Presentation at the Bayes on the Beach conference, Feb 7, 2024

The Bayesian Learning Rule

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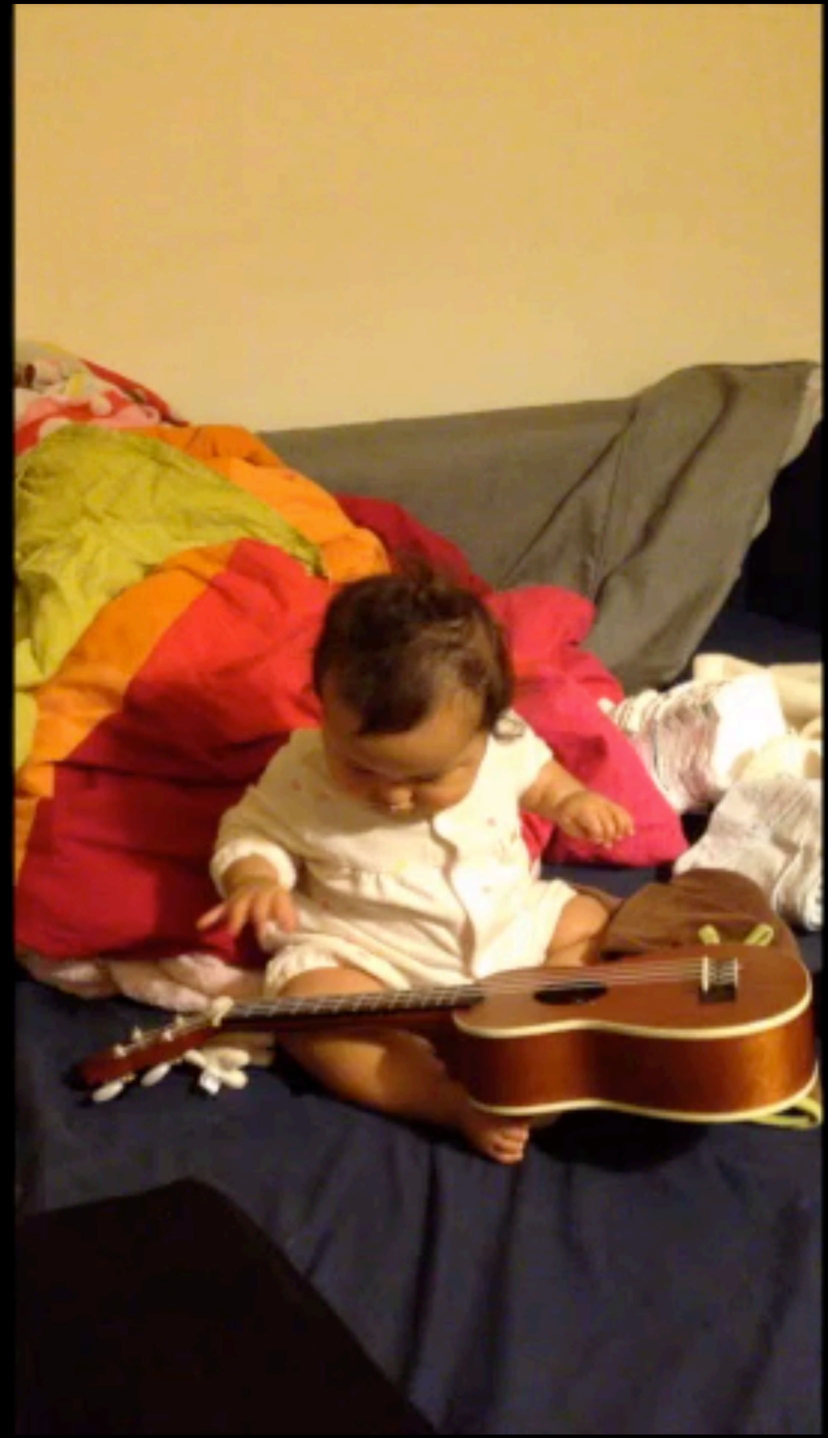
http://emtiyaz.github.io

Summary of recent research at https://emtiyaz.github.io/papers/symposium_2022.pdf

Slides available at https://emtiyaz.github.io/

Human Learning at the age of 6 months.



Converged at the age of 12 months

Transfer skills

at the age of 14 months

Fail because too slow or quick to adapt

https://www.youtube.com/watch?v=TxobtWAFh8o The video is from 2017

Adaptation in Machine Learning

- Even a small change may need retraining
- Huge amount of resources are required only few can afford (costly & unsustainable) [1,2, 3]
- Difficult to apply in "dynamic" settings (robotics, medicine, epidemiology, climate science, etc.)
- Our goal is to solve such challenges
  - Help in building safe and trustworthy AI
  - To reduce "magic" in deep learning (DL)

1. Diethe et al. Continual learning in practice, arXiv, 2019.
2. Paleyes et al. Challenges in deploying machine learning: a survey of case studies, arXiv, 2021.
3. https://www.youtube.com/watch?v=hx7BXih7zx8&t=897s

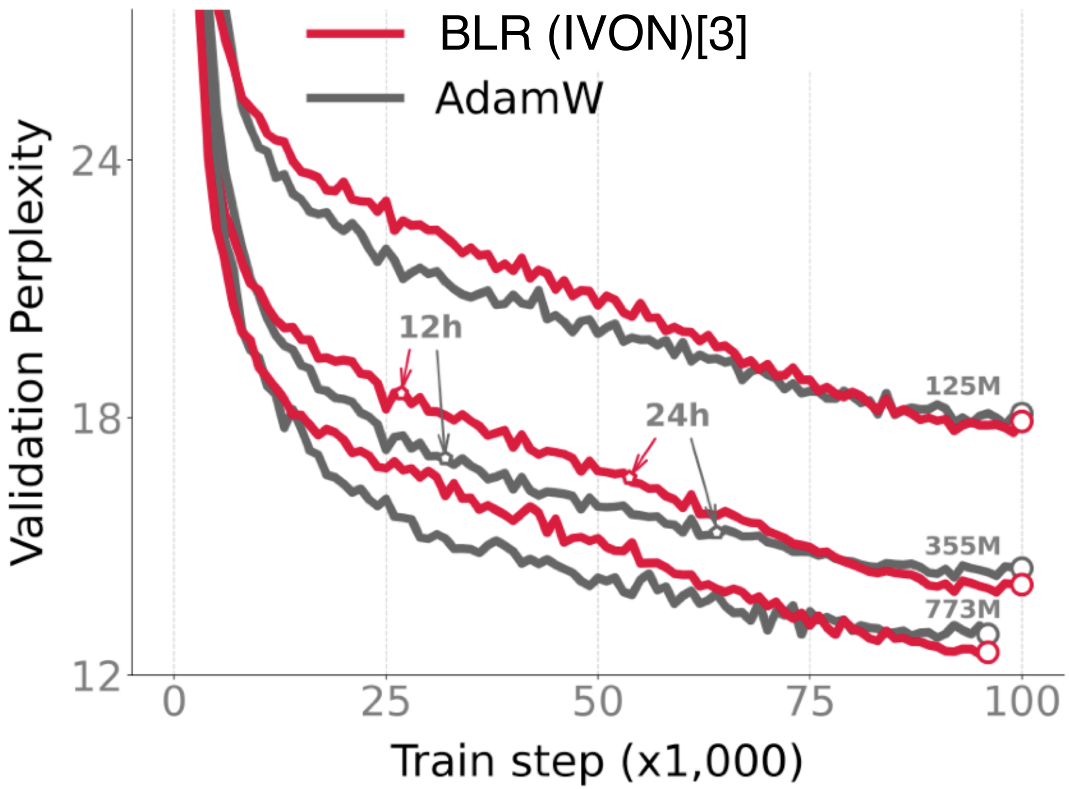
Bayesian Learning Rule [1]

- Bridge DL & Bayesian learning [2-5]
  - SOTA on GPT-2 and ImageNet [5]
- Improve other aspects of DL [5-7]
  - Calibration, uncertainty, memory etc.
  - Understand and fix model behavior
- Towards human-like quick adaptation

1. Khan and Rue, The Bayesian Learning Rule, JMLR (2023).
2. Khan, et al. Fast and scalable Bayesian deep learning by weight-perturbation in Adam, ICML (2018).
3. Osawa et al. Practical Deep Learning with Bayesian Principles, NeurIPS (2019).
4. Lin et al. Handling the positive-definite constraints in the BLR, ICML (2020).
5. Shen et al. Variational Learning is Effective for Large Deep Networks, Under review.
6. Daheim et al. Model merging by uncertainty-based gradient matching, ICLR (2024).
7. Nickl, Xu, Tailor, Moellenhoff, Khan, The memory-perturbation equation, NeurIPS (2023)

GPT-2 with Bayes

Better performance & uncertainty at the same cost [5]



Trained on OpenWebText data (49.2B tokens).

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On 355M, we get a gain of 0.4 in perplexity.

1. Khan, et al. "Fast and scalable Bayesian deep learning by weight-perturbation in Adam." *ICML* (2018).
2. Osawa et al. “Practical Deep Learning with Bayesian Principles.” NeurIPS (2019).
3. Shen et al. Variational Learning is Effective for Large Deep Networks, Under review.

