# The Language Organism
# Lecture 10: Iterated Bayesian Learning

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- We uncovered the importance of the *bottleneck* on cultural transmission
- It drives the evolution of structure because only structured languages can be stably transmitted through a bottleneck (without a bottleneck, language could stay holistic)
- This is a case of adaptation for learnability by a culturally evolving language

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- It drives the evolution of structure because only structured languages can be stably transmitted through a bottleneck (without a bottleneck, language could stay holistic)
- This is a case of adaptation for learnability by a culturally evolving language
- Earlier in the course, we looked at adaptation to *bias* (e.g. one-to-one constructor bias leading to optimal languages)
- Argued that this means that cultural evolution can potentially explain language structure (biological evolution by natural selection isn't the only possible explanation)

# But...

- Two possible problems:

    1. What is this thing called bias?
       How can we measure it?
       What is the bias of the syntactic learner from the last lecture, for example?

    2. If language ends up reflecting our learning biases, where does learning bias come from?

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    2. If language ends up reflecting our learning biases, where does learning bias come from?

- Could we simply be restating the Chomskyan position in different terms?

  Language mirrors biologically provided innate constraints

  vs.

  Language mirrors biologically provided learning bias

# We need a more general model

- Ideally, we'd like to be able to mix up a bunch of simple ingredients and work out what language should look like after cultural evolution has run for some time:
  - BIAS (i.e. what agents are born with)
  - LANGUAGE MODEL (i.e. set of possible languages, set of possible data)
  - BOTTLENECK (i.e. how much data a learner sees)
  - POPULATION MODEL (e.g. diffusion chain, closed group etc.)
  - OTHER FEATURES OF CULTURAL TRANSMISSION (e.g. errors)

# Towards a more general model of learning bias: a medical quiz

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  b. A cold

  c. Athlete’s foot

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- Resolving this question requires you to draw on two probabilities:
  - How likely is it that someone with the illness in question would exhibit that symptom?
  - How common is each illness?

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- If all we care about are the likelihood of the symptoms given each illness, we would conclude that your friend either has lung cancer or a cold

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- If all we care about are the prevalances of each illness, we would conclude that your friend either has a cold or athlete's foot
- But you didn't conclude this: you brought these two quantities together in a smart way. How did you do it?

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$$P(symptoms|illness)$$

  - The prior probability of each illness

$$P(illness)$$

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- Or, in full:

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- The term on the bottom (the probability of the symptoms independent of illness) is actually not very interesting to us, since it is the same for all illnesses.

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    utterances = symptoms
    languages = illnesses
    bias in favour of particular languages = prior for each illness

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- Children probably don't calculate sums in their head while learning, but if their learning process is sensible, we can characterise it this way

# Bayesian language learning

- Evaluate hypotheses about language given some prior bias (perhaps provided by your biology) and the data that you've heard

- You want to know the **posterior** but all you have direct access to is the **prior** and the **likelihood** (assuming you know how sentences are produced from a given model of language)

- Bayes' rule provides the solution:

$$P(h|d) = \frac{P(d|h)P(h)}{P(d)}$$

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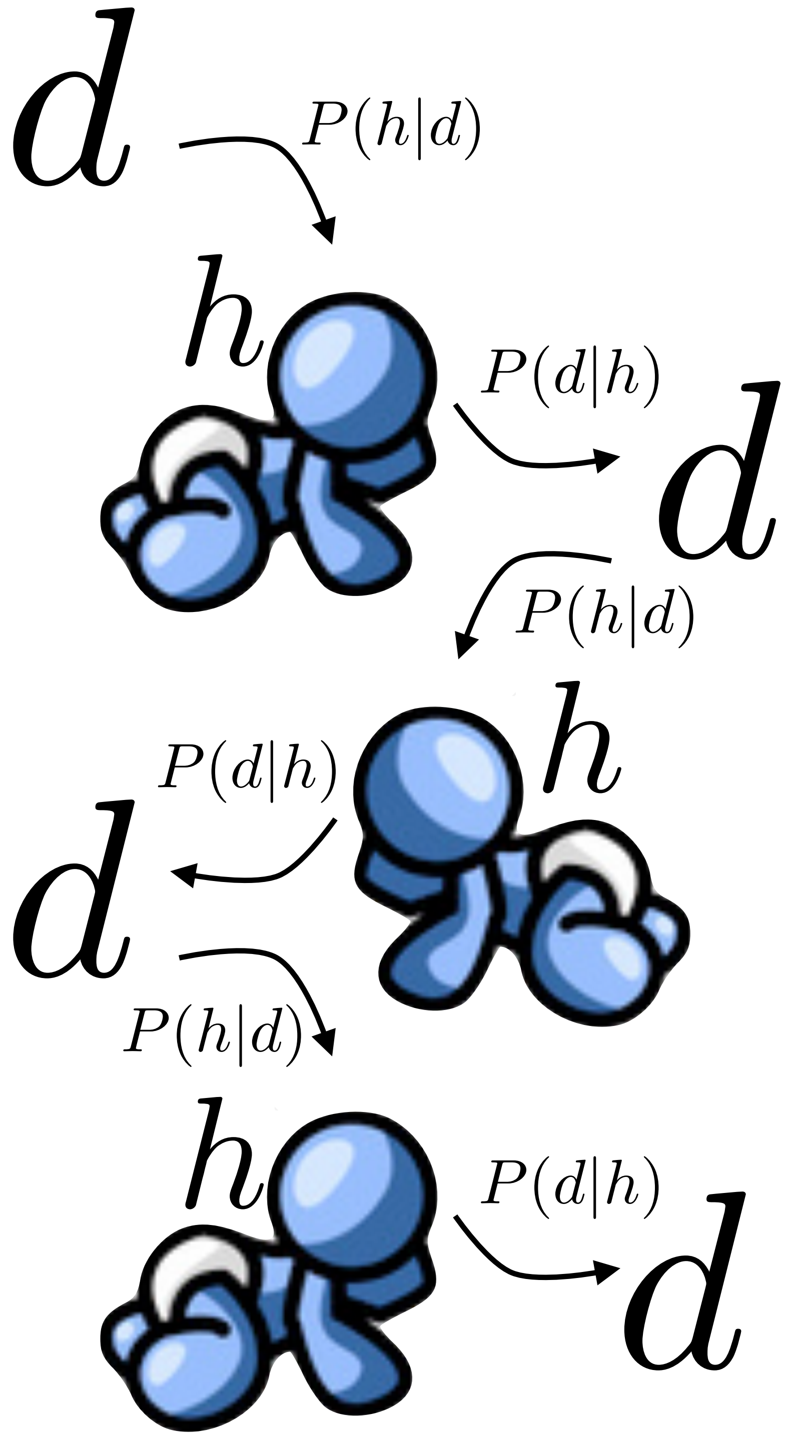
- Now we want to know what happens in a cultural-evolutionary context.

