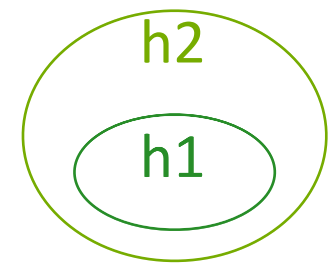
Bayesian inference & linguistic parameters

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



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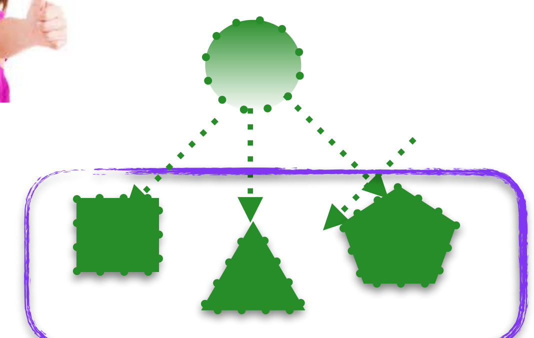
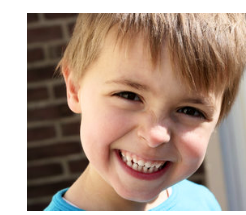
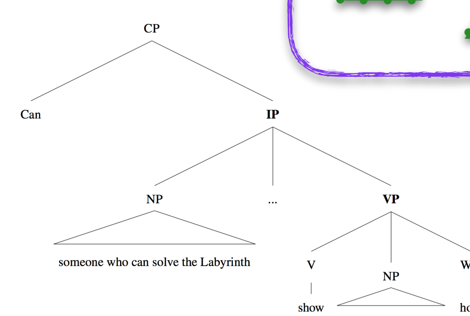
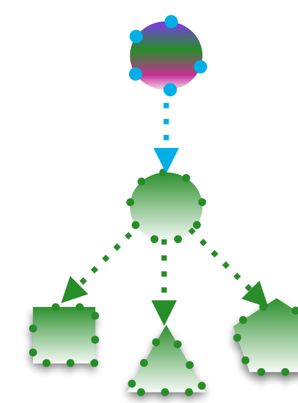








August 5, 2017:

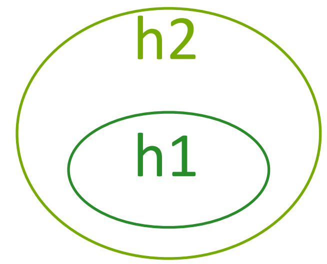
Norwegian Summer Institute on Language & Mind

University of Oslo

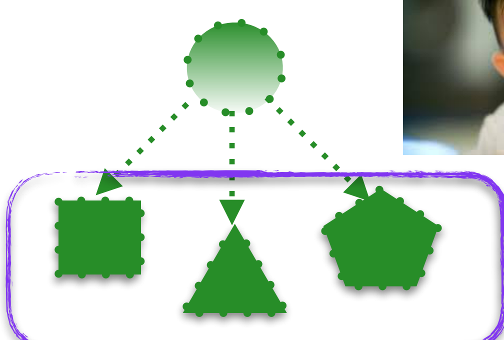
Today's Plan:
Bayesian inference & linguistic parameters

I. Bayesian reasoning

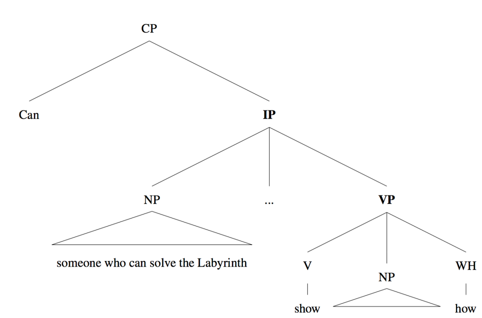
$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

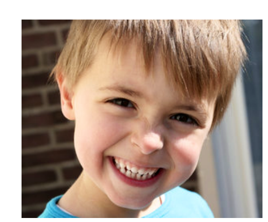


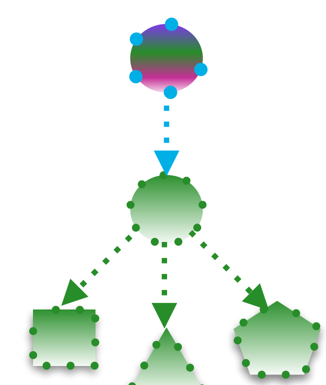
II. Parameters & overhypotheses



III. Structure dependence



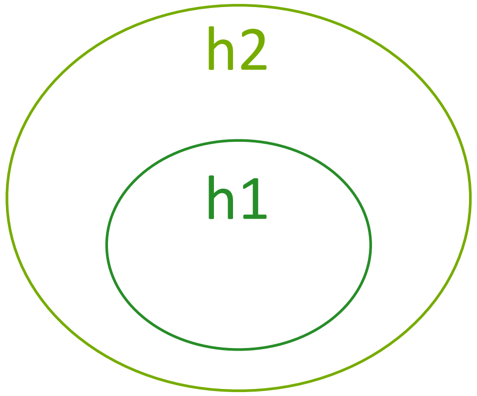




Today's Plan:
Bayesian inference & linguistic parameters

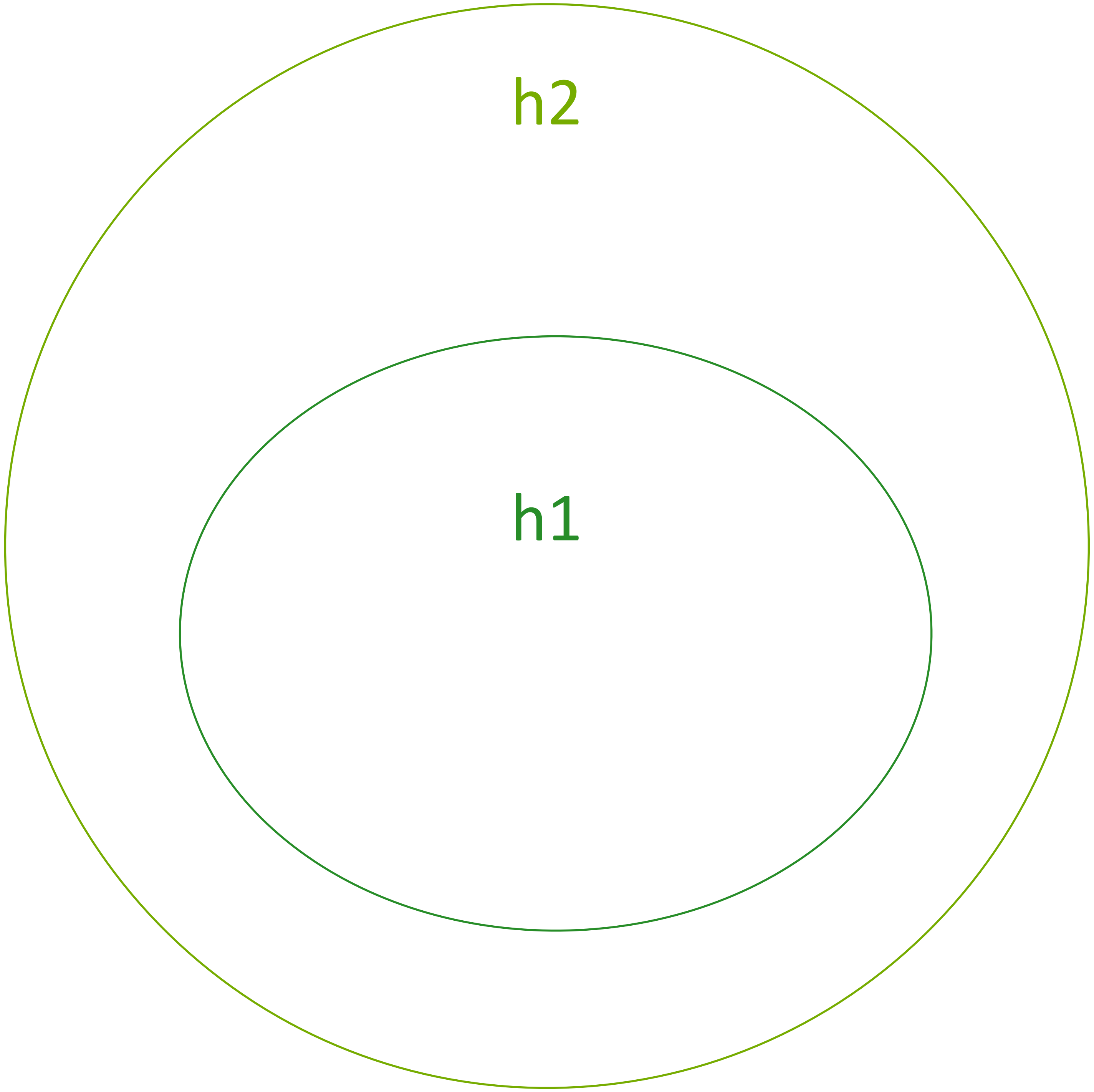
I. Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



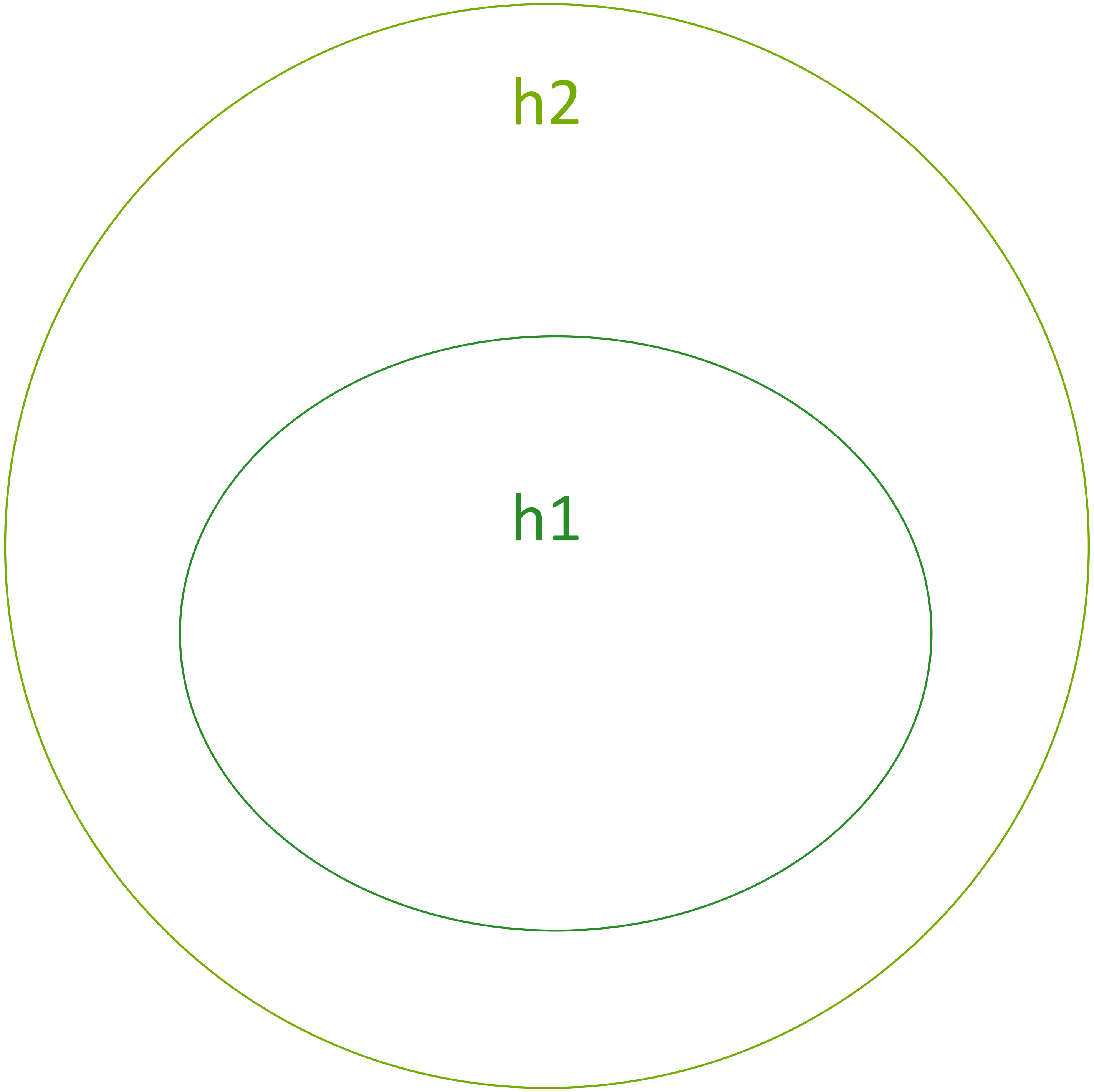
Bayesian reasoning

A Bayesian model assumes the learner has **some space of hypotheses H**…



Bayesian reasoning

A Bayesian model assumes the learner has **some space of hypotheses H**, each of which represents a possible explanation for how **the data D** in the data intake were generated.



Bayesian reasoning

A Bayesian model assumes the learner has **some space of hypotheses H**, each of which represents a possible explanation for how **the data D** in the data intake were generated.

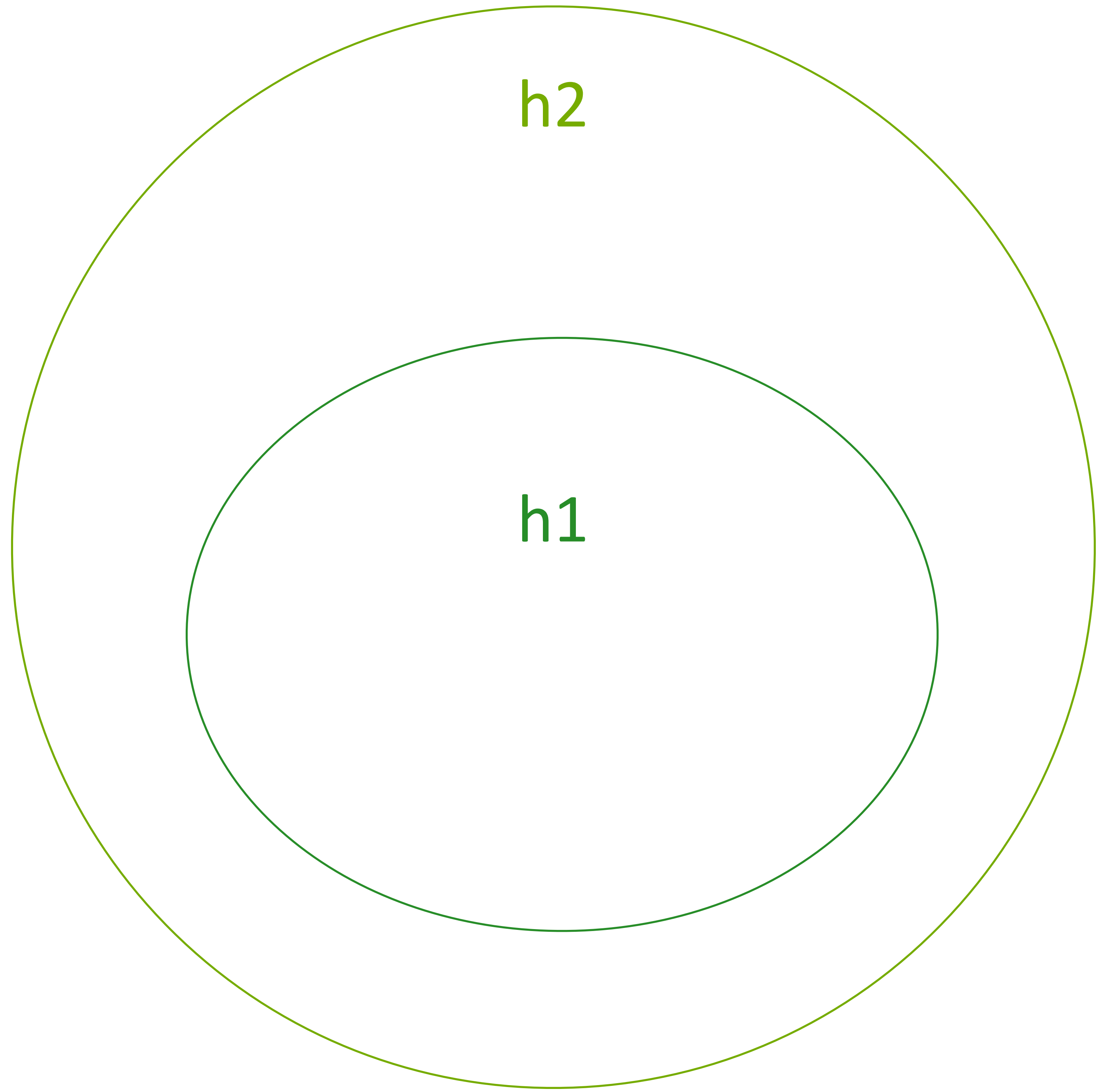
Example parameter:
Subject drop

English: **-subj-drop**
Requires Subject to be overt

Subject Verb
They drink

Verb
Drink

"They drink"



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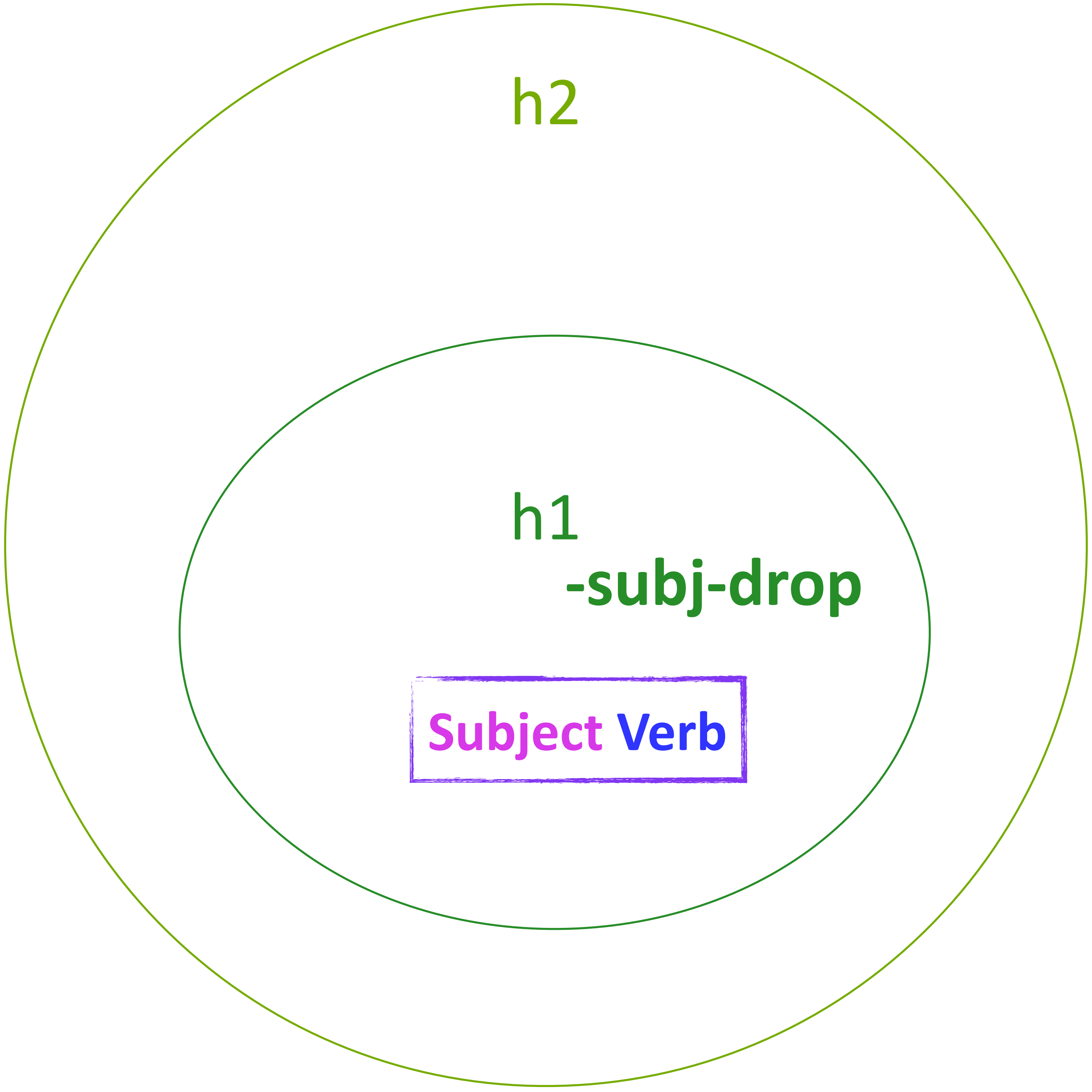


Bayesian reasoning

A Bayesian model assumes the learner has **some space of hypotheses H**, each of which represents a possible explanation for how **the data D** in the data intake were generated.

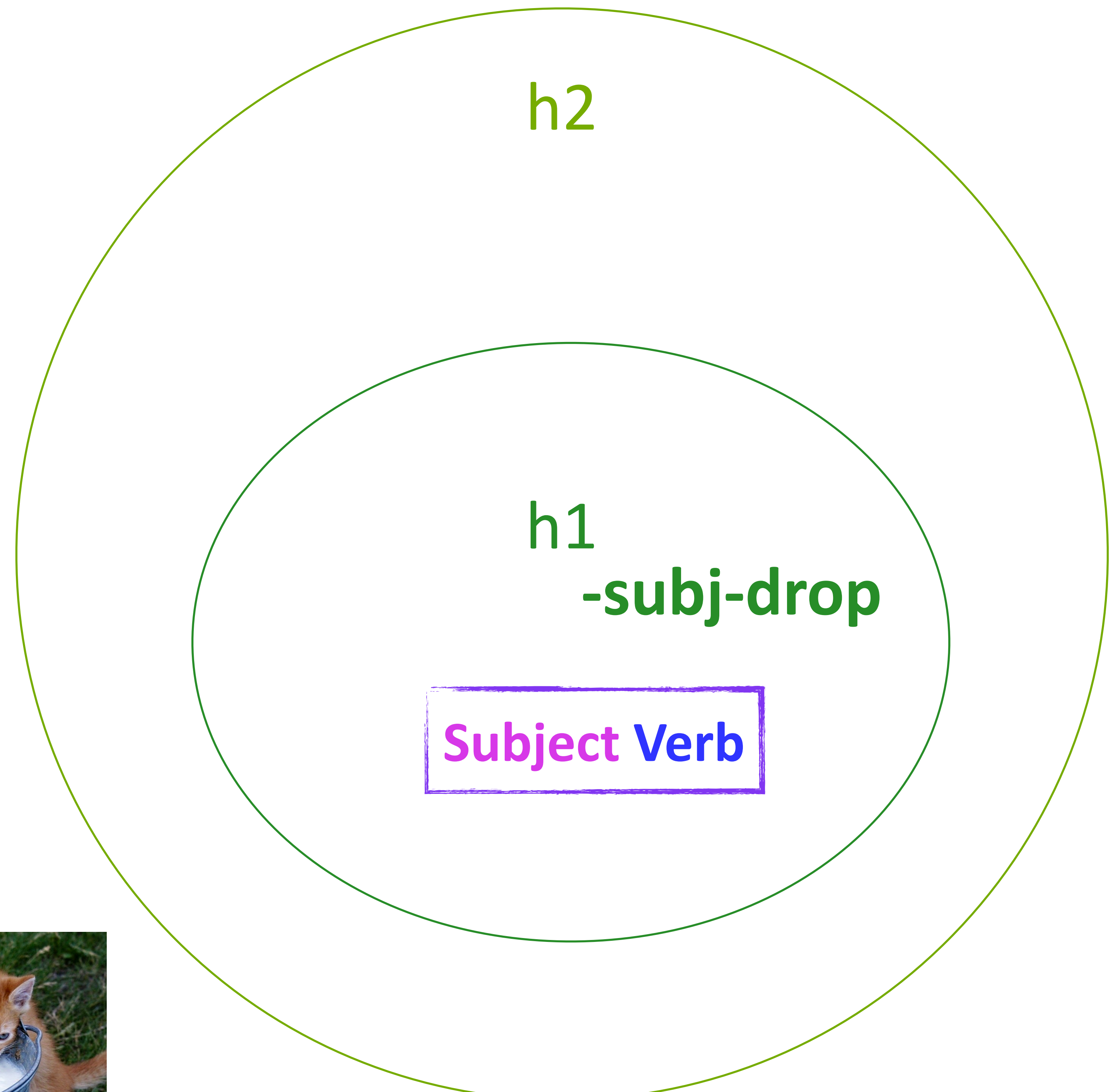
Example parameter:
Subject drop

Spanish: **+subj-drop**
Allows Subject to be overt or dropped

✔ **Subject Verb**
Ellos beben
they drink-3rd-pl

✔ **Verb**
Beben
drink-3rd-pl

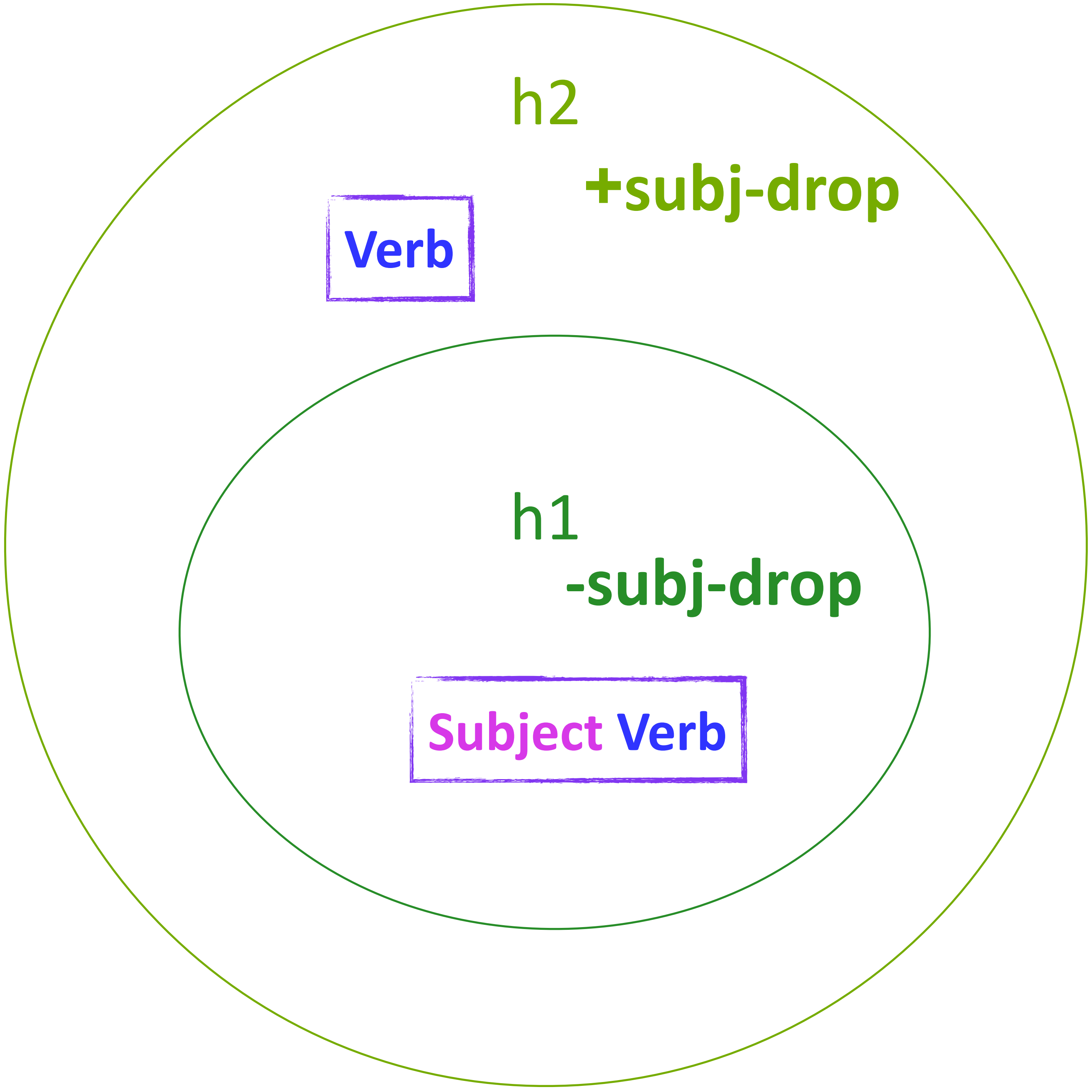
"*They drink*"



Bayesian reasoning

Given **D**, the modeled child's goal is to determine the probability of each possible hypothesis **h** ∈ **H**, written as **P (h|D)** - the ***posterior*** for that hypothesis.

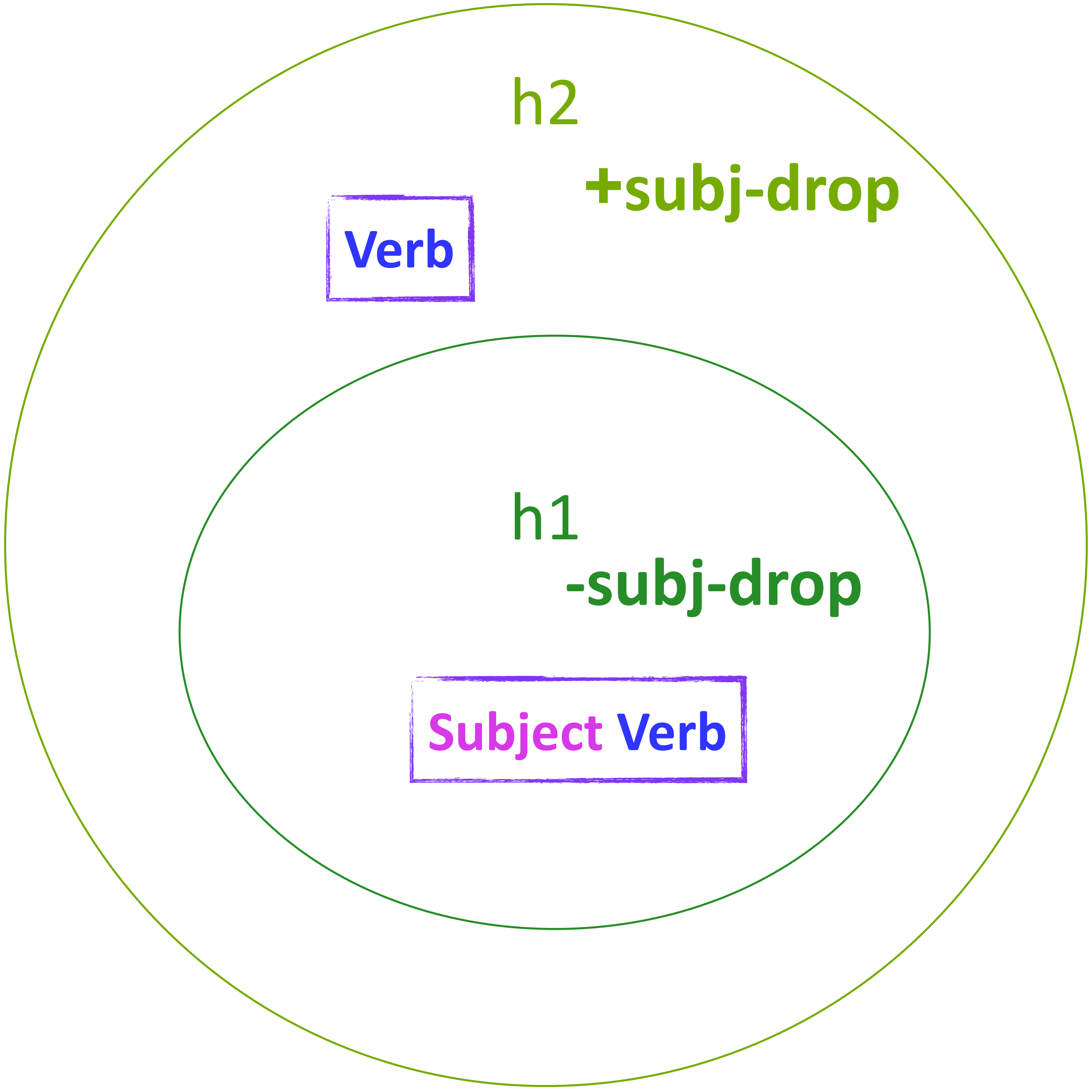
$$P(h|D)$$



Bayesian reasoning

This depends on a few different aspects (which have their own probabilities).

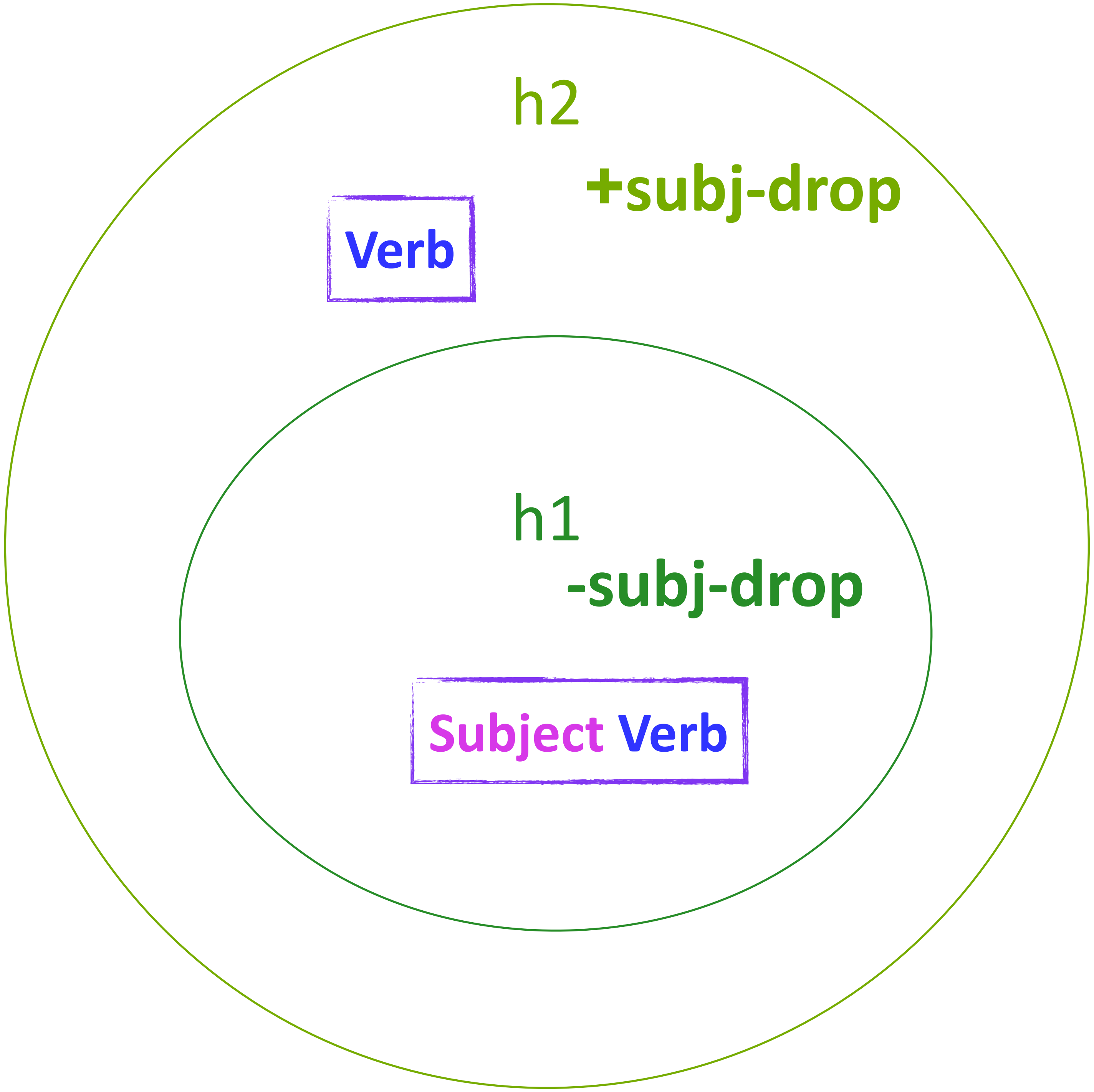
$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Bayesian reasoning

P (D|h) represents the *likelihood* of the data D given hypothesis h, and describes how compatible that hypothesis is with the data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



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P (D|h) represents the *likelihood* of the data D given hypothesis h, and describes how compatible that hypothesis is with the data.

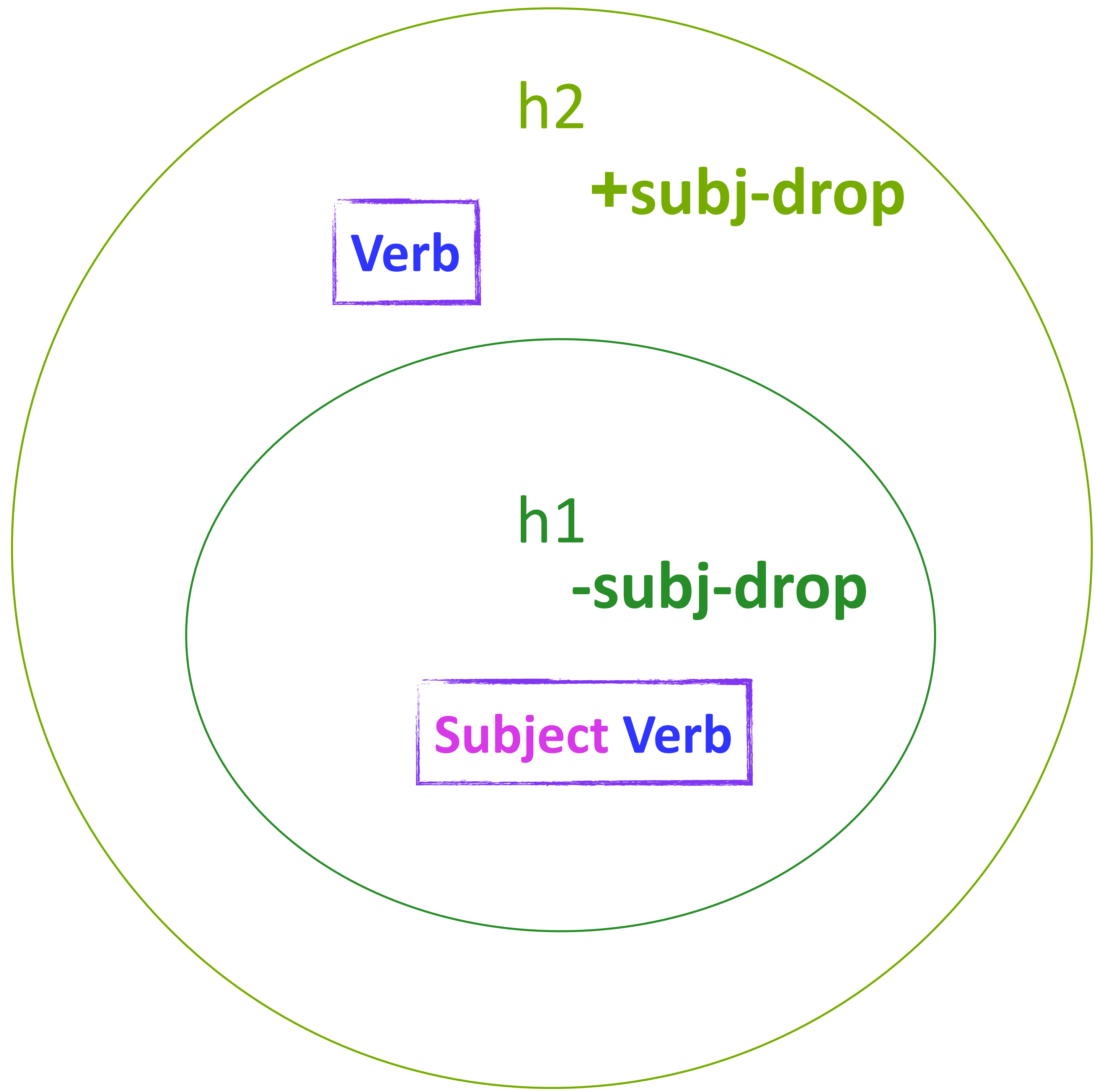
$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Data D

Verb

Subject Verb

What if the data intake contained both data point types?



Bayesian reasoning

P (D|h) represents the *likelihood* of the data D given hypothesis h, and describes how compatible that hypothesis is with the data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Data D

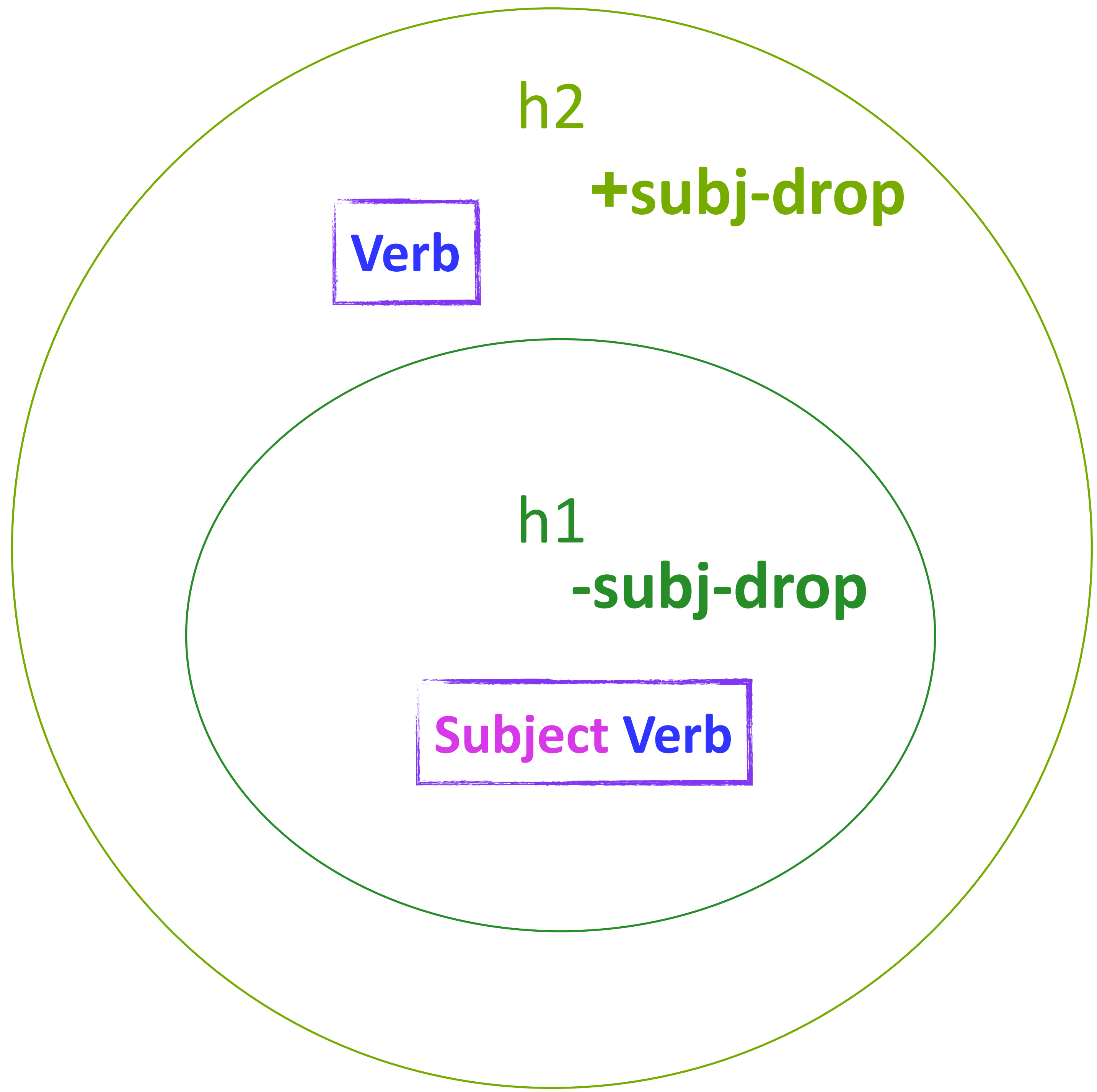
Verb

Subject Verb ✔

P(D | h1) = 1*

-subj-drop can account for Subject Verb.

Because this is the only data point it can generate in this scenario, the probability of generating D is 1/1 = 1.



Bayesian reasoning

P (D|h) represents the *likelihood* of the data D given hypothesis h, and describes how compatible that hypothesis is with the data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

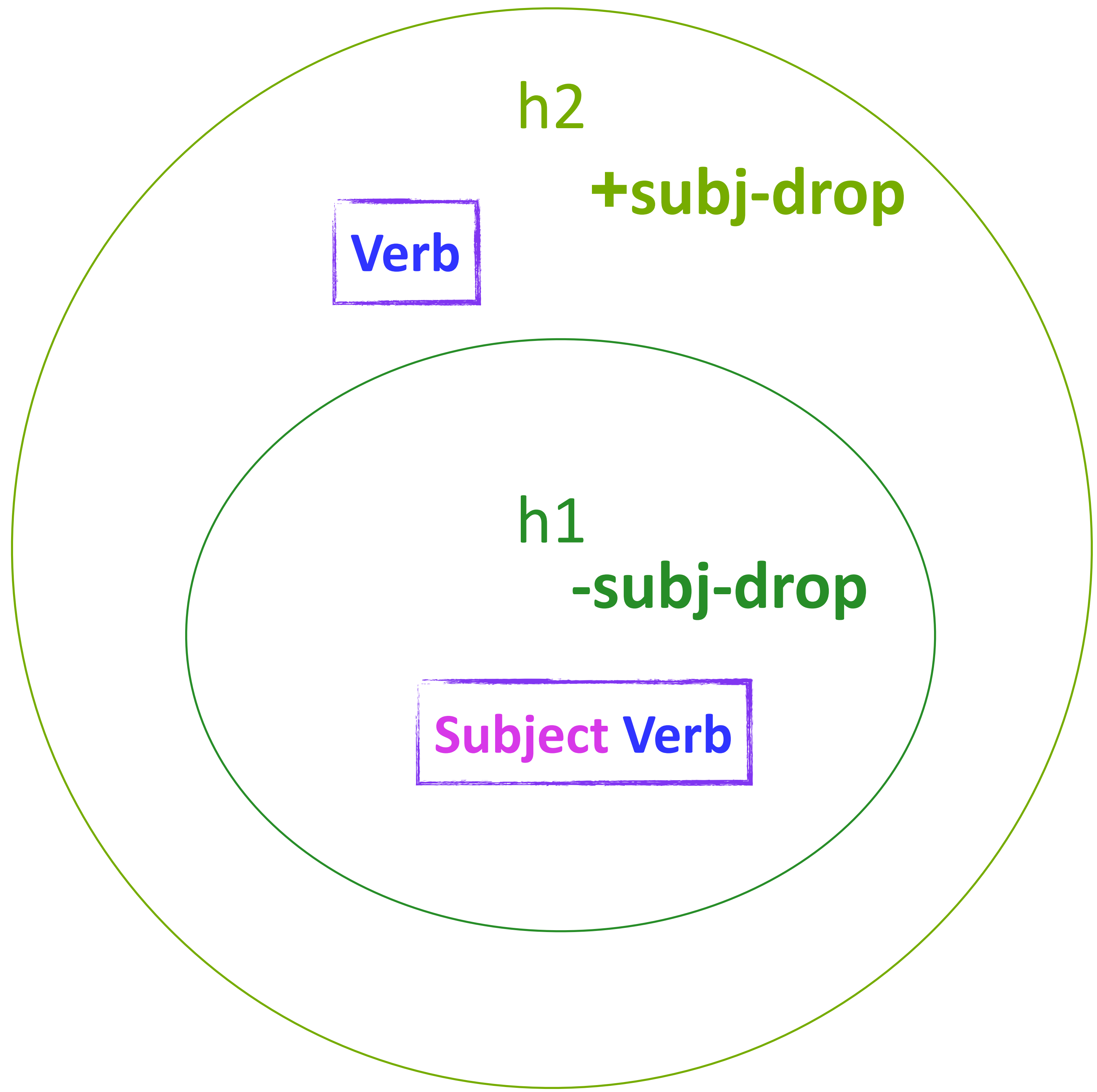
Data D

~~Verb~~

Subject Verb

P(D | h1) = 1* 0 = 0

-subj-drop can't account for Verb alone.



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P (D|h) represents the *likelihood* of the data D given hypothesis h, and describes how compatible that hypothesis is with the data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Data D

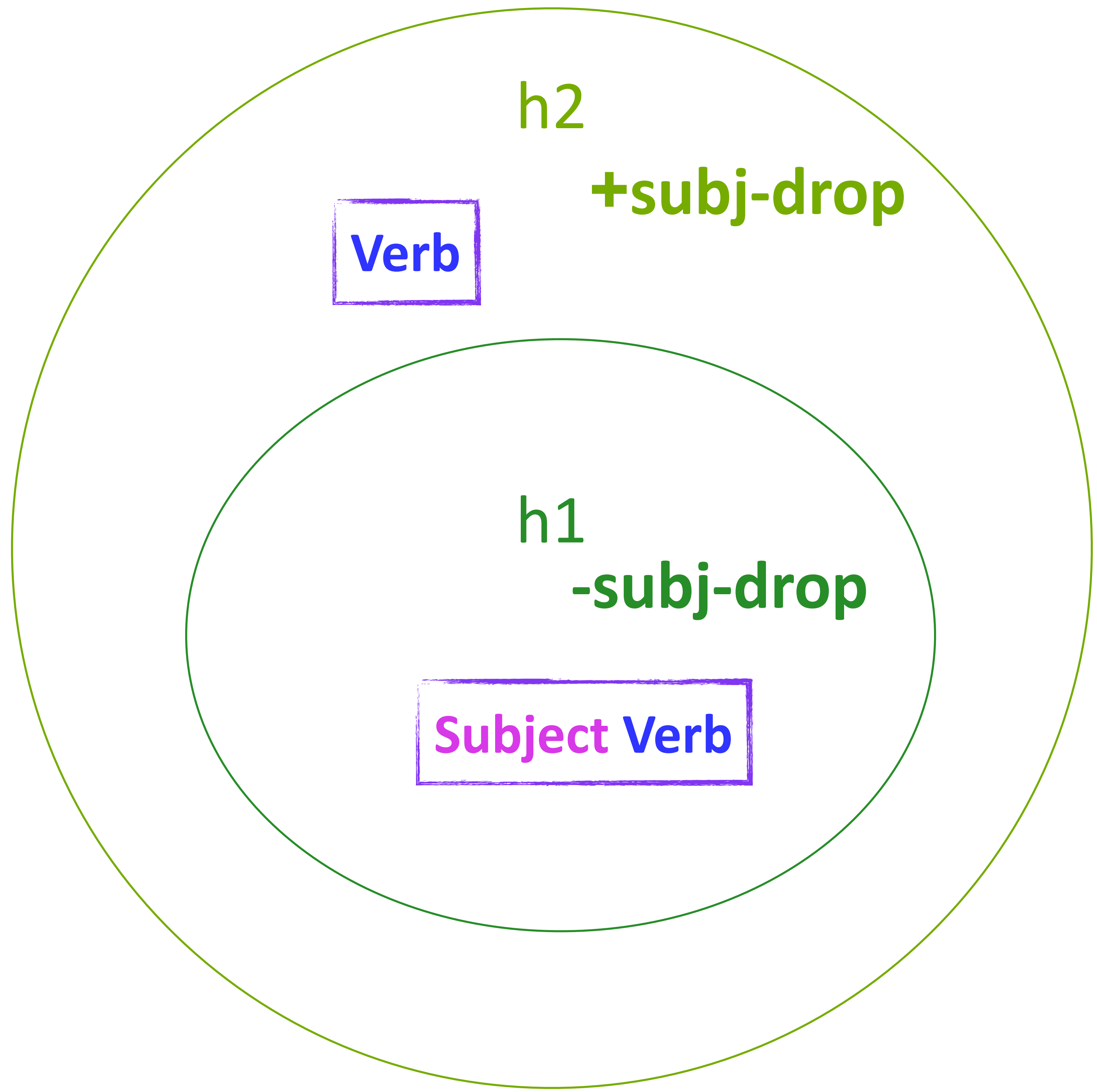
Verb

Subject Verb

P(D | h1) = 0

P(D | h2) = 1/2*1/2 = 1/4

+subj-drop can account for both data points. The probability of generating each one is 1/2.



Bayesian reasoning

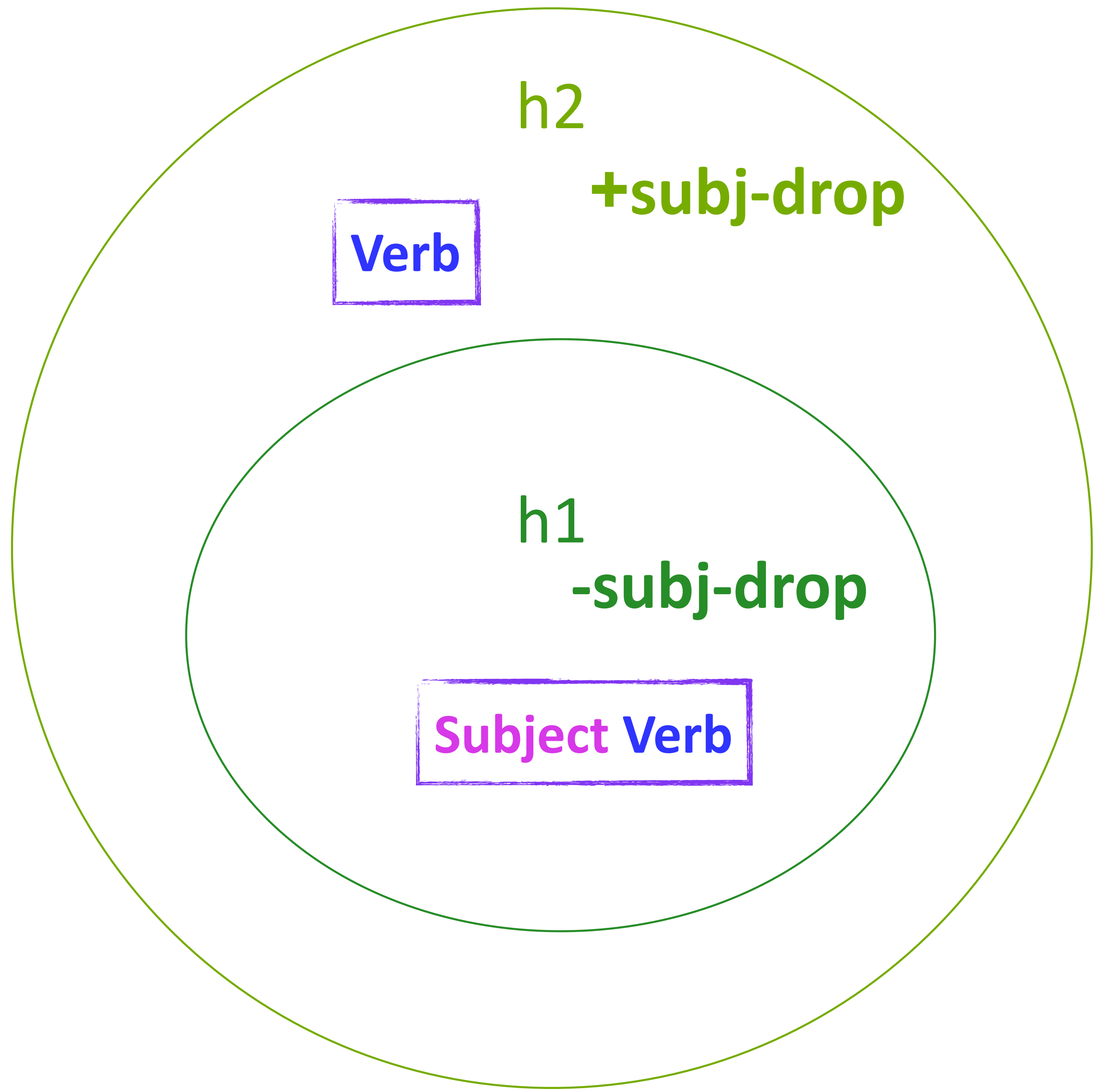
P (D|h) represents the *likelihood* of the data D given hypothesis h, and describes how compatible that hypothesis is with the data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Data D

Subject Verb

What if the data intake contained only this data point type?