Exponential Family

Natural parameters → λ

Sufficient Statistics → $T(\theta)$

Expectation parameters → μ

$$q(\theta) \propto \exp\left[\lambda^\top T(\theta)\right] \qquad \mu := \mathbb{E}_q[T(\theta)]$$

$$\mathcal{N}(\theta|m, S^{-1}) \propto \exp\left[-\frac{1}{2}(\theta - m)^\top S(\theta - m)\right]$$
$$\propto \exp\left[(Sm)^\top \theta + \mathrm{Tr}\left(-\frac{S}{2}\theta\theta^\top\right)\right]$$

Gaussian distribution	$q(\theta) := \mathcal{N}(\theta\|m, S^{-1})$
Natural parameters	$\lambda := \{Sm, -S/2\}$
Expectation parameters	$\mu := \{\mathbb{E}_q(\theta), \mathbb{E}_q(\theta\theta^\top)\}$

1. Wainwright and Jordan, Graphical Models, Exp Fams, and Variational Inference Graphical models 2008
2. Malago et al., Towards the Geometry of Estimation of Distribution Algos based on Exp-Fam, FOGA, 2011

Bayes and Conjugate Computations [1]

Multiplication of distribution = addition of (natural) params

Bayes rule: $\text{posterior} \propto \text{lik} \times \text{prior}$

$$e^{\lambda_{\text{post}}^\top T(\theta)} \propto e^{\lambda_{\text{lik}}^\top T(\theta)} \times e^{\lambda_{\text{prior}}^\top T(\theta)}$$

$$\text{log-posterior} = \text{log-lik} + \text{log-prior}$$

$$\lambda_{\text{post}} = \lambda_{\text{lik}} + \lambda_{\text{prior}}$$

This idea can be generalized through natural-gradients.

$$\lambda_{\text{post}} = \nabla_{\mu} \mathbb{E}_q [\text{log-lik} + \text{log-prior}]$$

Natural gradient (∇_{μ}) — Posterior "approximation" ($\mathbb{E}_q$)

1. Khan and Lin, Conjugate computation variational inference, AISTATS, 2017.

Bayes Rule as (Natural) Gradient Descent

$$\lambda_{\text{post}} \leftarrow \lambda_{\text{lik}} + \lambda_{\text{prior}}$$

Expected log-lik and log-prior are linear in μ [1]

$$\mathbb{E}_q[\text{log-lik}] = \lambda_{\text{lik}}^\top \mathbb{E}_q[T(\theta)] = \lambda_{\text{lik}}^\top \mu$$

Gradient wrt μ is simply the natural parameter

$$\nabla_\mu \mathbb{E}_q[\text{log-lik}] = \lambda_{\text{lik}}$$

So Bayes' rule can be written as (for an arbitrary q)

$$\lambda_{\text{post}} \leftarrow \nabla_\mu \mathbb{E}_q[\text{log-lik} + \text{log-prior}]$$

As an analogy, think of least-square = 1-step of Newton

1. Khan, Variational-Bayes Made Easy, AABI 2023.

Approximate Bayes

Bayes rule:

$$\text{posterior} \propto \text{lik} \times \text{prior}$$

Bayes as optimization [1], aka variational inference:

$$\min_{q \in \mathcal{Q}} \; \mathbb{E}_q[\text{log-lik}] + \text{KL}(q \| \text{prior})$$

Generalized Approx Bayesian learning:

log-lik + log-prior

$$\min_{q \in \mathcal{Q}} \; \mathbb{E}_{q(\theta)}[\ell(\theta)] - \mathcal{H}(q)$$

Entropy

Posterior approximation (expo-family)

1. Zellner, Optimal information processing and Bayes's theorem, The American Statistician, 1988.

The Bayesian Learning Rule

$$\min_{\theta} \ \ell(\theta) \qquad \text{vs} \qquad \min_{q \in \mathcal{Q}} \ \mathbb{E}_{q(\theta)}[\ell(\theta)] - \mathcal{H}(q)$$

Entropy

Posterior approximation (expo-family)

Bayesian Learning Rule [1,2] (natural-gradient descent)

Natural and Expectation parameters of q

$$\lambda \leftarrow \lambda - \rho \nabla_{\mu} \left\{ \mathbb{E}_q[\ell(\theta)] - \mathcal{H}(q) \right\}$$

Old belief   New information = natural gradients

Exploiting posterior's information geometry to derive existing algorithms as special instances by approximating q and natural gradients.

1. Khan and Rue, The Bayesian Learning Rule, JMLR, 2023
2. Khan and Lin. "Conjugate-computation variational inference…." AIstats (2017).

Warning!

- This natural gradient is different from the one what we (often) encounter in machine learning for Maximum-Likelihood
  - In MLE, the loss is the negative log probability distribution

$$\min_{\theta} - \log q(\theta) \Rightarrow F(\theta)^{-1} \nabla \log q(\theta)$$

  - Here, loss and distribution are two different entities, even possible unrelated

$$\min_{q} \mathbb{E}_q[\ell(\theta)] - \mathscr{H}(q) \Rightarrow F(\lambda)^{-1} \nabla_{\lambda} \mathbb{E}_q[\ell(\theta)]$$

Gradient Descent from Bayesian Learning Rule

(Euclidean) gradients as natural gradients

Bayesian learning rule:

Learning Algorithm	Posterior Approx.	Natural-Gradient Approx.	Sec.
	Optimization Algorithms		
Gradient Descent	Gaussian (fixed cov.)	Delta method	1.3
Newton's method	Gaussian	——"——	1.3
Multimodal optimization (New)	Mixture of Gaussians	——"——	3.2
	Deep-Learning Algorithms		
Stochastic Gradient Descent	Gaussian (fixed cov.)	Delta method, stochastic approx.	4.1
RMSprop/Adam	Gaussian (diagonal cov.)	Delta method, stochastic approx., Hessian approx., square-root scaling, slow-moving scale vectors	4.2
Dropout	Mixture of Gaussians	Delta method, stochastic approx., responsibility approx.	4.3
STE	Bernoulli	Delta method, stochastic approx.	4.5
Online Gauss-Newton (OGN) (New)	Gaussian (diagonal cov.)	Gauss-Newton Hessian approx. in Adam & no square-root scaling	4.4
Variational OGN (New)	——"——	Remove delta method from OGN	4.4
BayesBiNN (New)	Bernoulli	Remove delta method from STE	4.5
	Approximate Bayesian Inference Algorithms		
Conjugate Bayes	Exp-family	Set learning rate $\rho_t = 1$	5.1
Laplace's method	Gaussian	Delta method	4.4
Expectation-Maximization	Exp-Family + Gaussian	Delta method for the parameters	5.2
Stochastic VI (SVI)	Exp-family (mean-field)	Stochastic approx., local $\rho_t = 1$	5.3
VMP	——"——	$\rho_t = 1$ for all nodes	5.3
Non-Conjugate VMP	——"——	——"——	5.3
Non-Conjugate VI (New)	Mixture of Exp-family	None	5.4

See Section 1.3.1 in Khan and Rue, 2021

Gradient Descent from BLR

GD: $\theta \leftarrow \theta - \rho \nabla_\theta \ell(\theta)$

BLR: $m \leftarrow m - \rho \nabla_m \ell(m)$

"Global" to "local"
(the delta method)
$\mathbb{E}_q[\ell(\theta)] \approx \ell(m)$

$$m \leftarrow m - \rho \nabla_m \mathbb{E}_q[\ell(\theta)]$$

$$\lambda \leftarrow \lambda - \rho \nabla_\mu \left(\mathbb{E}_q[\ell(\theta)] - \mathcal{H}(q) \right)$$

Derived by choosing Gaussian with fixed covariance

Gaussian distribution $q(\theta) := \mathcal{N}(m, 1)$

Natural parameters $\lambda := m$

Expectation parameters $\mu := \mathbb{E}_q[\theta] = m$

Entropy $\mathcal{H}(q) := \log(2\pi)/2$

See Section 1.3.2 in Khan and Rue, 2021

Newton's Method from BLR

Newton's method: $\theta \leftarrow \theta - H_\theta^{-1}\left[\nabla_\theta \ell(\theta)\right]$

$$Sm \leftarrow (1-\rho) Sm - \rho \nabla_{\mathbb{E}_q(\theta)} \mathbb{E}_q[\ell(\theta)]$$

$$-\frac{1}{2} S \leftarrow (1-\rho)\left(-\frac{1}{2} S\right) - \rho \nabla_{\mathbb{E}_q(\theta\theta^\top)} \mathbb{E}_q[\ell(\theta)]$$

$$S \leftarrow (1-\rho) S + \rho 2 \nabla_{\mathbb{E}_q(\theta\theta^\top)} \mathbb{E}_q[\ell(\theta)]$$

$$\lambda \leftarrow \lambda - \rho \nabla_\mu \left(\mathbb{E}_q[\ell(\theta)] - \mathcal{H}(q)\right)$$

$$\lambda \leftarrow (1-\rho)\lambda - \rho \nabla_\mu \mathbb{E}_q[\ell(\theta)]$$

$$-\nabla_\mu \mathcal{H}(q) = \lambda$$

Derived by choosing a multivariate Gaussian

Gaussian distribution $q(\theta) := \mathcal{N}(\theta | m, S^{-1})$

Natural parameters $\lambda := \{Sm, -S/2\}$

Expectation parameters $\mu := \{\mathbb{E}_q(\theta), \mathbb{E}_q(\theta\theta^\top)\}$

1. Khan, et al. "Fast and scalable Bayesian deep learning by weight-perturbation in Adam." *ICML* (2018).

See Section 1.3.2 in Khan and Rue, 2021

Newton's Method from BLR

Newton's method: $\theta \leftarrow \theta - H_\theta^{-1}\left[\nabla_\theta \ell(\theta)\right]$

Set ρ =1 to get $\quad m \leftarrow m - H_m^{-1}[\nabla_m \ell(m)]$

$$m \leftarrow m - \rho S^{-1} \nabla_m \ell(m)$$
$$S \leftarrow (1-\rho) S + \rho H_m$$

