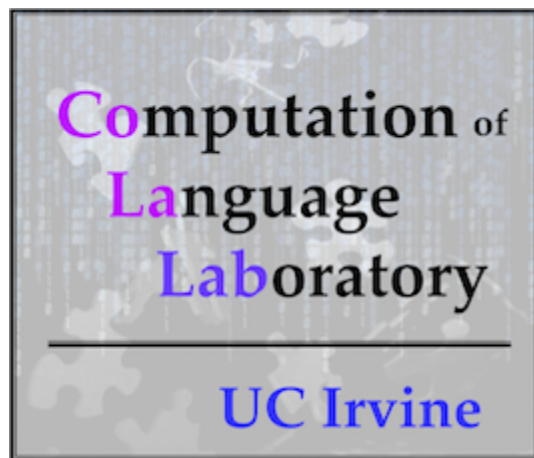


Computational models for language acquisition: Why, how, and what we can learn

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Simon Fraser University



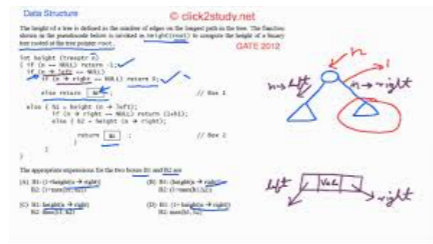
Today's Plan:

Computational models of language acquisition

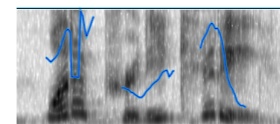
I. Why



II. How



III. What we can learn



Noun



Who does... is pretty?

another one

Every kitty didn't ...



Today's Plan:

Computational models of language acquisition

I. Why



Why language acquisition?

Babies are amazing at learning language



Babies are amazing at learning language



(C) 2013 Ryan North

www.qwantz.com

<http://www.qwantz.com/index.php?comic=2479>

Babies are amazing at learning language

Wait...what exactly do you know when you know a language?



Wait...what exactly do you know when you know a language?

A lot!



Wait...what exactly do you know when you know a language?

A lot!

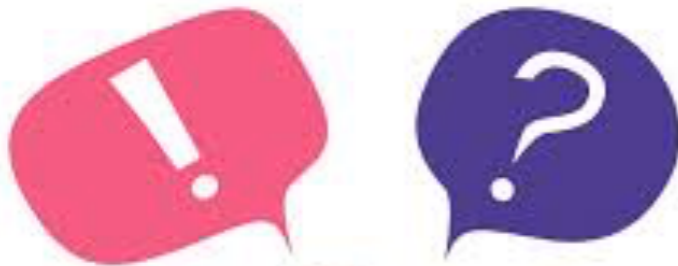
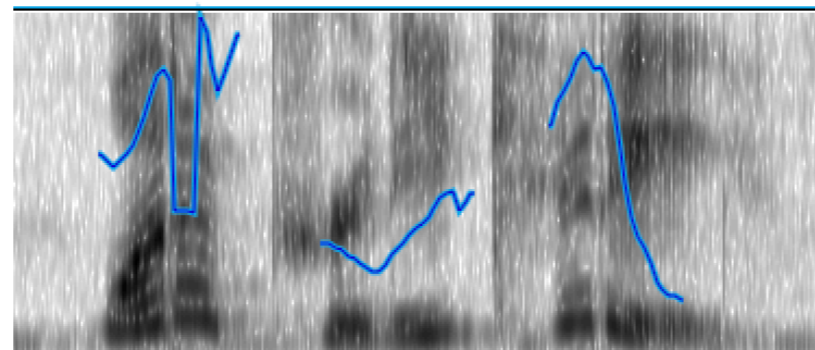
You know how to identify words in fluent speech (**speech segmentation**)



= wʌɹəprɪkɪɹi

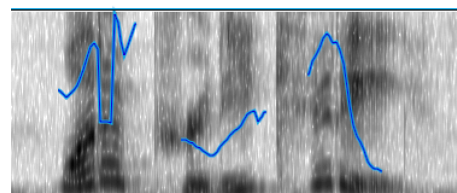
wʌɹ ə prɪɹi kɪɹi

what a pretty kitty!



Wait...what exactly do you know when you know a language?

A lot!



what a pretty kitty!

speech segmentation



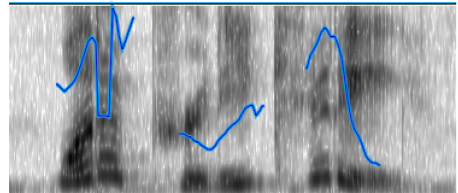
You know how to pronounce words (**metrical phonology**)

- ✓ KI tty
- ✗ ki TTY



Wait...what exactly do you know when you know a language?

A lot!



what a pretty kitty!

speech segmentation

✓ KI tty

✗ ki TTY

metrical phonology

You know that certain words behave like other words (syntactic categorization)

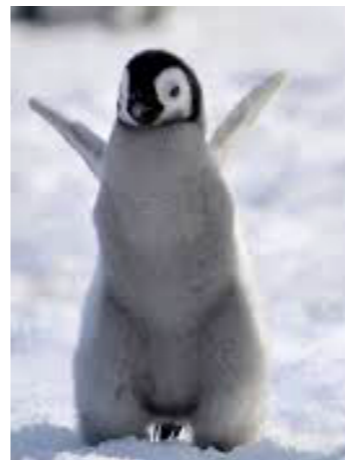
owl



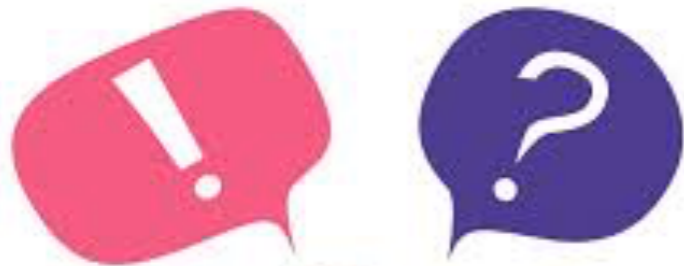
Noun

what a pretty ____!

penguin

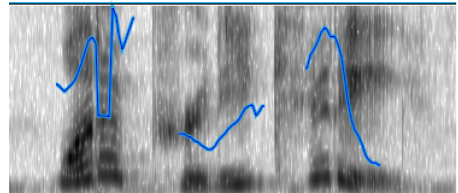


kitty



Wait...what exactly do you know when you know a language?

A lot!



what a pretty kitty!

speech segmentation

✓ KI tty
✗ ki TTY

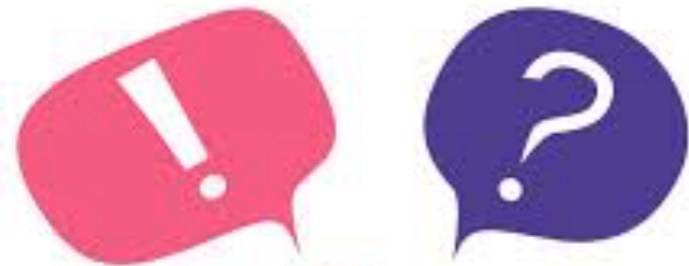
metrical phonology

Noun

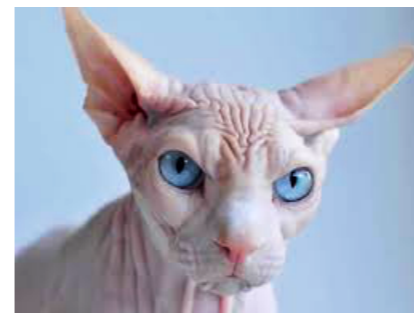
penguin owl
kitty

syntactic categorization

You know how to interpret words in context (syntax, semantics)

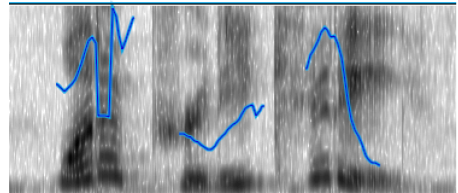


“Oh look — a pretty kitty!”
“Look — there’s another one!”



Wait...what exactly do you know when you know a language?

A lot!



what a pretty kitty!

speech segmentation

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metrical phonology

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penguin

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syntactic categorization

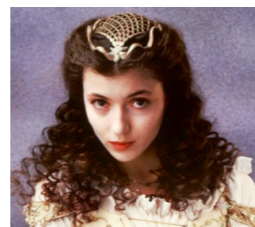
“Oh look — a pretty kitty!”
“Look — there’s another one!”

syntax, semantics



You know how to put words together to ask questions (syntax)

This kitty was bought as a present for someone.



Lily thinks this kitty is pretty.

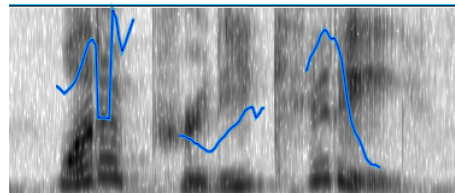


Who does Lily think the kitty for is pretty?



Wait...what exactly do you know when you know a language?

A lot!



what a pretty kitty!

speech segmentation

✓ KI tty

✗ ki TTY

metrical phonology

Noun

penguin

owl

kitty

syntactic categorization

Who does Lily think the kitty for is pretty?



syntax

“Oh look — a pretty kitty!”
“Look — there’s another one!”

syntax, semantics



You know how to identify the right interpretation in context (pragmatics)



“Every kitty didn’t sit on the stairs”

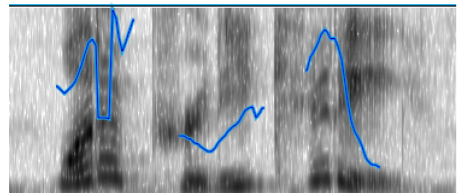
✗ No kitties sat on the stairs.

✓ Not all kitties sat on the stairs.



Wait...what exactly do you know when you know a language?

A lot!



what a pretty kitty!

speech segmentation

✓ KI tty

✗ ki TTY

metrical phonology

Noun

penguin

owl

kitty

syntactic categorization

Who does Lily think the kitty for is pretty?



syntax

“Oh look — a pretty kitty!”
“Look — there’s another **one!**”

syntax, semantics



“**Every** kitty didn’t sit on the stairs”

✓ **Not all** kitties sat on the stairs.

pragmatics



Wait...what exactly do you know when you know a language?

A lot!

metrical phonology

speech segmentation

syntactic categorization



syntax

pragmatics

syntax, semantics

So how exactly do children learn all this?

So how exactly do children learn all this?

We know they do it relatively quickly.

speech segmentation

metrical phonology

syntactic categorization

syntax

syntax, semantics

pragmatics

Much of the linguistic system is already known by **age 4**.



So how exactly do children learn all this?

They also don't seem to get a lot of **explicit instruction**. And when they do, they **don't really pay attention** to things that don't impact meaning.

(From Martin Braine)

Child: Want **other one spoon**, Daddy.

Father: You mean, you want **the other spoon**.

Child: Yes, I want **other one spoon**, please Daddy.

Father: Can you say "**the other spoon**"?

Child: **Other...one...spoon.**

Father: Say "**other**".

Child: Other.

Father: "**Spoon.**"

Child: Spoon.

Father: "**Other spoon.**"

Child: **Other...spoon. Now give me other one spoon?**



So how exactly do children learn all this?

They also don't seem to get a lot of **explicit instruction**. And when they do, they **don't really pay attention** to things that don't impact meaning.

What they're doing: **Extracting patterns** and **making generalizations** from the surrounding data mostly just by hearing examples of what's allowed in the language.



So how exactly do children learn all this?

What they're doing: **Extracting patterns** and **making generalizations** from the surrounding data mostly just by hearing examples of what's allowed in the language.

What's so hard about that?



So how exactly do children learn all this?

What's so hard about that?

There are often **many ways to generalize beyond the input**, and most of them aren't right.



???

“birdie”



“What a pretty **birdie!**”

So how exactly do children learn all this?

What's so hard about that?

There are often **many ways to generalize beyond the input**, and most of them aren't right.



???
“birdie”



“Look - a **birdie!**”

So how exactly do children learn all this?

What's so hard about that?

There are often **many ways to generalize beyond the input**, and most of them aren't right.



???
“birdie”



“Look at that **birdie!**”

So how exactly do children learn all this?

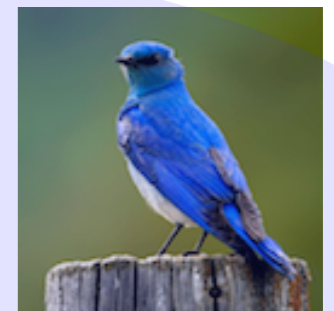
What's so hard about that?

There are often **many ways to generalize beyond the input**, and most of them aren't right.



How to generalize beyond the input?

???
"birdie"



So how exactly do children learn all this?

What's so hard about that?

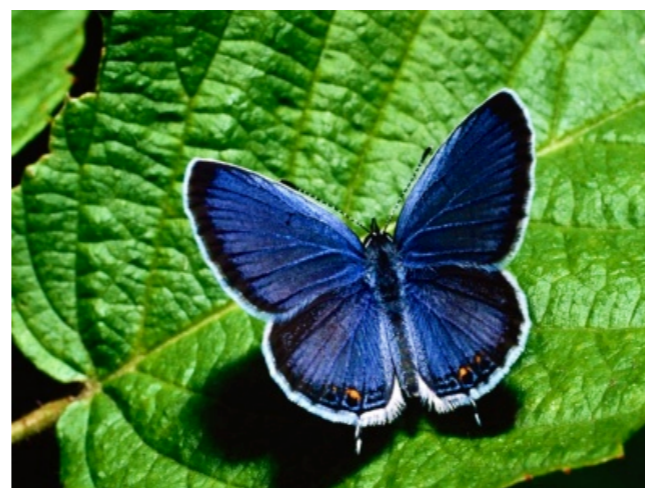
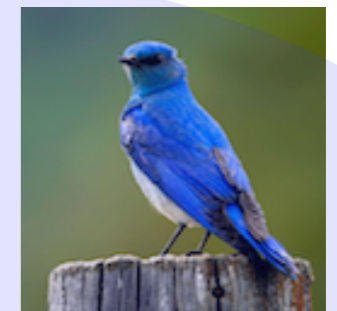
There are often **many ways to generalize beyond the input**, and most of them aren't right.



One hypothesis

+blue

“birdie”



So how exactly do children learn all this?

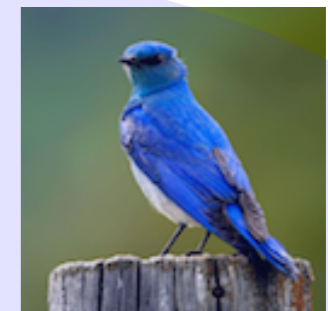
What's so hard about that?

There are often **many ways to generalize beyond the input**, and most of them aren't right.



Another hypothesis

+on branch
“birdie”



So how exactly do children learn all this?

What's so hard about that?

There are often **many ways to generalize beyond the input**, and most of them aren't right.

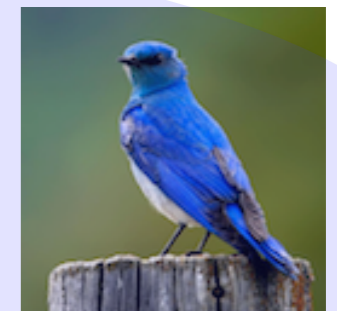


The right hypothesis



+bird

“birdie”



So how exactly do children learn all this?

What's so hard about that?

There are often **many ways to generalize beyond the input**, and most of them aren't right.



speech segmentation

metrical phonology

syntactic categorization

syntax

syntax, semantics

pragmatics

These kind of **induction problems** are everywhere in cognitive development, including language acquisition.

Language acquisition = Solving a lot of induction problems.

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We can also think about this as an **information processing task**.



Language acquisition = Solving a lot of induction problems.

We can also think about this as an **information processing task**.

Given the **available input**,



*Look at that kitty!
There's another one.*

Input

*Where did he hide?
What happened?*



Language acquisition = Solving a lot of induction problems.

We can also think about this as an **information processing task**.

Given the available input, **information processing done by human minds**



*Look at that kitty!
There's another one.*

Input

*Where did he hide?
What happened?*



Language acquisition = Solving a lot of induction problems.

We can also think about this as an **information processing task**.

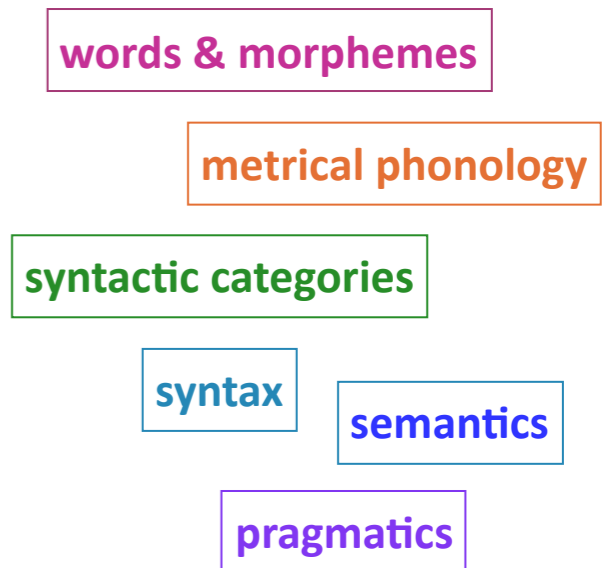
Given the available input, information processing done by human minds to build a **system of linguistic knowledge**



*Look at that kitty!
There's another one.*

Input

*Where did he hide?
What happened?*



Language acquisition = Solving a lot of induction problems.

We can also think about this as an **information processing task**.

Given the available input, information processing done by human minds to build a system of linguistic knowledge **whose output we observe**



*Look at that kitty!
There's another one.*

Input

*Where did he hide?
What happened?*



words & morphemes

metrical phonology

syntactic categories

syntax

semantics

pragmatics



*Where's the
kitty?*

*That one's
really cute.*



Language acquisition = Solving a lot of induction problems.

We can also think about this as an **information processing task**.

To understand how children solve the acquisition task, we need theories of representation and theories of development.



words & morphemes

metrical phonology

syntactic categories

syntax

semantics

pragmatics

*Look at that kitty!
There's another one.*

Input

*Where did he hide?
What happened?*

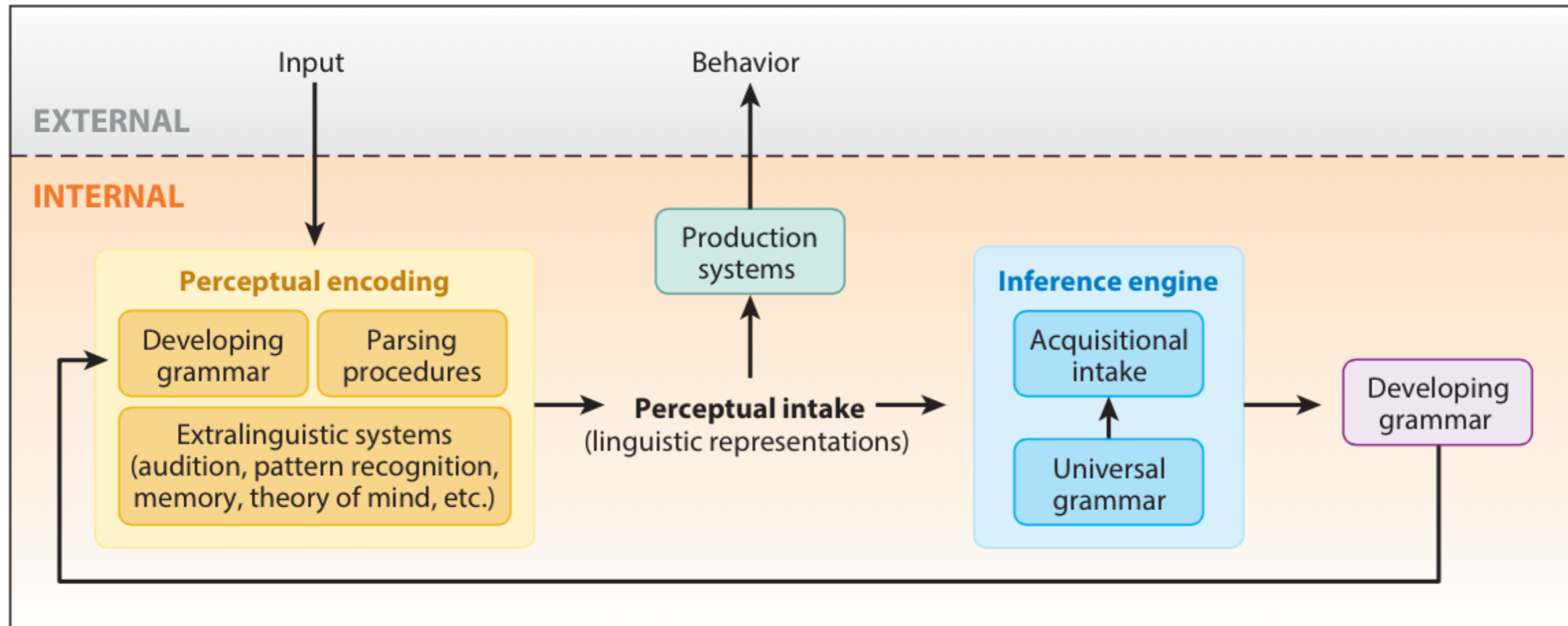


*Where's the
kitty?*

*That one's
really cute.*



Language acquisition = Solving a lot of induction problems.



Lidz & Gagliardi 2015



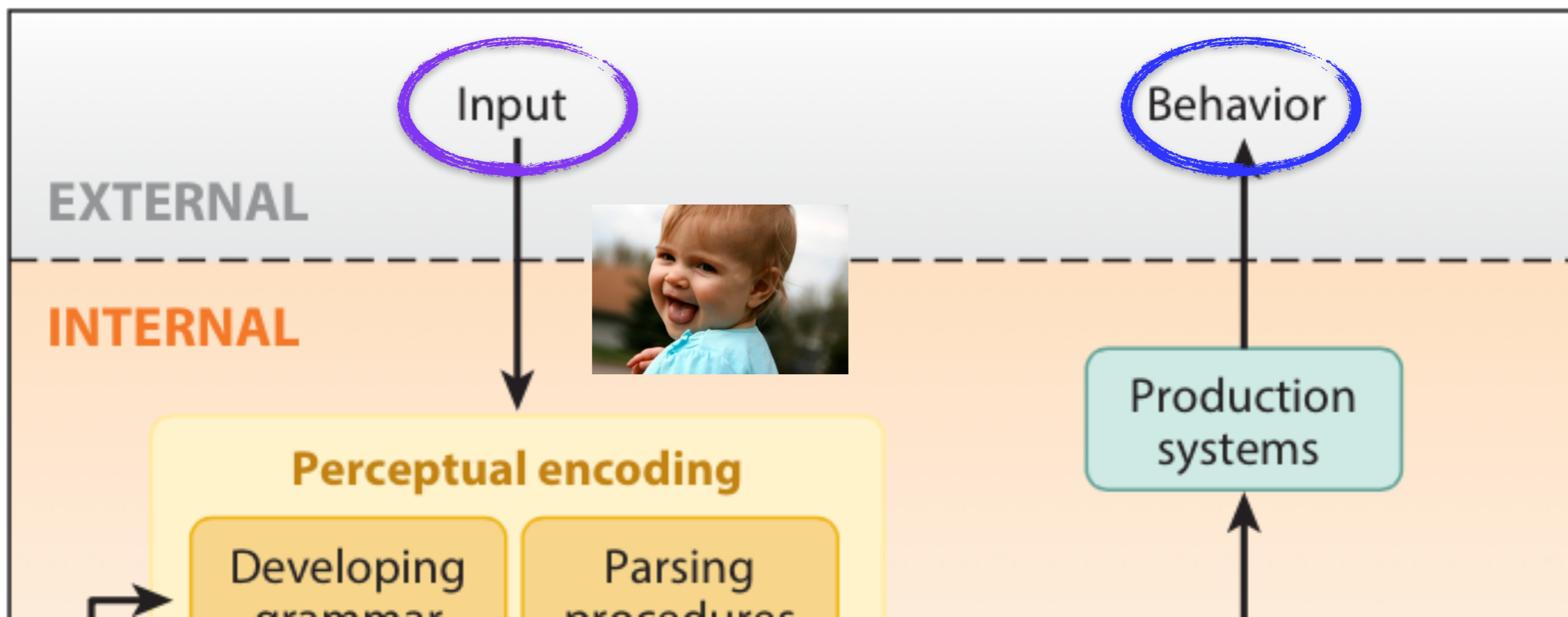
A framework that makes components of the acquisition task more explicit.

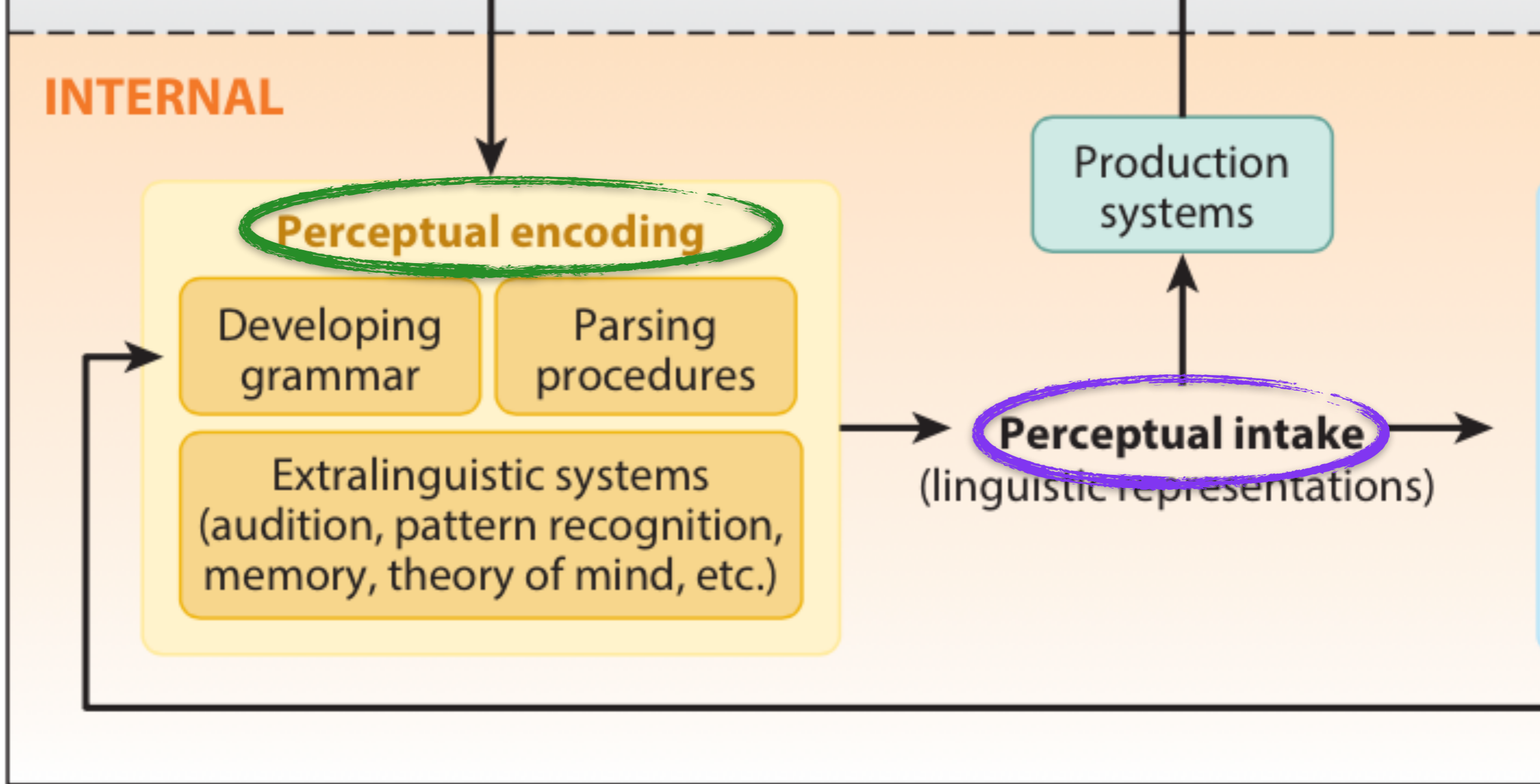
A framework that makes components of the acquisition task more explicit.

Distinguishes between things external to the child that we can observe (**input signal, child's behavior**) vs. things internal to the child (everything else).

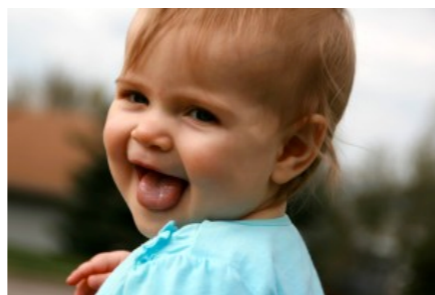
**Experimental &
Corpus methods**

Experimental methods



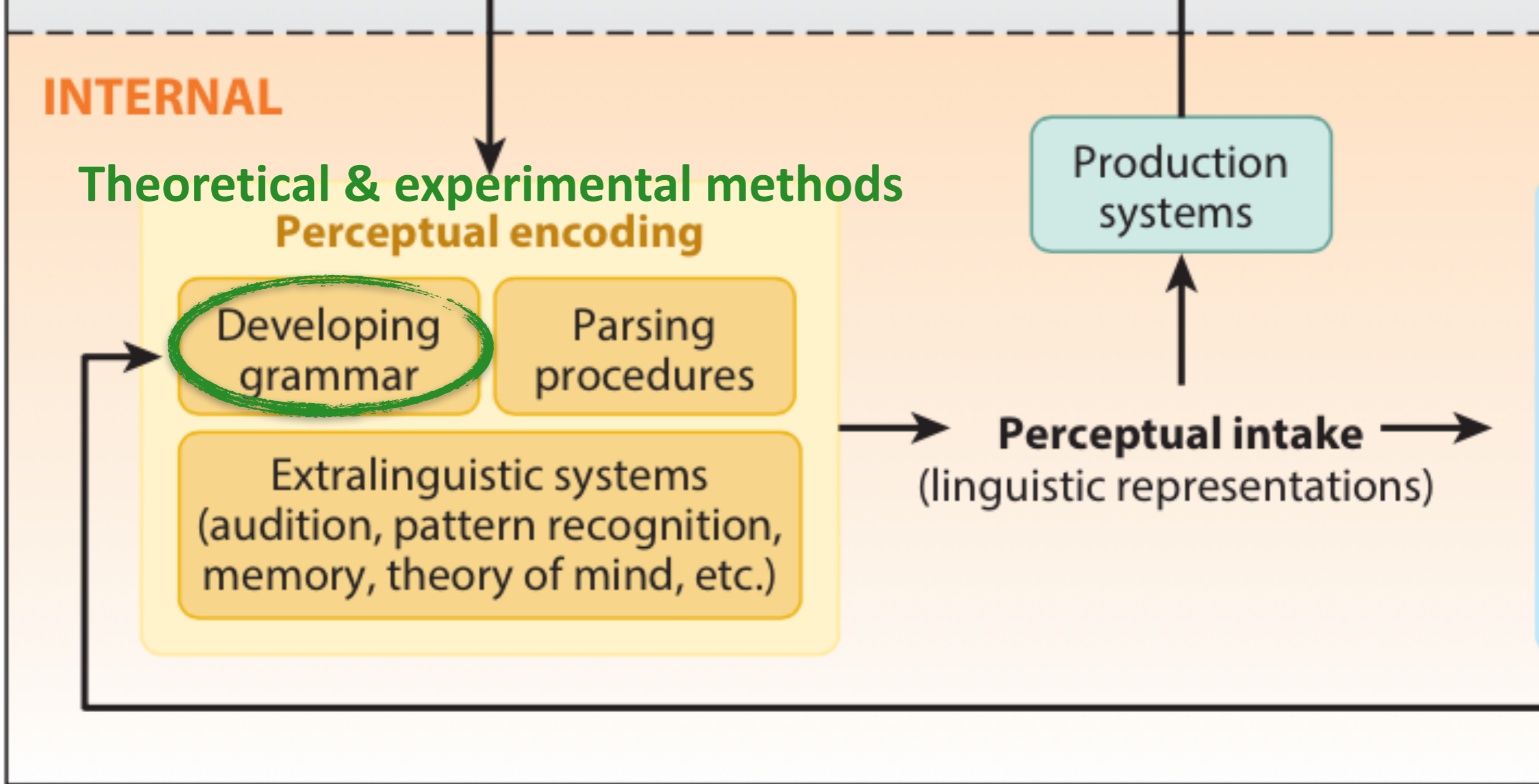


Lidz & Gagliardi 2015



Perceptual encoding:

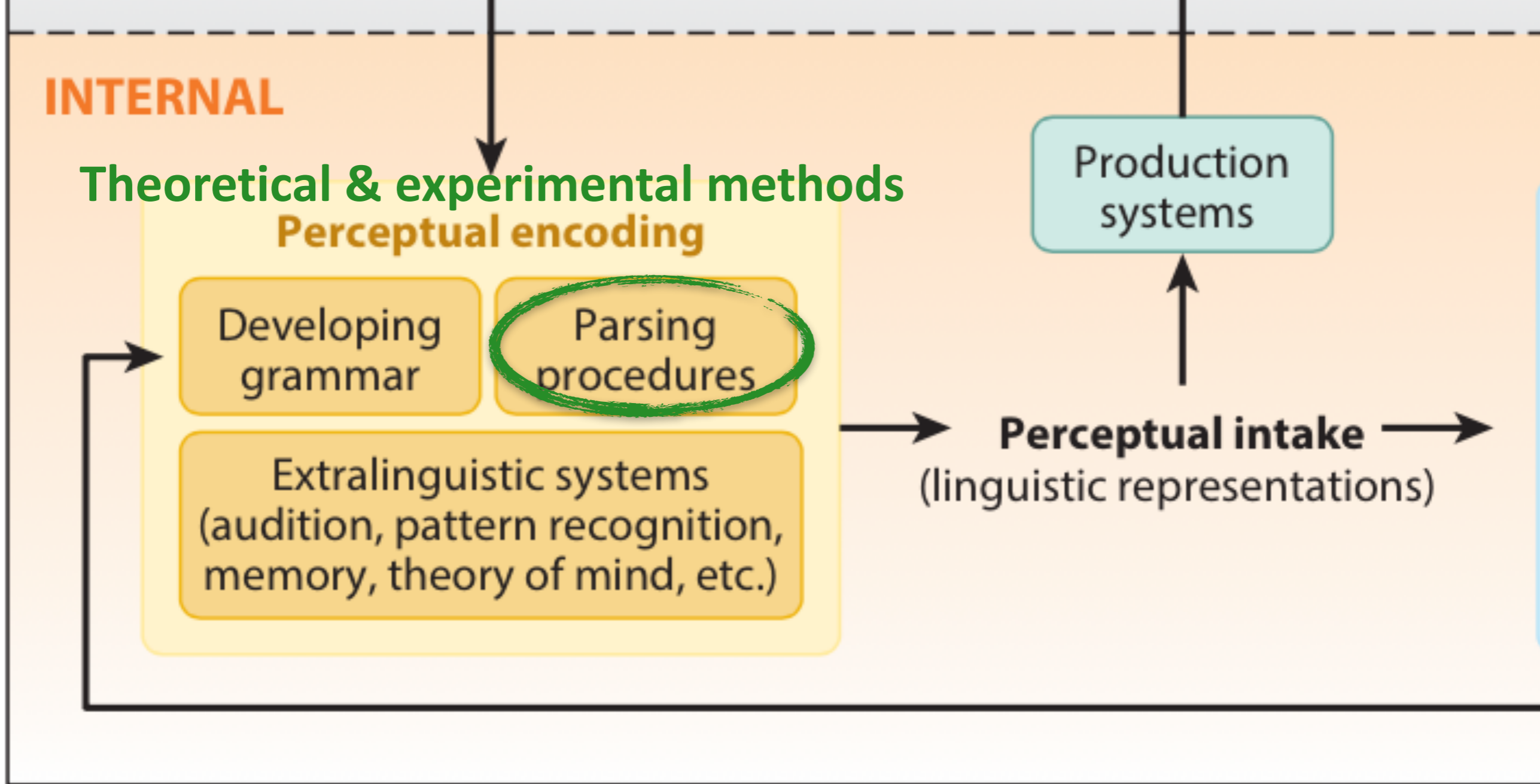
Turning the input signal into an internal linguistic representation = **perceptual intake**.