Bayesian reasoning

P (D|h) represents the *likelihood* of the data D given hypothesis h, and describes how compatible that hypothesis is with the data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

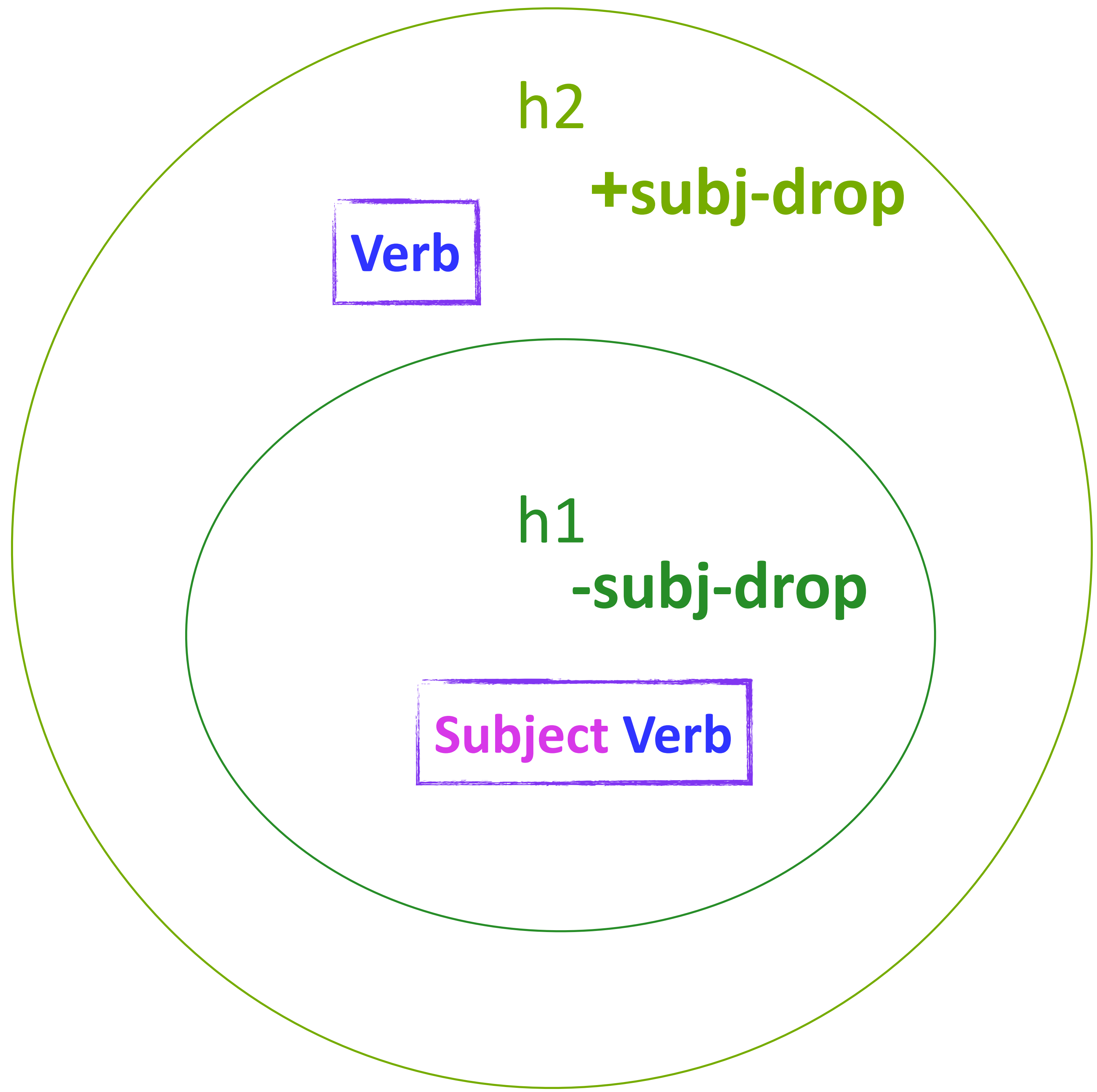
Data D

Subject Verb

P(D | h1) = 1

-subj-drop can account for it

Because this is the only data point it can generate in this scenario, the probability of generating D is 1/1 = 1.



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P (D|h) represents the *likelihood* of the data D given hypothesis h, and describes how compatible that hypothesis is with the data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Data D

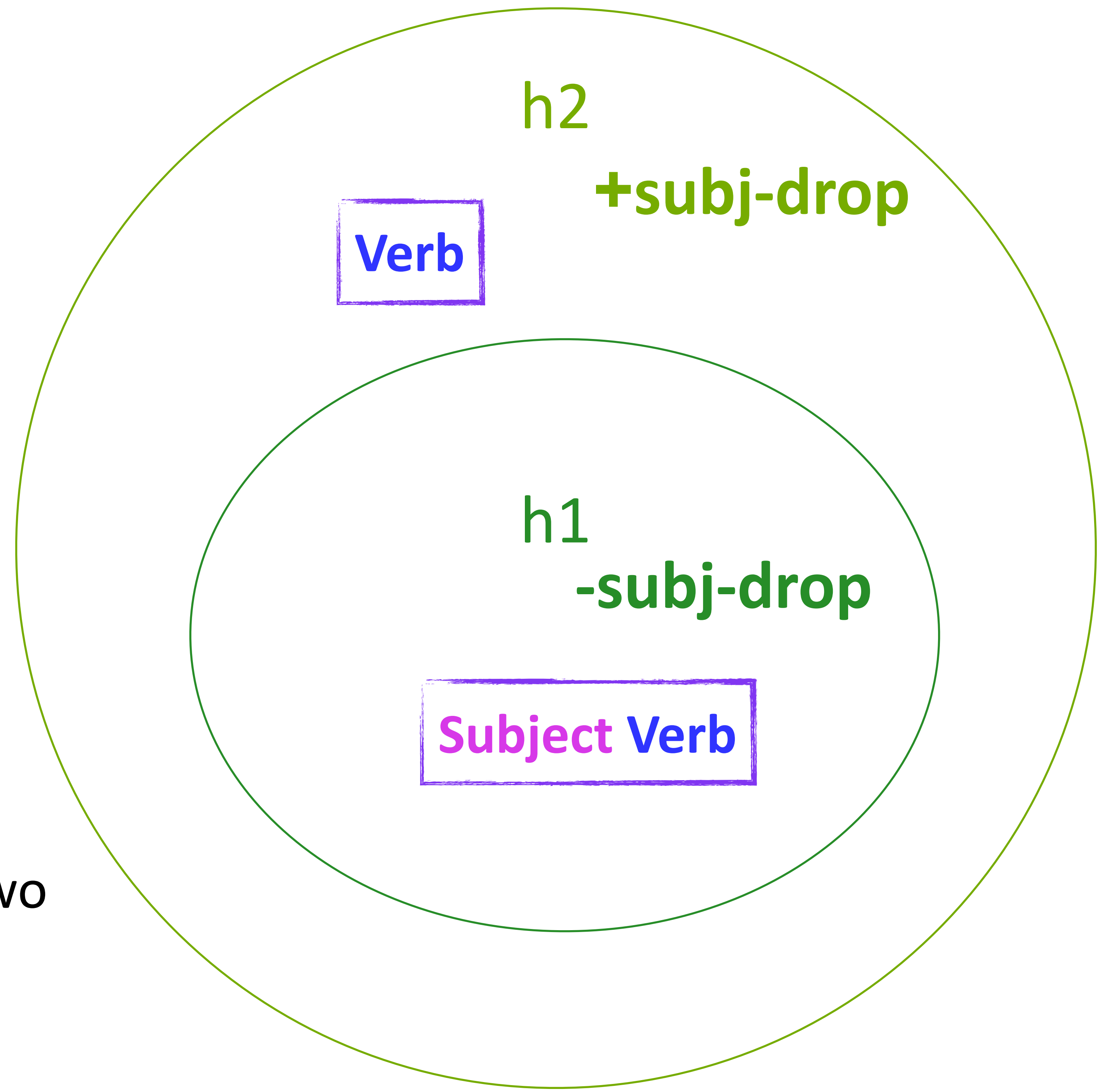
Subject Verb

$P(D \mid h1) = 1$

$P(D \mid h2) = 1/2$

+subj-drop can generate it too.

Because +subj-drop can generate two data points, the probability of generating this data point is 1/2.

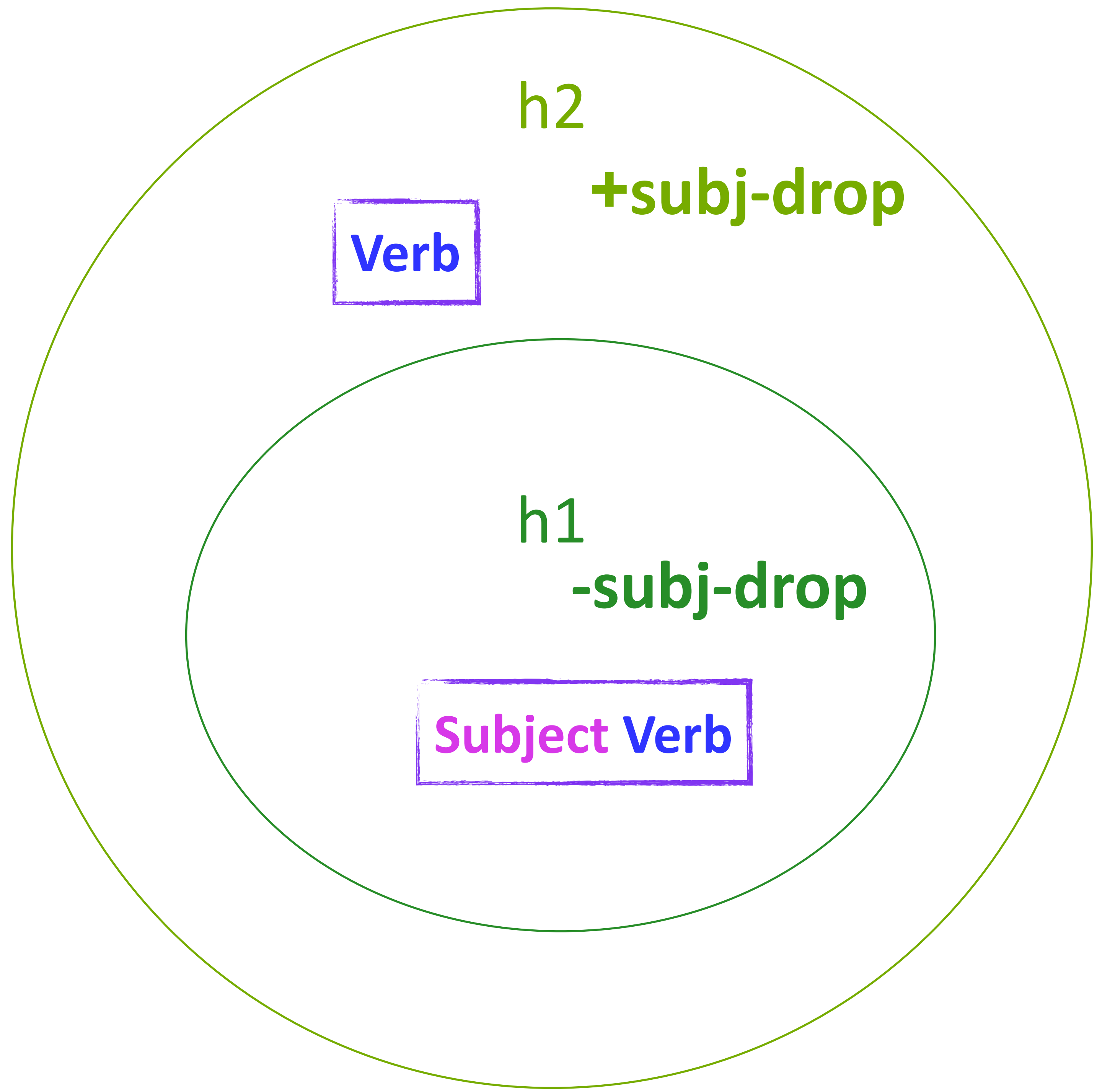


Bayesian reasoning

P (h) represents the *prior* of the hypothesis h, and represents the probability of the hypothesis before any data have been encountered. Intuitively, this corresponds to how plausible the hypothesis is, irrespective of any data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

This is often where considerations about the complexity of the hypothesis will be implemented.



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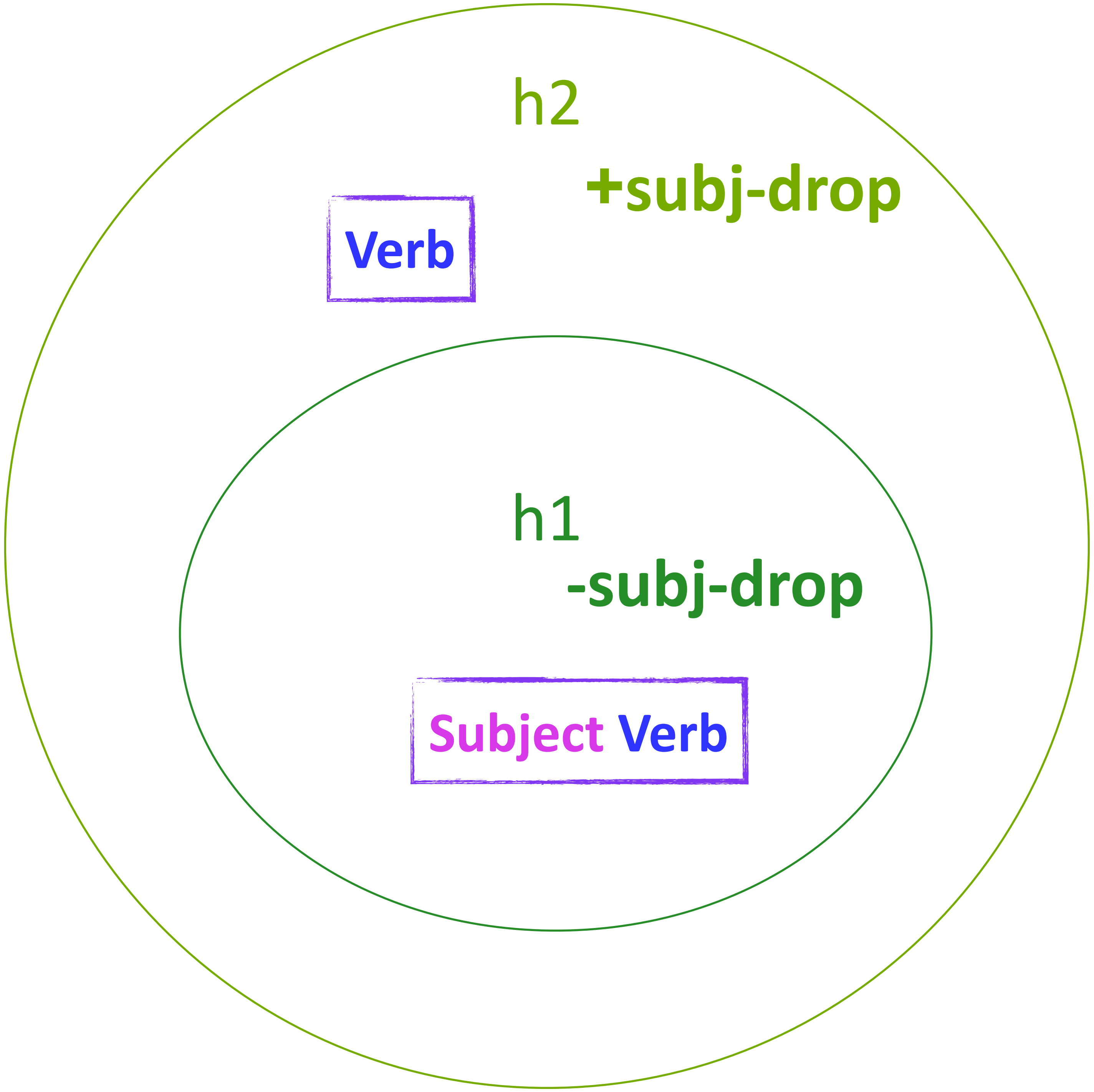
$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

If there's no reason to consider one hypothesis more complex than another, the hypotheses will typically receive **uniform** probability (all of them have the same probability).

This is typically 1 over the total hypotheses available.



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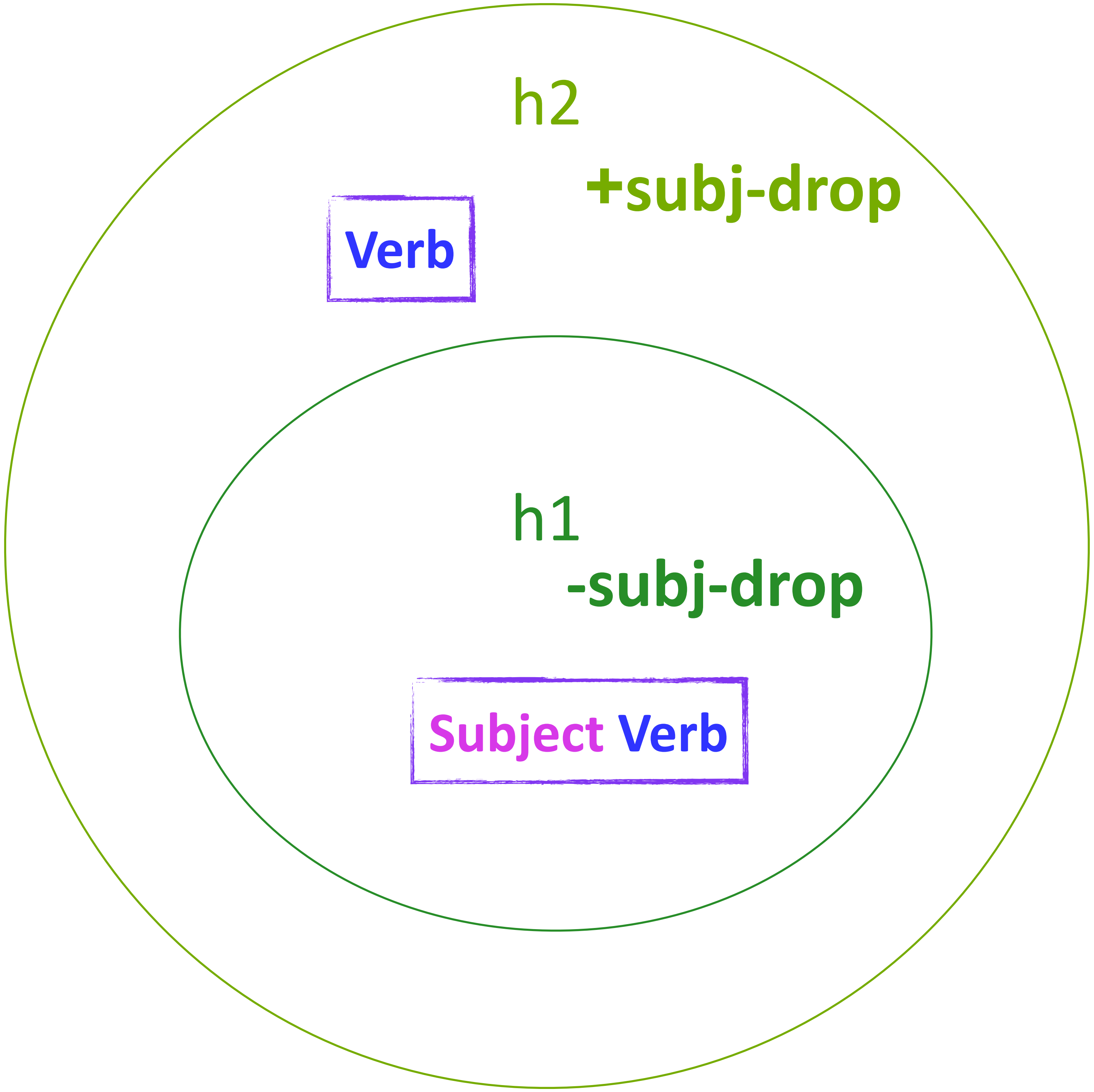
$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

uniform probability

P(h1) = 1/2

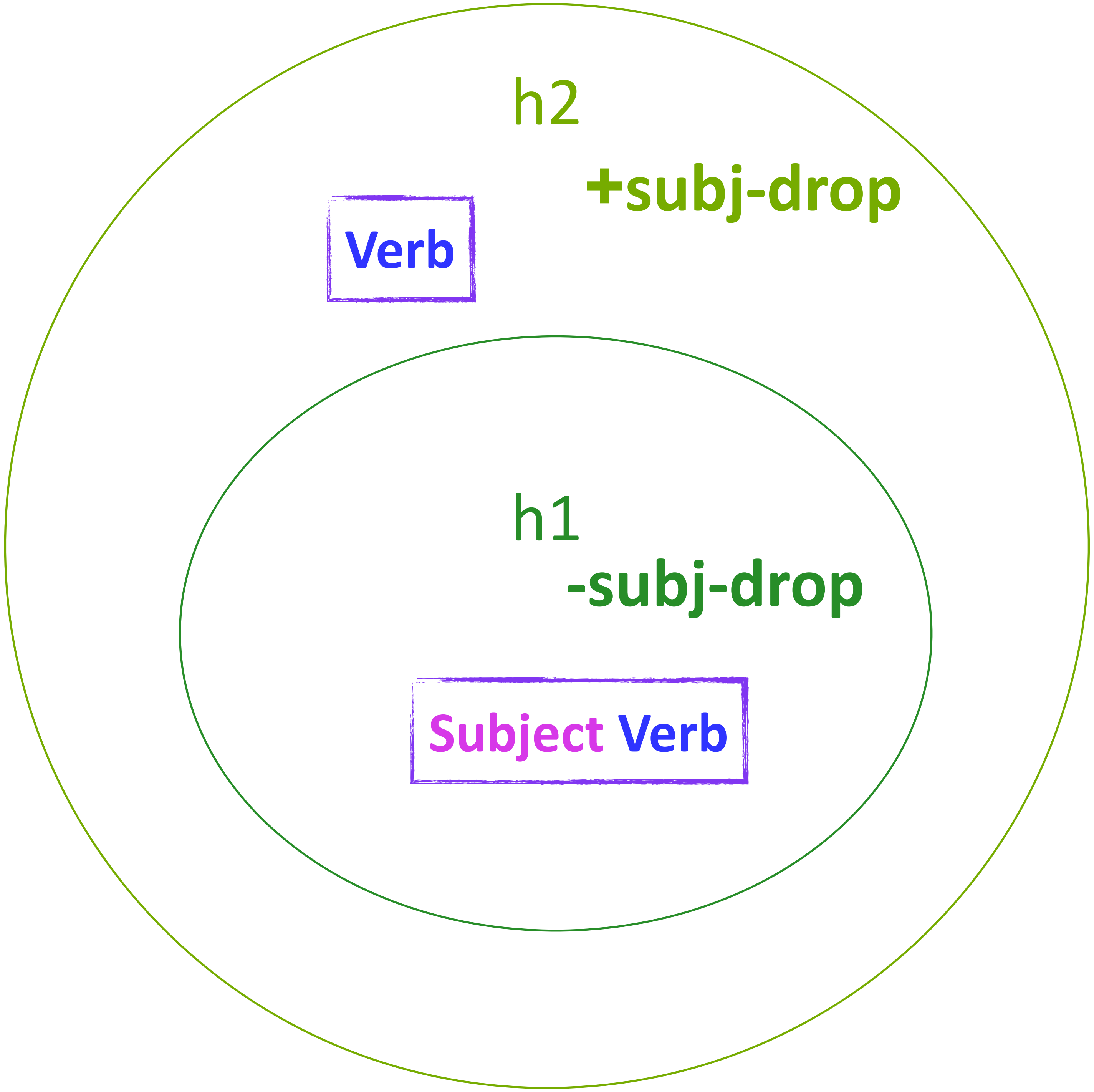
P(h2) = 1/2



Bayesian reasoning

P(D) represents the probability of the data irrespective of any hypothesis. It serves as a normalizing factor so that the posterior probabilities sum to 1.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Bayesian reasoning

P(D) is calculated by summing over all possible hypotheses the following:

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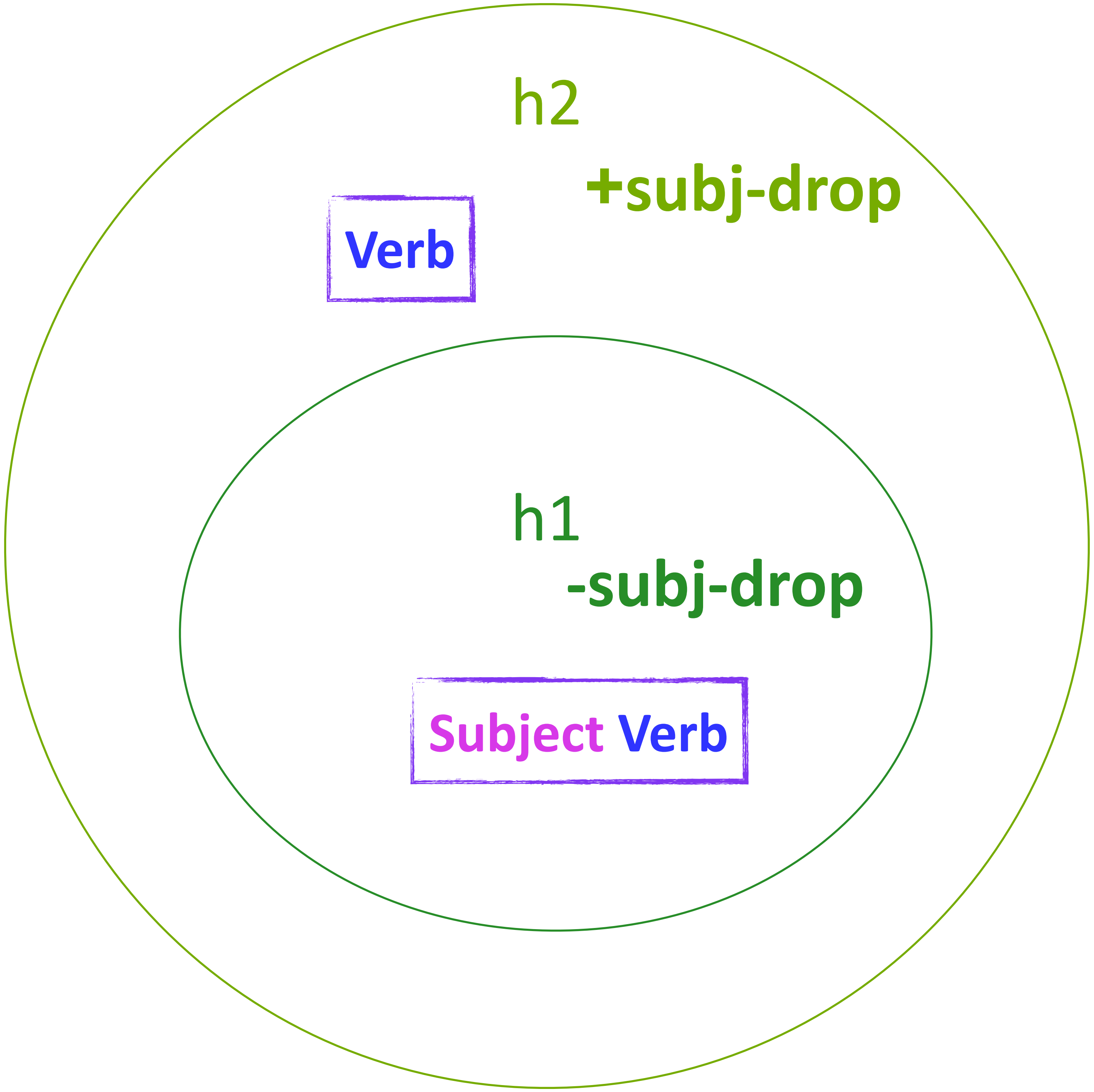

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P(D) is calculated by summing over all possible hypotheses the following:

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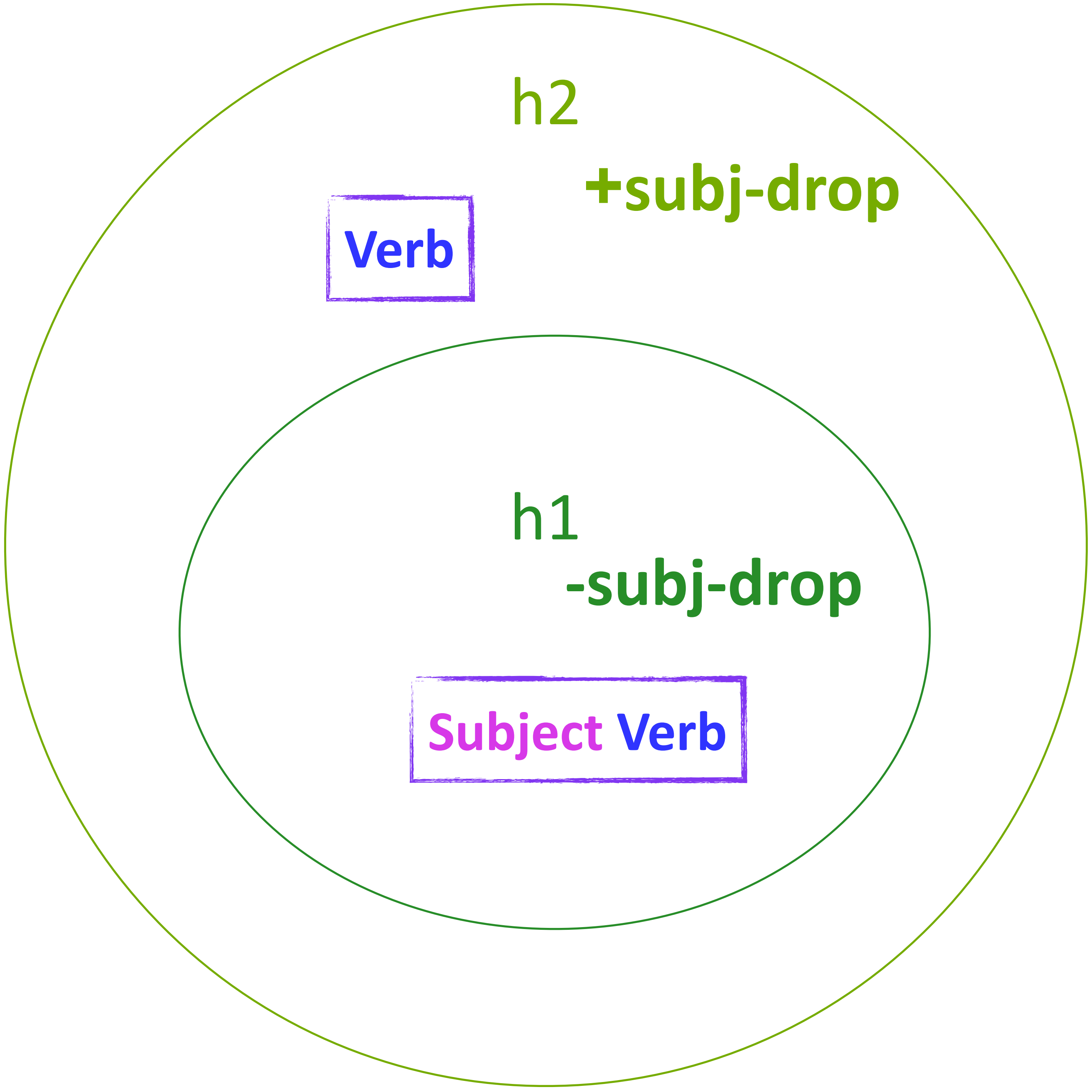

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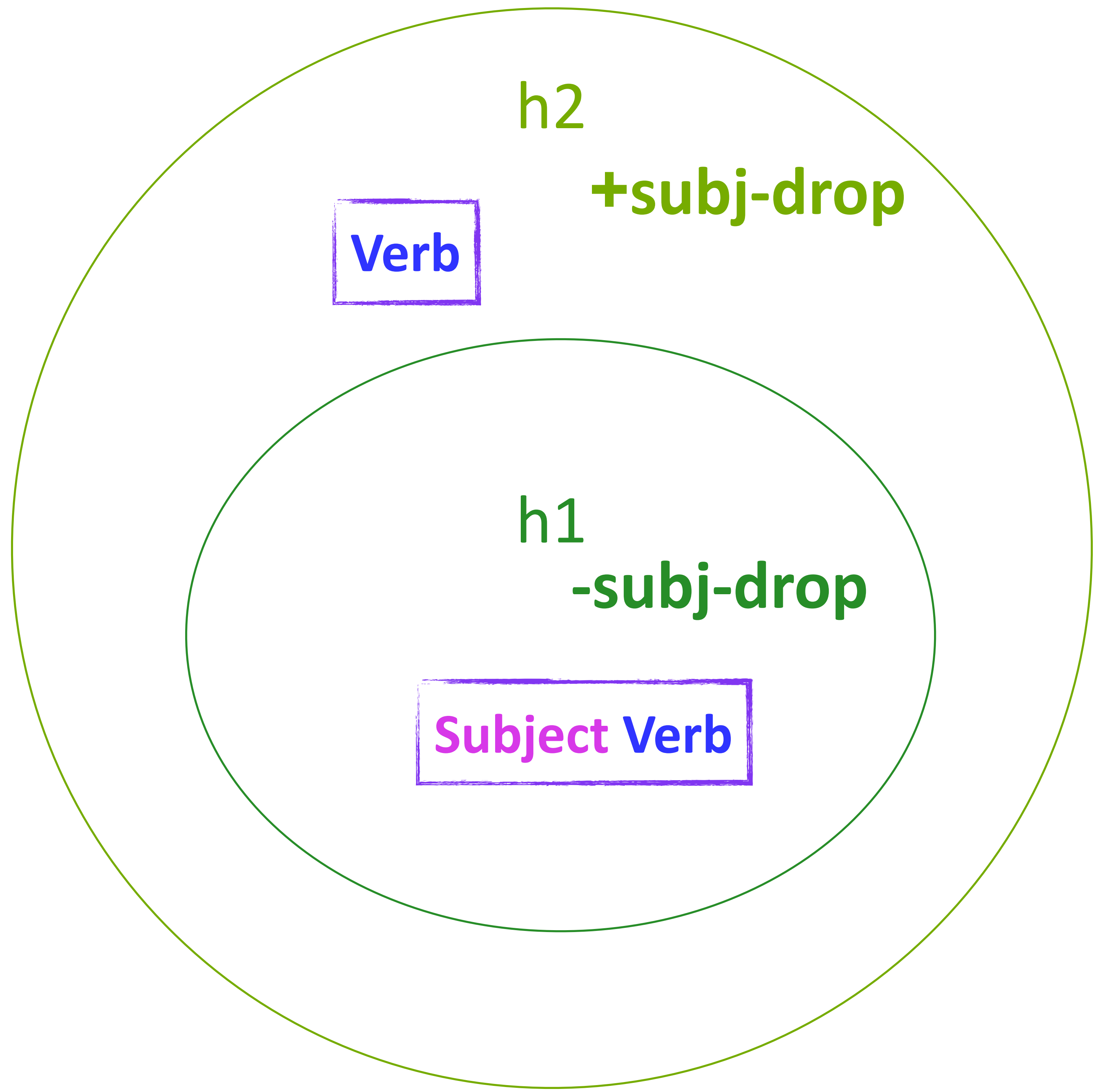

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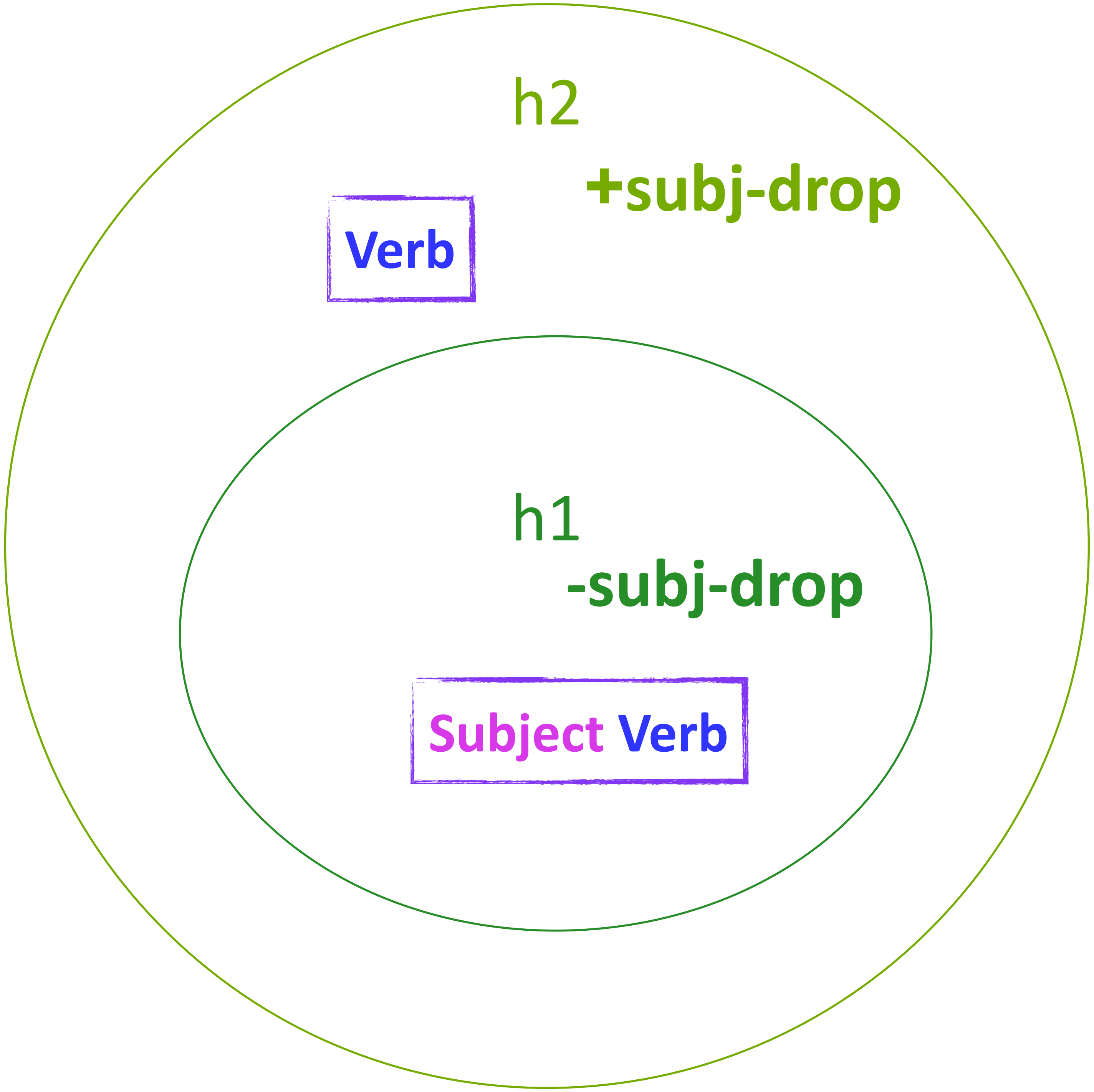
$$= \frac{P(D|h)*P(h)}{\sum_{h' \in H} P(D|h')*P(h')}$$

$$\propto P(D|h) * P(h)$$

Because we often only care about how one hypothesis compares to another, calculating P(D) can be skipped over.

Why is this so?



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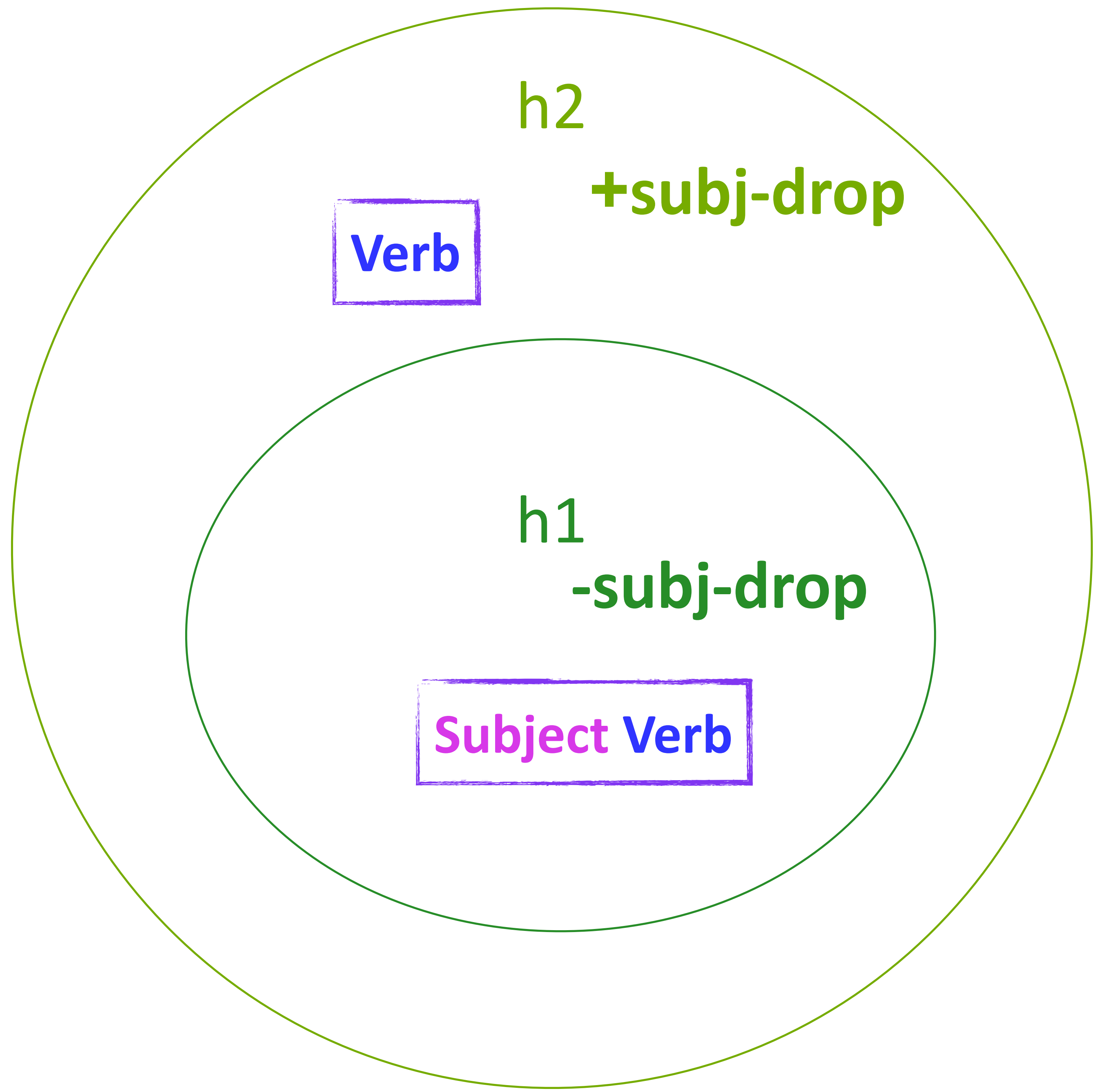
Data D

Subject Verb



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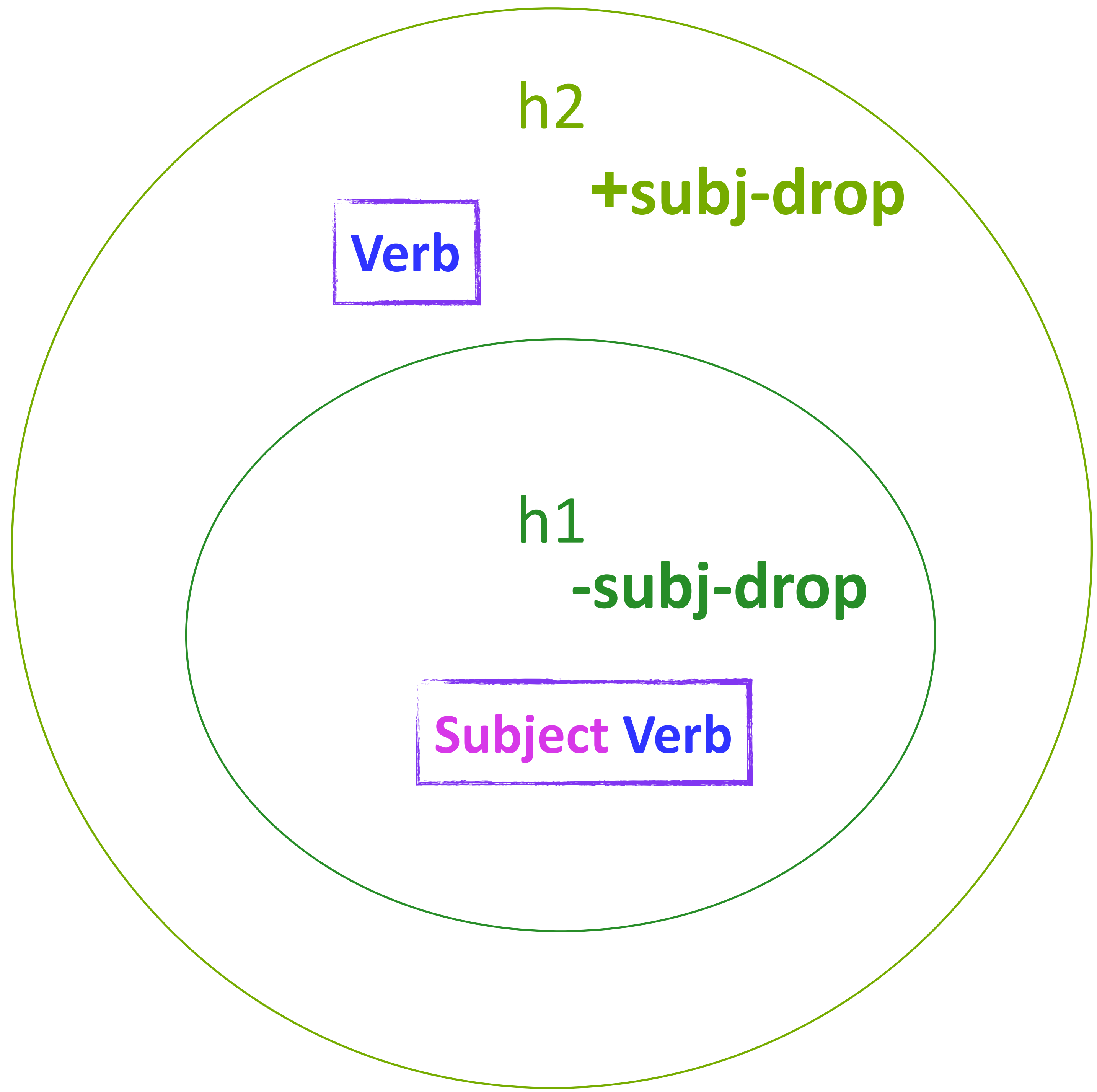
Subject Verb



likelihoods

P(D | h1) = 1

P(D | h2) = 1/2

Bayesian reasoning

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$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$= \frac{P(D|h)*P(h)}{\sum_{h' \in H} P(D|h')*P(h')}$$

$$\propto P(D|h) * P(h)$$

Data D

Subject Verb

likelihoods

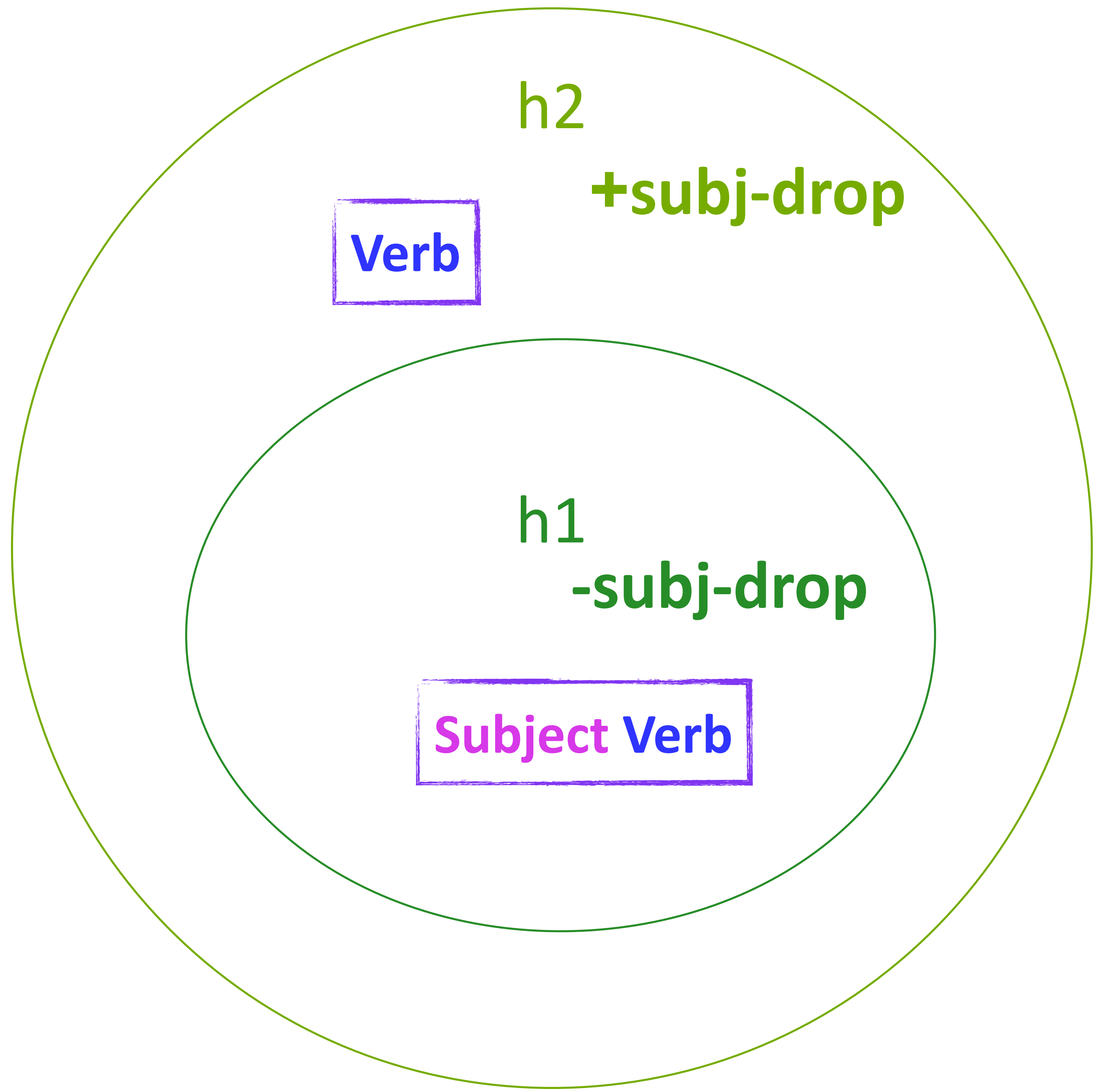
P(D | h1) = 1

P(D | h2) = 1/2

priors

P(h1) = 1/2

P(h2) = 1/2



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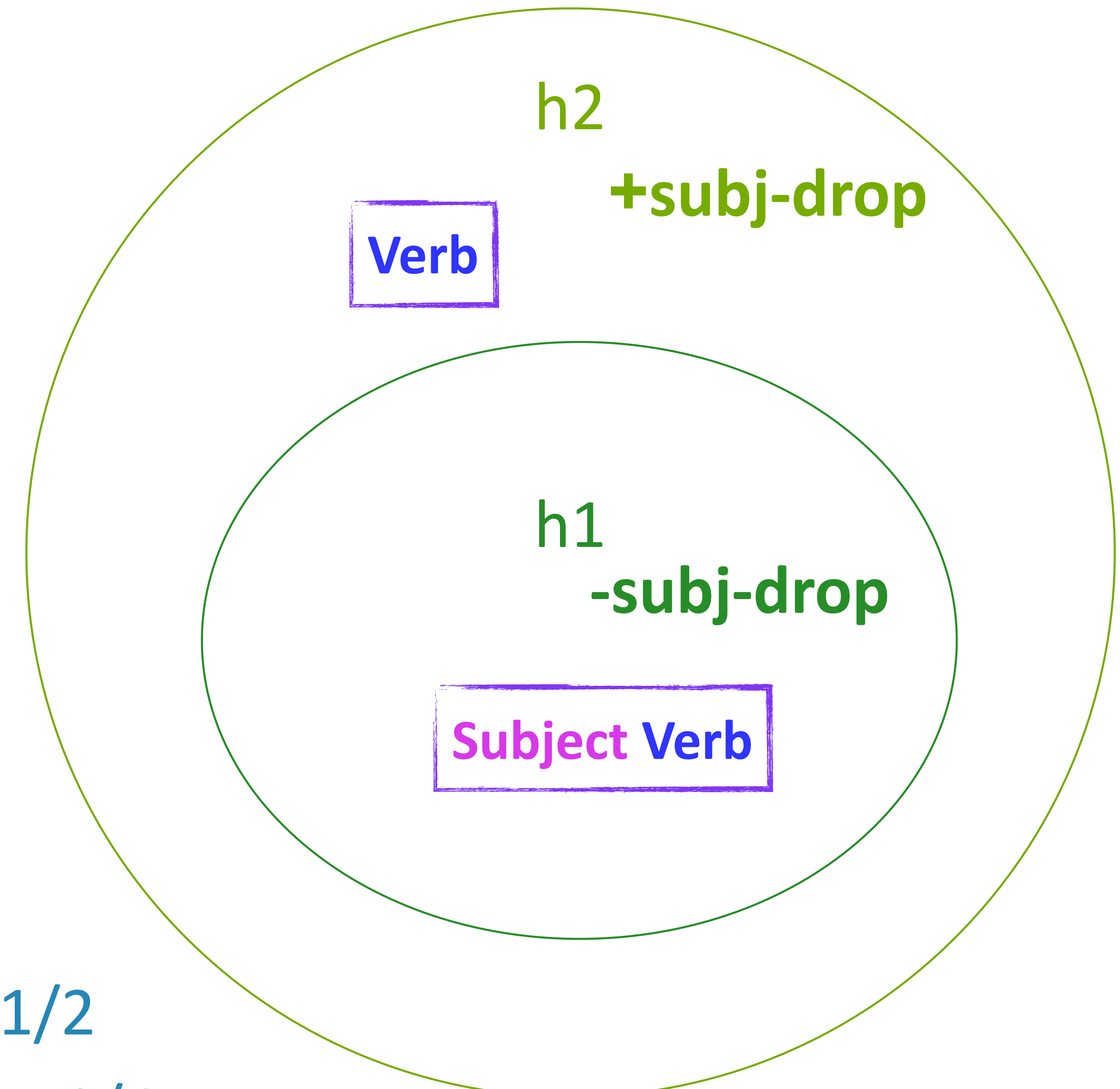