Delta Method
$\mathbb{E}_q[\ell(\theta)] \approx \ell(m)$

Express in terms of gradient and Hessian of loss:

$$\nabla_{\mathbb{E}_q(\theta)} \mathbb{E}_q[\ell(\theta)] = \mathbb{E}_q[\nabla_\theta \ell(\theta)] - 2\mathbb{E}_q[H_\theta] m$$

$$\nabla_{\mathbb{E}_q(\theta\theta^\top)} \mathbb{E}_q[\ell(\theta)] = \mathbb{E}_q[H_\theta]$$

$$Sm \leftarrow (1-\rho) Sm - \rho \nabla_{\mathbb{E}_q(\theta)} \mathbb{E}_q[\ell(\theta)]$$
$$S \leftarrow (1-\rho) S - \rho 2 \nabla_{\mathbb{E}_q(\theta\theta^\top)} \mathbb{E}_q[\ell(\theta)]$$

1. Khan, et al. "Fast and scalable Bayesian deep learning by weight-perturbation in Adam." *ICML* (2018).

See Section 4.2 in Khan and Rue, 2021

RMSprop/Adam from BLR

RMSprop

$$s \leftarrow (1-\rho)s + \rho[\hat{\nabla}\ell(\theta)]^2$$

$$\theta \leftarrow \theta - \alpha(\sqrt{s}+\delta)^{-1}\hat{\nabla}\ell(\theta)$$

BLR for Gaussian approx

$$S \leftarrow (1-\rho)S + \rho(H_\theta)$$

$$m \leftarrow m - \alpha S^{-1}\nabla_\theta \ell(\theta)$$

To get RMSprop, make the following choices

- Restrict covariance to be diagonal
- Replace Hessian by square of gradients
- Add square root for scaling vector

For Adam, use a Heavy-ball term with KL divergence as momentum (Appendix E in [1])

1. Khan, et al. "Fast and scalable Bayesian deep learning by weight-perturbation in Adam." *ICML* (2018).

BLR for large deep networks

RMSprop/Adam

$$\hat{g} \leftarrow \hat{\nabla}\ell(\theta)$$
$$\hat{h} \leftarrow \hat{g}^2$$
$$h \leftarrow (1-\rho)h + \rho\hat{h}$$
$$\theta \leftarrow \theta - \alpha(\hat{g} + \delta m)/(\sqrt{h} + \delta)$$

BLR variant called
Improved Variational Online Newton (IVON)

$$\hat{g} \leftarrow \hat{\nabla}\ell(\theta) \text{ where } \theta \sim \mathcal{N}(m, \sigma^2)$$
$$\hat{h} \leftarrow \hat{g} \cdot (\theta - m)/\sigma^2$$
$$h \leftarrow (1-\rho)h + \rho\hat{h} + \rho^2(h - \hat{h})^2/(2(h+\delta))$$
$$m \leftarrow m - \alpha(\hat{g} + \delta m)/(h + \delta)$$
$$\sigma^2 \leftarrow 1/(N(h+\delta))$$

Code to be released this month!
Initialization of h (& scaling with N) matter.

1. Khan, et al. "Fast and scalable Bayesian deep learning by weight-perturbation in Adam." *ICML* (2018).
2. Osawa et al. “Practical Deep Learning with Bayesian Principles.” NeurIPS (2019).
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4. Shen et al. “Variational Learning is effective for large neural networks.” (Under review)

IVON [3] got 1st prize in NeurIPS 2021 Approximate Inference Challenge

Watch Thomas Moellenhoff's talk at https://www.youtube.com/watch?v=LQInlN5EU7E.

Mixture-of-Gaussian Posteriors with an Improved Bayesian Learning Rule

Thomas Möllenhoff[1], Yuesong Shen[2], Gian Maria Marconi[1]
Peter Nickl[1], Mohammad Emtiyaz Khan[1]

1 Approximate Bayesian Inference Team
RIKEN Center for AI Project, Tokyo, Japan

2 Computer Vision Group
Technical University of Munich, Germany

Dec 14th, 2021 — NeurIPS Workshop on Bayesian Deep Learning

1. Khan, et al. "Fast and scalable Bayesian deep learning by weight-perturbation in Adam." *ICML* (2018).
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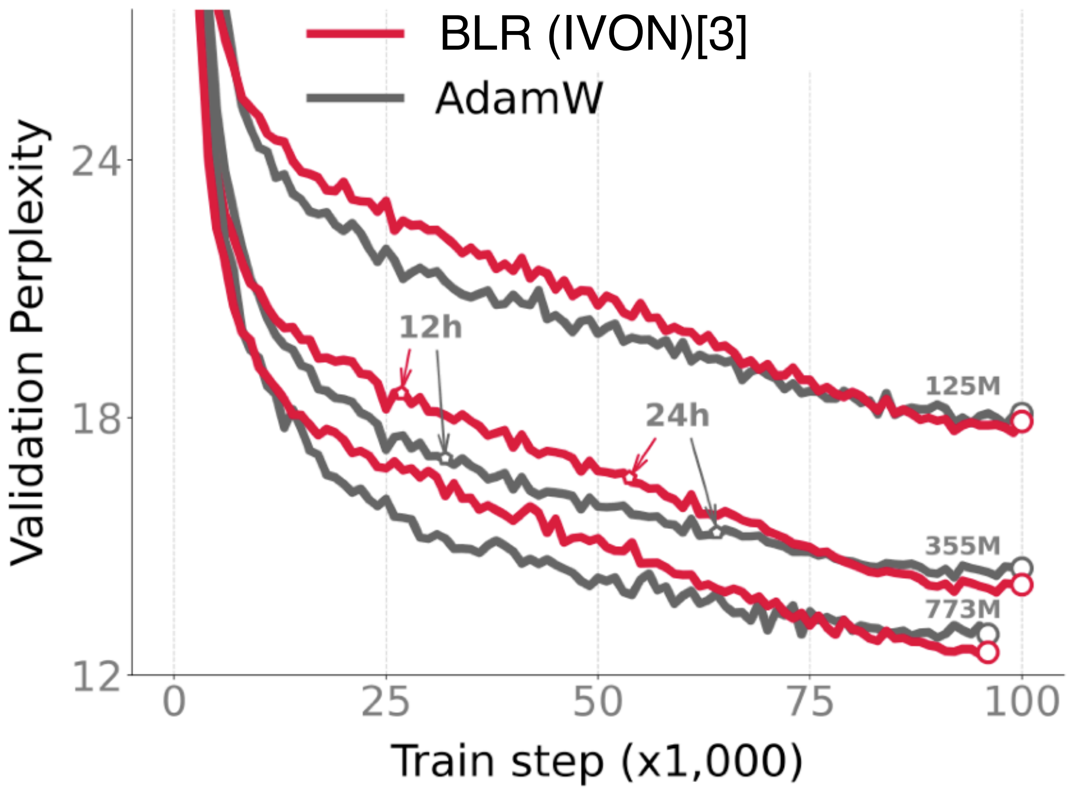
GPT-2 with Bayes

Better performance and uncertainty at the same cost



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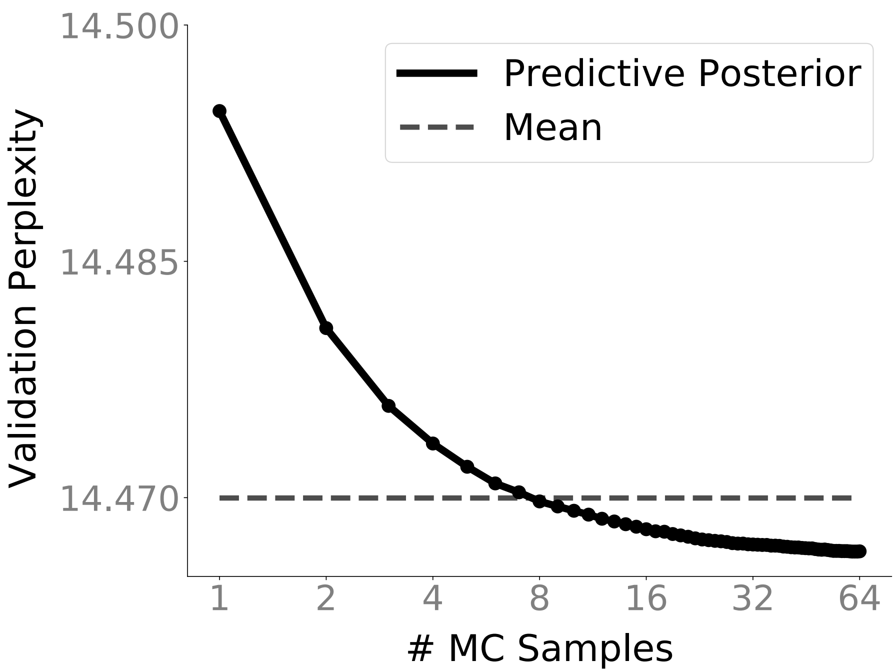
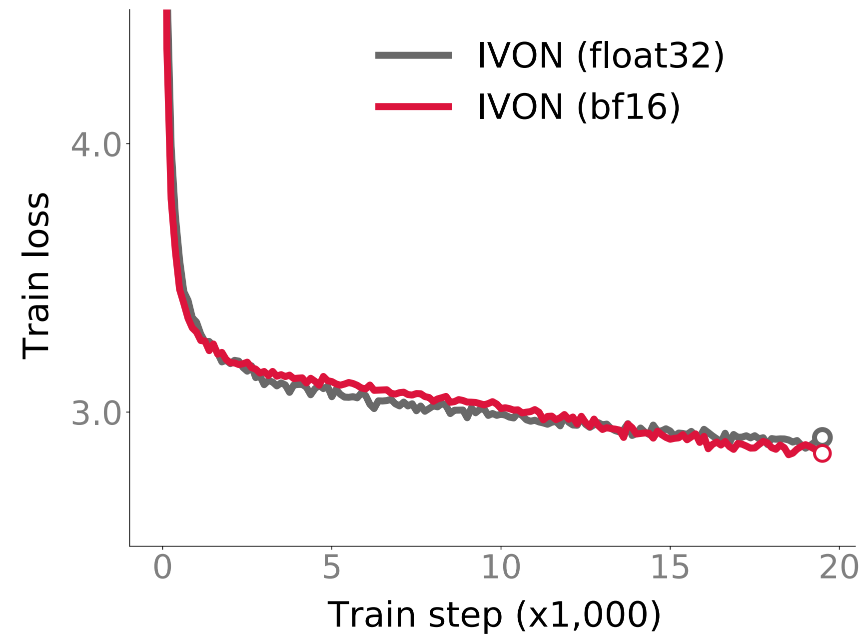
GPT-2 with Bayes

