Transfer Learning with Al Improves Estimation of Genomic Variation

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Background:

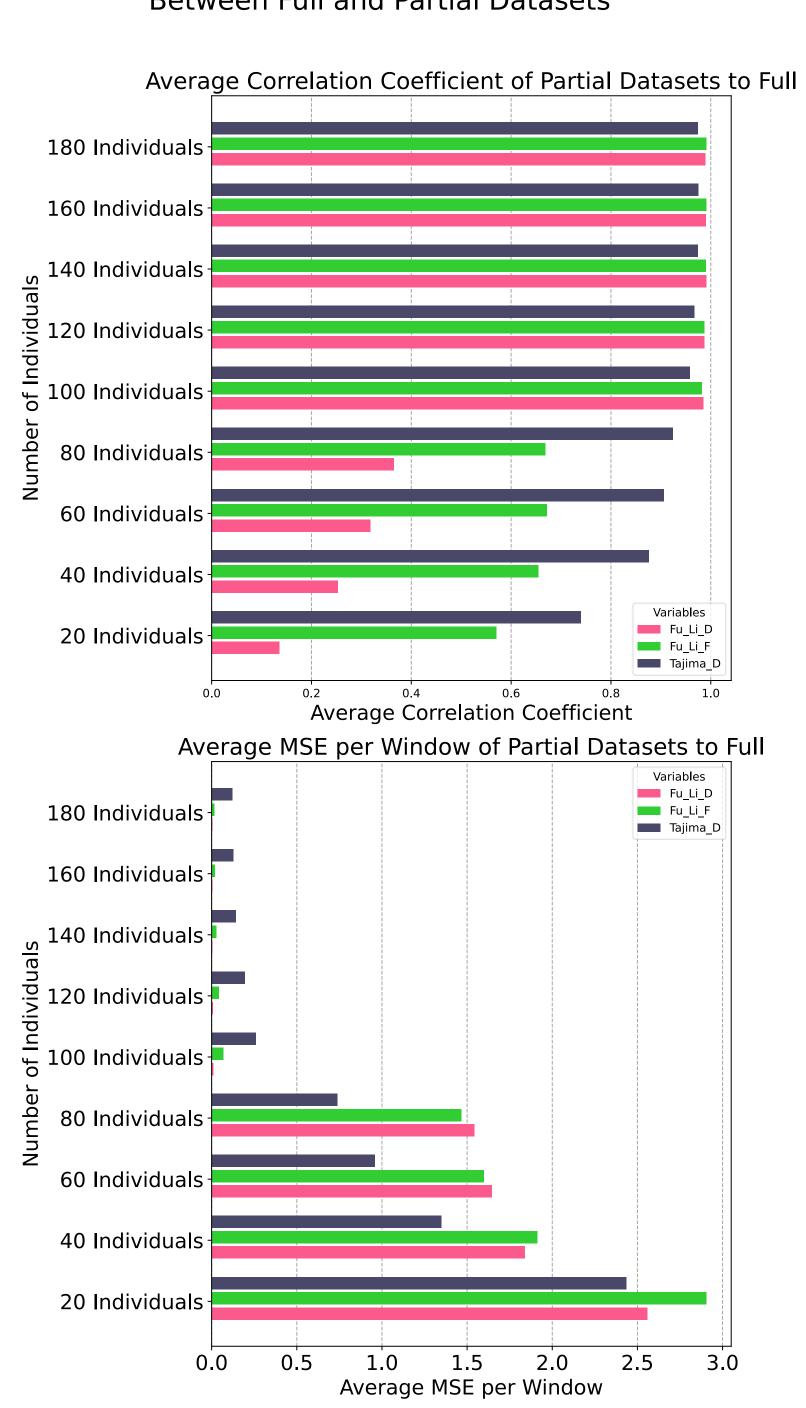
Traditional methods of estimating neutrality are sample size dependent

Neutral evolution, parametrized by mutation rate and population size, is a consistent stochastic process among species

Generative models, like GANs₁, have been used to estimate neutrality from genomic data.

We hypothesize deep learning and transfer learning will improve the estimation of neutrality in small sample sizes.

