The American Journal of Human Genetics, Volume 109

Supplemental information

The construction of cross-population polygenic

risk scores using transfer learning

Zhangchen Zhao, Lars G. Fritsche, Jennifer A. Smith, Bhramar Mukherjee, and Seunggeun Lee

Supplemental Information

1. Supplemental Figures



Figure S1. Prediction accuracy of TL-PRS(ind) and TL-PRS methods in simulations. (A) The proportion of causal variants is 0.1%; (B) The proportion of causal variants is 1.0%. In each setting, three different cross-population genetic correlations (0.4, 0.7 and 1.0) were considered. Heritability was fixed at 50%. Prediction accuracy was measured by the squared correlation (R²) between the simulated and predicted phenotypes in the testing dataset, averaged across 20 simulation replicates. Error bar indicates the standard deviation of R² across simulation replicates.



(b)

(a)



Figure S2. Cumulative event plot in terms of the top 10% PRS constructed by transfer learning methods and their baseline methods. Note that y-axes are on different scales in the different panels. (a) South Asian testing samples, Type 2 diabetes, Case: Control=419:2211; (b)South Asian testing samples, Coronary artery disease, Case: Control=362:2270; (c)African testing samples, Type 2 diabetes, Case: Control=177:1812; (d) African testing samples, Coronary artery disease, Case: Control=94:1902.

2. Supplemental Tables

Methods	Training dataset	Validation dataset	Testing dataset
TL-PRS	Only requires summary statistics	Individual-level data are recommended.	Requires individual-level data to assess prediction performance
TL-PRS (ind)	Requires individual-level data	Requires individual-level data	Requires individual-level data to assess prediction performance

Table S1. The model requirements of TL-PRS and TL-PRS (ind).

Target Population Trait		Total	Training	Validation	Testing
		sample	sample	sample	sample
		size	size	size	size
South Asian (SAS)	Simulation and real phenotypes	10,285	5,000	2,650	2,635
African (AFR)	real phenotypes	8,168	4,000	2,169	1,999

Table S2. List of data sets used in simulations and analyses of real phenotypes.

Method	Pre-training data	Training data (target	Validation data (target	Testing data (target ancestry
	(GWAS summary	ancestry group)	ancestry group)	group)
	statistics of source			
	ancestry, and 1000			
	Genome Project Data)			
	Train PT using pre- training data.	Select the hyperparameters	Assess prediction	
PT	Individual-level data	training and validation data	. Individual-level data are	performance using
	are required.	required.	individual-level data.	
	Train Lsum using pre-	Select the hyperparameters	using the combination of	Assess prediction
Lsum	Individual-level data	training and validation data	. Individual-level data are	performance using
	are required.	required.	individual-level data.	
	Train PRS-CS using	Select the hyperparameters	Assess prediction	
PRS-CS	pre-training data.	training and validation data	performance using	
	are required.	not required.	individual-level data.	
	Pre-train Lsum using	Validate the pre-trained	Select hyper parameters of	
	pre-training data.	baseline Lsum model, and	the TL-PRS-Lsum model	Assess prediction
TL-PRS-	Individual-level data	use it to train TL-PRS-	using validation data.	performance using
Lsum	are required.	Lsum. Individual-level	Individual-level data are	individual-level data.
		data are not required.	recommended.	
	Pre-train PRS-CS	Validate the pre-trained	Select hyper parameters of	
	using pre-training data.	baseline PRS-CS model,	the TL-PRS-CS model	Assess prediction
TL-PRS-CS	Individual-level data	and use it to train TL-	using validation data.	performance using
	are required.	PRS-CS. Individual-level	Individual-level data are	individual-level data.
		data are not required.	recommended.	

1		`
(h	1
Ľ	~	,

Method	Training data (target ancestry group)	Validation data (target ancestry group)	Testing data (target ancestry group)
PT-multi Lsum-multi PRS-CSx	Select the weights (hyperparameter) to models using combination of training a Individual-level data are required to fin	linearly combine single-source prediction nd validation data. e-tune the weight parameter.	Assess prediction performance using individual-level data
MTL-PRS-Lsum MTL-PRS-CS	Select the weights to construct the baseline Lsum-multi/PRS-CSx model, and then implement TL-PRS. Individual-level data are not required.	Select hyper parameters of the MTL- PRS models using validation data. Individual-level data are recommended.	Assess prediction performance using individual-level data

Table S3. The implementation of prediction methods in the simulation and application of UK Biobank (a) The implementation of single-source prediction methods. (b) The implementation of multi-source prediction methods.

		0.1% Causal		1% Causal			
Genetic Correlation		0.4	0.7	1	0.4	0.7	1
TL-PRS-	Selected						
Lsum	learning	1000	100	100	1000	100	100
	rate	(100,1000)	(100,100)	(10,100)	(100,1000)	(100,100)	(100,100)
	Selected						
	iteration	3	10	3	3	12	4
		(2,14)	(8,11)	(2,7)	(2,8)	(9,13)	(3,6)
TL-PRS-CS	Selected						
	learning	1000	1000	100	1000	1000	100
	rate	(1000,1000)	(1000,1000)	(100,100)	(1000,1000)	(1000,1000)	(100,1000)
	Selected						
	iteration	7	3	10	8	4	14
		(6,8)	(2,4)	(7,13)	(7,9)	(3,4)	(3,15)

Table S4. The selected learning rates and iterations of TL-PRS-Lsum and TL-PRS-CS in simulations. Two different percentages of causal variants (0.1% and 1% causal variants) and three different cross-population genetic correlations (0.4, 0.7, and 1.0) were considered. The value in each cell is the median and the values in the parentheses represents the 1st and 3rd quartile of the distribution.

