

Journal Club



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A deep learning framework for characterization of genotype data

Kristiina Ausmees,  Carl Nettelblad

doi: <https://doi.org/10.1101/2020.09.30.320994>

[https://github.com/richelbilderbeek/
journal_club_20220120](https://github.com/richelbilderbeek/journal_club_20220120)

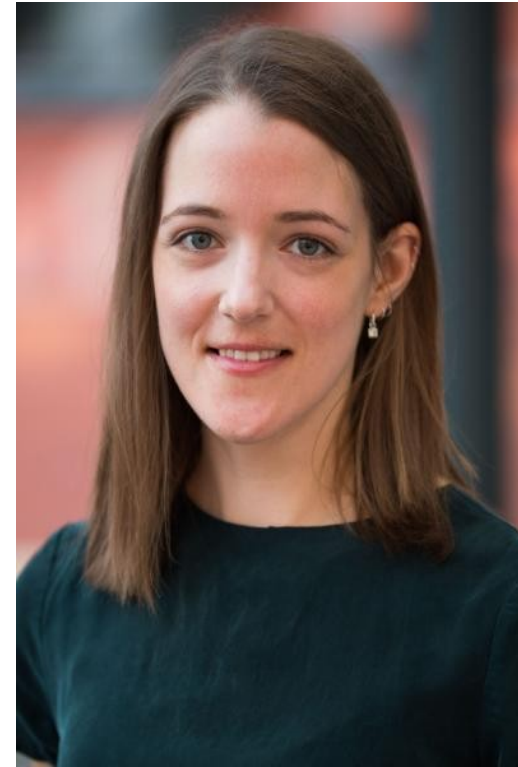


Why this article

Google 'GWAS + "machine learning"' for 2021
Start of collaboration



Carl Nettelblad



Kristiina Ausmees

Background



Can we order genomes?

Similar genomes close

Because then we can ...

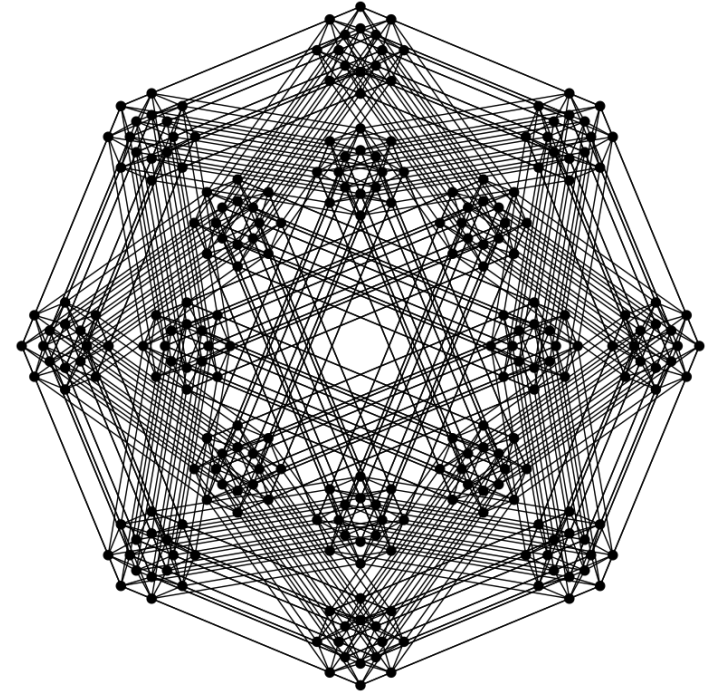
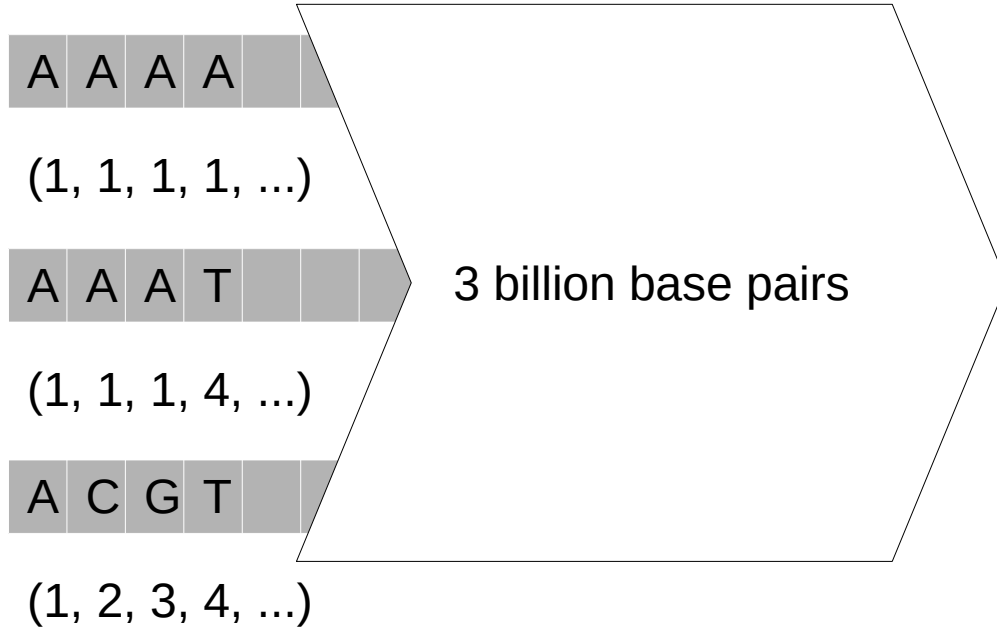
See amount of genetic variation

