MIT EECS
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CSAIL

Variational Bayes and beyond: Foundations of scalable Bayesian inference

Tamara Broderick
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Electrical Engineering & Computer Science
MIT

http://www.tamarabroderick.com/tutorials.html

Bayesian inference

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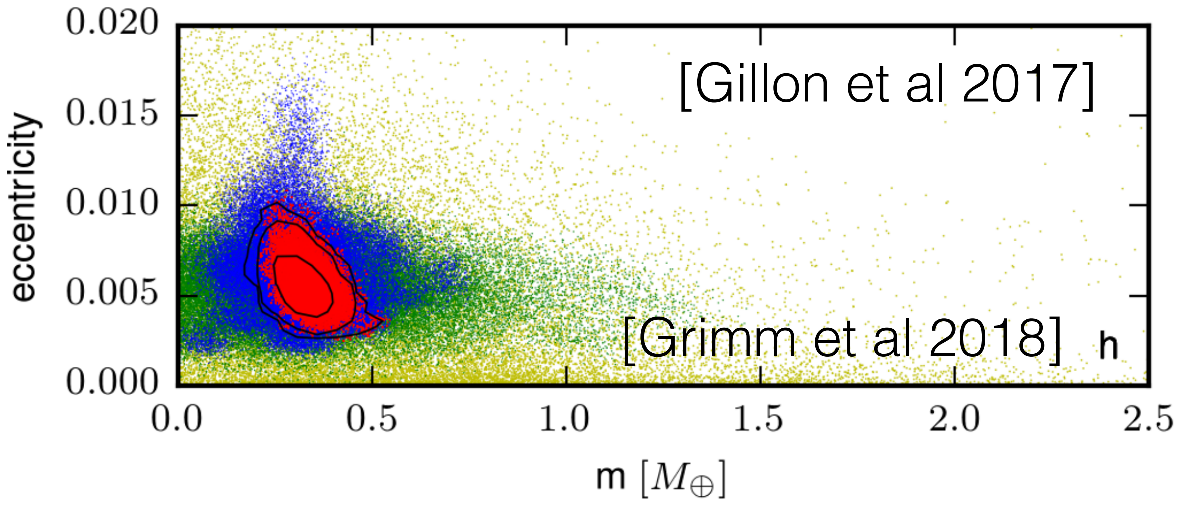

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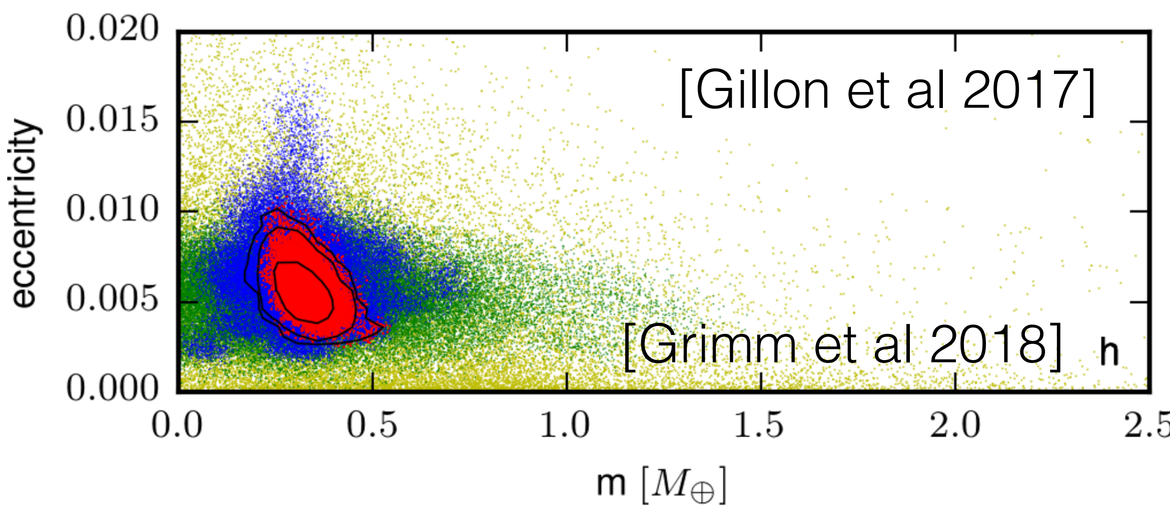

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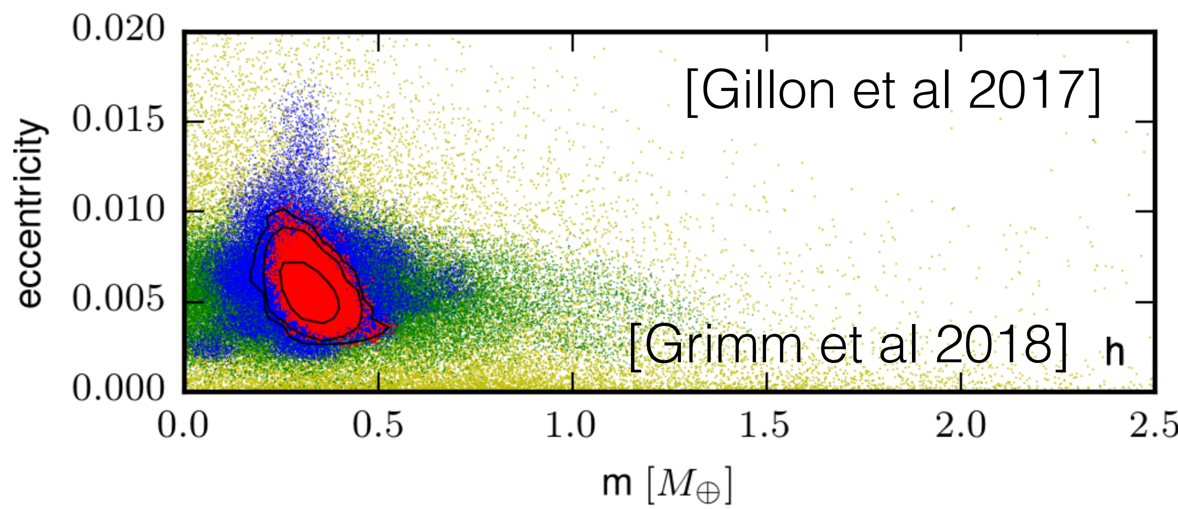

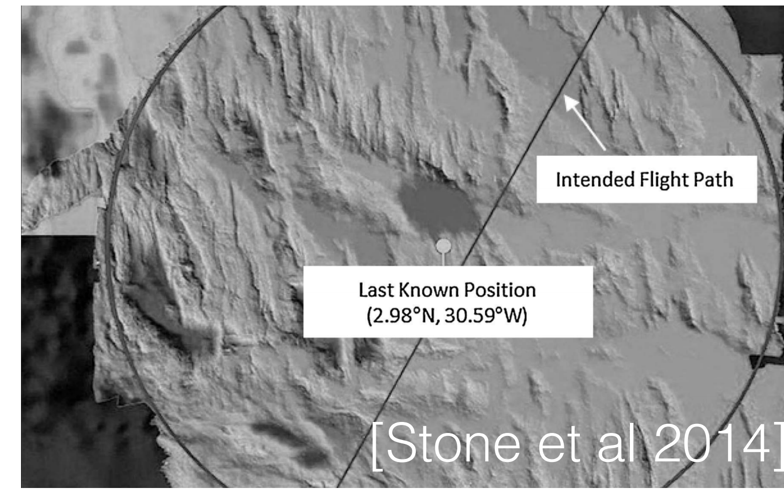

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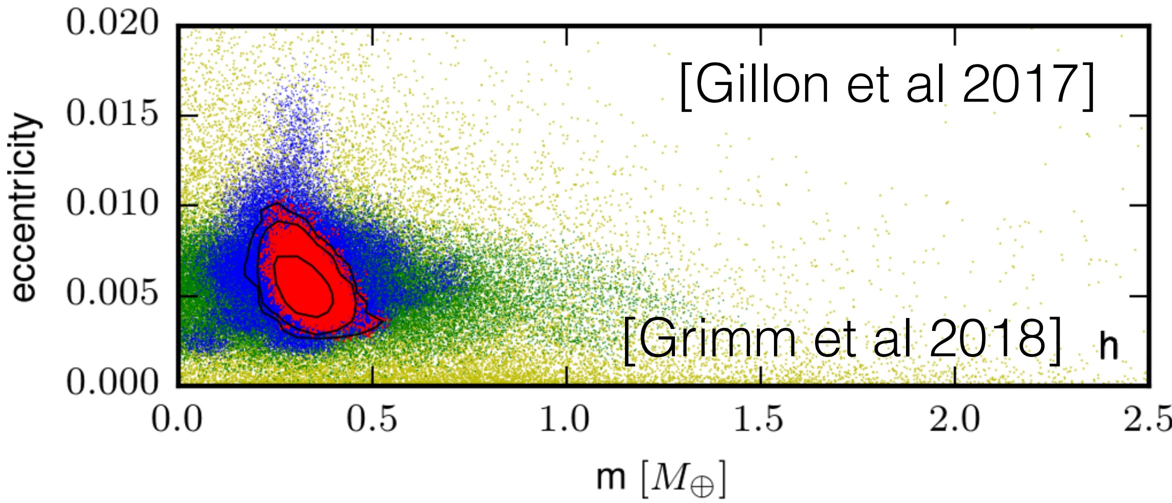

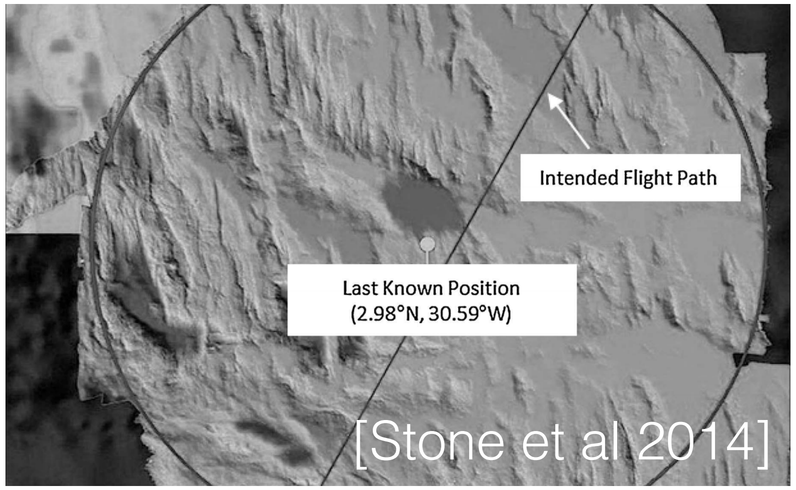

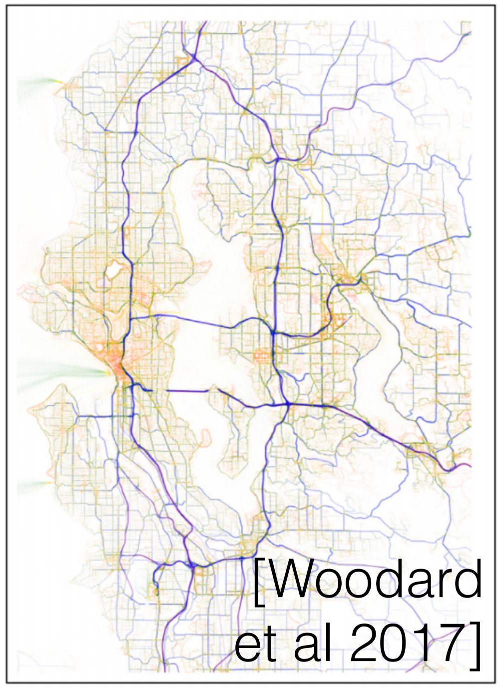

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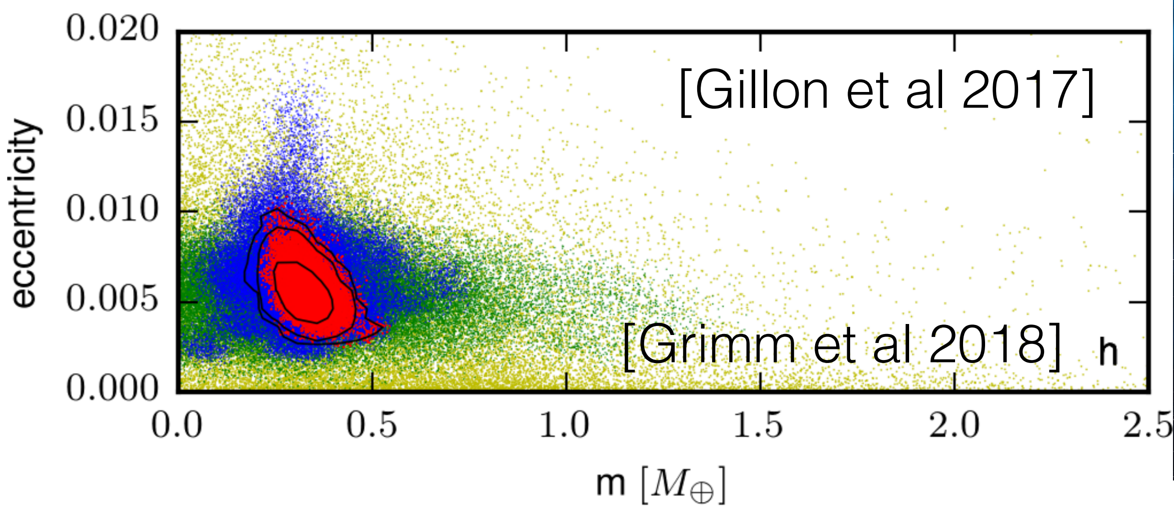

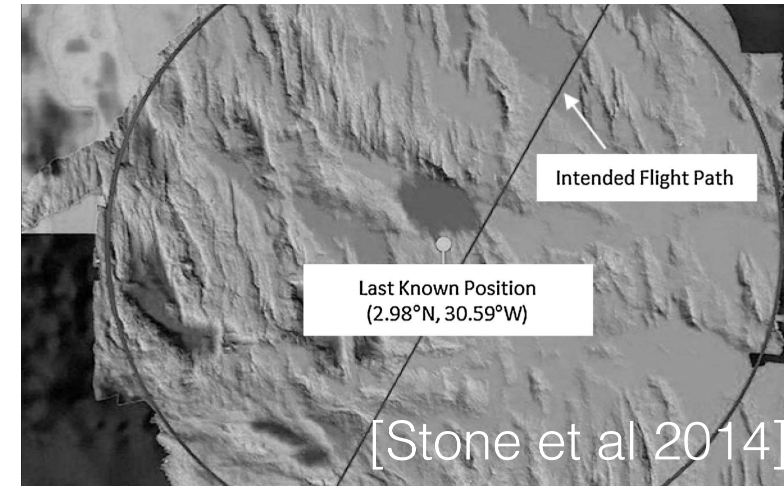

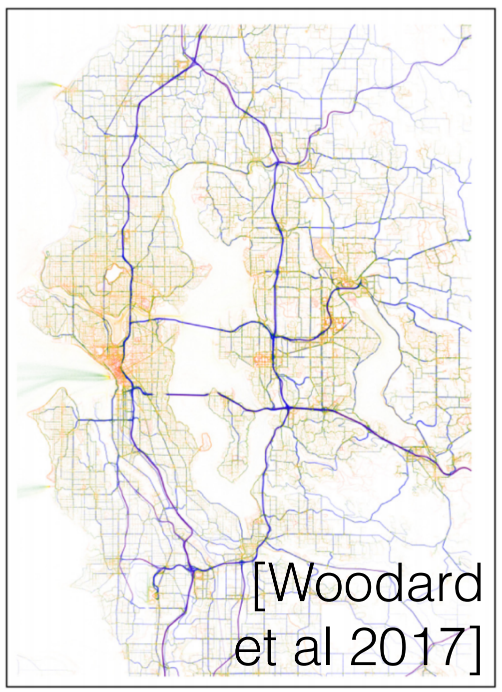

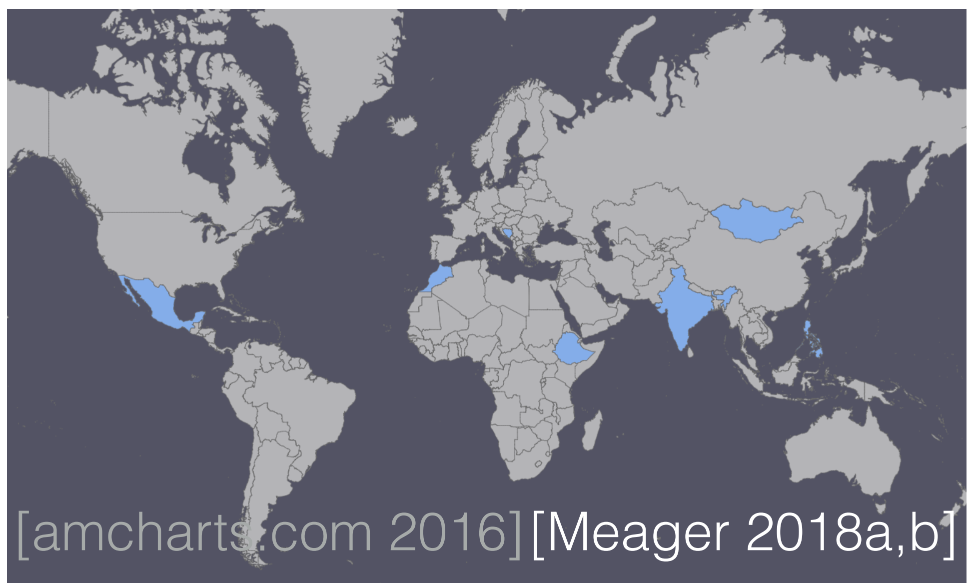

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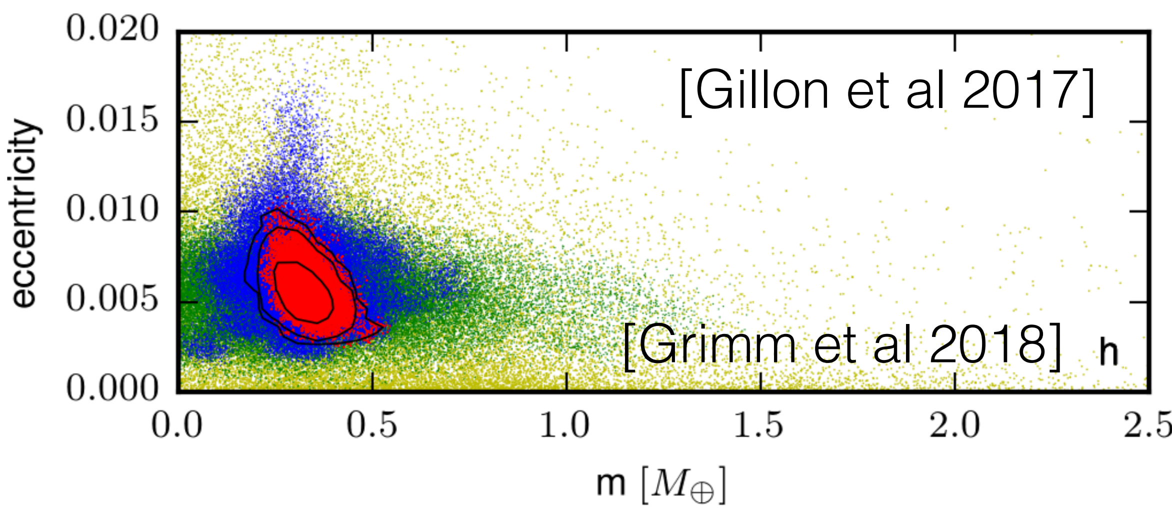

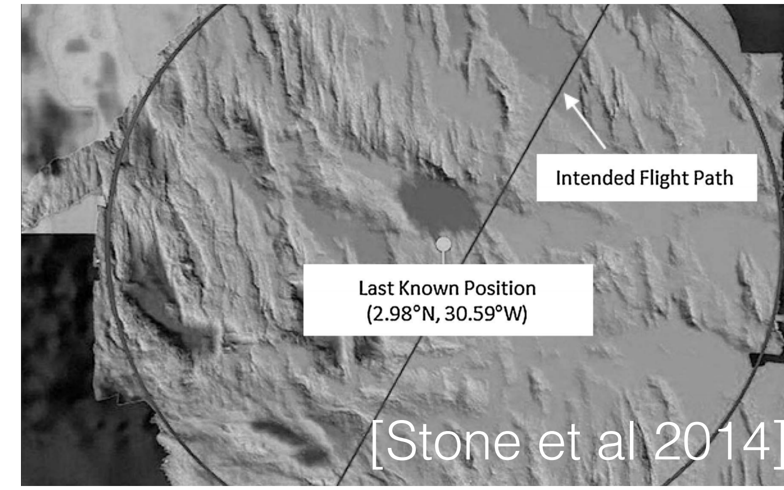

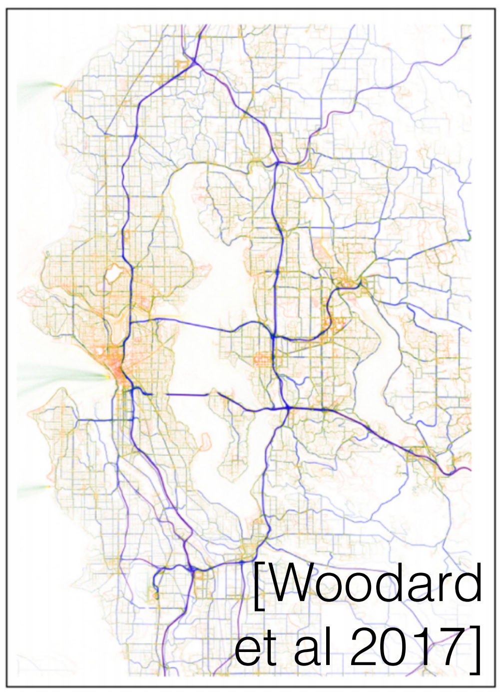

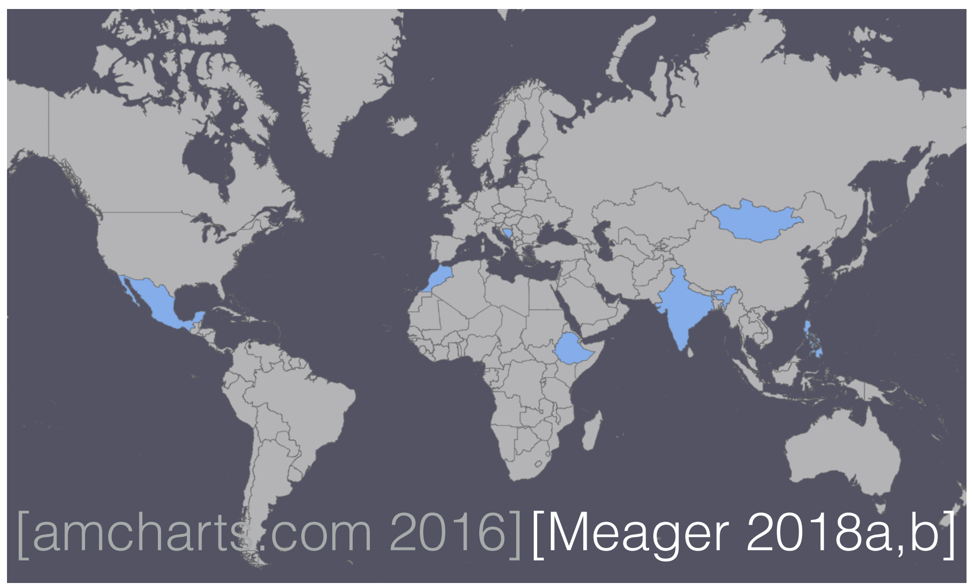

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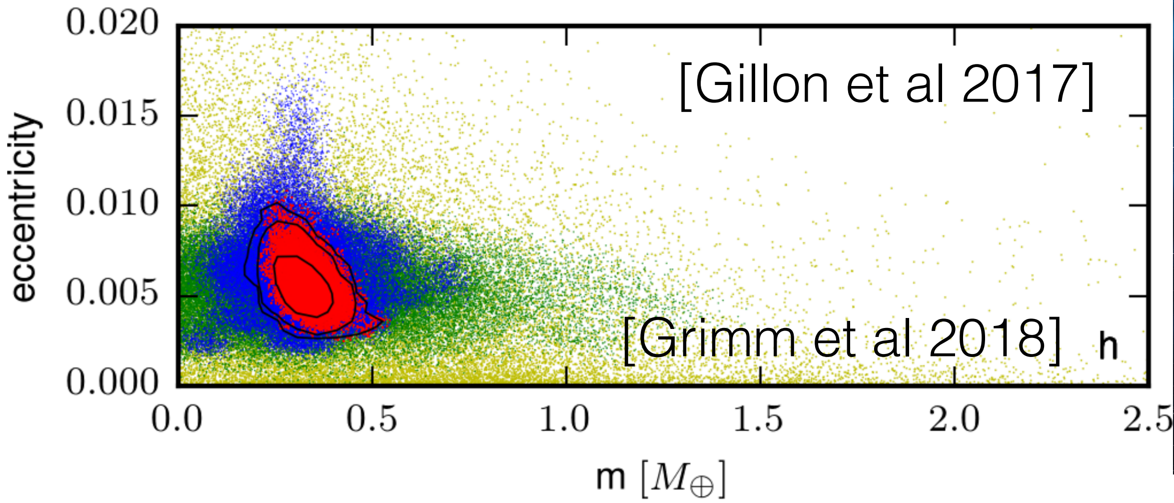

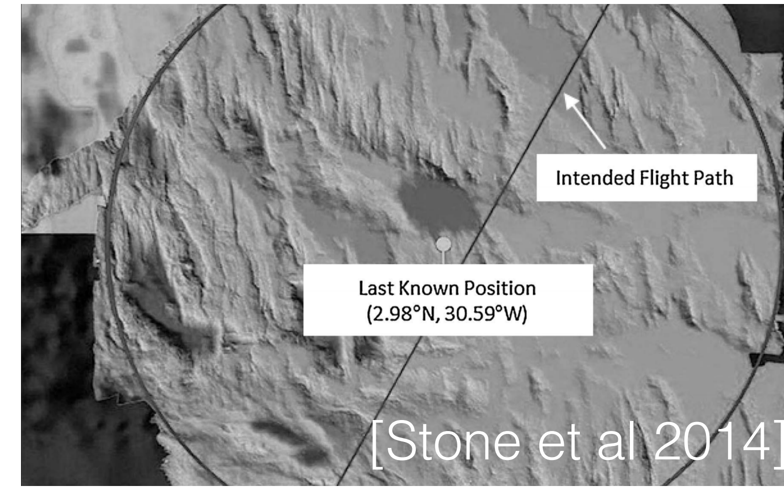

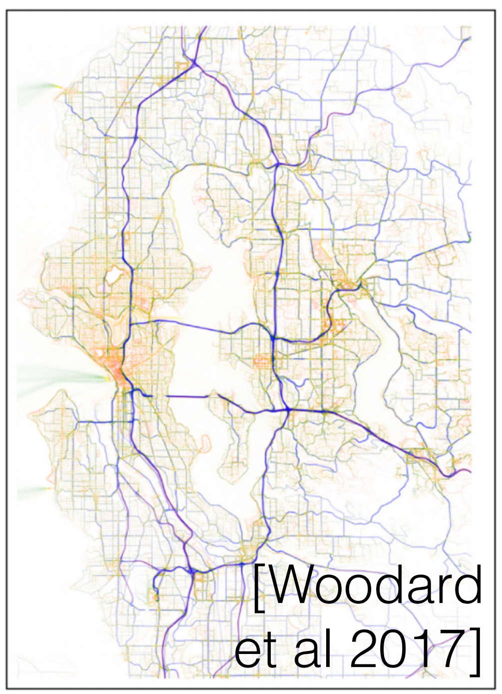

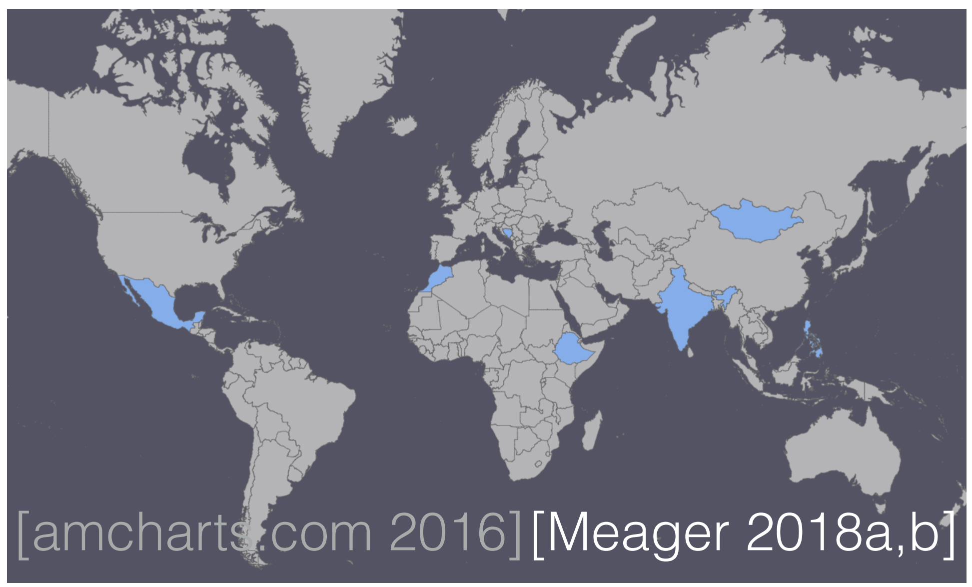

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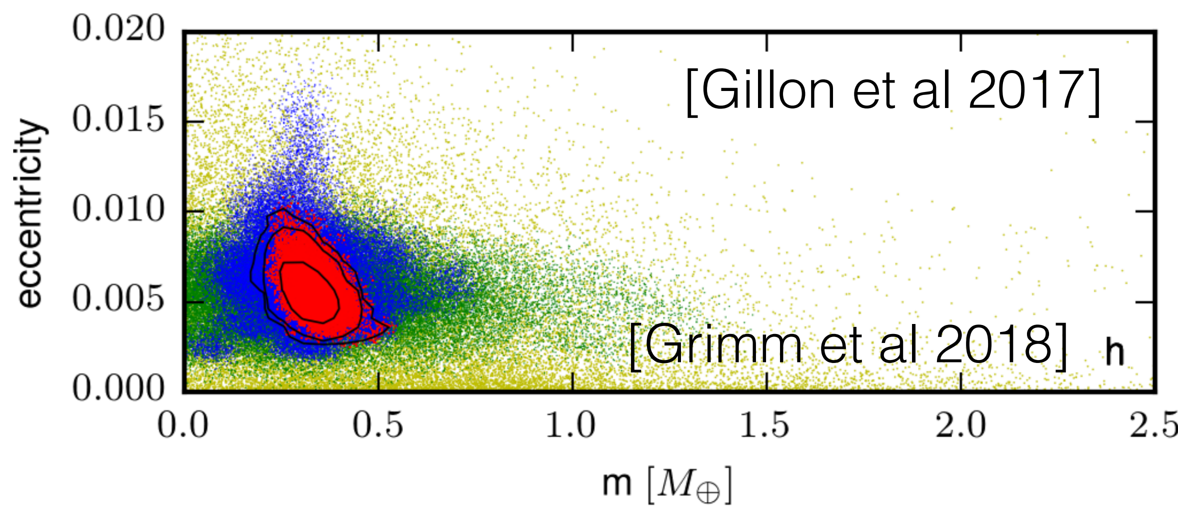
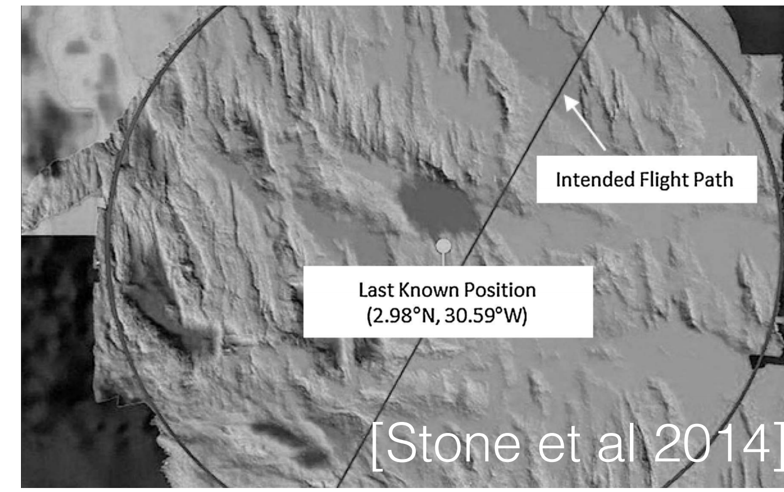
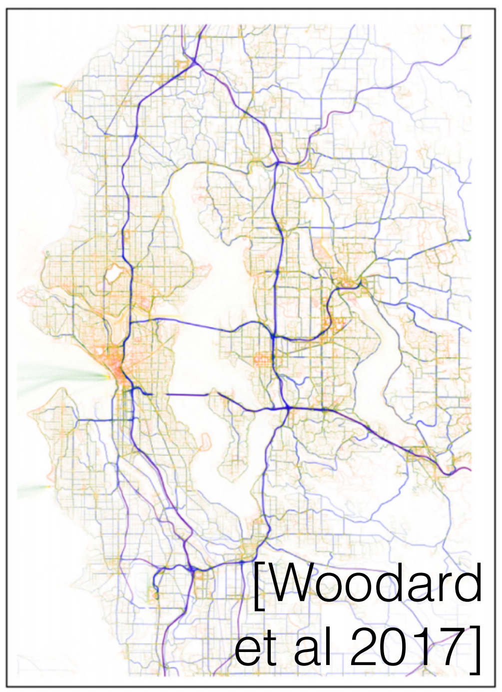
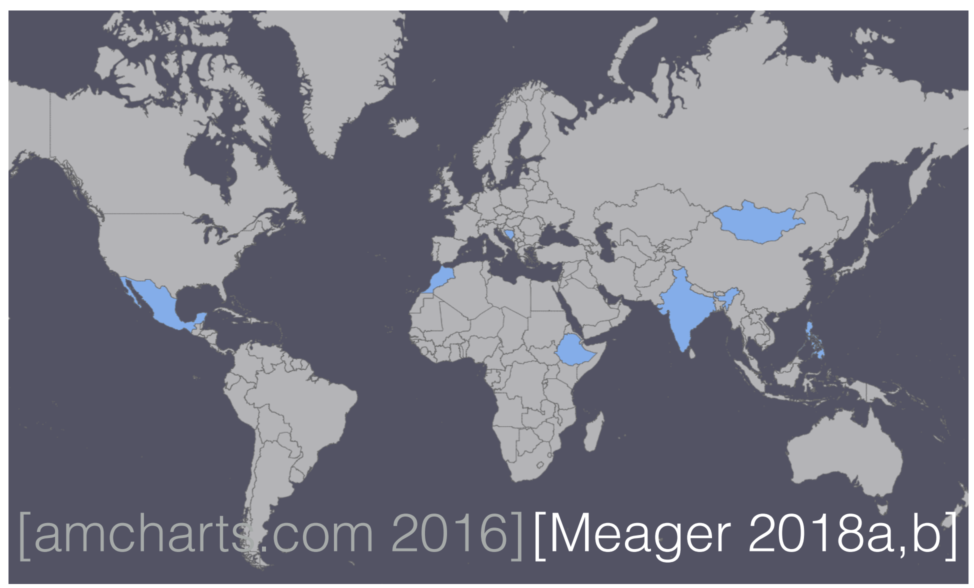


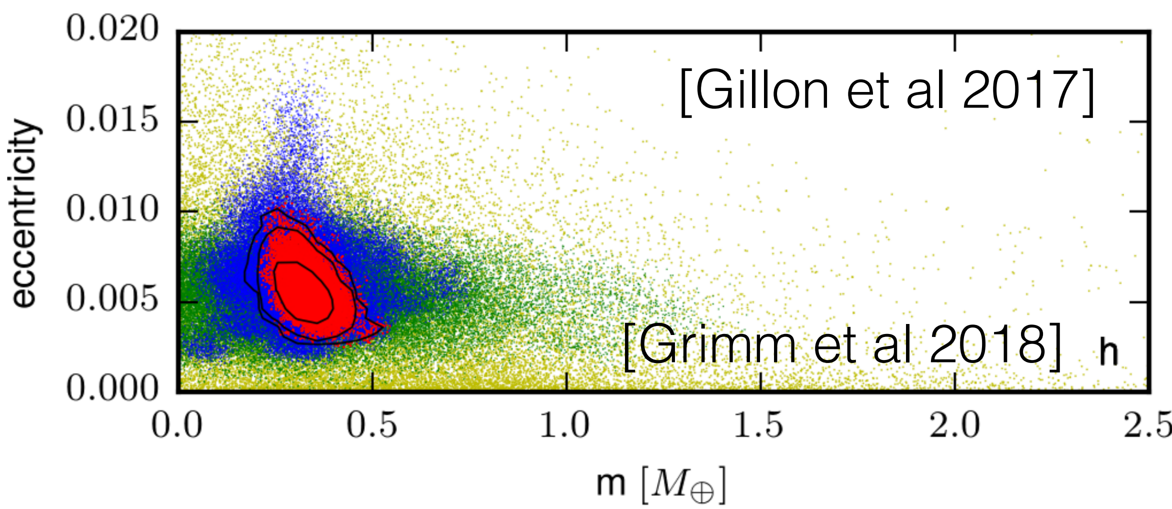


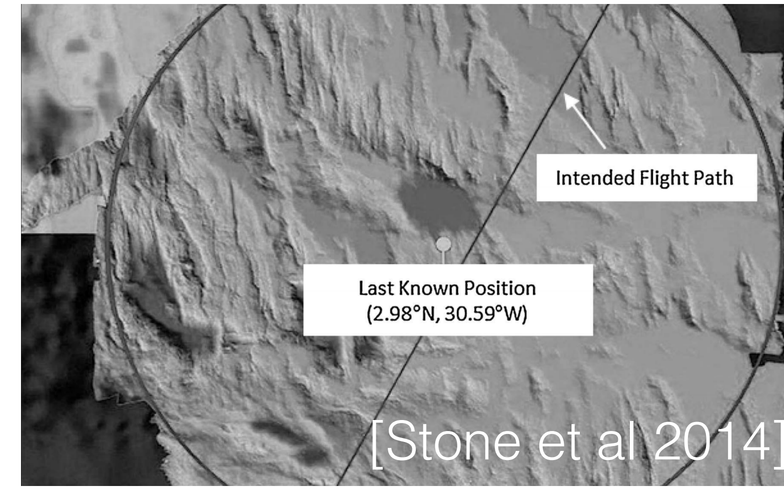


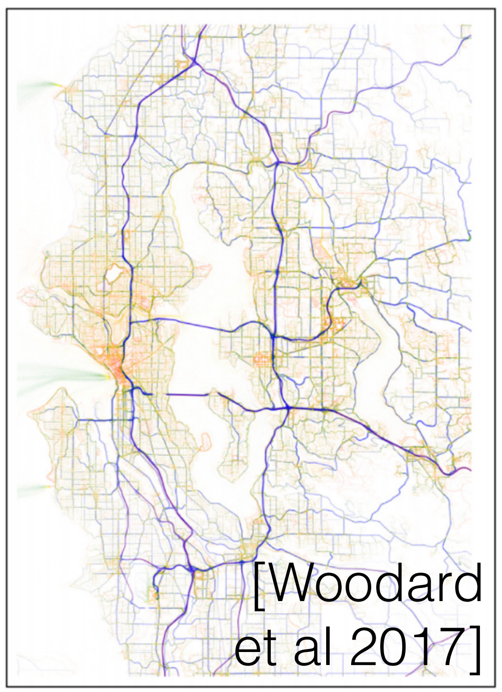


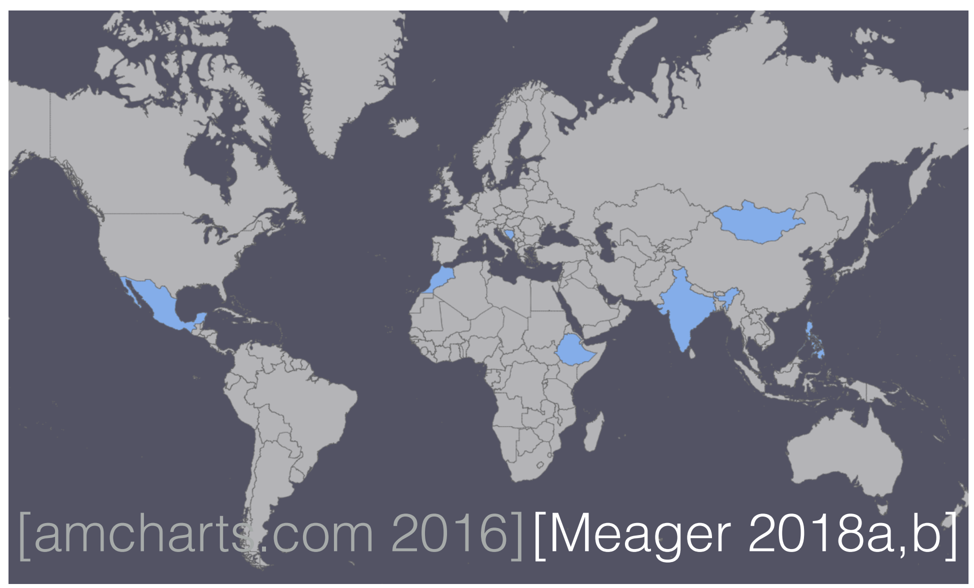
- Goals: good point estimates, uncertainty estimates

Bayesian inference



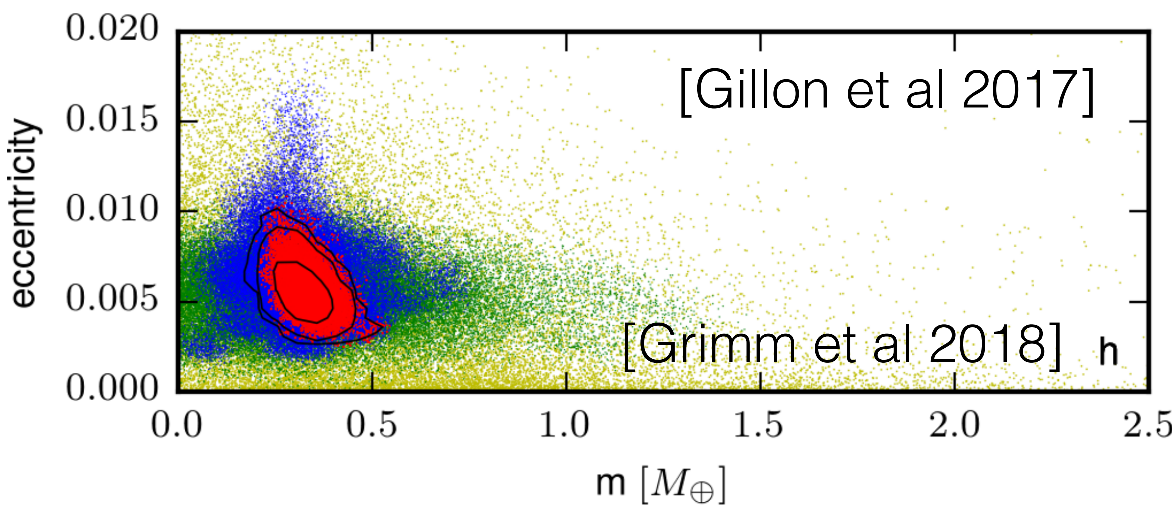


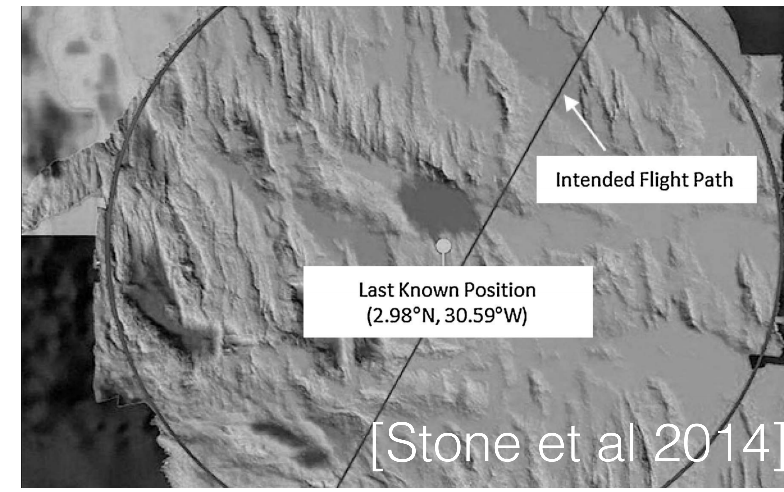


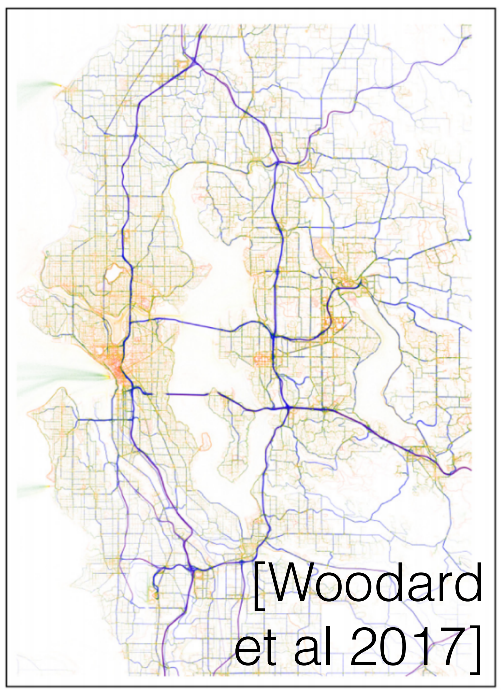


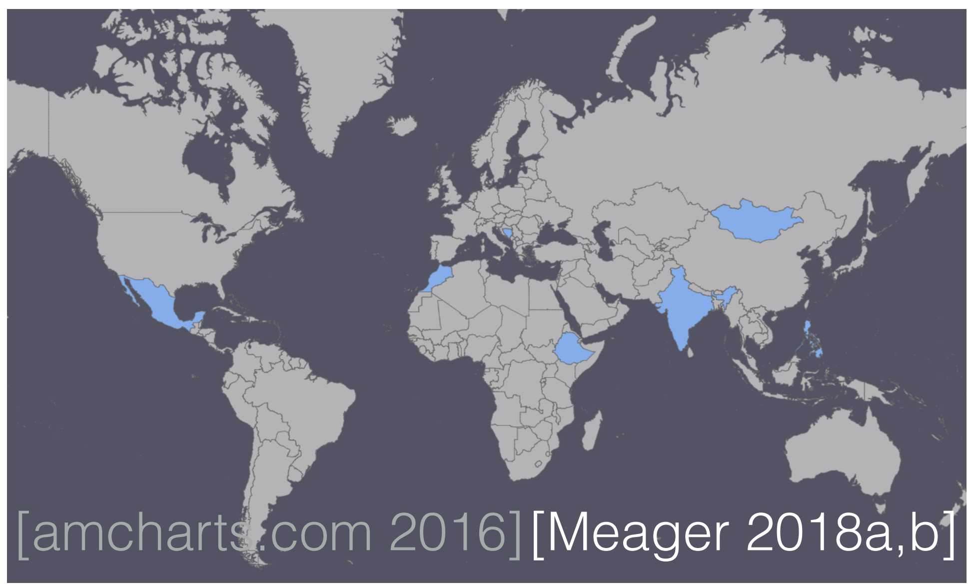
- Goals: good point estimates, uncertainty estimates
  - More: interpretable, modular, expert info

Bayesian inference









[mc-stan.org]

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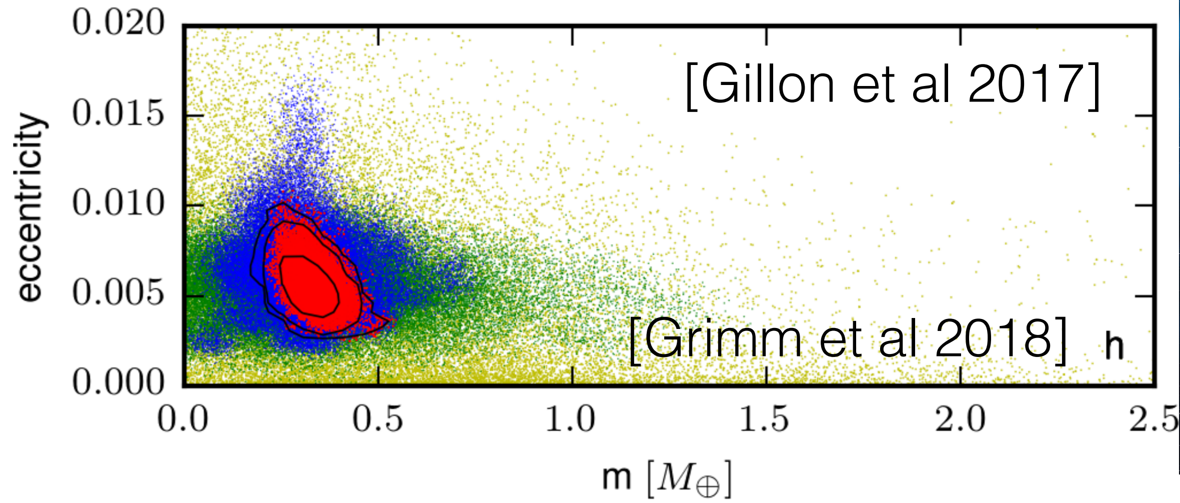
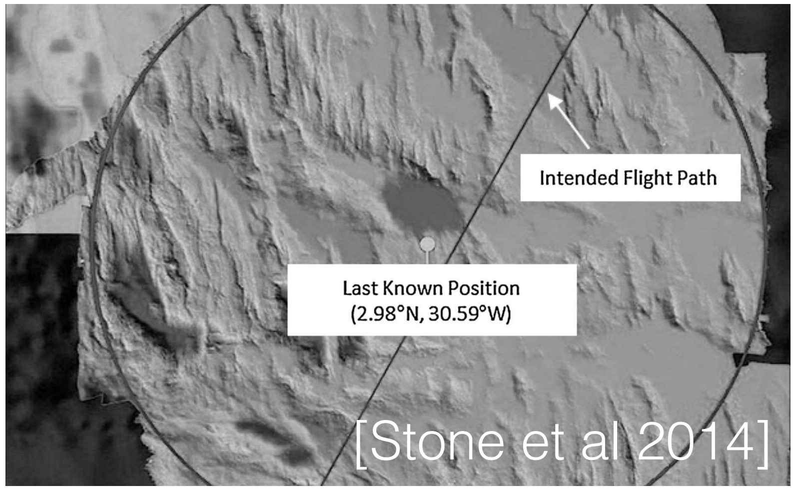
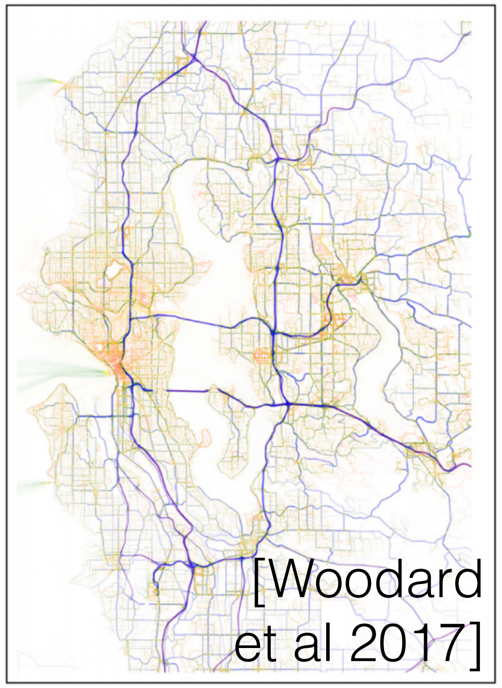
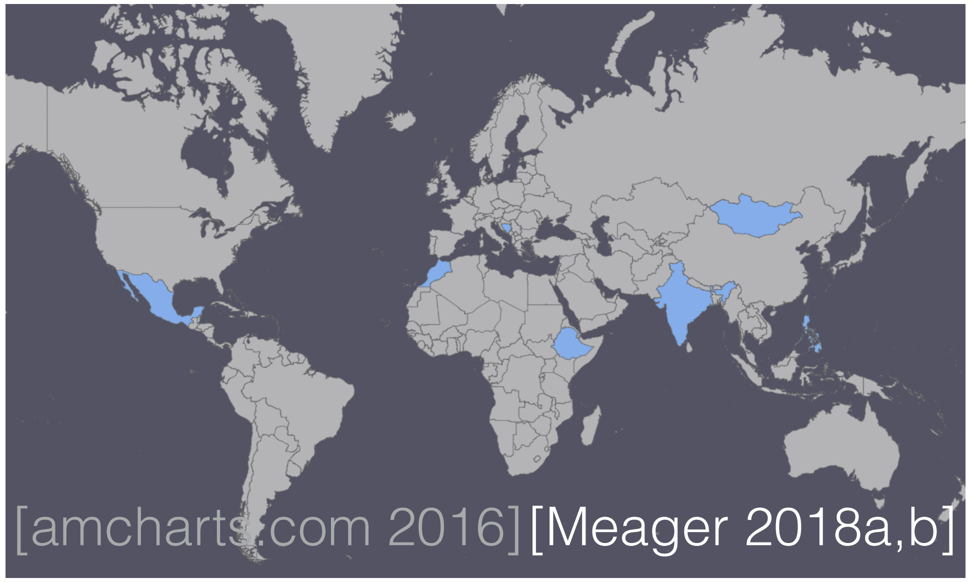
Bayesian inference









[mc-stan.org]

- Goals: good point estimates, uncertainty estimates
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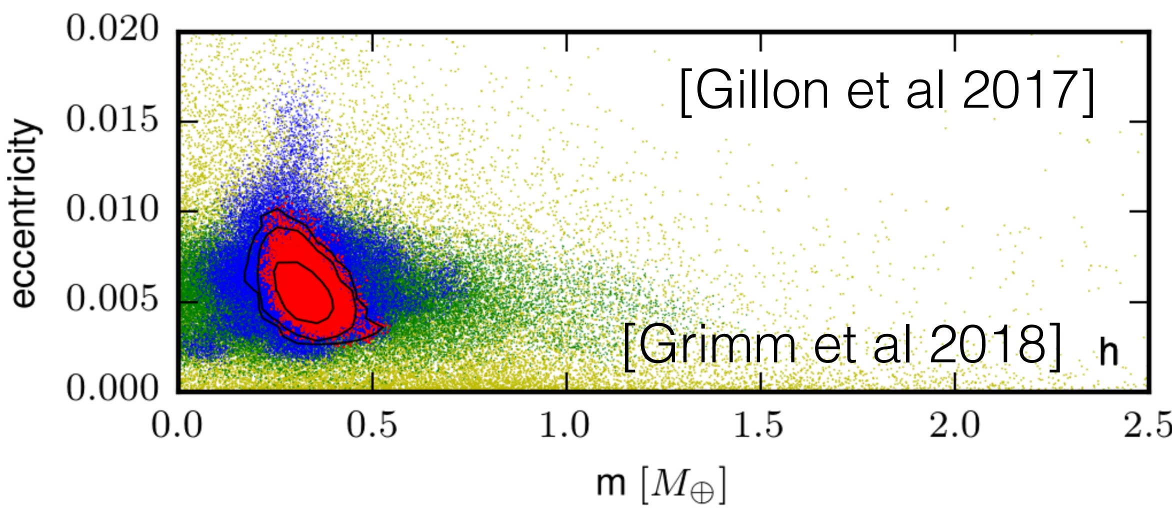
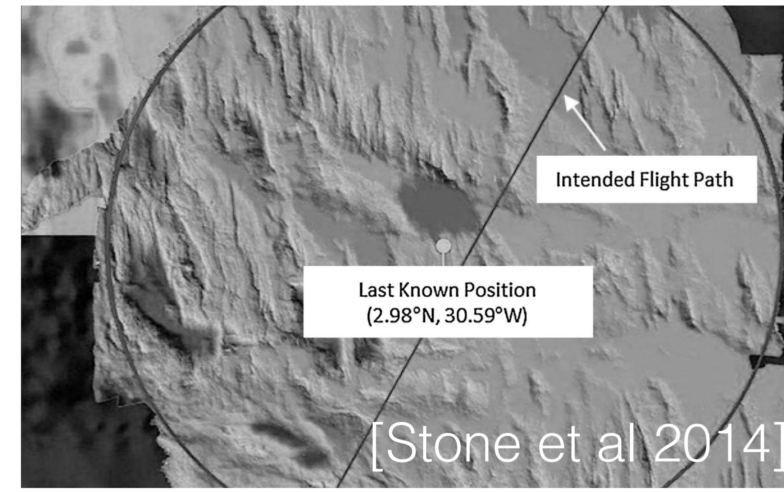
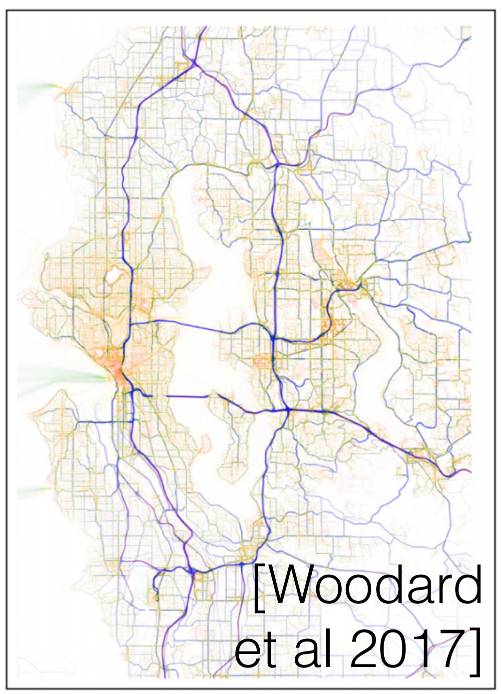
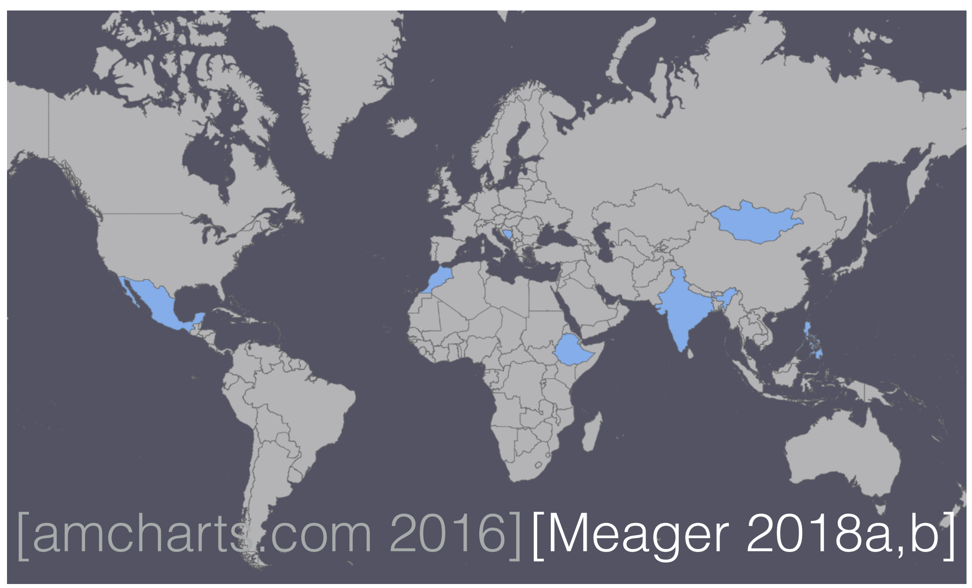
- Challenge: speed (compute, user), reliable inference

Bayesian inference









[mc-stan.org]

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- Challenge: speed (compute, user), reliable inference
- Uncertainty doesn't have to disappear in large data sets

Variational Bayes

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- Modern problems: often large data, large dimensions

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[Blei et al 2003]

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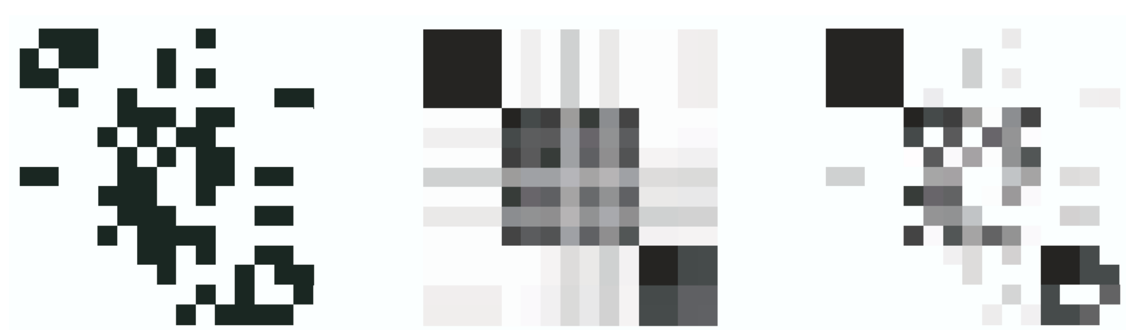

[Airoldi et al 2008]

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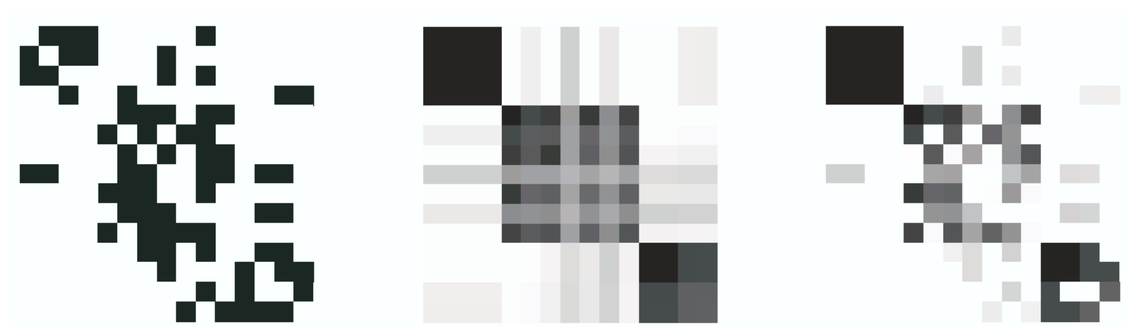

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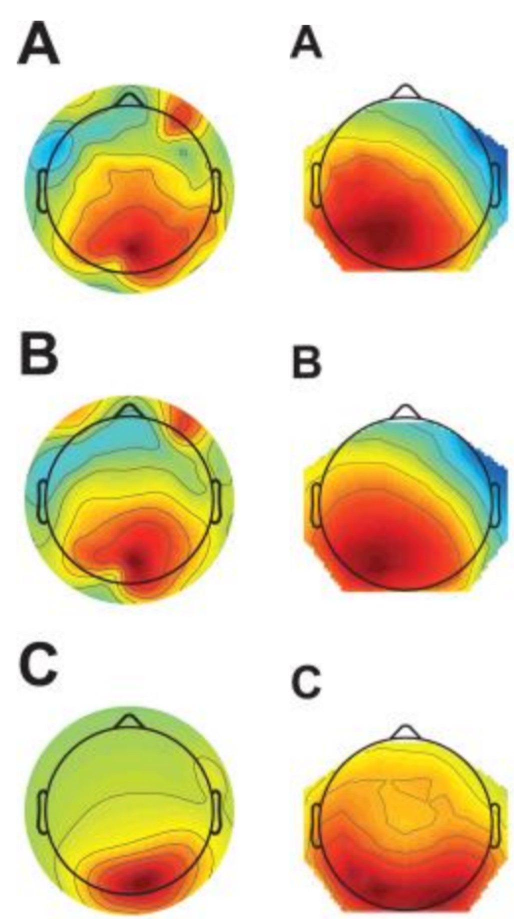

[Gershman et al 2014]

[Blei et al 2018]

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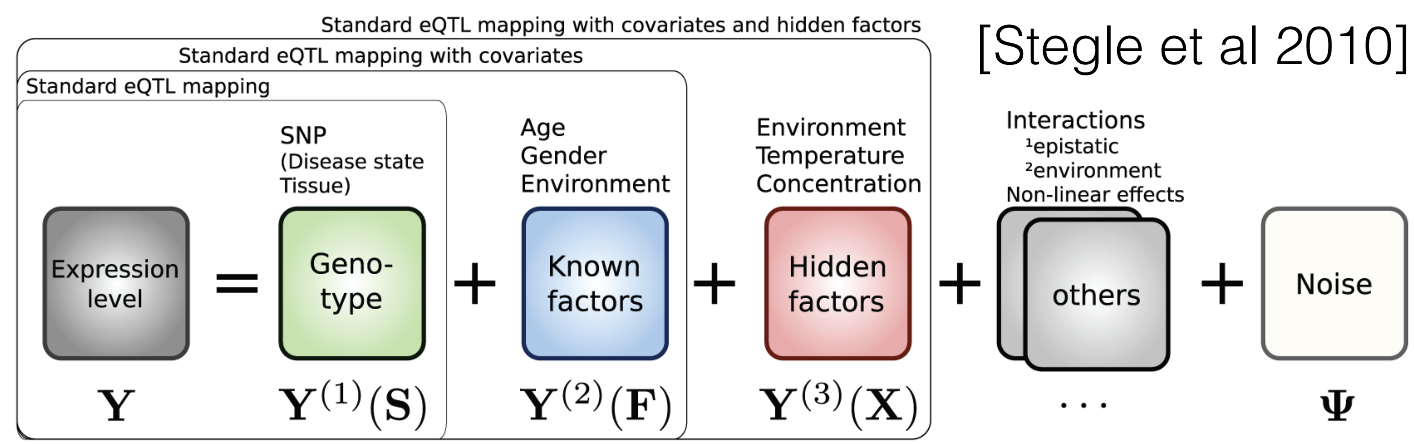
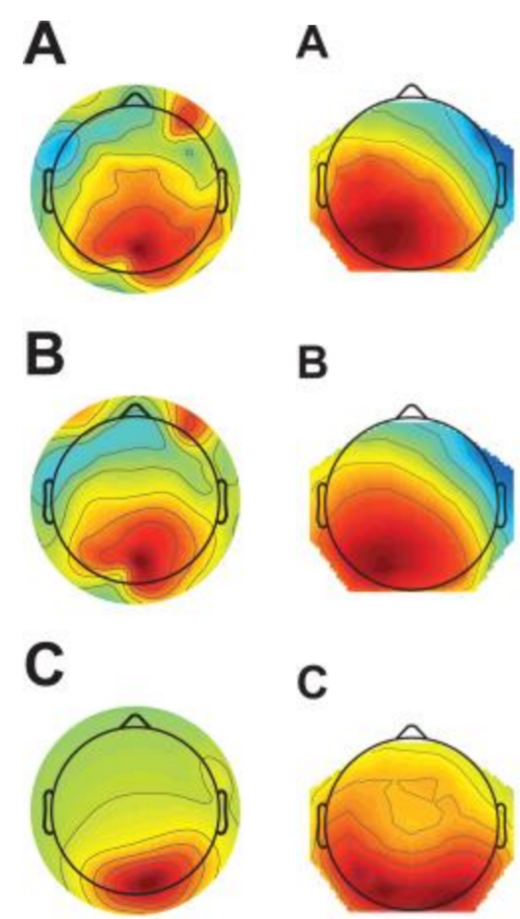
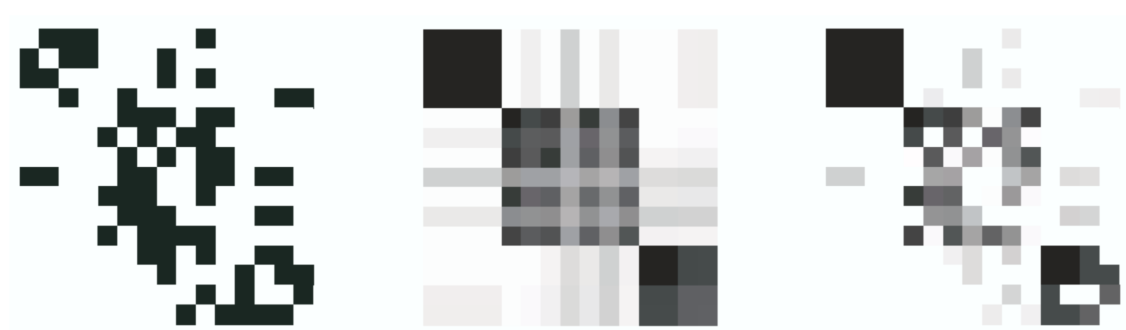


[Stegle et al 2010]





[Airoldi et al 2008]

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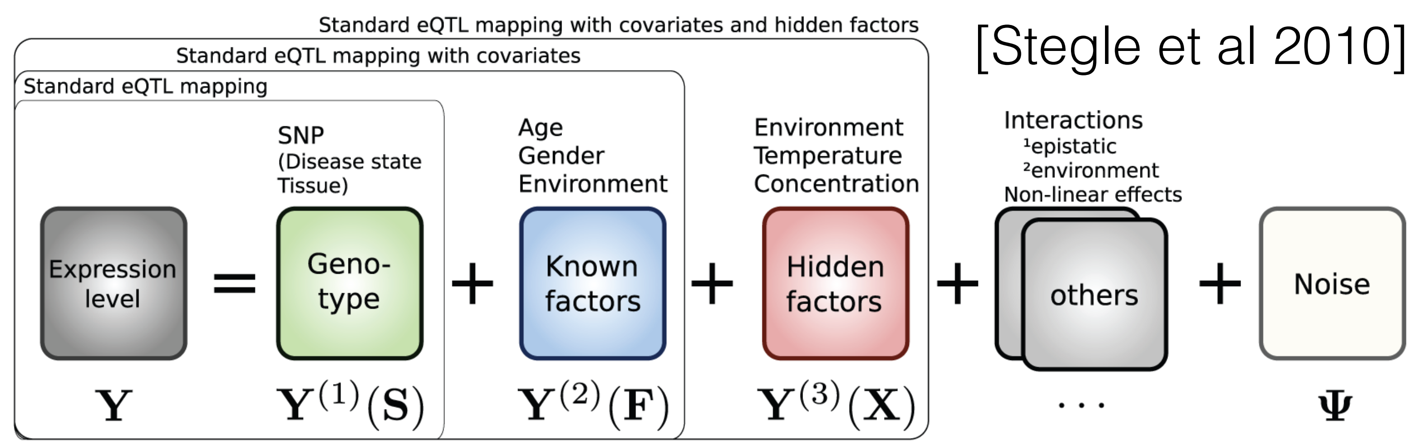

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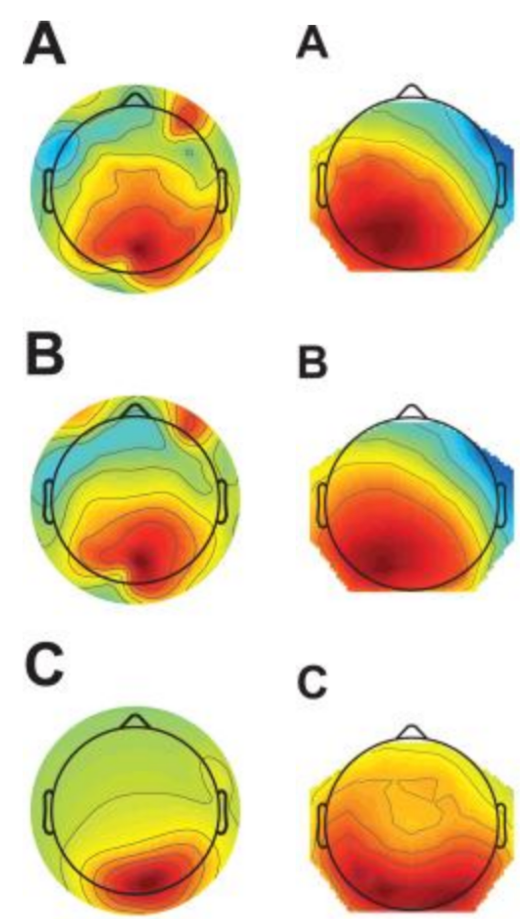

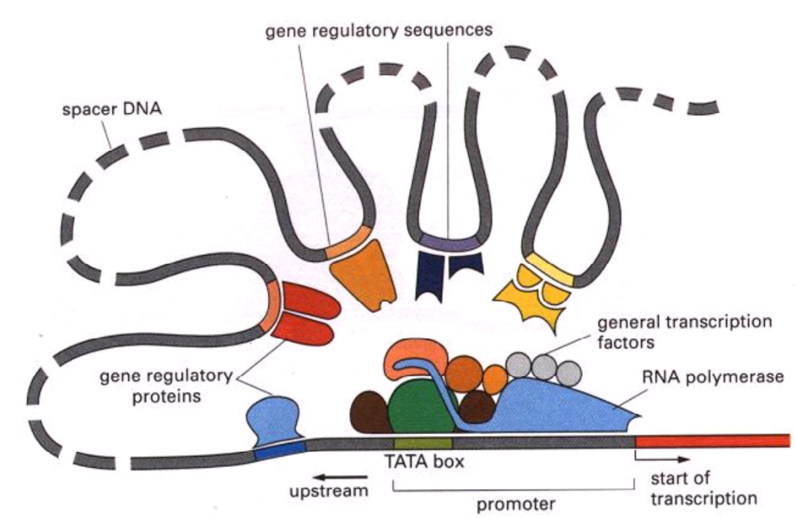

[Xing et al 2004]
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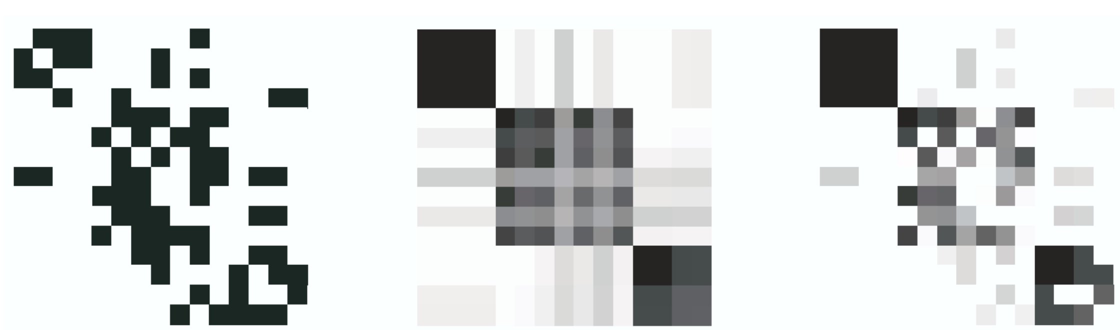

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Roadmap

- Bayes & Approximate Bayes review

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- What is:
  - Variational Bayes (VB)
  - Mean-field variational Bayes (MFVB)

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Roadmap

- Bayes & Approximate Bayes review
- What is:
  - Variational Bayes (VB)
  - Mean-field variational Bayes (MFVB)
- Why use VB?
- When can we trust VB?
- Where do we go from here?

