While you are waiting...

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Simulating Language
Lecture 13: Iterated Bayesian Learning, culture, innateness

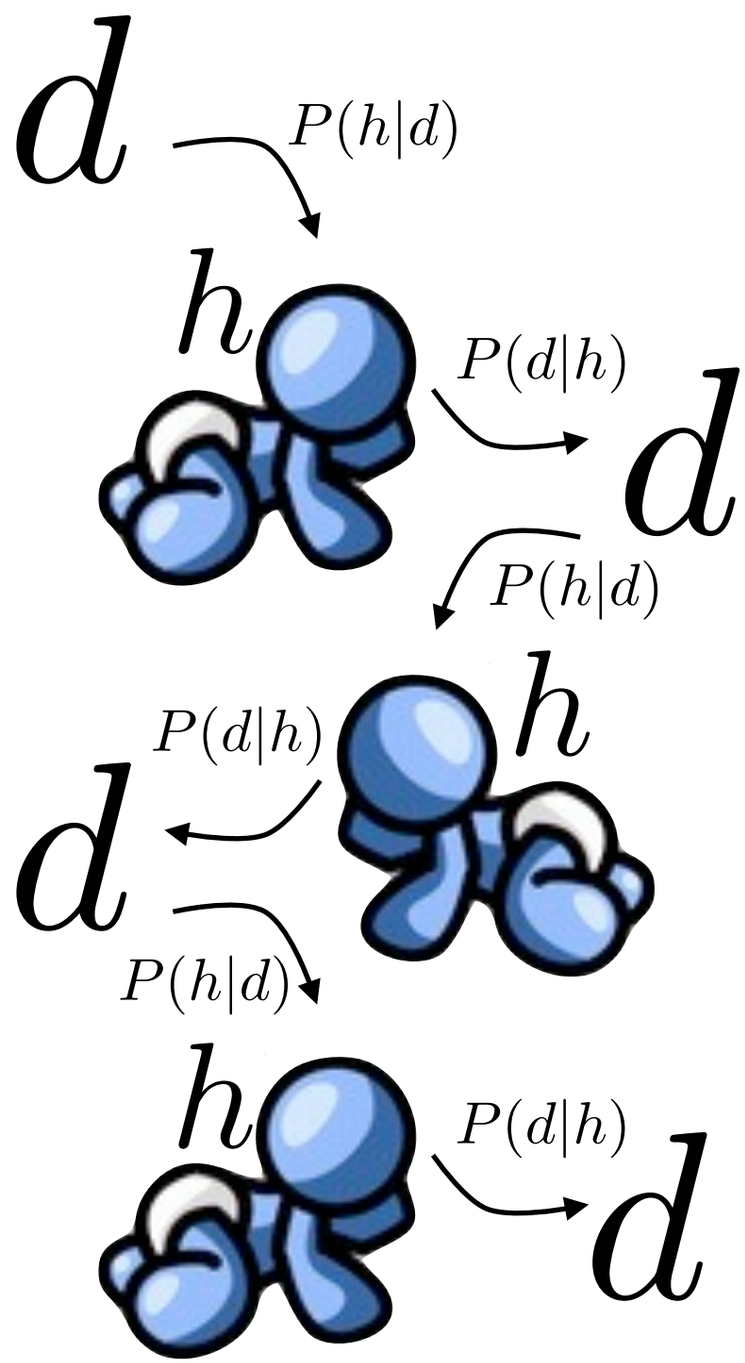
Kenny Smith

kenny.smith@ed.ac.uk

Last week's lecture ...

- 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
- Earlier in the course, we looked at adaptation to *bias*
- Weak or hard-to-detect biases in learners can have strong effects over iterated learning
    - Acquisition test vs maintenance/construction tests

A reminder: Iterated Bayesian Learning



First results (Griffiths & Kalish 2007)

- Try out different models of language, different bottlenecks, different amounts of noise

- See how the process of cultural transmission takes the prior bias of the learner and gives rise to the actual resulting patterns of language

- What would you predict, based on the models you have seen so far?

- **The types of languages we see should:**

  A. be completely unconstrained by the biases of language learners

  B. reflect the biases of language learners, but in an interestingly complex way (weak biases have strong effects, bottleneck matters, etc)

  C. directly reflect the biases of language learners

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First results (Griffiths & Kalish 2007)

- Try out different models of language, different bottlenecks, different amounts of noise

- See how the process of cultural transmission takes the prior bias of the learner and gives rise to the actual resulting patterns of language

- Their result:

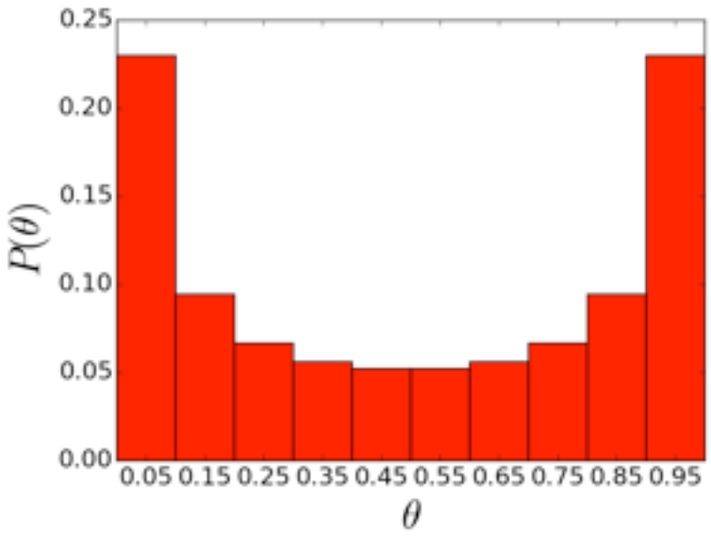
  Bottleneck does nothing
  Noise does nothing
  Details of language model do nothing

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

You have already seen this result

- Cast your mind back to lecture 10, beta-binomial model, learners estimating frequencies of two competing linguistic variants

α = 0.1



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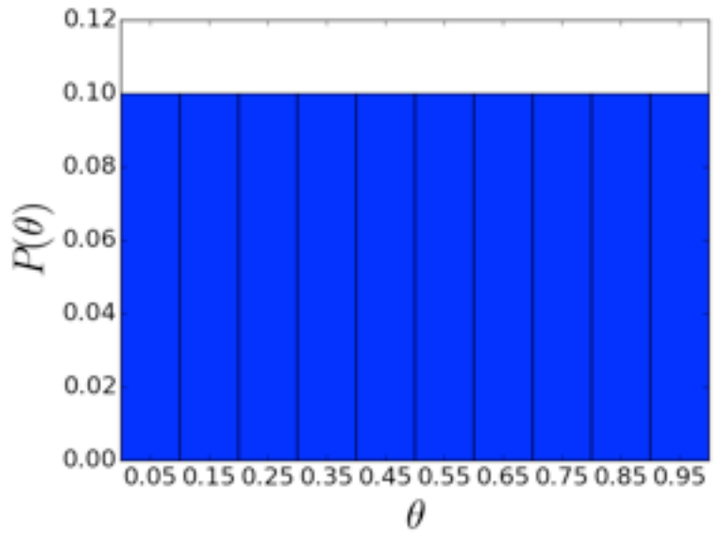

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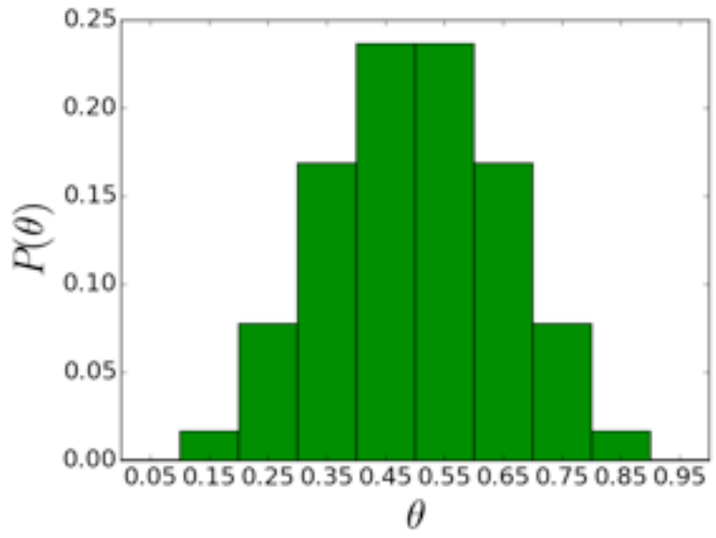

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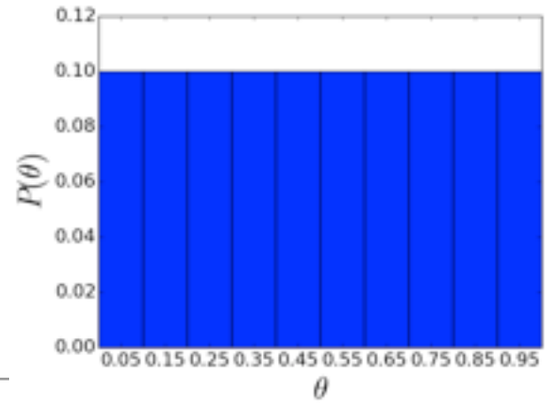

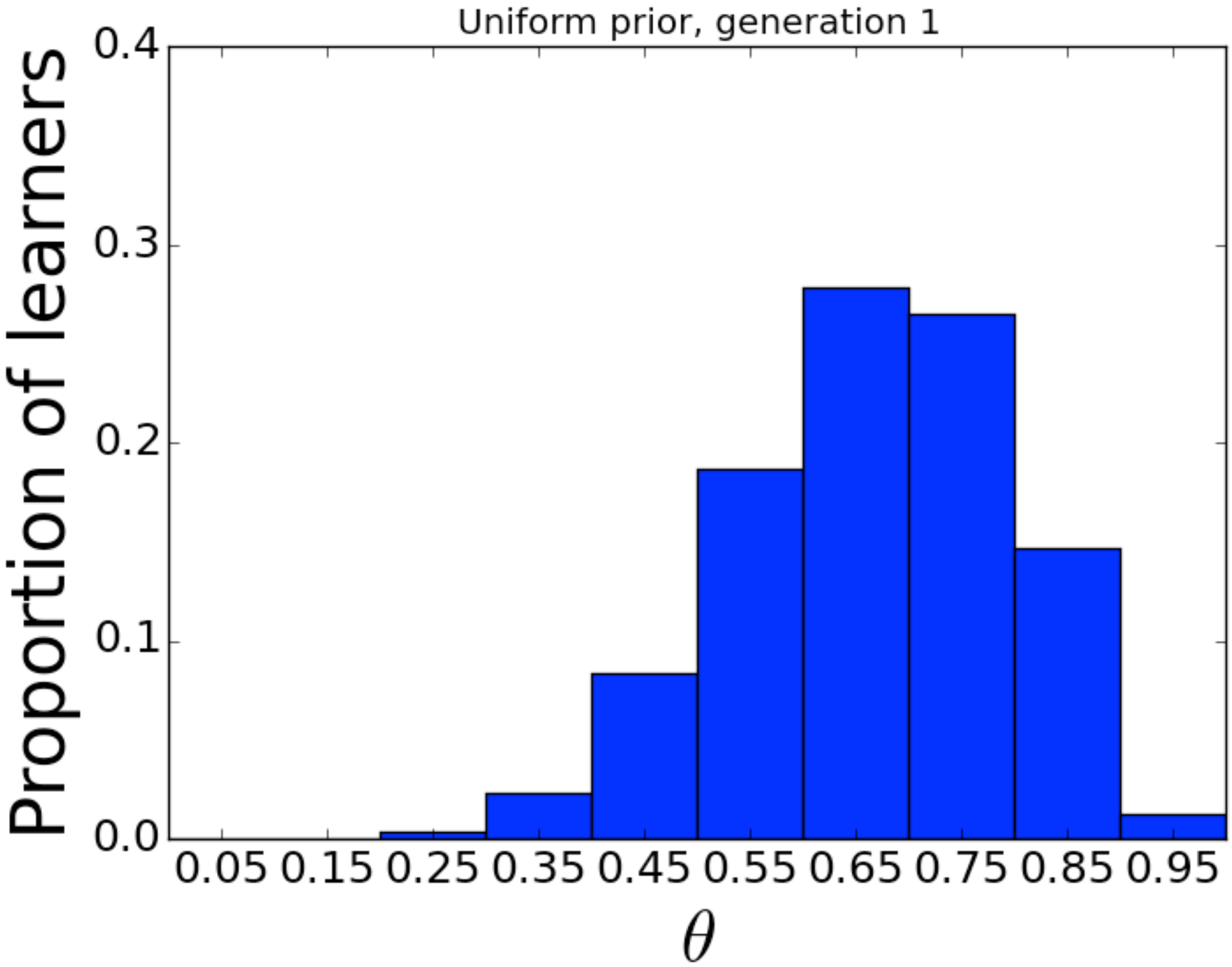

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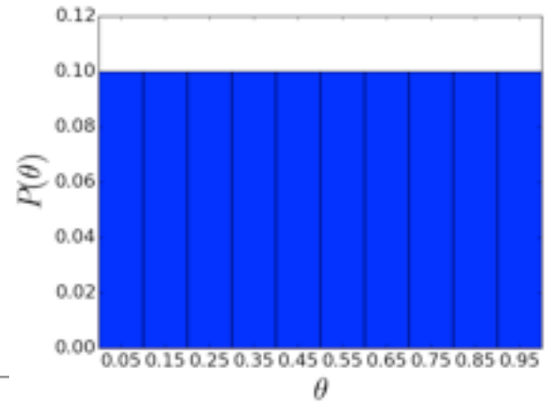

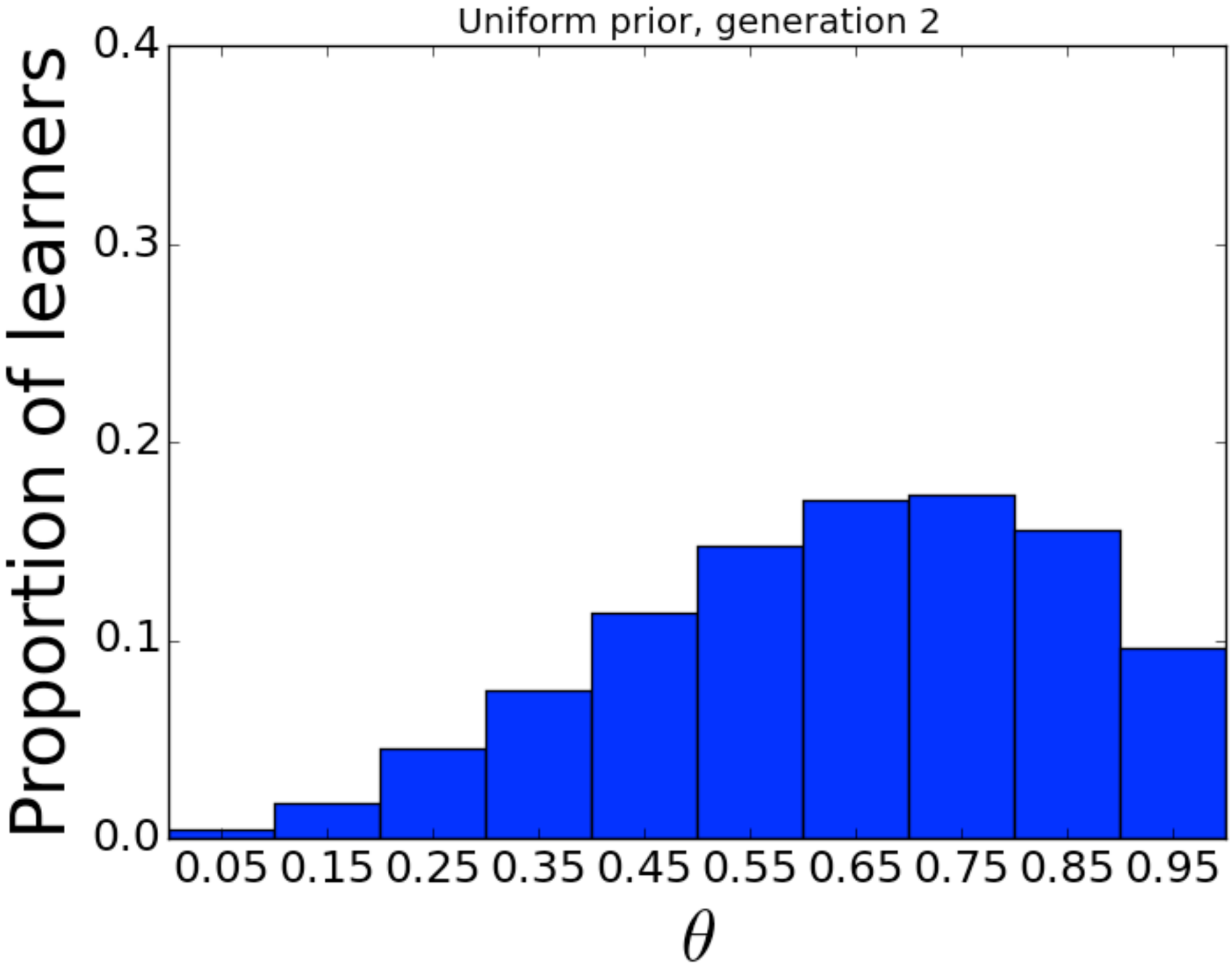

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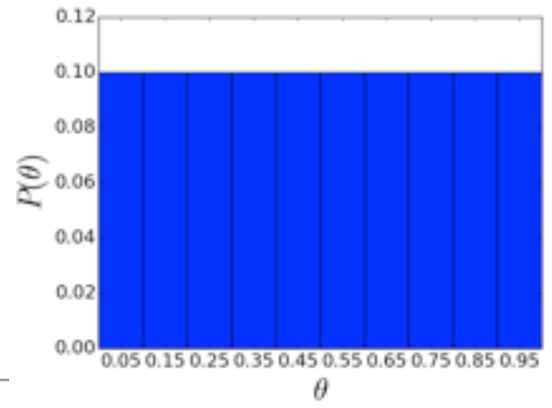

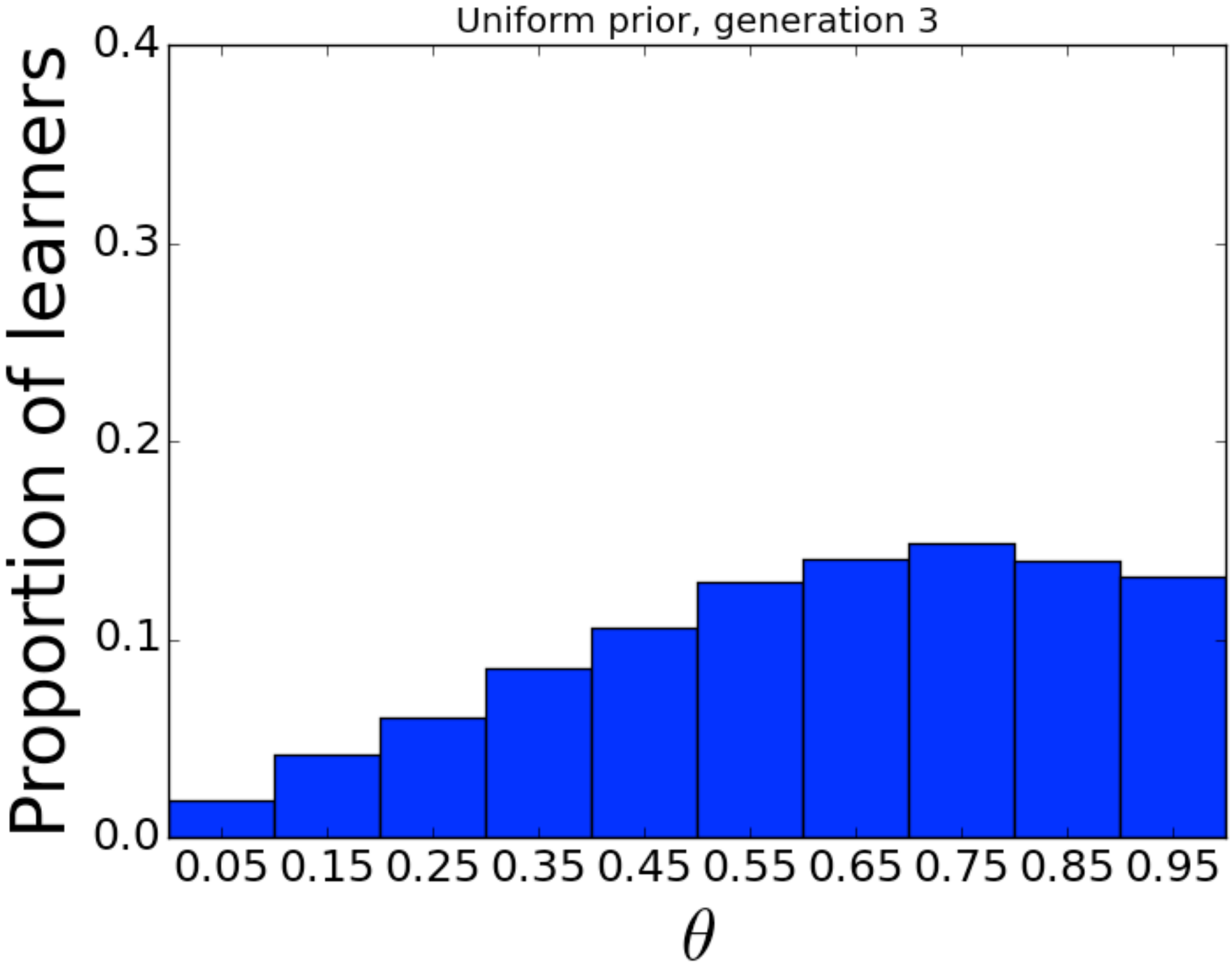

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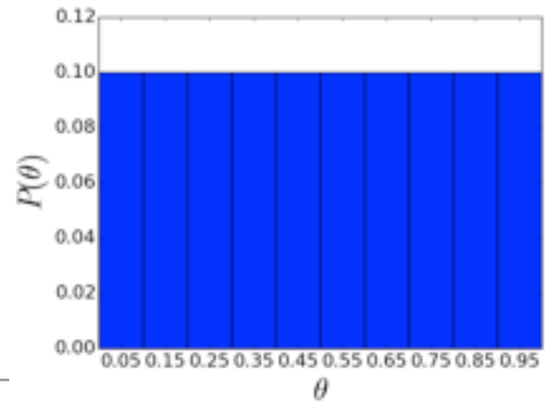