likelihoods

P(D | h1) = 1

P(D | h2) = 1/2

priors

P(h1) = 1/2

P(h2) = 1/2

likelihood * prior

P(D | h1) * P(h1) = 1 * 1/2 = 1/2

P(D | h2) * P(h2) = 1/2 * 1/2 = 1/4

Bayesian reasoning

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Data D

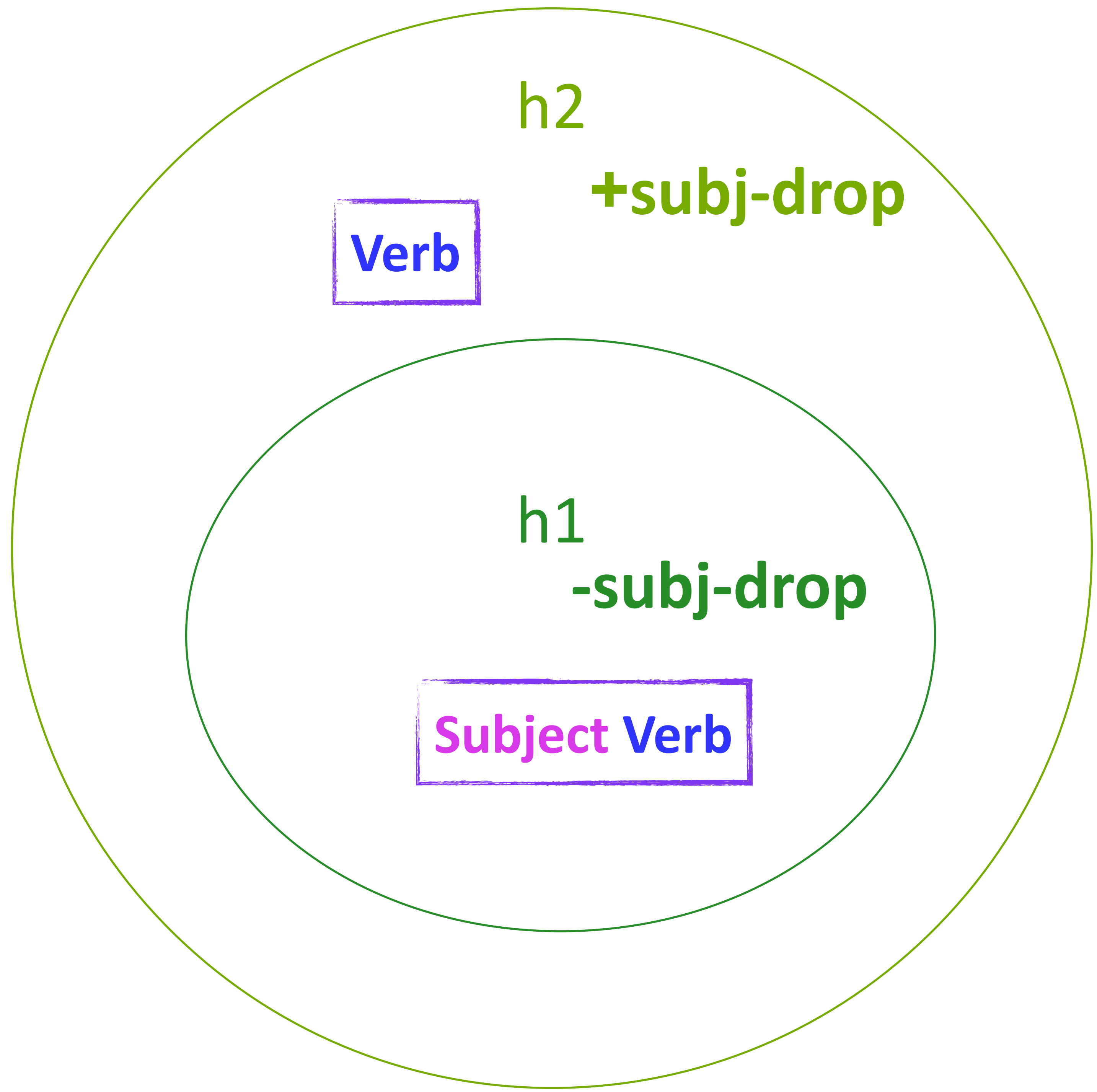
Subject Verb

likelihood * prior

P(D | h1) * P(h1) = 1/2

P(D | h2) * P(h2) = 1/4

sum 3/4



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Data D

$\boxed{\text{Subject Verb}}$

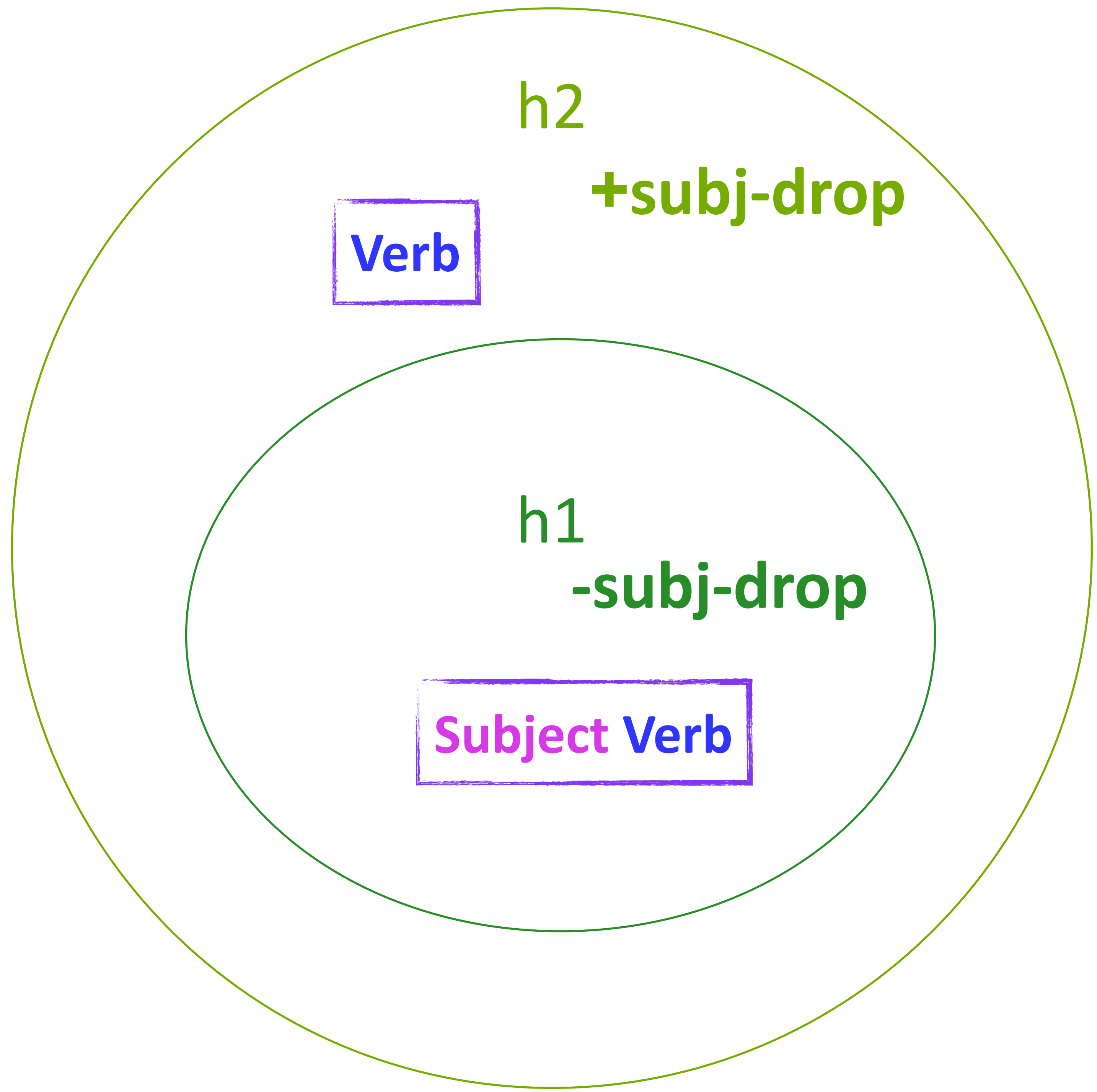
likelihood * prior

P(D | h1) * P(h1) = 1/2

P(D | h2) * P(h2) = 1/4

sum 3/4

P(h1 | D) =



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$$\propto P(D|h) * P(h)$$

Data D

Subject Verb

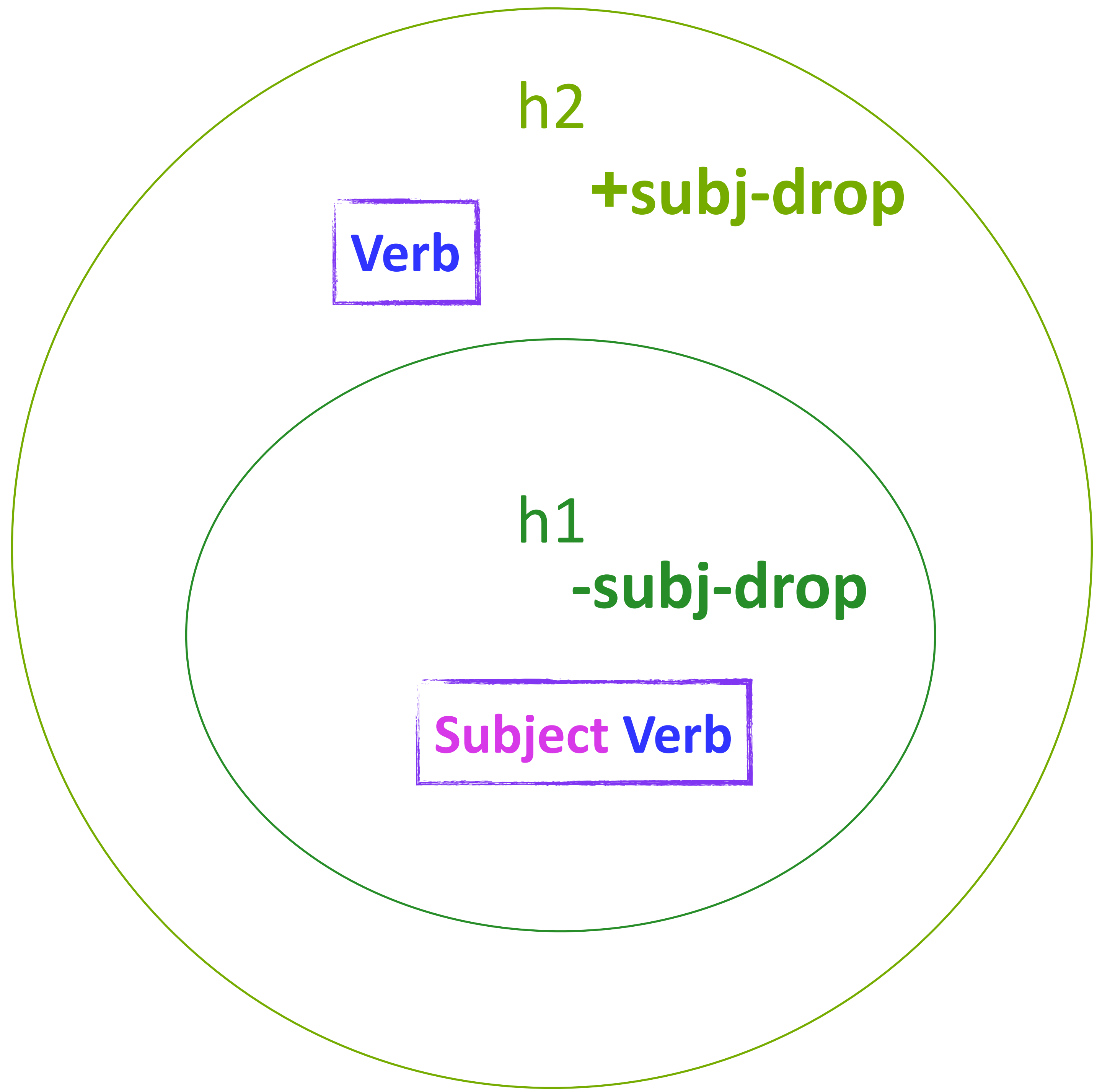
likelihood * prior

P(D | h1) * P(h1) =

P(D | h2) * P(h2) = 1/4

sum

$$P(h1 \mid D) = \frac{1/2}{\mathbf{3/4}} = 2/3$$



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$$\propto P(D|h)*P(h)$$

Data D

Subject Verb

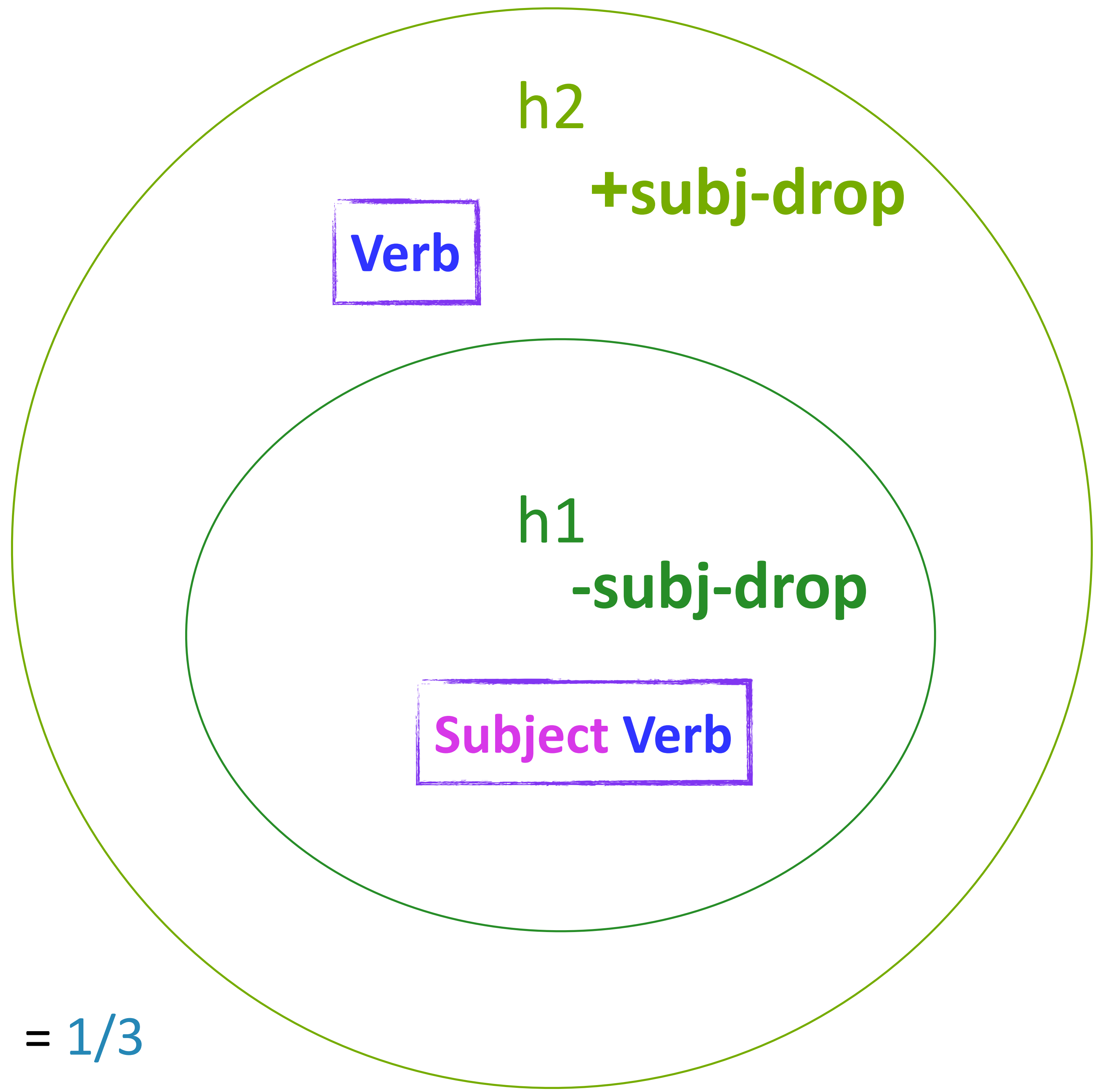
likelihood * prior

P(D | h1) * P(h1) = 1/2

P(D | h2) * P(h2) =

sum

P(h1 | D) = 2/3 P(h2 | D) = $\frac{1/4}{\mathbf{3/4}}$ = 1/3



Bayesian reasoning

P(D) is calculated by summing over all possible hypotheses the following:

the likelihood of the hypothesis * the prior of the hypotheses.

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$= \frac{P(D|h)*P(h)}{\sum_{h'\in H} P(D|h')*P(h')}$$

$$\propto P(D|h) * P(h)$$

Data D

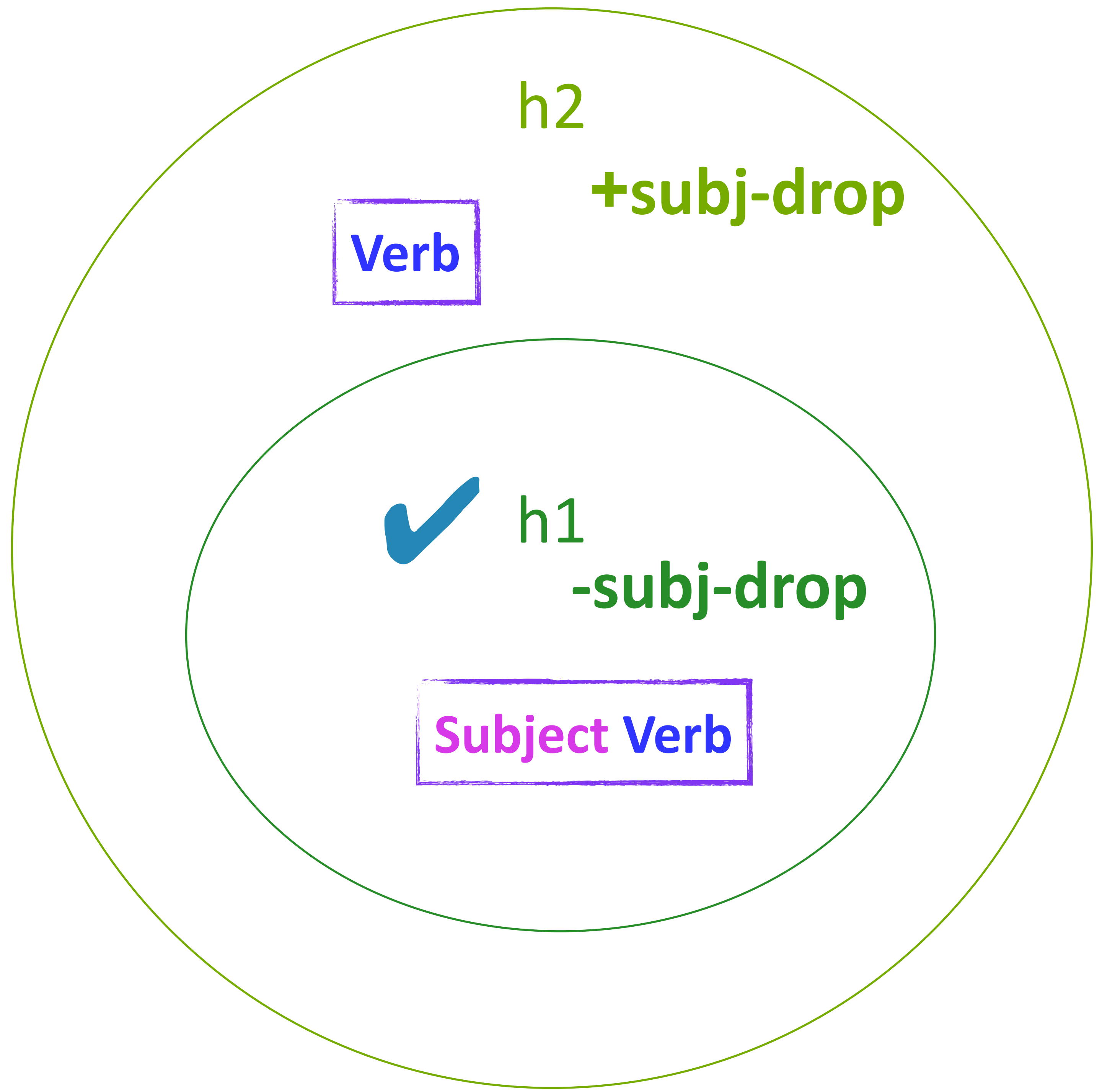
Subject Verb

likelihood * prior

P(D | h1) * P(h1) = 1/2

P(D | h2) * P(h2) = 1/4

sum 3/4



P(h1 | D) = **2/3** P(h2 | D)= **1/3**

Conclusion: h1 is now twice as likely as h2

Bayesian reasoning

P(D) is calculated by summing over all possible hypotheses the following:

the likelihood of the hypothesis * the prior of the hypotheses.

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$= \frac{P(D|h)*P(h)}{\sum_{h' \in H} P(D|h')*P(h')}$$

$$\propto P(D|h) * P(h)$$

Data D

Subject Verb

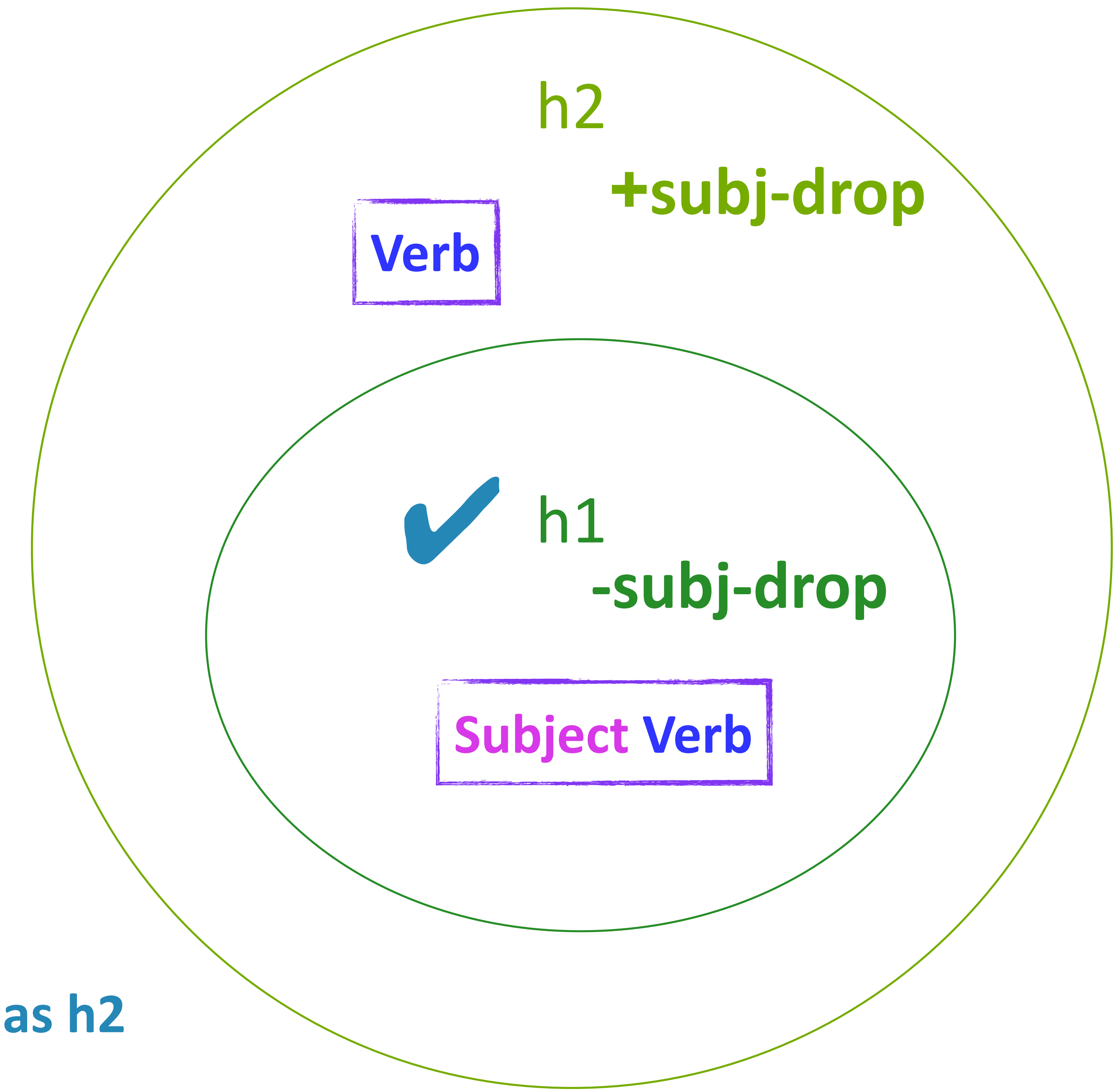
likelihood * prior

P(D | h1) * P(h1) = **1/2**

P(D | h2) * P(h2) = **1/4**

Same

Conclusion: h1 is now twice as likely as h2



Bayesian reasoning

P(D) is calculated by summing over all possible hypotheses the following:

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$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

$$= \frac{P(D|h) * P(h)}{\sum_{h' \in H} P(D|h') * P(h')}$$

$$\propto P(D|h) * P(h)$$

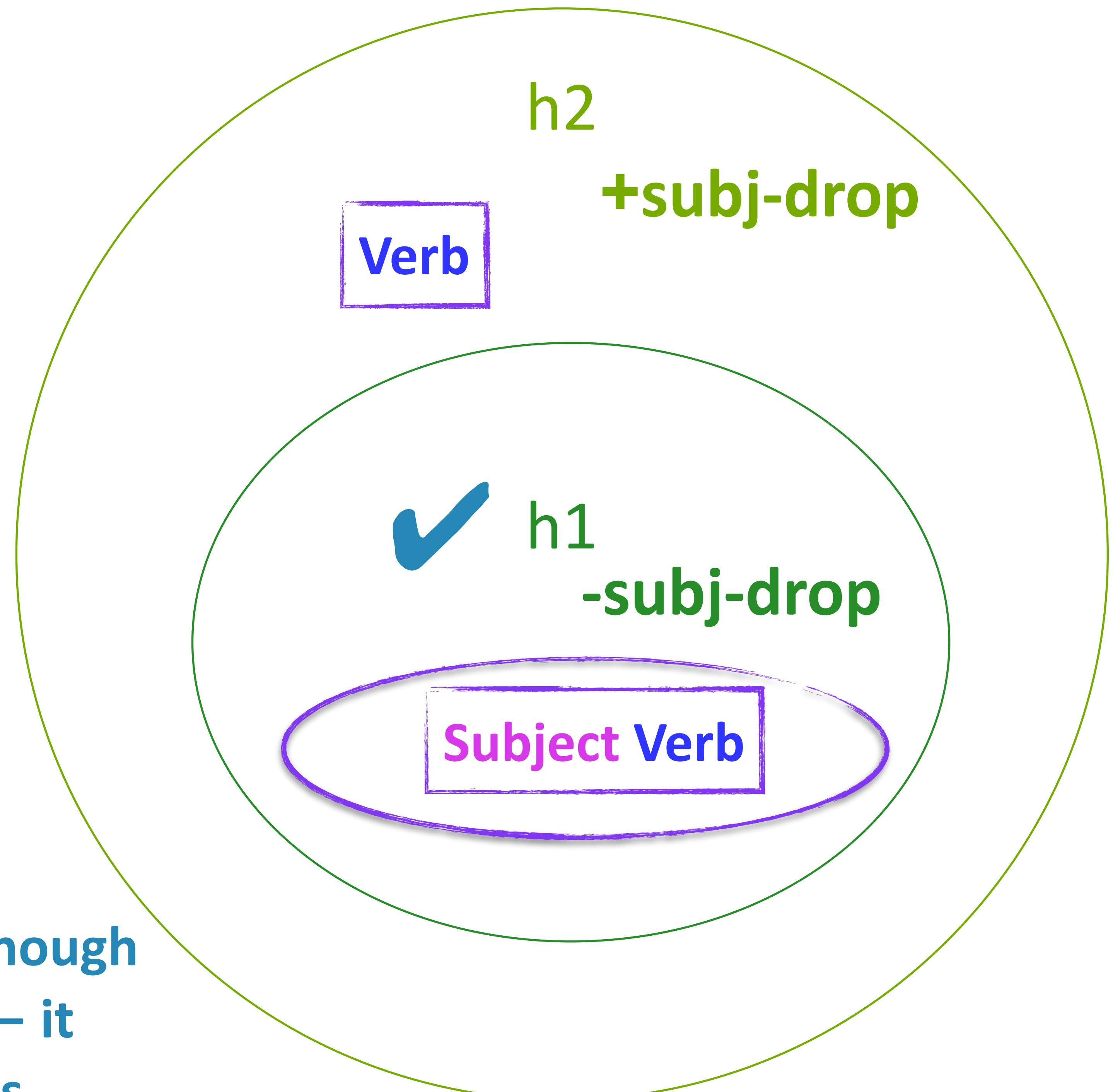
Data D

Subject Verb

likelihood * prior

P(D | h1) * P(h1) = **1/2**

P(D | h2) * P(h2) = **1/4**



h1 is now twice as likely as h2 even though the data point seen was ambiguous — it was compatible with both hypotheses.

Bayesian reasoning

P(D) is calculated by summing over all possible hypotheses the following:

the likelihood of the hypothesis * the prior of the hypotheses.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

$$= \frac{P(D|h) * P(h)}{\sum_{h' \in H} P(D|h') * P(h')}$$

$$\propto P(D|h) * P(h)$$

Data D

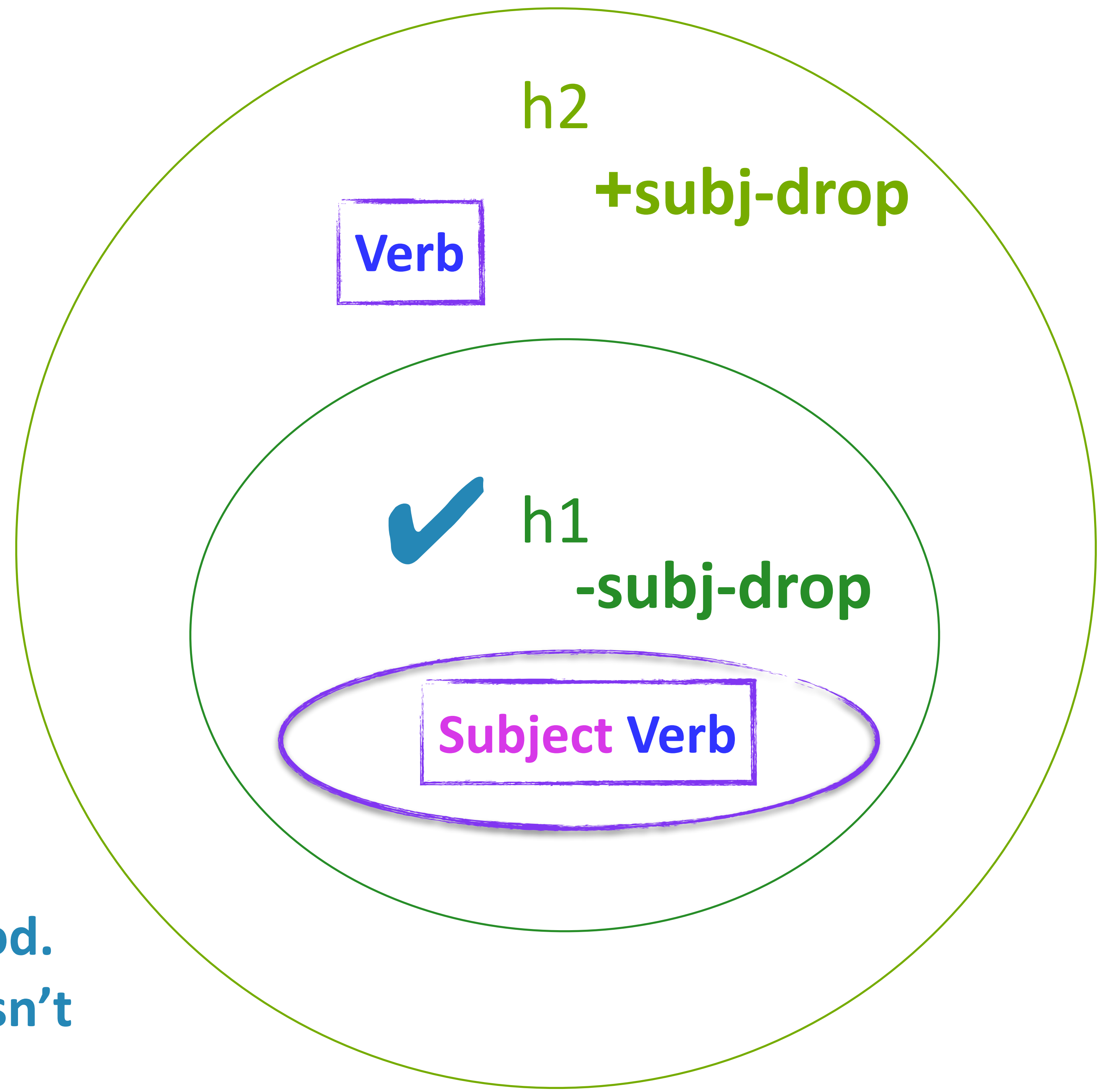
Subject Verb

likelihood * **prior**

P(D | h1) * P(h1) = **1/2**

P(D | h2) * P(h2) = **1/4**

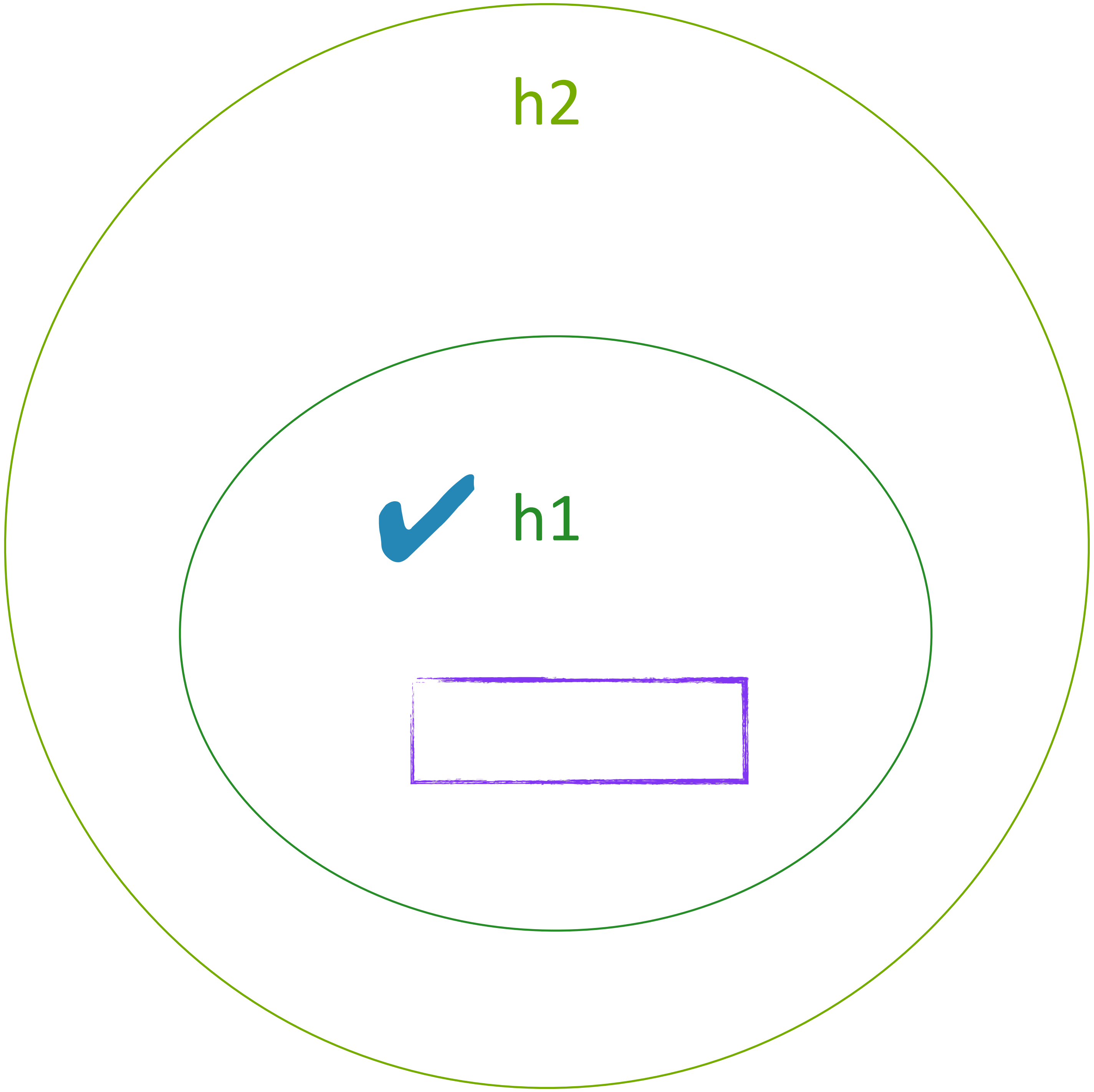
The reason is because of the likelihood. h1 is a better fit for the data -- it doesn't predict other data like h2 does.



Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

We have behavioral evidence that very young children reason in a way that leads to similar conclusions when given this kind of scenario.



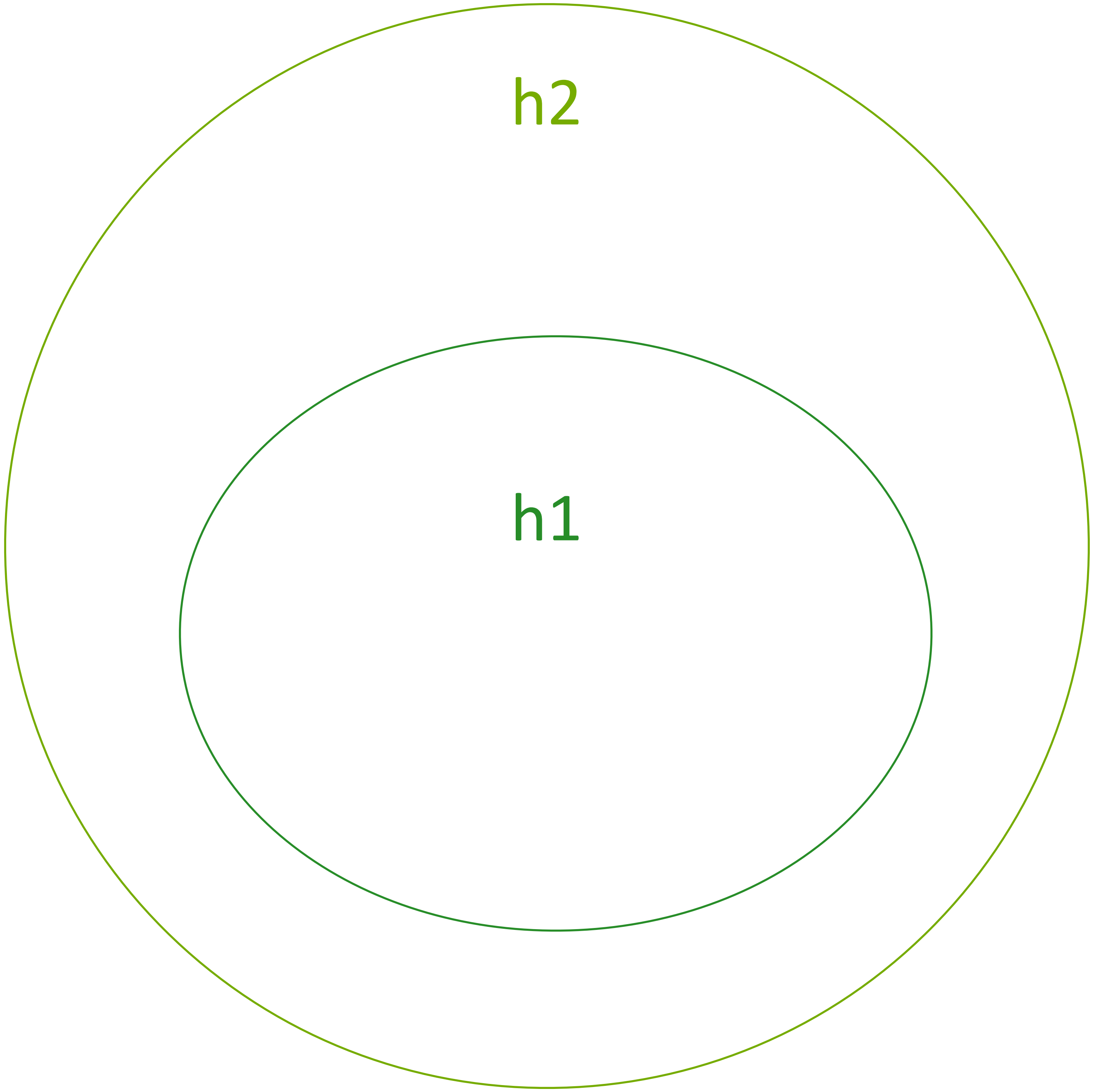
Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study

Infants were trained on data from an artificial language, which consisted of words following a certain pattern.

Data D

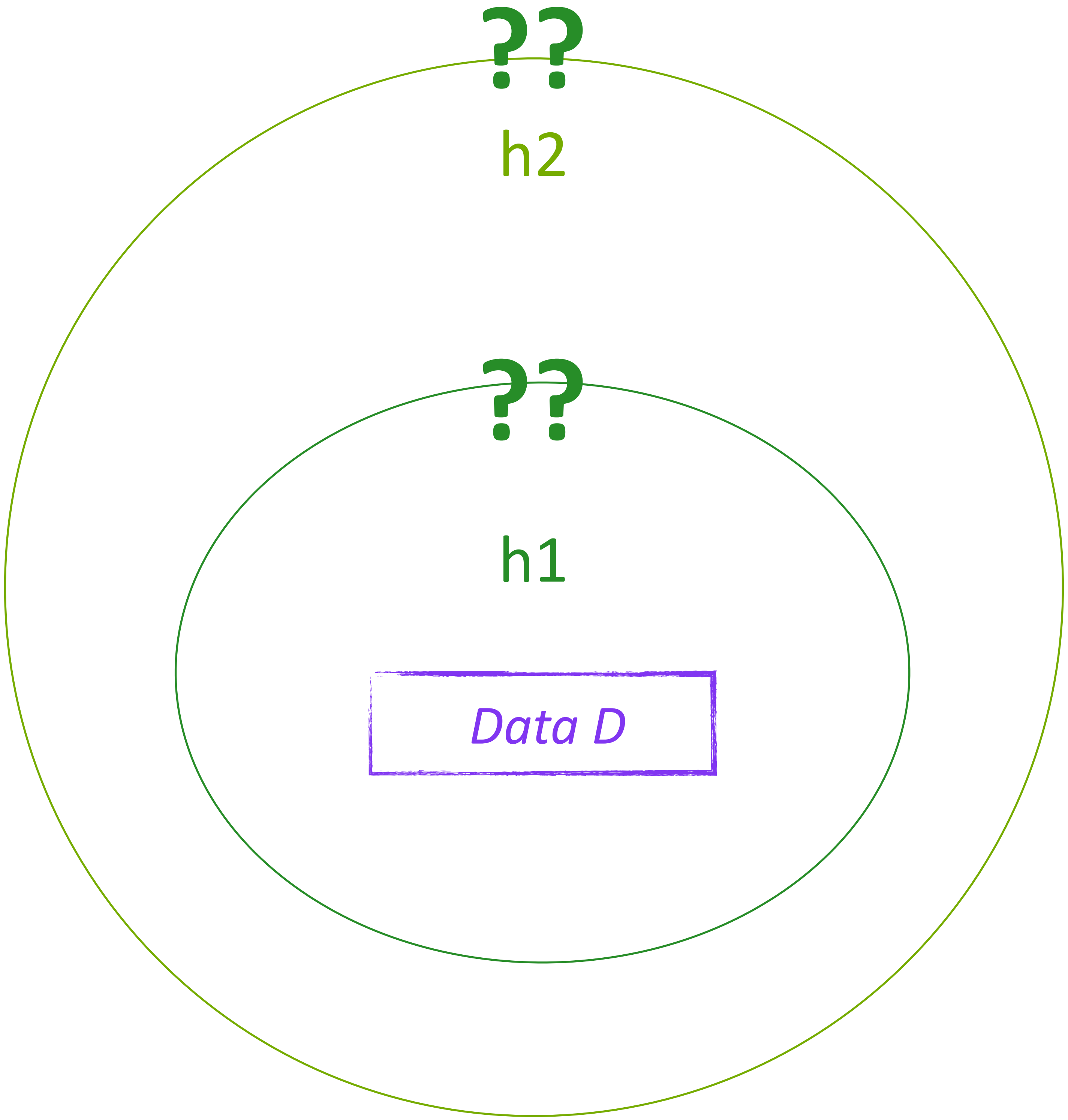


Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study

The infant's job: determine the **generalization** that describes the pattern for words of the artificial language.

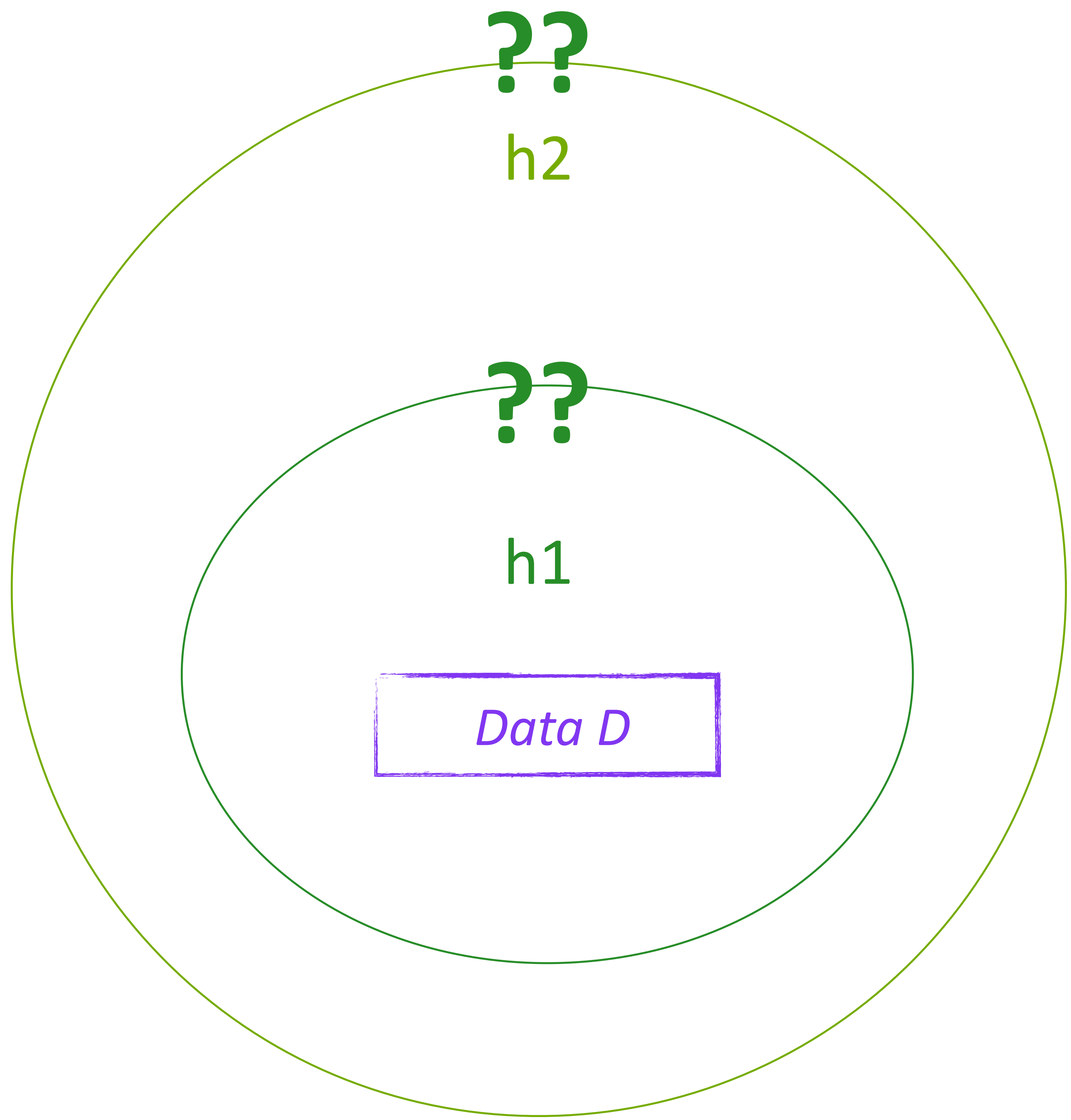


Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study

Marcus et al. (1999) found that very young infants will notice that words made up of 3 syllables follow a pattern that can be represented as AAB or ABA.



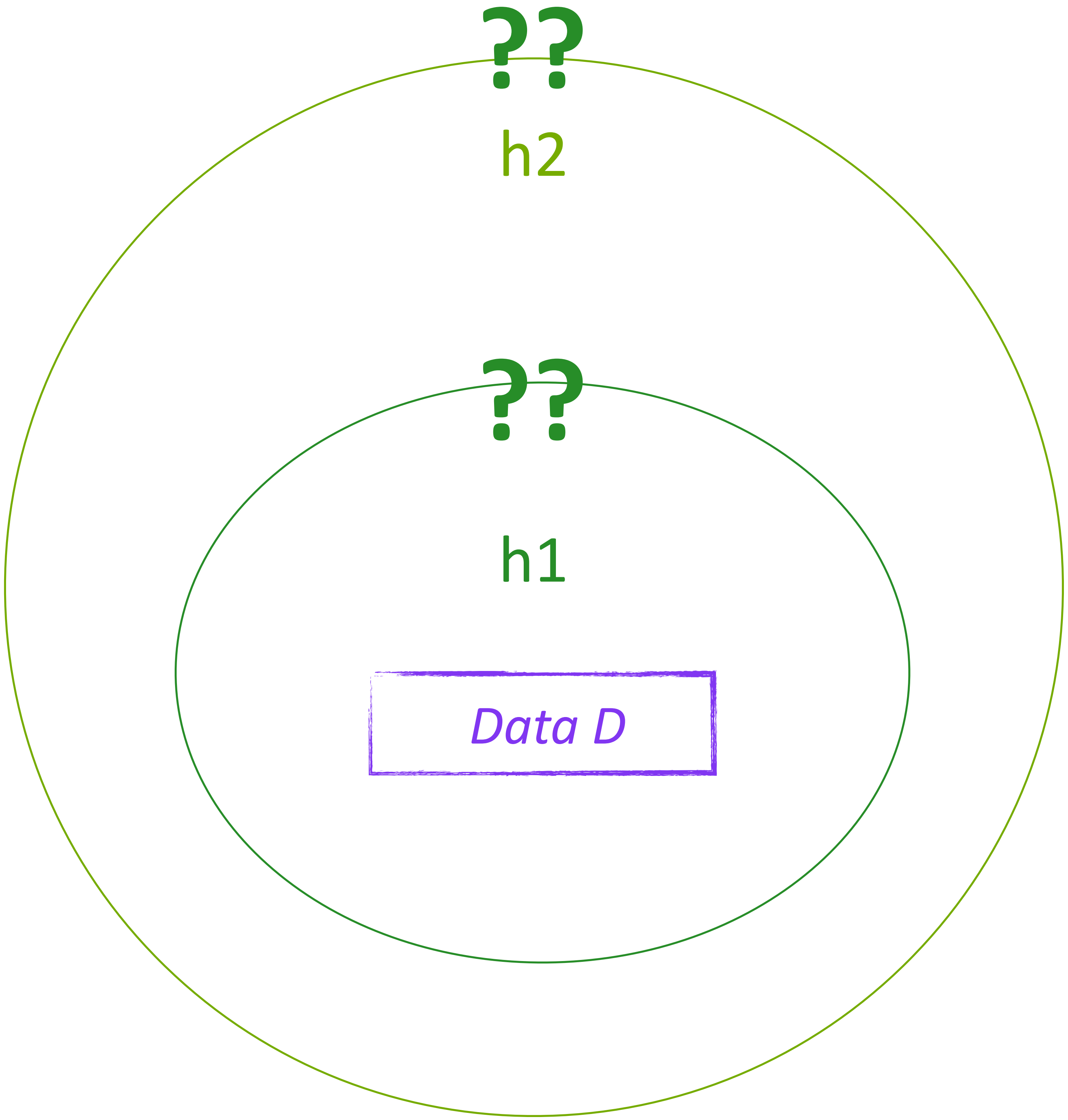
Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study

Marcus et al. (1999) found that very young infants will notice that words made up of 3 syllables follow a pattern that can be represented as AAB or ABA.

Example:
A syllables = le, wi
B syllables = di, je



Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

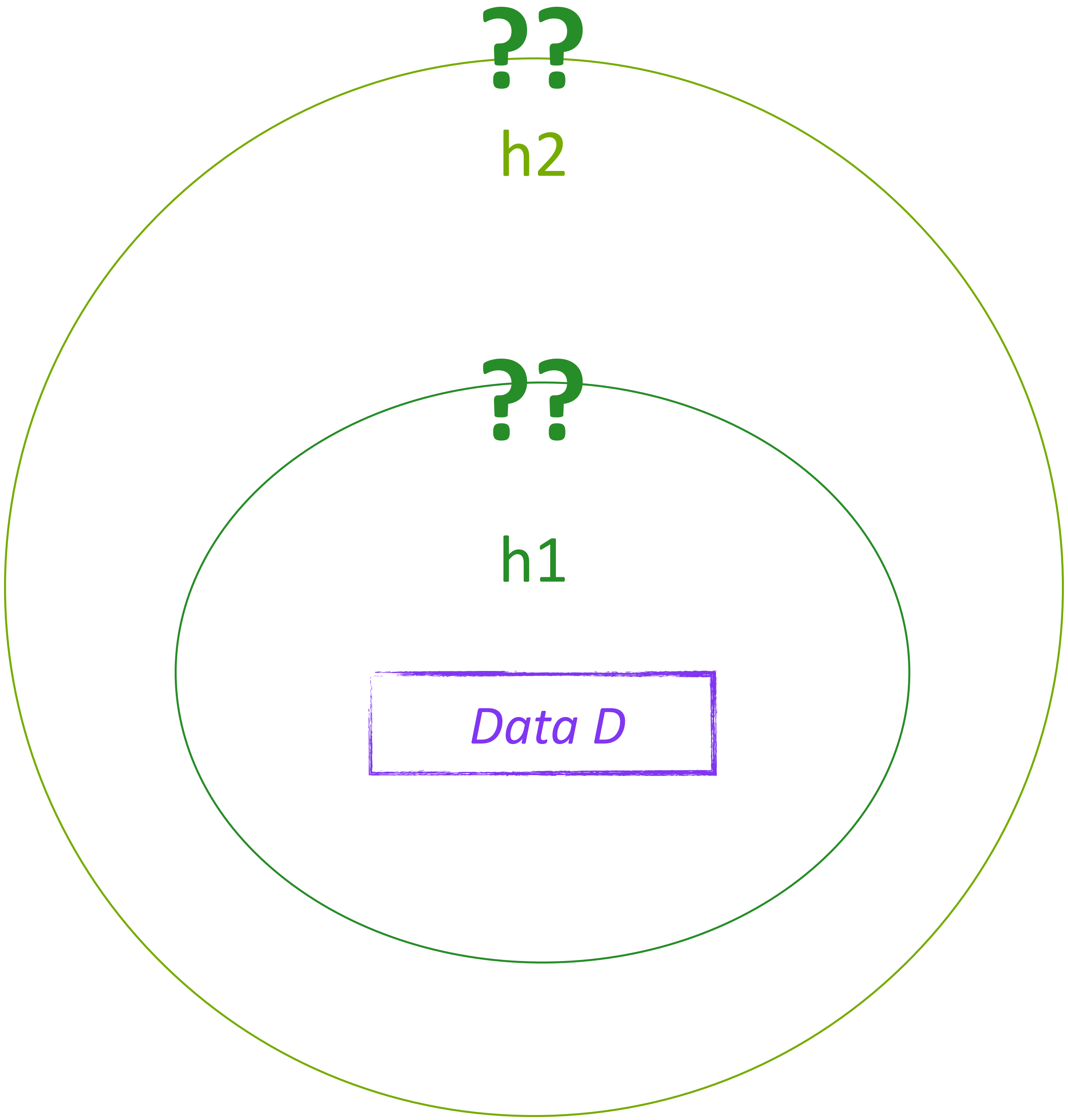
Gerken 2006, 2010
artificial language study

AAB or ABA

A syllables = le, wi
B syllables = di, je

AAB language words:
lele**di**, lele**je**, wiwi**di**, wiwi**je**

ABA language words:
le**di**le, le**je**le, wi**di**wi, wi**je**wi



Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study

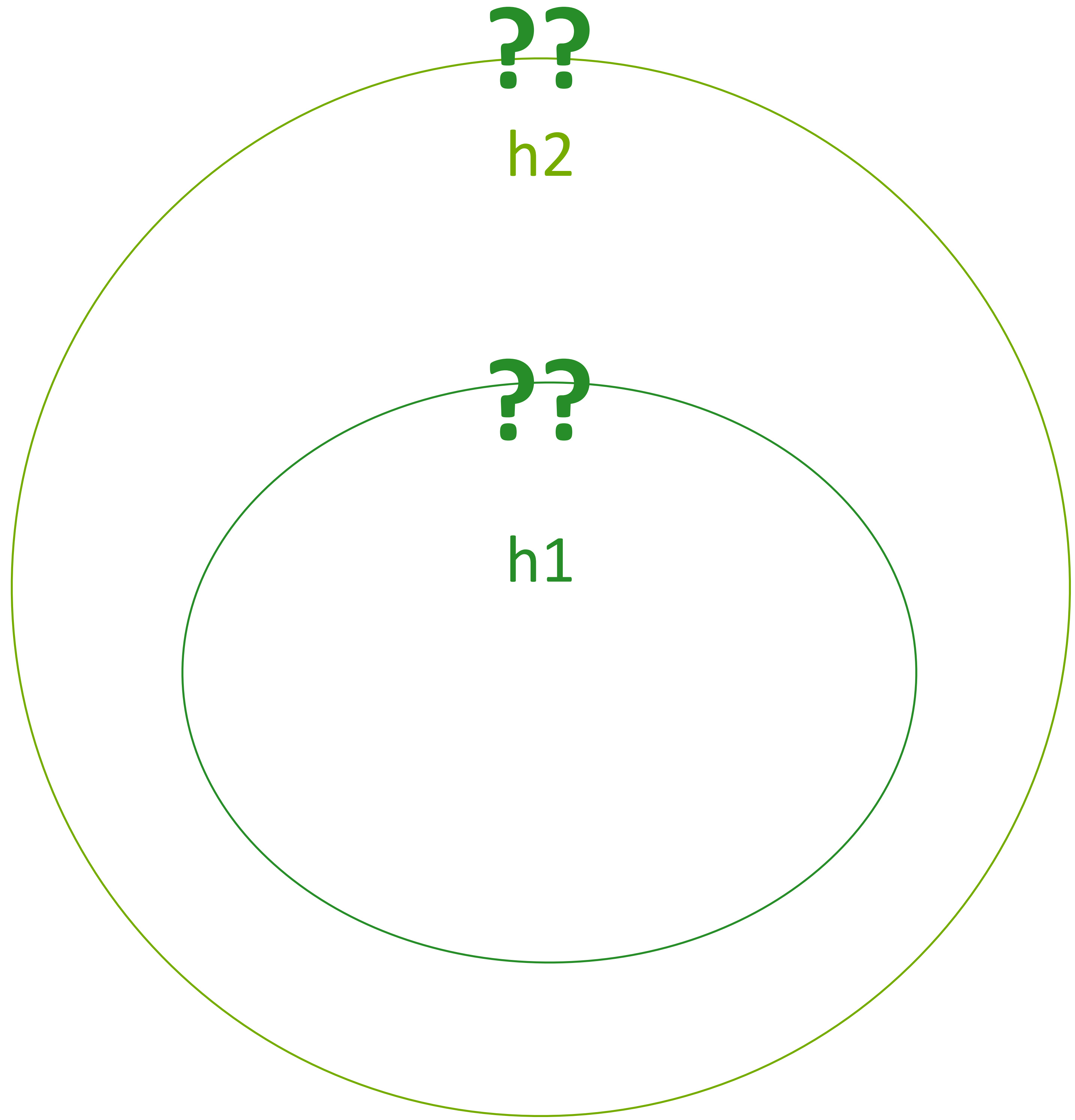
AAB or ABA

AAB language words:
leledi, leleje, wiwidi, wiwije

ABA language words:
ledile, lejele, widiwi, wijewi

What kind of generalization would children make if they were given particular kinds of data from these same artificial languages?