- How does having particular bias affect the outcome of cultural evolution given particular bottlenecks, levels of noise (error) on production, and so on?

- We can put it in an iterated learning model

# Iterated Bayesian Learning




What will happen to *h* over time?

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  Bottleneck does nothing
  Noise does nothing
  Details of language model do nothing

- Given enough time, the end result of cultural evolution always reflects the prior bias and nothing else

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- Hmmm...

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- Whole thing revolves around a very subtle point

  - How do you decide, given the posterior, whether your friend has cancer, a cold or athlete's foot?

  - How do you decide, given the posterior, which language to select?

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    (If it's more likely to be a cold than cancer, tell them you think it's a cold)
- Griffith & Kalish (2007) were using *sampling.* Kirby et al. (2007) tried MAP.

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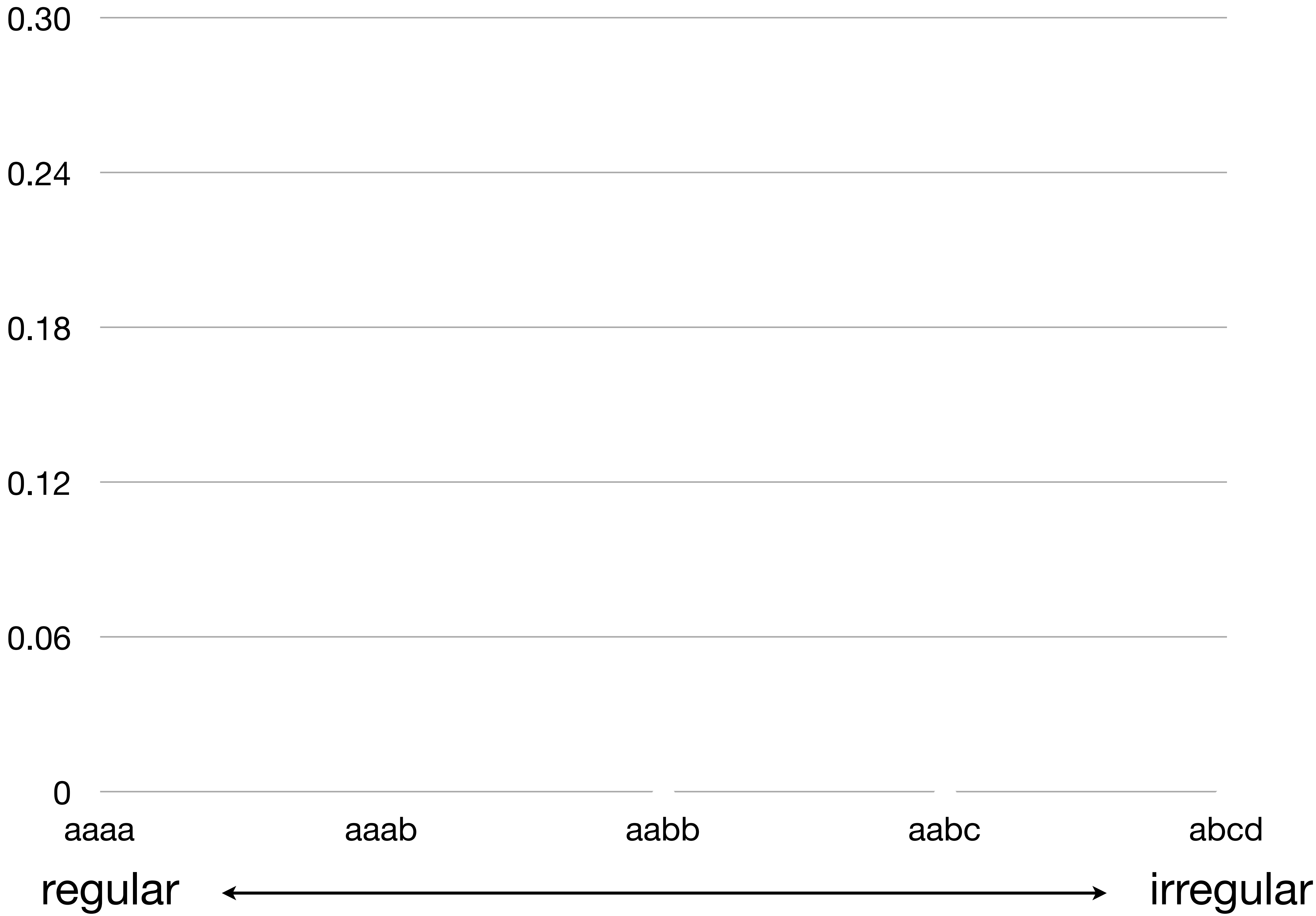
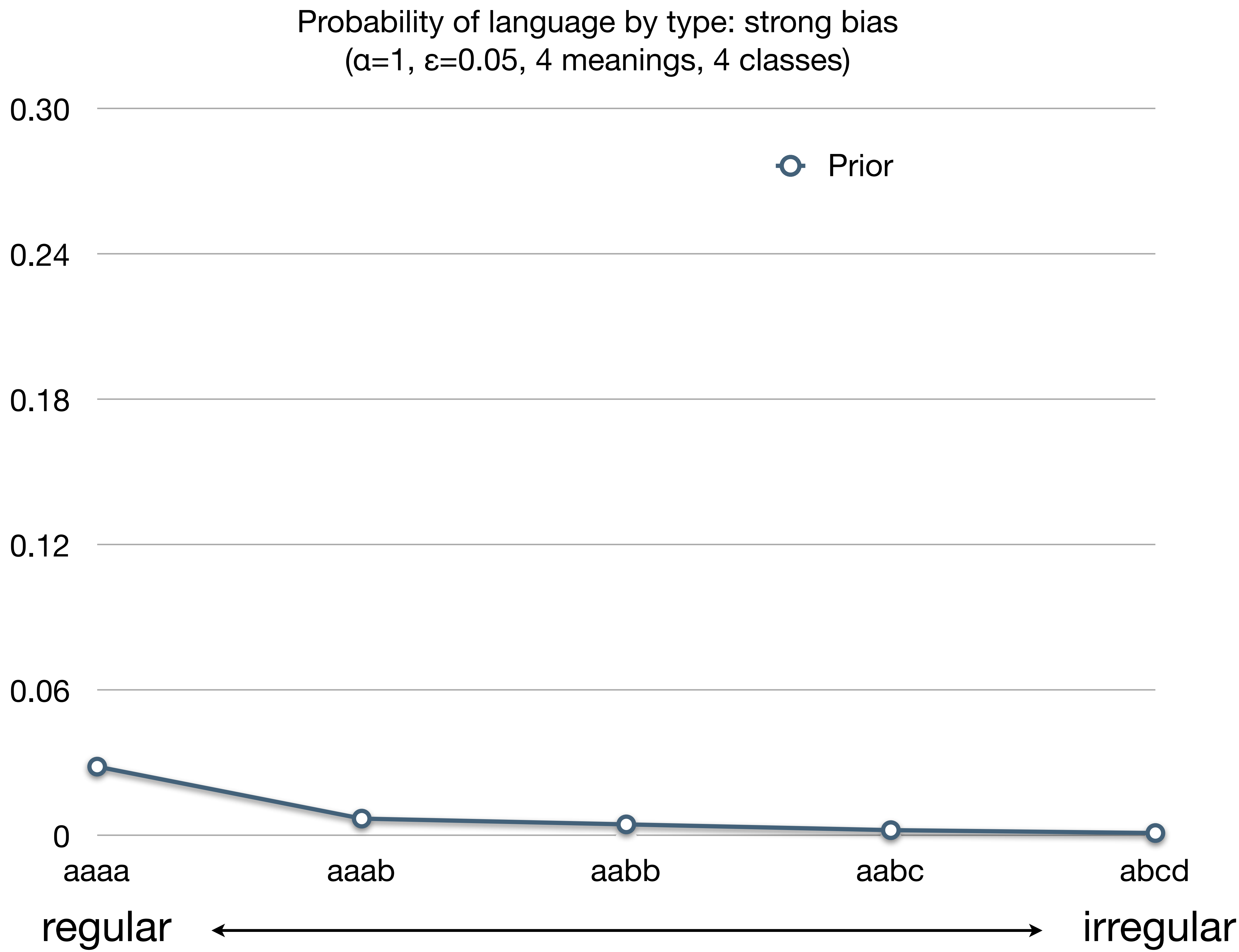
- Model language as a set of meanings
- These meanings can be expressed regularly, or irregularly
- Start with the assumption that there is a slight innate bias in favour of regularity
    - We can vary the strength of this bias
    - It is reasonable to assume a simple bias like this is not language-specific
- Assume learners pick the best (i.e. MAP) hypothesis. What happens?