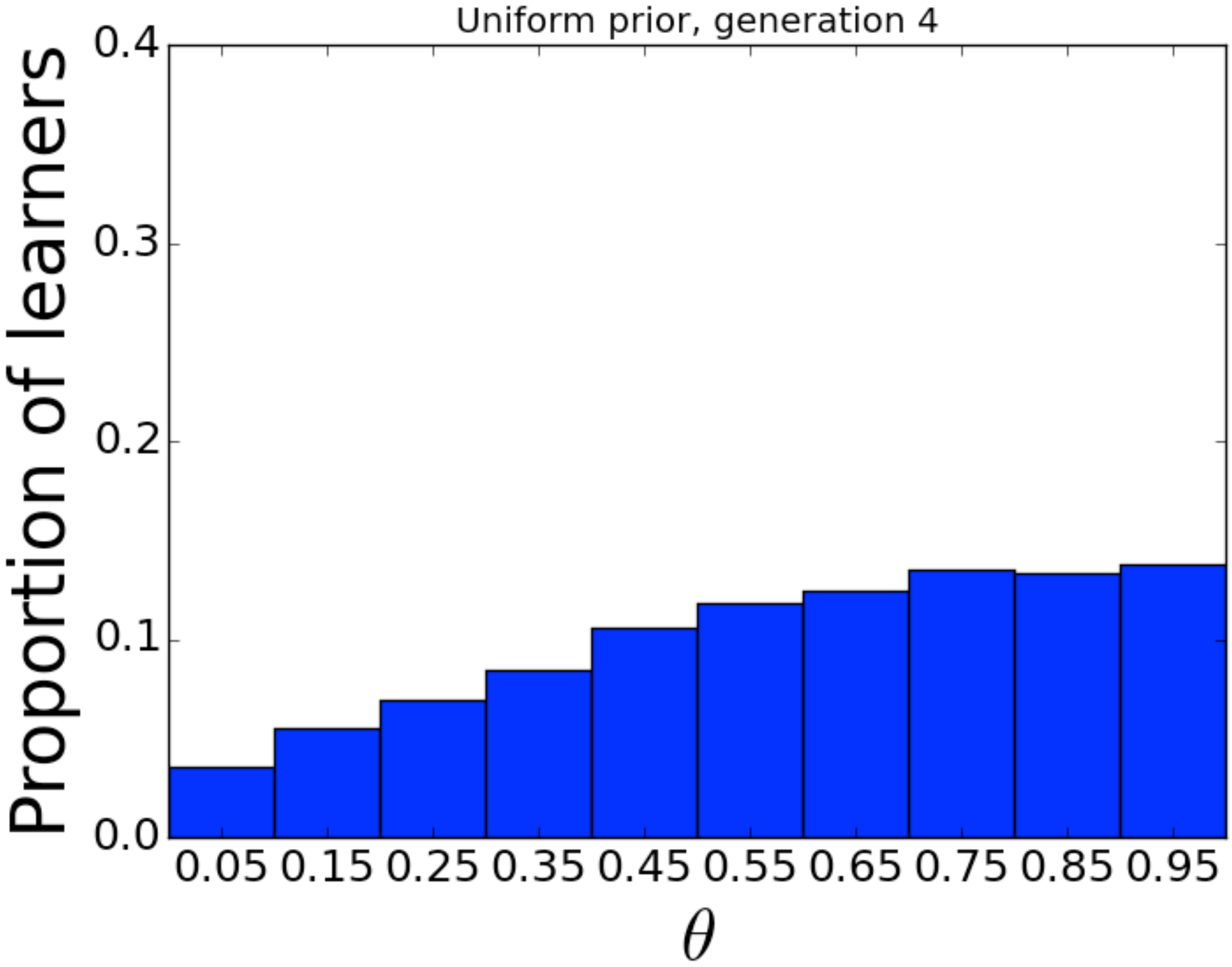

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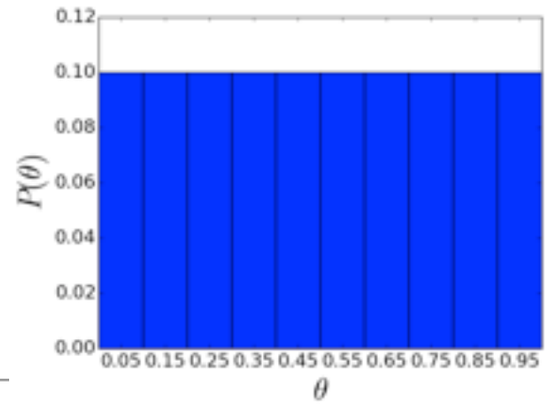

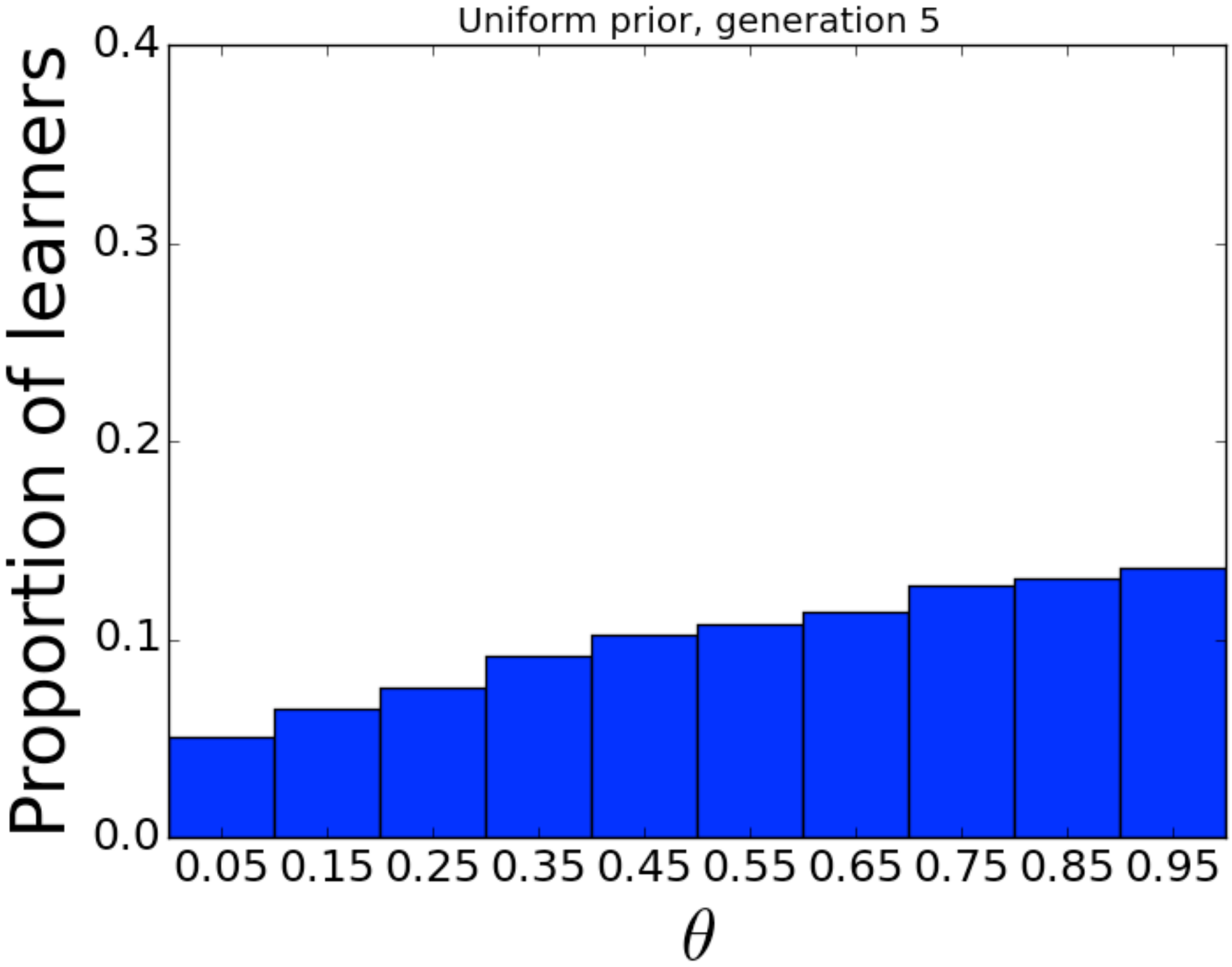

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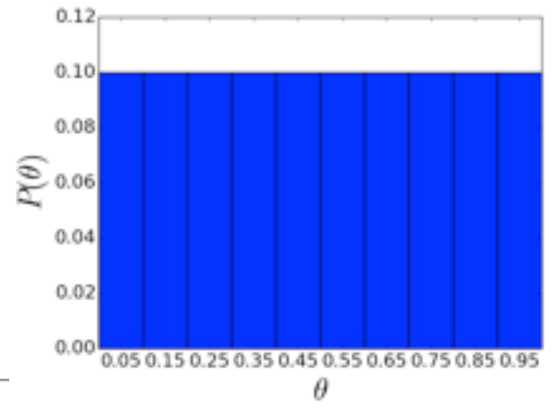

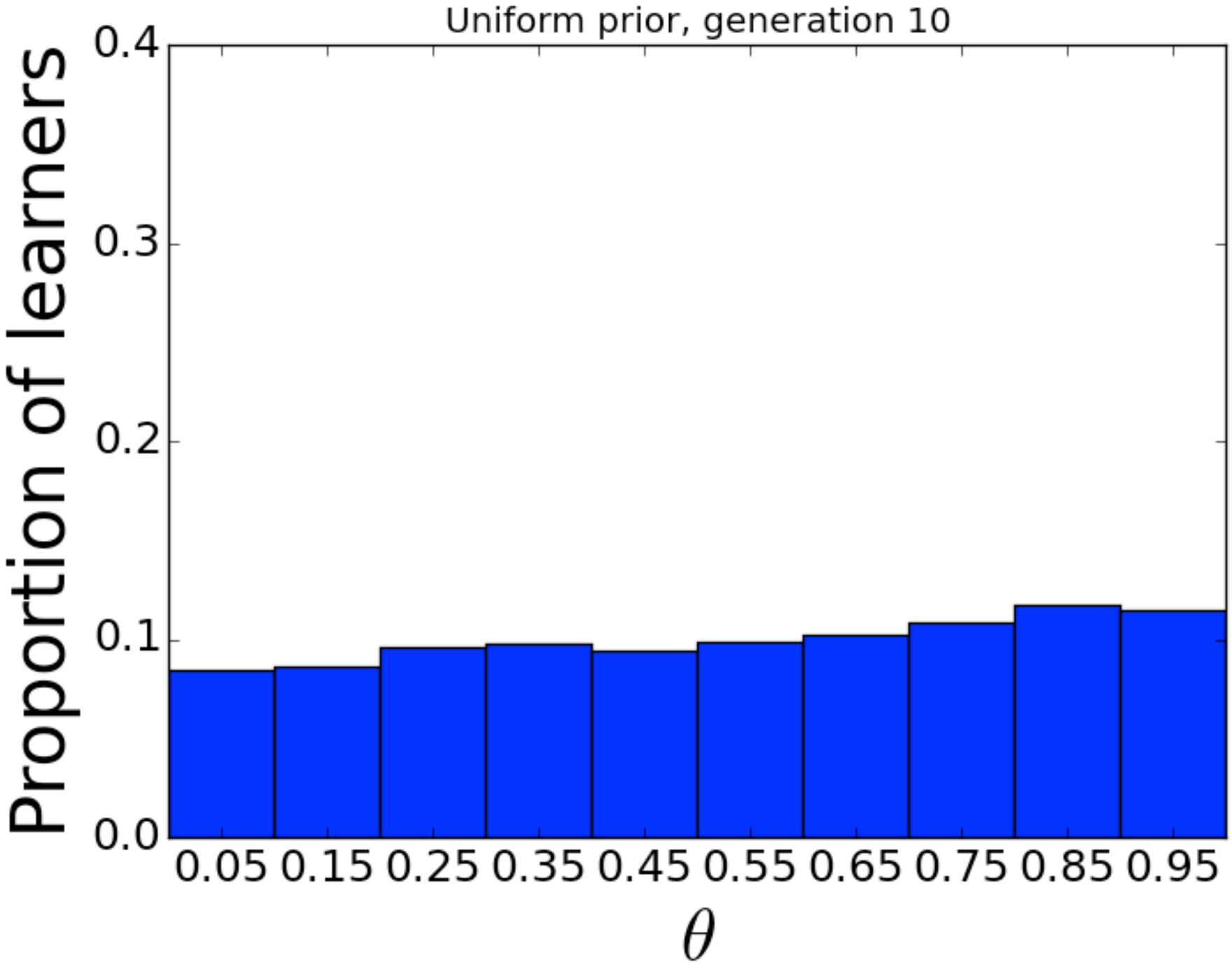

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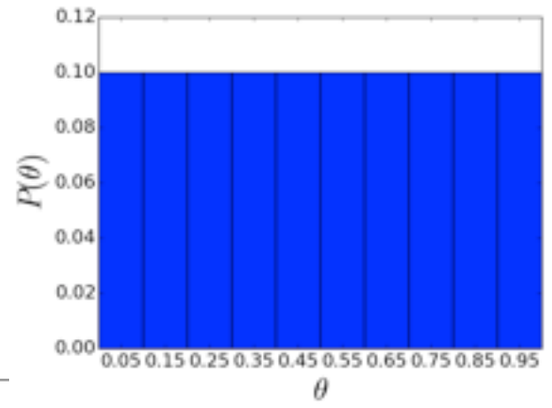

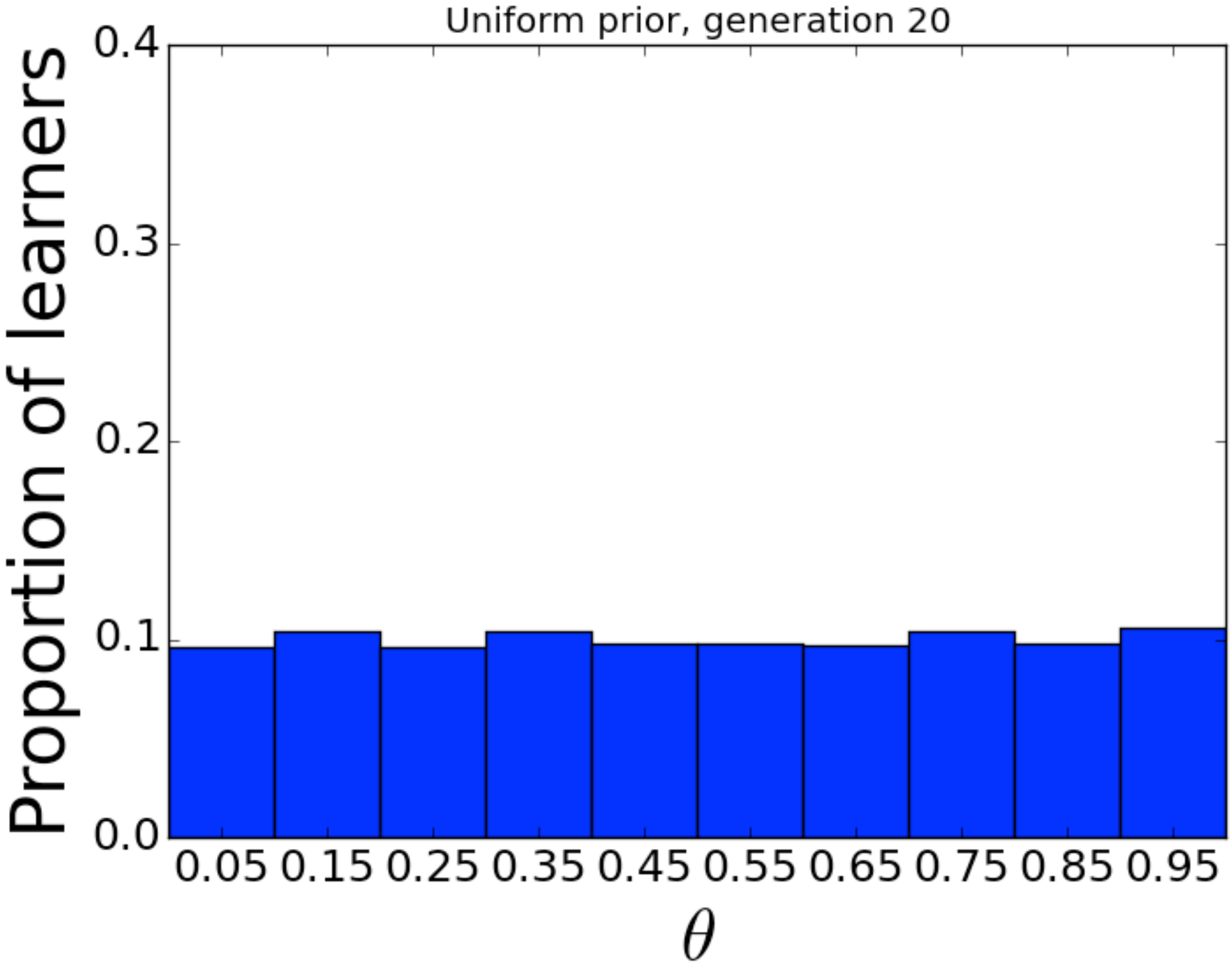

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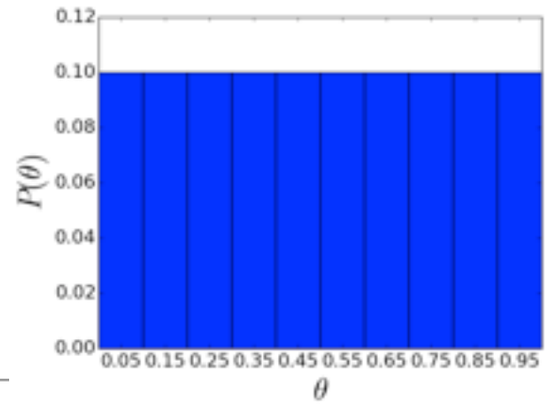

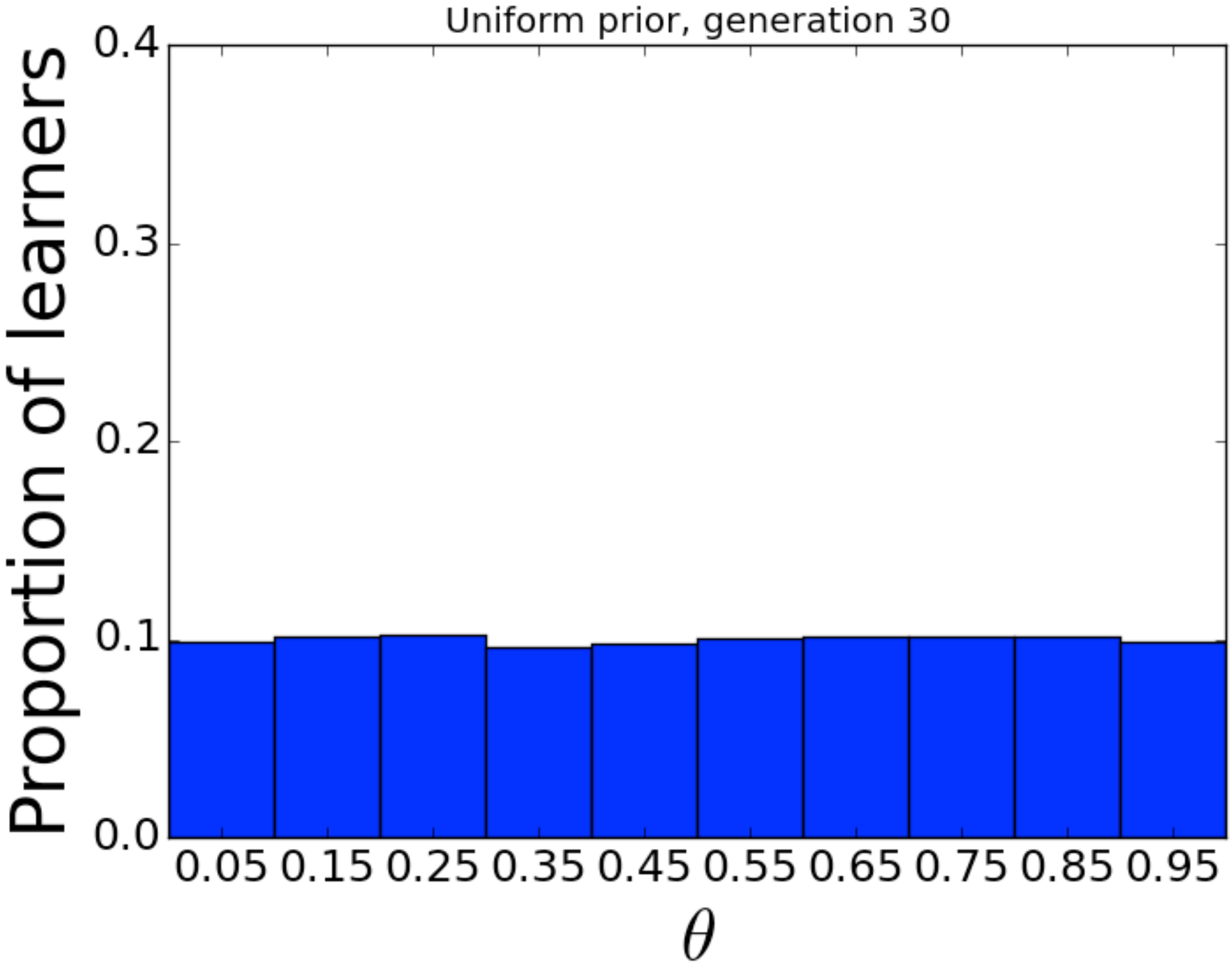

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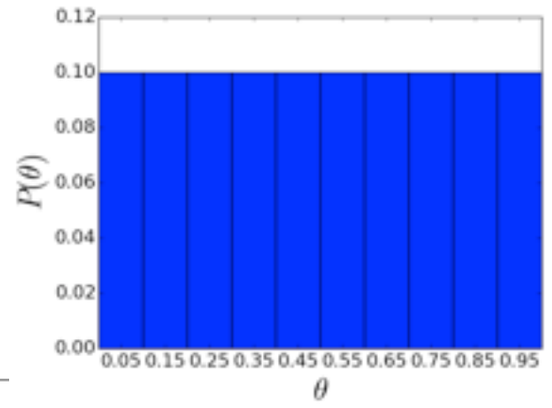

