Domain adaptation techniques preserve model accuracy across MRI imaging modalities

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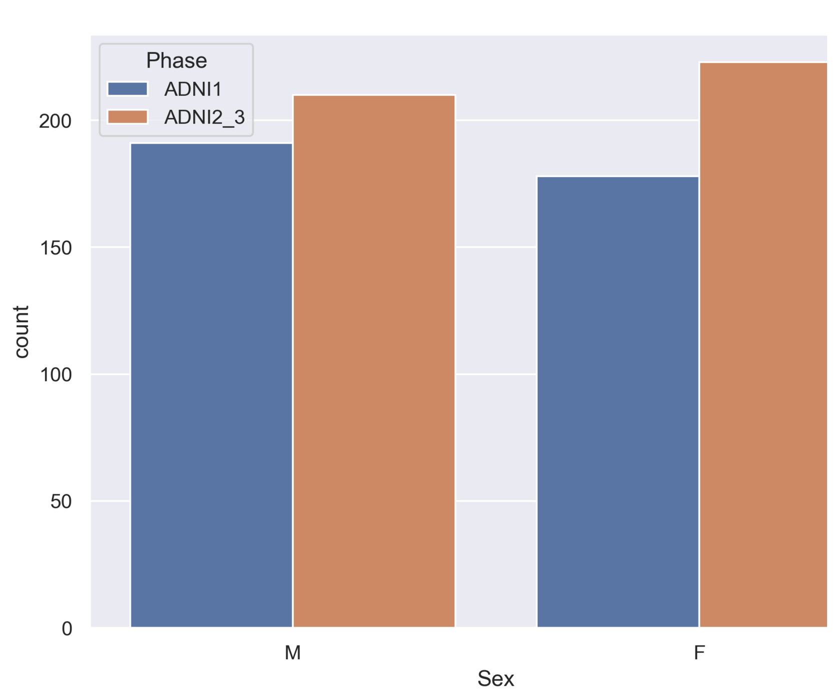
Key Results

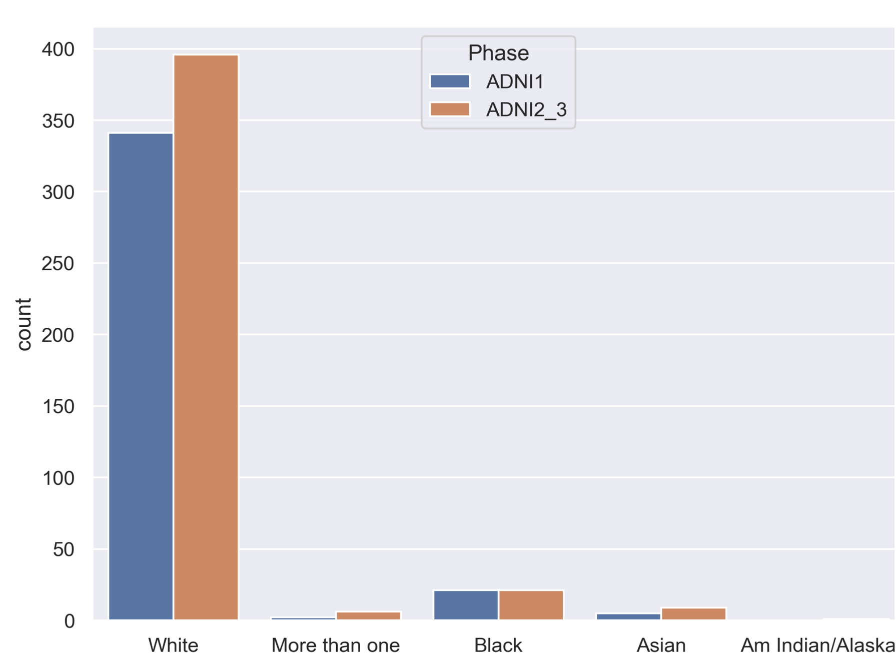
- Differences between data collection domains compromise generalizability of ML models for Alzheimer's prediction.
- MUSE MRI features indicate a clear distribution shift.
- We introduce a hyperparameter tuning flow for domain adaptation by up-weighting the target domain's samples.

