

# Coffee Talk #9

March 15, 2023

*Ozgur Taylan Turan*



# Modeling Machine Learning Multiverse<sup>1</sup>

<sup>1</sup>S. J. Bell, O. P. Kampman, J. Dodge, and N. D. Lawrence (Oct. 12, 2022). *Modeling the Machine Learning Multiverse*. arXiv: 2206.05985 [cs, stat]

# Why this paper?

- Interesting effort...

# Aim

- Present a principled framework for backed up claims...
- A step closer to reproducibility...

# Introduction

## Multiverse Analysis <sup>1</sup>

- Psychology background...
- Make all the possible choices at the same time!
- Mostly related to dataset construction.
- Different choices affect the outcome/conclusion!

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<sup>1</sup>S. Steegen, F. Tuerlinckx, A. Gelman, and W. Vanpaemel (Sept. 1, 2016). "Increasing Transparency Through a Multiverse Analysis". In: *Perspectives on Psychological Science* 11.5, pp. 702–712. ISSN: 1745-6916. DOI: 10.1177/1745691616658637

# Introduction

## Machine Learning

- Again possible choices (batch size, learning rate architecture etc.)
- CLAIM: With this method we can investigate the effect of each choice...

# Multiverse Exploration

**search space**  $\mathcal{X}$  (claim: often continuous) and **evaluation function**  $l \rightarrow$  multiverse

Due to search space being too large  $\rightarrow$  GP surrogate and explore the space using Bayesian experimental design!

# Multiverse Exploration

- Sample initial design  $X_0 \sim \mathcal{X}$  and evaluate  $Y_0 = l(X_0)$  [They select Sobol sequence as initial design]
- Fit a GP model to  $X_0$  and  $Y_0$
- Use acquisition function  $a$  on  $f$  to sample and evaluate a new batch  $(X_i, Y_i)$
- Repeat until a stopping criterion... [Bayes factor :=  $\frac{P(X, Y | K_{shared})}{P(X, Y | K_{additive})}$ ]
- Sensitivity analysis



# Multiverse Exploration

## Caveat:

- $a$  Integrated Variance Reduction  $\rightarrow$  nasty integral  $\rightarrow$  Monte-Carlo approx.
- Difference with standard optimization!

# Optimization vs Exploration

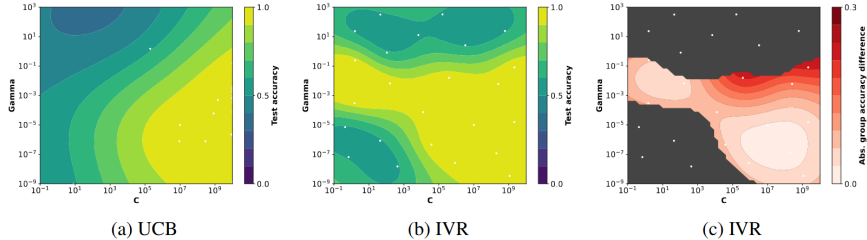


Figure 1: Contour plot of GP-predicted mean test accuracy over search space of  $C$  and  $\gamma$  (Gamma) as explored by (a) UCB and (b) IVR acquisition functions. (c) Secondary objectives, e.g. minimizing group-level outcome differences, may vary along the IVR-revealed plateau.

- Premature optimization hinders our understanding...
- Not to throw shade at optimization!

# When is Adaptive optimization helpful?

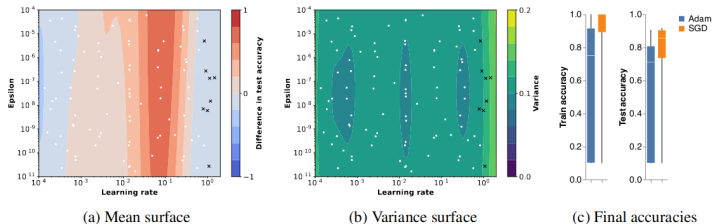
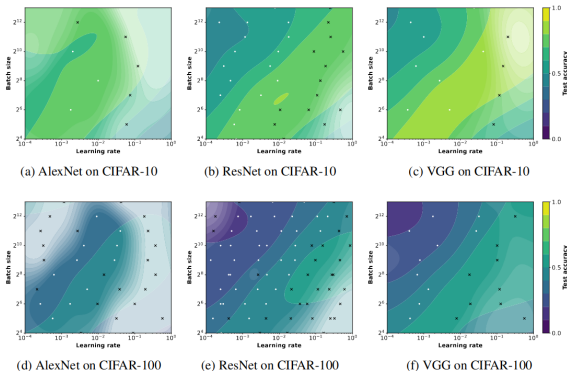


Figure 2: Contour plot of GP-predicted (a) mean difference in test accuracy (SGD - Adam) and (b) variance over the search space of learning rate and  $\epsilon$ . Red regions indicate SGD with momentum outperforms Adam. White points are successful trials; black crosses failed. (c) Final train and test accuracies. Whiskers extend to min and max. Note SGD train accuracy has median, UQ and max 1.0.

- SGD with momentum vs Adam
- Opposing the claims of <sup>1</sup> SGD>Adam

<sup>1</sup>A. C. Wilson, R. Roelofs, M. Stern, N. Srebro, and B. Recht (May 21, 2018). *The Marginal Value of Adaptive Gradient Methods in Machine Learning*. arXiv: 1705.08292 [cs, stat]

# Is there a large-batch generalization gap?



- Many Researchers: batch size  $\uparrow$   
 $\rightarrow$  generalization  $\downarrow$
- Batch-size by itself does not explain the generalization performance!

Figure 4: Contour plot of GP-predicted mean test accuracy over the search space of learning rate, batch size, dataset and model. White points are trials with training accuracy  $\geq 0.99$ ; black crosses were excluded. Overlaid translucent regions indicate high training error. For Tiny ImageNet see fig. S4; for variance see fig. S5. The discrepancy between contours and data points in (a) is due to the coregonalized model sharing information across functions.

# Conclusions

- By using a multiverse analysis, researchers and practitioners gain more robust claims and better understanding of the consequences of their decisions.

THANKS!