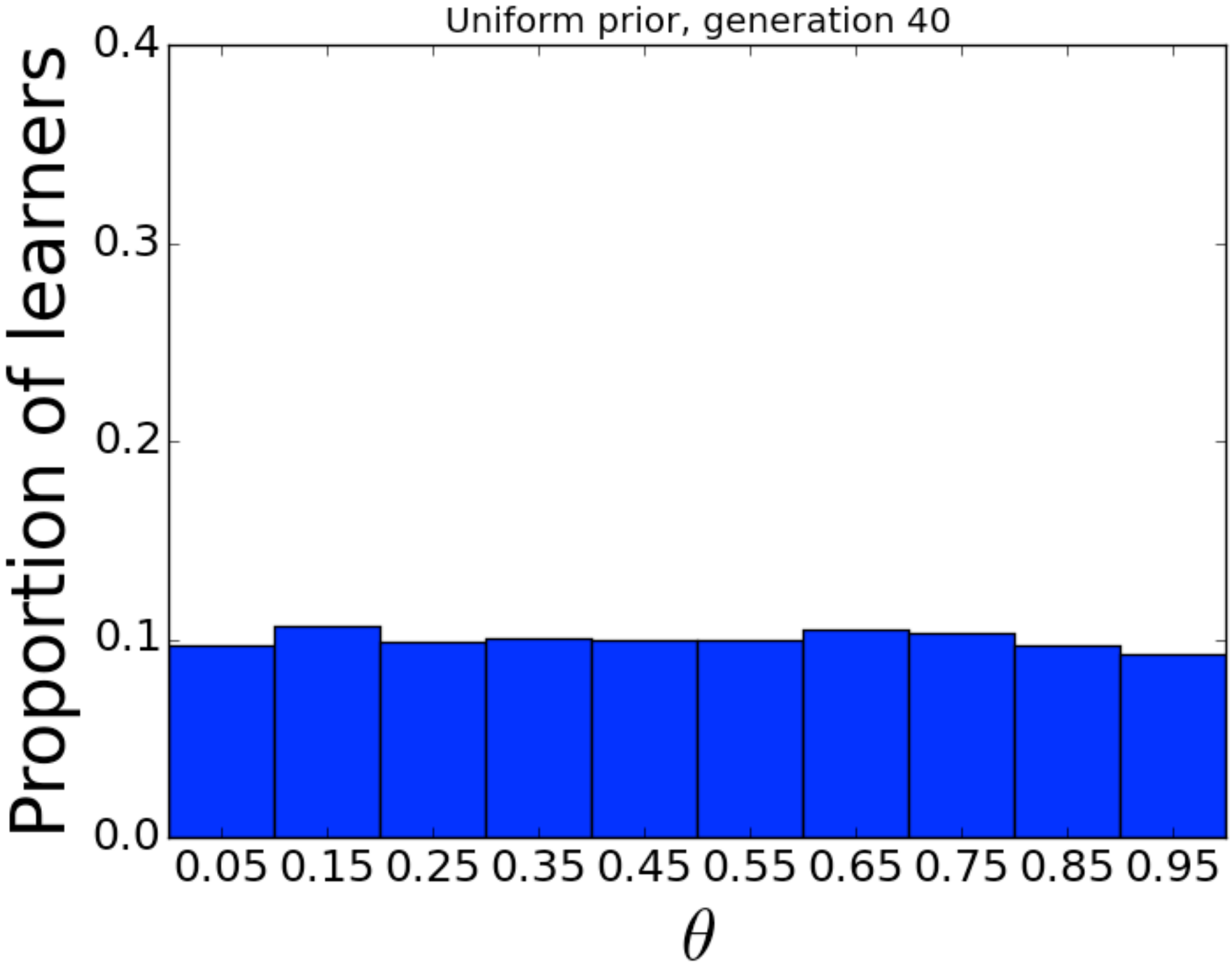

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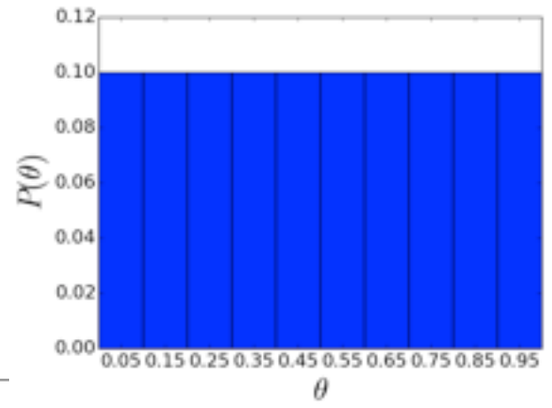

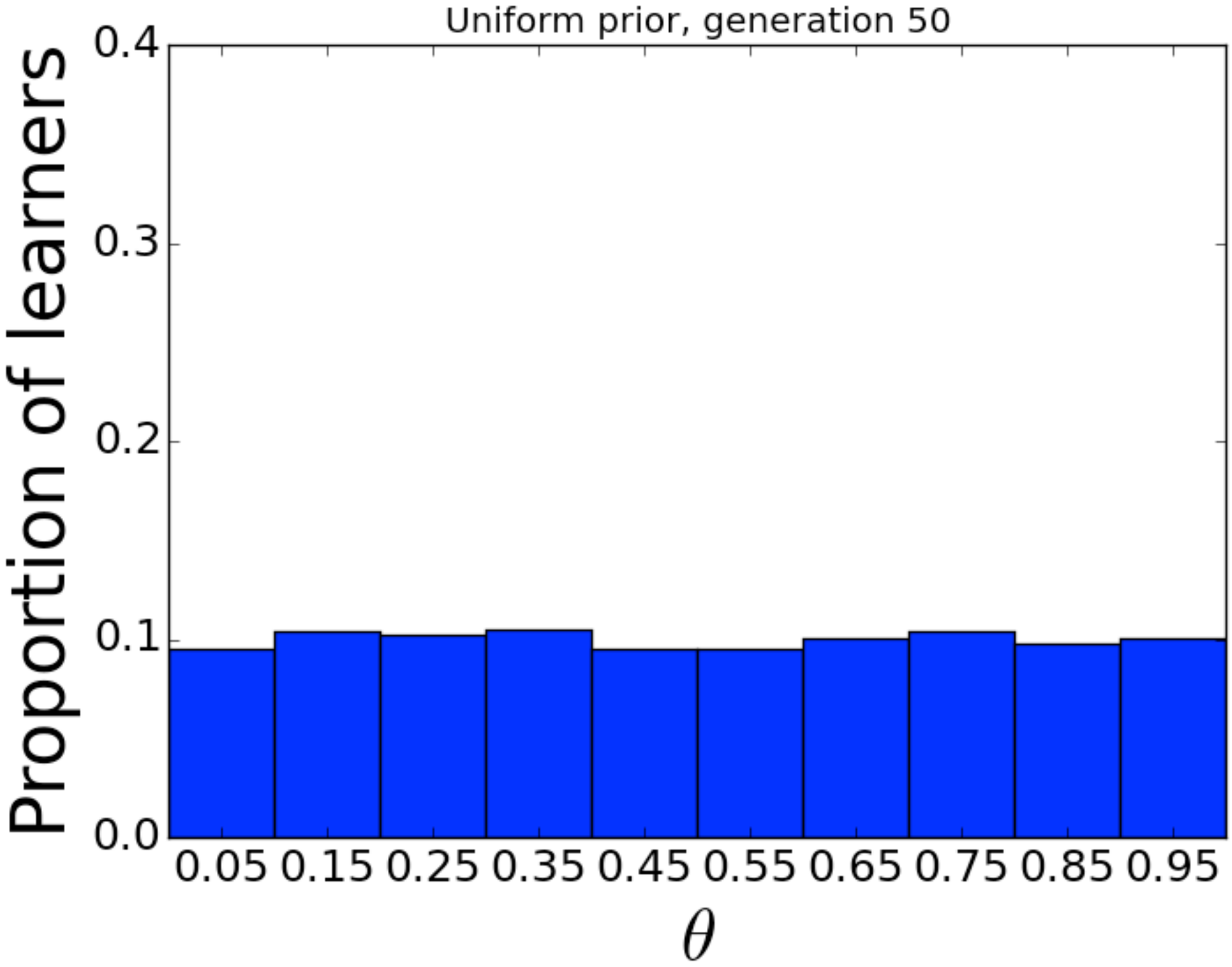

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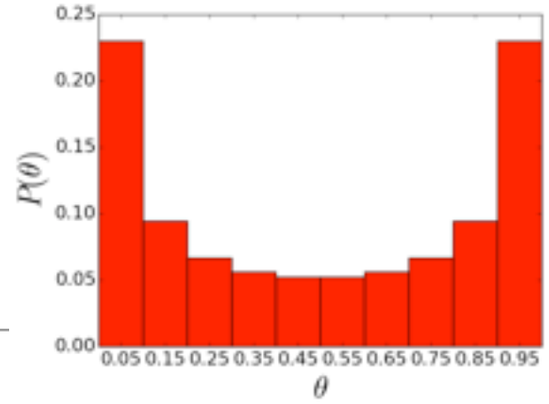

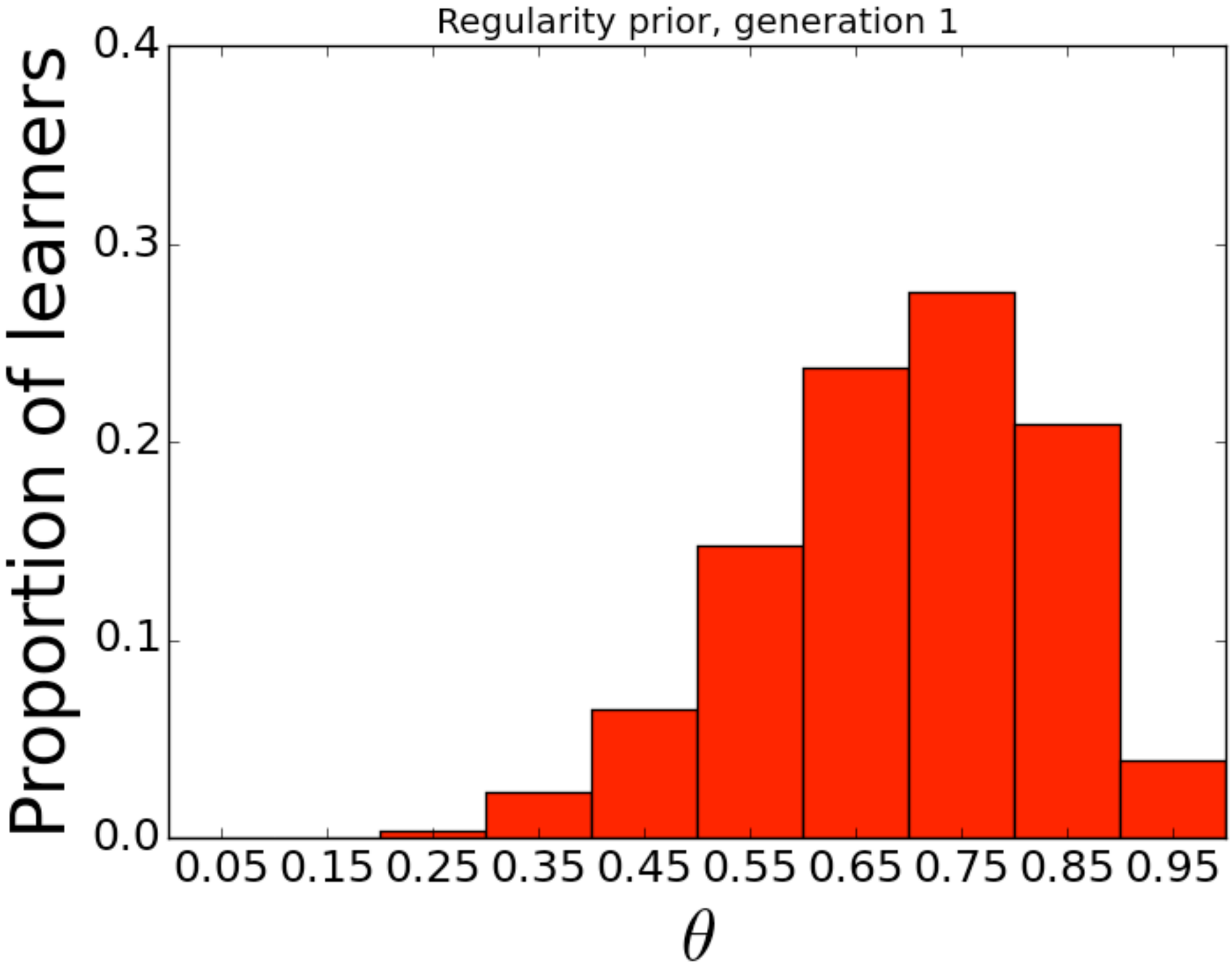

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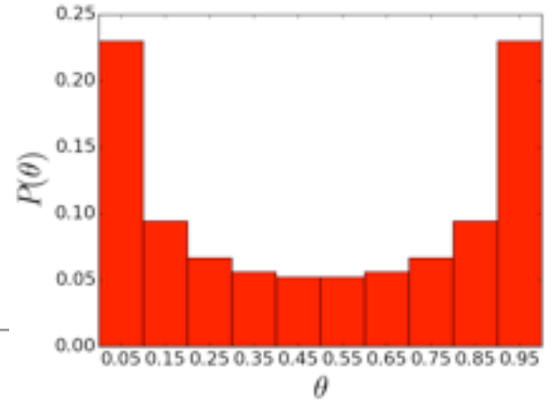

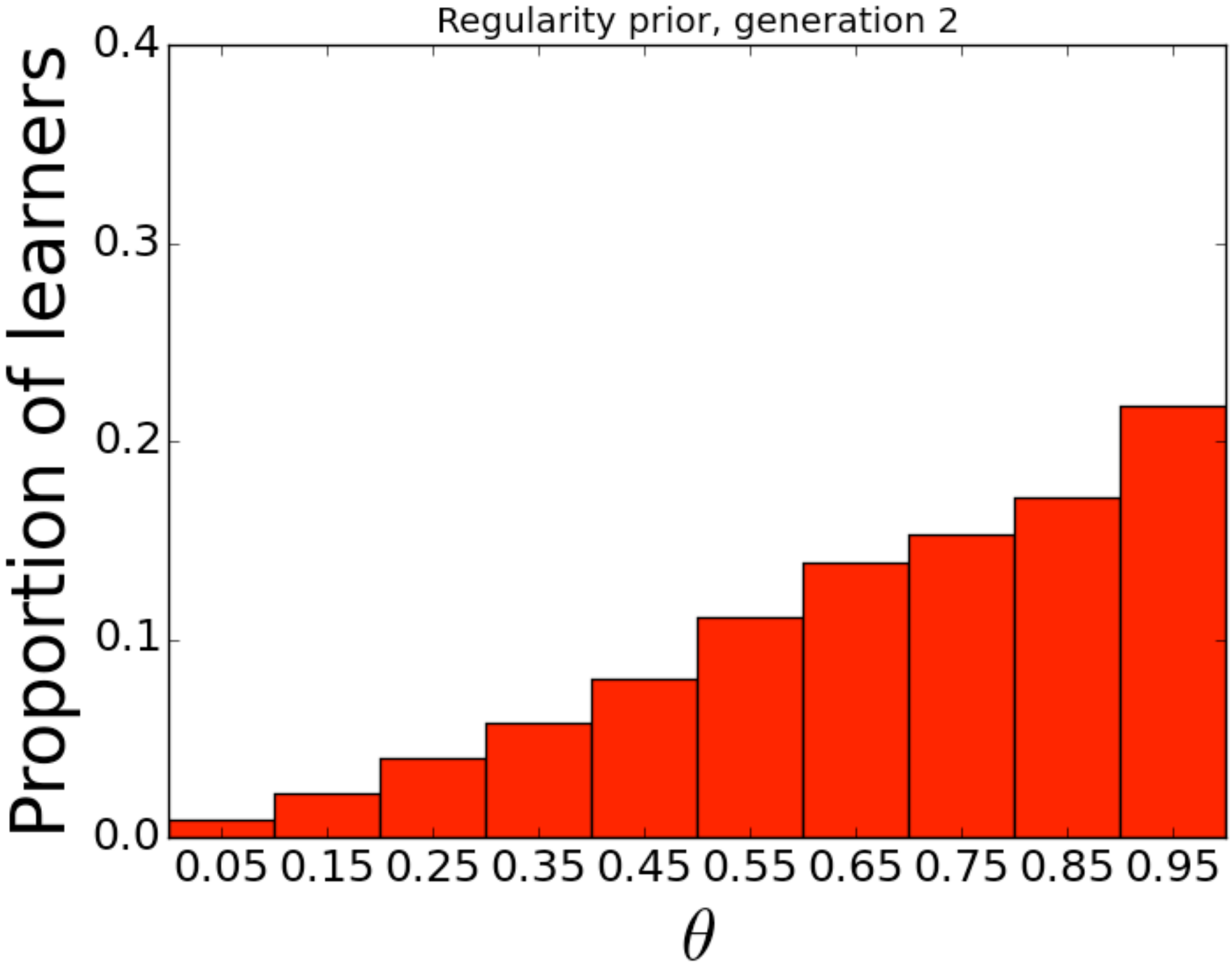

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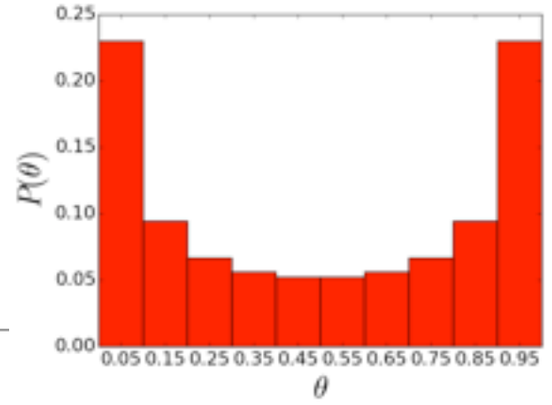

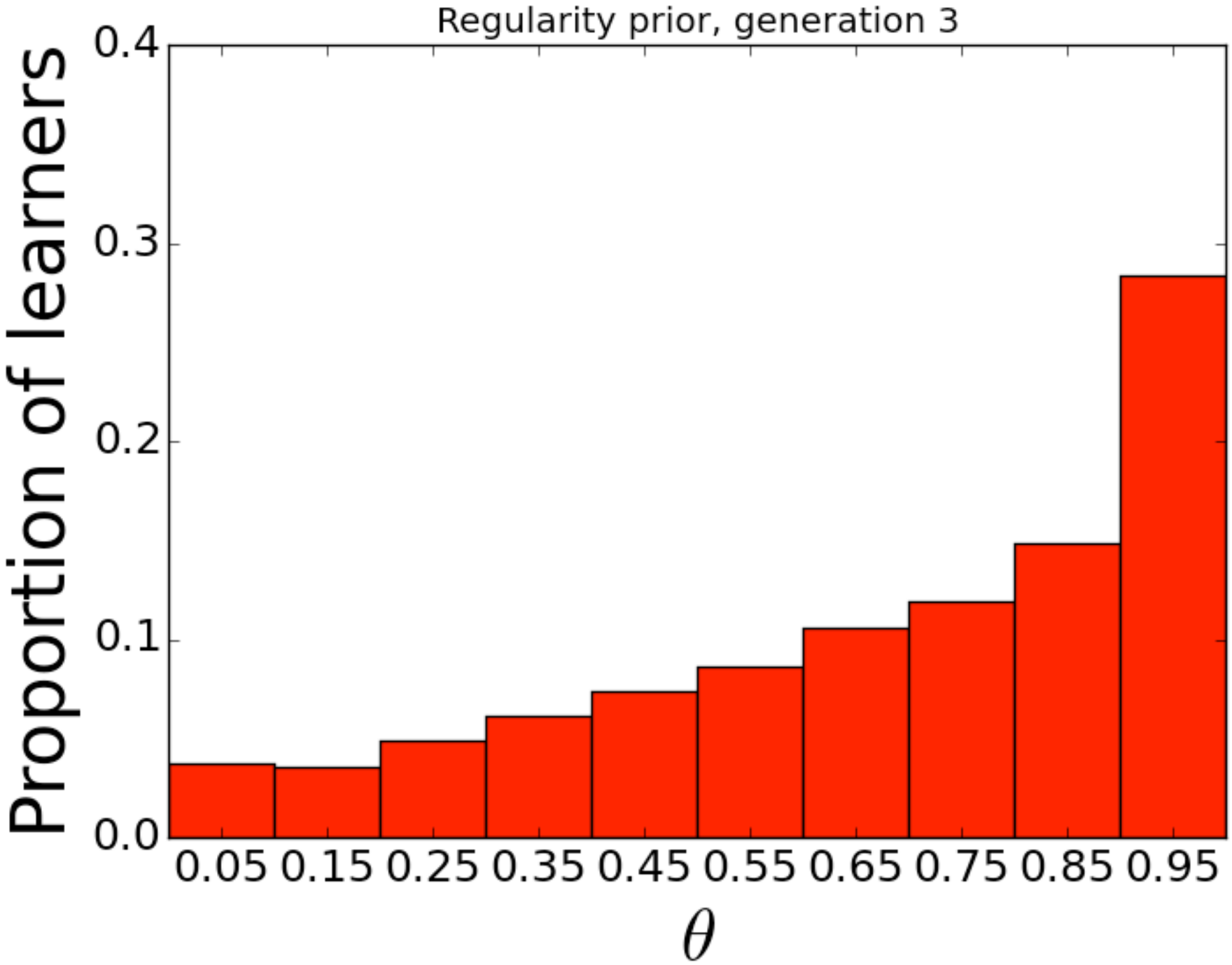

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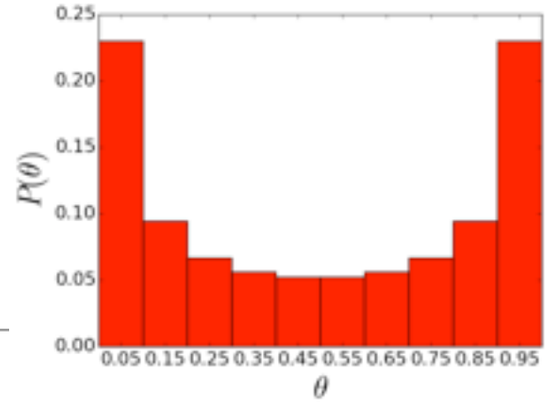