Posterior averaging improve the result. Can also train on low-precision (a stable optimizer)





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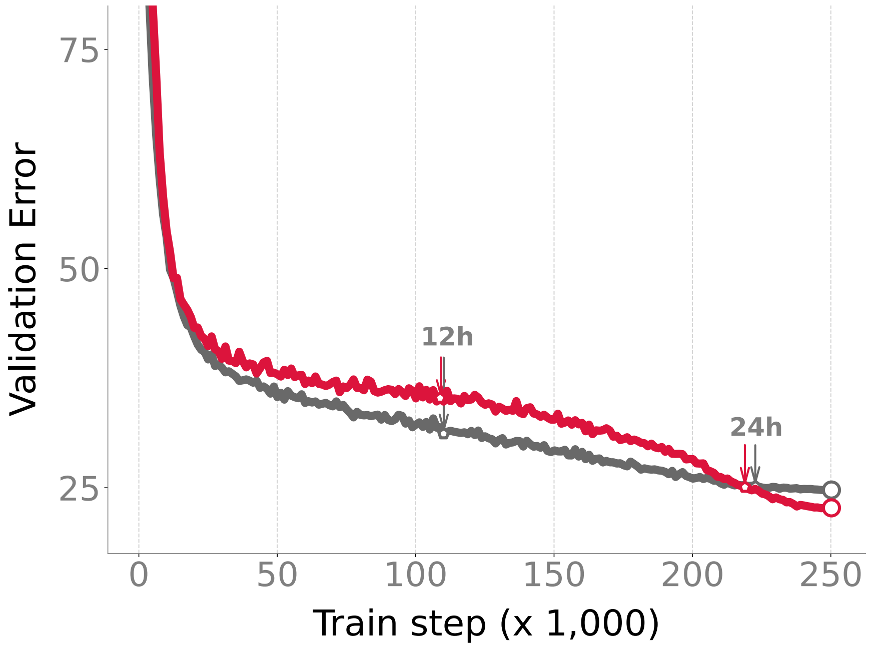
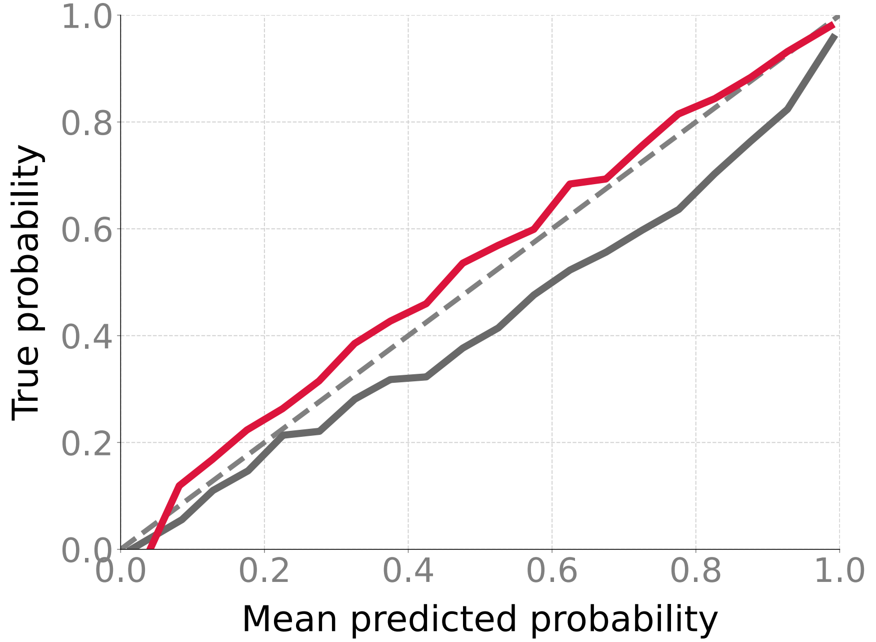
ImageNet on ResNet-50 (25.6M)

2% better accuracy over AdamW and 1% over SGD. Better calibration (ECE of 0.022 vs 0.066)

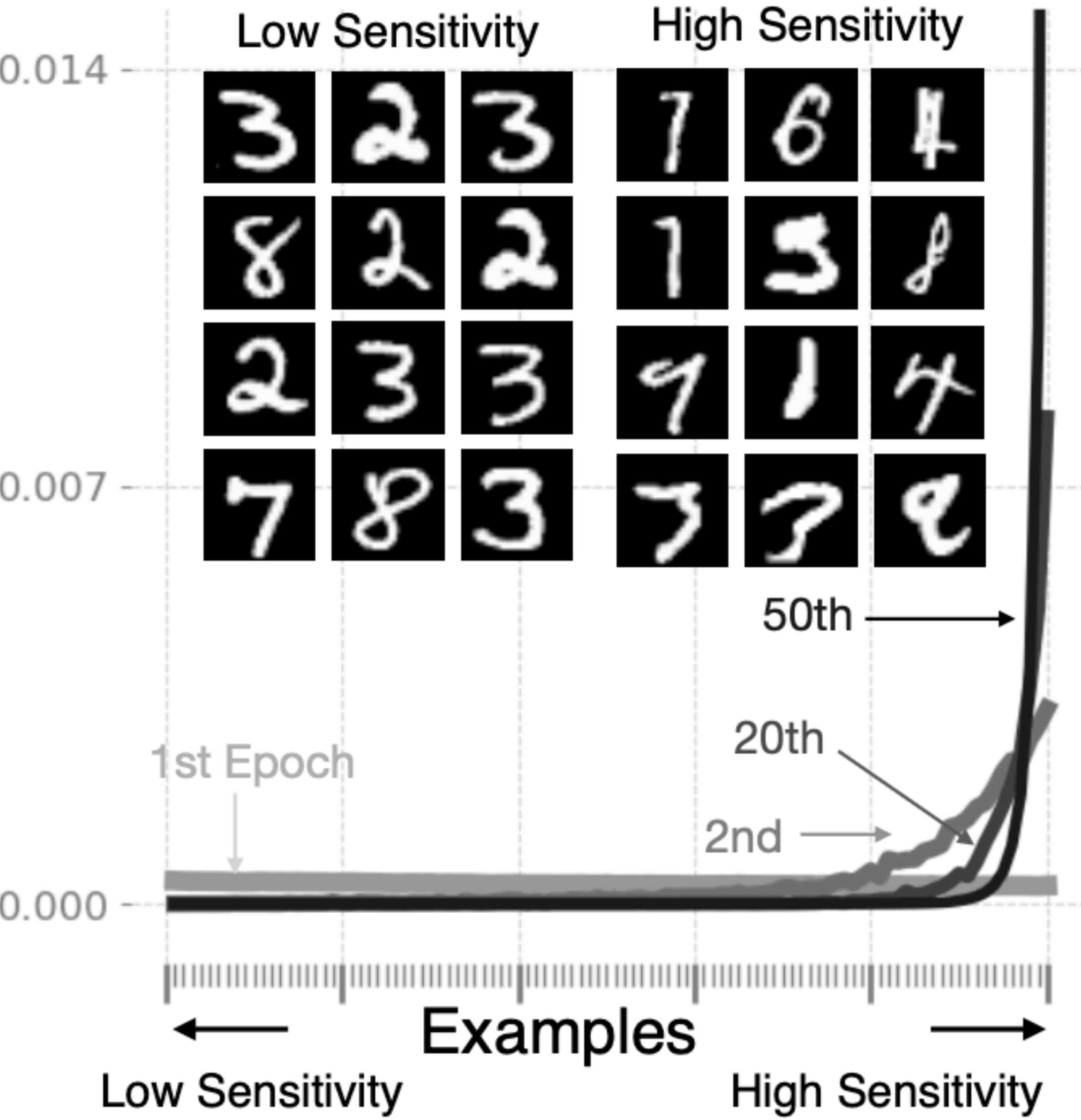




ImageNet on ResNet-50 (25.6M)

No severe overfitting like AdamW while improving accuracy over SGD consistently & better uncertainty