Identify population structure

Do ancestry mapping

Simulate genotypes

It is easy to order genomes



$$d(p, q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_i - q_i)^2 + \cdots + (p_n - q_n)^2}.$$

Background



**Can we order genomes
in a smart way?**

Similar genomes close

Because then we can ...

See amount of genetic
variation

Identify population structure

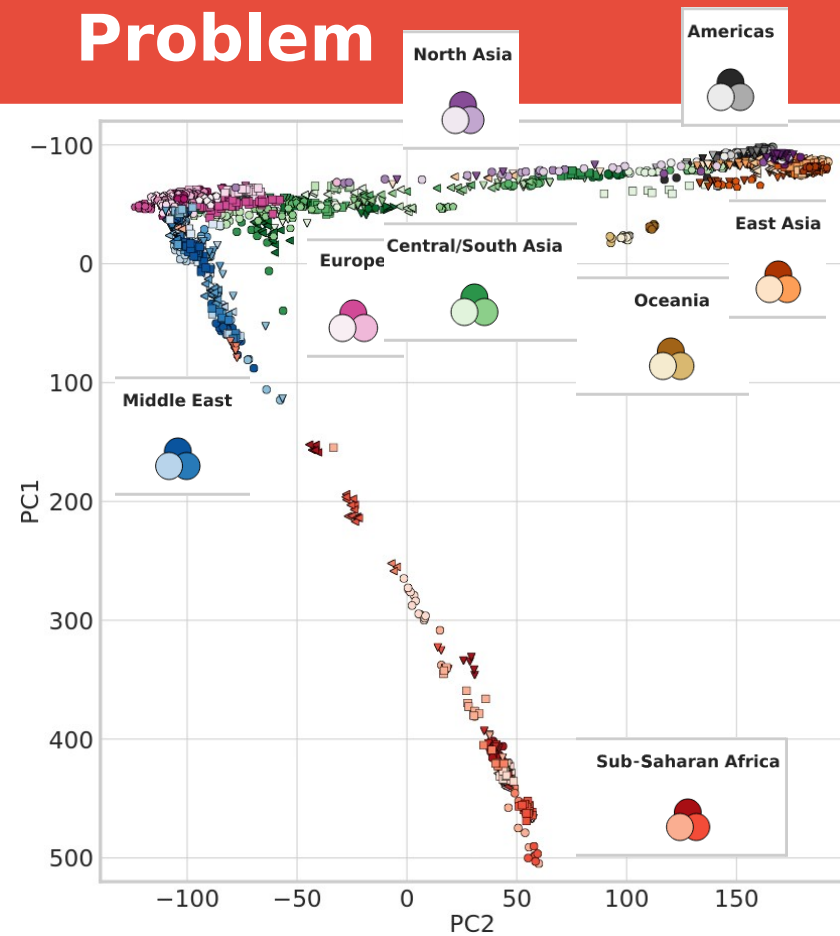
Do ancestry mapping

Simulate genotypes

**Dimensionality
reduction**

https://upload.wikimedia.org/wikipedia/commons/b/bc/DNA_representation.jpg

Problem

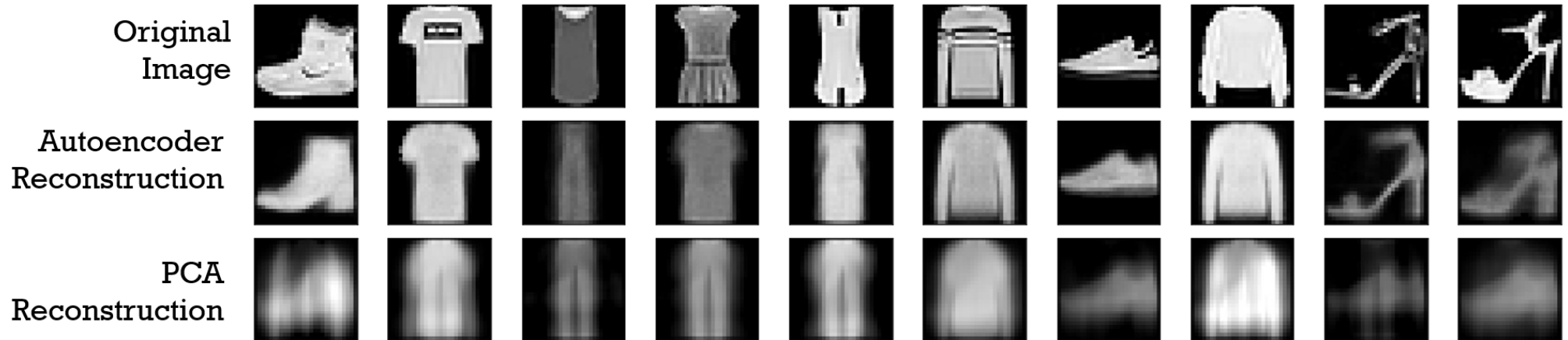


PCA reduces dimensionality linearly
Typical V shape
Overlap in first 2 dimensions