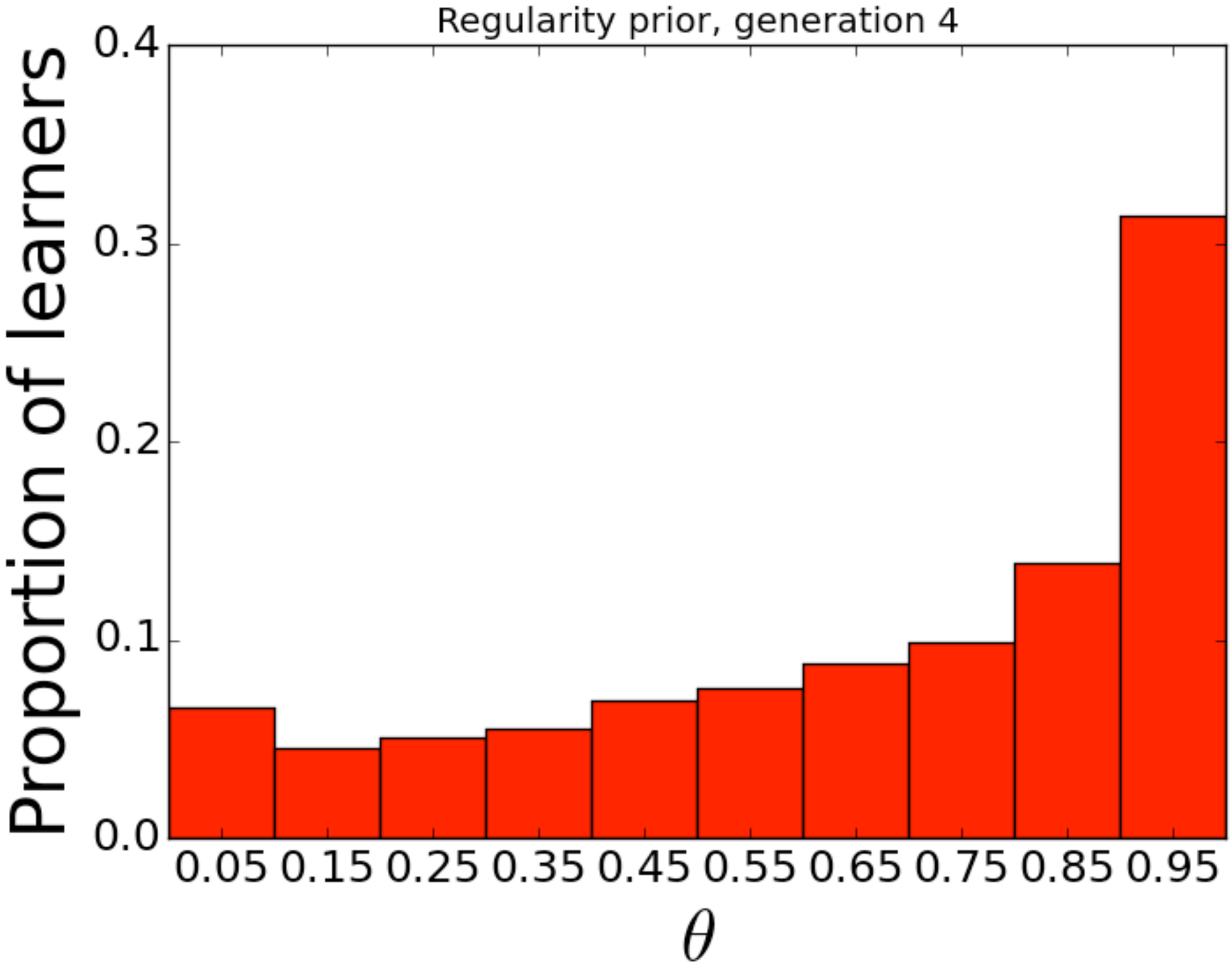

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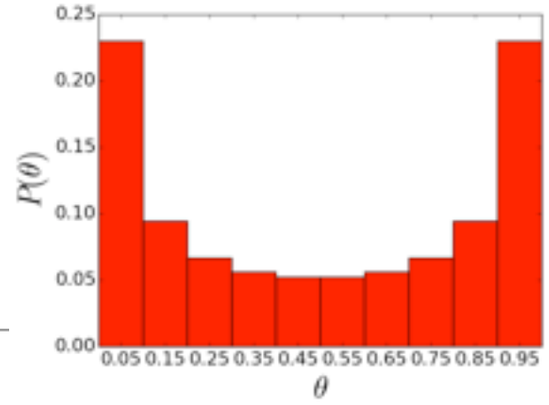

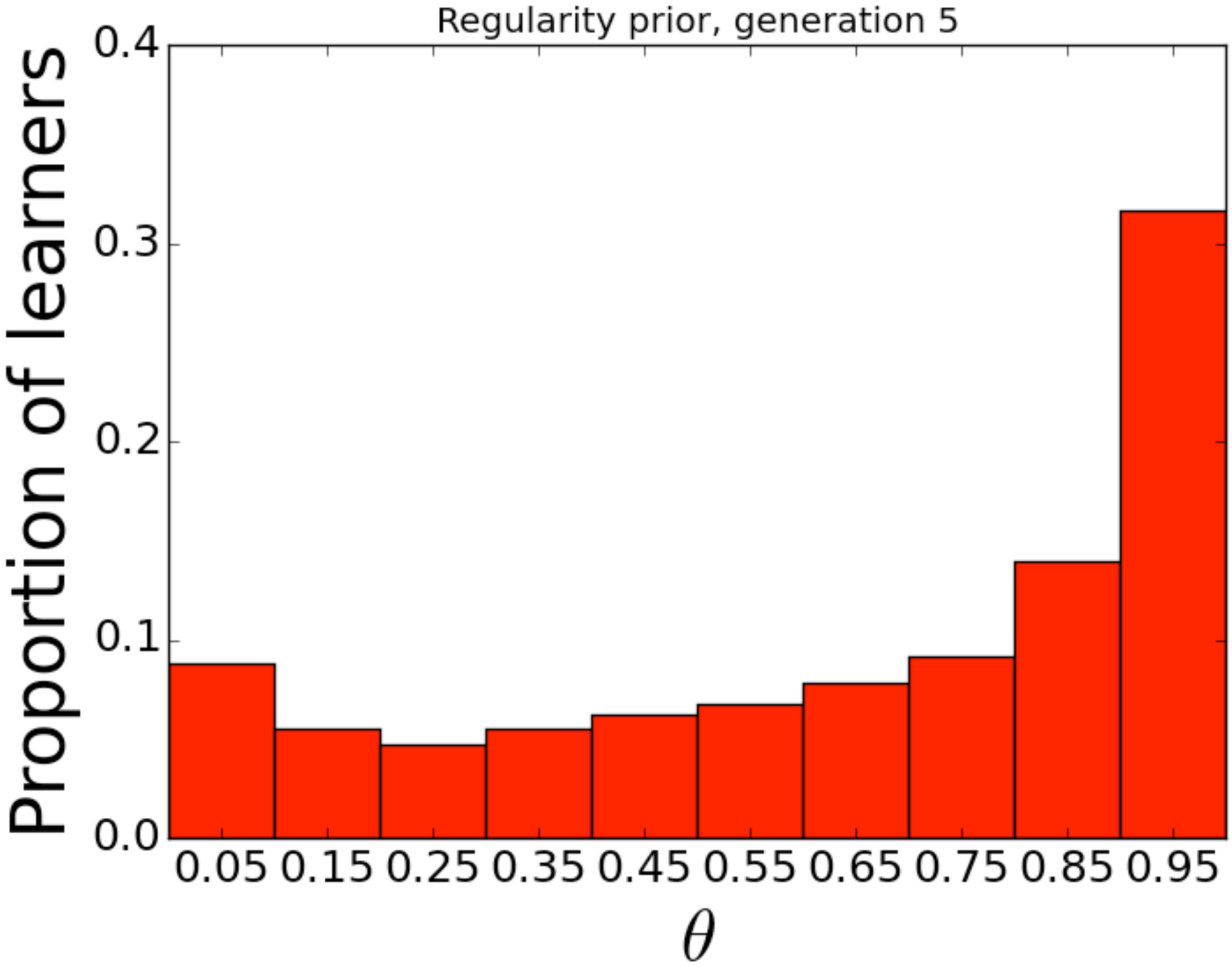

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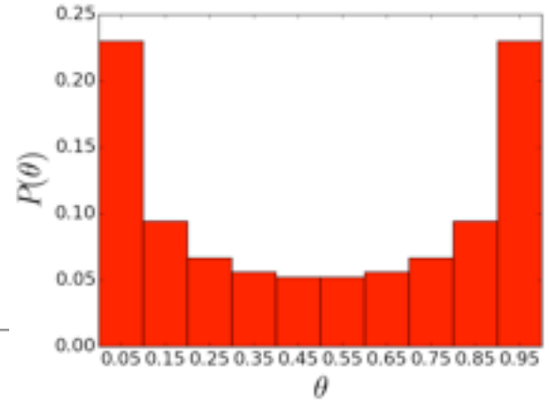

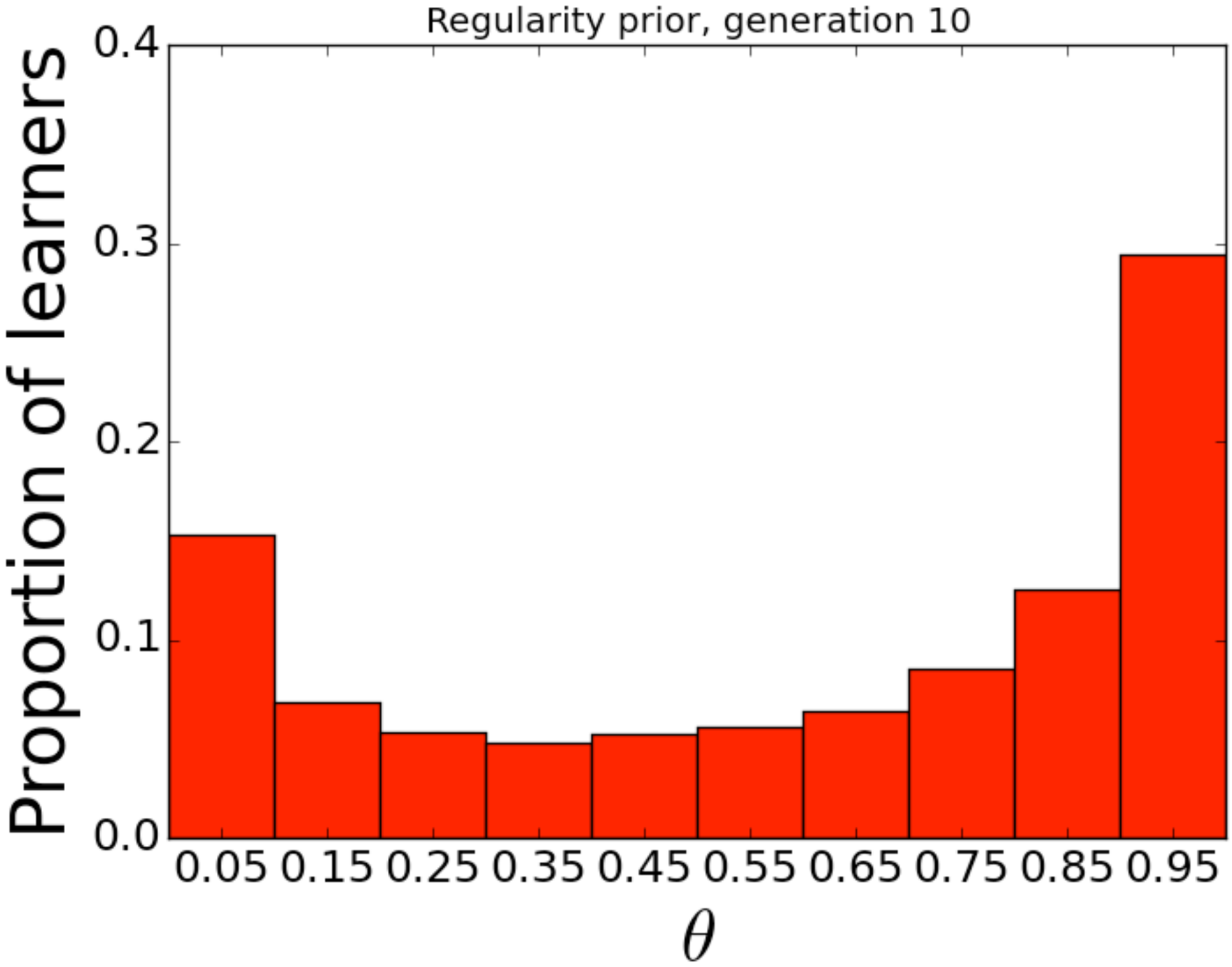

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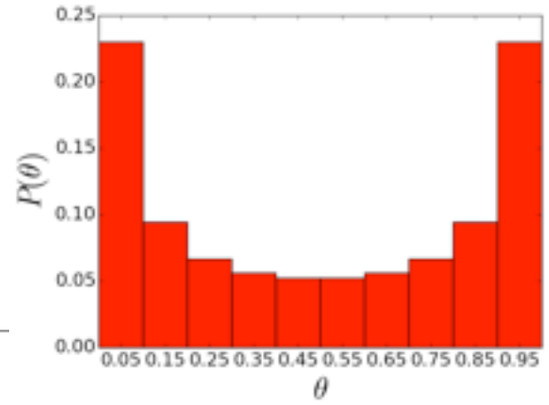

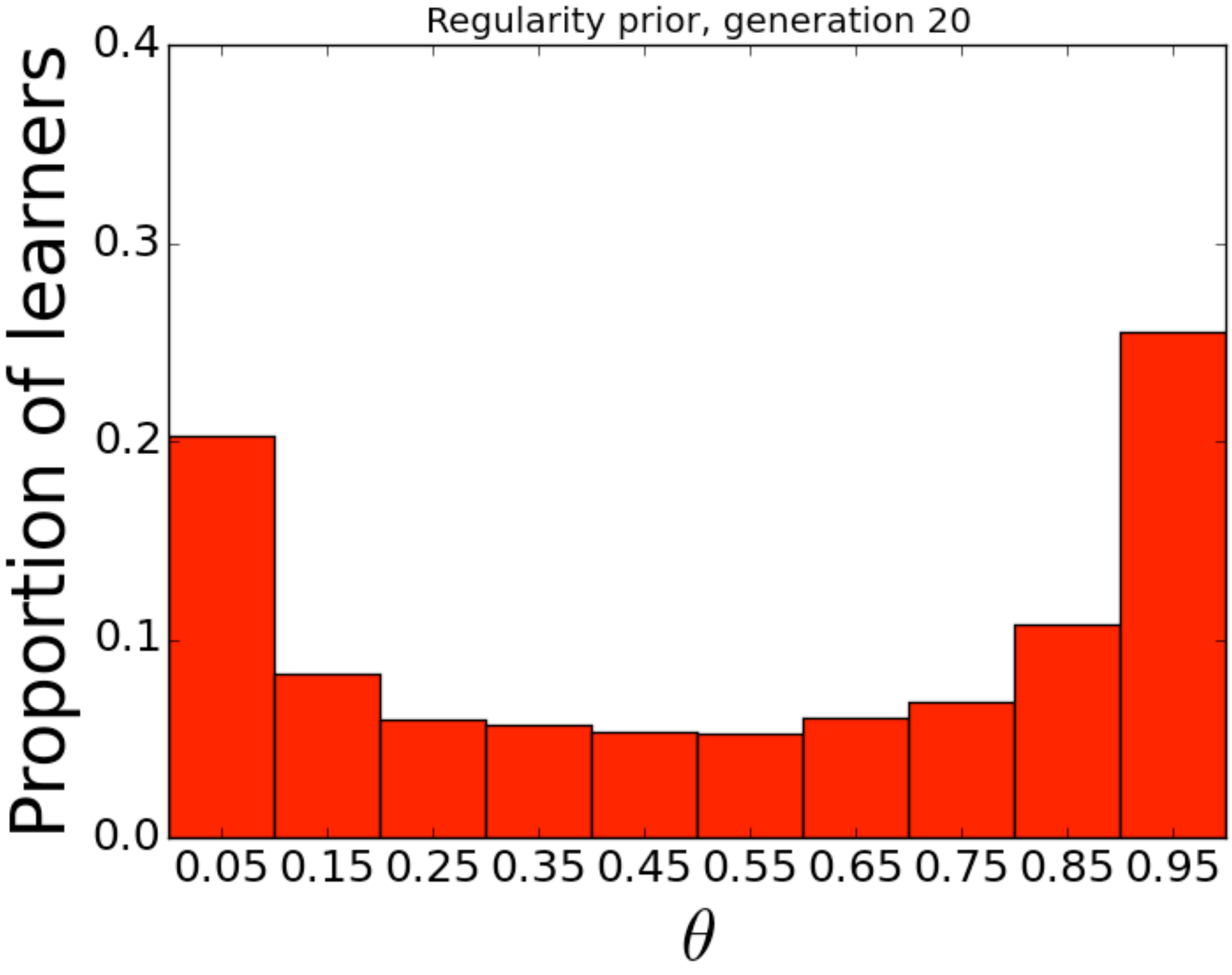

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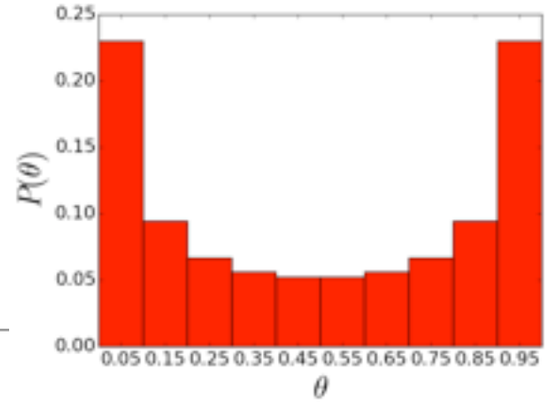