Probability of language by type: strong bias
(α=1, ε=0.05, 4 meanings, 4 classes)

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0.30
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Prior
aaaa
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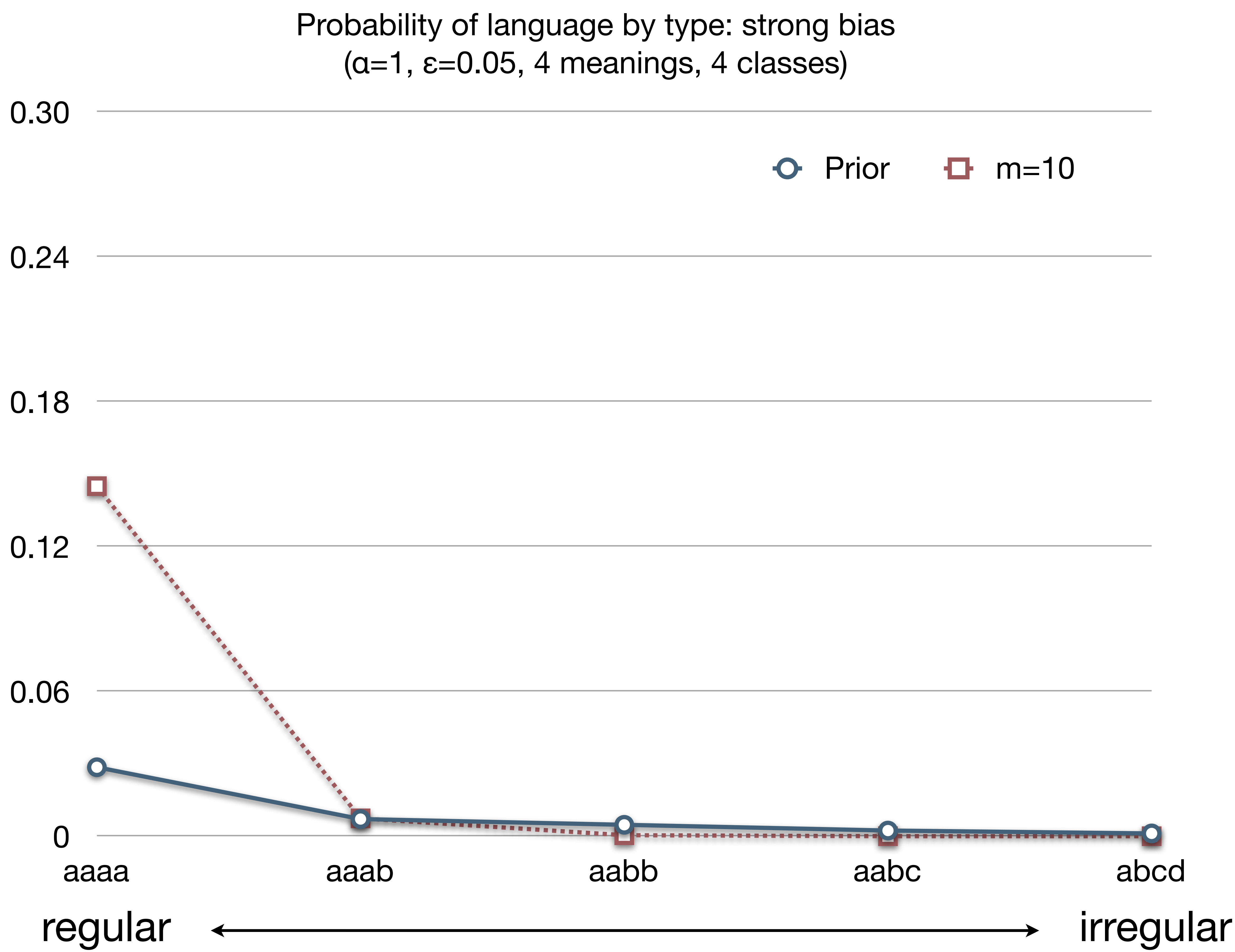