Dataset & Model	Epochs	Method	Top-1 Acc. ↑	Top-5 Acc. ↑	NLL ↓	ECE ↓	Brier ↓
ImageNet-1k **ResNet-50** (25.6M params)	100	AdamW	74.56$_{\pm 0.24}$	92.05$_{\pm 0.17}$	1.018$_{\pm 0.012}$	0.043$_{\pm 0.001}$	0.352$_{\pm 0.003}$
		SGD	**76.18**$_{\pm 0.09}$	**92.94**$_{\pm 0.05}$	**0.928**$_{\pm 0.003}$	0.019$_{\pm 0.001}$	**0.330**$_{\pm 0.001}$
		IVON@mean	**76.14**$_{\pm 0.11}$	92.83$_{\pm 0.04}$	0.934$_{\pm 0.002}$	0.025$_{\pm 0.001}$	**0.330**$_{\pm 0.001}$
		IVON	**76.24**$_{\pm 0.09}$	**92.90**$_{\pm 0.04}$	**0.925**$_{\pm 0.002}$	**0.015**$_{\pm 0.001}$	**0.330**$_{\pm 0.001}$
	200	AdamW	+2% 75.16$_{\pm 0.14}$	92.37$_{\pm 0.03}$	1.018$_{\pm 0.003}$	0.066$_{\pm 0.002}$	0.349$_{\pm 0.002}$
		SGD	+1% 76.63$_{\pm 0.45}$	93.21$_{\pm 0.25}$	0.917$_{\pm 0.026}$	0.038$_{\pm 0.009}$	0.326$_{\pm 0.006}$
		IVON@mean	77.30$_{\pm 0.08}$	93.58$_{\pm 0.05}$	0.884$_{\pm 0.002}$	0.035$_{\pm 0.002}$	**0.316**$_{\pm 0.001}$
		IVON	**77.46**$_{\pm 0.07}$	**93.68**$_{\pm 0.04}$	**0.869**$_{\pm 0.002}$	**0.022**$_{\pm 0.002}$	**0.315**$_{\pm 0.001}$
TinyImageNet **ResNet-18** (11M params, wide)	200	AdamW	+15% 47.33$_{\pm 0.90}$	71.54$_{\pm 0.95}$	6.823$_{\pm 0.235}$	0.421$_{\pm 0.008}$	0.913$_{\pm 0.018}$
		SGD	+1% 61.39$_{\pm 0.18}$	82.30$_{\pm 0.22}$	1.811$_{\pm 0.010}$	0.138$_{\pm 0.002}$	0.536$_{\pm 0.002}$
		IVON@mean	**62.41**$_{\pm 0.15}$	**83.77**$_{\pm 0.18}$	1.776$_{\pm 0.018}$	0.150$_{\pm 0.005}$	0.532$_{\pm 0.002}$
		IVON	**62.68**$_{\pm 0.16}$	**84.12**$_{\pm 0.24}$	**1.528**$_{\pm 0.010}$	**0.019**$_{\pm 0.004}$	**0.491**$_{\pm 0.001}$
TinyImageNet **PreResNet-110** (4M params, deep)	200	AdamW	+10% 50.65$_{\pm 0.0*}$	74.94$_{\pm 0.0*}$	4.487$_{\pm 0.0*}$	0.357$_{\pm 0.0*}$	0.812$_{\pm 0.0*}$
		AdaHessian	55.03$_{\pm 0.53}$	78.49$_{\pm 0.34}$	2.971$_{\pm 0.064}$	0.272$_{\pm 0.005}$	0.690$_{\pm 0.008}$
		SGD	+2% 59.39$_{\pm 0.50}$	81.34$_{\pm 0.30}$	2.040$_{\pm 0.040}$	0.176$_{\pm 0.006}$	0.577$_{\pm 0.007}$
		IVON @mean	**60.85**$_{\pm 0.39}$	**83.89**$_{\pm 0.14}$	1.584$_{\pm 0.009}$	0.053$_{\pm 0.002}$	**0.514**$_{\pm 0.003}$
		IVON	**61.25**$_{\pm 0.48}$	**84.13**$_{\pm 0.17}$	**1.550**$_{\pm 0.009}$	**0.049**$_{\pm 0.002}$	**0.511**$_{\pm 0.003}$
CIFAR-100 **ResNet-18** (11M params, wide)	200	AdamW	+11% 64.12$_{\pm 0.43}$	86.85$_{\pm 0.51}$	3.357$_{\pm 0.071}$	0.278$_{\pm 0.005}$	0.615$_{\pm 0.008}$
		SGD	+.7% 74.46$_{\pm 0.17}$	92.66$_{\pm 0.06}$	1.083$_{\pm 0.007}$	0.113$_{\pm 0.001}$	0.376$_{\pm 0.001}$
		IVON@mean	74.51$_{\pm 0.24}$	92.74$_{\pm 0.19}$	1.284$_{\pm 0.013}$	0.152$_{\pm 0.003}$	0.399$_{\pm 0.002}$
		IVON	**75.14**$_{\pm 0.34}$	**93.30**$_{\pm 0.19}$	**0.912**$_{\pm 0.009}$	**0.021**$_{\pm 0.003}$	**0.344**$_{\pm 0.003}$



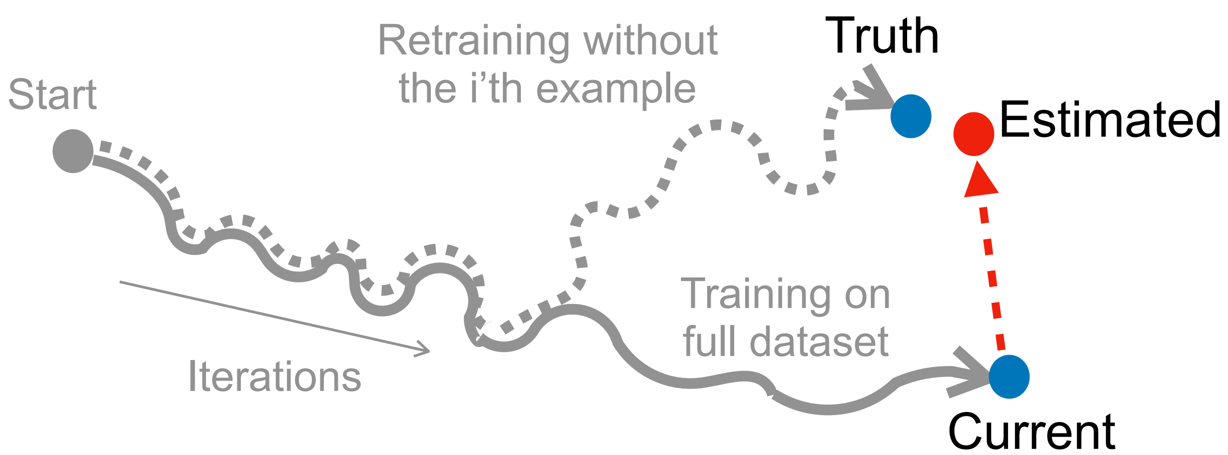
Sensitivity to data is easy to compute "during" training.

MNIST on MLP. Also work at large scale (ImageNet)

1. Nickl, Xu, Tailor, Moellenhoff, Khan, The memory-perturbation equation, NeurIPS, 2023

Sensitivity to Training Data

Past information with most influence on the present

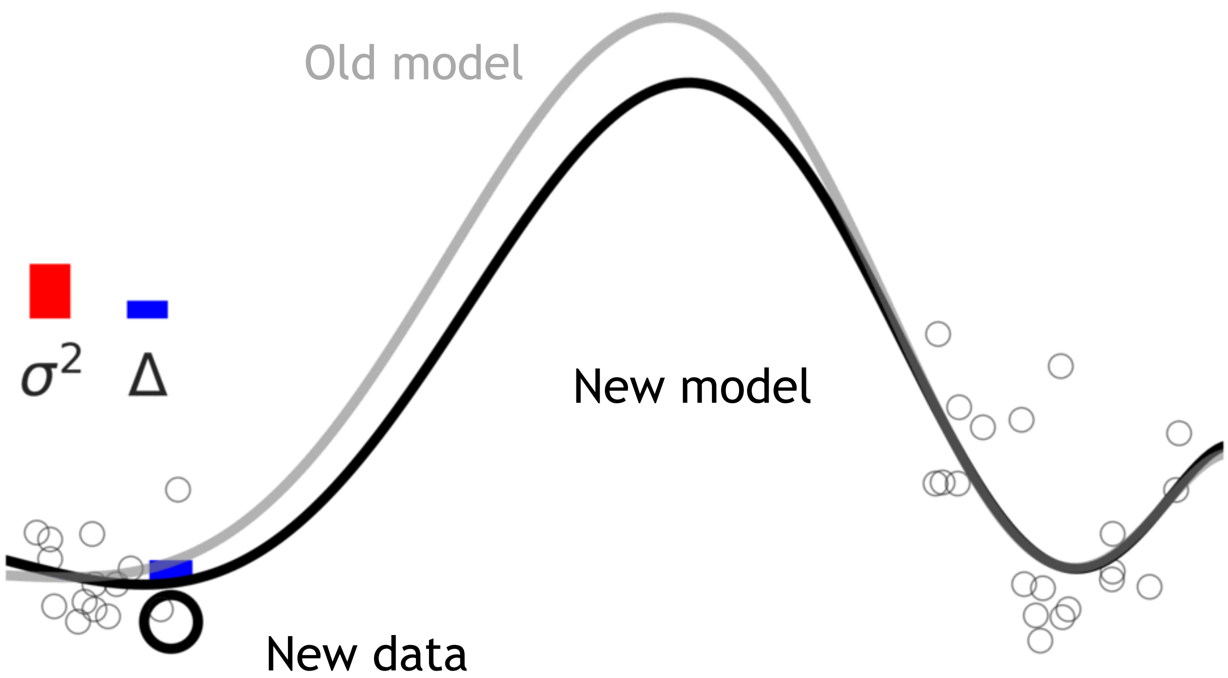


Estimating it without retraining: Using the BLR, we can recover all sorts of influence criteria used in literature.

Memory Perturbation

How sensitive is a model to its training data?