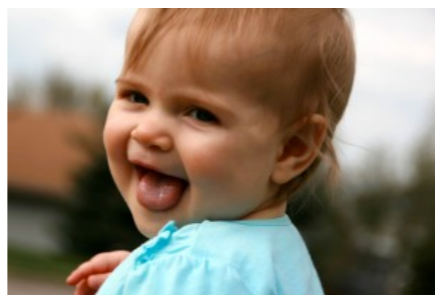
Lidz & Gagliardi 2015



Perceptual encoding:
Involves **current grammar**

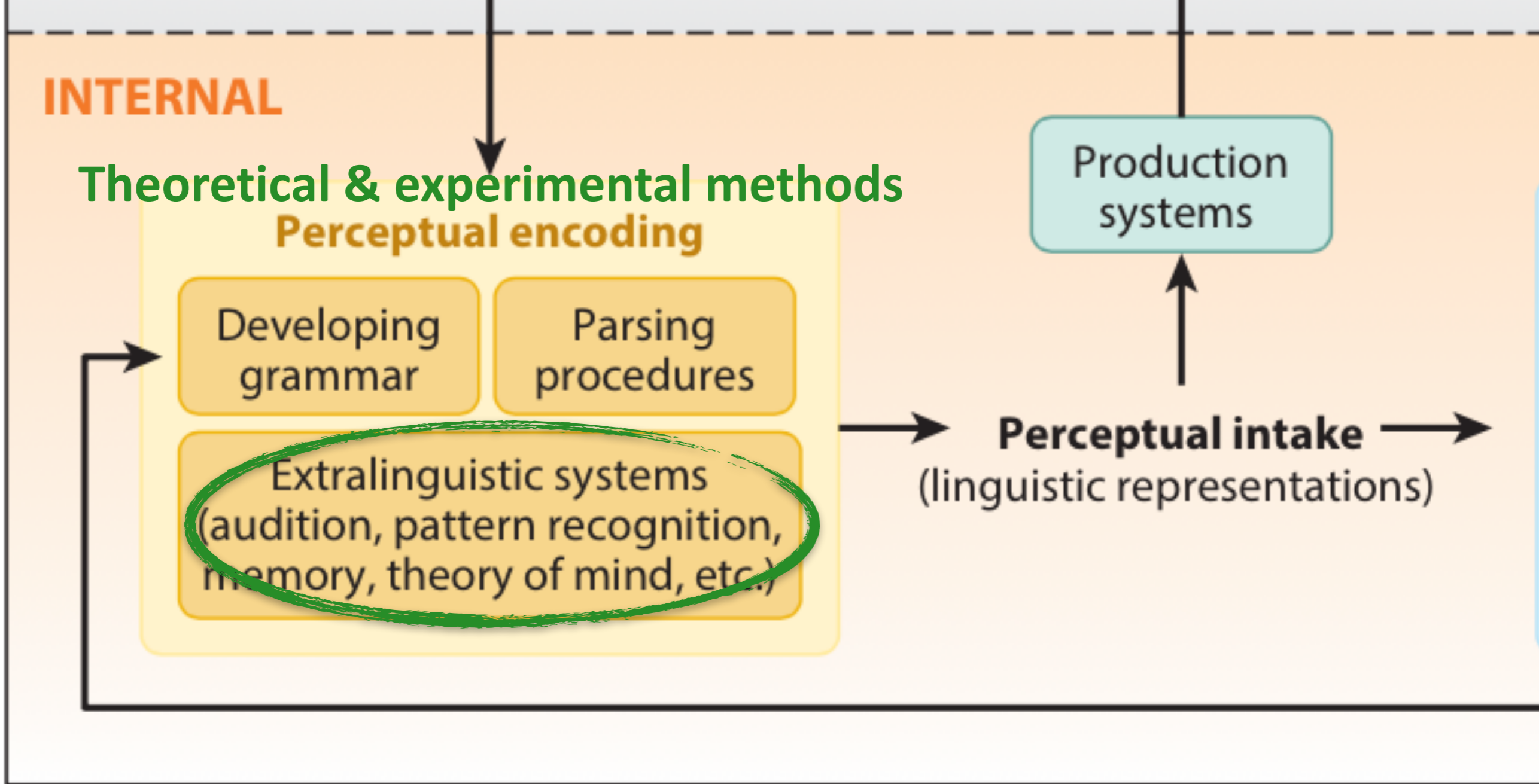


Lidz & Gagliardi 2015



Perceptual encoding:

Involves current grammar being **deployed in real time to parse** the input

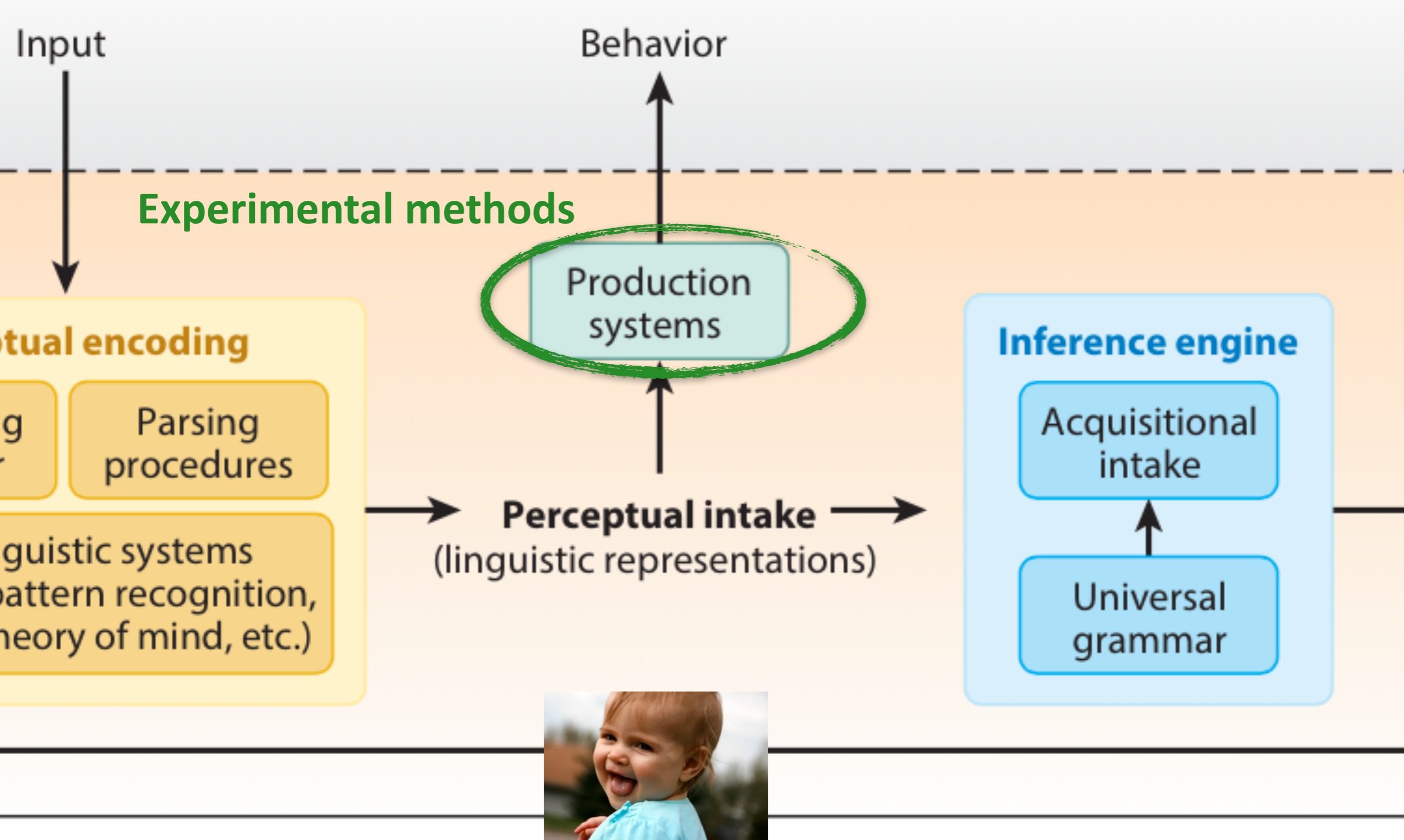


Lidz & Gagliardi 2015



Perceptual encoding:

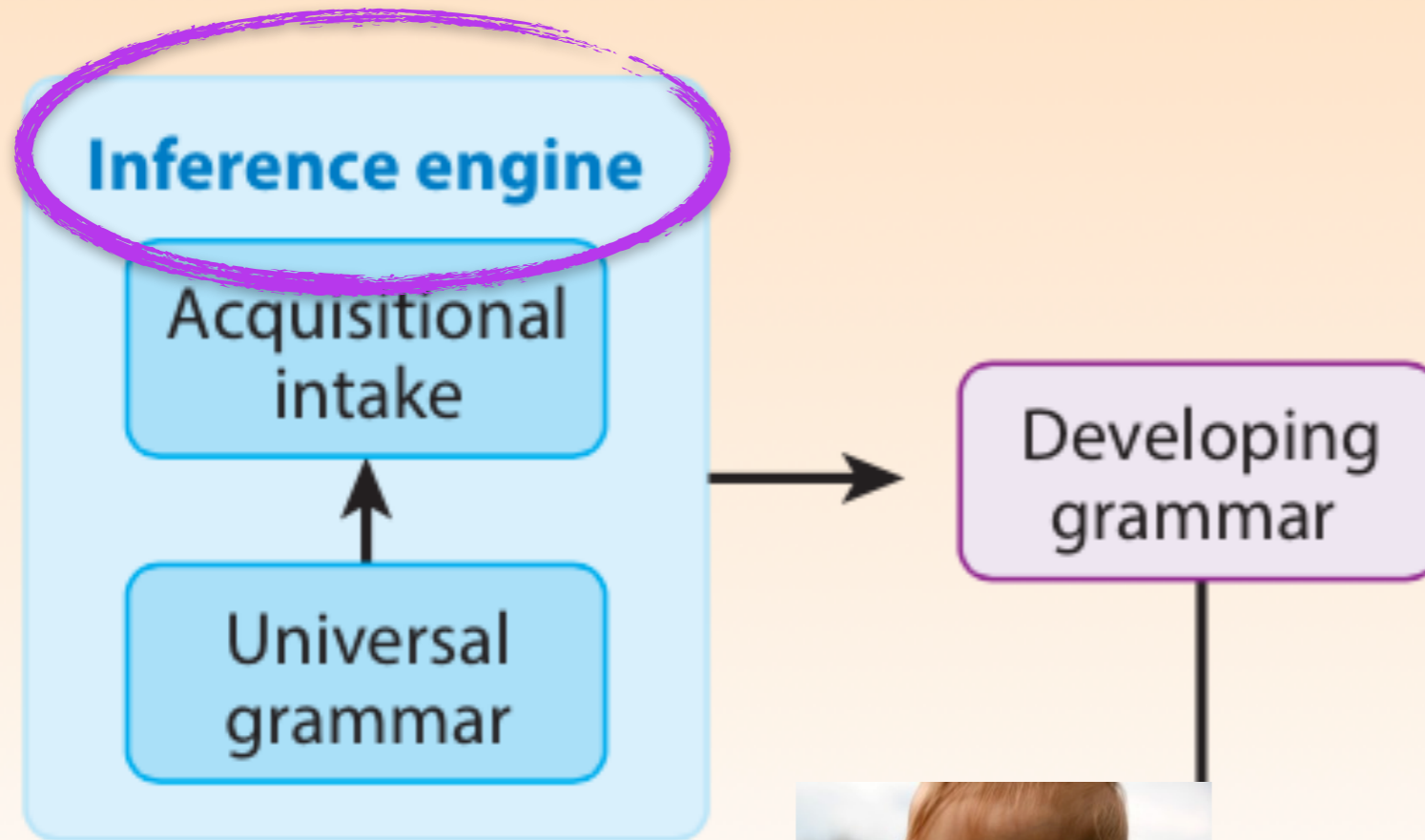
Involves current grammar being deployed in real time to parse the input often drawing on **extralinguistic systems**



Generating observable **behavior**

Involves current linguistic representations being used by **production systems**.

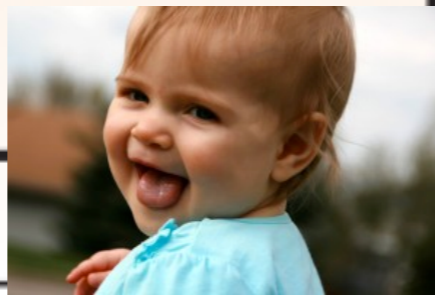
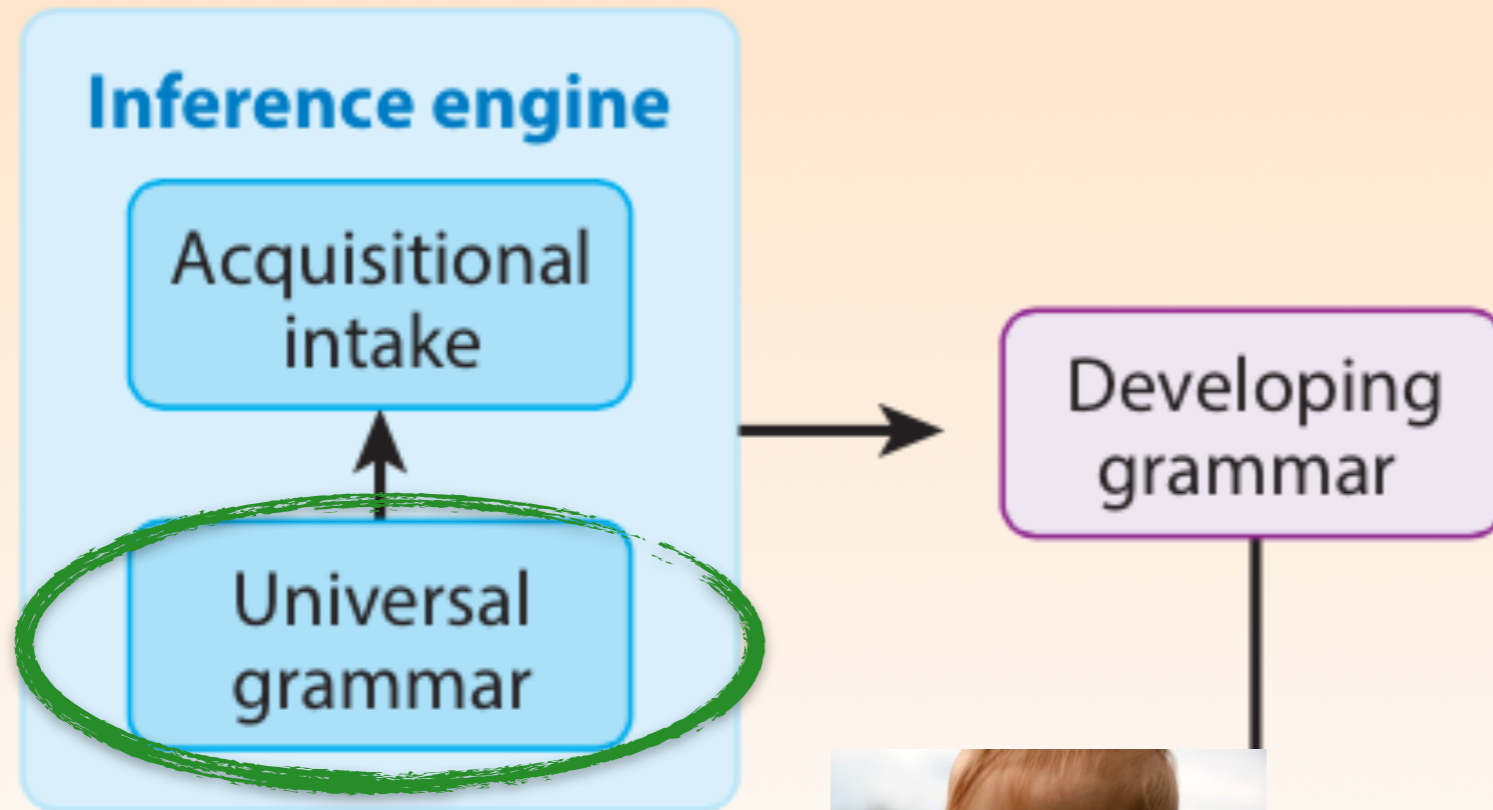
Experimental & computational methods



Doing **inference**

Generalization happens

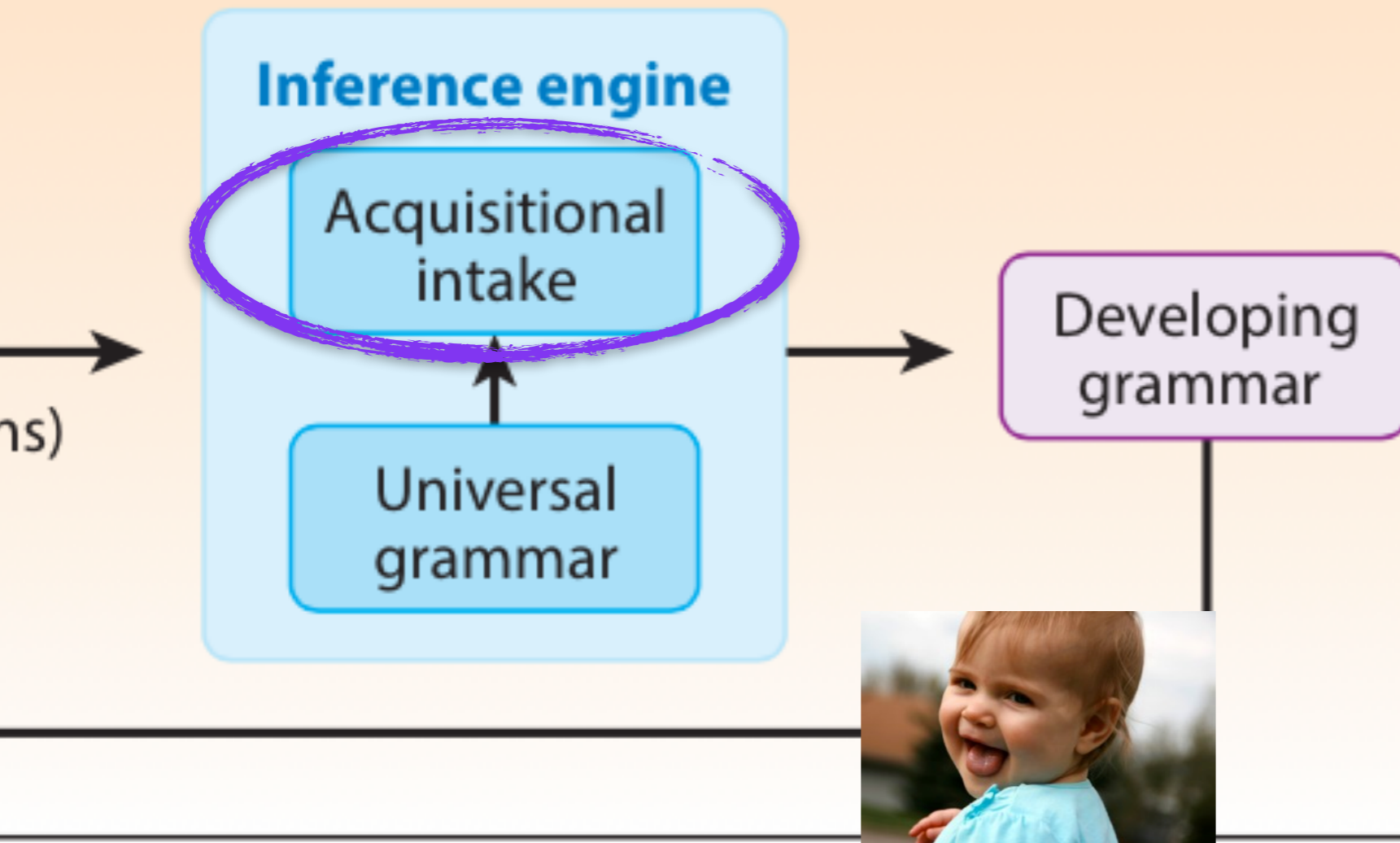
Theoretical & computational methods



Doing inference

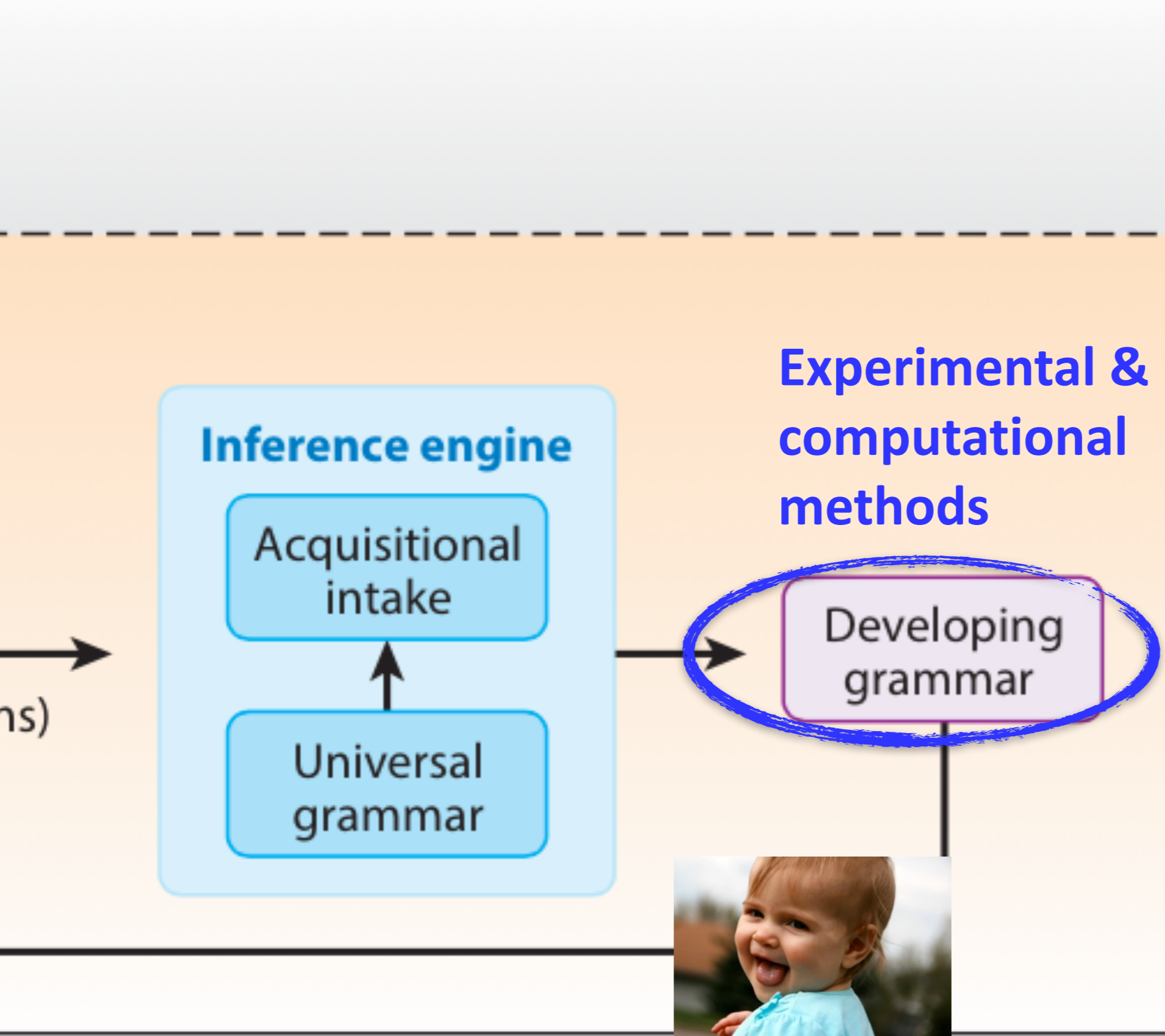
Generalization happens by using **existing learning biases**, (some of which may be innate and language-specific)

Theoretical & computational methods



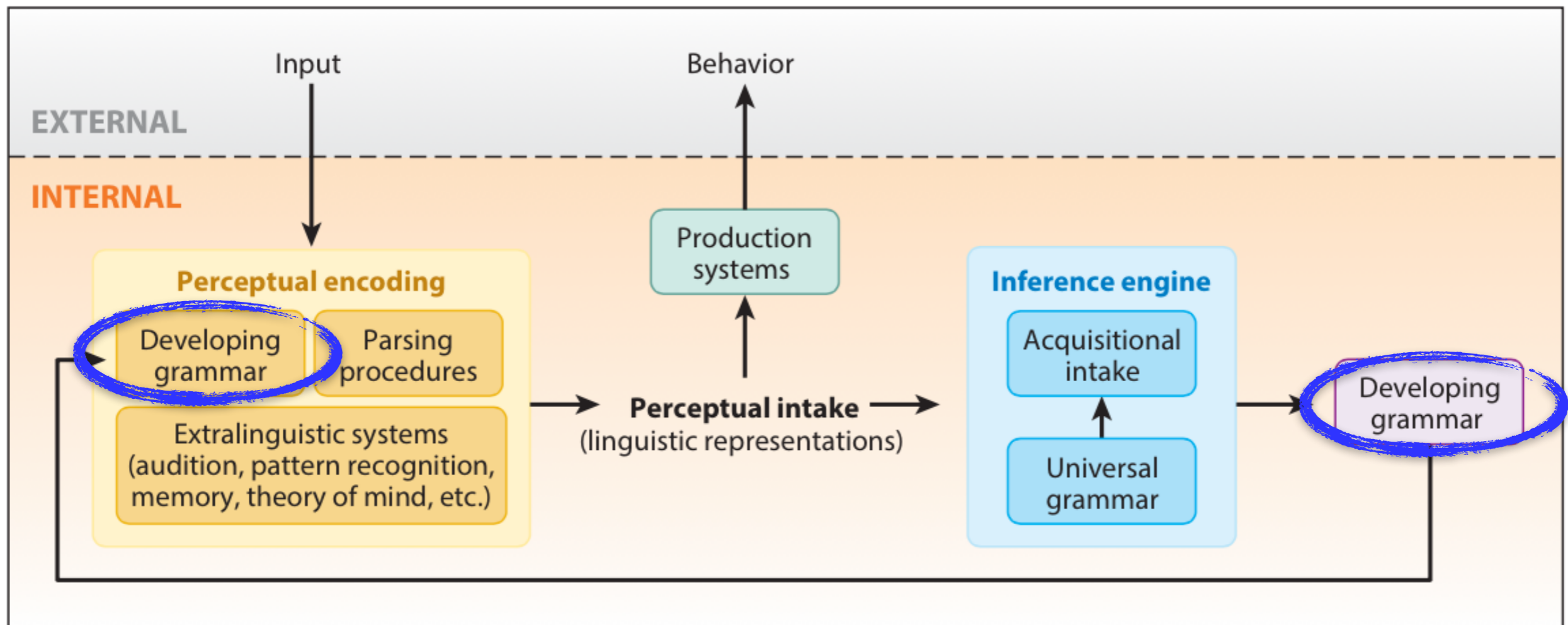
Doing inference

Generalization happens by using existing learning biases, (some of which may be innate and language-specific) operating over the **acquisitional intake** — what's perceived as relevant for acquisition

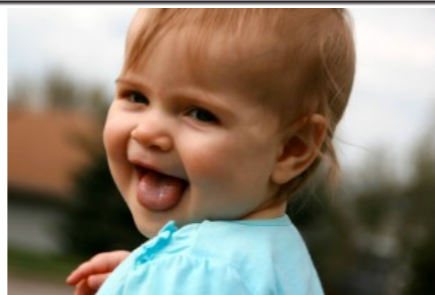


Doing inference

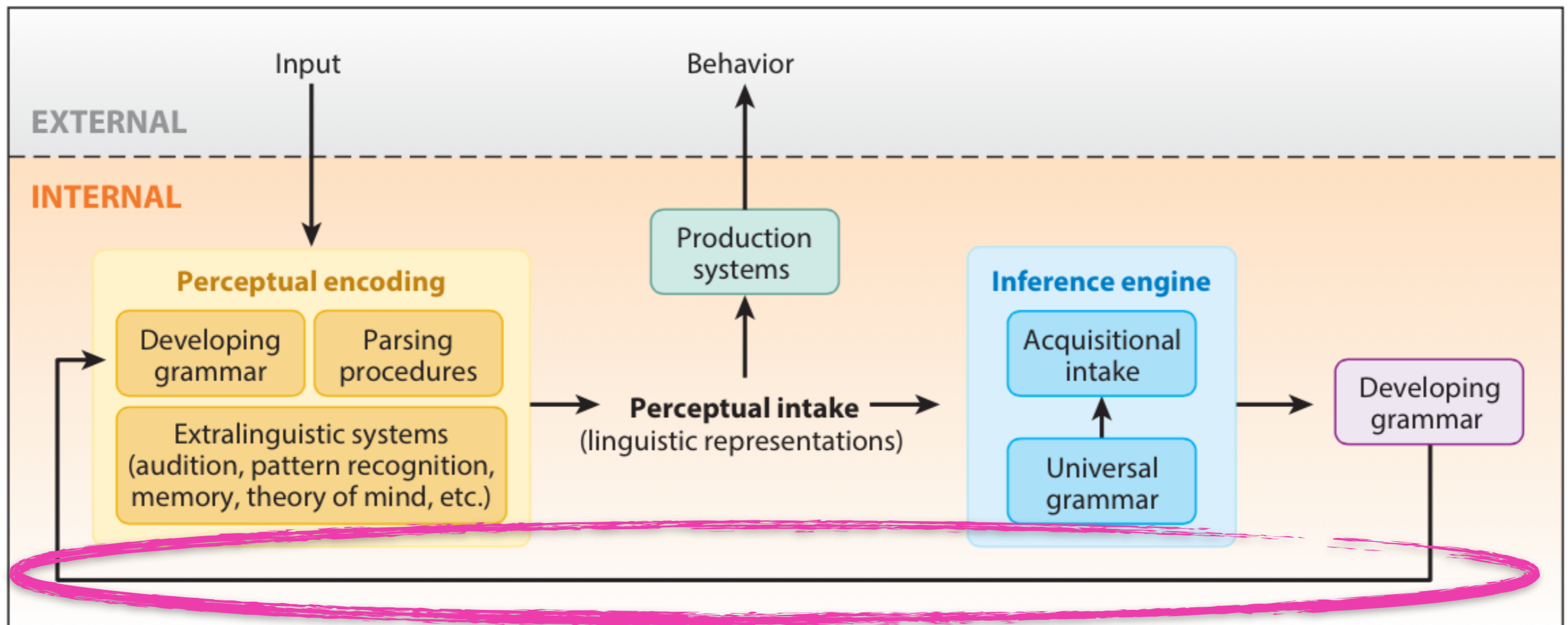
Generalization happens by using existing learning biases, (some of which may be innate and language-specific) operating over the acquisitional intake — what's perceived as relevant for acquisition to produce the most **up-to-date hypotheses** about linguistic knowledge



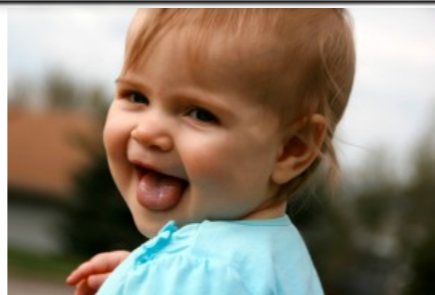
Lidz & Gagliardi 2015



The current linguistic hypotheses are
used in subsequent perceptual encoding



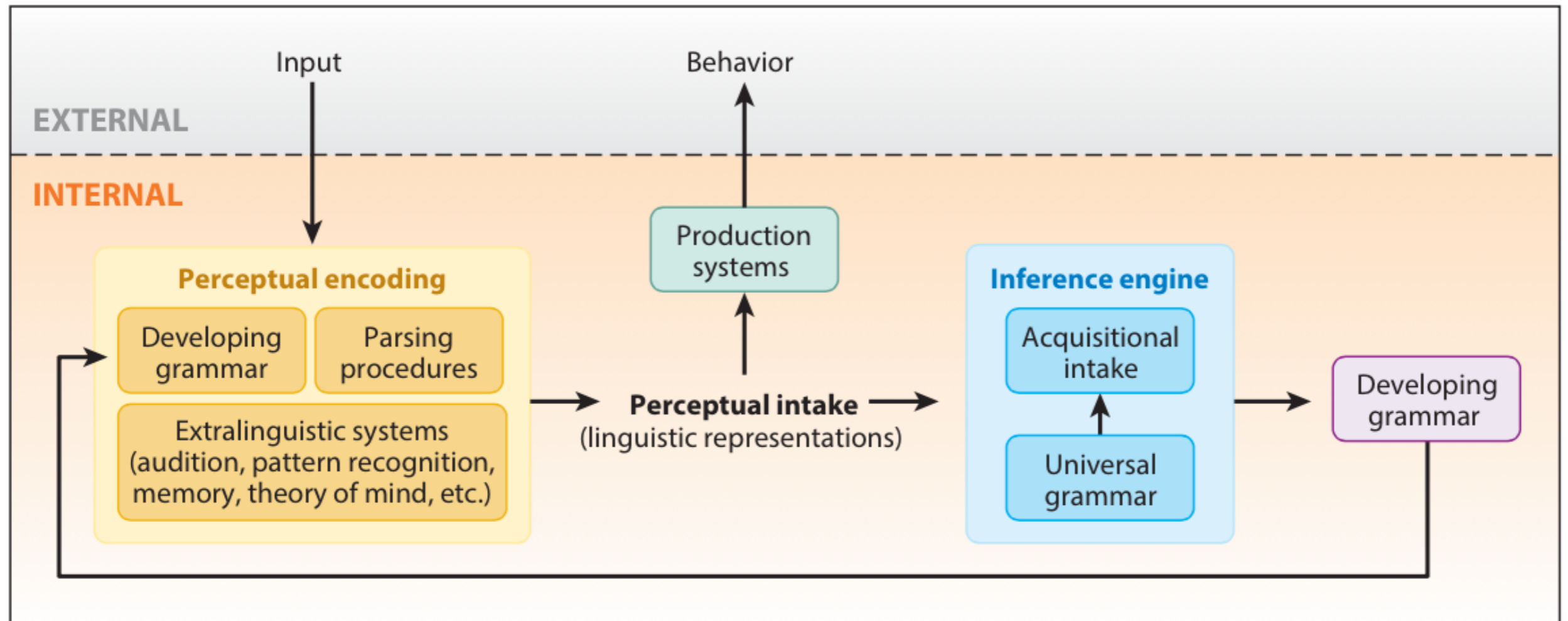
Lidz & Gagliardi 2015



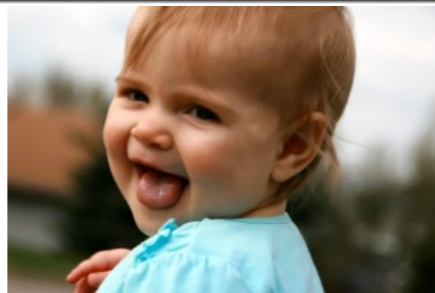
Experimental methods

This whole process happens over and over again throughout the **learning period**

This is language acquisition



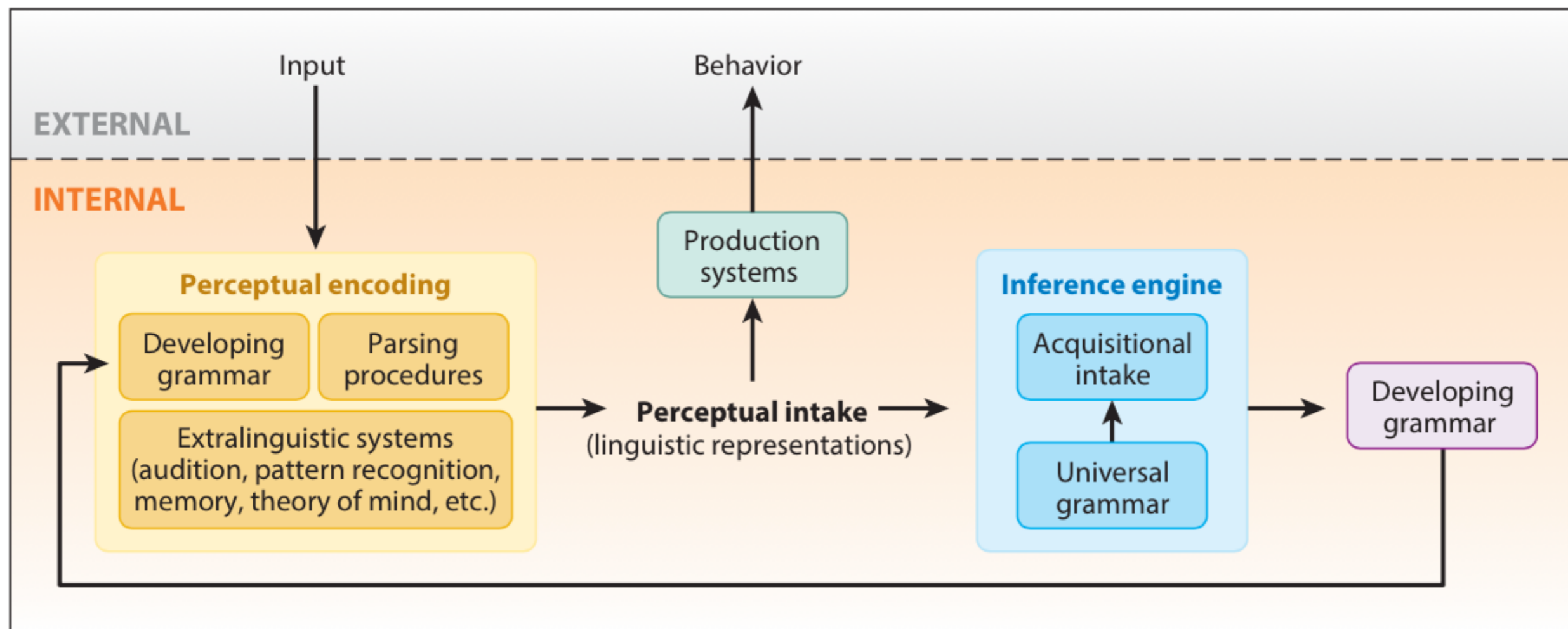
Lidz & Gagliardi 2015



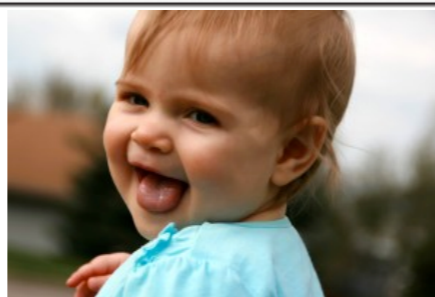
Corpus Experimental
Theoretical Computational

An informative computational model of language acquisition captures these important pieces in an **empirically-grounded** way.

This is language acquisition ...which involves solving induction problems



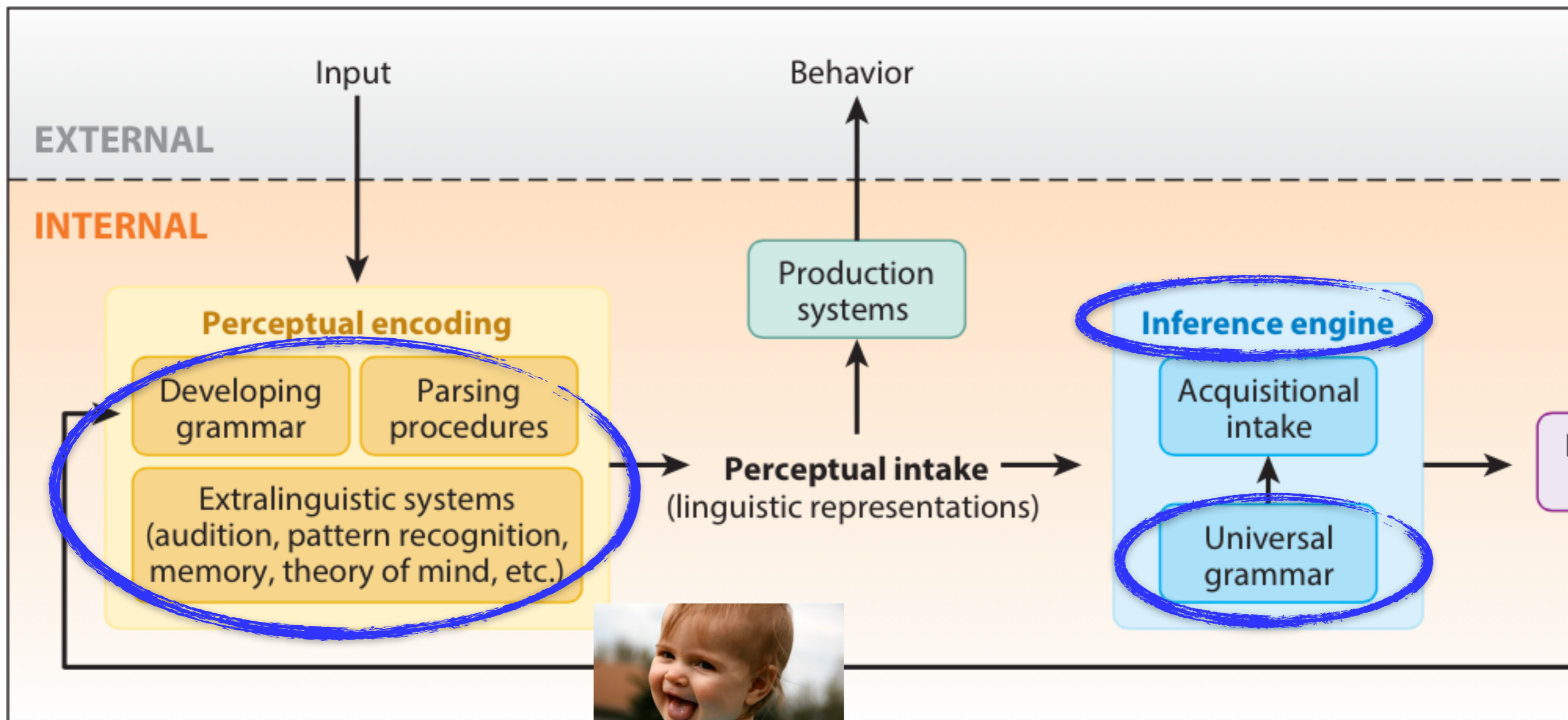
Lidz & Gagliardi 2015



Informative computational models = informative about
the learning strategies children use to solve **induction problems**

Learning strategies children use to solve induction problems

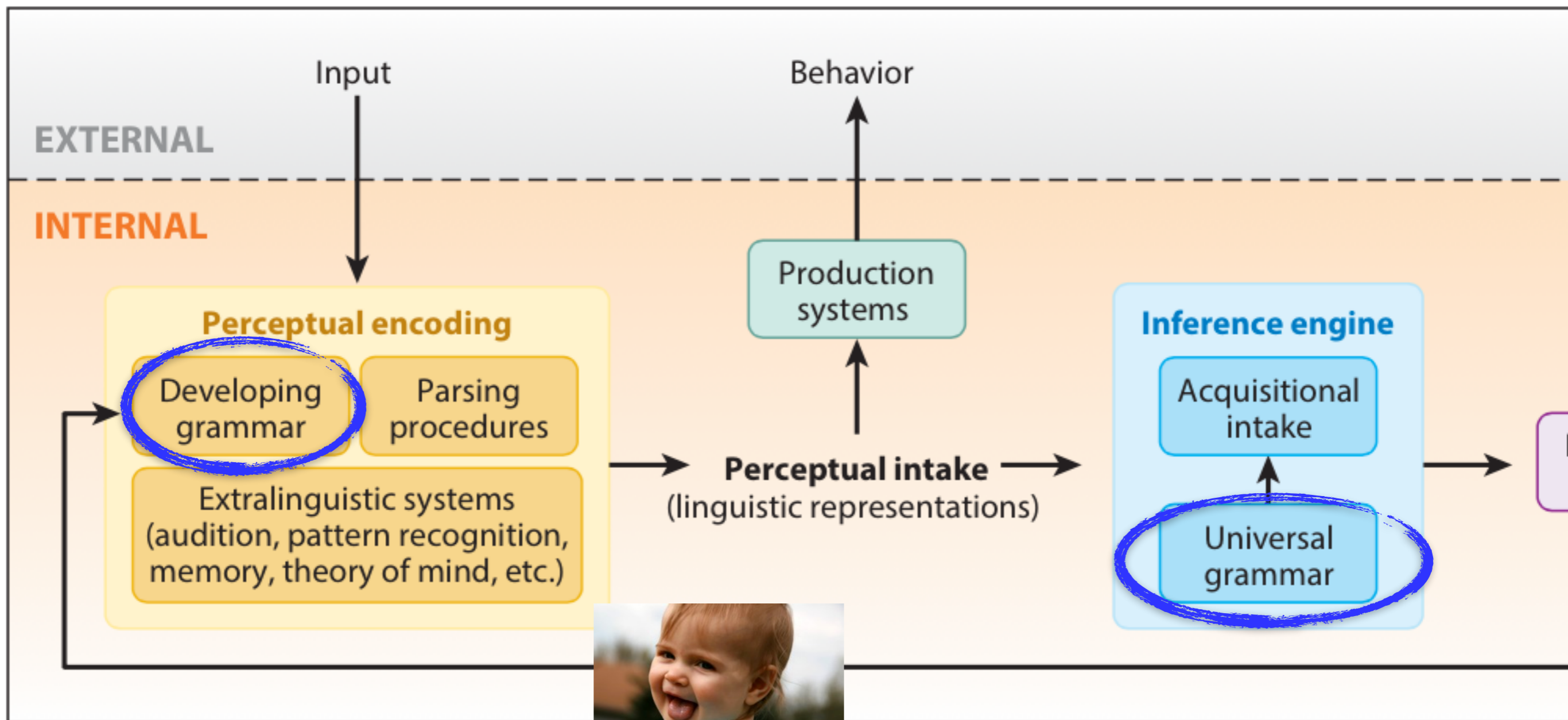
A successful learning strategy is an existence proof that linguistic knowledge is attainable using the knowledge, learning biases, and capabilities comprising that strategy.