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Bayesian inference

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parameters

θ

Bayesian inference

parameters

$p(\theta)$

prior

Bayesian inference

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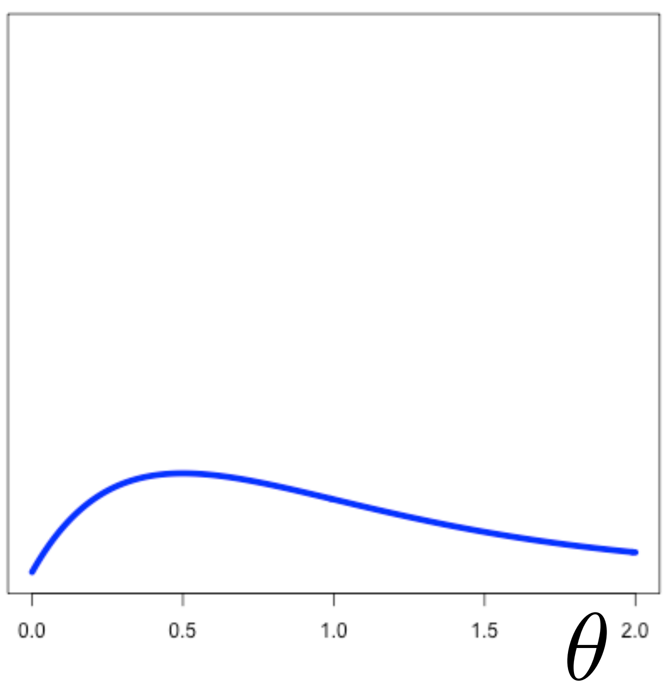
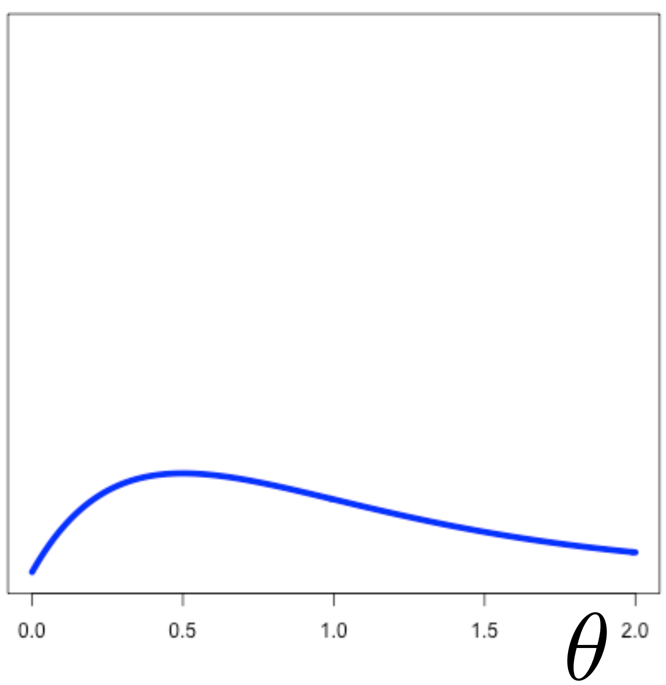


Bayesian inference

parameters

$$p(y_{1:N}|\theta)p(\theta)$$

likelihood prior



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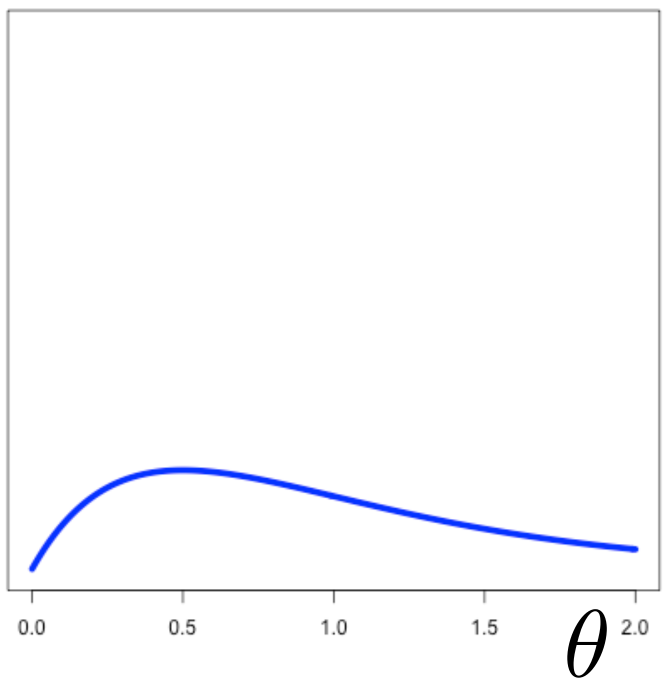

Bayesian inference

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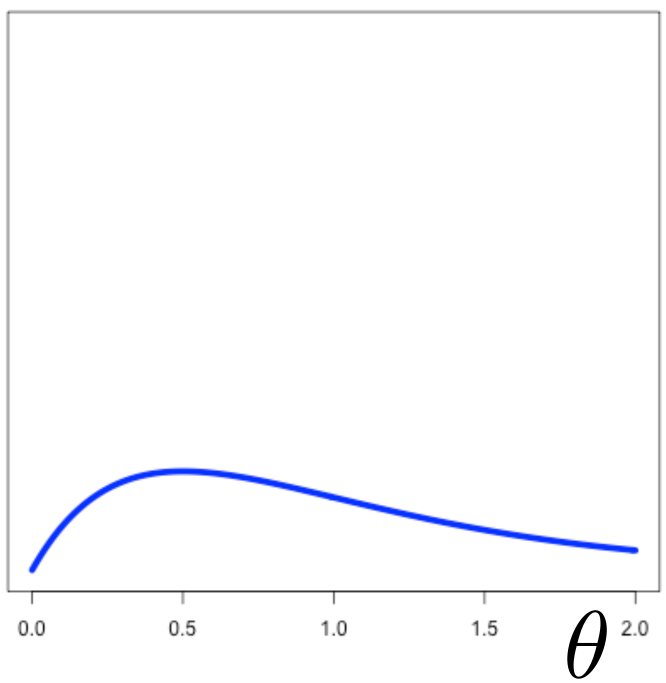
$$p(\theta|y_{1:N}) \propto_\theta p(y_{1:N}|\theta)p(\theta)$$

posterior likelihood prior



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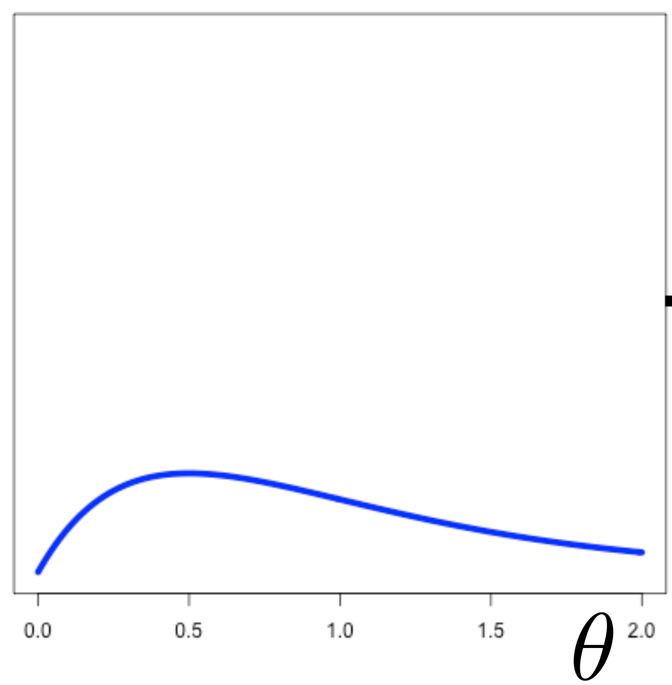

Bayes Theorem

Bayesian inference

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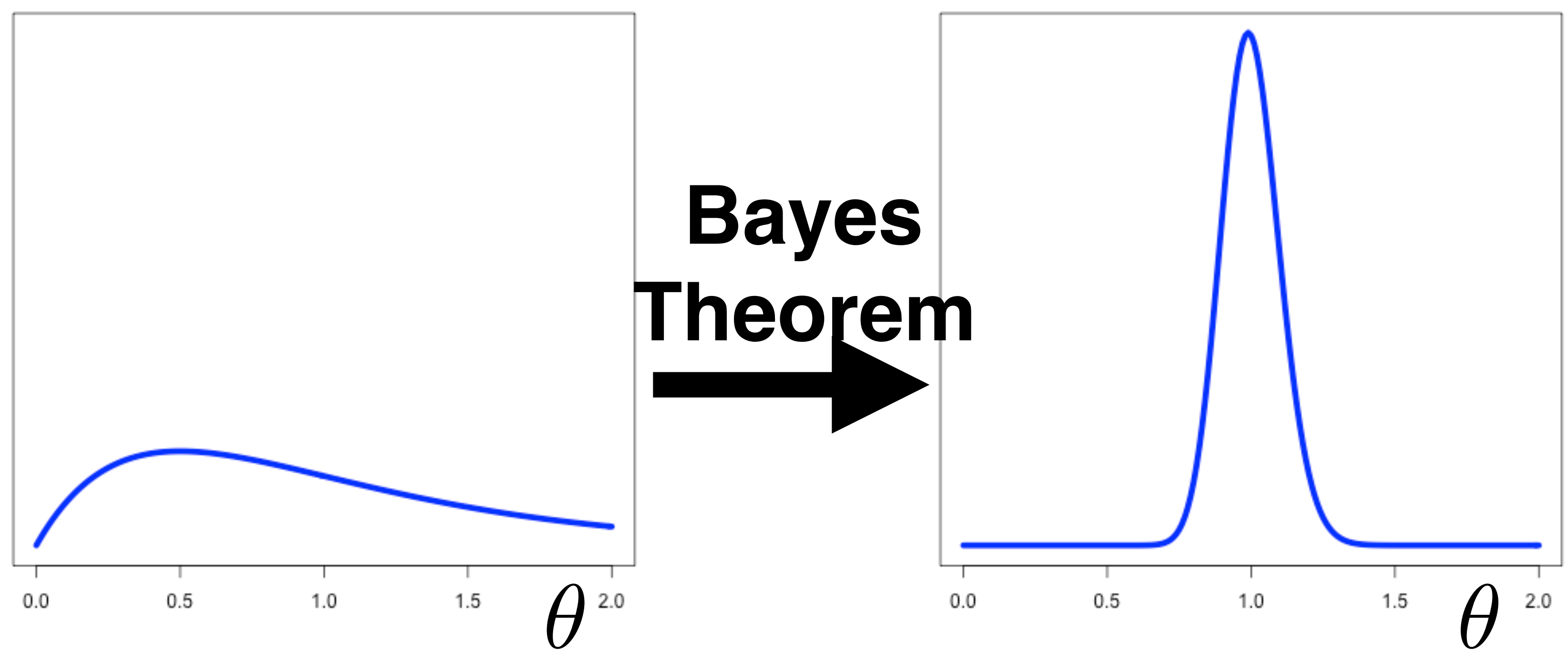

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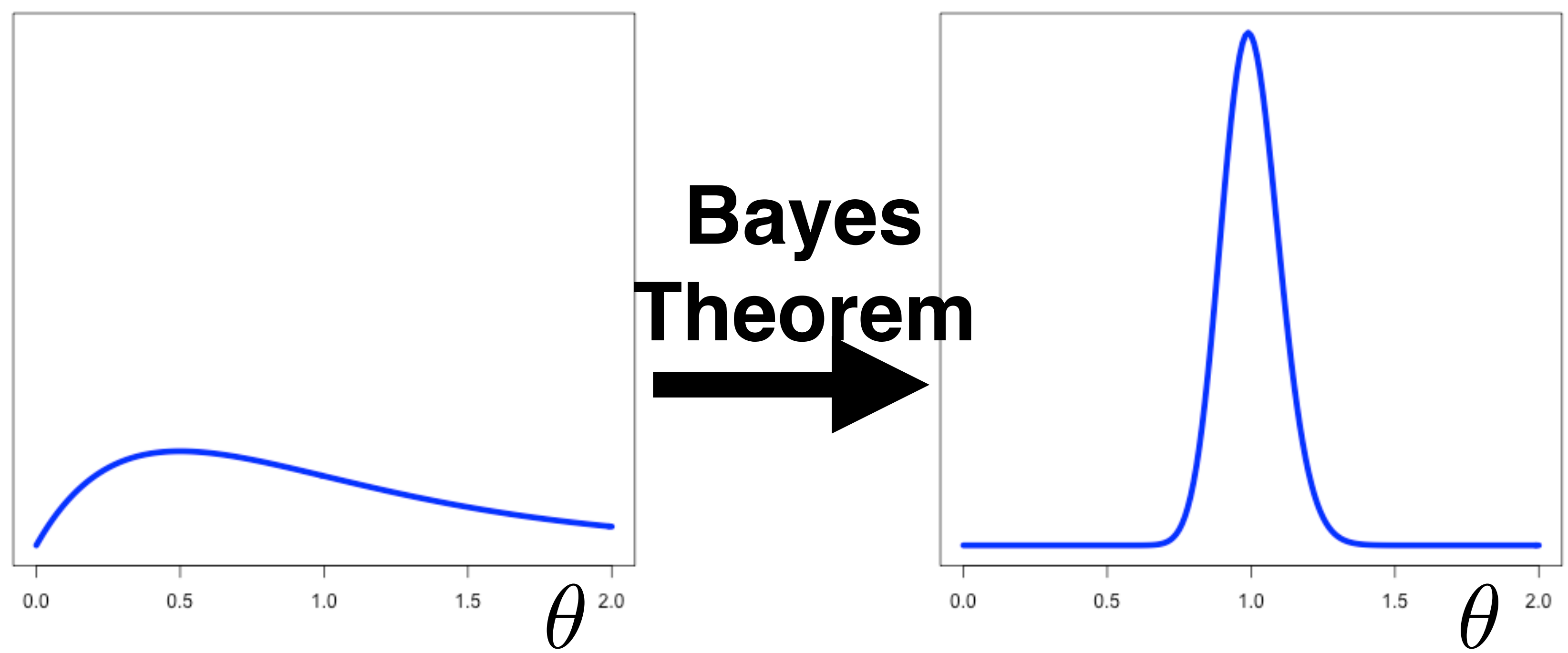

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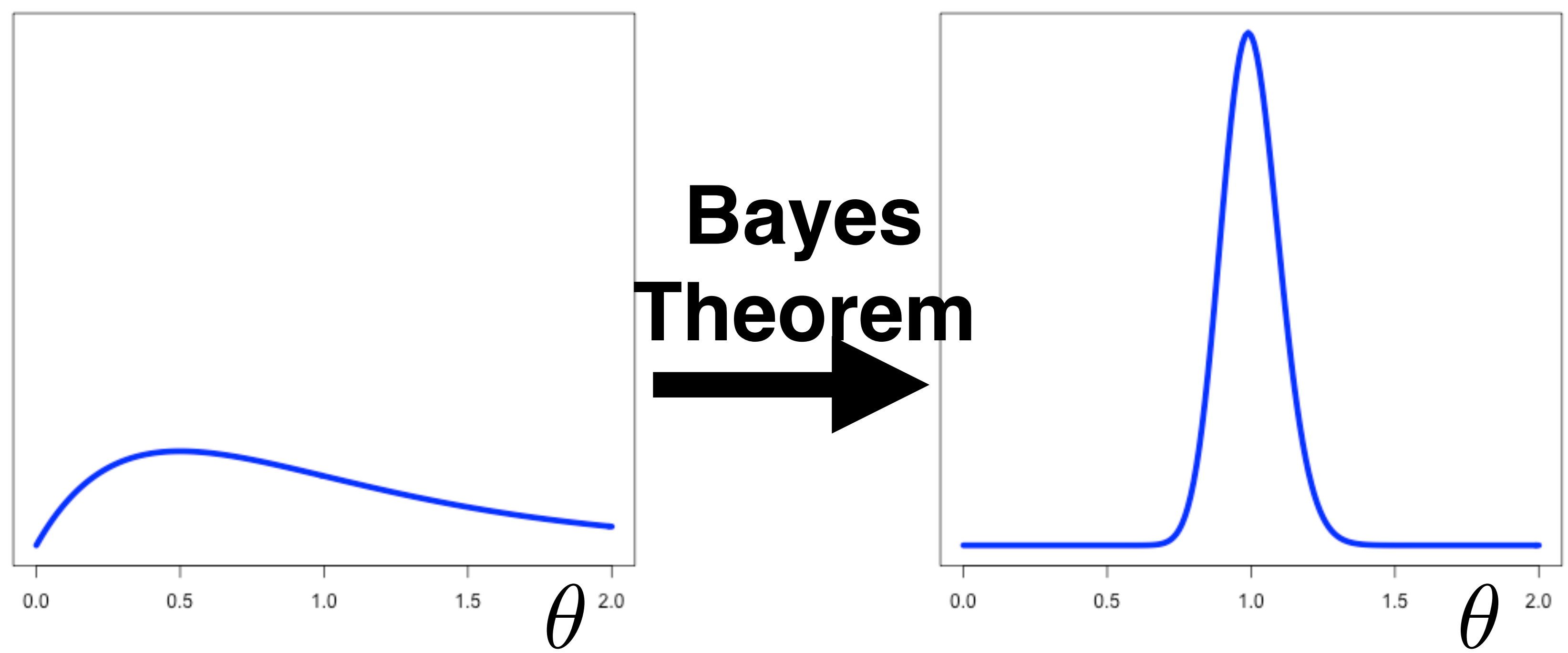

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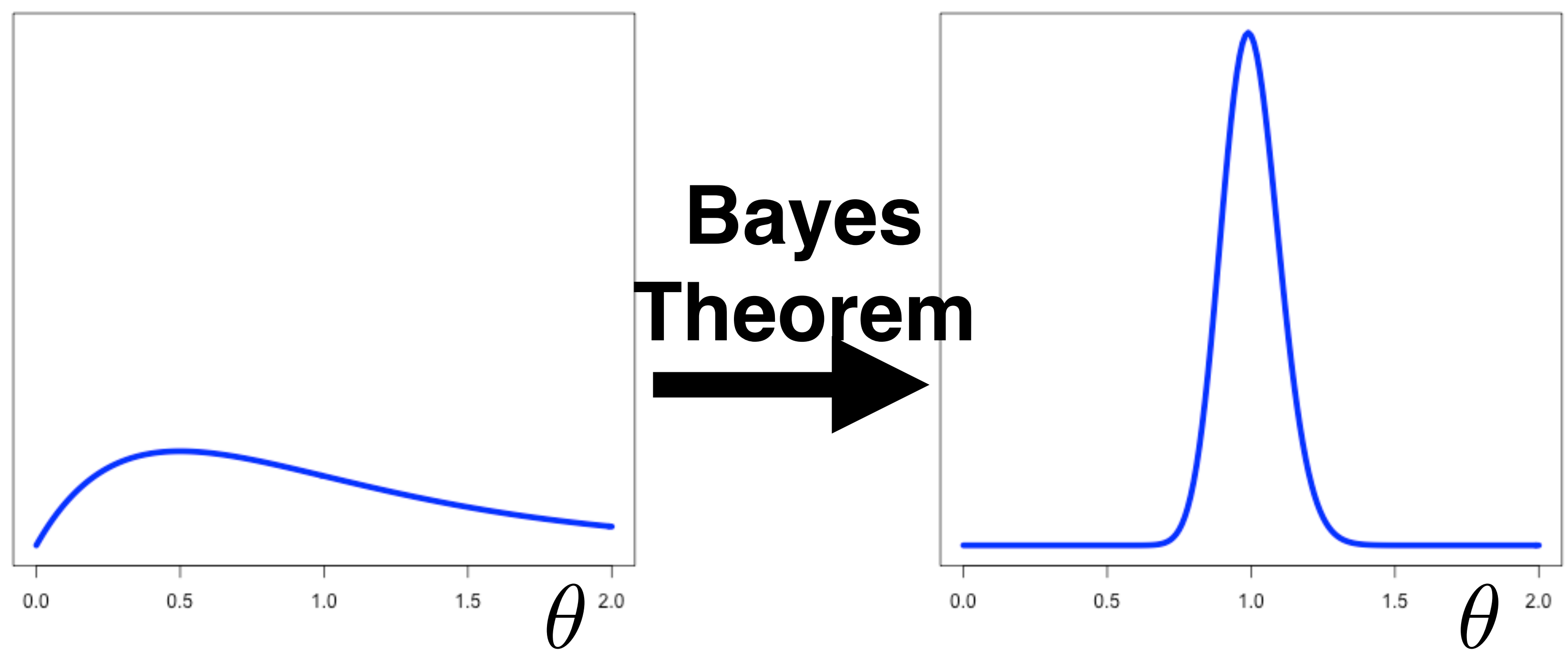

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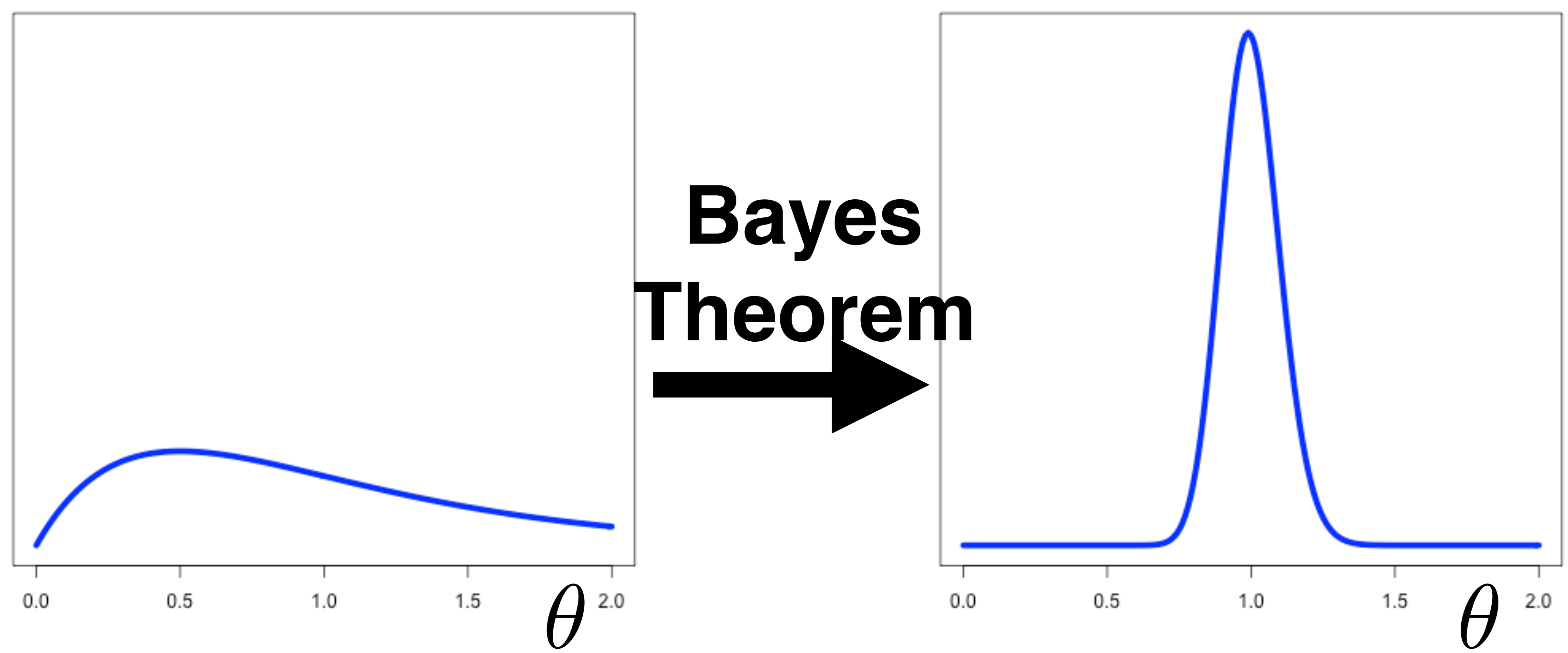

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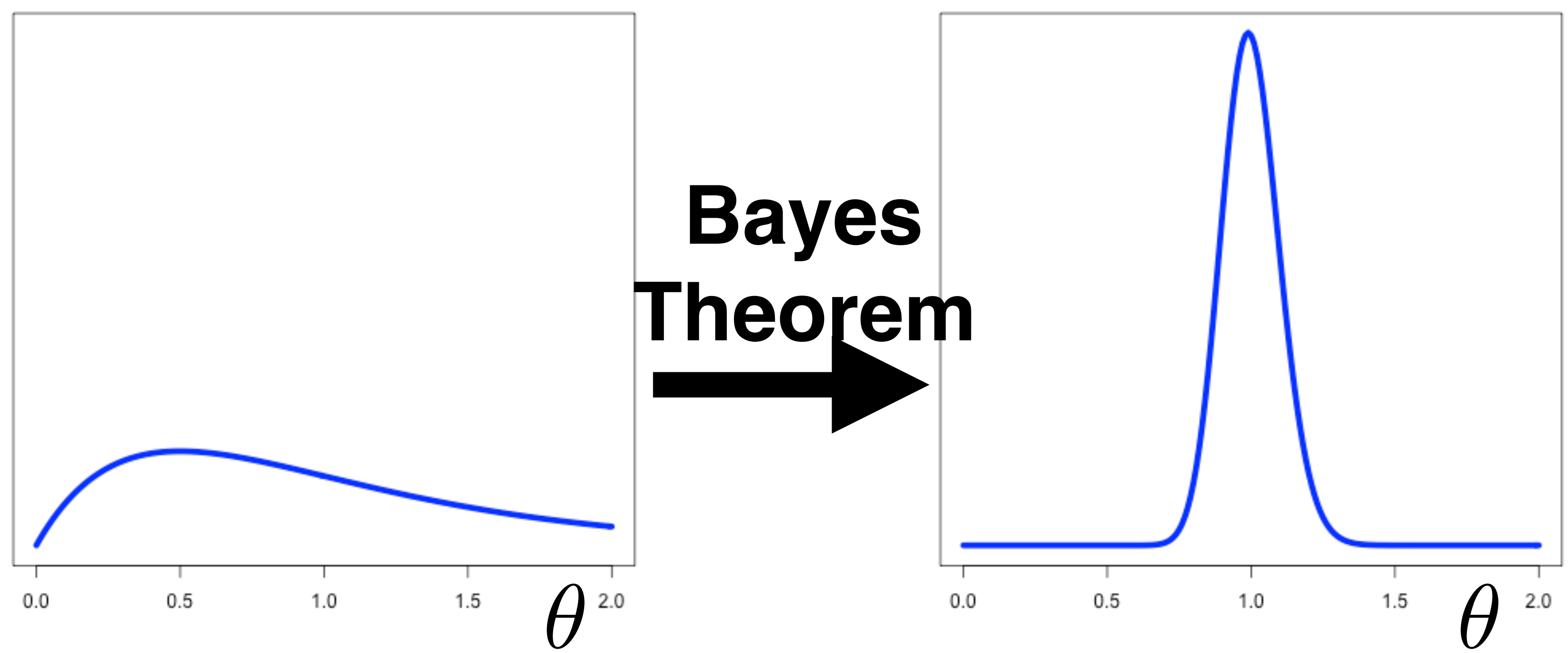

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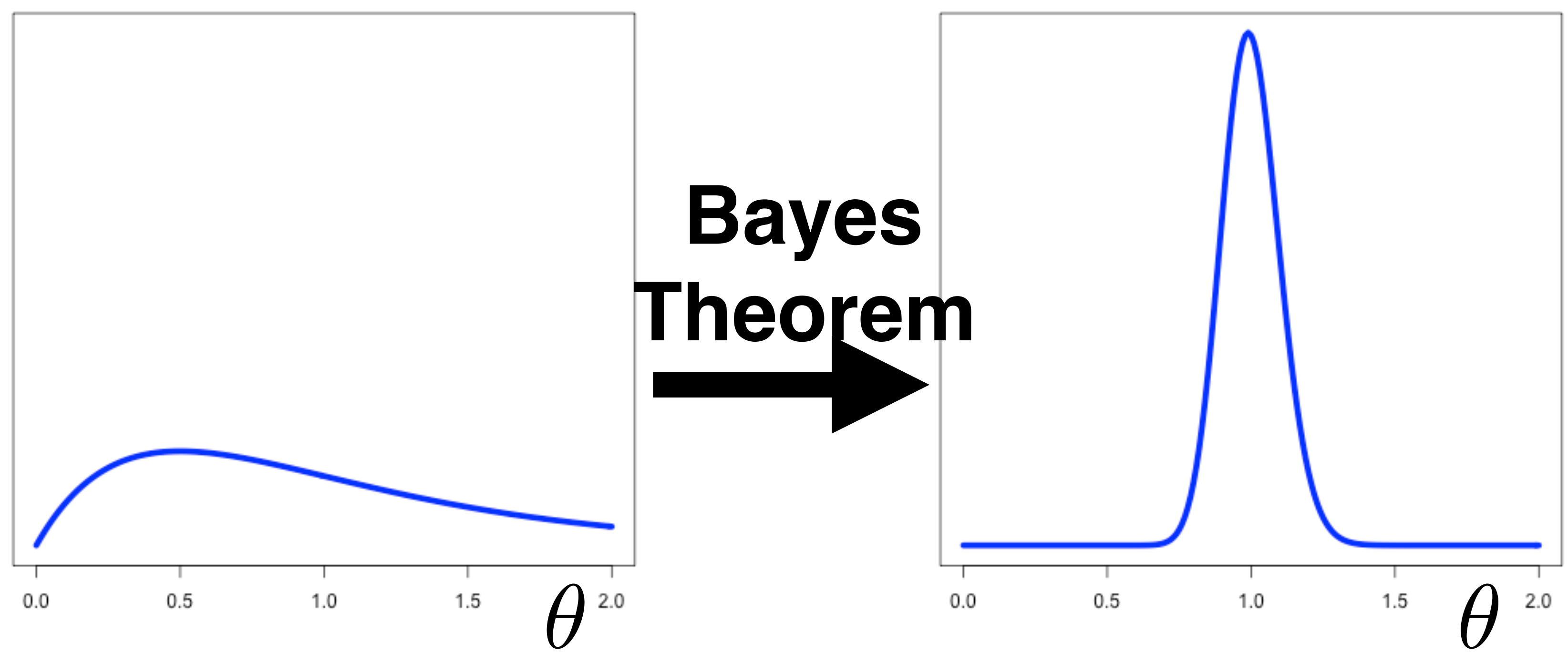

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Bayesian inference

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$$p(\theta|y_{1:N}) = p(y_{1:N}|\theta)p(\theta)/p(y_{1:N})$$

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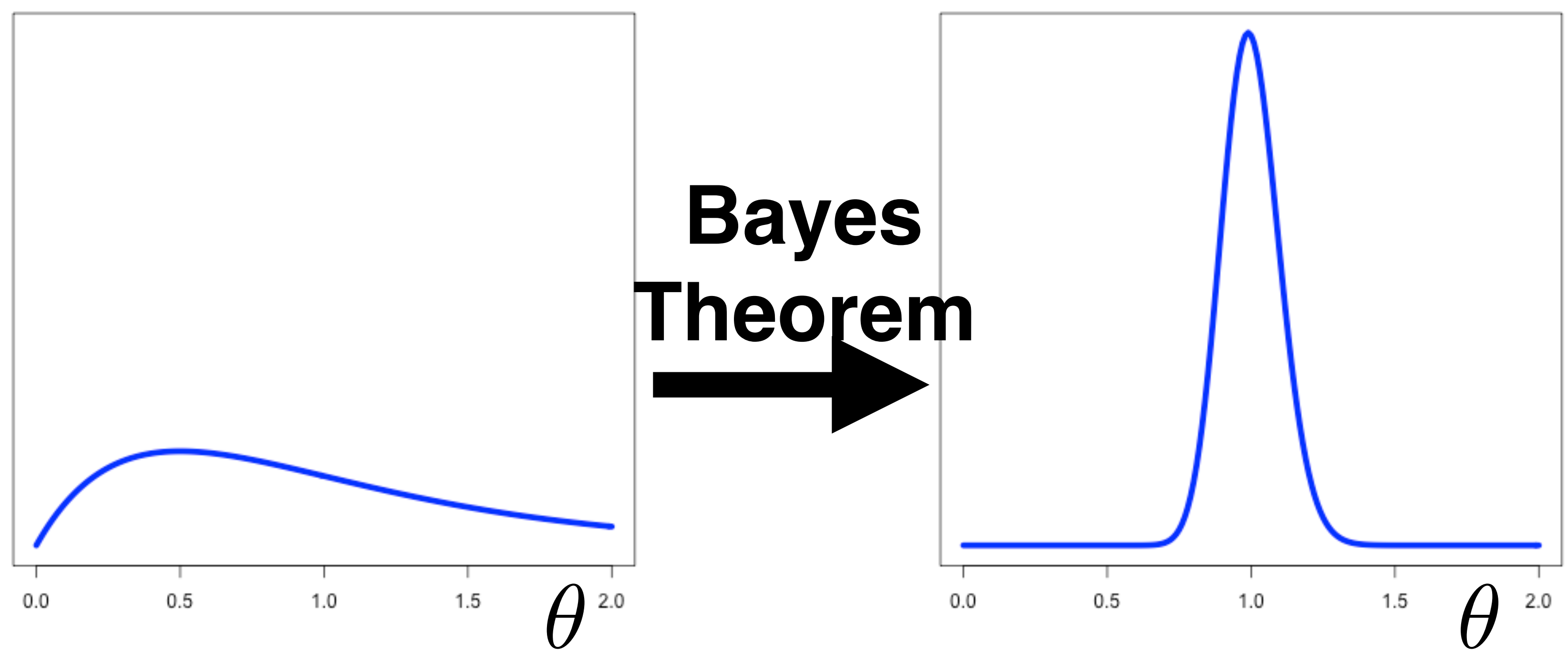

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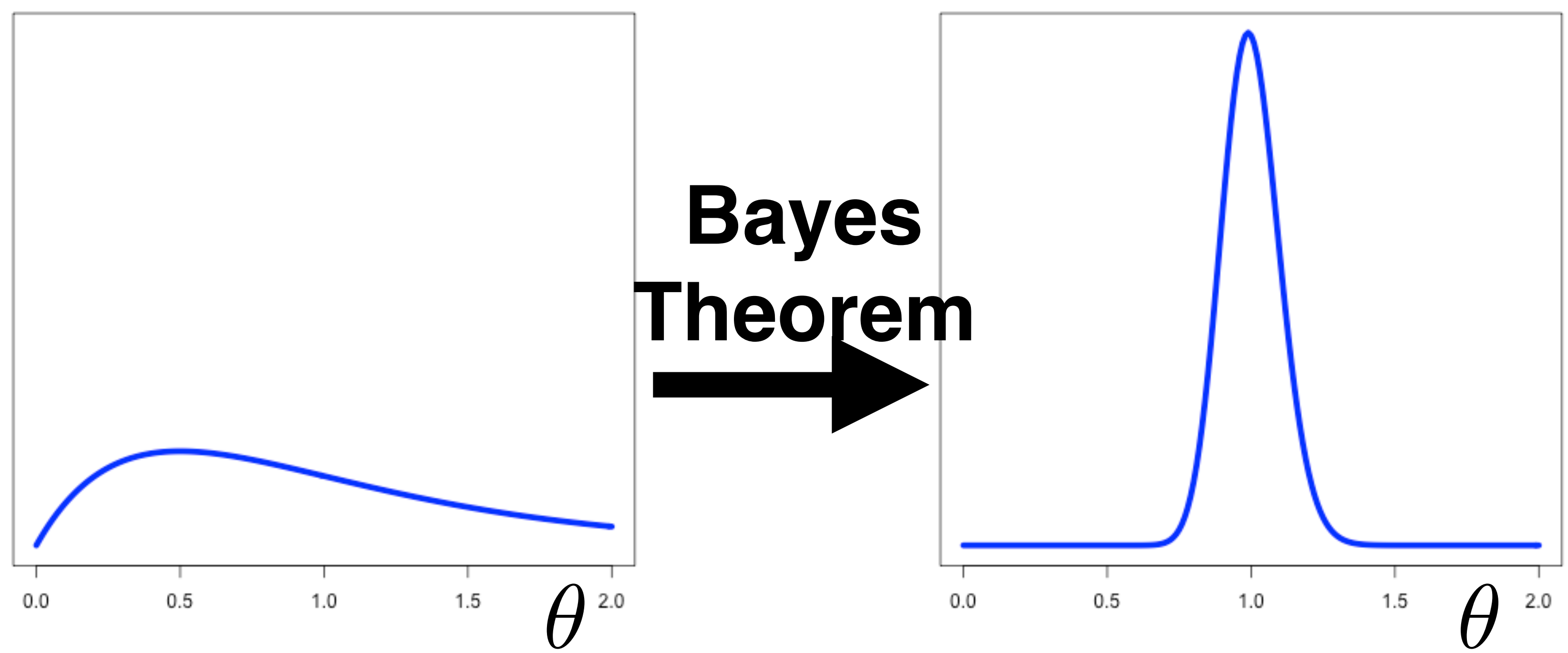

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$$p(\theta|y_{1:N}) = p(y_{1:N}|\theta)p(\theta) / \int p(y_{1:N}, \theta) d\theta$$

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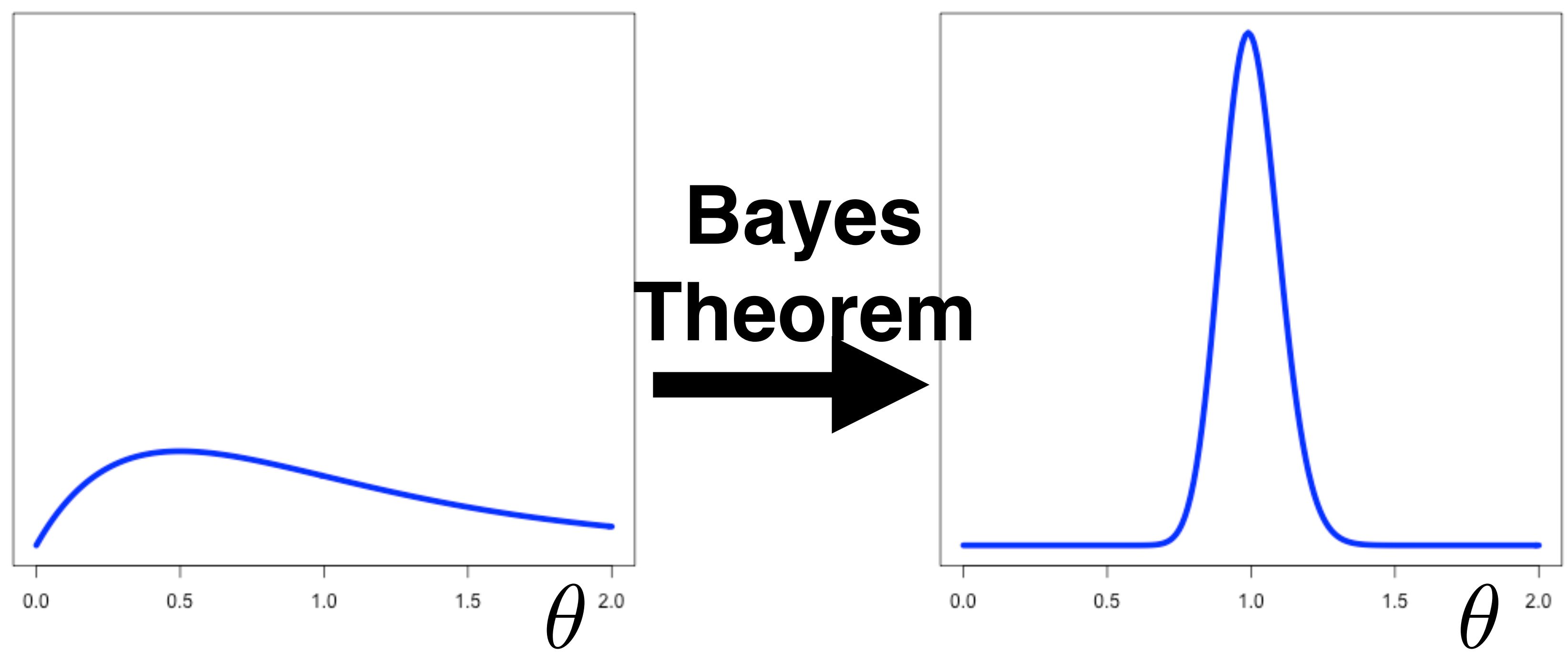

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- Gold standard: Markov Chain Monte Carlo (MCMC)

[Bardenet, Doucet, Holmes 2017]

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Instead: an optimization approach

- Approximate posterior with q^*

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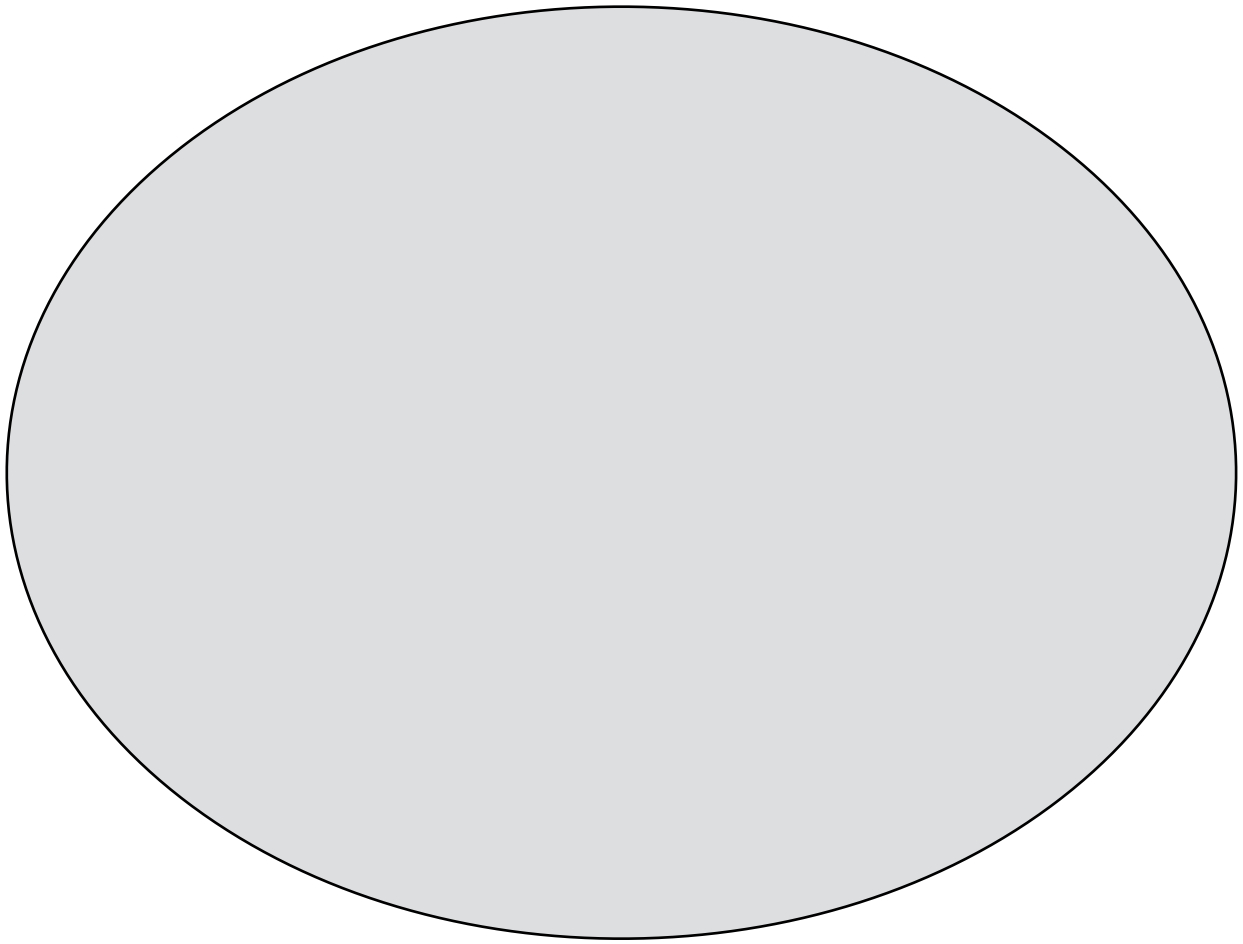

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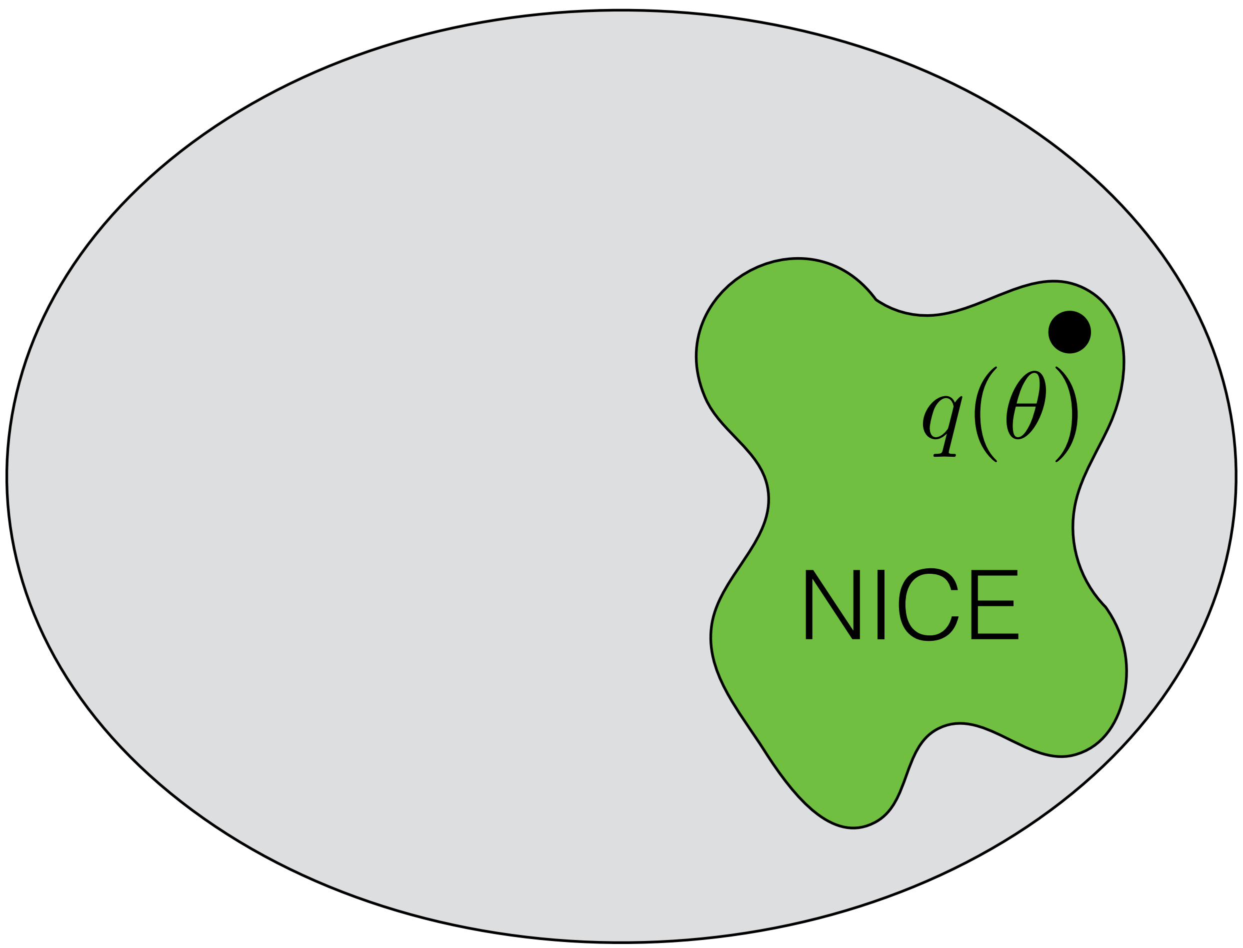

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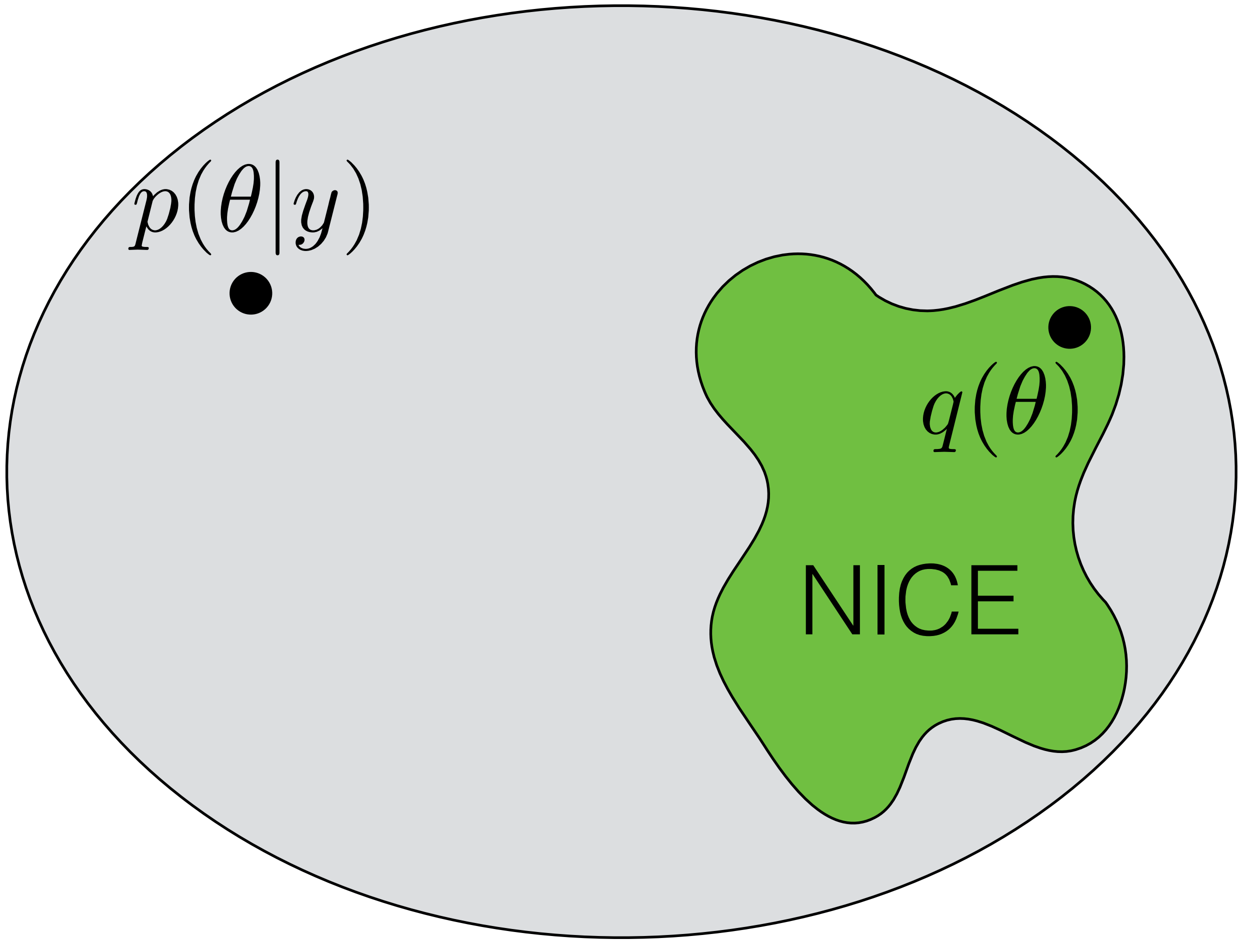

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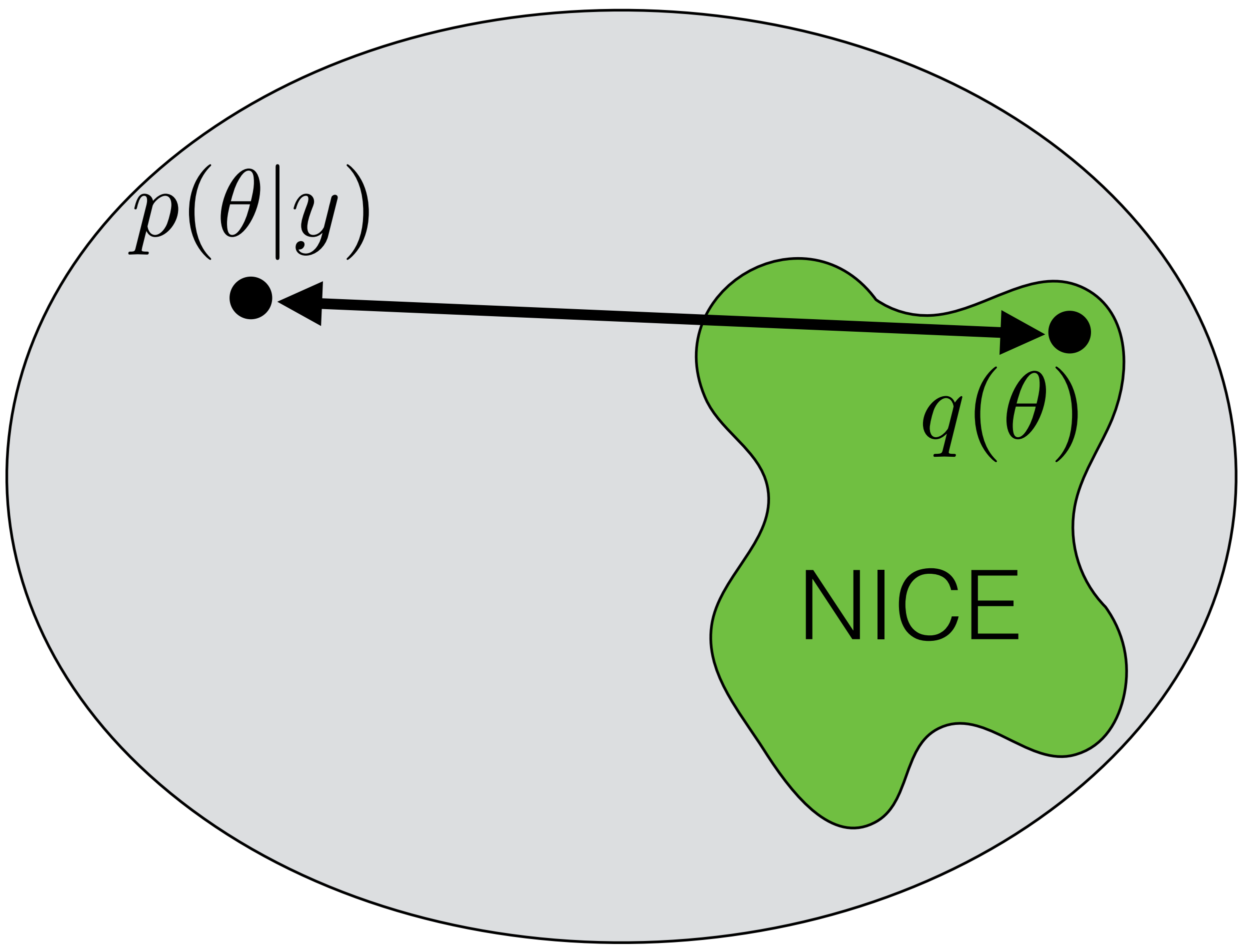

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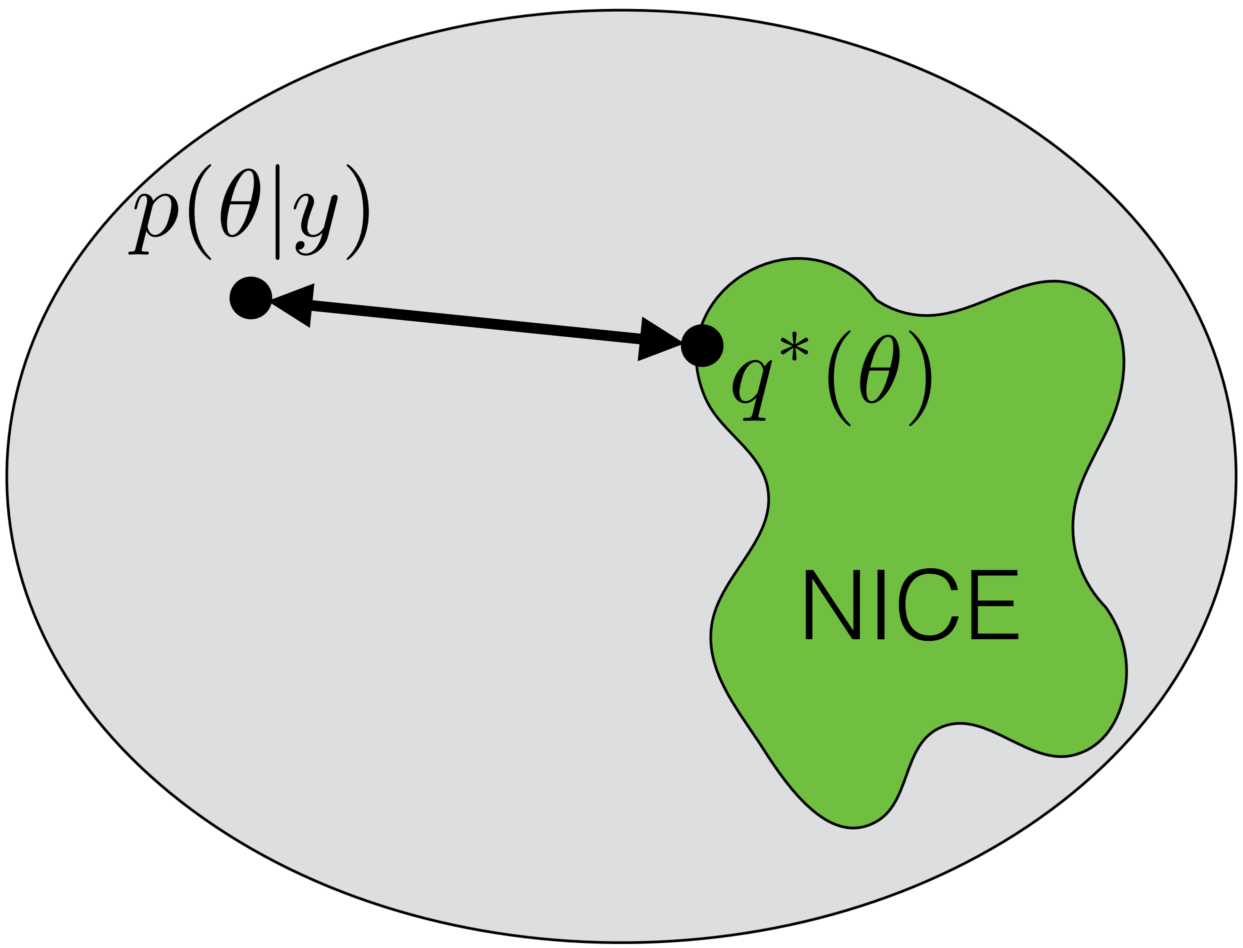

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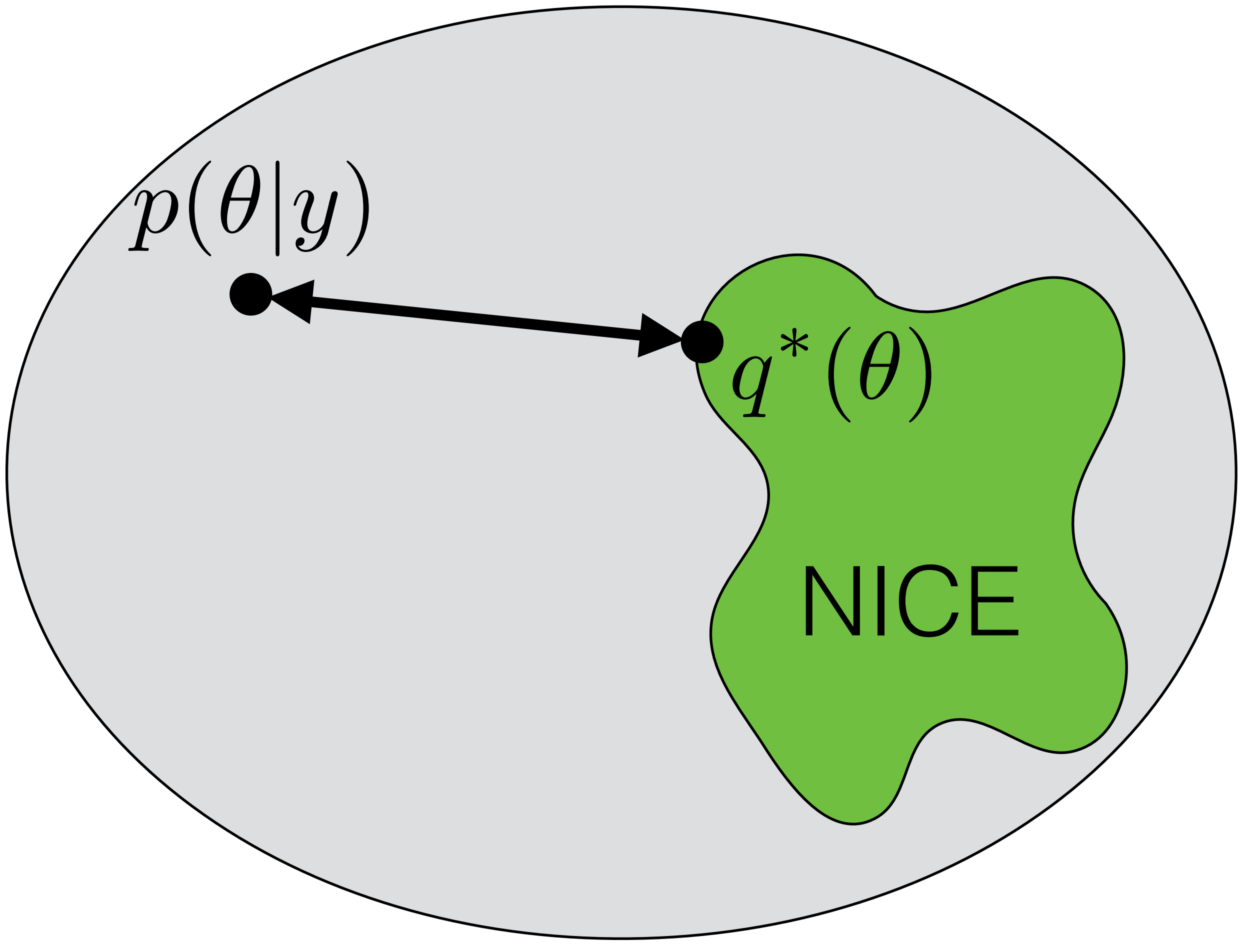

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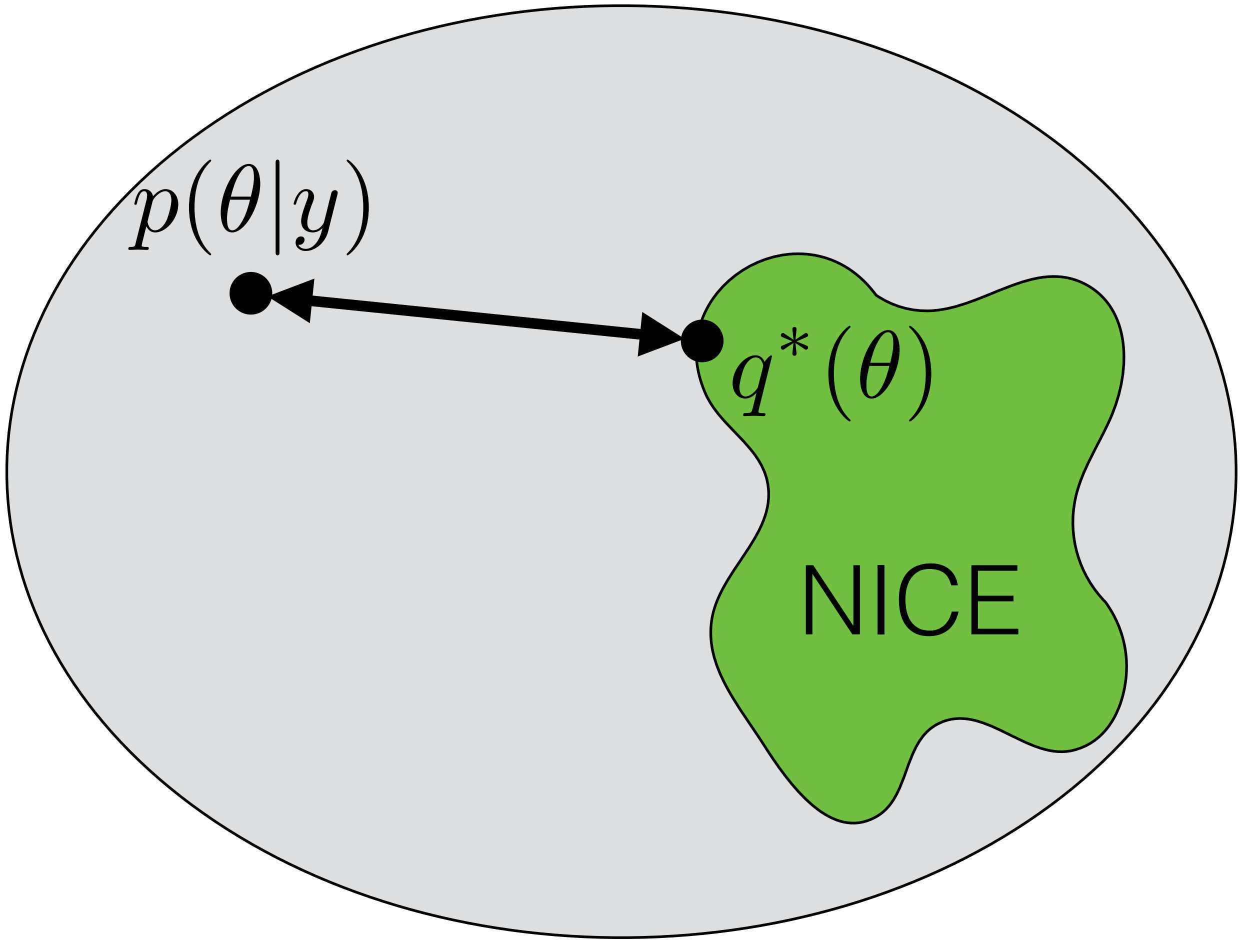

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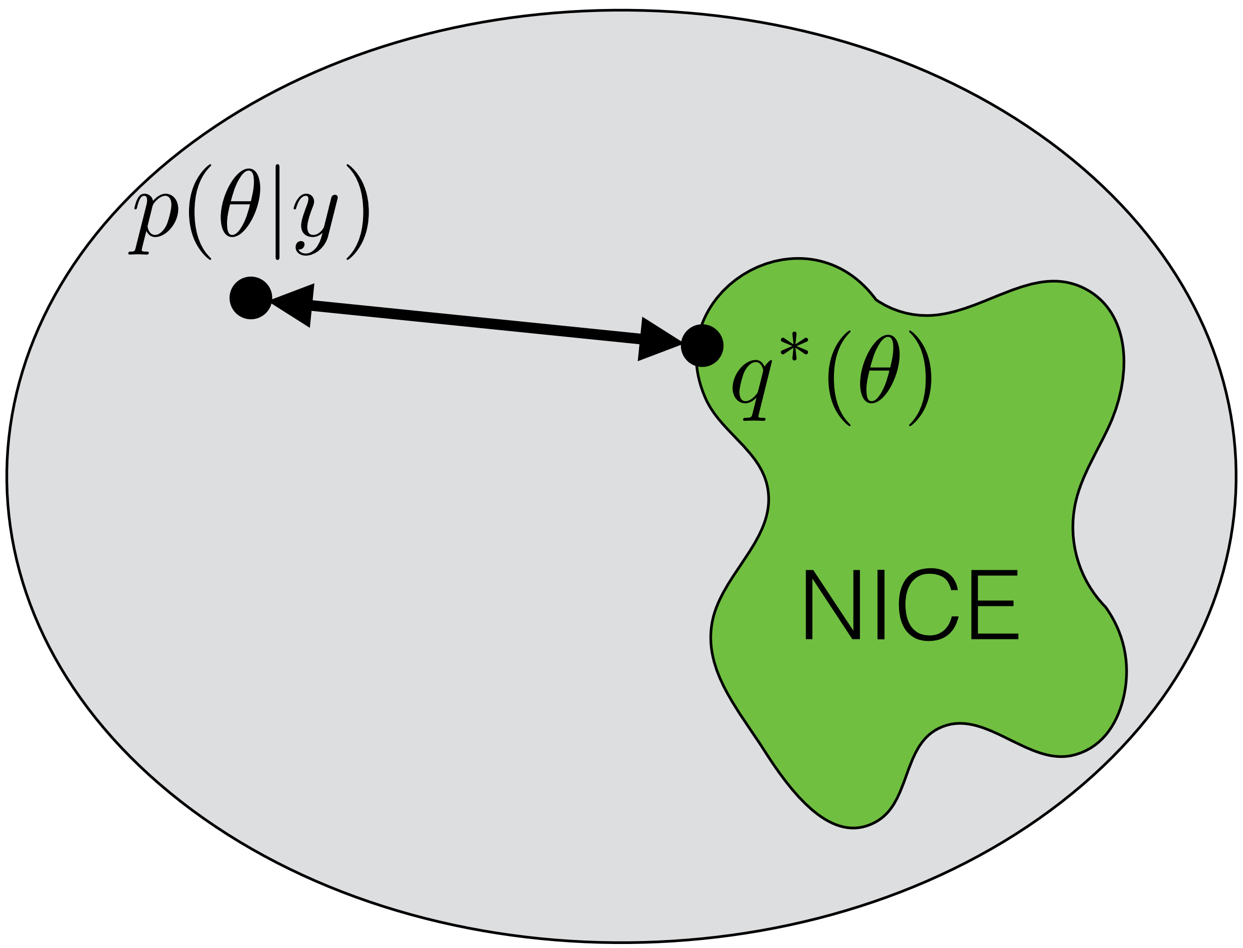

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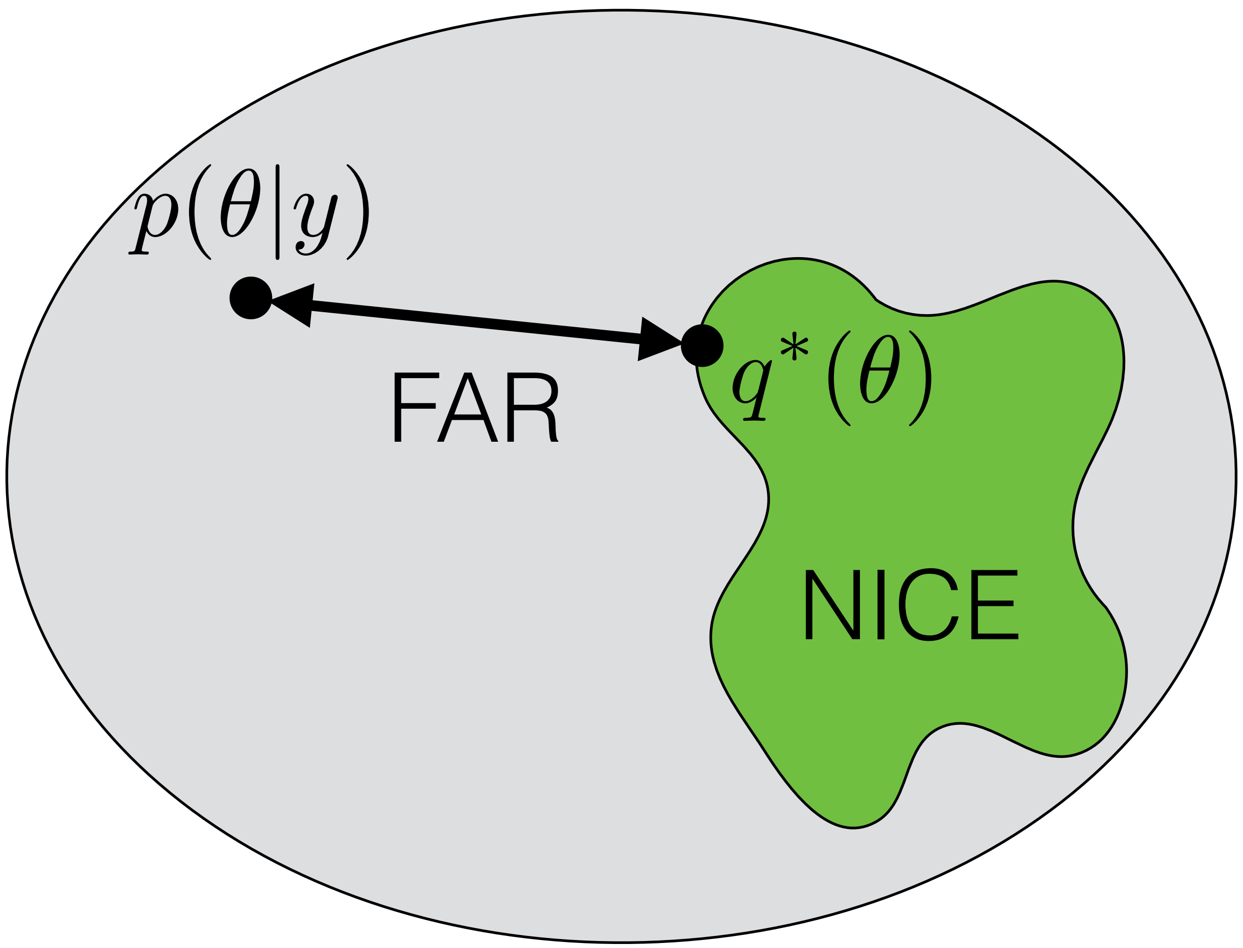

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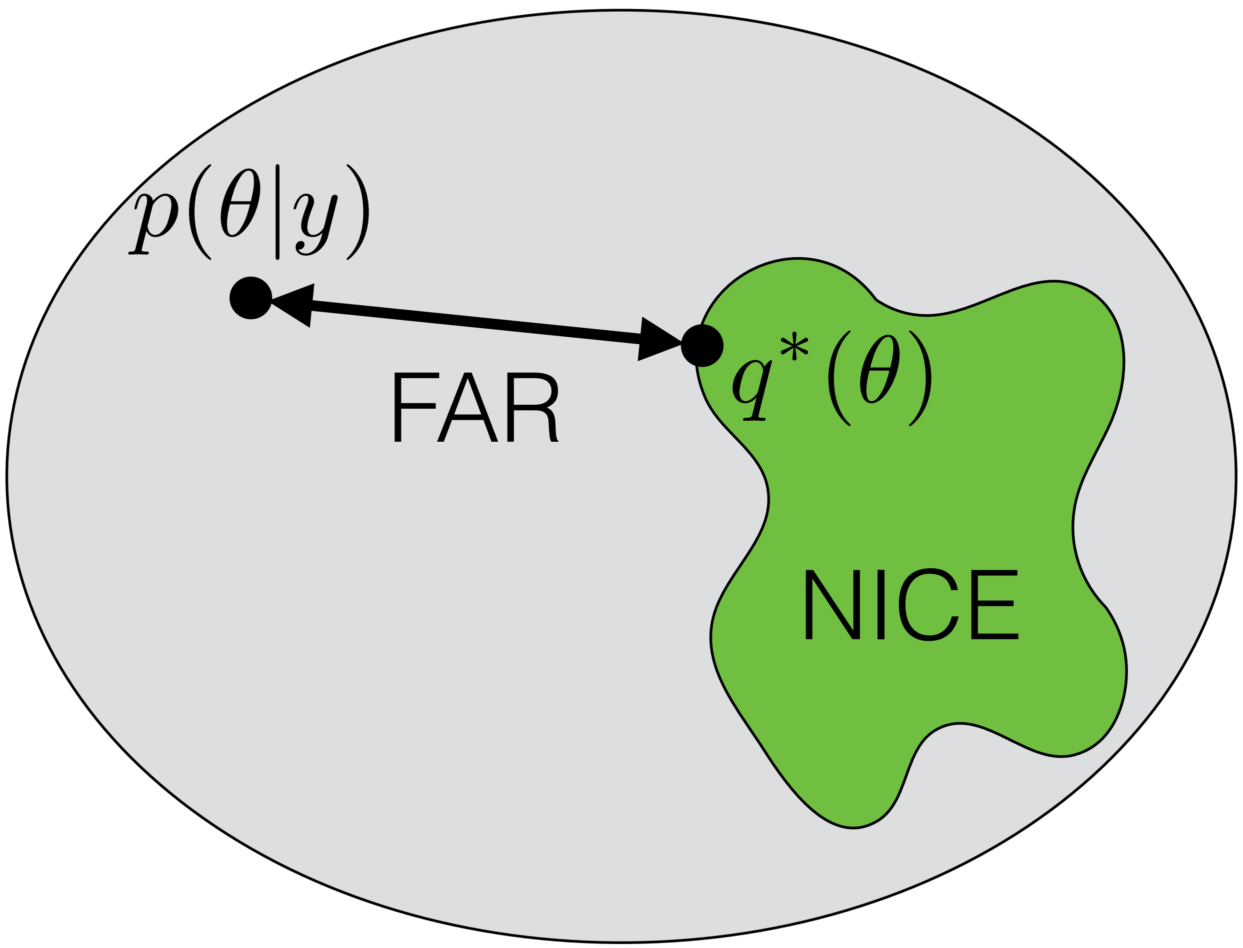

