

Variational Continual Learning

Alejandro Santorum Varela, David Goldfarb, Vishaal Udandara



Introduction

Variational

$$q_t(\theta) = \arg \min_{q \in \mathcal{Q}} \text{KL} \left(q(\theta) \parallel \frac{1}{Z_t} q_{t-1}(\theta) p(\mathcal{D}_t | \theta) \right)$$

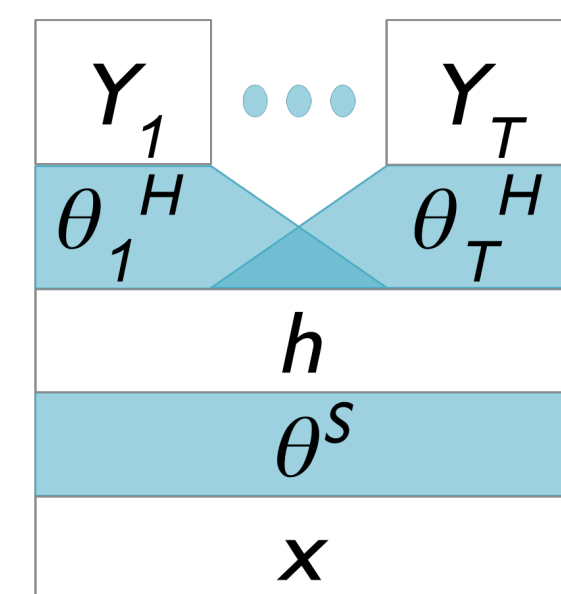
Continual Learning



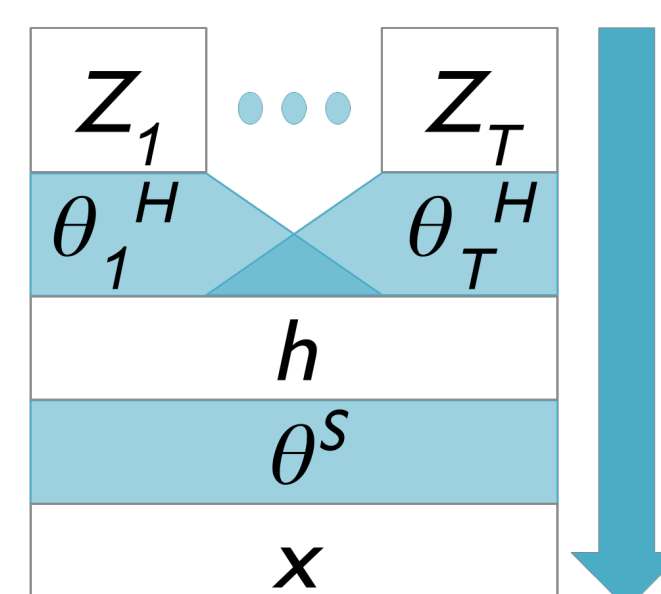
- Continual Learning (CL) requires balance between:
 - Plasticity (Catastrophic Forgetting)
 - Stability (Inability to adapt)