> Average Neutrality Stat Correlation and MSE Between Full and Partial Datasets



Methods:

Data

WGS 1000 Genomes Project data₂

Two foundational populations, (TSI, IBS), 217 individuals

Two transfer populations (CHB, KHV), 20 individuals

Preprocessing

Filter sites with measurable selective or demographic effects

Training

Train a Variational Autoencoder₃ (VAE) on remaining neutral sites

Transfer Learning

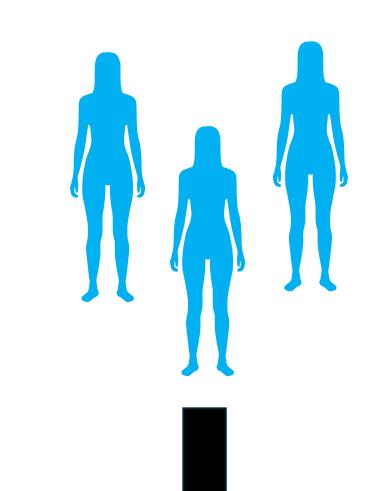
Fine-tune the model on the transfer dataset

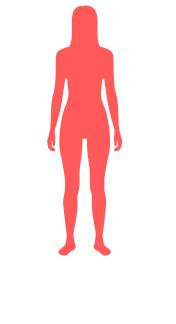
Use Lower learning rate, fewer epochs

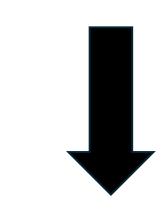
Assessment

Analyze reconstruction error scores to assess performance

Use Tajima's D, Fu and Li's D and F as benchmarks for both full and partial datasets