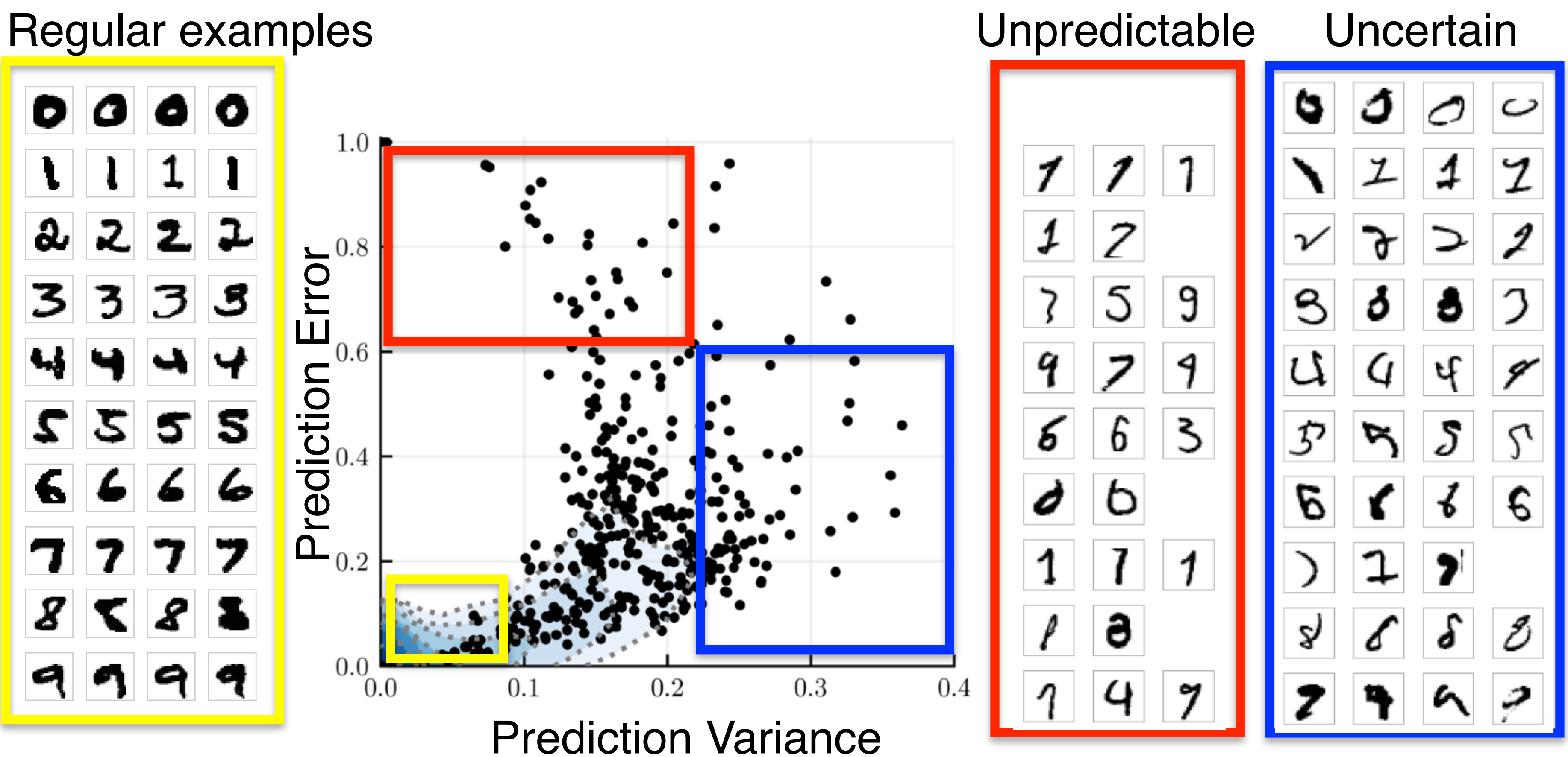
Deviation (Δ) = predictionError *predictionVariance



1. Cook. Detection of Influential Observations in Linear Regression. Technometrics. ASA 1977
2. Nickl, Xu, Tailor, Moellenhoff, Khan, The memory-perturbation equation, NeurIPS, 2023

Memory Maps using the BLR

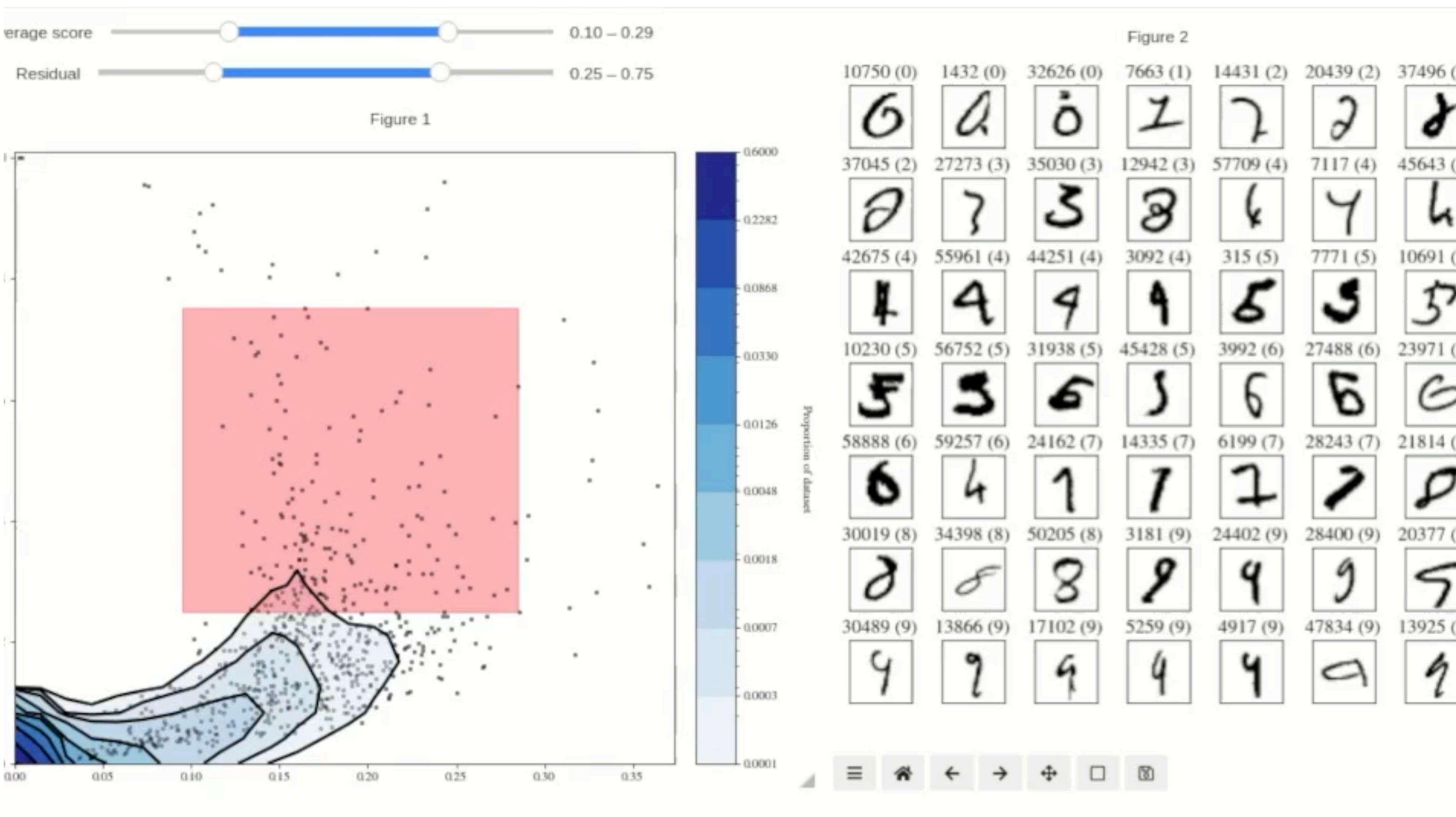
Understand generic ML models and algorithms.