Data D



Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

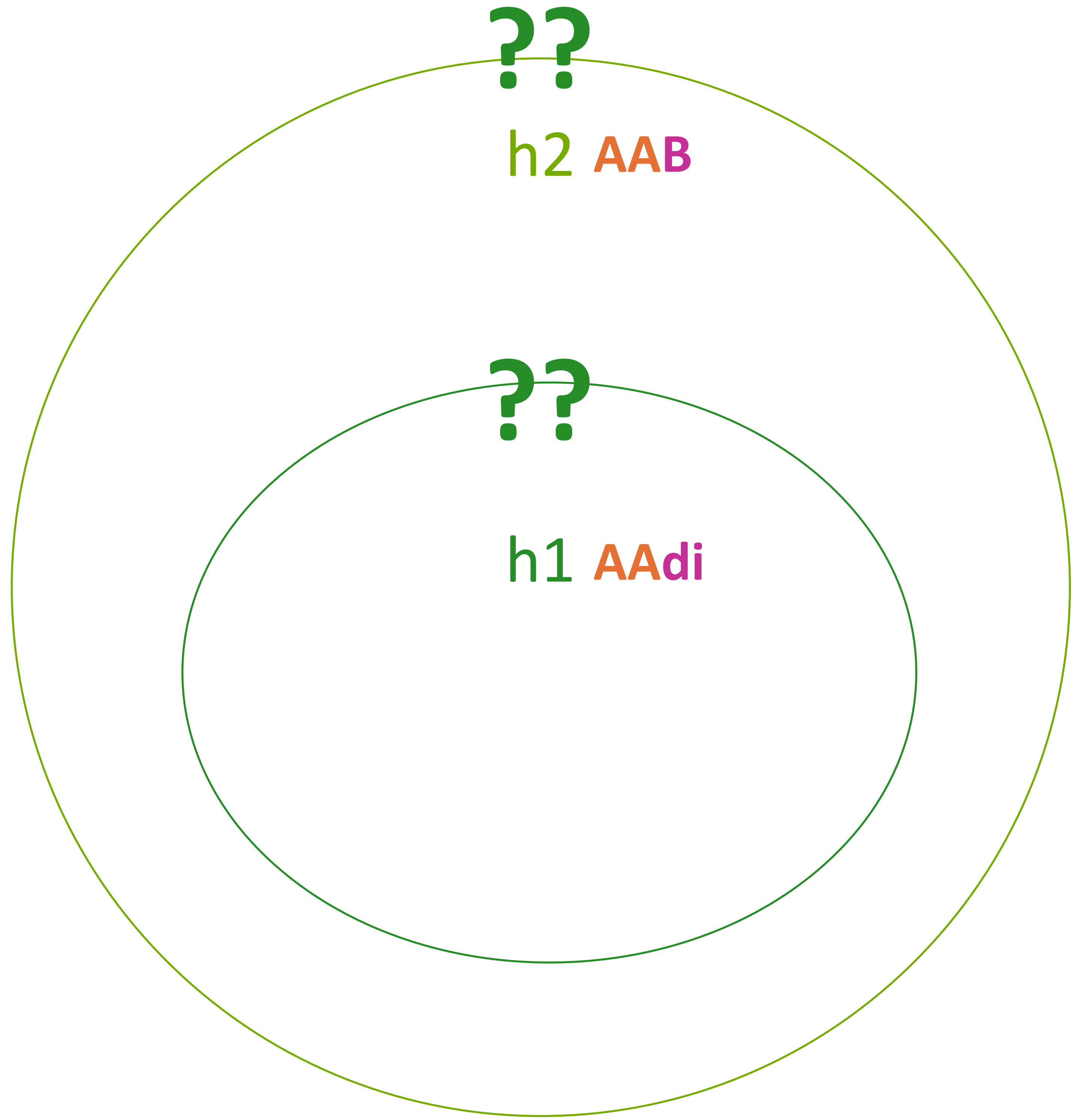
Gerken 2006, 2010
artificial language study

AAB

	di	je	li	we
le	leledi	leleje	leleli	lelewe
wi	wiwidi	wiwije	wiwili	wiwiwe
ji	jijidi	jijije	jijili	jijiwe
de	dededi	dedeje	dedeli	dedewe

Infants only see a subset of the language

Data D



Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

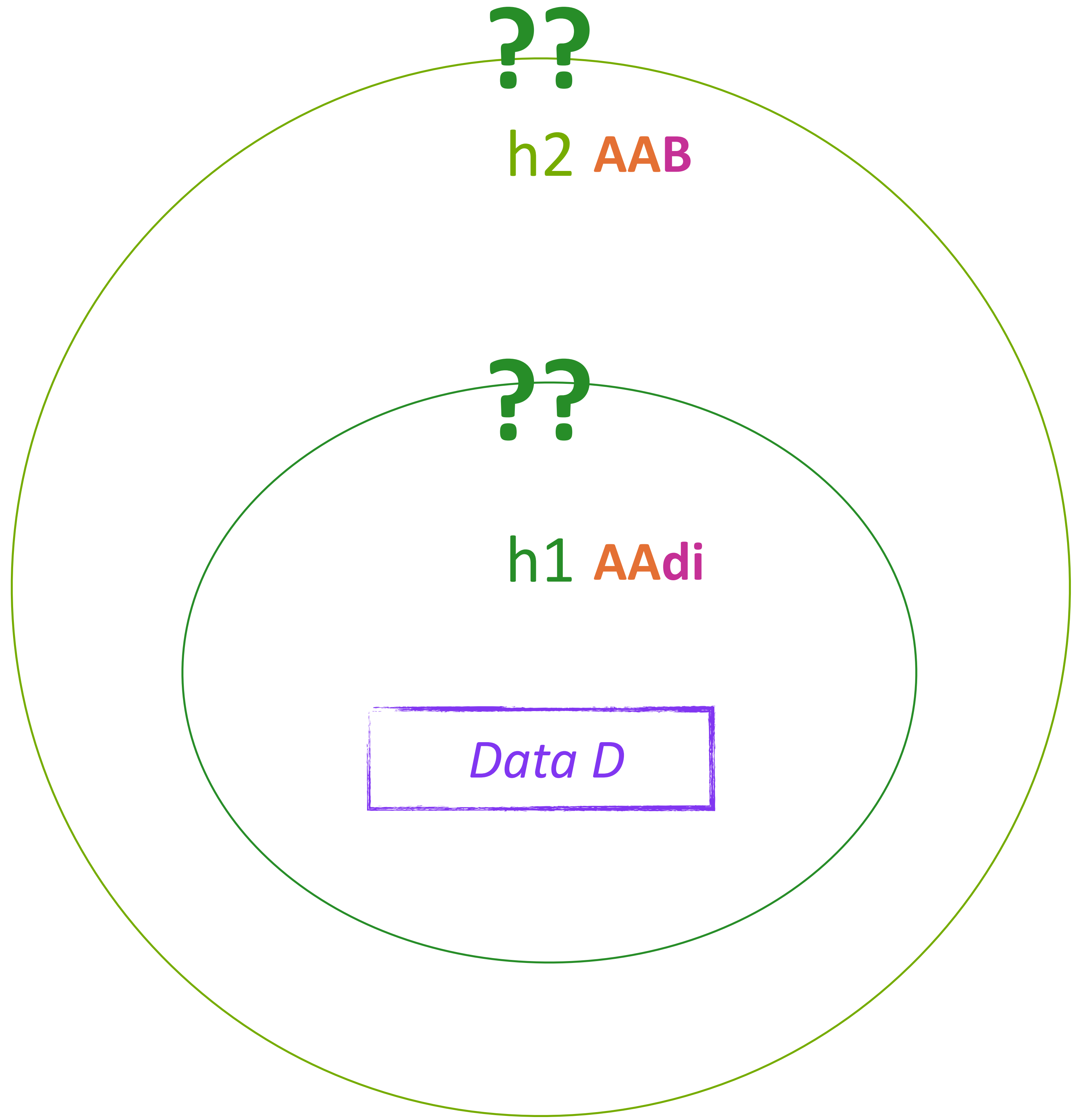
Gerken 2006, 2010
artificial language study

	di	je	li	we
le	leledi	leleje	leleli	lelewe
wi	wiwidi	wiwije	wiwili	wiwiwe
ji	jijidi	jijije	jijili	jijiwe
de	dededi	dedeje	dedeli	dedewe

Experimental condition

Training on four word types:
leledi, wiwidi, jijidi, dededi

Consistent with both a less-general hypothesis (h1) and a more-general hypothesis (h2).



Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study

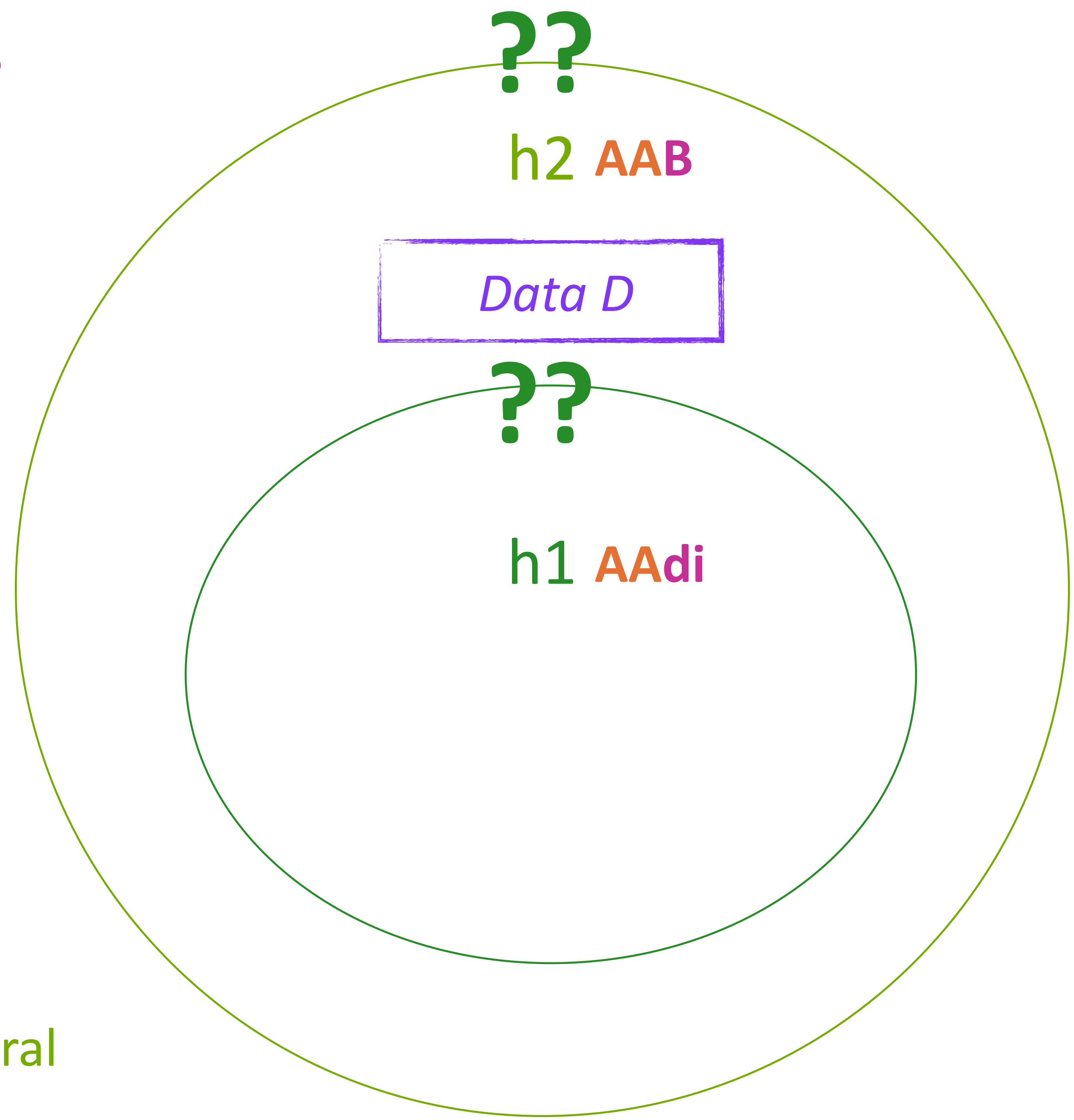
AAB

	di	je	li	we
le	leledi	leleje	leleli	lelewe
wi	wiwidi	wiwije	wiwili	wiwiwe
ji	jijidi	jijije	jijili	jijiwe
de	dededi	dedeje	dedeli	dedewe

Control condition

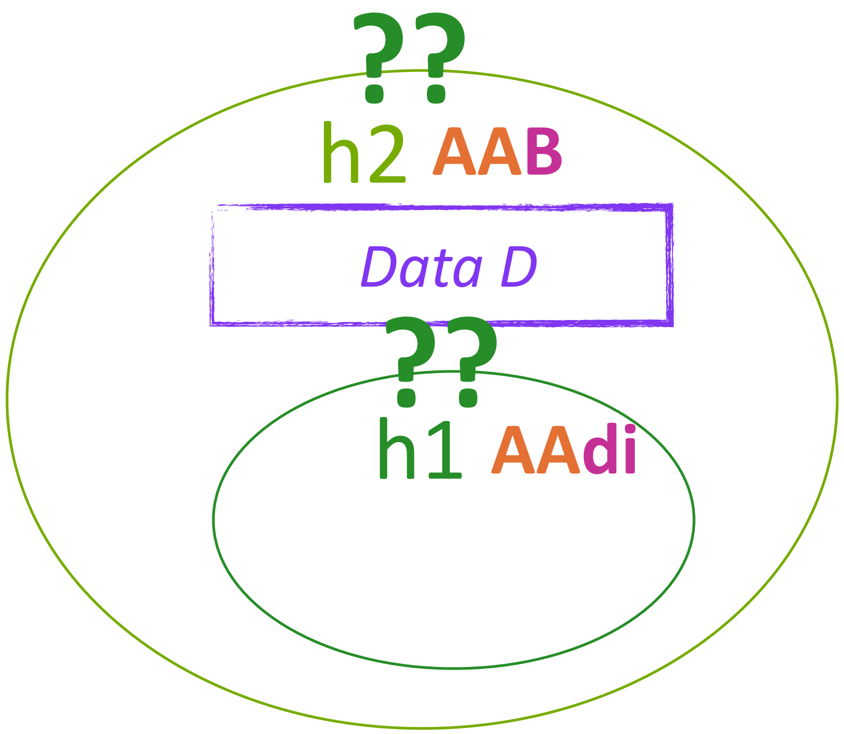
Training on four word types:
leledi, wiwije, jijili, dedewe

Consistent only with the more-general hypothesis (h2).



Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

	di	je	li	we
le	leledi	leleje	leleli	lelewe
wi	wiwidi	wiwije	wiwili	wiwiwe
ji	jijidi	jijije	jijili	jijiwe
de	percedi	dedeje	dedeli	dedewe

Control condition

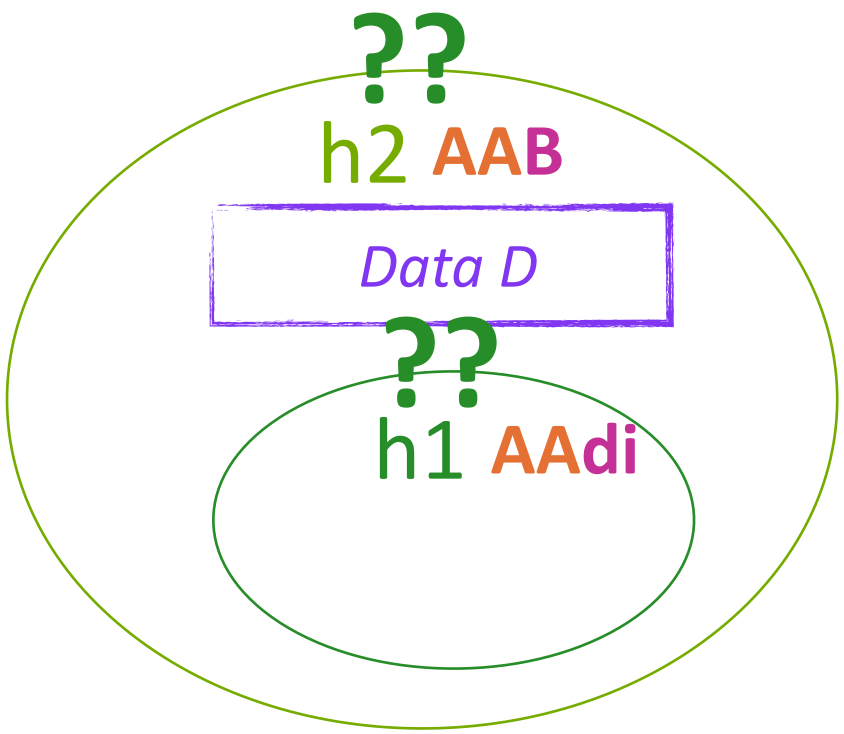
Training on four word types:
leledi, wiwije, jijili, dedewe

Consistent only with the more-general hypothesis (h2).

This control condition is used to see what children's behavior is when the data are only consistent with one of the generalizations.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

	di	je	li	we
le	leledi	leleje	leleli	lelewe
wi	wiwidi	wiwije	wiwili	wiwiwe
ji	jijidi	jijije	jijili	jijiwe
de	percentage dededi	dedeje	dedeli	dedewe

Control condition

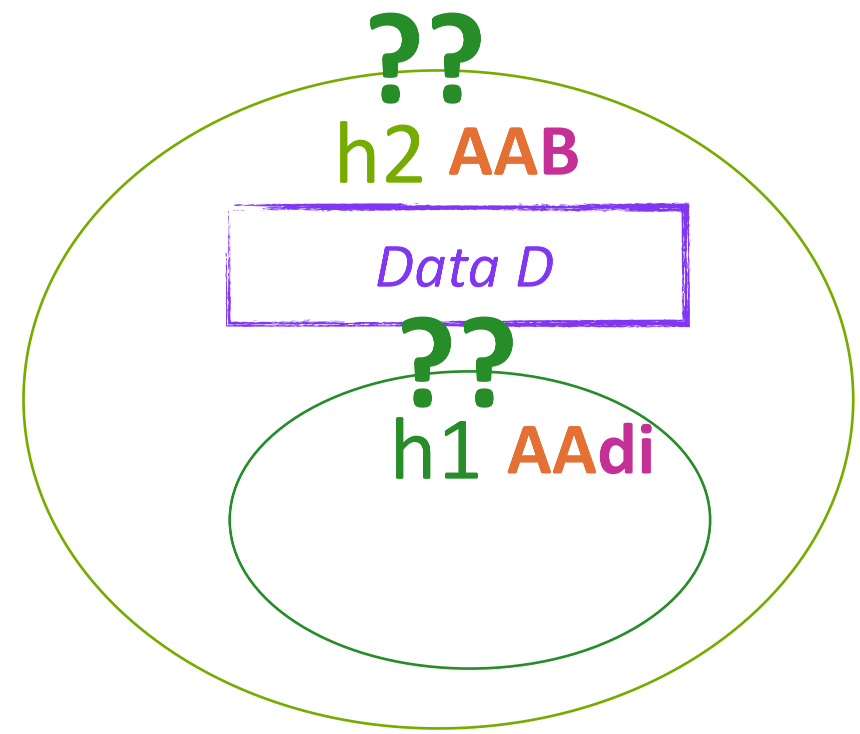
Training on four word types:
leledi, wiwije, jijili, dedewe

Consistent only with the more-general hypothesis (h2).

If children fail to make the generalization in the control condition, then the results in the experimental condition will not be informative. (Perhaps the task was too hard for children.)

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

Control condition

leledi, wiwije, jijili, dedewe

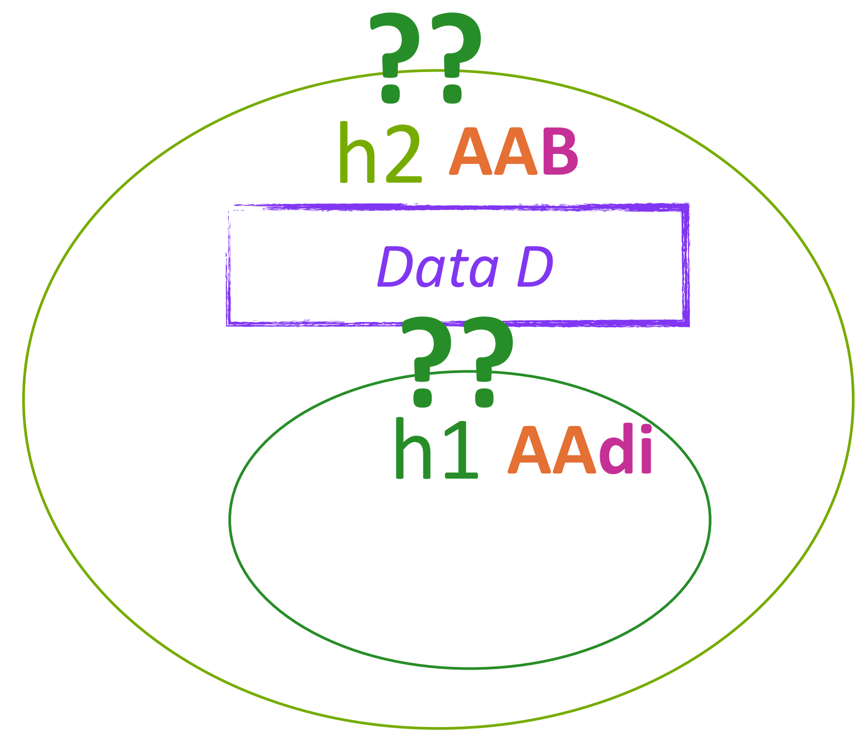
Training: 2 minutes hearing artificial language words

Test: AAB pattern words using novel syllables vs.
ABA pattern words using novel syllables

Ex: novel syllables: ko, ba
kokoba vs.
kobako

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

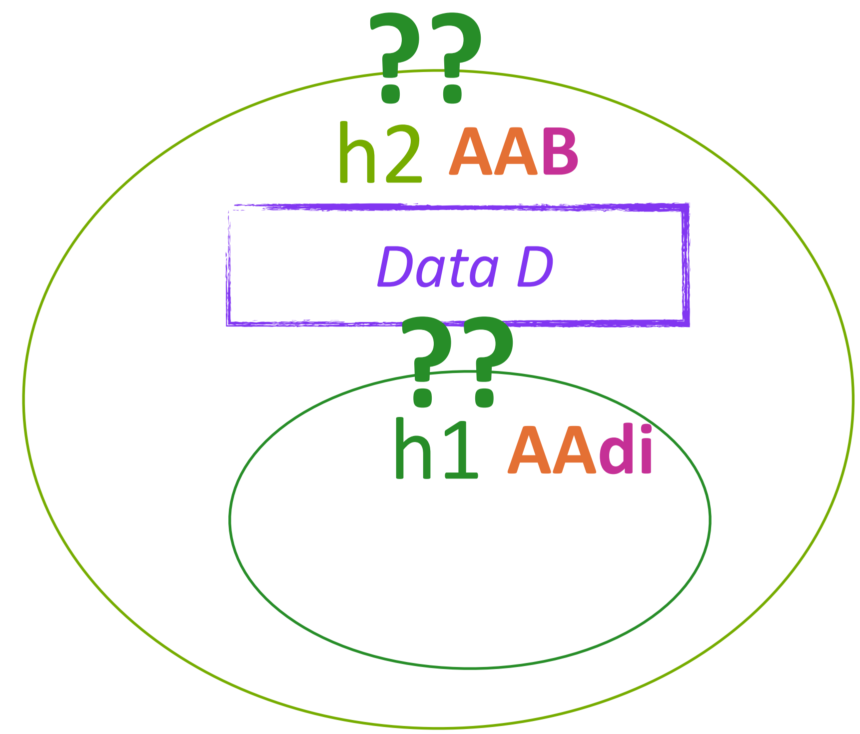
Control condition

Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako

Behavior: If children learn the more-general pattern (AAB), they will prefer to listen to an AAB pattern word like kokoba, over a word that does not follow the AAB pattern, like kobako.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

Control condition

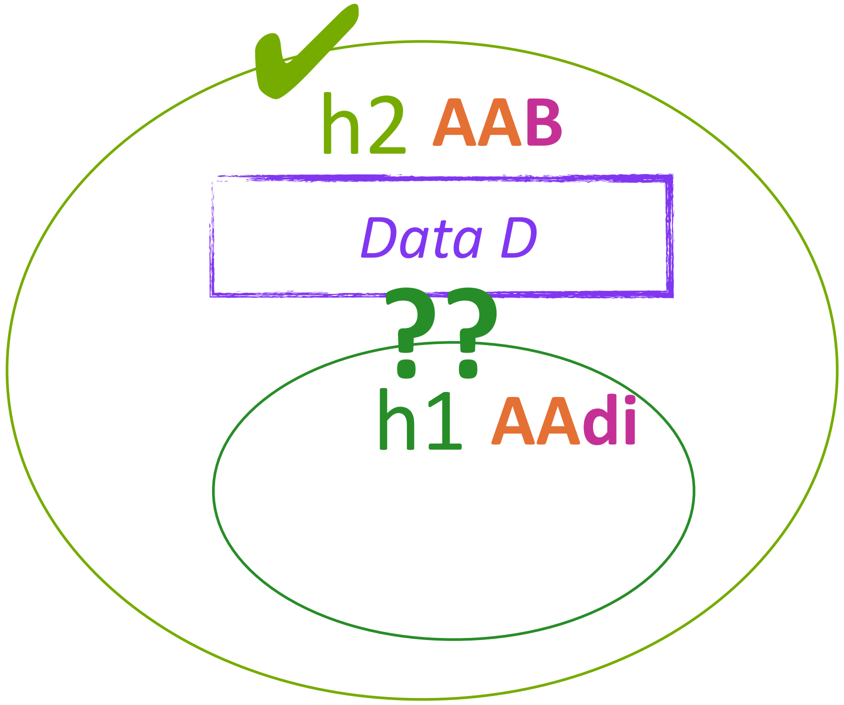
Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako

✔

Behavior: Children listened longer on average to test items consistent with the AAB pattern [13.51 sec], as opposed to items inconsistent with it [10.14 sec].

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

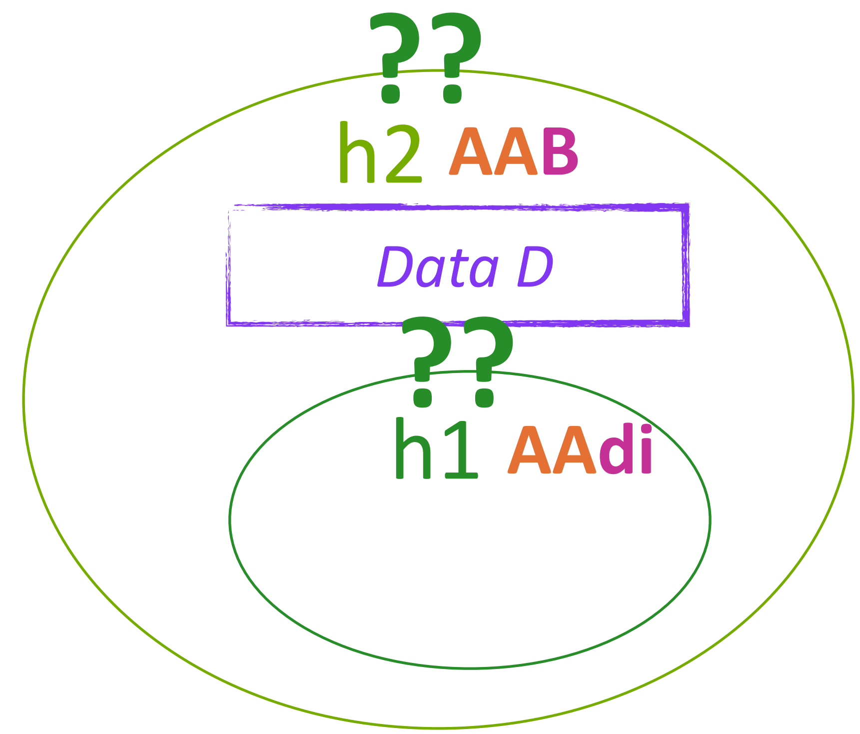
Control condition

Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako
Behavior	✔

They can notice the AAB pattern and make the generalization from this artificial language data. This task isn't too hard for infants.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

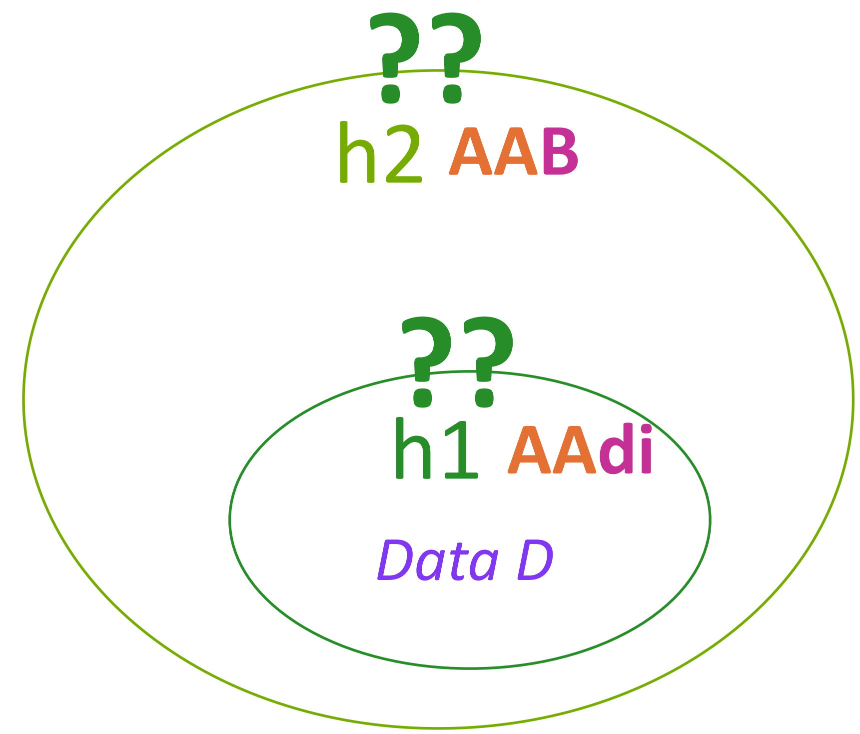
Control condition

Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako
Behavior	✔

What about the experimental condition?

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

Control condition

Training leledi, wiwije, jijili, dedewe

Test kokoba vs. kobako

Behavior ✔

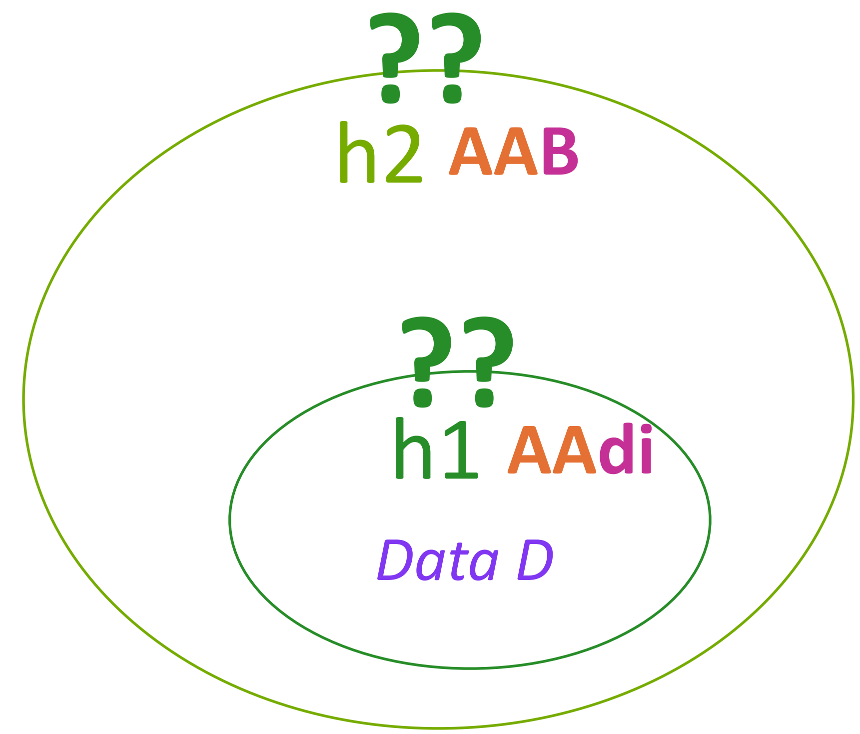
Experimental condition

Training leledi, wiwidi, jijidi, dededi

Consistent with both a less-general hypothesis (h1) and a more-general hypothesis (h2).

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

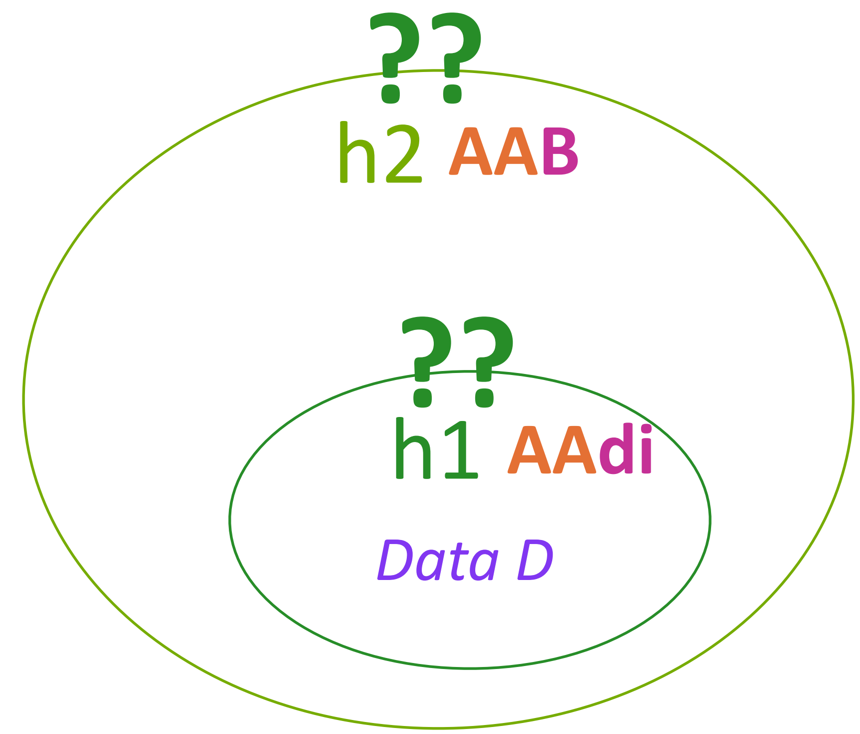
	Control condition
Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako
Behavior	✔

	Experimental condition
Training	leledi, wiwidi, jijidi, dededi
Test	kokoba vs. kobako
	✔

Behavior: If children learn the more-general pattern (AAB), they will prefer to listen to an AAB pattern word like kokoba, over a word that does not follow the AAB pattern, like kobako.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

Control condition

Training leledi, wiwije, jijili, dedewe

Test kokoba vs. kobako

Behavior ✔

Experimental condition

Training leledi, wiwidi, jijidi, dededi

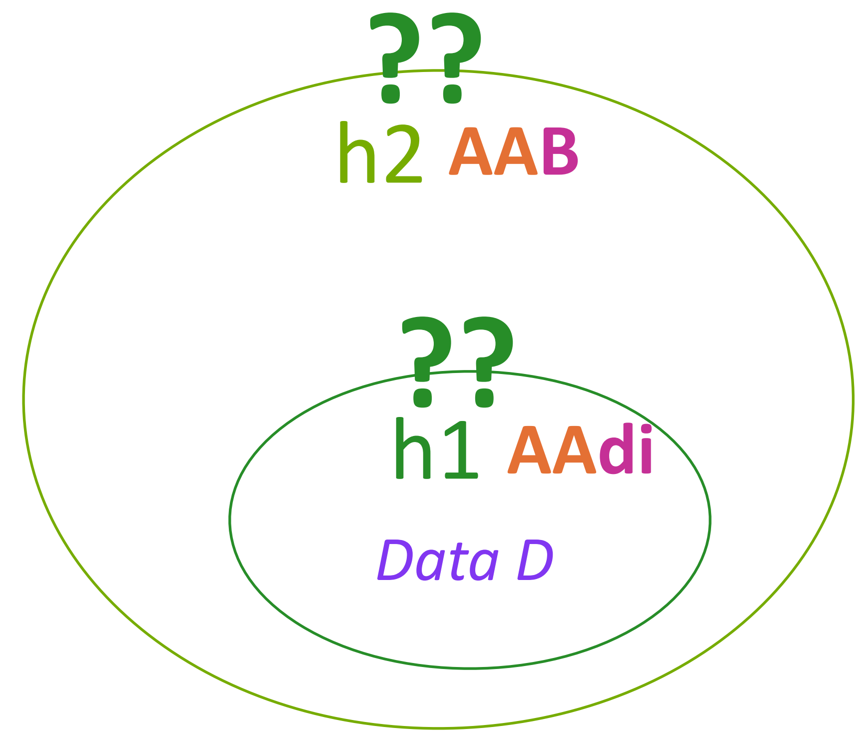
Test kokoba vs. kobako

??

Behavior: If children learn the less-general pattern (AAdi) or no pattern at all, they will not prefer to listen to an AAB pattern word like kokoba, over a word that does not follow the AAB pattern, like kobako.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

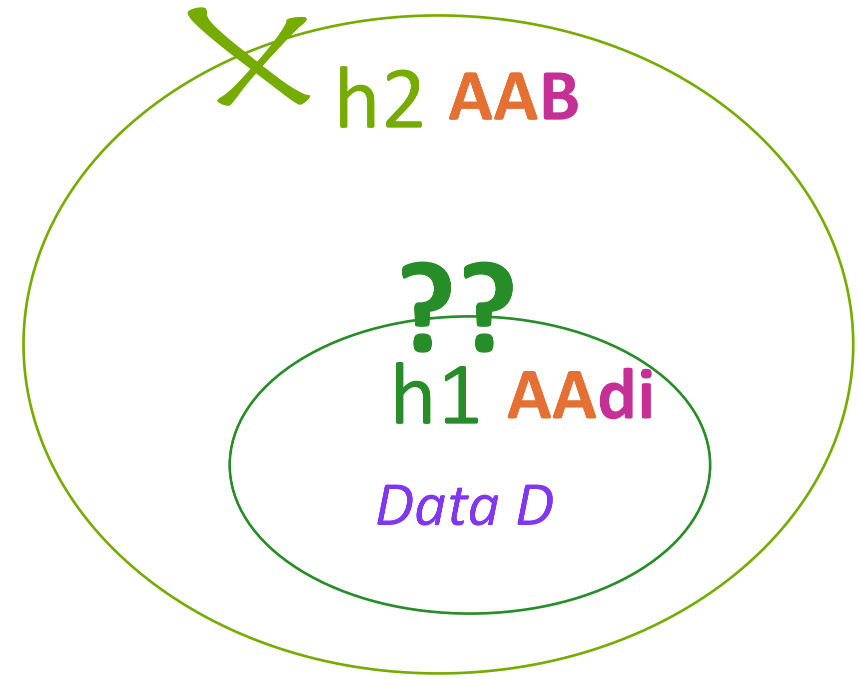
	Control condition
Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako
Behavior	✔

	Experimental condition
Training	leledi, wiwidi, jijidi, dededi
Test	kokoba vs. kobako
Behavior	??

Behavior: Children did ***not*** listen longer on average to test items consistent with the AAB pattern [10.74 sec], as opposed to items inconsistent with it [10.18 sec].

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

Control condition

Training leledi, wiwije, jijili, dedewe

Test kokoba vs. kobako

Behavior ✔

Experimental condition

Training leledi, wiwidi, jijidi, dededi

Test kokoba vs. kobako

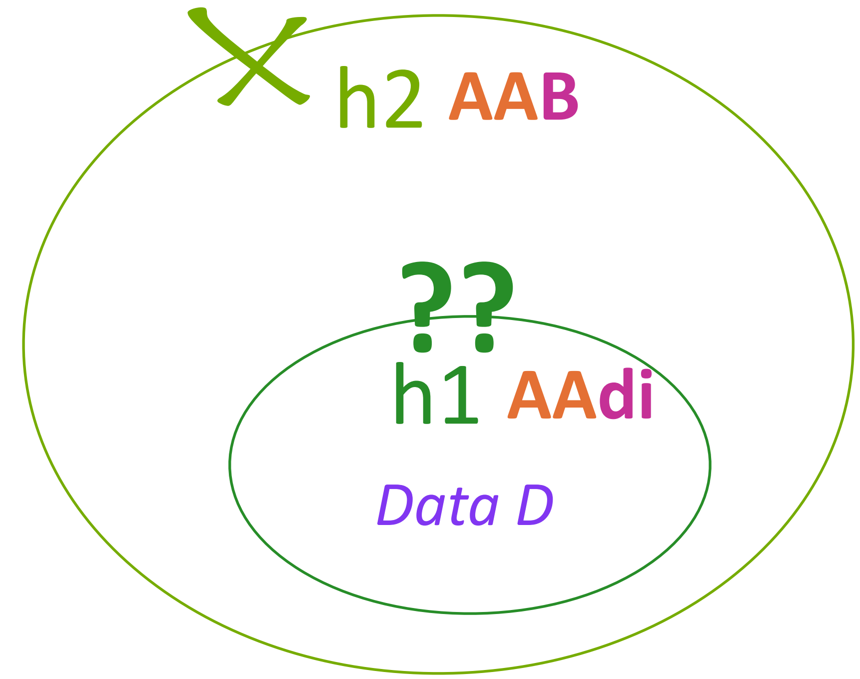
Behavior ??

They don't learn the more-general pattern. They either learned the less-general pattern or no pattern at all.

Which one is it?

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

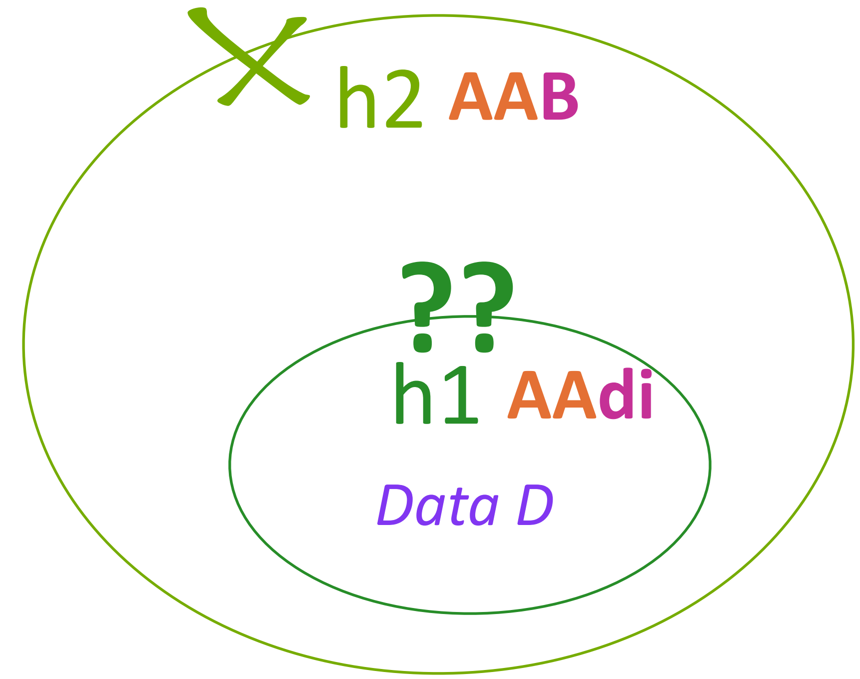
	Control condition
Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako
Behavior	✔

	Experimental condition
Training	leledi, wiwidi, jijidi, dededi
Test	kokoba vs. kobako
Behavior	??
Test	kokodi vs. kodiko
	✔

Behavior: If they learn the less-general pattern, they'll prefer to listen to AAdi words like kokodi.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

Control condition

Training leledi, wiwije, jijili, dedewe

Test kokoba vs. kobako

Behavior ✔

Experimental condition

Training leledi, wiwidi, jijidi, dededi

Test kokoba vs. kobako

Behavior ??

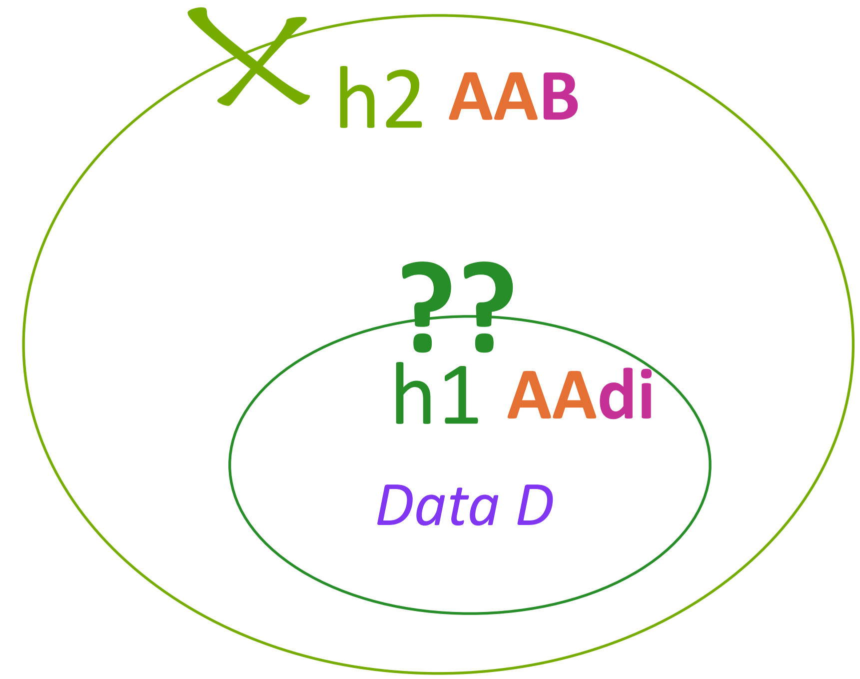
Test kokodi vs. kodiko

??

Behavior: If they learn no pattern at all, they'll (again) have no preference.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

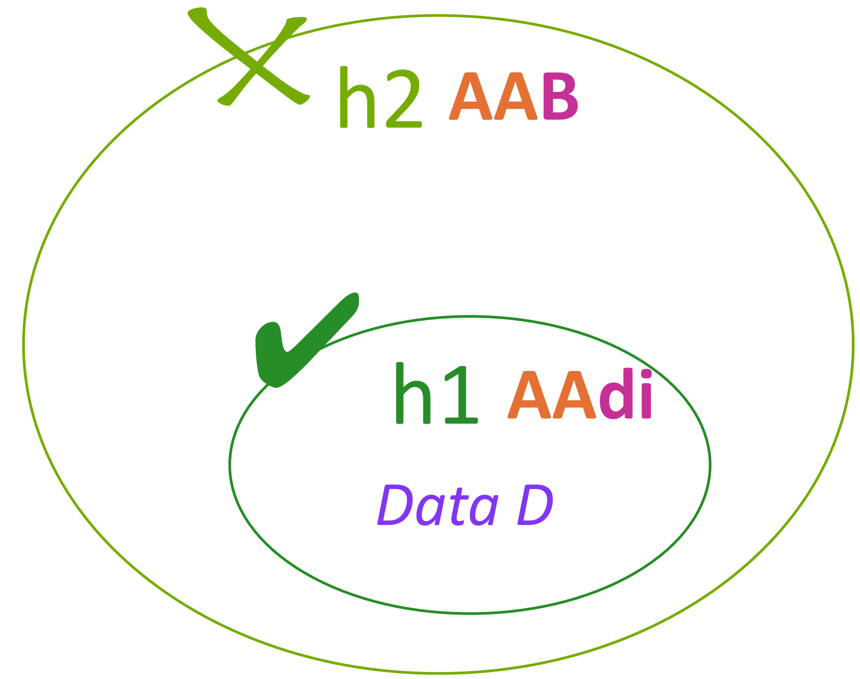
	Control condition
Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako
Behavior	✔

	Experimental condition
Training	leledi, wiwidi, jijidi, dededi
Test	kokoba vs. kobako
Behavior	??
Test	kokodi vs. kodiko
Behavior	✔

Children prefer to listen to novel words that follow the less-general AAdi pattern [9.33 sec] over novel words that don't [6.25 sec].

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

Task type: Head Turn Preference Procedure with 9-month-olds

Control condition

Training	leledi, wiwije, jijili, dedewe
Test	kokoba vs. kobako
Behavior	✔

Experimental condition

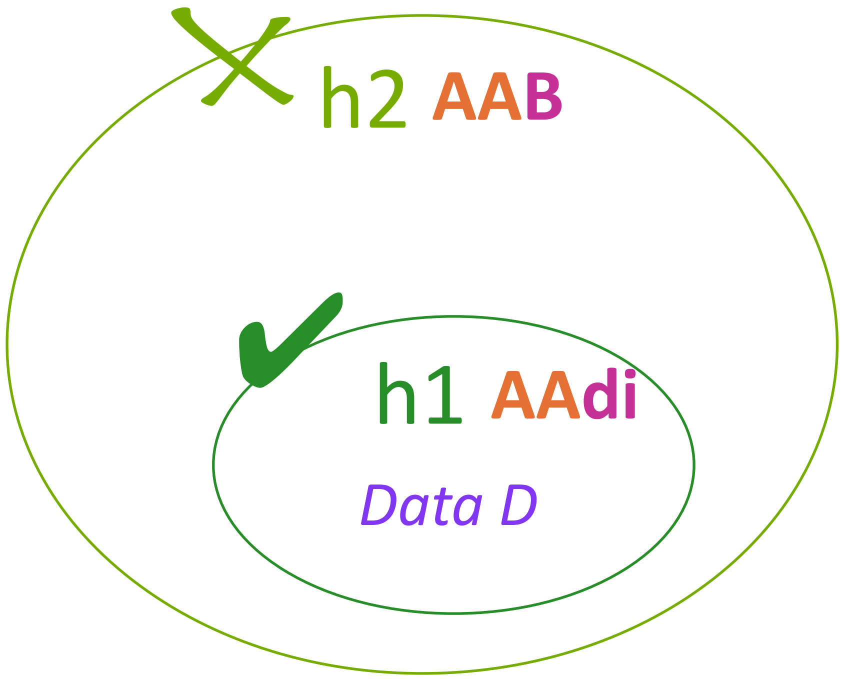
Training	leledi, wiwidi, jijidi, dededi
Test	kokoba vs. kobako
Behavior	??
Test	kokodi vs. kodiko
Behavior	✔

This means that given ambiguous data, they make the less-general generalization (h1) — just like a Bayesian learner would!

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study



Training leledi, wiwidi, jijidi, dededi

Test kokodi vs. kodiko

Behavior ✔

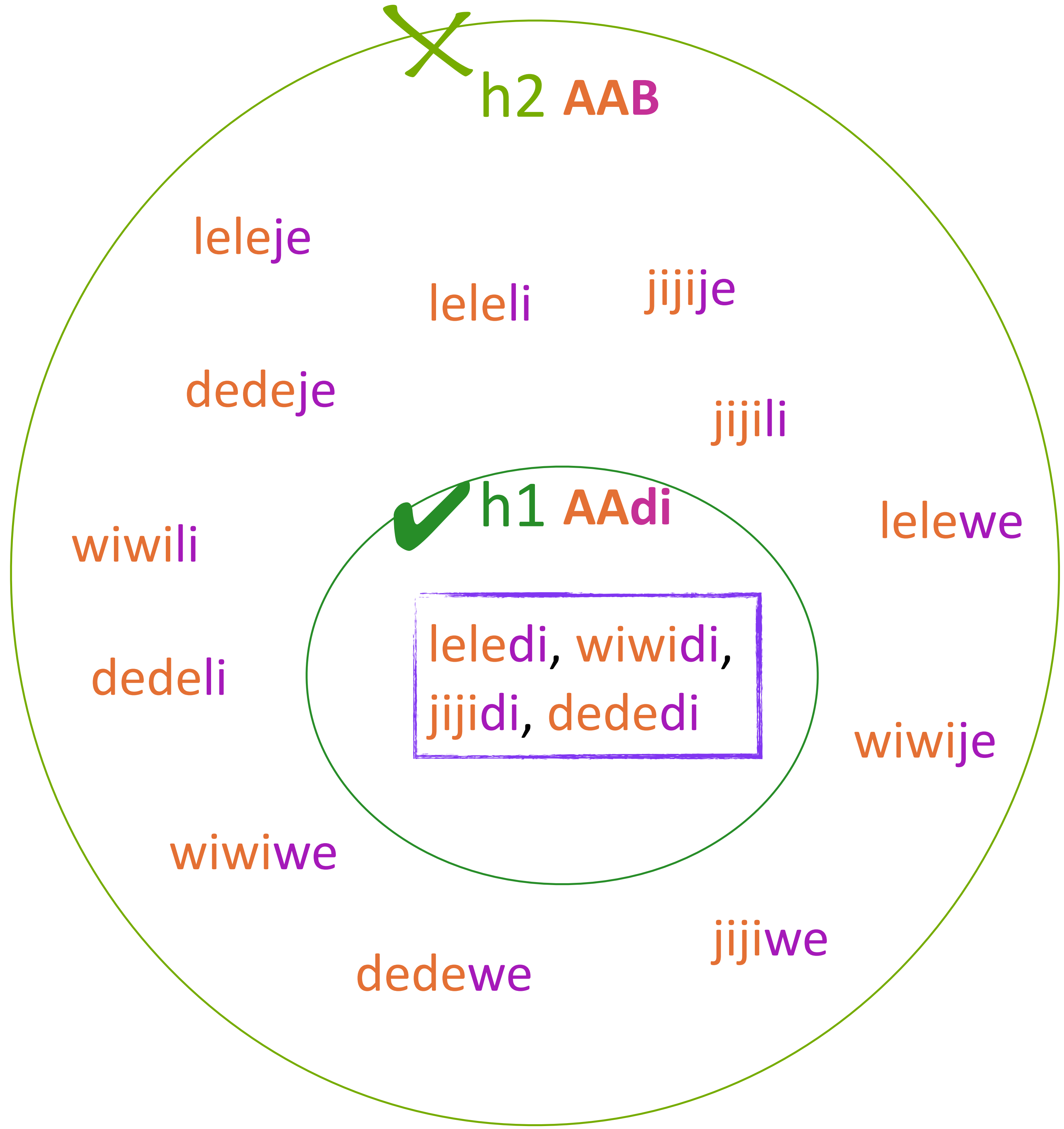
Let's remind ourselves why this is

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study

	di	je	li	we
le	leledi	leleje	leleli	lelewe
wi	wiwidi	wiwije	wiwili	wiwiwe
ji	jijidi	jijije	jijili	jijiwe
de	dededi	dedeje	dedeli	dedewe



Bayesian reasoning

Gerken 2006, 2010
artificial language study

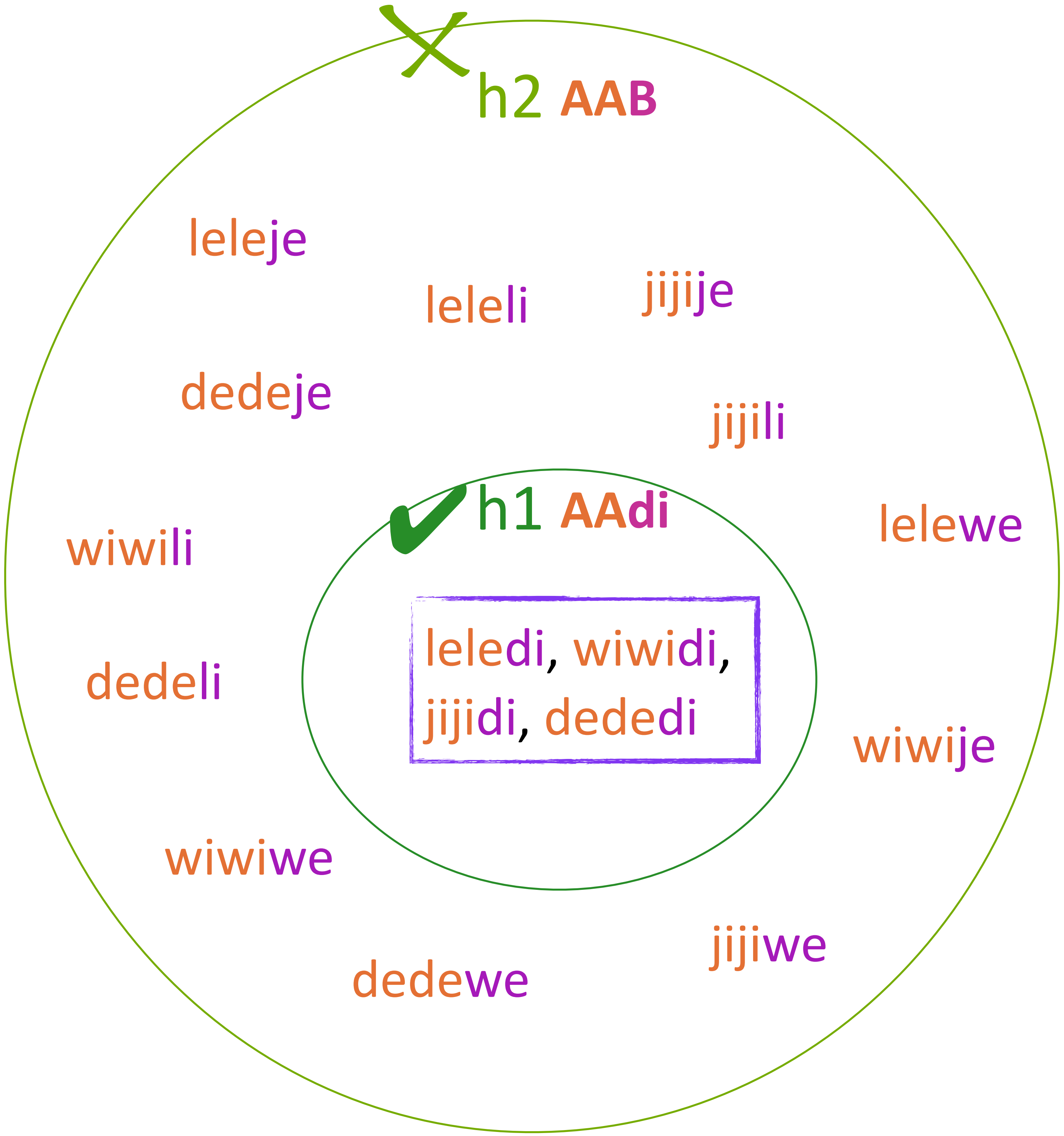
$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

likelihoods

P(D | h1) = 1/4*1/4*1/4*1/4 = 1/256

These are the only 4 data that can be generated, and so the probability of generating each one is 1/4. Let's focus on the types in the data intake, so we just have these four.



Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

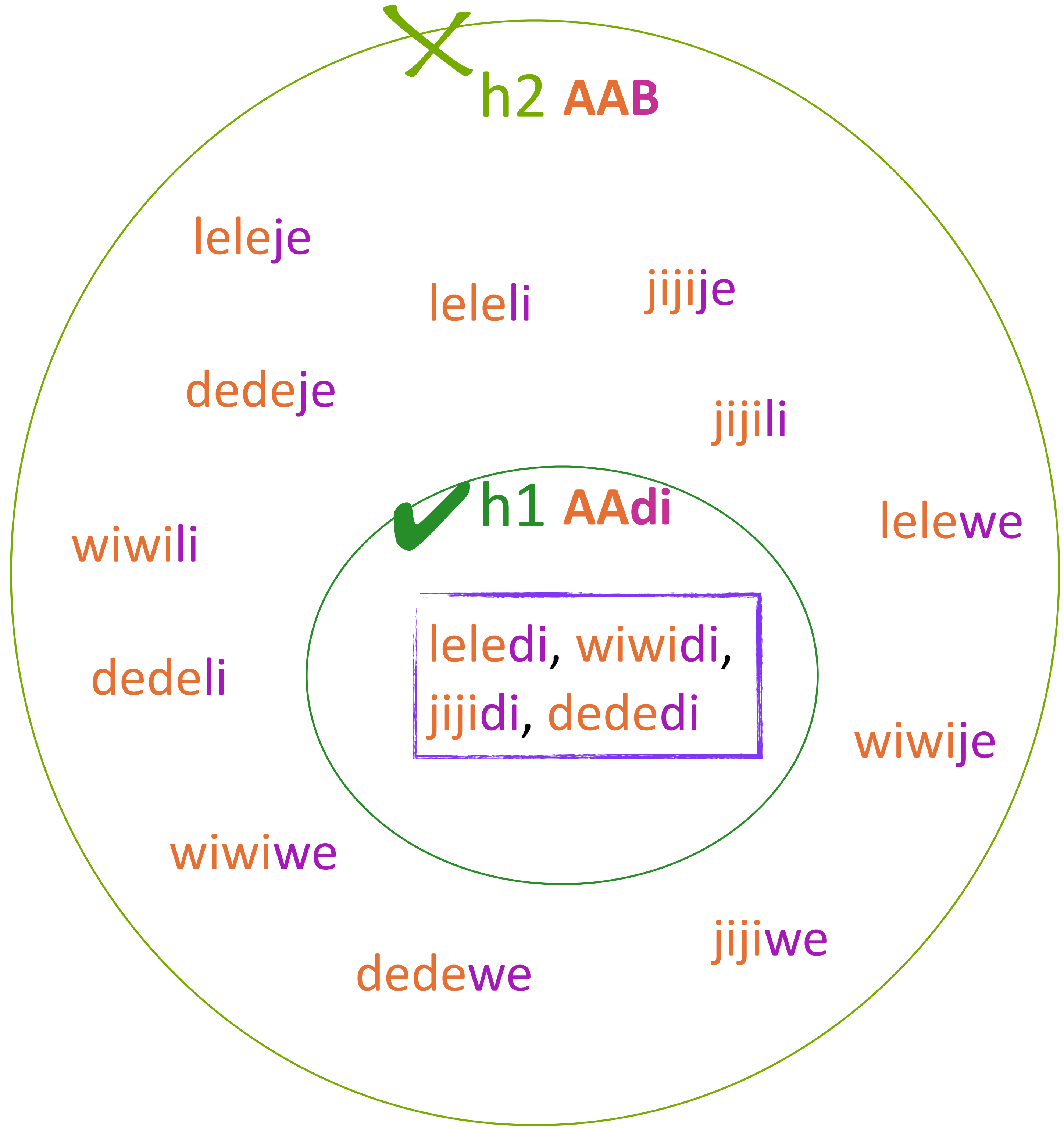
$$\propto P(D|h) * P(h)$$

likelihoods

P(D | h1) = 1/256

P(D | h2) = 1/16*1/16*1/16*1/16
= 1/65536

These are 16 data that can be generated, and so the probability of generating each one is 1/16.



Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

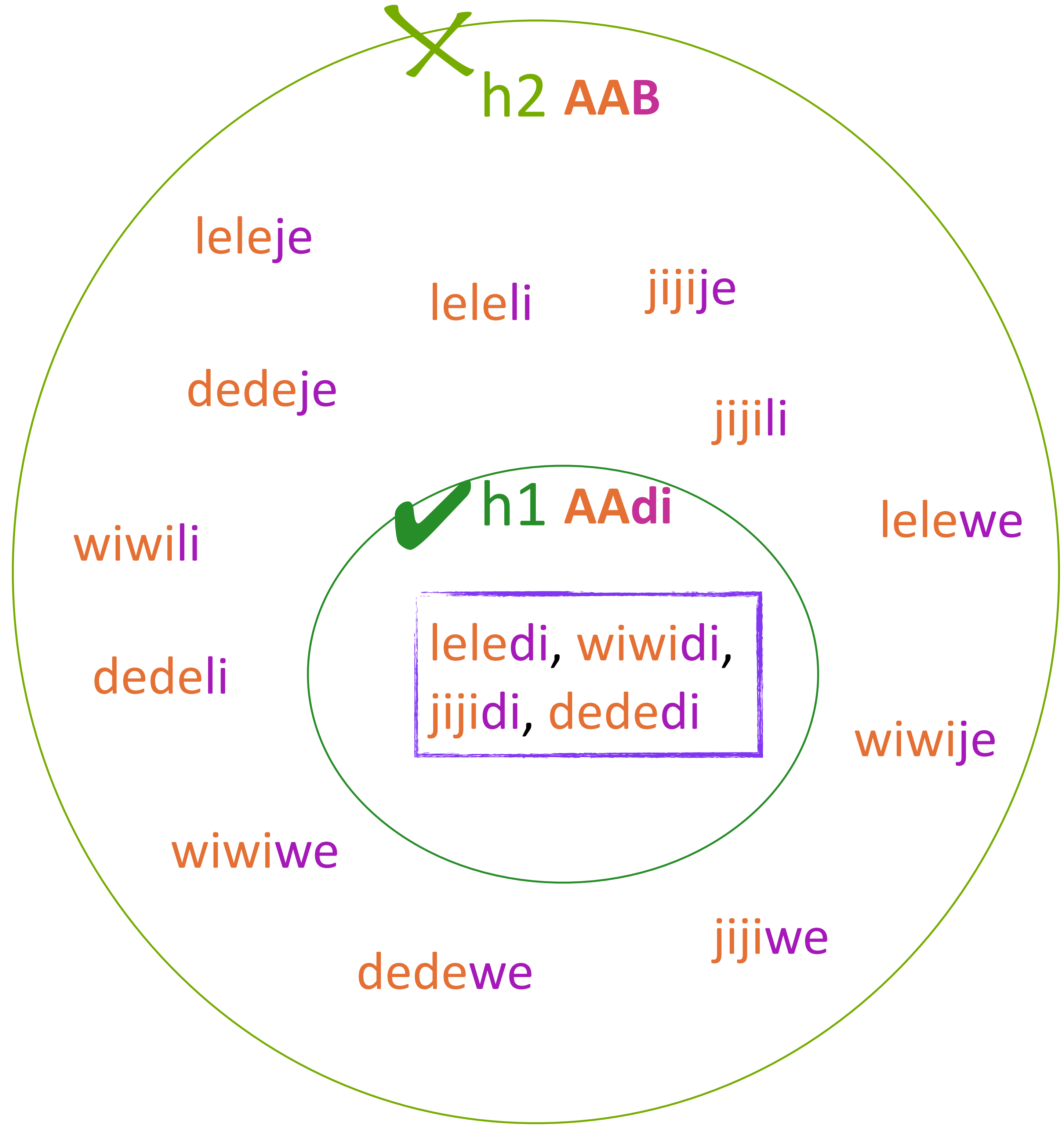
likelihoods

P(D | h1) = 1/256

P(D | h2) = 1/65536

priors

Let’s assume the hypotheses are equally complex a priori, so they have uniform prior probability.



Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

likelihoods

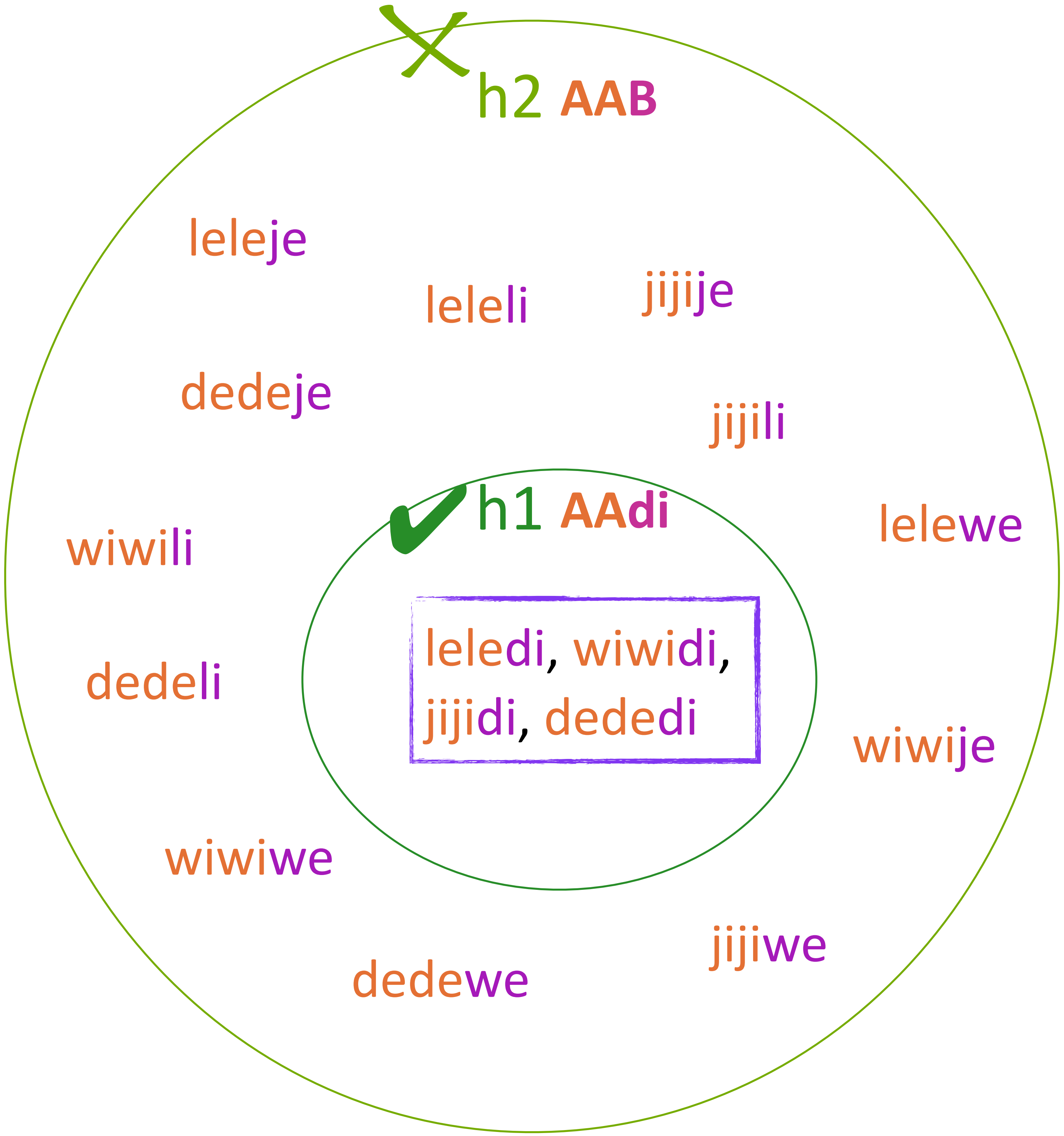
P(D | h1) = 1/256

P(D | h2) = 1/65536

priors

P(h1) = 1/2

P(h2) = 1/2



Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

likelihoods

P(D | h1) = 1/256

P(D | h2) = 1/65536

priors

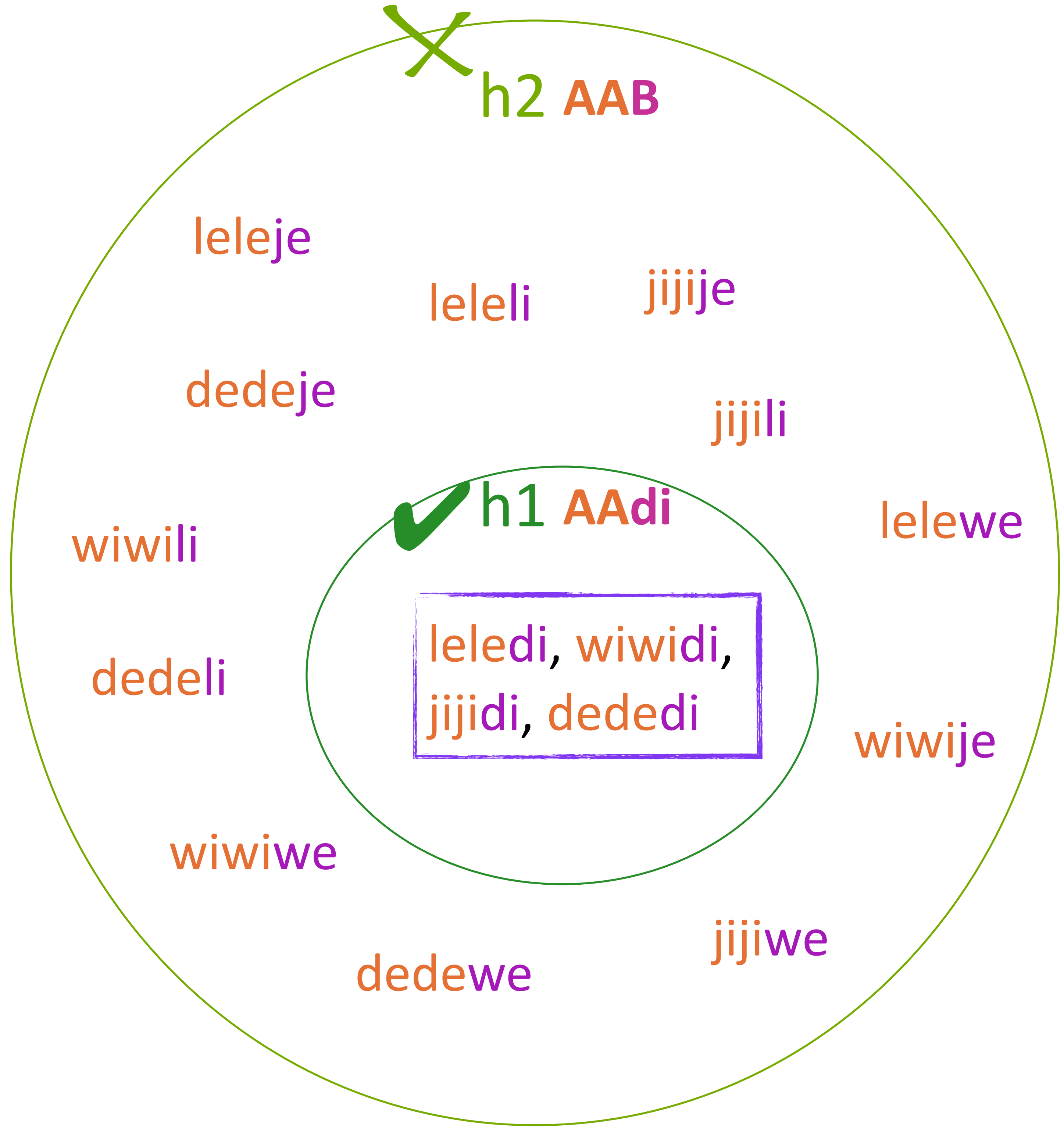
P(h1) = 1/2

P(h2) = 1/2

posteriors

P(h1 | D) ∝ 1/256 * 1/2

P(h2 | D) ∝ 1/65536 * 1/2



Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$\propto P(D|h)*P(h)$$

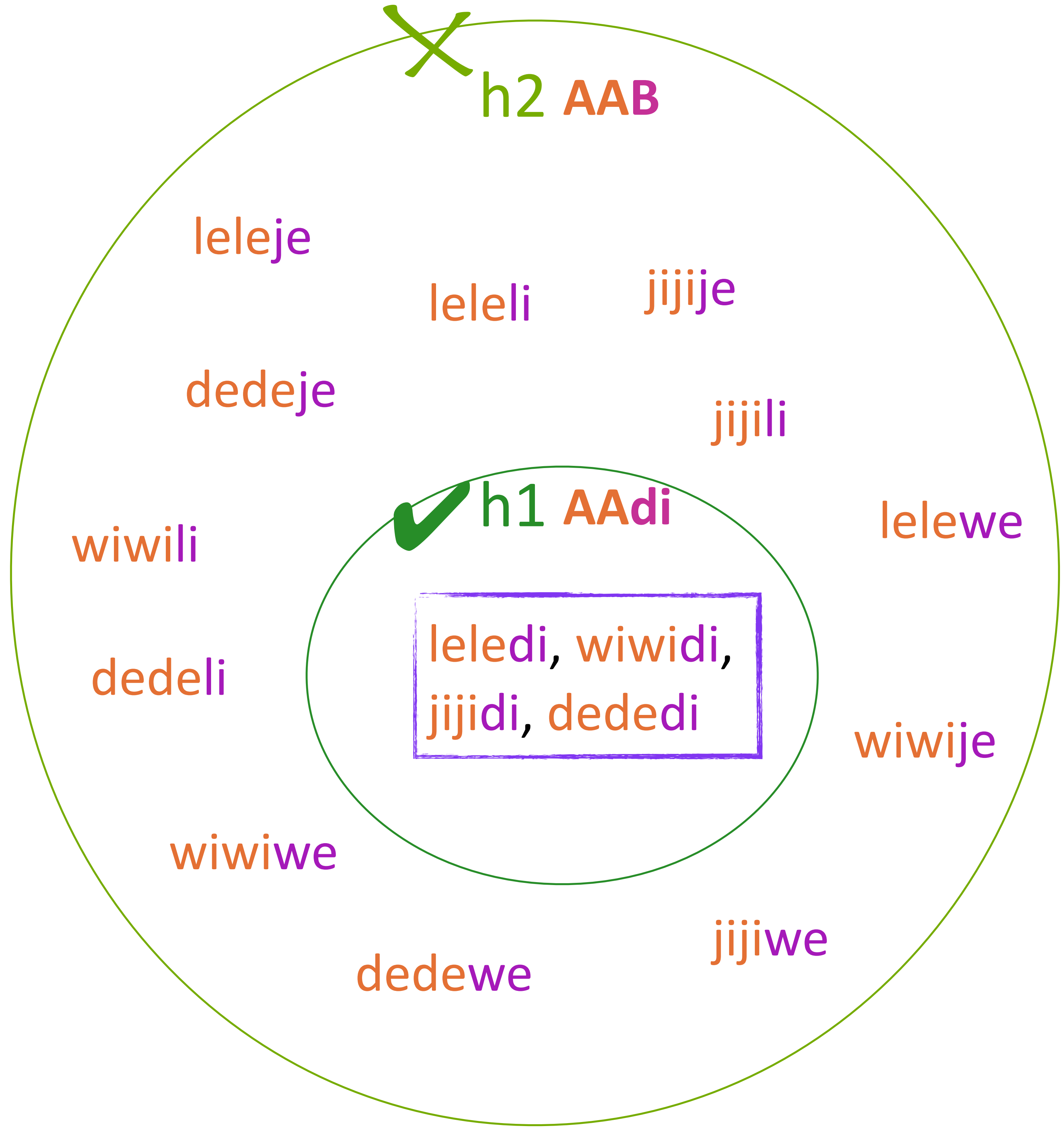
likelihoods	**priors**
P(D | h1) = 1/256	P(h1) = 1/2
P(D | h2) = 1/65536	P(h2) = 1/2

posteriors

P(h1 | D) ∝ **1/256** * 1/2
P(h2 | D) ∝ **1/65536** * 1/2

h1 is 256 times (1/256 vs. 1/65536) as probable as h2

Therefore, prefer h1.



Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

likelihoods

P(D | h1) = 1/256

P(D | h2) = 1/65536

priors

P(h1) = 1/2

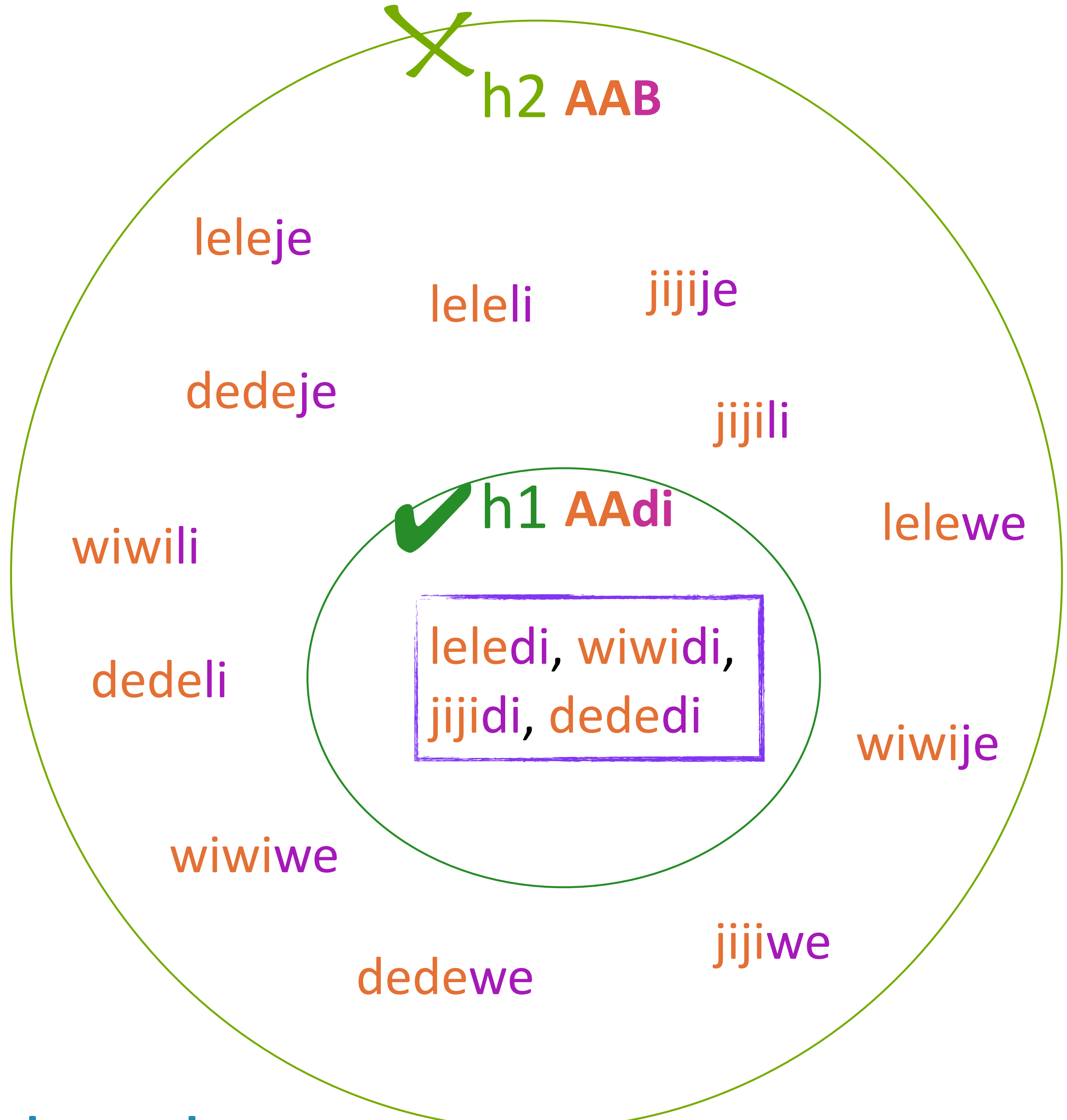
P(h2) = 1/2

posteriors

P(h1 | D) ∝ **1/256** * 1/2
P(h2 | D) ∝ **1/65536** * 1/2

Note how it's the likelihood doing all the work.

Therefore, prefer h1.



Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

Another important point:
Bayesian learners are sensitive
to **counterexamples**.

Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

sensitive to **counterexamples**

If even one word in the intake **wasn't compatible** with the less-general AAdi pattern, a Bayesian learner would notice that and shift beliefs.

Bayesian reasoning

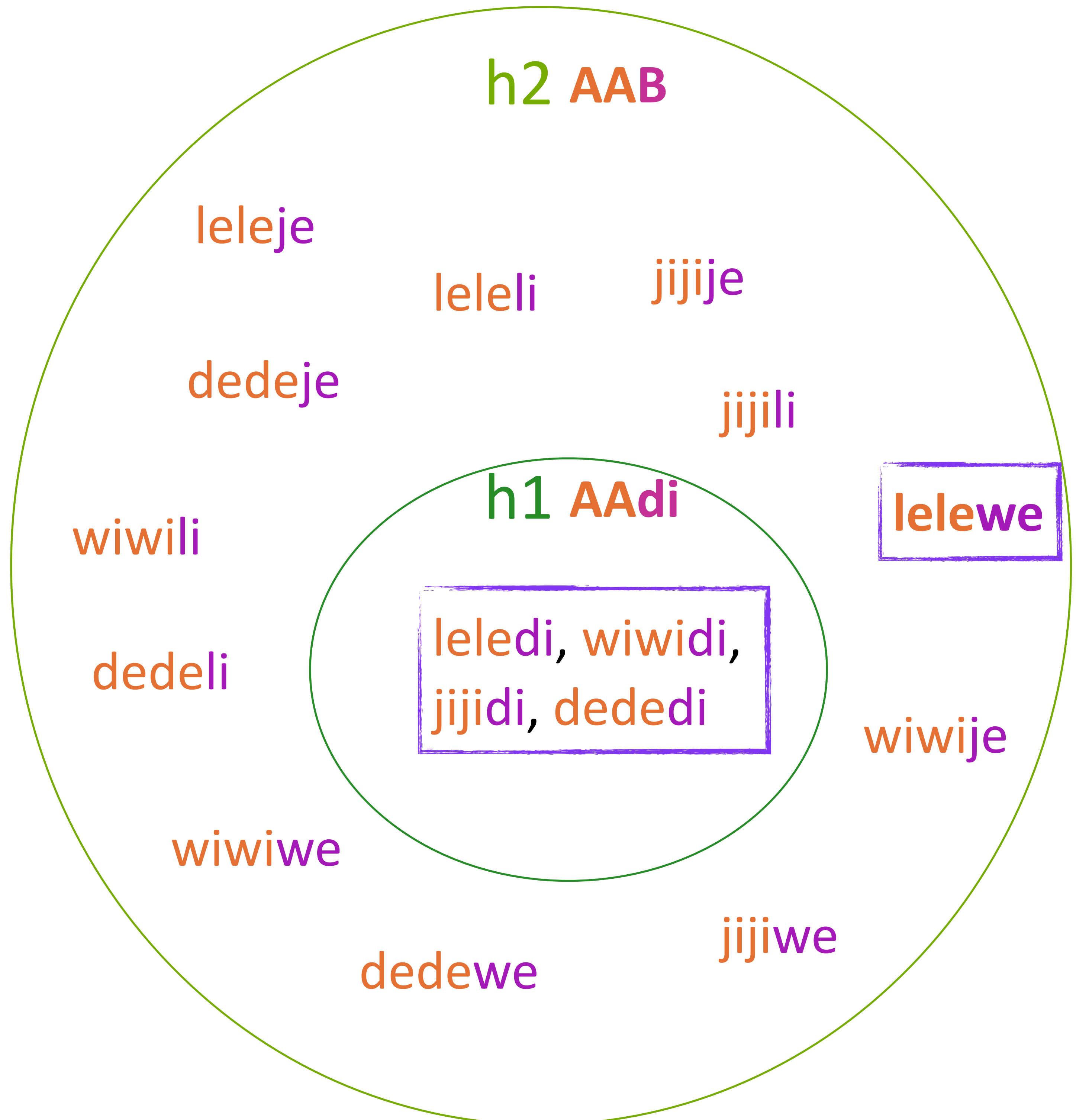
Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

sensitive to **counterexamples**

If even one word in the intake **wasn't compatible** with the less-general AAdi pattern, a Bayesian learner would notice that and shift beliefs.



Why? This has to do with the likelihood.

Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

sensitive to **counterexamples**

likelihood
P(D | h1) = 1/4*1/4*1/4*1/4 * **0** = 0

These are the only 4 data that can be generated, and so the probability of generating each one is 1/4 **except the last one, which can't be generated.**

Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

sensitive to **counterexamples**

likelihood

P(D | h1) = 0

P(D | h2) = 1/16*1/16*1/16*1/16*1/16
= 1/1048576

In contrast, even though the other data points have a smaller probability of being generated by h2, the last one *can* be generated, so **the likelihood isn't 0**.

Bayesian reasoning

Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

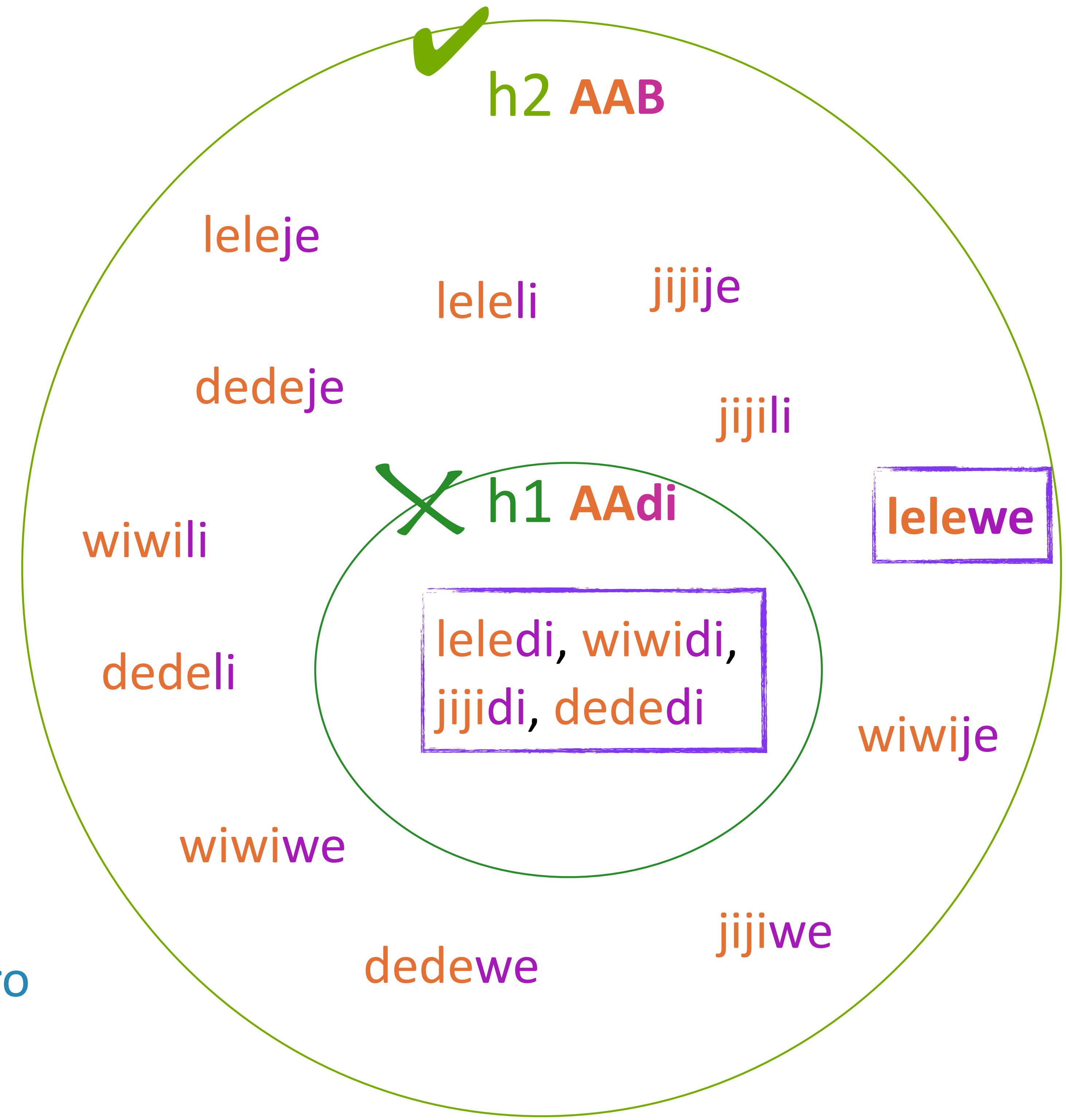
$$\propto P(D|h) * P(h)$$

sensitive to **counterexamples**

likelihood
P(D | h1) = 0

P(D | h2) = 1/1048576

This means only h2 will have a non-zero posterior, and so the Bayesian learner prefers h2.



Bayesian reasoning

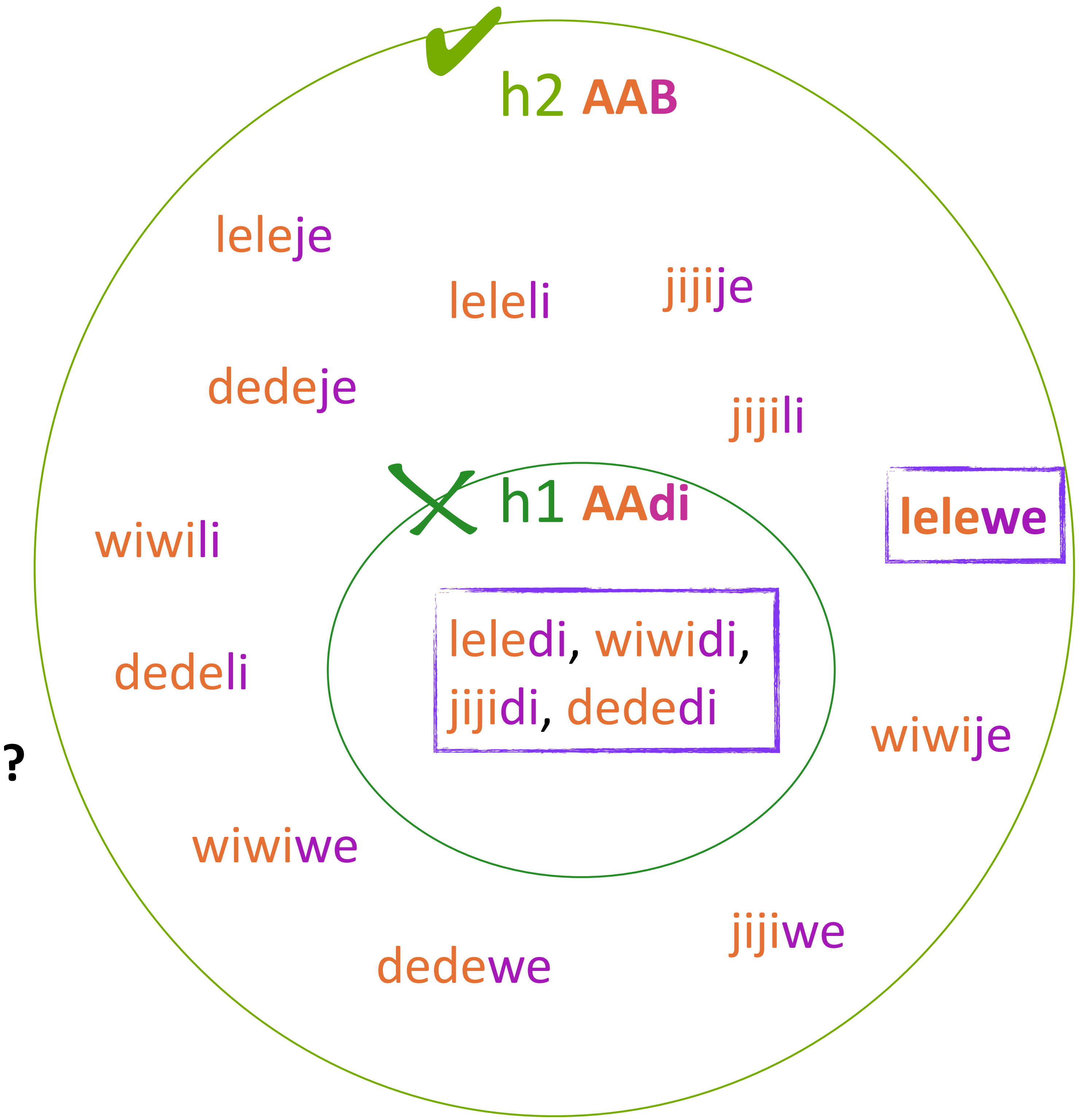
Gerken 2006, 2010
artificial language study

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

$$\propto P(D|h) * P(h)$$

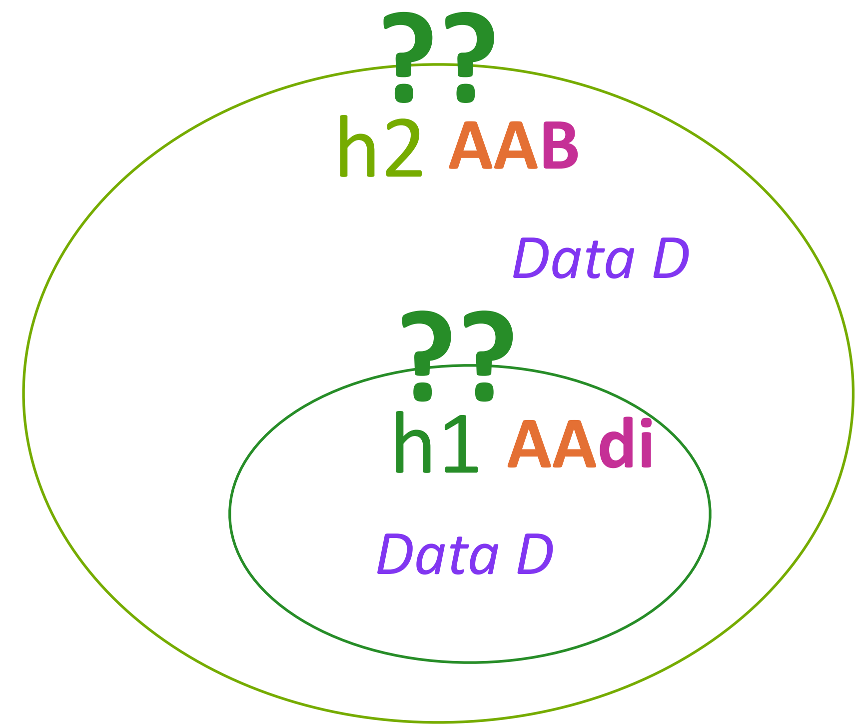
sensitive to **counterexamples**

Do 9-month-olds reason this way too?



Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

sensitive to **counterexamples**

Task type: Head Turn Preference Procedure

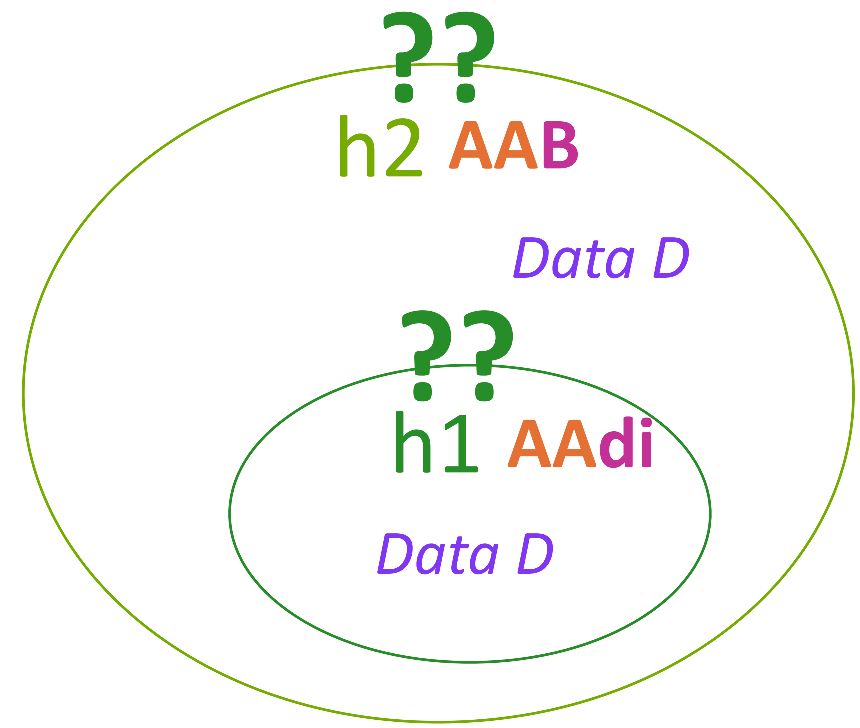
with 9-month-olds

Training leledi, wiwidi, jijidi, dededi + 3 AAB examples (like lelewe)

2 minutes **a few seconds at the end**

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

sensitive to **counterexamples**

Task type: Head Turn Preference Procedure

with 9-month-olds

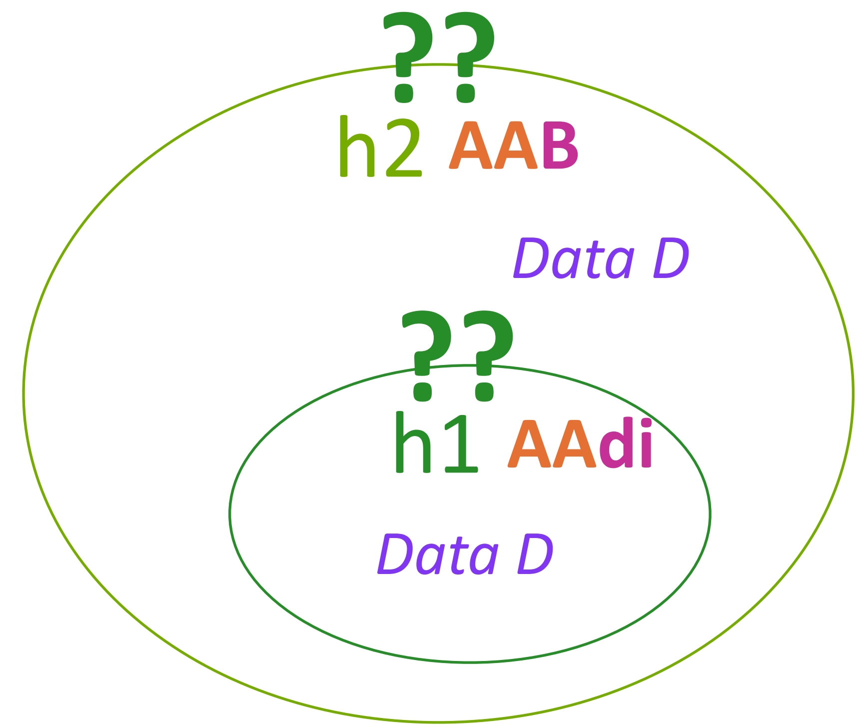
Training leledi, wiwidi, jijidi, dededi + 3 AAB examples (like lelewe)

2 minutes **a few seconds at the end**

Test kokoba vs. kobako

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

sensitive to **counterexamples**

Task type: Head Turn Preference Procedure
with 9-month-olds

Training leledi, wiwidi, jijidi, dededi + 3 AAB examples (like lelewe)

2 minutes **a few seconds at the end**

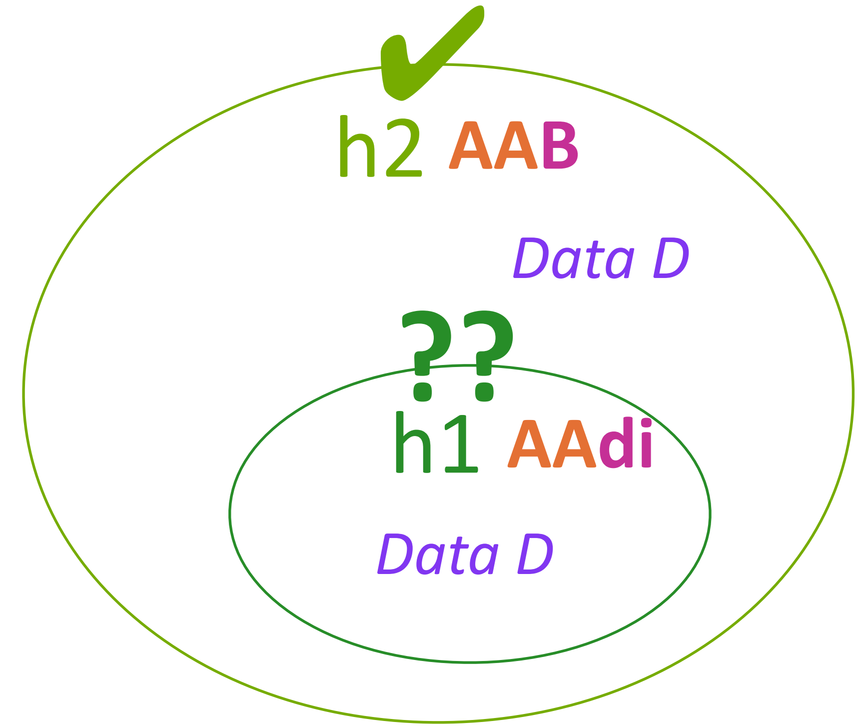
Test kokoba vs. kobako

Behavior ✔

Behavior: If they learn the more-general pattern from these three counterexamples, they'll prefer to listen to AAB words like kokoba.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

sensitive to **counterexamples**

Task type: Head Turn Preference Procedure with 9-month-olds

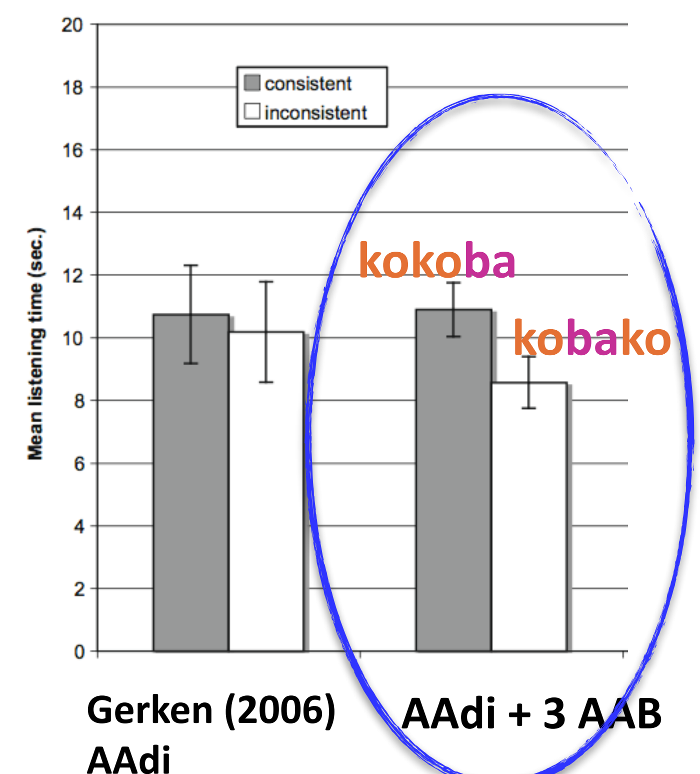
Training leledi, wiwidi, jijidi, dededi + 3 AAB examples (like lelewe)

2 minutes **a few seconds at the end**

Test kokoba vs. kobako

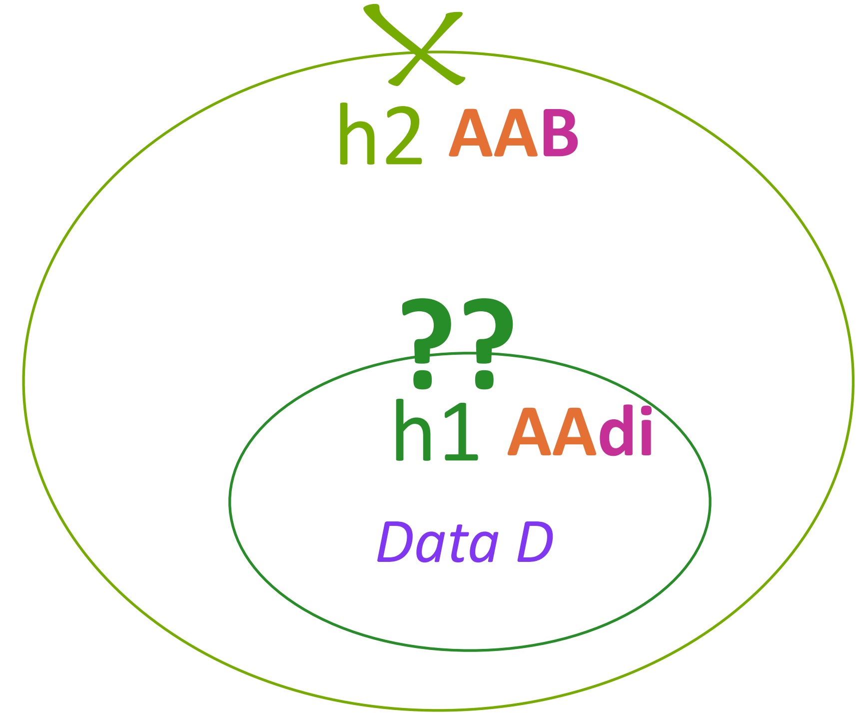
Behavior ✔

Children prefer to listen to novel words that follow the more-general AAB pattern [~11 sec] over novel words that don't [~8 sec]



Bayesian reasoning

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

sensitive to **counterexamples**

Task type: Head Turn Preference Procedure with 9-month-olds

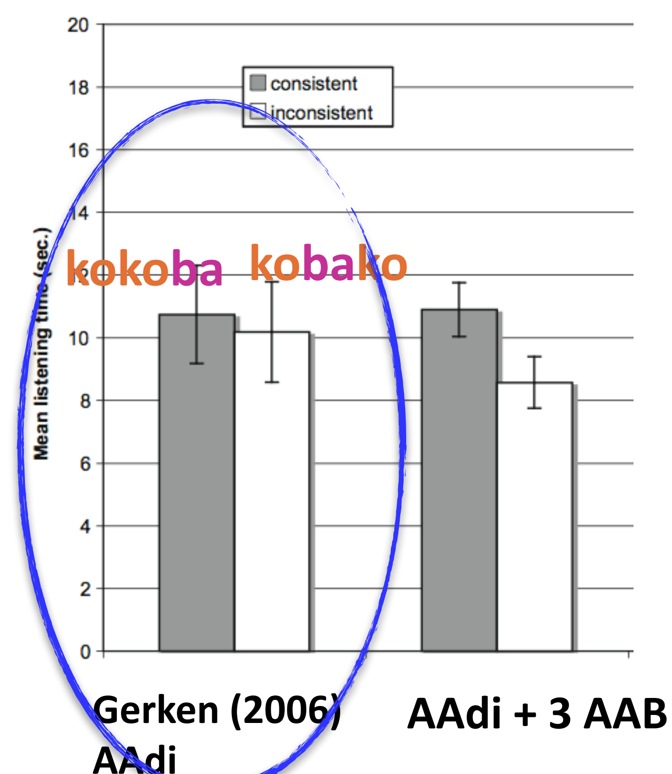
Training leledi, wiwidi, jijidi, dededi + 3 AAB examples (like lelewe)

2 minutes **a few seconds at the end**

Test kokoba vs. kobako

Behavior ✔

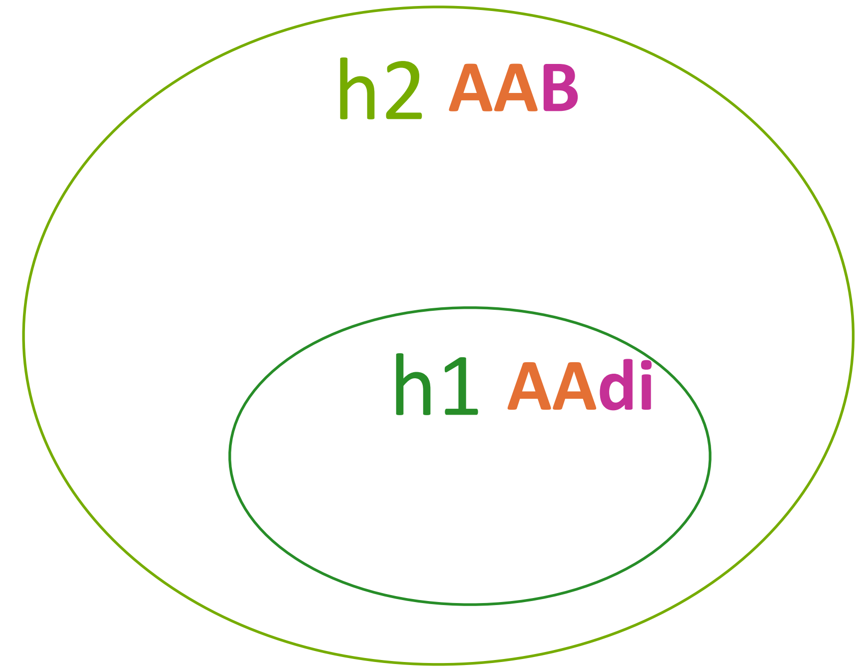
This is noticeably different than their behavior when they only hear AAdi examples in their intake.



Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

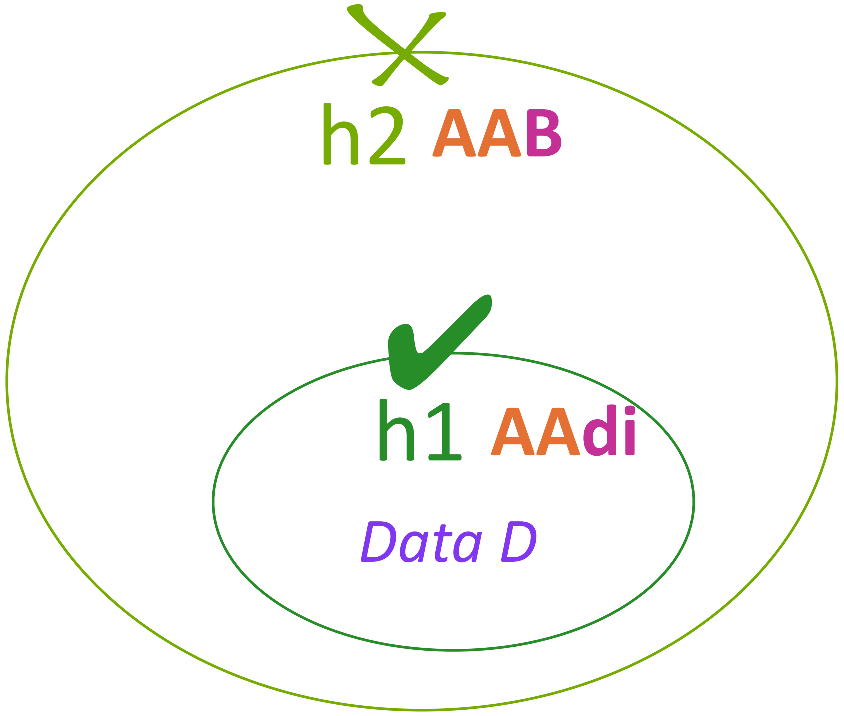
Gerken 2006, 2010
artificial language study



Takeaway: At 9 months, infants show probabilistic reasoning abilities similar to a Bayesian learner.

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$



Gerken 2006, 2010
artificial language study

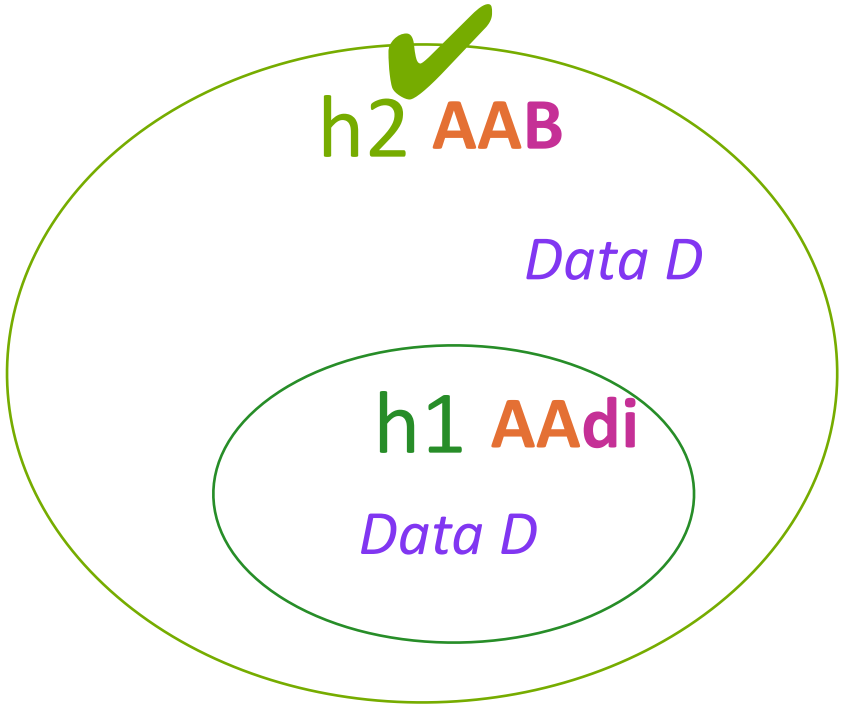
Takeaway: At 9 months, infants show probabilistic reasoning abilities similar to a Bayesian learner.

When given ambiguous data compatible with two hypotheses, a less-general and more-general one, they choose the less-general one (which gives a higher likelihood to the data).

Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

Gerken 2006, 2010
artificial language study



Takeaway: At 9 months, infants show probabilistic reasoning abilities similar to a Bayesian learner.

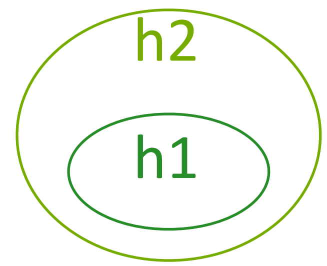
✔ambiguous data = less-general hypothesis

When given even a very few counterexamples that are only compatible with the more-general hypothesis, they shift their beliefs accordingly.