Hypothesis

Convolutional autoencoders seem promising

Can work with noisy data as well

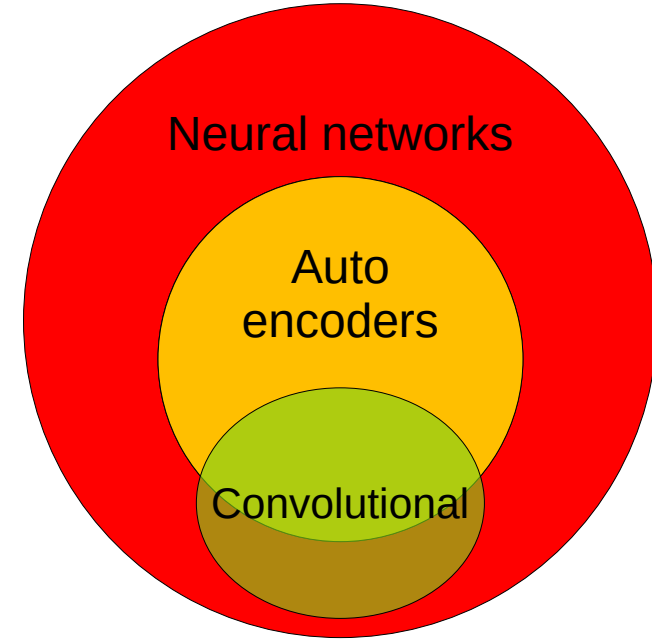
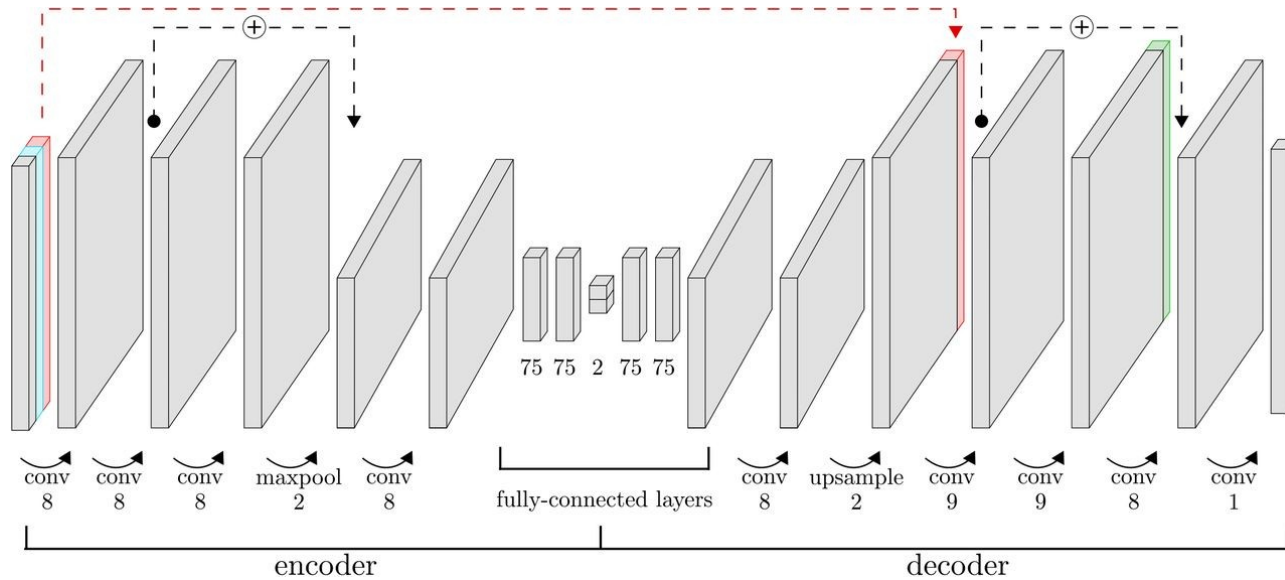


[https://commons.wikimedia.org/wiki/
File:Reconstruction_autoencoders_vs_PCA.png](https://commons.wikimedia.org/wiki/File:Reconstruction_autoencoders_vs_PCA.png)