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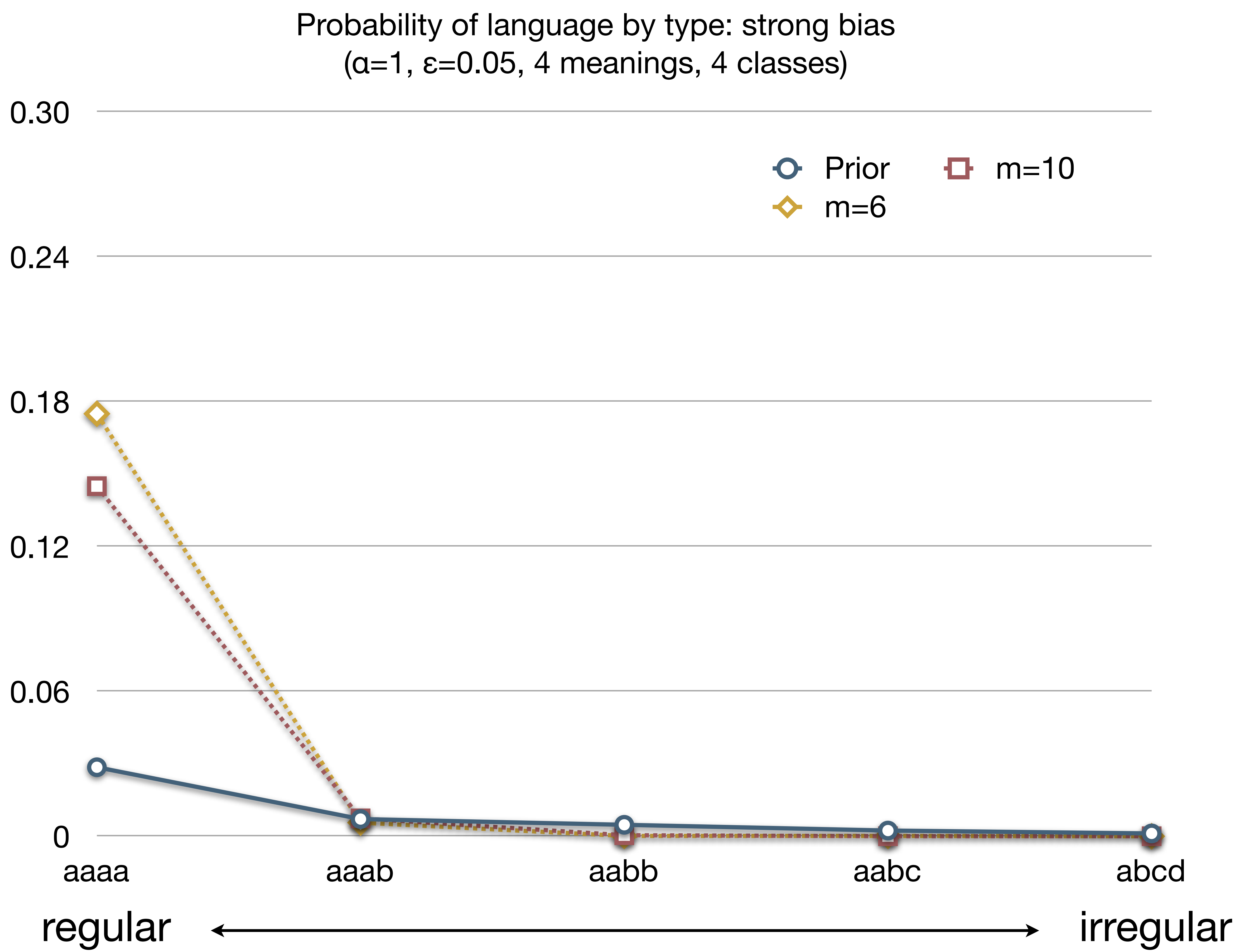
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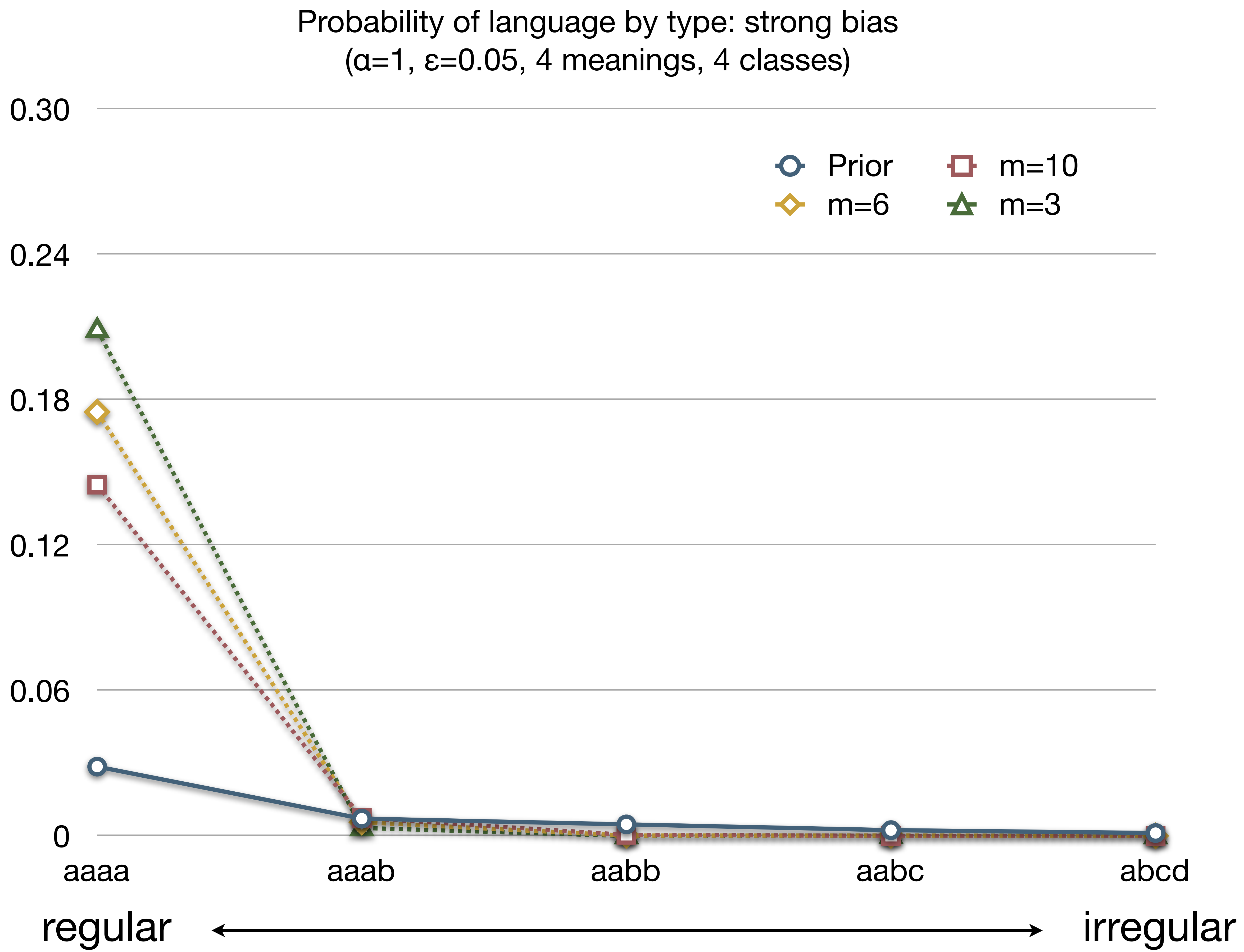