1. Tailor, Chang, Swaroop, Nalisnick, Solin, Khan, Memory maps to understand models (under review)

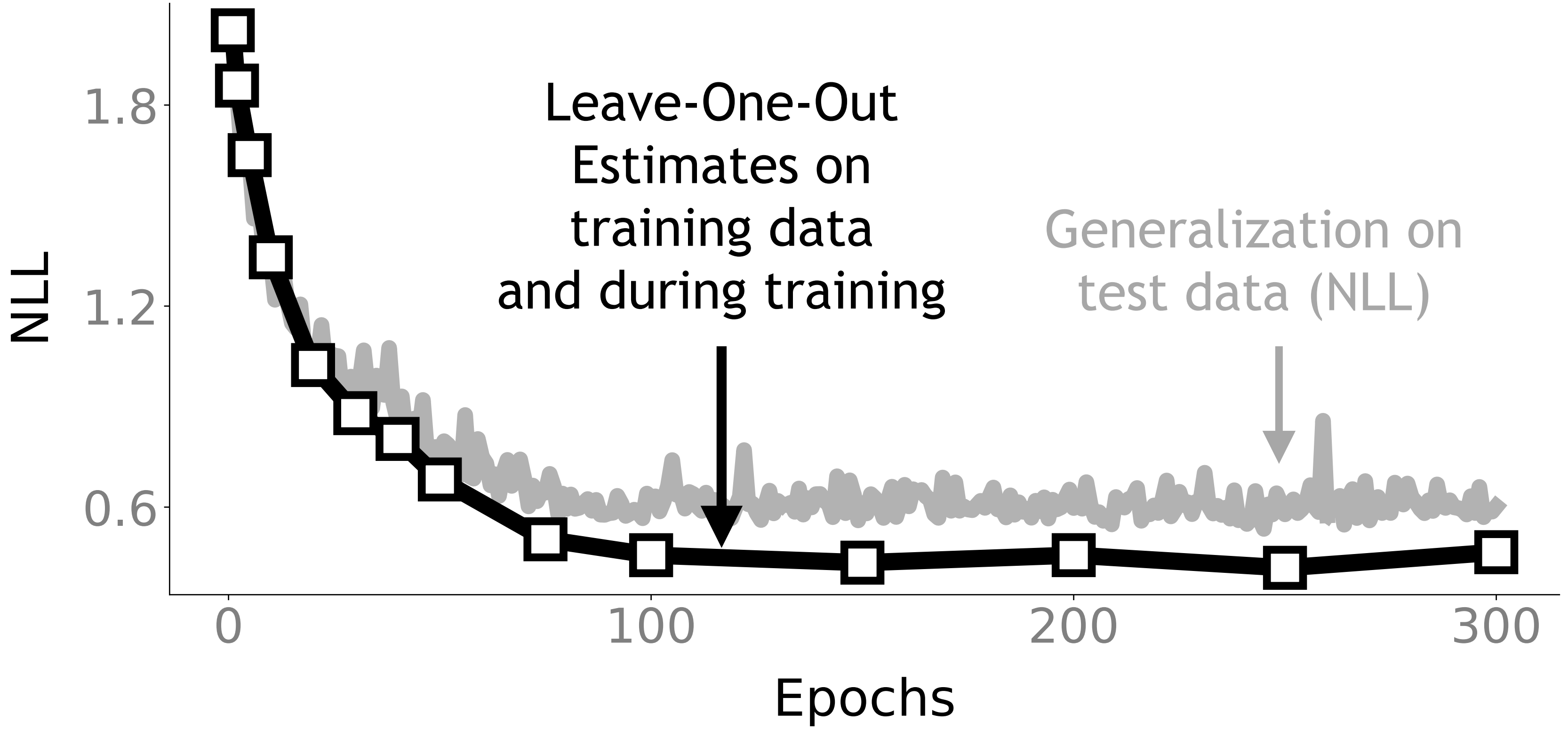
A Tool for Data-Scientists

Understand the memory of a model.



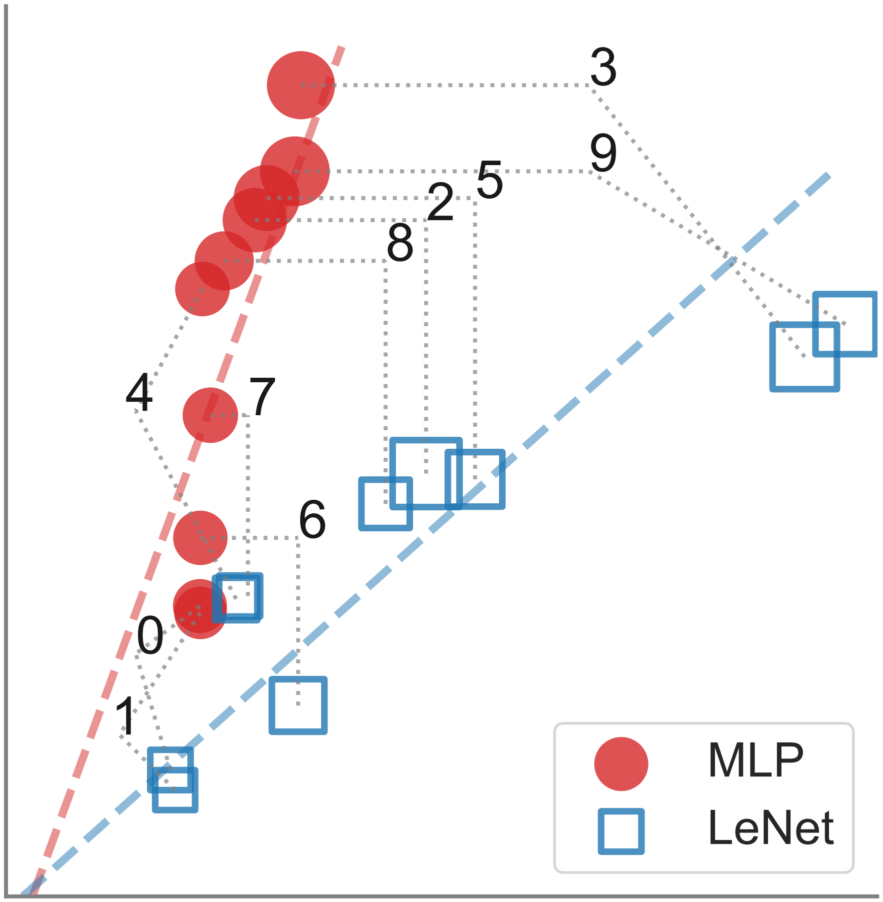
Predict Generalization during Training

CIFAR10 on ResNet-20 using IVON. SGD or Adam do not work as well.



Answering "What-If" Questions

What if we removed a class from MNIST?

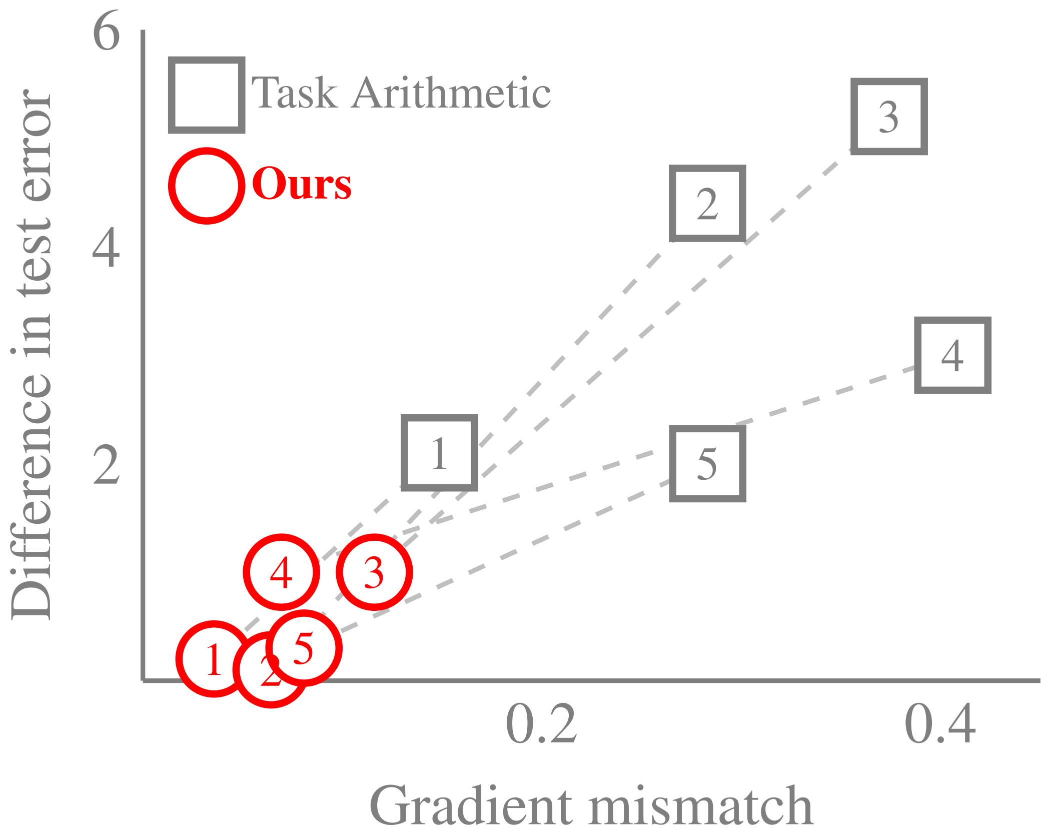


Estimates on training data (no retraining)

Test Performance (NLL) by brute-force retraining

Answering “What-If” Questions

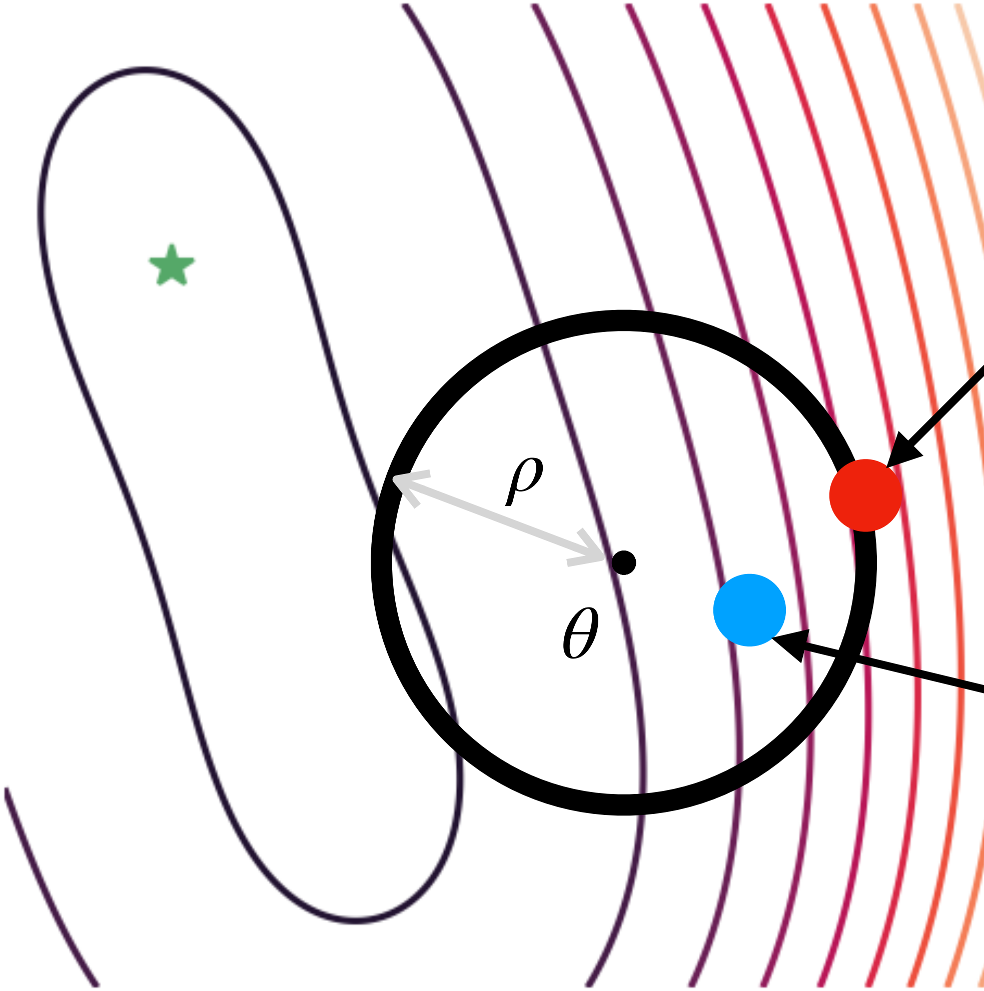
What if we merge fine-tuned large-language models?