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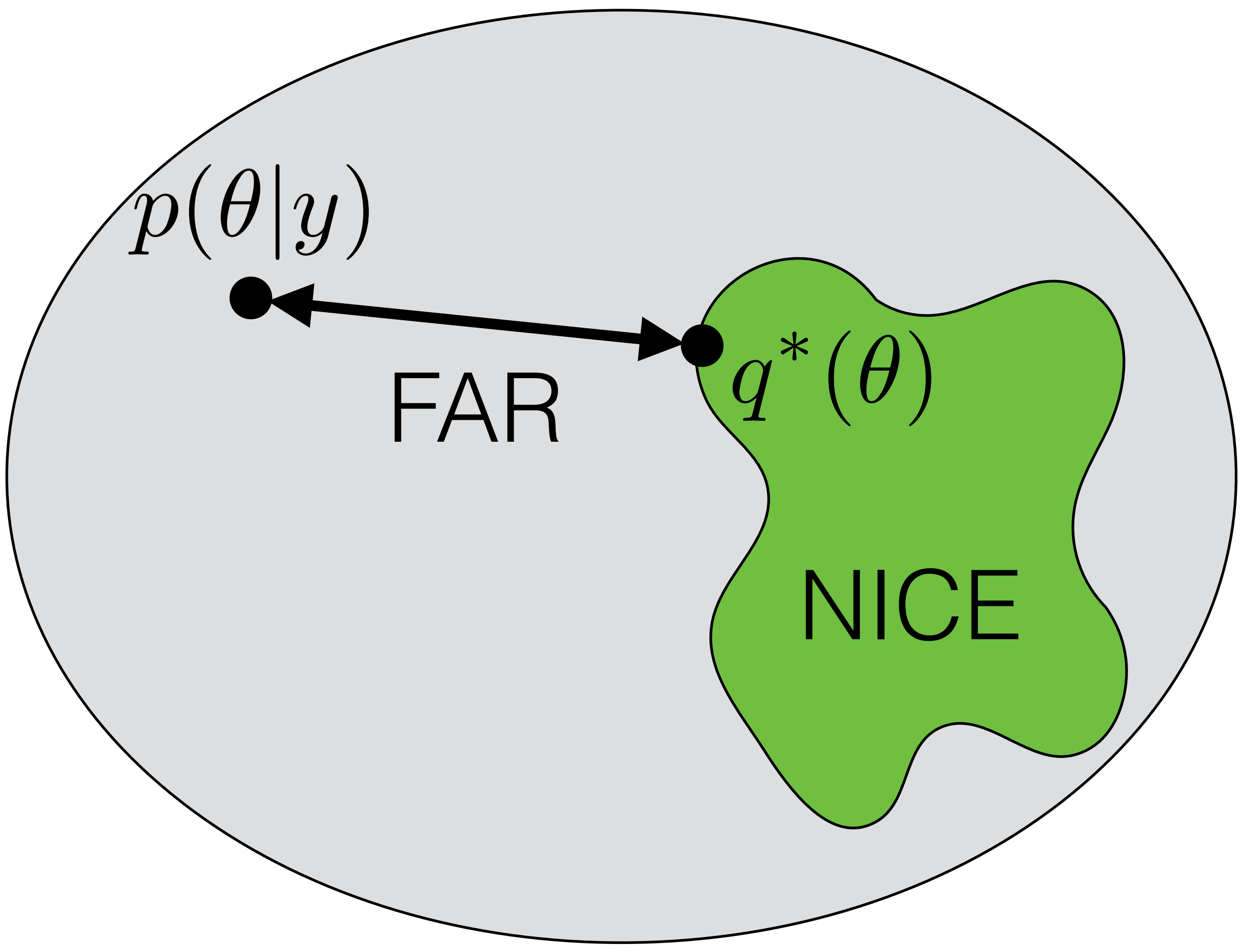

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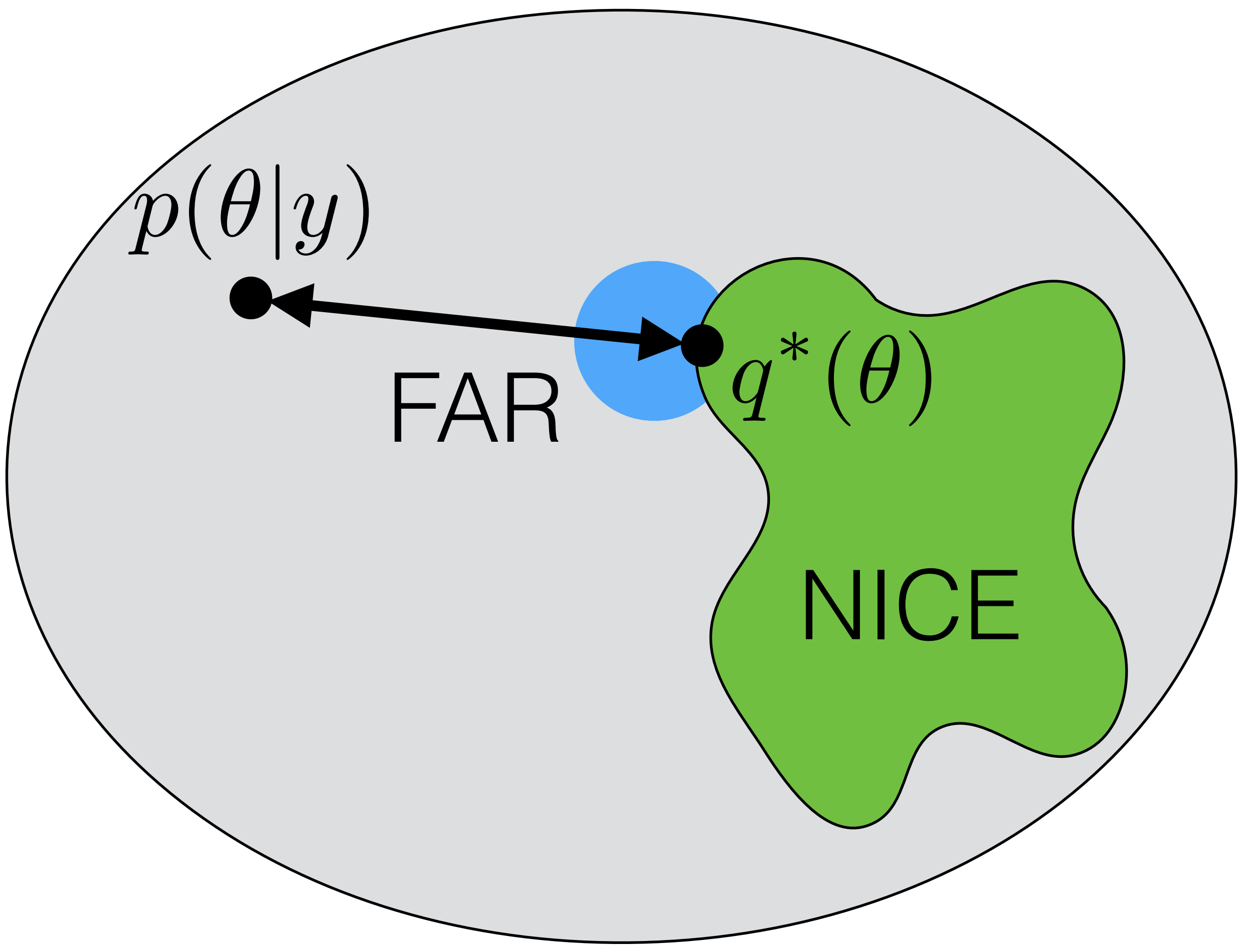

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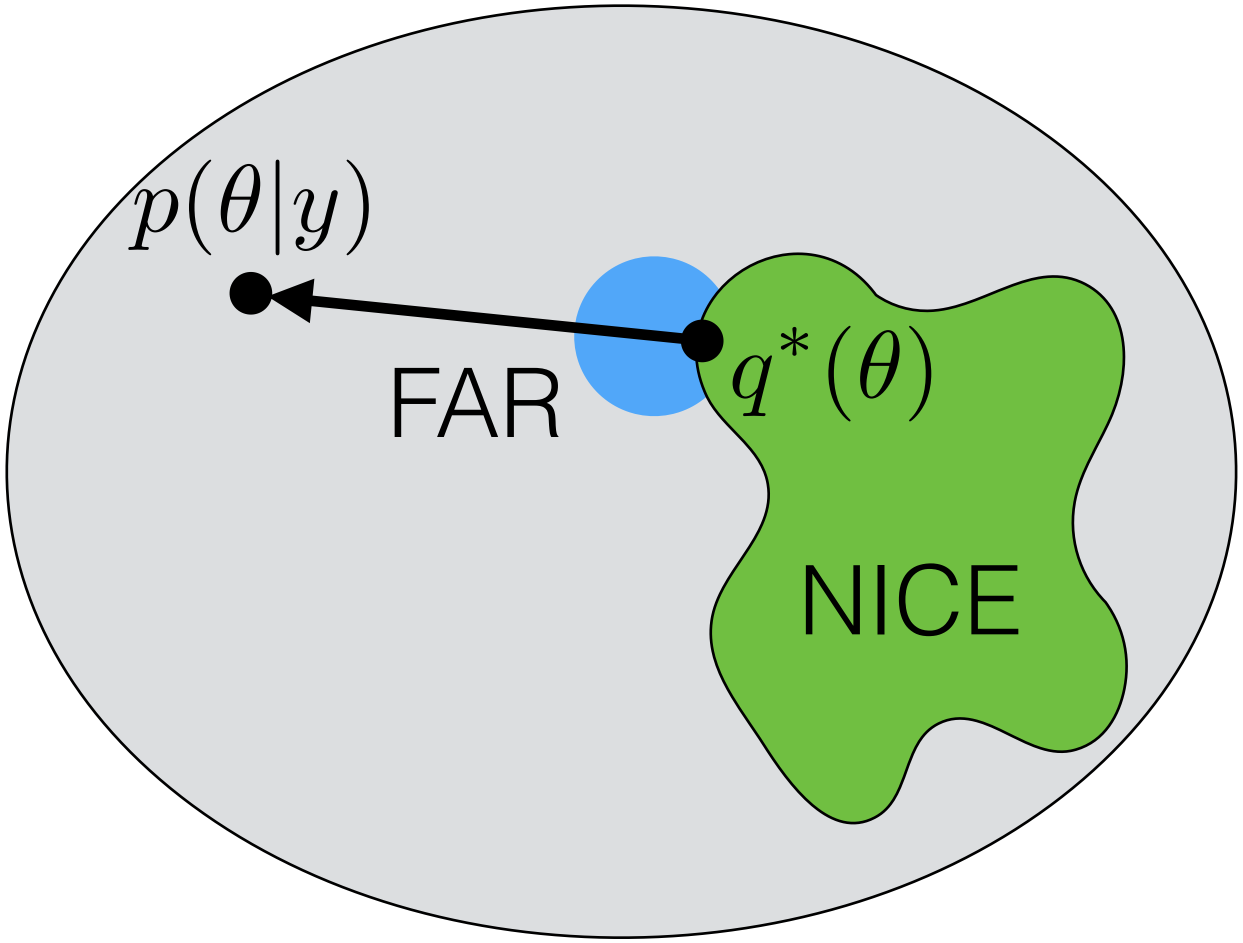

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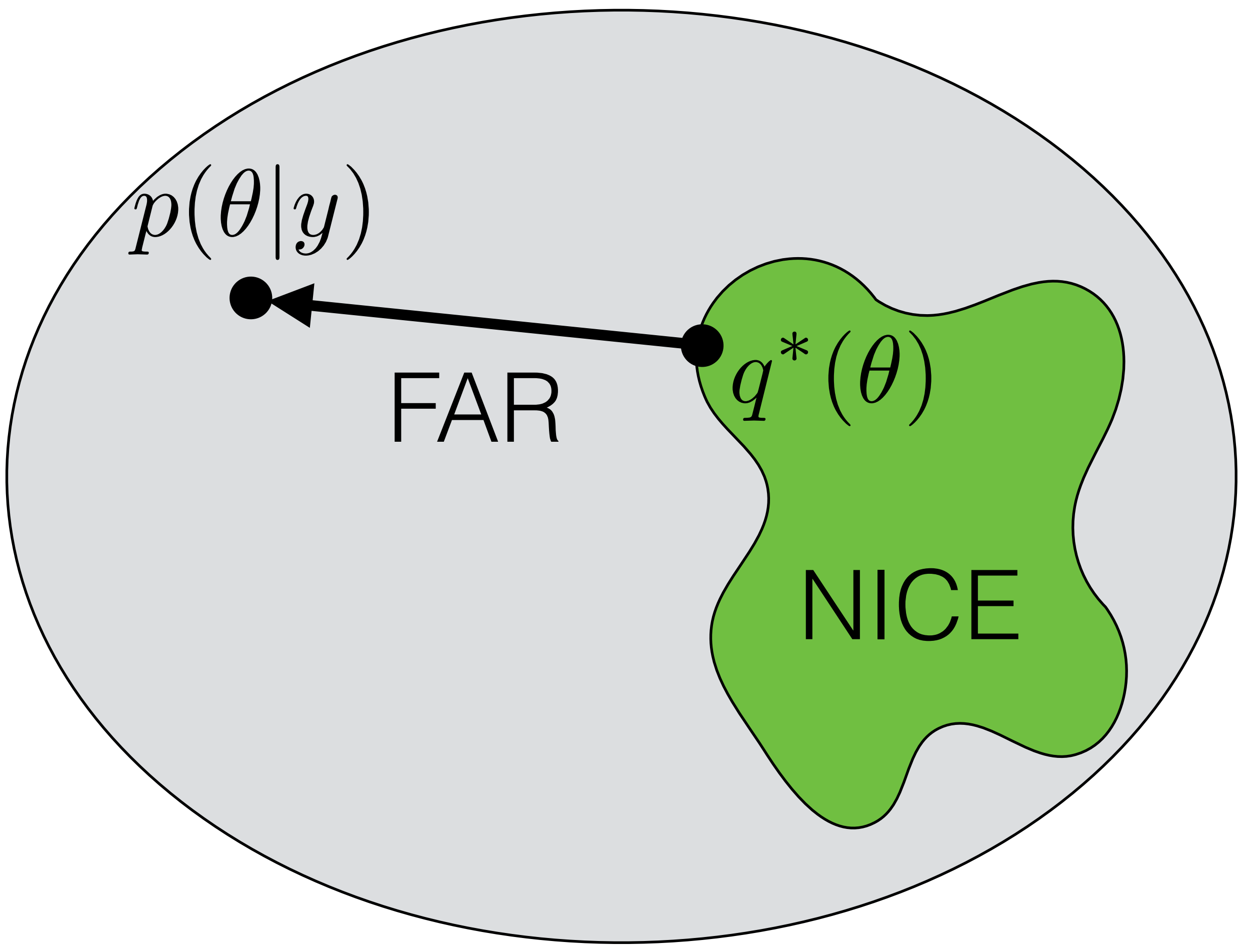

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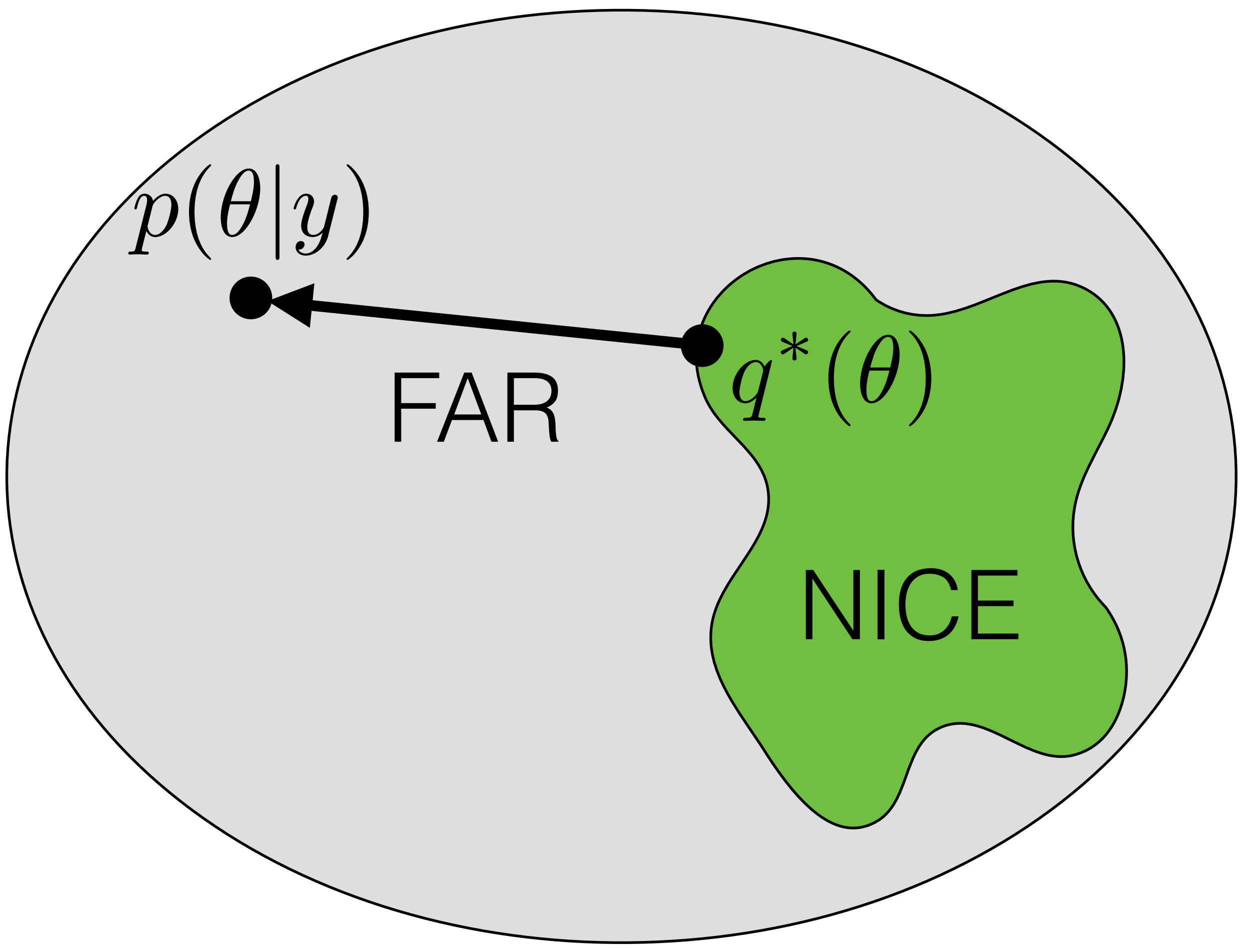

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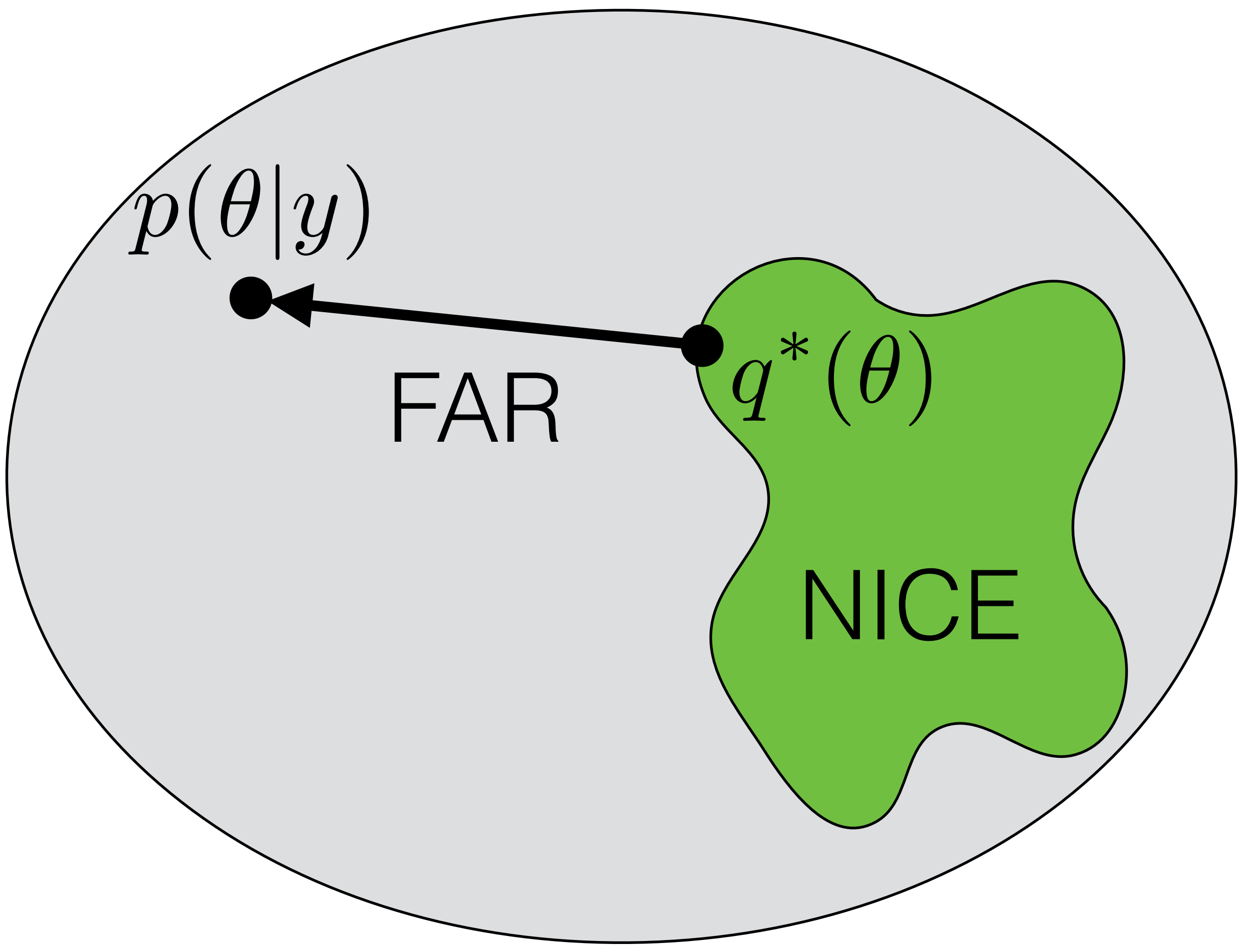

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- VB practical success: point estimates and prediction

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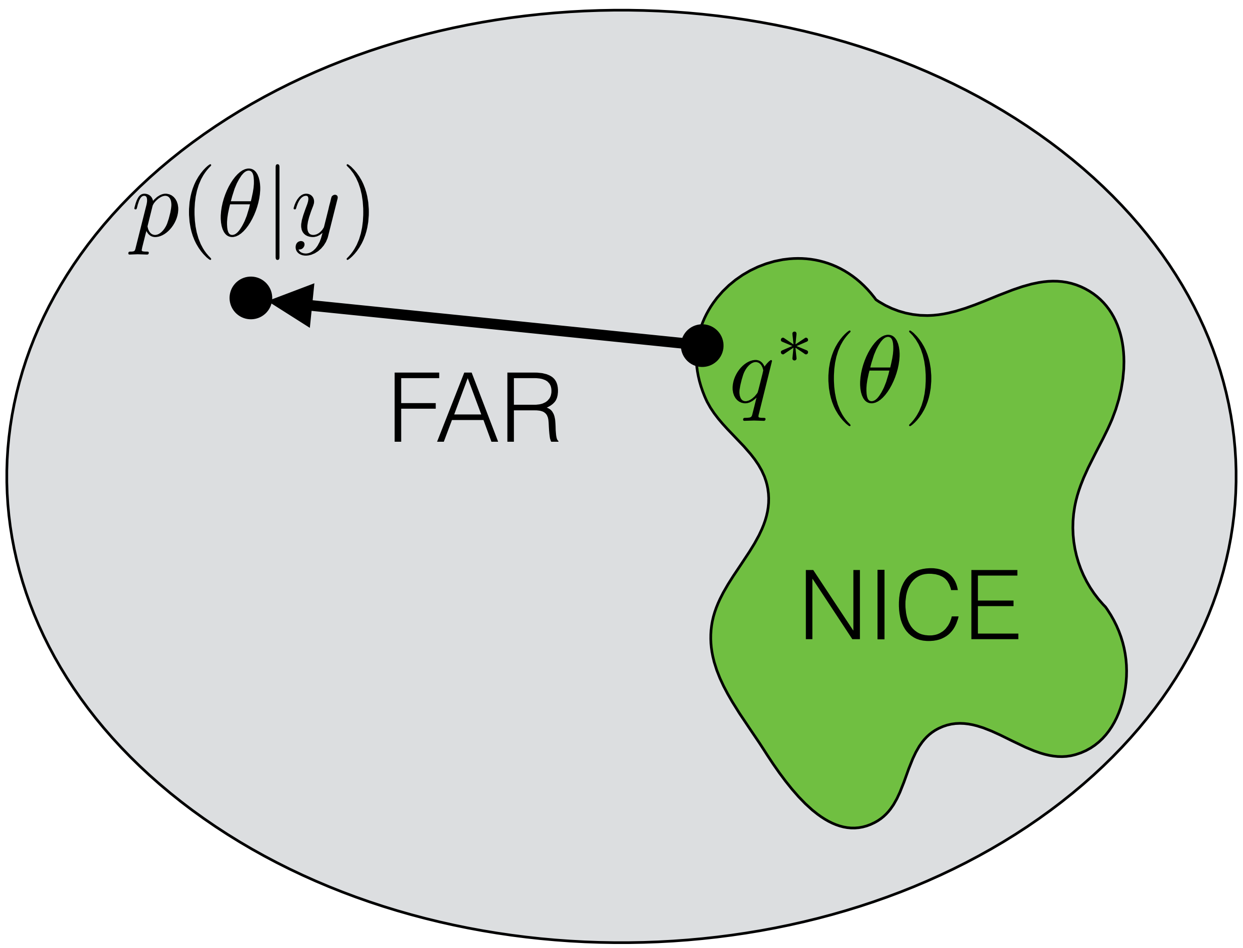

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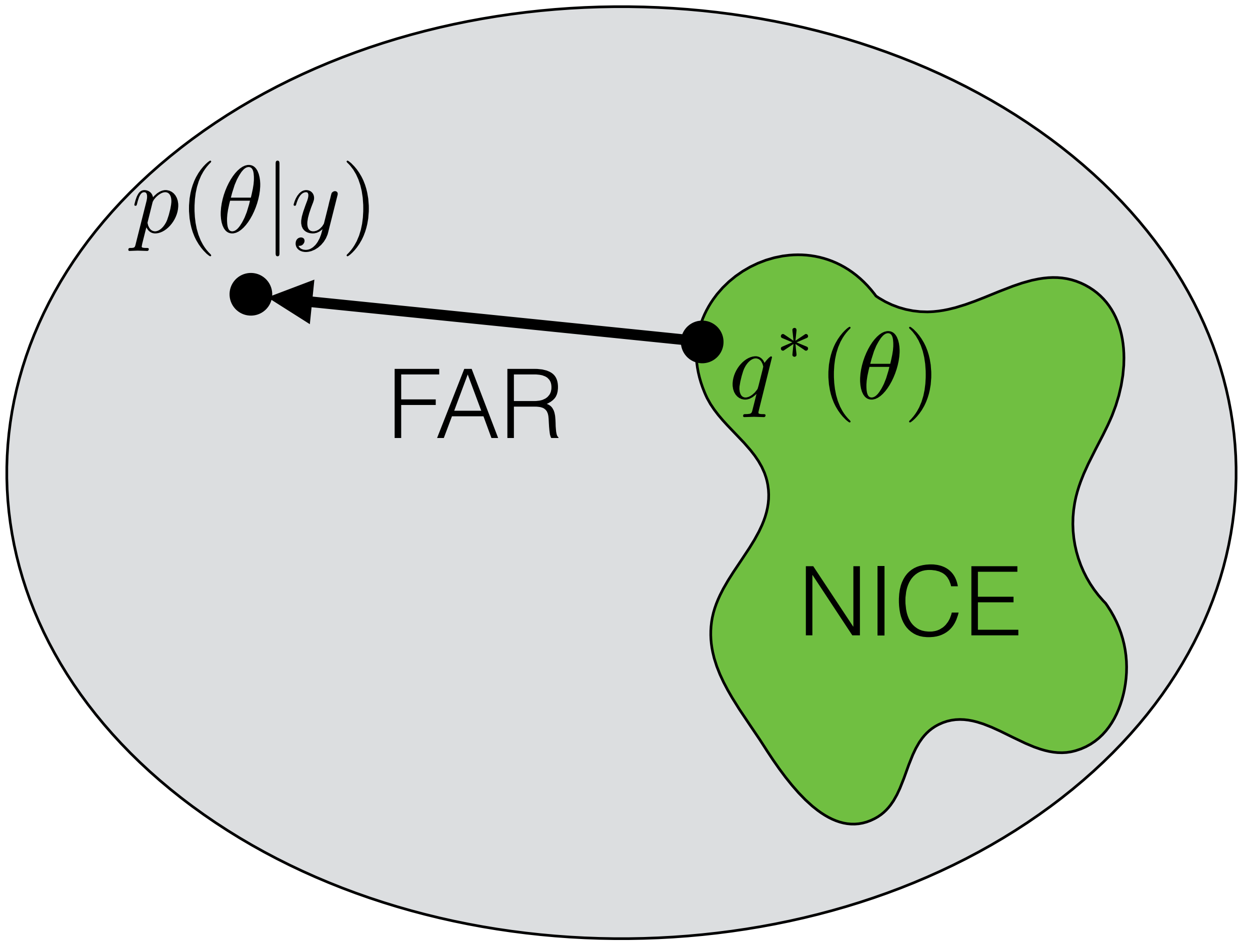

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$$KL(q(\cdot)||p(\cdot|y))$$

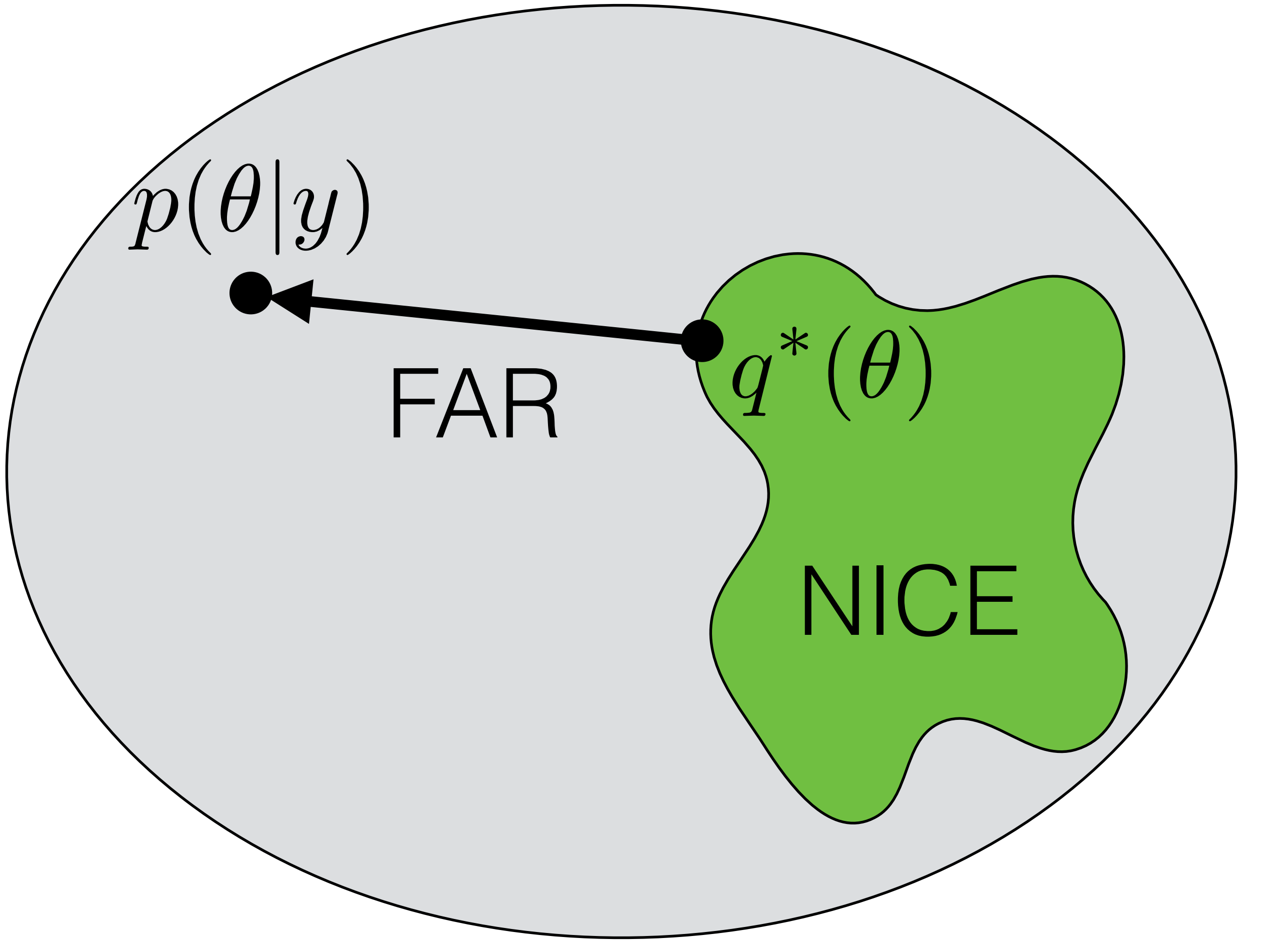
- VB practical success: point estimates and prediction, fast, streaming, distributed (3.6M Wikipedia, 350K Nature)

[Broderick, Boyd, Wibisono, Wilson, Jordan 2013]

Why KL?

- Variational Bayes

$$q^* = \mathrm{argmin}_{q \in Q} \mathrm{KL}\left(q(\cdot) || p(\cdot|y)\right)$$



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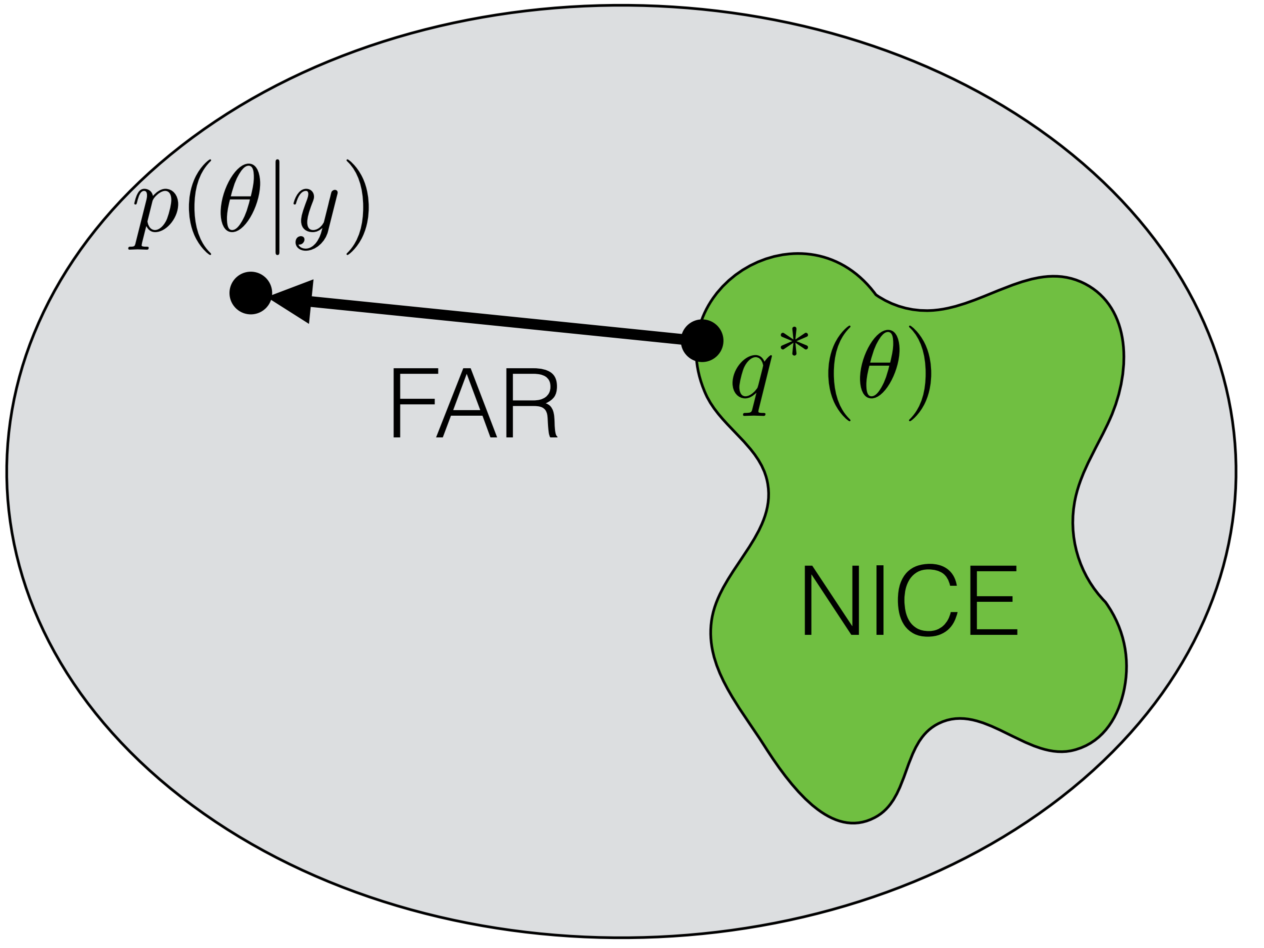

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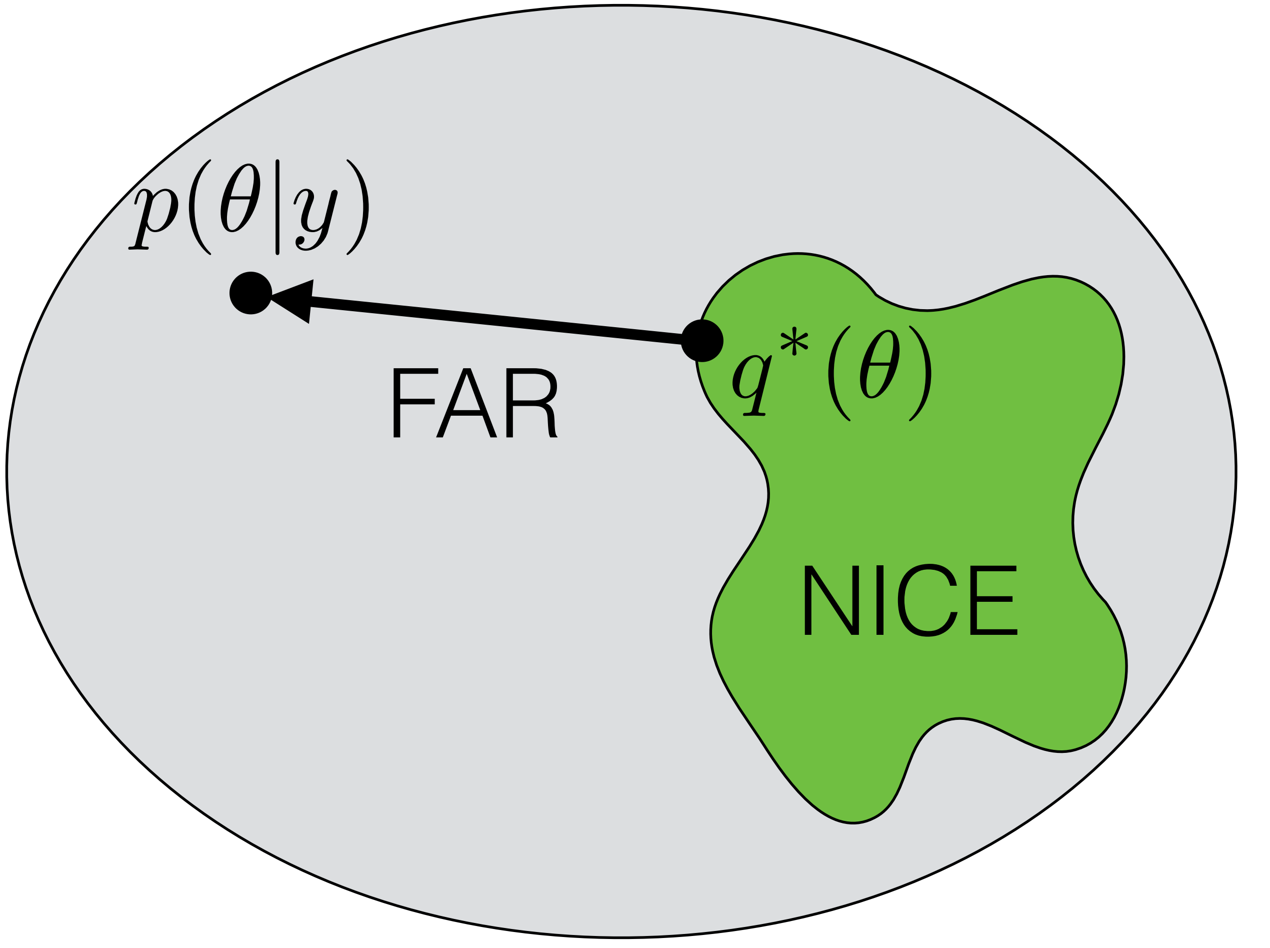

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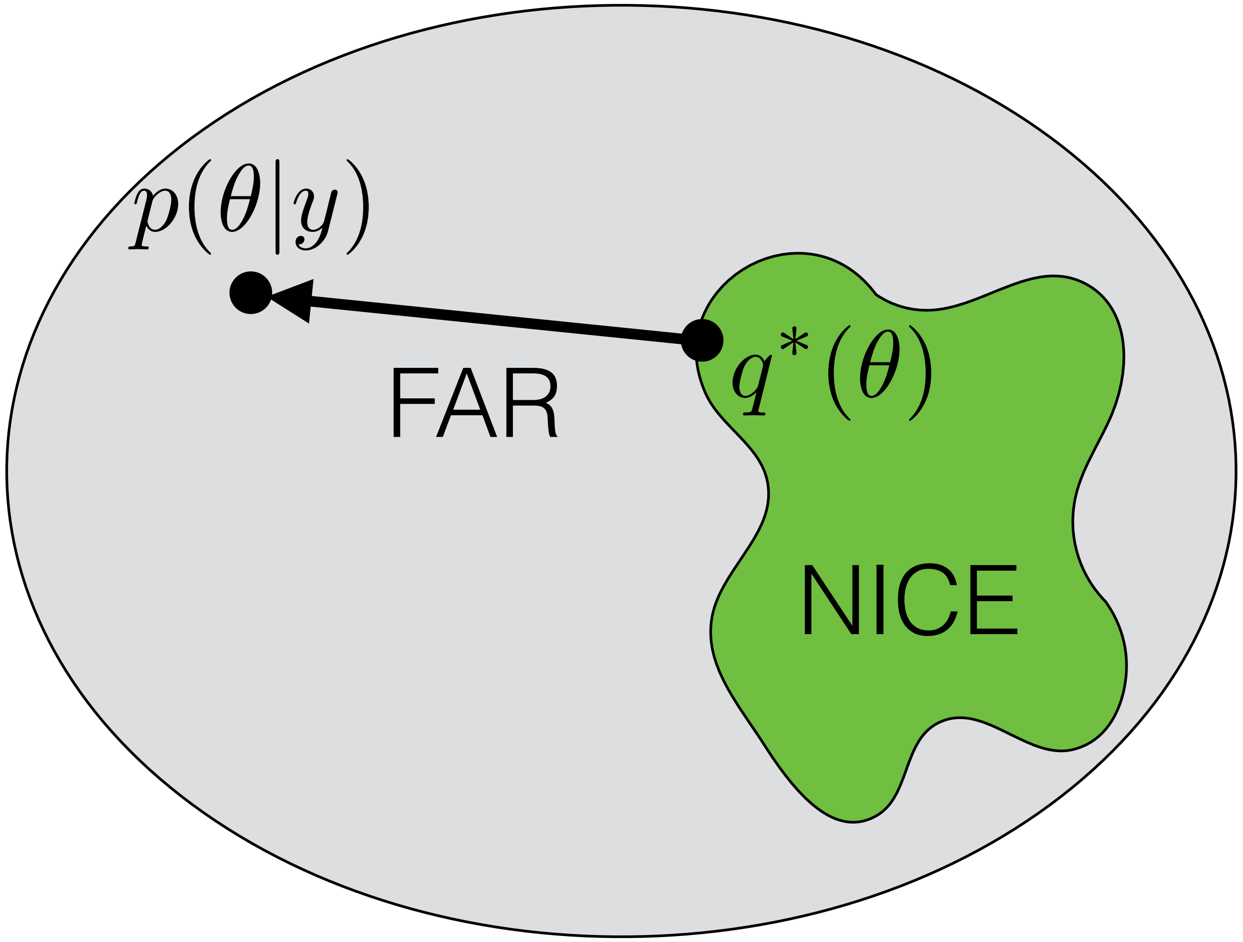

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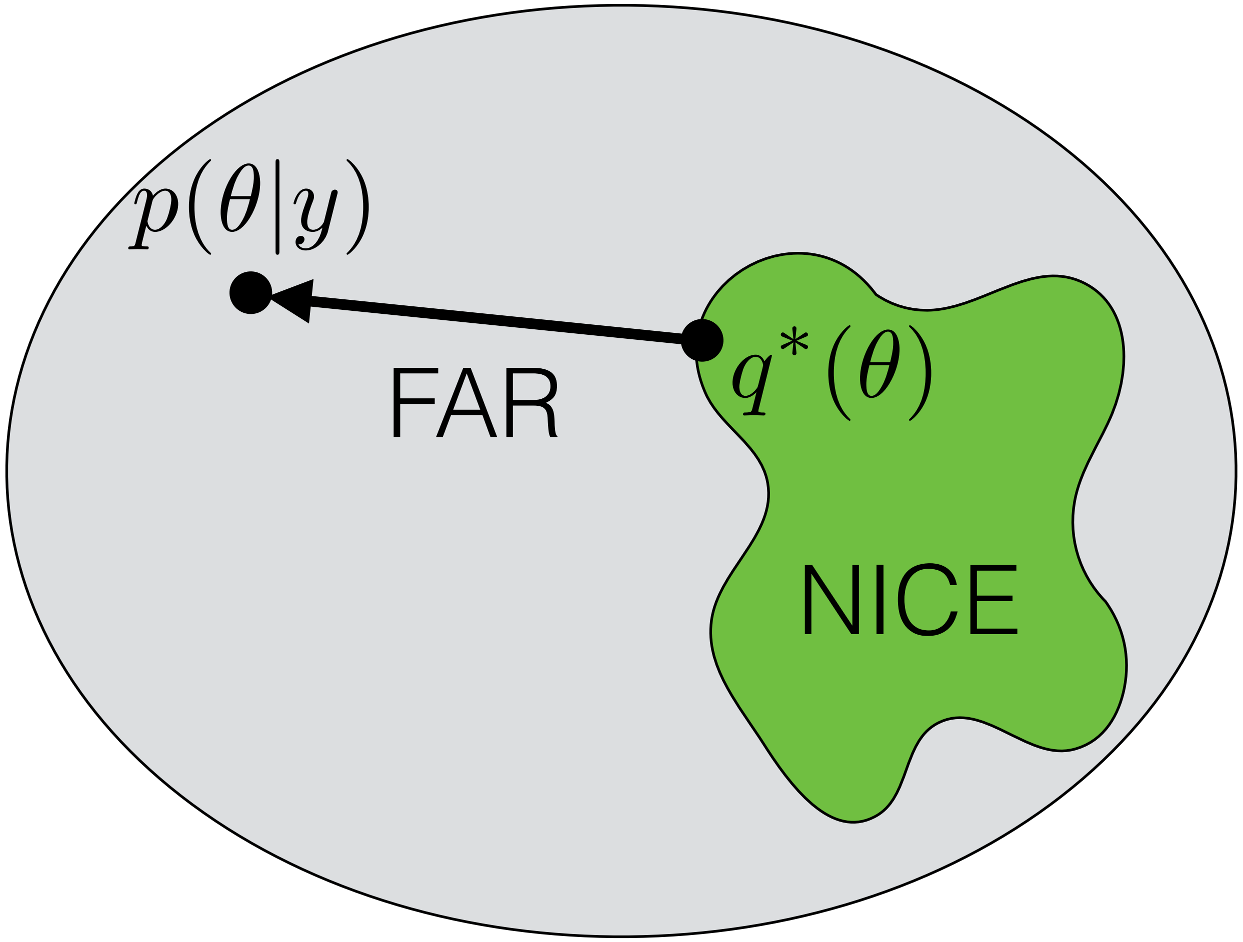

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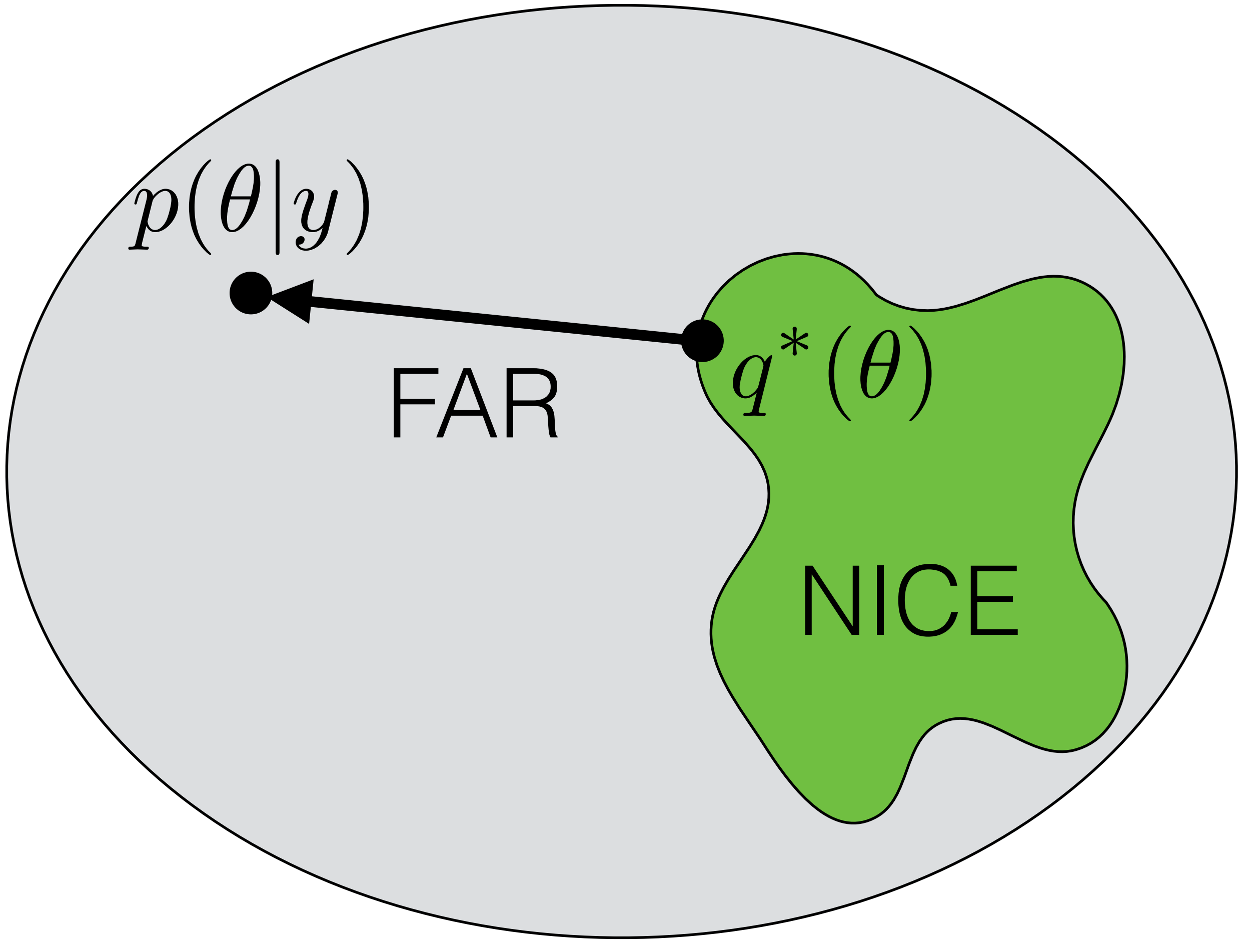

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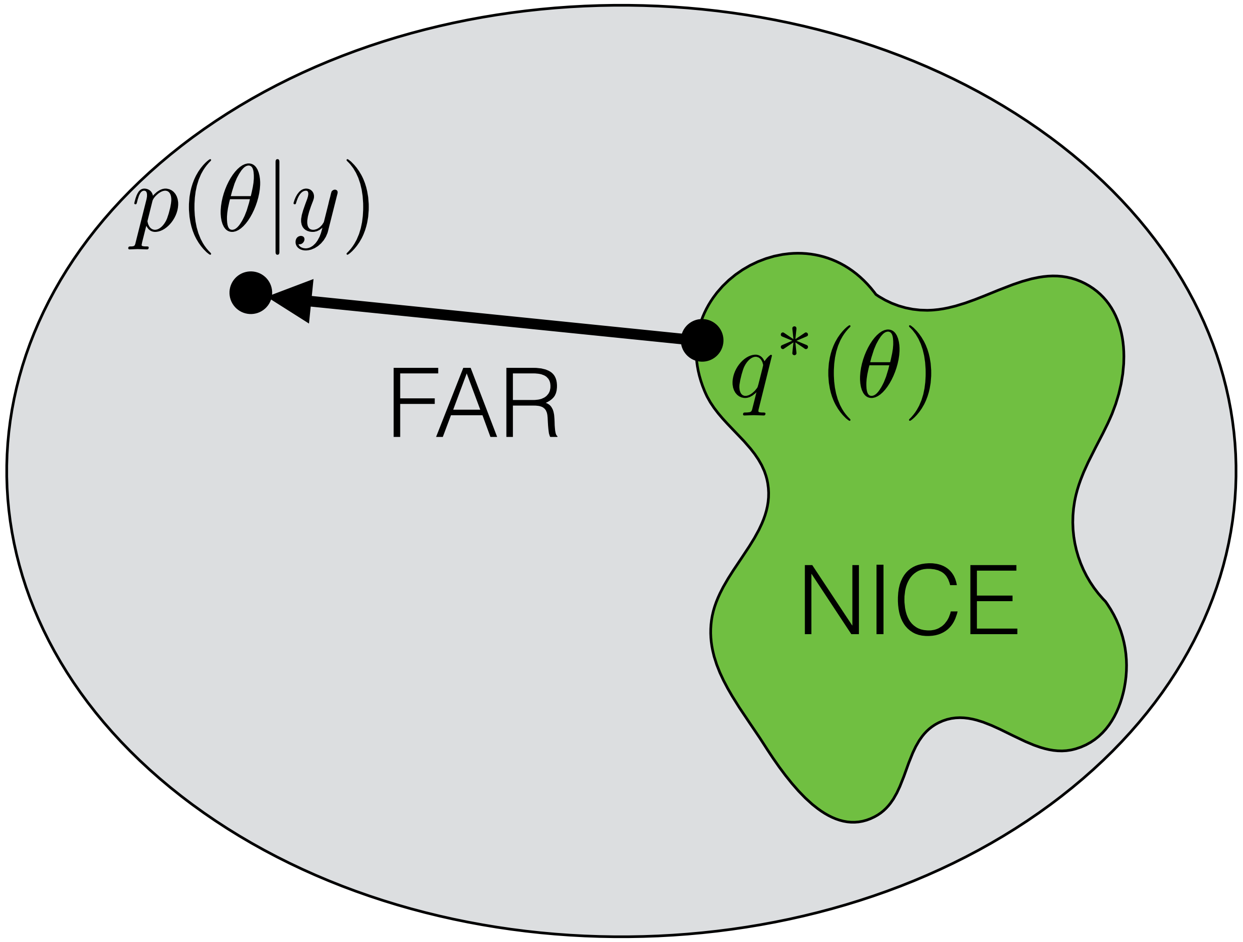

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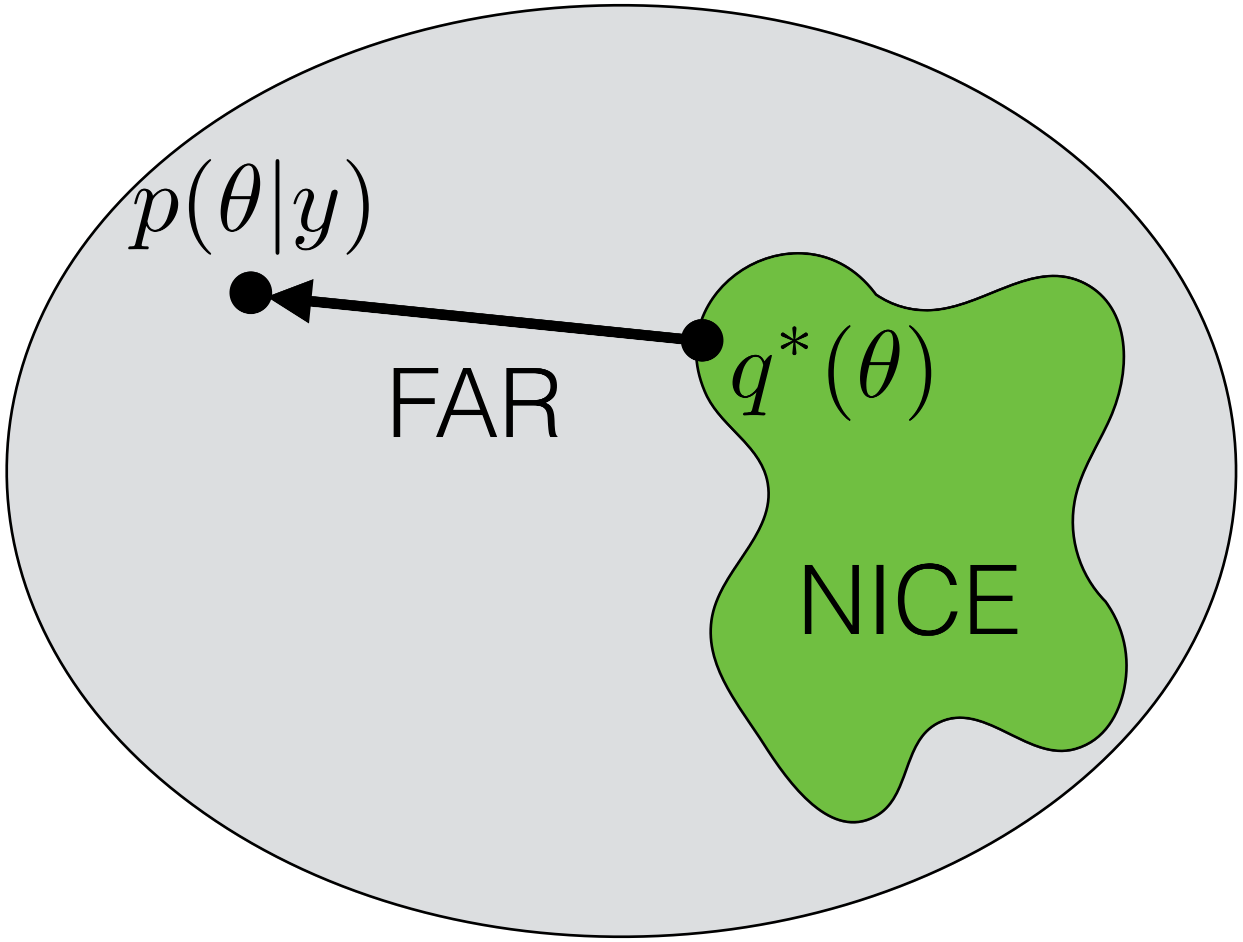

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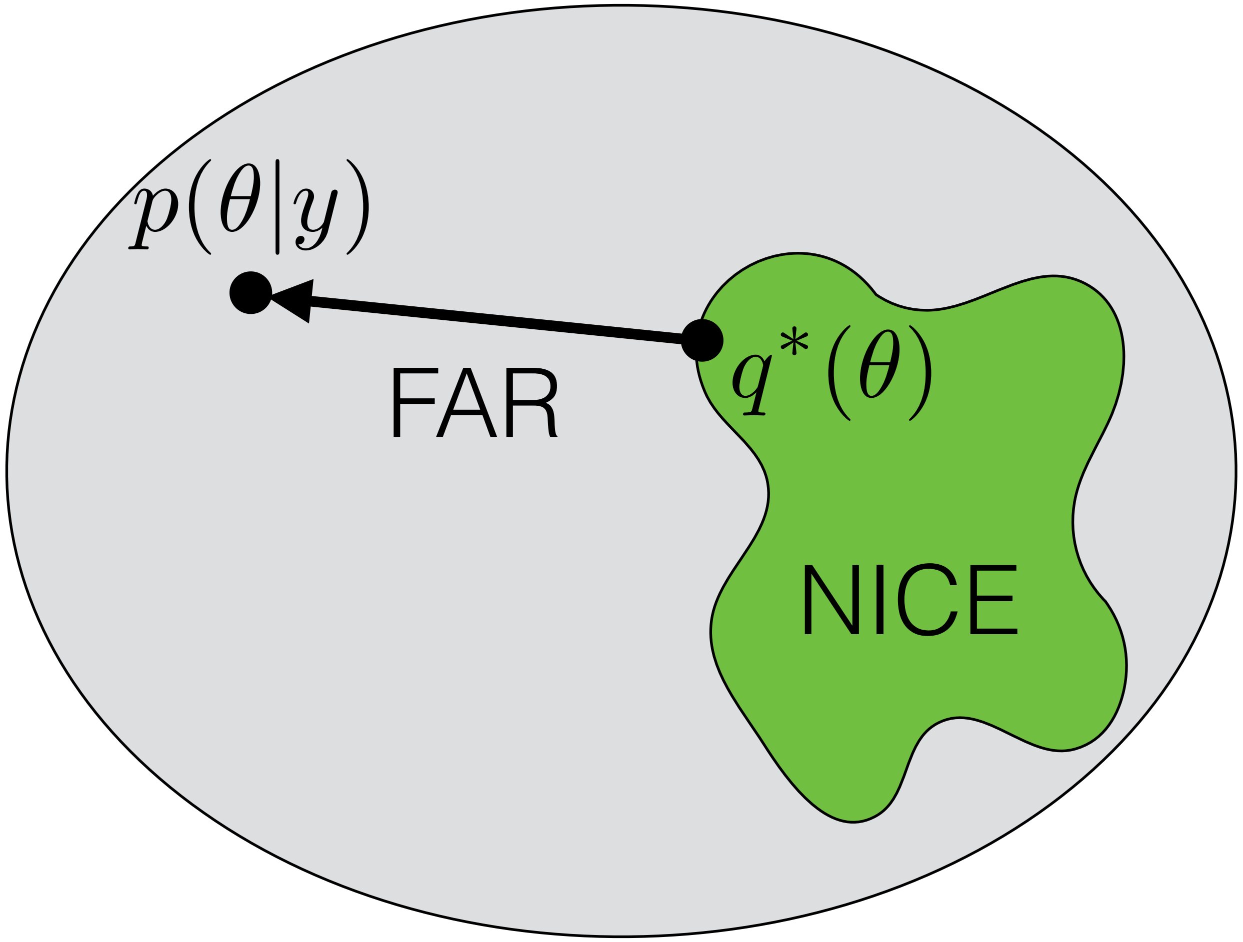

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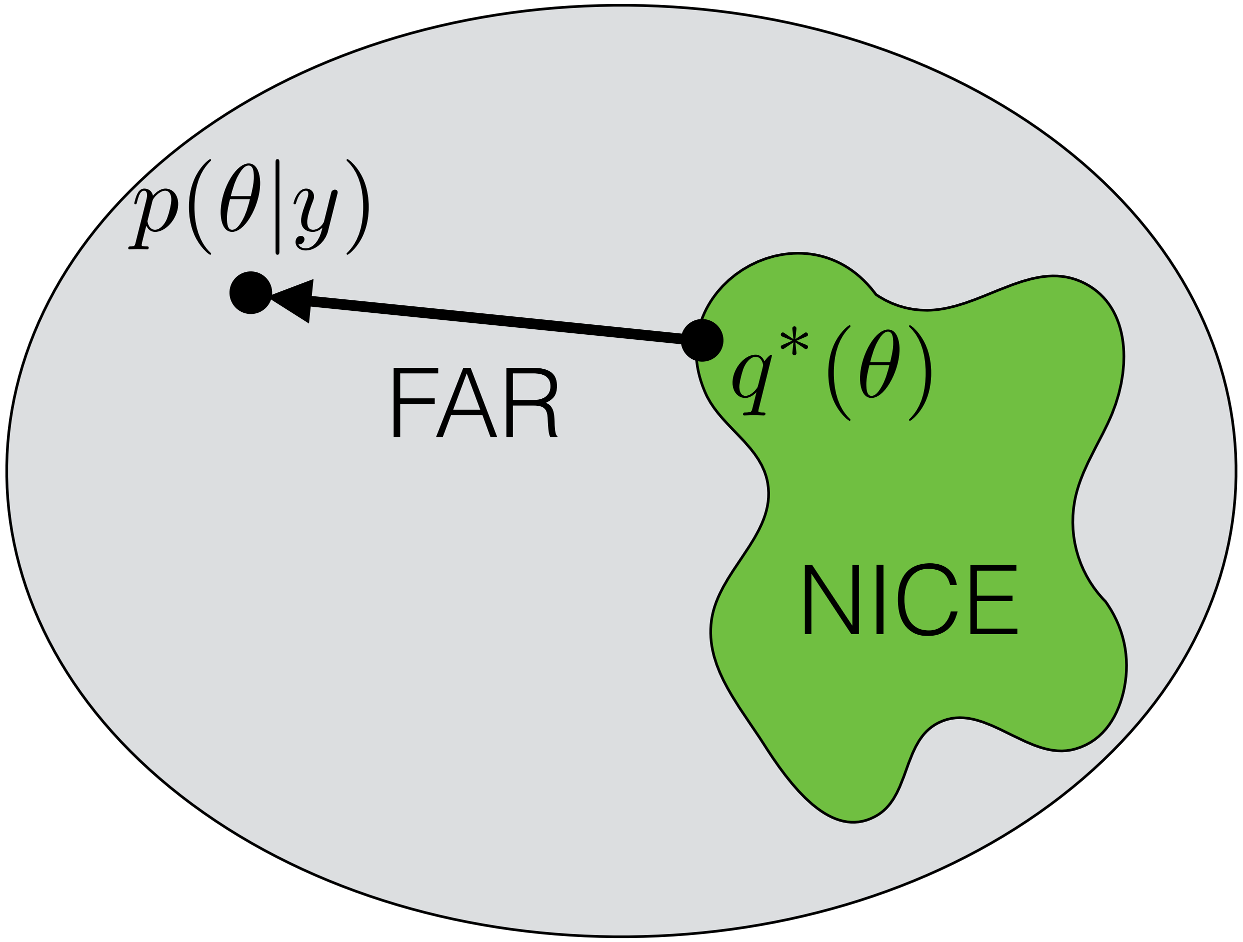

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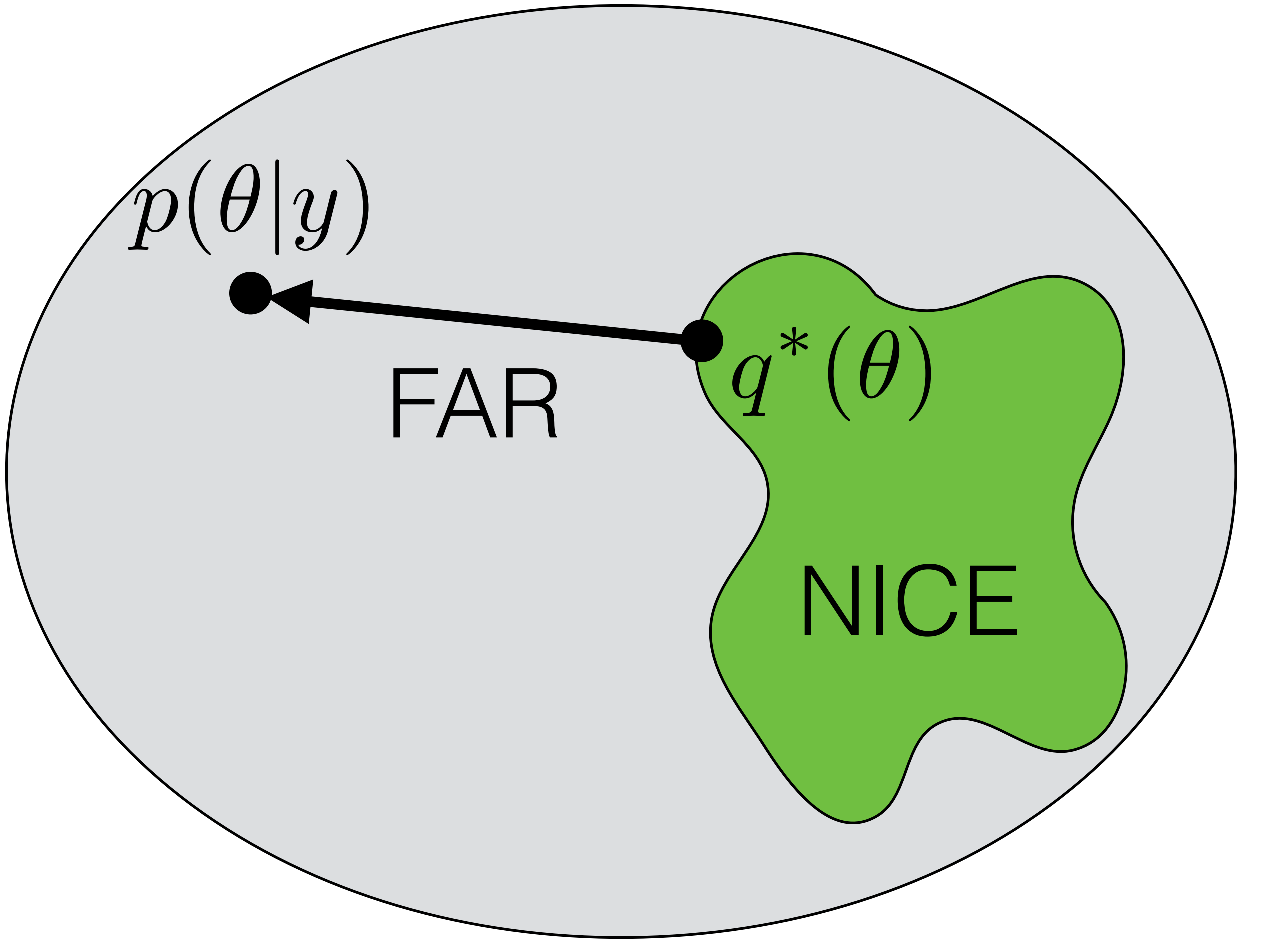

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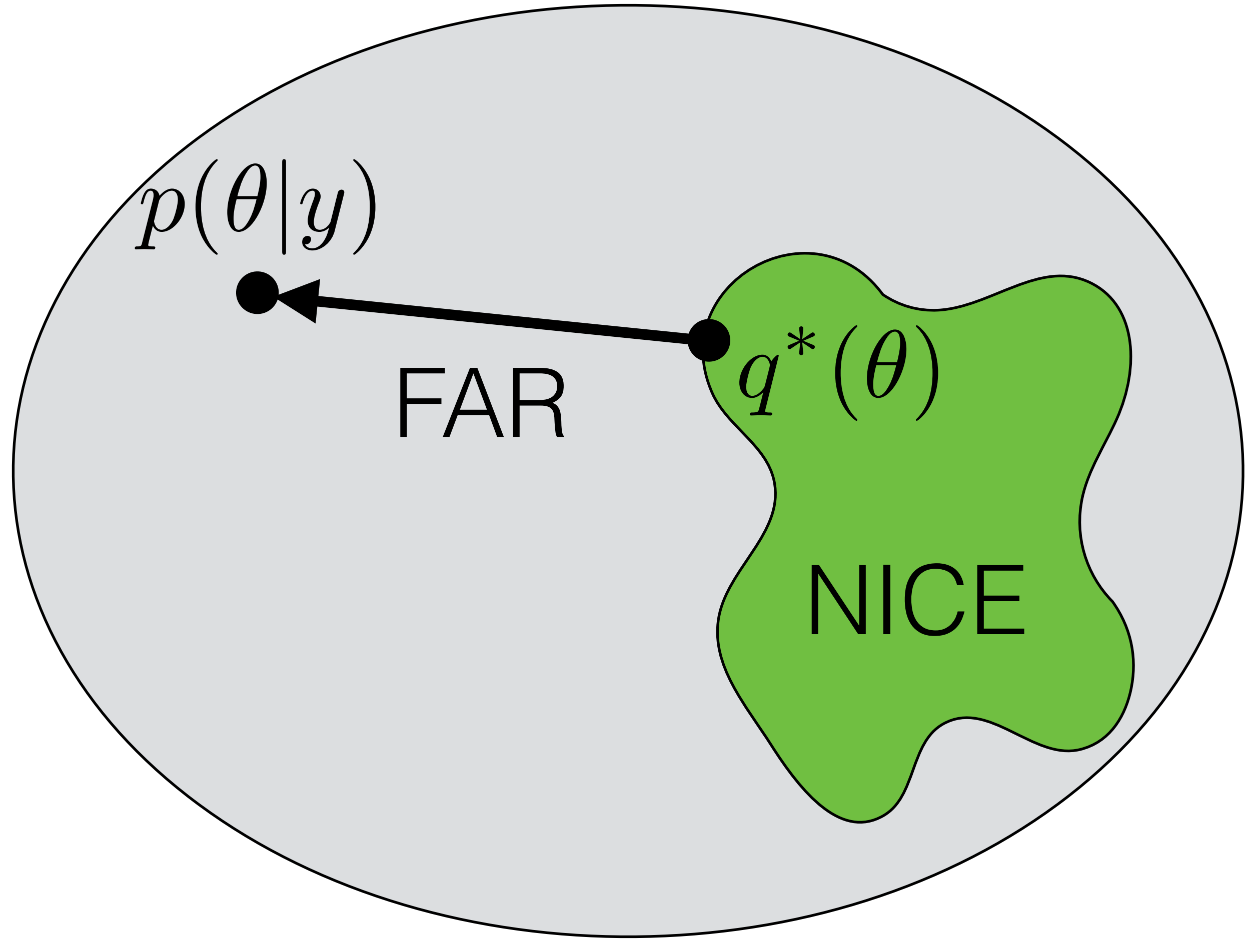