Method

Set up a convolutional autoencoder
See how well it performs

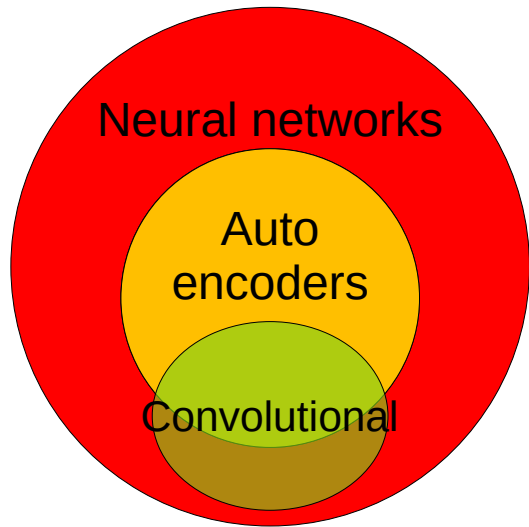
NEW



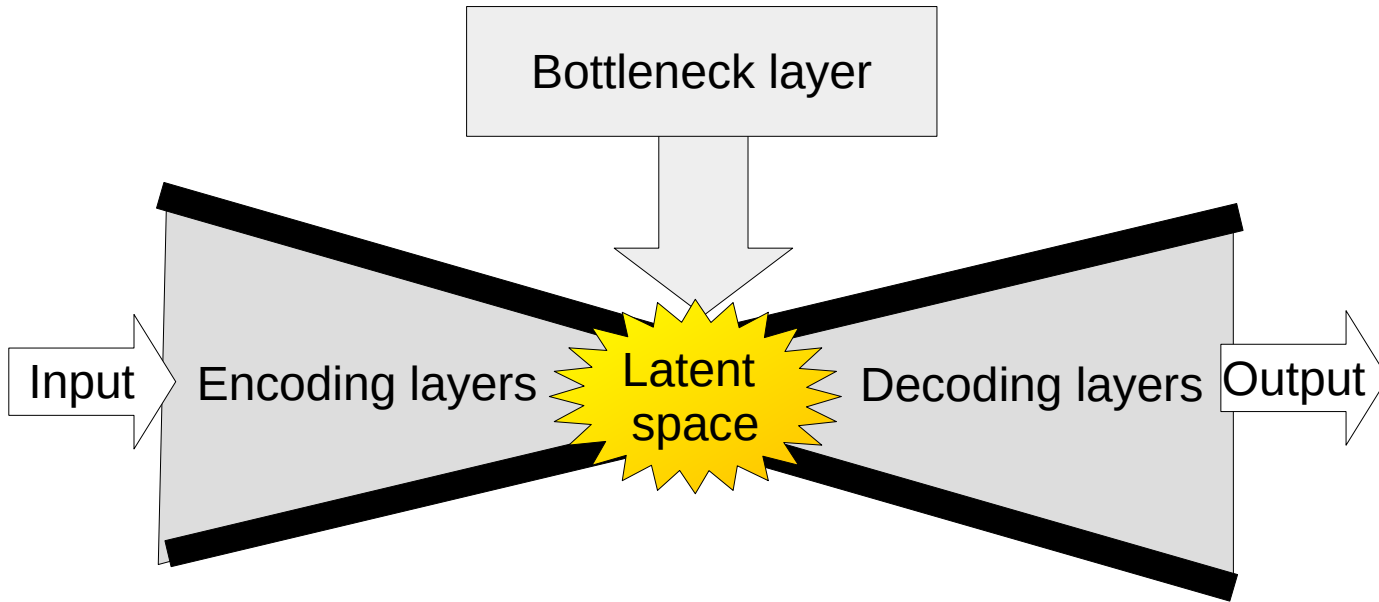
What is a convolutional autoencoder?

Convolutional: preprocess the data, i.e. do not only use the raw data

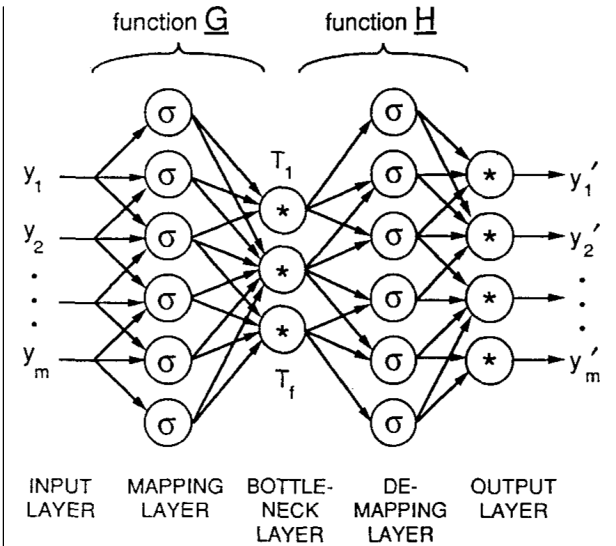
Autoencoder: type of neural network that learns how to encode data



What is an autoencoder?