Domain Shift as a Concept

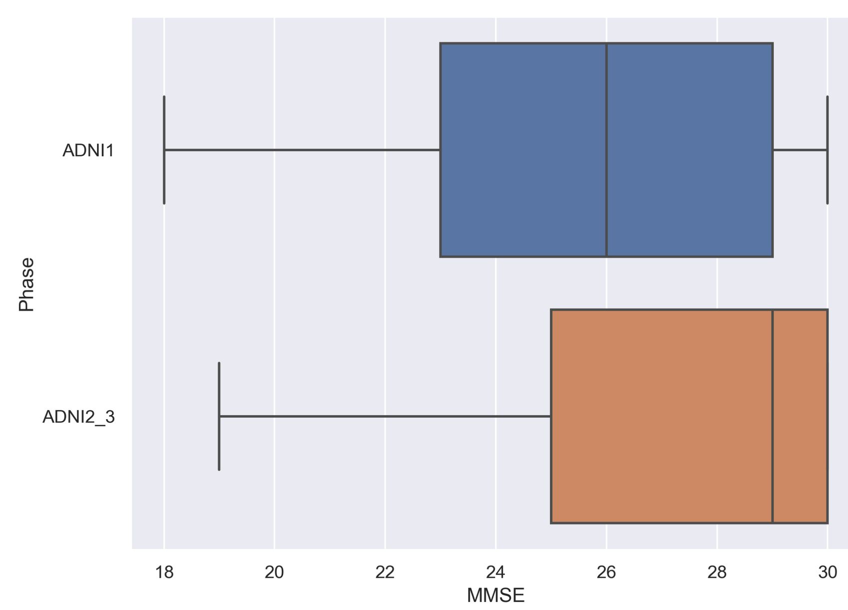
- Same ML task, but **different distribution.**
- Important issue for large-scale models.

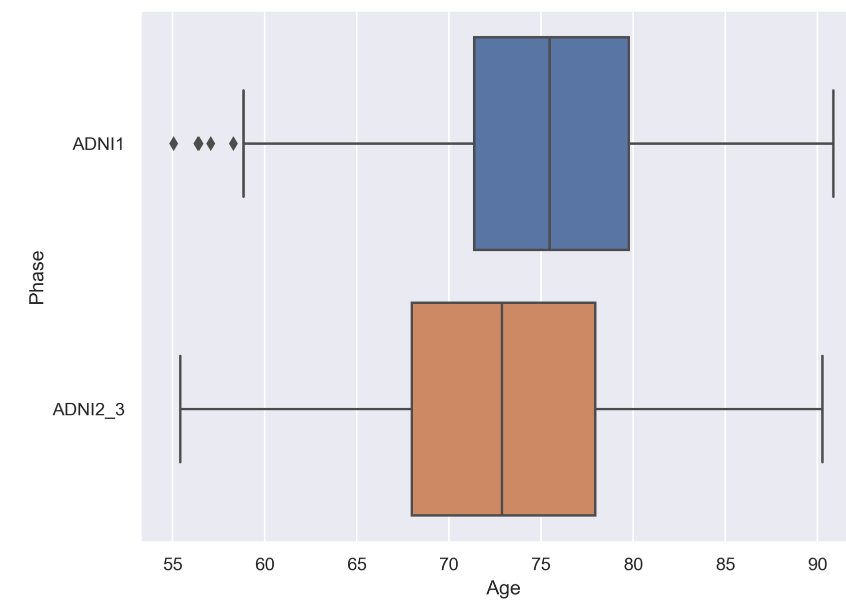
Sex and Race across Domains





MMSE and Age across Domains





Heterogeneous MRI Features

PCA Visualization of MUSE Features

Kilmogorov-Smirnov $p < 1e{-}10$

Model Accuracy Across Phases

		Test		
		ADNI1	ADNI2/3	Combined
Train	ADNI1 (n=369)	0.919	0.893	0.904
	ADNI2/3 (n=433)	0.878	0.942	0.913
	Combined	0.892	0.977	0.938

Applying Domain Weights

- Performance is skewed by domain.

$$l = -w_n(y_n \log(p_n) + (1 - y_n)\log(1 - p_n))$$

- Use case for class imbalance + domain shift

AutoML HPO for Weights

- Sample-weight parameter in AutoGluon
- Ray can do HPO over **continuous space**
- Combined training set: 0.98 accuracy
  - Optimal alpha: weight ADNI2/3 by 0.74
- Exclude half of ADNI1: 0.97 accuracy
  - Optimal alpha: weight ADNI2/3 by 0.4

Future Directions

- Nonlinear relationship between frequency ratio and alpha -> raises questions
- Representation-based learning approaches