Learning strategies children use to solve induction problems

Important learning strategy components include

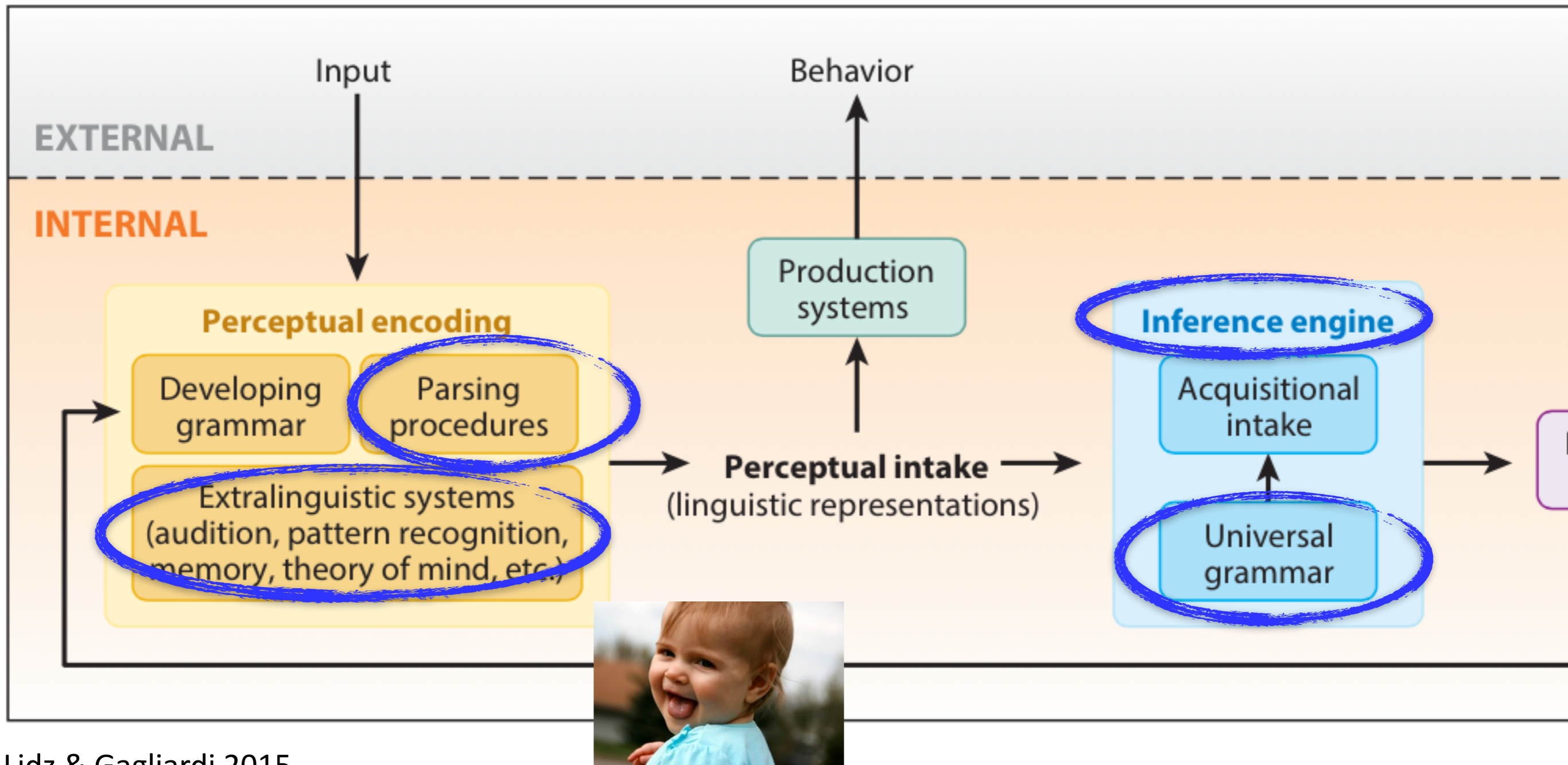
- knowledge (= theories of **representation**)



Learning strategies children use to solve induction problems

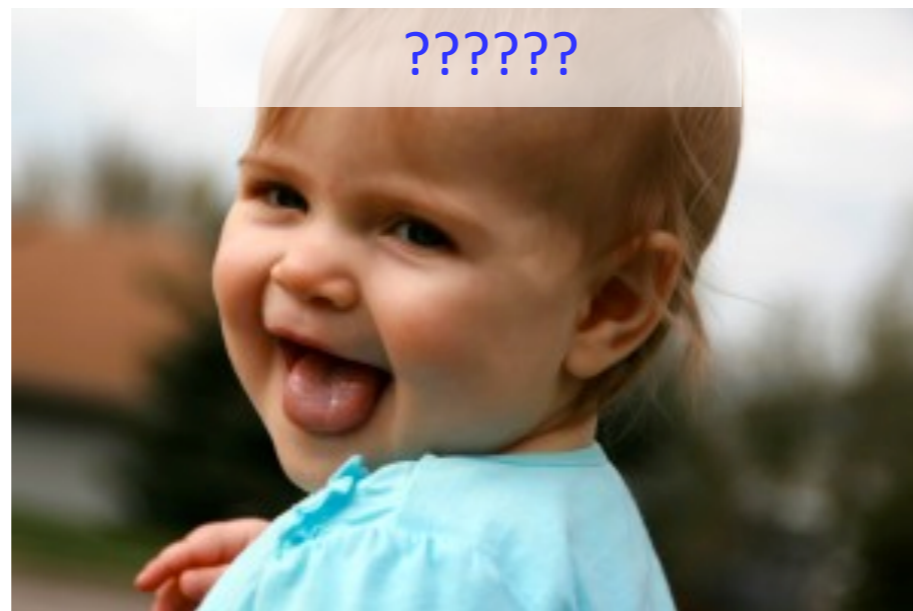
Important learning strategy components include

- knowledge (= theories of **representation**)
- biases & capabilities that must exist for that knowledge to be successfully deployed during acquisition (= theories of the **learning process**).



Learning strategies children use to solve **induction problems**

And this is what we really want to know about!



And this is what we really want to know about!



Which learning strategies could children be using?

(Pearl in press, Phillips & Pearl in press, Bar-Sever & Pearl 2016, Phillips & Pearl 2015a, 2015b, 2014a, 2014b, 2012; Pearl 2014, Pearl et al. 2011, Pearl et al. 2010)

And this is what we really want to know about!



Which learning strategies could children be using?

Which learning biases are necessary?

(Pearl, Ho, & Detrano in press, 2014; Pearl & Mis 2016, Pearl & Sprouse 2015, 2013a, 2013b, Pearl & Mis 2011, Pearl & Lidz 2009, Pearl 2008, Pearl & Weinberg 2007)

And this is what we really want to know about!



Which learning strategies could children be using?

Which learning biases are necessary?

Which knowledge representations are learnable — and which aren't?

(Pearl, Ho, & Detrano in press, 2014; Pearl in press, Pearl 2011, Pearl 2009)

And this is what we really want to know about!



Which learning strategies could children be using?

Which learning biases are necessary?

Which knowledge representations are learnable — and which aren't?

When do children learn different aspects of the linguistic system?

(Nguyen & Pearl in prep., Bates, Pearl, & Braunwald in prep., Caponigro, Pearl et al. 2012, Caponigro, Pearl et al. 2011)

And this is what we really want to know about!



Which learning strategies could children be using?

Which learning biases are necessary?

Which knowledge representations are learnable — and which aren't?

When do children learn different aspects of the linguistic system?

What factors affect children's observable behavior?

(Nguyen & Pearl in prep., Savinelli, Scontras, & Pearl 2017)

And this is what we really want to know about!



Which learning strategies could children be using?

Which learning biases are necessary?

Which knowledge representations are learnable — and which aren't?

When do children learn different aspects of the linguistic system?

What factors affect children's observable behavior?

Why we do computational modeling: It can help us find out!



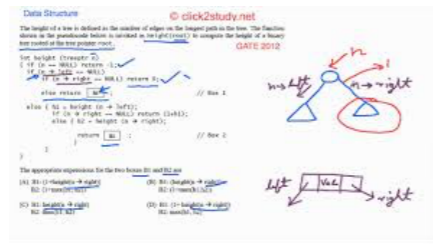
Today's Plan:

Computational models of language acquisition

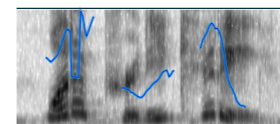
I. Why



II. How



III. What we can learn



Noun



Who does... is pretty?

✓ KI tty

another one

Every kitty didn't ...



Today's Plan:

Computational models of language acquisition

II. How

Data Structure © click2study.net

The height of a tree is defined as the number of edges on the longest path to its leaf. The function shown in the pseudocode below is invoked as `height(root)` to compute the height of a binary tree rooted at the tree pointer `root`.

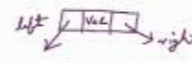
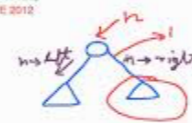
```
int height (TreeNode T)
{
  if (T == NULL) return -1;
  if (T == NULL) return -1;
  if (T->left == NULL) return 0;
  else return 1 + height(T->left); // Max 1
}

int height (TreeNode T)
{
  if (T == NULL) return -1;
  if (T->left == NULL) return 0;
  else {
    int h1 = height(T->left);
    int h2 = height(T->right);
    return 1 + max(h1, h2); // Max 2
  }
}
```

The appropriate responses for the two boxes B1 and B2 are

(A) B1: <code>height(T->right)</code>	(B) B1: <code>height(T->right)</code>
(C) B1: <code>height(T->right)</code>	(D) B1: <code>height(T->right)</code>

GATE 2012



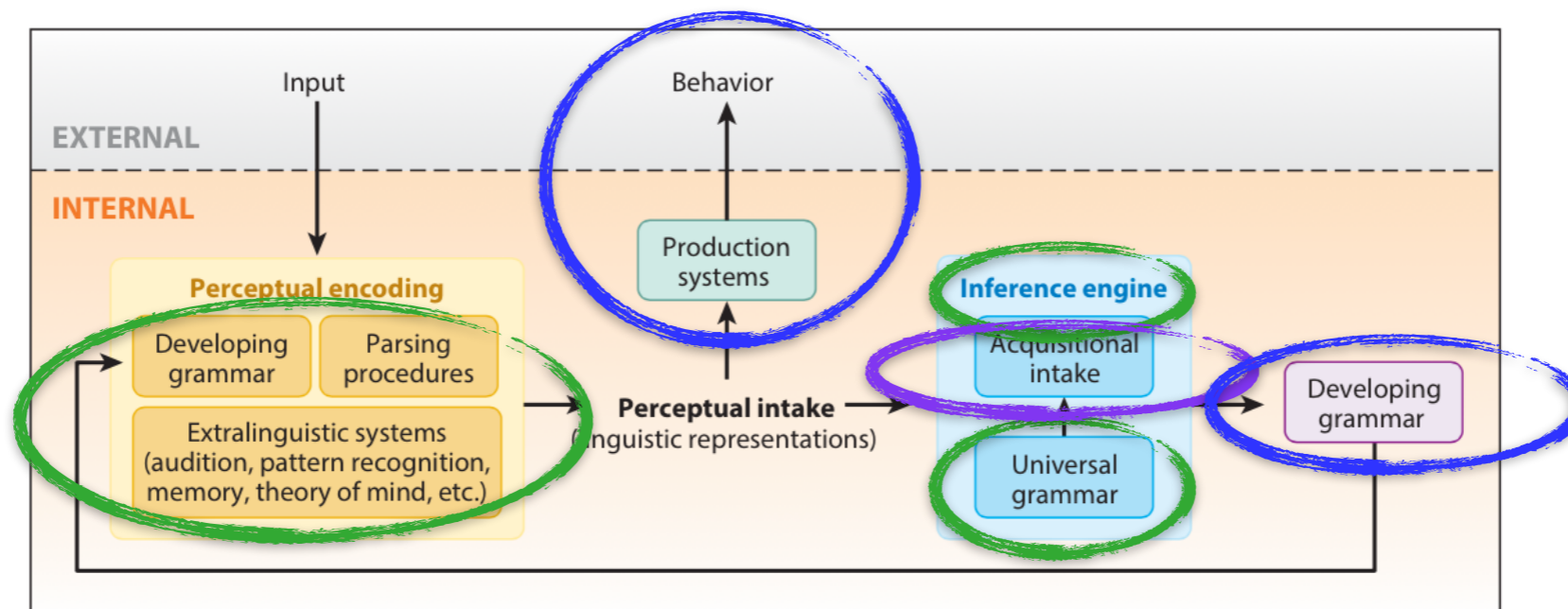
How do we model language acquisition?



What **level** of model do you want to build?

A **very basic** question:

Is it possible for the child with a **specific initial state** to use the **acquisitional intake** to achieve the **target state**?



Lidz & Gagliardi 2015

Computational-level (Marr 1982)

Is this the right conceptualization of the acquisition task? Do we have the right goal in mind?

How do we model language acquisition?

What **level** of model do you want to build?

Computational-level

A **very basic** question:

Is it possible for the child with a **specific initial state** to use the **acquisitional intake** to achieve the **target state**?

Helpful for determining **if this implementation of the acquisition task is the right one.**

Are these **useful** learning assumptions for children to have? Are these **useful** linguistic representations?



How do we model language acquisition?

What **level** of model do you want to build?

Computational-level

A **very basic** question:

Is it possible for the child with a **specific initial state** to use the **acquisitional intake** to achieve the **target state**?

This is typically implemented as an **ideal learner model**, which isn't concerned with the cognitive limitations and incremental learning restrictions children have.

(That is, **useful** for children is different from **useable** by children in real life.)



How do we model language acquisition?

What **level** of model do you want to build?

Computational-level

A **very basic** question:

Is it possible for the child with a **specific initial state** to use the **acquisitional intake** to achieve the **target state**?



Practical note:

Doing a computational-level analysis is often a really good idea to make sure we've got the right conceptualization of the acquisition task (see Pearl 2011 for the trouble you can get into when you don't do this first).



How do we model language acquisition?

What **level** of model do you want to build?

Computational-level

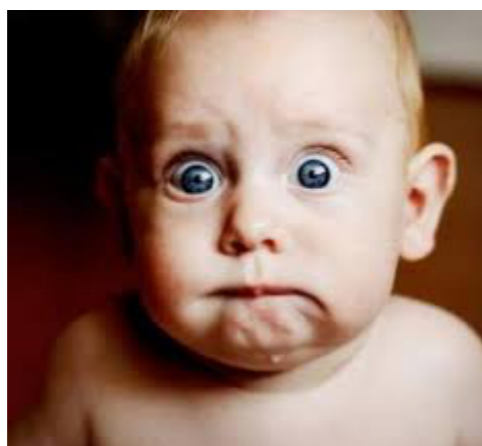
A **very basic** question:

Is it possible for the child with a **specific initial state** to use the **acquisitional intake** to achieve the **target state**?

(What happened in a nutshell in Pearl 2011)

Why do none of these learning strategies work?

Because they're solving the wrong acquisition task...oops.



How do we model language acquisition?

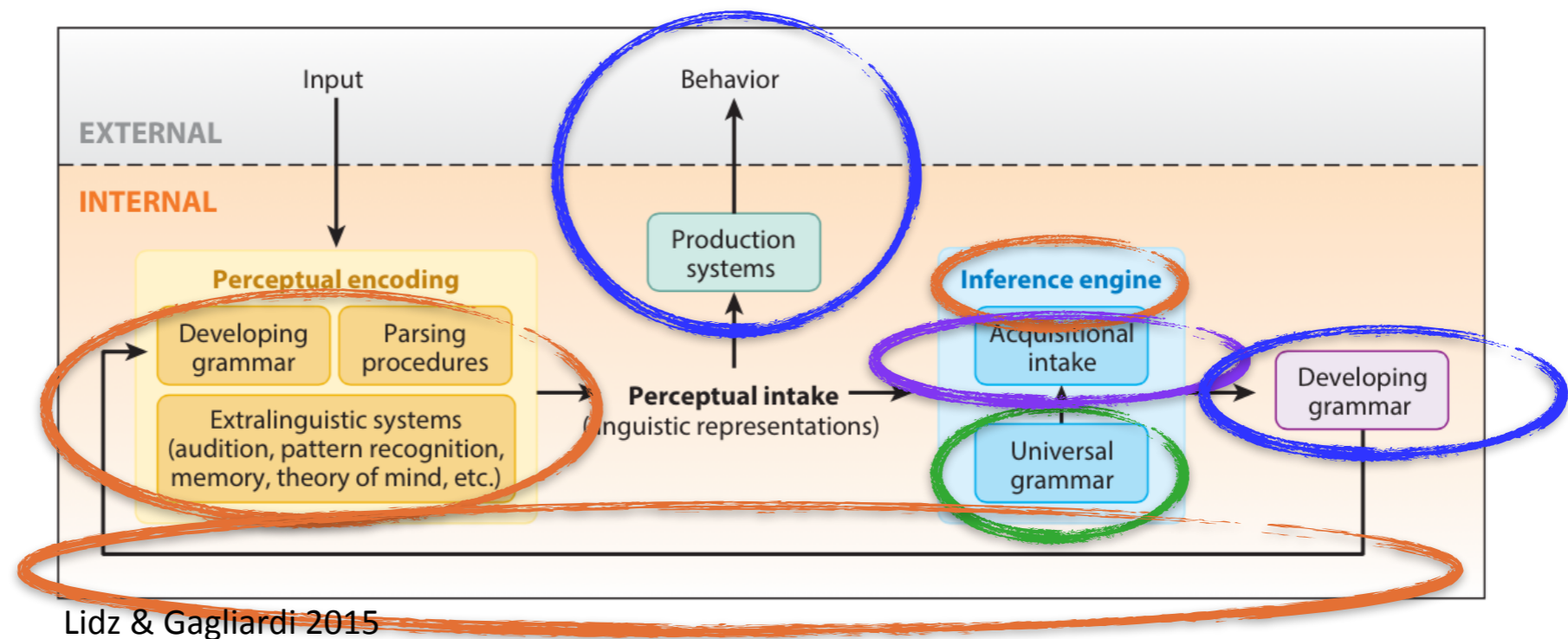
What **level** of model do you want to build?

Computational-level



Another basic question:

Is it possible for the child with a **specific initial state** to use the **acquisitional intake** to achieve the **target state** in the **amount of time** children typically get to do it, given the **incremental nature of learning** and **children's cognitive constraints**?



Lidz & Gagliardi 2015

How do we model language acquisition?

What **level** of model do you want to build?

Computational-level



Another basic question:

Is it possible for the child with a **specific initial state** to use the **acquisitional intake** to achieve the **target state** in the **amount of time** children typically get to do it, given the **incremental nature of learning** and **children's cognitive constraints**?

Algorithmic-level (Marr 1982)

Is it possible for children to use this strategy? That is, once we know it's **useful for children**, it's important to make sure it's also **useable by children**.



How do we model language acquisition?

What **level** of model do you want to build?

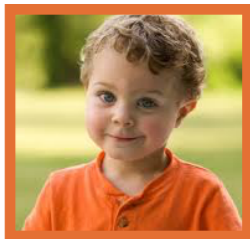


Computational-level

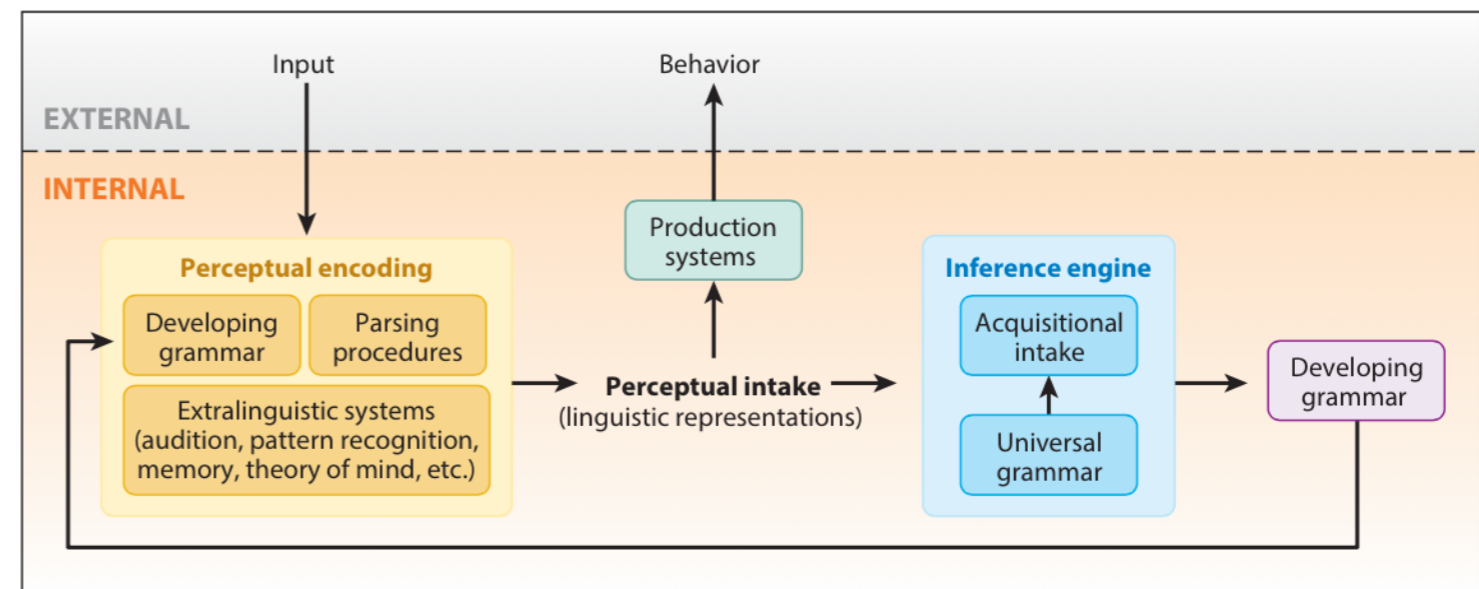


Another important (not so basic) question: If we have an algorithm that seems **useable** by children to **usefully solve an acquisition task**, how is it **implemented** in the brain?

Algorithmic-level



Implementational-level



Lidz & Gagliardi 2015

How do we model language acquisition?

What **level** of model do you want to build?

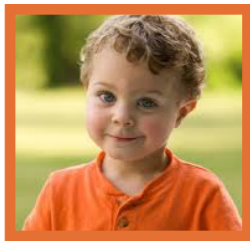


Computational-level



Another important (not so basic) question: If we have an algorithm that seems **useable** by children to **usefully solve an acquisition task**, how is it **implemented** in the brain?

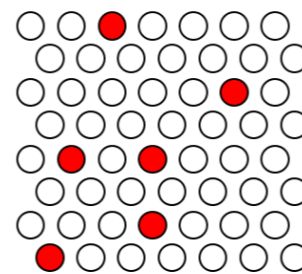
Algorithmic-level



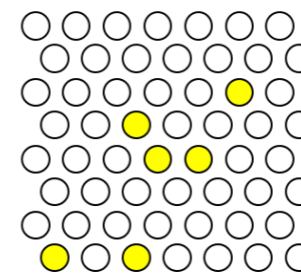
Implementational-level

This isn't easy to model yet.

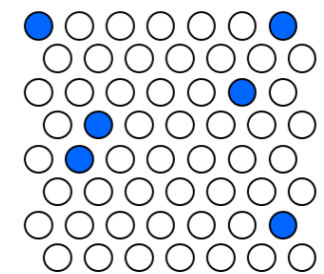
Advances in natural language processing: ways to encode complex information into distributed representations like what we think the brain uses.



Cat



Dog



Fish

(Levy & Goldberg 2014, Iyyer et al 2014, Rashkin et al. 2016)

How do we model language acquisition?

What **level** of model do you want to build?



The types I'll tell you about today

Computational-level

Algorithmic-level

Implementational-level



How do we model language acquisition?

Computational-level



So let's say you've figured out what level of model is appropriate to build. **Now what?**

Time to actually build it!

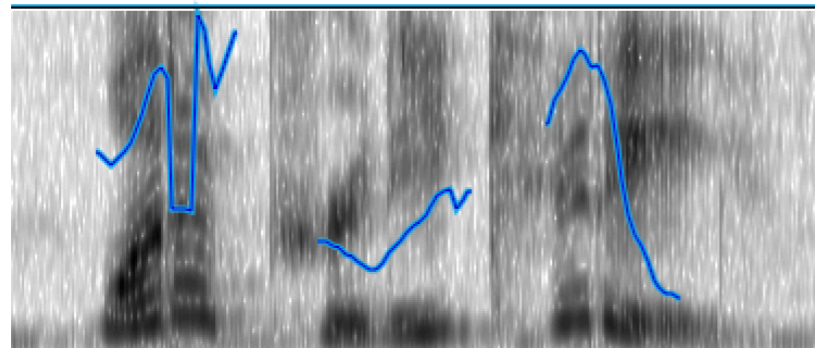
Algorithmic-level



Let's look at an example with speech segmentation

How do we model language acquisition?

An example with speech segmentation



= wʌtəprɪtkɪtɪ

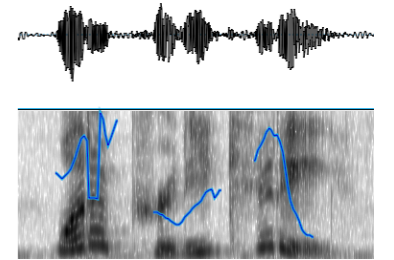
wʌt ə prɪtɪ kɪtɪ

what a pretty kitty!



How do we model language acquisition?

An example with speech segmentation



what a pretty kitty!

(1) Decide what kind of learner the model represents

This depends on what task you're modeling

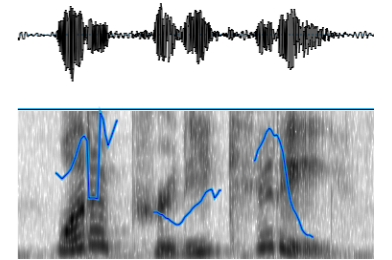
For the first stages of speech segmentation:

Typically developing 6- to 8-month-old child learning first language



How do we model language acquisition?

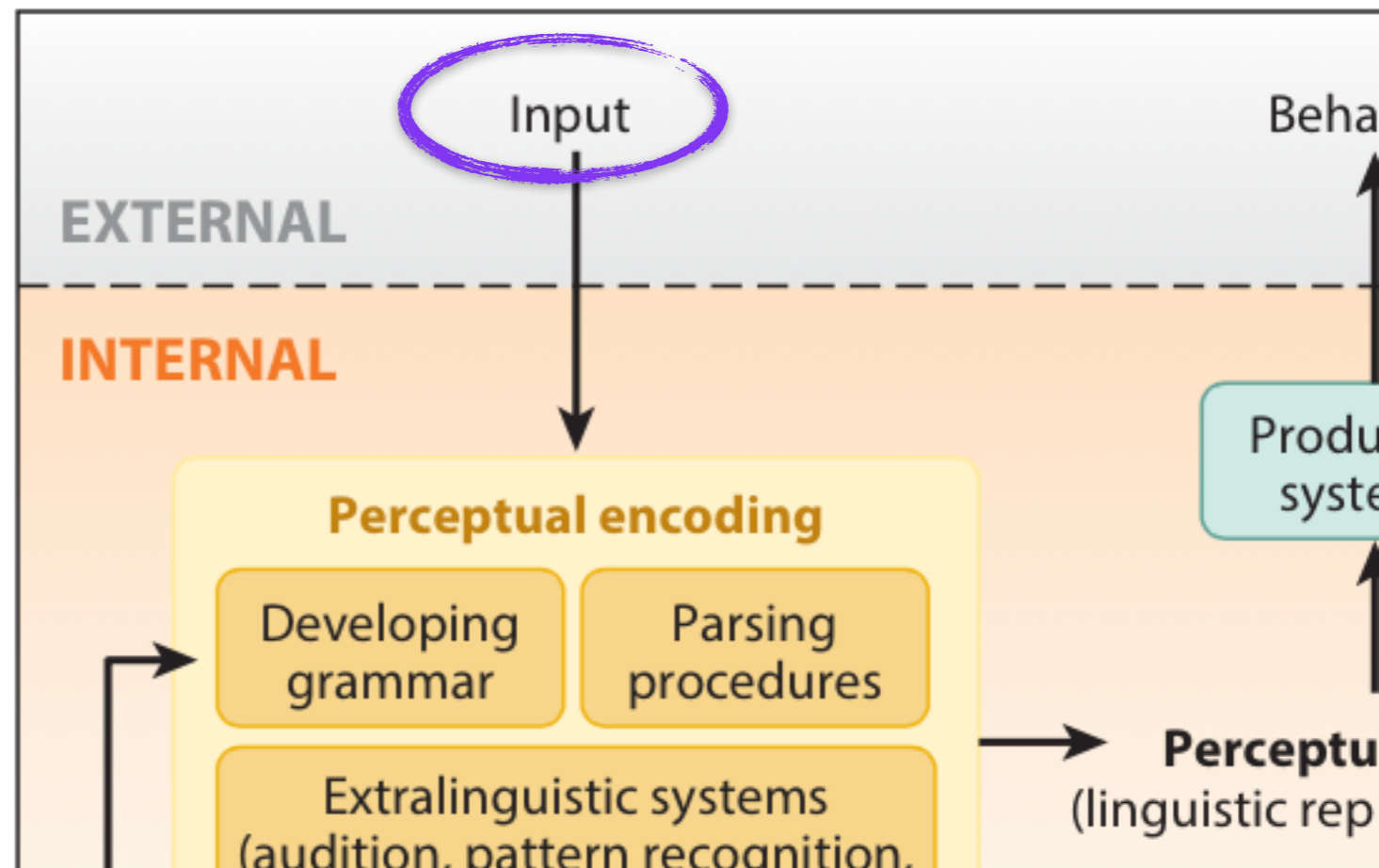
An example with speech segmentation



what a pretty kitty!

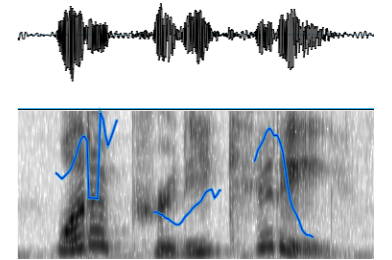
(2) Decide what data the child learns from (input)

This depends on your acquisition theory and the empirical data available



How do we model language acquisition?

An example with speech segmentation



what a pretty kitty!

(2) Decide what data the child learns from (input)

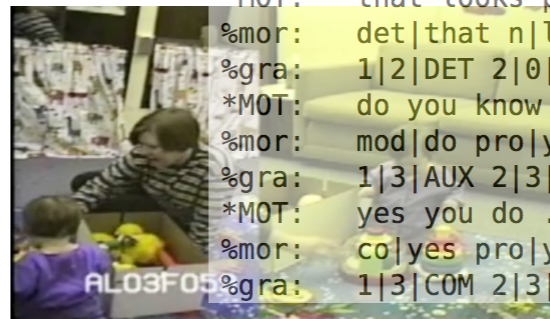
Example empirical data: CHILDES database

<http://childes.talkbank.org>

CHILDES Child Language Data Exchange System

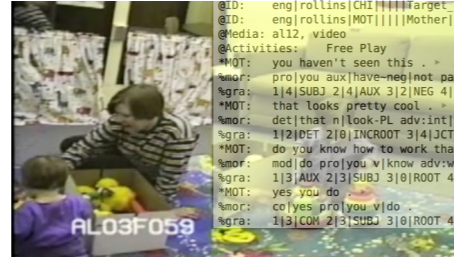
Video/audio recordings of speech samples, along with transcriptions and some structural annotations.

```
@Loc: Eng-NA-MOR/Rollins/al12.cha
@PID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: CHI Target_Child , MOT Mother
@ID: eng|rollins|CHI|||||Target_Child|||
@ID: eng|rollins|MOT|||||Mother|||
@Media: al12, video
@Activities: Free Play
*MOT: you haven't seen this . >
%mor: pro|you aux|have~neg|not part|see&PASTP pro:dem|this .
%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|0|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool . >
%mor: det|that n|look-PL adv:int|pretty adj|cool .
%gra: 1|2|DET 2|0|INCRROOT 3|4|JCT 4|2|XMOD 5|2|PUNCT
*MOT: do you know how to work that . >
%mor: mod|do pro|you v|know adv:wh|how inf|to v|work pro:dem|that .
%gra: 1|3|AUX 2|3|SUBJ 3|0|ROOT 4|3|OBJ 5|6|INF 6|4|XCOMP 7|6|OBJ 8|3|PUNCT
*MOT: yes you do . >
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%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
```

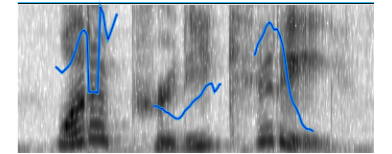


How do we model language acquisition?

An example with speech segmentation

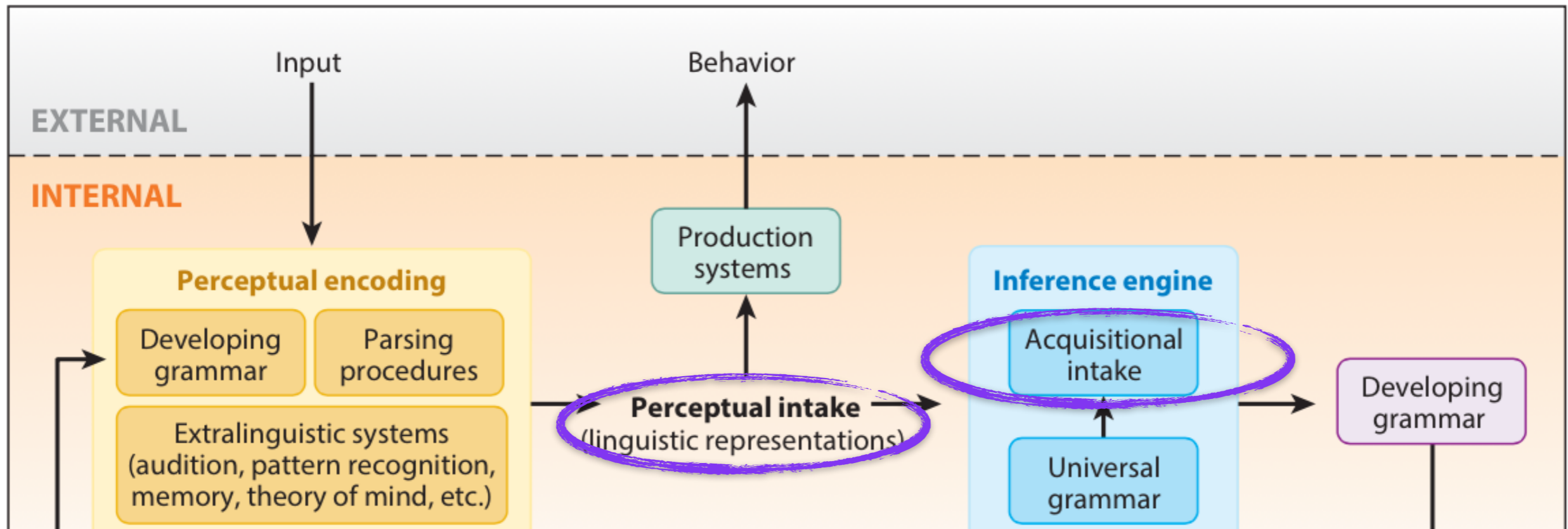


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@Begin
@Languages: eng
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@ID: eng|rollins|CHI|Target_Child|
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*MOT: yes you do .
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%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
```



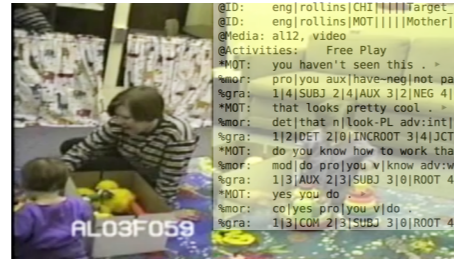
what a pretty kitty!

- (3) Decide how the child perceives the data, and which data are relevant (intake)
- This depends on your acquisition theory



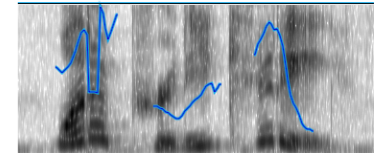
How do we model language acquisition?

An example with speech segmentation



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@Media: al12_video
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%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
    
```



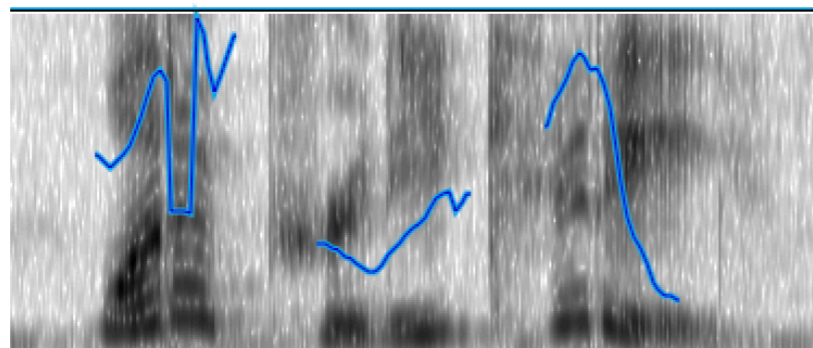
what a pretty kitty!

(3) Decide how the child perceives the data,
and which data are relevant (intake)



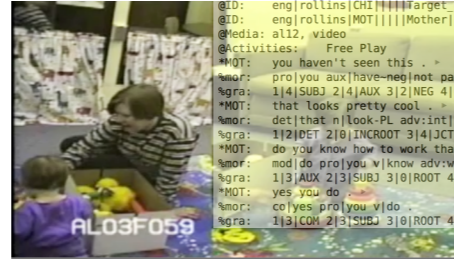
syllables with stress

= w¹Λ rə pɹ¹ɪ rɪ k¹ɪ rɪ



How do we model language acquisition?