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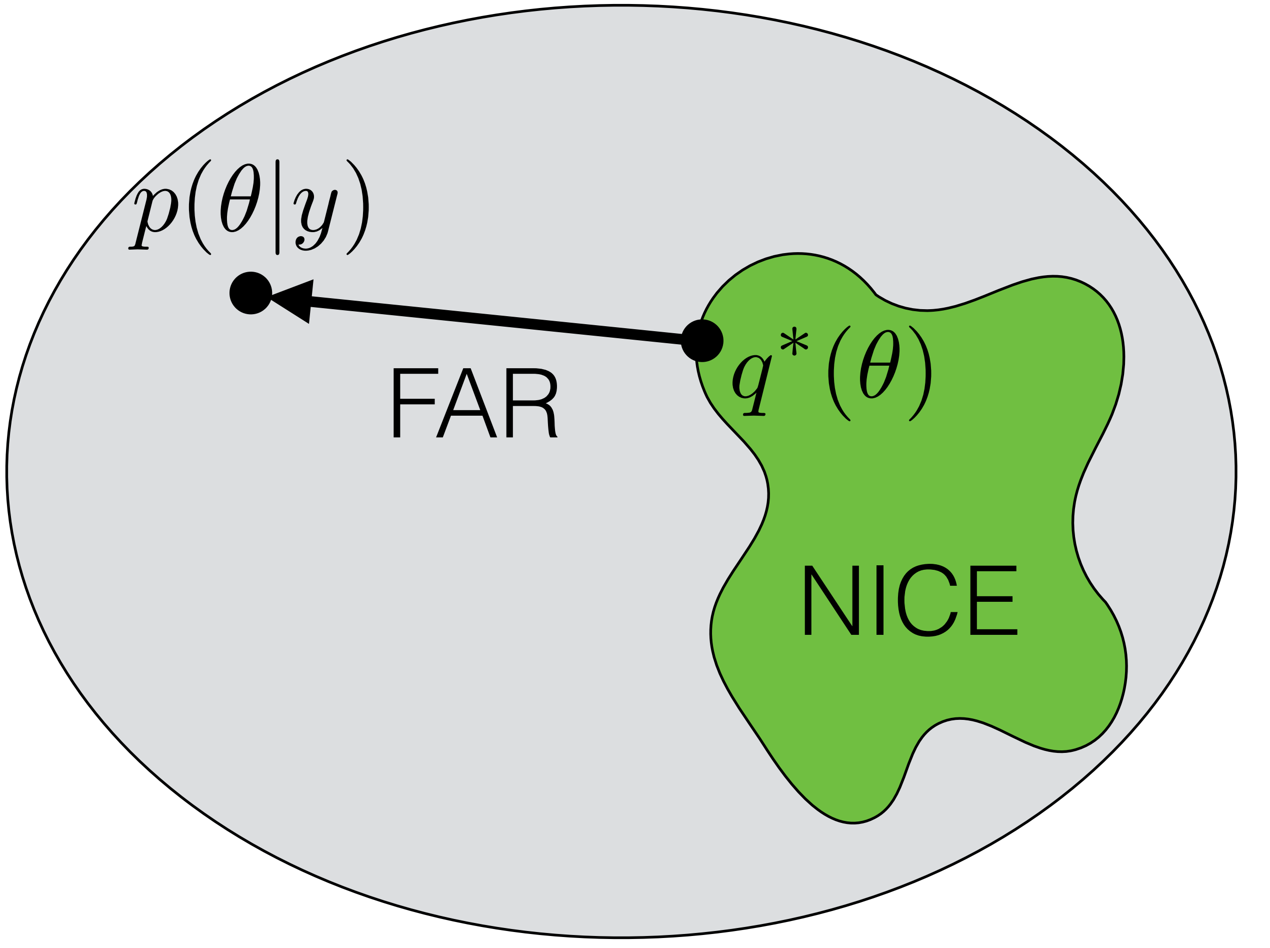

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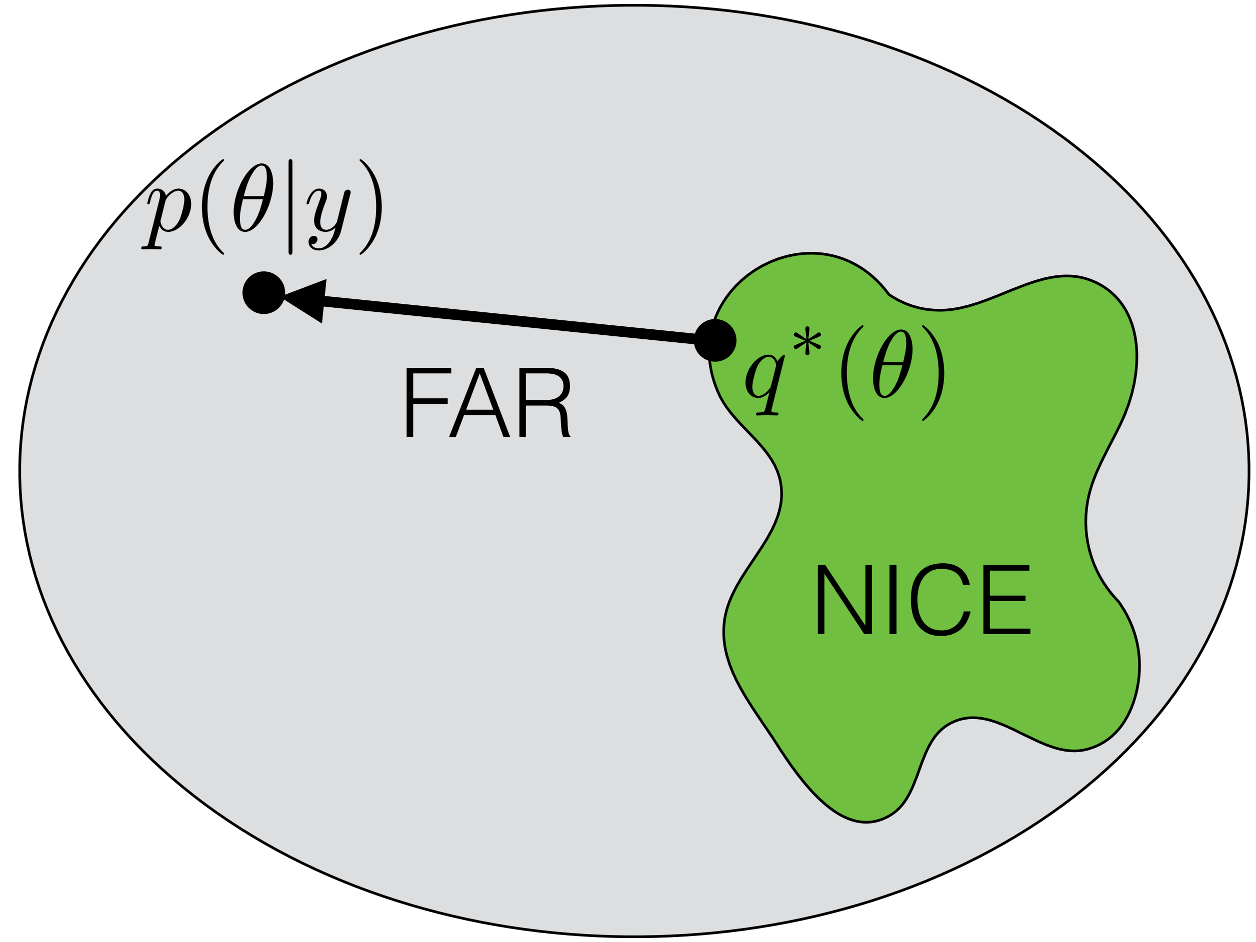

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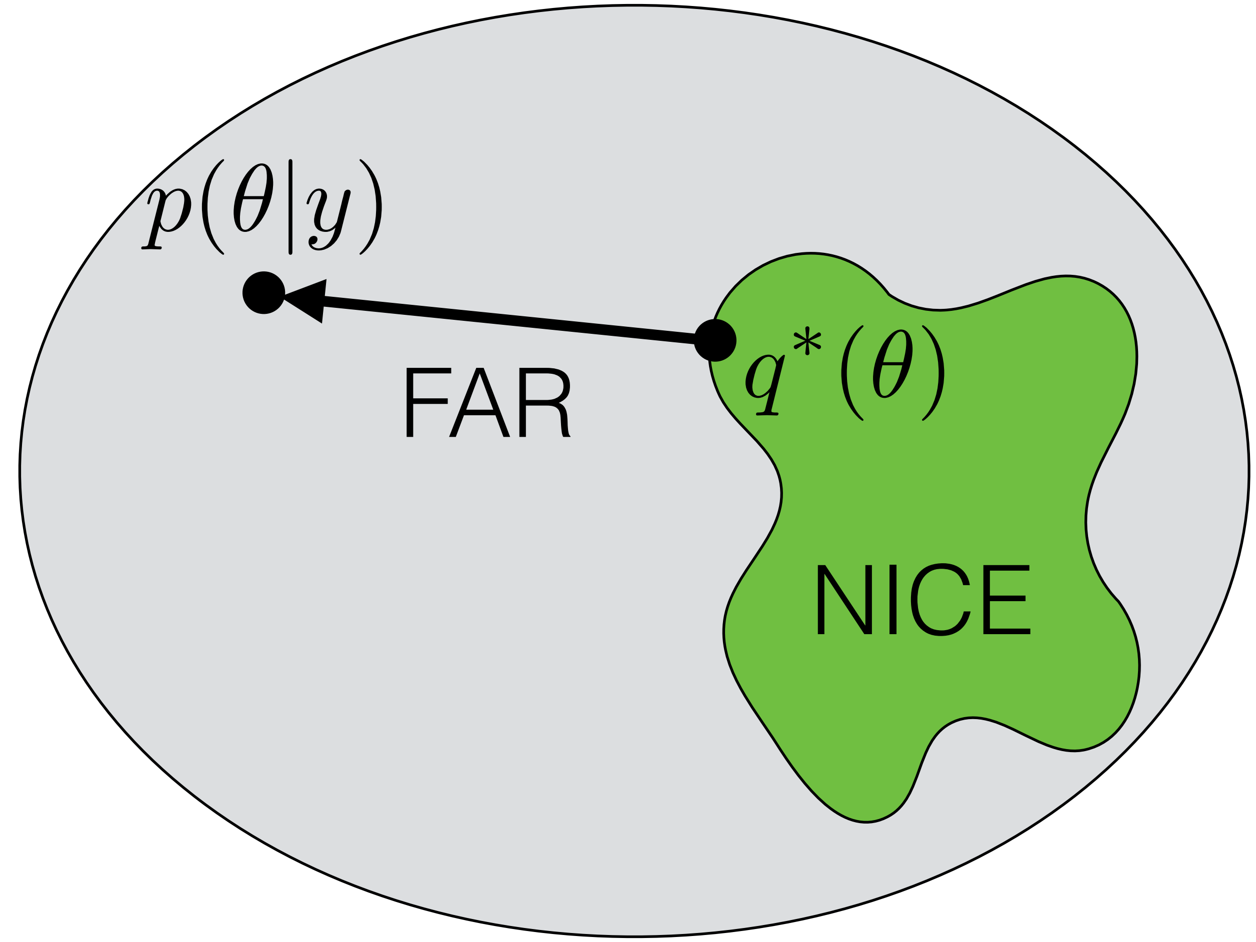

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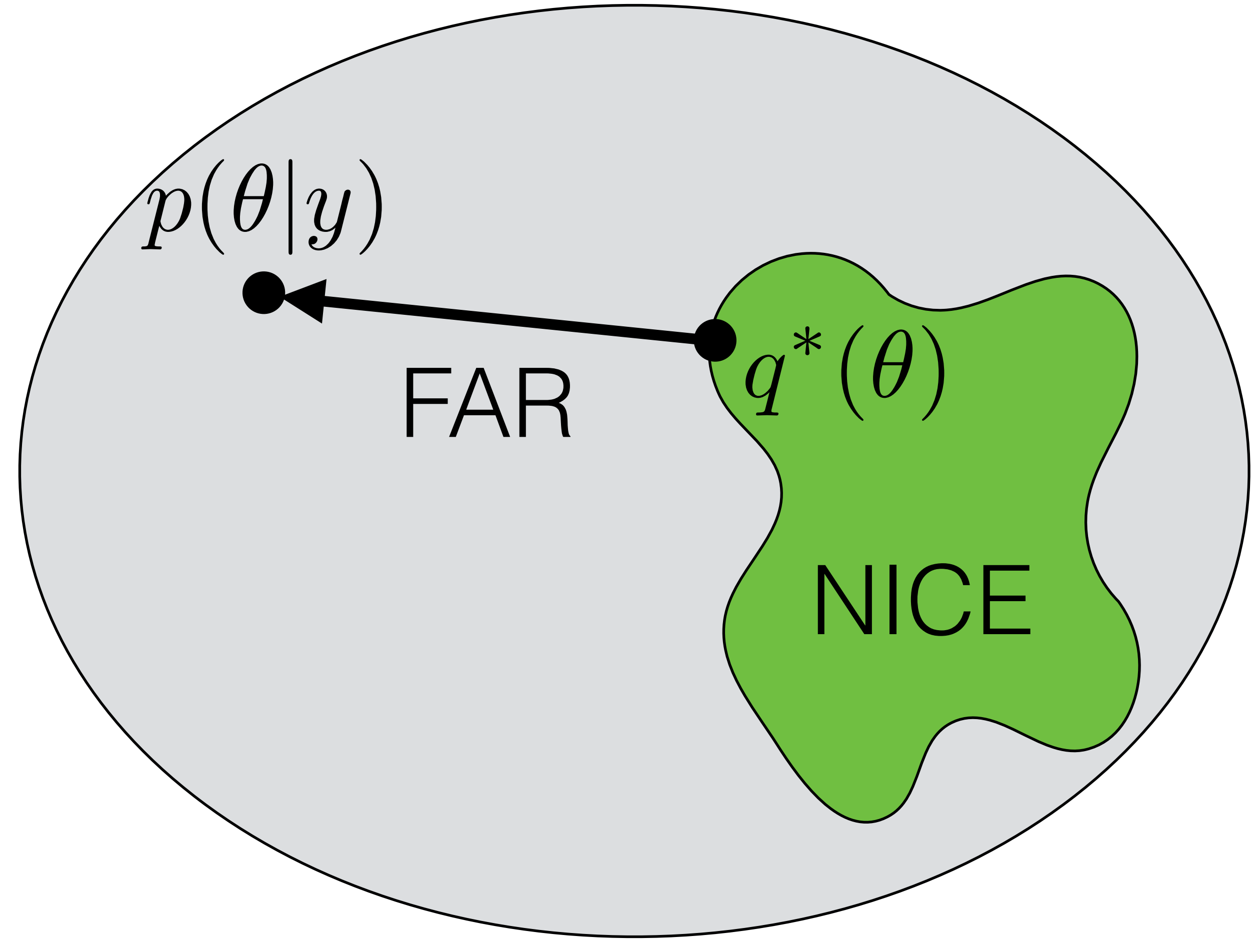

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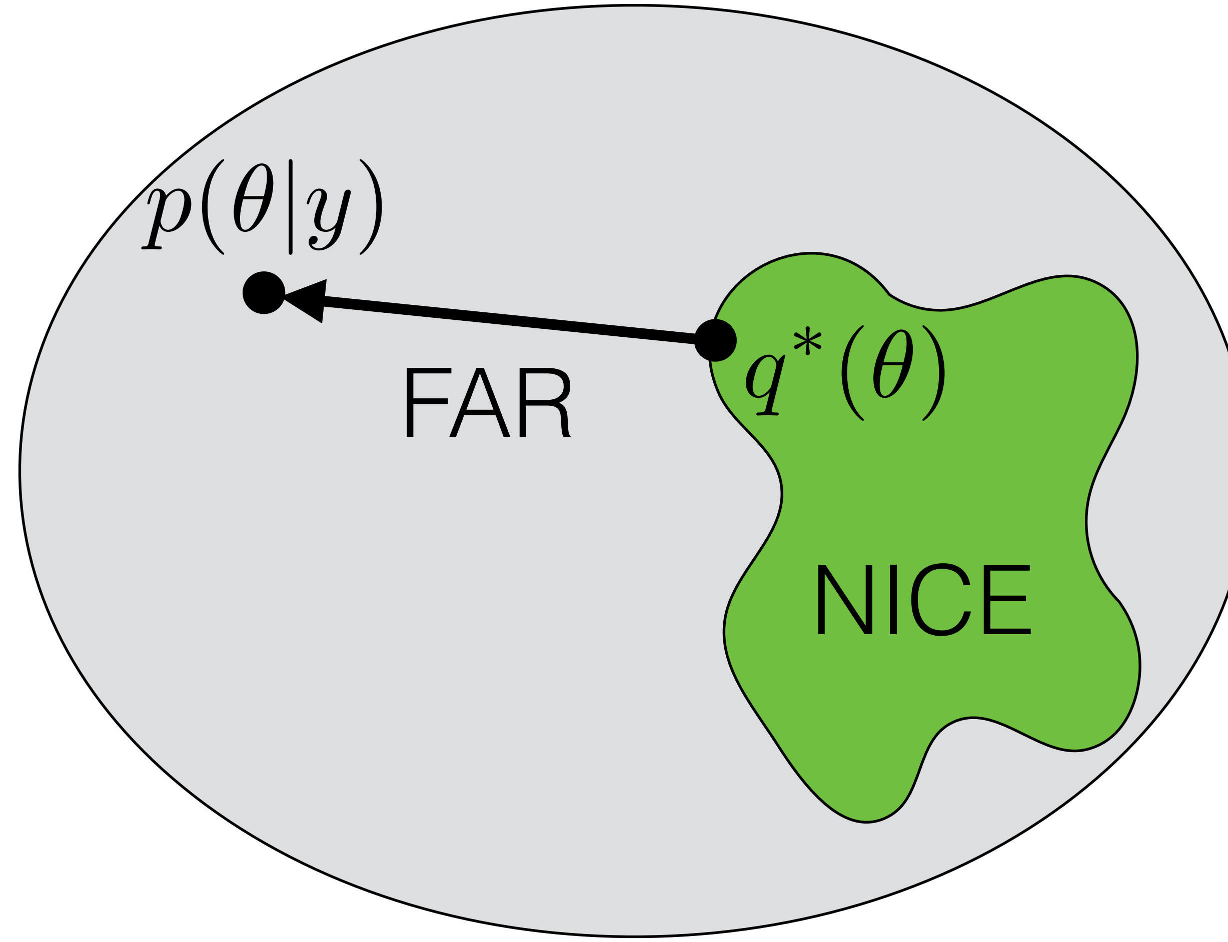

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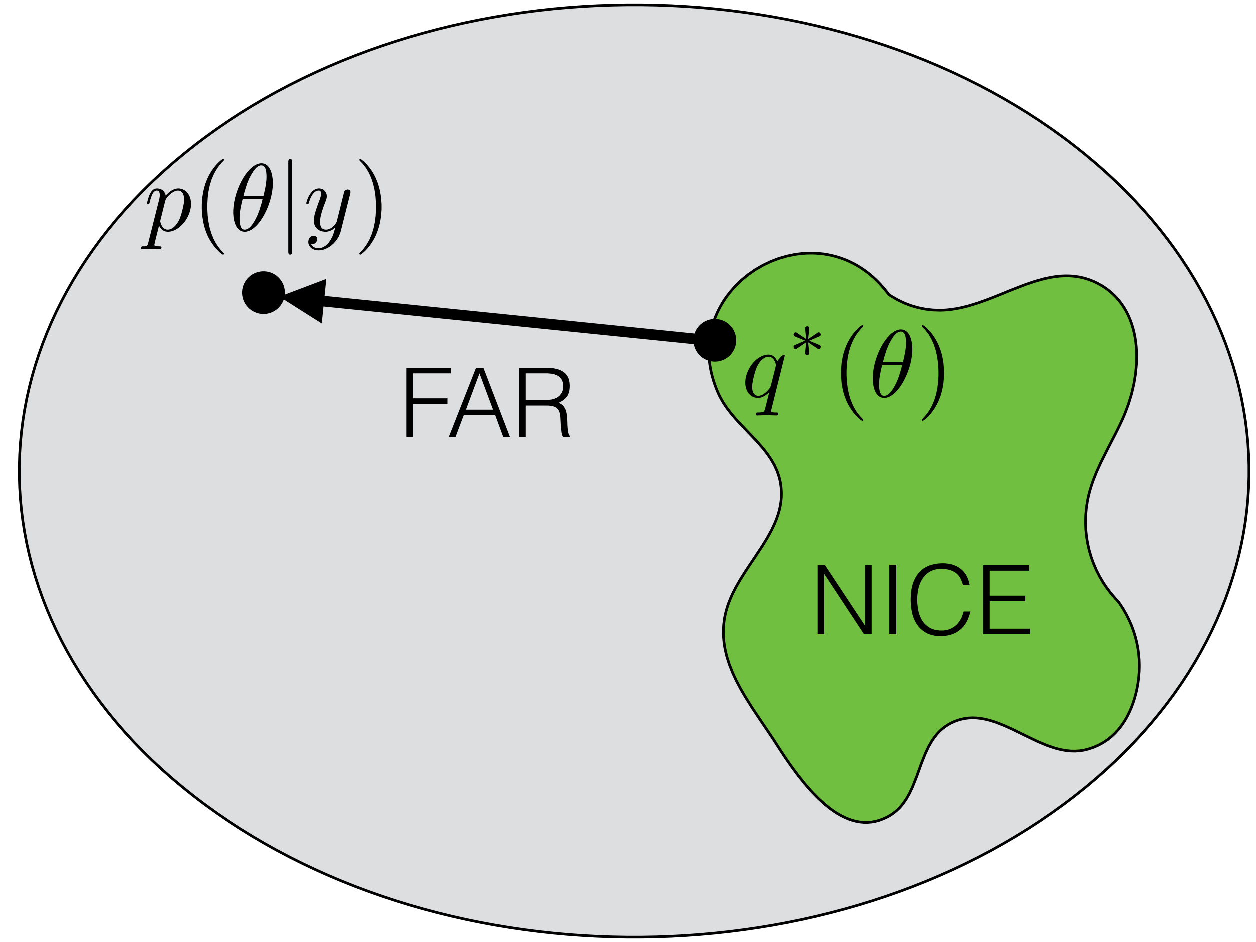

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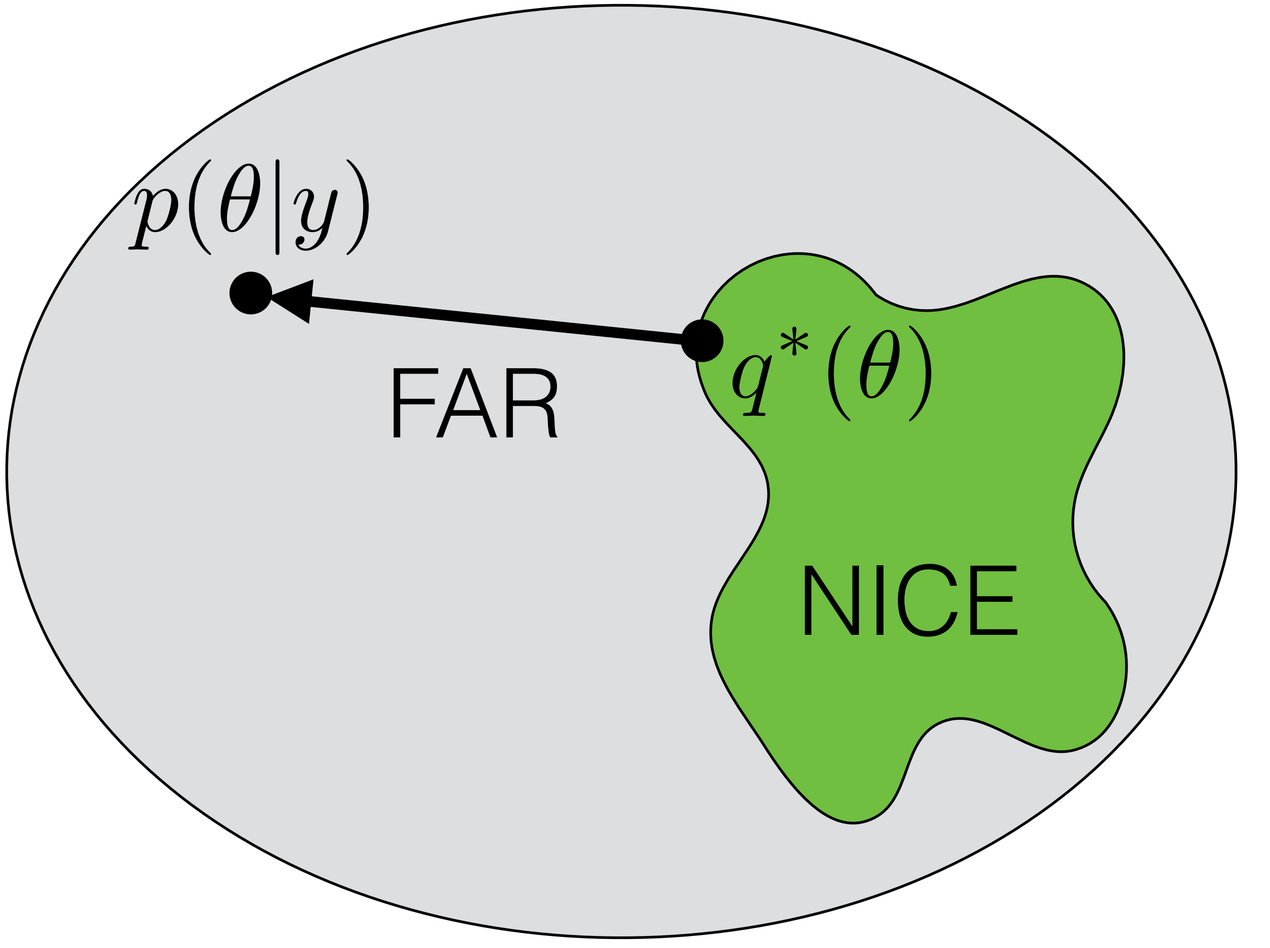

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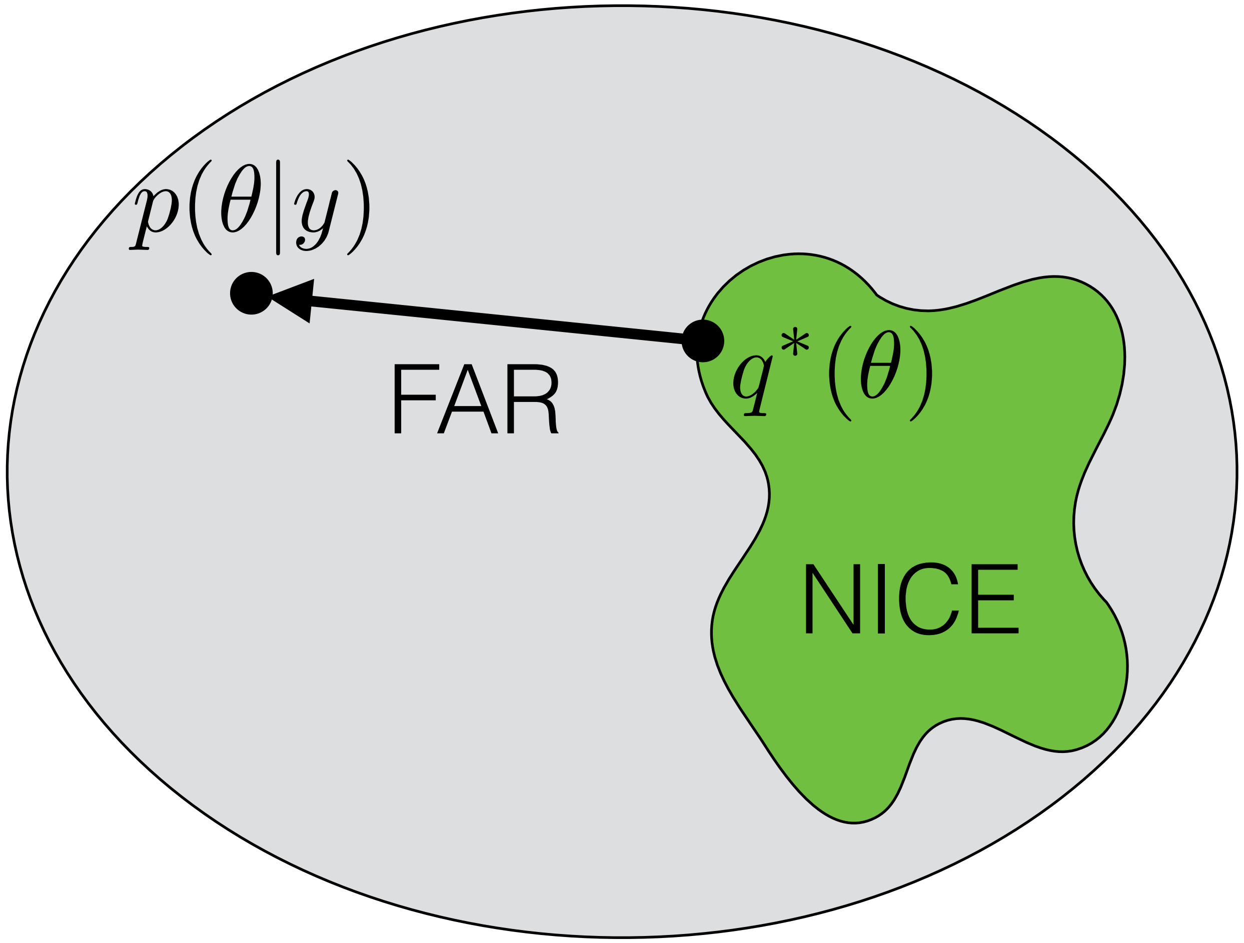

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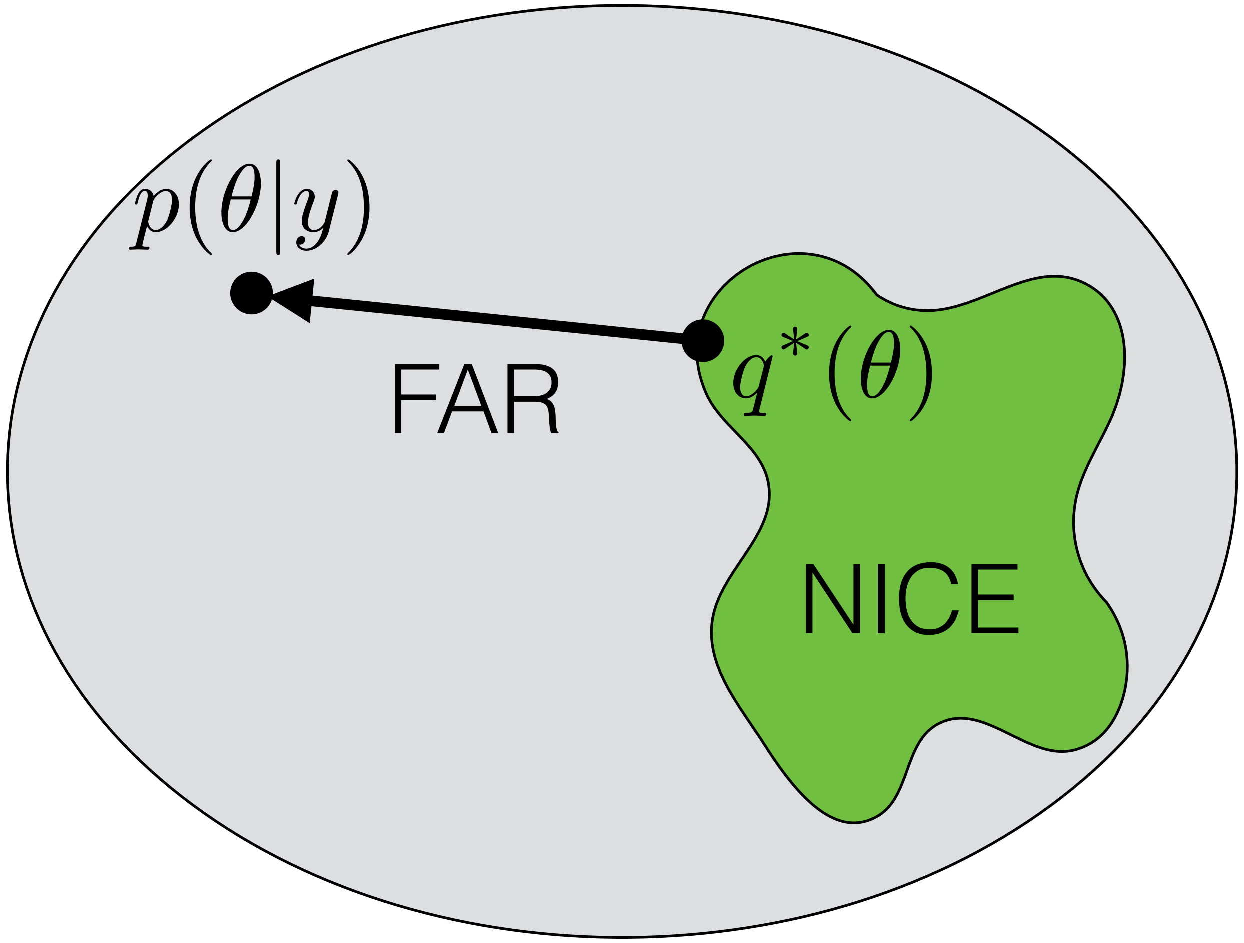

Choose "NICE" distributions

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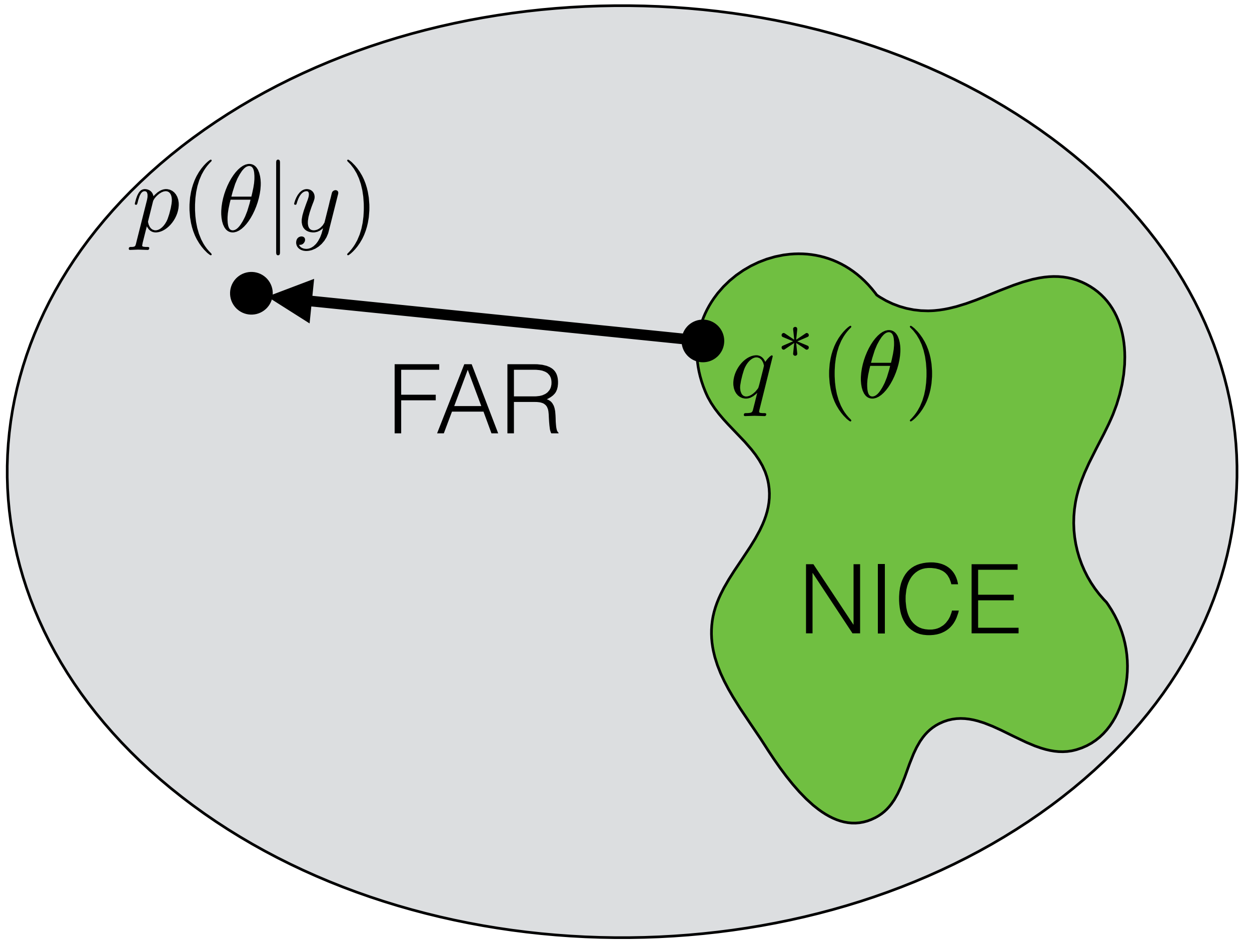

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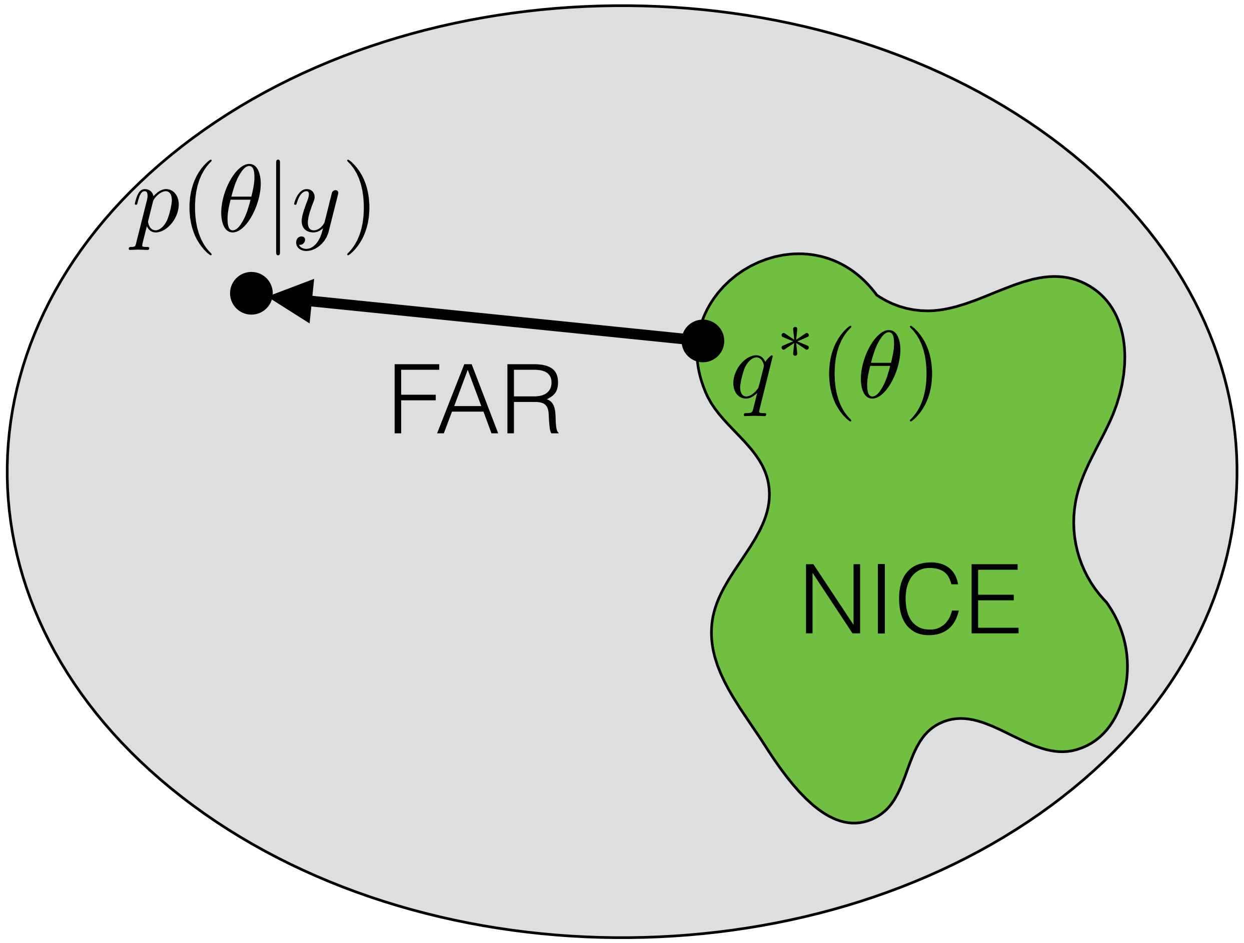

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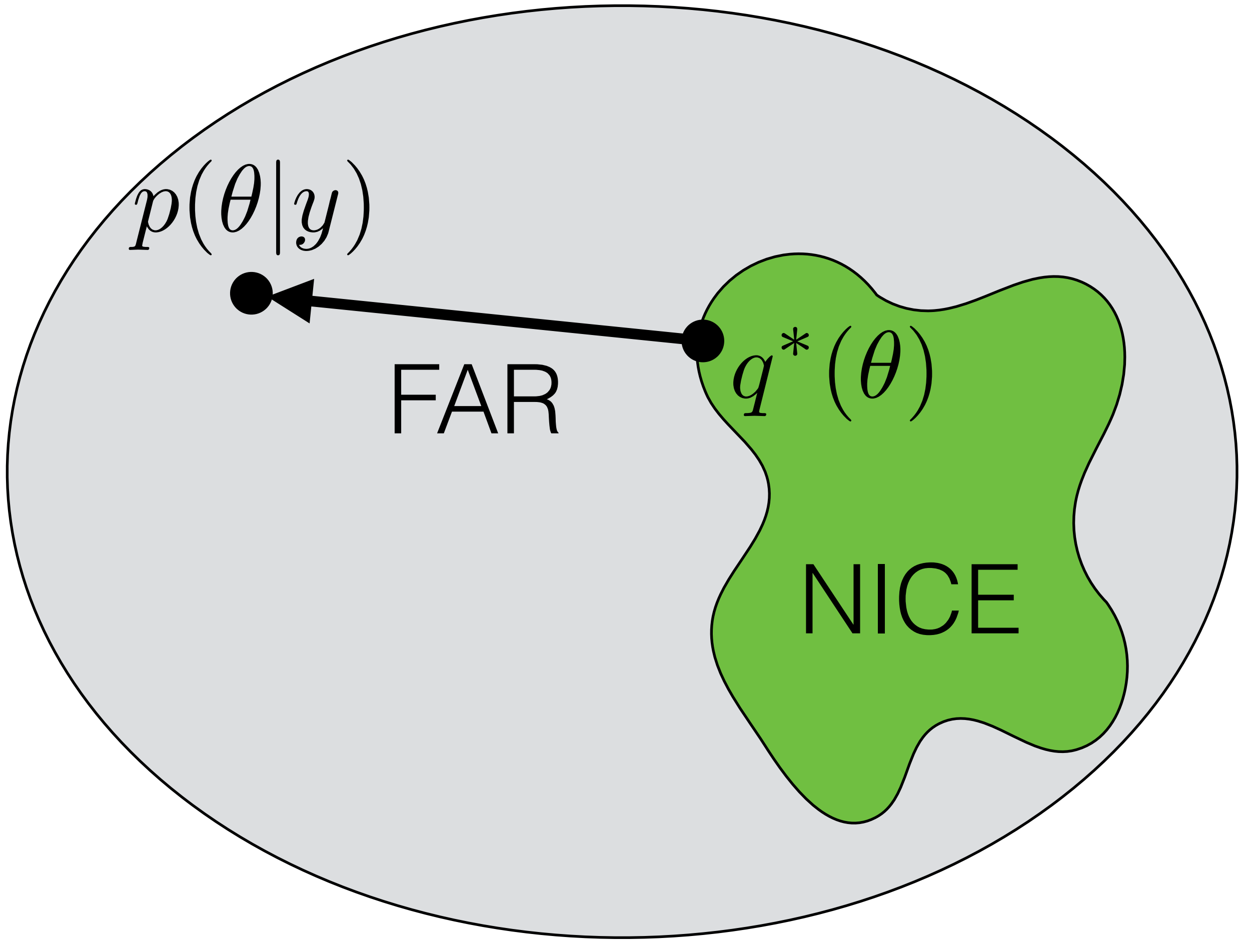

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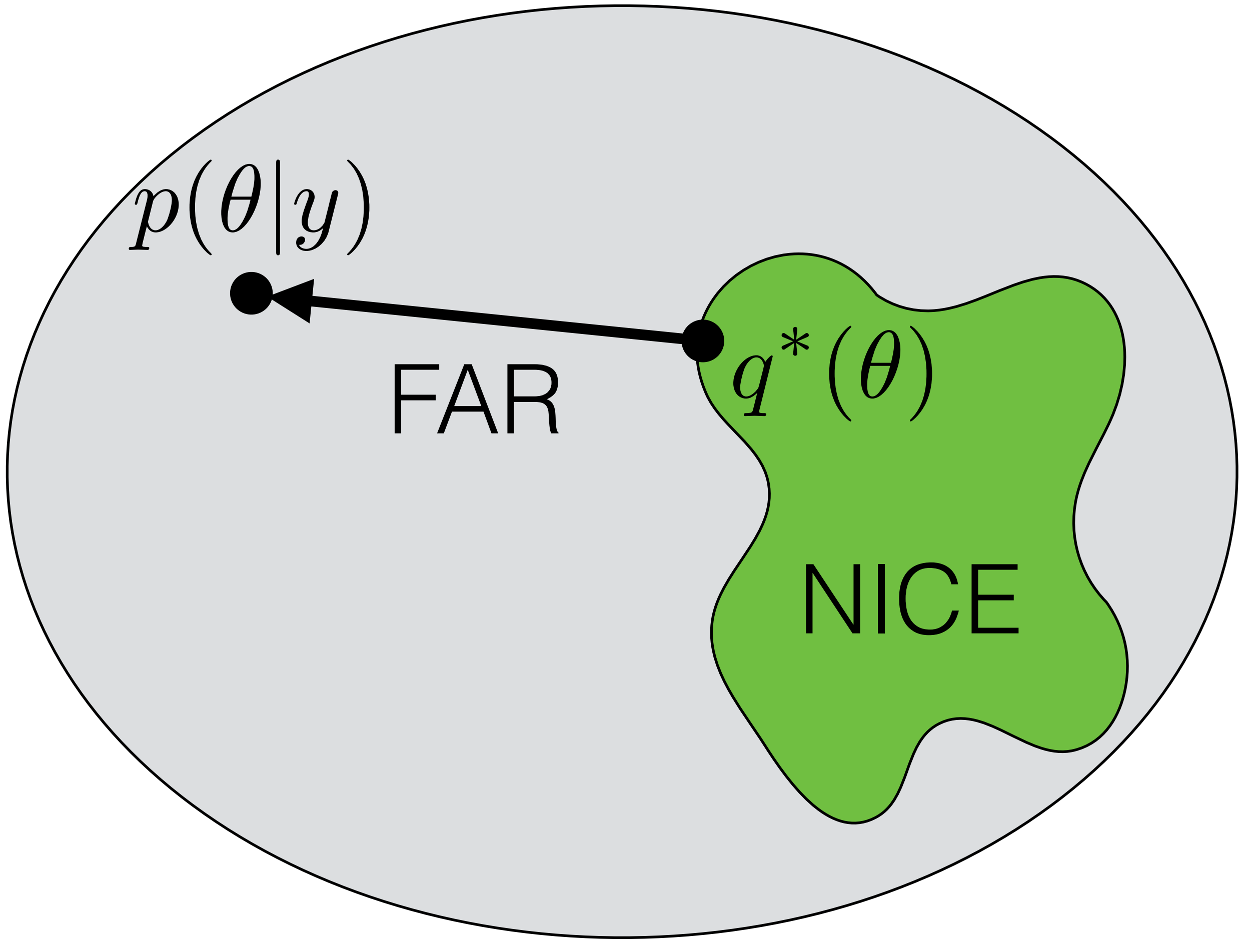

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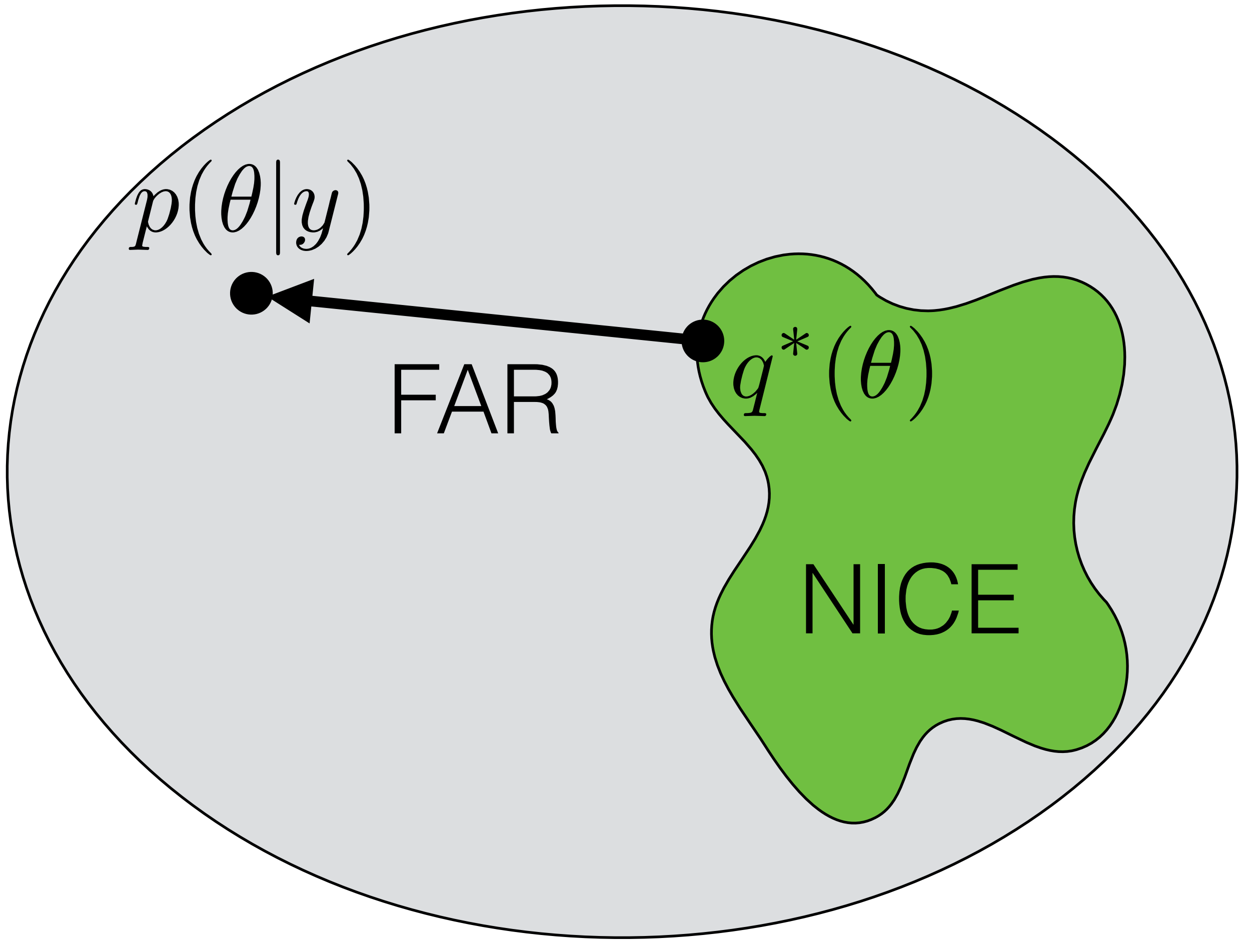

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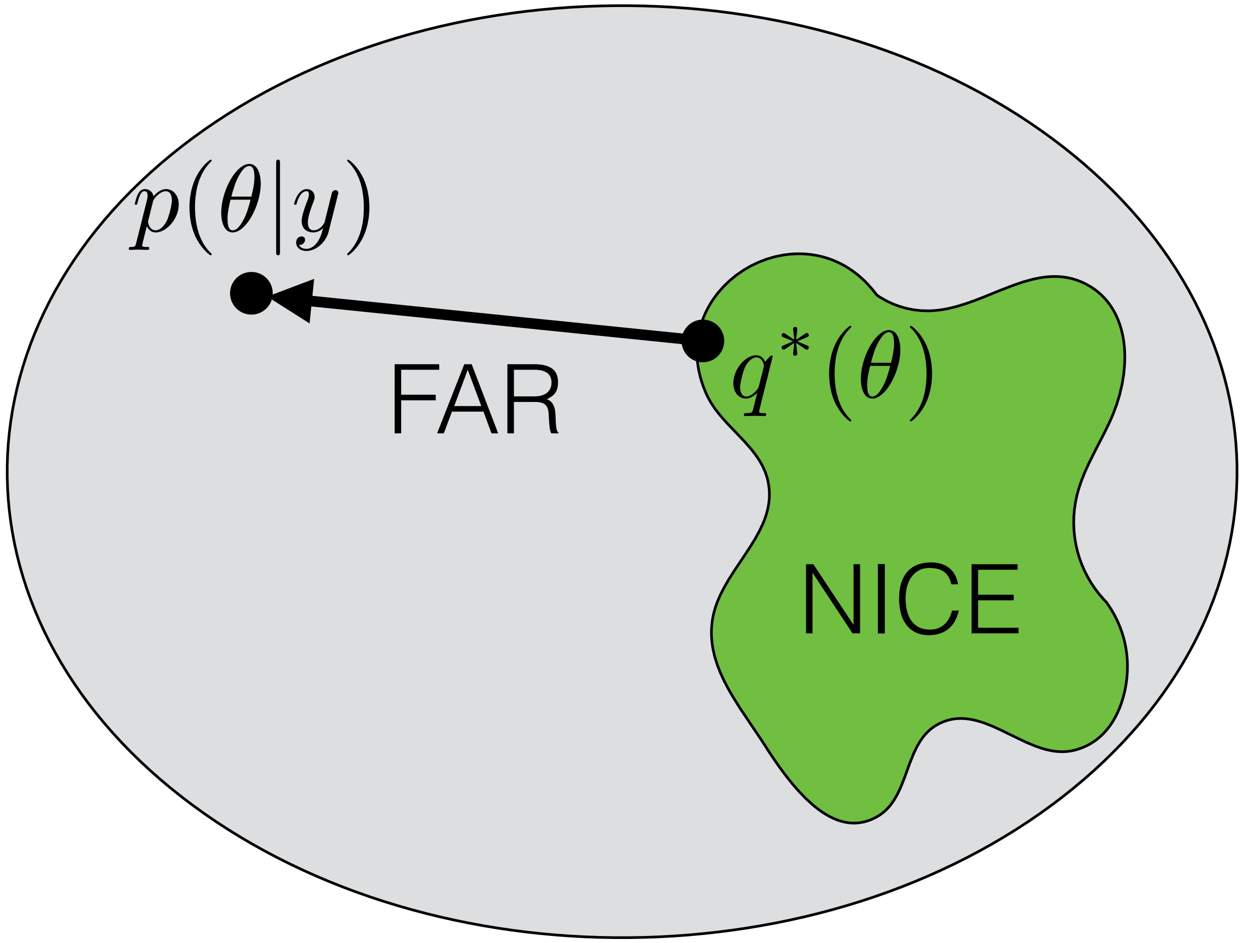

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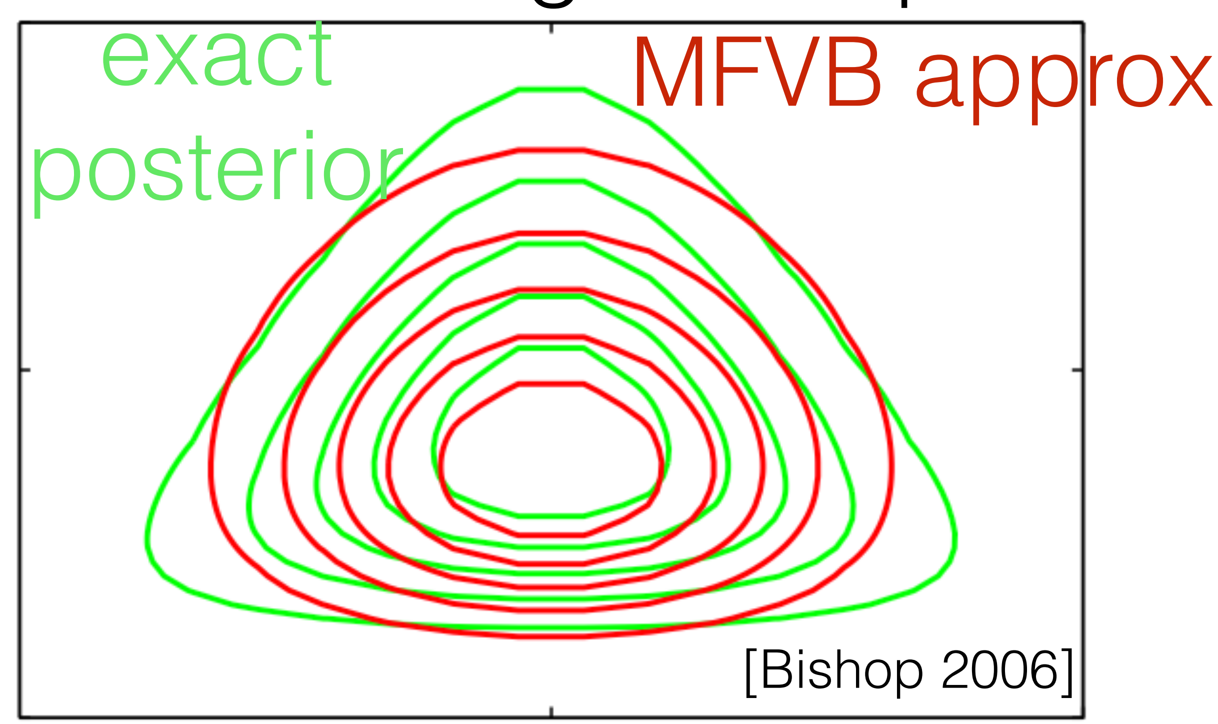

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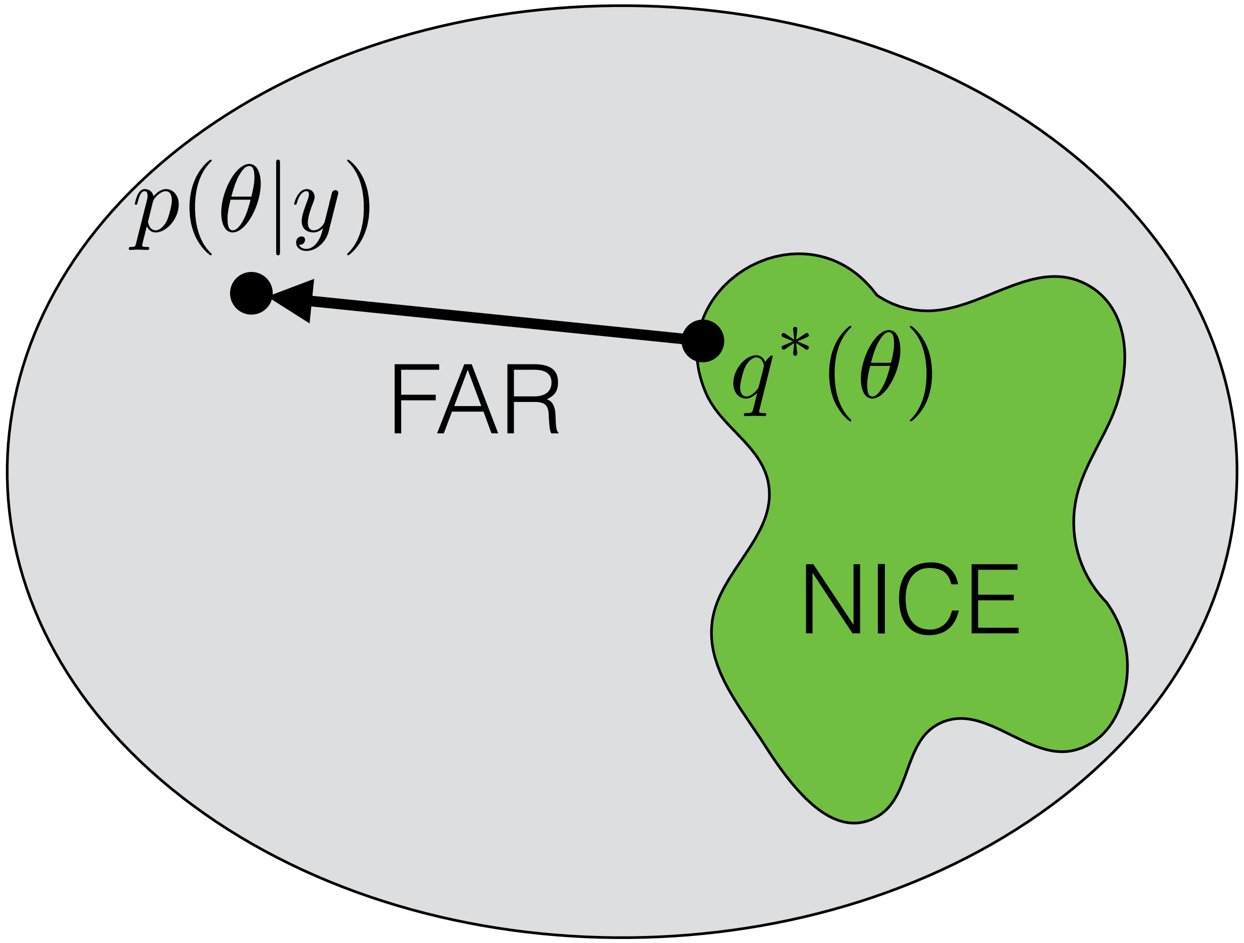

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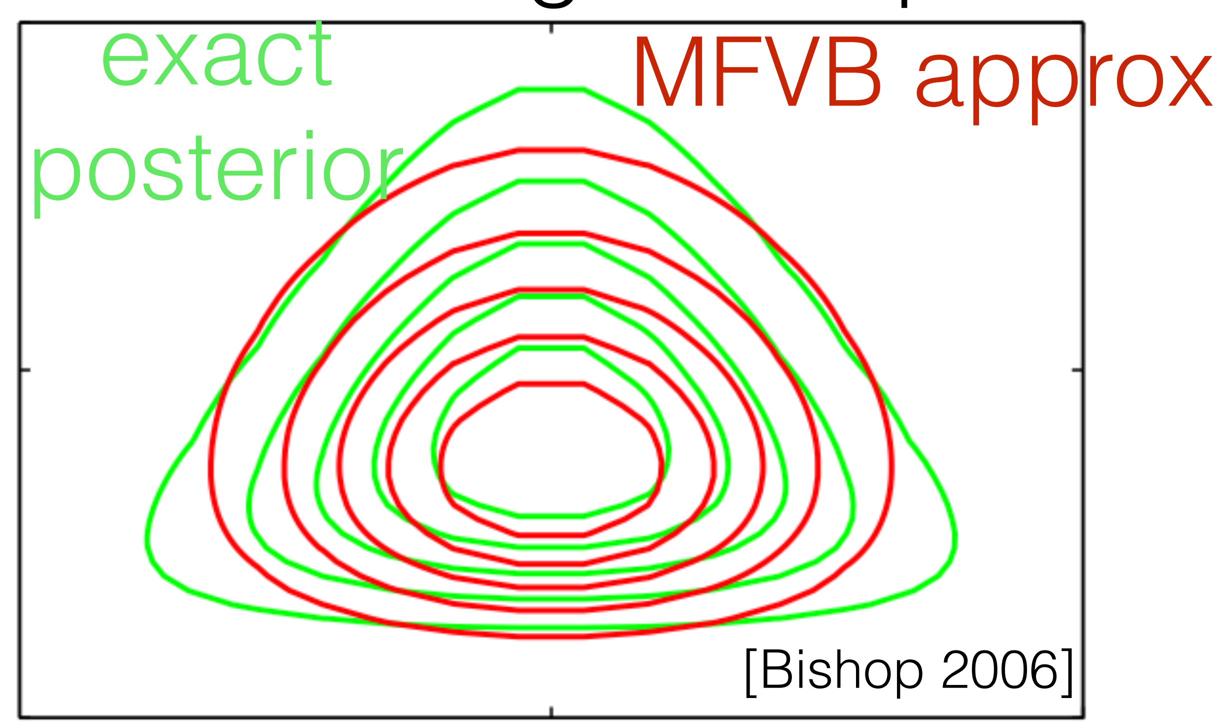

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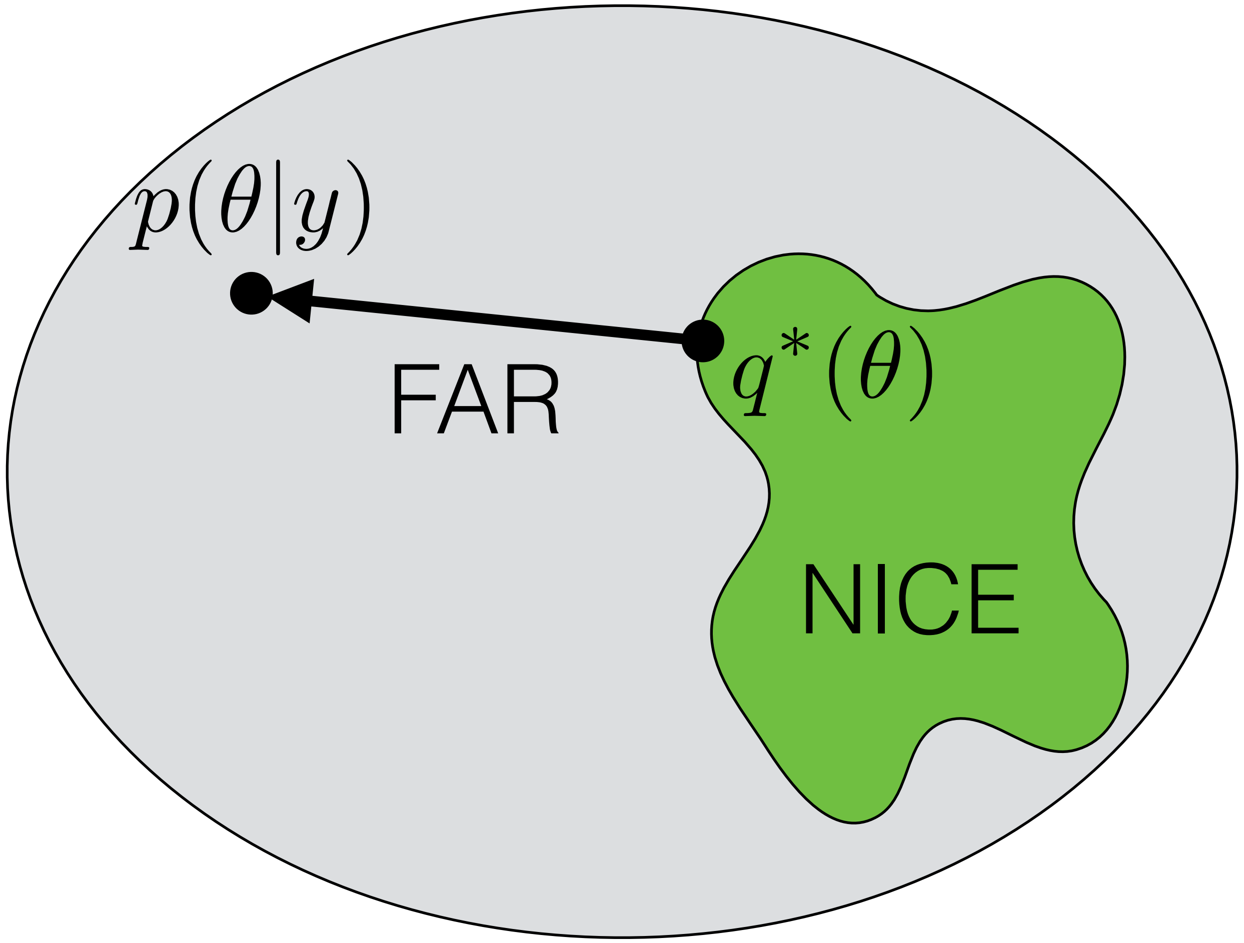

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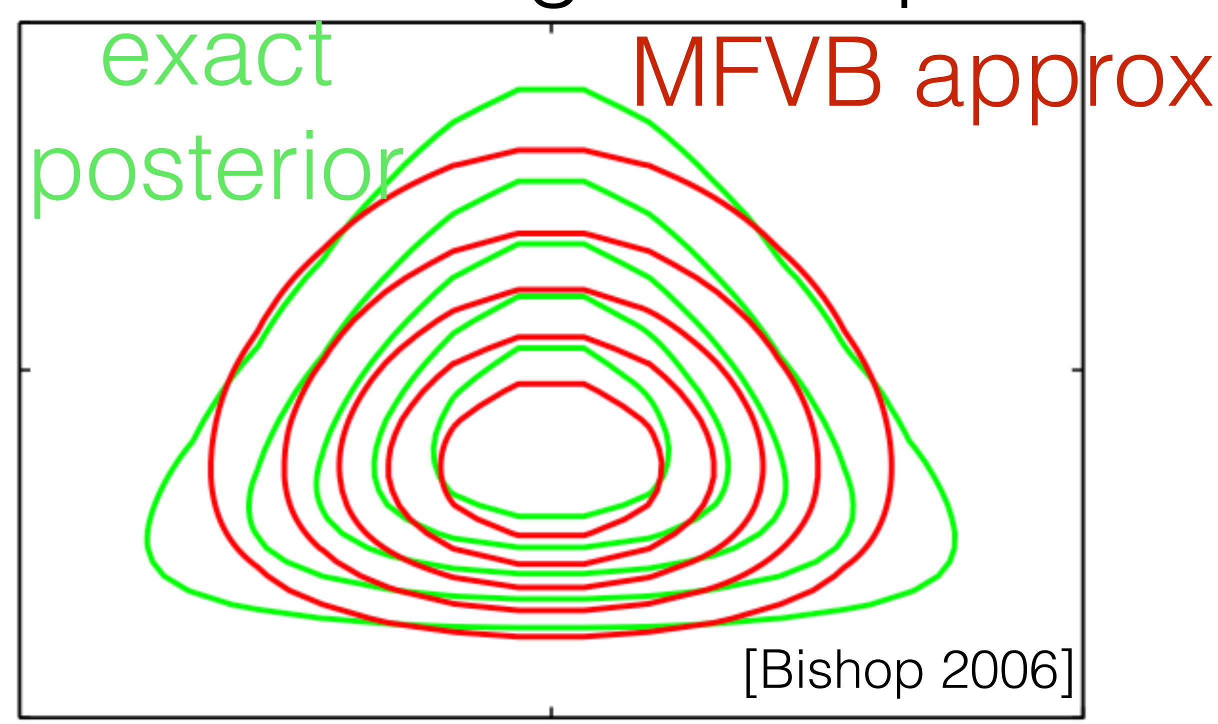
- One option: Coordinate descent in $q_1, \ldots, q_J$



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Use q^* to approximate $p(\cdot|y)$

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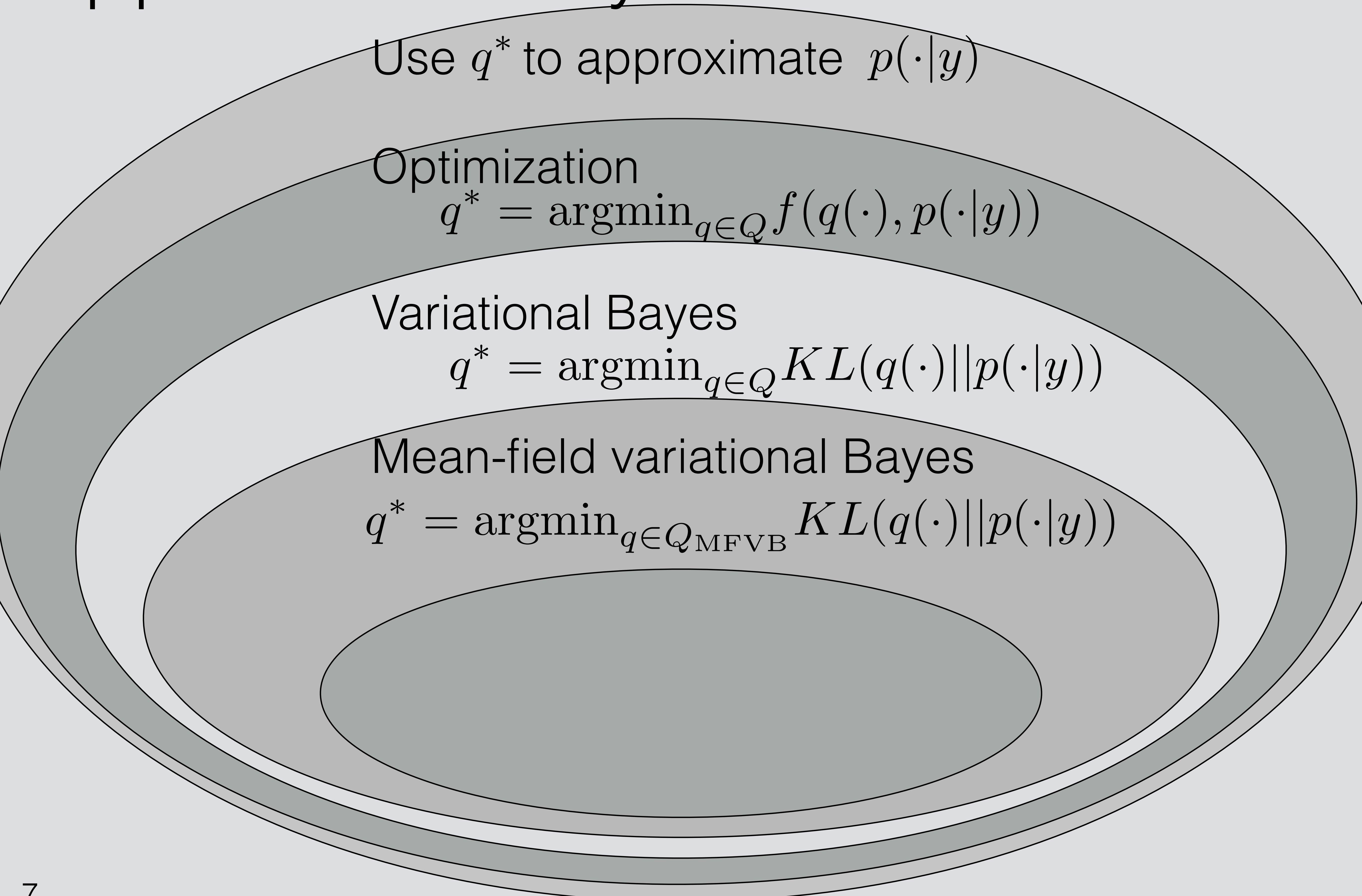

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Roadmap

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- What is:
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- Why use VB?
- When can we trust VB?
- Where do we go from here?