Goal: *learn* to represent/label data,
nonlinearly

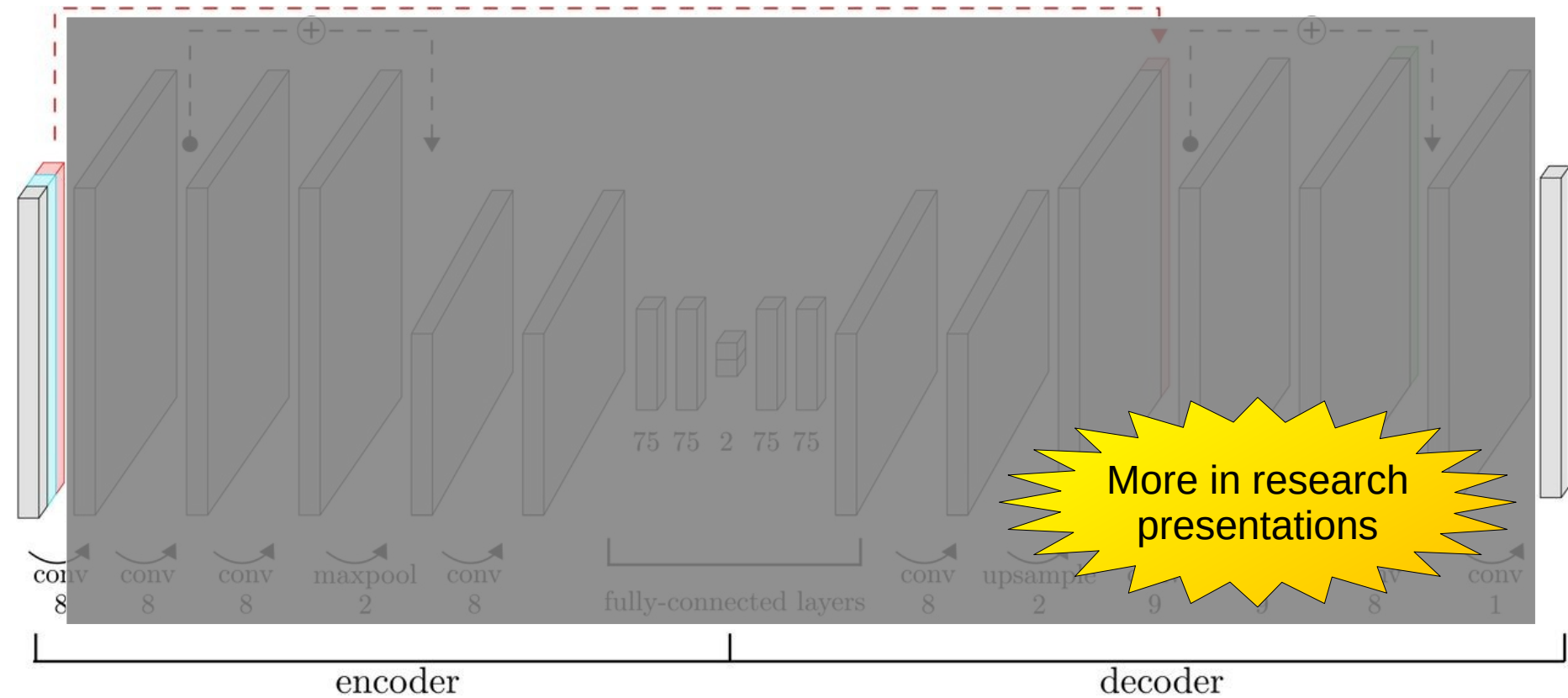


$$Y = \{ y_1, y_2, \dots \}$$

$$Y' = \{ y'_1, y'_2, \dots \}$$

$$\text{Loss function} = E = Y - Y'$$

GCAE



Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

How well does GCAE perform?