RoBERTa
on IMDB

1. Daheim et al. Model merging by uncertainty-based gradient matching, ICLR (2024).

SAM as an Optimal relaxation of Bayes



SAM: $\sup_{|\epsilon|<\rho} \ell(\theta + \epsilon)$

Our work: Fenchel Biconjugate

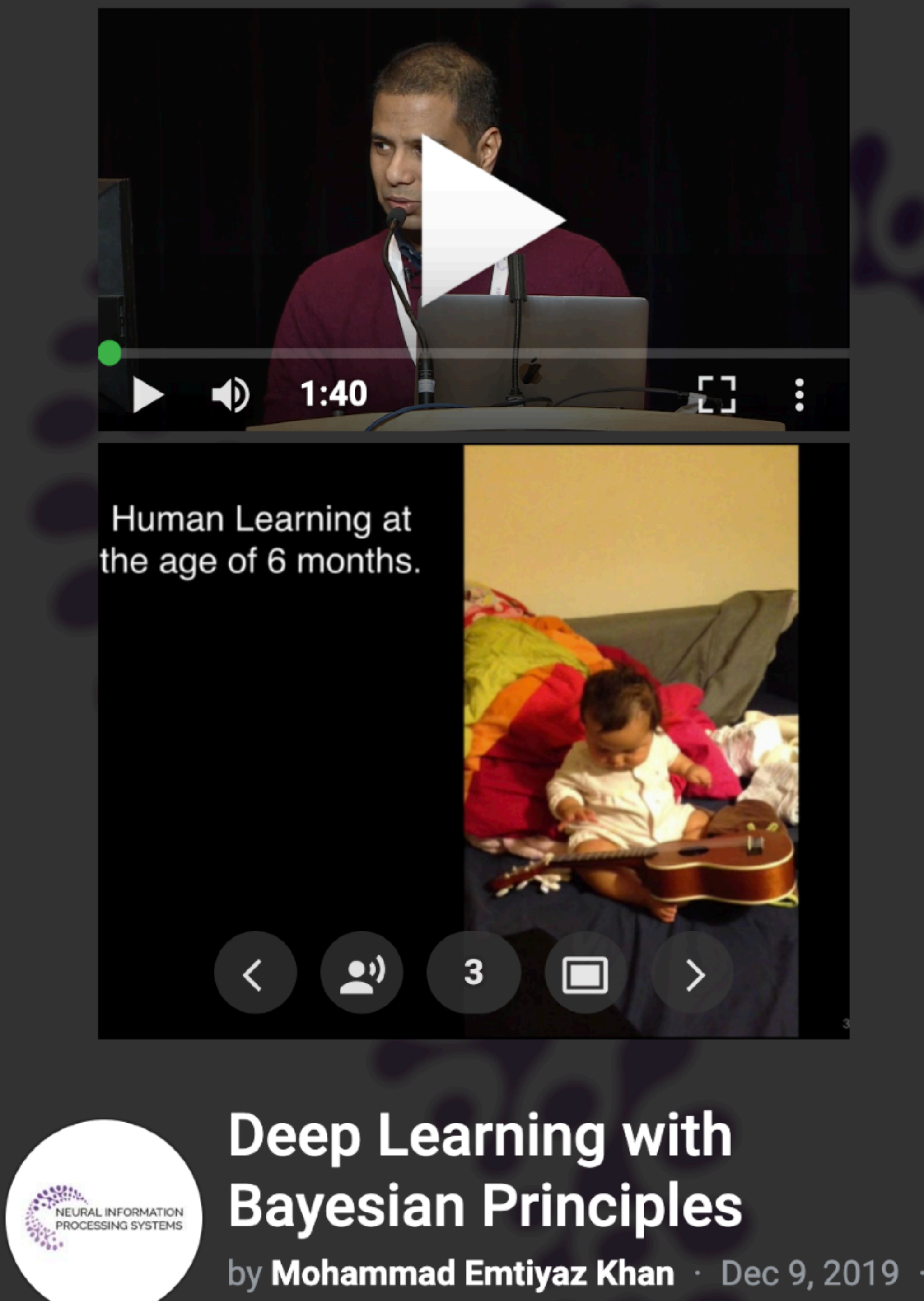
Bayes: $\mathbb{E}_{\epsilon \sim \mathcal{N}(0,\sigma^2)}[\ell(\theta + \epsilon)]$

1. Foret et al. Sharpness-Aware Minimization for Efficiently Improving Generalization, ICLR, 2021
2. Moellenhoff and Khan, SAM as an Optimal Relaxation of Bayes, Under review, 2022

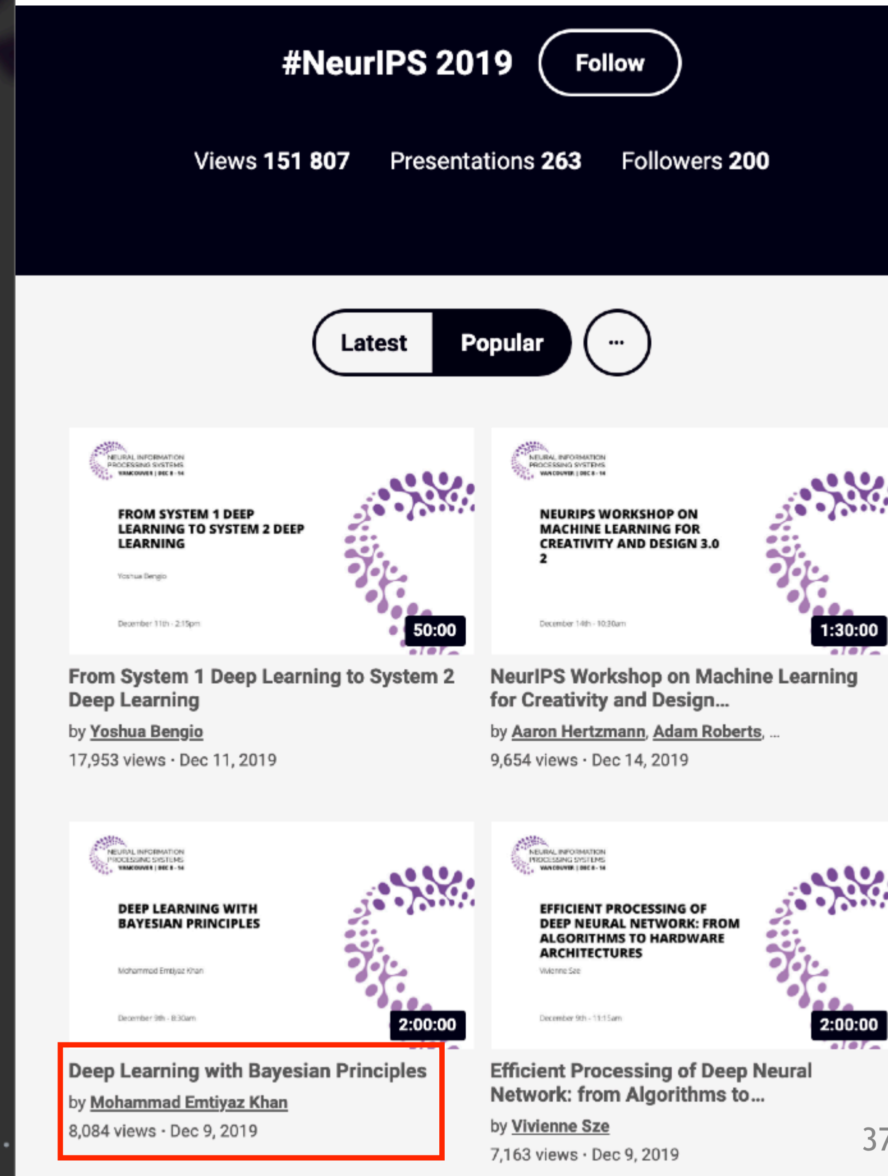
Bayesian Learning Rule [1]

- Bridge DL & Bayesian learning [2-5]
  - SOTA on GPT-2 and ImageNet [5]
- Improve DL [5-7]
  - Calibration, uncertainty, memory etc.
  - Understand and fix model behavior
- Towards human-like quick adaptation

1. Khan and Rue, The Bayesian Learning Rule, JMLR (2023).
2. Khan, et al. Fast and scalable Bayesian deep learning by weight-perturbation in Adam, ICML (2018).
3. Osawa et al. Practical Deep Learning with Bayesian Principles, NeurIPS (2019).
4. Lin et al. Handling the positive-definite constraints in the BLR, ICML (2020).
5. Shen et al. Variational Learning is Effective for Large Deep Networks, Under review.
6. Daheim et al. Model merging by uncertainty-based gradient matching, ICLR (2024).
7. Nickl, Xu, Tailor, Moellenhoff, Khan, The memory-perturbation equation, NeurIPS (2023)



NeurIPS 2019 Tutorial



The webpage is available at https://bayesduality.github.io/, and Twitter account @BayesDuality

The Bayes-Duality Project

Toward AI that learns adaptively, robustly, and continuously, like humans

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Many thanks to our group members and collaborators (many not on this slide).

We are always looking for new collaborations.

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