Methods

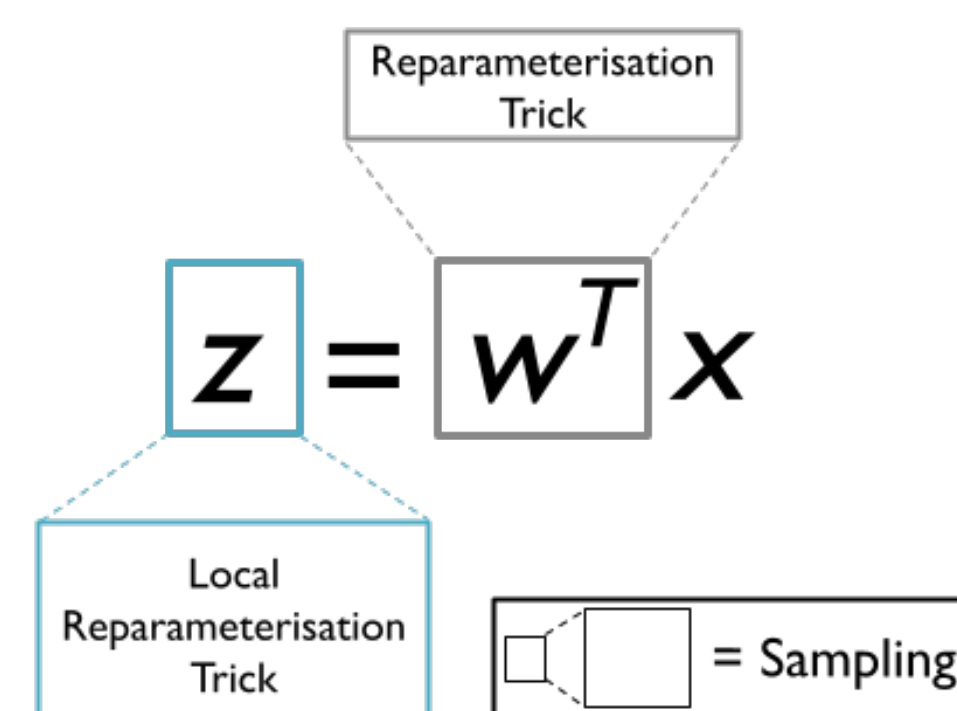
Discriminative Model



Generative Model

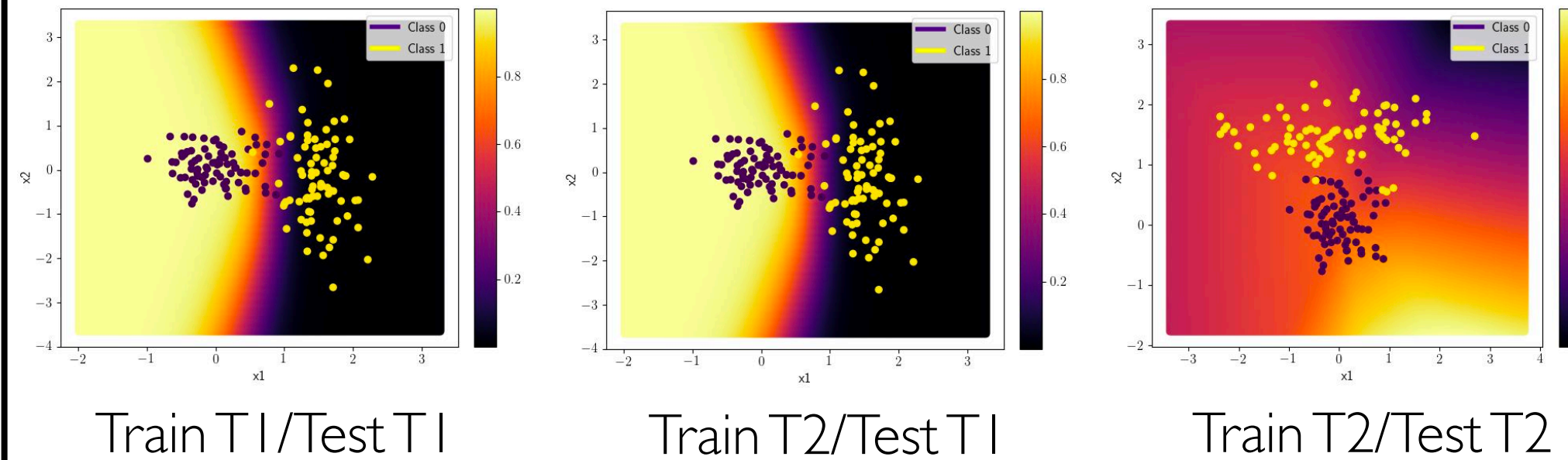


- Sampling:

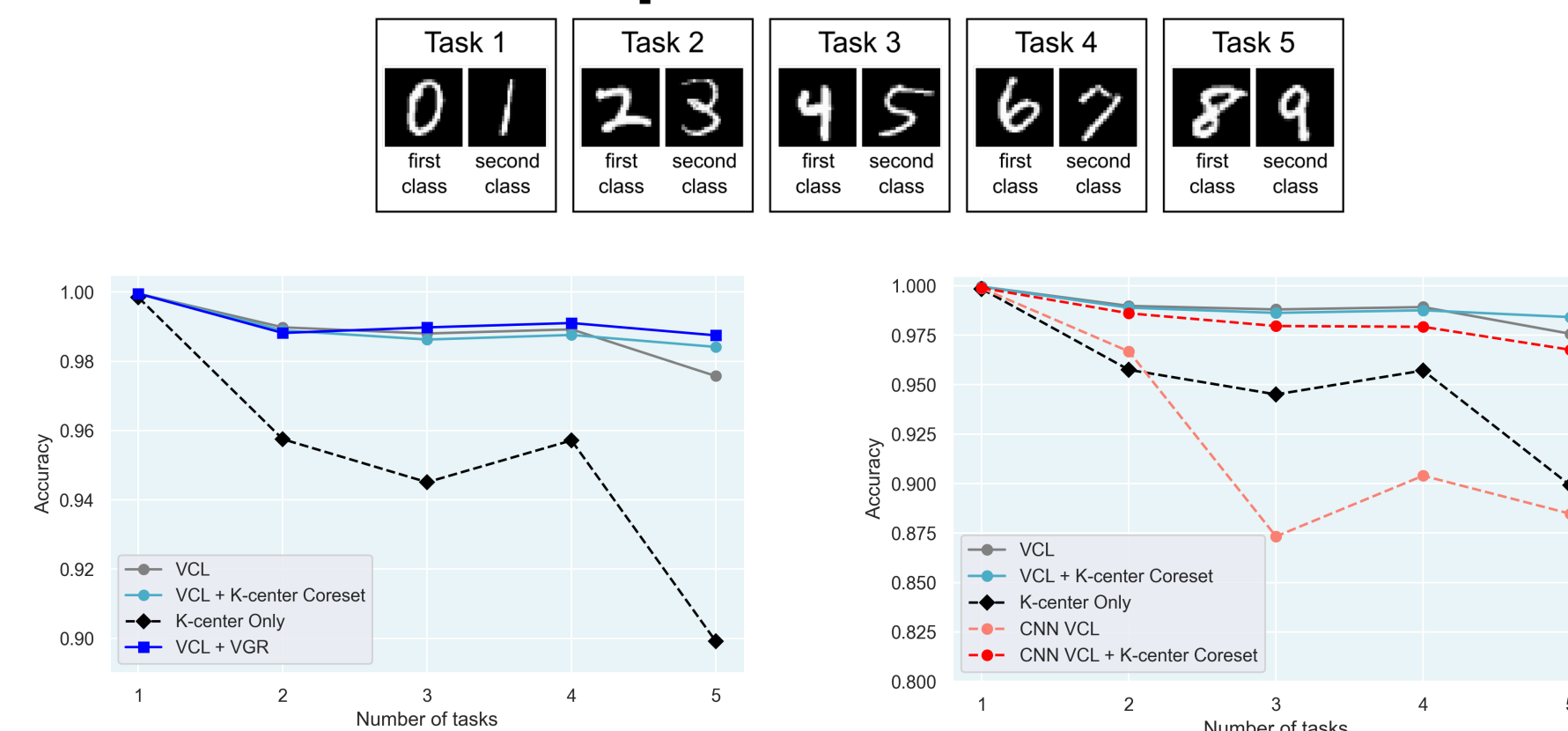


- Architectures:
 - Fully-Connected
 - CNNs
- Coreset Memory Enhancement:
 - Random Coresets
 - K-Center Coresets
 - Variational Generative Replay (VGR)