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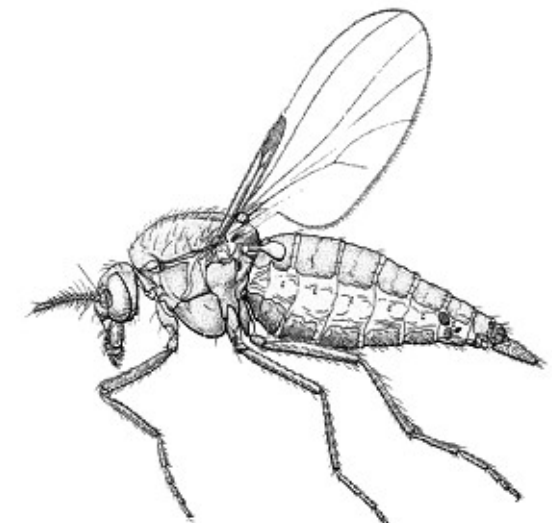
Midge wing length

- Catalogued midge wing lengths (mm) $y = (y_1, \ldots, y_N)$



[CSIRO 2004]

[Hoff 2009; Grogan, Wirth 1981; MacKay 2003; Bishop 2006]

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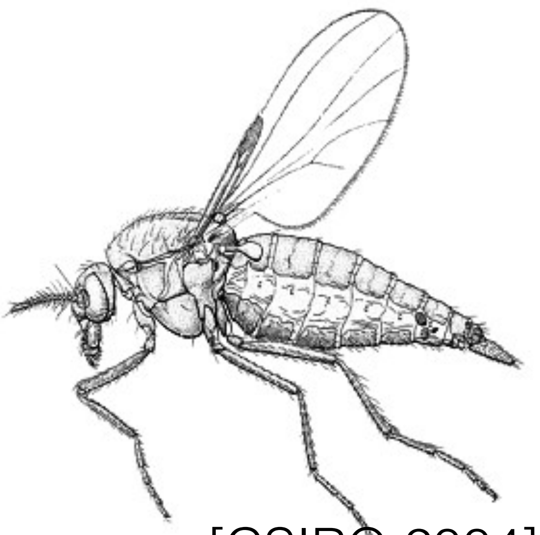

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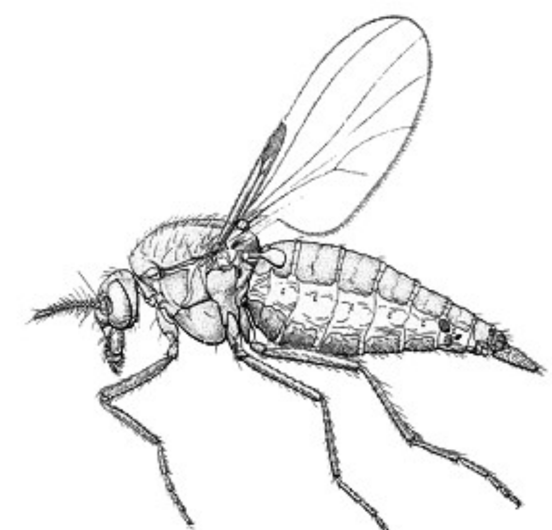

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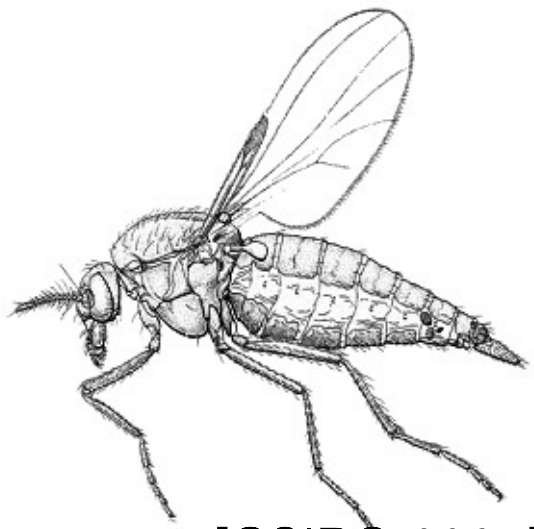

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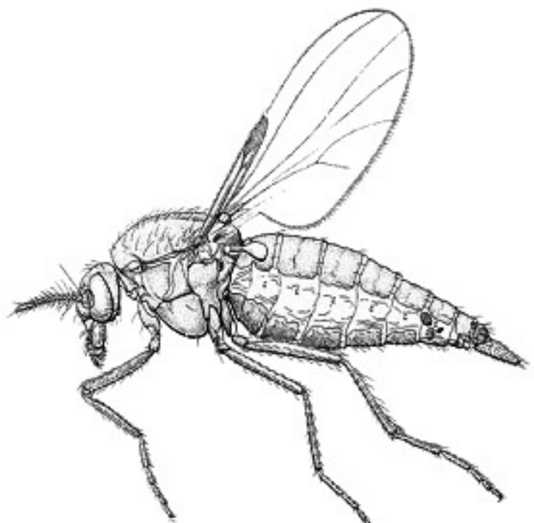

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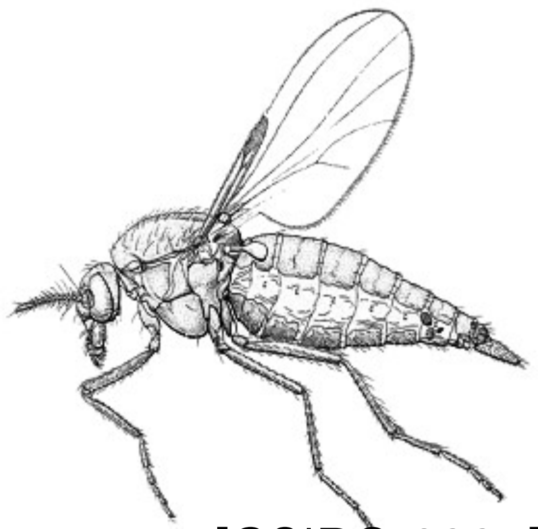

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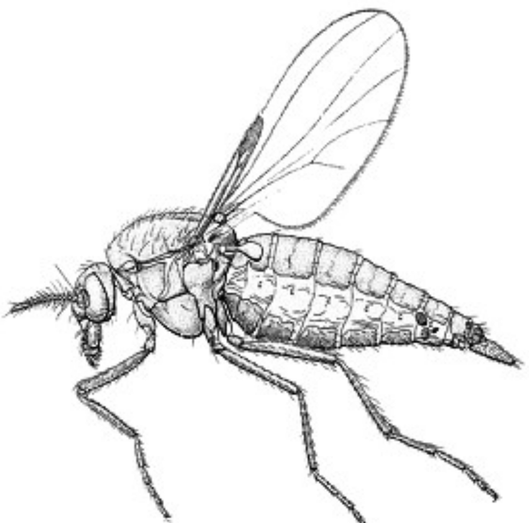

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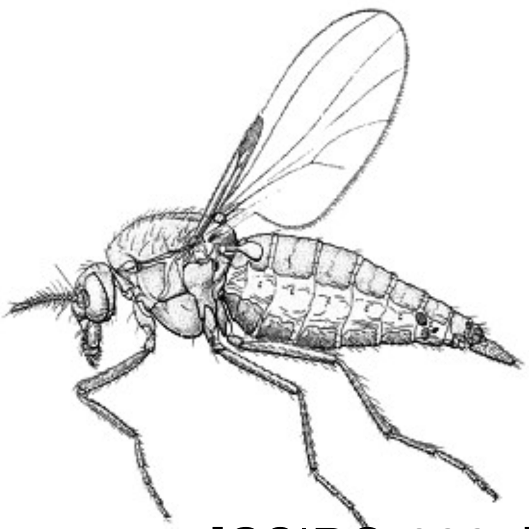

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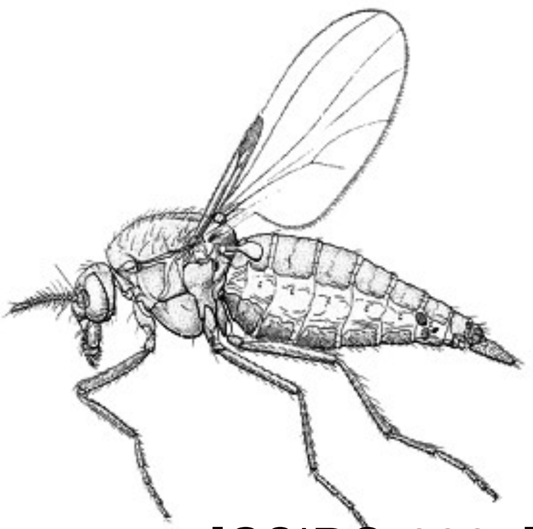

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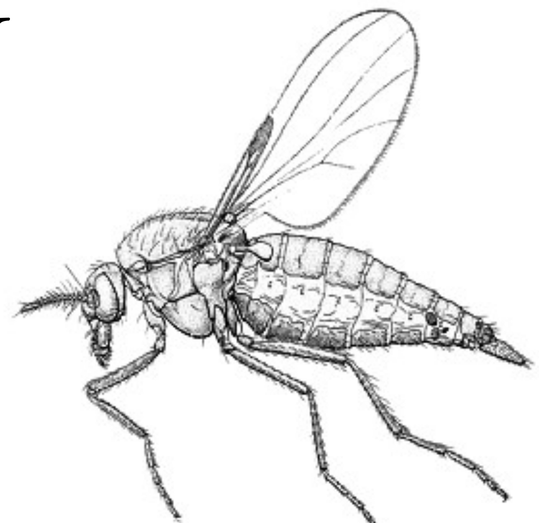

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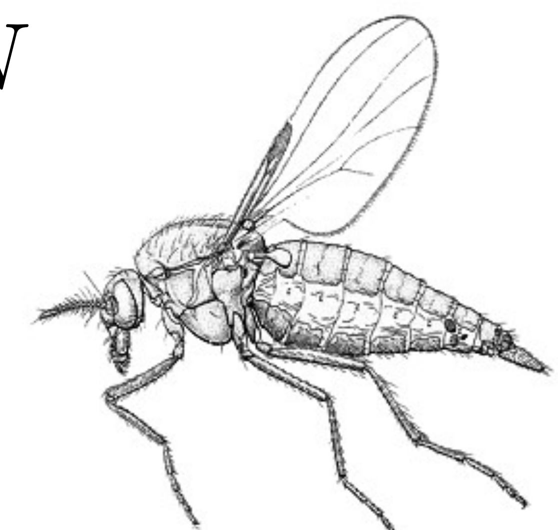

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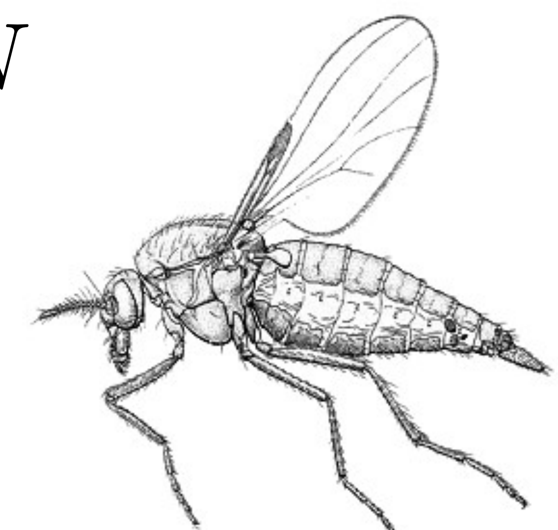

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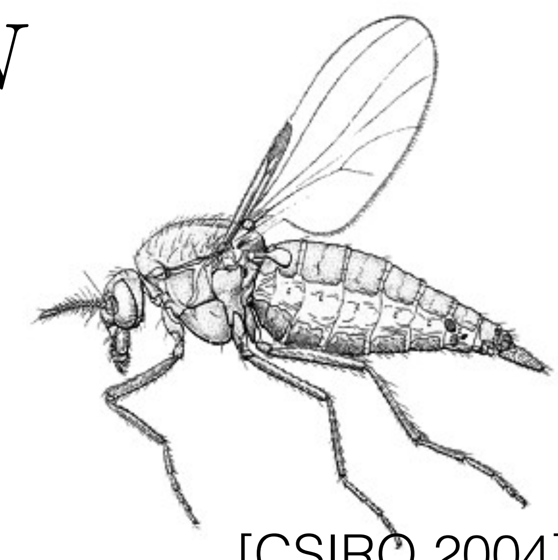

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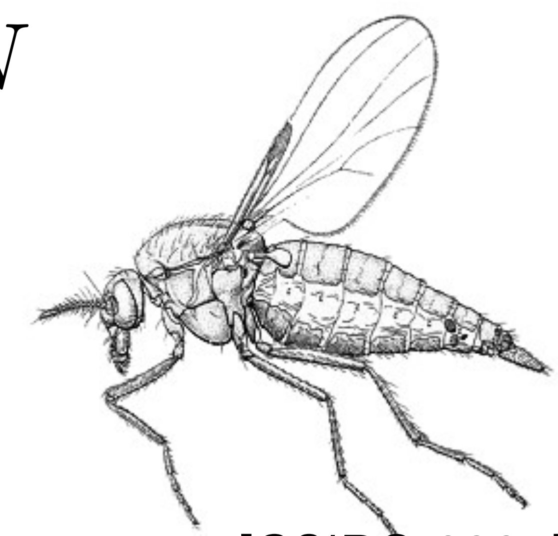

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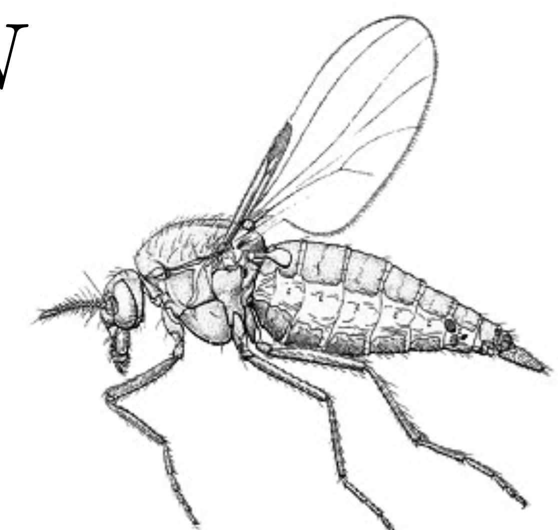

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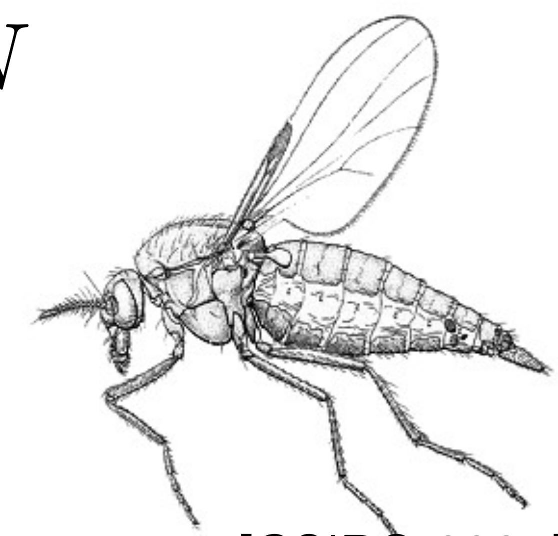

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"variational parameters"

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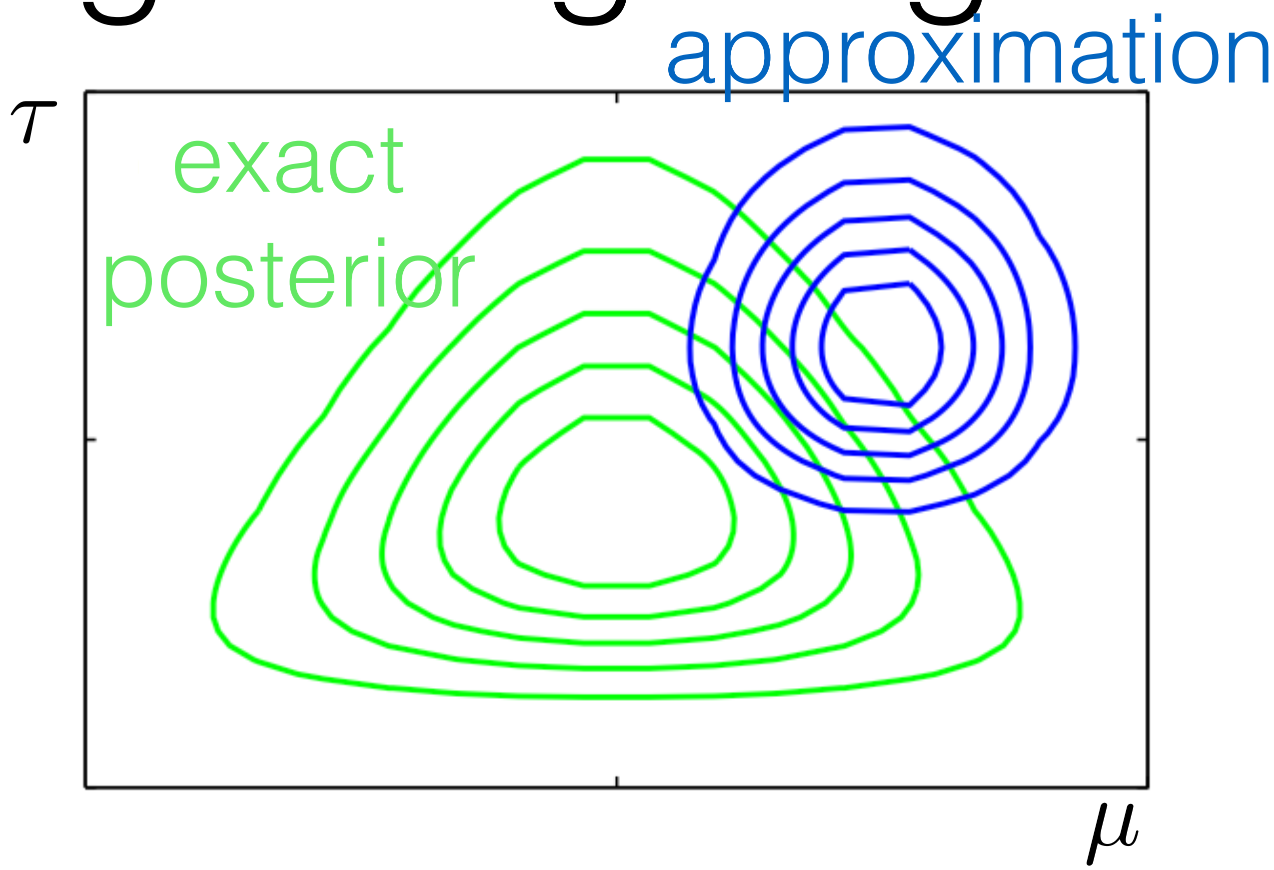

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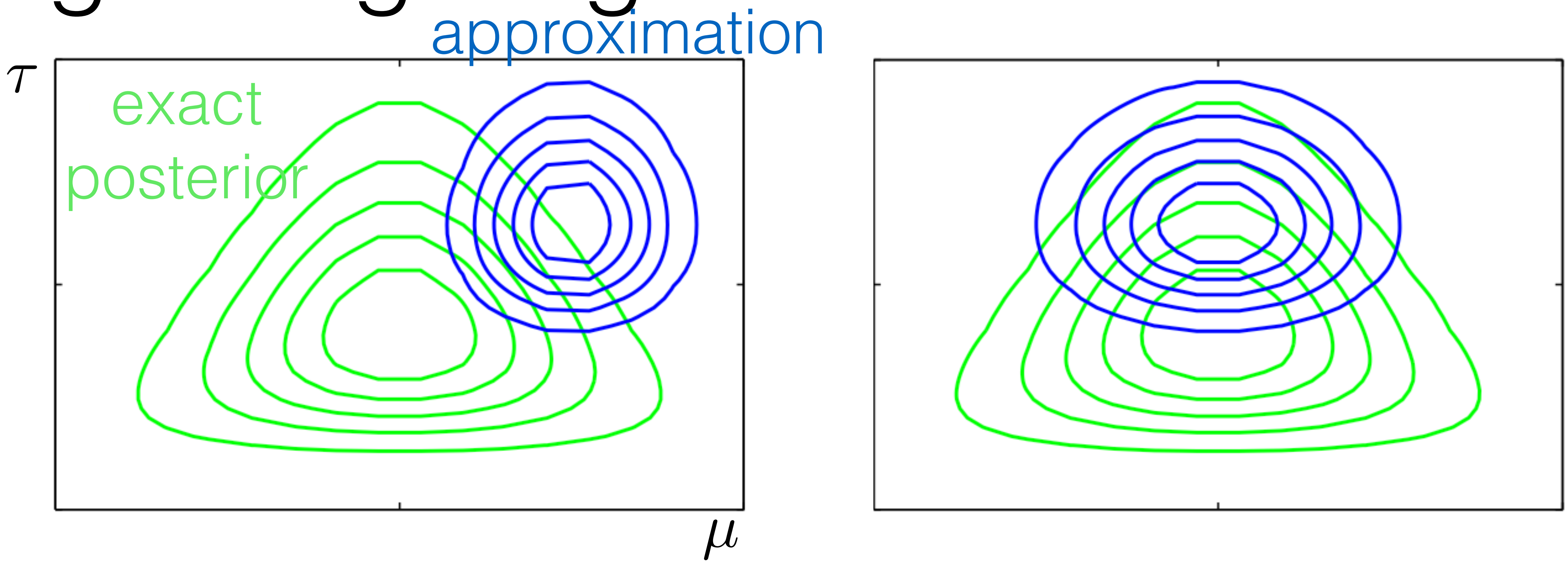

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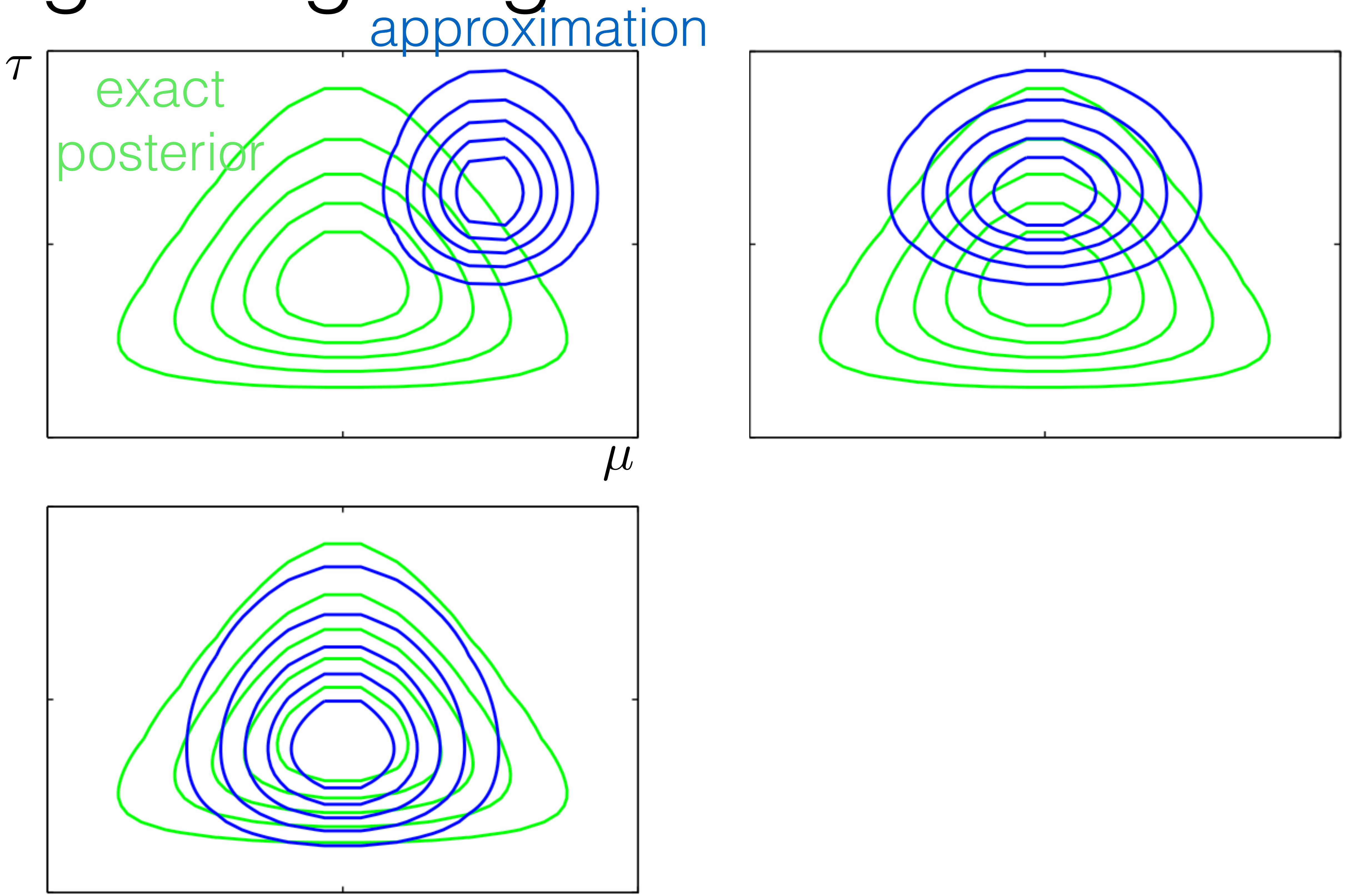

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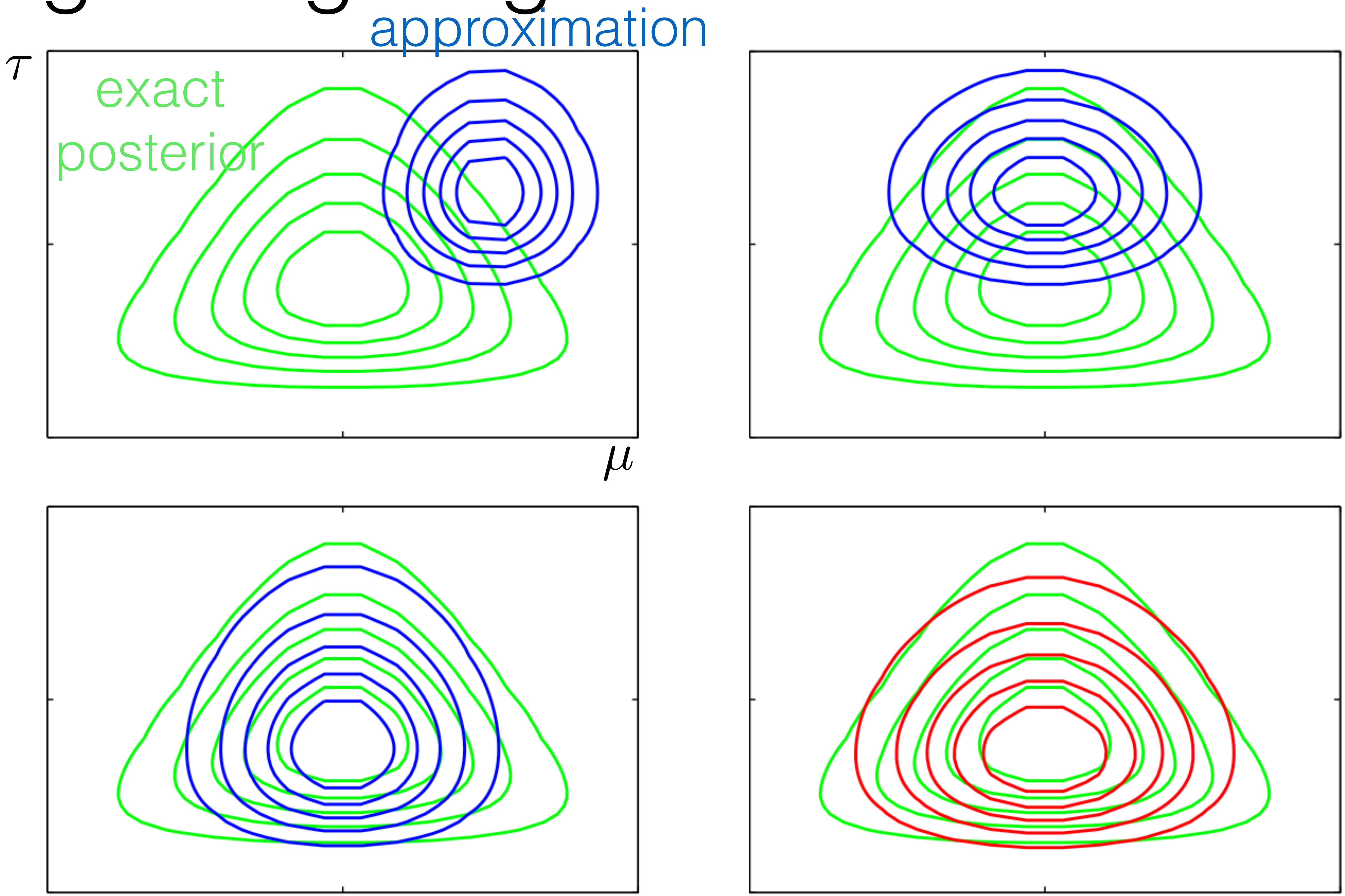

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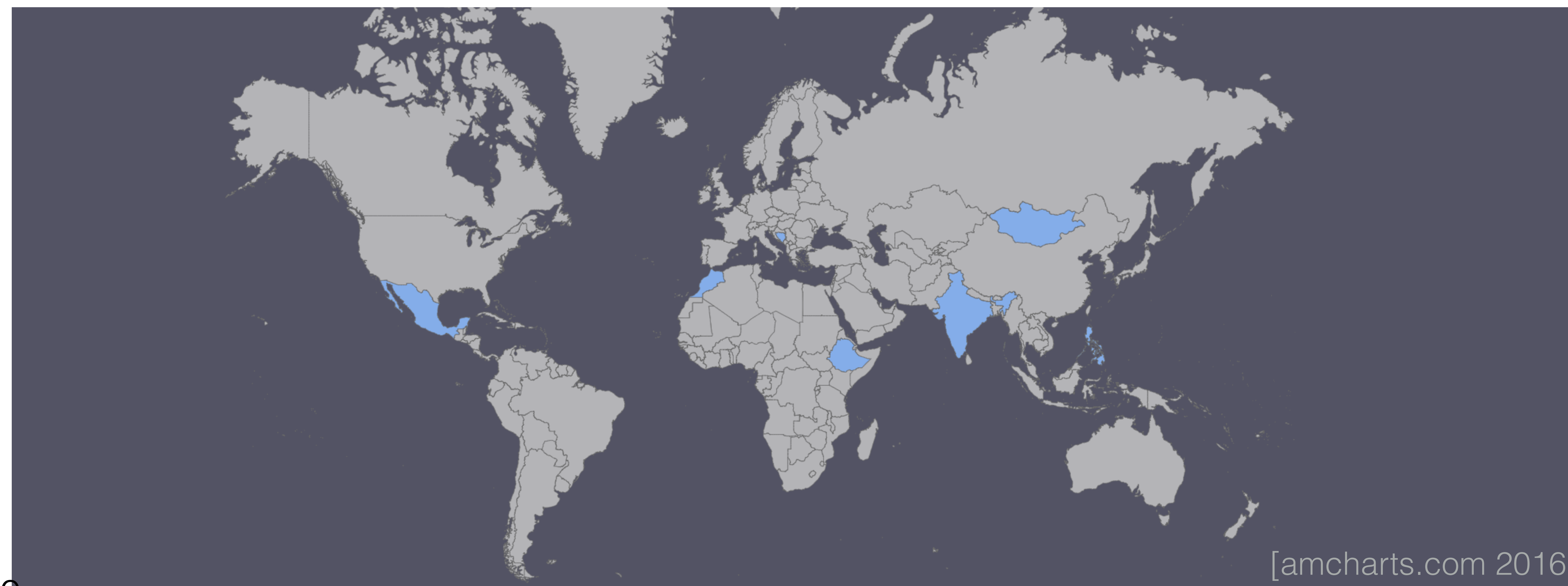
Microcredit Experiment



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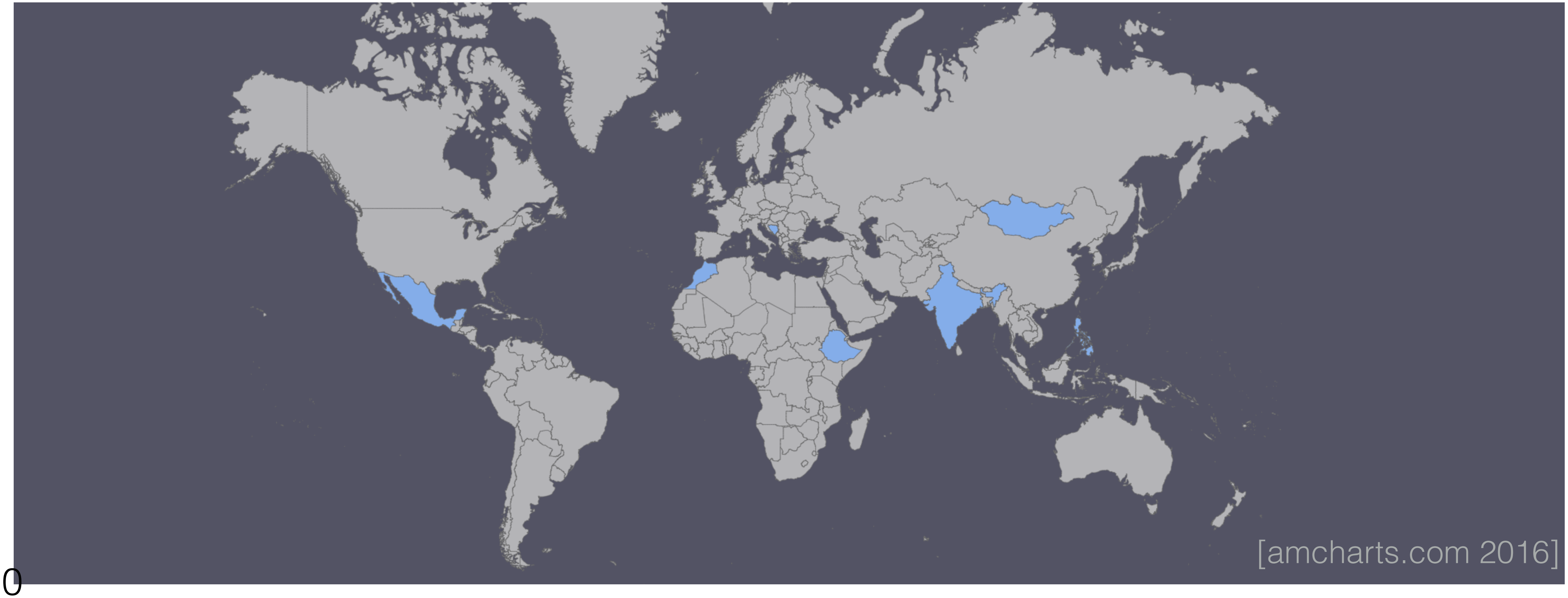

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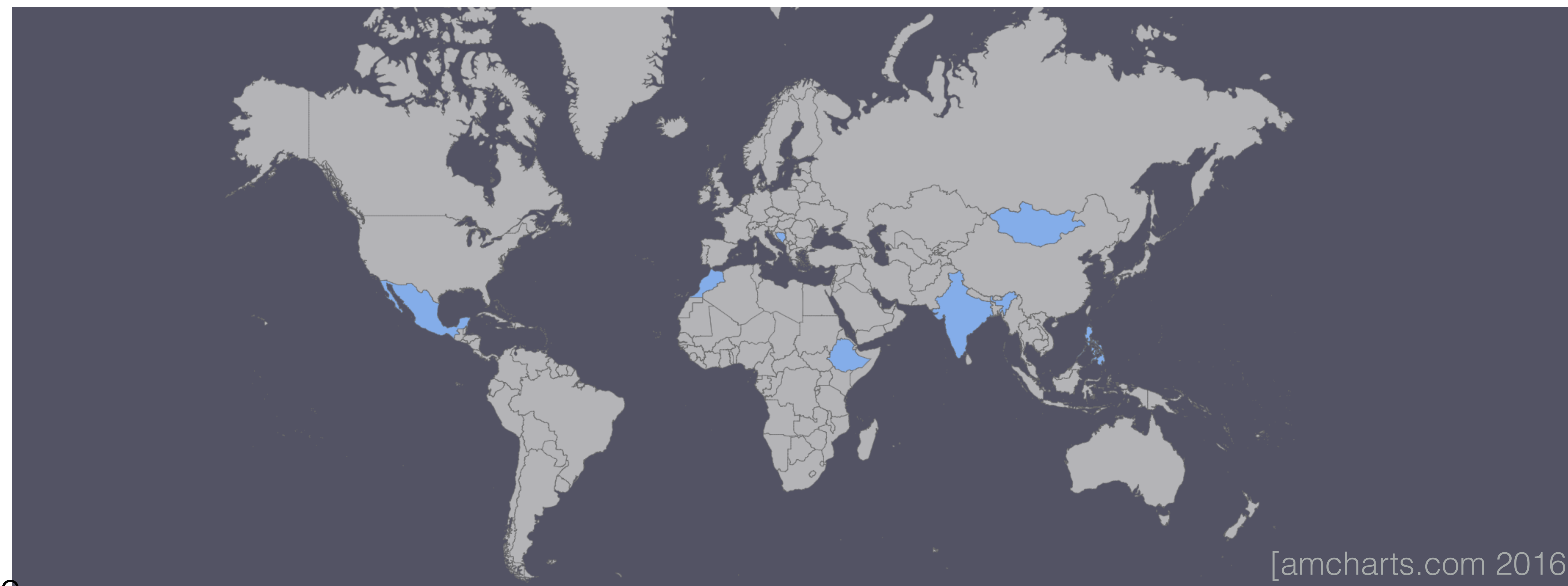

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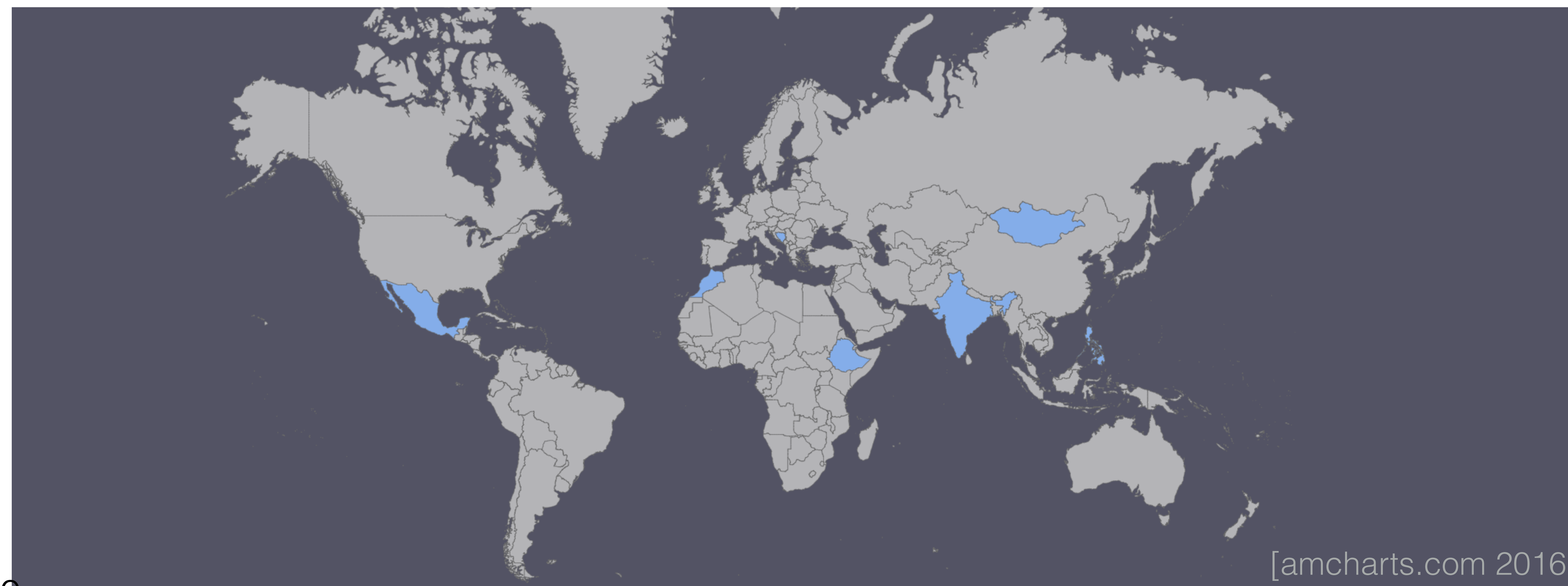

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$$y_{kn}$$

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$$\sigma_k^{-2} \overset{iid}{\sim} \Gamma(a, b) \qquad C \sim \mathrm{Sep\&LKJ}(\eta, c, d)$$

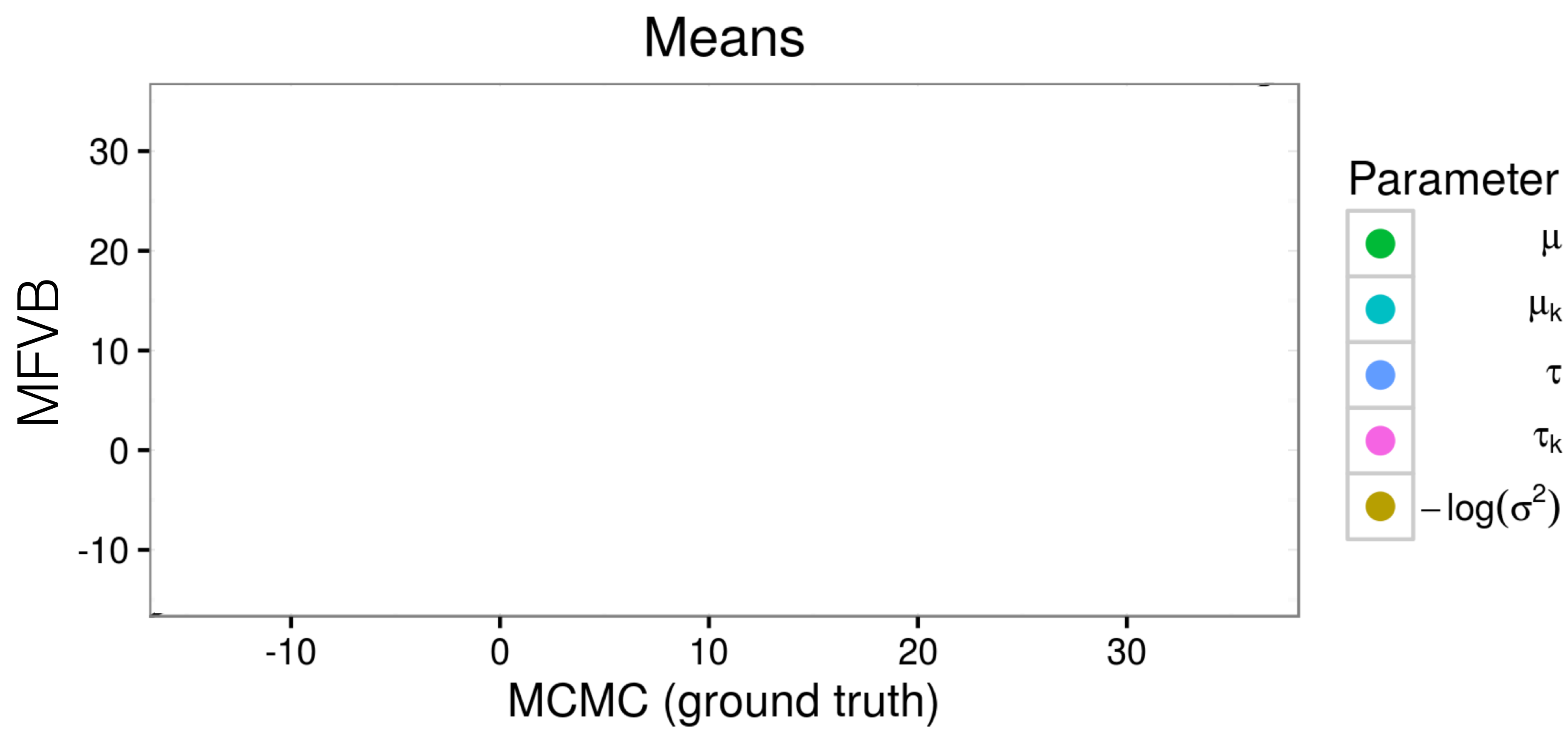
Microcredit

MFVB: Do we need to check the output?

Microcredit

MFVB: How will we know if it's working?

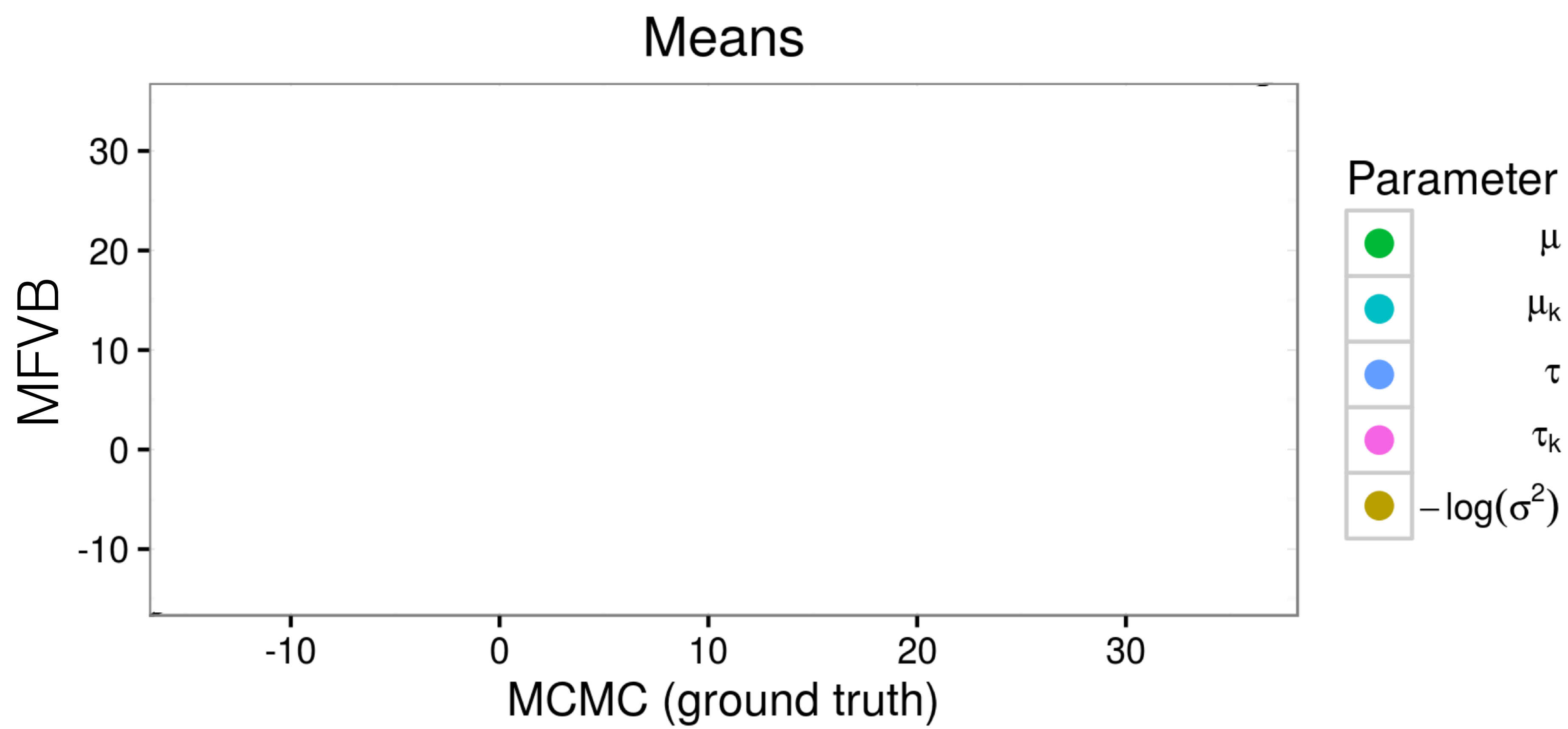
Microcredit



[Giordano, Broderick, Meager, Huggins, Jordan 2016]

Microcredit

- *One set* of 2500 MCMC draws: **45 minutes**



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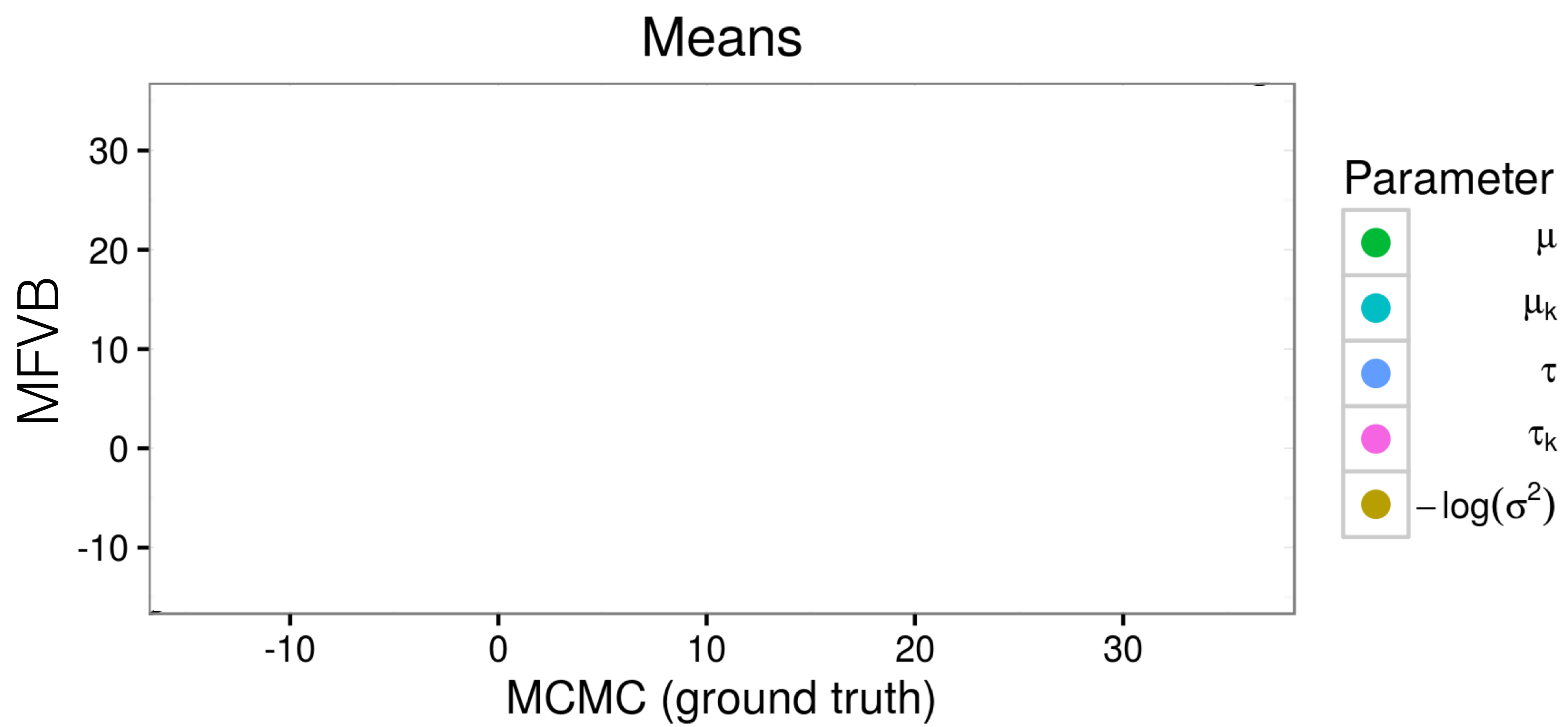

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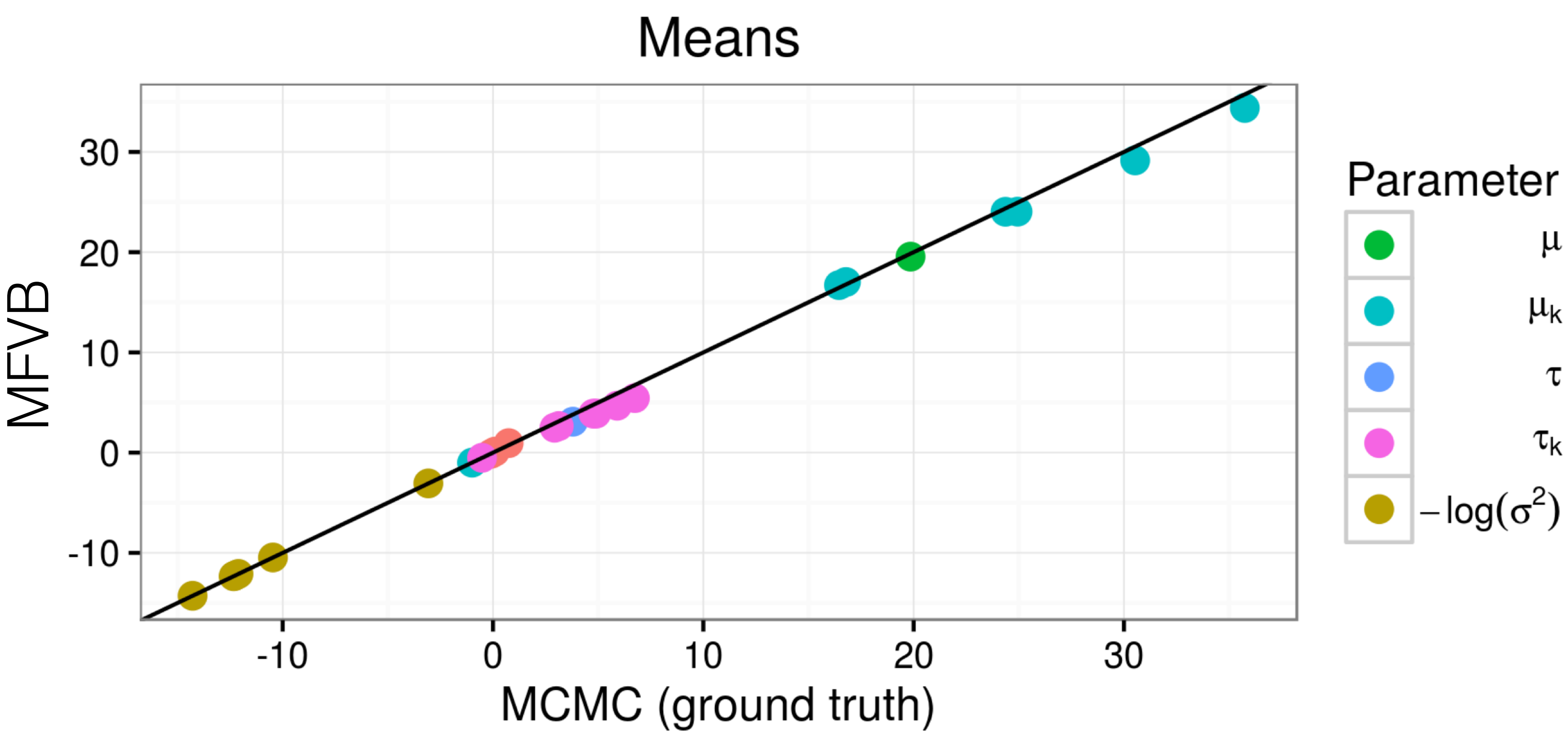

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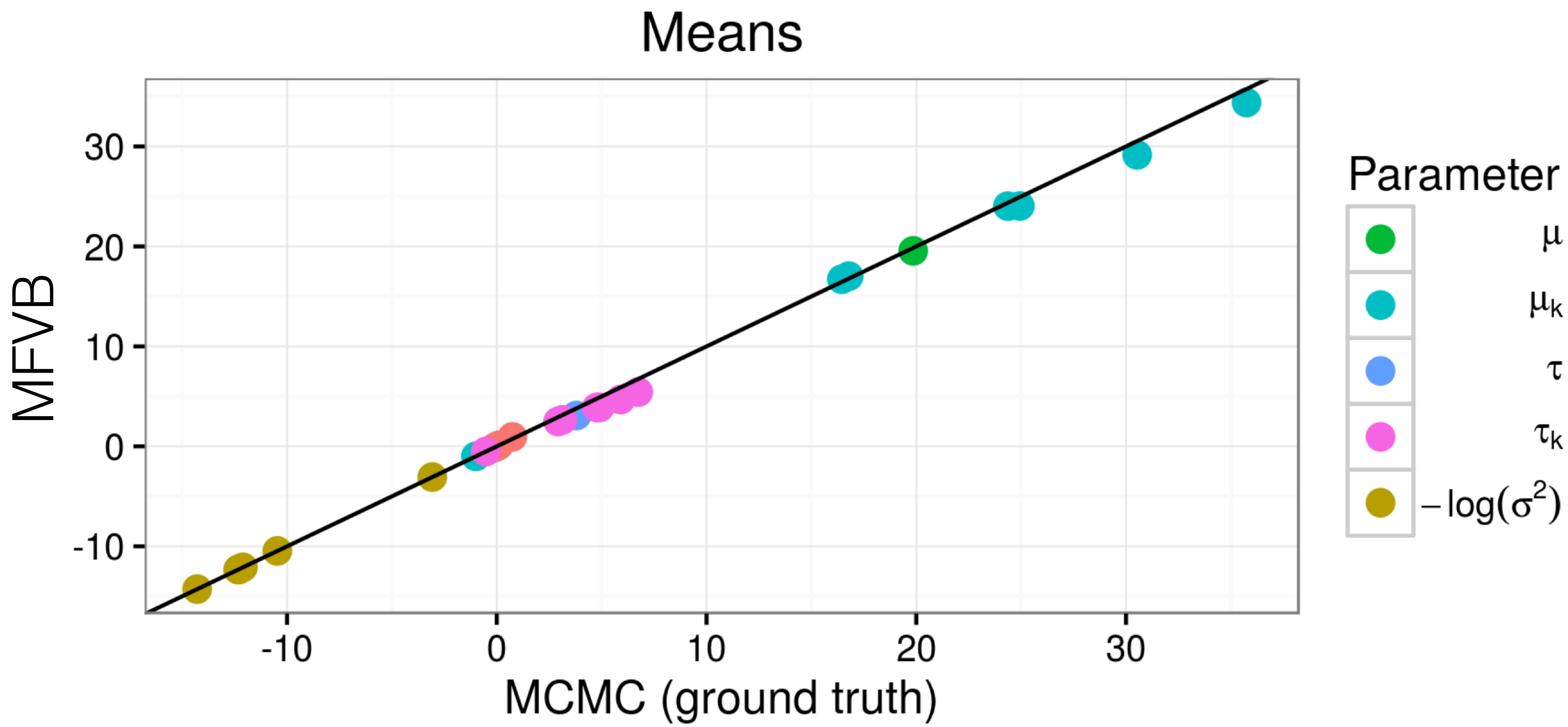

Criteo Online Ads Experiment

- Click-through conversion prediction
- Q: Will a customer (e.g.) buy a product after clicking?

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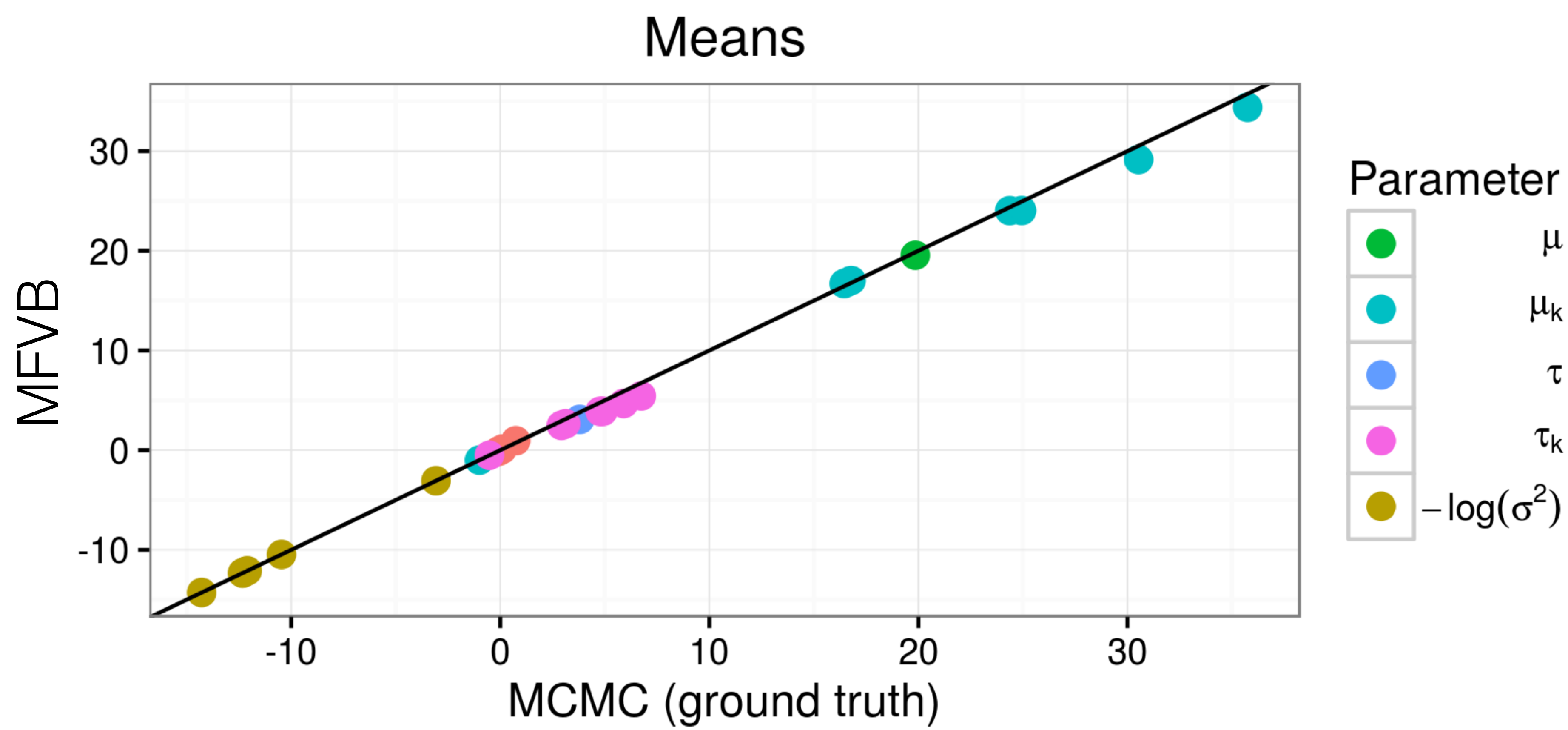

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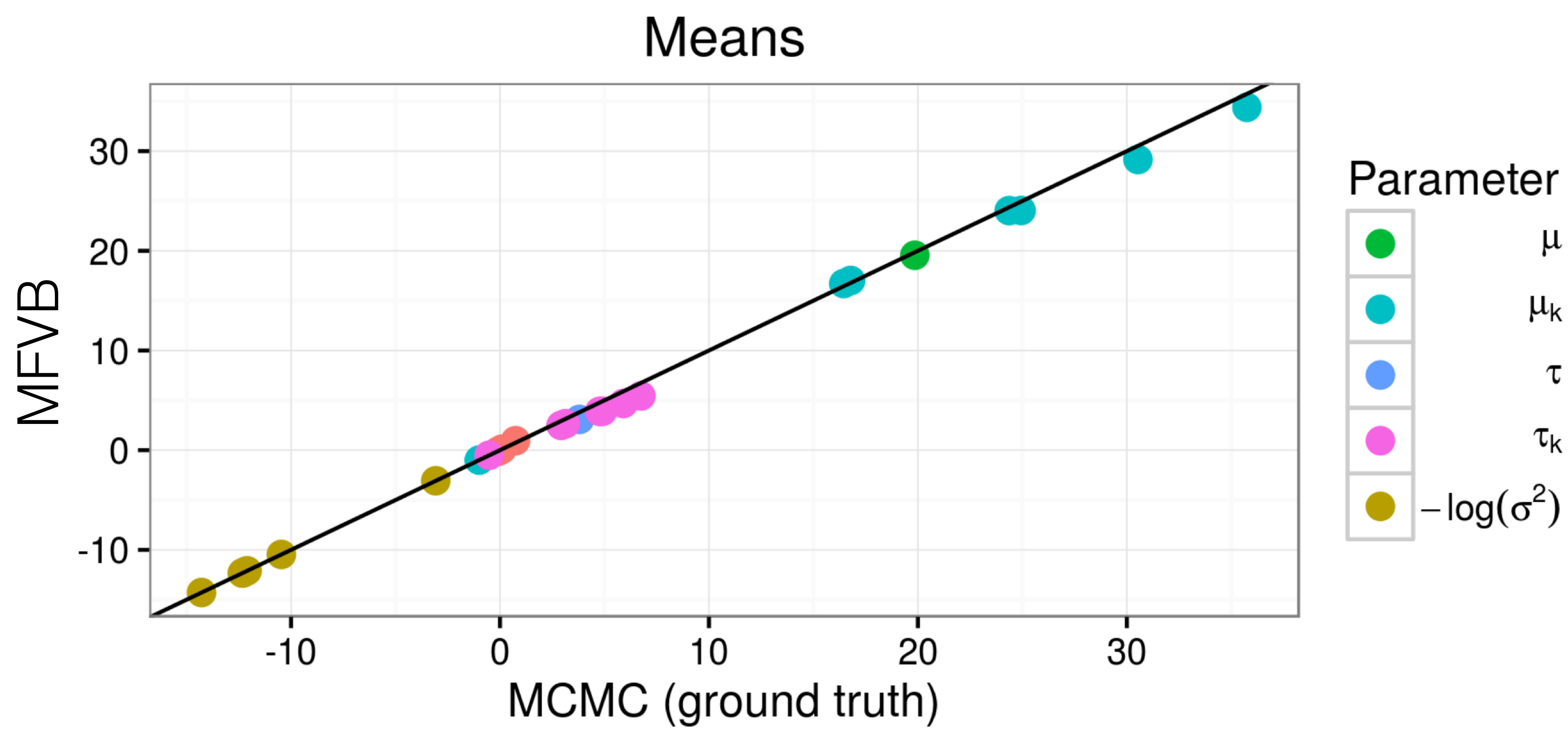

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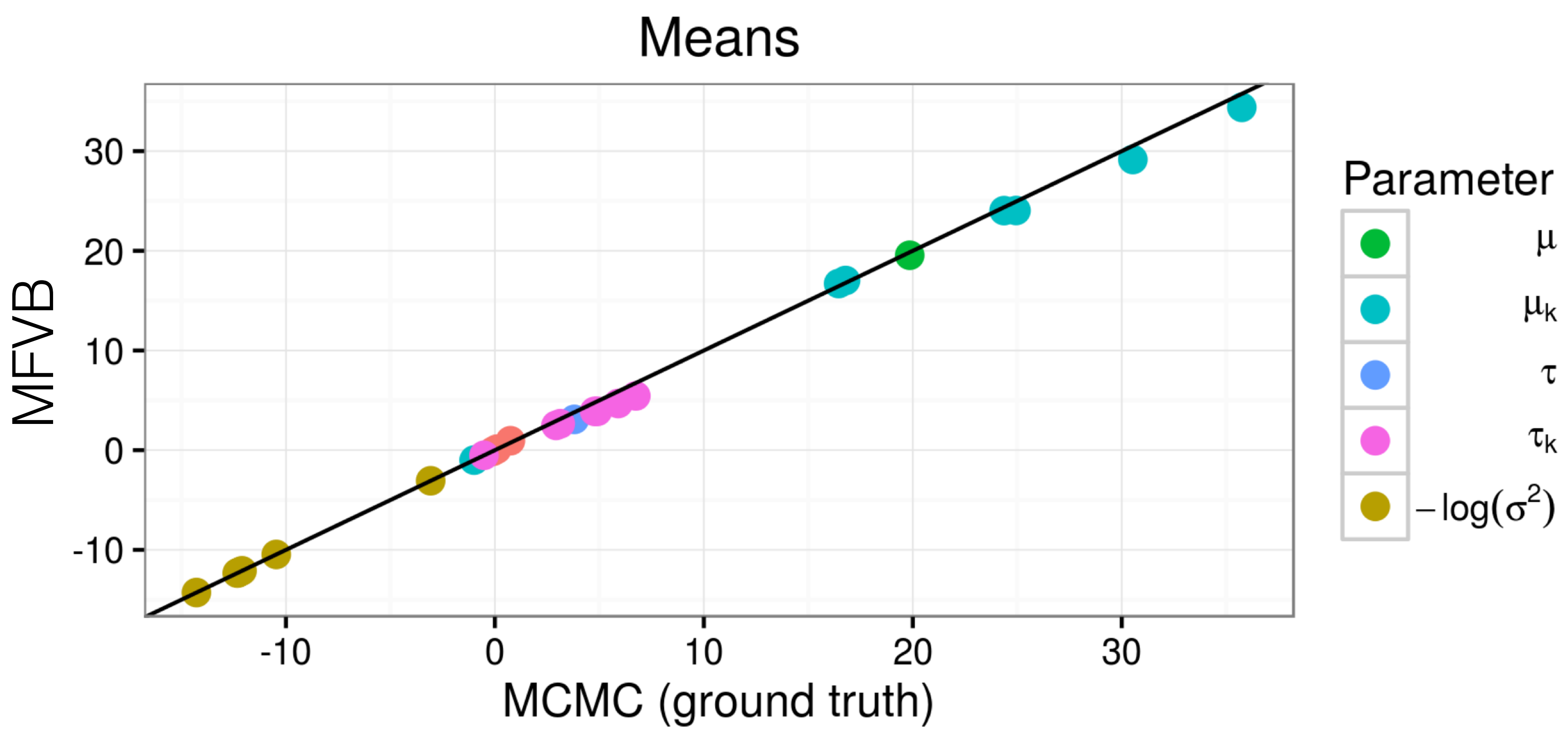

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- Logistic GLMM; N = 61,895 subset to compare to MCMC

[Giordano, Broderick, Meager, Huggins, Jordan 2016; Giordano, Broderick, Jordan 2018]

Criteo Online Ads Experiment

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Criteo Online Ads Experiment

- MAP: **12 s**

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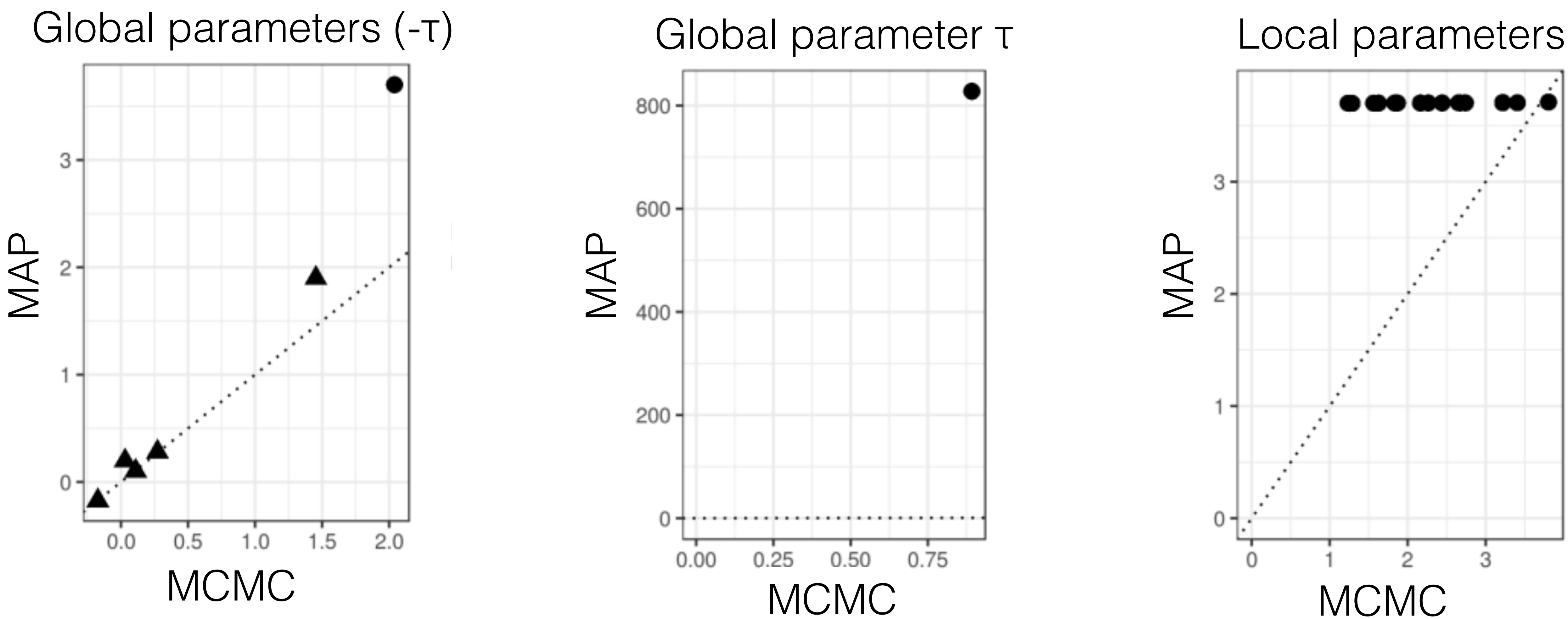

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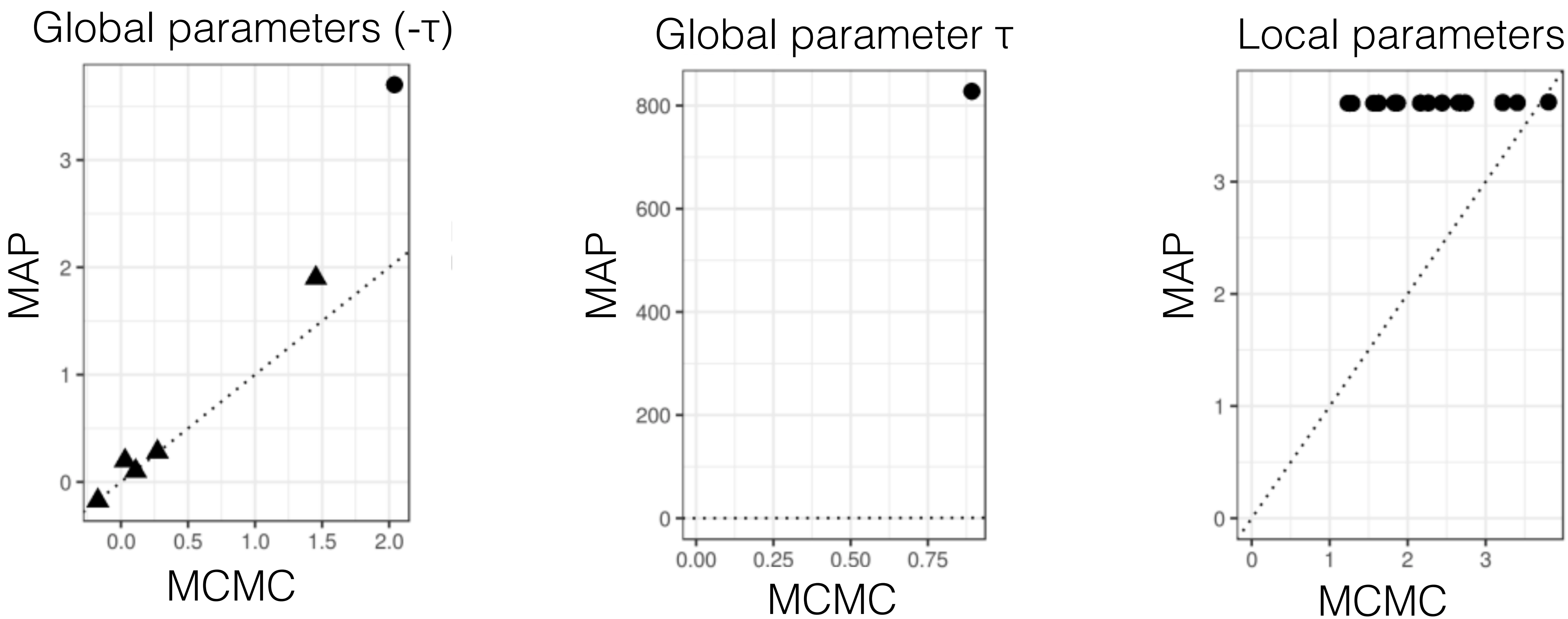