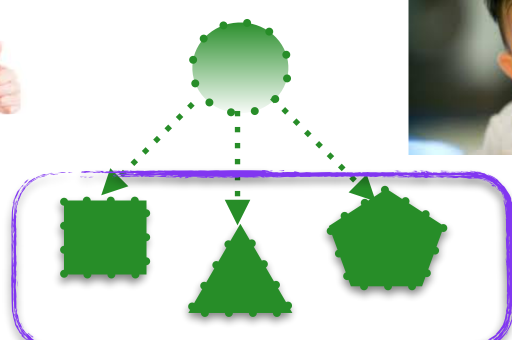
Today's Plan:
Bayesian inference & linguistic parameters

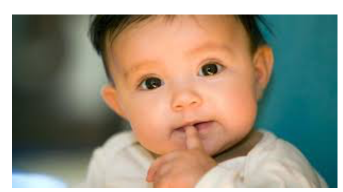
I. Bayesian reasoning

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

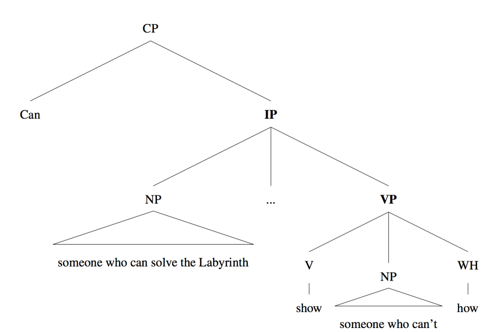


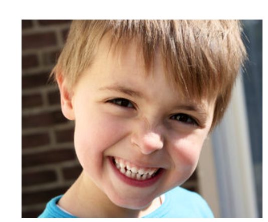
II. Parameters & overhypotheses

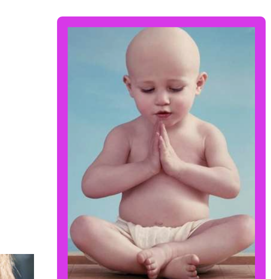


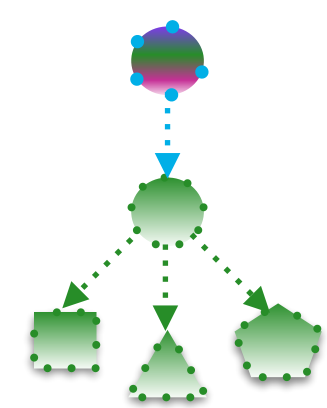


III. Structure dependence



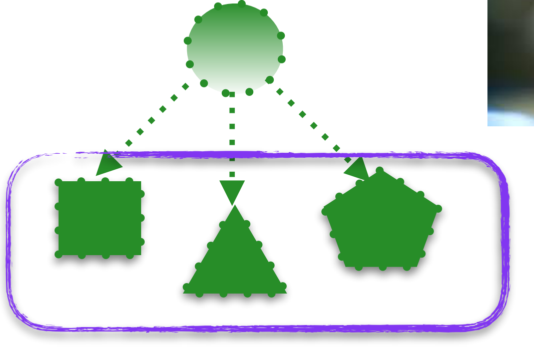




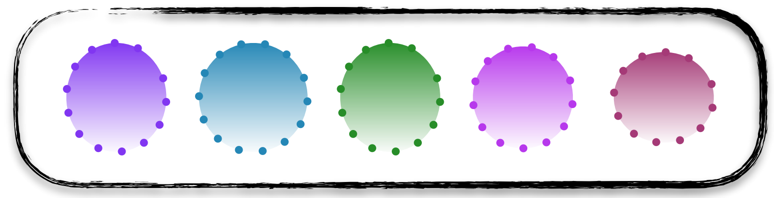


Today's Plan:
Bayesian inference & linguistic parameters

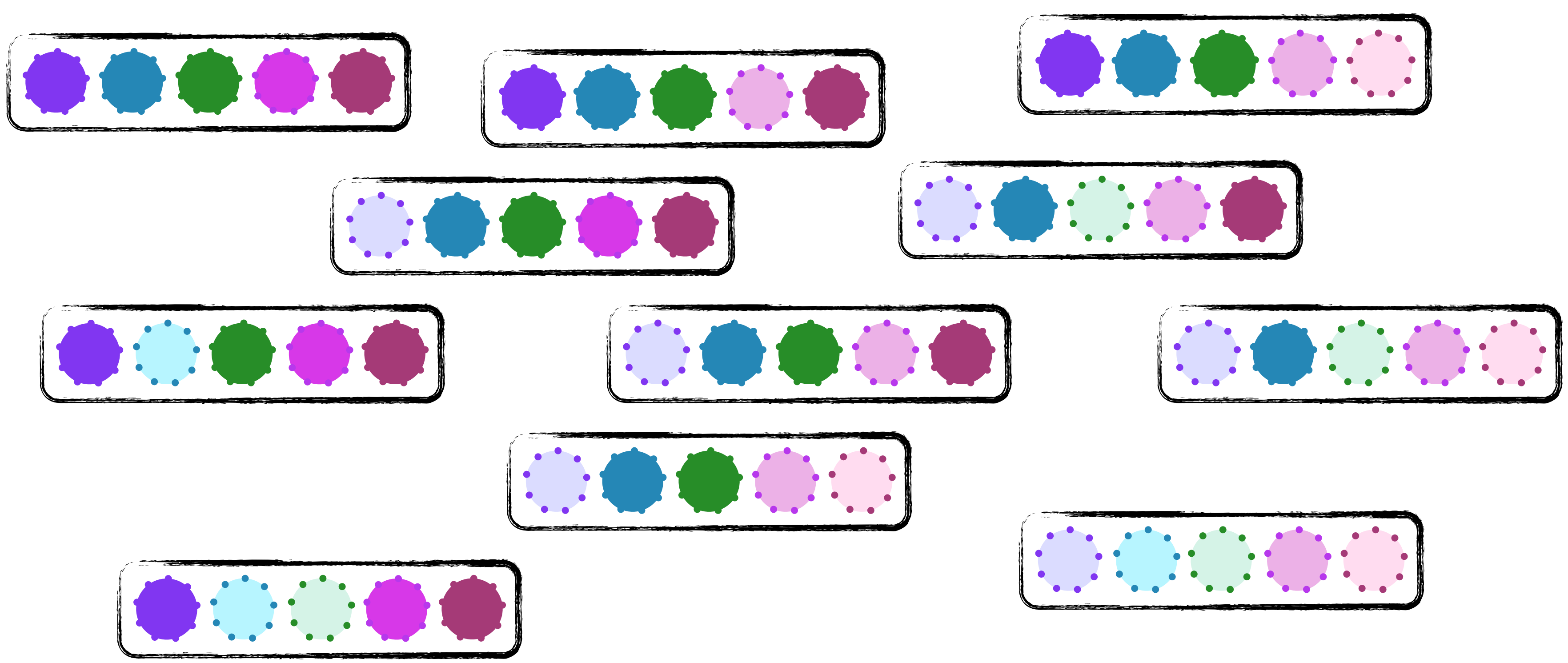
II. Parameters & overhypotheses



Parameters & overhypotheses

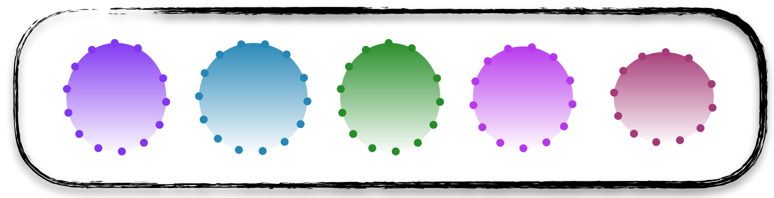


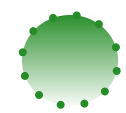
Remember:
We can think of grammars as collections of parameter values.



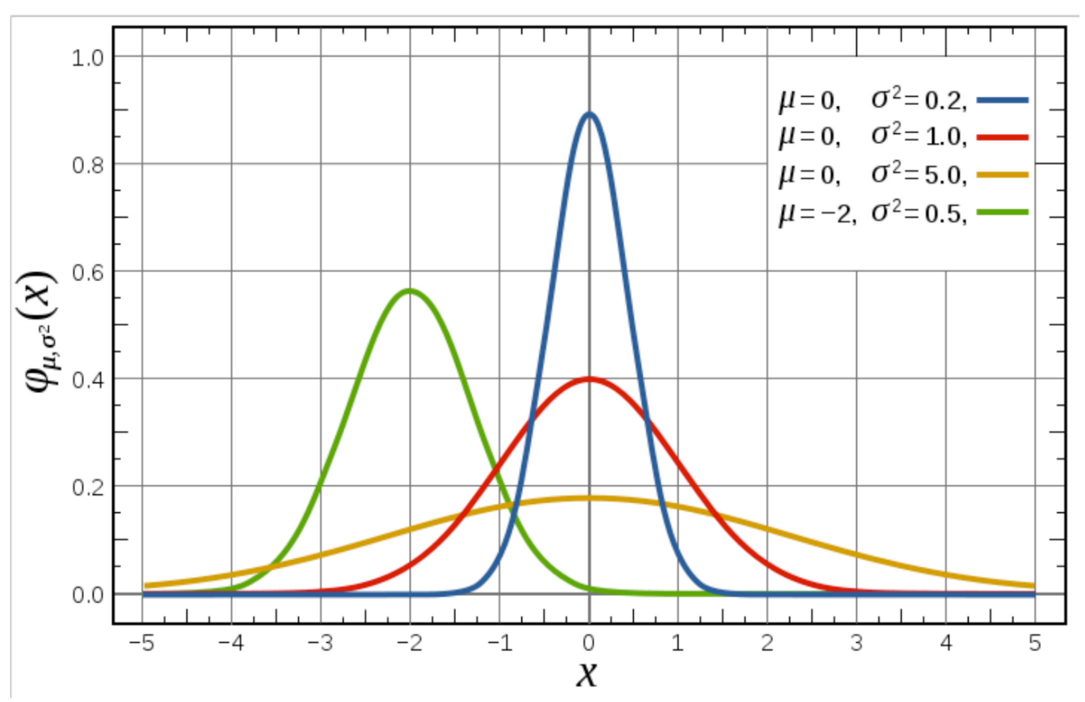
Parameters & overhypotheses

grammar

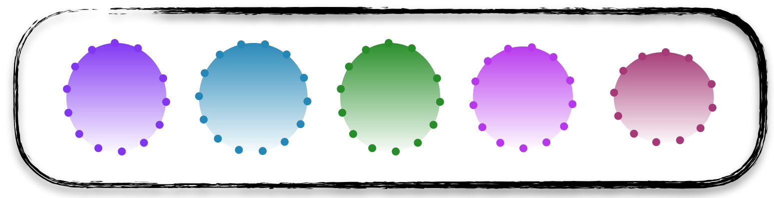


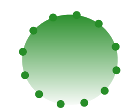


A parameter (and its specific value) determines what we predict will be observed in the world in a variety of situations.



Parameters & overhypotheses

grammar 

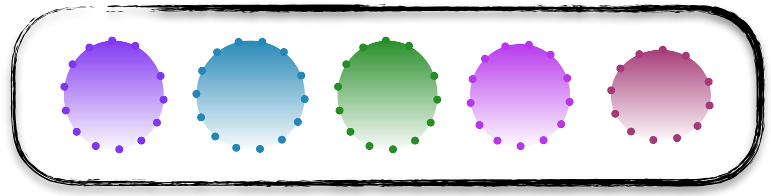
A parameter determines what we predict will be observed. 

Example: Head-directionality

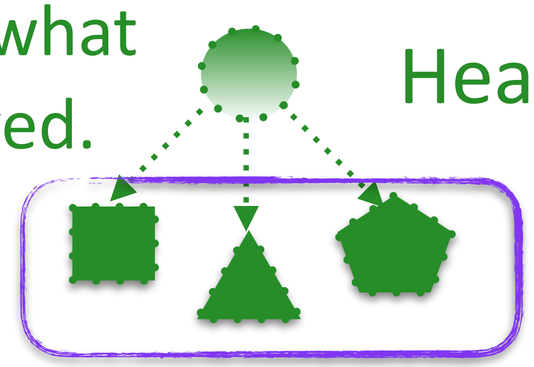
Linguistic parameters correspond to the properties that vary across human languages.

Parameters & overhypotheses

grammar



A parameter determines what we predict will be observed.

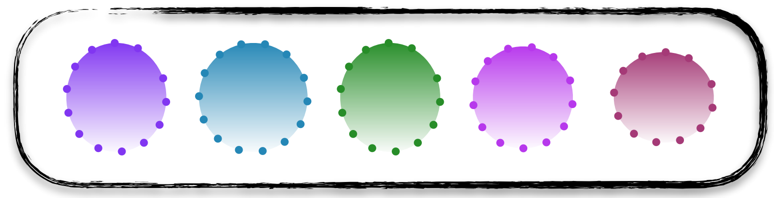


Head-directionality

The fact that parameters connect to multiple structural properties is a very good thing for acquisition. This is because a child can learn about that parameter's value by observing many different kinds of examples in the language.

Parameters & overhypotheses

grammar

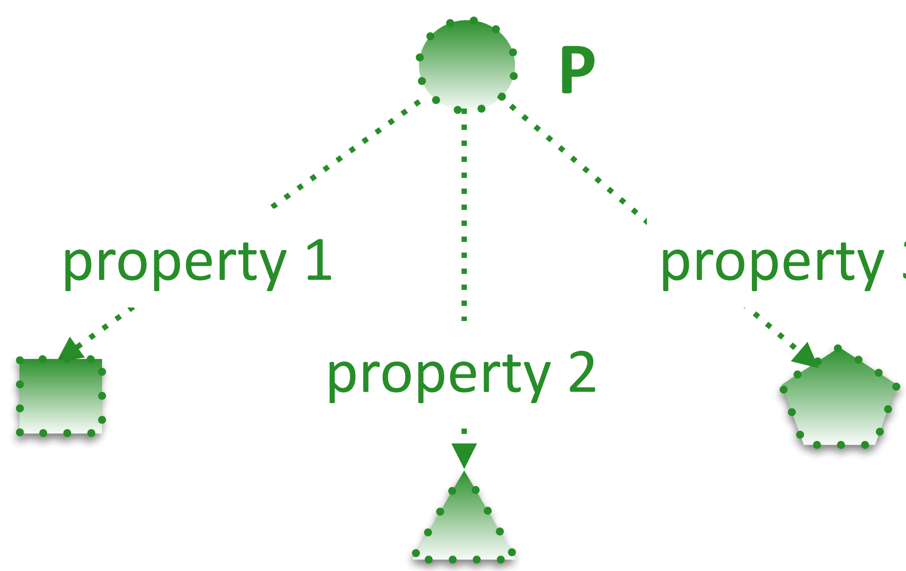


A parameter determines what we predict will be observed.

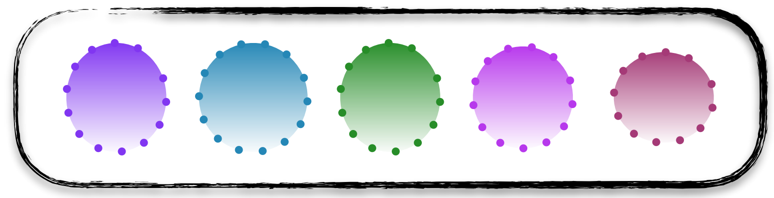
Head-directionality

good for acquisition

Let's assume a number of **properties** are all connected to parameter **P**, which can take one of two values: a or b.



Parameters & overhypotheses

grammar 

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Head-directionality

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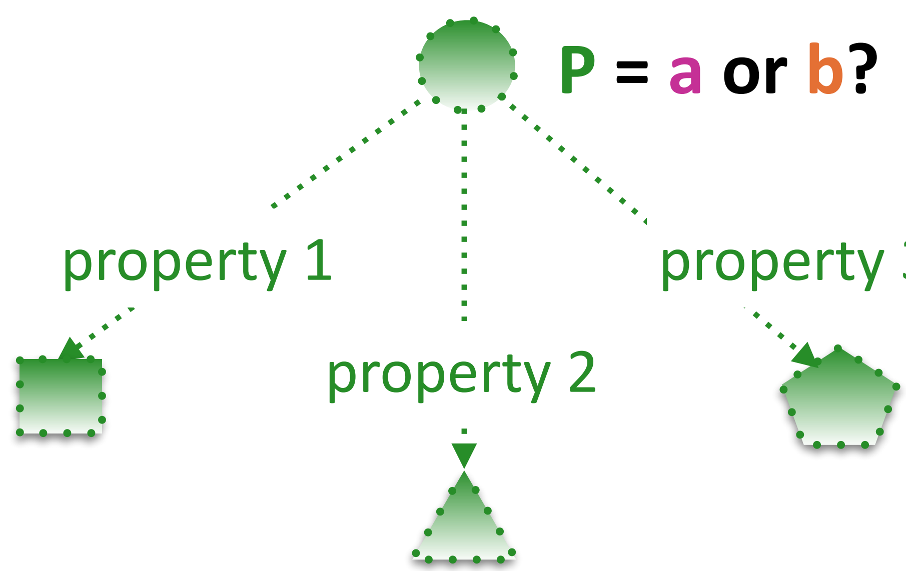
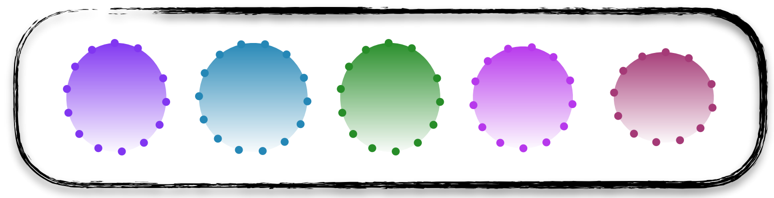


Parameters & overhypotheses

grammar



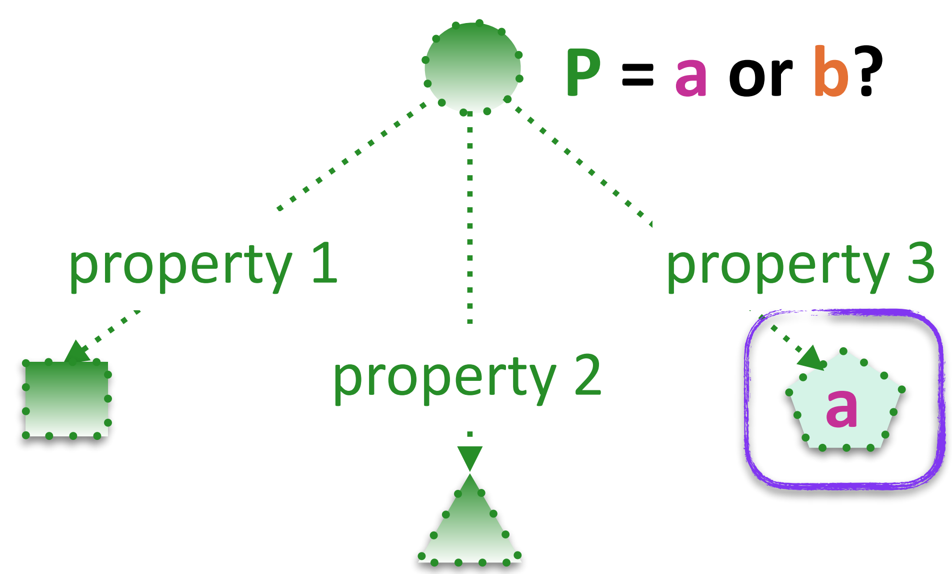
A parameter determines what we predict will be observed.

Head-directionality

good for acquisition

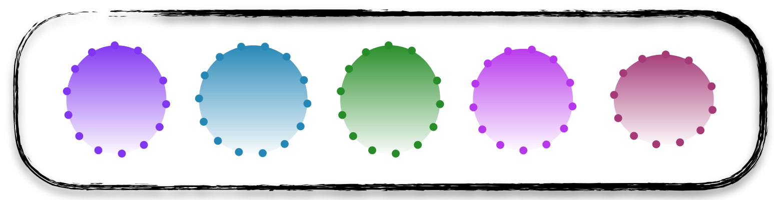
How do we learn whether property 3 shows behavior a or b?

One way is to observe instances of property 3 in the intake.



Parameters & overhypotheses

grammar

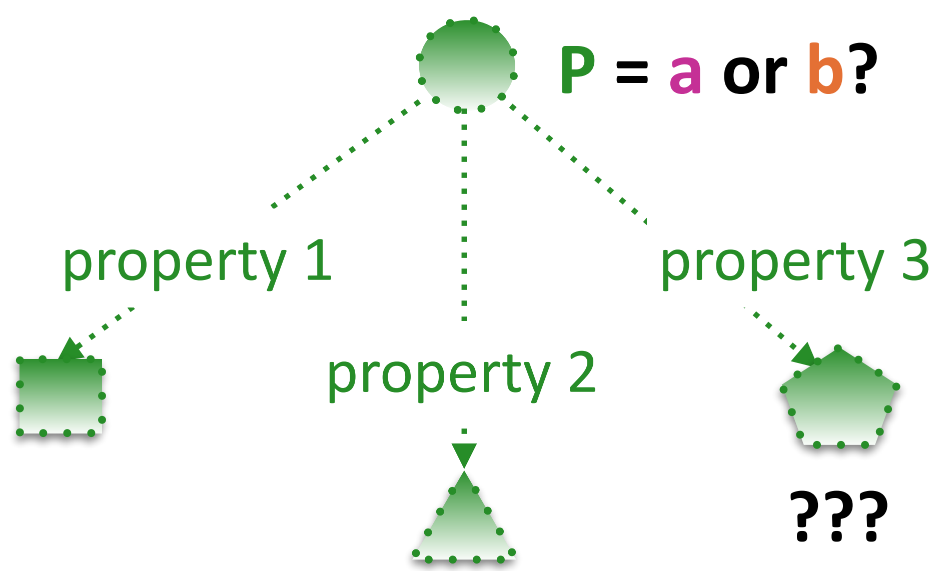


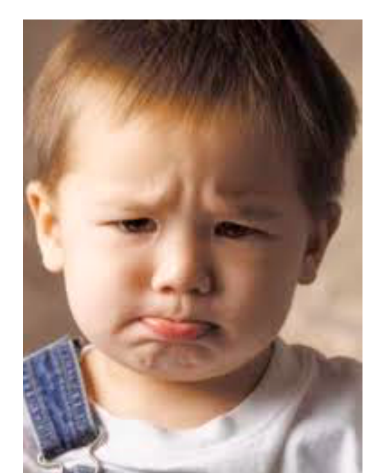
A parameter determines what we predict will be observed.

Head-directionality

good for acquisition

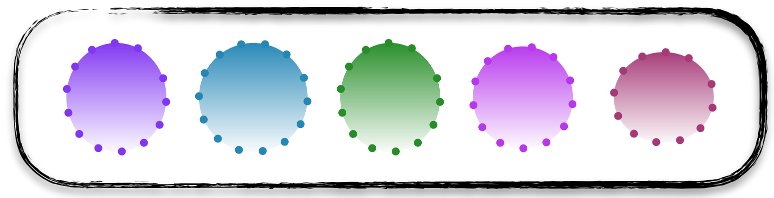
But what if property 3 occurs very rarely? We might never see any examples of property 3.





Parameters & overhypotheses

grammar

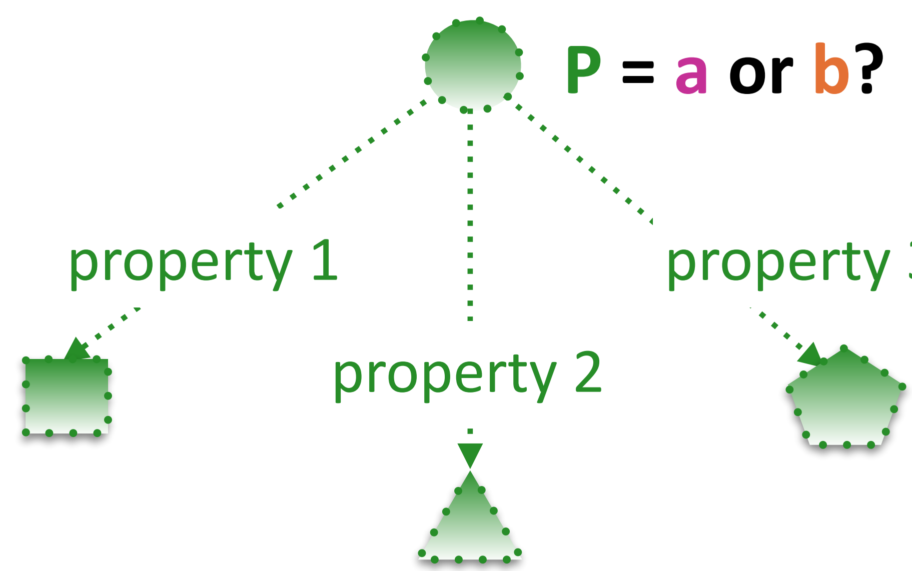


A parameter determines what we predict will be observed.

Head-directionality

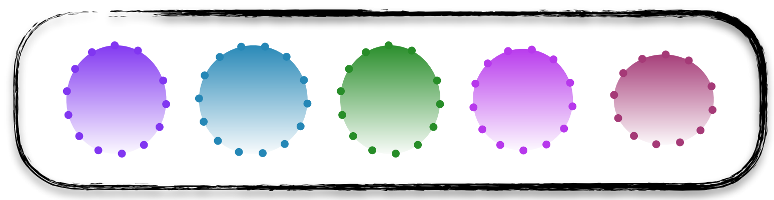
good for acquisition

Fortunately, because property 3 is connected to P, we can learn the value for property 3 by learning the value of P.



Parameters & overhypotheses

grammar

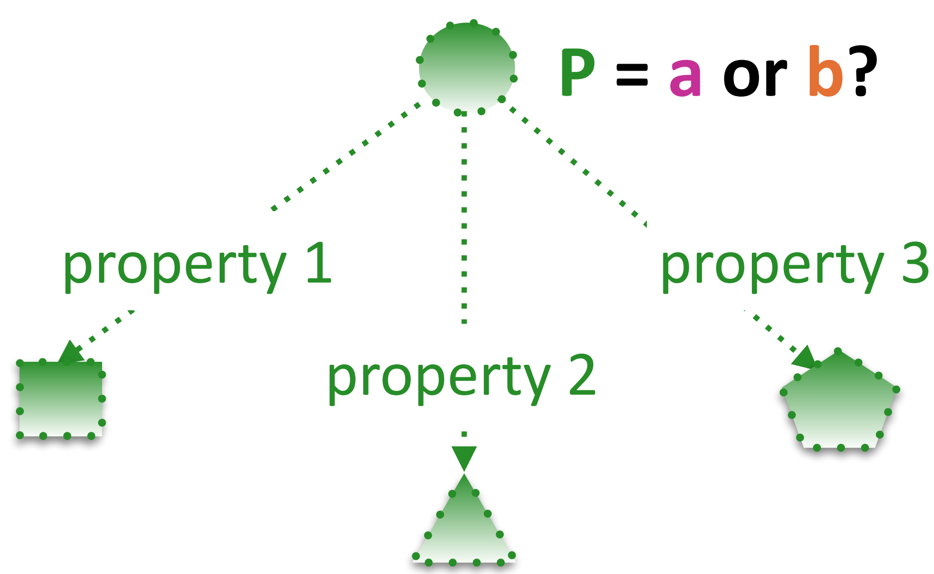


A parameter determines what we predict will be observed.

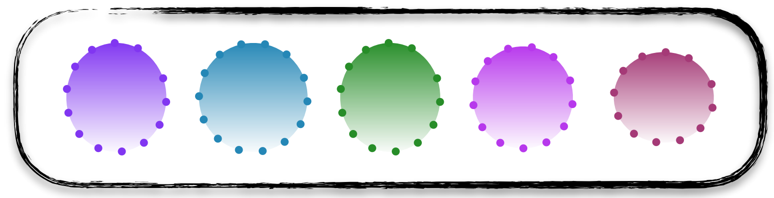
Head-directionality

good for acquisition

Also fortunately, P is connected to properties 1 and 2.



Parameters & overhypotheses

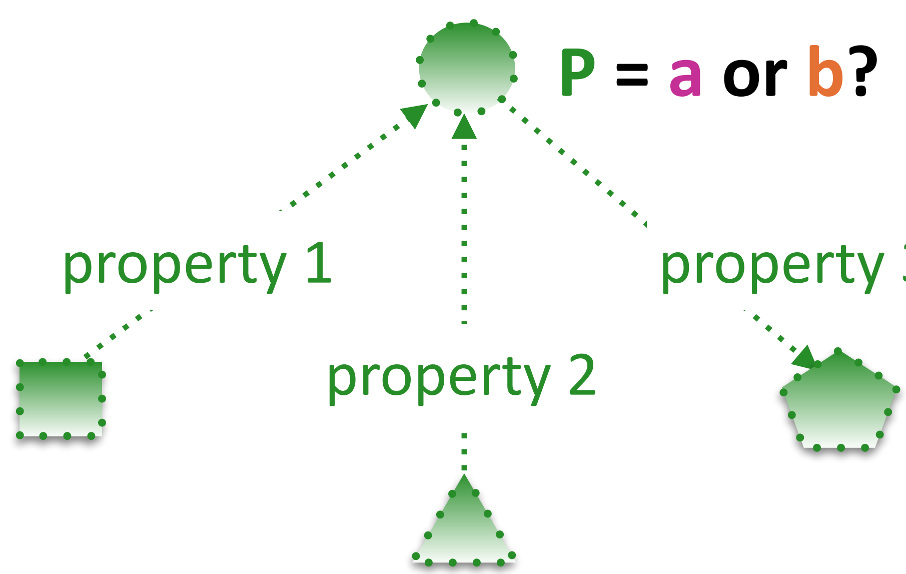
grammar 

A parameter determines what we predict will be observed.

Head-directionality

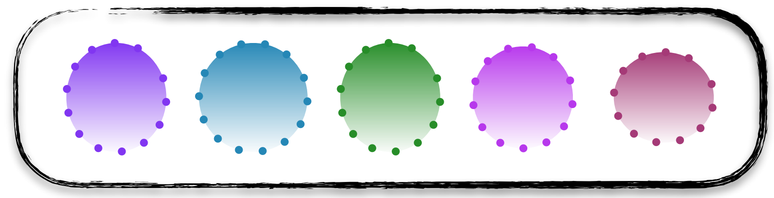
good for acquisition

This means we can learn the value of P from property 1 or property 2.



Parameters & overhypotheses

grammar

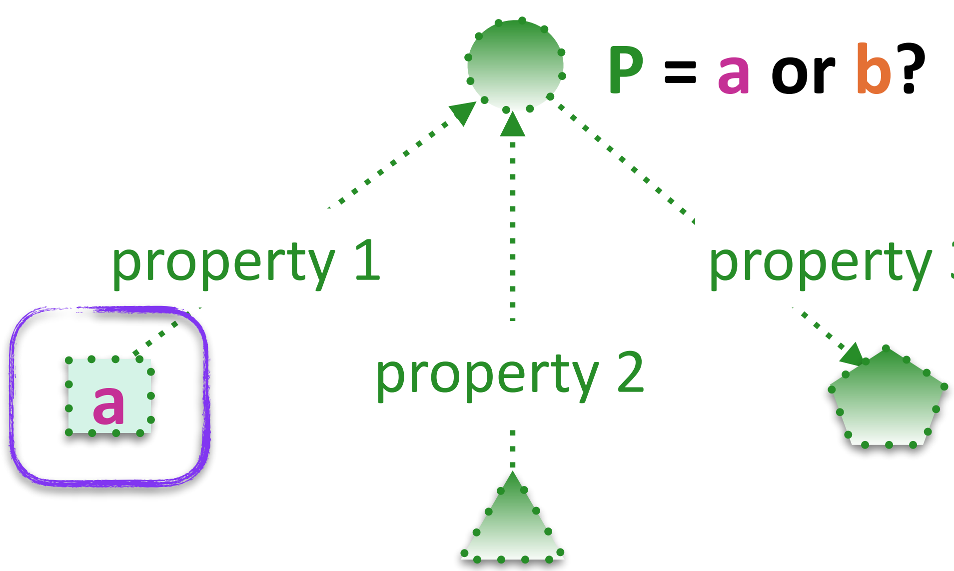


A parameter determines what
we predict will be observed.

Head-directionality

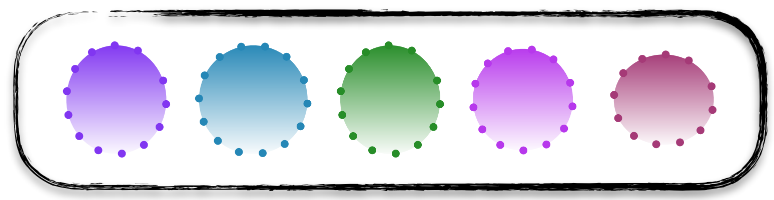
good for acquisition

Suppose we see an example of property 1 with value **a**.



Parameters & overhypotheses

grammar

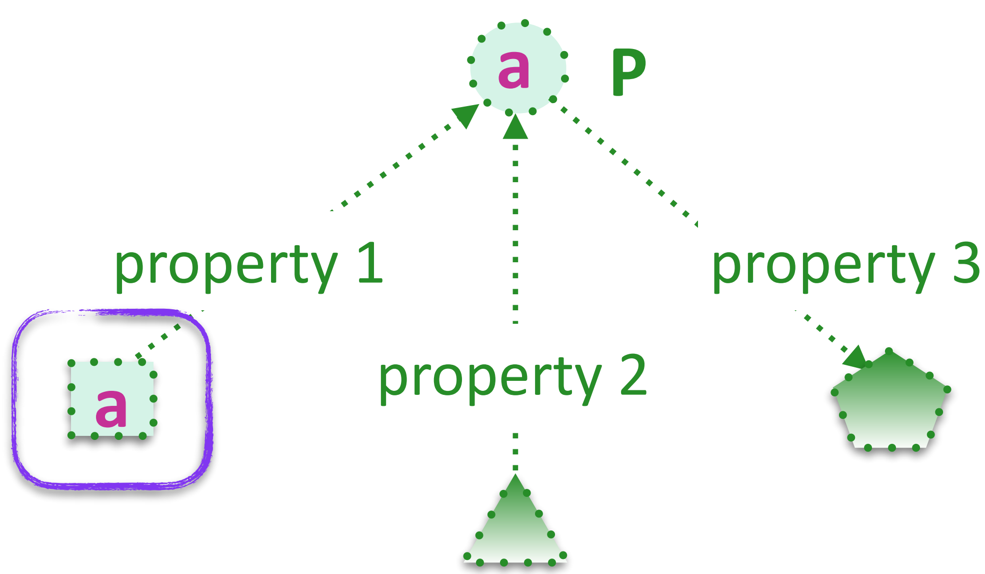


A parameter determines what we predict will be observed.

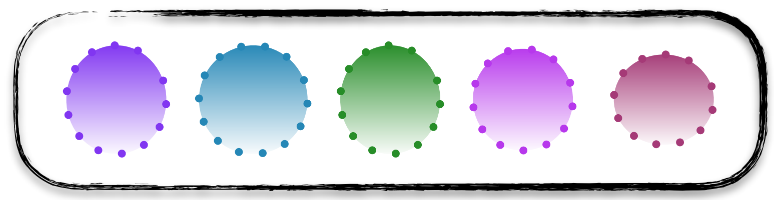
Head-directionality

good for acquisition

This means P also should have value a.



Parameters & overhypotheses

grammar 

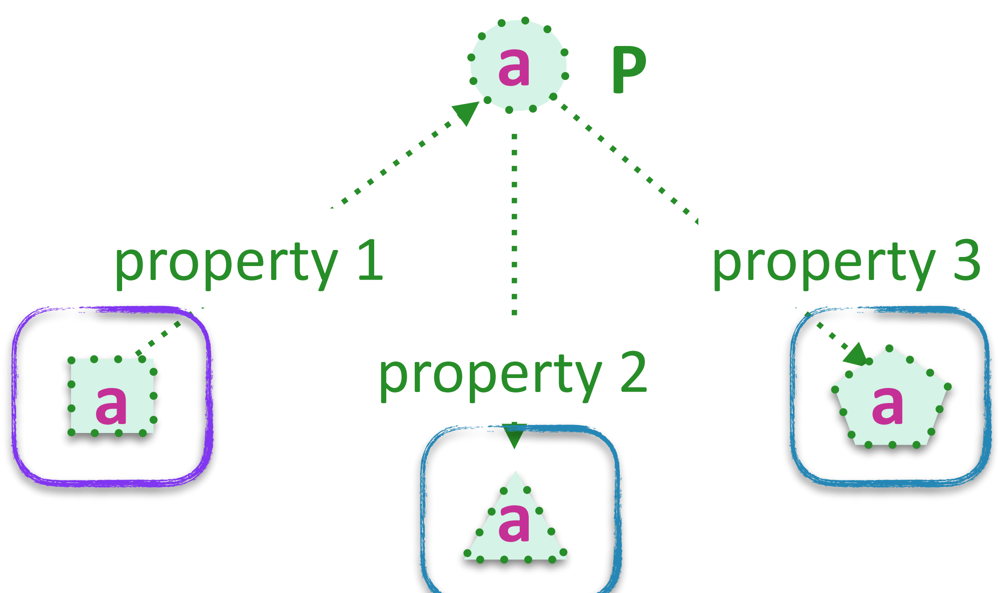
A parameter determines what
we predict will be observed.

Head-directionality

good for acquisition

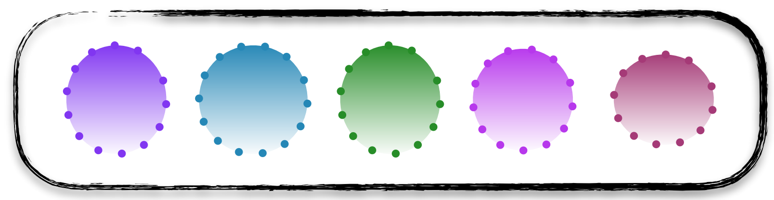
So, we can make predictions for all the other properties connected to P, even if we've never seen examples of them.

This is great!



Parameters & overhypotheses

grammar

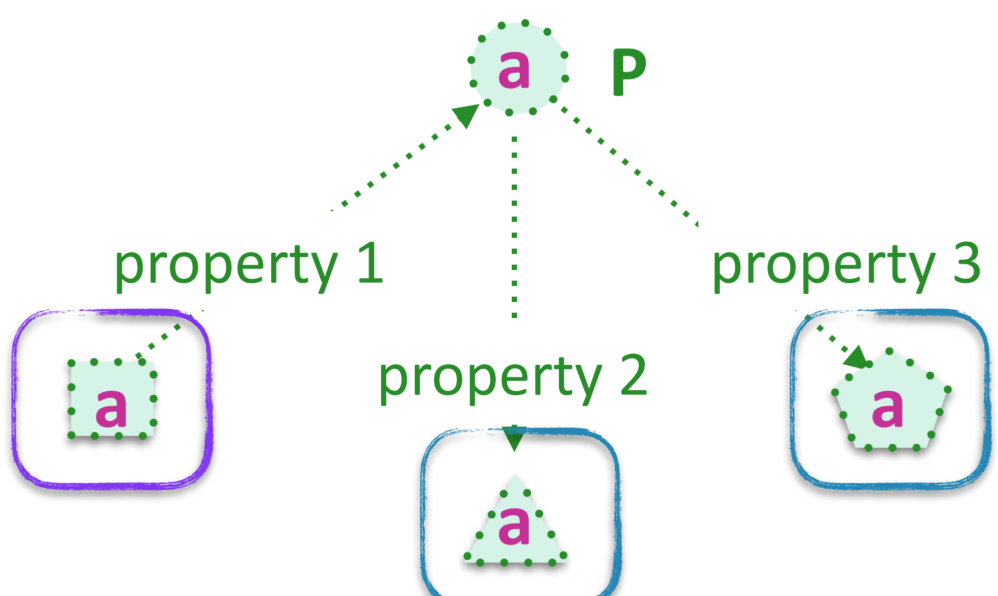


A parameter determines what
we predict will be observed.

Head-directionality

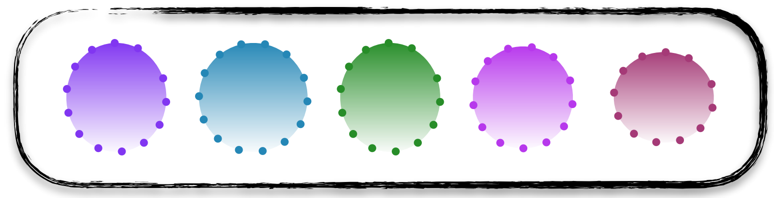
good for acquisition

This highlights another benefit - we don’t have to learn the behavior of each structure individually.



Parameters & overhypotheses

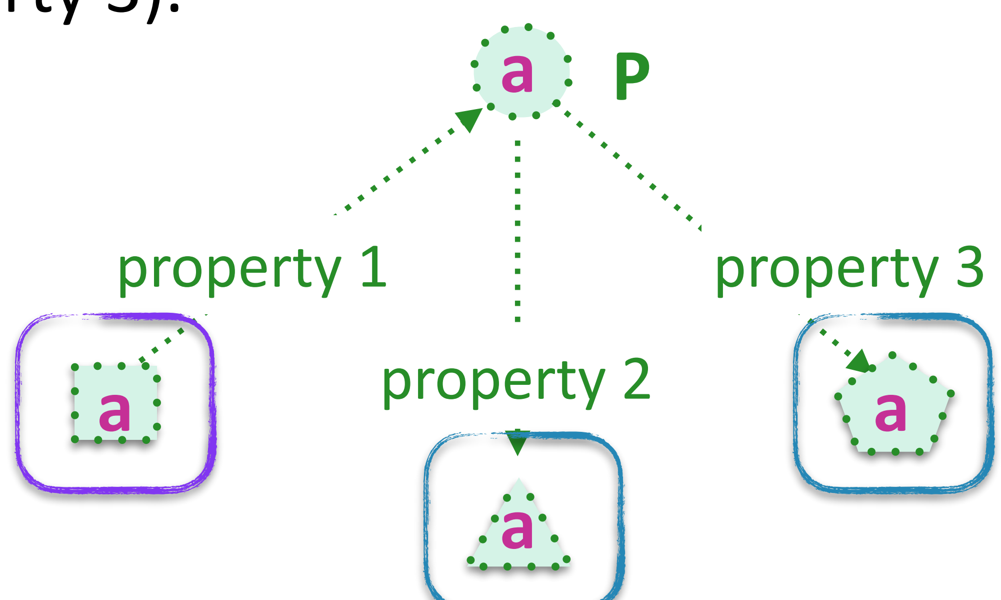
grammar



A parameter determines what
we predict will be observed.

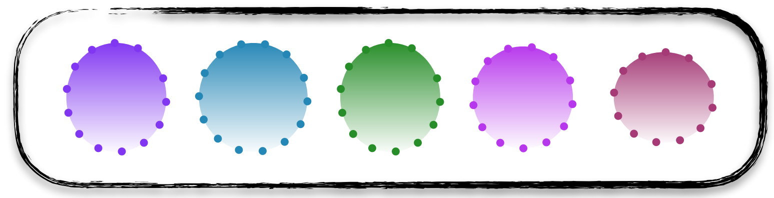
Head-directionality

good for acquisition
Instead, we can observe some properties (like property 1) and infer the right behavior for the remaining properties (like property 2 and property 3).



Parameters & overhypotheses

grammar

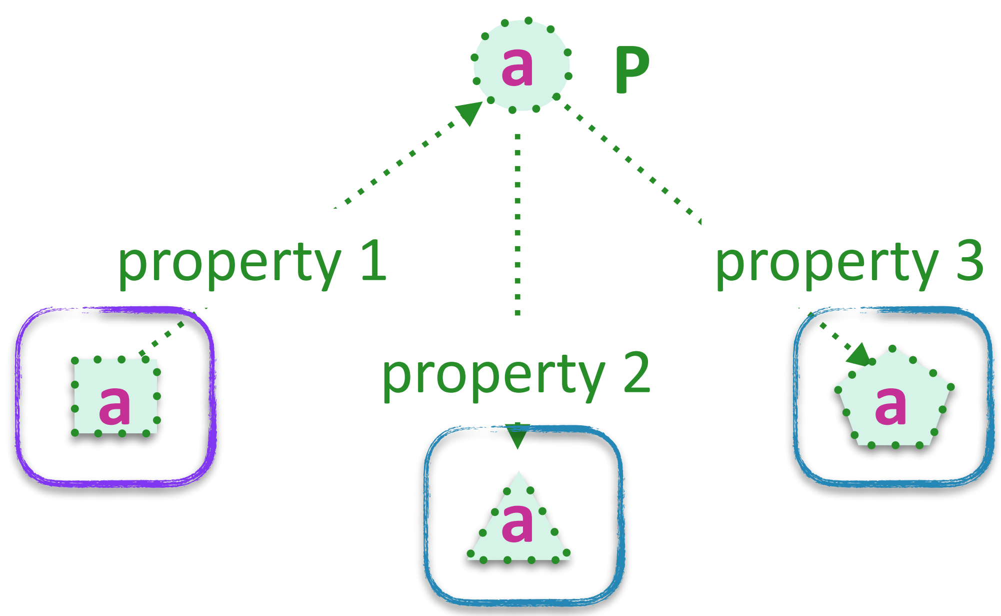


A parameter determines what we predict will be observed.

Head-directionality

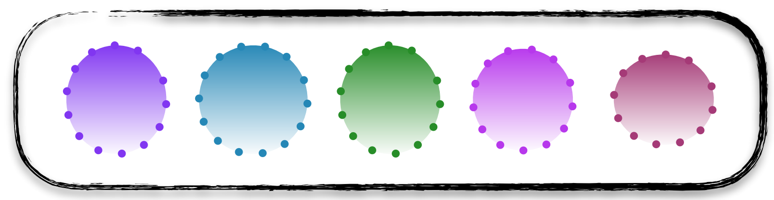
good for acquisition

That is, instead of having to make 3 decisions (one for properties 1, 2, and 3), we actually only need to make one decision - is P a or b?



Parameters & overhypotheses

grammar

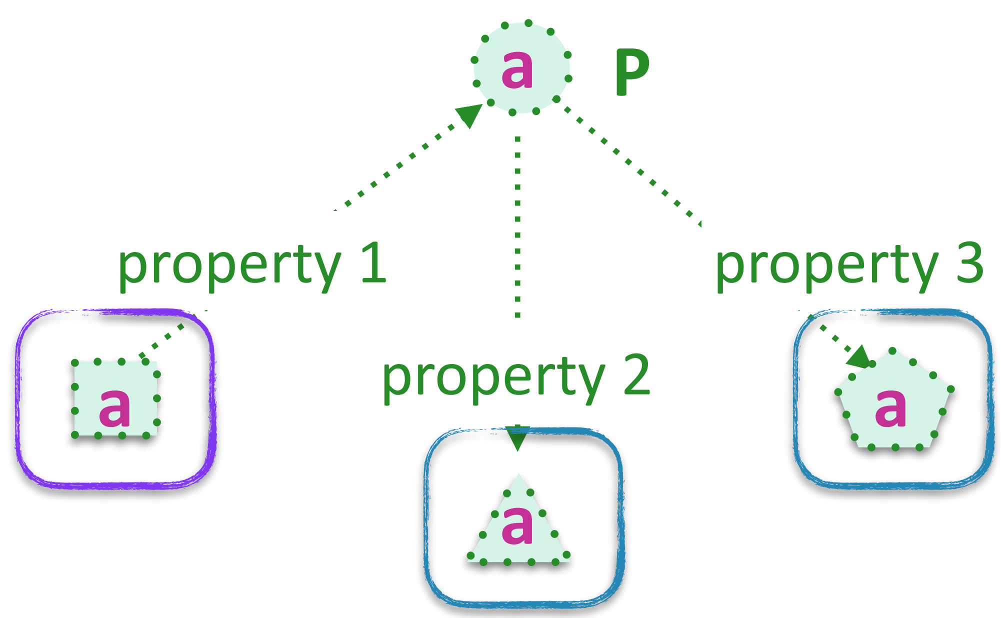


A parameter determines what
we predict will be observed.

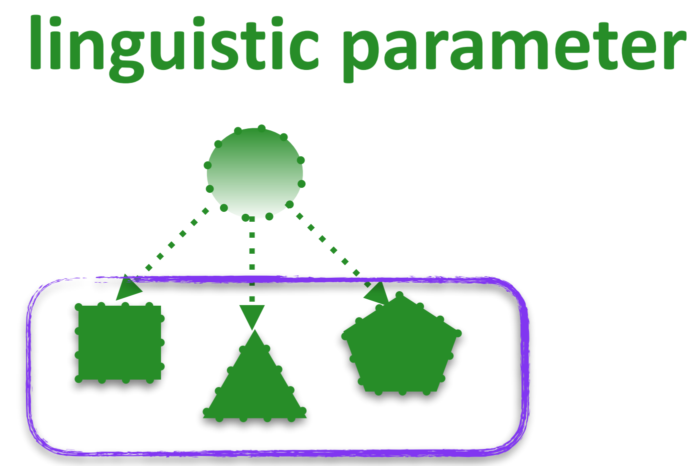
Head-directionality

good for acquisition

The intake is used to make this one decision, which generates useful predictions for other properties of the language.



Parameters & overhypotheses

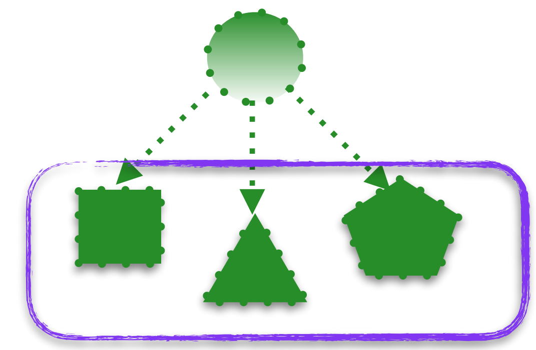


Overhypotheses in hierarchical Bayesian learning are generalizations made at a more abstract level, which cover many different data types.

In this way, they're similar in spirit to linguistic parameters.

Parameters & overhypotheses

linguistic parameter



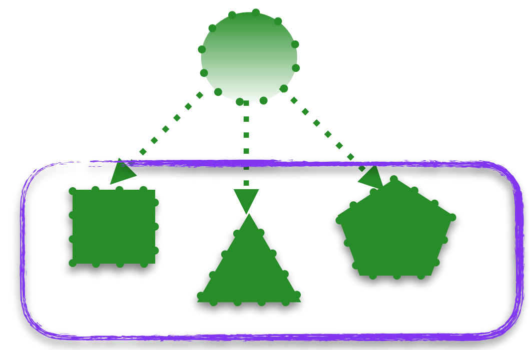
Overhypotheses

Non-linguistic example

Suppose you're observing the contents of marble bags.

Parameters & overhypotheses

linguistic parameter



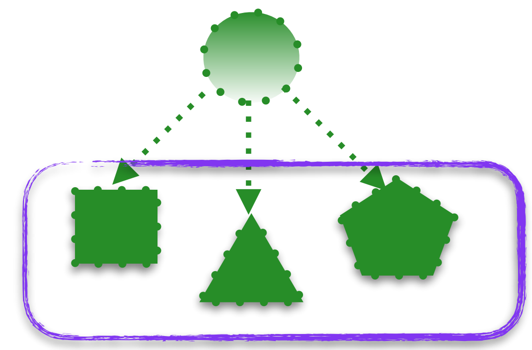
Overhypotheses

Non-linguistic example

The first bag you look at has 20 black marbles.

Parameters & overhypotheses

linguistic parameter



Overhypotheses

Non-linguistic example

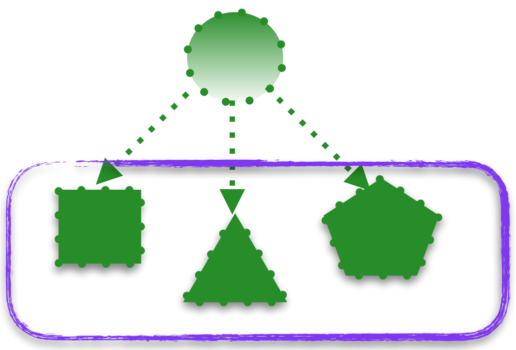
The second bag you look at has 20 white marbles.

20

20

Parameters & overhypotheses

linguistic parameter

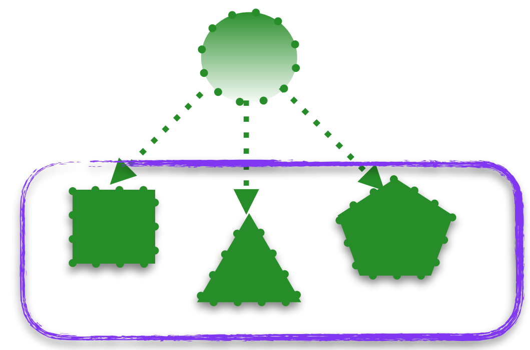


Overhypotheses

Non-linguistic example

Parameters & overhypotheses

linguistic parameter



Overhypotheses

Non-linguistic example

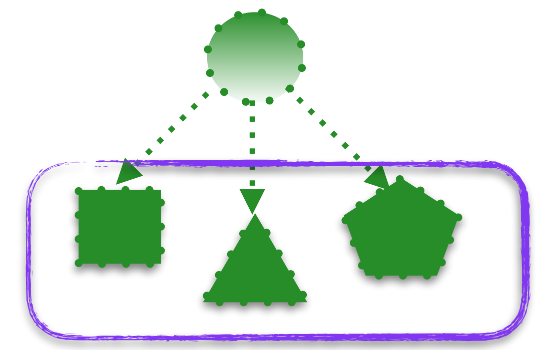
The third and fourth bags you look at have 20 black marbles.

Parameters & overhypotheses

Overhypotheses

Non-linguistic example

linguistic parameter



You get a fifth bag and pull out a single marble. It’s white.

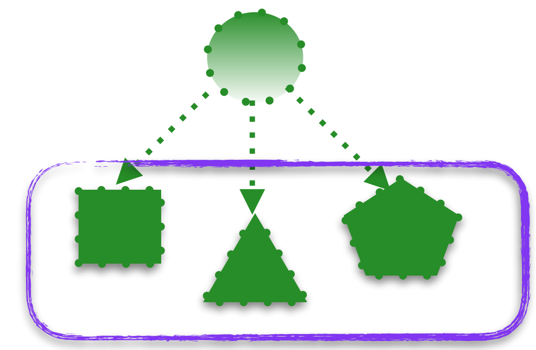
1 

Parameters & overhypotheses

Overhypotheses

Non-linguistic example

linguistic parameter



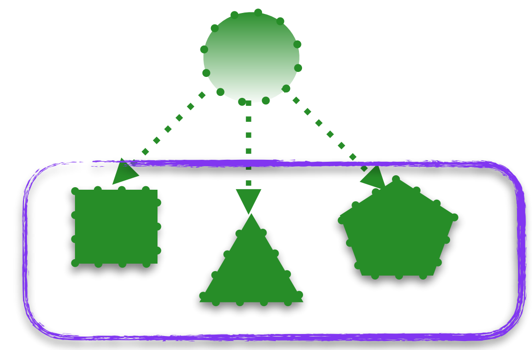
What do you predict about the color distribution of the rest of the marbles in the bag?

1 

20  **20**  **20**  **20** 

Parameters & overhypotheses

linguistic parameter



Overhypotheses

Non-linguistic example

Probably that they're all white!

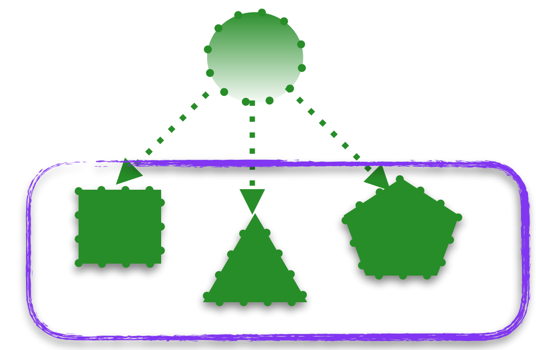
1 

20 

20  **20**  **20**  **20** 

Parameters & overhypotheses

linguistic parameter



Overhypotheses

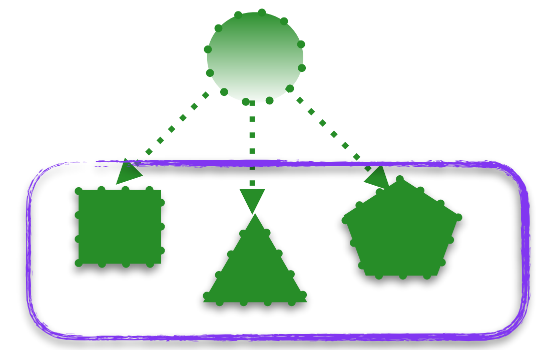
Non-linguistic example

What if you then get another bag and pull out a single purple marble from it? What would you predict?

1 

Parameters & overhypotheses

linguistic parameter



Overhypotheses

Non-linguistic example

Probably that all the rest of the marbles in the bag are purple, too!

1 

20 

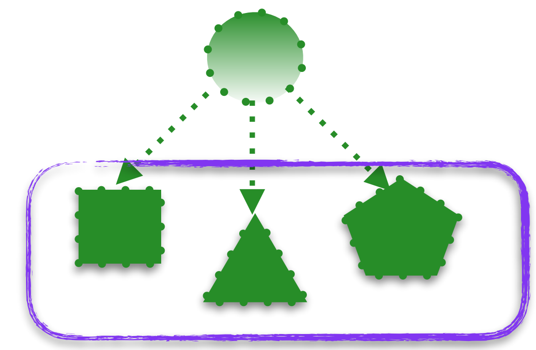
20 

20 

20 

Parameters & overhypotheses

linguistic parameter



Overhypotheses

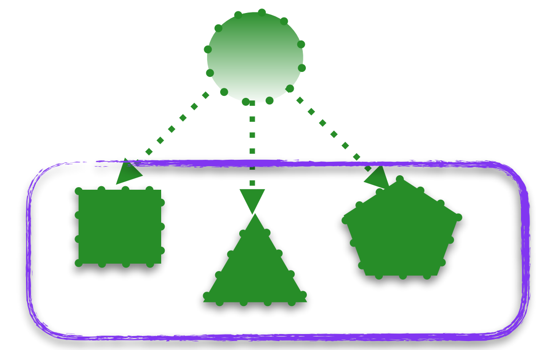
Non-linguistic example

Why does this happen?