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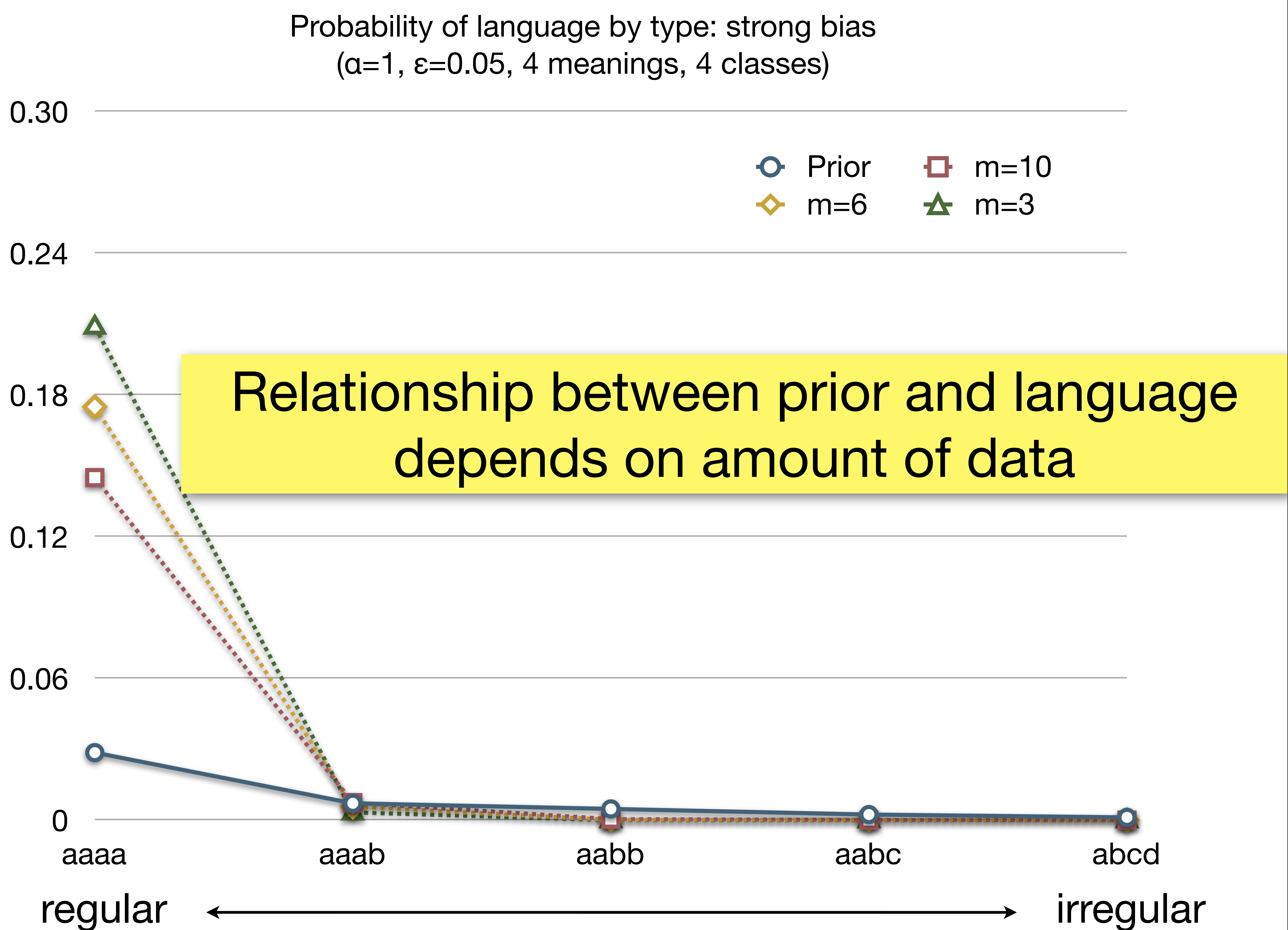
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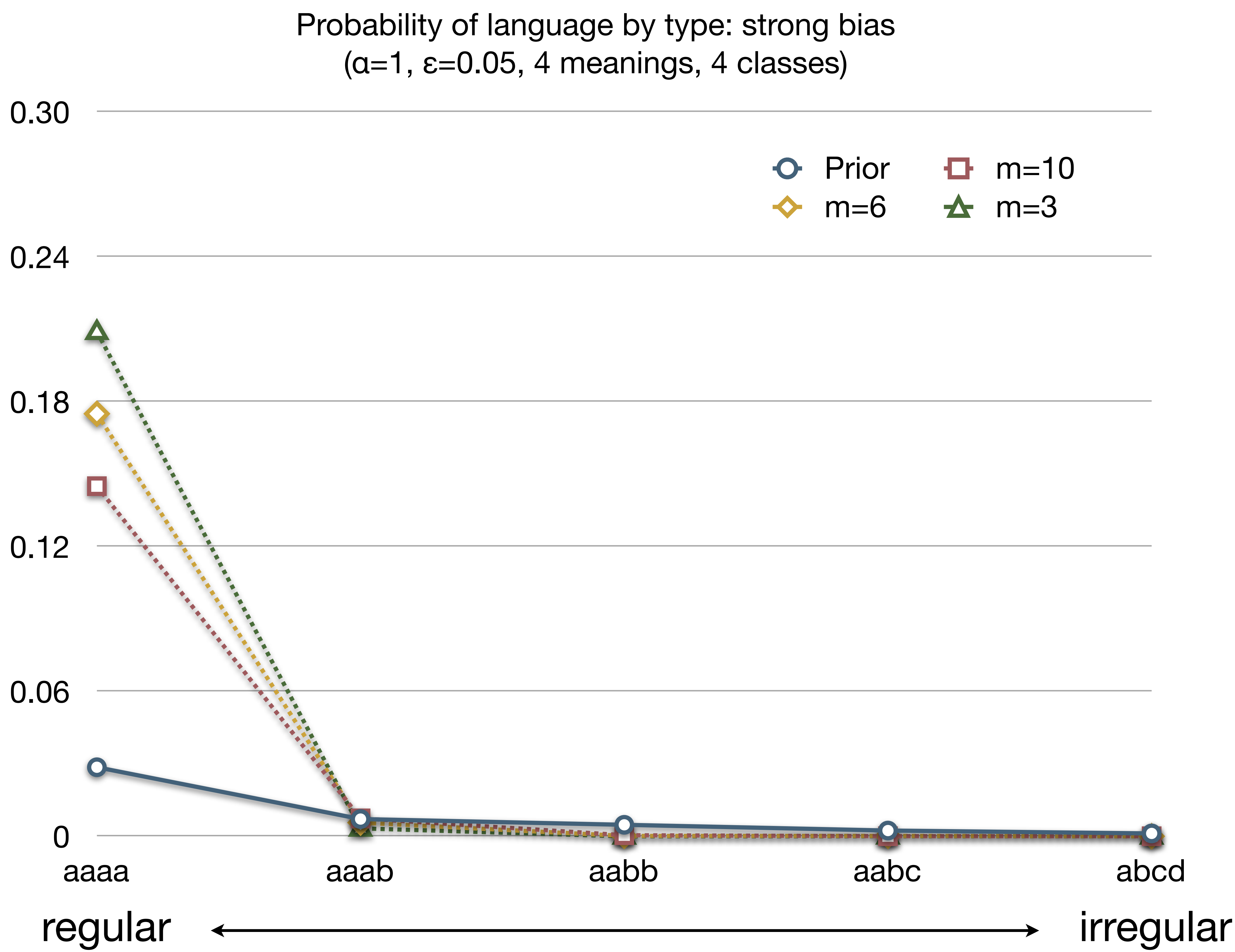