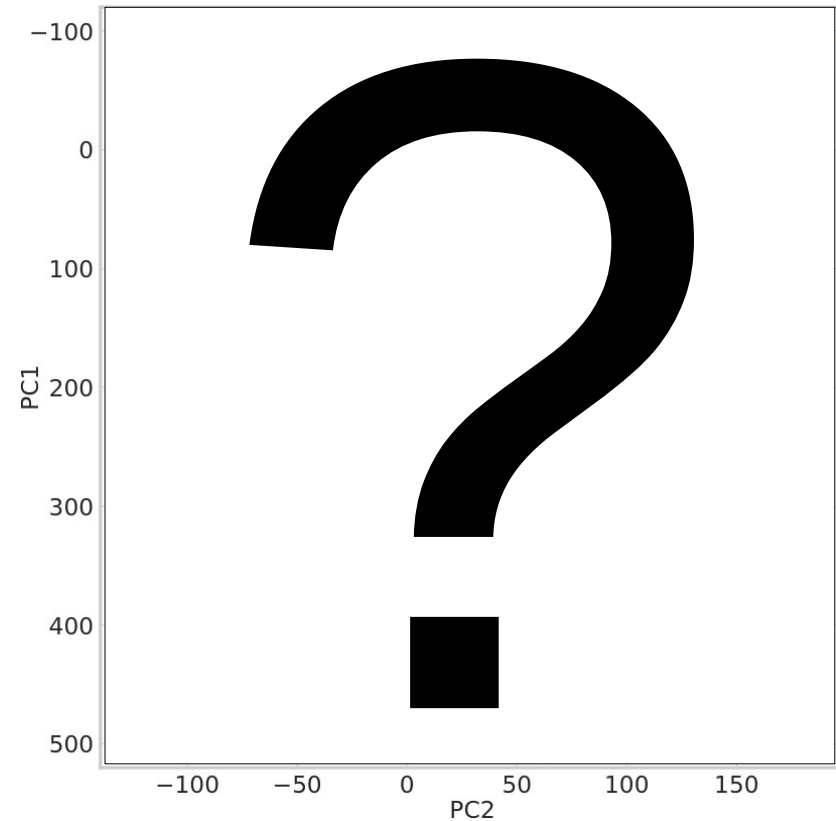
genotype separation

deduce genotype origin

rare and common alleles

LD

Separating genotypes



Affymetrix Human Origins SNP array
2,067 unrelated humans from 166 populations