Toy Task



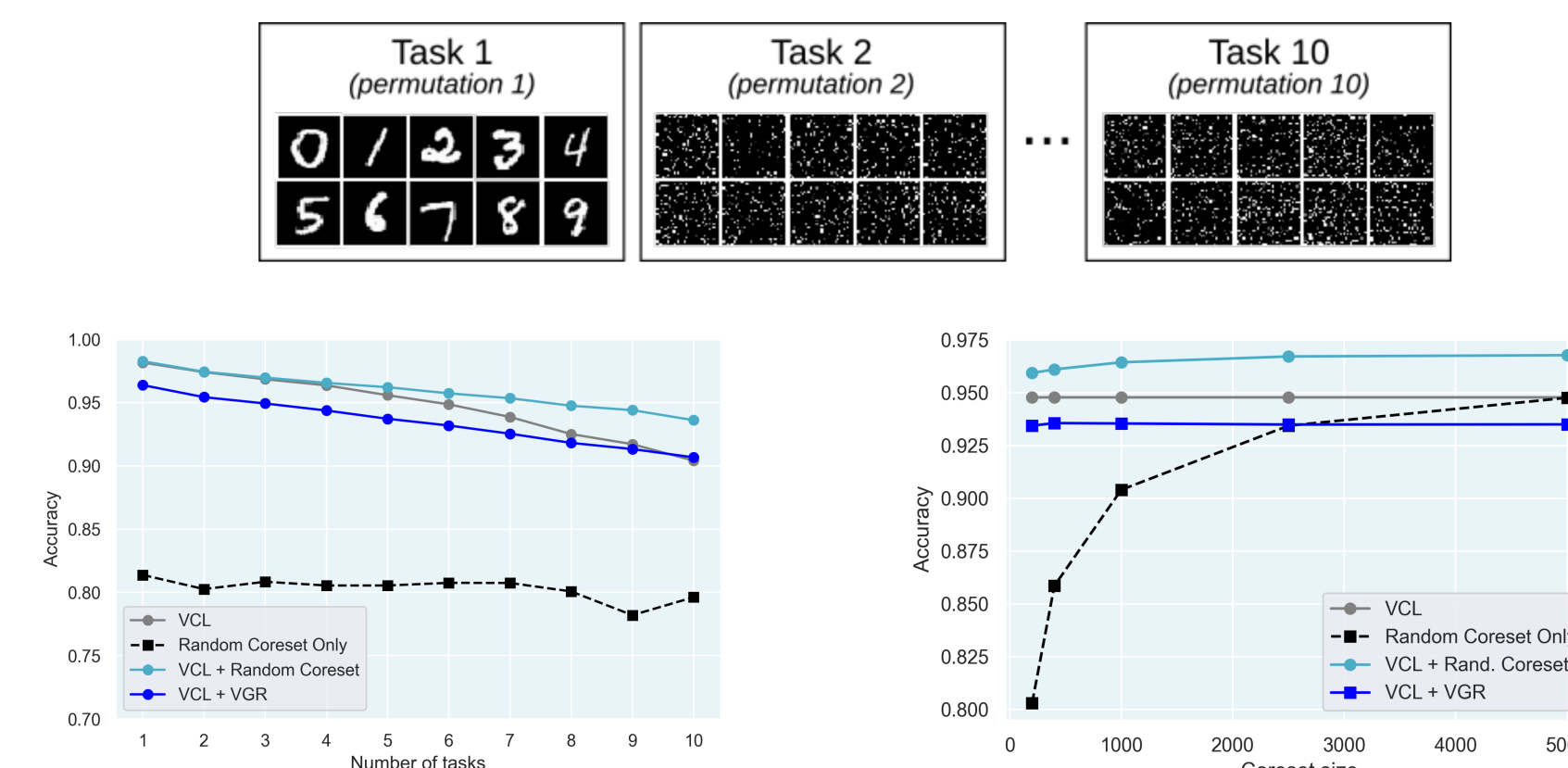
Split-MNIST



- VCL avoids catastrophic forgetting
- VGR improves on explicit coreset
- CNN: complexity vs. performance