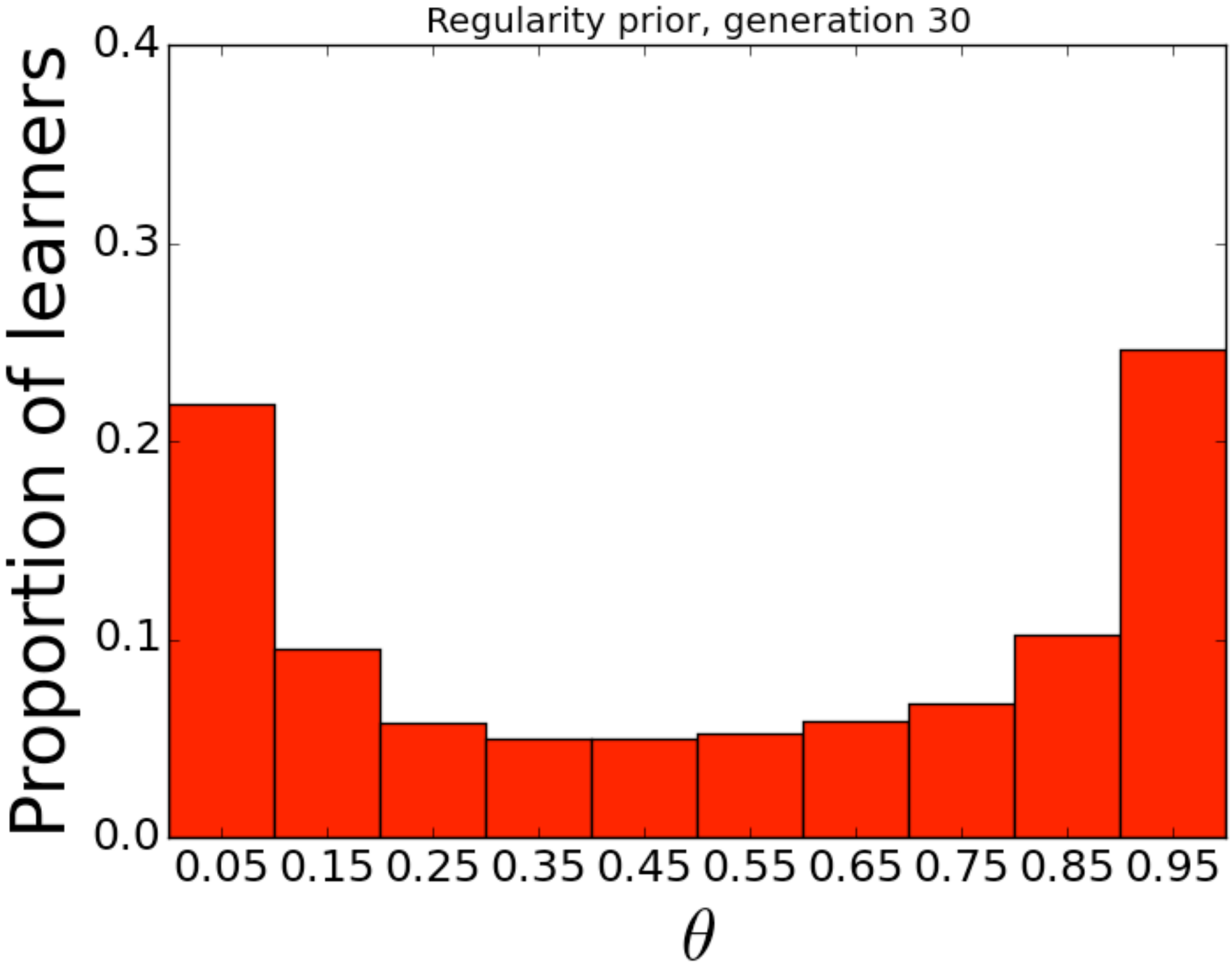

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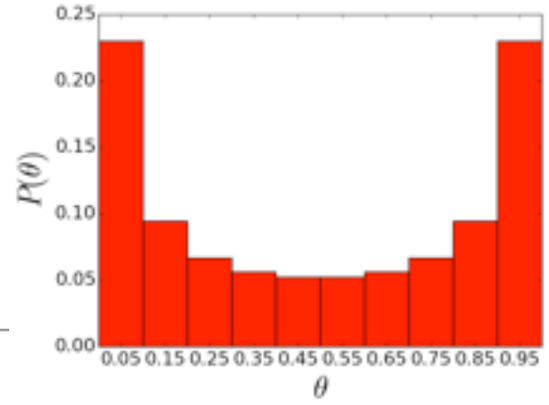

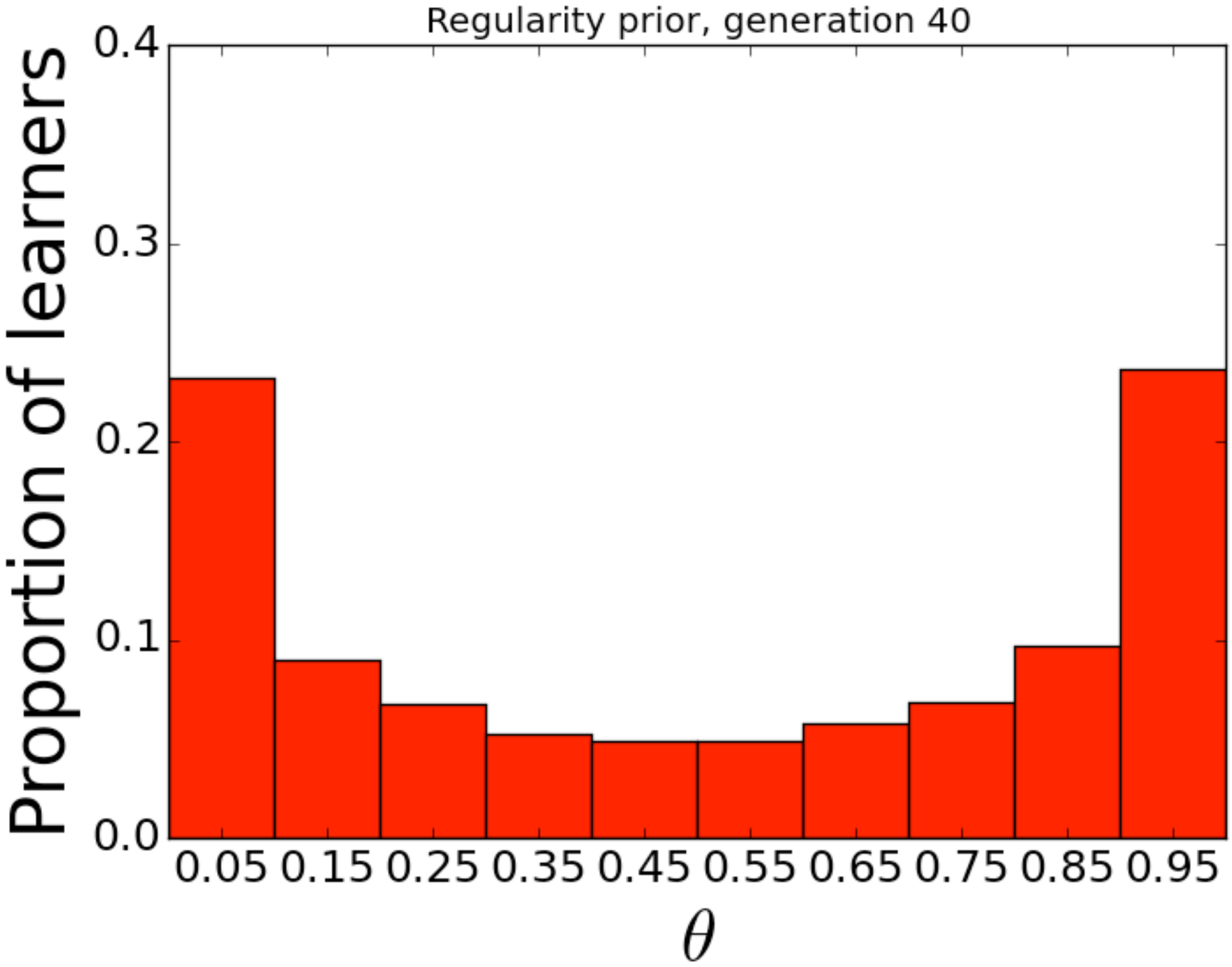

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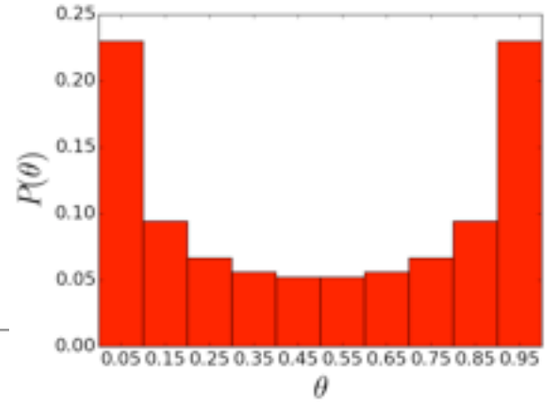

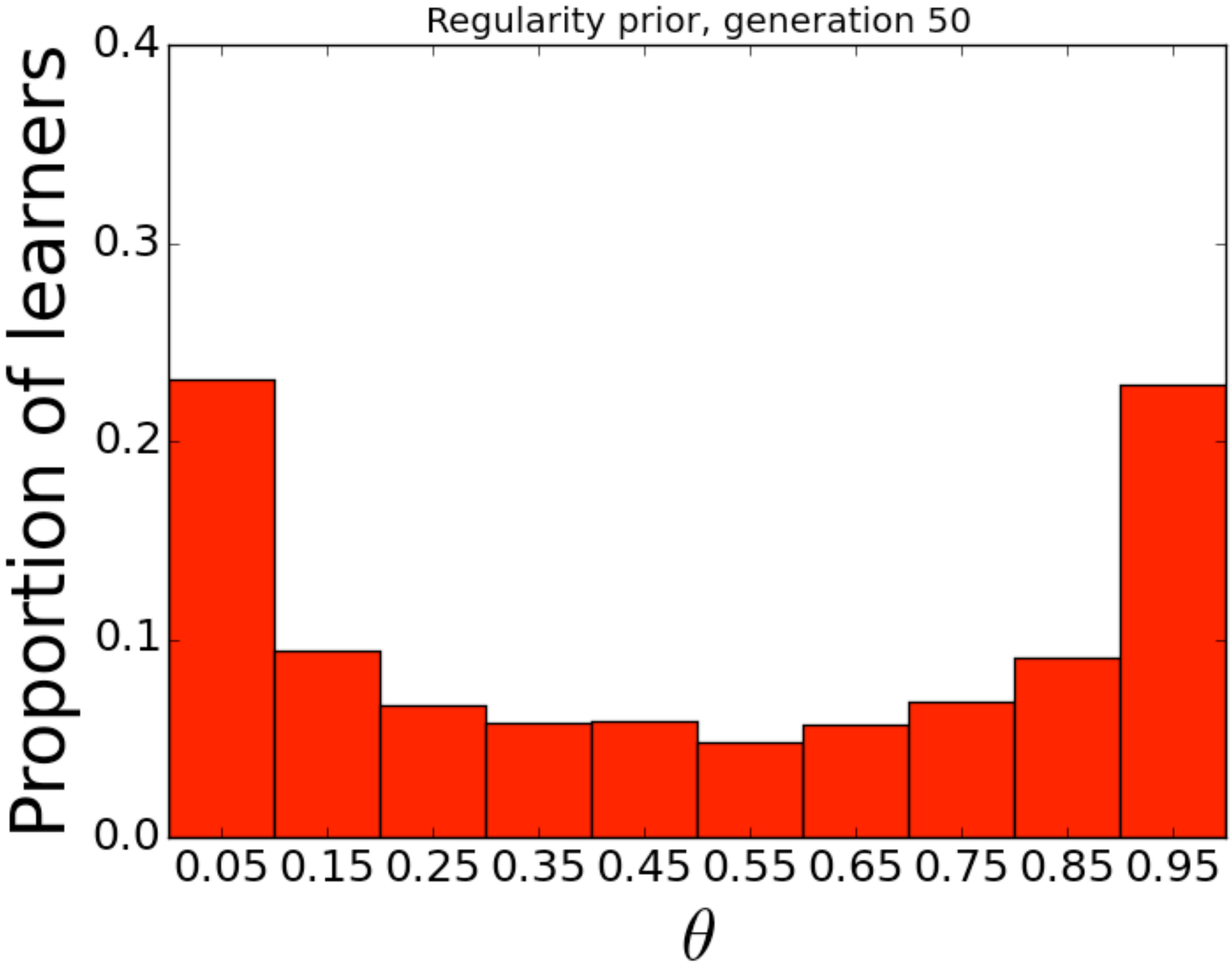

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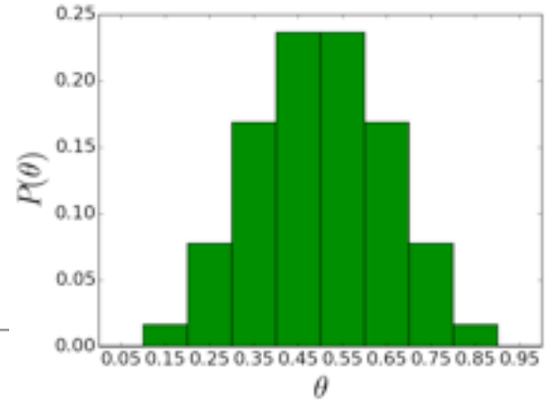

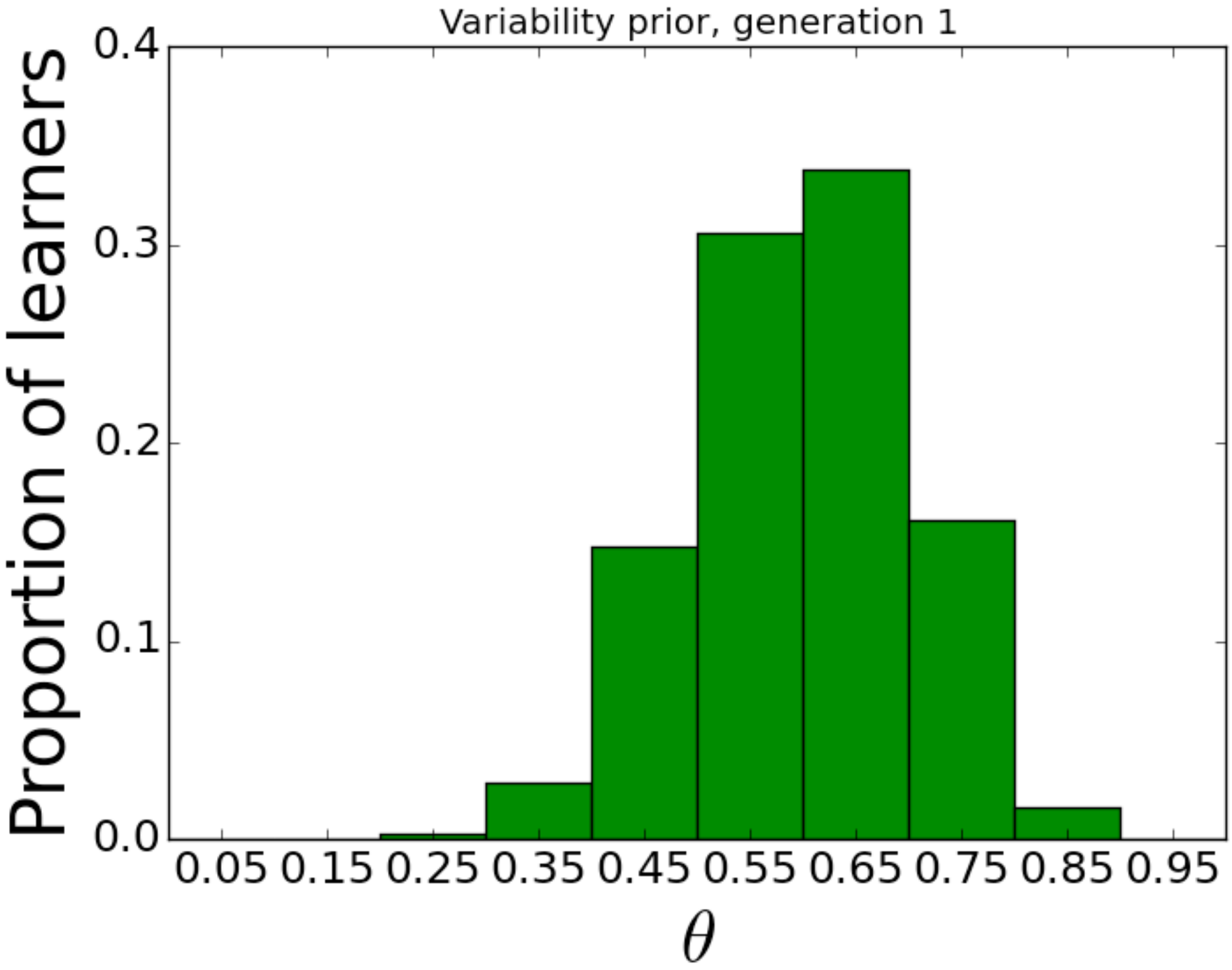

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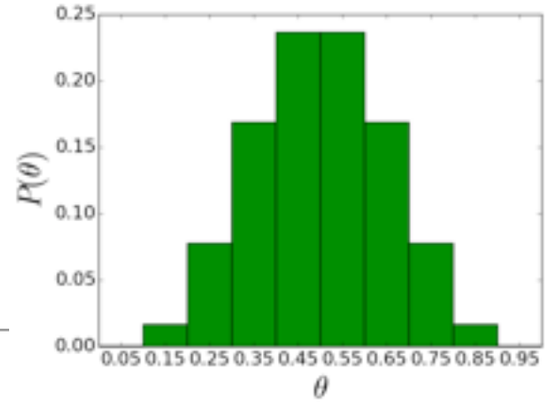

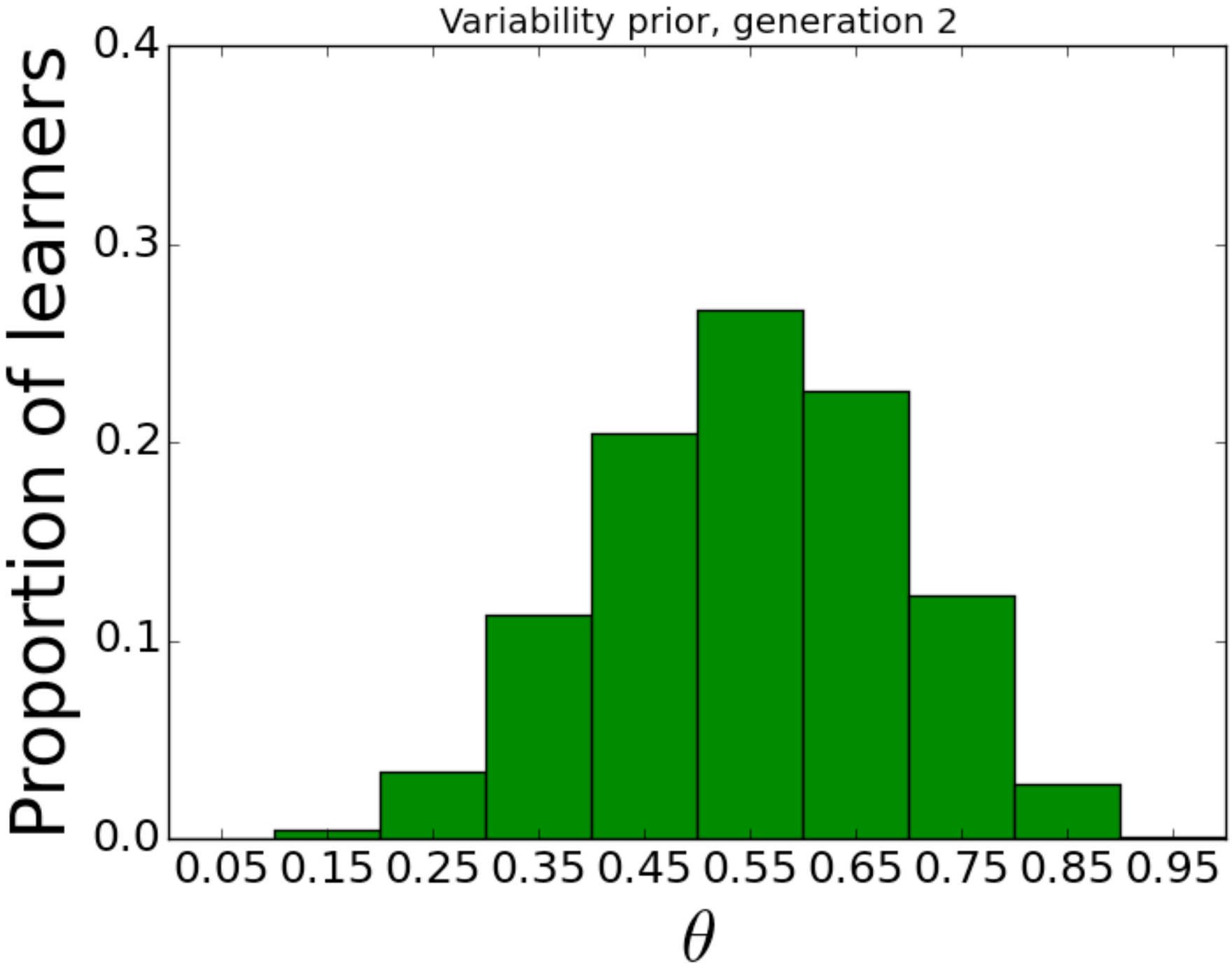

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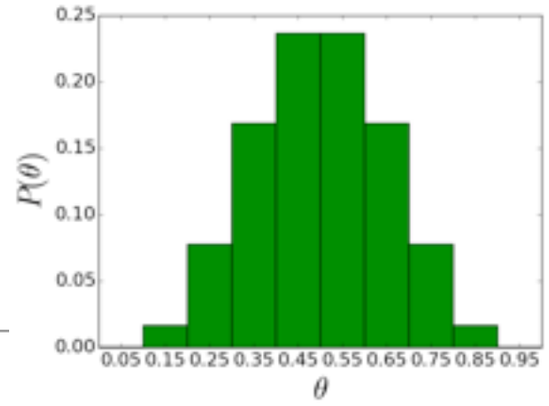