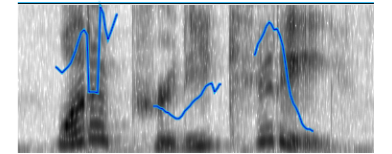
An example with speech segmentation



```

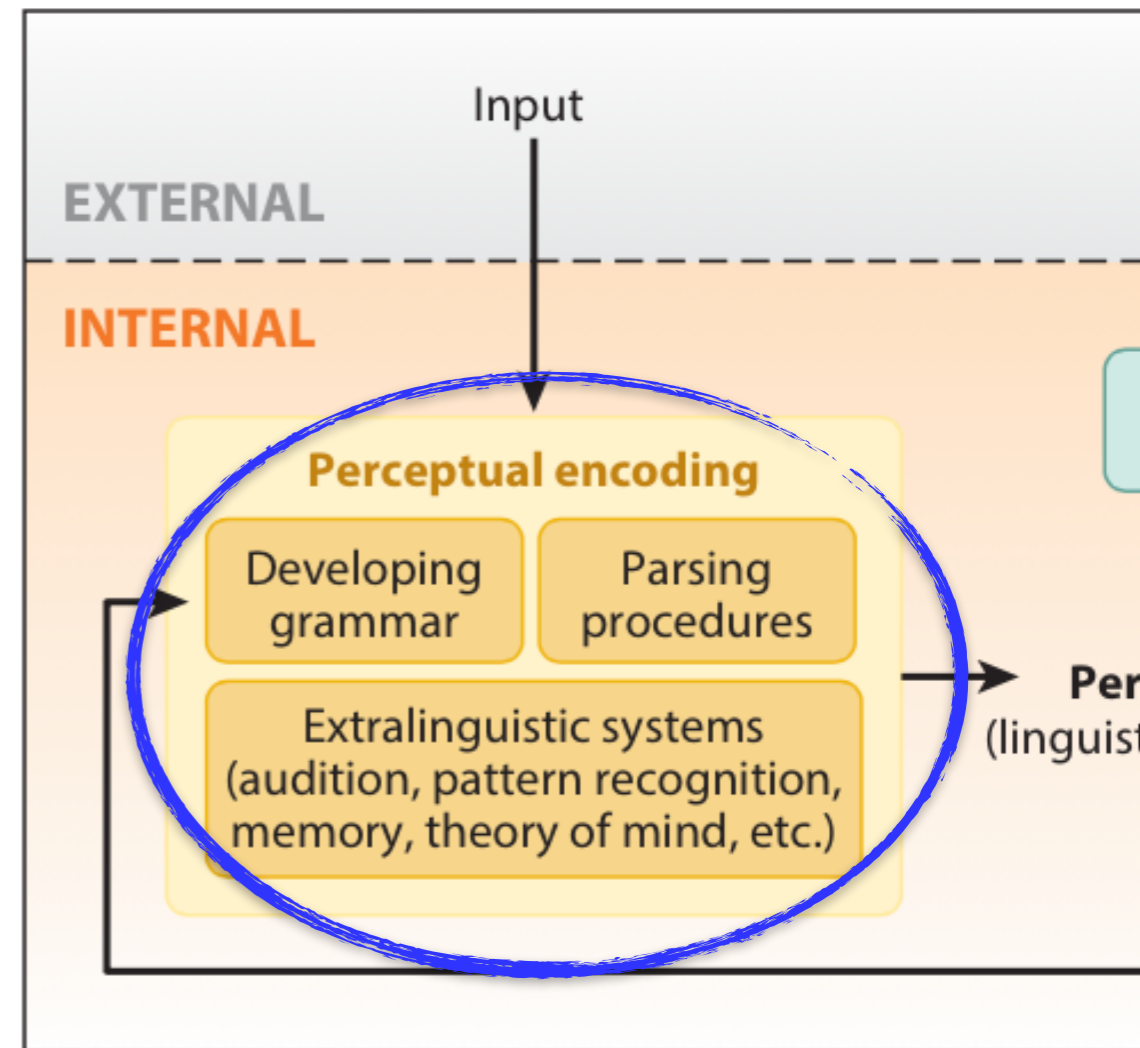
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*MOT: yes you do .
%mor: co|yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
    
```

= w^lΛ rə pr^li ri k^li ri



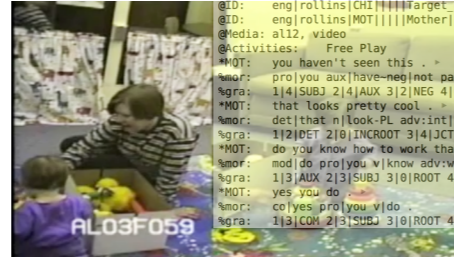
what a pretty kitty!

Many models will try to make **cognitively plausible** assumptions about how the child is representing and processing input data



How do we model language acquisition?

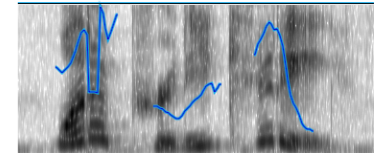
An example with speech segmentation



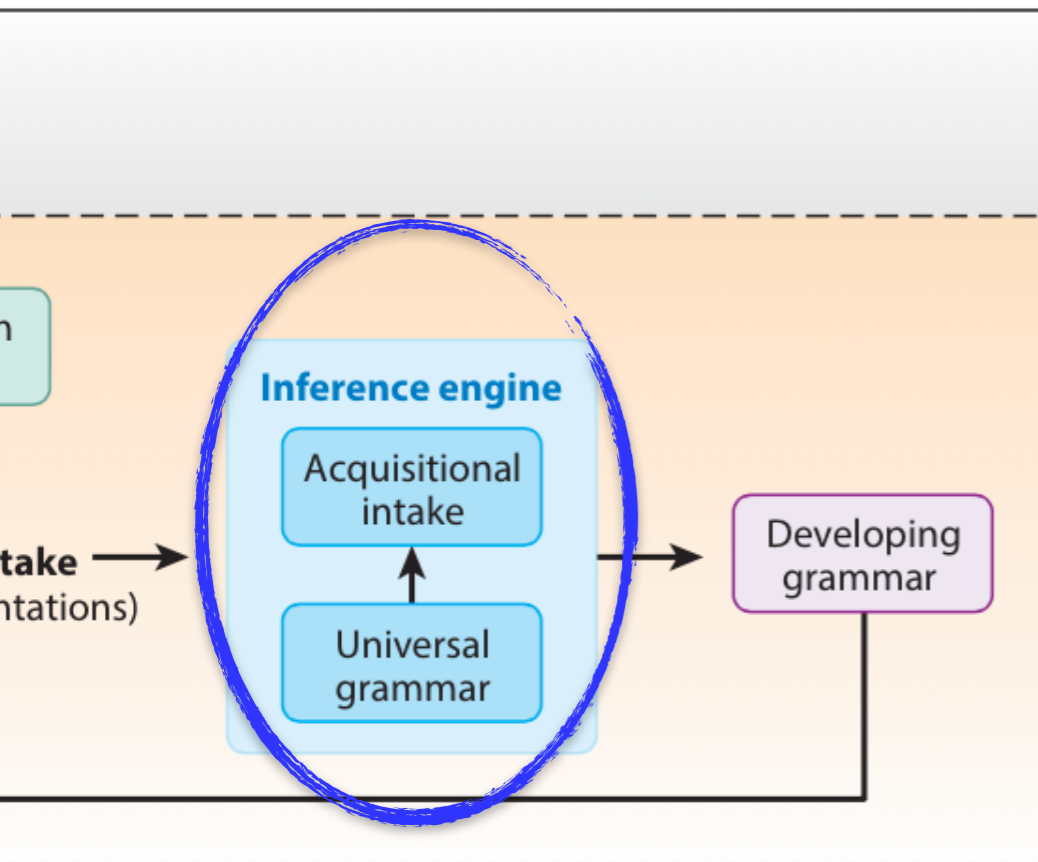
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```

= w'ʌ rə pr'i ri k'i ri



what a pretty kitty!

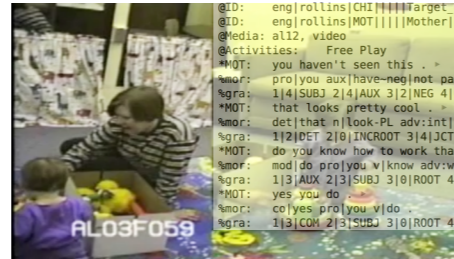


(4) Decide what hypotheses the child has and what information is being tracked in the input

This depends on your acquisition theory

How do we model language acquisition?

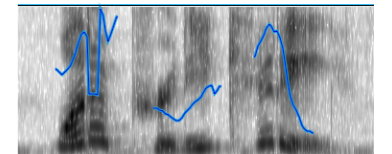
An example with speech segmentation



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@Participants: CHI Target_Child , MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: al12_video
@Activities: Free Play
*MOT: you haven't seen this .
%mor: pro|you aux|have-neg|not part|see&PASTP pro:dem|this .
%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|8|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool .
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%gra: 1|2|DET 2|8|INGROOT 3|4|JCT 4|2|XMOD 5|2|PUNCT
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```

= w^lʌ rə pɹ^li ri k^li ri



what a pretty kitty!

(4) Decide what **hypotheses** the child has and what information is being tracked in the input

Example hypotheses: what the words are

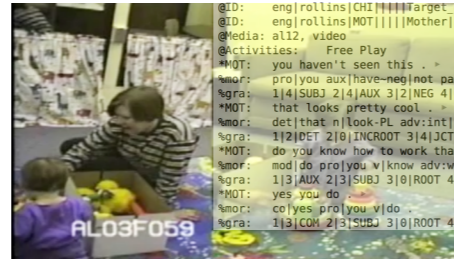
w^lʌrə
pɹ^li ri
k^li ri

w^lʌ
rə
pɹ^li rik^li ri

w^lʌrə
pɹ^li rik^li ri

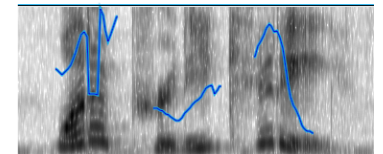
How do we model language acquisition?

An example with speech segmentation



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@Languages: eng
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@Activities: Free Play
*MOT: you haven't seen this .
%mor: pro|you aux|have-neg|not part|see&PASTP pro:dem|this .
%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|8|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool .
%mor: det|that n|look-PL adv:int|pretty adj|cool .
%gra: 1|2|DET 2|8|INGROOT 3|4|JCT 4|2|XMOD 5|2|PUNCT
*MOT: do you know how to work that .
%mor: mod|do pro|you v|know adv:wh|how inf|to v|work pro:dem|that .
%gra: 1|3|AUX 2|3|SUBJ 3|8|ROOT 4|3|OBJ 5|6|INF 6|4|XCOMP 7|6|OBJ 8|3|PUNCT
*MOT: yes you do .
%mor: co|yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|8|ROOT 4|3|PUNCT
    
```



= w^lΛ rə pɪ^lɪ ri k^lɪ ri

what a pretty kitty!

w^lΛrə
pɪ^lɪri
k^lɪri

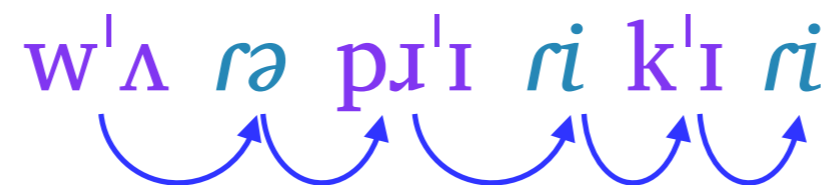
w^lΛ
rə
pɪ^lɪrik^lɪri

w^lΛrə
pɪ^lɪrik^lɪri

(4) Decide what hypotheses the child has and what **information** is being tracked in the input

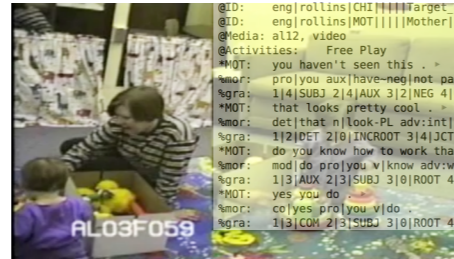
Example information:

transitional probability between syllables,
stress on syllables



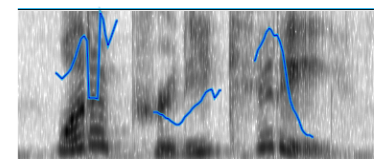
How do we model language acquisition?

An example with speech segmentation



```

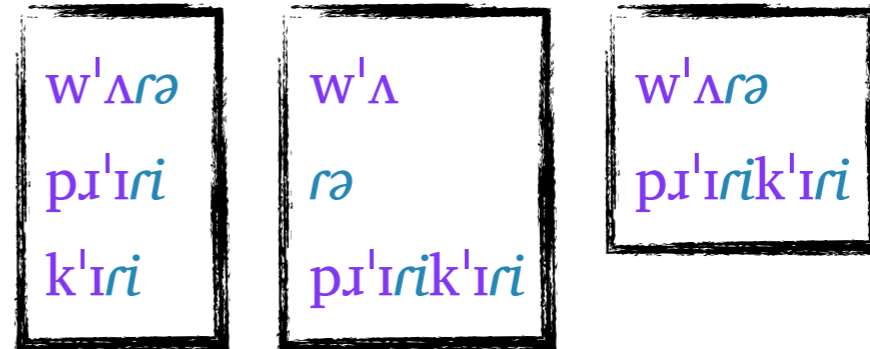
@Loc: Eng-NA-MOR/Rollins/al12.cha
@PID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: CHI Target_Child , MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: al12_video
@Activities: Free Play
*MOT: you haven't seen this .
%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|8|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool .
%mor: det|that n|look-PL adv:int|pretty adj|cool .
%gra: 1|2|DET 2|8|INGROOT 3|4|JCT 4|2|XMOD 5|2|PUNCT
*MOT: do you know how to work that .
%mor: mod|do pro|you v|know adv:wh|how inf|to v|work pro:dem|that .
%gra: 1|3|AUX 2|3|SUBJ 3|0|ROOT 4|3|OBJ 5|6|INF 6|4|XCOMP 7|6|OBJ 8|3|PUNCT
*MOT: yes you do .
%mor: c|yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
    
```



= w^lΛ rə pɪ^li ri k^li ri

what a pretty kitty!

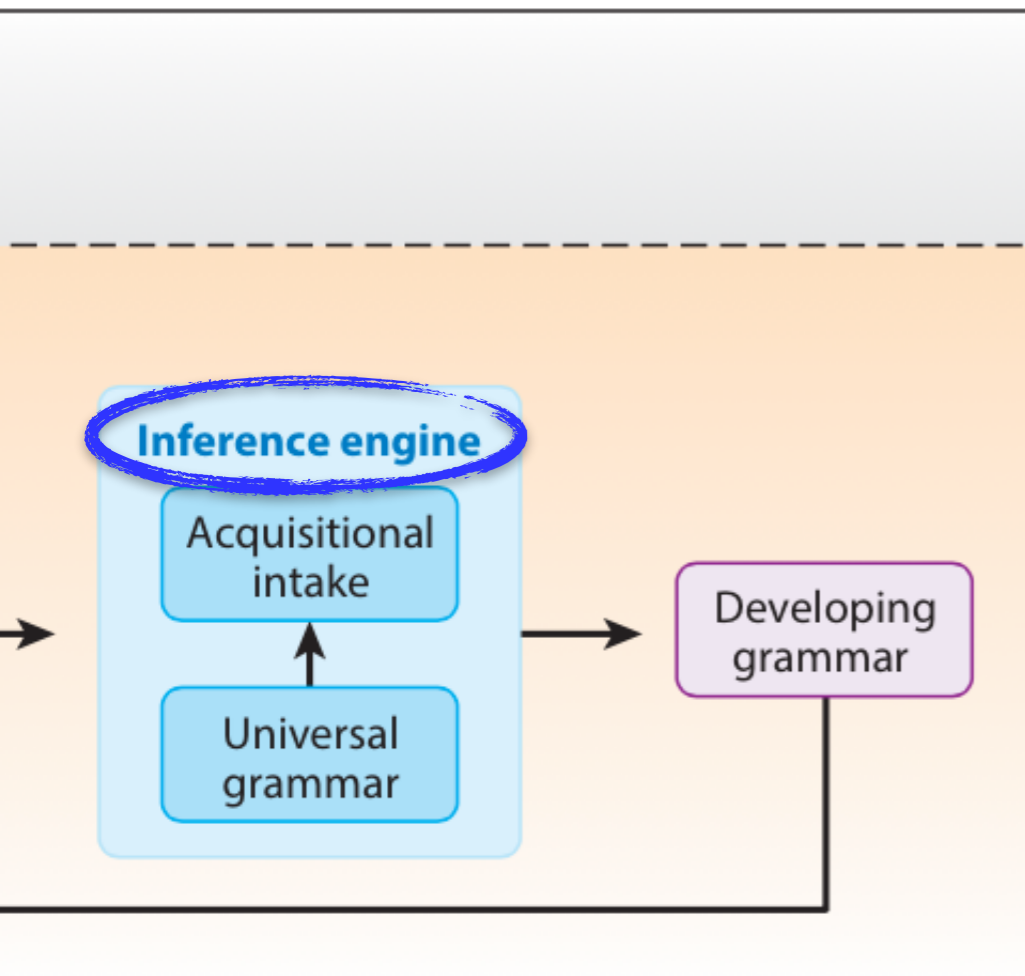
w^lΛ rə pɪ^li ri k^li ri



(5) Decide how belief in different hypotheses is updated

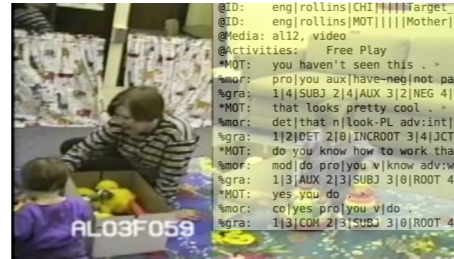
This depends on your acquisition theory

Example: based on **transitional probability** between syllables



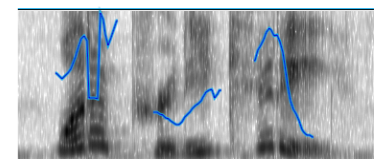
How do we model language acquisition?

An example with speech segmentation



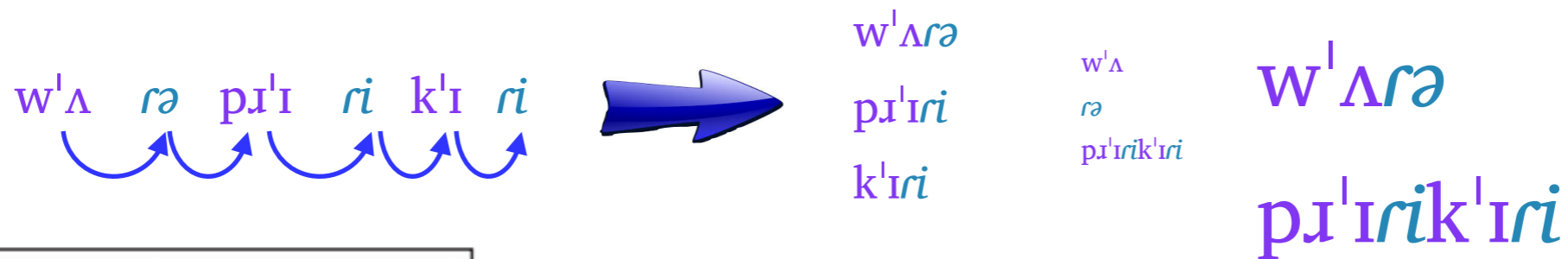
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@Begin
@Languages: eng
@Participants: CHI Target_Child, MOT Mother
@ID: eng|rollins|CHI|Target_Child|
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@Media: al12_video
@Activities: Free Play
*MOT: you haven't seen this .
%mor: pro|you aux|have-neg|not part|see&PASTP pro:dem|this .
%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|8|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool .
%mor: det|that n|look-PL adv:int|pretty adj|cool .
%gra: 1|2|DET 2|8|INGROOT 3|4|JCT 4|2|XMOD 5|2|PUNCT
*MOT: do you know how to work that .
%mor: mod|do pro|you v|know adv:wh|how inf|to v|work pro:dem|that .
%gra: 1|3|AUX 2|3|SUBJ 3|0|ROOT 4|3|OBJ 5|6|INF 6|4|XCOMP 7|6|OBJ 8|3|PUNCT
*MOT: yes you do .
%mor: col:yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
    
```



= w'Λ rə pɪ'ɪ ri k'ɪ ri

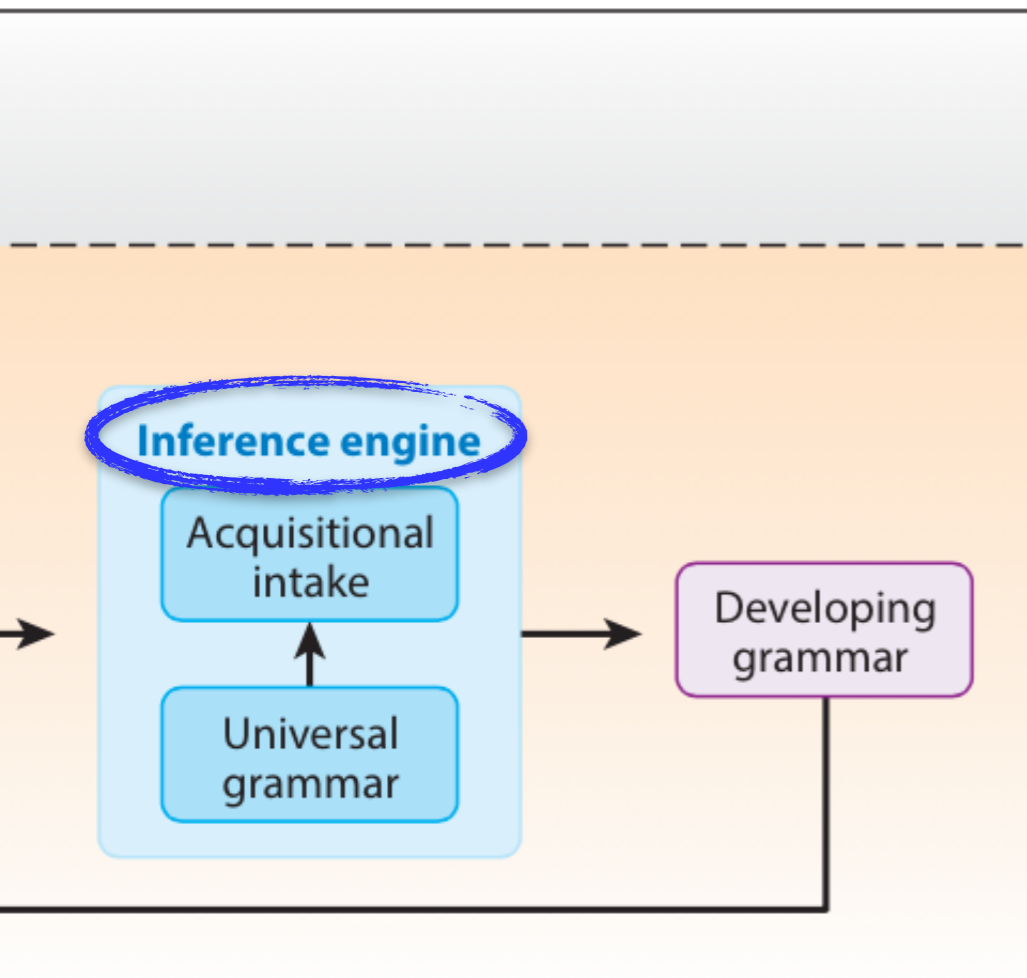
what a pretty kitty!



(5) Decide how belief in different hypotheses is updated

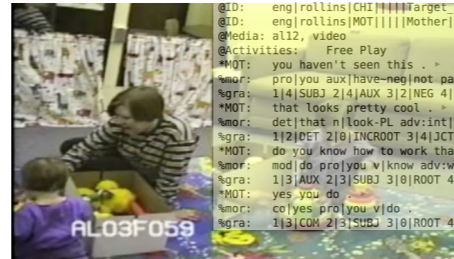
This depends on your acquisition theory

Example: based on **transitional probability** between syllables



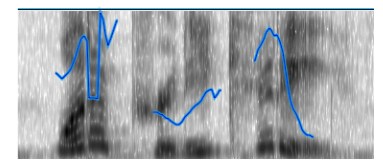
How do we model language acquisition?

An example with speech segmentation



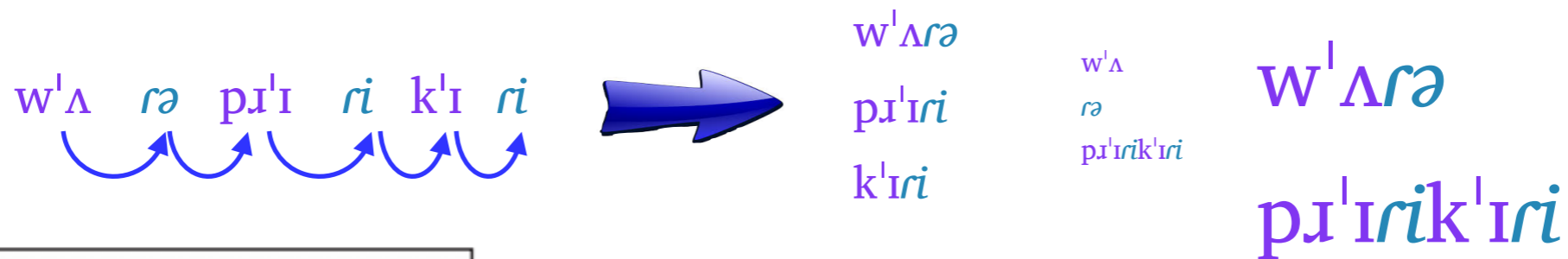
```

@Loc: Eng-NA-MOR/Rollins/al12.cha
@PID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: CHI Target_Child, MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: al12, video
@Activities: Free Play
*MOT: you haven't seen this .
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%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|0|ROOT 5|4|OBJ 6|4|PUNCT
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%gra: 1|3|AUX 2|3|SUBJ 3|0|ROOT 4|3|OBJ 5|6|INF 6|4|XCOMP 7|6|OBJ 8|3|PUNCT
*MOT: yes you do .
%mor: c|yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
    
```



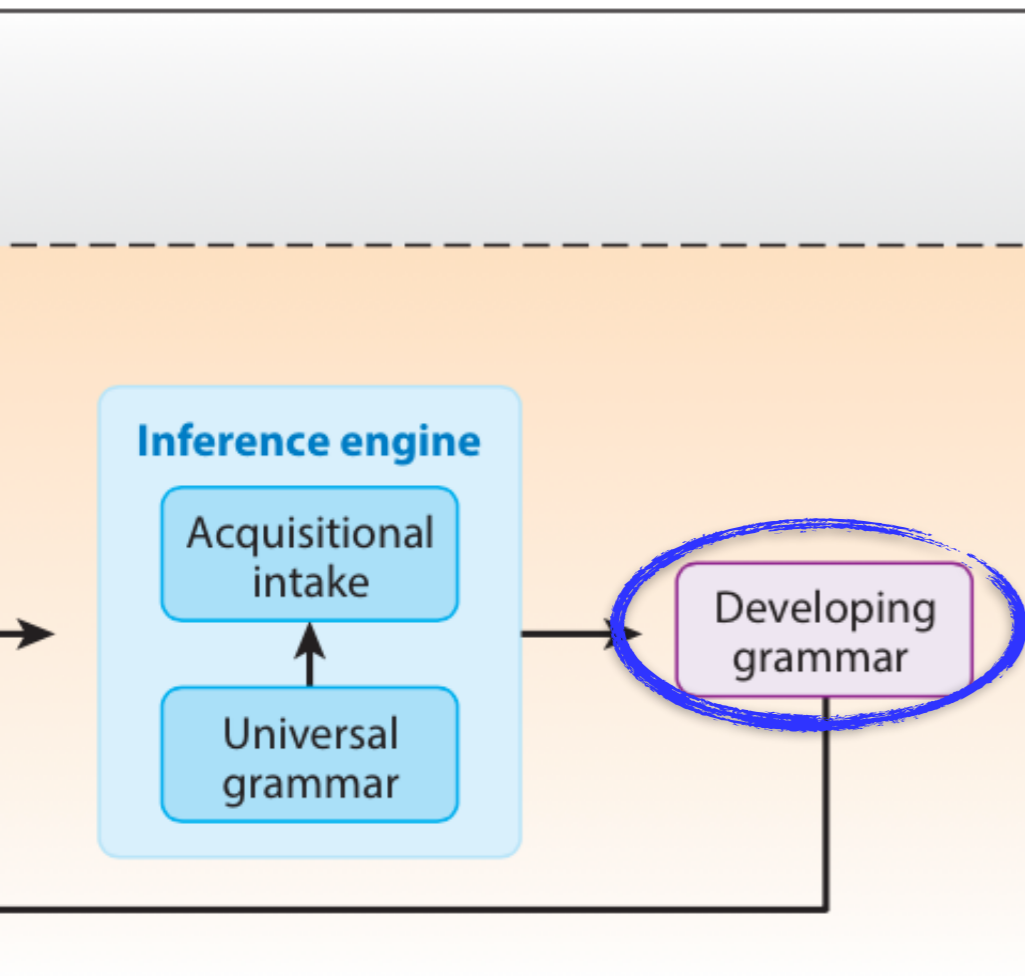
= w'ʌ rə pɹ'i ri k'i ri

what a pretty kitty!



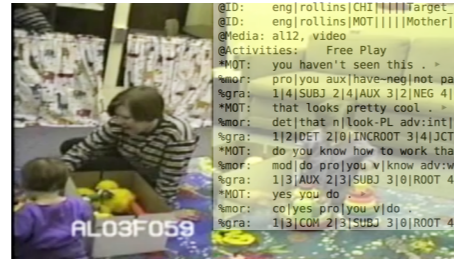
(6) Decide what the measure of success is

This can be based on your theory ...



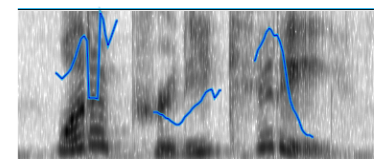
How do we model language acquisition?

An example with speech segmentation



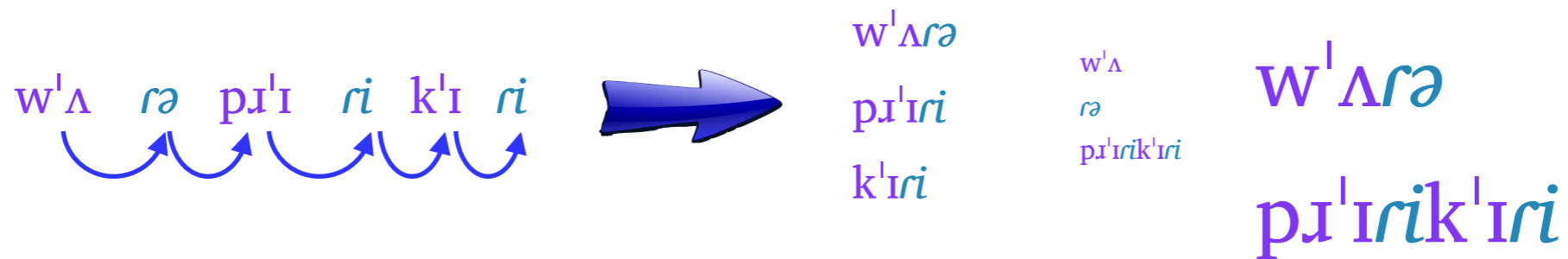
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@Loc: Eng-NA-MOR/Rollins/al12.cha
@PID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: CHI Target_Child , MOT Mother
@ID: eng|rollins|CHI|Target_Child|
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@Media: al12_video
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*MOT: you haven't seen this .
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%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|0|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool .
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*MOT: yes you do .
%mor: co|yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
    
```



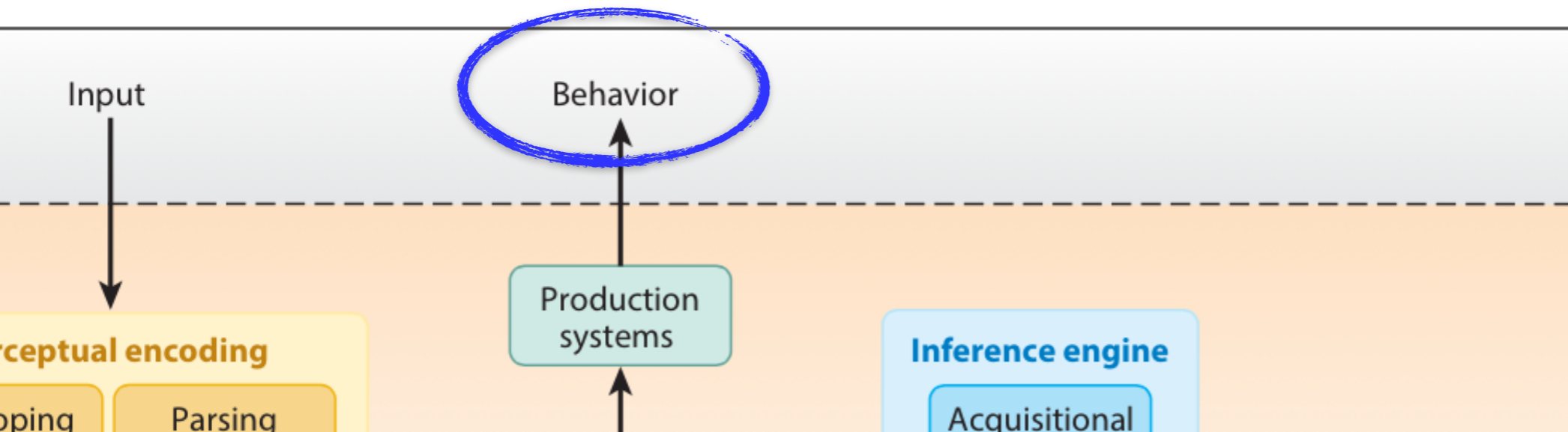
= w'ʌ rə pɪ'ɪ ri k'ɪ ri

what a pretty kitty!



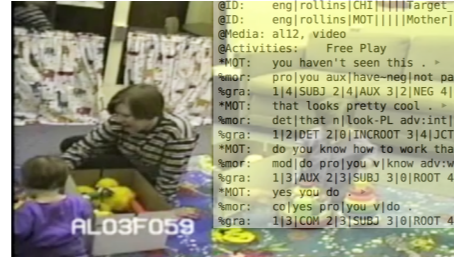
(6) Decide what the measure of success is

This can be based on your theory or empirical data about behavior

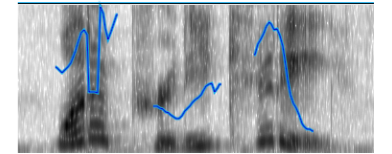


How do we model language acquisition?

An example with speech segmentation

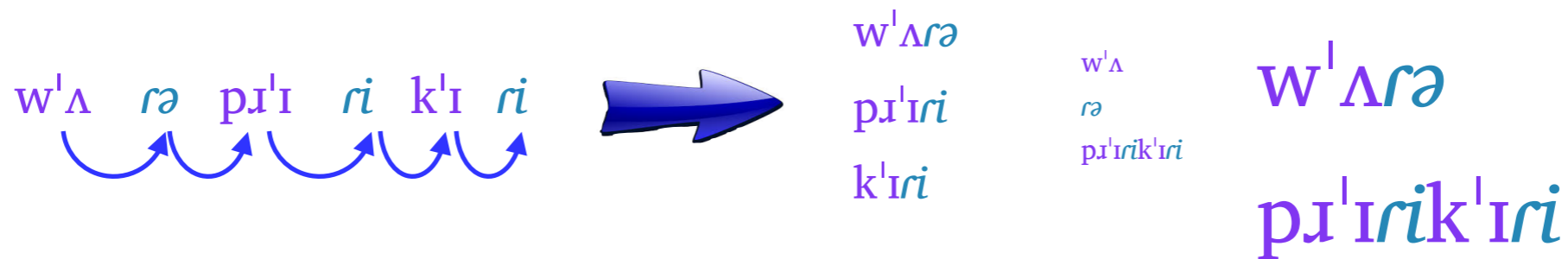


```
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@PID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: CHI Target_Child, MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: al12_video
@Activities: Free Play
*MOT: you haven't seen this .
%mor: pro|you aux|have-neg|not part|see&PASTP pro:dem|this .
%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|8|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool .
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%gra: 1|2|DET 2|8|INGROOT 3|4|JCT 4|2|XMOD 5|2|PUNCT
*MOT: do you know how to work that .
%mor: mod|do pro|you v|know adv:wh|how inf|to v|work pro:dem|that .
%gra: 1|3|AUX 2|3|SUBJ 3|8|ROOT 4|3|OBJ 5|6|INF 6|4|XCOMP 7|6|OBJ 8|3|PUNCT
*MOT: yes you do .
%mor: c|yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|8|ROOT 4|3|PUNCT
```



= w¹ʌ rə pɹ¹i ri k¹i ri

what a pretty kitty!



(6) Decide what the measure of success is

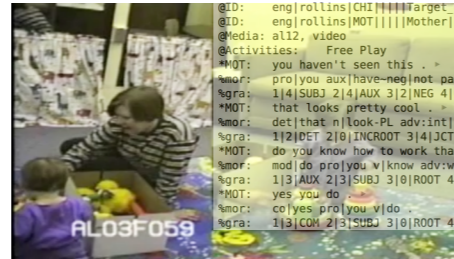
Example developing knowledge
Proto-lexicon of word forms

This can be based on your **theory**
or empirical data about behavior

w¹ʌr *what*
ə *a*
pɹ¹i ri *pretty*
k¹i ri *kitty*

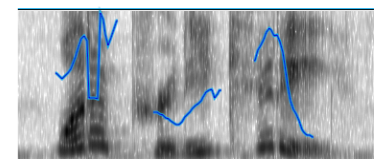
How do we model language acquisition?

An example with speech segmentation



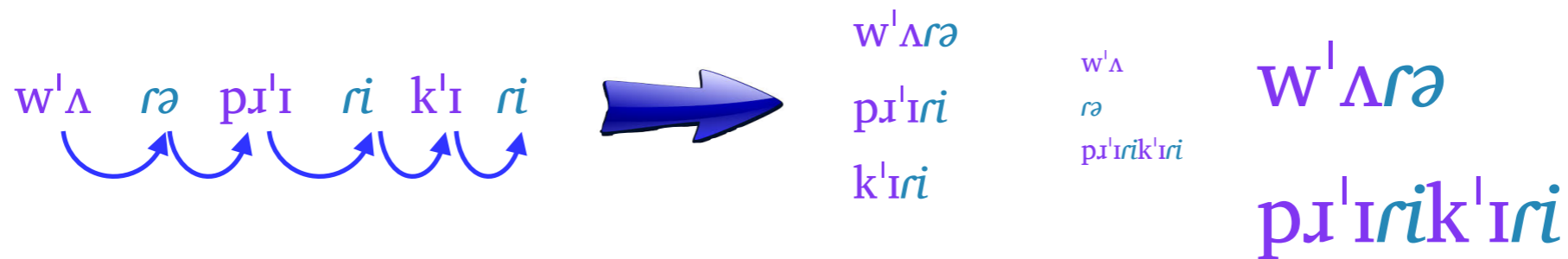
```