Target	trait	Best approach (rank 1)	Rank 2	Rank 3	
population					
South Asian	HDL	MTL-PRS-CS	MTL-PRS-Lsum	TL-PRS-CS(UKBB)	
	LDL	MTL-PRS-Lsum	Lsum-multi	MTL-PRS-CS	
	BMI	Lsum-multi	MTL-PRS-Lsum	MTL-PRS-CS	
	TG	Lsum-multi	PRS-CSx	MTL-PRS-CS	
	SBP	MTL-PRS-Lsum	MTL-PRS-CS	PRS-CSx	
	DBP	MTL-PRS-CS	TL-PRS-CS(UKBB)	MTL-PRS-Lsum	
	HGT	MTL-PRS-Lsum	MTL-PRS-CS	TL-PRS-Lsum(UKBB)	
	CAD	MTL-PRS-CS	PRS-CSx	Lsum-multi	
	T2D	MTL-PRS-CS	MTL-PRS-Lsum	PRS-CSx	
African	HDL	MTL-PRS-CS	PRS-CSx	MTL-PRS-Lsum	
	LDL	TL-PRS-Lsum(BBJ)	MTL-PRS-Lsum	TL-PRS-Lsum(UKBB)	
	BMI	MTL-PRS-Lsum	Lsum-multi	MTL-PRS-CS	
	TG	MTL-PRS-CS	TL-PRS-CS(UKBB)	PRS-CSx	
	SBP	TL-PRS-CS(UKBB)	PRS-CSx	MTL-PRS-CS	
	DBP	MTL-PRS-CS	TL-PRS-CS(UKBB)	PRS-CSx	
	HGT	MTL-PRS-Lsum	lsum-multi	MTL-PRS-CS	
	CAD	PT(UKBB)	MTL-PRS-CS	PT-multi	
	T2D	MTL-PRS-CS	PRS-CS(UKBB)	TL-PRS-CS(UKBB)	

Table S7. The top three methods for all nine traits in the South Asian and African ancestries in terms of predicted R². Single-source prediction methods (PT, Lsum, TL-PRS-Lsum, PRS-CS, TL-PRS-CS) based on UKBB and BBJ GWAS results and multi-source PRS methods (PT-multi, Lsum-multi, MTL-PRS-Lsum, PRS-CSx, MTL-PRS-CS) were included in the comparison and our approaches were highlighted using italics.

(a)							
	0.1% Causal			1% Causal			
Genetic Correlation	0.4	0.7	1	0.4	0.7	1	
РТ	0.051 (0.011)	0.159 (0.026)	0.319 (0.019)	0.042 (0.007)	0.126 (0.012)	0.251 (0.016)	
Lsum	0.060 (0.012)	0.188 (0.023)	0.380 (0.020)	0.053 (0.008)	0.157 (0.016)	0.317 (0.014)	
TL-PRS-							
Lsum	0.205 (0.017)	0.267 (0.023)	0.389 (0.018)	0.083 (0.011)	0.175 (0.014)	0.321 (0.014)	
PRS-CS	0.050 (0.012)	0.165 (0.024)	0.331 (0.017)	0.045 (0.006)	0.133 (0.016)	0.268 (0.015)	
TL-PRS-CS	0.073 (0.013)	0.177 (0.024)	0.333 (0.016)	0.064 (0.009)	0.146 (0.015)	0.270 (0.016)	

	0.1% Causal			1% Causal			
Genetic Correlation	0.4	0.7	1	0.4	0.7	1	
РТ	0.049 (0.011)	0.156 (0.023)	0.309 (0.017)	0.034 (0.007)	0.104 (0.015)	0.210 (0.014)	
Lsum	0.060 (0.011)	0.186 (0.023)	0.373 (0.019)	0.045 (0.007)	0.134 (0.016)	0.268 (0.014)	
TL-PRS-							
Lsum	0.190 (0.021)	0.262 (0.019)	0.382 (0.017)	0.069 (0.009)	0.152 (0.017)	0.273 (0.014)	
PRS-CS	0.047 (0.012)	0.148 (0.023)	0.304 (0.020)	0.038 (0.006)	0.112 (0.017)	0.222 (0.014)	
TL-PRS-CS	0.070 (0.013)	0.161 (0.023)	0.307 (0.020)	0.059 (0.008)	0.127 (0.018)	0.226 (0.014)	

Table S8. Prediction accuracy of single-source polygenic prediction methods in simulations. Two different percentages of causal variants (0.1% and 1% causal variants) and three different cross-population genetic correlations (0.4, 0.7 and 1.0) were considered. Heritability was fixed at 50%. Prediction accuracy was measured by the squared correlation (\mathbb{R}^2) between the simulated and predicted phenotypes in the testing dataset, averaged across 20 simulation replicates. The number in the parentheses indicates the standard deviation of \mathbb{R}^2 across simulation replicates. (a) Simulation with 100,000 European GWAS sample size; (b) Simulation with 50,000 European GWAS sample size.

(h)