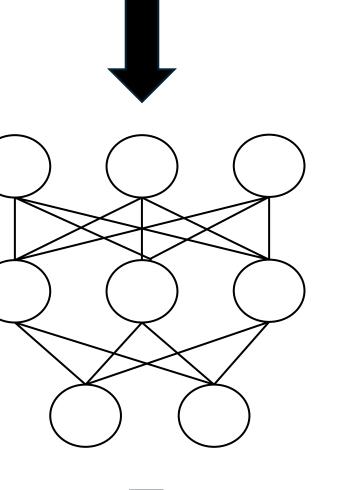


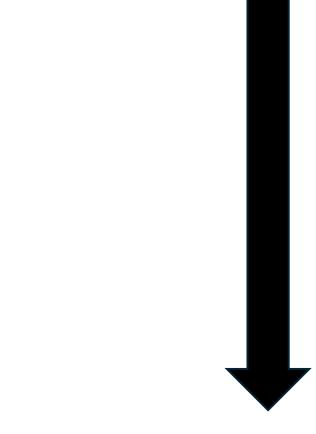


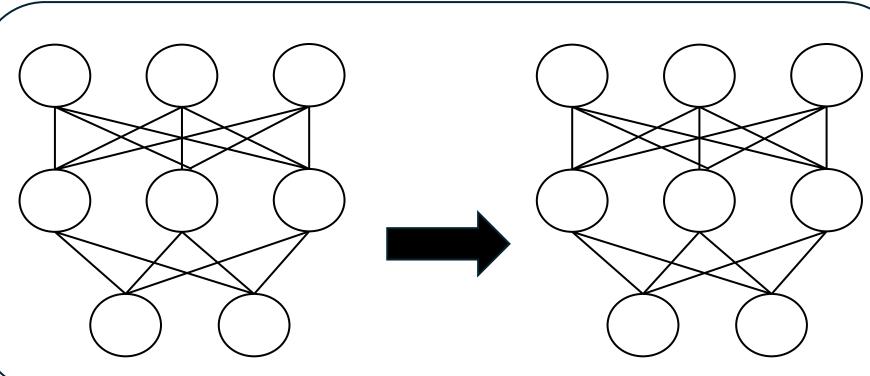


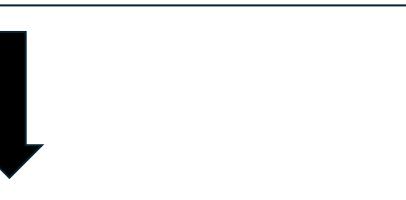


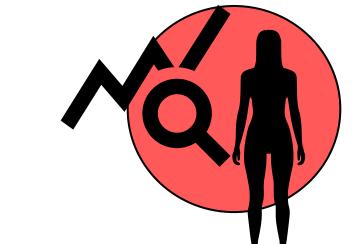


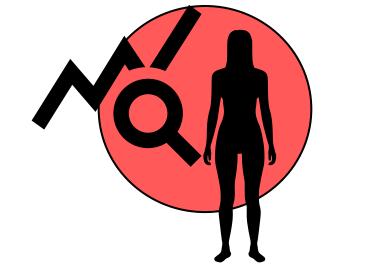












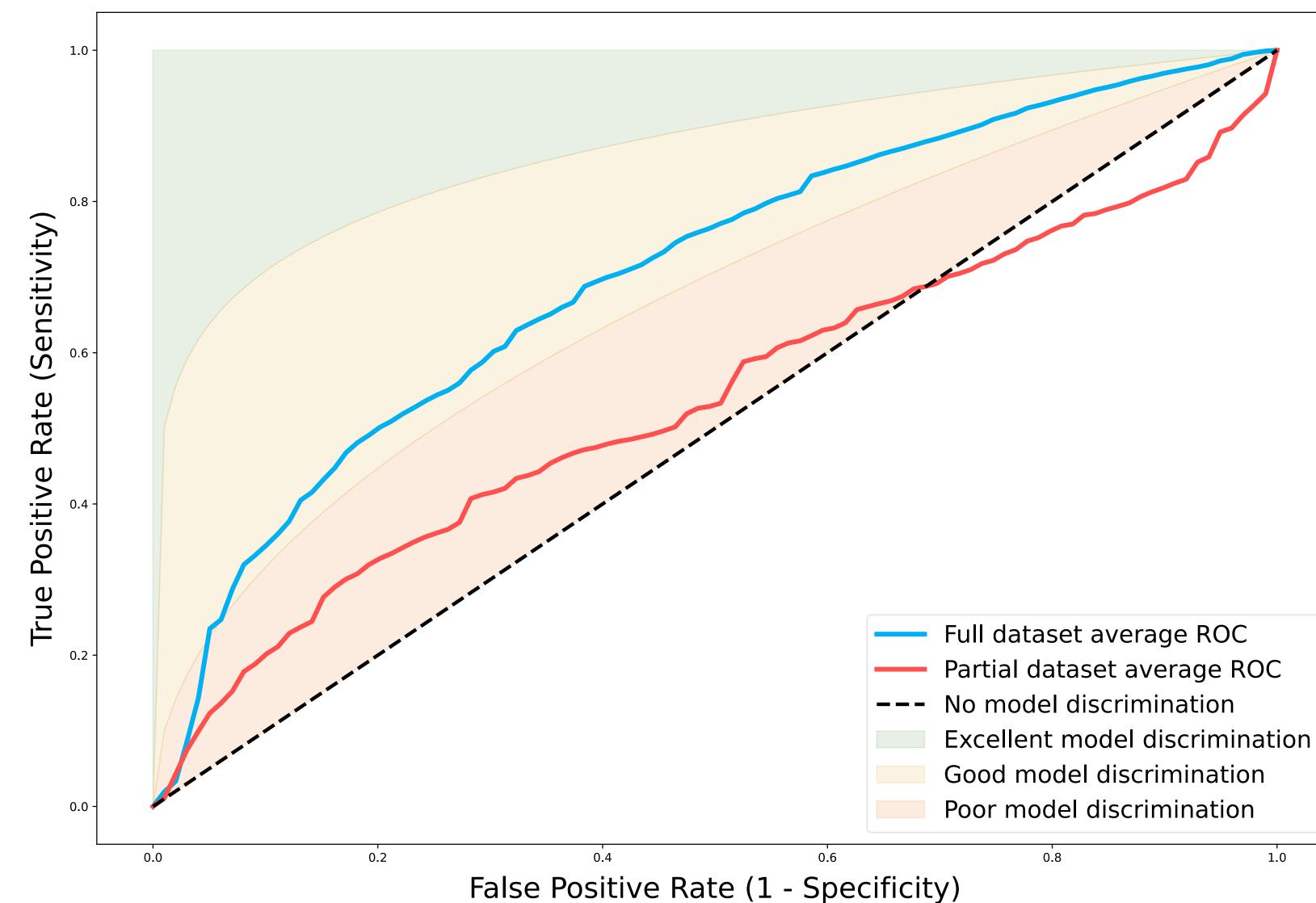
Results/Discussion:

Transfer learning neutrality estimates were more consistent with larger sample sizes (202 individuals) than smaller ones (20 individuals).

Population genetic inference in low-sampled populations was improved with transfer learning, given sufficient training data.

Given the broad importance of estimating in population genetics analyses, transfer learning might be able to help improve inferences from the kind of data biologists are able to collect.

Transfer learning ROC Curves on Full/Partial Datasets Using Summary Stats



Citations:

I. Riley et al. 2024, Genetics

2. 1000 Genomes Project Consortium 2015, Nature

3. Higgins et al. 2017, ICLR

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