@Loc: Eng-NA-MOR/Rollins/al12.cha
@PID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: CHI Target_Child , MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: al12, video
@Activities: Free Play
*MOT: you haven't seen this .
%mor: pro|you aux|have-neg|not part|see&PASTP pro:dem|this .
%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|8|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool .
%mor: det|that n|look-PL adv:int|pretty adj|cool .
%gra: 1|2|DET 2|8|INGROOT 3|4|JCT 4|2|XMOD 5|2|PUNCT
*MOT: do you know how to work that .
%mor: mod|do pro|you v|know adv:wh|how inf|to v|work pro:dem|that .
%gra: 1|3|AUX 2|3|SUBJ 3|8|ROOT 4|3|OBJ 5|6|INF 6|4|XCOMP 7|6|OBJ 8|3|PUNCT
*MOT: yes you do .
%mor: co|yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|8|ROOT 4|3|PUNCT
    
```



= w'ʌ rə pɹɪ ri k'i ri

what a pretty kitty!

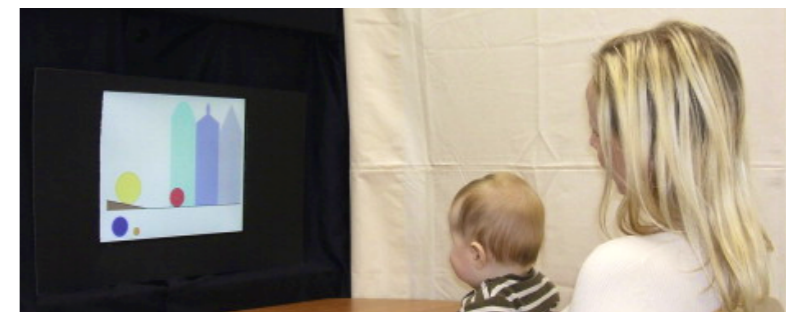


w'ʌr *what*
 ə *a*
 pɹɪri *pretty*
 k'i ri *kitty*

(6) Decide what the measure of success is

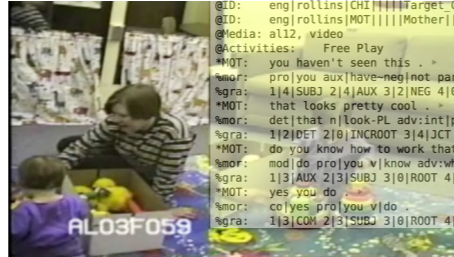
This can be based on your theory
 or **empirical data about behavior**

Example behavior indicating developed knowledge:
 Recognizing useful units (such as words) in a fluent
 speech stream, as indicated by **looking time behavior**



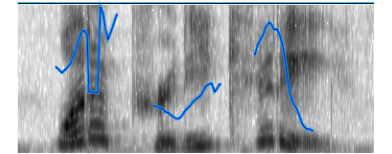
How do we model language acquisition?

An example with speech segmentation



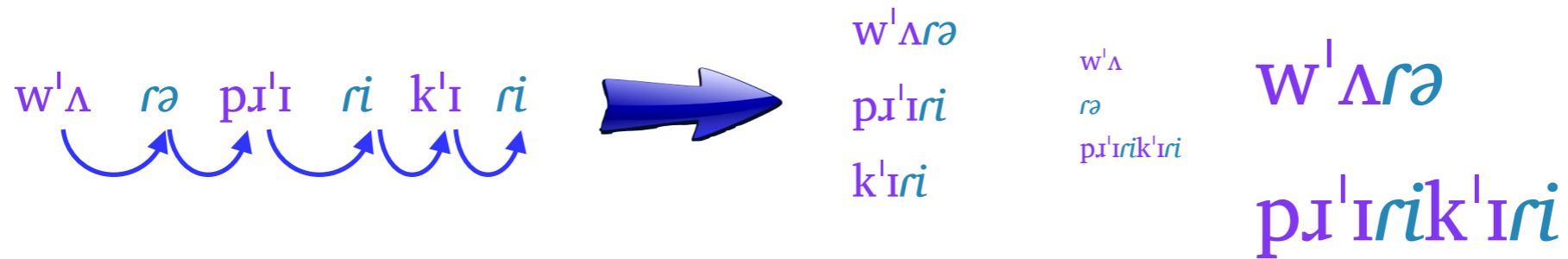
```

@Loc: Eng-NA-MOR/Rollins/al12.cha
@PID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: CHI Target_Child , MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: al12, video
@Activities: Free Play
*MOT: you haven't seen this .
%mor: pro|you aux|have-neg|not part|see&PASTP pro:dem|this .
%gra: 1|4|SUBJ 2|4|AUX 3|2|NEG 4|8|ROOT 5|4|OBJ 6|4|PUNCT
*MOT: that looks pretty cool .
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%gra: 1|2|DET 2|8|INGROOT 3|4|JCT 4|2|XMOD 5|2|PUNCT
*MOT: do you know how to work that .
%mor: mod|do pro|you v|know adv:wh|how inf|to v|work pro:dem|that .
%gra: 1|3|AUX 2|3|SUBJ 3|0|ROOT 4|3|OBJ 5|6|INF 6|4|XCOMP 7|6|OBJ 8|3|PUNCT
*MOT: yes you do .
%mor: co|yes pro|you v|do .
%gra: 1|3|COM 2|3|SUBJ 3|0|ROOT 4|3|PUNCT
    
```



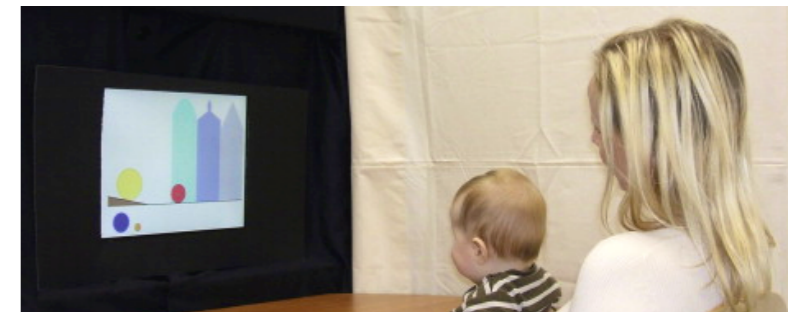
= w¹ʌ rə pɹ¹ɪ rɪ k¹ɪ rɪ

what a pretty kitty!



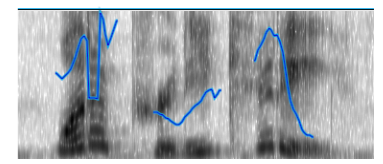
This is the heart of the model

w ¹ ʌr	what
ə	a
pɹ ¹ ɪrɪ	pretty
k ¹ ɪrɪ	kitty



How do we model language acquisition?

An example with speech segmentation



```
@loc: Eng-NA-MOR/Rollins/al12.cha
@ID: 11312/r-0001702-1
@begin
@languages: eng
@participants: OIE Target_Child , MOT Mother
@ID: eng|rollins|OIE|Target_Child|
@ID: eng|rollins|MOT|Mother|
@media: a12, video
@activities: Free Play
*MOT: you haven't seen this . . .
*MO: pro|yns aux|have-neg|not part|see|PASTP prd|en|this .
  1:14|S|B| 2:14|A|X 3:12|B|G 4:0|ROOT 5:4|O|B 6:4|PUNCT
*MOT: that looks pretty cool .
*MO: get|that n|look-PL adv|int|pretty adj|cool
  1:18|B|E|G| 2:18|ROOT 3:14|DET 4:12|O|N|S|A|D|E|C|T
*MO: do you know how to work that . . .
*MO: mod|do mod|do v|know adv|rel|how int|to v|work prd|en|that
  1:19|A|X 2:13|S|B| 3:0|ROOT 4:13|O|B 5:6|I|N|F 6:4|A|C|O|P|P 7:6|O|B 8:13|PUNCT
*MO: yes|pls do
*MO: yes|pls do
  1:13|COM 2:13|S|B| 3:0|ROOT 4:13|PUNCT
```

= w'ʌ rə pɪ'ɪ ri k'ɪ ri



what a pretty kitty!

w'ʌ rə pɪ'ɪ ri k'ɪ ri

w'ʌ rə
pɪ'ɪ ri
k'ɪ ri
w'ʌ rə
rə
pɪ'ɪ rɪ k'ɪ ri
w'ʌ rə
what
a
pɪ'ɪ ri pretty
k'ɪ ri kitty

(7) Implement the model in a programming language of choice



Data Structure © click2study.net

The height of a tree is defined as the number of edges on the longest path to the leaf. The function shown in the pseudocode below is written in C to compute the height of a binary tree rooted at the tree pointer root.

```
int height (treeptr T)
{ if (T == NULL) return -1;
  if (T->left == NULL)
  { if (T->right == NULL) return 0;
    else return 1; // Box 1
  }
  else { h1 = height (T->left);
        if (h1 > right) == NULL) return (1+h1);
        else { h2 = height (T->right);
              return (h1 > h2) ? h1 : h2; // Box 2
            }
  }
}
```

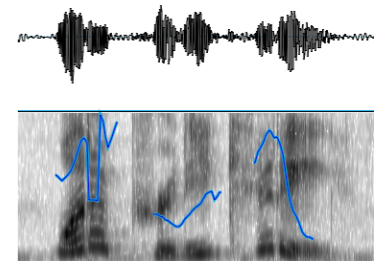
The appropriate expressions for the two boxes B1 and B2 are

(A) B1: (1+height(T->right)) B2: (1+max(h1,h2))
 (B) B1: (1+max(h1,h2)) B2: (1+max(h1,h2))
 (C) B1: height(T->right) B2: max(h1,h2)
 (D) B1: (1+height(T->right)) B2: max(h1,h2)



How do we model language acquisition?

An example with speech segmentation



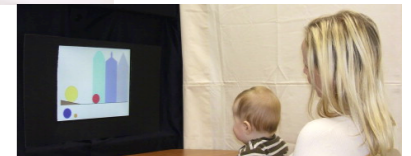
= w¹ʌ rə prɪ'ɪ ri kɪ'ɪ ri

w¹ʌ rə prɪ'ɪ ri kɪ'ɪ ri



w¹ʌrə
prɪ'ɪri kɪ'ɪri

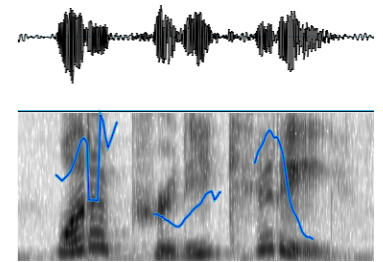
(8) See how well the model did w.r.t. the measure of success



Example developing knowledge	w ¹ ʌr	what
Proto-lexicon of word forms	ə	a
	???	prɪ'ɪri pretty
		kɪ'ɪri kitty

How do we model language acquisition?

An example with speech segmentation



= w¹ʌ rə pɪ¹ri k¹ri

w¹ʌ rə pɪ¹ri ri k¹ri ri



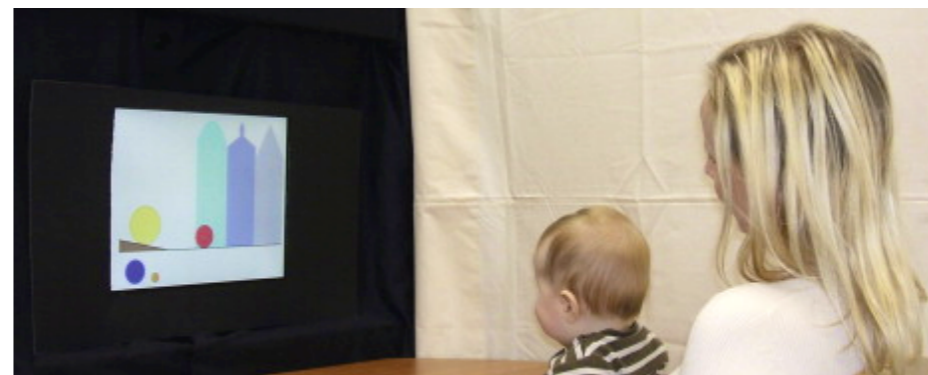
what a pretty kitty!

w¹ʌrə
pɪ¹ri
k¹ri
w¹ʌ
rə
pɪ¹rik¹ri
w¹ʌrə
a
pɪ¹ri
k¹ri
what
a
pretty
kitty

(8) See how well the model did w.r.t. the measure of success

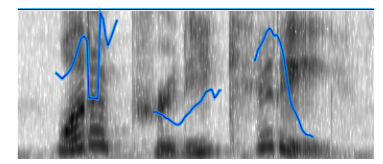
Recognizing useful units (such as words) in a fluent speech stream, as indicated by **looking time behavior**

???



How do we model language acquisition?

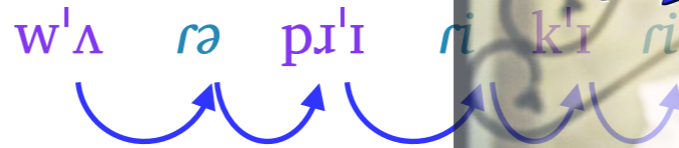
An example with speech segmentation



```
@Loc: Eng-NA-MOR/Rollins/al12.cha
@ID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: OIE Target_Child , MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: a12, video
@Activities: Free Play
*MOT: you haven't seen this . . .
*MO: pro|jnu auz|have-neg|not part|see|PASTP pr:den|this .
*MO: 114|S|B3 214|A|X 312|BEG 4|0|ROOT 5|4|0B3 0|4|PUNCT
*MO: that looks pretty cool .
*MO: get|that n|look-PL adv:|int|pretty ad|cool
*MO: do you know how to work that . .
*MO: en|doe a|k|g|v|know adv:|h|how int|to v|work pr:den|that
*MO: 5|3|A|X 2|3|S|B3 3|0|ROOT 4|3|0B3 5|6|INF 0|4|ACOMP 7|6|0B3 0|3|PUNCT
*MO: yes|ple do
*MO: o|ves pr:|oc|?|do
*MO: 1|3|COM 2|3|S|B3 3|0|ROOT 4|3|PUNCT
```

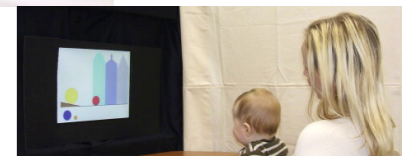
= w'ʌ rə pɪ'ɪ ri k'ɪ ri

???



what a pretty kitty!

w'ʌrə
pɪ'ɪri
k'ɪri
w'ʌrə
rə
pɪ'ɪrik'ɪri
w'ʌrə
a
pɪ'ɪri
pretty
k'ɪri
kitty



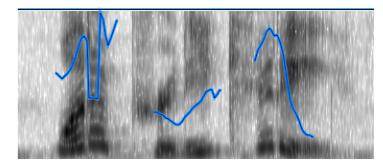
(8) See how well the model did w.r.t. the measure of success

From this, we can determine how well the model did — and more importantly, how well the strategy implemented concretely in the model did.



How do we model language acquisition?

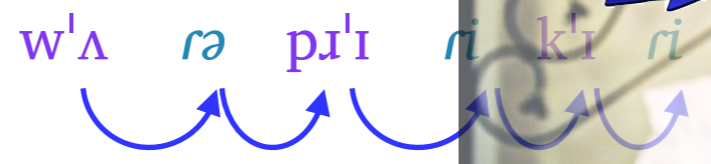
An example with speech segmentation



```
@Loc: Eng-NA-MOR/Rollins/al12.cha
@ID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: OIE Target_Child , MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: a12, video
@Activities: Free Play
*MOT: you haven't seen this . . .
*MOE: projyuz axi|have-neg|not part|see|PASTP pro:den|this .
*MOE: 114|S|B3 214|A|X 312|NEG 4|0|ROOT 5|4|OB3 6|4|PUNCT
*MOE: that looks pretty cool .
*MOE: get|that n|look-PL adv:int|pretty adj|cool
*MOE: 313|S|B3|0|ROOT 314|DET 412|V|O|S|PUNCT
*MOE: do you know how to work that . . .
*MOE: en:doe|en:q|q|v|know adv:wh|how int|to v|work pro:den|that .
*MOE: 513|A|X 213|S|B3 310|ROOT 413|OB3 516|INF 614|ACOMP 716|OB3 813|PUNCT
*MOE: yes|pls do
*MOE: 615|V|O|ROOT 716|GO
*MOE: 113|COM 213|S|B3 310|ROOT 413|PUNCT
```

= w'ʌ rə prɪ'ɪ ri kɪ'ɪ ri

???



what a pretty kitty!

w'ʌ rə
prɪ'ɪ ri
kɪ'ɪ ri
w'ʌ rə
prɪ'ɪ ri kɪ'ɪ ri

(9) Interpret the results for other people who aren't you so they know why they should care

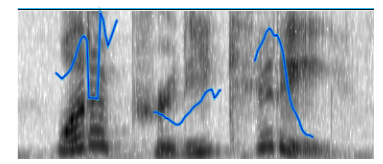


w'ʌ rə what
ə a
prɪ'ɪ ri pretty
kɪ'ɪ ri kitty

“The modeled child has the same **developing knowledge** as we think 8-month-olds do. This strategy can be what they're using!”

How do we model language acquisition?

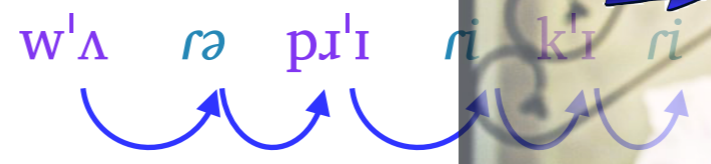
An example with speech segmentation