Relationship between prior and language depends on amount of data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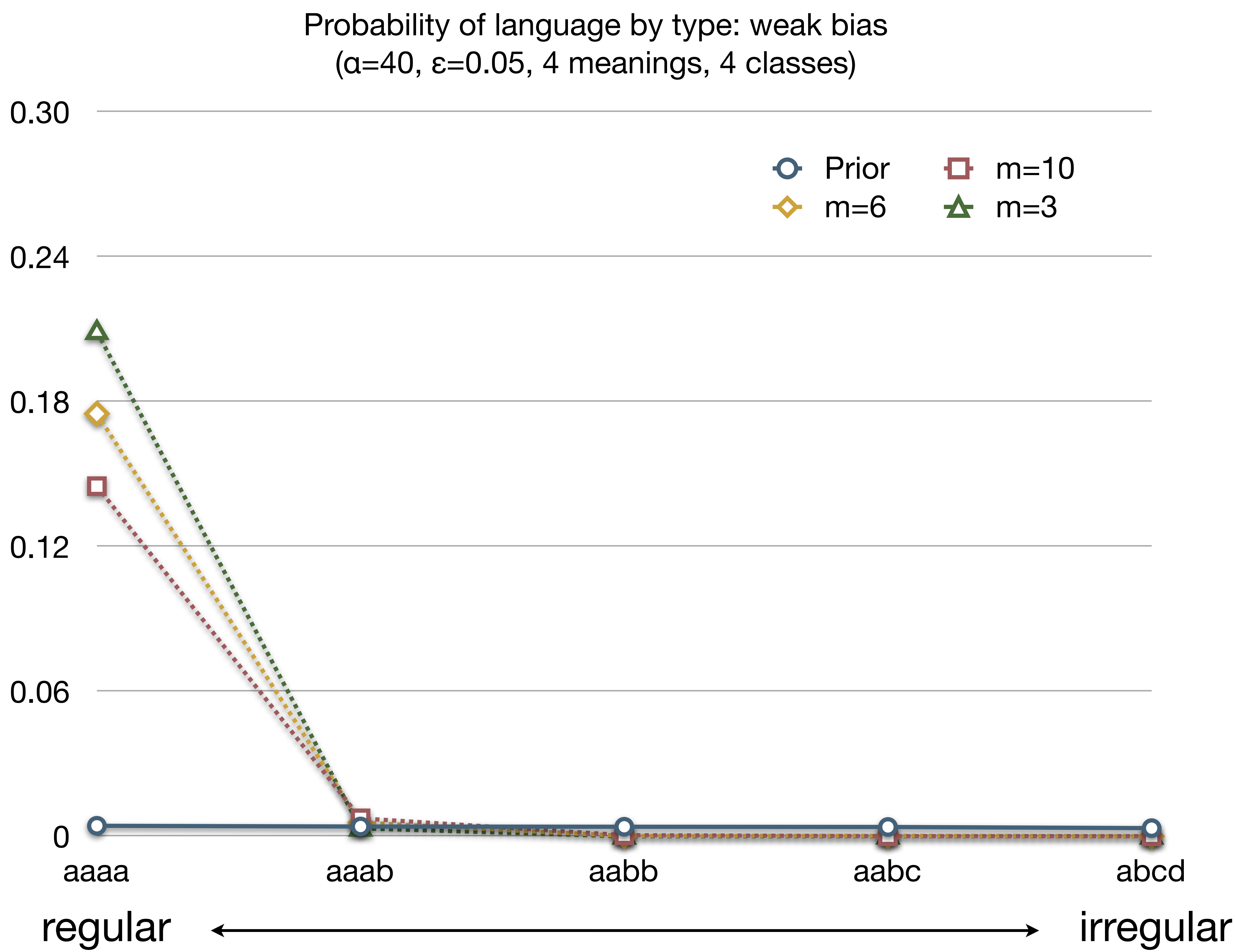