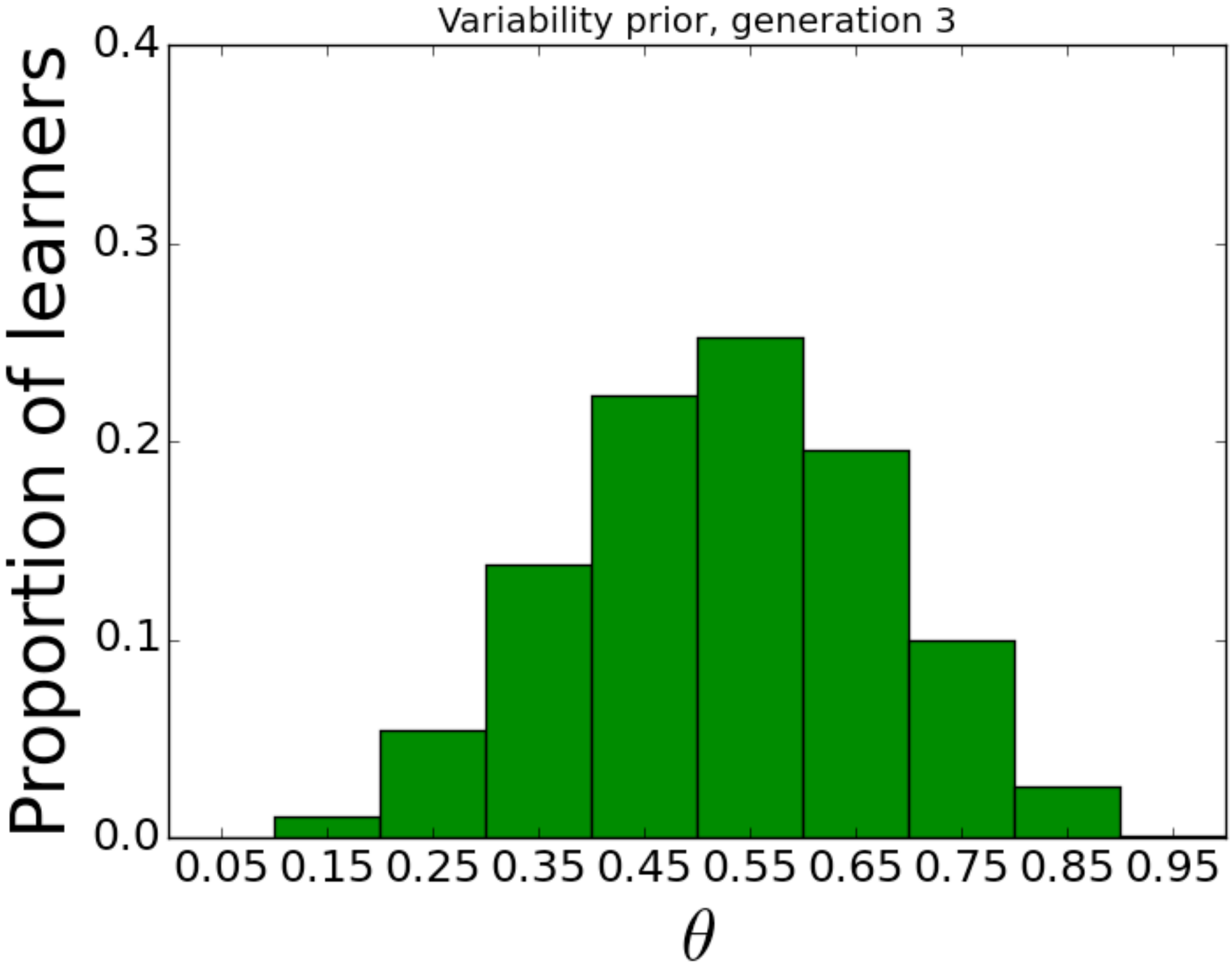

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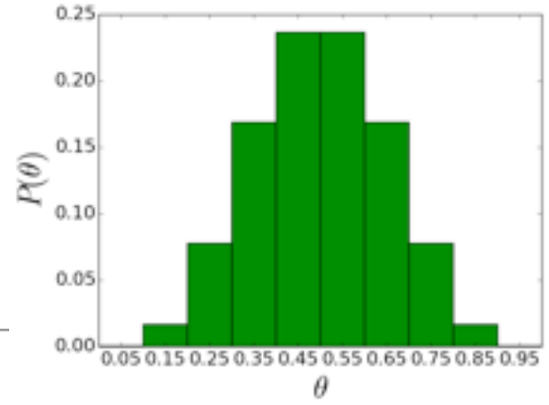

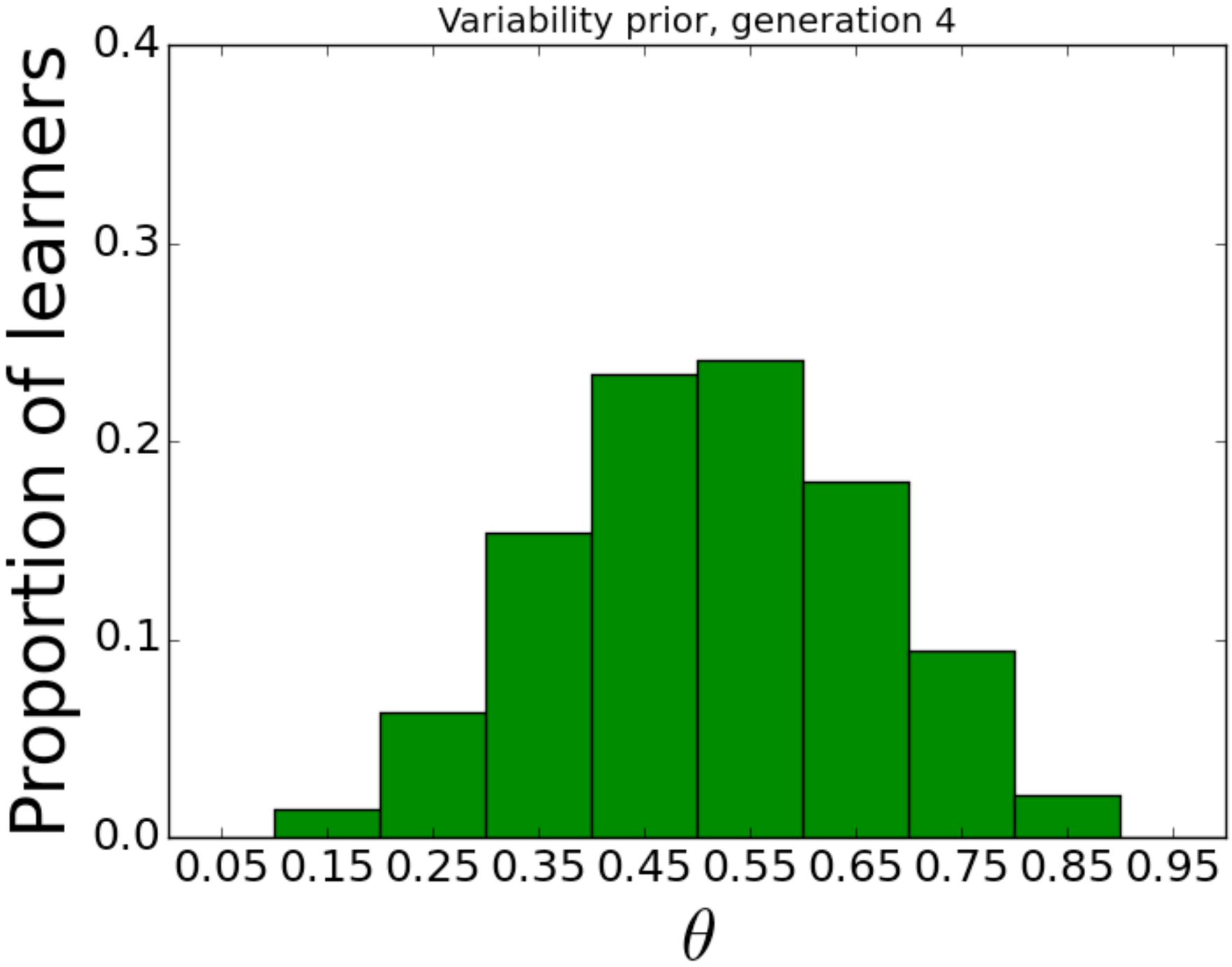

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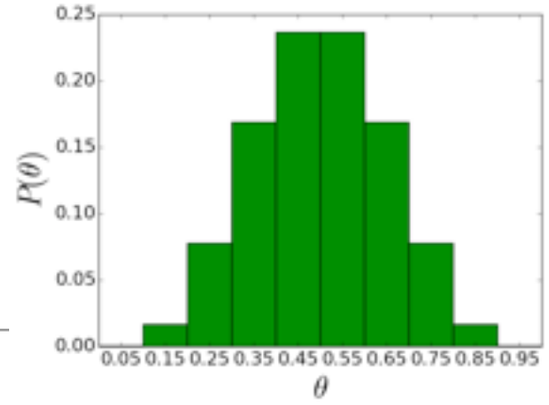

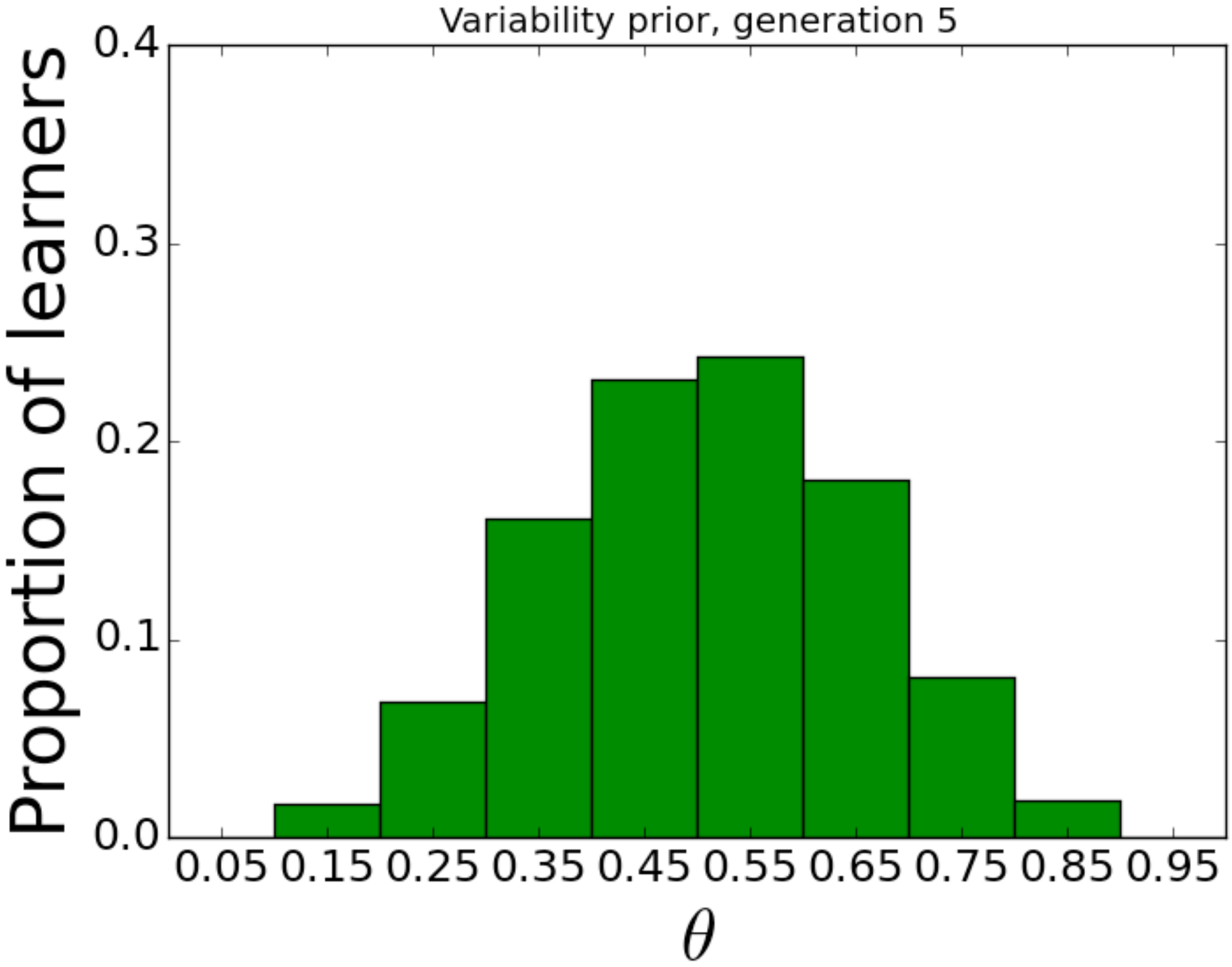

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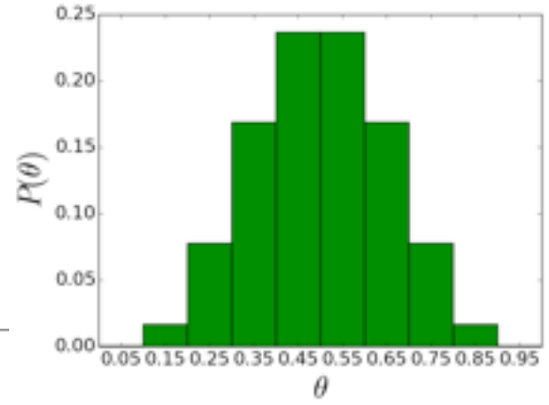
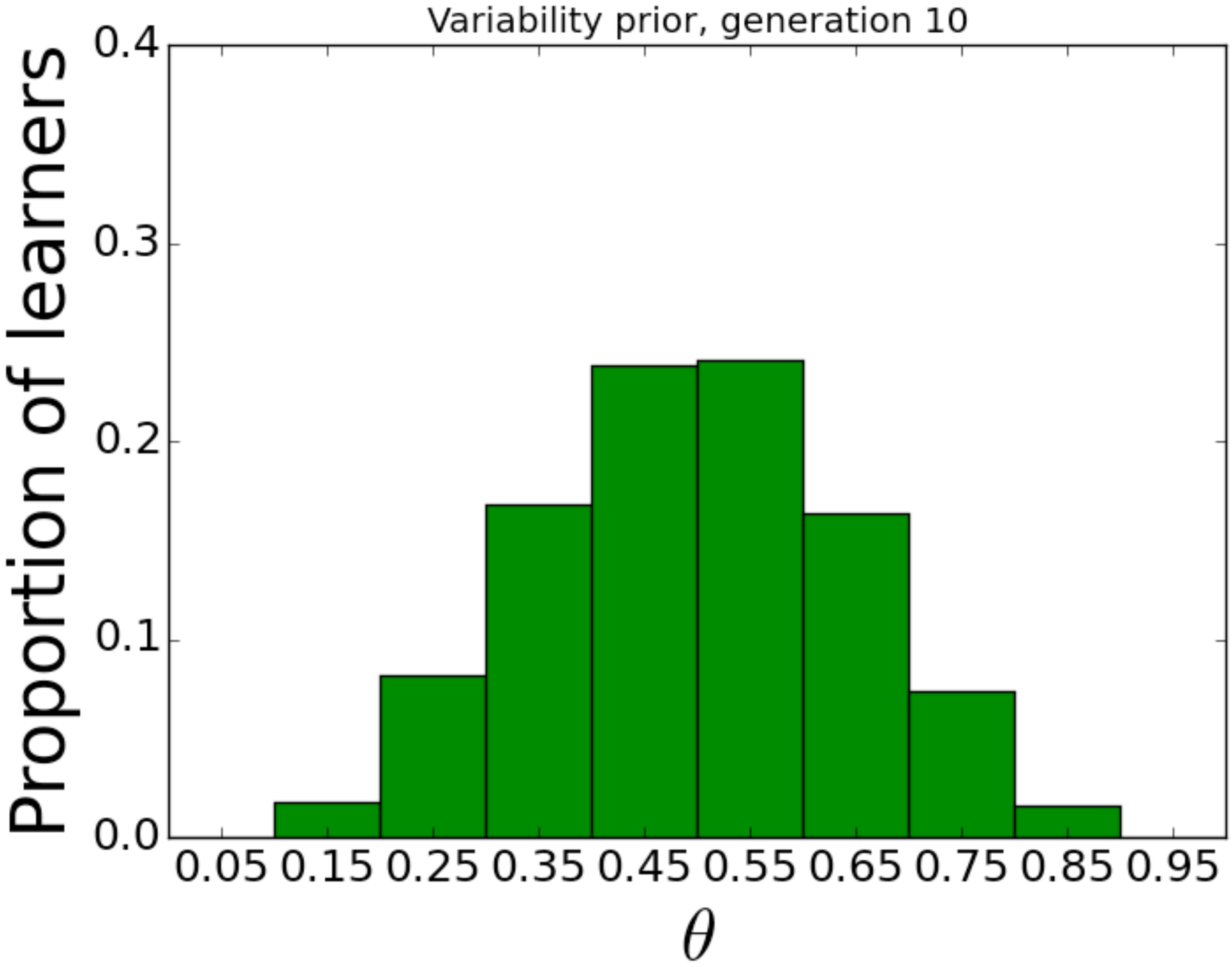
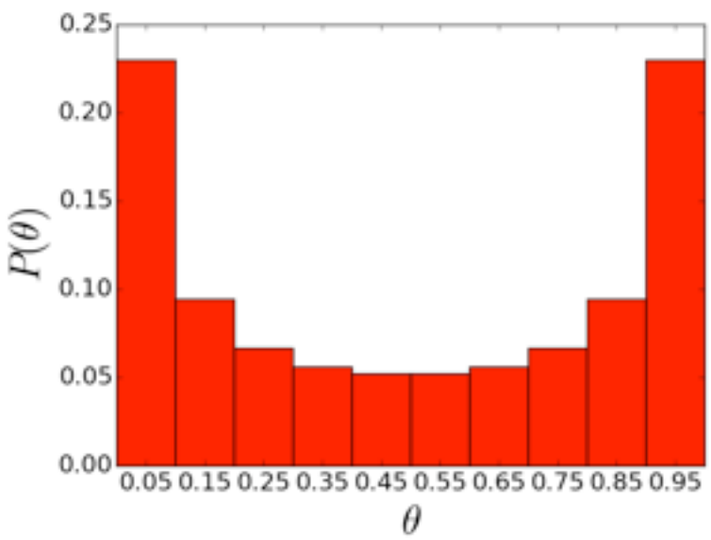
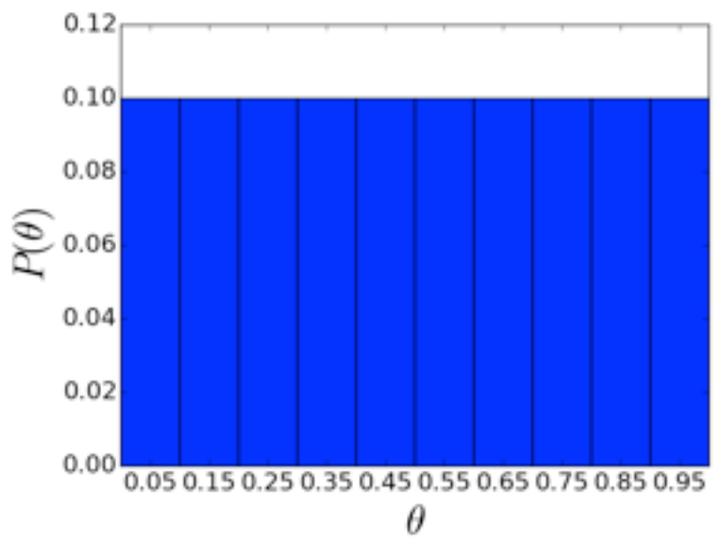


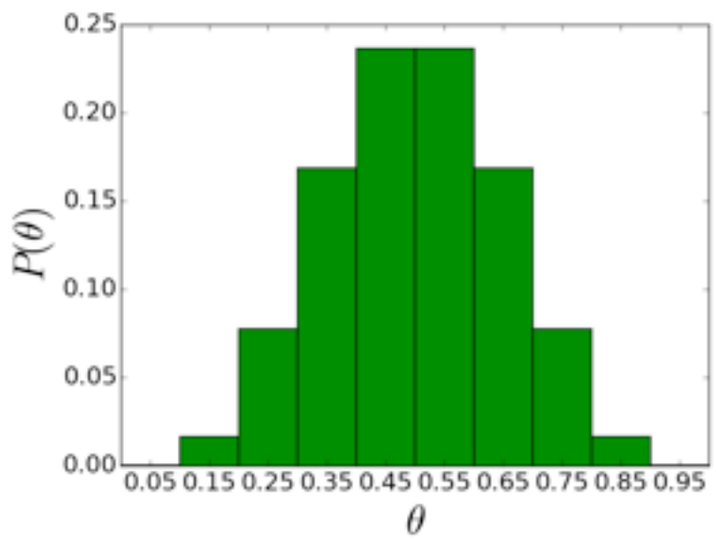


Culture converges to the prior

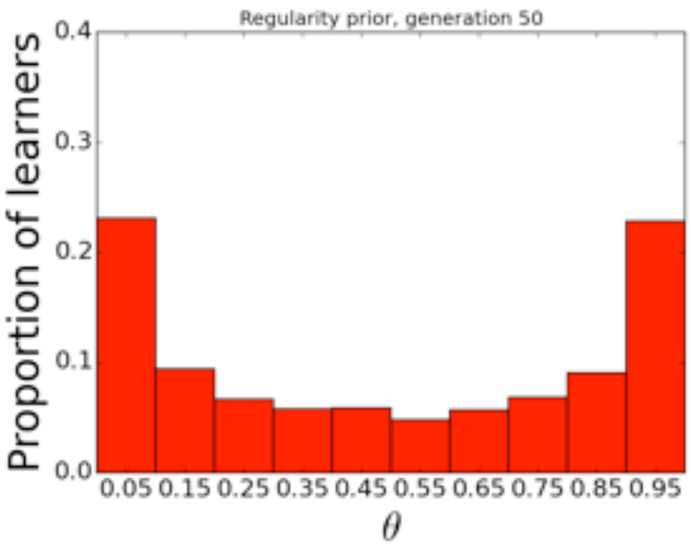
- Priors

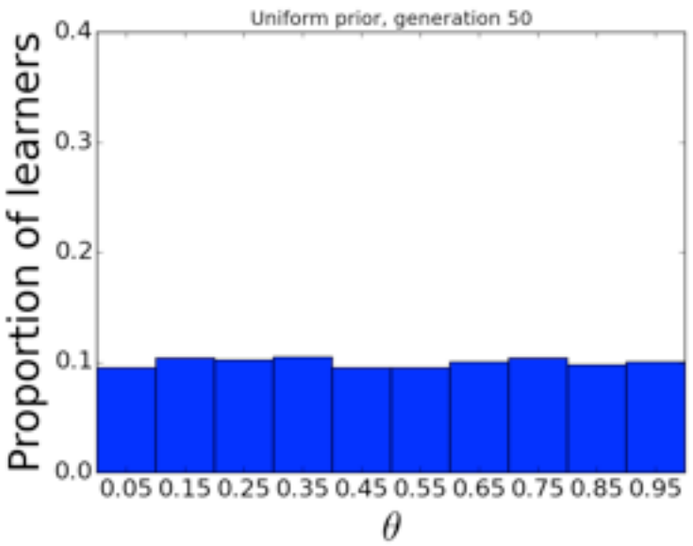


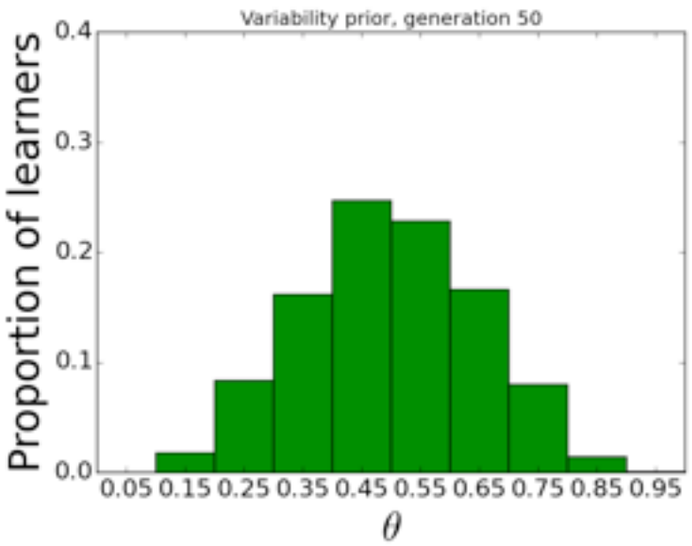




- Distribution of languages after 50 generations







What is the relationship between languages and language learners here?