```
@Loc: Eng-NA-MOR/Rollins/all2.cha
@ID: 11312/c-00017262-1
@Begin
@Languages: eng
@Participants: OIE Target_Child , MOT Mother
@ID: eng|rollins|CHI|Target_Child|
@ID: eng|rollins|MOT|Mother|
@Media: a12, video
@Activities: Free Play
*MOT: you haven't seen this . . .
*MO: pro|ju|au|have-not part|seePASTP pro|den|this .
*MO: 114|S|B|214|A|X|3|2|NEG|4|0|ROOT|5|4|OB|3|4|PUNCT
*MO: that looks pretty cool .
*MO: get|that|I|look-PL adv|int|pretty adj|cool
*MO: do you know how to work that . . .
*MO: end|do|know|v|know adv|v|how|int|to v|work pro|den|that .
*MO: 1|3|A|X|2|1|S|B|3|3|0|ROOT|4|3|OB|3|5|6|INF|6|4|AC|PP|7|6|OB|3|4|3|PUNCT
*MO: yes|we do
*MO: oh yes|pro|ject|I|do
*MO: 1|3|COM|2|1|S|B|3|3|0|ROOT|4|3|PUNCT
```

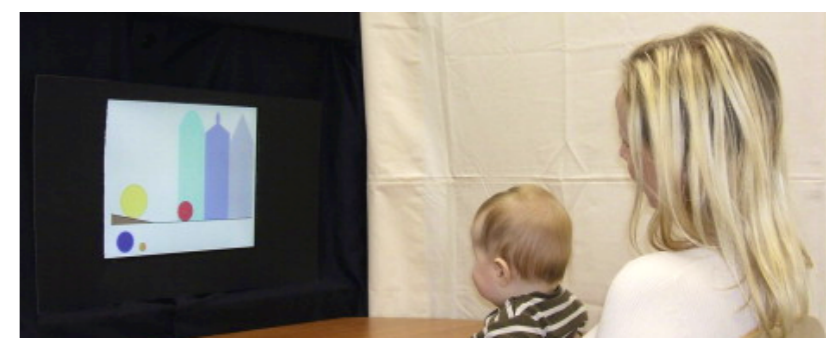
= w'ʌ rə prɪ'ri ri kɪ'ri

???



what
a
pretty
kitty

(9) Interpret the results for other people who aren't you so they know why they should care



“The modeled child can reproduce the **behavior we see in 8-month-olds**. This strategy could be what they're using to generate that behavior!”

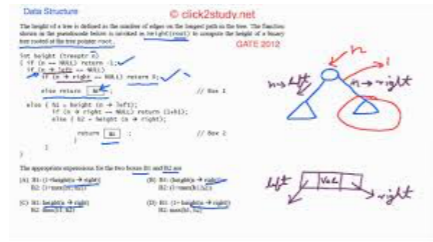
Today's Plan:

Computational models of language acquisition

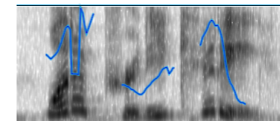
I. Why



II. How



III. What we can learn



Noun



✓ KI tty

Who does... is pretty?

another one

Every kitty didn't ...



Today's Plan:

Computational models of language acquisition

III. What we can learn

speech segmentation

metrical phonology

syntactic categorization

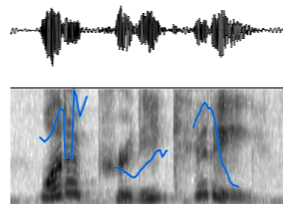
syntax



Who does... is pretty?

another one

Every kitty didn't ...



Noun

✓ KI tty

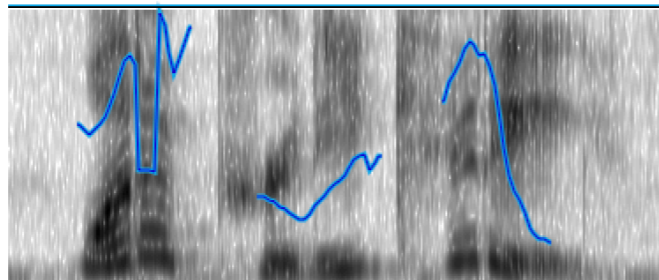


pragmatics

syntax, semantics

What we can learn

speech segmentation



= wʌɹəprɪkɪɹi

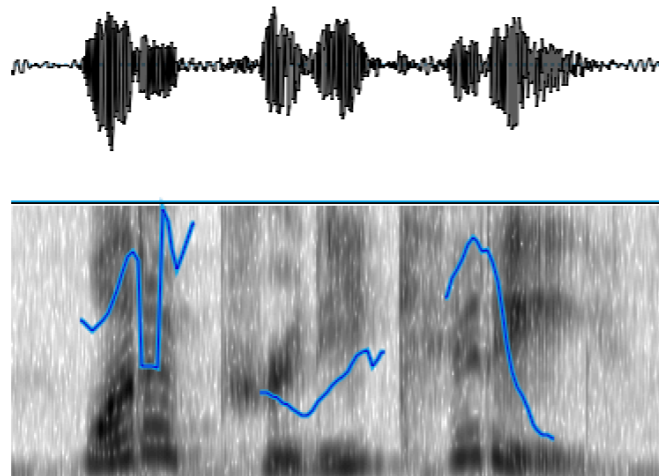
wʌɹ ə prɪɹi kɪɹi

what a pretty kitty!



What we can learn

speech segmentation



= wʌɹəprɪkɪɹi
wʌɹ ə prɪɹi kɪɹi
what a pretty kitty!

Investigating a Bayesian inference strategy for the very early stages of speech segmentation occurring around six months

Phillips & Pearl 2012, 2014a, 2014b,
2015a, 2015b, Pearl & Phillips in press

$$P(s|u) \propto P(s)P(u|s)$$

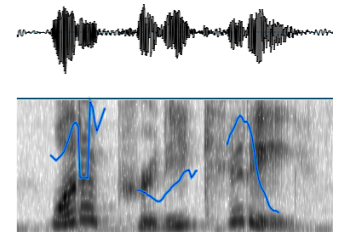


What we can learn

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$

speech segmentation



= $w\lambda r\theta p\lambda i r i k i r i$
 $w\lambda r \quad \theta \quad p\lambda i r i \quad k i r i$
what a pretty kitty!

Strategy: Identify a proto-lexicon of words that best generates the observable fluent speech utterances

Mathematically encoded preferences:

$w\lambda r\theta$
 $p\lambda i r i$
 $k i r i$

$w\lambda$
 $r\theta$
 $p\lambda i r i k i r i$

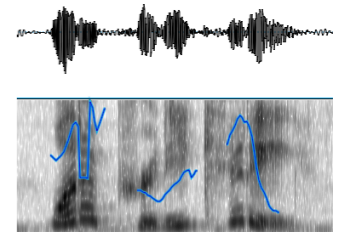
$w\lambda r\theta$
 $p\lambda i r i k i r i$

What we can learn

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$

speech segmentation



= *wΛrəpɹɪkɪrɪ*
wΛr ə pɹɪrɪ kɪrɪ
what a pretty kitty!

Strategy: Identify a proto-lexicon of words that best generates the observable fluent speech utterances

Mathematically encoded preferences:

(1) Prefer **shorter** words

wΛrə
pɹɪrɪ
kɪrɪ

wΛ
rə
pɹɪrɪkɪrɪ

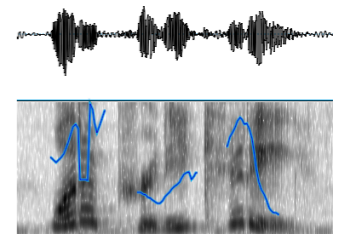
wΛrə
pɹɪrɪkɪrɪ

What we can learn

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$

speech segmentation



= $w\lambda r\theta p\lambda i r i k i r i$
 $w\lambda r \quad \theta \quad p\lambda i r i \quad k i r i$
what a pretty kitty!

Strategy: Identify a proto-lexicon of words that best generates the observable fluent speech utterances

Mathematically encoded preferences:

- (1) Prefer shorter words
- (2) Prefer lexicons with **fewer** words

$w\lambda r\theta$
 $p\lambda i r i$
 $k i r i$

$w\lambda$
 $r\theta$
 $p\lambda i r i k i r i$

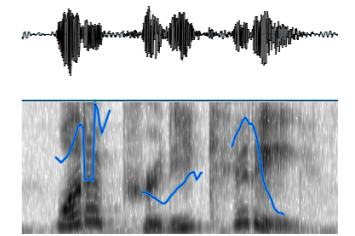
$w\lambda r\theta$
 $p\lambda i r i k i r i$

What we can learn

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$

speech segmentation



= $w\lambda r\theta p\lambda i r i k i r i$
 $w\lambda r \quad \theta \quad p\lambda i r i \quad k i r i$
what a pretty kitty!

Strategy: Identify a proto-lexicon of words that best generates the observable fluent speech utterances

Mathematically encoded preferences:

- (1) Prefer shorter words
- (2) Prefer lexicons with fewer words

$w\lambda r\theta$
 $p\lambda i r i$
 $k i r i$

$w\lambda$
 $r\theta$
 $p\lambda i r i k i r i$

$w\lambda r\theta$
 $p\lambda i r i k i r i$

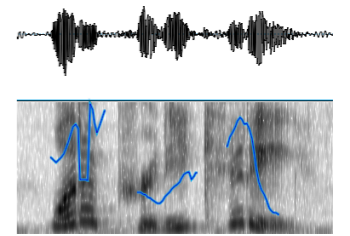
Find the **best segmentation**

What we can learn

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$

speech segmentation



= $w\lambda r\theta p\lambda i r i k i r i$
 $w\lambda r \quad \theta \quad p\lambda i r i \quad k i r i$
what a pretty kitty!

Strategy: Identify a proto-lexicon of words that best generates the observable fluent speech utterances

Mathematically encoded preferences:

- (1) Prefer shorter words
- (2) Prefer lexicons with fewer words

$w\lambda r\theta$
 $p\lambda i r i$
 $k i r i$

$w\lambda$
 $r\theta$
 $p\lambda i r i k i r i$

$w\lambda r\theta$
 $p\lambda i r i k i r i$

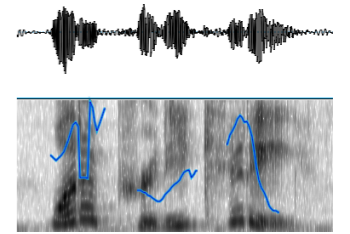
Find the best segmentation that balances these proto-lexicon preferences

What we can learn

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$

speech segmentation



= $w\lambda r\epsilon p\lambda i r i k i r i$
 $w\lambda r \epsilon p\lambda i r i k i r i$
what a pretty kitty!

Strategy: Identify a proto-lexicon of words that best generates the observable fluent speech utterances

Mathematically encoded preferences:

- (1) Prefer shorter words
- (2) Prefer lexicons with fewer words

$w\lambda r\epsilon$
 $p\lambda i r i$
 $k i r i$

$w\lambda$
 $r\epsilon$
 $p\lambda i r i k i r i$

$w\lambda r\epsilon$
 $p\lambda i r i k i r i$

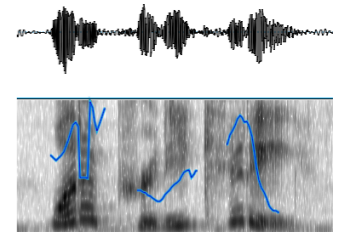
Find the best segmentation that balances these proto-lexicon preferences and can generate the observable fluent speech utterances

What we can learn

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$

speech segmentation



= wʌɹəpɹɪkɪɹɪ
wʌɹ ə pɹɪ kɪɹɪ
what a pretty kitty!



Is it **useful**?

Computational-level modeled learners using this strategy segment fairly well, given realistic English child-directed speech data.



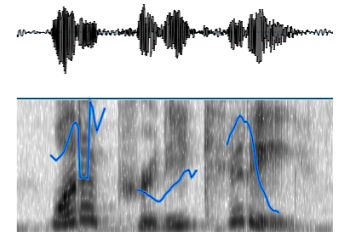
The inferred proto-lexicons, while not perfect, are very **useful for subsequent stages** of language acquisition.

What we can learn

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$

speech segmentation



= $w\lambda r \text{ } \text{ə} \text{ } p\text{r}\text{i} \text{ } k\text{i} \text{r}\text{i}$
wλr ə prɪ kɪrɪ
what a pretty kitty!

✓ Is it **useful**?



✓ Is it **useable**?

Algorithmic-level modeled learners with cognitive constraints on their inference and memory can still use this strategy and segment English quite well.

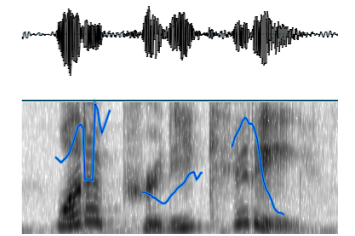


What we can learn

speech segmentation

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$



= *wʌɹəprɪkɪɹi*
wʌɹ ə prɪɹi kɪɹi
what a pretty kitty!

✓ Is it **useful**?



✓ Is it **useable**?



✓ Does it work for **different languages**?

It segments well for languages with different morphology and syllable properties: *Spanish, Italian, German, Hungarian, Japanese, Farsi*

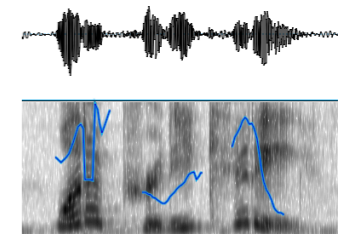


What we can learn

speech segmentation

Bayesian inference

$$P(s|u) \propto P(s)P(u|s)$$



= $\omega\lambda\epsilon\mu\iota\kappa\iota\tau\iota$
 $\omega\lambda\epsilon \ \mu\iota\kappa\iota \ \kappa\iota\tau\iota$
what a pretty kitty!



Is it **useful**?



Is it **useable**?



Does it work for
different languages?



Bayesian inference seems to be a good proposal for a very early speech segmentation strategy.

What we can learn

speech segmentation

metrical phonology

syntactic categorization

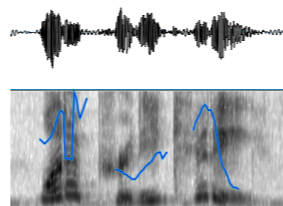
syntax



Who does... is pretty?

another one

Every kitty didn't ...



Noun

✓ KI tty



pragmatics

syntax, semantics

What we can learn

metrical phonology

✓ KI tty

✗ ki TTY



What we can learn

metrical phonology

- ✓ a DO ra ble
- ✗ A do RA ble
- ✗ a DO ra BLE
- ✓ KI tty
- ✗ ki TTY



What we can learn

metrical phonology

✓ a DO ra ble
✗ A do RA ble
✗ a DO ra BLE

✓ KI tty
✗ ki TTY

Our underlying **knowledge representation** of the metrical phonology system allows us to generate these **metrical stress** preferences.

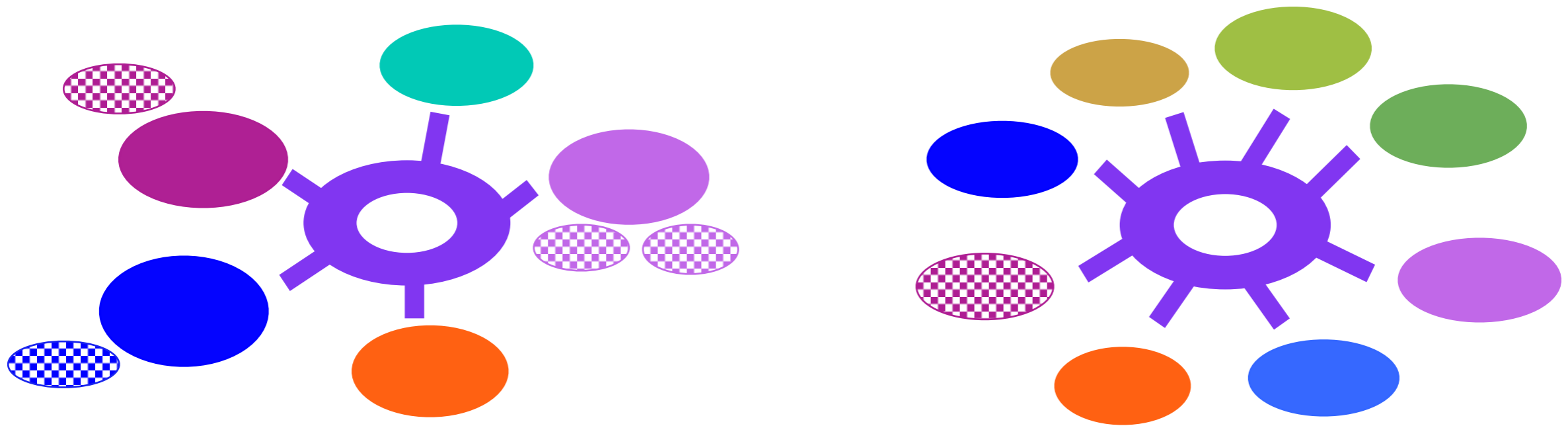
What we can learn

metrical phonology

- ✓ a DO ra ble
- ✓ KI tty
- ✗ A do RA ble
- ✗ ki TTY
- ✗ a DO ra BLE

knowledge representation options

parameters whose values must be set



English

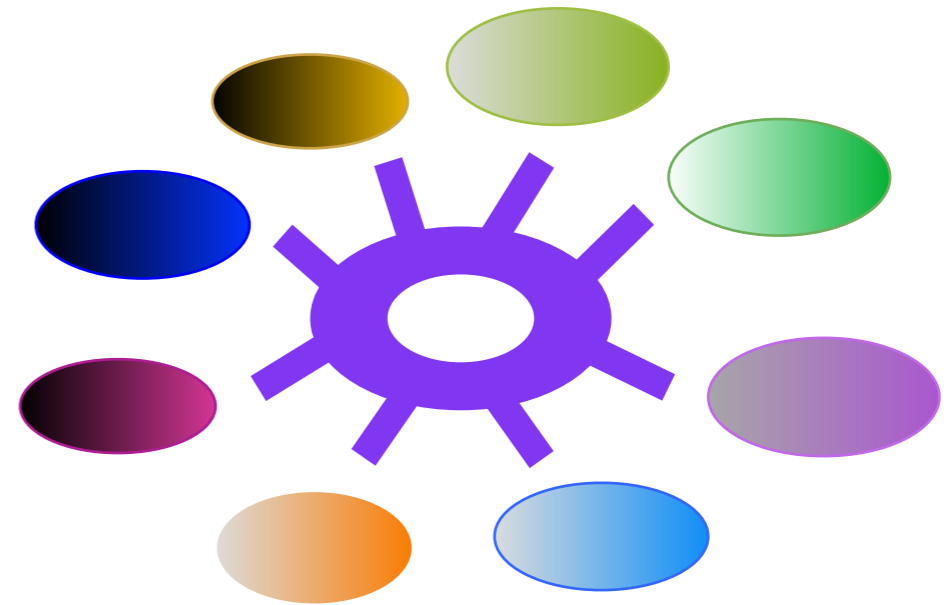
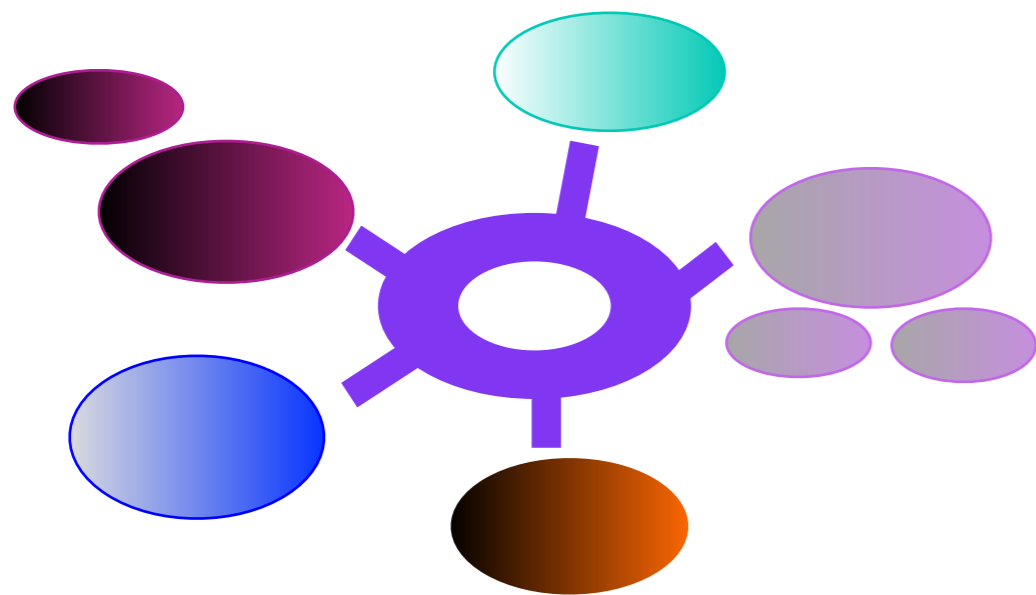
What we can learn

metrical phonology

- ✓ a DO ra ble
- ✓ KI tty
- ✗ A do RA ble
- ✗ ki TTY
- ✗ a DO ra BLE

knowledge representation options

parameters whose values must be set



English

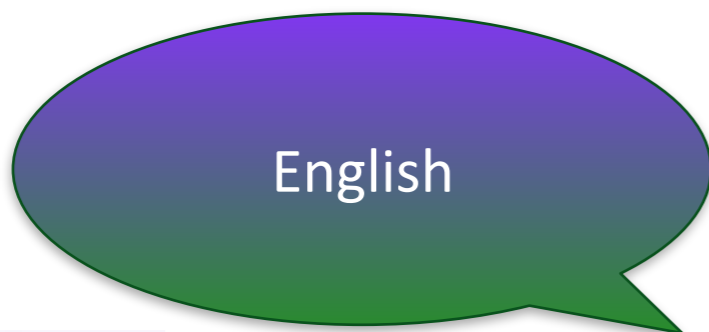
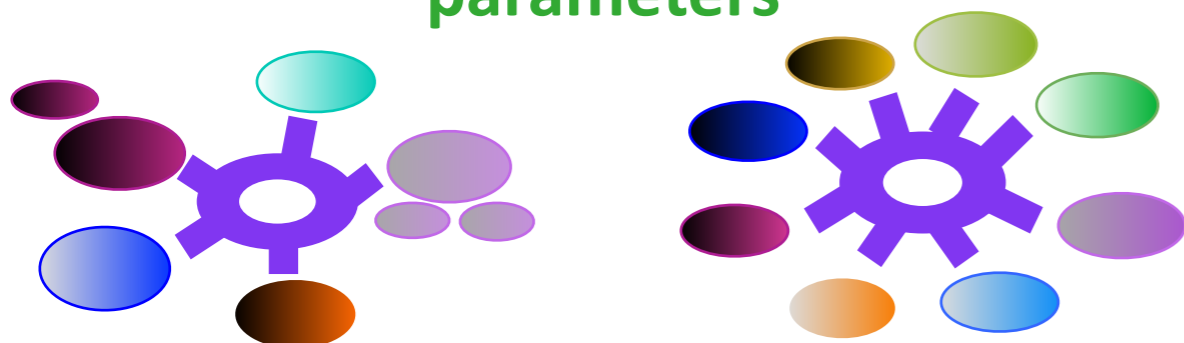
What we can learn

metrical phonology

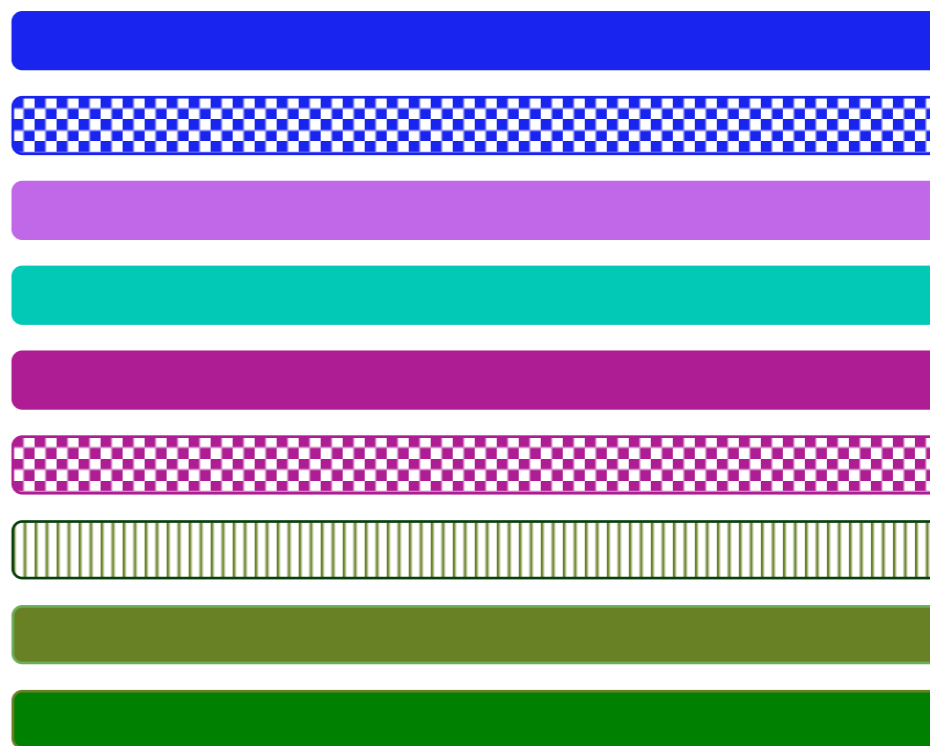
- ✓ a DO ra ble
- ✓ KI tty
- ✗ A do RA ble
- ✗ ki TTY
- ✗ a DO ra BLE

knowledge representation options

parameters



Violable constraints that must be ranked



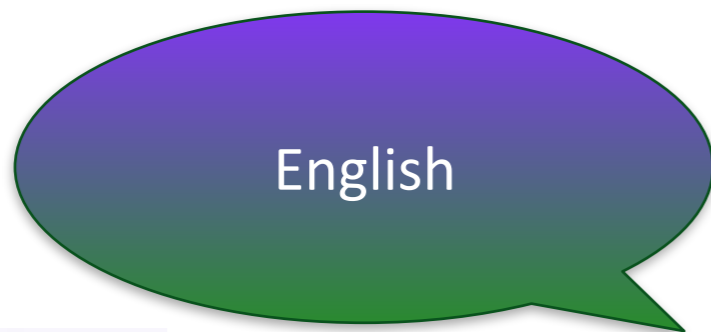
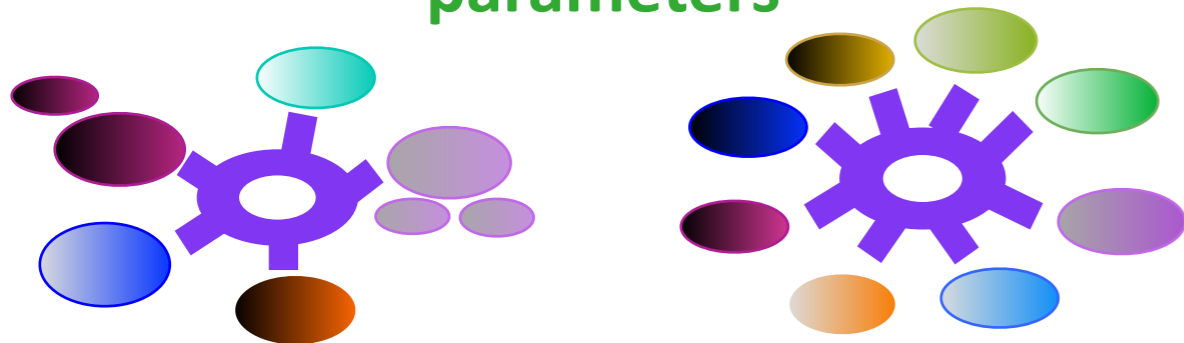
What we can learn

metrical phonology

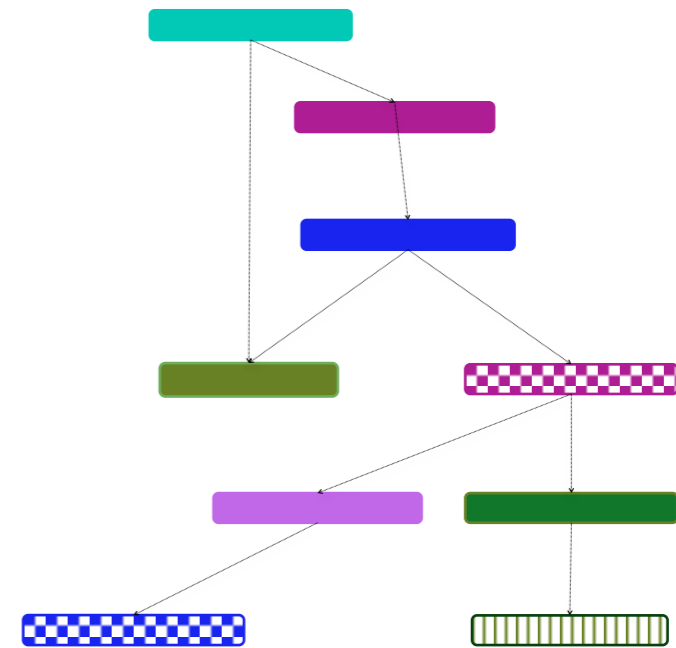
- ✓ a DO ra ble
- ✓ KI tty
- ✗ A do RA ble
- ✗ ki TTY
- ✗ a DO ra BLE

knowledge representation options

parameters



Violable constraints that must be ranked

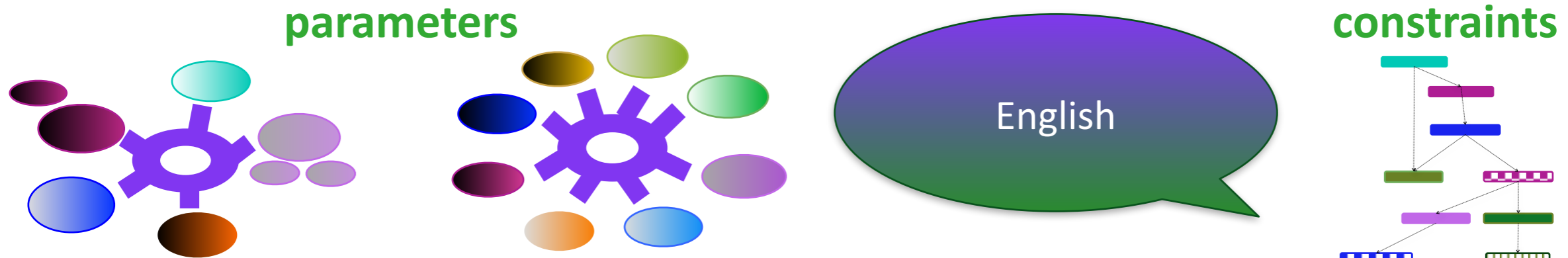


What we can learn

metrical phonology

- ✓ a DO ra ble
- ✗ A do RA ble
- ✗ a DO ra BLE
- ✓ KI tty
- ✗ ki TTY

knowledge representation options



These representations have some similarities, but aren't obviously using identical variables.

How do we choose among these representations and their English versions?

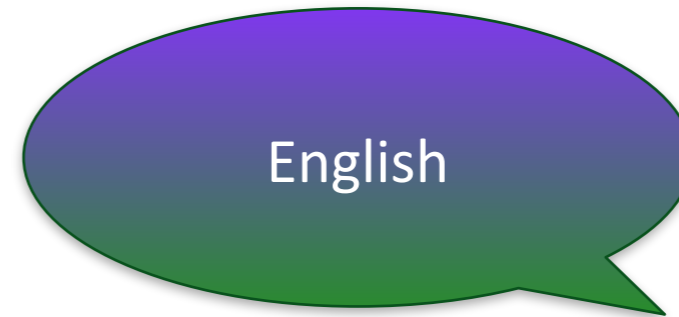
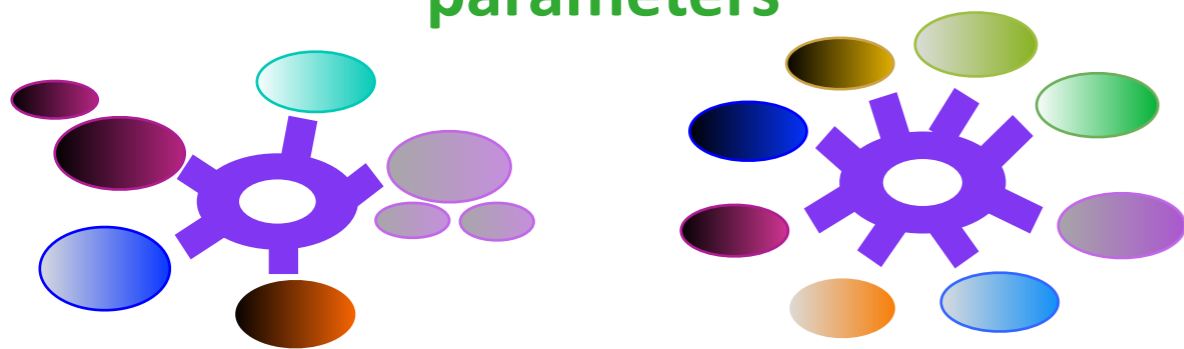
What we can learn

metrical phonology

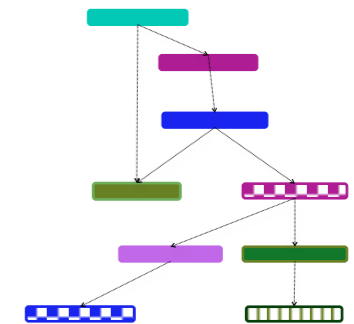
- ✓ a DO ra ble
- ✗ A do RA ble
- ✗ a DO ra BLE
- ✓ KI tty
- ✗ ki TTY

knowledge representation options

parameters



constraints



How do we choose among these representations and their English versions?

Answer: Let's see **how learnable they are** from the English data children typically encounter!

Pearl et al. 2014, Pearl 2017, Pearl et. al in press

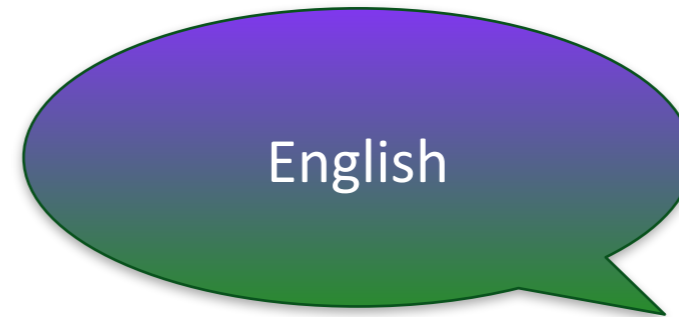
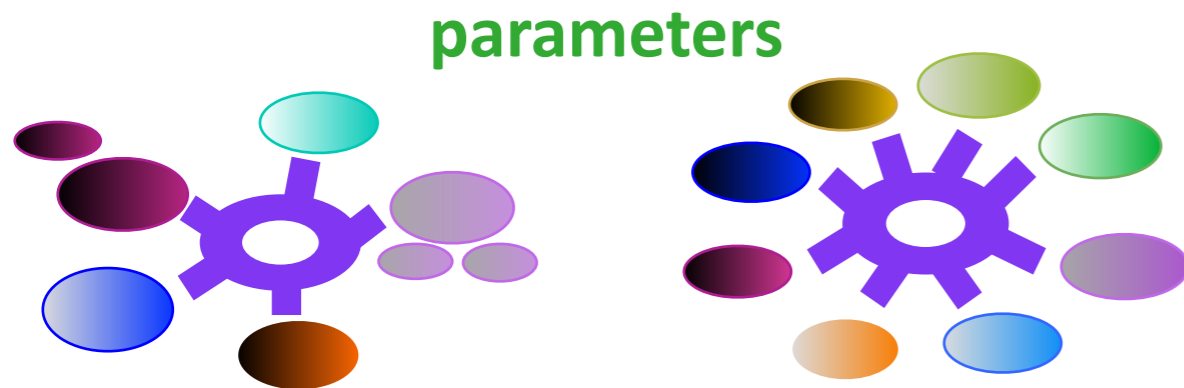


What we can learn

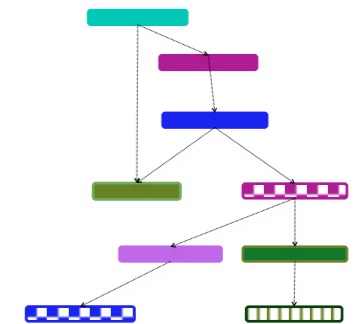
metrical phonology

- ✓ a DO ra ble
- ✗ A do RA ble
- ✗ a DO ra BLE
- ✓ KI tty
- ✗ ki TTY

knowledge representation options



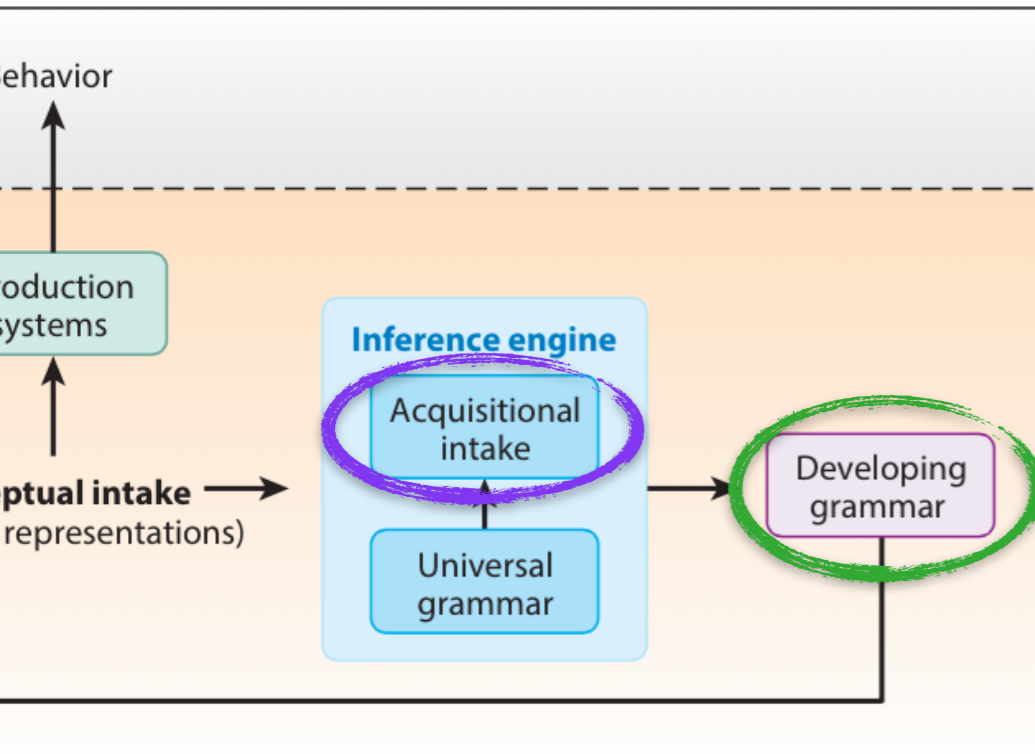
constraints



how learnable they are

Computational-level analysis

Modeled learners given realistic samples of English child-directed speech can identify **parameter combinations** or **constraint rankings** that are very good at accounting for the input especially if children use **a data filter**.



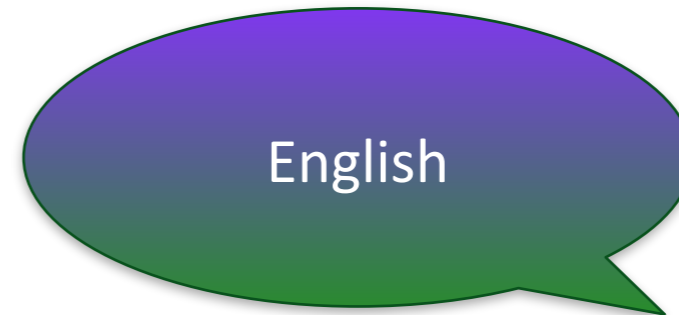
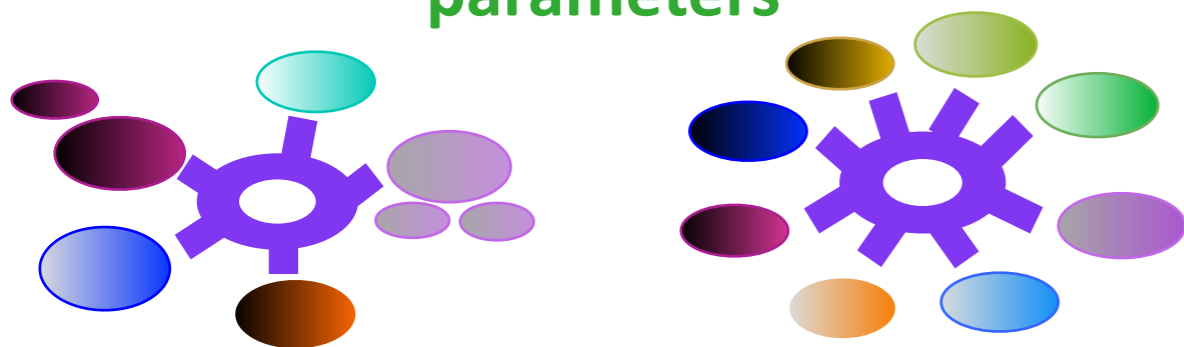
What we can learn

metrical phonology

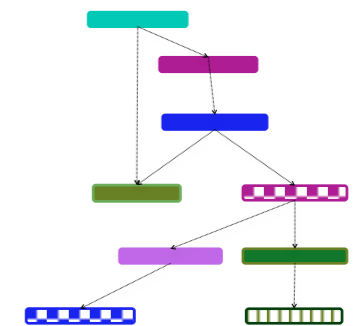
- ✓ a DO ra ble
- ✓ KI tty
- ✗ A do RA ble
- ✗ ki TTY
- ✗ a DO ra BLE

knowledge representation options

parameters



constraints



how learnable they are

Computational-level analysis

But the best options for English data **aren't** the ones currently proposed for English.



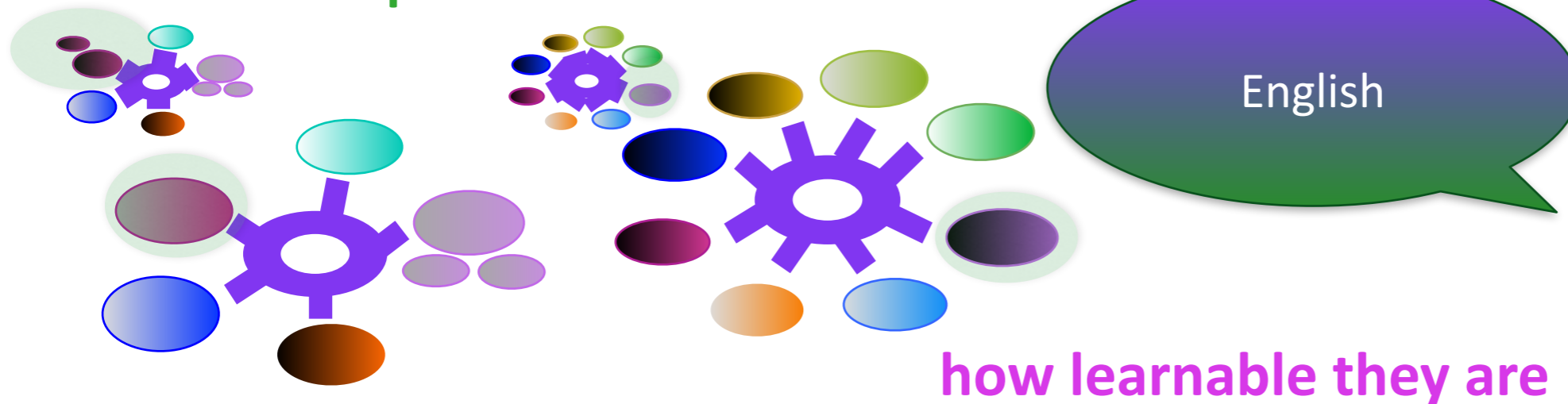
What we can learn

metrical phonology

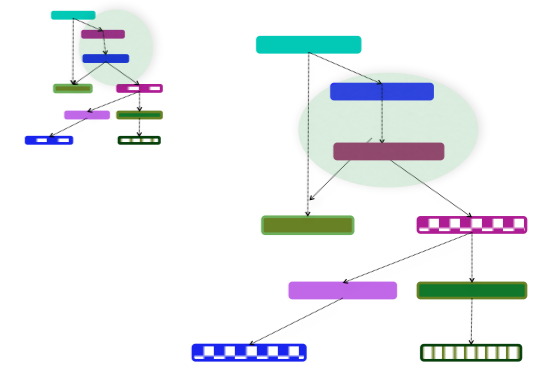
- ✓ a DO ra ble
- ✓ KI tty
- ✗ A do RA ble
- ✗ ki TTY
- ✗ a DO ra BLE

knowledge representation options

parameters



constraints



Computational-level analysis

Other options (differing very slightly) are much more easily learnable.

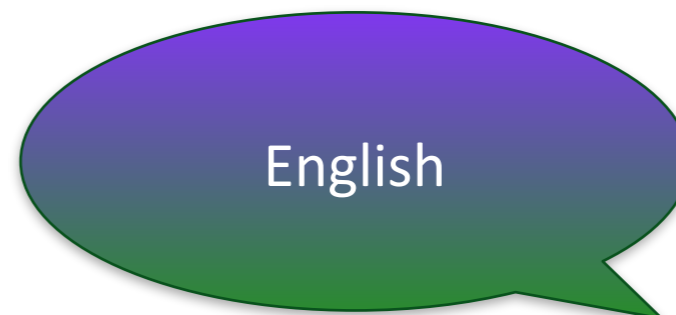
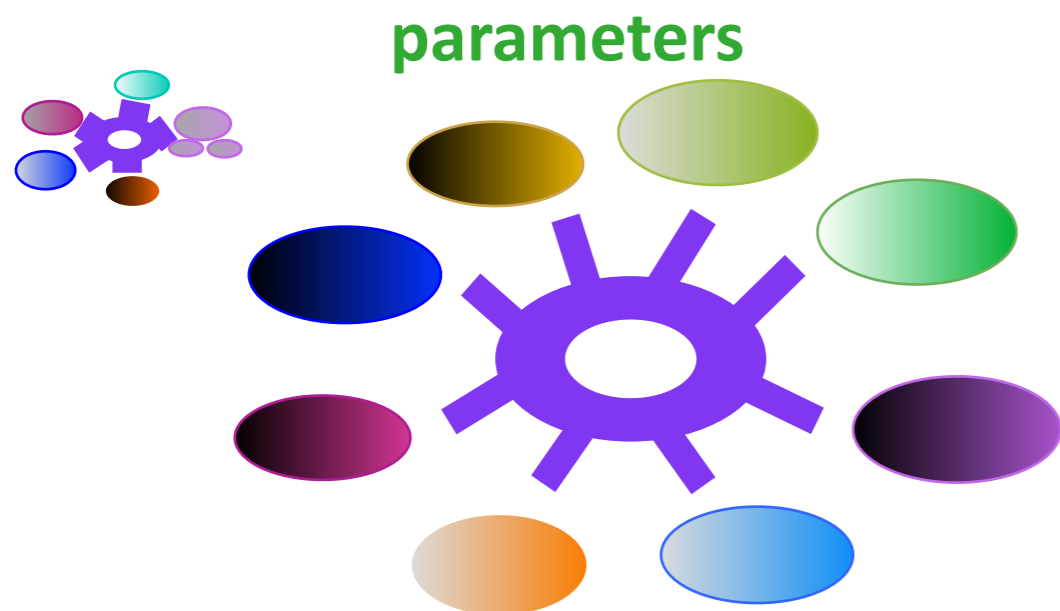


What we can learn

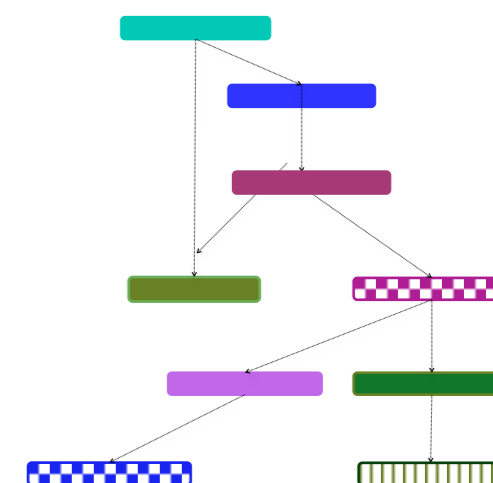
metrical phonology

- ✓ a DO ra ble
- ✗ A do RA ble
- ✗ a DO ra BLE
- ✓ KI tty
- ✗ ki TTY

knowledge representation options

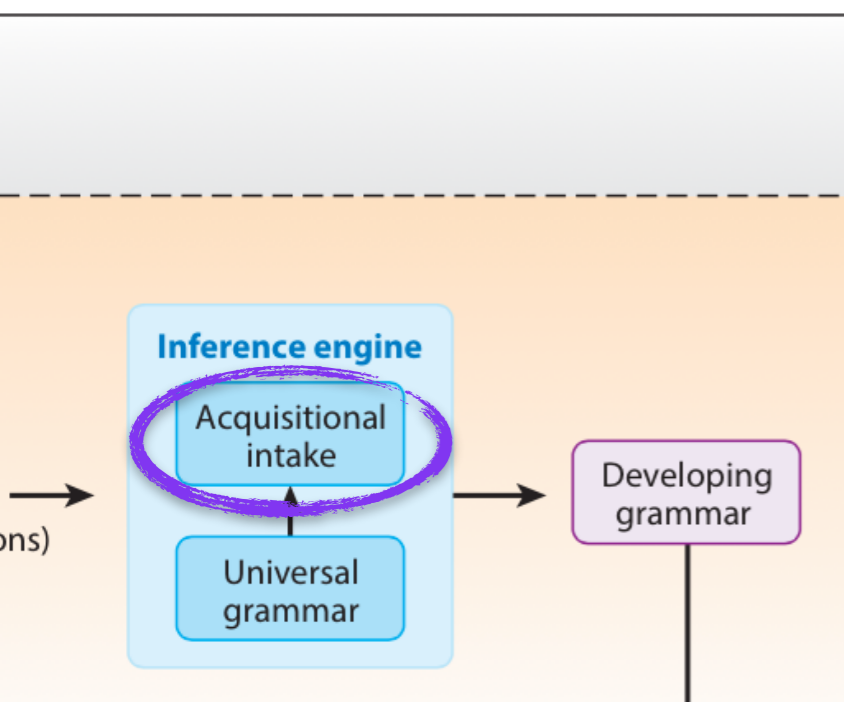


constraints



how learnable they are

Computational-level analysis



And **two** do particularly well when a **data filter** is in place.

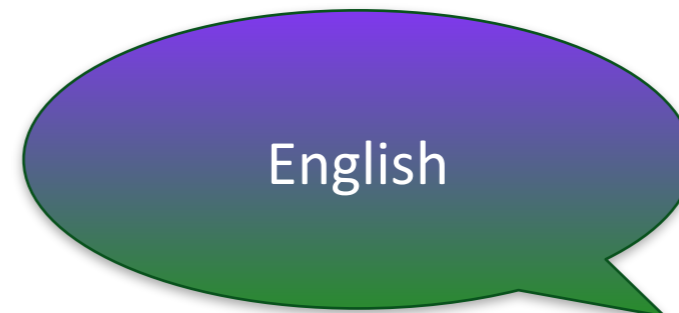
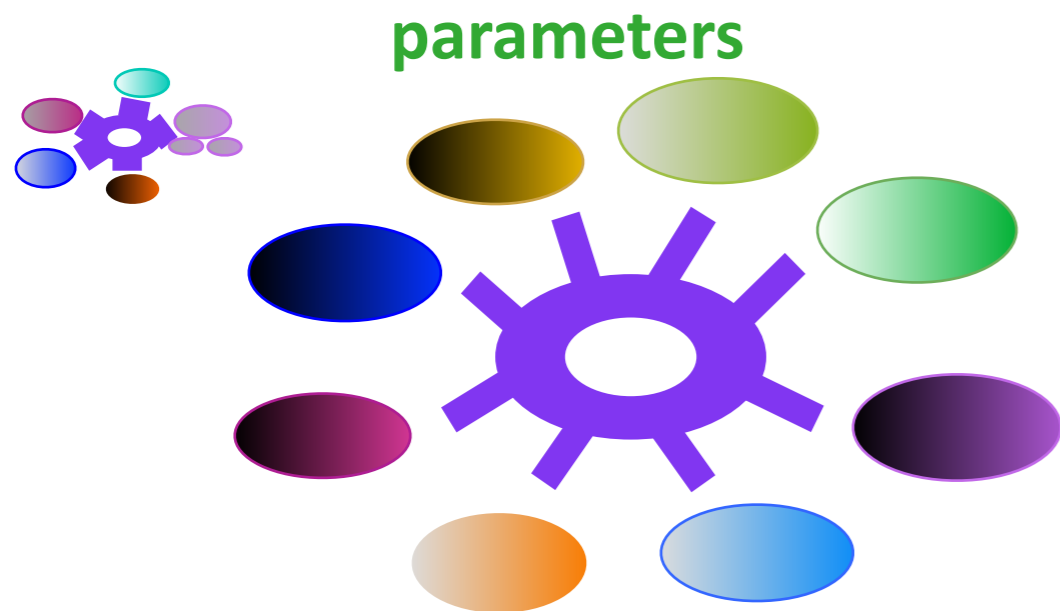


What we can learn

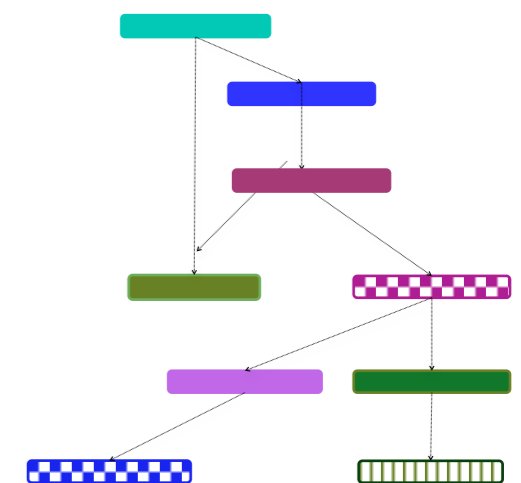
metrical phonology

- ✓ a DO ra ble
- ✗ A do RA ble
- ✗ a DO ra BLE
- ✓ KI tty
- ✗ ki TTY

knowledge representation options



constraints



By modeling acquisition, we provide support for these two theories of English representation.



What we can learn

speech segmentation

metrical phonology

syntactic categorization

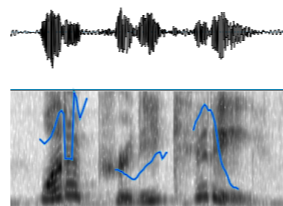
syntax



Who does... is pretty?

another one

Every kitty didn't ...



Noun

✓ KI tty



pragmatics

syntax, semantics

What we can learn

syntactic categorization

glitter



idea



unicorn



penguin



Noun

owl



kitty



What we can learn

syntactic categorization

idea
glitter unicorn
Noun
penguin owl
kitty

Nouns behave similarly:

They can combine with certain types of words to make larger units (like Noun Phrases).

What we can learn

syntactic categorization

Determiner + Noun (“the **kitty**”)

[NP → Det + N]



idea
glitter unicorn
Noun
penguin owl

Nouns behave similarly:

They can combine with certain types of words to make larger units (like Noun Phrases).

What we can learn

syntactic categorization



dax

idea

glitter

unicorn

penguin

Noun

owl

kitty

Determiner + Noun (“the ”)

[NP → Det + N]

Rule with **category Noun** = new phrases with words of **category Noun**

This is very handy for generating new expressions we haven't heard before.



What we can learn

syntactic categorization



idea
glitter unicorn
Noun
penguin owl
kitty

Determiner + Noun (“the dax ”)

[NP → Det + N]

Rule with category Noun = new phrases with words of category Noun

This is very handy for generating new expressions we haven't heard before.



What we can learn

syntactic categorization

idea
glitter unicorn
Noun owl
penguin kitty

We have many categories in human language.

Some are **open-class** — it's easy to add new words to them.

What we can learn

syntactic categorization

idea
glitter unicorn
Noun
penguin owl
kitty

We have many categories in human language.

Some are **open-class** — it's easy to add new words to them.

[VP → Negation + V]

It's not **daxing**
- it's dancing!



surprise stand
Verb
find dance
adore

What we can learn syntactic categorization

idea
glitter unicorn
Noun
penguin owl
kitty

We have many categories in human language.

Some are **open-class** — it's easy to add new words to them.

dax
surprise stand
Verb
find dance
adore

What we can learn

syntactic categorization

idea unicorn
glitter
Noun owl
penguin
surprise stand
kitty
Verb dance
find adore

We have many categories in human language.

Some are **closed-class** — the words in them are fixed.

[VP → **Negation** + **V**]

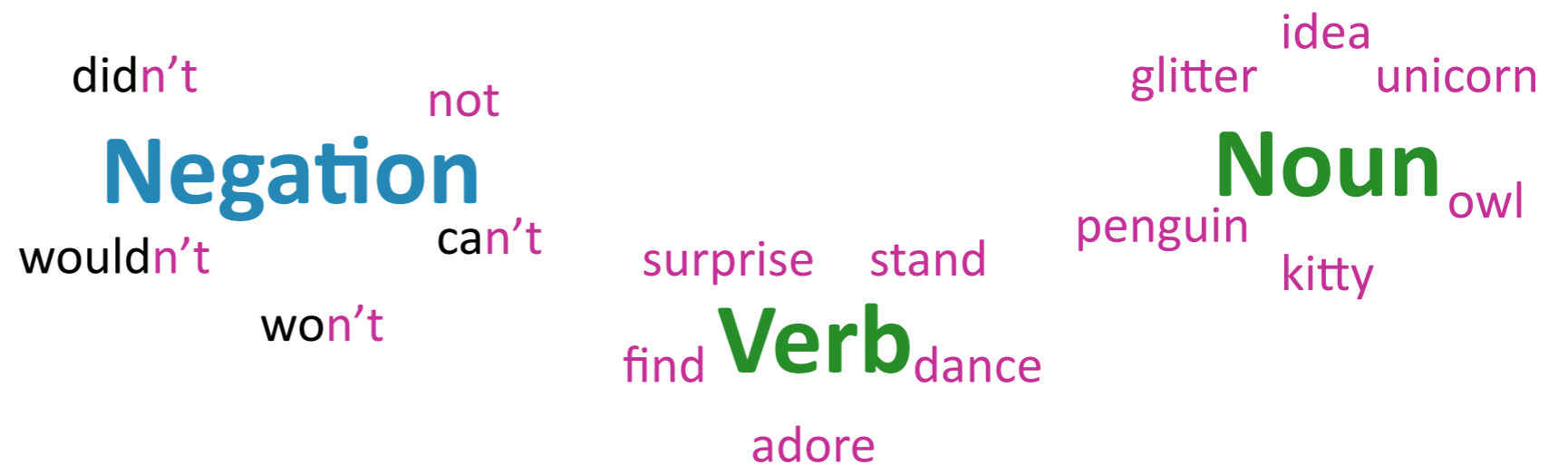
It's **not** daxing
- it's dancing!



didn't not
Negation
wouldn't can't
won't

What we can learn

syntactic categorization

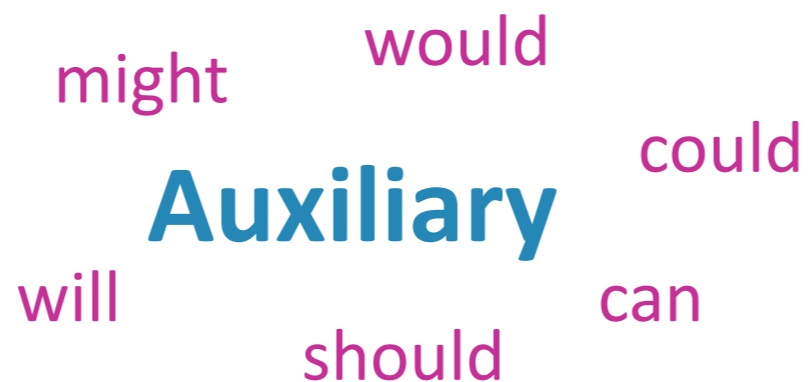


We have many categories in human language.

Some are **closed-class** — the words in them are fixed.

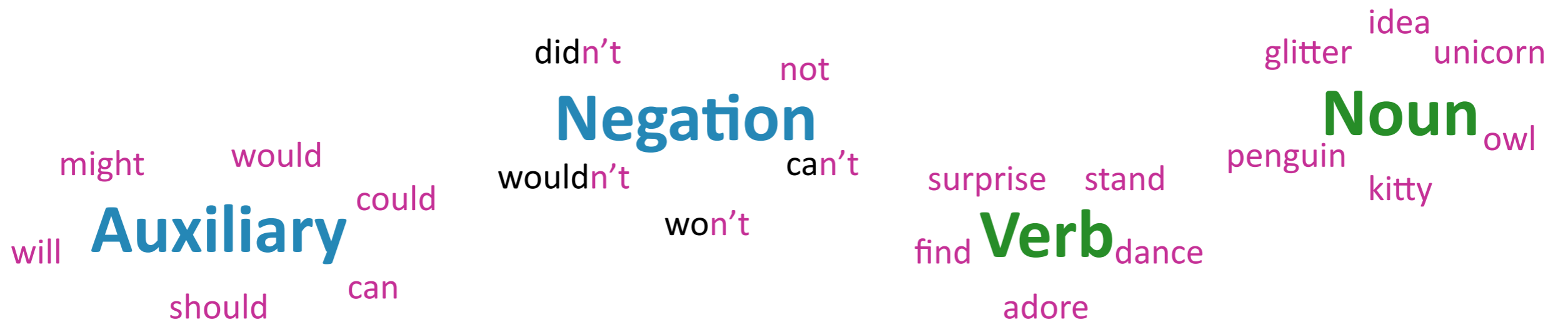
[VP → Auxiliary + V]

It **would** sing
if it **could** sing



What we can learn

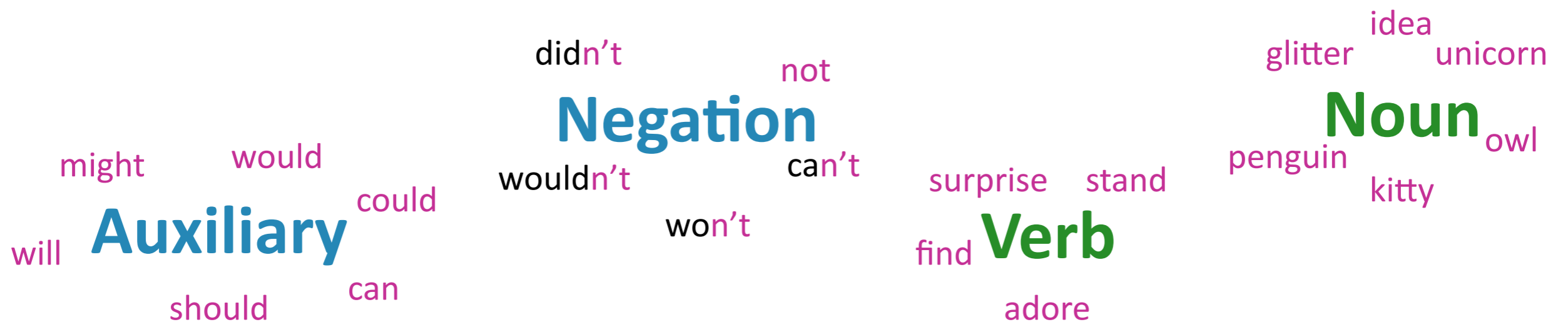
syntactic categorization



There's significant debate on when these categories develop.

What we can learn

syntactic categorization



There's significant debate on when these categories develop.

Easy to observe: When children know individual **words**.

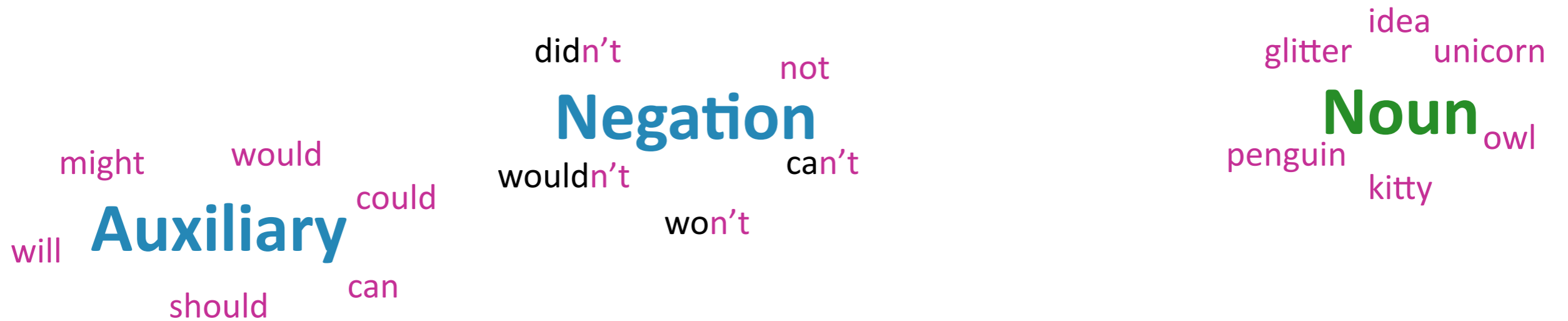


dance



What we can learn

syntactic categorization



There's significant debate on when these categories develop.

Harder to observe: When children have recognized these words belong to **categories**.

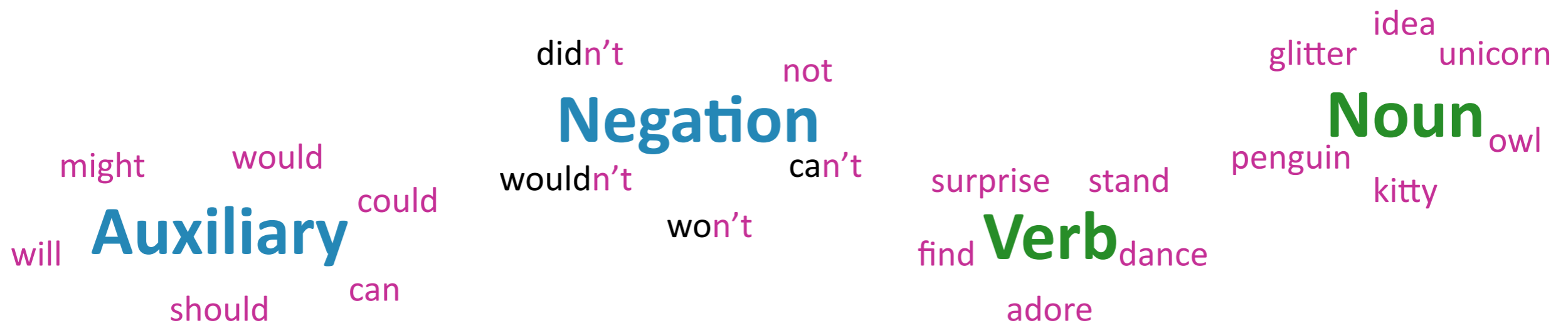


surprise adore stand
find **Verb** ???
dance

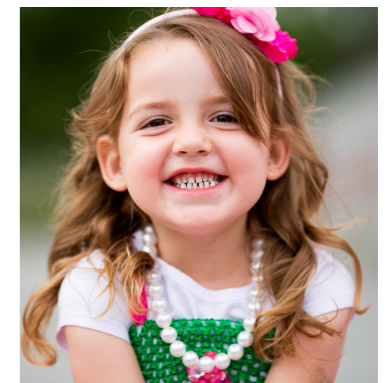


What we can learn