1 

Parameters & overhypotheses

linguistic parameter



Overhypotheses

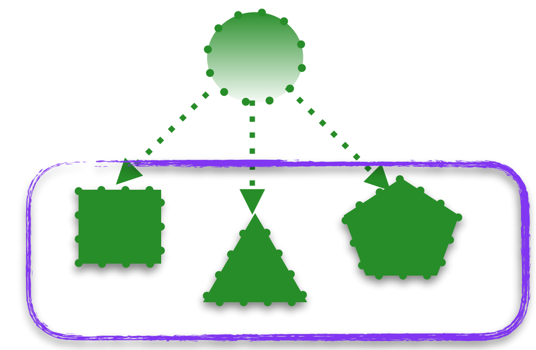
Non-linguistic example

It seems like you're learning something about the color distribution *in general* (not just for a particular bag): all marbles in a bag have the same color.

1

Parameters & overhypotheses

linguistic parameter



Overhypotheses

Non-linguistic example

This allows you to make predictions when you've only seen a single marble of whatever color from a bag.

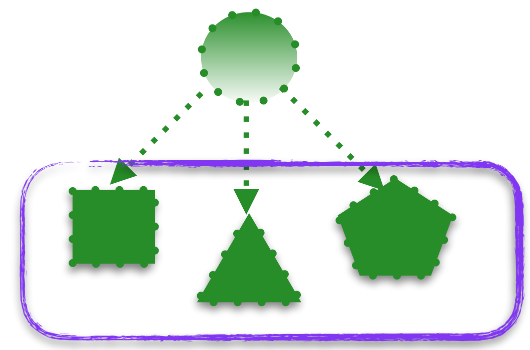
1

Parameters & overhypotheses

Overhypotheses

Non-linguistic example

linguistic parameter



overhypothesis

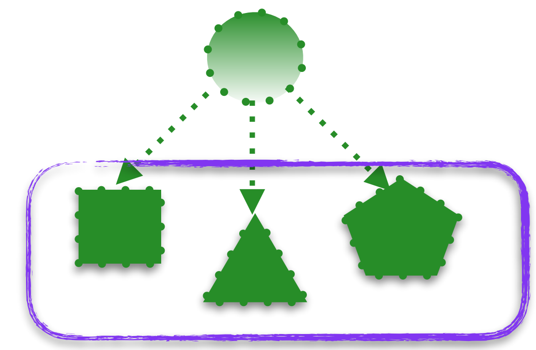
all the same color

all black | all white | all black | all black

20  20  20  20 

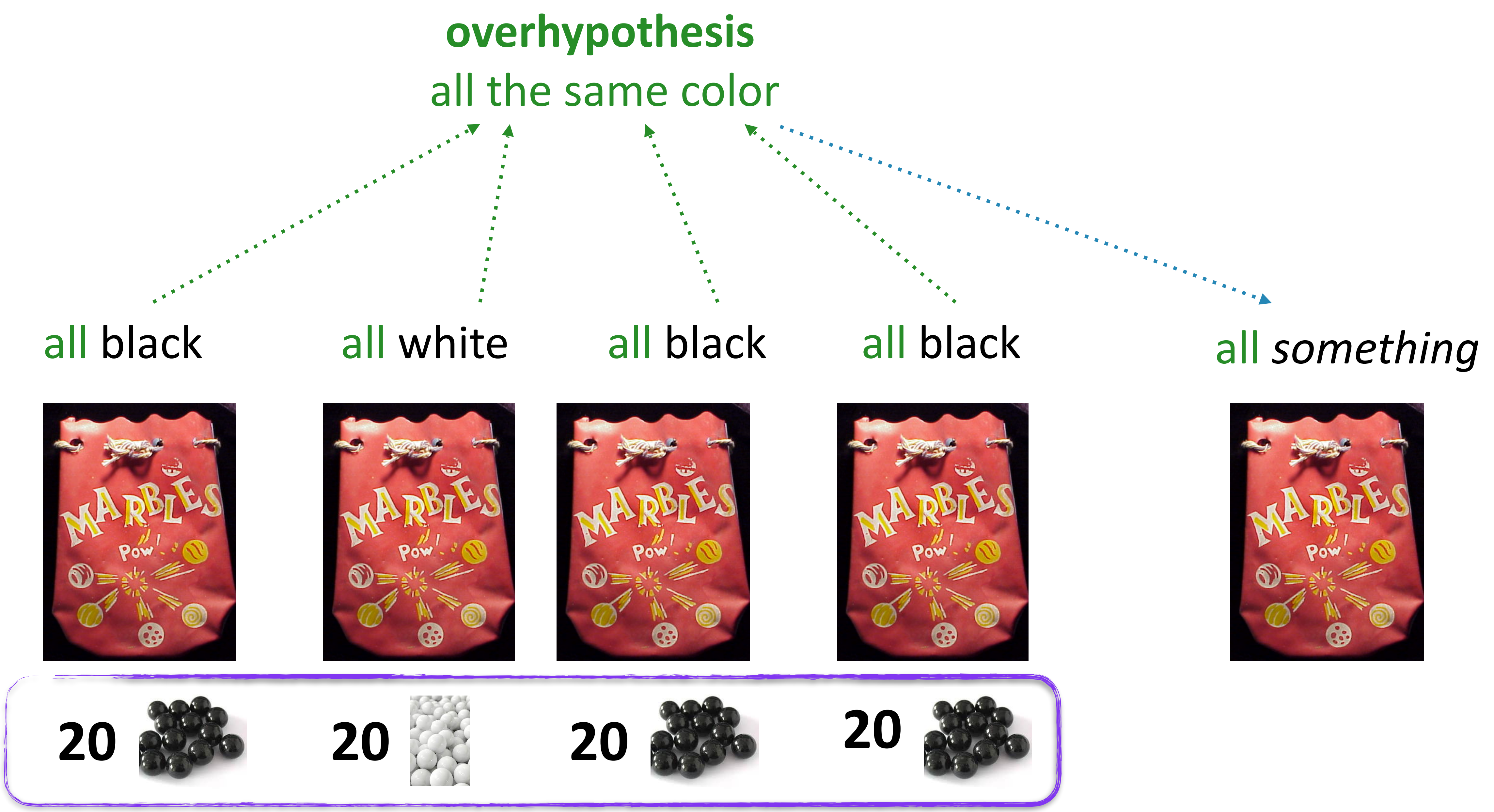
Parameters & overhypotheses

linguistic parameter



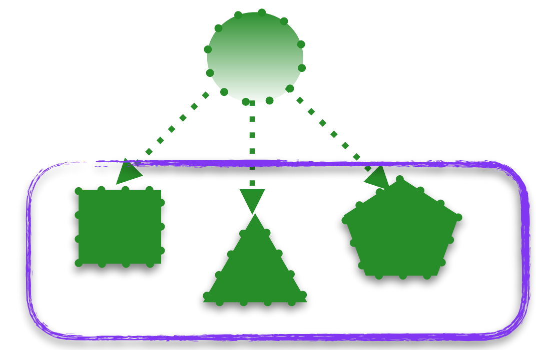
Overhypotheses

Non-linguistic example



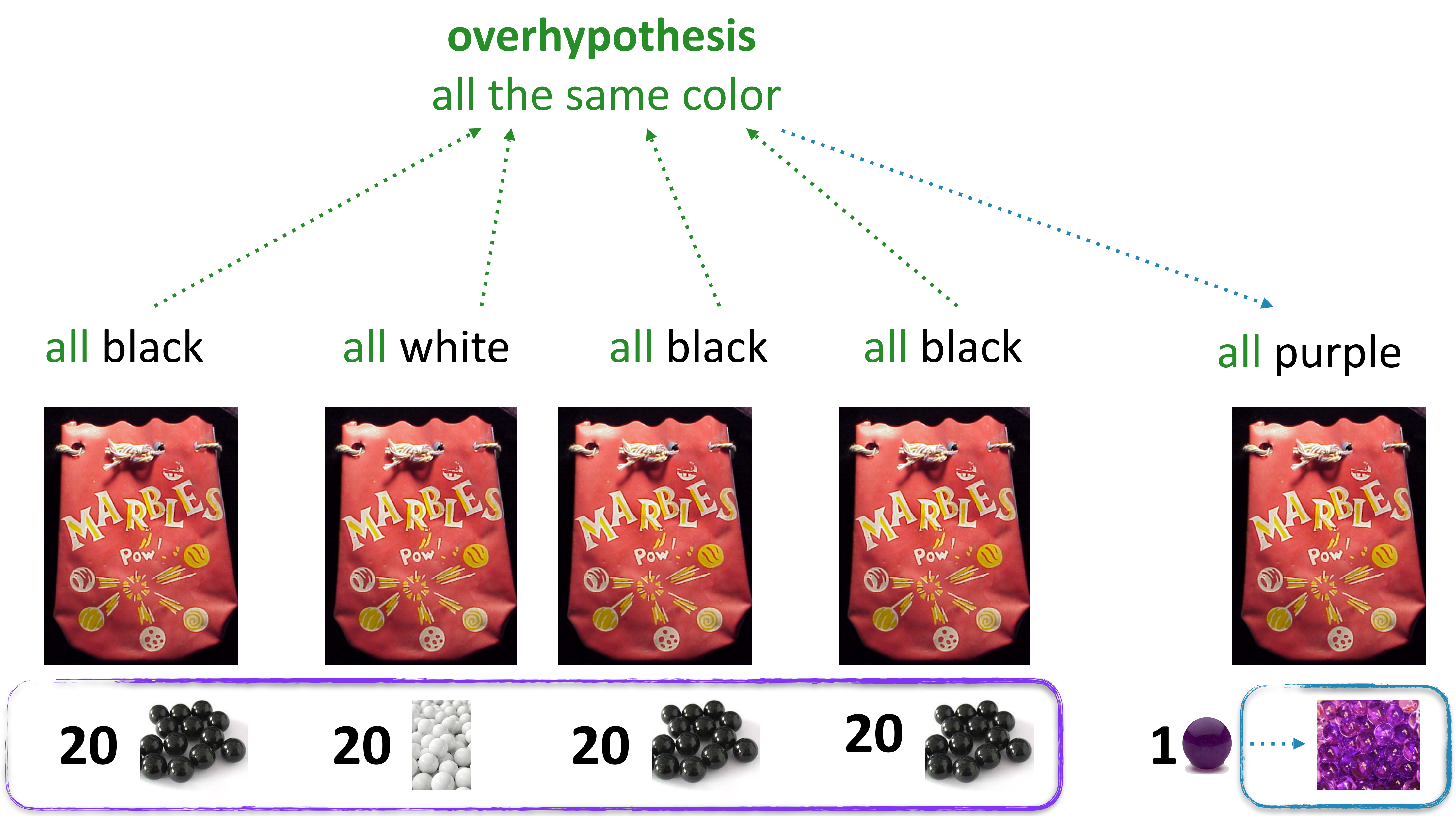
Parameters & overhypotheses

linguistic parameter



Overhypotheses

Non-linguistic example

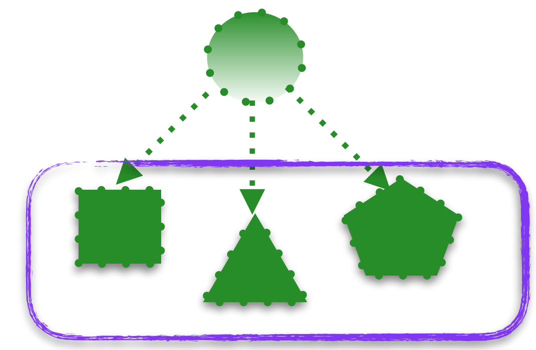


Parameters & overhypotheses

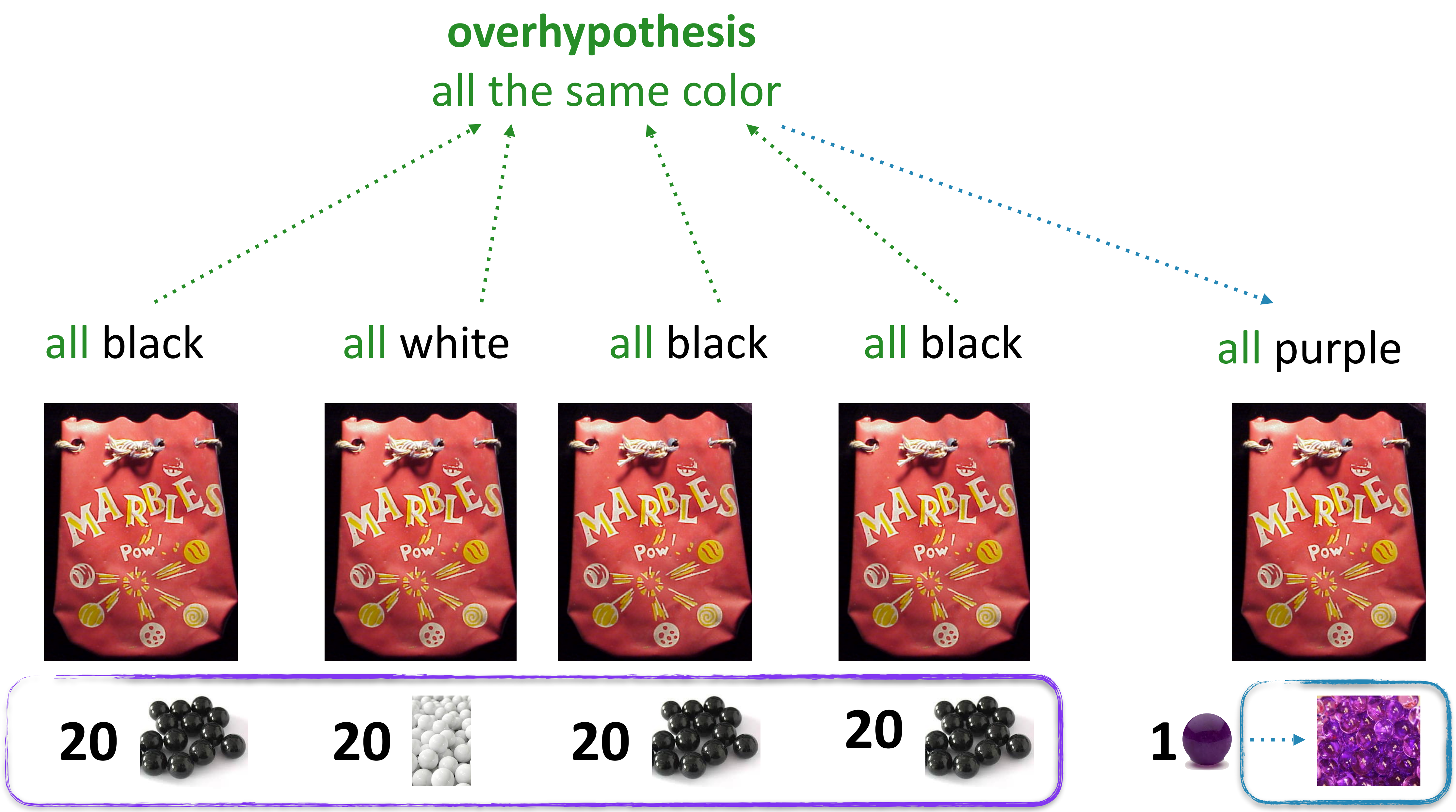
Overhypotheses

Non-linguistic example

linguistic parameter



Seem familiar?



Parameters & overhypotheses

Overhypotheses

Non-linguistic example

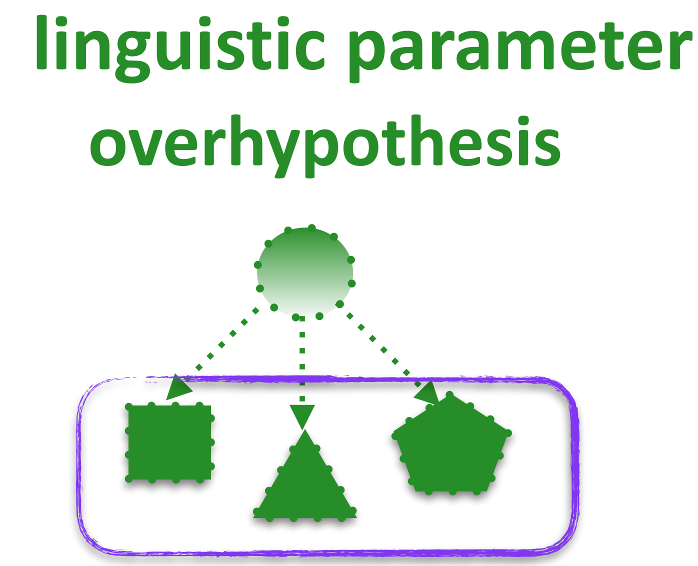
linguistic parameter

Seem familiar?

overhypothesis
all the same color

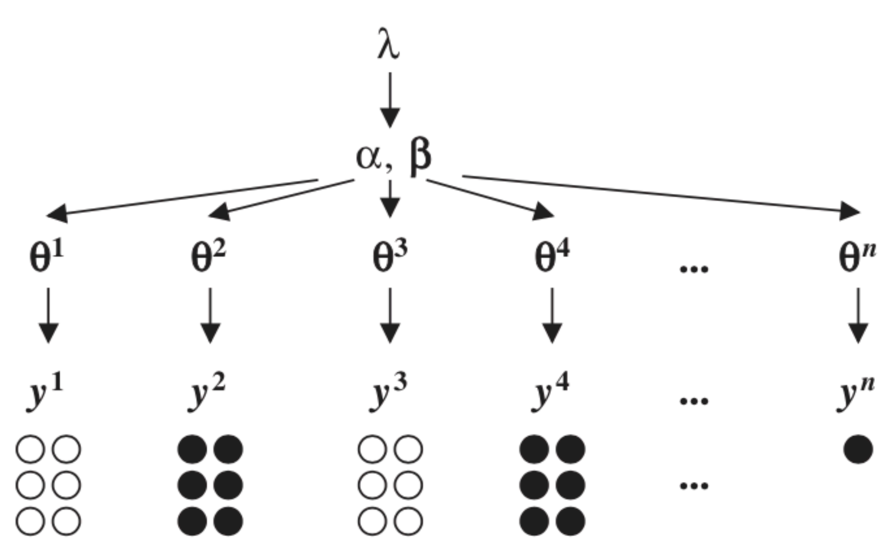
all black | all white | all black | all black | all purple

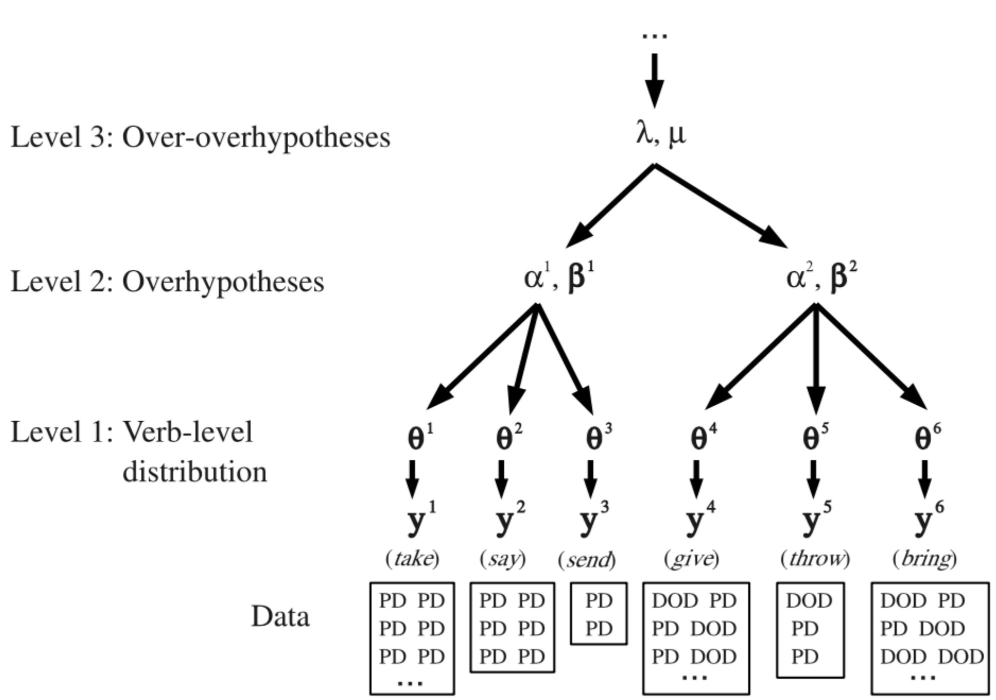
Parameters & overhypotheses



Bayesian learning models are able to learn overhypotheses, provided they know **what the parameters are** and **the range of values those parameters can take**.

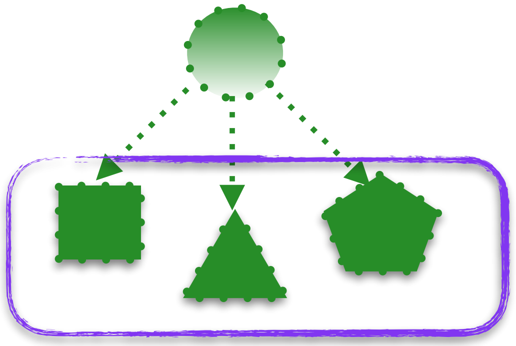
(ex: Kemp, Perfors, & Tenenbaum 2007, Perfors, Tenebaum, & Wonnacott 2010).





Parameters & overhypotheses

linguistic parameter
overhypothesis

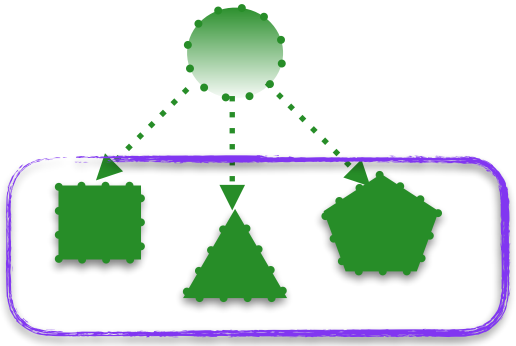


Bayesian learning models are able to learn overhypotheses, provided they know **what the parameters are** and **the range of values those parameters can take**.

What about real learners (children)?

Parameters & overhypotheses

linguistic parameter
overhypothesis



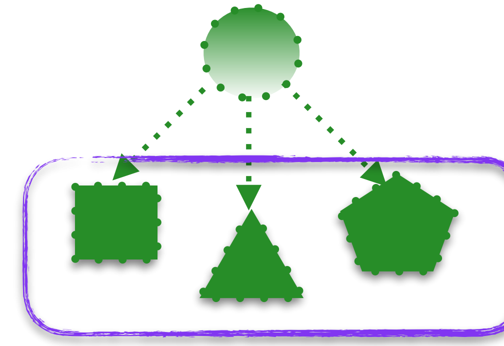
Dewar & Xu 2010
9-month-olds

When provided with partial evidence about a few objects in a few categories, can infants form a more abstract generalization (an overhypothesis) that then applies to a new category?

Parameters & overhypotheses

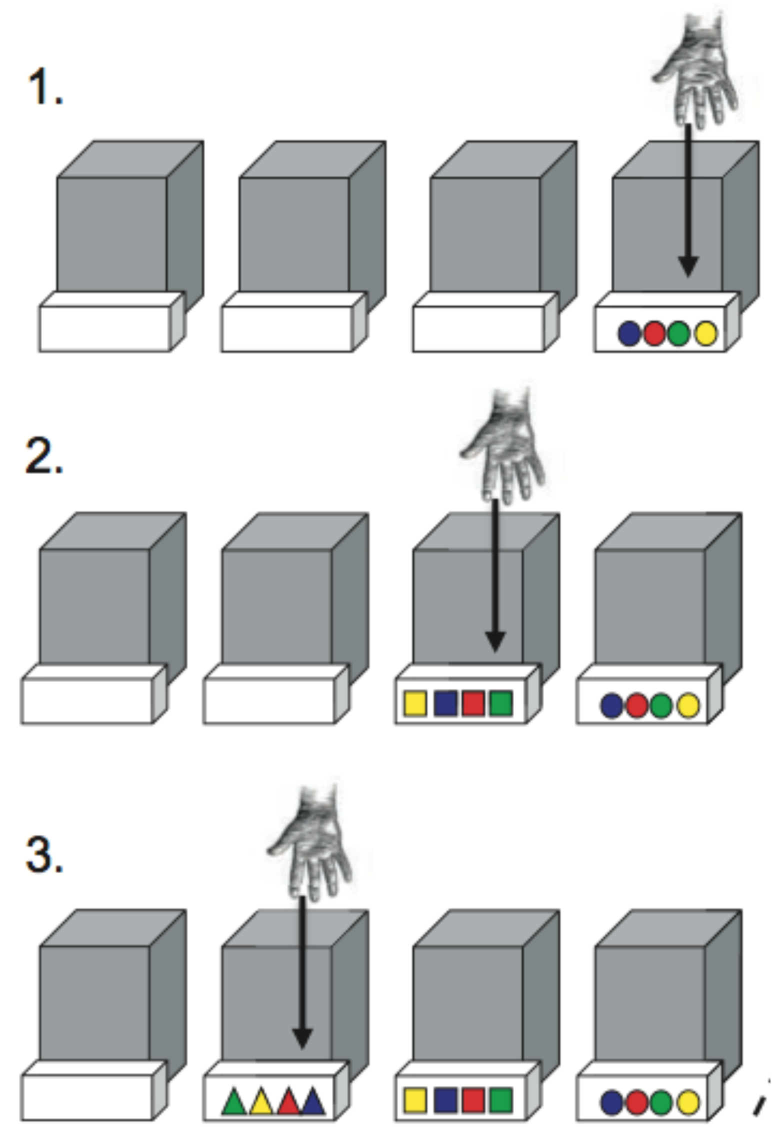
Dewar & Xu 2010
9-month-olds

linguistic parameter
overhypothesis



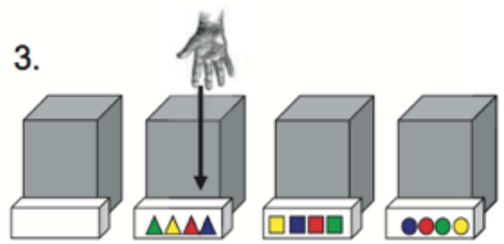
Training trials:

Observe four different objects pulled out by experimenter who had her eyes closed - the objects are **different colors but always have the same shape**.

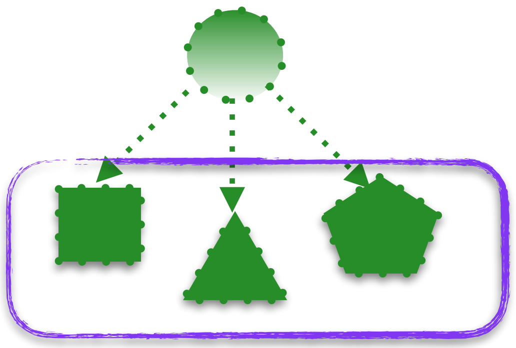


Parameters & overhypotheses

Dewar & Xu 2010
9-month-olds



linguistic parameter
overhypothesis



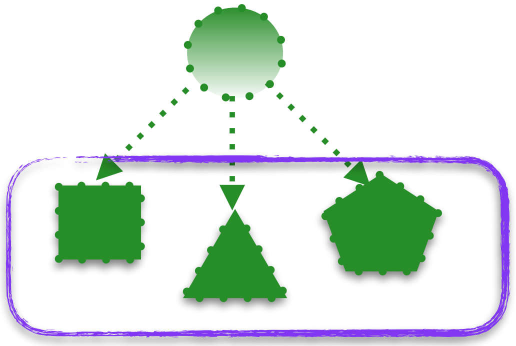
Training: different colors but same shape

Experimental condition

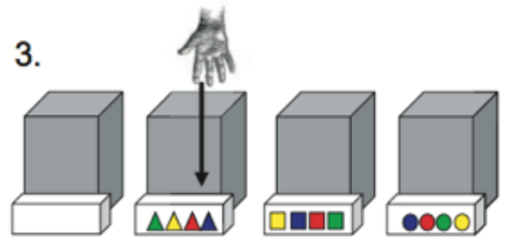
If infants create an overhypothesis that all objects in a box have the same shape…

Parameters & overhypotheses

linguistic parameter
overhypothesis



Dewar & Xu 2010
9-month-olds

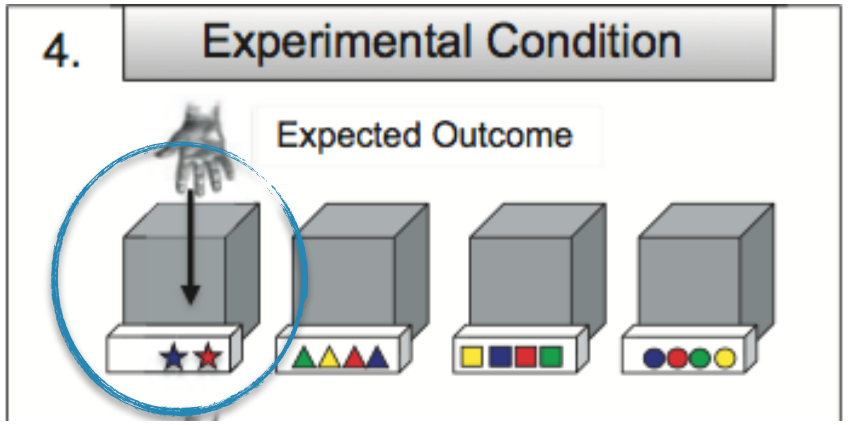


Training: different colors but same shape

Experimental condition

If infants create an overhypothesis that all objects in a box have the same shape…

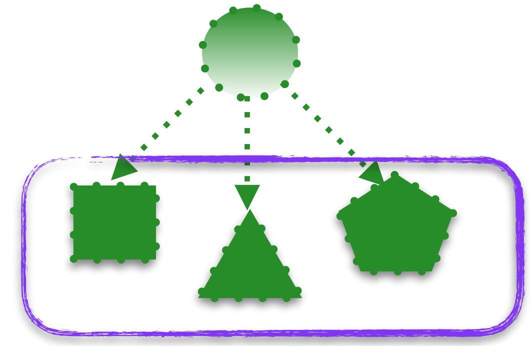
they should expect the experimenter to pull out all the same shape from a new box.



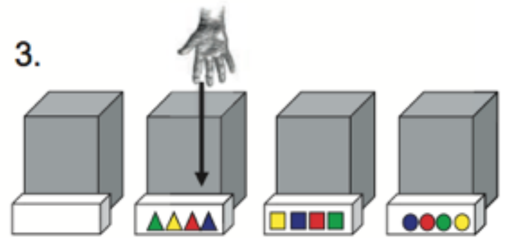
This shouldn't be surprising, and so infants shouldn't look as long at it.

Parameters & overhypotheses

linguistic parameter
overhypothesis



Dewar & Xu 2010
9-month-olds

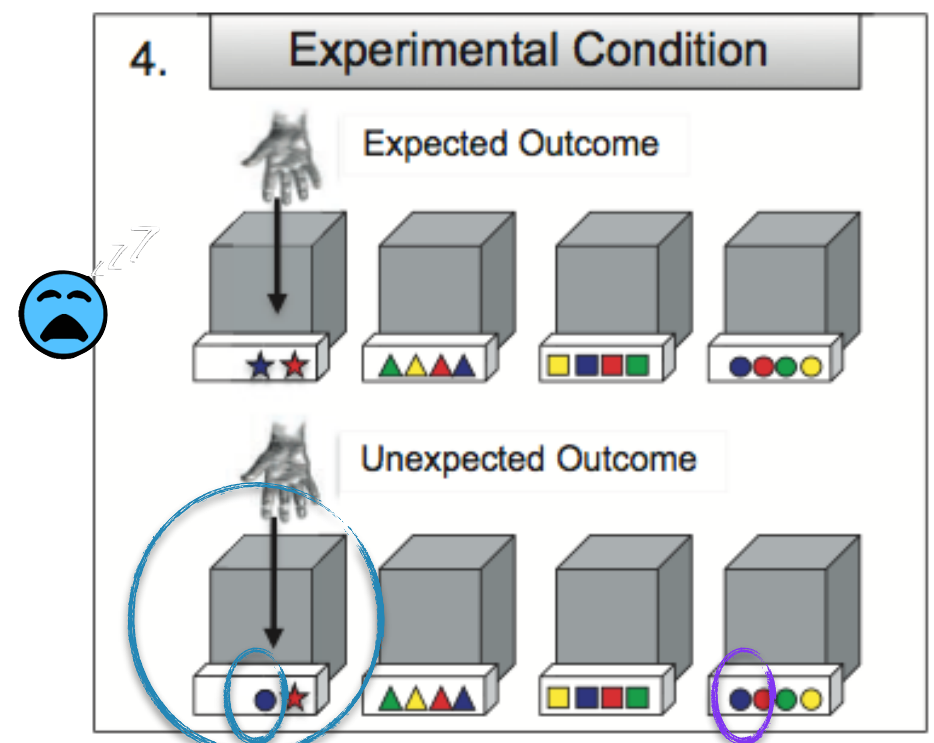


Training: different colors but same shape

Experimental condition

If infants create an overhypothesis that all objects in a box have the same shape…

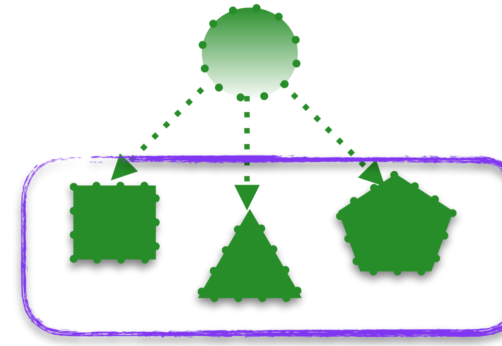
they shouldn't expect the experimenter to pull out different shapes from a new box, even if one is a shape they've seen before.



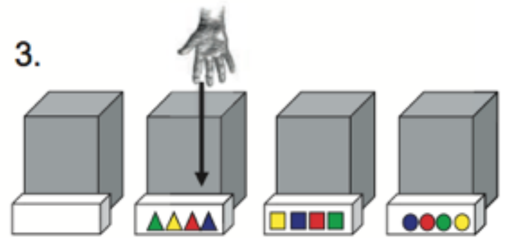
This should be surprising, and so infants should look longer at it.

Parameters & overhypotheses

linguistic parameter
overhypothesis



Dewar & Xu 2010
9-month-olds



Training: different colors but same shape

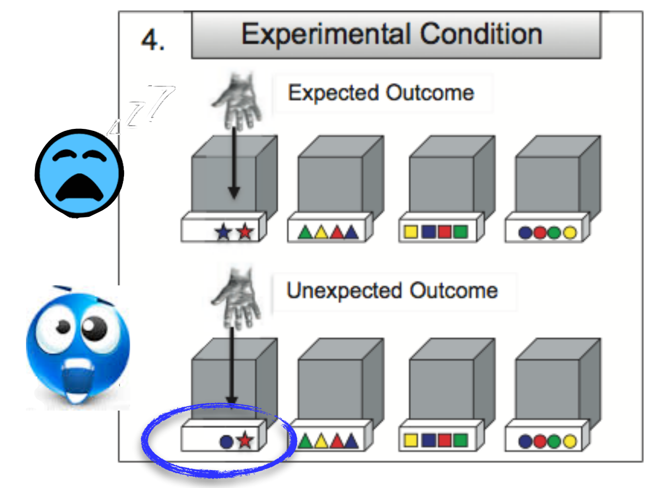
Control condition

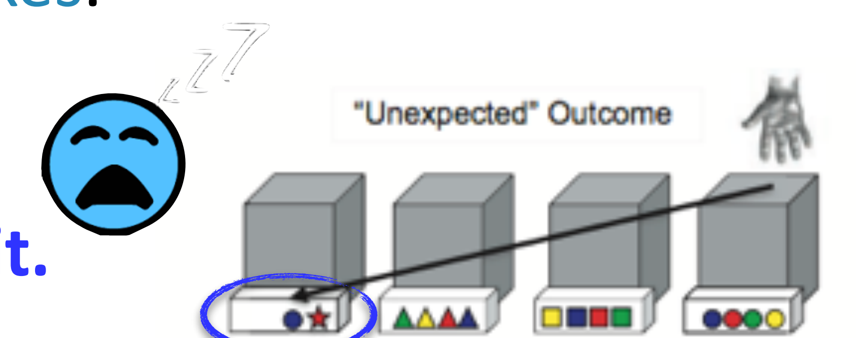
If infants create an overhypothesis that all objects in a box have the same shape…

they should expect the experimenter to pull out different shapes from different boxes.

This shouldn't be surprising, and so infants shouldn't look as long at it.

Experimental condition

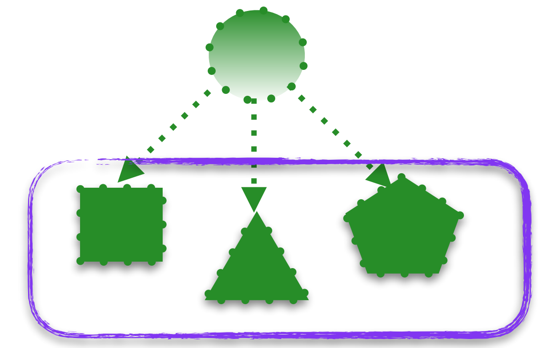




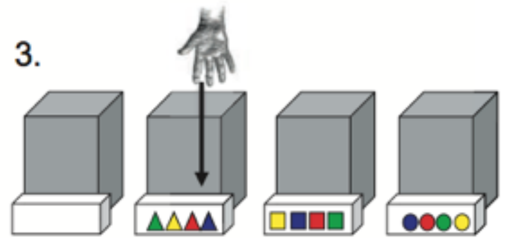
Note how this outcome looks identical to the experimental condition outcome.

Parameters & overhypotheses

linguistic parameter
overhypothesis



Dewar & Xu 2010
9-month-olds



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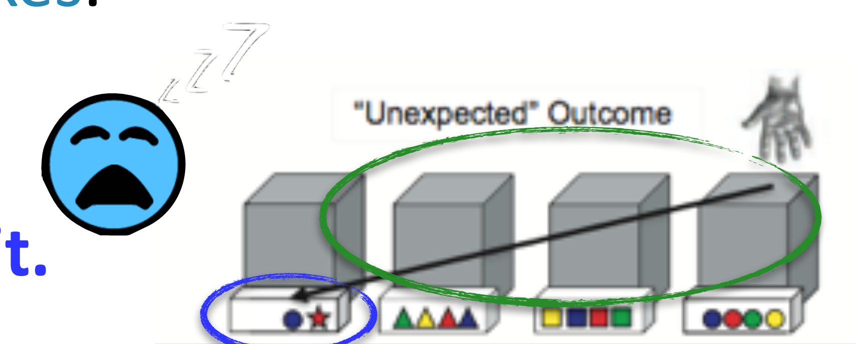
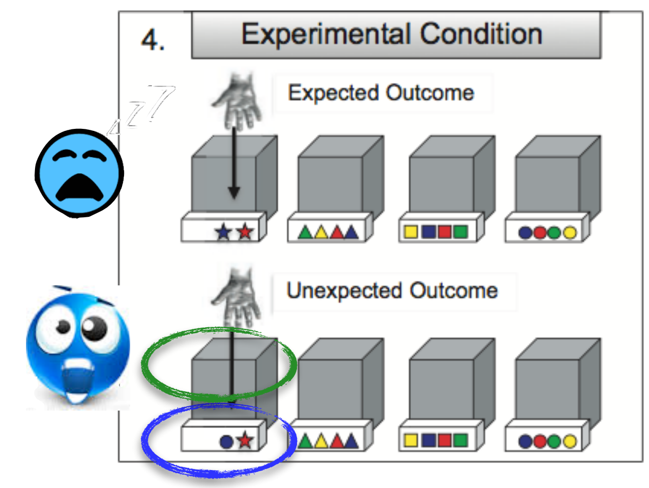


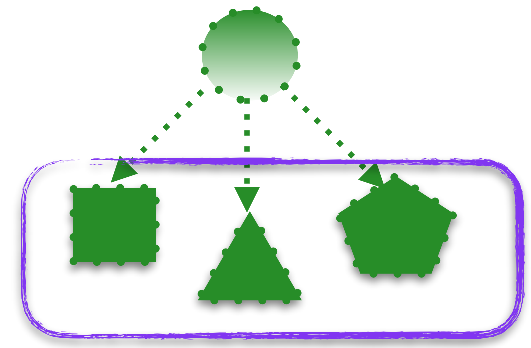
Experimental condition



The only difference is how the outcome was **generated** (from the same box or from different boxes — which is what the overhypothesis is about).

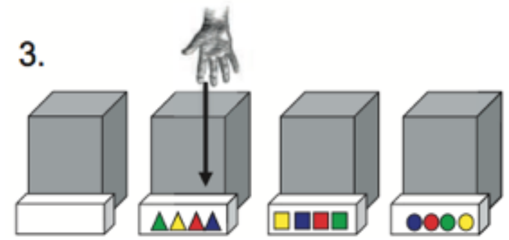
Parameters & overhypotheses

linguistic parameter
overhypothesis



Dewar & Xu 2010
9-month-olds

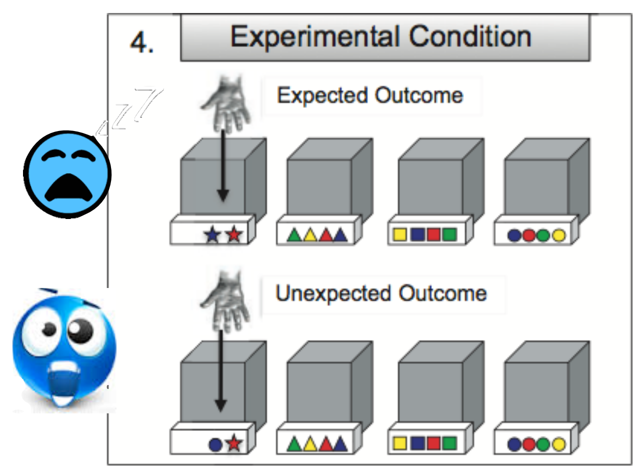
Training:
different colors but same shape



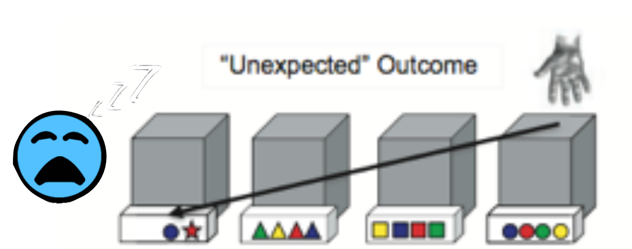
If infants create an overhypothesis that all objects in a box have the same shape

Experimental condition

This is what we expect.



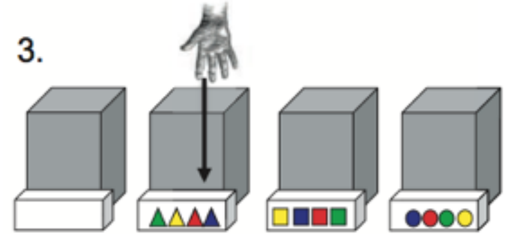
Control condition



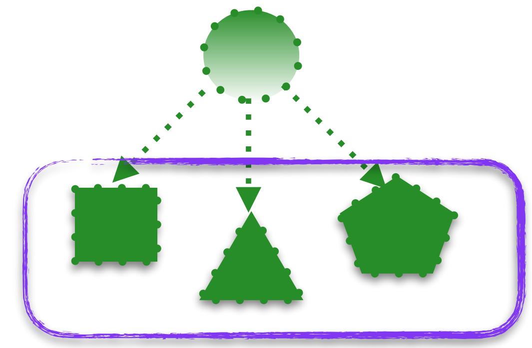
Parameters & overhypotheses

Dewar & Xu 2010
9-month-olds

Training:
different colors but same shape

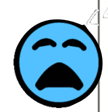


linguistic parameter
overhypothesis

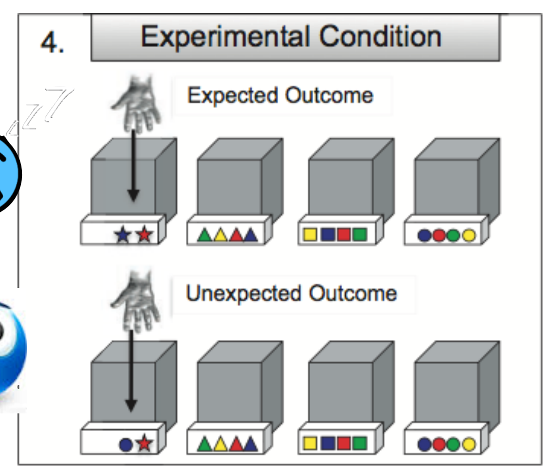


If infants create an overhypothesis that all objects in a box have the same shape

Experimental condition

~11.32 sec 

~14.28 sec 



And this is exactly what happened!

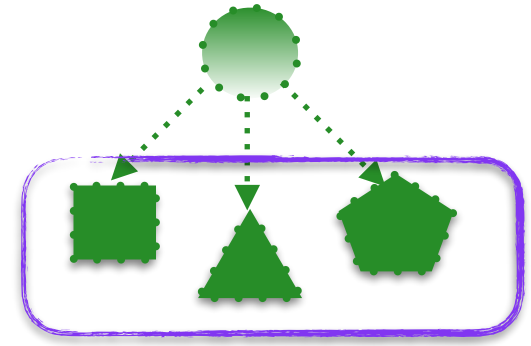
Control condition

~10.3-11.0 sec 

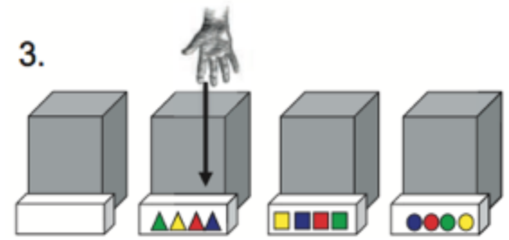
Dewar & Xu 2010
9-month-olds

Parameters & overhypotheses

linguistic parameter
overhypothesis

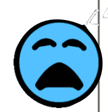


Training:
different colors but same shape



If infants create an overhypothesis that all objects in a box have the same shape

Experimental condition

~11.32 sec 

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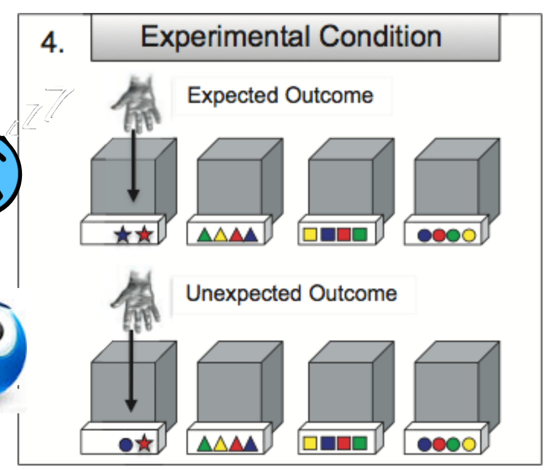


9-month-olds appear able to form overhypotheses from very limited data sets.

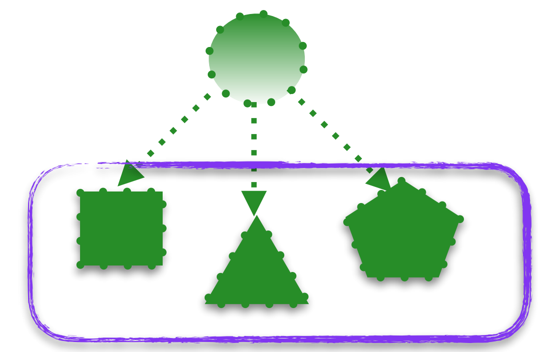
Control condition

~10.3-11.0 sec 

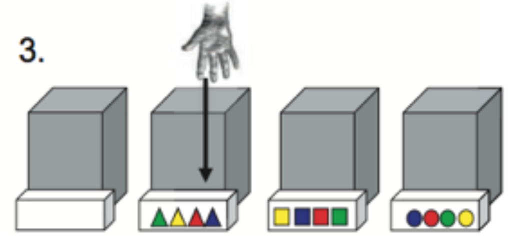
Parameters & overhypotheses

Dewar & Xu 2010
9-month-olds

linguistic parameter
overhypothesis

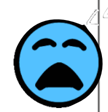


Training:
different colors but same shape

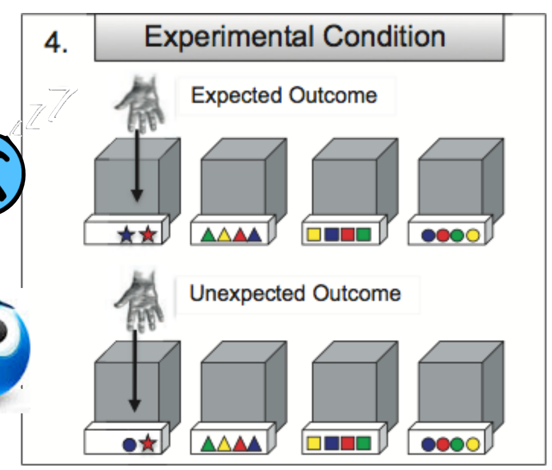


If infants create an overhypothesis that all objects in a box have the same shape

Experimental condition

~11.32 sec 

~14.28 sec 



Hopefully, this means they can also use linguistic parameters to learn, since parameters are similar to overhypotheses about language!

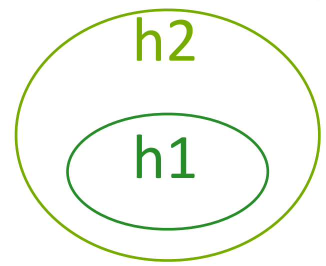
Control condition

~10.3-11.0 sec 

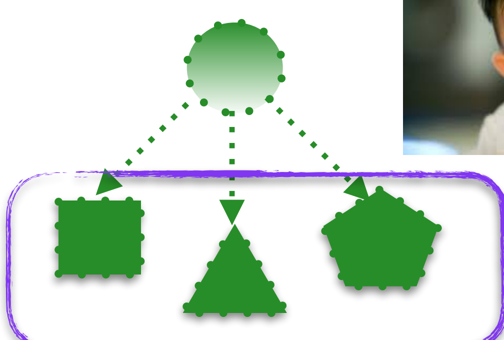
Today's Plan:
Bayesian inference & linguistic parameters

I. Bayesian reasoning

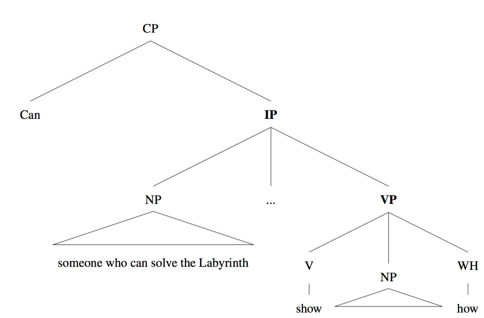
$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

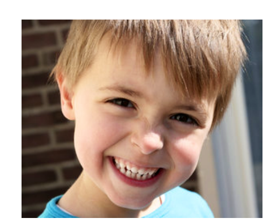


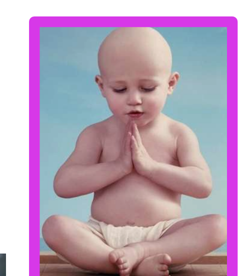
II. Parameters & overhypotheses

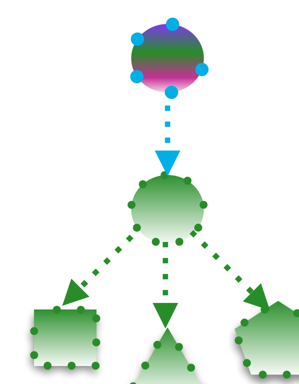


III. Structure dependence



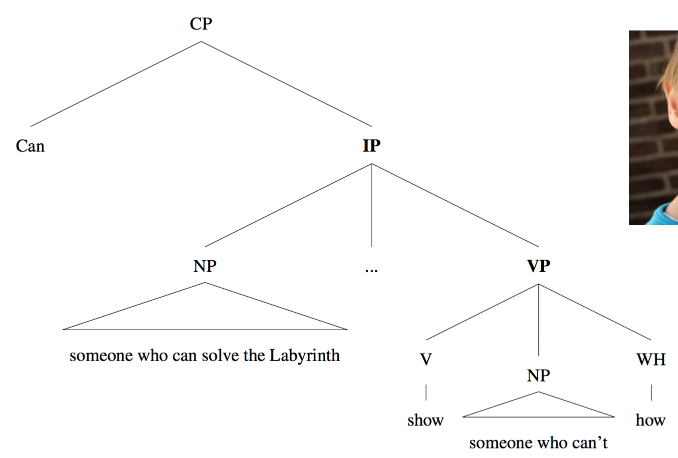


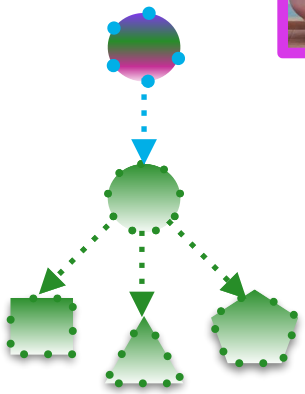




Today's Plan:
Bayesian inference & linguistic parameters

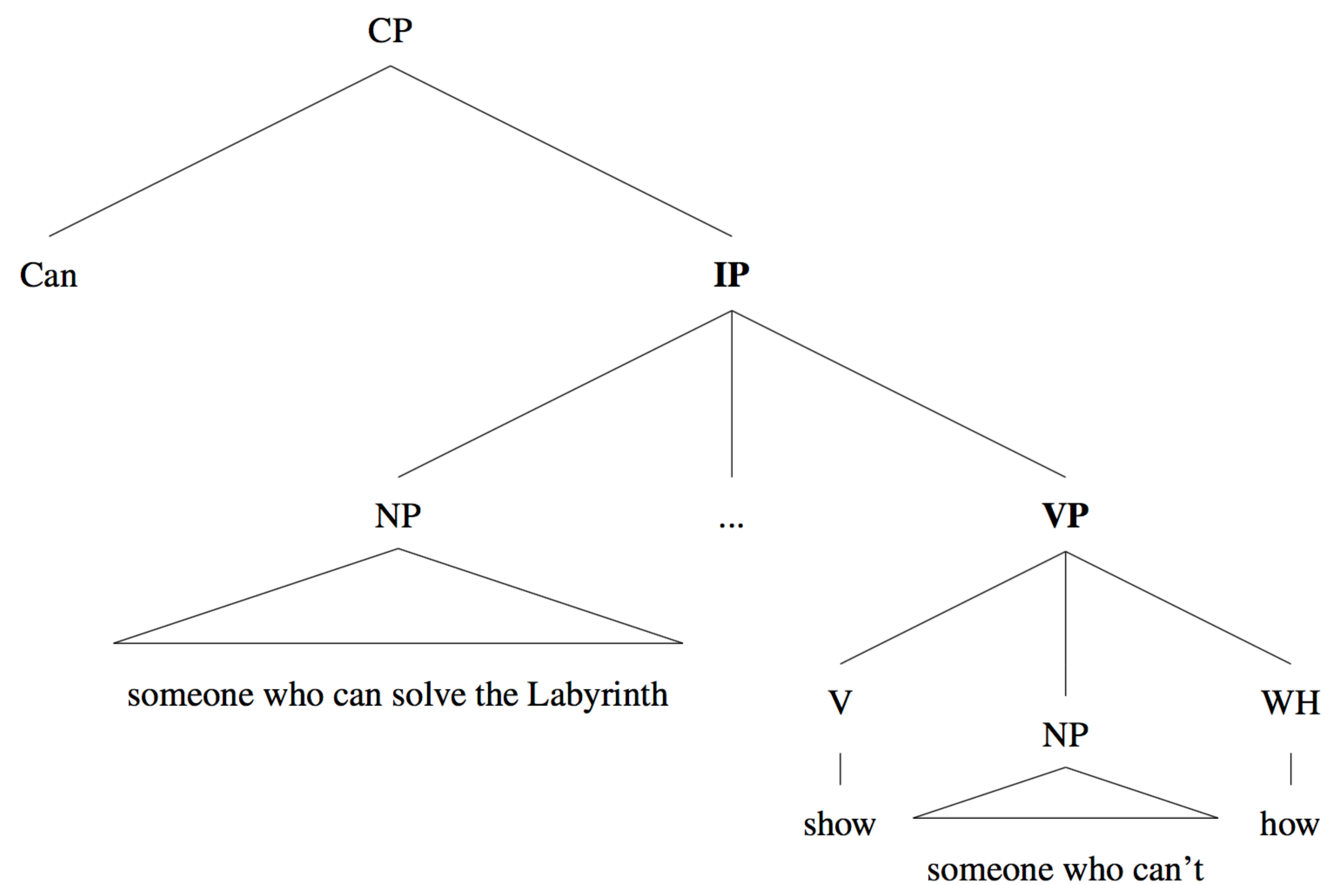
III. Structure dependence





Structure dependence

Idea: Rules for word order **depend on linguistic structure**



Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Statement

Jareth can alter time.

How do we turn this into a question whose answer is either yes or no?

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Yes/No question

Can Jareth alter time?

What changed?

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Statement

Jareth can alter time.

Yes/No question

Can Jareth alter time?

Where the auxiliary *can* appears.

Where the noun/subject *Jareth* appears.

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Statement

Jareth can alter time.

Yes/No question

Can Jareth alter time?

Where the auxiliary *can* appears.

Where the noun/subject *Jareth* appears.

The child's job: Figure out the rule for turning statements into yes/no questions.

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Rule: Something about one or both of these?

Where the auxiliary *can* appears.

Where the noun/subject *Jareth* appears.

Let's look at some additional data.