- The types of languages we see in the world should:

A. be completely unconstrained by the biases of language learners

B. reflect the biases of language learners, but in an interestingly complex way (weak biases have strong effects, bottleneck matters, etc)

C. directly reflect the biases of language learners

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Hang on a minute...

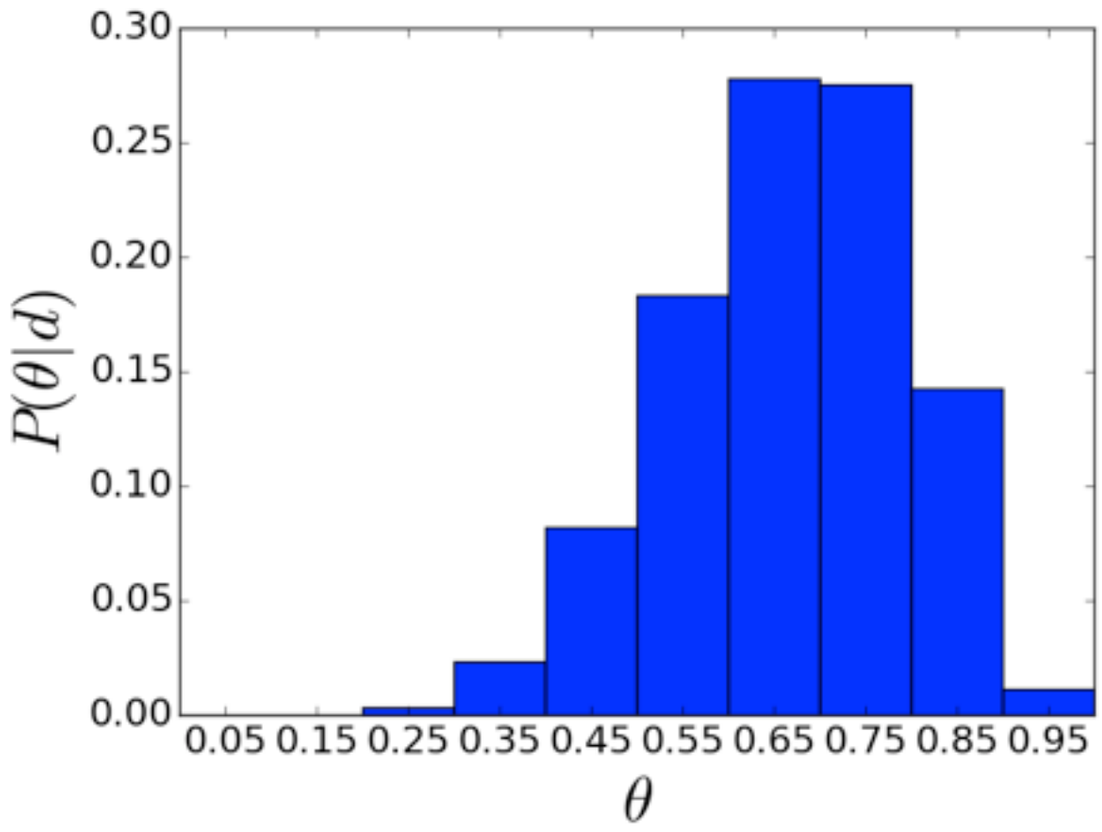
- This runs counter to the results from Kirby's (2002) simulation
    - He argued that it was the bottleneck that was driving adaptation of the language
- It also runs counter to the spirit of all the stuff I have been saying throughout this course!
    - I argued that cultural evolution has something important to add
- If prior bias is what is innate to the learner, then the Griffiths & Kalish result suggests that the universal properties of language are just a straightforward reflection of innateness
- Hmmm...

Some subtleties in the model

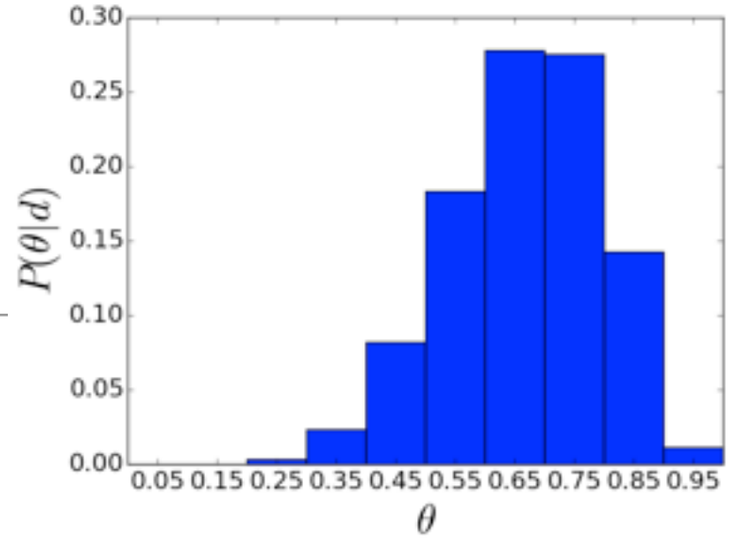
- Kirby, Dowman & Griffiths (2007): tried to square the Bayesian model with what we **thought** we knew about cultural evolution of language

- Whole thing revolves around a very subtle point
  - How do you decide, given the posterior, which language to select?

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



Sampling vs. MAP



- There are (at least) two sensible choices:
  - Sampling: given a particular distribution of probabilities, pick your hypothesis from the distribution proportionally.

    (If it's ten times more likely to be language A than language B, 10% of the time pick language B)

  - MAP: given a particular distribution of probabilities, pick the best. This is called the maximum a-posteriori (MAP) hypothesis

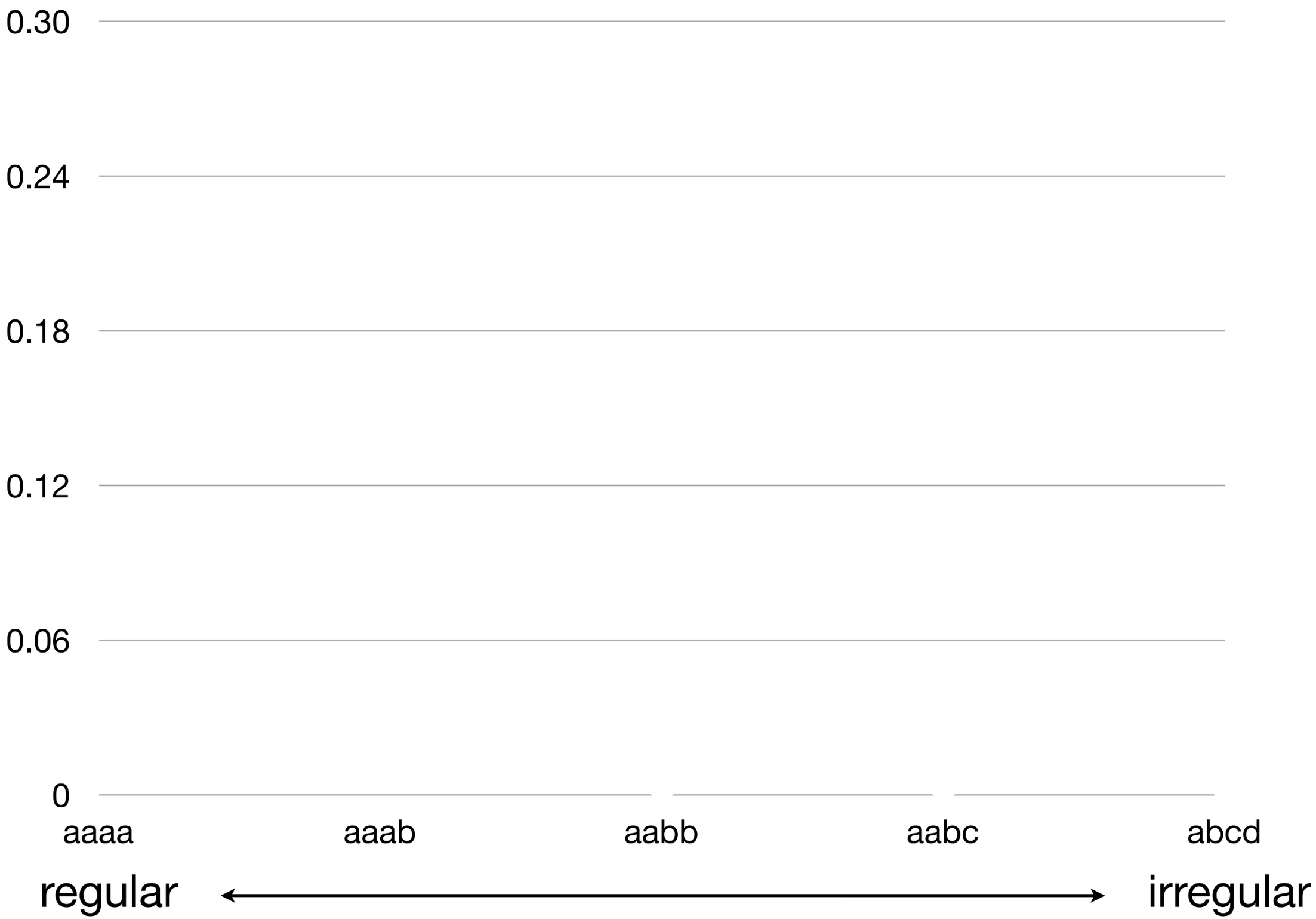
    (If it's more likely to be language A than language B, pick language A)

- Griffith & Kalish (2007) were using *sampling.* Kirby et al. (2007) tried MAP.

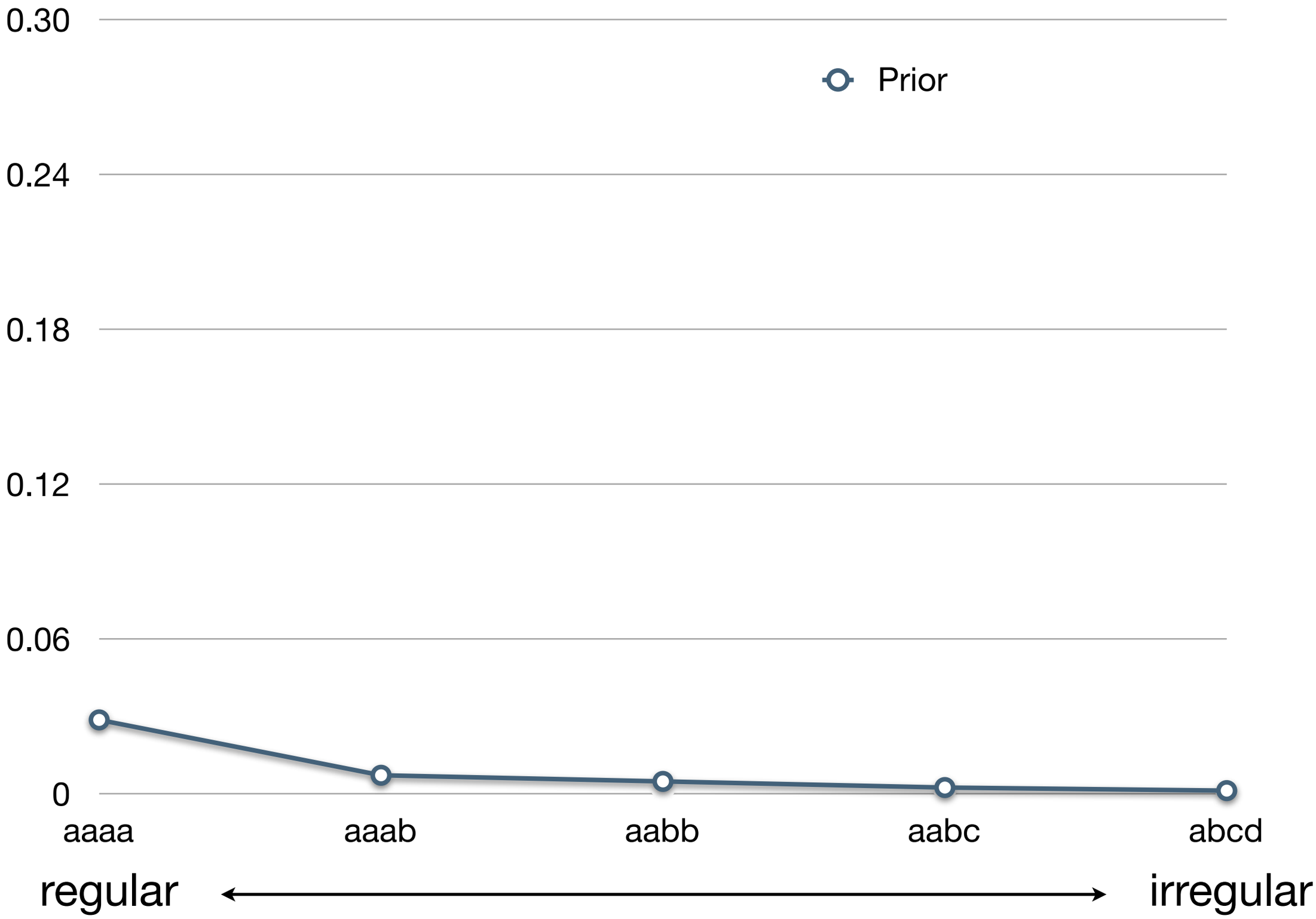
A final model: the evolution of regularity

- 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)



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



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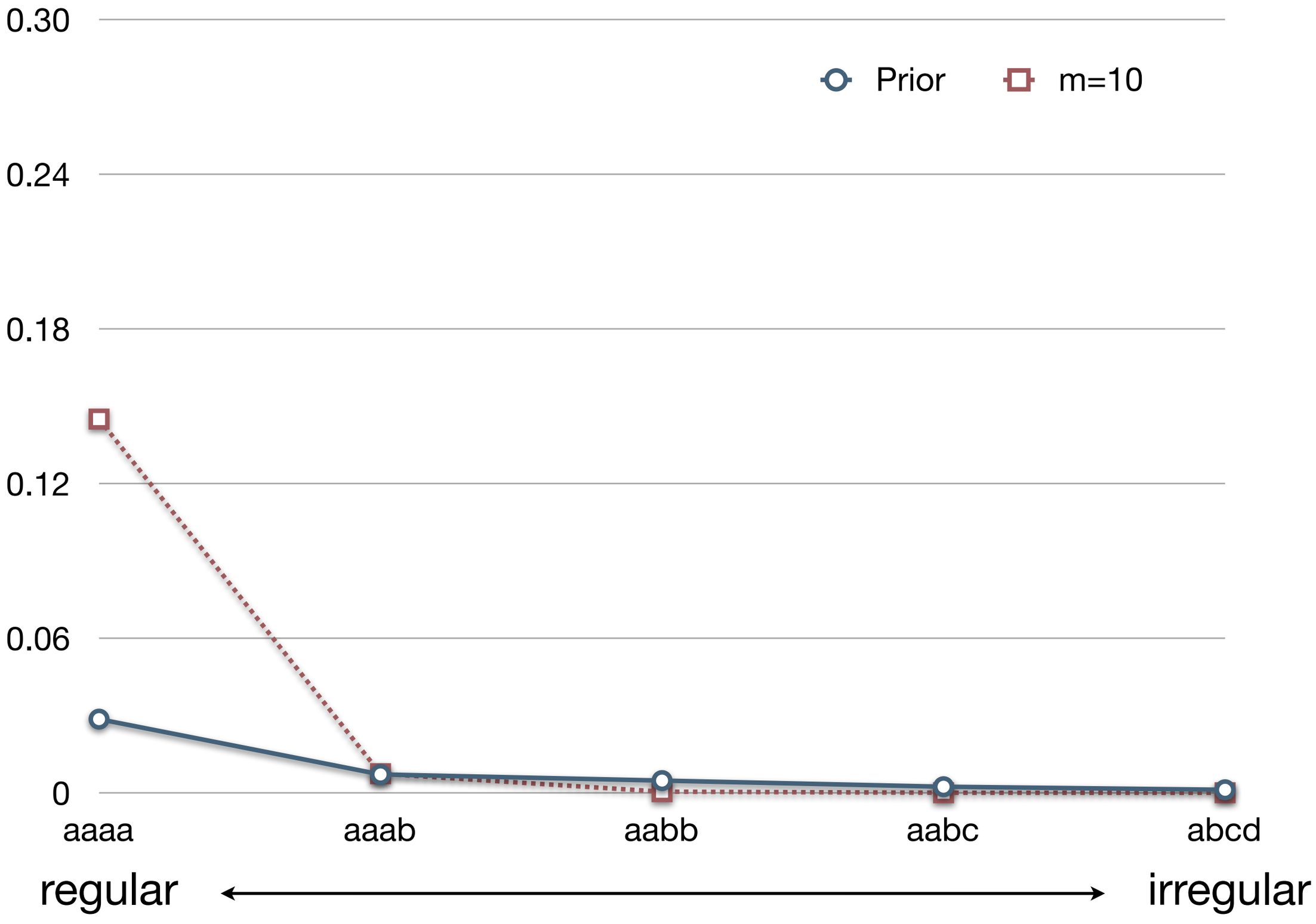

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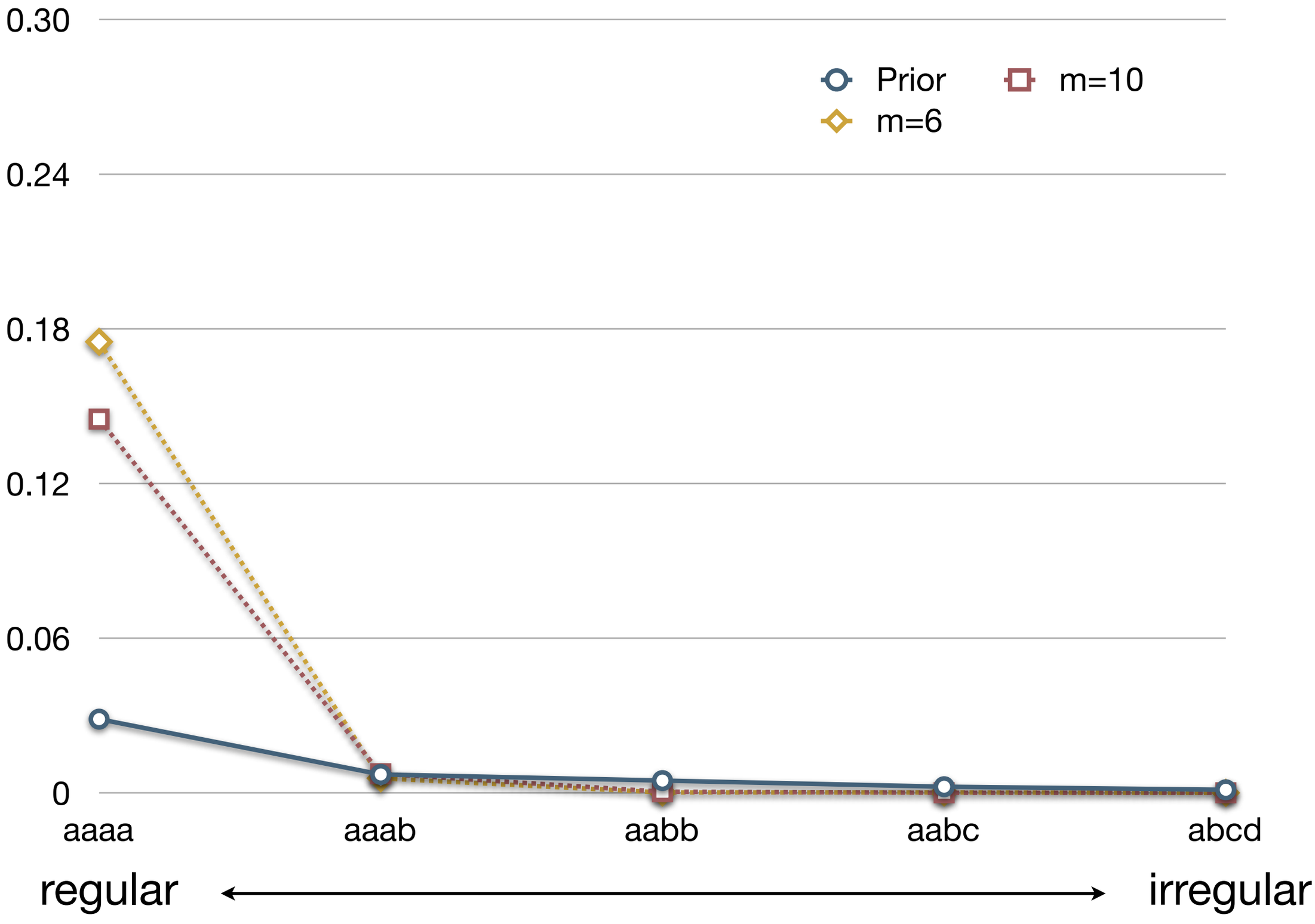