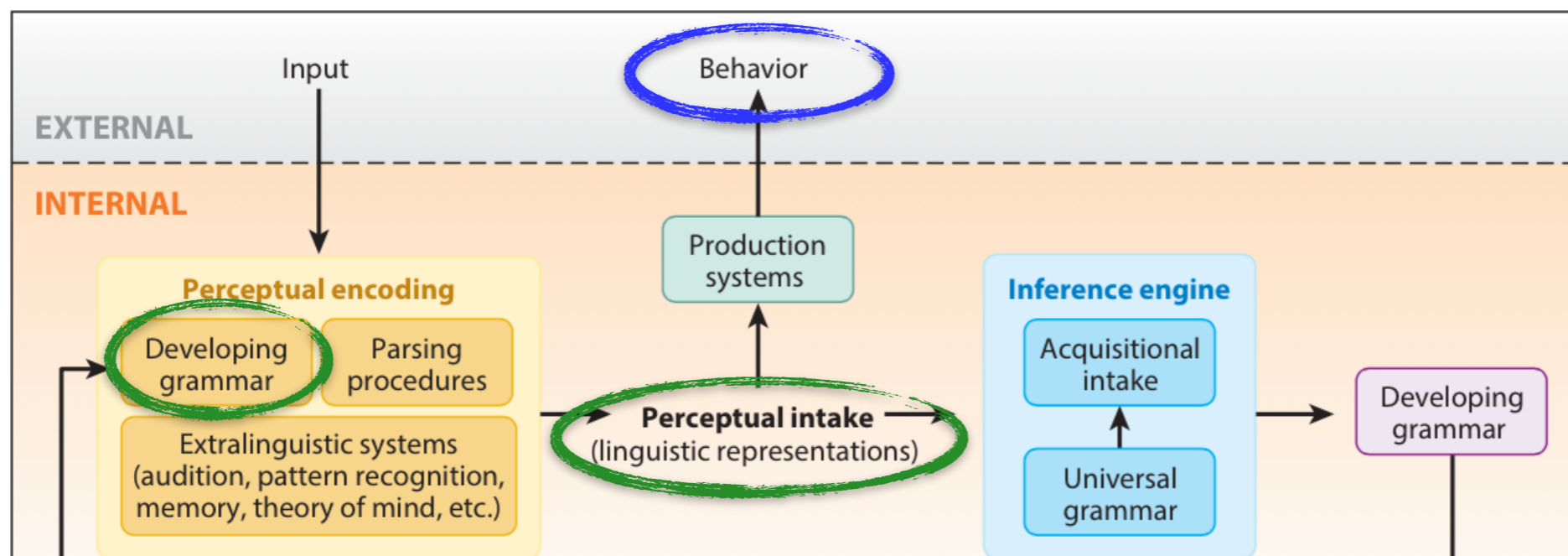
syntactic categorization



What we can do: Computational-level analysis of children's productions, using formal metrics that describe how children generate their utterances given their underlying representations

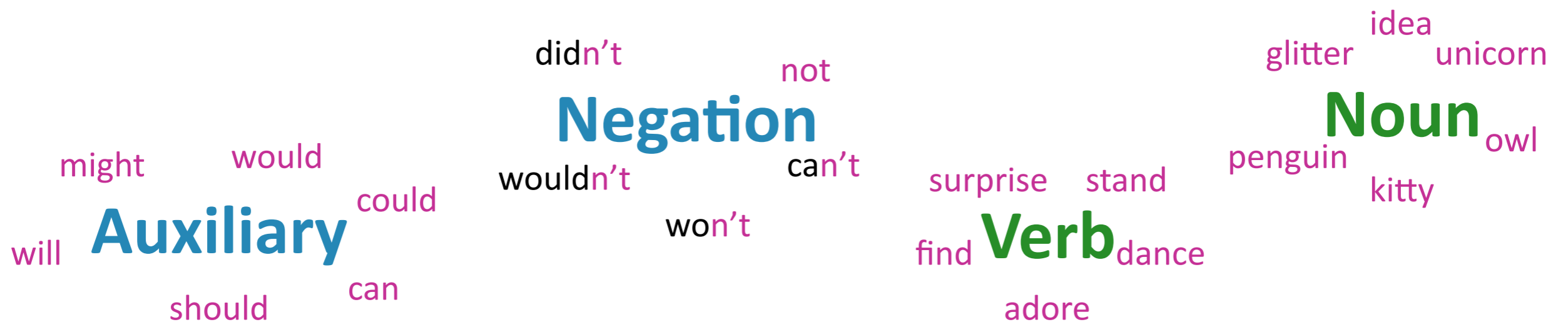


Bates, Pearl & Braunwald, in prep.



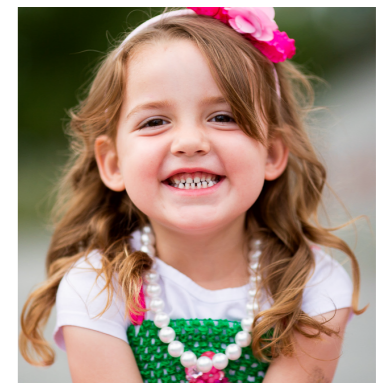
What we can learn

syntactic categorization



Computational-level

Analyzing the utterances produced by a single American English child between the ages of 20 and 24 months



What we can learn

syntactic categorization



Computational-level

Analyzing the utterances produced by a single American English child between the ages of 20 and 24 months



Utterances compatible with having **adult-like closed-class categories**, but **not adult-like open-class categories**.

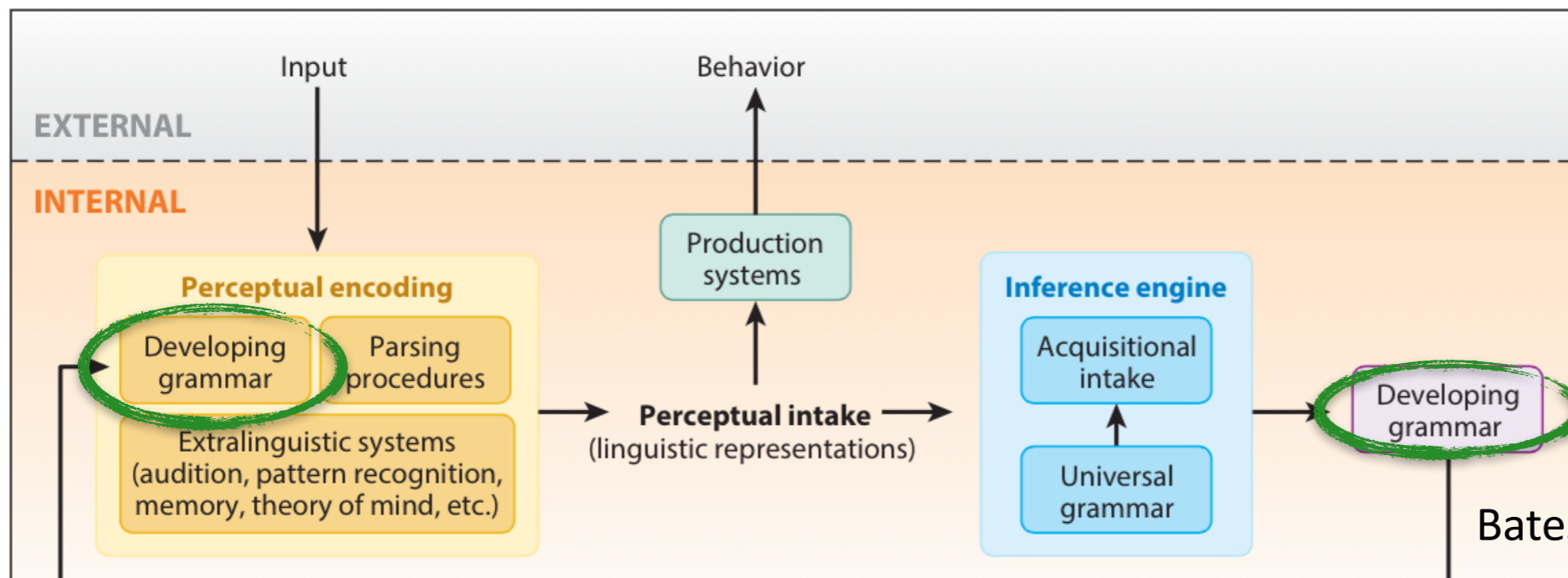
What we can learn

syntactic categorization



Computational-level

This suggests that **closed-class categories** may develop into an adult-like state earlier than open-class categories and **much earlier than previously thought**.



Bates, Pearl & Braunwald, in prep.

What we can learn

speech segmentation

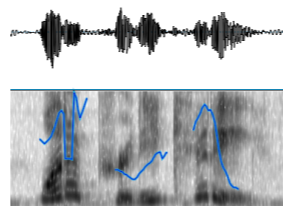
metrical phonology

syntactic categorization

syntax



Who does ... is pretty? another one
Every kitty didn't ...



Noun

✓ KI tty



pragmatics

syntax, semantics

What we can learn

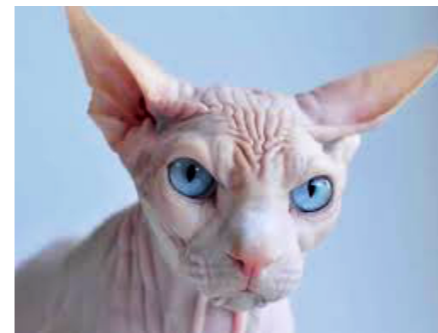
syntax, semantics

another one

“Oh look — a pretty kitty!”



“Look — there’s another **one**!”



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



“Look — there’s another one!”

Interpretation: another pretty kitty

same

syntactic category

???



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



“Look — there’s another one!”

Interpretation: another

same

syntactic category

???

bigger than a plain **Noun**

Noun

pretty **kitty**

What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



“Look — there’s another one!”

Interpretation: another ~~the~~ pretty kitty

same

syntactic category

???

smaller than a full **Noun Phrase**

Noun Phrase

the

Noun

pretty kitty

What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



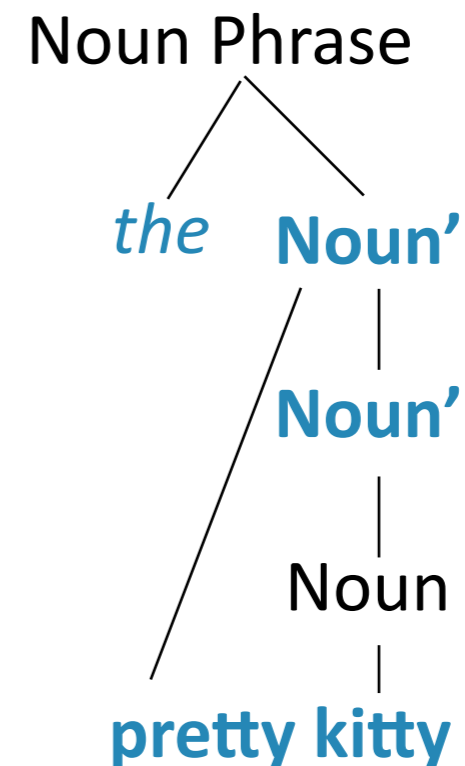
“Look — there’s another one!”

Interpretation: another

same
syntactic category

???

In-between category **Noun'**
that includes strings with nouns
and modifiers+nouns



What we can learn

syntax, semantics

another one

“Oh look — a pretty **kitty!**”

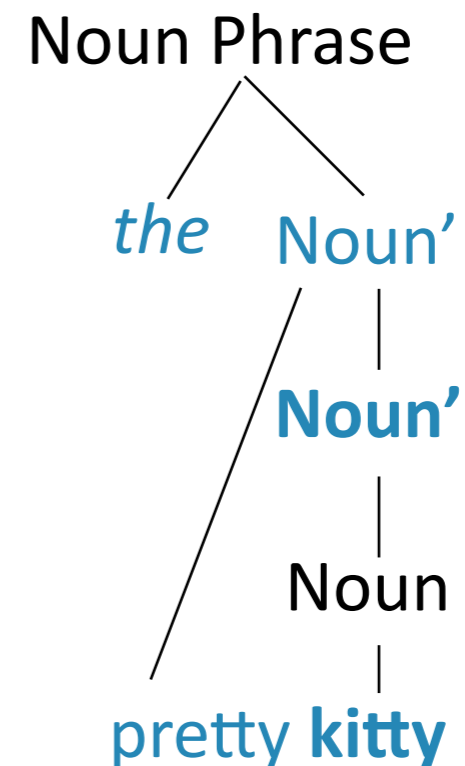
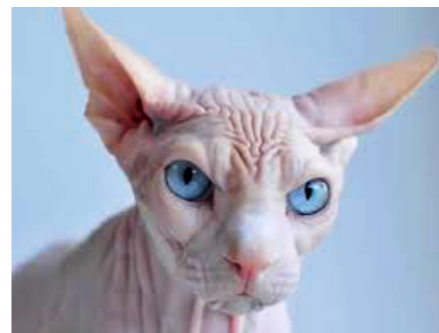


“Look — there’s another **one!**”

Interpretation: another

same
syntactic category

This is why we can also interpret **one** as just **kitty**.



What we can learn

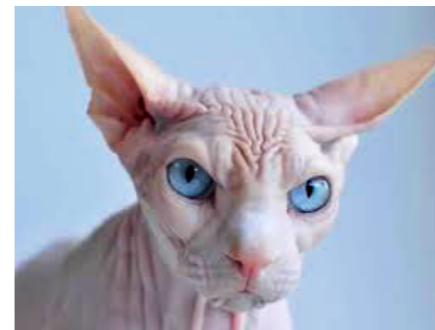
syntax, semantics

another one

“Oh look — a pretty kitty!”



“Do you see another *one*?”



Lidz, Waxman, & Freedman 2003:
18-month-old interpretations

What we can learn

syntax, semantics

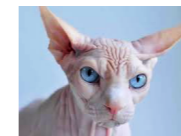
another one

“Oh look — a pretty kitty!”



“Do you see another one?”

pretty kitty
Noun'



Lidz, Waxman, & Freedman 2003:
18-month-old interpretations

What we can learn

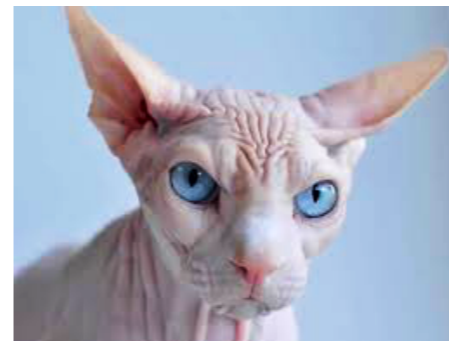
syntax, semantics

another one

“Oh look — a pretty kitty!”



“Do you see another kitty?”



another *one*
pretty kitty
Noun'



Lidz, Waxman, & Freedman 2003:
18-month-old interpretations

What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



“Do you see another kitty?”



another *one*
pretty kitty
Noun'



Lidz, Waxman, & Freedman 2003:
18-month-old interpretations

What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



“Do you see another pretty kitty?”



another *one*
pretty kitty
Noun'



Lidz, Waxman, & Freedman 2003:
18-month-old interpretations

What we can learn

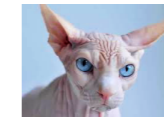
syntax, semantics

another one

“Oh look — a pretty kitty!”



“Do you see another pretty kitty?”



another *one*
pretty kitty
Noun'



Lidz, Waxman, & Freedman 2003:
18-month-old interpretations

What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



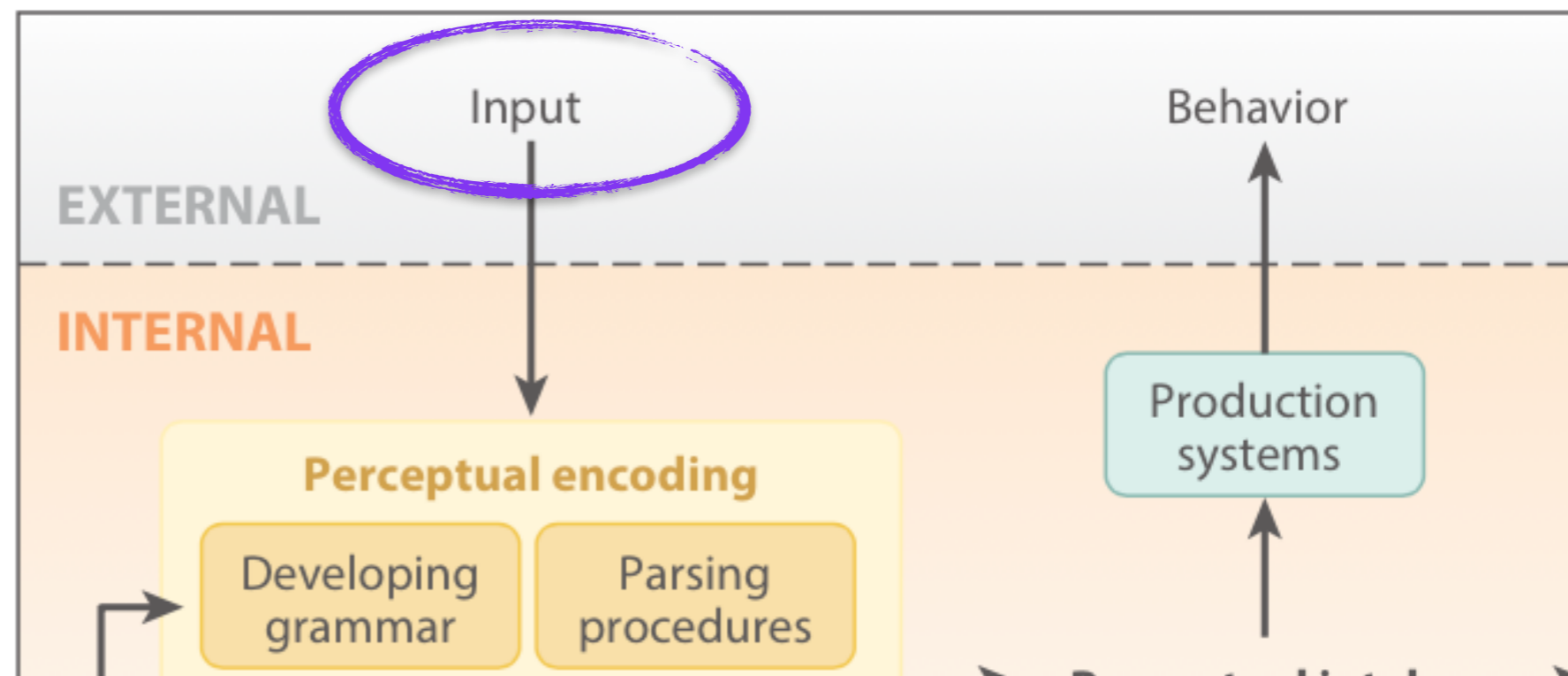
Noun'
pretty kitty

“Do you see another one ?”



Several learning strategies implemented with **algorithmic-level** modeled learners, given **realistic** samples of English child-directed speech.

Pearl & Mis 2016



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



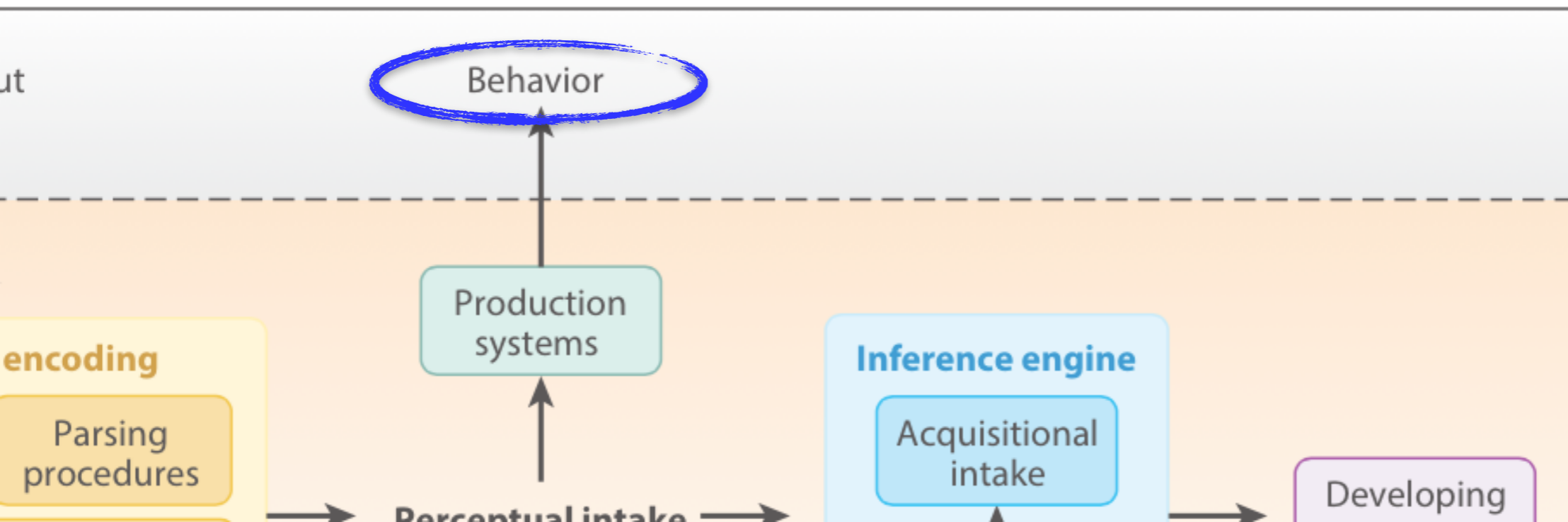
Noun'
pretty kitty

“Do you see another one ?”



Algorithmic-level

Evaluated on whether they matched
18-month-old looking preferences.



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



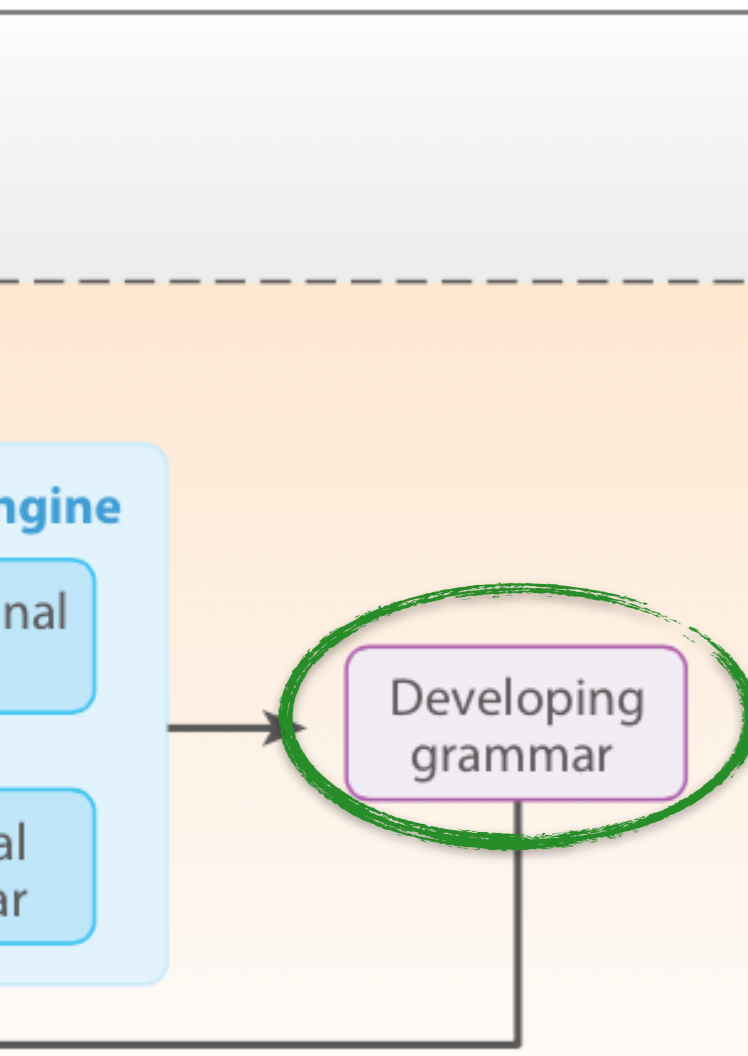
Noun'
pretty kitty

“Do you see another one ?”



Algorithmic-level

Two strategies were successful at generating the 18-month-old behavior. We can then look inside the modeled learner and see what the underlying representations were.



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”

Algorithmic-level

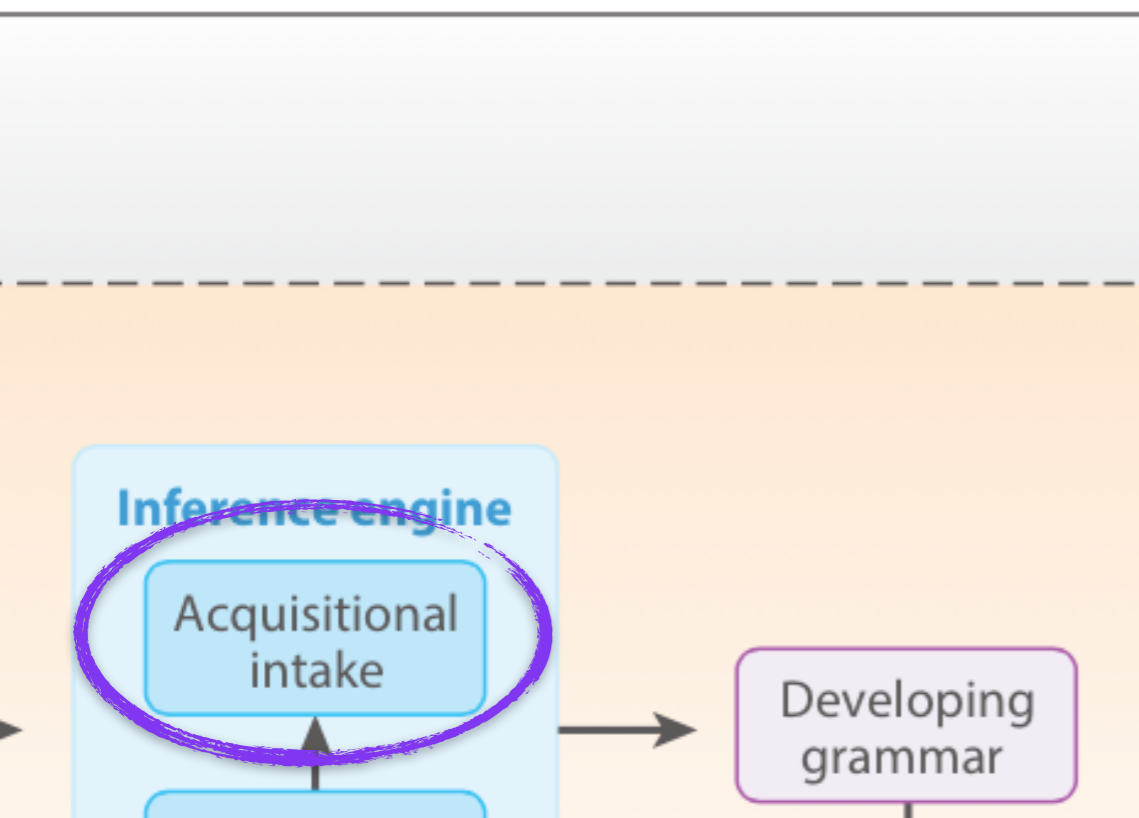


Noun'
pretty kitty

“Do you see another one ?”



Strategy 1: Ignore some of the available one data in the input



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”

Algorithmic-level



“Do you see another one ?”



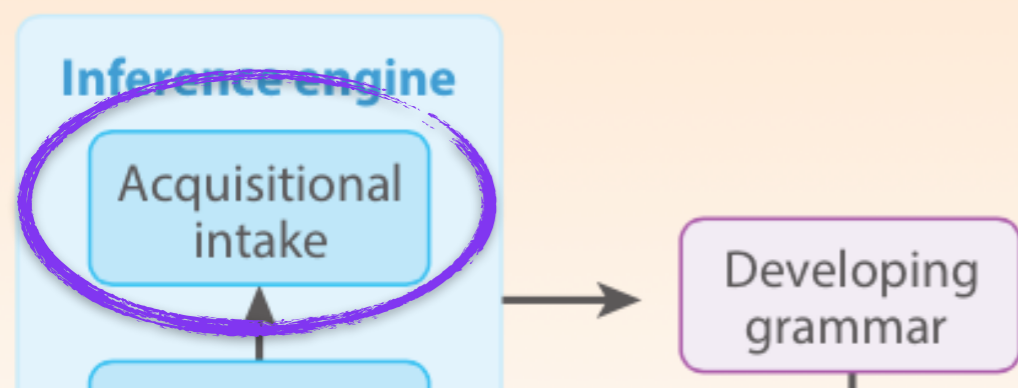
Strategy 1: Ignore some of the available one data in the input

Adult representations

✓ Noun'
pretty kitty

But...required additional situational context to be present to succeed.

Less robust



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”

Algorithmic-level

Strategy 1: Ignore



Less robust

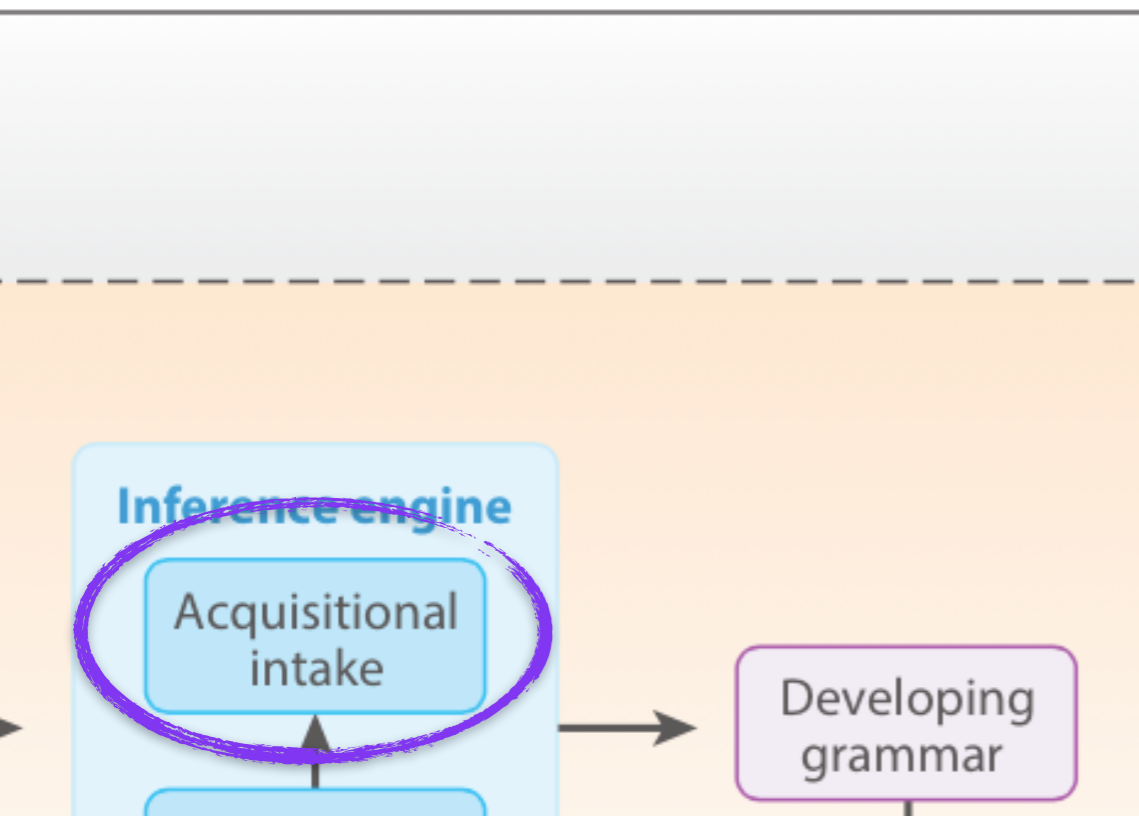


Noun'
pretty kitty

“Do you see another one ?”



Strategy 2: Include other pronoun data besides one data in the intake



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”

Algorithmic-level

Strategy 1: Ignore



Less robust



“Do you see another one?”



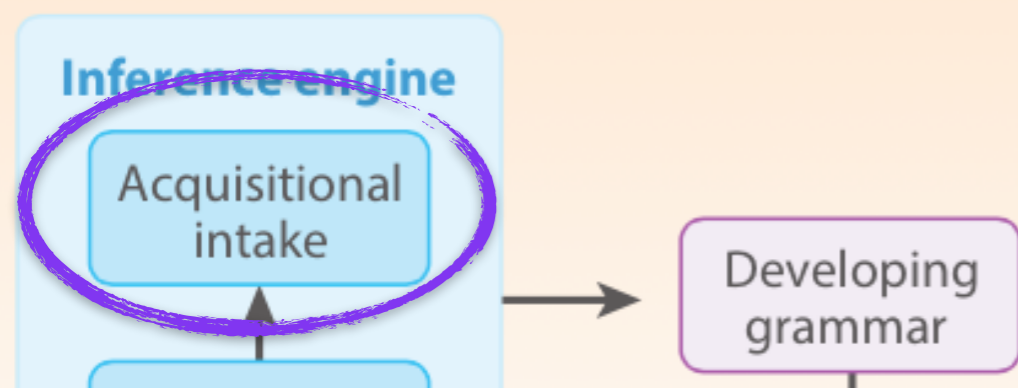
Strategy 2: Include other pronoun data besides one data in the intake

Immature representations

Noun' only in certain linguistic contexts
pretty kitty ✗ otherwise Noun

But...does this for pretty much any situational context.

More robust



What we can learn

syntax, semantics

another one

“Oh look — a pretty kitty!”



Noun'
pretty kitty

Algorithmic-level



Strategy 1: Ignore

Less robust

Strategy 2: Include other



More robust

“Do you see another one ?”



By modeling, we have two concrete proposals for how children learn the knowledge they do by 18 months.

This also motivates future experimental work to distinguish these two possibilities.



What we can learn

speech segmentation

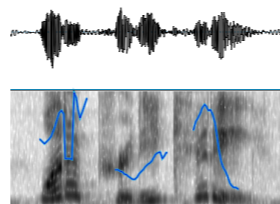
metrical phonology

syntactic categorization

syntax



Who does ... is pretty? another one
Every kitty didn't ...



Noun

✓ KI tty



pragmatics

syntax, semantics

What we can learn

syntax

This kitty was bought as a present for someone.

Lily thinks this kitty is pretty.



What's going on here?

Who does Lily think the kitty for is pretty?



What does Lily think is pretty, and who does she think it's for?



What we can learn

syntax

Who does 

Lily think the kitty for is pretty?



What's going on here?

There's a **dependency** between the wh-word *who* and where it's understood (**the gap**)

Who does Lily think the kitty for ___ is pretty?



This dependency is **not allowed** in English.

One explanation: The dependency crosses a “syntactic island” (Ross 1967)



What we can learn

syntax

Who does 

Lily think the kitty for is pretty?



What's going on here?

syntactic island

Who does Lily think the kitty for ___ is pretty?



Jack is somewhat tricky.

He claimed he bought something.

What did Jack make the claim that he bought ___?



What we can learn

syntax

Who does 

Lily think the kitty for is pretty?



What's going on here?

syntactic island

Who does Lily think the kitty for ___ is pretty?



What did Jack make the claim that he bought ___ ?



Jack is somewhat tricky.

He claimed he bought something.

Elizabeth wondered if he actually did and what it was.

What did Elizabeth wonder whether Jack bought ___ ?



What we can learn

syntax

Who does 

Lily think the kitty for is pretty?



What's going on here?

syntactic island

Who does Lily think the kitty for ___ is pretty?



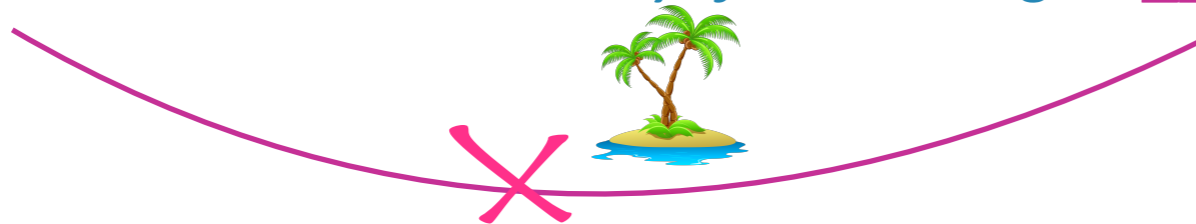
What did Jack make the claim that he bought ___ ?



What did Elizabeth wonder whether Jack bought ___?



What did Elizabeth worry if Jack bought ___ ?



Jack is somewhat tricky.

He claimed he bought something.

Elizabeth worried it was something dangerous.



What we can learn

syntax

Who does 

syntactic island

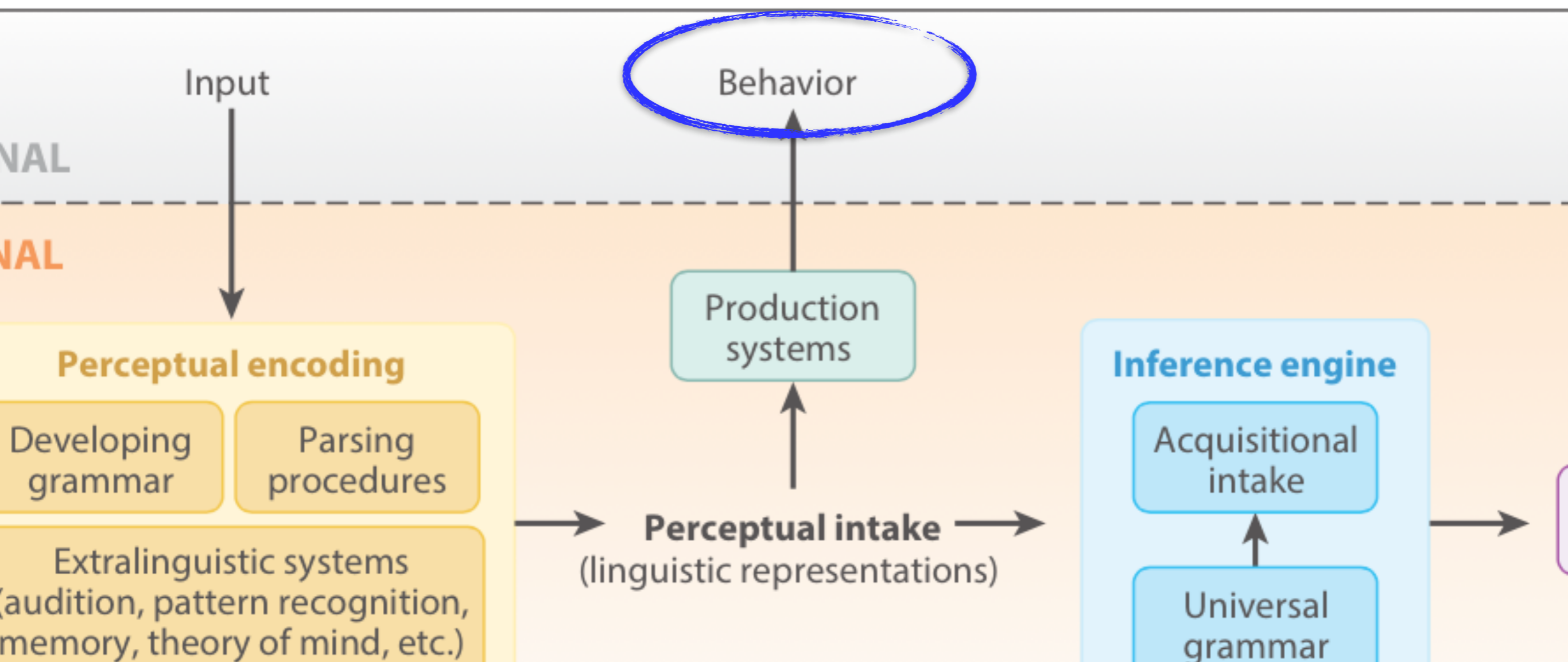
Lily think the kitty for is pretty?



Who does Lily think the kitty for ___ is pretty?



Adults **judge** these dependencies to be far worse than many others, including others that are very similar except that they don't cross syntactic islands (Sprouse et al. 2012).



What we can learn

syntax

Who does



Lily think the kitty for is pretty?

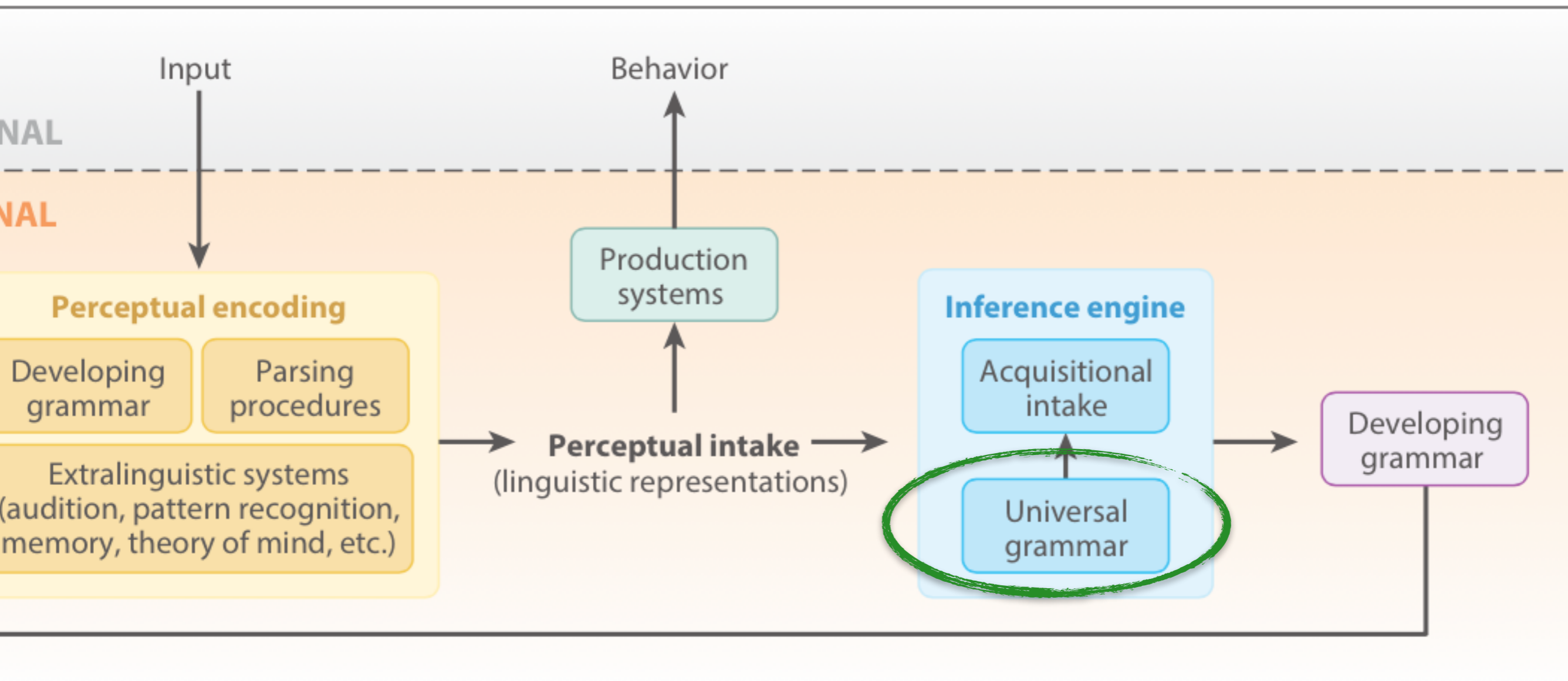


syntactic island

Who does Lily think the kitty for ___ is pretty?



Previous learning theories suggested children need syntactic-island-specific innate knowledge.



What we can learn

syntax

Who does



Lily think the kitty for is pretty?



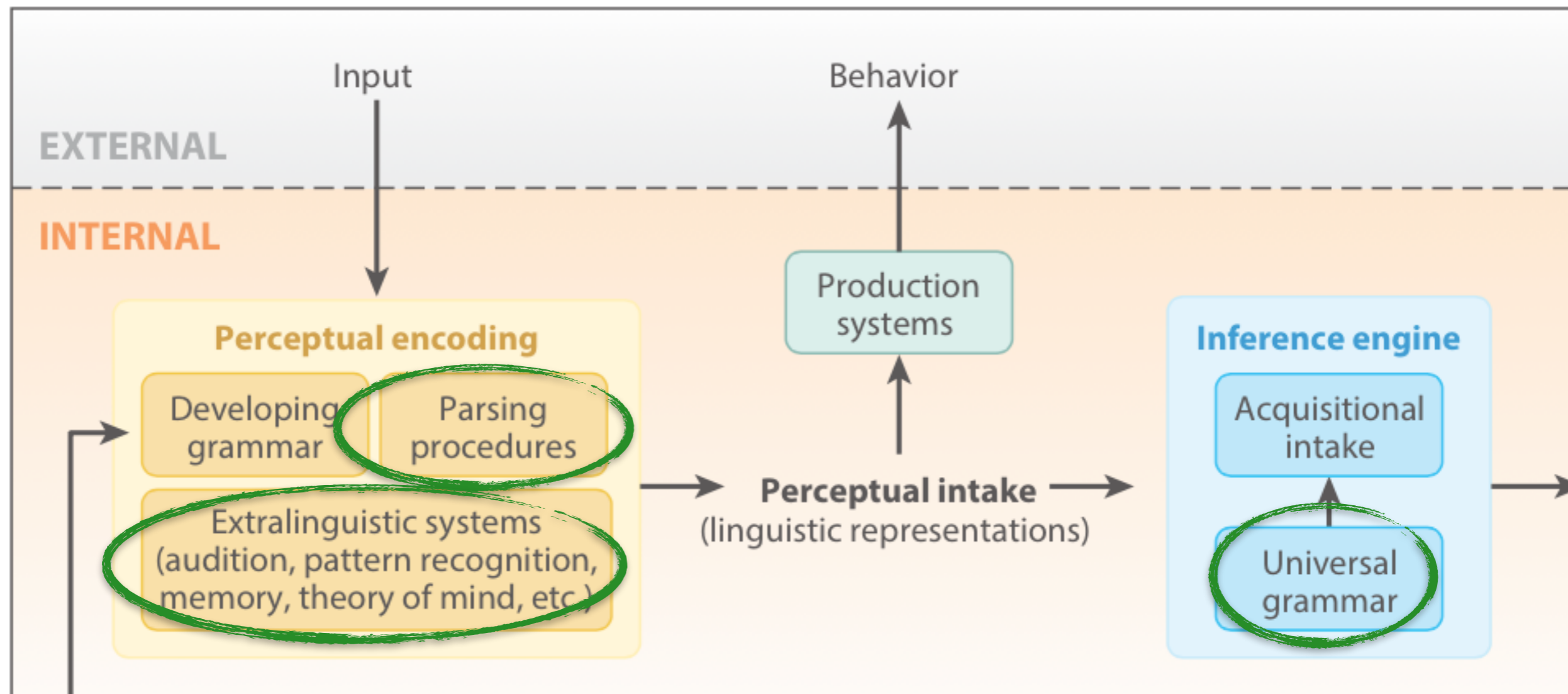
syntactic island

Who does Lily think the kitty for ___ is pretty?



An alternative learning strategy suggests children need **less-specific linguistic prior knowledge** along with **probabilistic learning**.

Pearl & Sprouse (2013a, 2013b, 2015)



What we can learn

syntax

Who does



Lily think the kitty for is pretty?

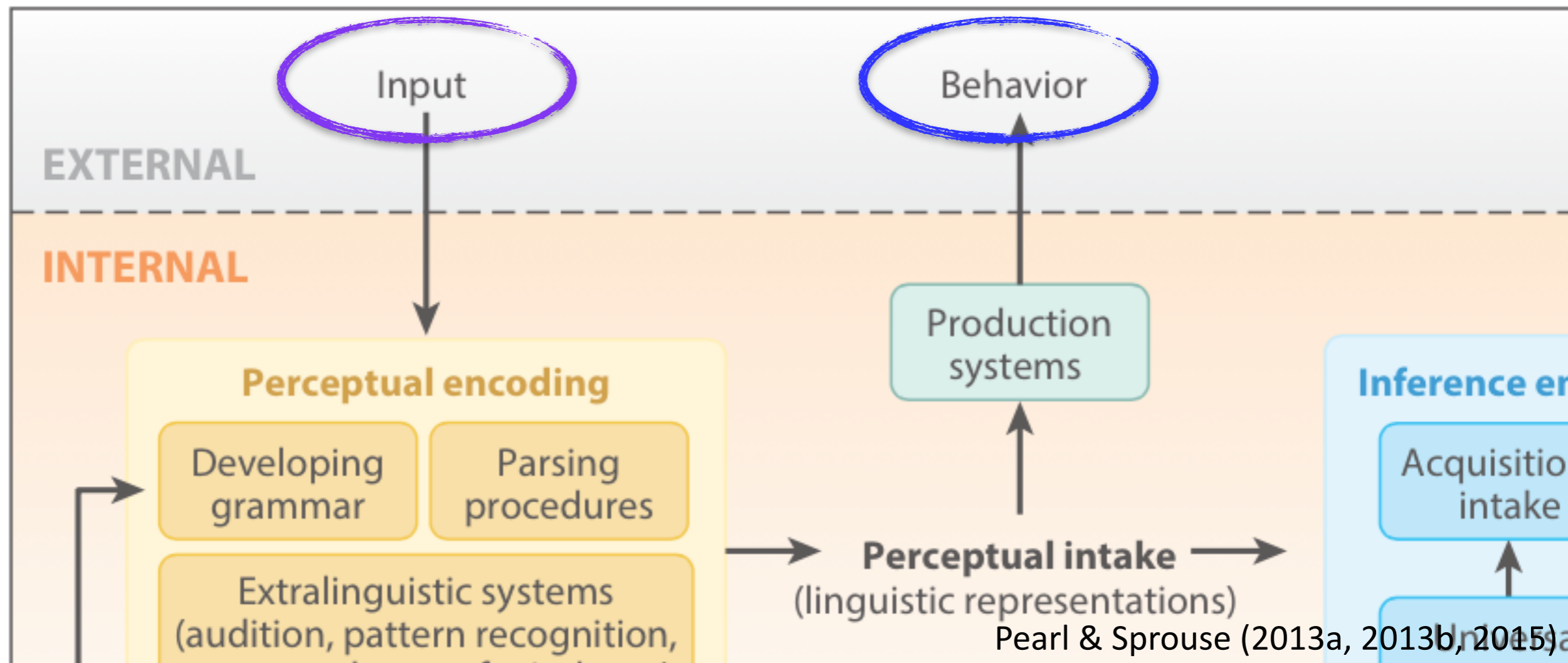


syntactic island

Who does Lily think the kitty for ___ is pretty?



This alternative strategy was implemented in an **algorithmic-level** learning model that learned from **realistic samples of child-directed speech**. The modeled learner was able to reproduce the **pattern of adult judgments**.



What we can learn

syntax

Who does



Lily think the kitty for is pretty?

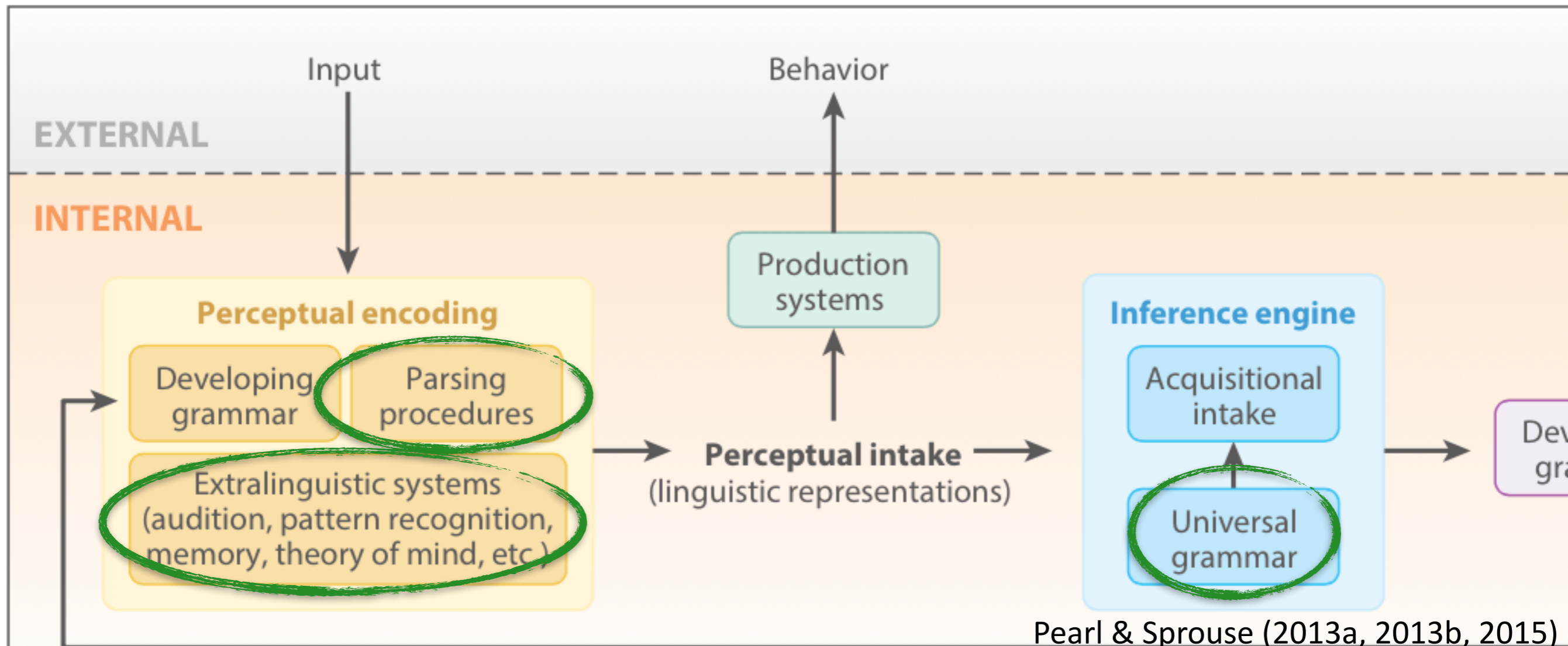


syntactic island

Who does Lily think the kitty for ___ is pretty?



Upshot: Children can learn these **sophisticated restrictions** without relying as much on very specific linguistic knowledge that's necessarily innate.



What we can learn

speech segmentation

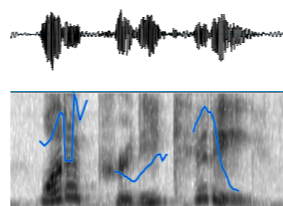
metrical phonology

syntactic categorization

syntax



Who does ... is pretty? another one
Every kitty didn't ...



Noun

✓ KI tty



pragmatics

syntax, semantics

What we can learn

pragmatics

“Every kitty didn’t sit on the stairs”

✗ No kitties sat on the stairs.

✓ Not all kitties sat on the stairs.



Why are two interpretations available?

Quantifier scope

What we can learn

pragmatics

Quantifier scope

“**Every** kitty didn’t sit on the stairs”



✗ No kitties sat on the stairs.

✓ Not all kitties sat on the stairs.



What we can learn

pragmatics

Quantifier scope

“**Every** kitty didn’t sit on the stairs”



surface \forall kitties k \neg k sat on the stairs

“For all kitties k , it’s not true that k sat on the stairs”

X No kitties sat on the stairs.

✓ Not all kitties sat on the stairs.



What we can learn

pragmatics

Quantifier scope

“Every kitty didn’t sit on the stairs”



surface \forall kitties k \neg k sat on the stairs

“For all kitties k , it’s not true that k sat on the stairs”

X No kitties sat on the stairs.

inverse \neg \forall kitties k , k sat on the stairs

“It’s not true that for all kitties k , k sat on the stairs”

✓ Not all kitties sat on the stairs.



What we can learn

pragmatics

Quantifier scope

✓ “Every kitty didn’t sit on the stairs”



surface



No kitties sat on the stairs.

inverse



✓ Not all kitties sat on the stairs.



Adults



What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”



surface



No kitties sat on the stairs.

inverse



??
Not all kitties sat on the stairs.



5-year-olds

But why?

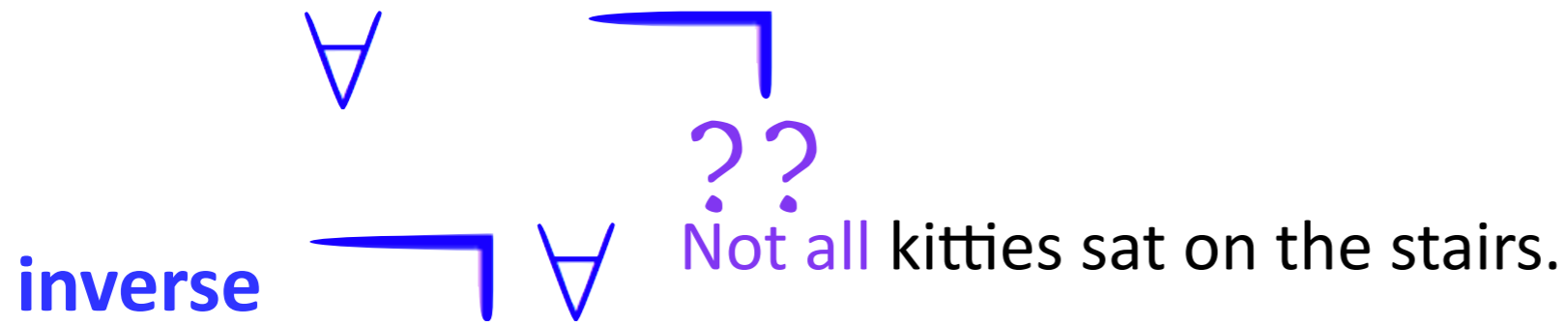


What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”



5-year-olds



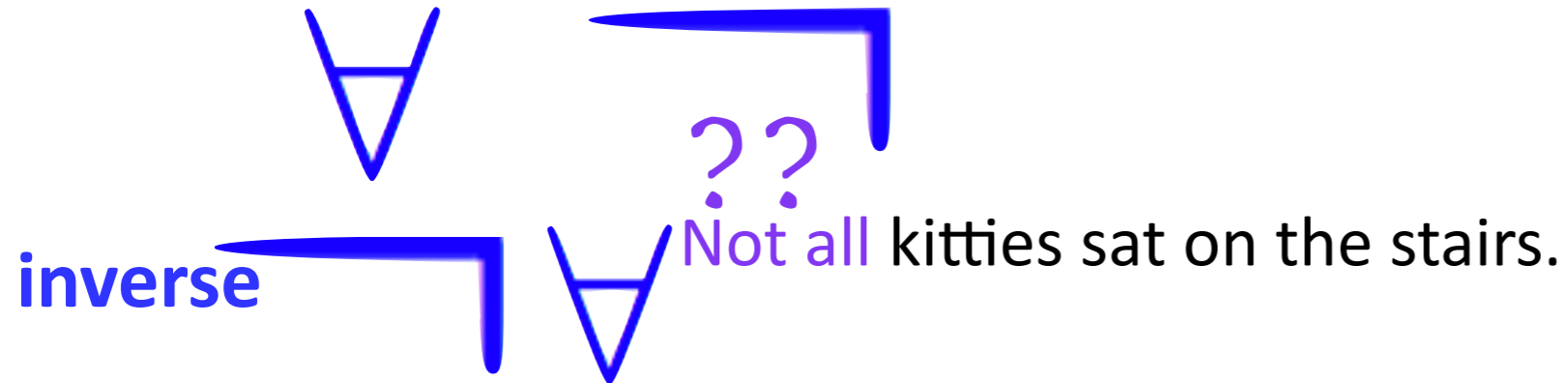
One idea: grammatical processing problem

What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”



5-year-olds



One idea: grammatical processing problem

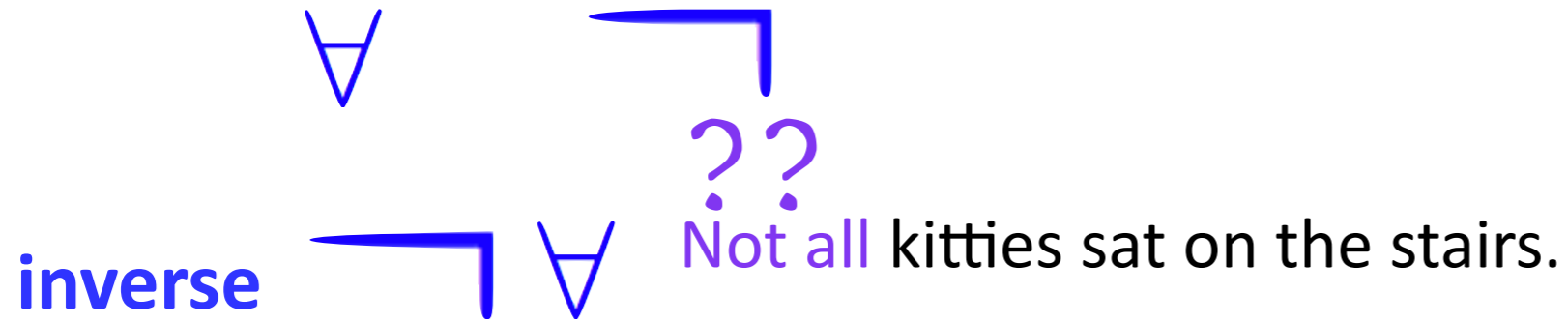
The **inverse scope** is harder to get from the surface string.

What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”



5-year-olds



One idea: grammatical processing problem

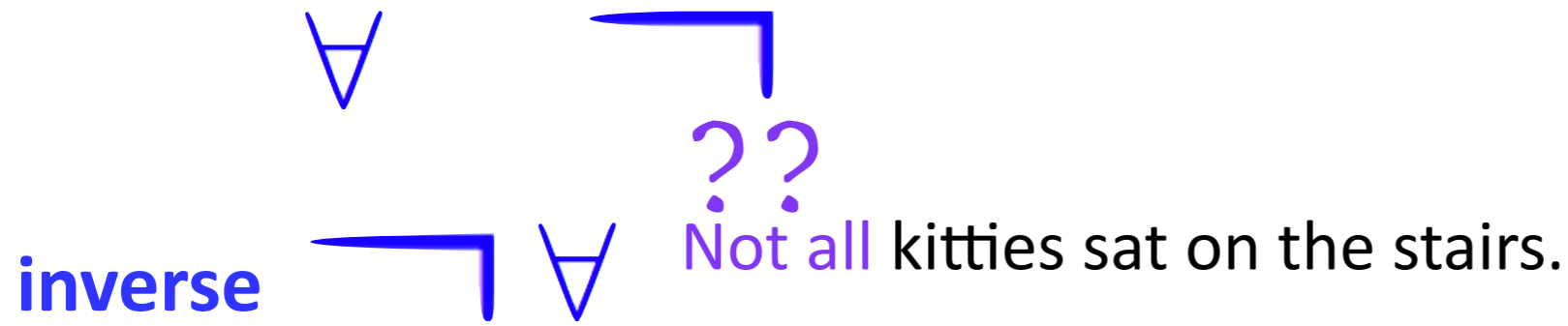
Another idea: pragmatic context management problem.

What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”



Did none of the kitties sit on the stairs?

Do kitties like stairs?

QUD *How many kitties sat on the stairs?*

5-year-olds

One idea: **grammatical processing** problem

Another idea: **pragmatic context** management problem.

Children thought the topic of conversation (the implicit **Question Under Discussion**) was something else and this utterance doesn't answer that QUD very well.



What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”

inverse \forall \neg \forall ??
Not all kitties sat on the stairs.

Kitties don’t like stairs

expectations about the world

Kitties love stairs.

Kitties don’t care about stairs.



5-year-olds



One idea: **grammatical processing** problem

Another idea: **pragmatic context** management problem.

QUD

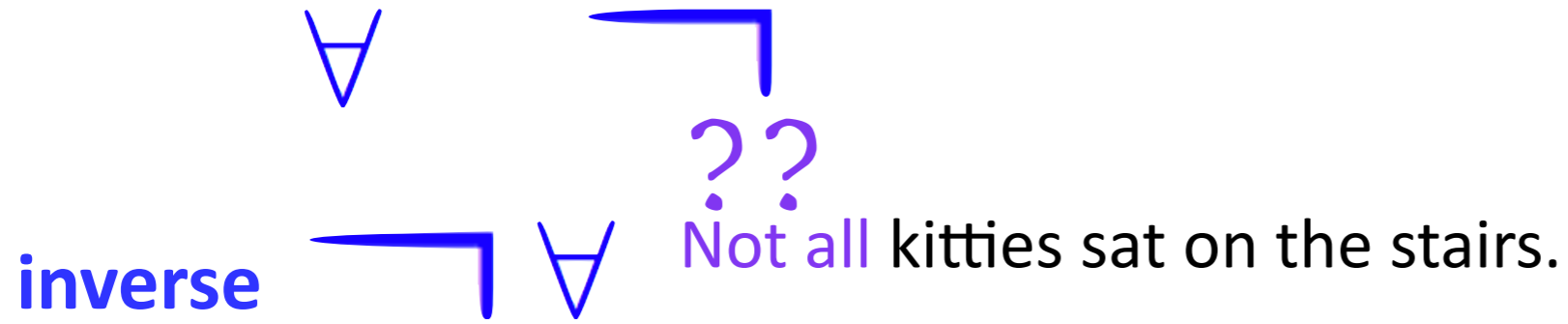
Children’s prior **expectations about the world** make this utterance less informative.

What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”



QUD

grammatical processing

expectations about the world

5-year-olds



It’s hard to manipulate only one of these factors in experimental research investigating children’s responses.

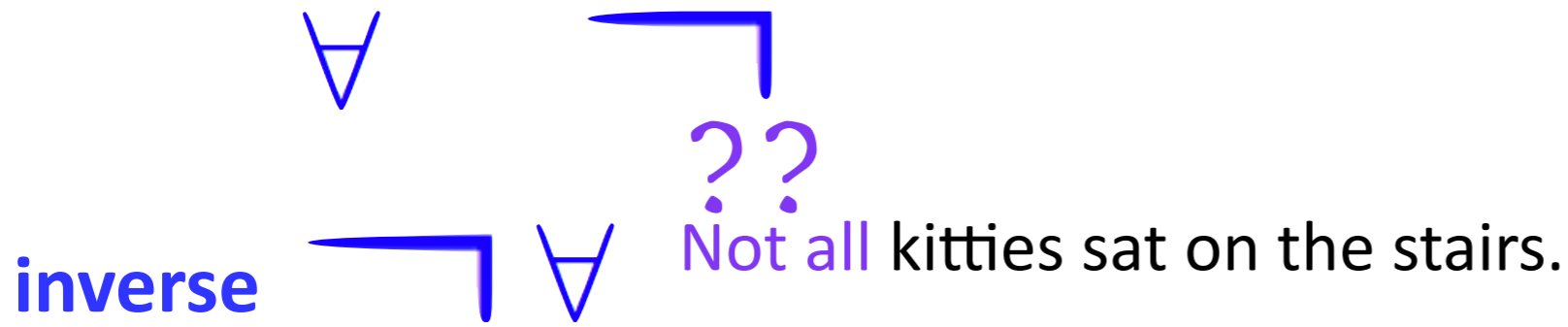


What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”



QUD

grammatical processing

expectations about the world

5-year-olds



Using a **computational-level** model that formalizes the separate contribution of each factor, we can determine which ones have the largest impact on **children’s observed behavior**.

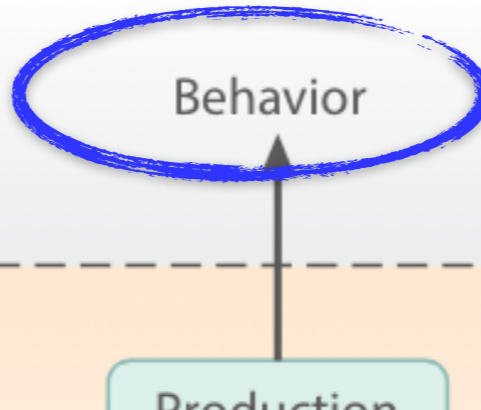
Savinelli, Scontras, & Pearl 2017

EXTERNAL

INTERNAL

Behavior

Production

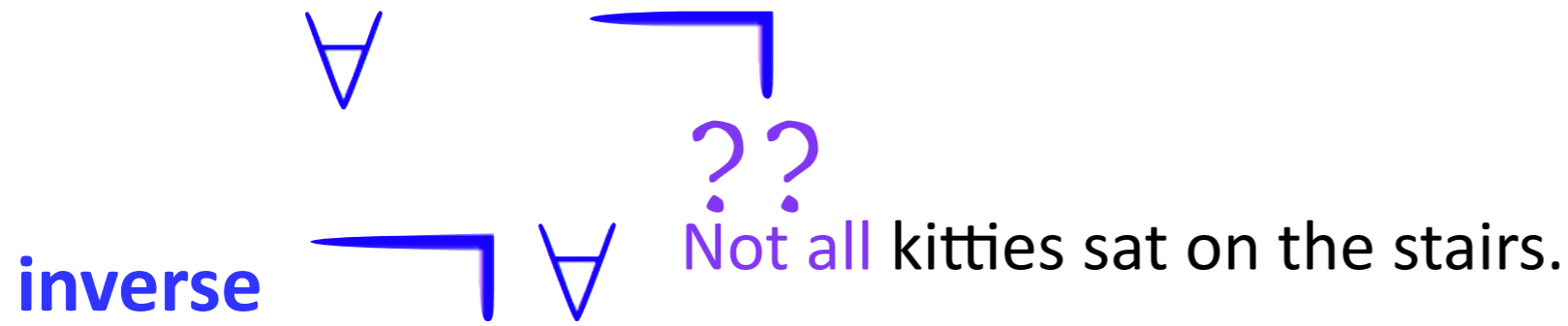


What we can learn

pragmatics

Quantifier scope

X “Every kitty didn’t sit on the stairs”



QUD

grammatical processing

expectations about the world

5-year-olds



The **pragmatic** factors seem to be the driving force behind children’s behavior. This suggests that 5-year-olds are still developing their ability to manage the pragmatic context of a conversation as well as adults do.

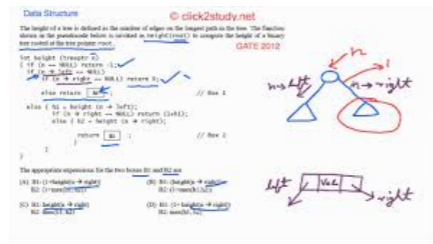
Today's Plan:

Computational models of language acquisition

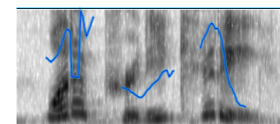
I. Why



II. How



III. What we can learn



Noun



✓ KI tty

Who does... is pretty?

another one

Every kitty didn't ...



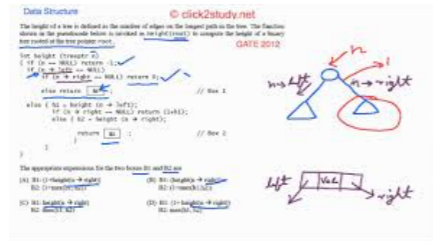
Today's Plan:

Computational models of language acquisition

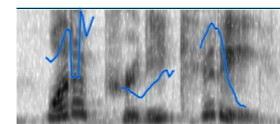
- I. Why: Because language acquisition is pretty amazing and we want to understand how it works



II. How



III. What we can learn



Noun

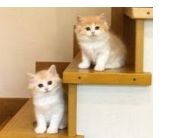


✓ KI tty

Who does... is pretty?

another one

Every kitty didn't ...



Today's Plan:

Computational models of language acquisition

- I. Why: Because language acquisition is pretty amazing and we want to understand how it works



II. How: By building informative computational models

Data Structure © click2study.net

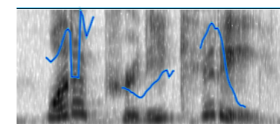
The height of a tree is defined as the number of edges on the longest path in the tree. The function shown in the pseudocode below is intended to calculate the height of a binary tree rooted at the tree pointer root.