Probability of language by type: weak bias
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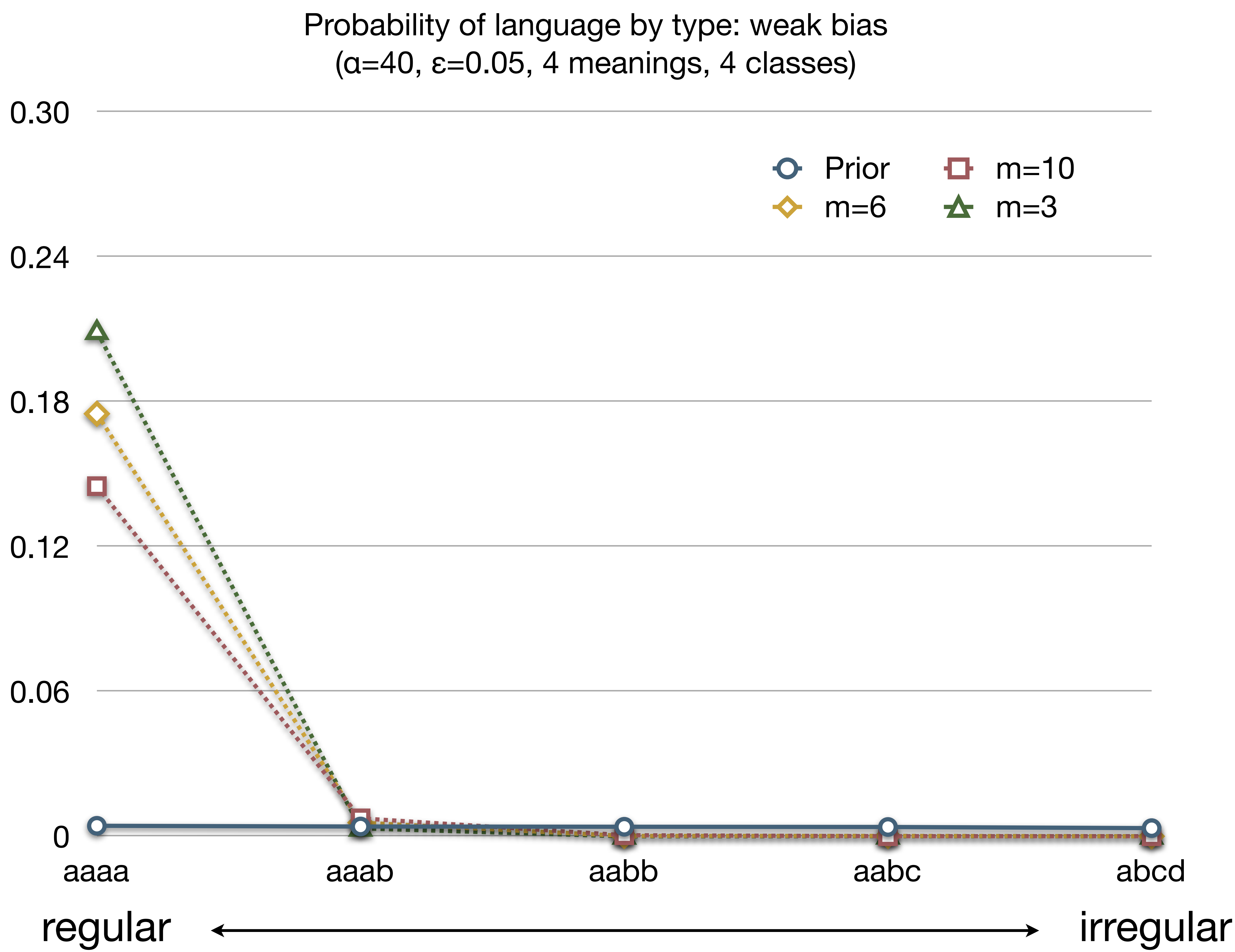
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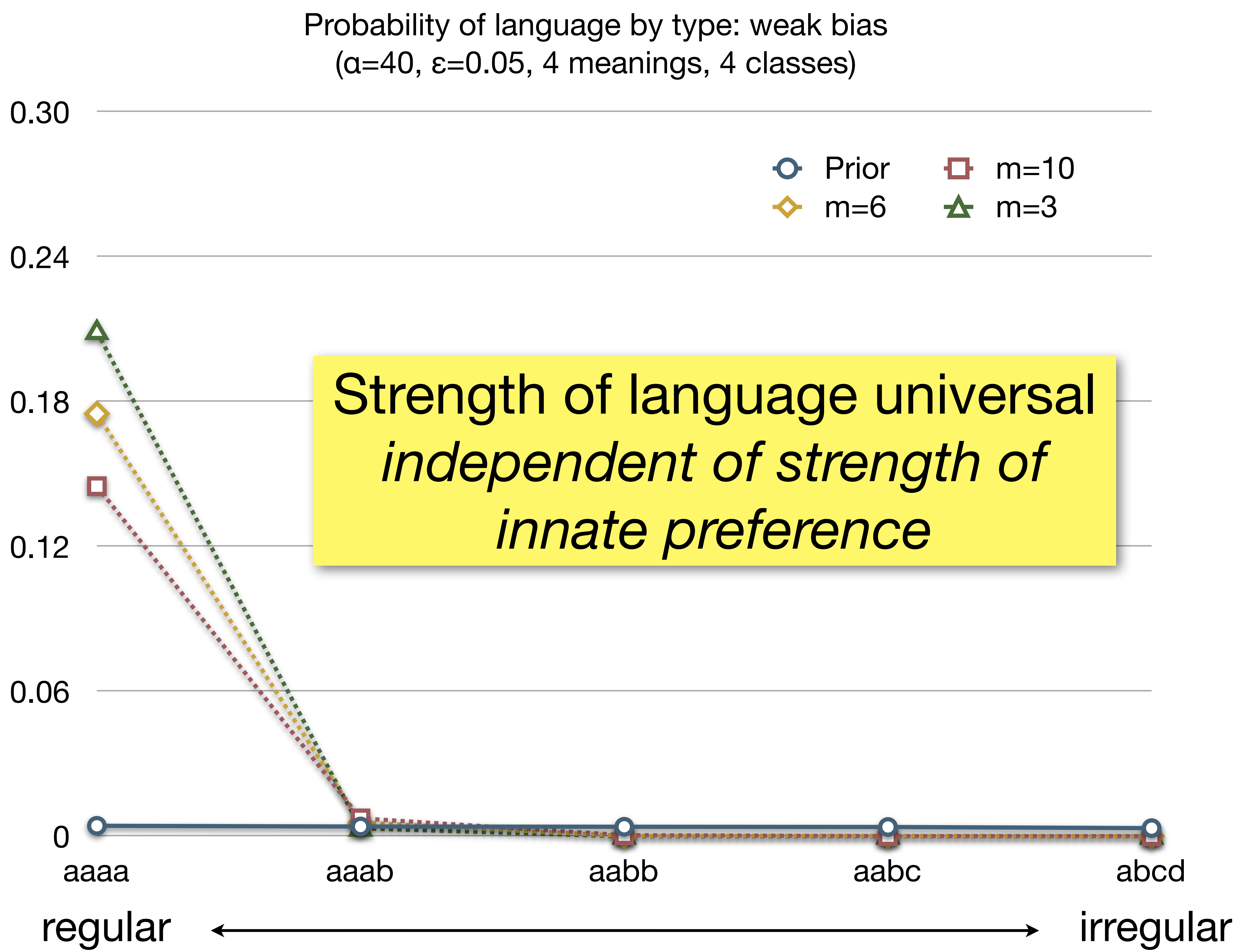
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- If you assume social learning is about maximising the chance of converging on what other people are doing (i.e. selecting the MAP hypothesis), then cultural evolution does a lot of work for you
- Very weak innate biases are all that's needed to explain strong linguistic universals
- If we see universals in language, then we should not be assuming that these are hard-coded as strong-constraints in the genes