- MAP: **12 s**
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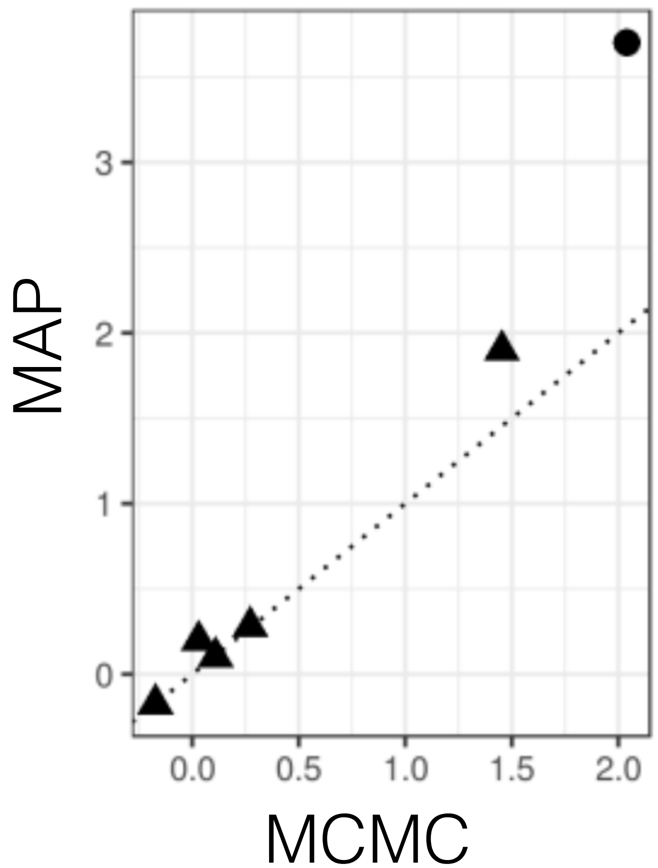
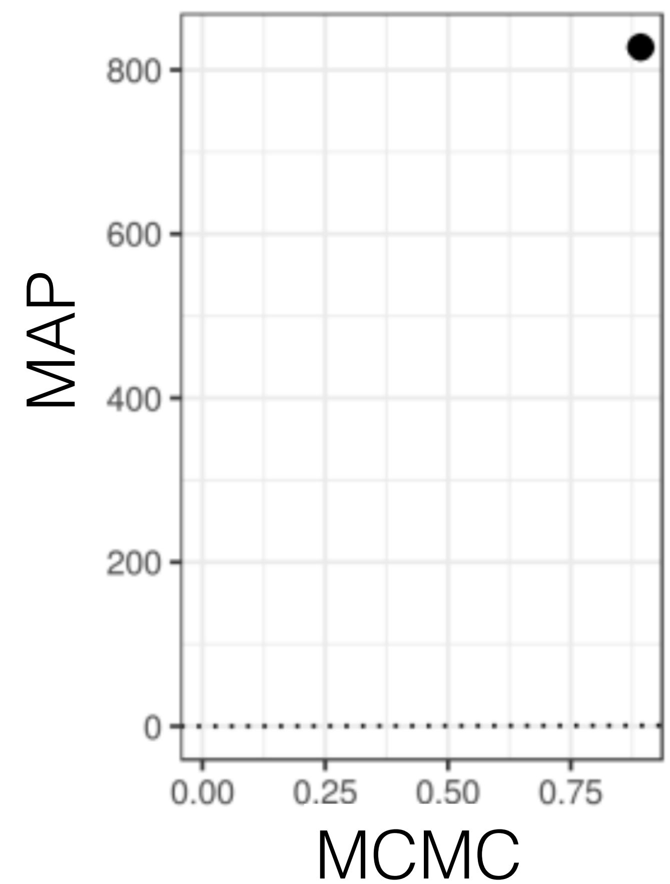
Criteo Online Ads Experiment

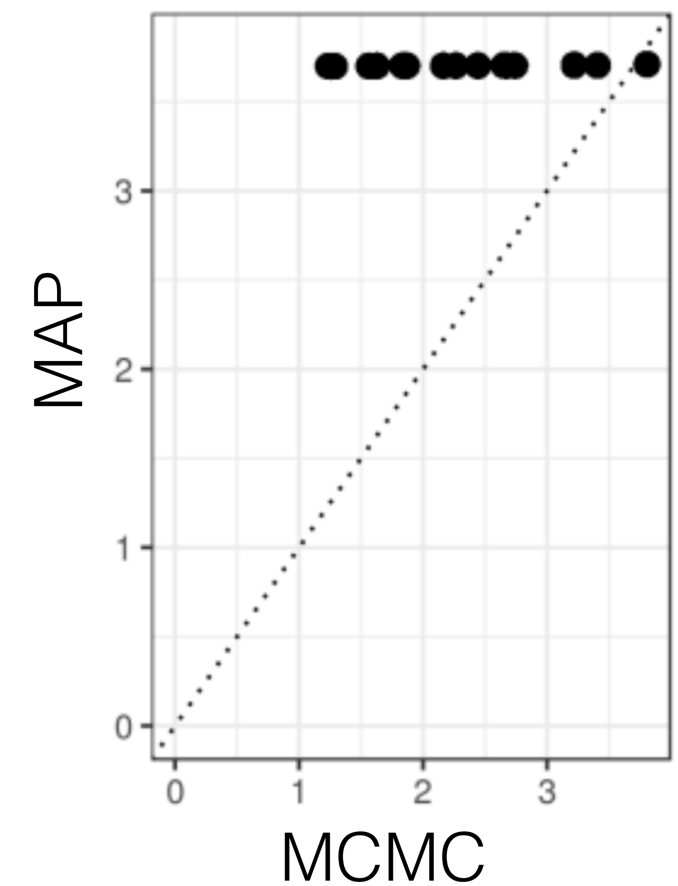
Global parameters (-τ)



Global parameter τ



Local parameters



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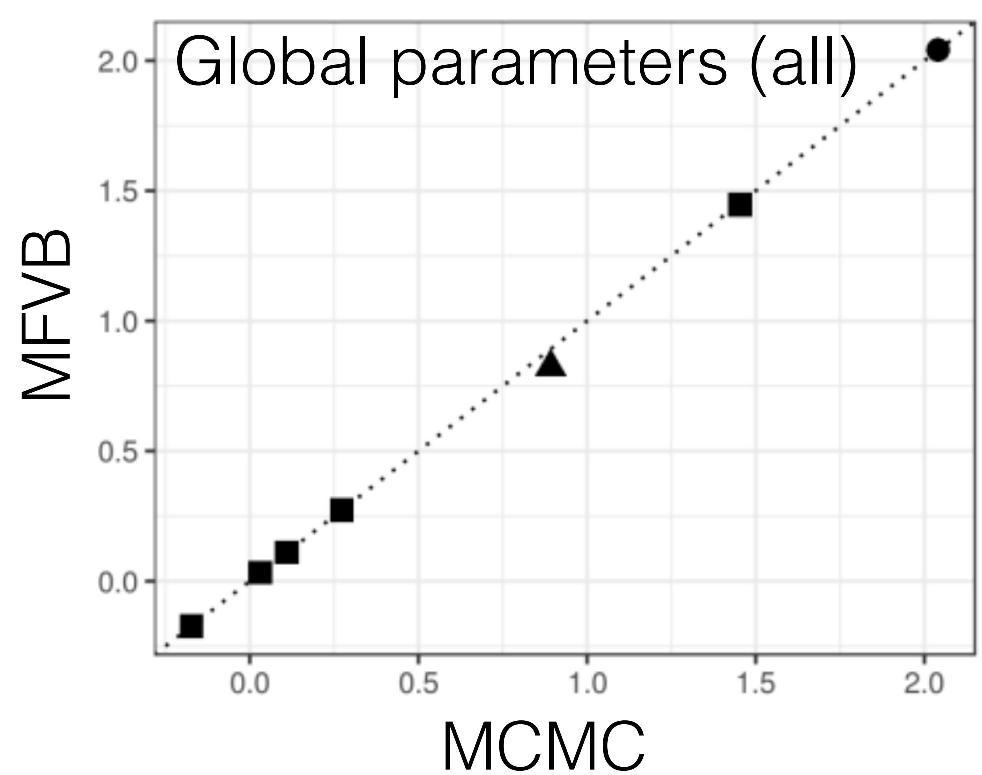

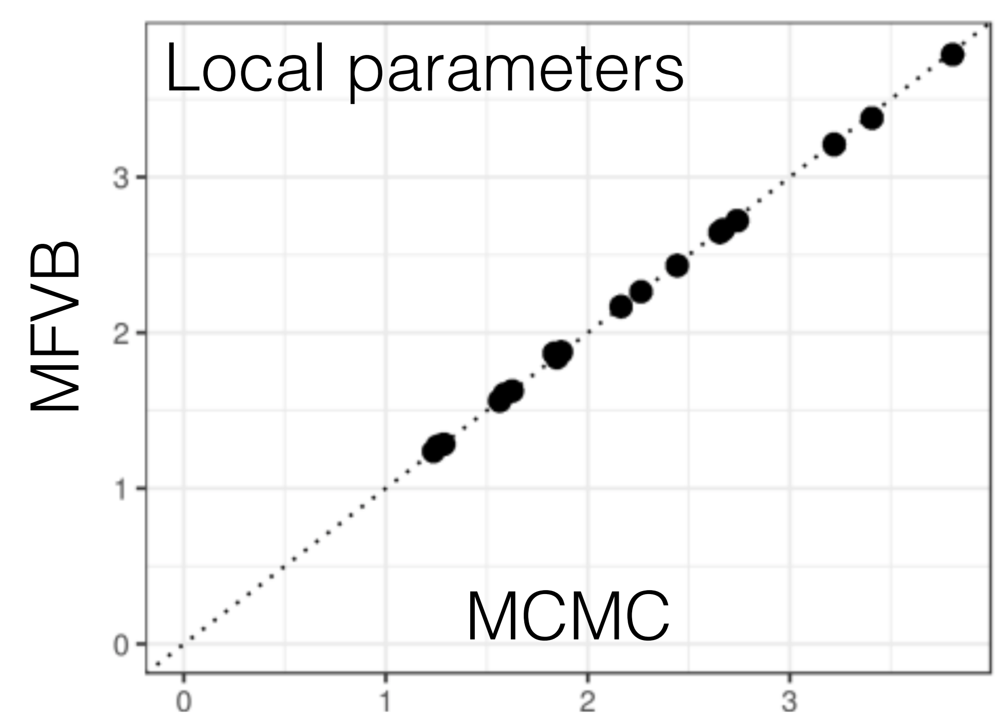

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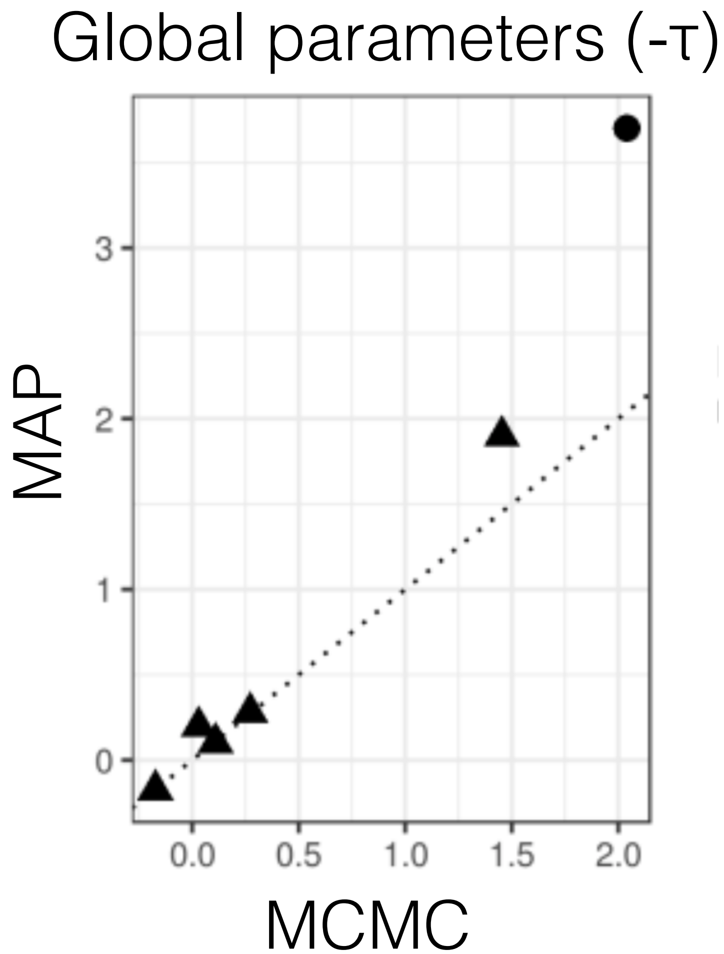

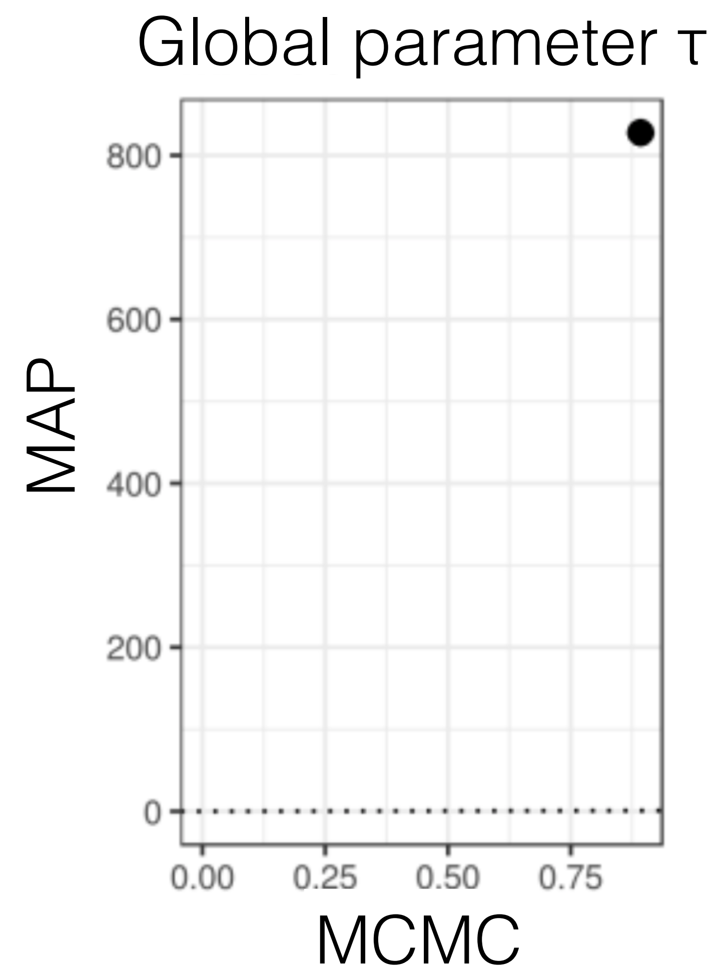

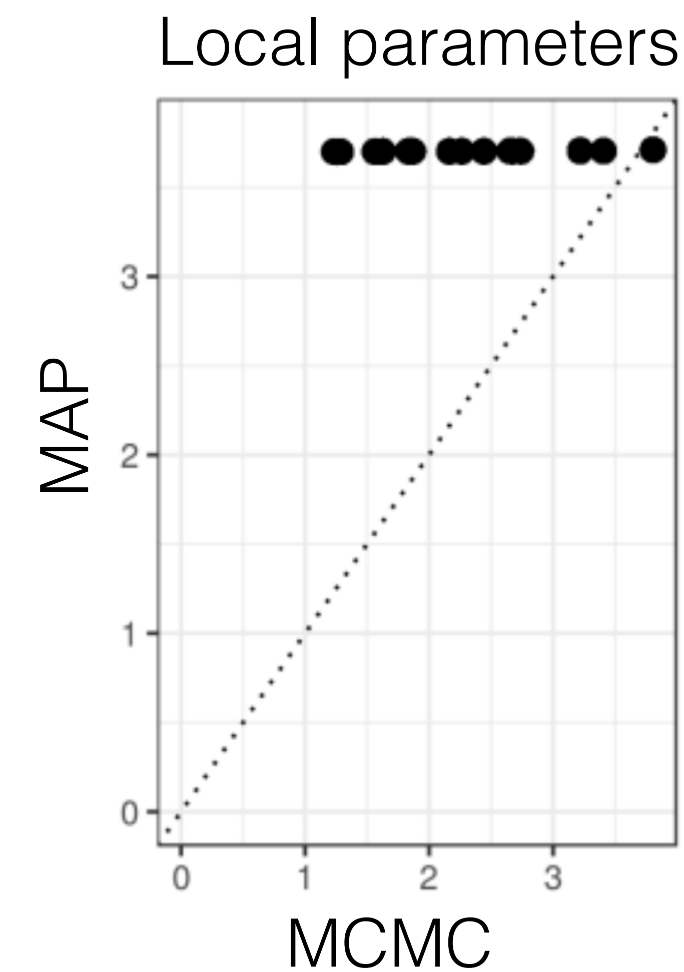

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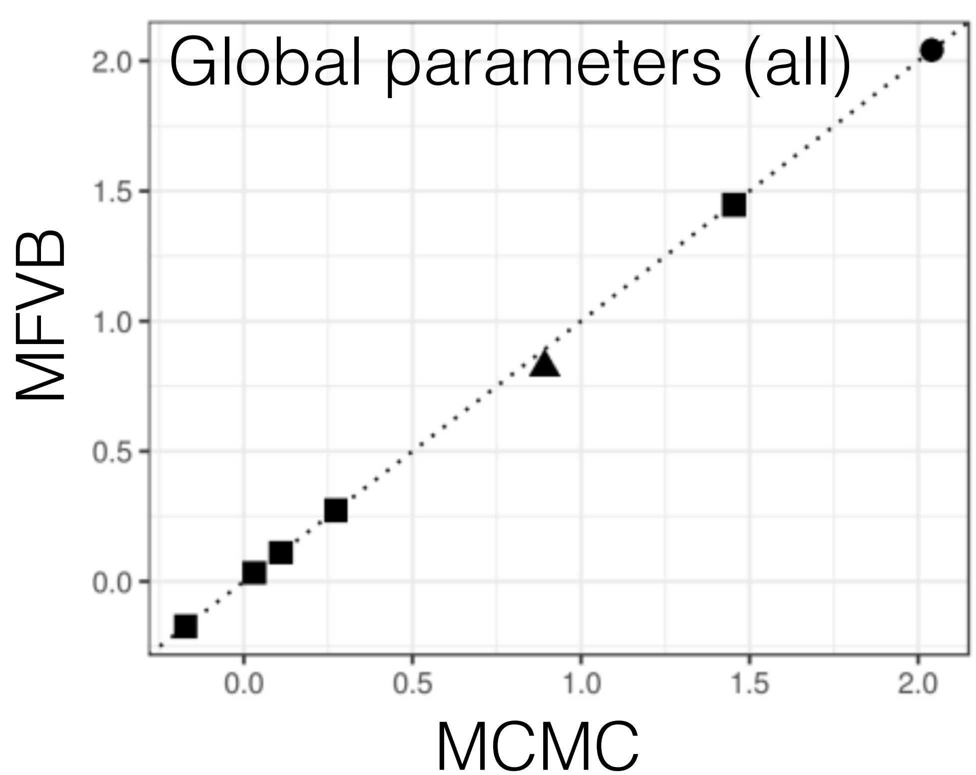

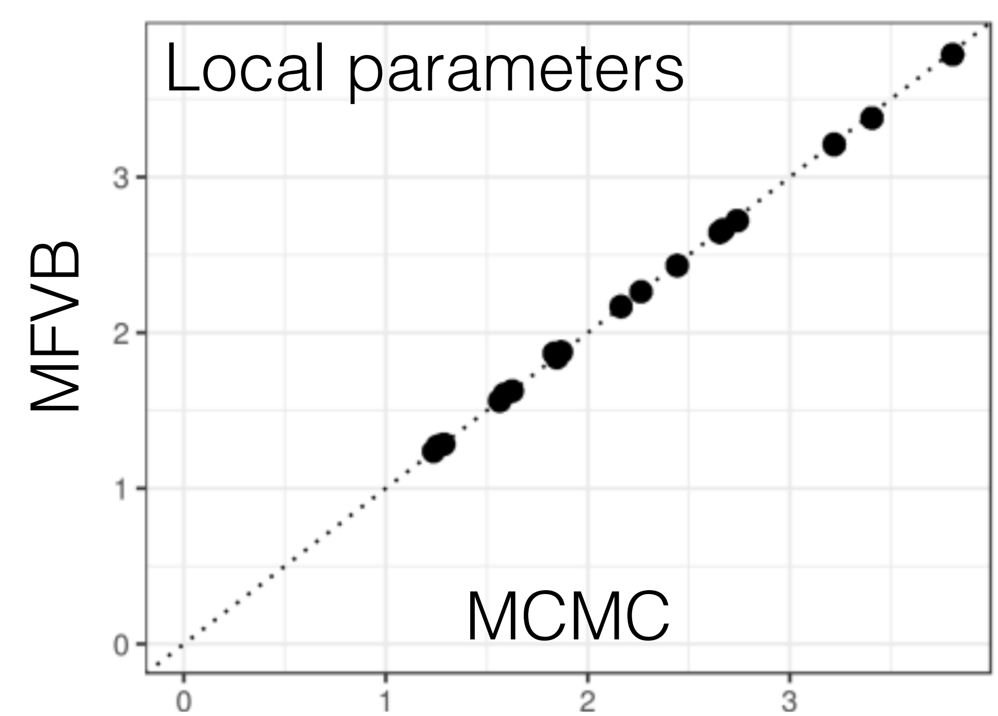

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Roadmap

- Bayes & Approximate Bayes review
- What is:
  - Variational Bayes (VB)
  - Mean-field variational Bayes (MFVB)
- Why use VB?
- When can we trust VB?
- Where do we go from here?

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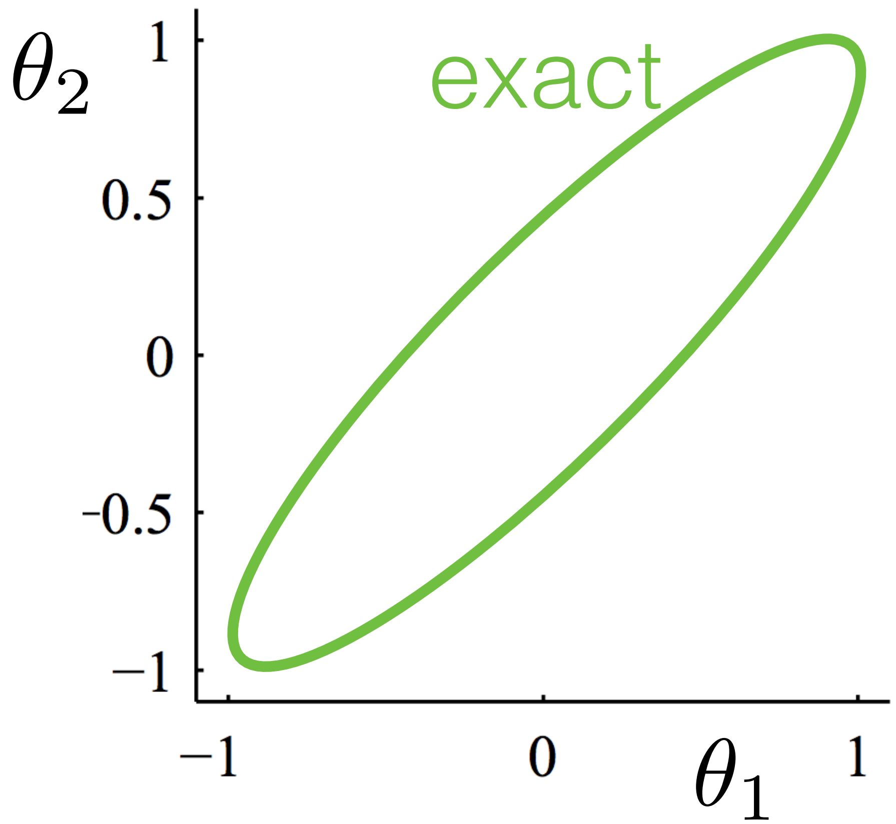

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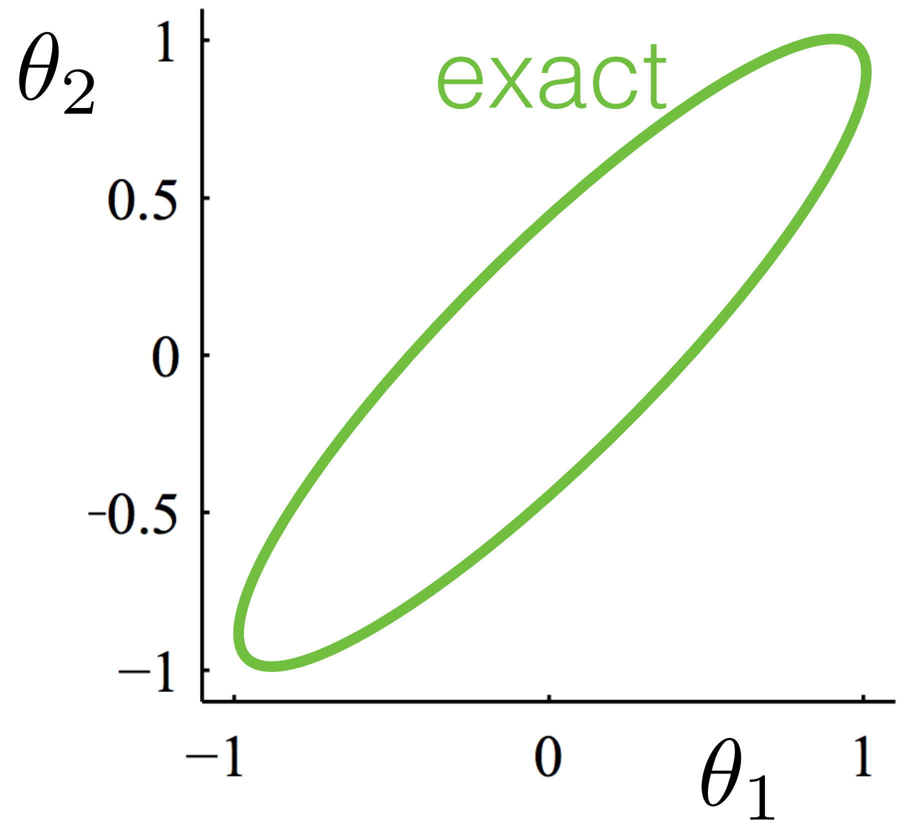

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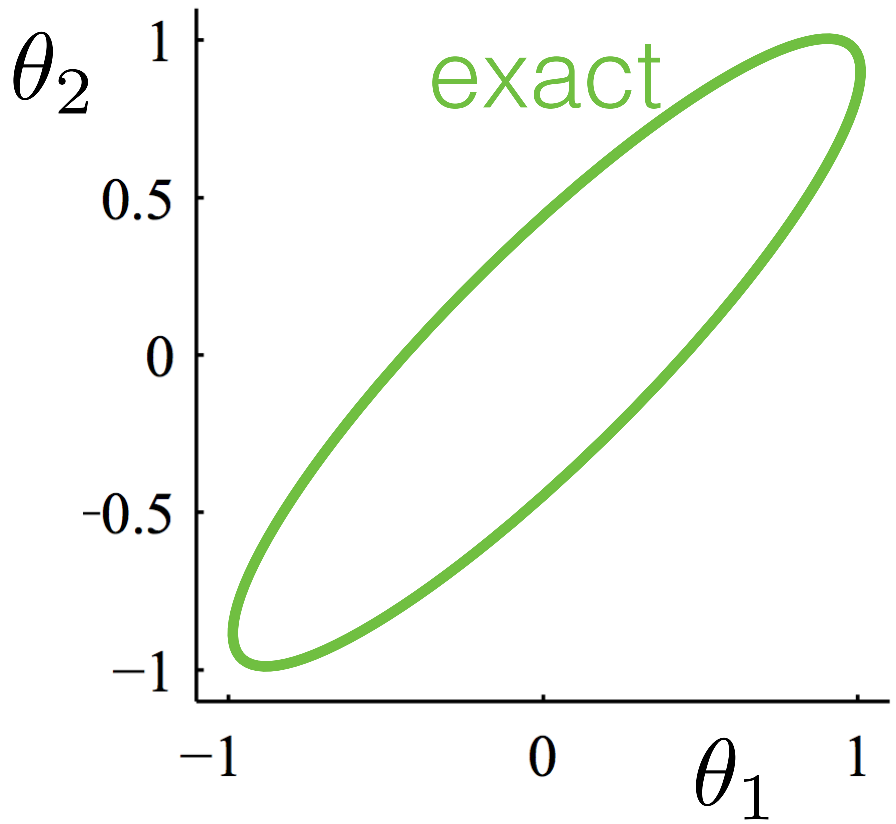

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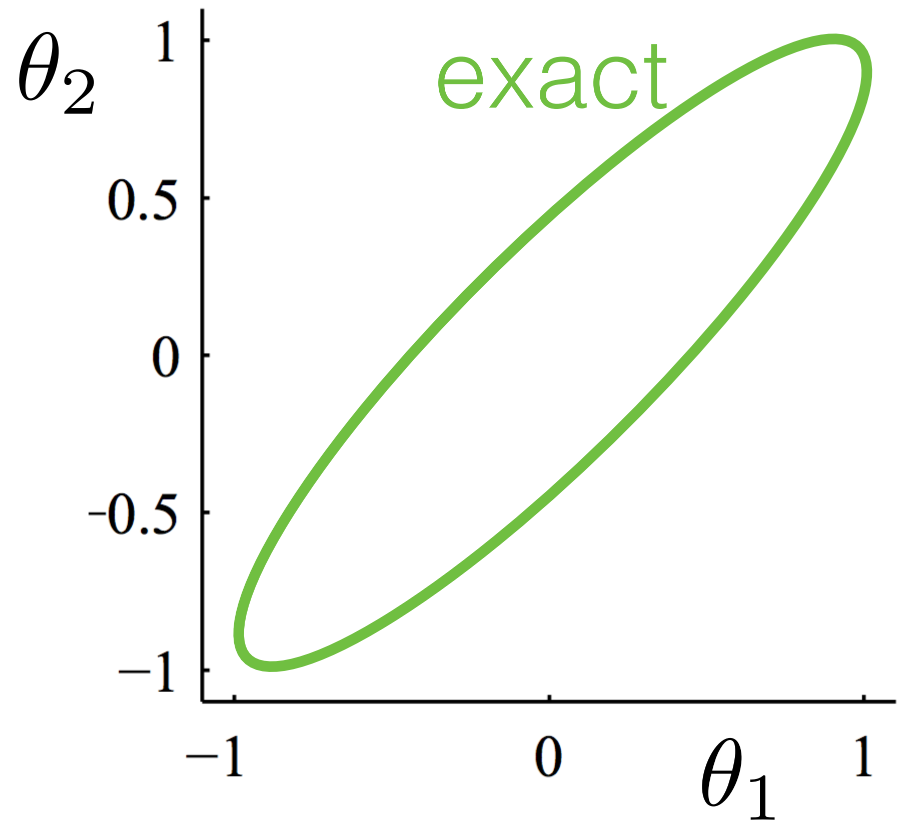

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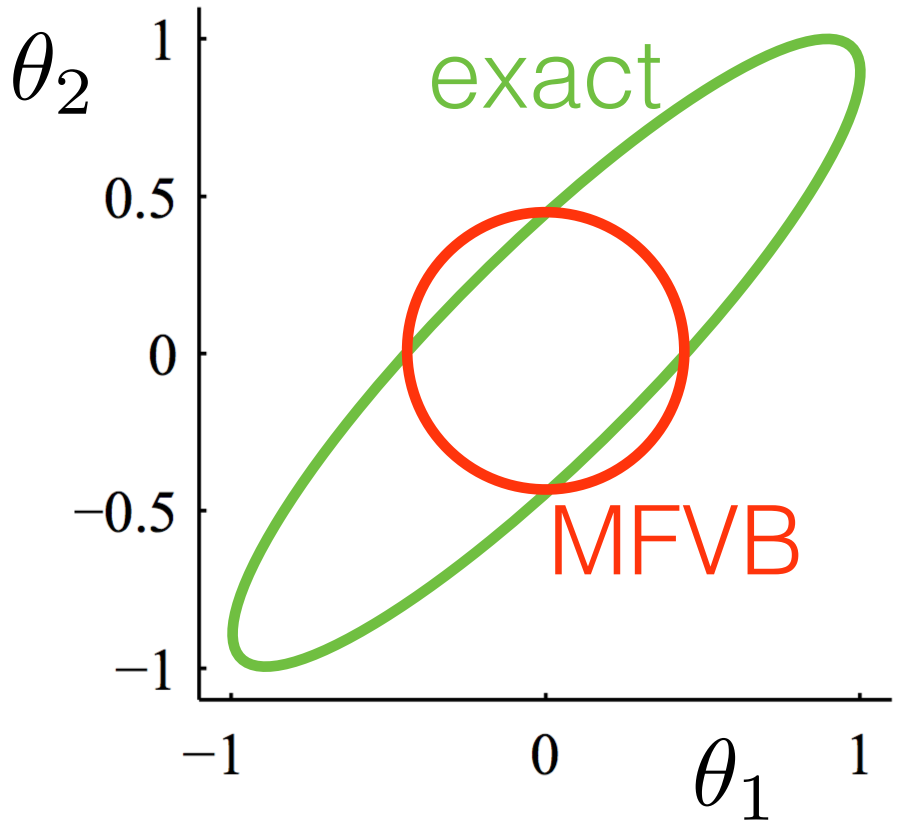

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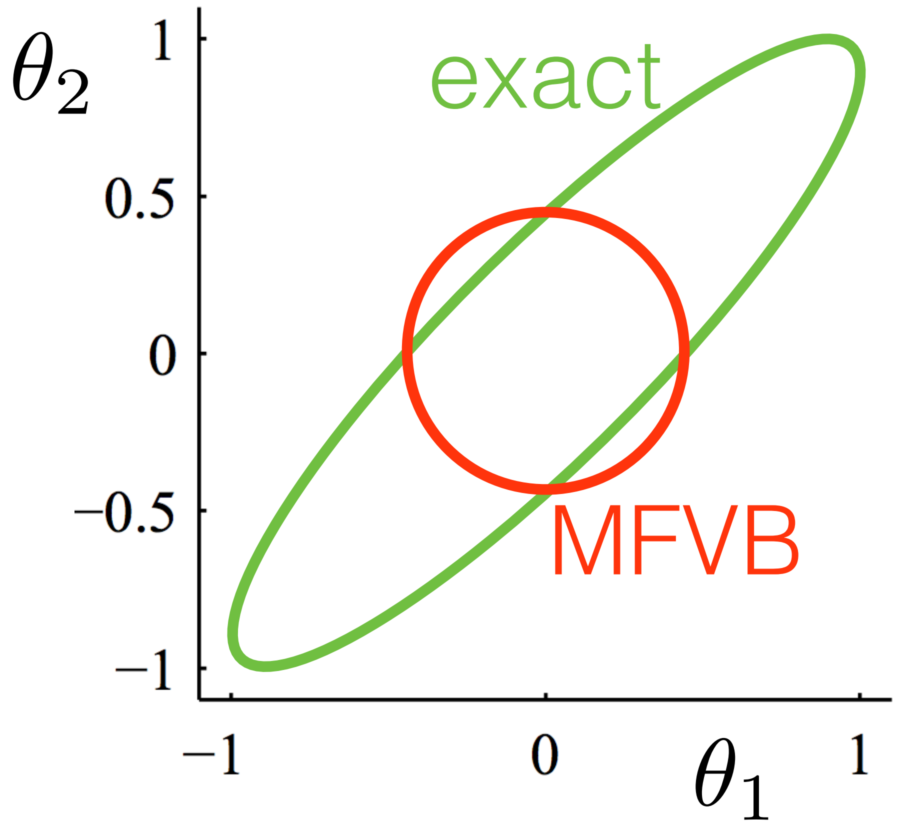

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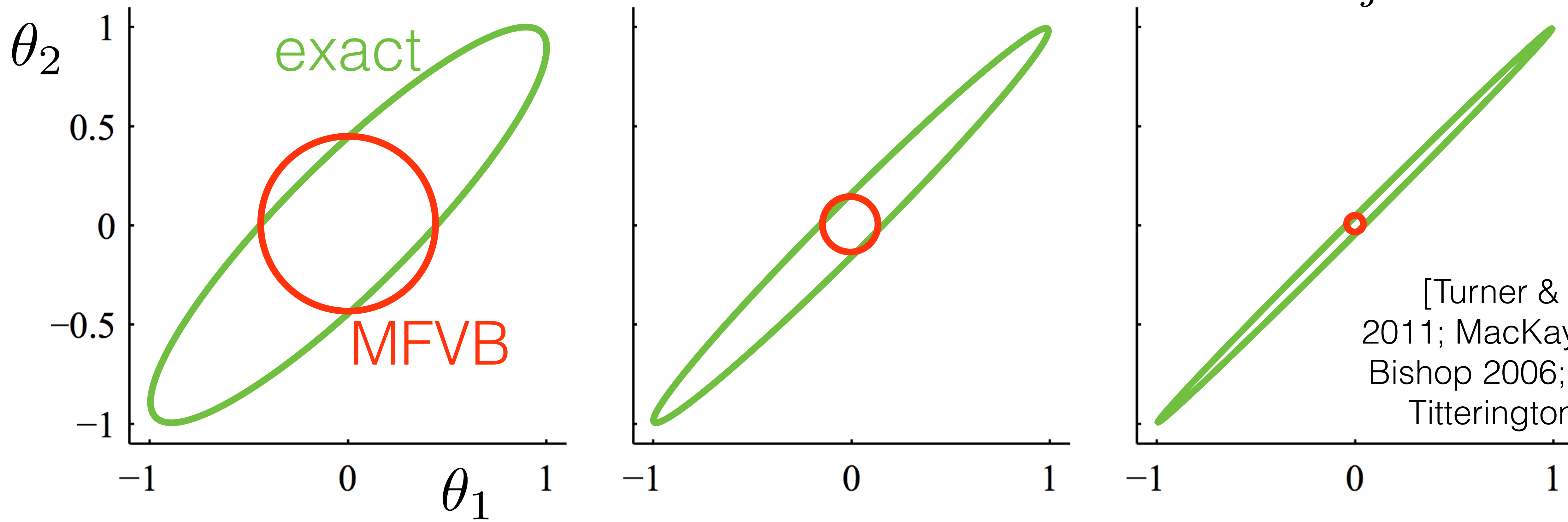

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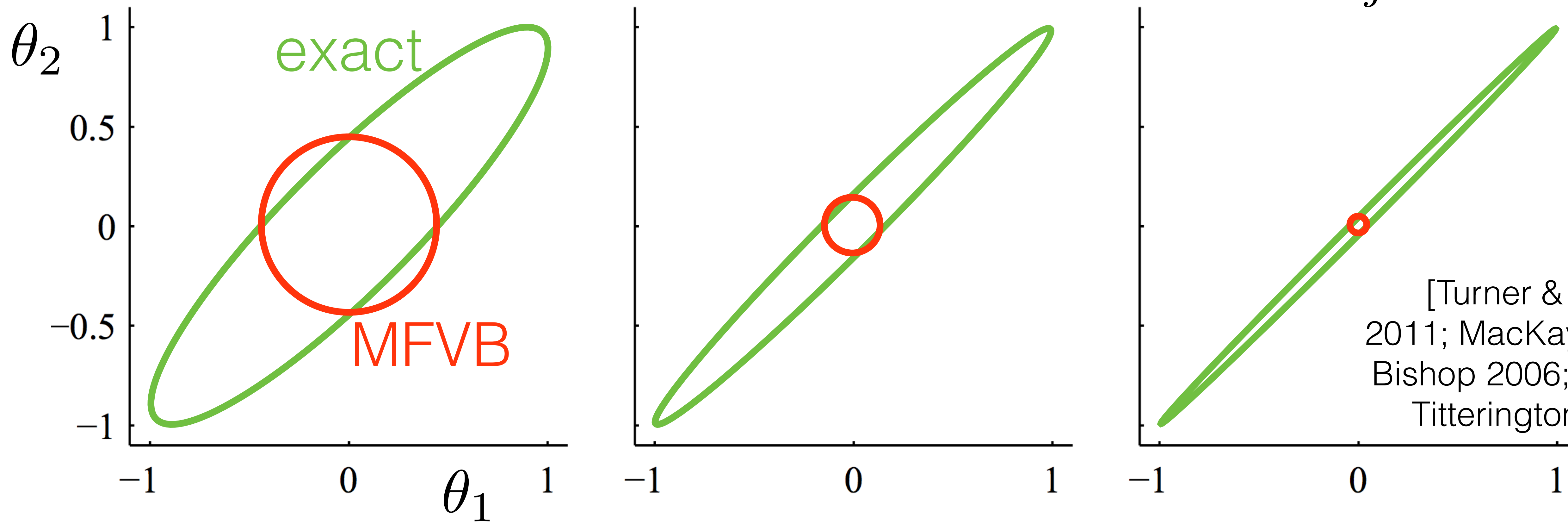

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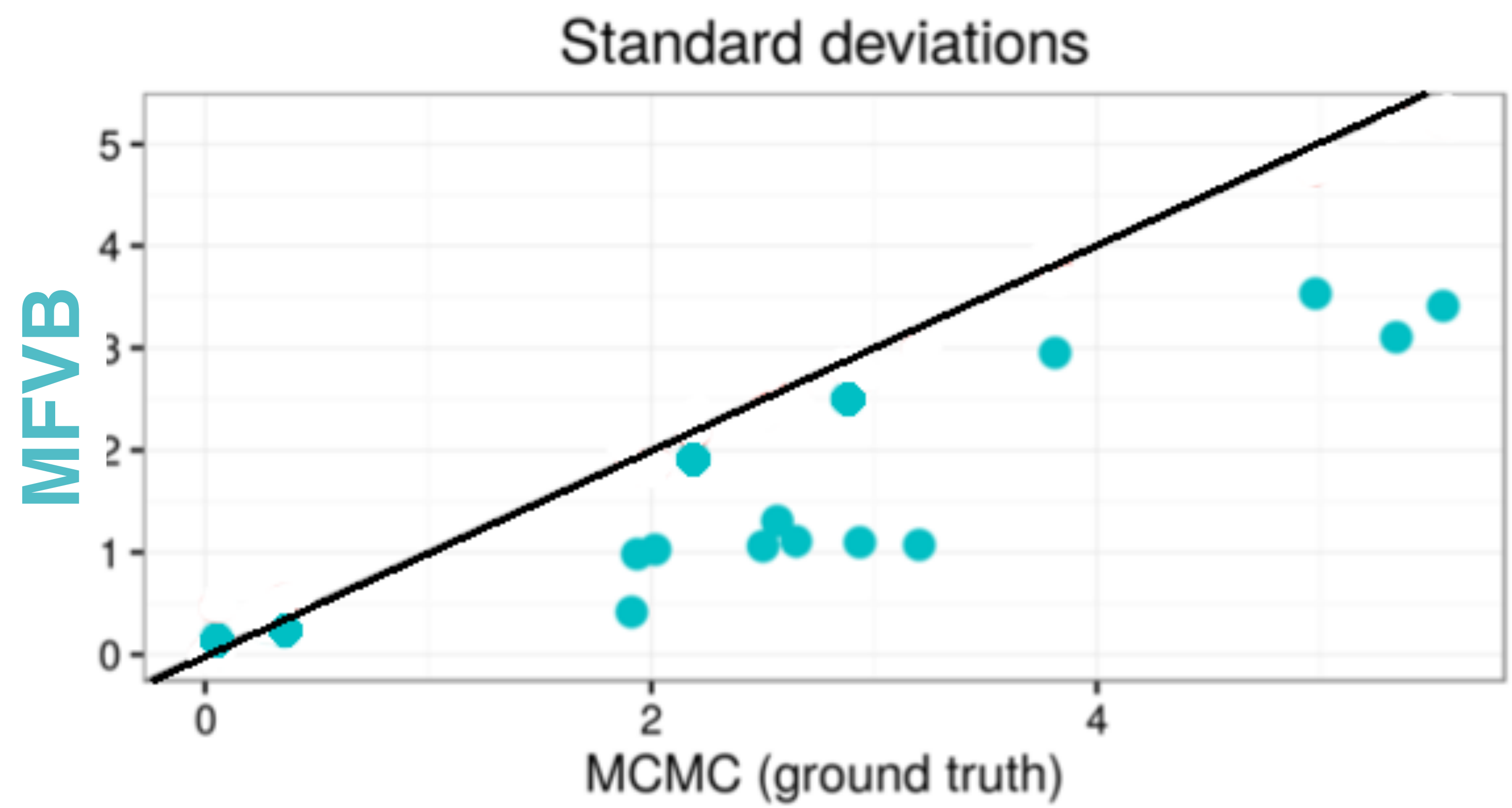

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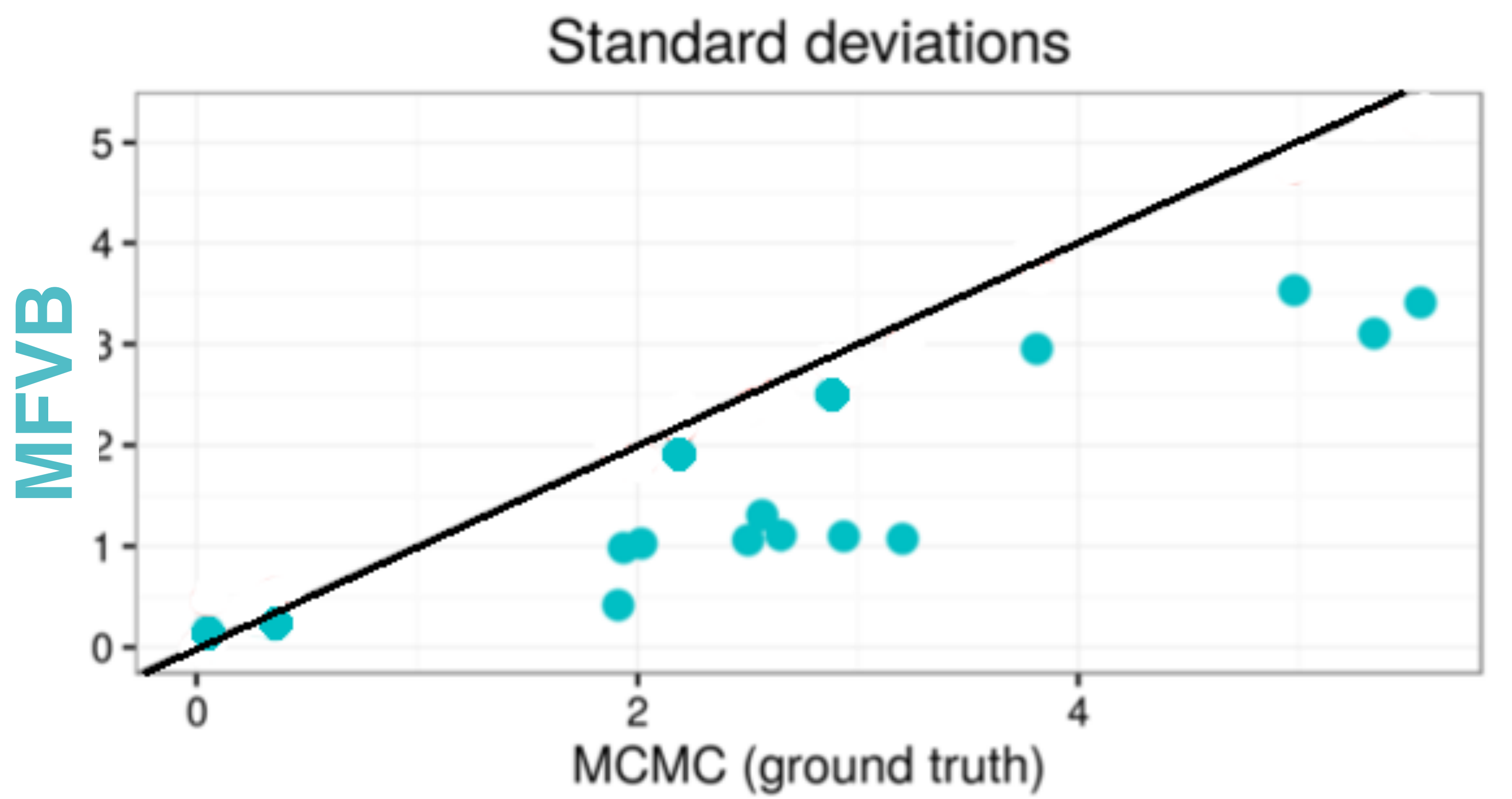

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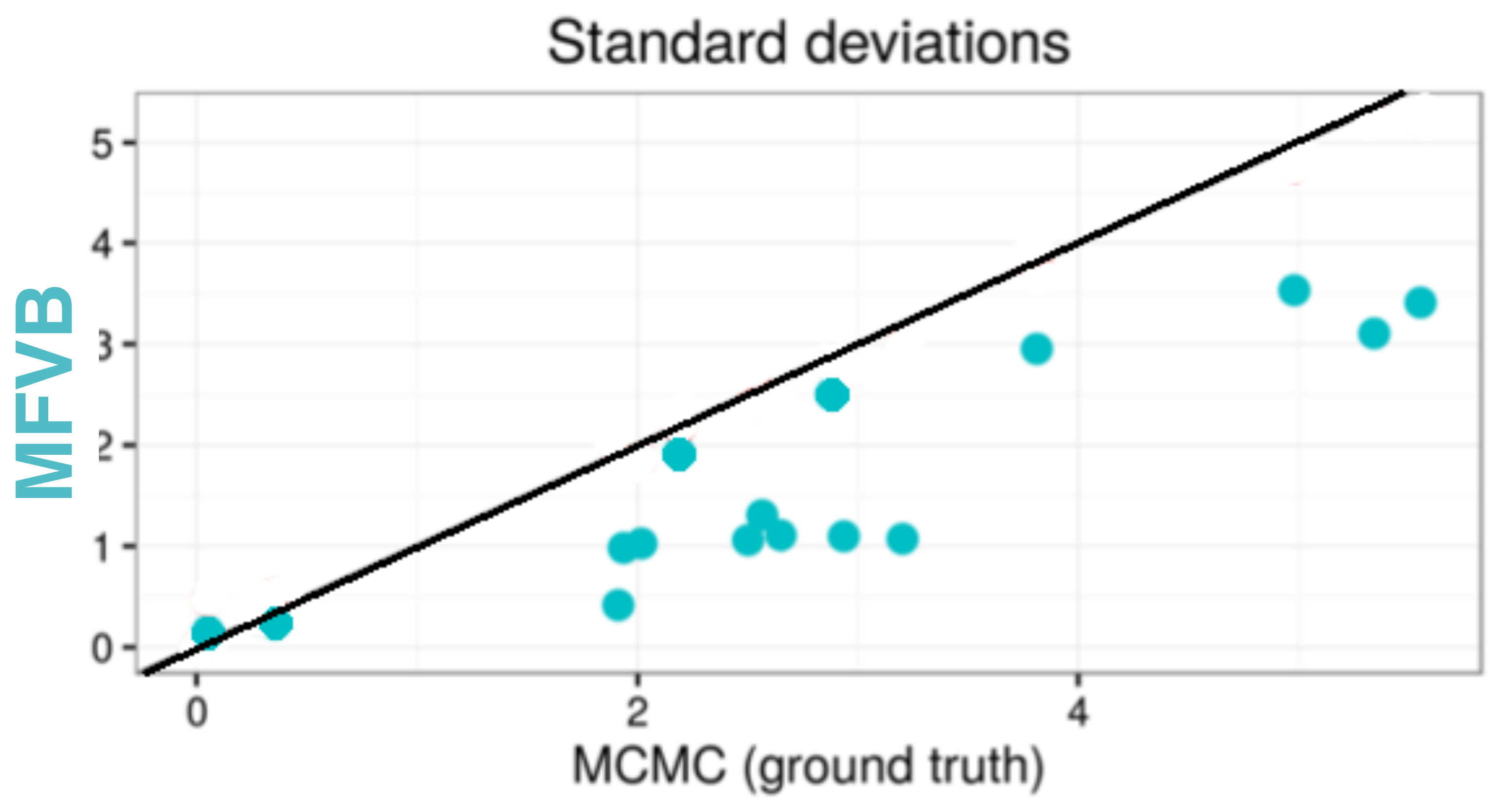

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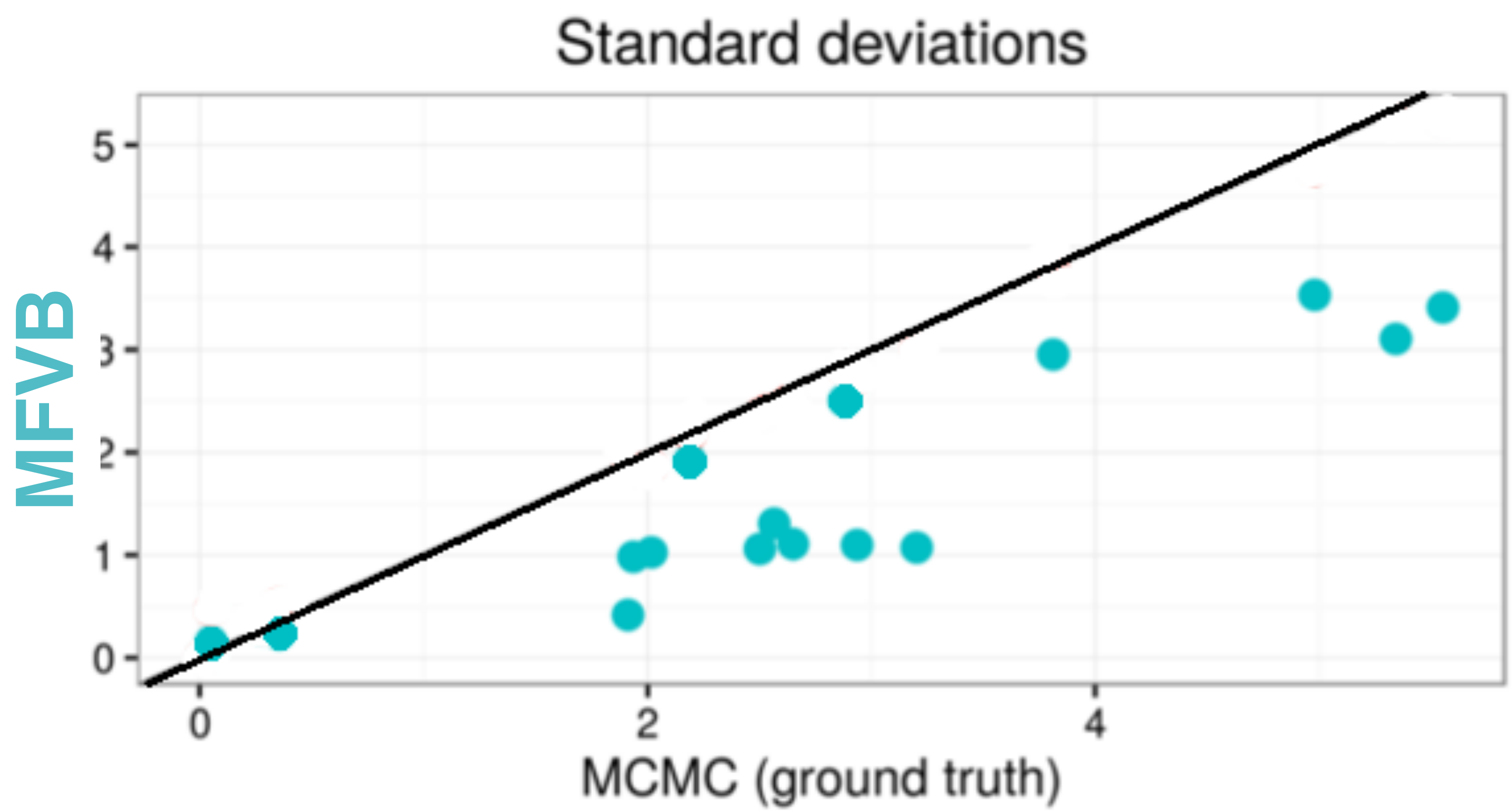

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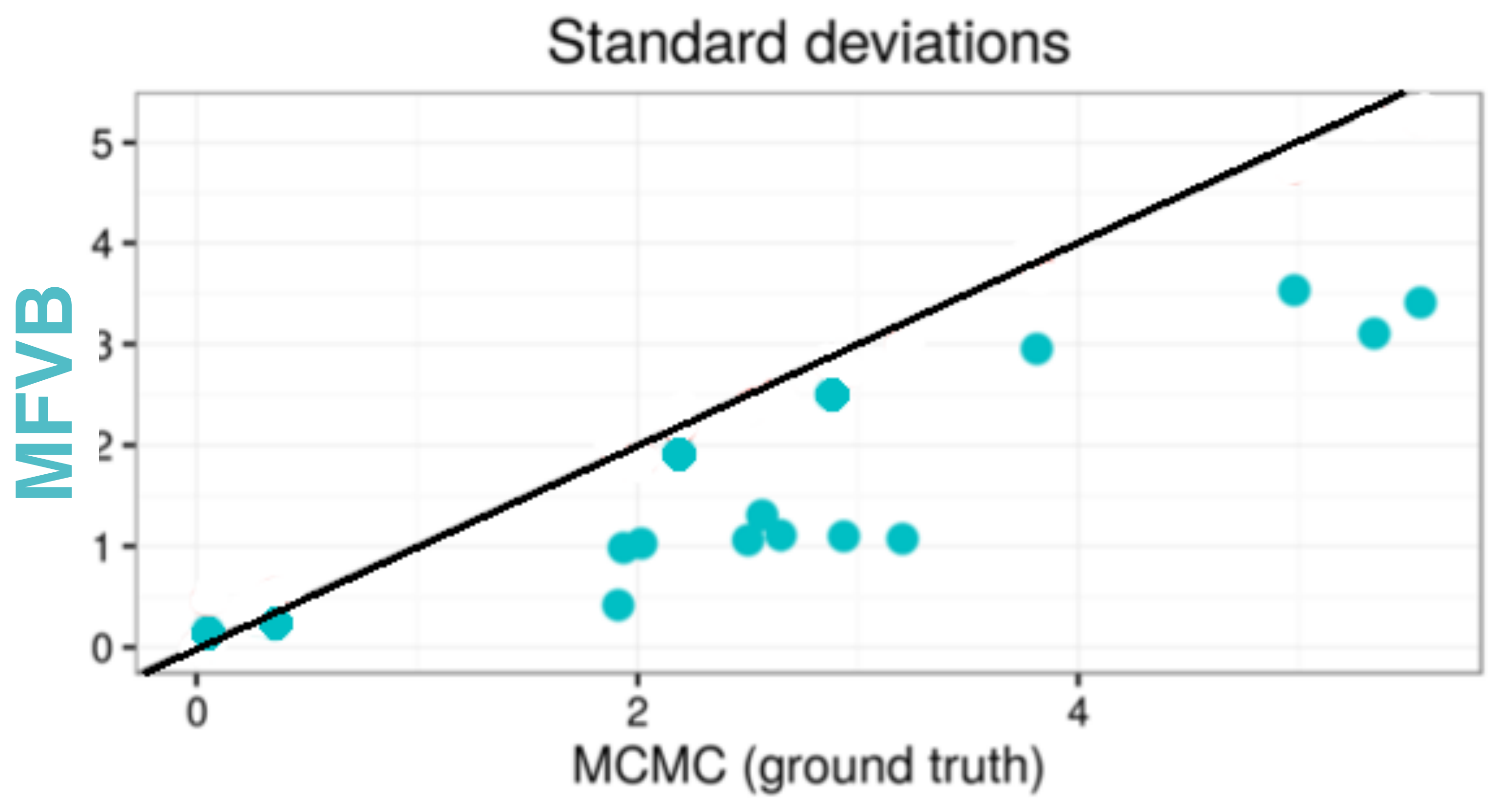
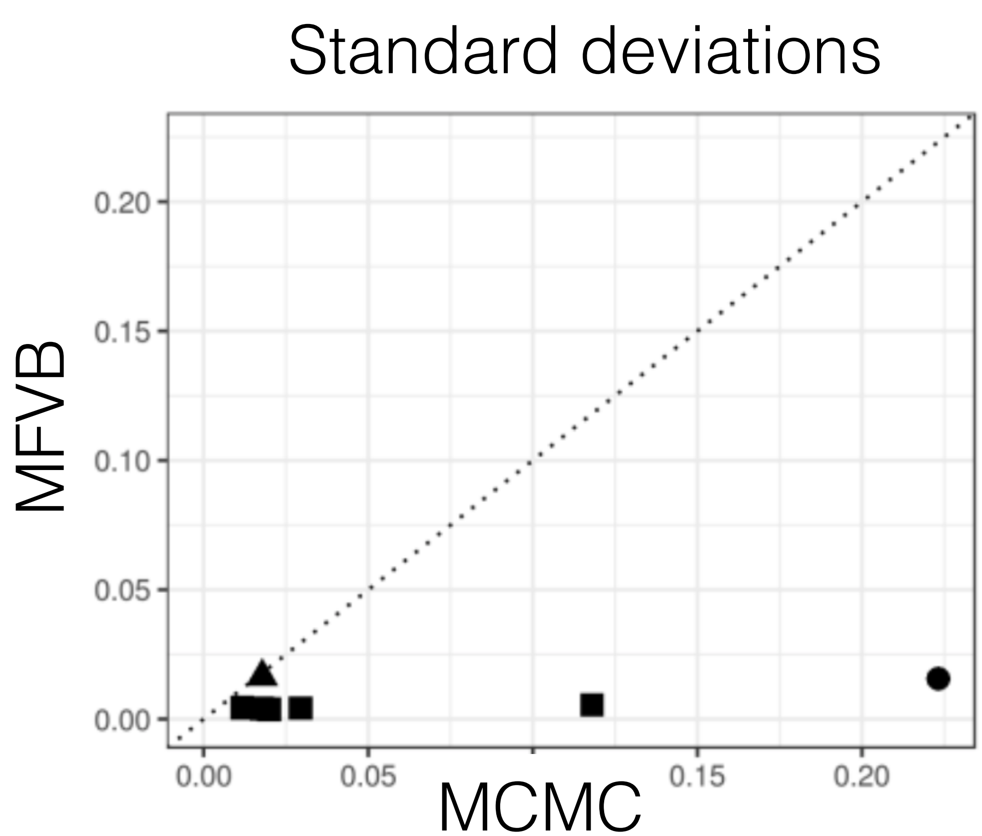


- Criteo online ads experiment



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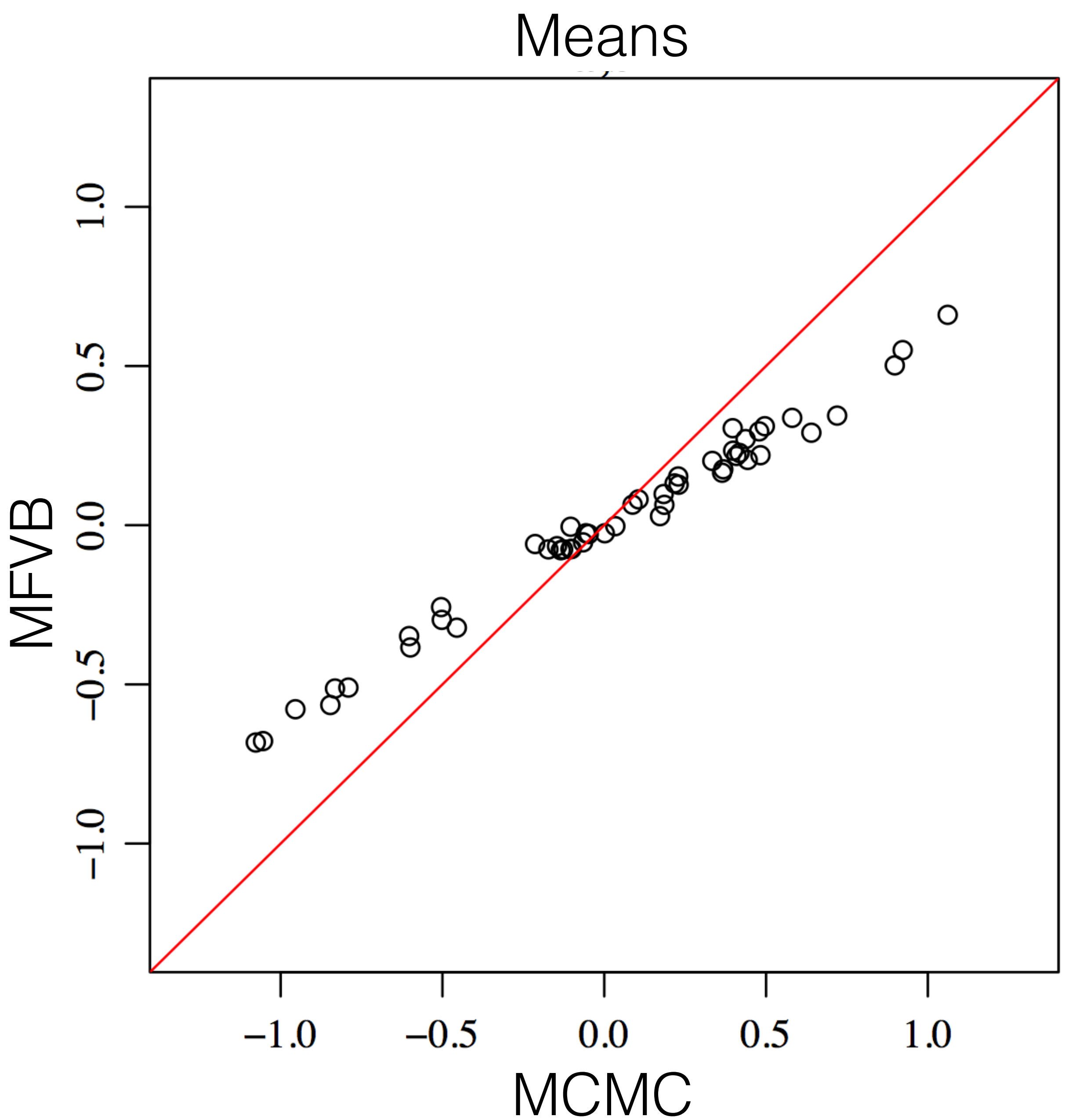

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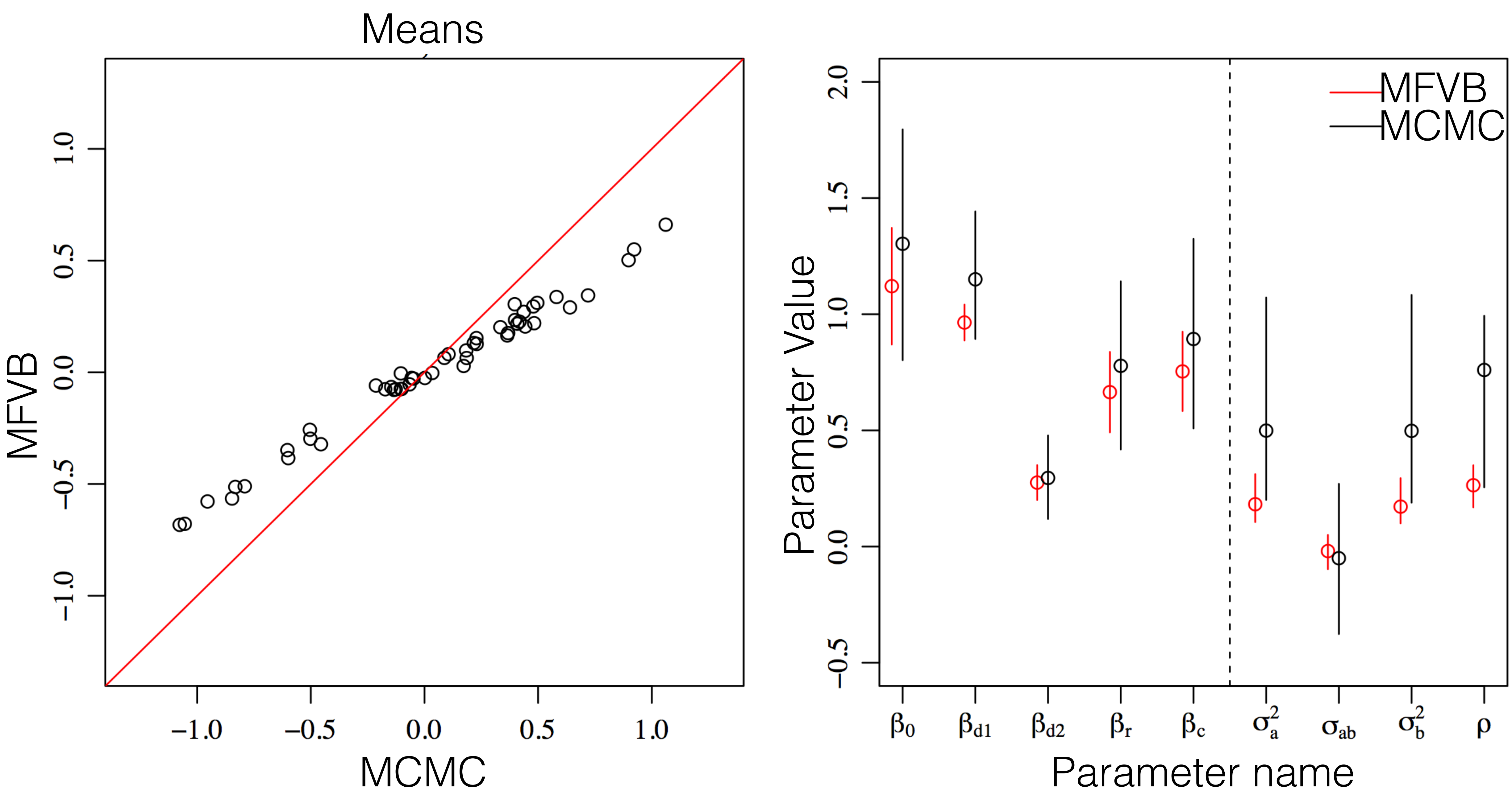

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Posterior means: revisited

- Want to predict college GPA y_n

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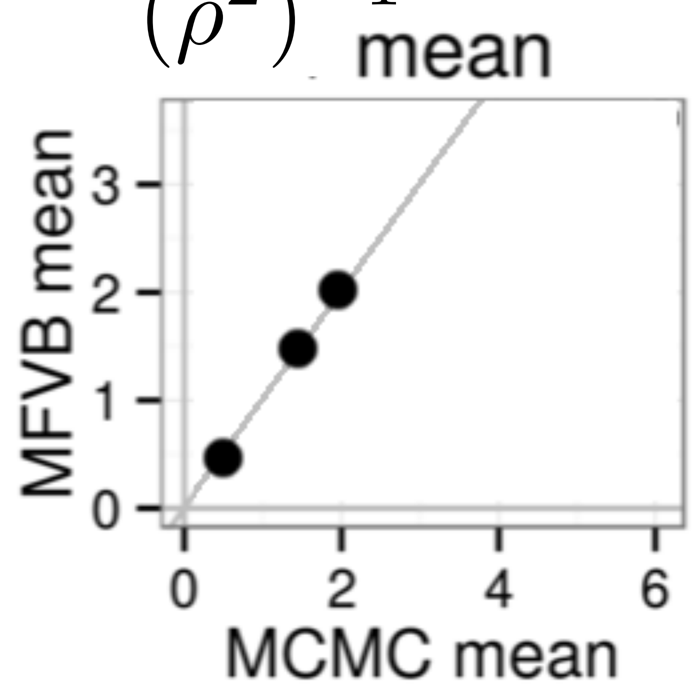

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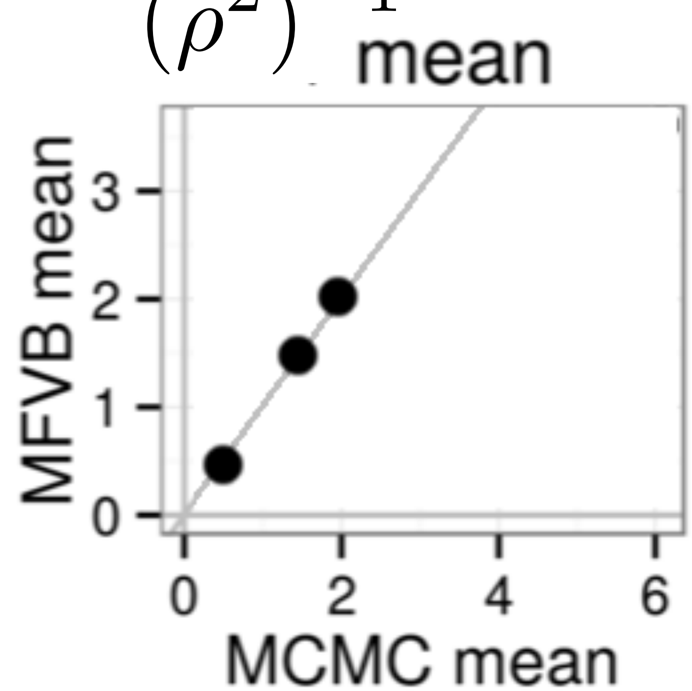

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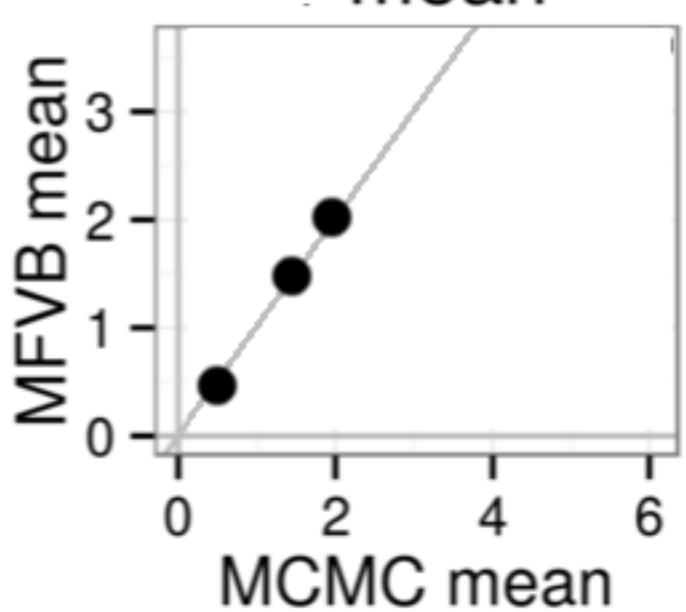

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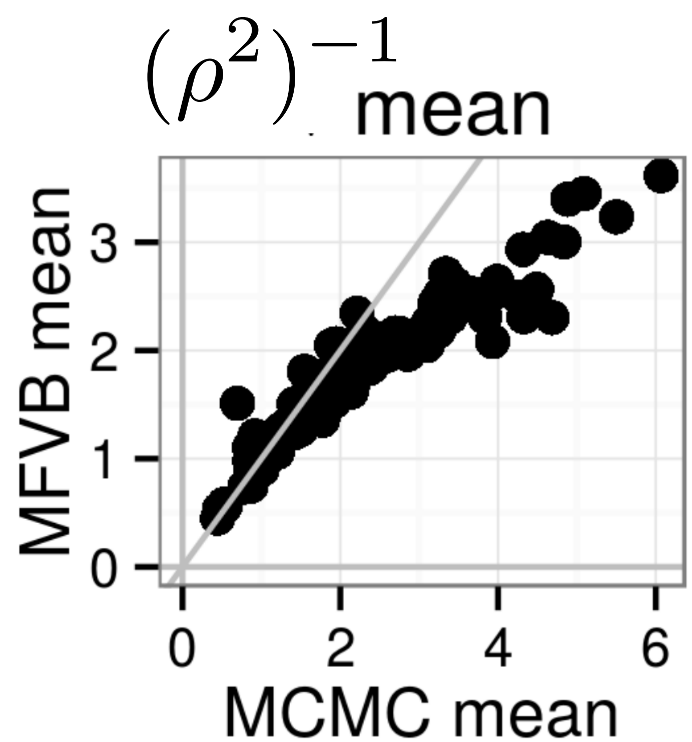

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Approximate Bayesian inference

Use q^* to approximate $p(\cdot|y)$

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$$q^* = \operatorname{argmin}_{q \in Q} f(q(\cdot), p(\cdot|y))$$

Variational Bayes

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Mean-field variational Bayes

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- Coordinate descent
- Stochastic variational inference (SVI) [Hoffman et al 2013]
- Automatic differentiation variational inference (ADVI) [Kucukelbir et al 2015, 2017]

How deep is the issue?