```
int height (TreeNode *root) {
    if (root == NULL) return -1;
    if (root->left == NULL) return 0;
    else return 1 + max (height (root->left), height (root->right));
}
```

The appropriate expressions for the two boxes B1 and B2 are

B1: (1) height->right	B2: (1) height->right
B1: (2) root->right	B2: (2) root->right
B1: (3) height->left	B2: (3) height->right
B1: (4) root->left	B2: (4) root->right

III. What we can learn



Noun



✓ KI tty

Who does... is pretty?

another one

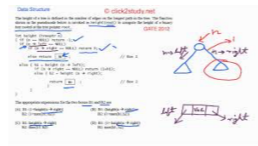
Every kitty didn't ...



Today's Plan:

Computational models of language acquisition

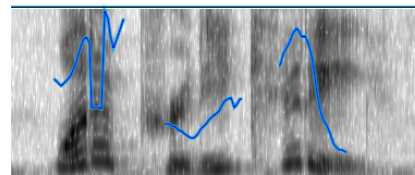
- I. Why: Because language acquisition is pretty amazing and we want to understand how it works



- II. How: By building informative computational models



III. What we can learn: A lot about a lot



speech segmentation

✓ KI tty

metrical phonology



Who does... is pretty?



syntax

Noun

syntactic categorization

another one



syntax, semantics



pragmatics

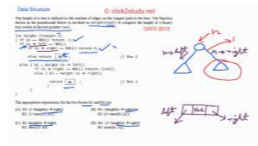


Every kitty didn't ...

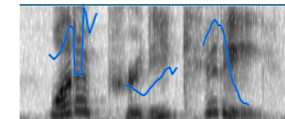
Today's Plan:

Computational models of language acquisition

- I. Why: Because language acquisition is pretty amazing and we want to understand how it works



- II. How: By building informative computational models



Noun



- III. What we can learn: A lot about a lot

✓ KI tty



another one



This is a great tool - so let's use it to understand how linguistic representations develop!

Who does... is pretty?

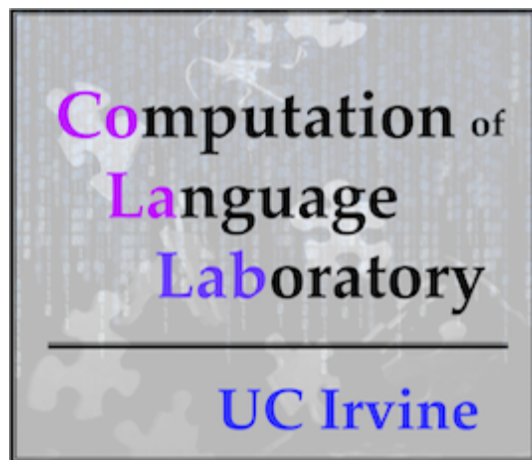
Every kitty didn't ...



Thank you!

Lawrence Phillips Timothy Ho Zephyr Detrano
Alandi Bates Sue Braunwald Galia Bar-sever
Jon Sprouse Ben Mis Greg Scontras K.J. Savinelli
Jeff Lidz Members of CoLaLab

Audiences at: CSUF 2016, GLEEFUL 2016, GALANA 2015



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Who does... is pretty? KI tty

another *one*

Every kitty didn't ...