Rule? Swap the order of the first two words

Rule? Swap the order of the subject and the auxiliary

Rule? Move the first noun to the second position

Rule? Move the auxiliary to the first position

And there are others…

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Anyone who can wish away their brother would be tempted to do it.

Would anyone who can wish away their brother be tempted to do it?

This one doesn't capture the pattern.

~~**Rule? Swap the order of the first two words**~~

Rule? Swap the order of the subject and the auxiliary

Rule? Move the first noun to the second position

Rule? Move the auxiliary to the first position

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Anyone who can wish away their brother would be tempted to do it.

Would anyone who can wish away their brother be tempted to do it?

Which auxiliary and what's "swapping" mean if they're not next to each other?

Rule? Swap the order of the subject and the auxiliary

Rule? Move the first noun to the second position

Rule? Move the auxiliary to the first position

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Anyone who can wish away their brother would be tempted to do it.

Would anyone who can wish away their brother be tempted to do it?

This doesn't handle "would" being in the first position.

~~**Rule? Move the first noun to the second position**~~

Rule? Move the auxiliary to the first position

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Anyone who can wish away their brother **would** be tempted to do it.

Would anyone who can wish away their brother be tempted to do it?

Which auxiliary?

Rule? Move the auxiliary to the first position

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Anyone who can wish away their brother **would** be tempted to do it.

Would anyone who can wish away their brother be tempted to do it?

This would capture the first question's pattern too.

Rule? Move the last auxiliary to the first position

Let's look at some additional data.

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Anyone who can wish away their brother **would** be tempted to do it.

Would anyone who can wish away their brother be tempted to do it?

Someone who can solve the labyrinth **can** show someone else who can't how.

Can someone who can solve the labyrinth show someone else who can't how?

This doesn't capture the pattern.

Rule? Move the last auxiliary to the first position

Now what?

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

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Would anyone who can wish away their brother be tempted to do it?

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Can someone who can solve the labyrinth show someone else who can't how?

This doesn't capture the pattern.

Rule? Move the last auxiliary to the first position

Let's try incorporating structure.

Structure dependence

Rules for word order **depend on linguistic structure**

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Can Jareth alter time?

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Would anyone who can wish away their brother be tempted to do it?

Someone who can solve the labyrinth **can** show someone else who can't how.

Can someone who can solve the labyrinth show someone else who can't how?

✔ **Rule? Move the main clause auxiliary to the first position**

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Anyone who can wish away their brother **would** be tempted to do it.

Would anyone who can wish away their brother be tempted to do it?

Main subject

Someone who can solve the labyrinth **can** show someone else who can't how.

Can someone who can solve the labyrinth show someone else who can't how?

✔ **Rule? Move the main clause auxiliary to the first position**

Structure dependence

Rules for word order **depend on linguistic structure**

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Would anyone who can wish away their brother be tempted to do it?

Main subject **Main objects**

Someone who can solve the labyrinth **can** show someone else who can't how.

Can someone who can solve the labyrinth show someone else who can't how?

✔ **Rule? Move the main clause auxiliary to the first position**

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Would anyone who can wish away their brother be tempted to do it?

Main subject **Main verb phrase** **Main objects**

Someone who can solve the labyrinth **can** show someone else who can't how.

Can someone who can solve the labyrinth show someone else who can't how?

✔ **Rule? Move the main clause auxiliary to the first position**

Structure dependence

Rules for word order **depend on linguistic structure**

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Main subject **Main verb phrase** **Main objects**

Someone who can solve the labyrinth **can** show someone else who can't how.

Can someone who can solve the labyrinth show someone else who can't how?

✔ **Rule? Move the main clause auxiliary to the first position**

This also works for the other examples.

Structure dependence

Rules for word order **depend on linguistic structure**

An example: Yes/No question formation in English

Jareth can alter time.

Can Jareth alter time?

Anyone who can wish away their brother **would** be tempted to do it.

Would anyone who can wish away their brother be tempted to do it?

Main subject **Main verb phrase** **Main objects**

Someone who can solve the labyrinth **can** show someone else who can't how.

Can someone who can solve the labyrinth show someone else who can't how?

✔ **Rule? Move the main clause auxiliary to the first position**

Because this rule refers to clause structure, it's structure-dependent.

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

✔ **Rule? Move the main clause auxiliary to the first position**

When do children figure this out?

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

✔ **Rule? Move the main clause auxiliary to the first position**

Crain & Nakayama 1987

Elicited productions from three- to five-year-olds

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

✔ **Rule? Move the main clause auxiliary to the first position**

Crain & Nakayama 1987

Elicited productions from three- to five-year-olds







"Ask Jabba if…

"…the boy who can see Mickey Mouse is happy."
"…the boy who is happy can see Mickey Mouse."

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

✔ **Rule? Move the main clause auxiliary to the first position**

Crain & Nakayama 1987

Elicited productions from three- to five-year-olds

Common errors that occurred:

(Restarts)
- simplifying the subject so main clause auxiliary is more accessible

"**Is** the boy who can see Mickey Mouse, **is** he happy?"

"**Can** the boy who is happy, **can** he see Mickey Mouse?

"Ask Jabba if…

"…the boy who can see Mickey Mouse ***is*** *happy."*

"…the boy who is happy ***can*** *see Mickey Mouse."*

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

✔ **Rule? Move the main clause auxiliary to the first position**

Crain & Nakayama 1987

Elicited productions from three- to five-year-olds

Common errors that occurred:

(Restarts) - simplifying the subject so main clause auxiliary is more accessible

(Initial *is* prefix) - giving up (sort of a generic question marking)

"Is *the boy who can see Mickey Mouse **is** happy*?"

"Is *the boy who is happy **can** see Mickey Mouse*?"

"Ask Jabba if…

*"…the boy who can see Mickey Mouse **is** happy."*

*"…the boy who is happy **can** see Mickey Mouse."*

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

✔ **Rule? Move the main clause auxiliary to the first position**

Crain & Nakayama 1987

Elicited productions from three- to five-year-olds

Common errors that occurred:

(Restarts) - simplifying the subject so main clause auxiliary is more accessible

(Initial *is* prefix) - giving up (sort of a generic question marking)

Errors that *didn't* occur (Structure-independent auxiliary movement)

*"Can the boy who __ see Mickey Mouse **is** happy?"*

*"Is the boy who __ happy **can** see Mickey Mouse?*

"Ask Jabba if...

*"...the boy who can see Mickey Mouse **is** happy."*

*"...the boy who is happy **can** see Mickey Mouse."*

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

✔ **Rule? Move the main clause auxiliary to the first position**

Crain & Nakayama 1987

Elicited productions from three- to five-year-olds

Common errors that occurred:

(Restarts) - simplifying the subject so main clause auxiliary is more accessible

(Initial *is* prefix) - giving up (sort of a generic question marking)

Errors that *didn't* occur (Structure-independent auxiliary movement)

How we can interpret this: As young as three years old, children have some very specific constraints on the kind of hypotheses they'll consider for complex yes/no questions.

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

By three years old, children have some very specific constraints on hypotheses about word order.

How could they learn this?

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

By three years old, children have some very specific constraints on hypotheses about word order.

A potential input issue

Most of the yes/no question data children encounter (particularly before the age of 3) consists of simple yes/no questions compatible with many different rules.

Jareth can alter time.

Can Jareth alter time?

Rule? Swap the order of the first two words

Rule? Swap the order of the subject and the auxiliary

Rule? Move the first noun to the second position

Rule? Move the auxiliary to the first position

Rule? Move the main clause auxiliary to the first position

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

By three years old, children have some very specific constraints on hypotheses about word order.

A potential input issue

Most of the yes/no question data children encounter (particularly before the age of 3) consists of simple yes/no questions compatible with many different rules.

Jareth can alter time.

Can Jareth alter time?

But structure-dependence is a very ***general* property** about language…

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

By three years old, children have some very specific constraints on hypotheses about word order.

A potential input issue

Most of the yes/no question data children encounter (particularly before the age of 3) consists of simple yes/no questions compatible with many different rules.

Jareth can alter time.

Can Jareth alter time?

It could be an **overhypothesis** about language.

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

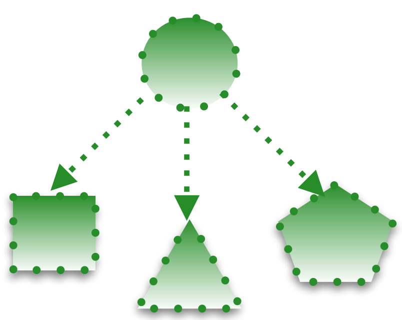
By three years old, children have some very specific constraints on hypotheses about word order.

A potential input issue

Most of the yes/no question data children encounter (particularly before the age of 3) consists of simple yes/no questions compatible with many different rules.

Jareth can alter time.

Can Jareth alter time?



The girl in the Labyrinth thought something.

What did the girl in the Labyrinth think?

And this overhypothesis would connect to many other structures besides yes/no questions.

Structure dependence

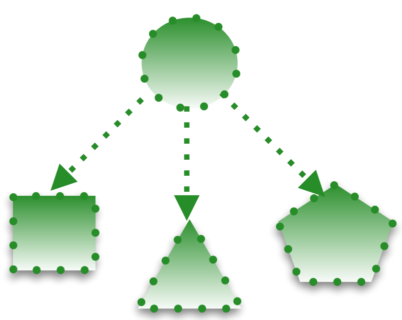
Rules for word order **depend on linguistic structure**

Yes/No question formation in English

By three years old, children have some very specific constraints on hypotheses about word order.

A potential input issue

Most of the yes/no question data children encounter (particularly before the age of 3) consists of simple yes/no questions compatible with many different rules.

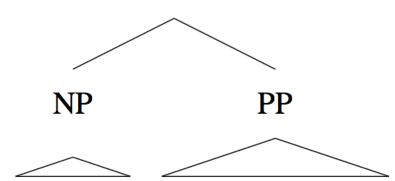


Jareth can alter time.

Can Jareth alter time?

The girl in the Labyrinth thought something.

What did the girl in the Labyrinth think?



The girl in the Labyrinth

And this overhypothesis would connect to many other structures besides yes/no questions.

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

By three years old, children have some very specific constraints on hypotheses about word order.

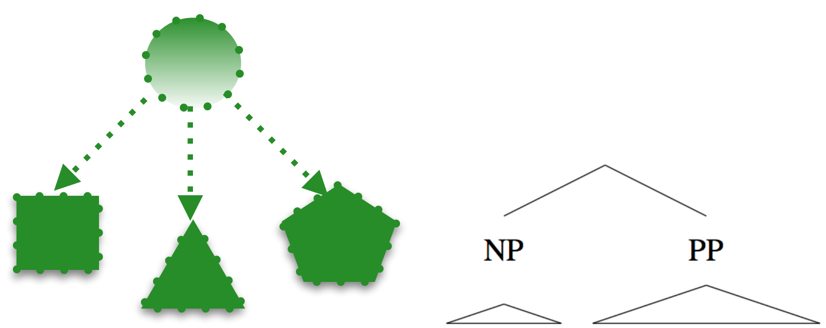
A potential input issue - may not be as bad

Children could encounter a lot of data that might favor structured representations over unstructured ones (e.g., linear structures)

overhypothesis

Jareth can alter time.

Can Jareth alter time?



The girl in the Labyrinth thought something.

What did the girl in the Labyrinth think?

The girl in the Labyrinth

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Yes/No question formation in English

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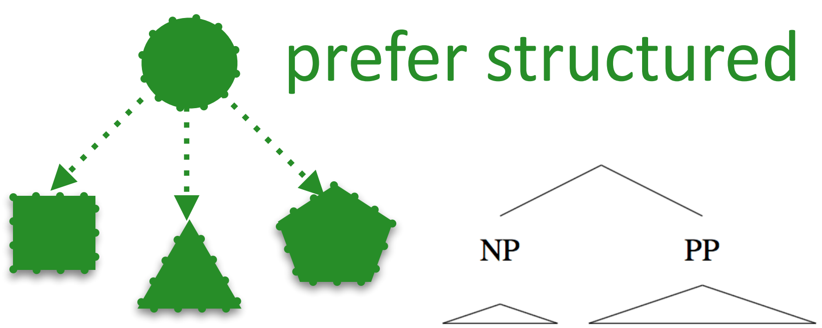
A potential input issue - may not be as bad

Children could encounter a lot of data that might favor structured representations over unstructured ones (e.g., linear structures)

overhypothesis

prefer structured representations



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The girl in the Labyrinth

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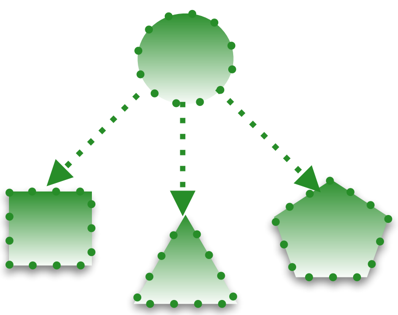
Perfors, Tenenbaum, & Regier 2011



computational-level modeled learner

Structure dependence

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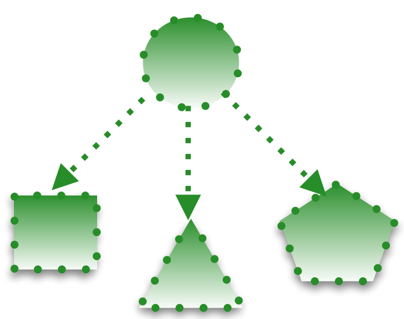
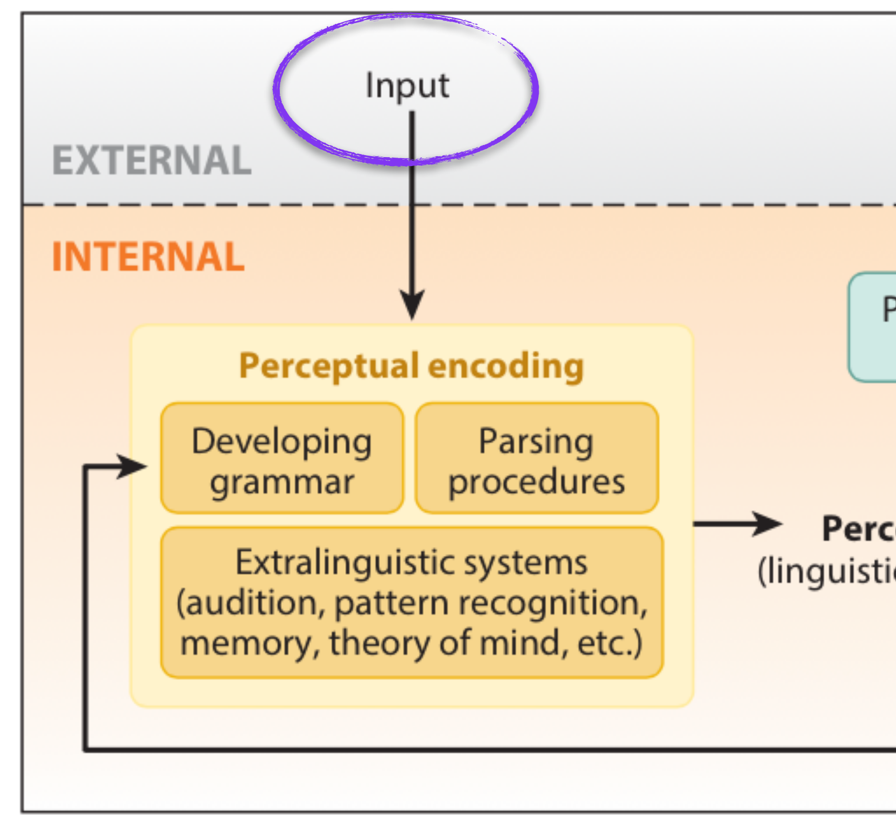
Perfors, Tenenbaum, & Regier 2011



Learned from realistic samples of child-directed English speech



Lidz & Gagliardi 2015

Structure dependence

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Yes/No question formation in English

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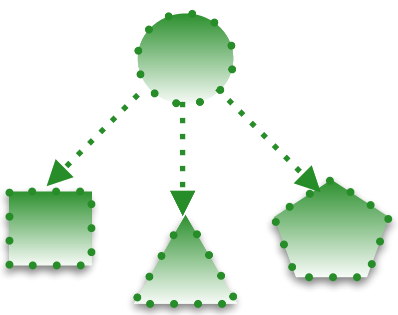
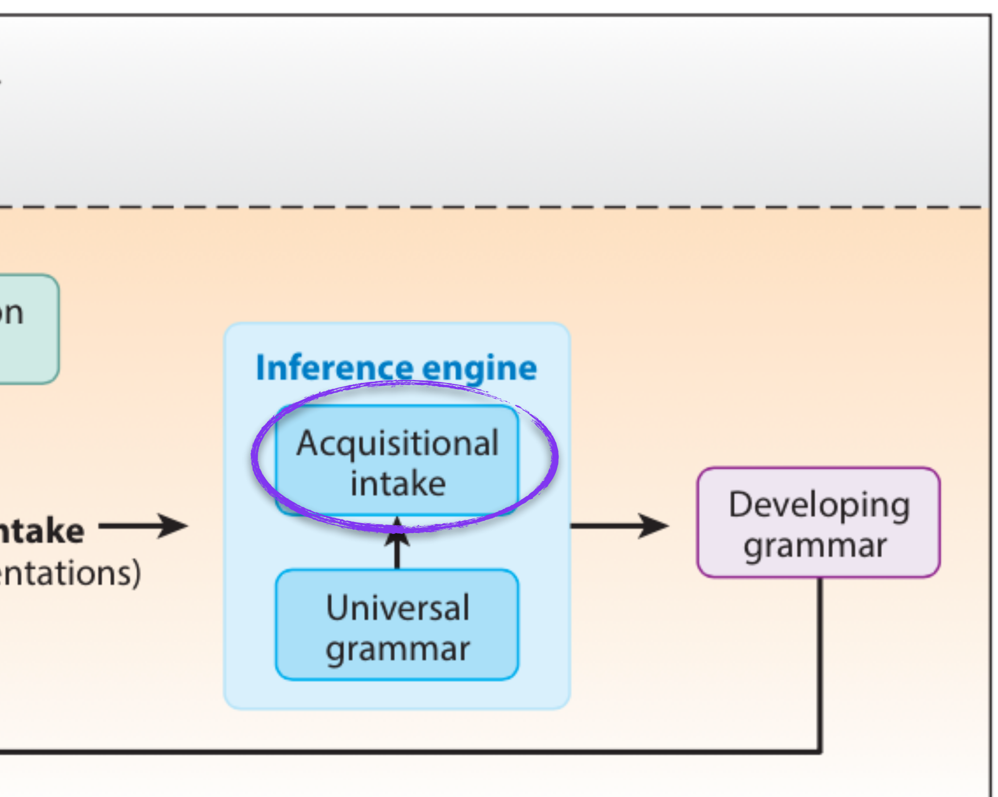
Perfors, Tenenbaum, & Regier 2011



Learned from realistic samples of child-directed English speech abstracted into syntactic category sequences



Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

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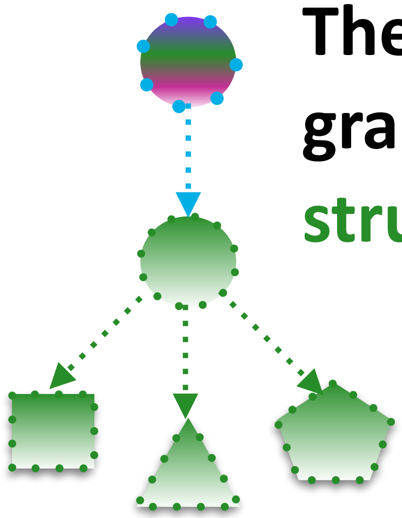
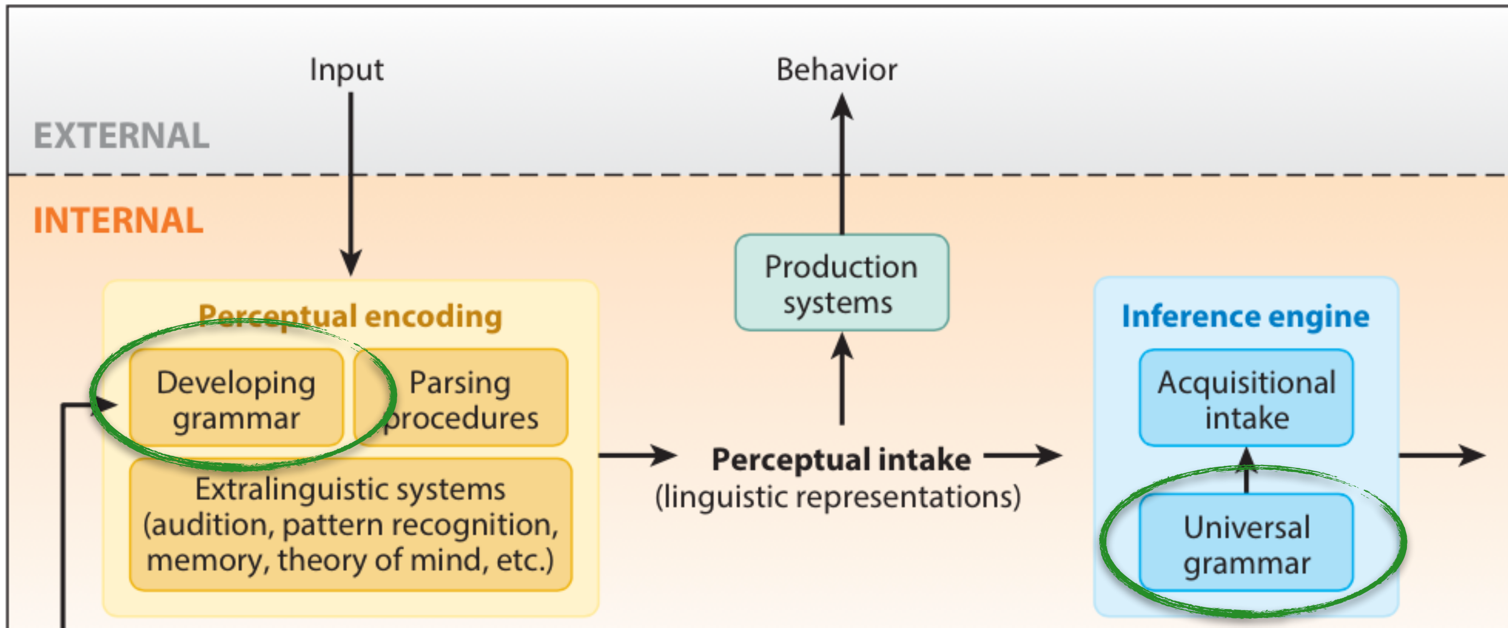
Perfors, Tenenbaum, & Regier 2011

Hypotheses



There are different types of grammars available (e.g., structure-dependent vs. linear)



Structure dependence

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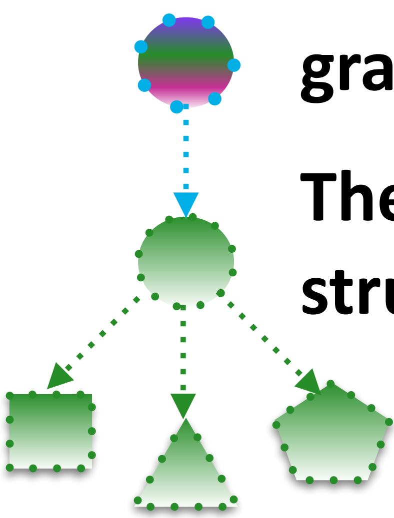
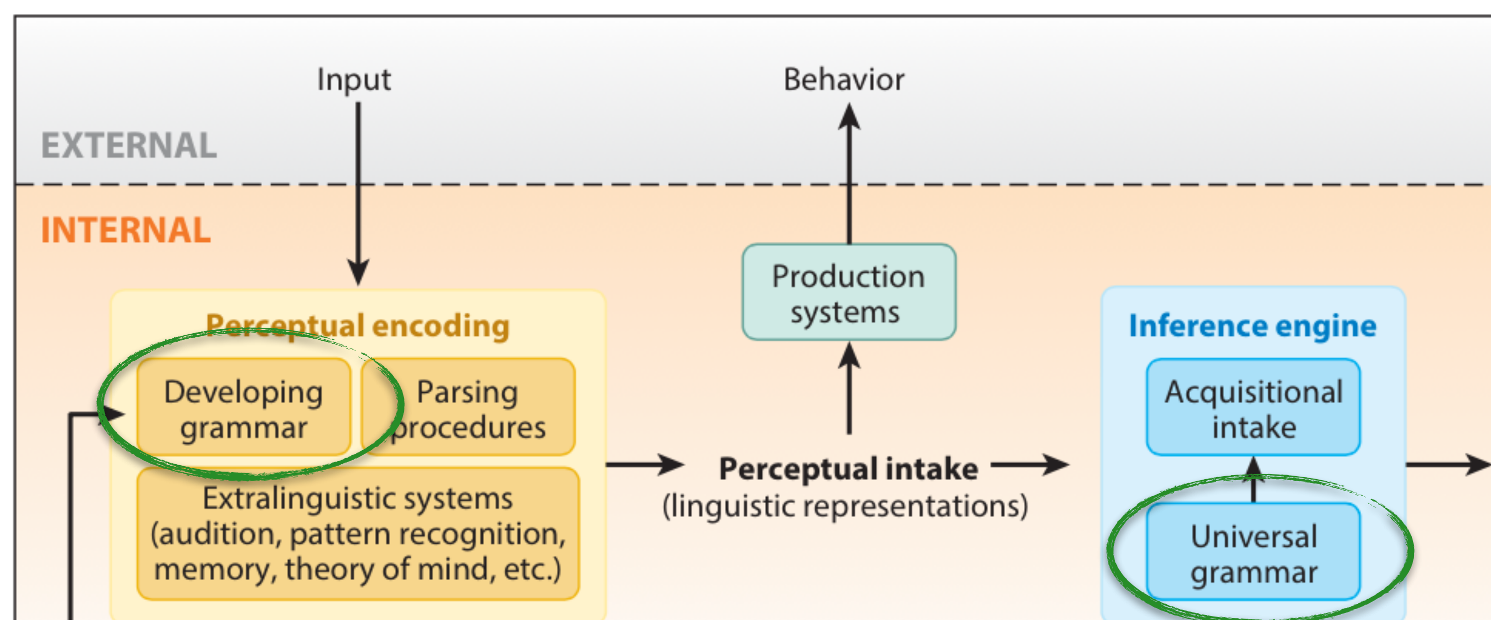
Perfors, Tenenbaum, & Regier 2011

Hypotheses



grammar type

There are specific grammars of each type (e.g., different structure-dependent grammars)



Structure dependence

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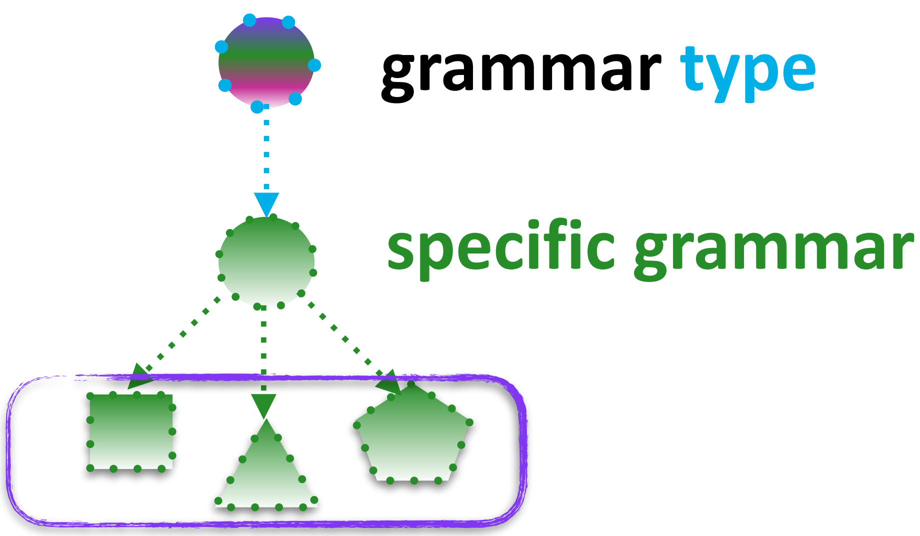
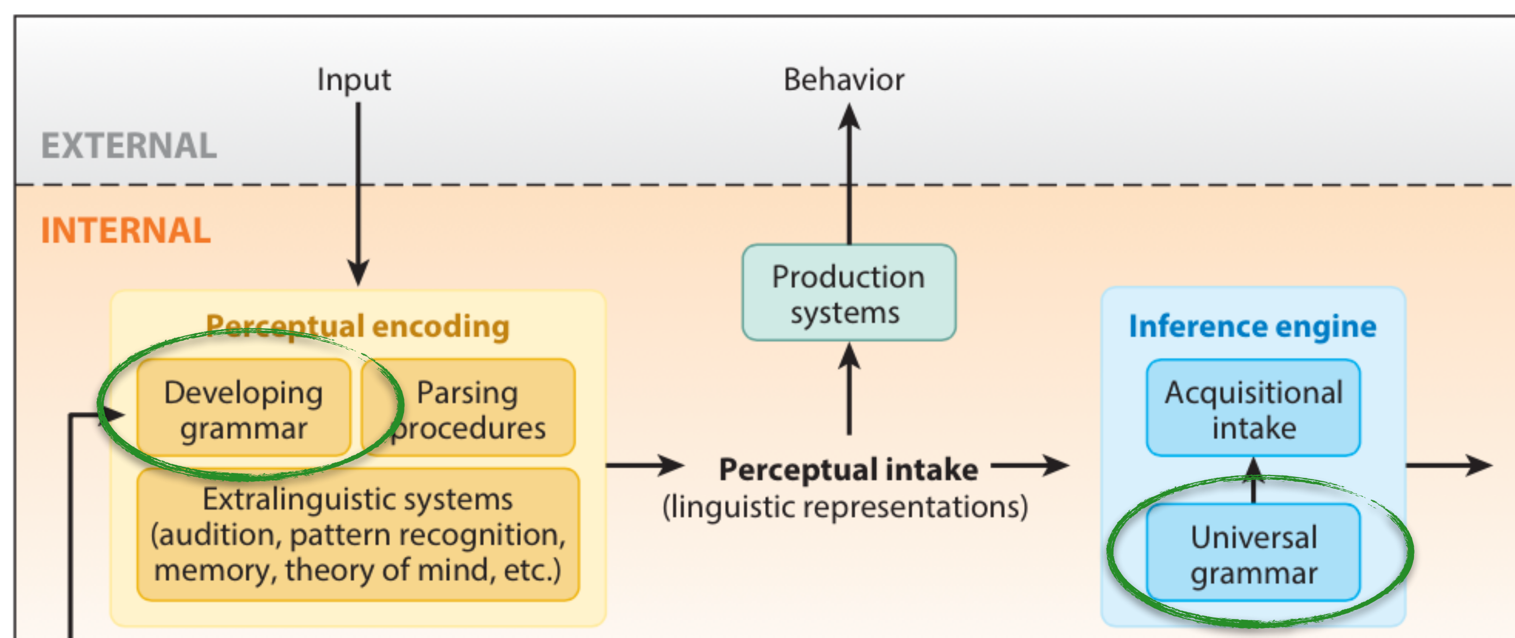
Perfors, Tenenbaum, & Regier 2011

Hypotheses



Each grammar connects to specific structures in the observable data



Structure dependence

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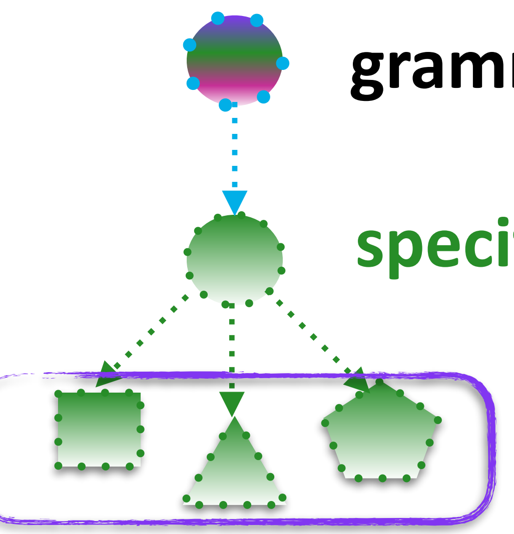
Perfors, Tenenbaum, & Regier 2011



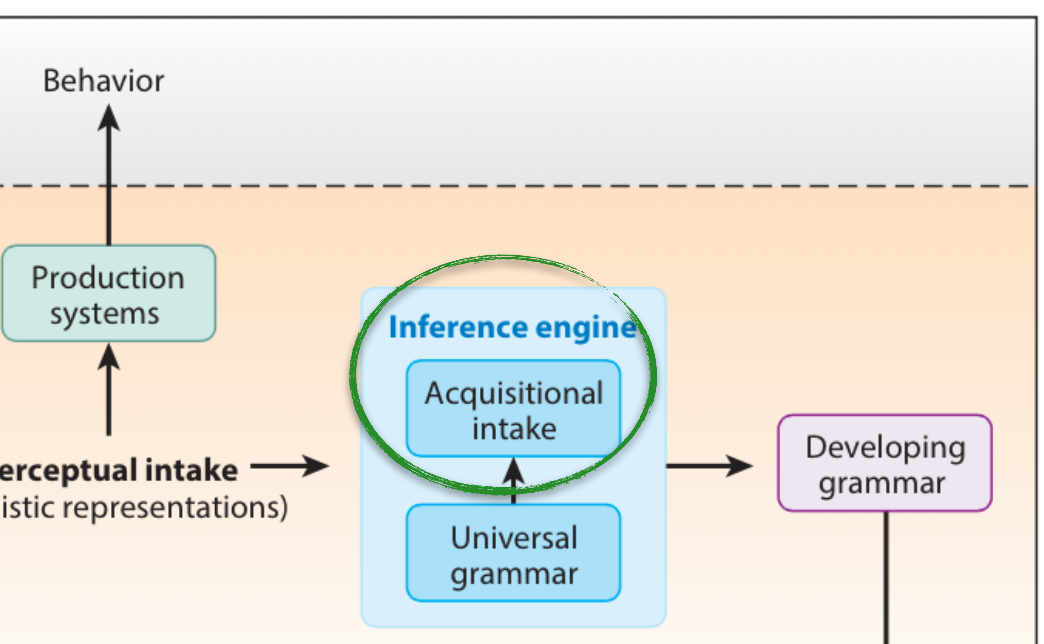
grammar type

specific grammar

structures in observable data

Use Bayesian inference to infer the best grammar type & specific grammar, given the child-directed speech data.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$



Structure dependence

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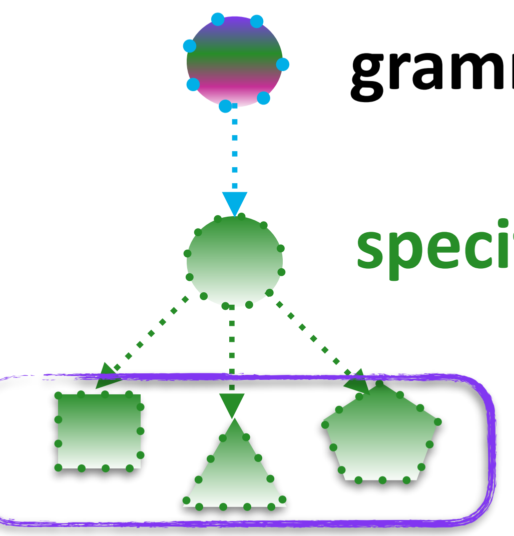
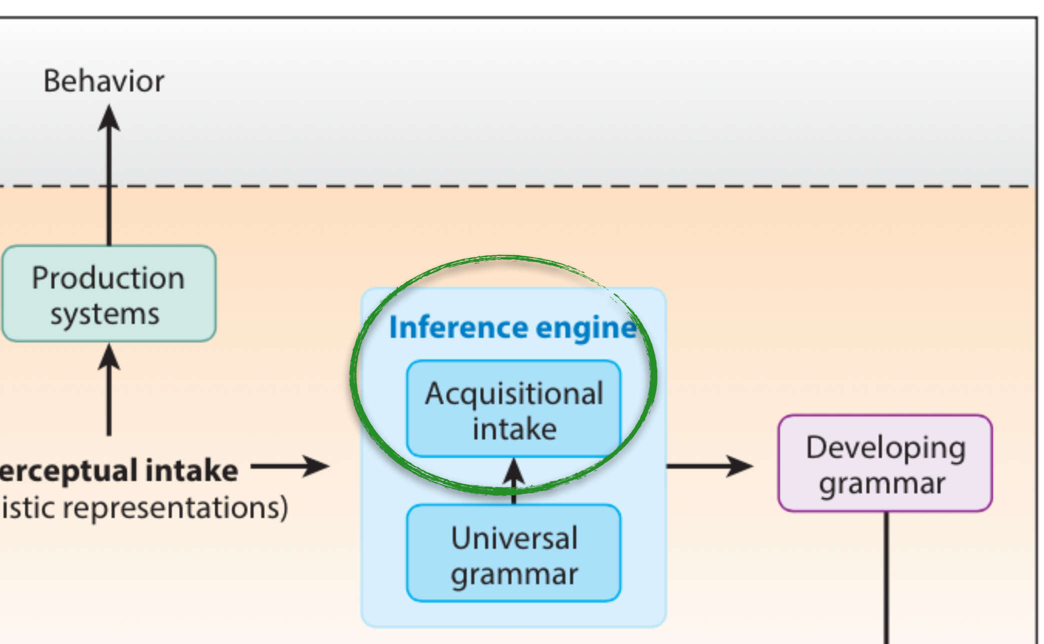


grammar type

specific grammar

structures in observable data



Note: The priors for different grammars aren't equal. Structure-dependent grammars are more complex than other grammar types being considered, and so have lower prior probability.

$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

This means structure-dependent grammars are actually *disfavored* a priori!

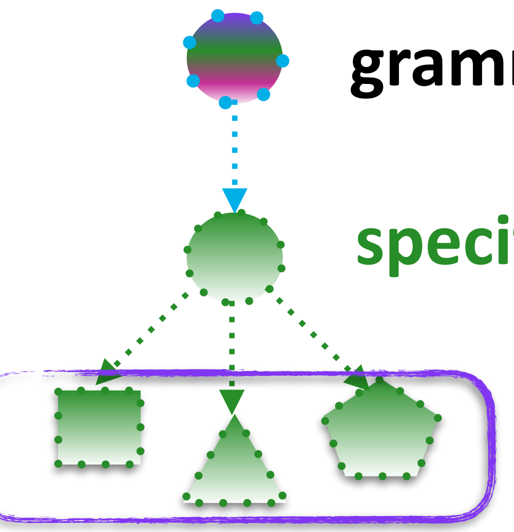
Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

By three years old, children have some very specific constraints on hypotheses about word order.

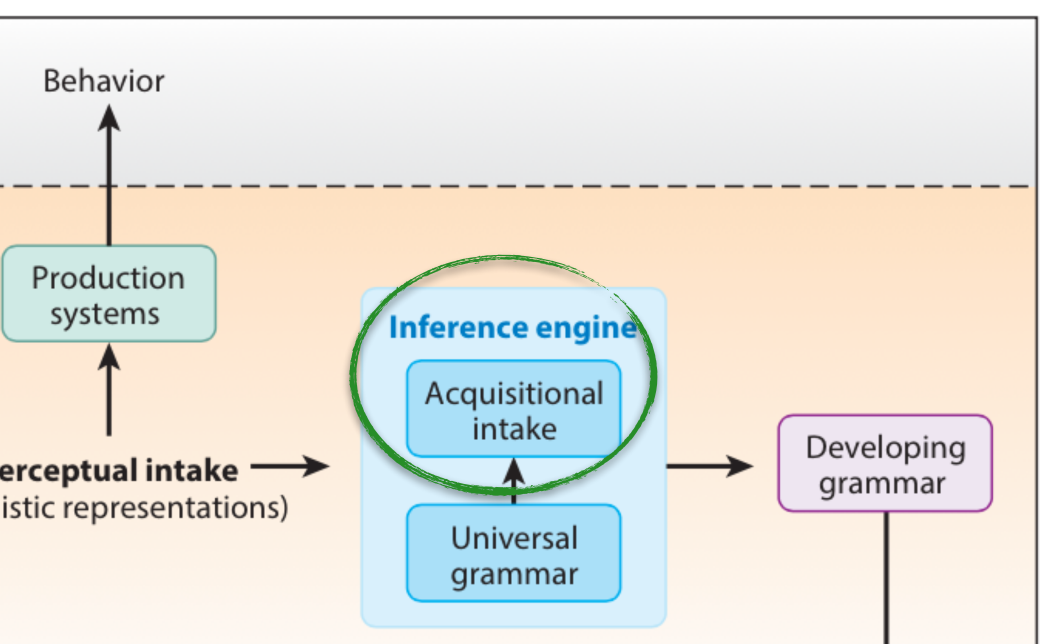
Perfors, Tenenbaum, & Regier 2011



grammar type

specific grammar

structures in observable data



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$$P(h|D) = \frac{P(D|h) * P(h)}{P(D)}$$

This means they really have to do a better job accounting for the data to be preferred!

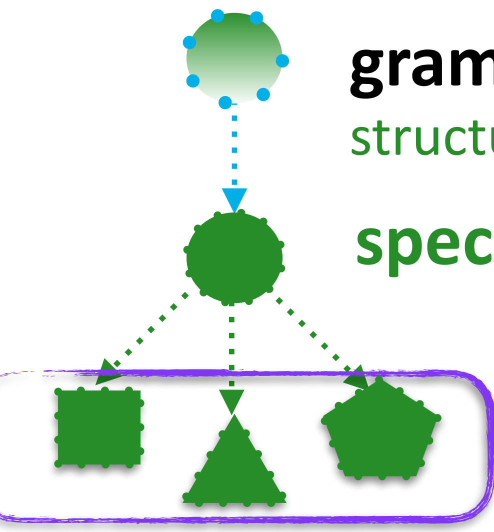
Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

By three years old, children have some very specific constraints on hypotheses about word order.

Perfors, Tenenbaum, & Regier 2011

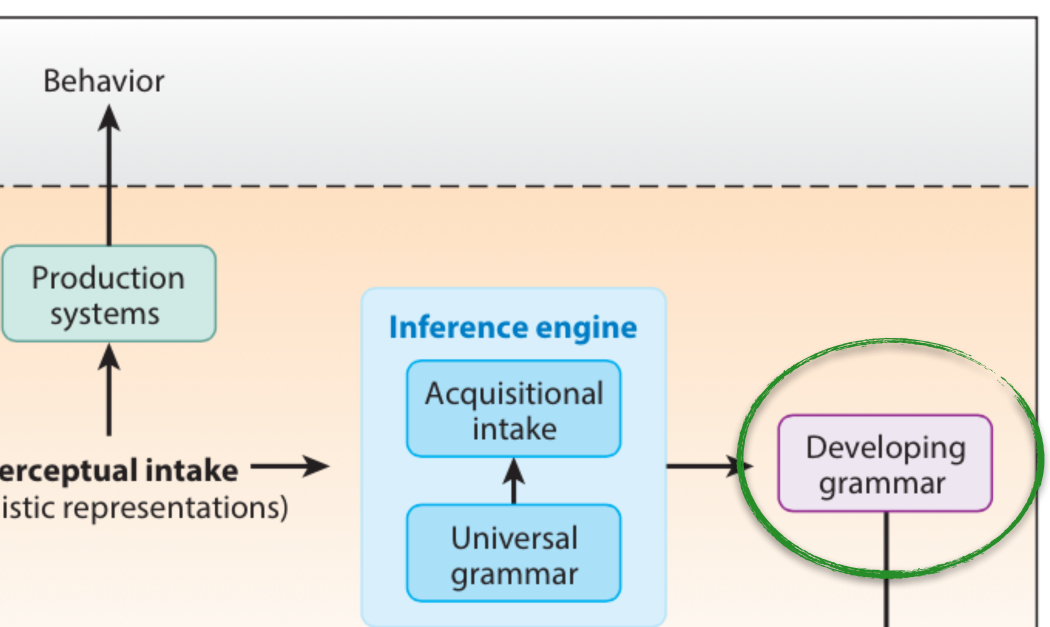


grammar type

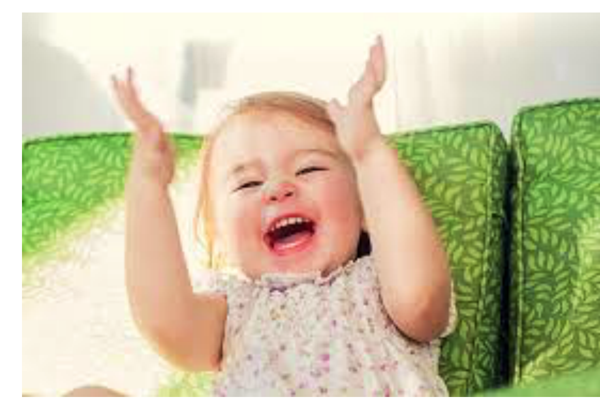
structure-dependent

specific grammar

structures in observable data



And this is exactly what happens!



$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

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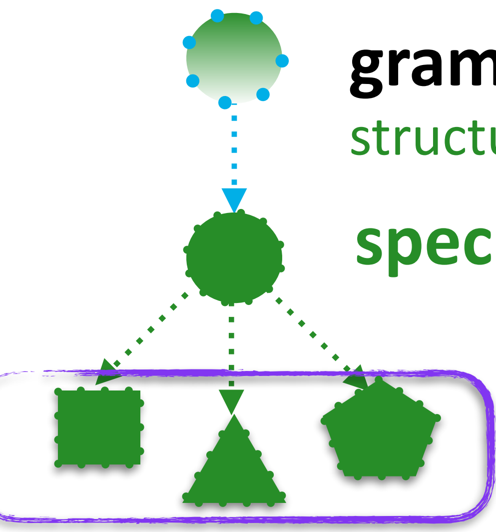
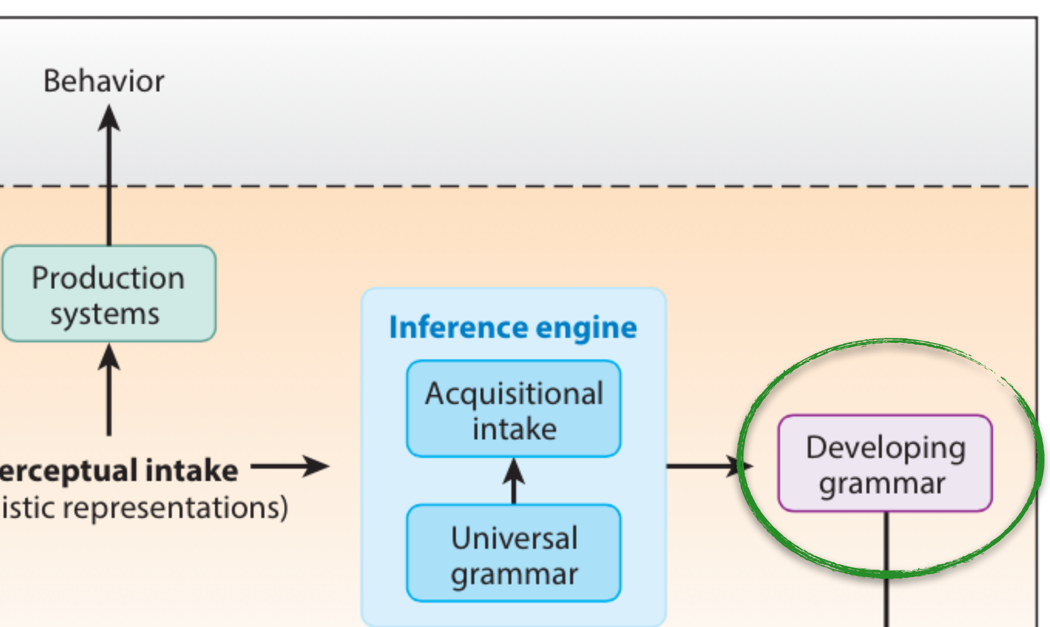
Perfors, Tenenbaum, & Regier 2011



grammar type
structure-dependent

specific grammar

structures in observable data



Even for the earliest child-directed speech samples (directed at children **two years old**), the structure-dependent grammar types are preferred.

Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

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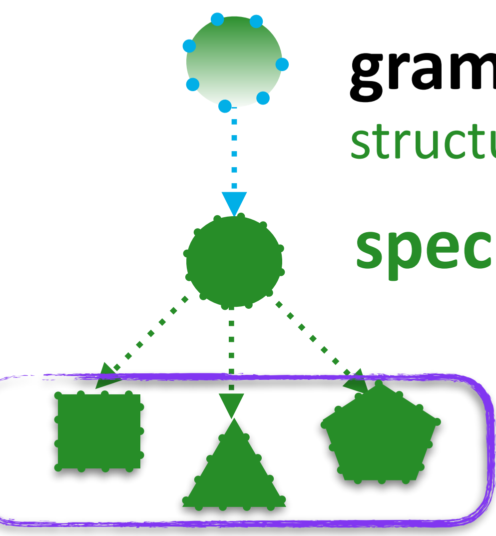
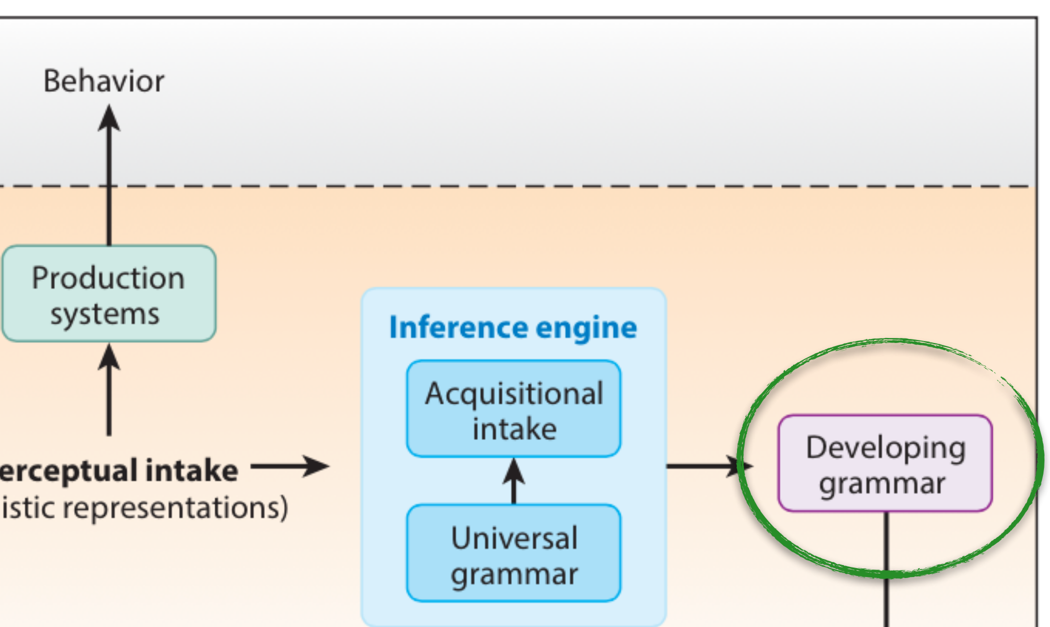


grammar type
structure-dependent

specific grammar

structures in observable data

two years old



Why? Because many different data types favor structure-dependent representations over other simpler representations.

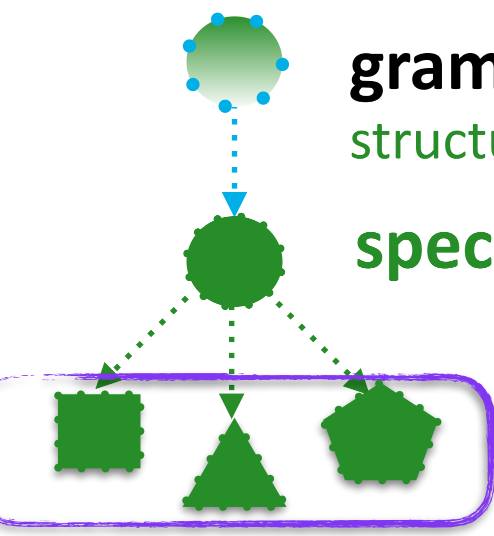
Structure dependence

Rules for word order **depend on linguistic structure**

Yes/No question formation in English

$$P(h|D) = \frac{P(D|h)*P(h)}{P(D)}$$

Perfors, Tenenbaum, & Regier 2011

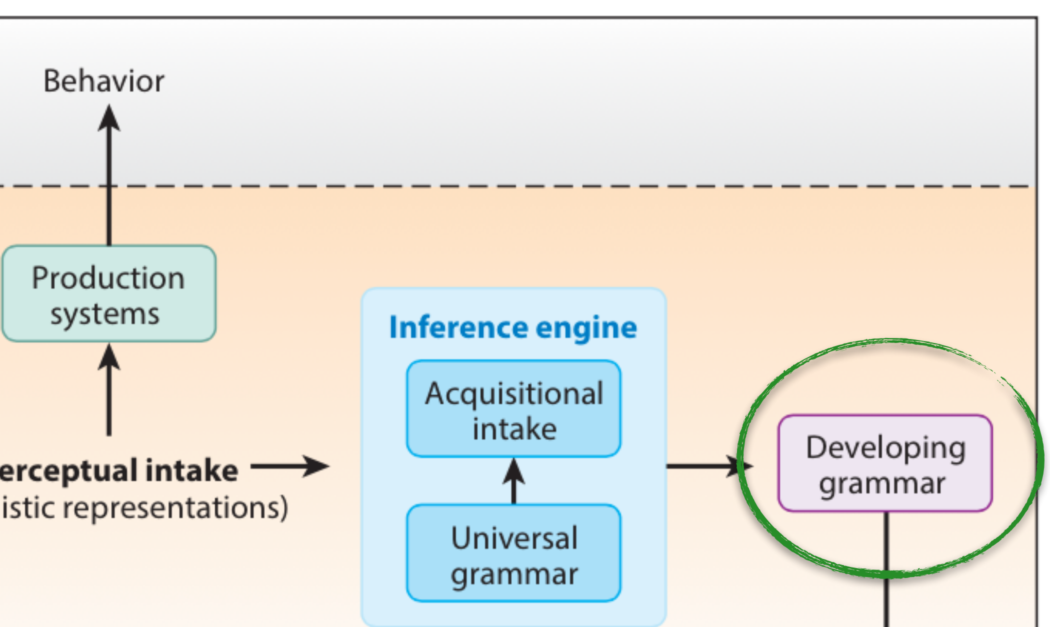


grammar type
structure-dependent

specific grammar

structures in observable data

two years old



By three years old, children have some very specific structure-dependent constraints on hypotheses about word order.

Structure dependence

Rules for word order **depend on linguistic structure**

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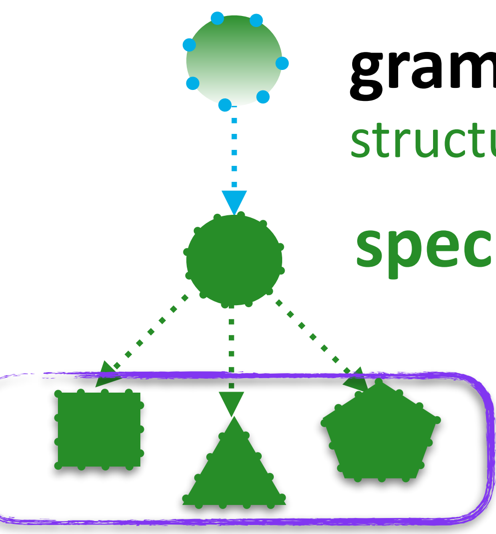
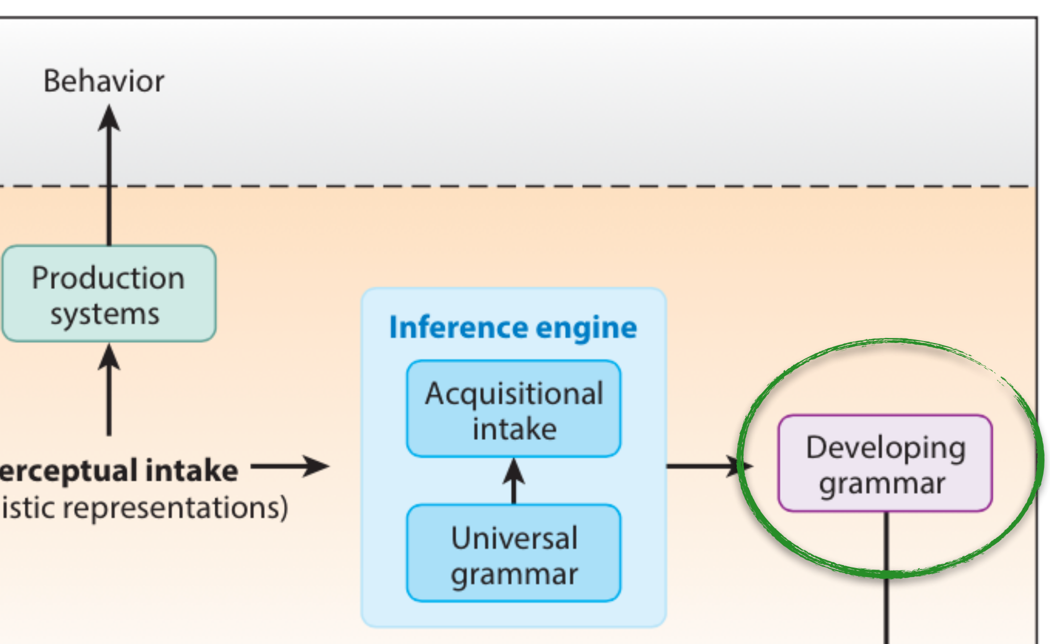


grammar type
structure-dependent

specific grammar

structures in observable data

two years old



Yes/No question formation in English

And so these structure-dependent representations make hypothesizing structure-dependent rules much more probable.

Thank you!

Computation of
Language
Laboratory

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