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Algorithm

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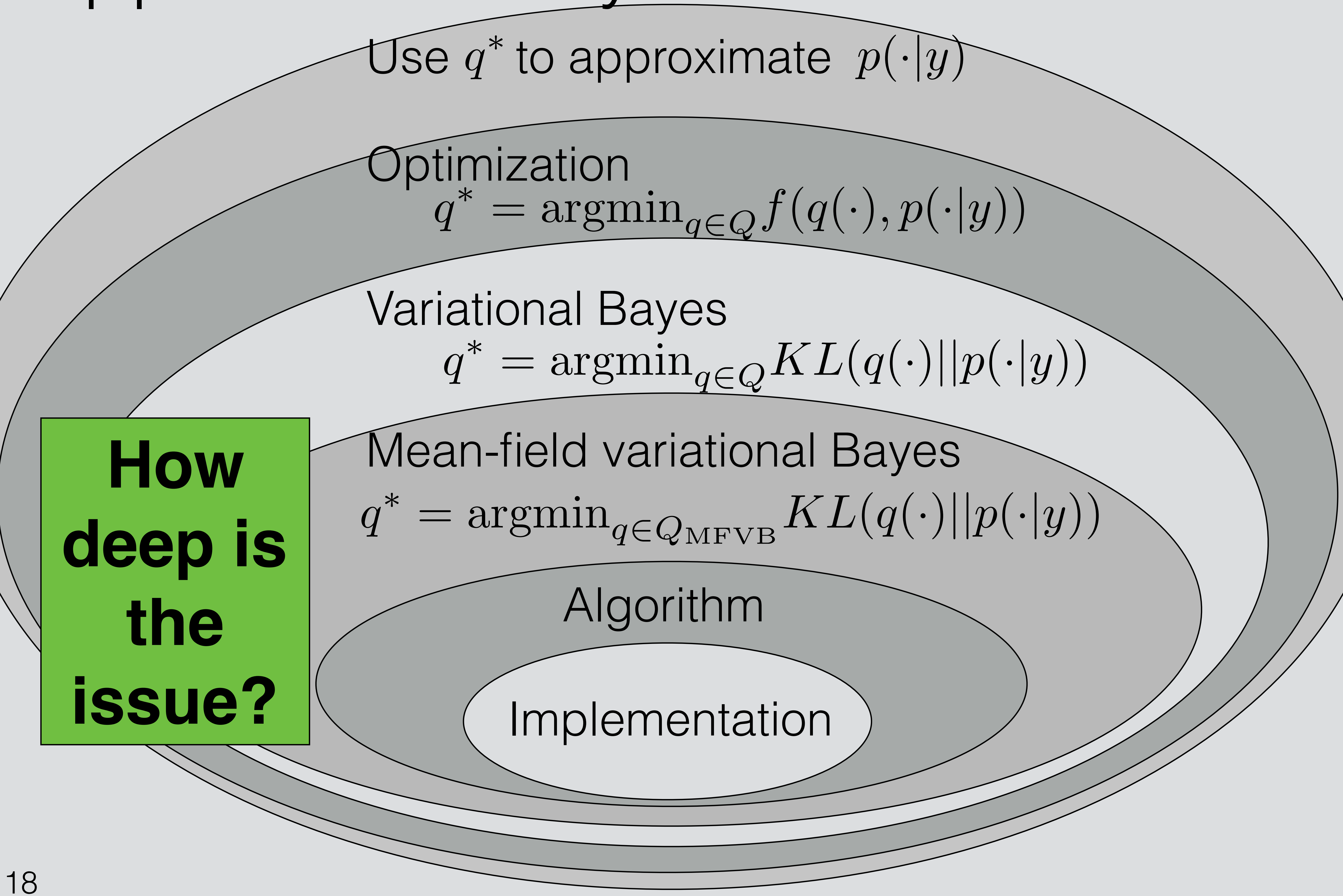

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Use q^* to approximate $p(\cdot|y)$

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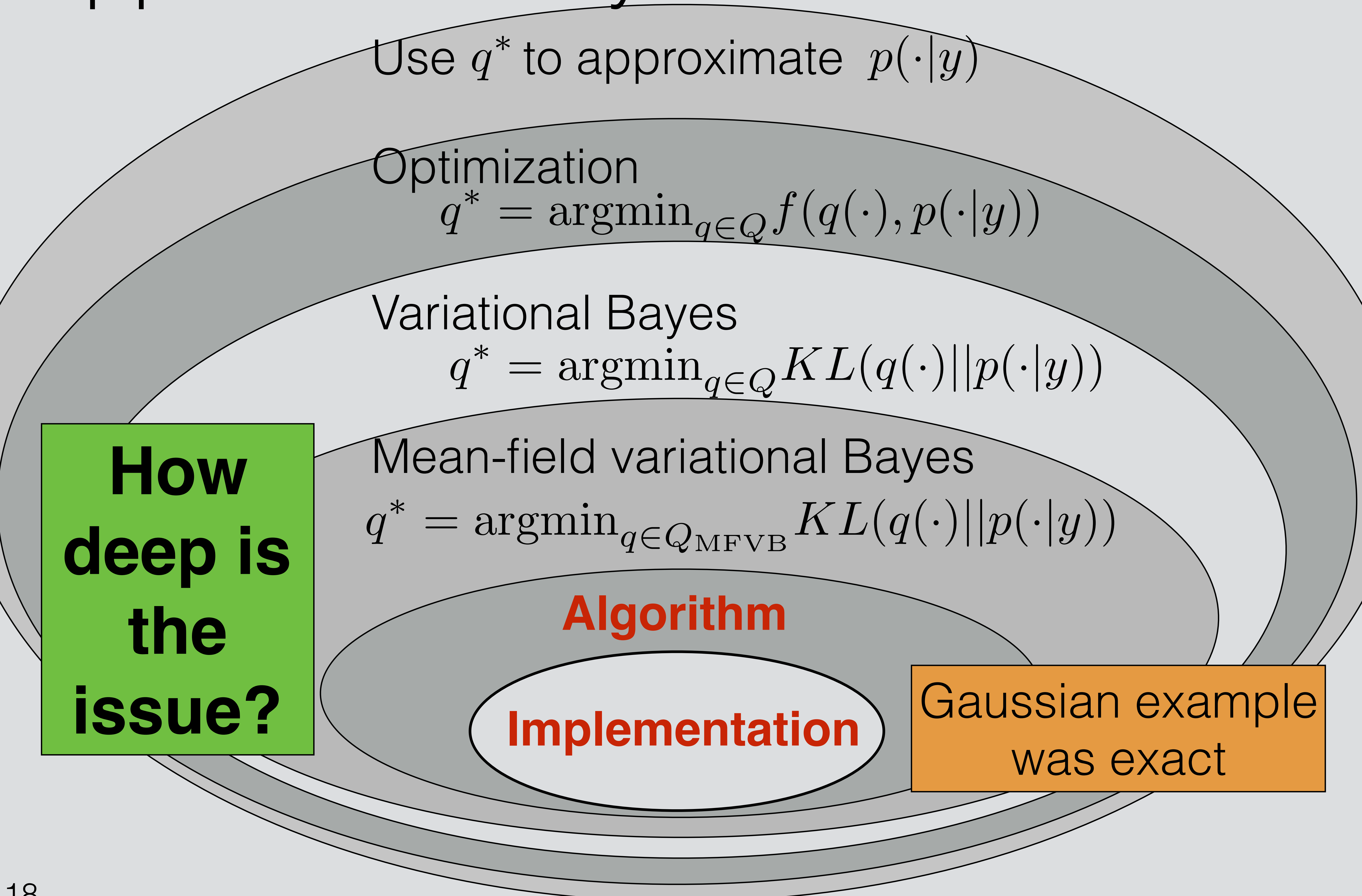

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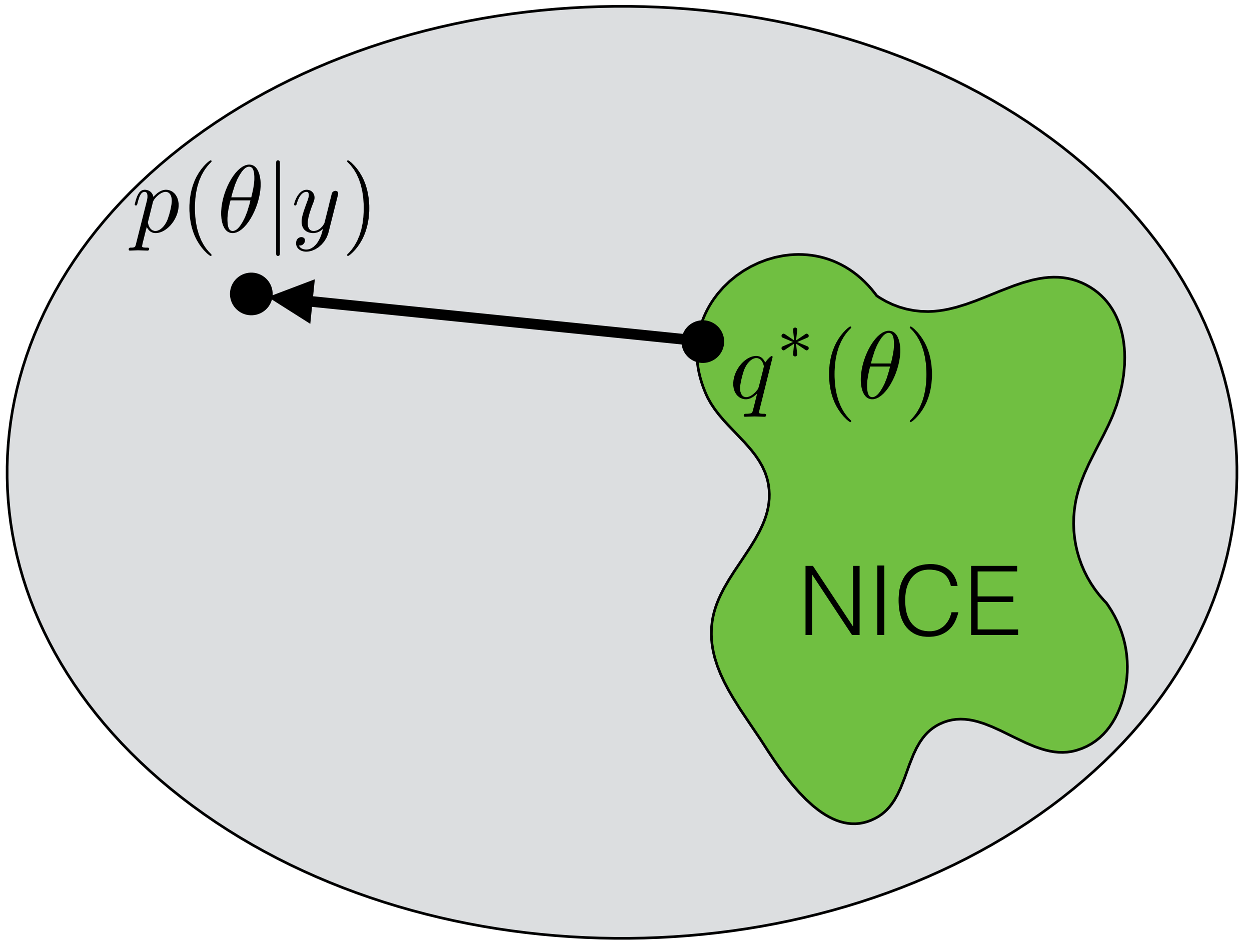

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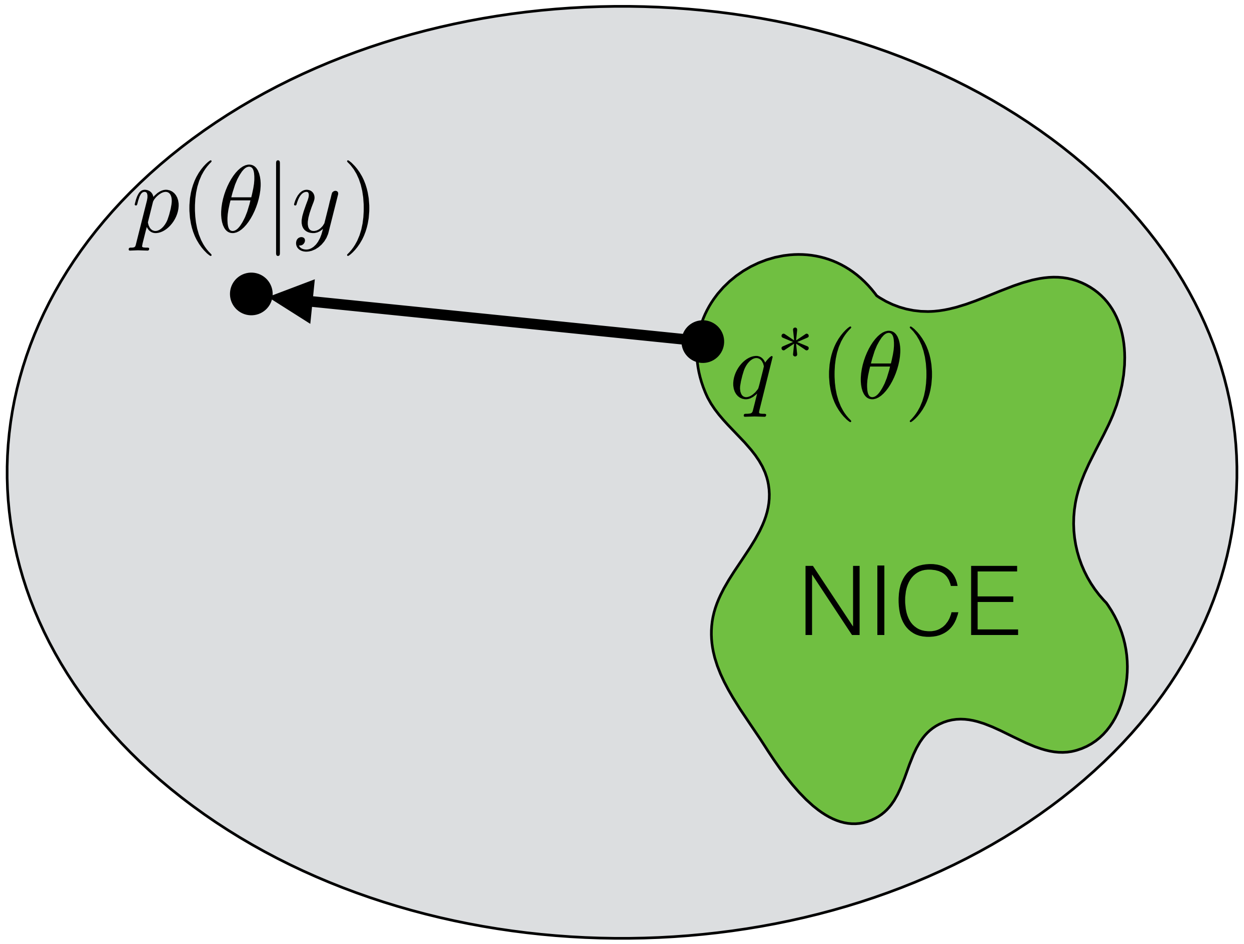

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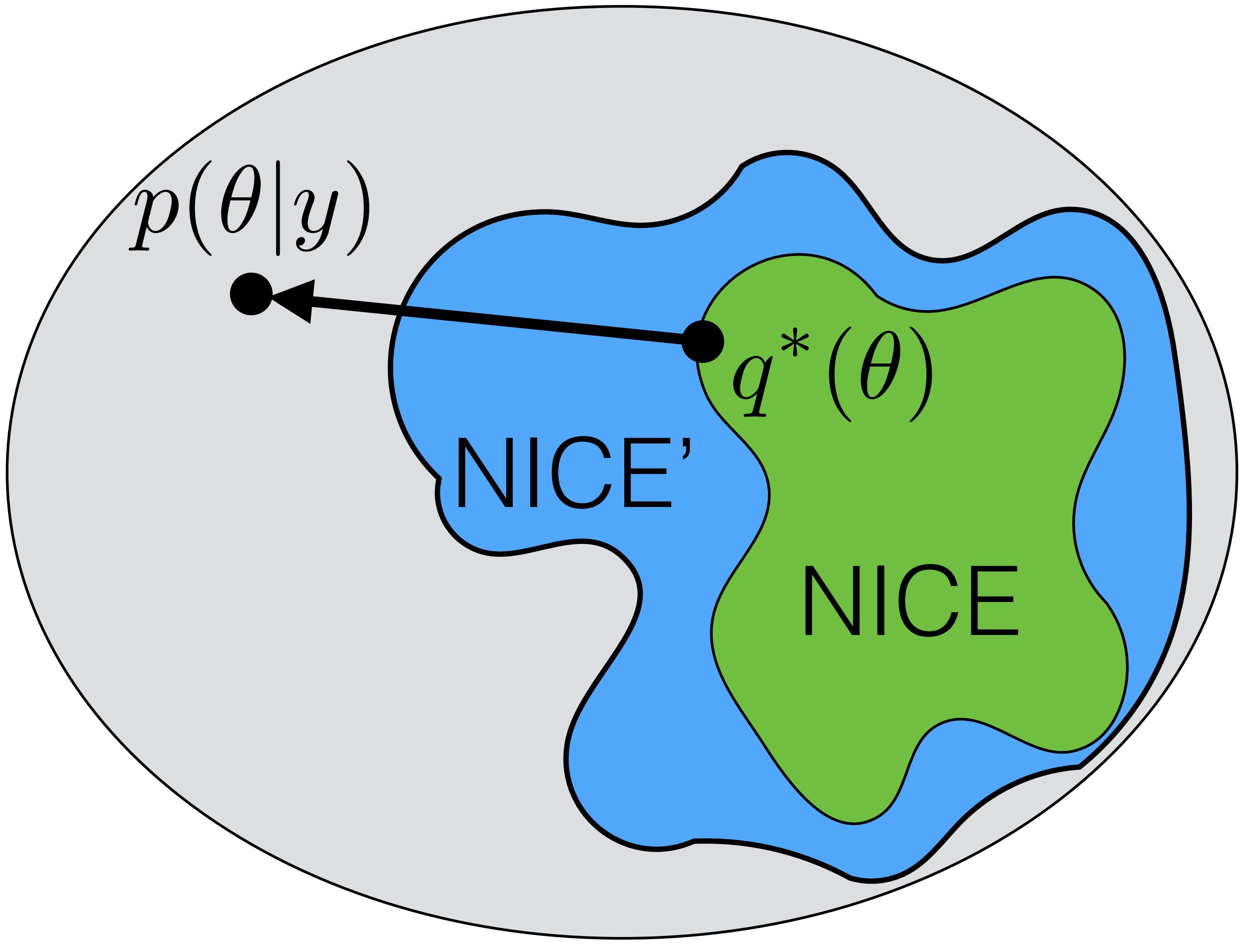

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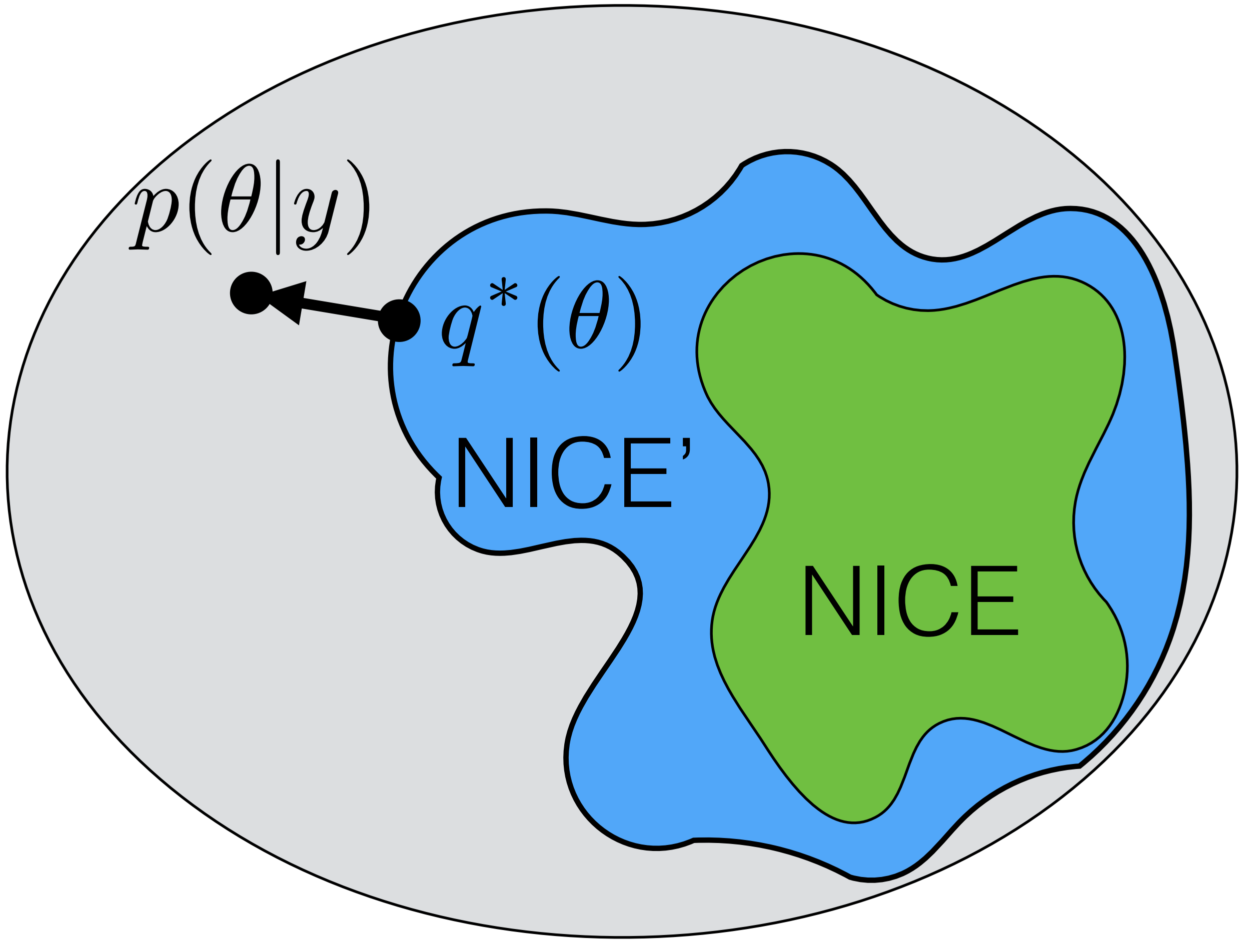

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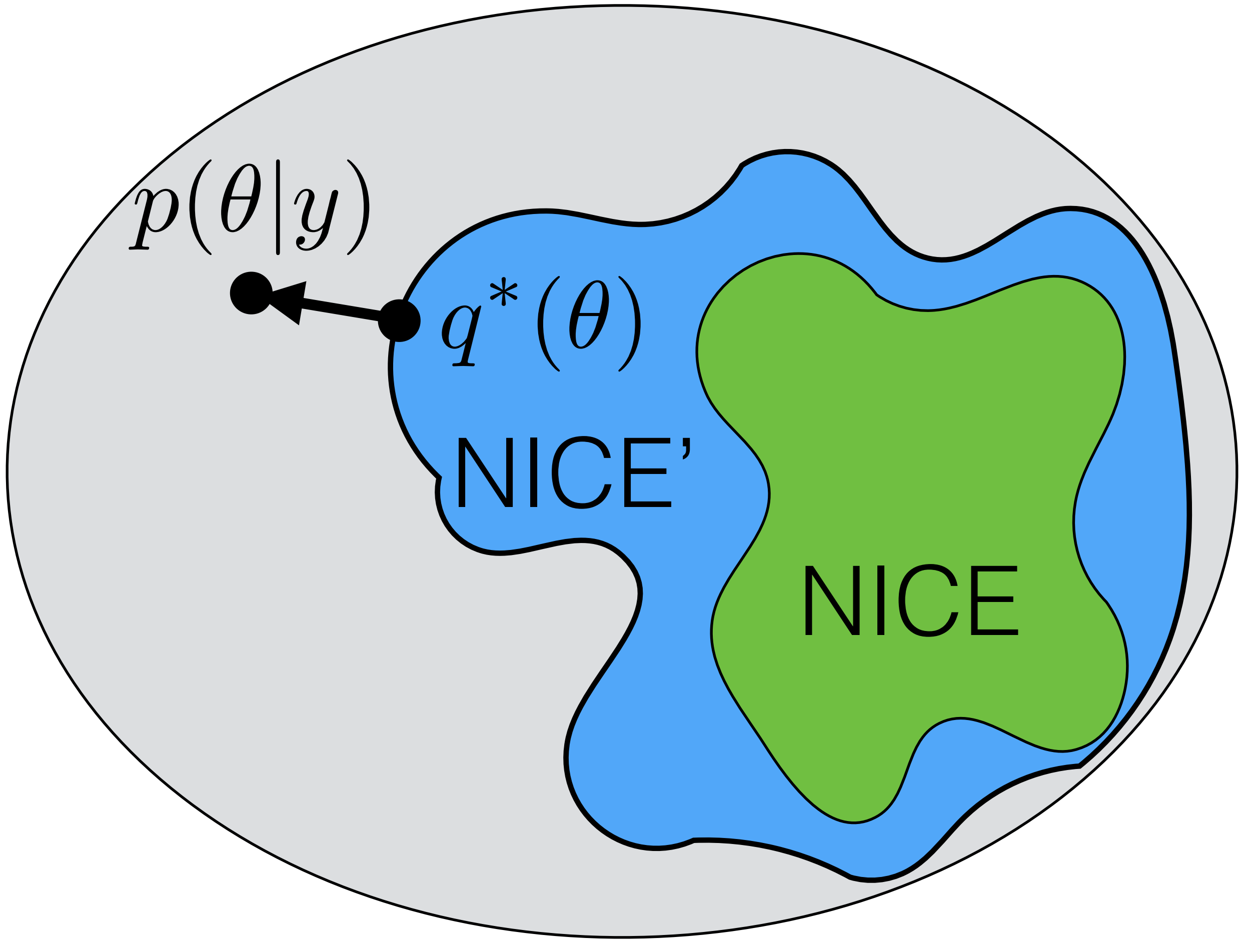

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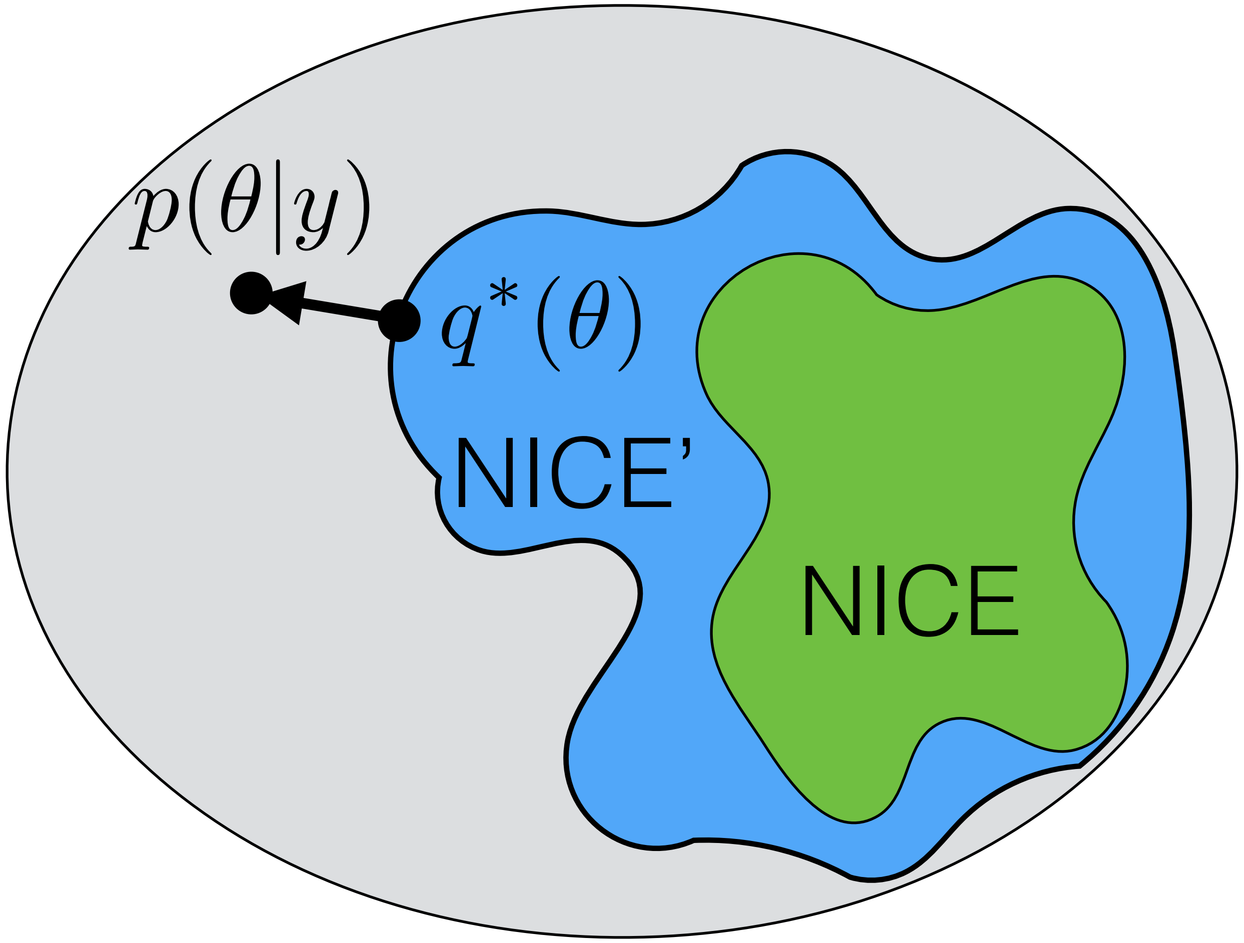

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- But how much worse can the estimates be? And could it have just been the implementation?

[Baqué et al 2017; Huggins, Karsprzak, Campbell, Broderick 2019]

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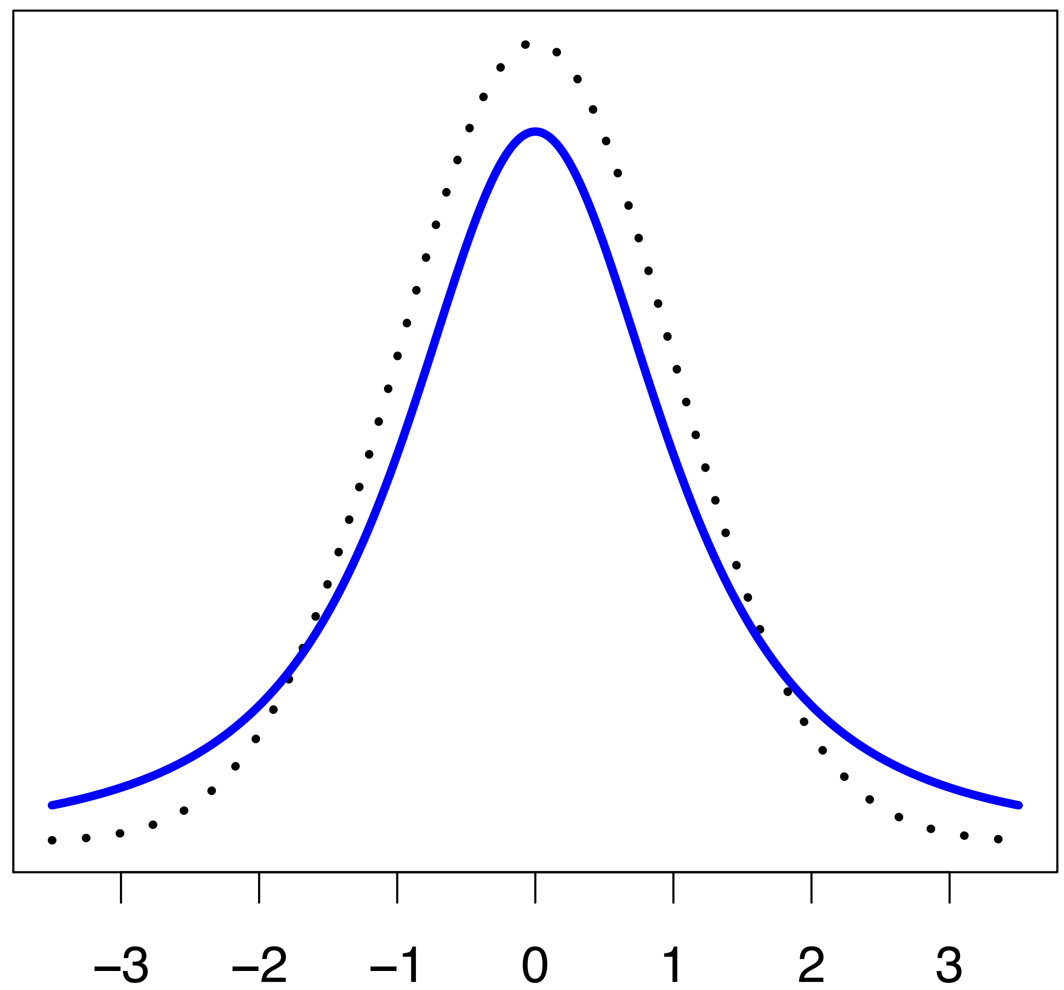

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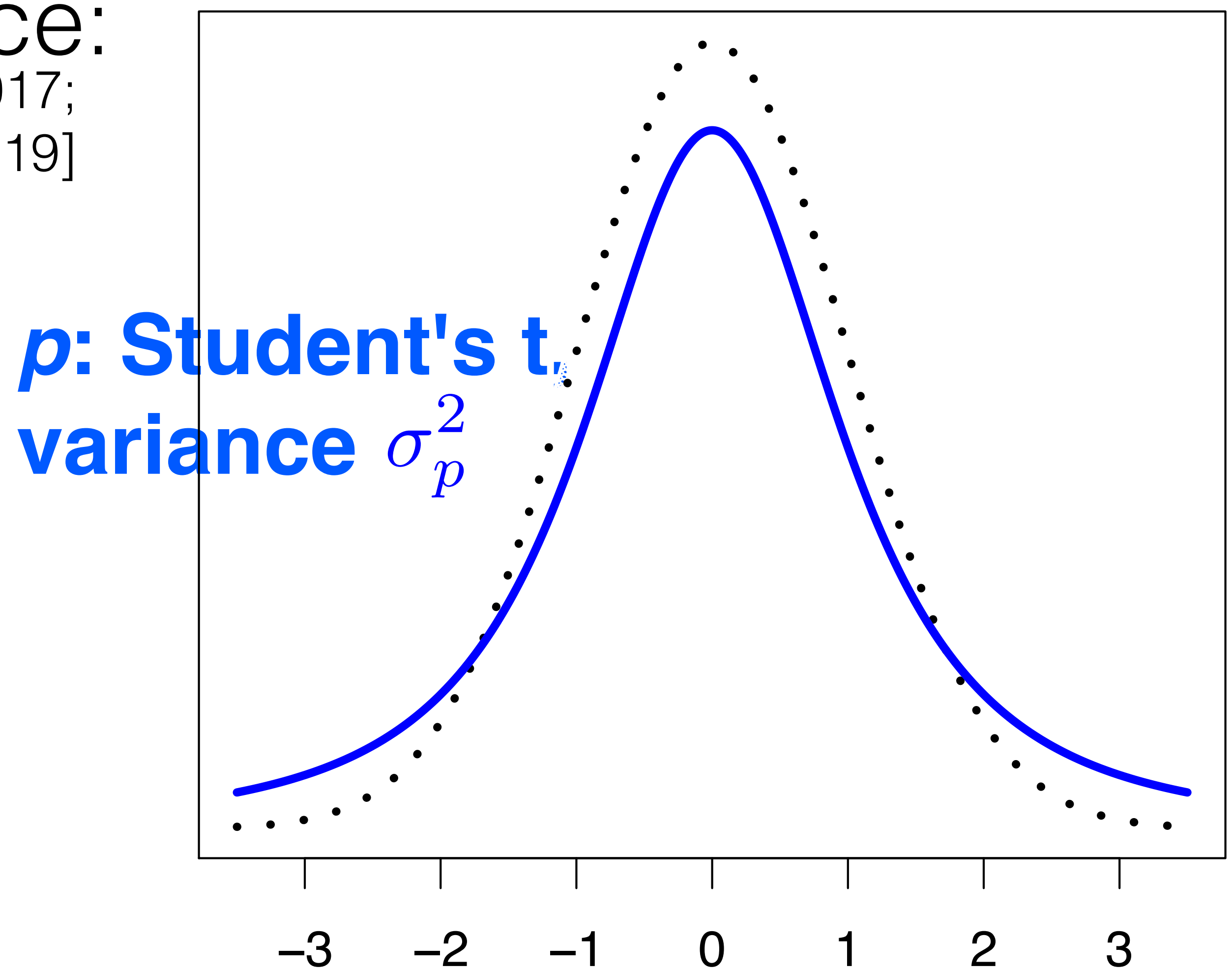

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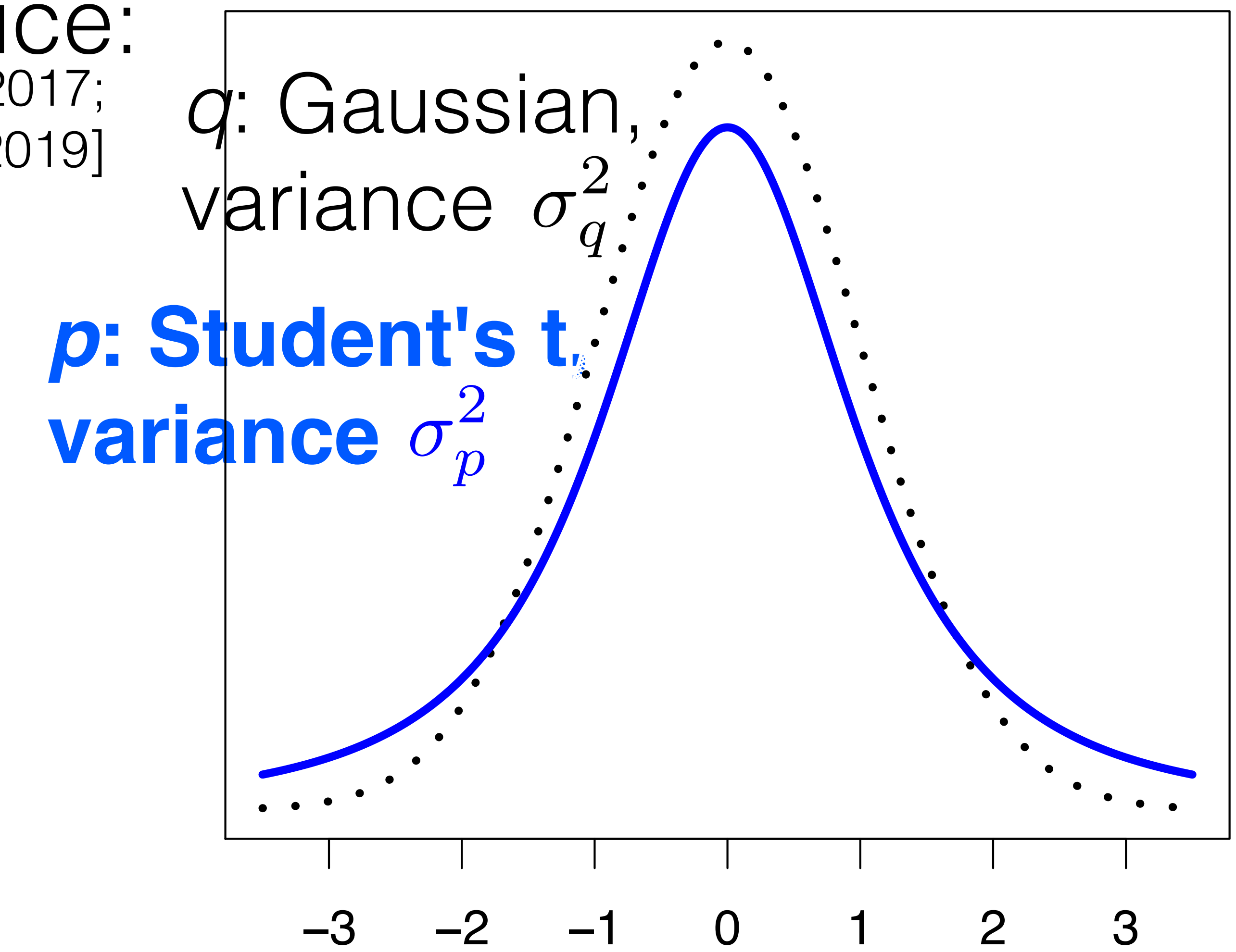

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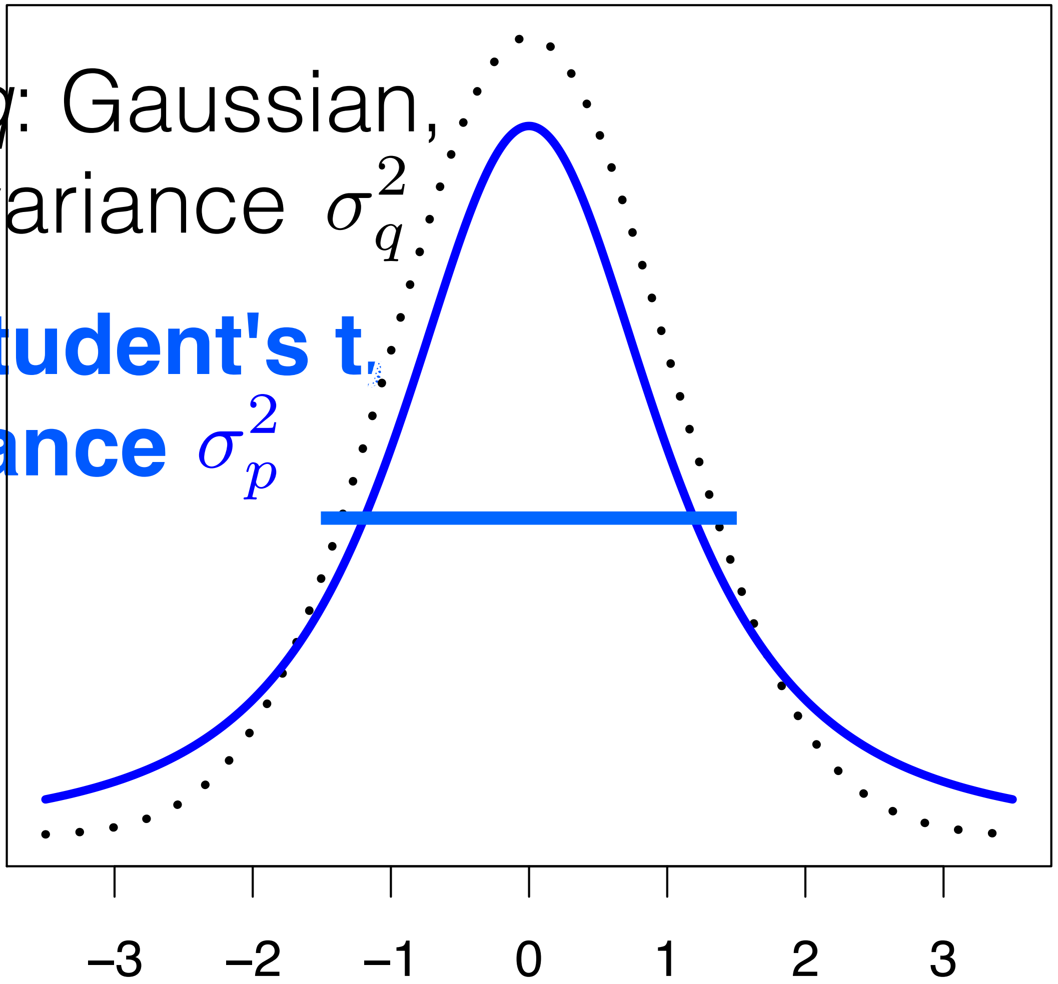

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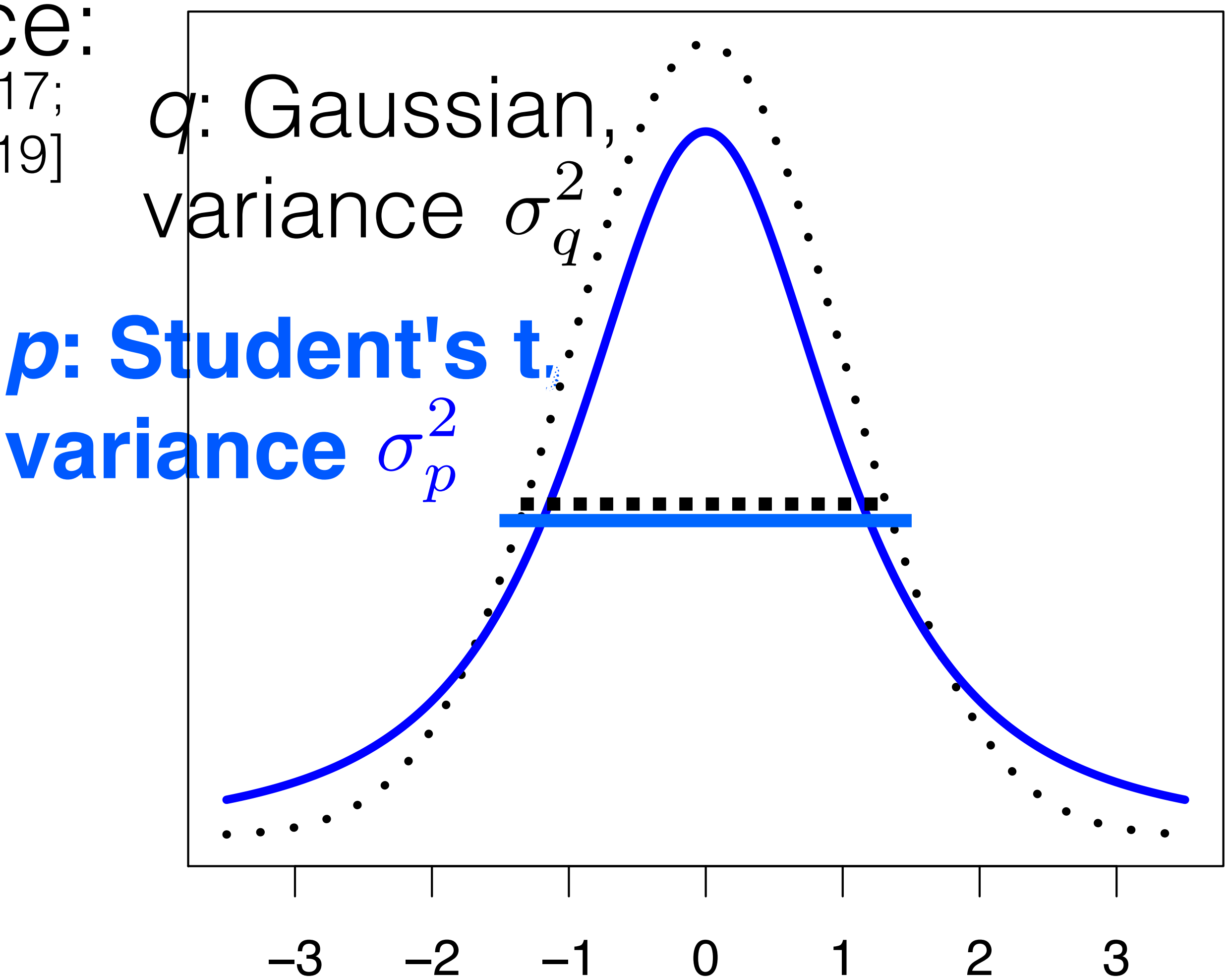

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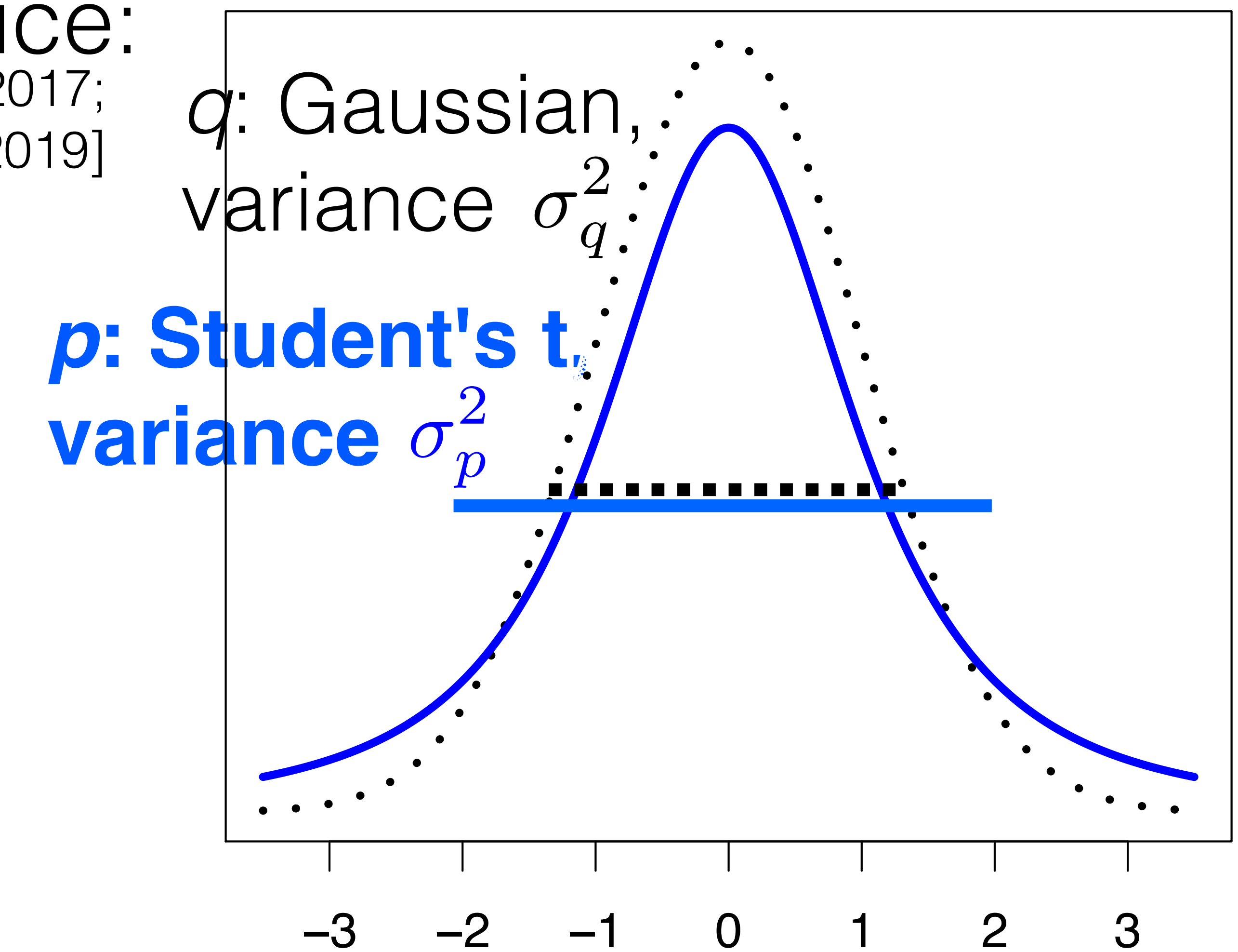

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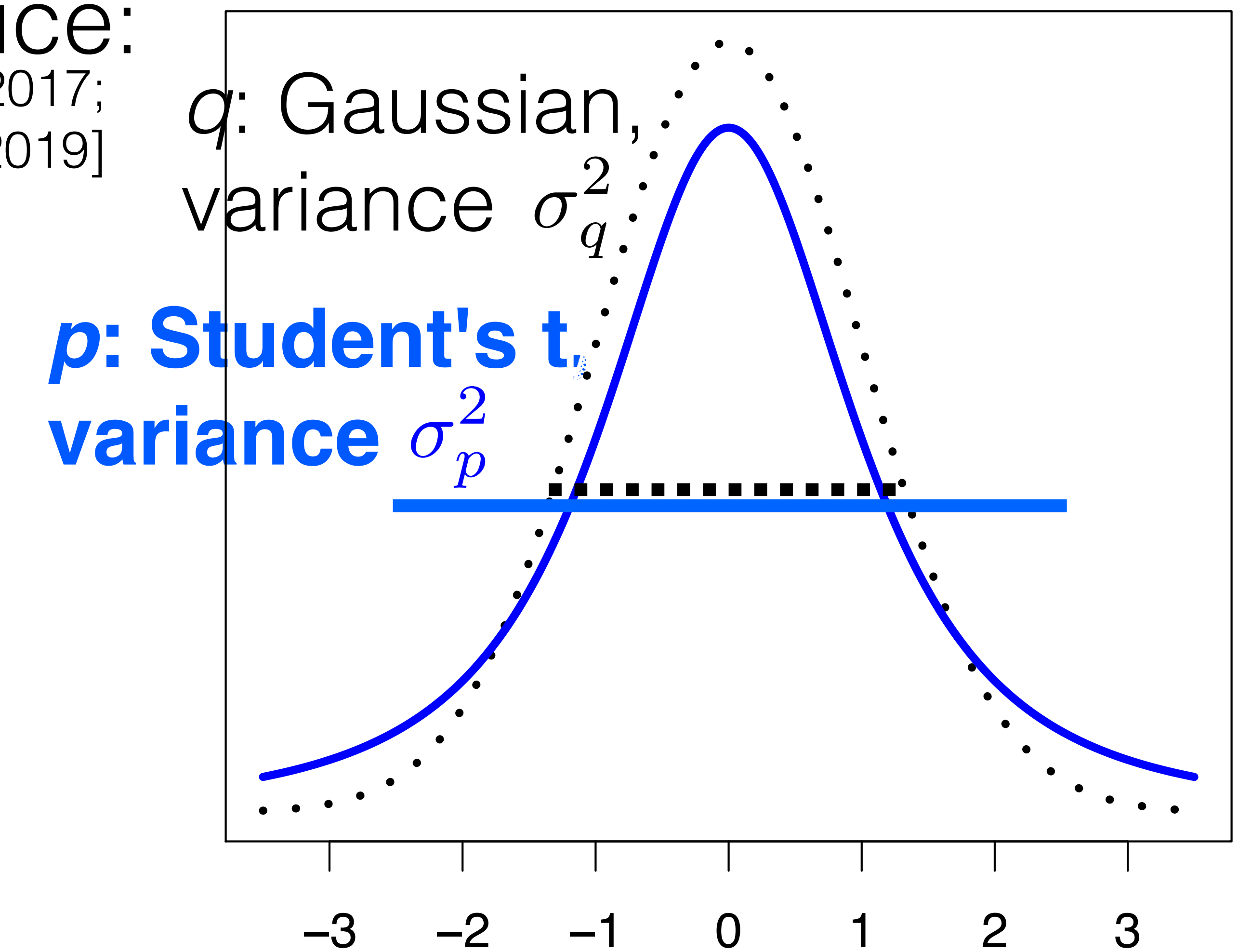

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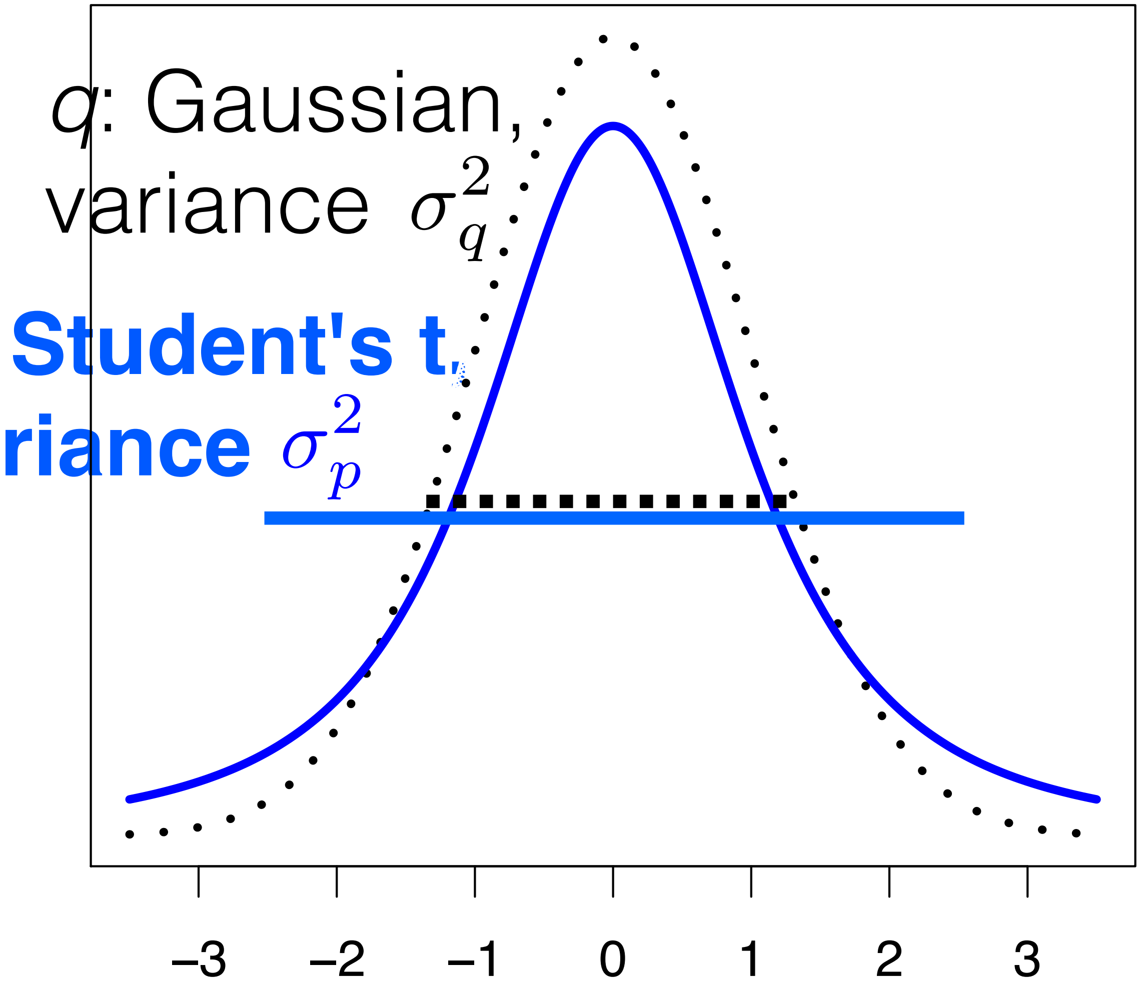

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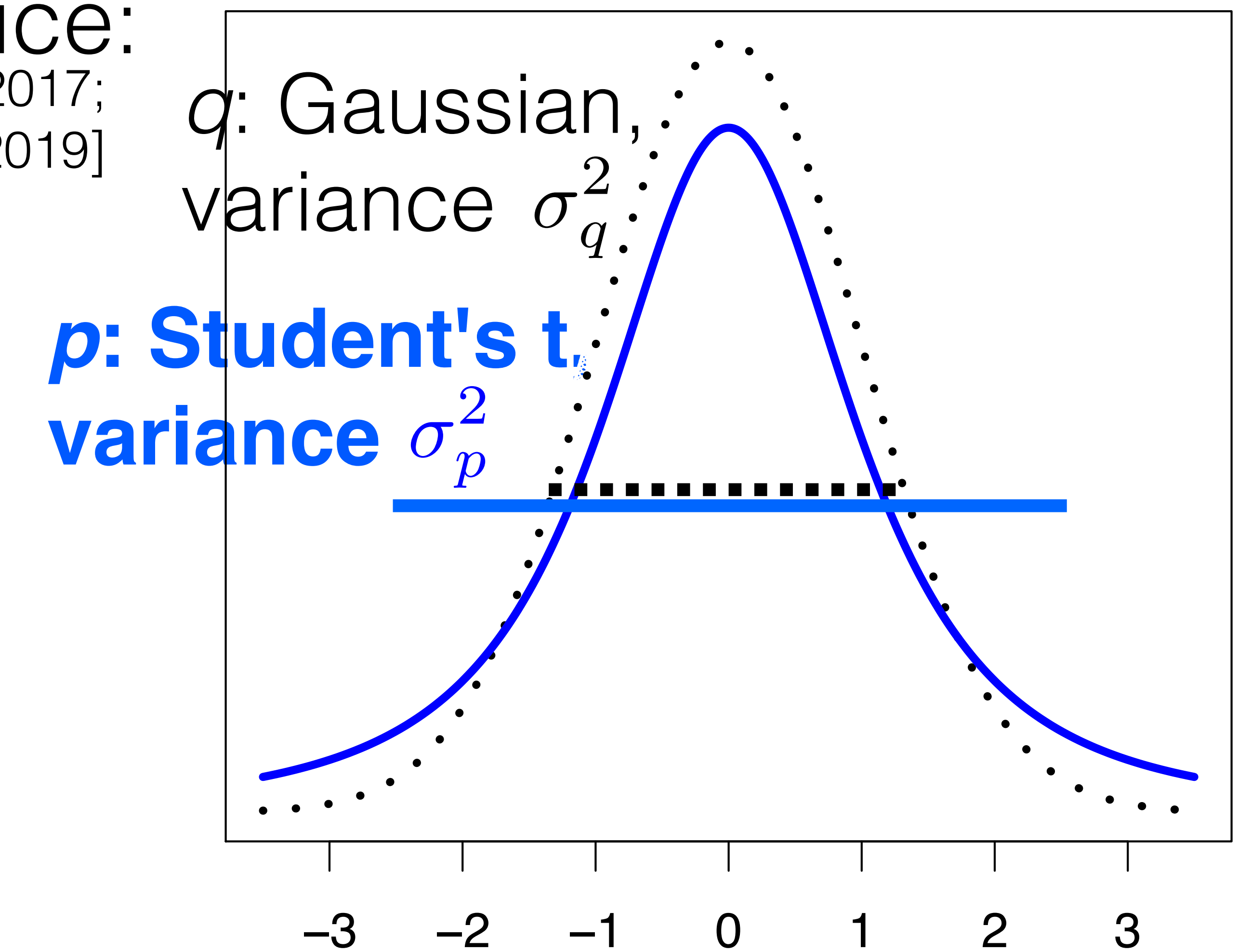

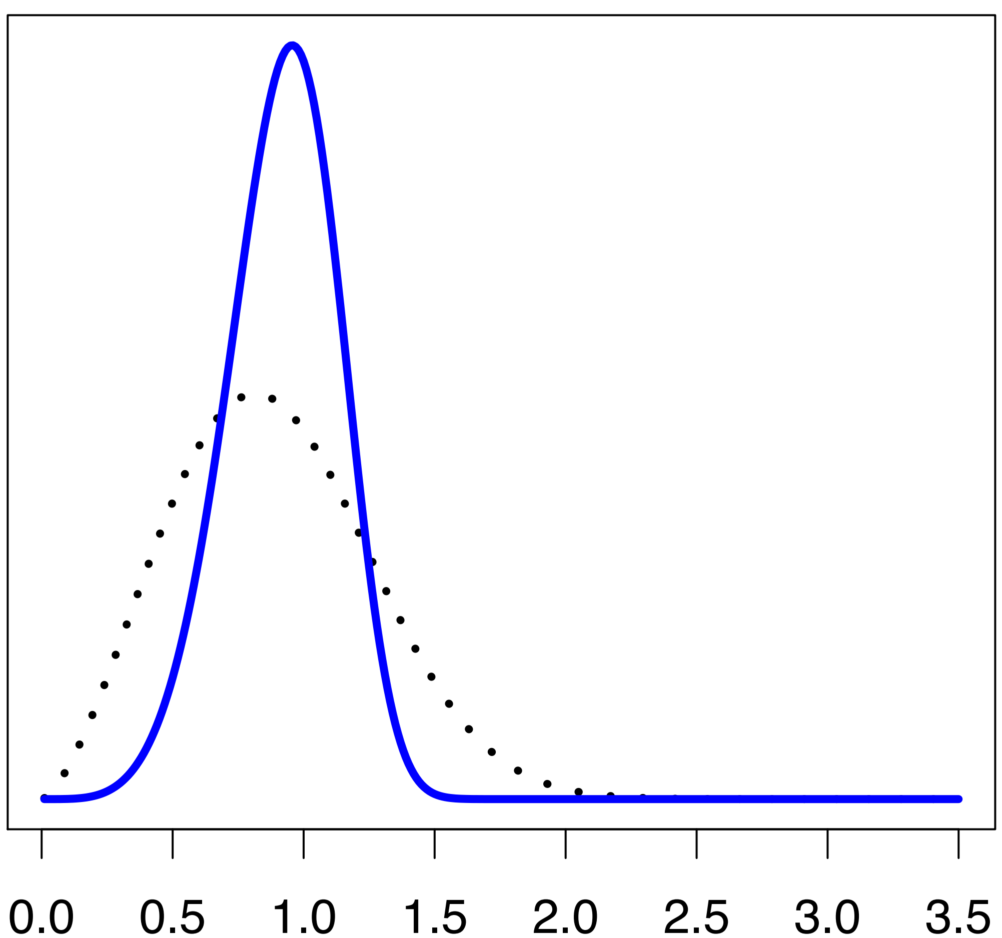

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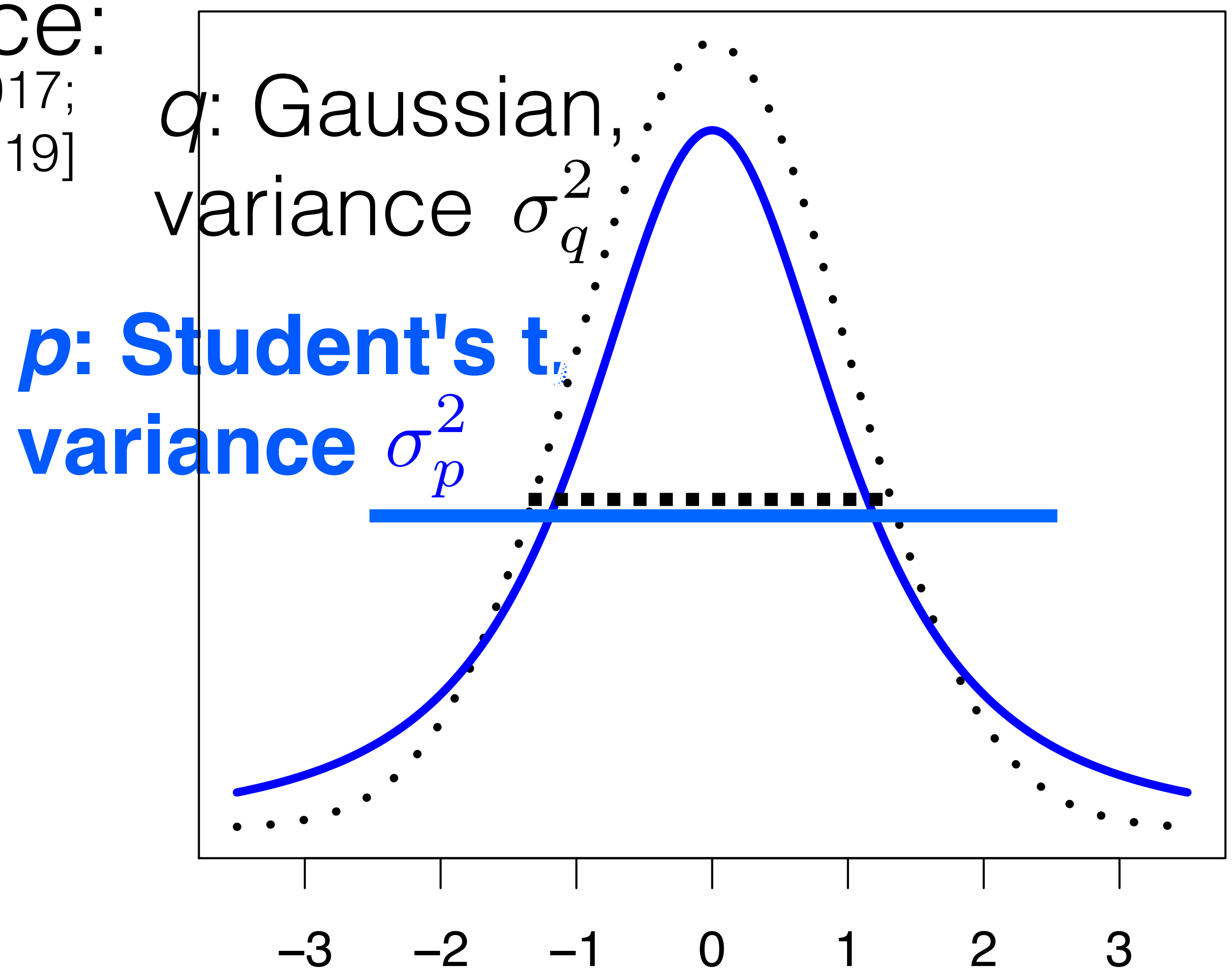

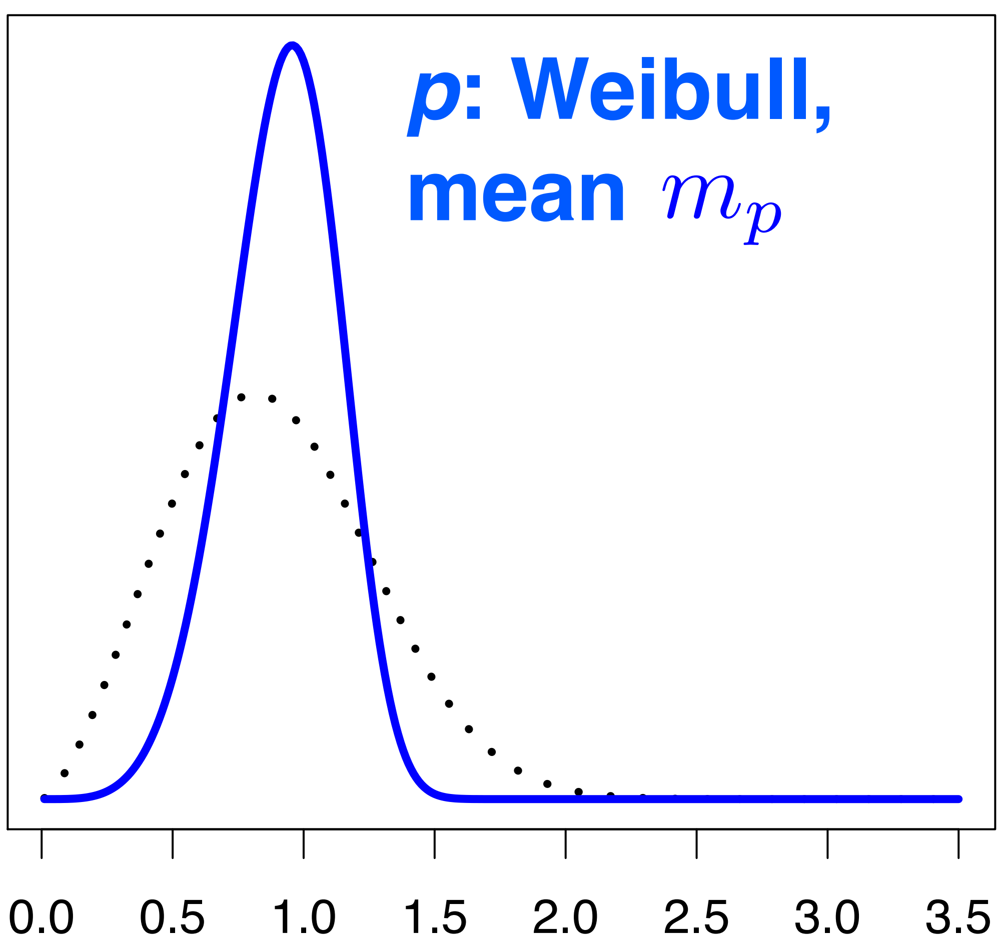

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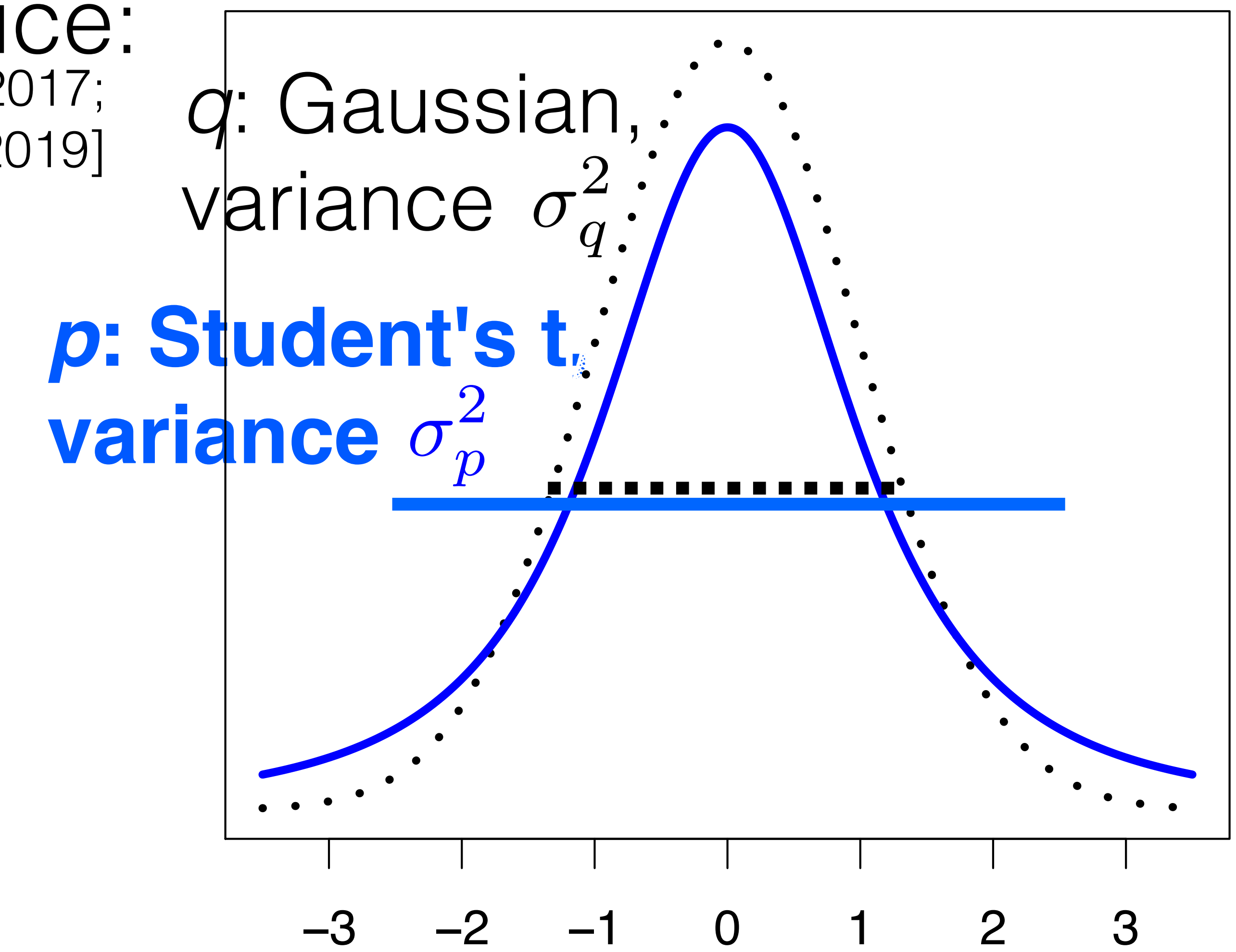