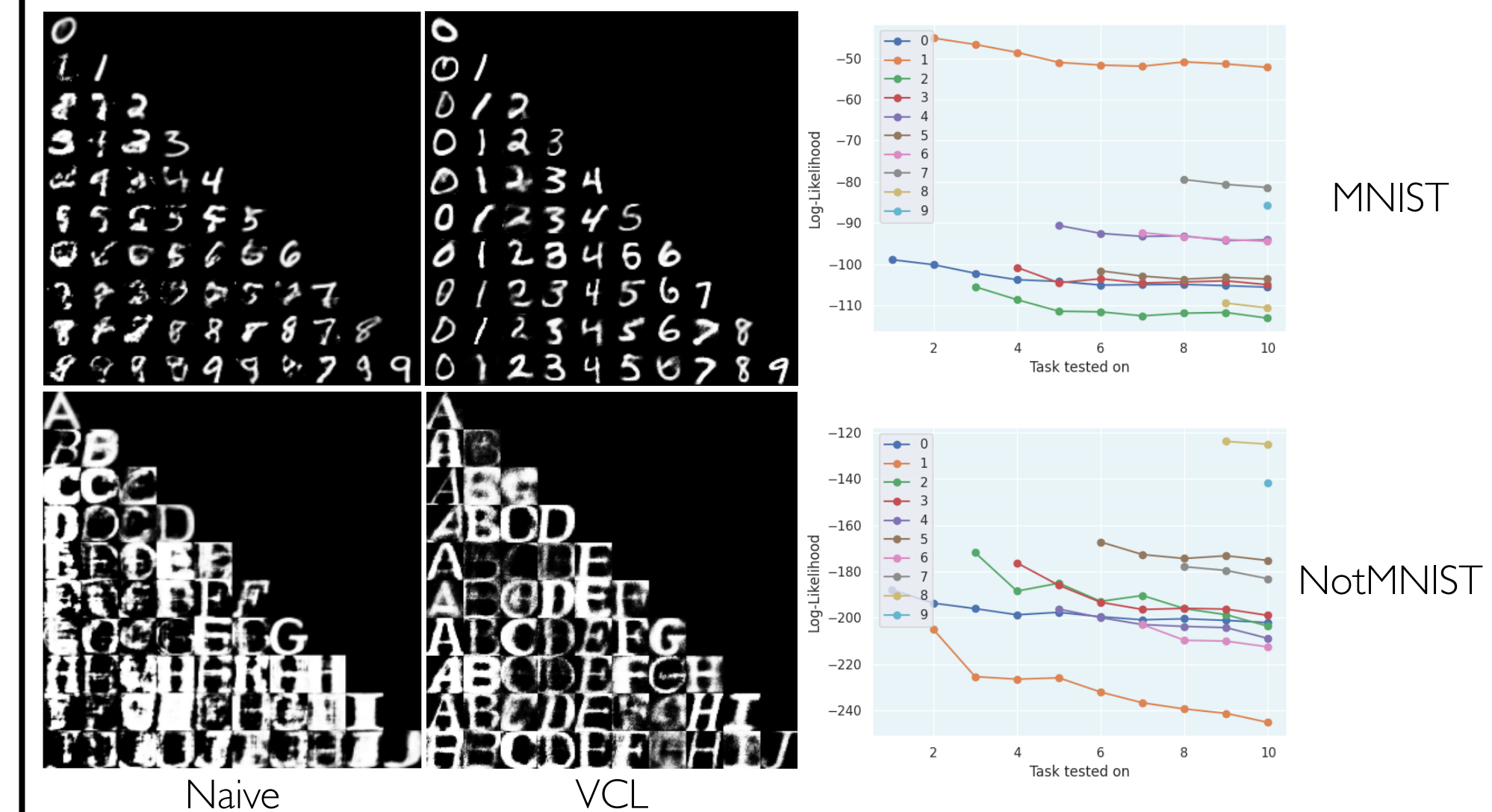
	# of parameters	Accuracy
VCL	268800	97.57 %
VCL + Coreset		98.41 %
CNN VCL	9768	88.48 %
CNN VCL + Coreset		96.76 %

Permuted-MNIST



- VGR: underperforms from unstructured images
- Performance plateaus with coreset size

Generation



- VCL preserves old tasks' structure
- VCL outperforms other generative CL methods

Conclusion

- Variational methods improve over naive CL approaches
- VCL applies to both discriminative and generative models
- Coresets improve both naive and VCL performance
 - Selection algorithm inconsequential
- VGR reduces coreset memory footprint
- VCL can be applied to CNNs
 - CNN matches FC performance with fewer parameters
 - LRT suboptimal for CNNs

References

- Cuong V. Nguyen et. al, Variational Continual Learning, 2018
- Sebastian Farquhar et. al, A Unifying Bayesian View of Continual Learning, 2019
- Diederik P. Kingma et. al, Variational Dropout and the Local Reparameterization Trick, 2015
- Gido M. van de Ven et. al, Generative replay with feedback connections as a general strategy for continual learning, 2019

Code available at <https://github.com/goldfarbDave/vcl>