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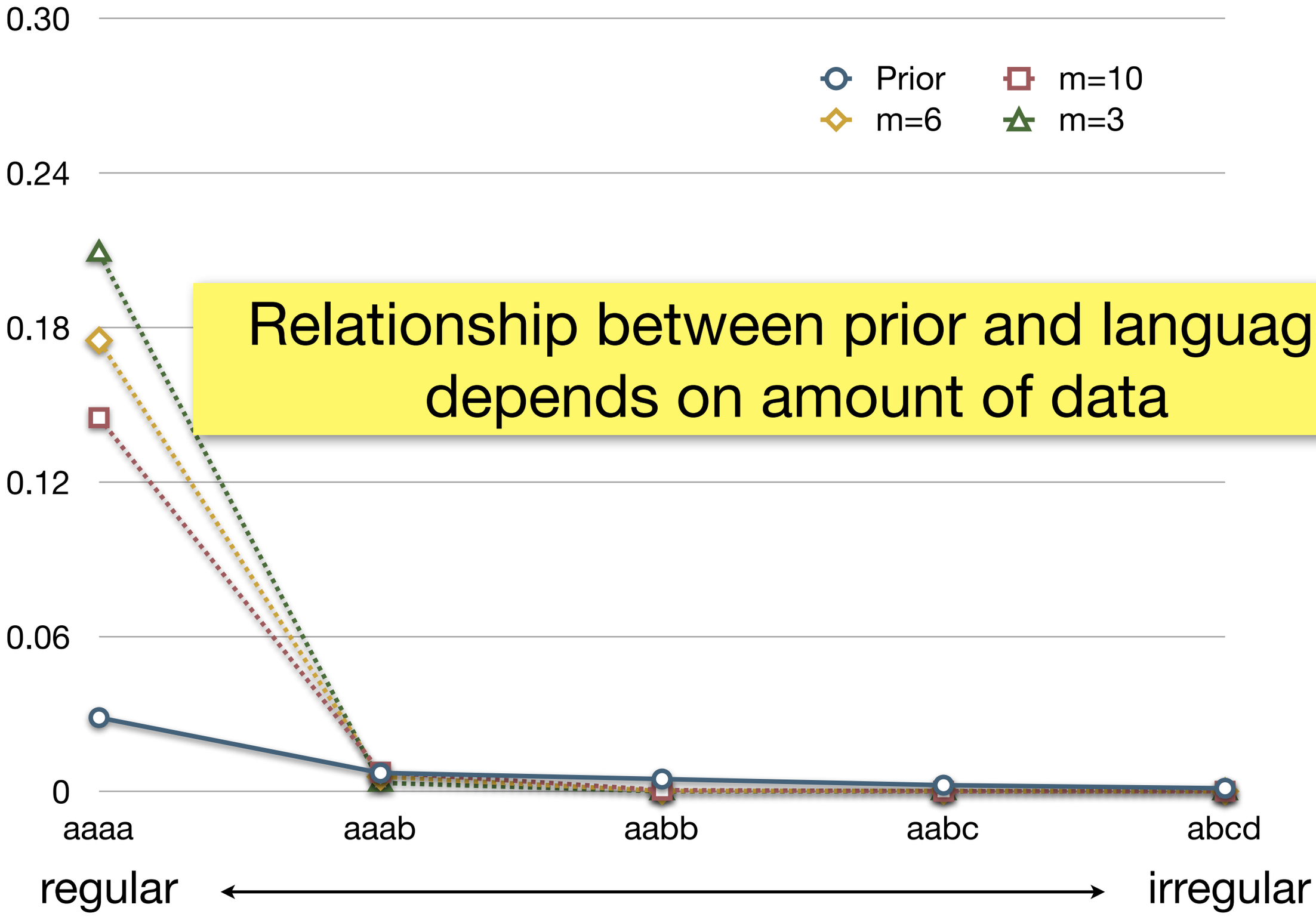
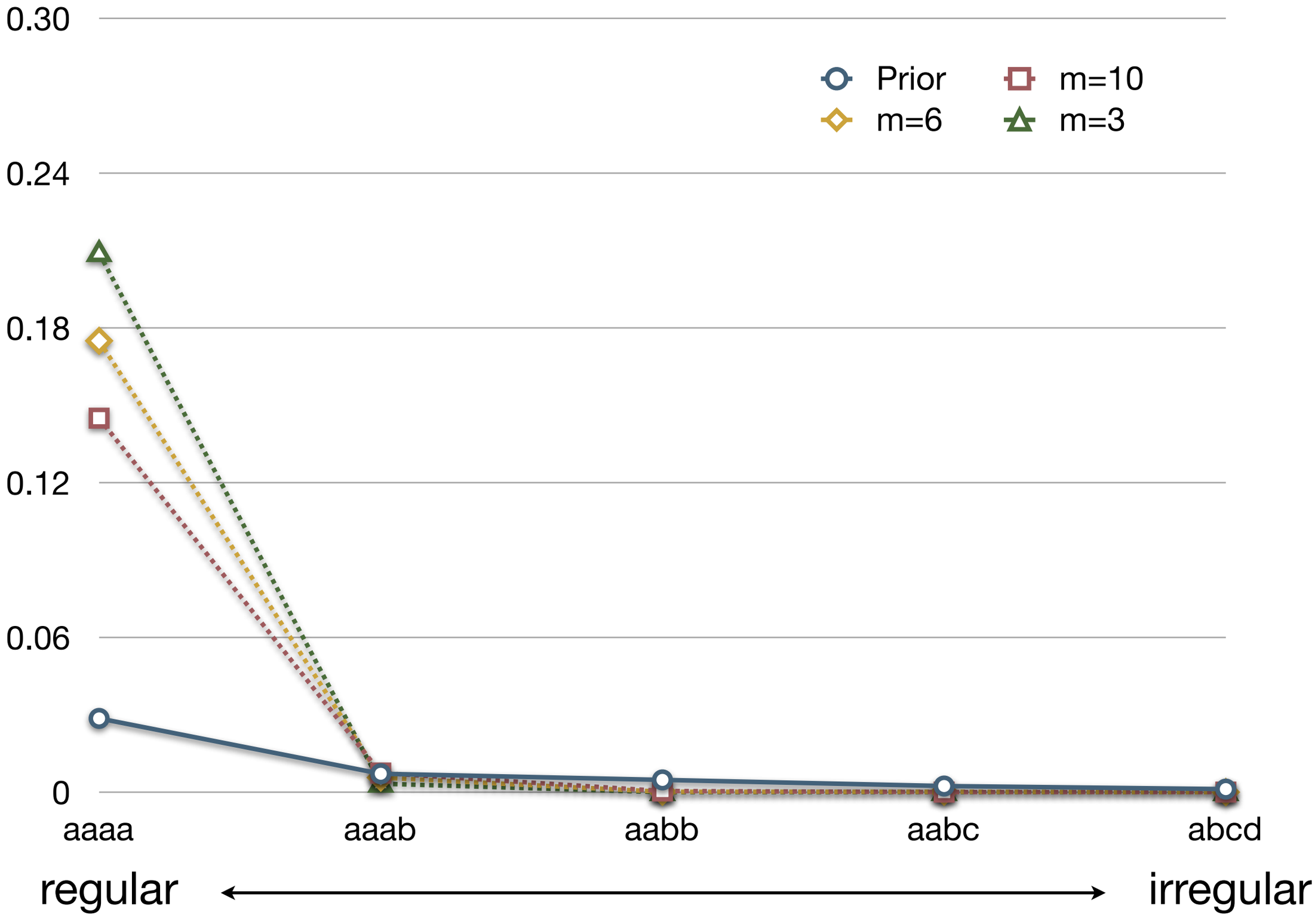
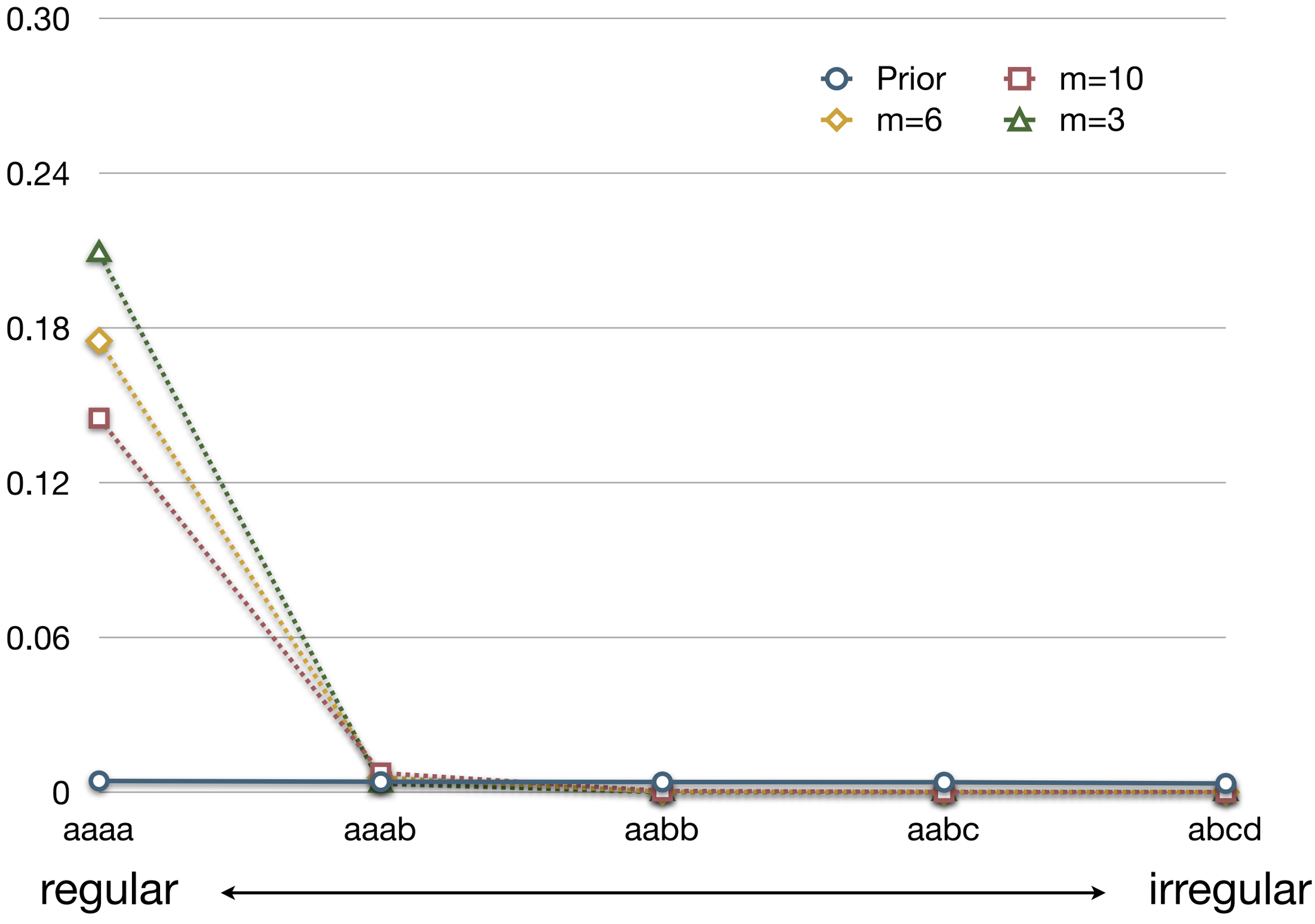


Relationship between prior and language depends on amount of data

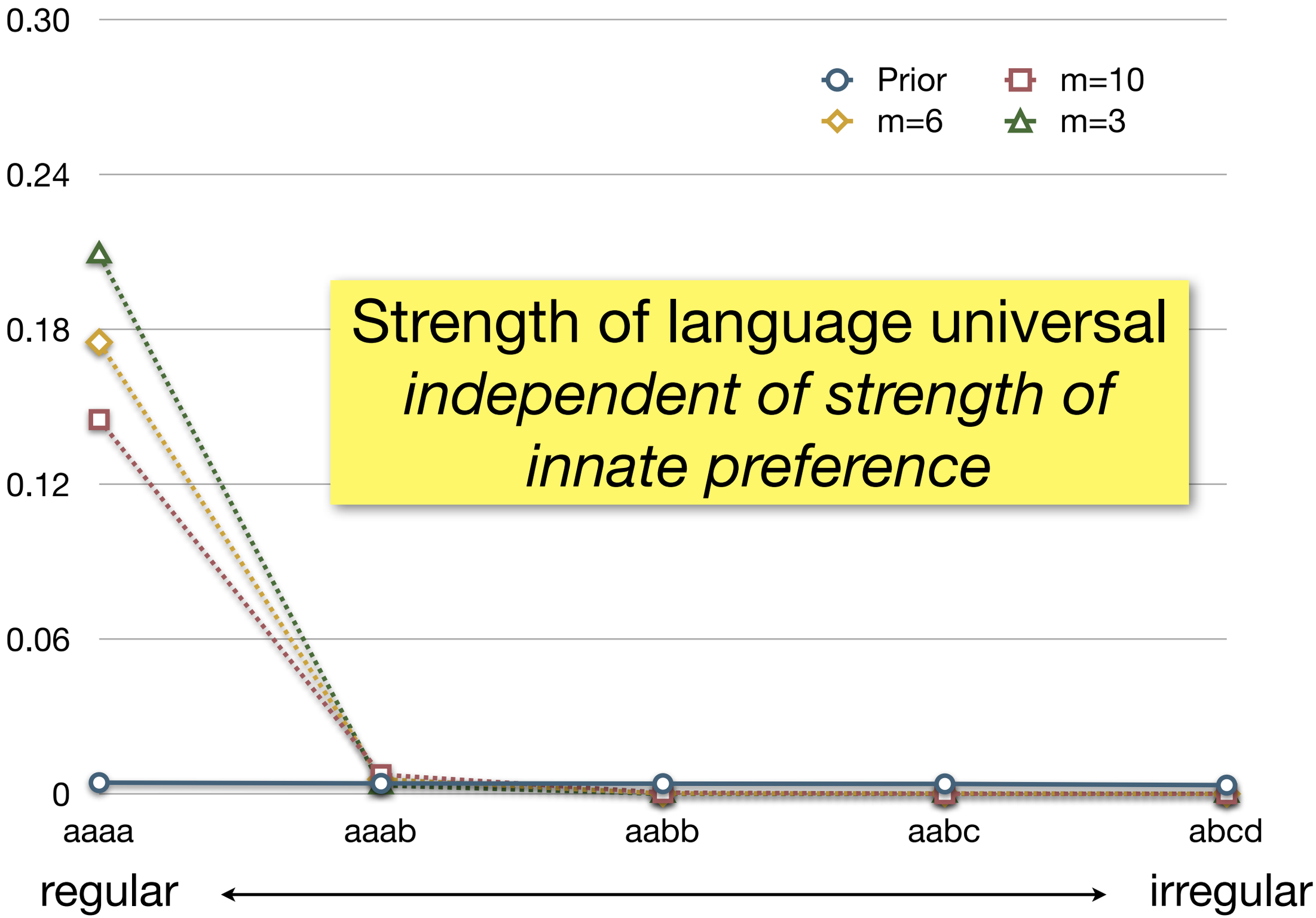
Probability of language by type: strong bias
(α=1, ε=0.05, 4 meanings, 4 classes)



Probability of language by type: weak bias
(α=40, ε=0.05, 4 meanings, 4 classes)



Probability of language by type: weak bias
(α=40, ε=0.05, 4 meanings, 4 classes)



Strength of language universal *independent of strength of innate preference*

Conclusions

- Iterated Bayesian Learning allows us to more precisely understand the relationship between learning bias and eventual language structure

- 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

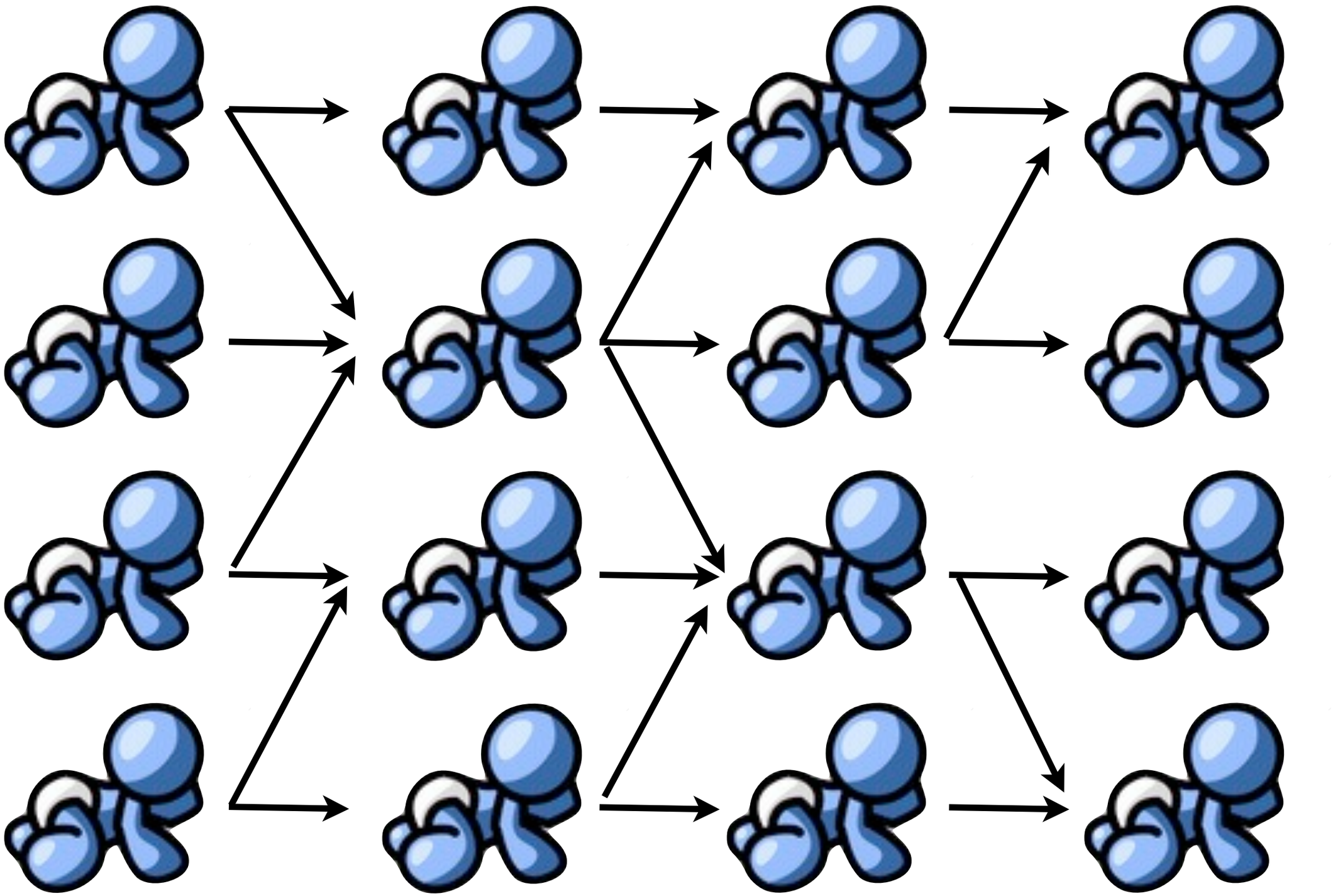
- If we see universals in language, then we should not be assuming that these are hard-coded as strong constraints in the genes

Extra material (if there is time)

Sampling vs MAP: which is right?

- If language learning is like sampling, language universals probably closely reflect learner biases. If it's like MAP, they don't.
- How can we tell which is right?
    - Run experiments on real people to see if they behave like they are sampling or selecting the MAP language
    - Maybe evolution will favour one alternative over the other?
        - See final lecture
    - Maybe one of these results is an unrepresentative special case
        - For instance: what happens if we go beyond long skinny diffusion chains and look at transmission in populations?
        - Smith (2009), Burkett & Griffiths (2010)

Moving to populations



Sampler **populations** look like MAP populations!

- In populations, when samplers learn from multiple teachers:

  No convergence to the prior

  Amplification of weak biases

  Bottleneck effects

  …

- **Play with this yourself in Friday's lab**

References

- Griffiths, T. L. and Kalish, M. L. (2007) Language evolution by iterated learning with Bayesian agents. *Cognitive Science, 31,* 441-480.

- Kirby, S., Dowman, M. and Griffiths, T. (2007) Innateness and culture in the evolution of language. *Proceedings of the National Academy of Sciences, 104,* 5241-5245.

- Smith, K. (2009). Iterated learning in populations of Bayesian agents. In N.A. Taatgen & H. van Rijn (Eds.), *Proceedings of the 31th Annual Conference of the Cognitive Science Society* (pp. 697-702). Austin, TX: Cognitive Science Society.