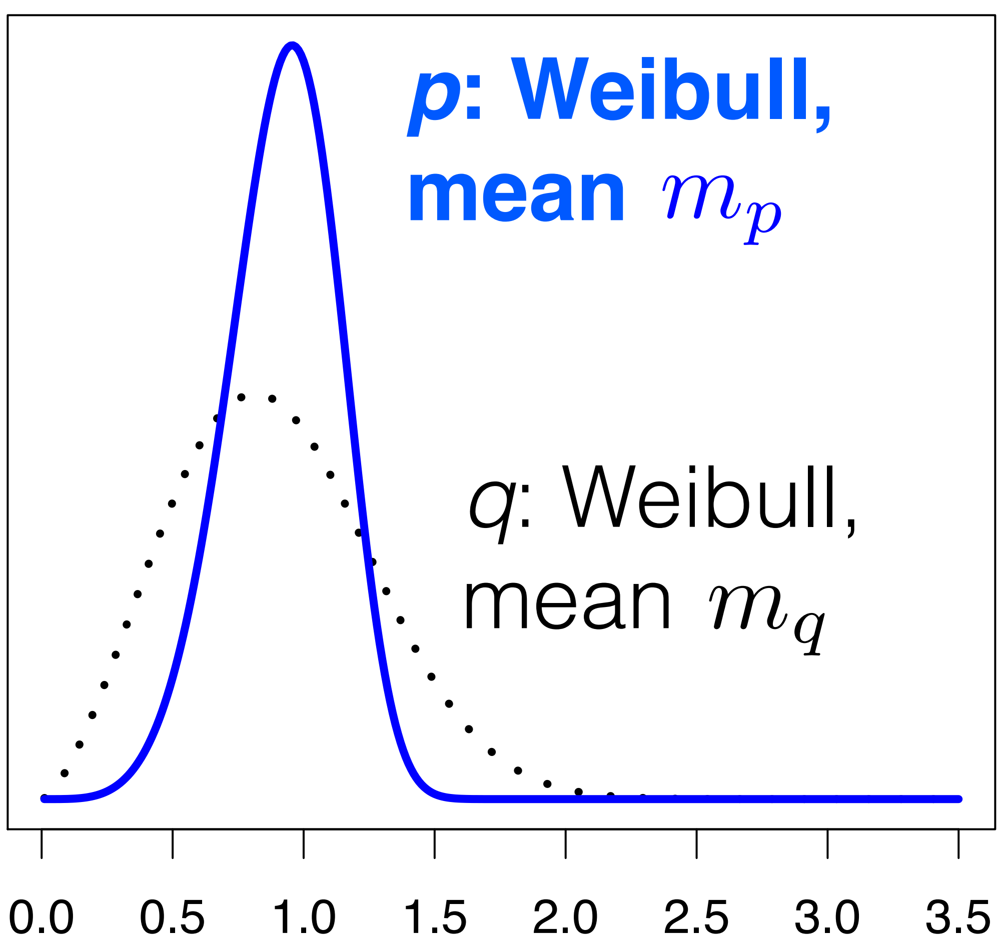

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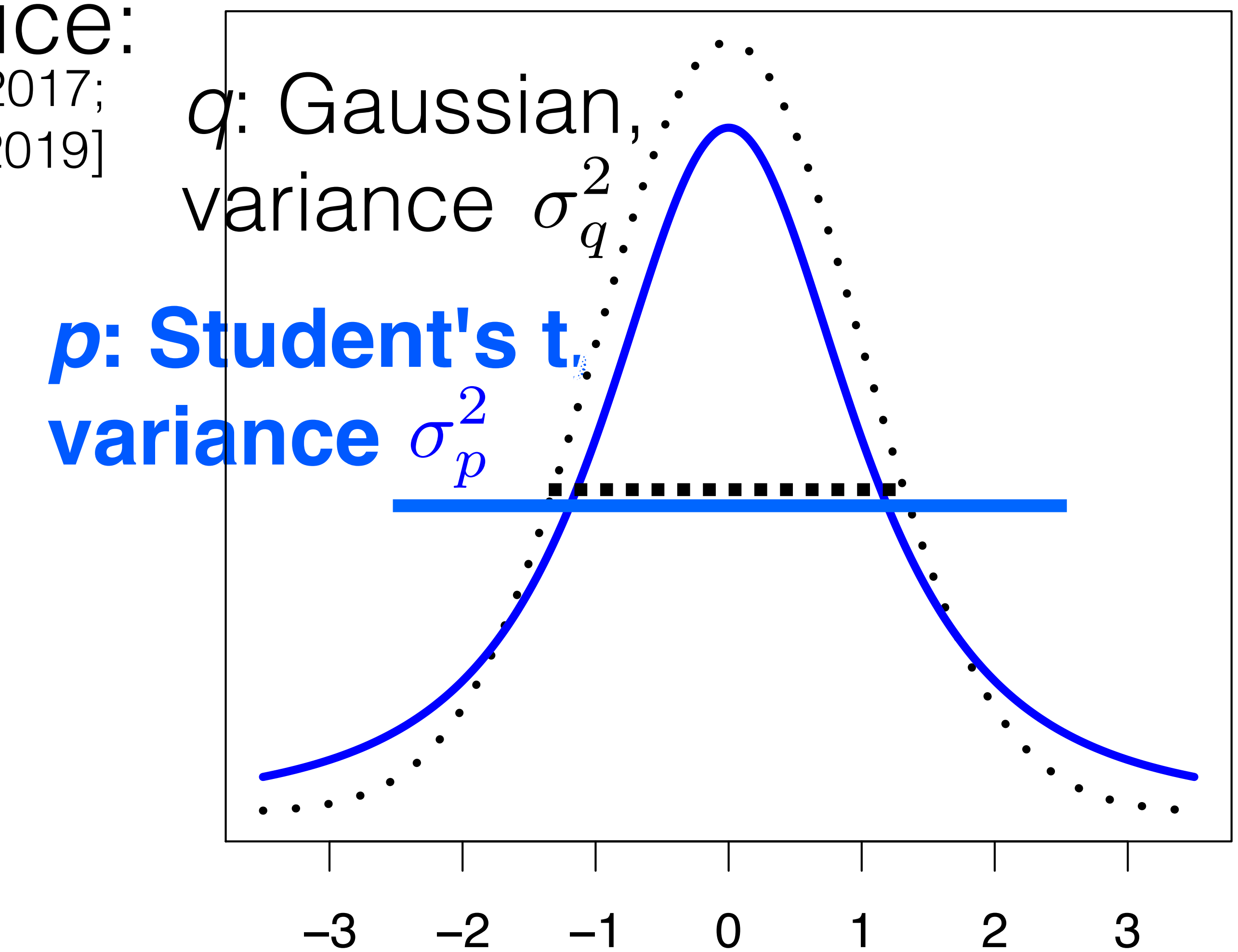

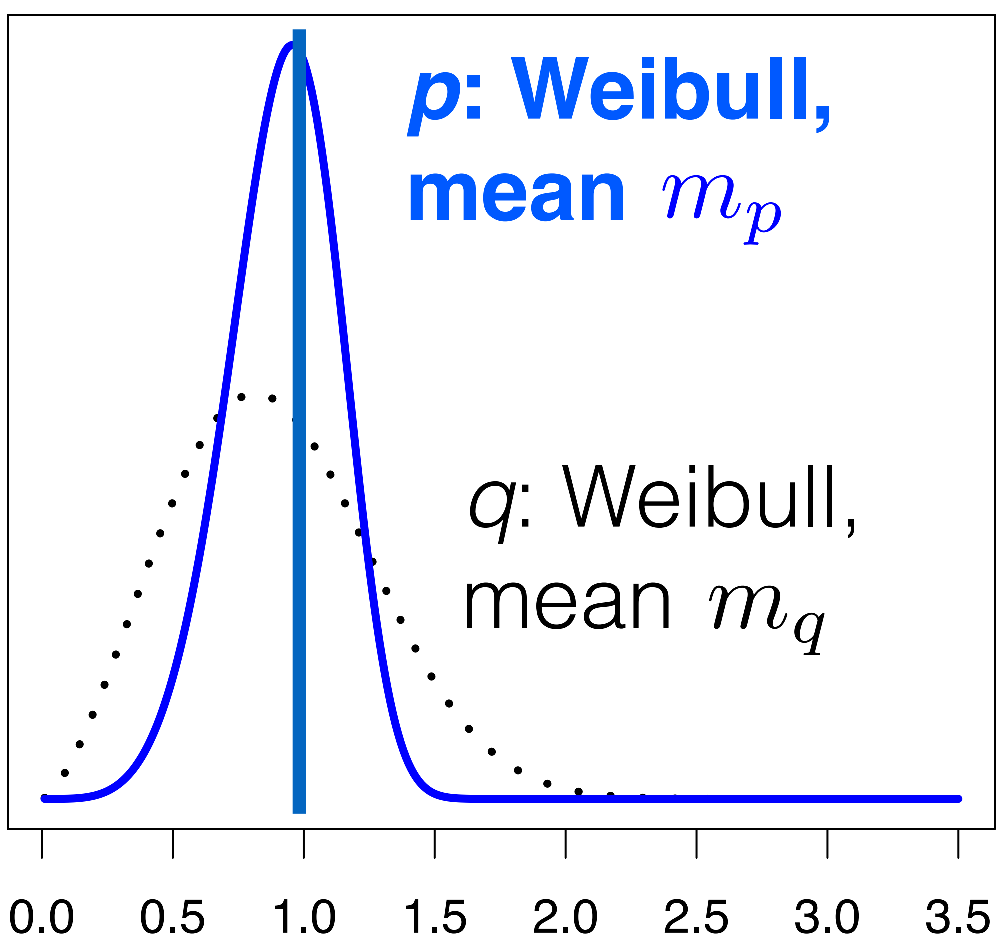

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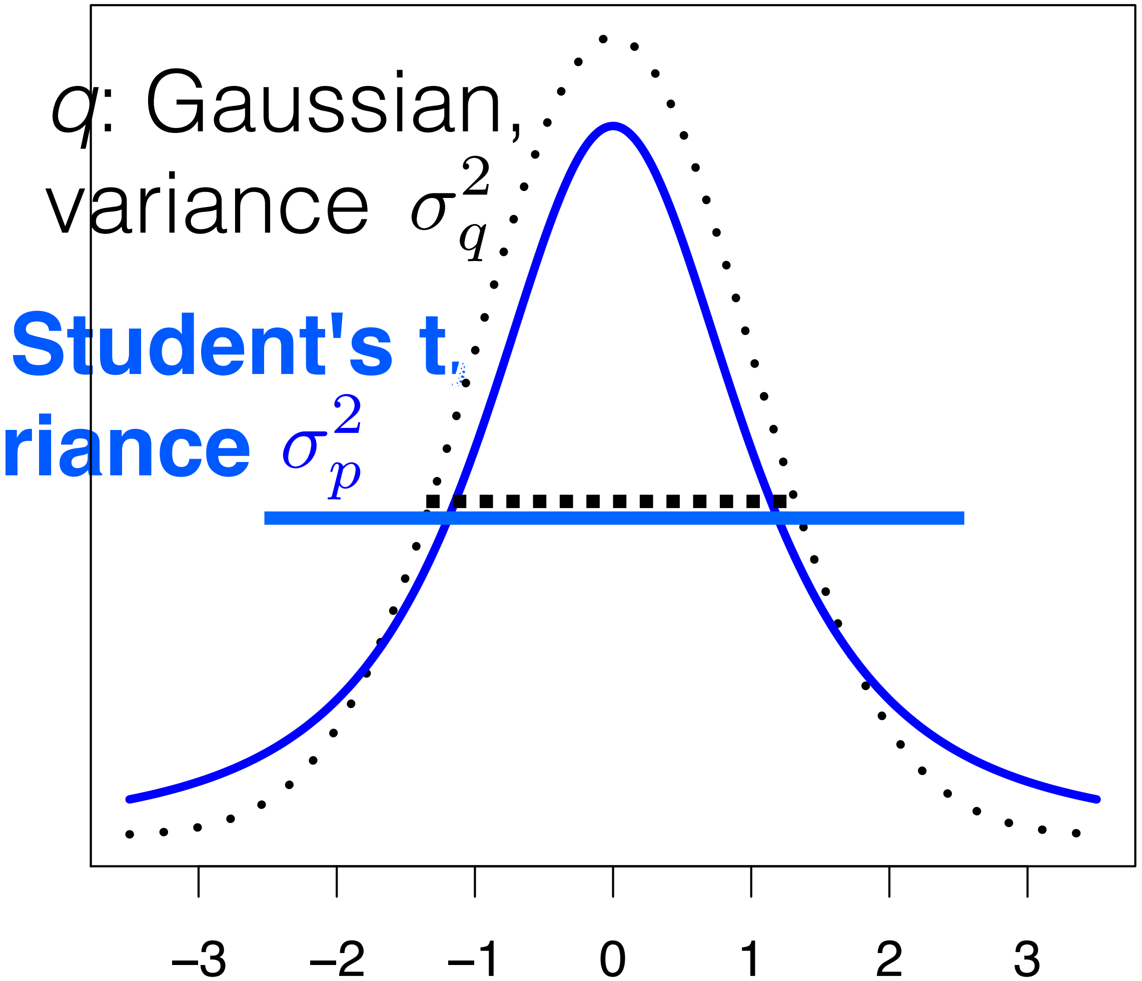

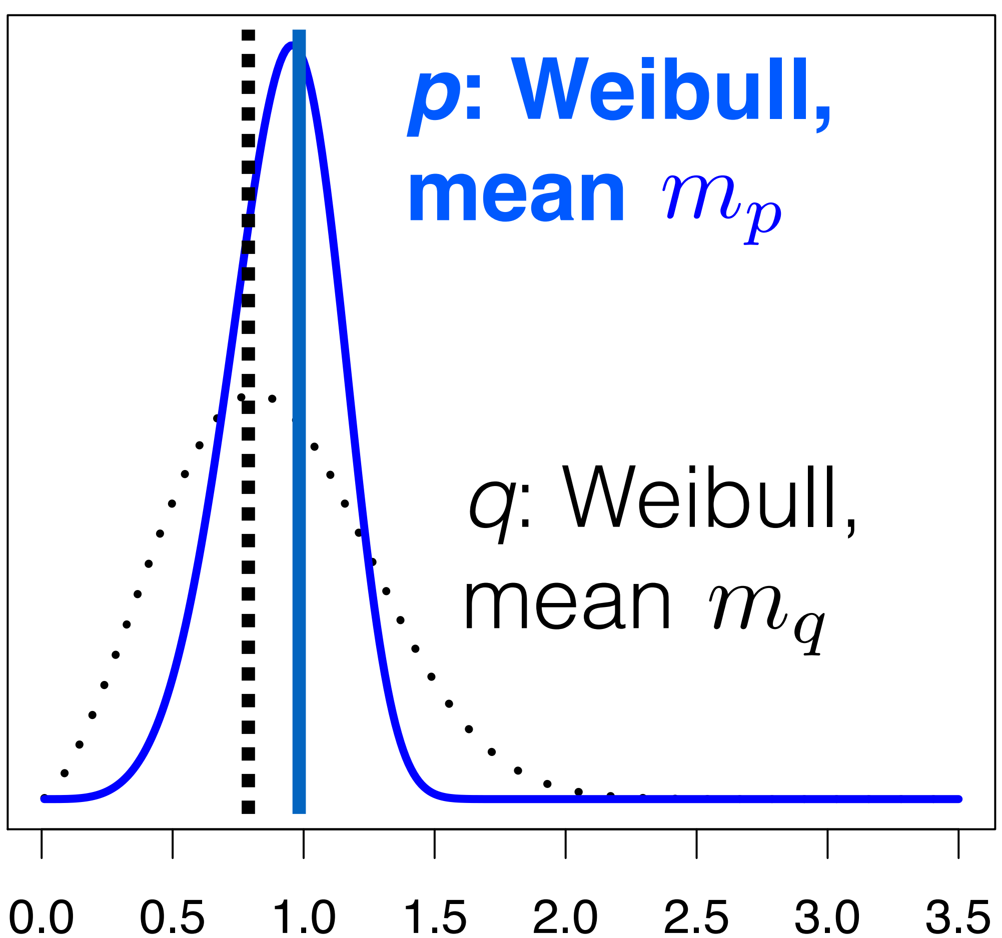

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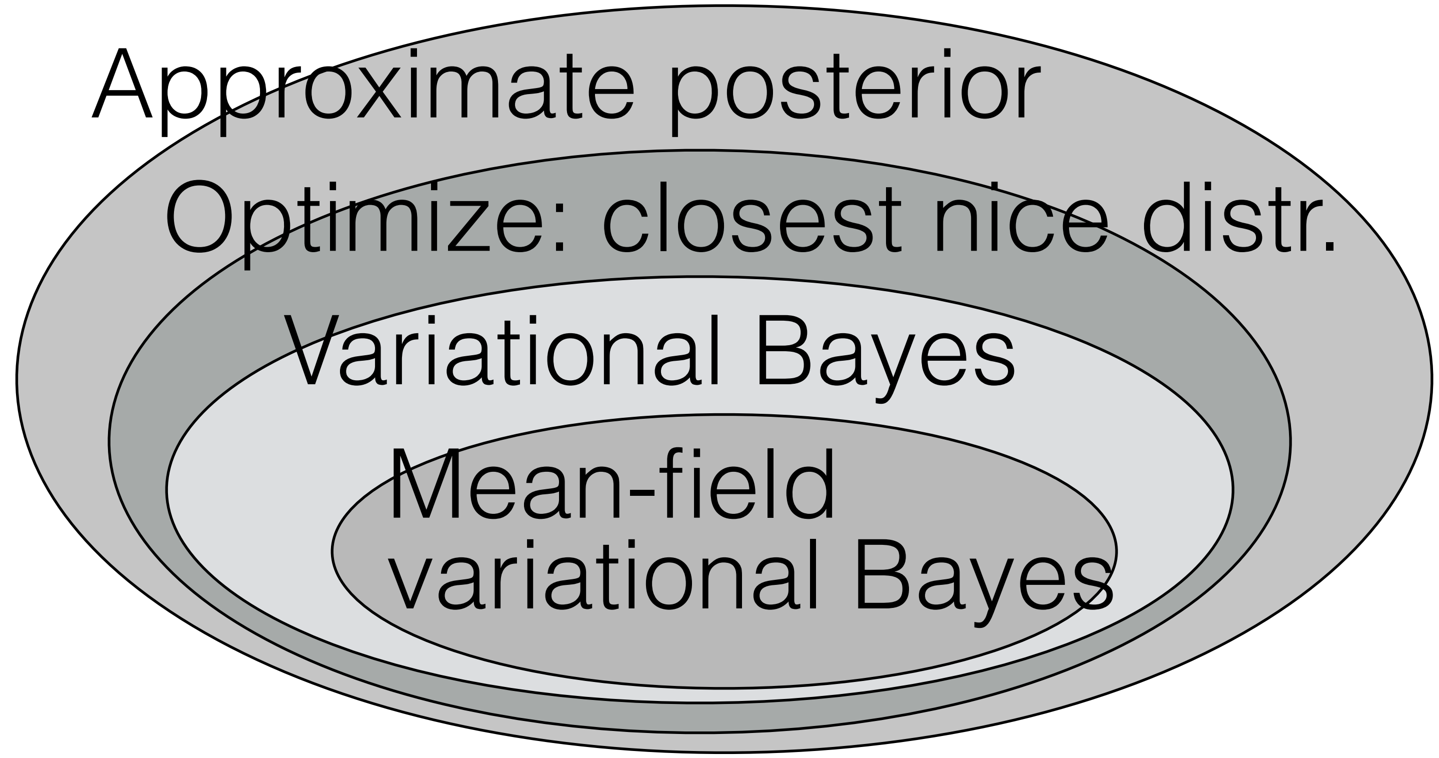

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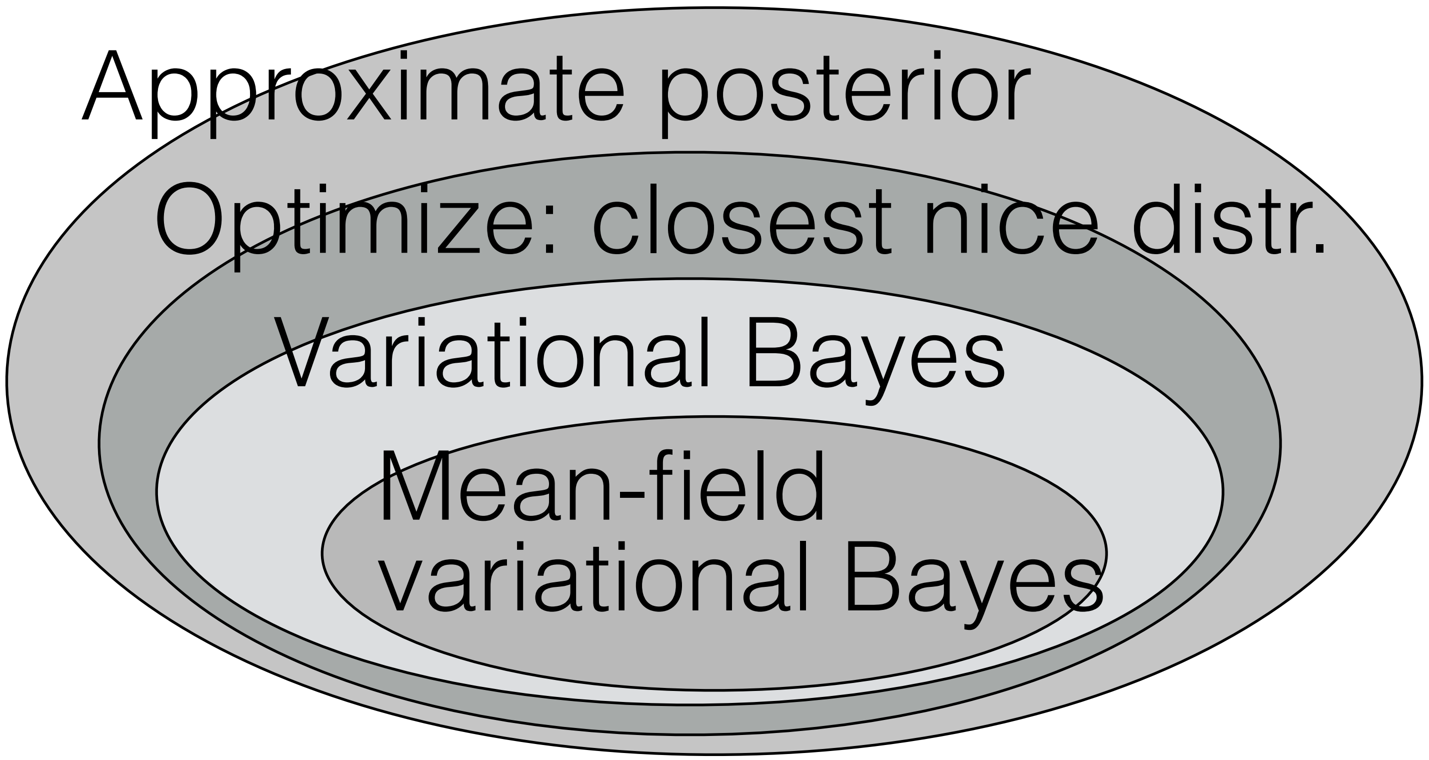

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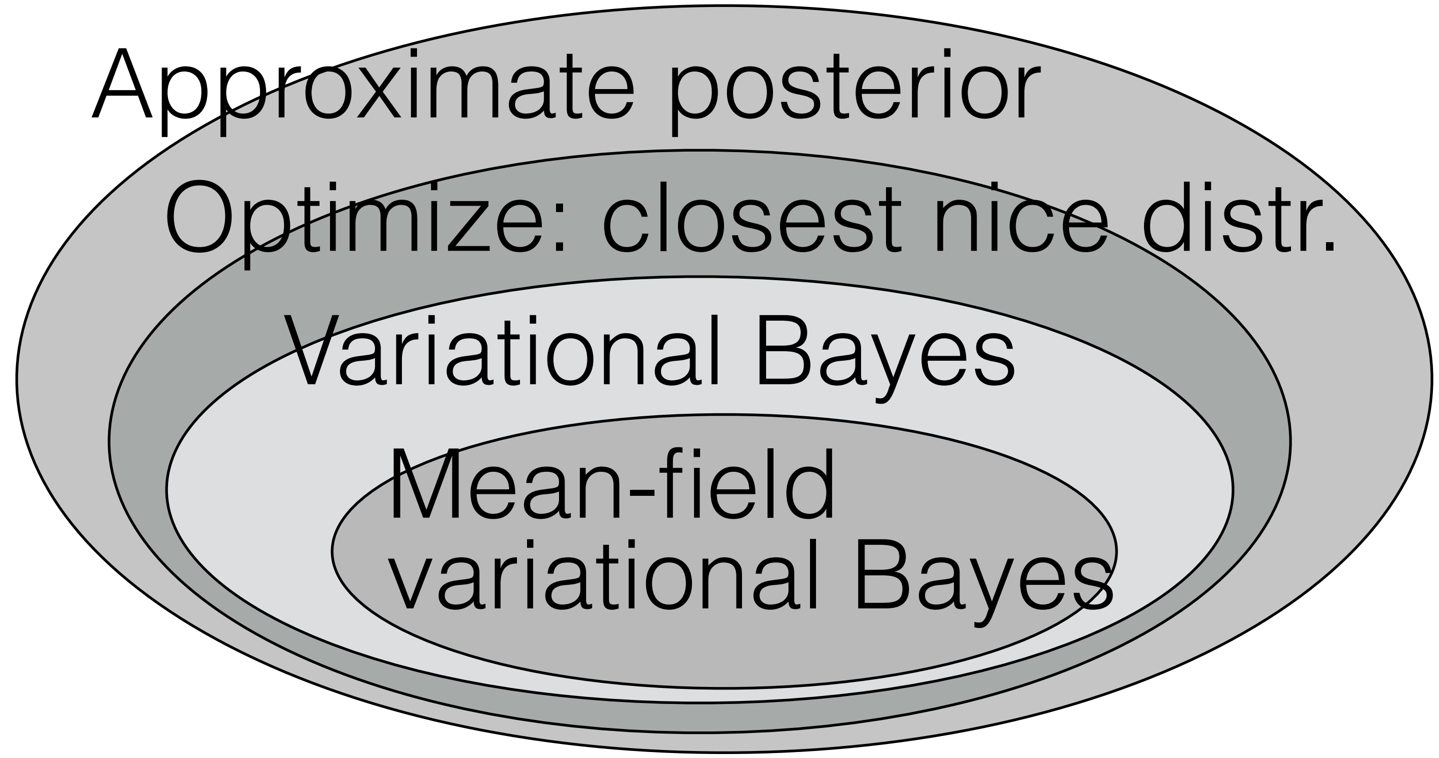

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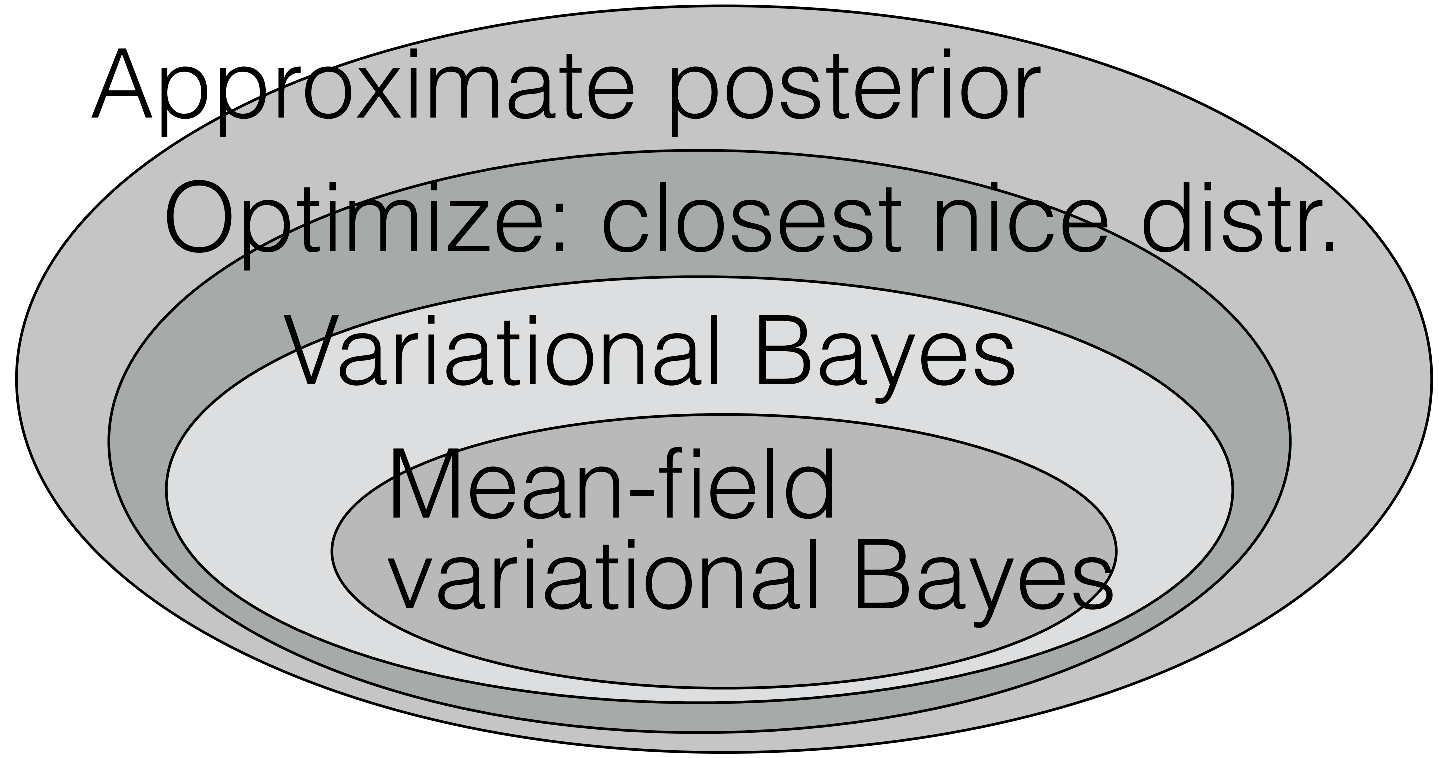

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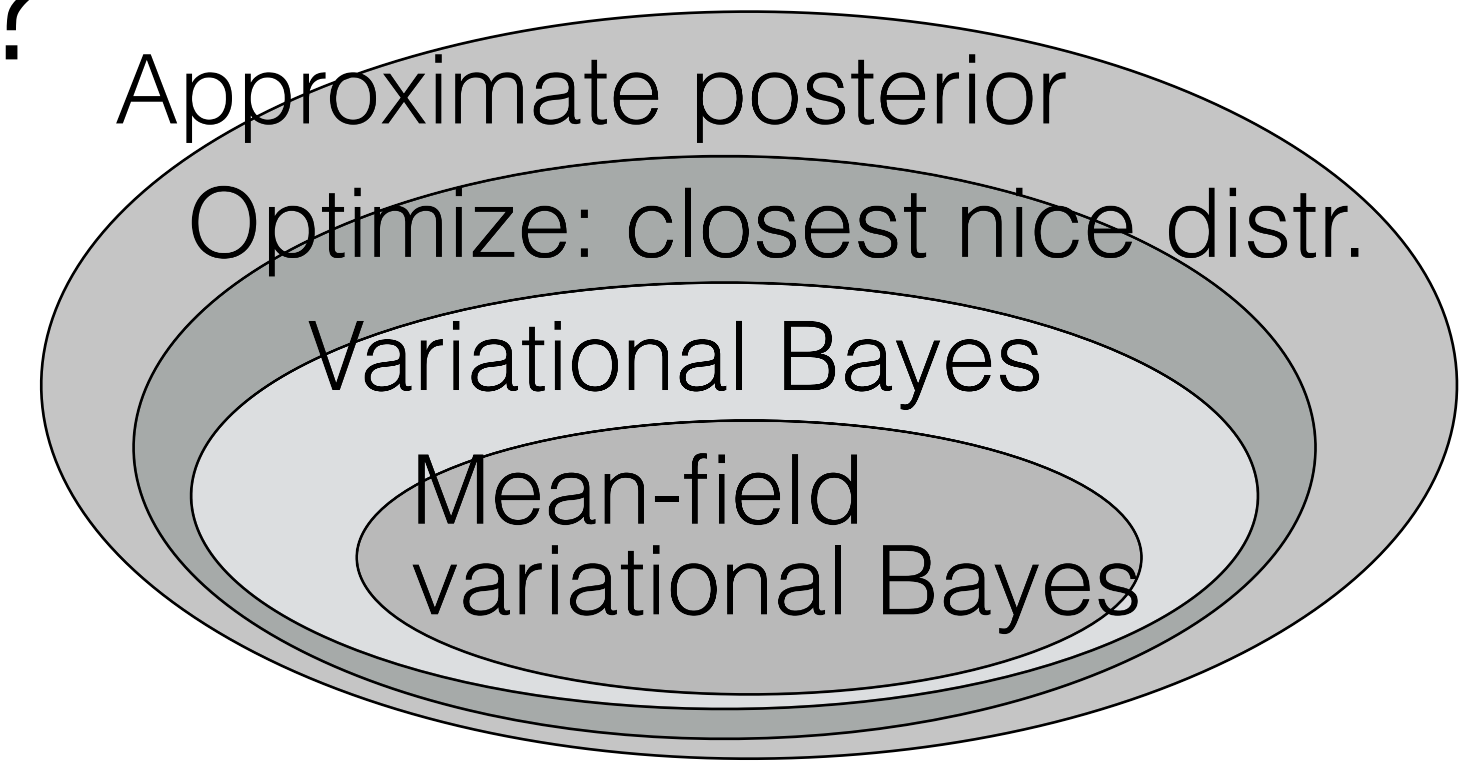

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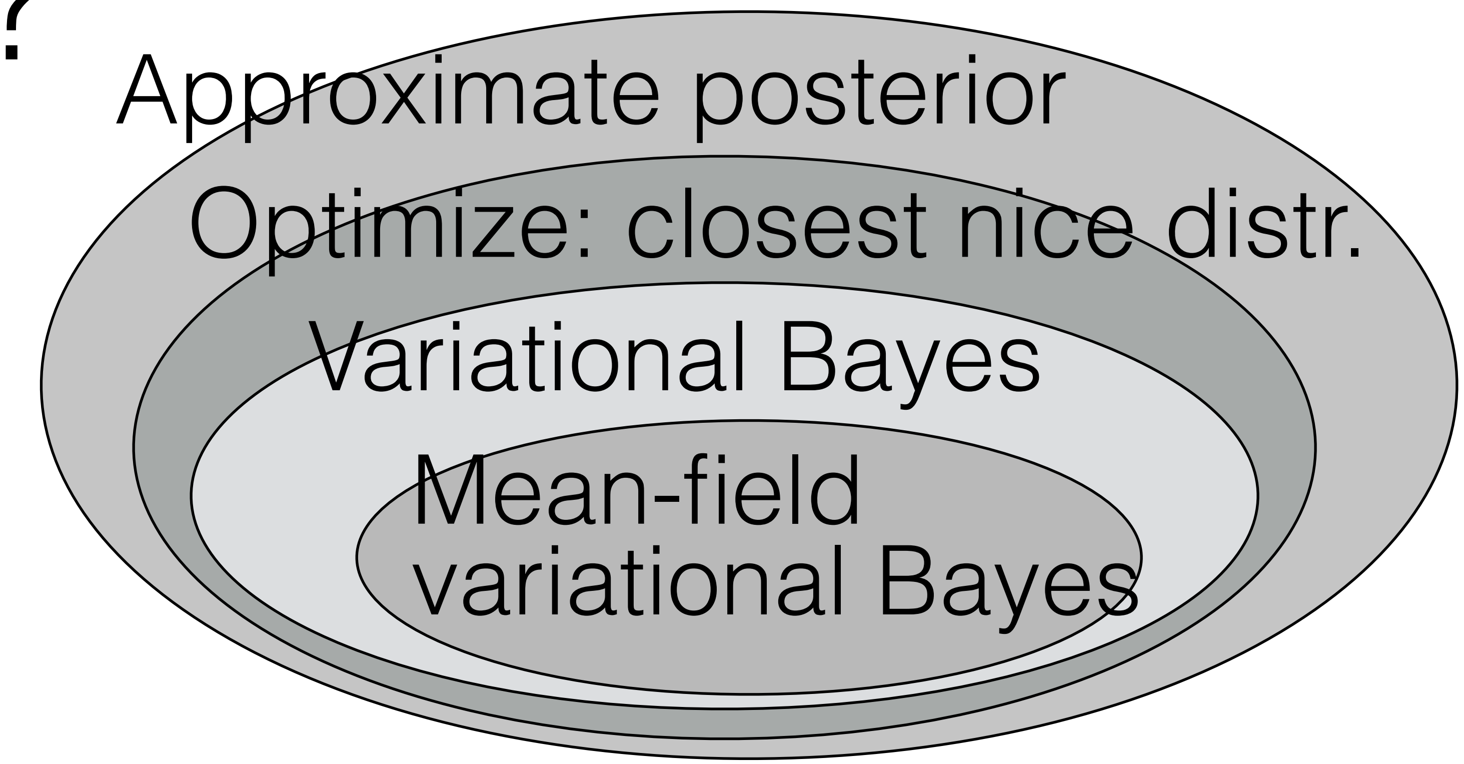

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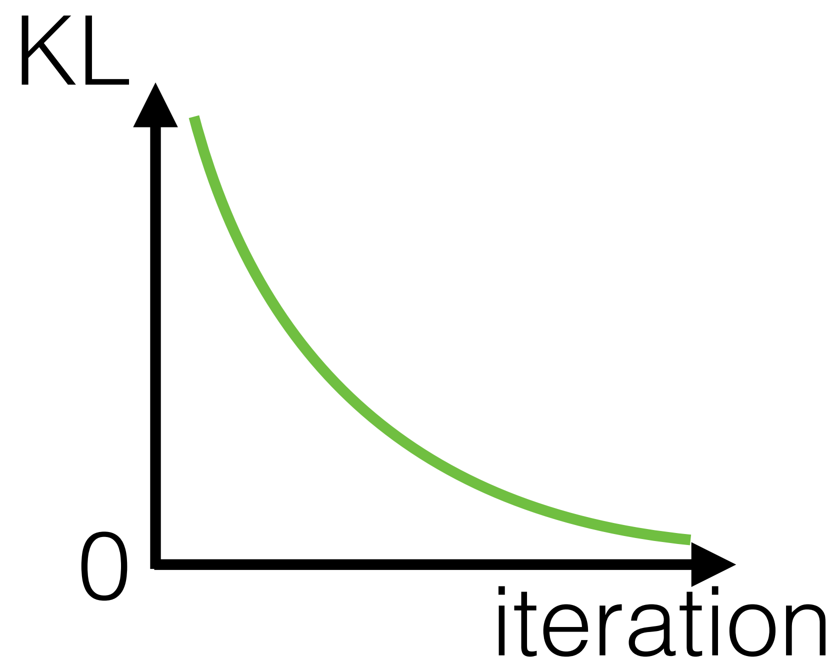

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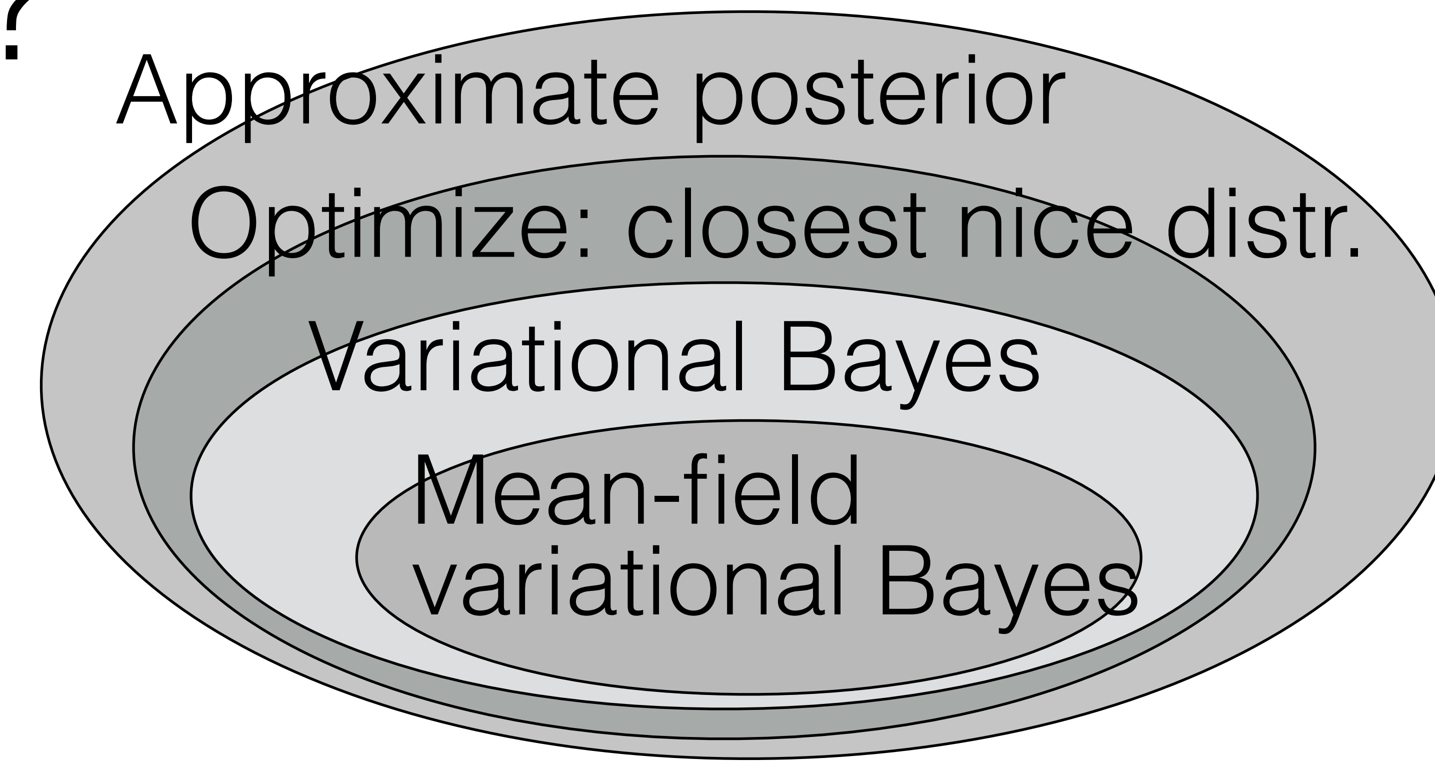

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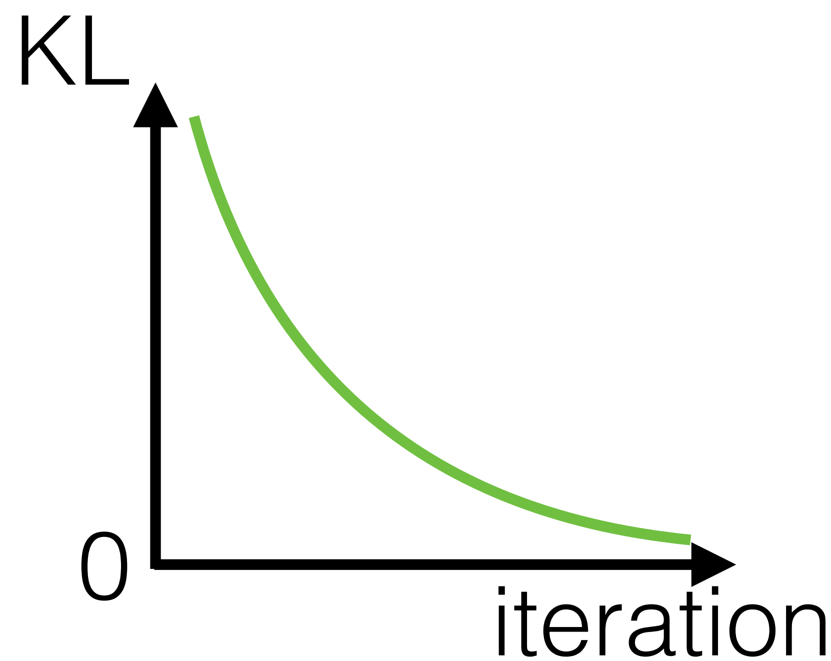

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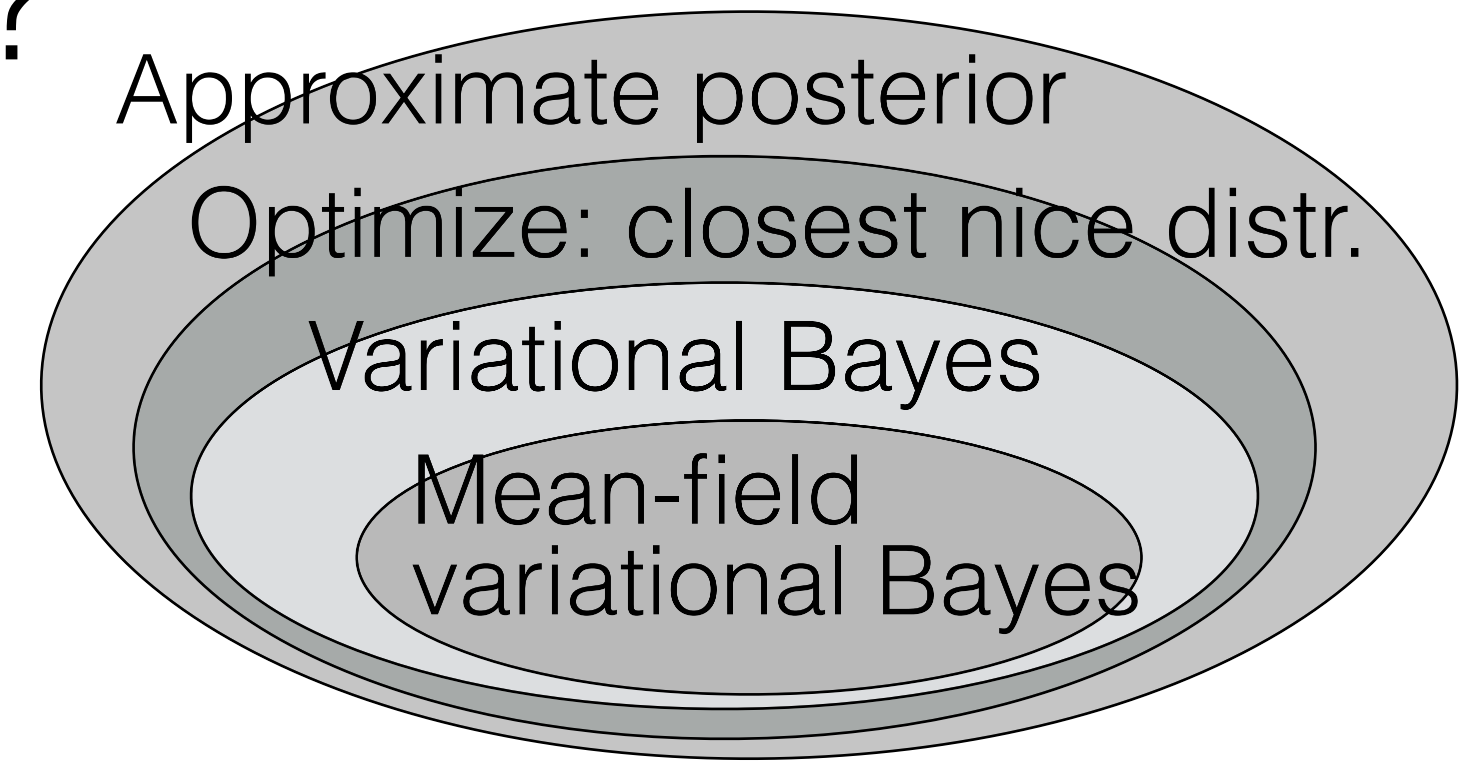

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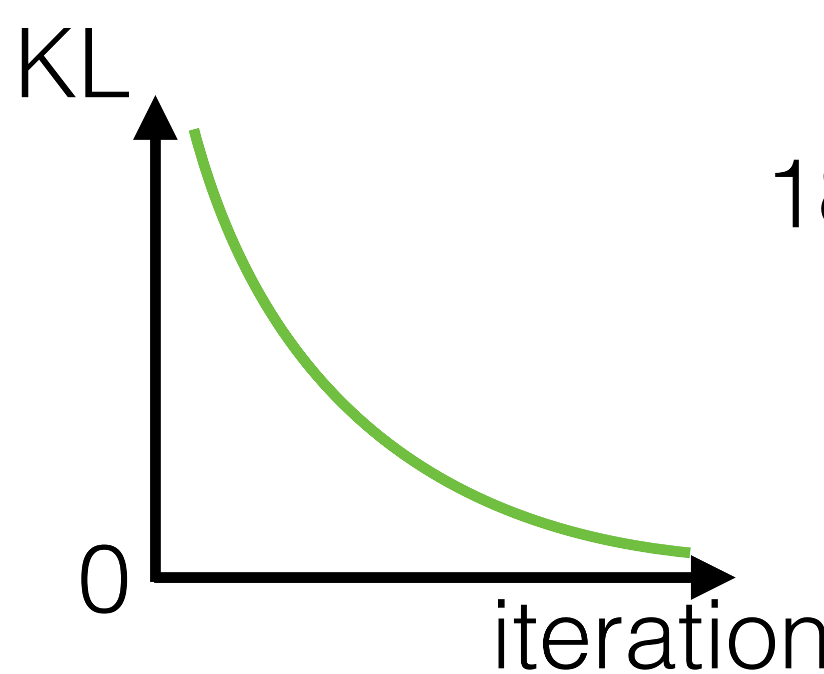

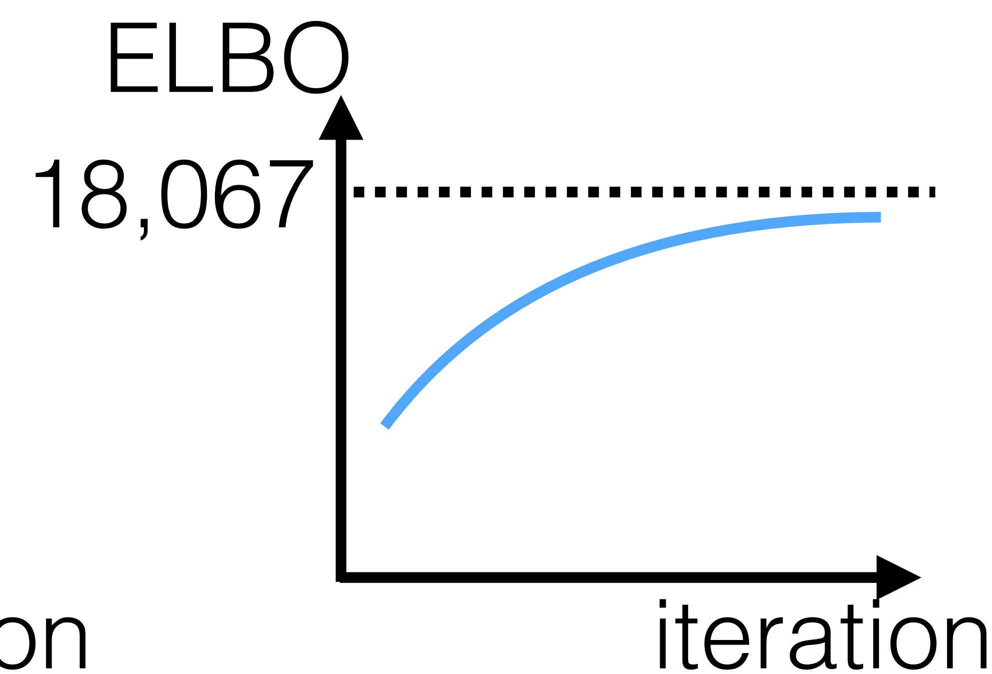

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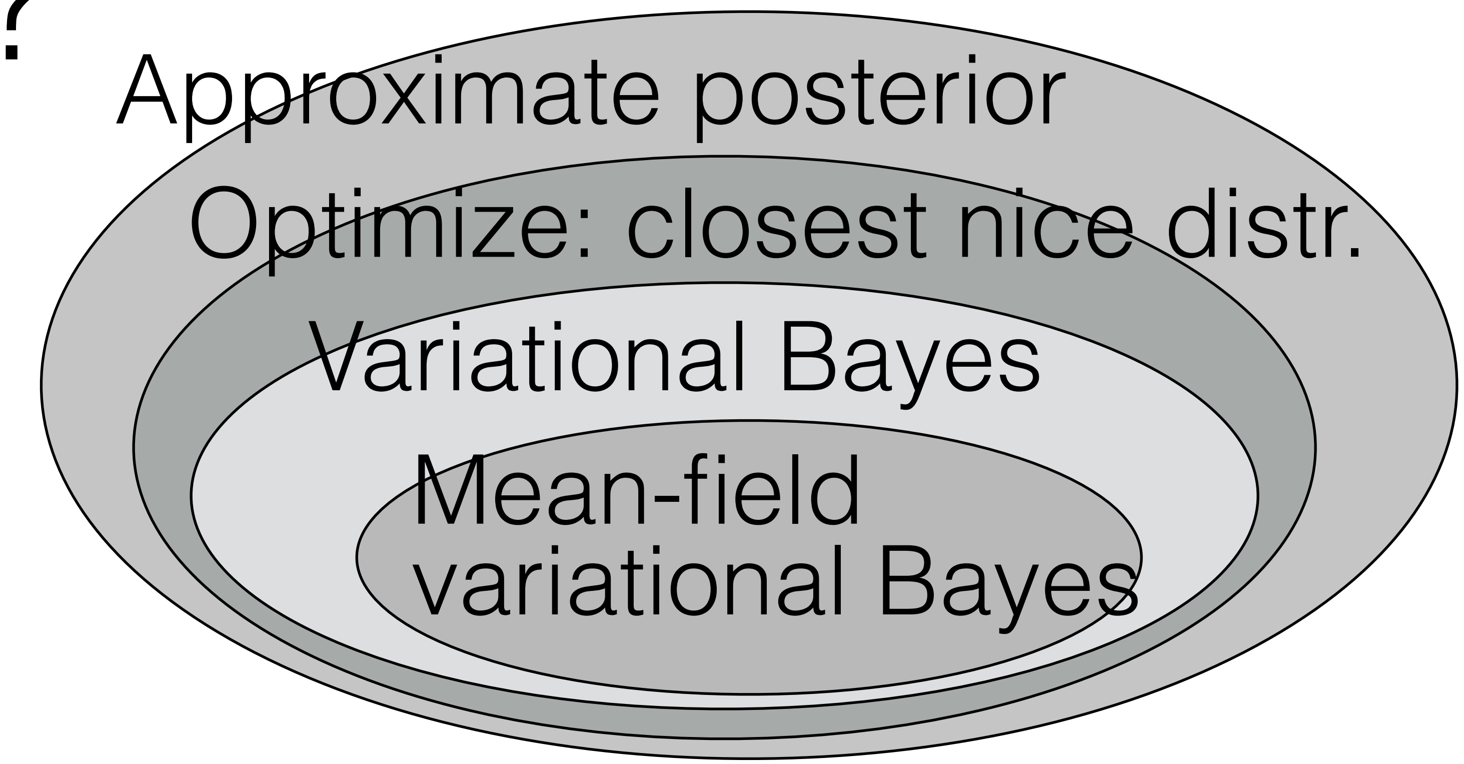

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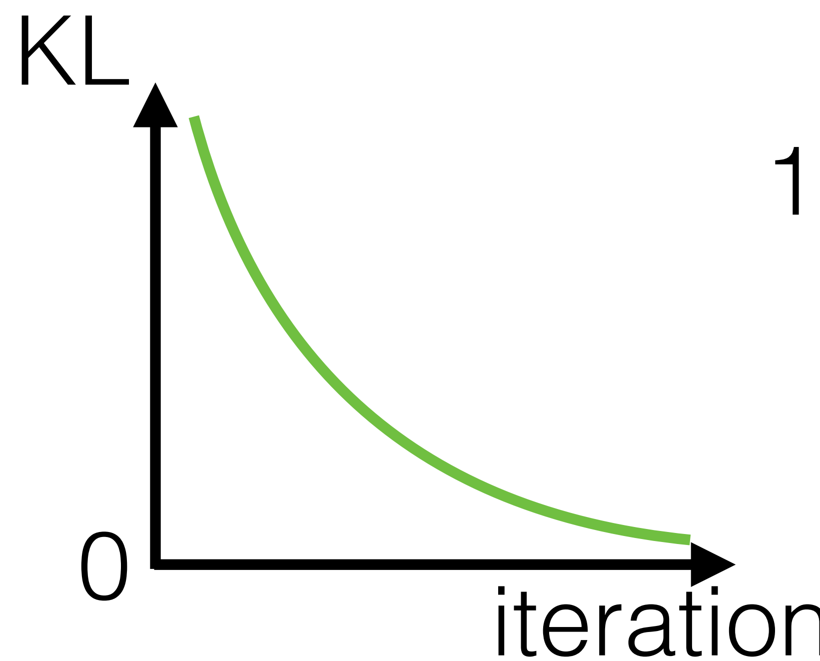
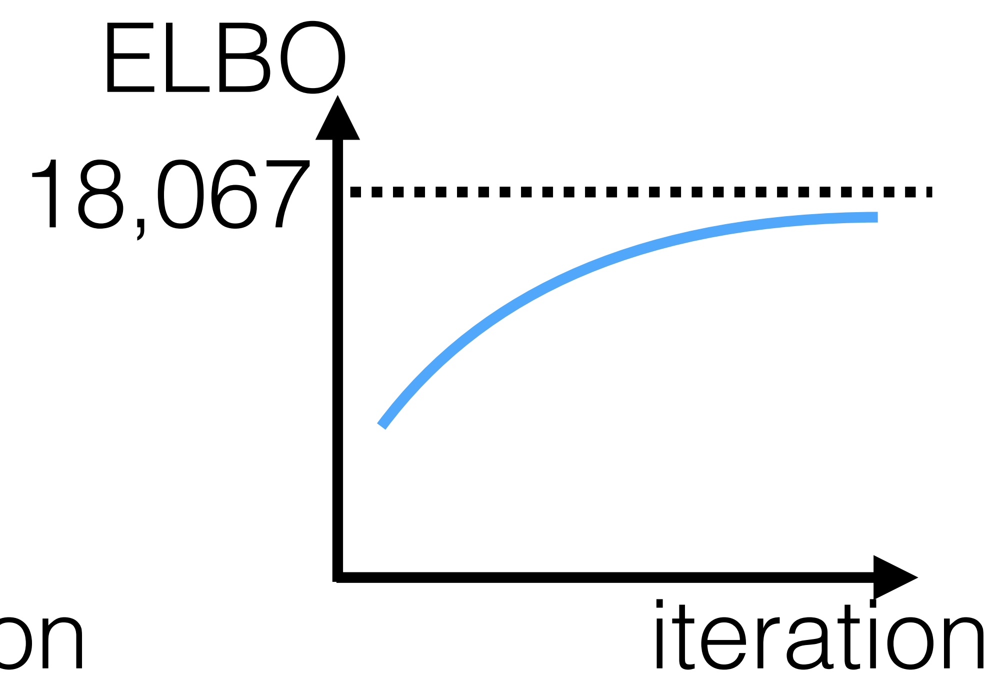
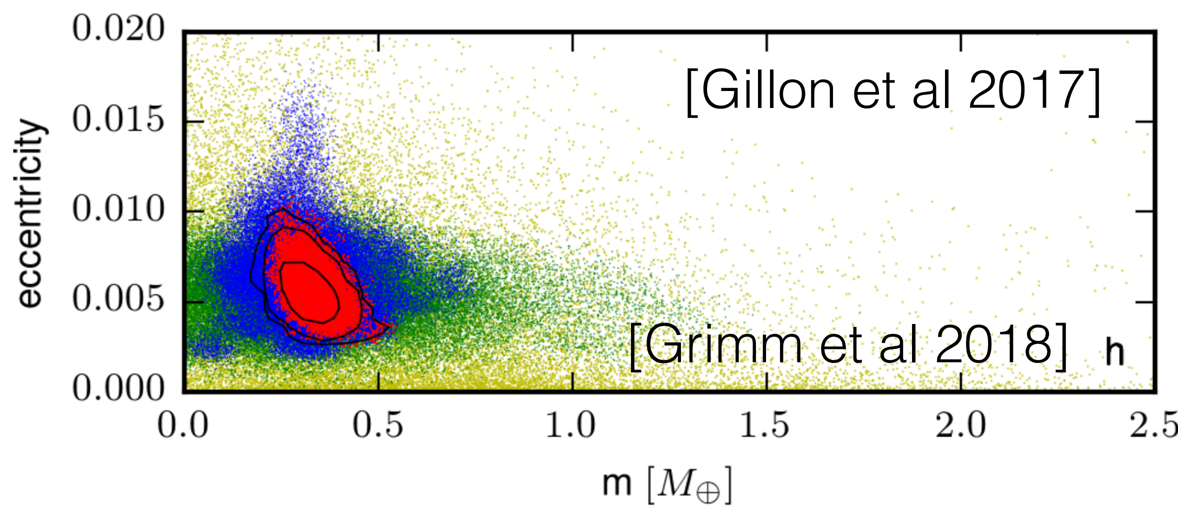


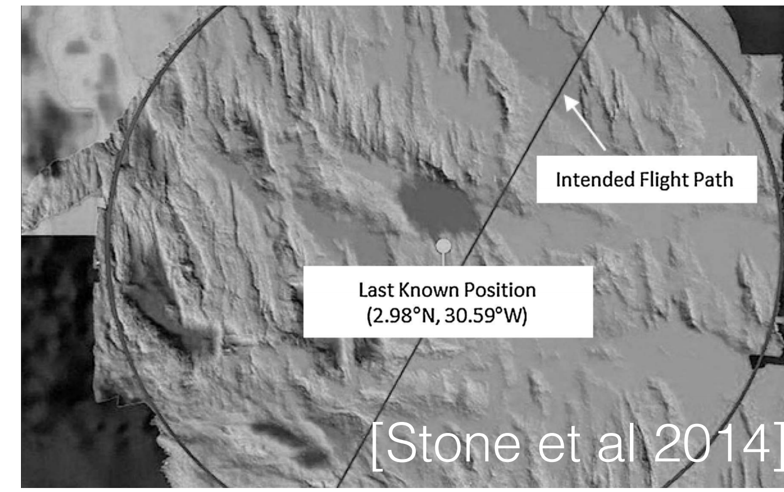


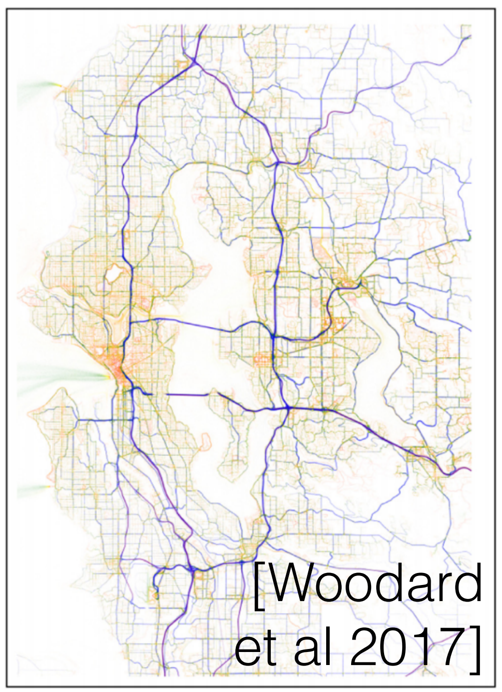
[Gorham, Mackey 2015, 2017; Chwialkowski, Strathmann, Gretton 2016; Jitkrittum et al 2017; Talts et al 2018; Yao et al 2018, etc.] → “Yes, but did it work? Evaluating variational inference” ICML 2018

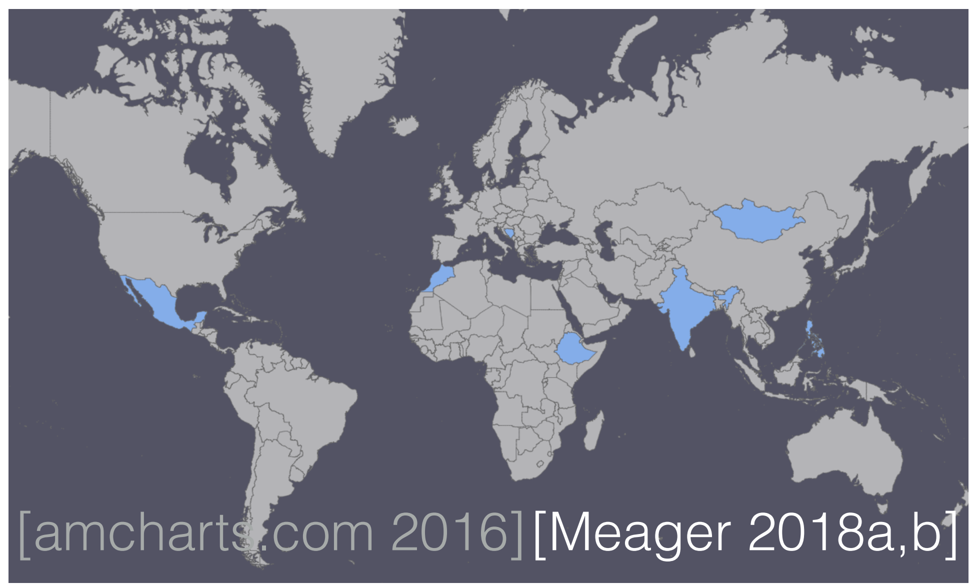
[Huggins, Kasprzak, Campbell, Broderick, 2019] → “Practical posterior error bounds from variational objectives”

Bayesian inference









[mc-stan.org]

- Goals: good point estimates, uncertainty estimates

- Challenge: speed (compute, user), reliable inference

What to read next

Textbooks and Reviews

- Bishop. *Pattern Recognition and Machine Learning*, Ch 10. 2006.
- Blei, Kucukelbir, McAuliffe. Variational inference: A review for statisticians, *JASA* 2016.
- MacKay. *Information Theory, Inference, and Learning Algorithms*, Ch 33. 2003.
- Murphy. *Machine Learning: A Probabilistic Perspective*, Ch 21. 2012.
- Ormerod, Wand. Explaining Variational Approximations. *Amer Stat* 2010.
- Turner, Sahani. Two problems with variational expectation maximisation for time-series models. In *Bayesian Time Series Models*, 2011.
- Wainwright, Jordan. Graphical models, exponential families, and variational inference. *Foundations and Trends in Machine Learning*, 2008.

Our Experiments

- RJ Giordano, T Broderick, and MI Jordan. Linear response methods for accurate covariance estimates from mean field variational Bayes. *NeurIPS* 2015.
- RJ Giordano, T Broderick, R Meager, J Huggins, and MI Jordan. Fast robustness quantification with variational Bayes. *ICML Data4Good Workshop* 2016.
- RJ Giordano, T Broderick, and MI Jordan. Covariances, robustness, and variational Bayes. *Journal of Machine Learning Research*, 2018.
- J Huggins, M Kasprzak, T Campbell, T Broderick. Practical posterior error bounds from variational objectives, 2019. ArXiv:1910.04102.

References (1/6)

R Agrawal, T Campbell, JH Huggins, and T Broderick. Data-dependent compression of random features for large-scale kernel approximation. *AISTATS* 2019.

R Bardenet, A Doucet, and C Holmes. "On Markov chain Monte Carlo methods for tall data." *Journal of Machine Learning Research* 18.1 (2017): 1515-1557.

AG Baydin, BA Pearlmutter, AA Radul, and JM Siskind. "Automatic differentiation in machine learning: a survey." *Journal of Machine Learning Research*, 2018.

DM Blei, A Kucukelbir, and JD McAuliffe. "Variational inference: A review for statisticians." *Journal of the American Statistical Association* 112.518 (2017): 859-877.

T Broderick, N Boyd, A Wibisono, AC Wilson, and MI Jordan. Streaming variational Bayes. *NeurIPS* 2013.

CM Bishop. *Pattern Recognition and Machine Learning*. Springer-Verlag New York, 2006.

T Campbell and T Broderick. Automated scalable Bayesian inference via Hilbert coresets. *Journal of Machine Learning Research*, 2019.

T Campbell and T Broderick. Bayesian Coreset Construction via Greedy Iterative Geodesic Ascent. *ICML* 2018.

RJ Giordano, T Broderick, and MI Jordan. "Linear response methods for accurate covariance estimates from mean field variational Bayes." *NeurIPS* 2015.

R Giordano, T Broderick, R Meager, J Huggins, and MI Jordan. "Fast robustness quantification with variational Bayes." *ICML 2016 Workshop on #Data4Good: Machine Learning in Social Good Applications*, 2016.

RJ Giordano, T Broderick, and MI Jordan. Covariances, robustness, and variational Bayes. *Journal of Machine Learning Research*, 2018.

References (2/6)

J Gorham and L Mackey. "Measuring sample quality with Stein's method." *NeurIPS* 2015.

J Gorham, and L Mackey. "Measuring sample quality with kernels." ArXiv:1703.01717 (2017).

PD Hoff. *A first course in Bayesian statistical methods*. Springer Science & Business Media, 2009.

MD Hoffman, DM Blei, C Wang, and J Paisley. "Stochastic variational inference." *The Journal of Machine Learning Research* 14.1 (2013): 1303-1347.

JH Huggins, T Campbell, and T Broderick. Coresets for scalable Bayesian logistic regression. *NeurIPS* 2016.

JH Huggins, RP Adams, and T Broderick. PASS-GLM: Polynomial approximate sufficient statistics for scalable Bayesian GLM inference. *NeurIPS* 2017.

J Huggins, T Campbell, M Kasprzak, T Broderick. Practical bounds on the error of Bayesian posterior approximations: A nonasymptotic approach, 2018. ArXiv:1809.09505.

J Huggins, M Kasprzak, T Campbell, T Broderick. Practical posterior error bounds from variational objectives, 2019. ArXiv:1910.04102.

A Kucukelbir, R Ranganath, A Gelman, and D Blei. Automatic variational inference in Stan. *NeurIPS* 2015.

A Kucukelbir, D Tran, R Ranganath, A Gelman, and DM Blei. Automatic differentiation variational inference. *Journal of Machine Learning Research* 18.1 (2017): 430-474.

DJC MacKay. *Information Theory, Inference, and Learning Algorithms*. Cambridge University Press, 2003.

Stan (open source software). http://mc-stan.org/ Accessed: 2018.

References (3/6)

S Talts, M Betancourt, D Simpson, A Vehtari, and A Gelman. Validating Bayesian Inference Algorithms with Simulation-Based Calibration. ArXiv:1804.06788 (2018).

RE Turner and M Sahani. Two problems with variational expectation maximisation for time-series models. In D Barber, AT Cemgil, and S Chiappa, editors, *Bayesian Time Series Models*, 2011.

Y Yao, A Vehtari, D Simpson, and A Gelman. Yes, but Did It Work?: Evaluating Variational Inference. *ICML* 2018.

Application References (4/6)

Abbott, Benjamin P., et al. "Observation of gravitational waves from a binary black hole merger." *Physical Review Letters* 116.6 (2016): 061102.

Abbott, Benjamin P., et al. "The rate of binary black hole mergers inferred from advanced LIGO observations surrounding GW150914." *The Astrophysical Journal Letters* 833.1 (2016): L1.

Airoldi, Edoardo M., David M. Blei, Stephen E. Fienberg, and Eric P. Xing. "Mixed membership stochastic blockmodels." *Journal of Machine Learning Research* 9.Sep (2008): 1981-2014.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. "Latent Dirichlet allocation." *Journal of Machine Learning Research* 3.Jan (2003): 993-1022.

Chati, Yashovardhan Sushil, and Hamsa Balakrishnan. "A Gaussian process regression approach to model aircraft engine fuel flow rate." *Cyber-Physical Systems (ICCPS), 2017 ACM/IEEE 8th International Conference on*. IEEE, 2017.

Gershman, Samuel J., David M. Blei, Kenneth A. Norman, and Per B. Sederberg. "Decomposing spatiotemporal brain patterns into topographic latent sources." NeuroImage 98 (2014): 91-102.

Gillon, Michaël, et al. "Seven temperate terrestrial planets around the nearby ultracool dwarf star TRAPPIST-1." *Nature* 542.7642 (2017): 456.

Grimm, Simon L., et al. "The nature of the TRAPPIST-1 exoplanets." *Astronomy & Astrophysics* 613 (2018): A68.

Application References (5/6)

Grogan Jr, William L., and Willis W. Wirth. "A new American genus of predaceous midges related to Palpomyia and Bezzia (Diptera: Ceratopogonidae). Un nuevo género Americano de purrujas depredadoras relacionadas con Palpomyia y Bezzia (Diptera: Ceratopogonidae)." *Proceedings of the Biological Society of Washington*. 94.4 (1981): 1279-1305.

Kuikka, Sakari, Jarno Vanhatalo, Henni Pulkkinen, Samu Mäntyniemi, and Jukka Corander. "Experiences in Bayesian inference in Baltic salmon management." *Statistical Science* 29.1 (2014): 42-49.

Meager, Rachael. "Understanding the impact of microcredit expansions: A Bayesian hierarchical analysis of 7 randomized experiments." *AEJ: Applied*, to appear, 2018a.

Meager, Rachael. "Aggregating Distributional Treatment Effects: A Bayesian Hierarchical Analysis of the Microcredit Literature." Working paper, 2018b.

Stegle, Oliver, Leopold Parts, Richard Durbin, and John Winn. "A Bayesian framework to account for complex non-genetic factors in gene expression levels greatly increases power in eQTL studies." PLoS computational biology 6.5 (2010): e1000770.

Stone, Lawrence D., Colleen M. Keller, Thomas M. Kratzke, and Johan P. Strumpfer. "Search for the wreckage of Air France Flight AF 447." *Statistical Science* (2014): 69-80.

Woodard, Dawn, Galina Nogin, Paul Koch, David Racz, Moises Goldszmidt, and Eric Horvitz. "Predicting travel time reliability using mobile phone GPS data." *Transportation Research Part C: Emerging Technologies* 75 (2017): 30-44.

Xing, Eric P., Wei Wu, Michael I. Jordan, and Richard M. Karp. "LOGOS: a modular Bayesian model for de novo motif detection." Journal of Bioinformatics and Computational Biology 2.01 (2004): 127-154.

Additional image references (6/6)

amCharts. Visited Countries Map. https://www.amcharts.com/visited_countries/ Accessed: 2016.

Baltic Salmon Fund. https://www.en.balticsalmonfund.org/about_us Accessed: 2018.

ESO/L. Calçada/M. Kornmesser. 16 October 2017, 16:00:00. Obtained from: https://commons.wikimedia.org/wiki/File:Artist%E2%80%99s_impression_of_merging_neutron_stars.jpg || Source: https://www.eso.org/public/images/eso1733a/ (Creative Commons Attribution 4.0 International License)

J. Herzog. 3 June 2016, 17:17:30. Obtained from: https://commons.wikimedia.org/wiki/File:Airbus_A350-941_F-WWCF_MSN002_ILA_Berlin_2016_17.jpg (Creative Commons Attribution 4.0 International License)

E. Xing. 2003. Slides “LOGOS: a modular Bayesian model for de novo motif detection.” Obtained from: https://www.cs.cmu.edu/~epxing/papers/Old_papers/slide_CSB03/CSB1.pdf Accessed: 2018.