No sex chromosomes

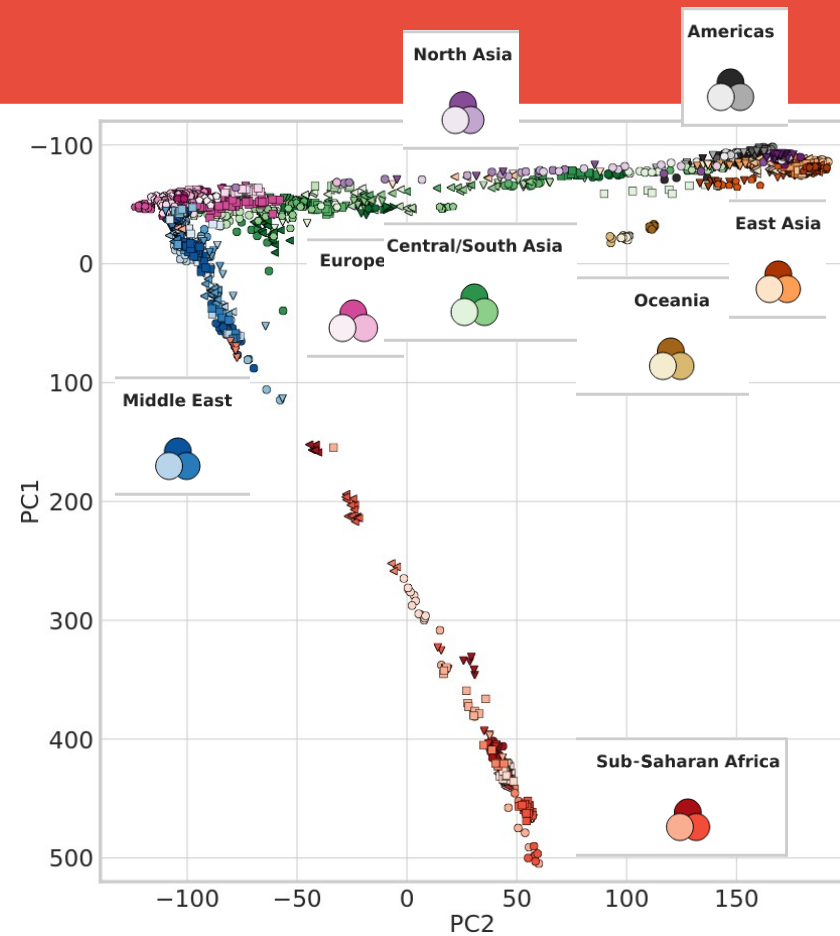
Remove $MAF < 1\%$

LD pruning, remove $R^2 > 0.2$

160,858 biallelic sites

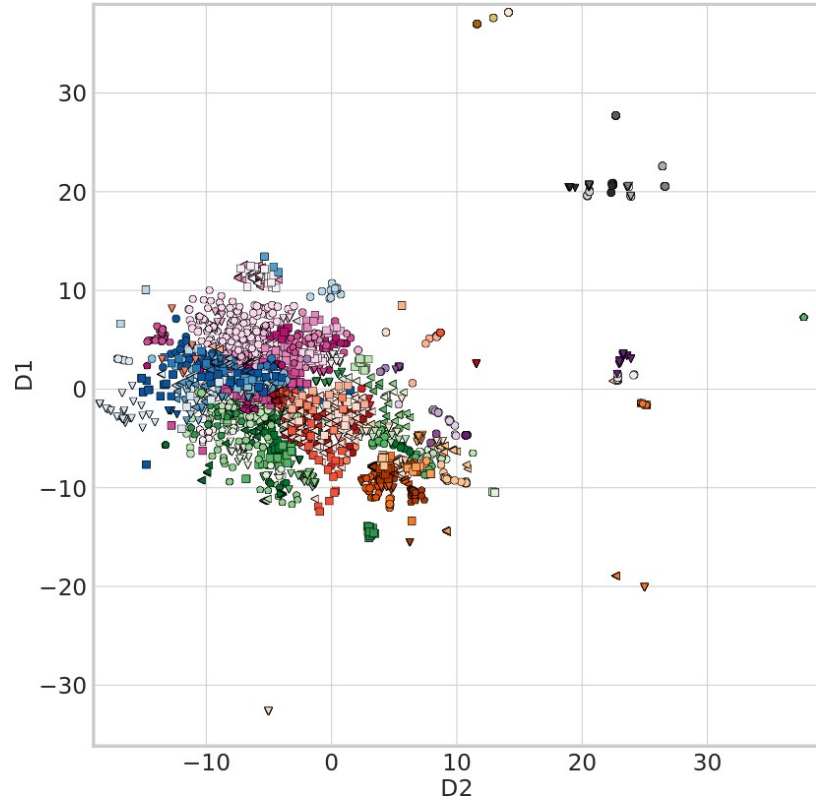
Show genotypes in first 2 PCs

PCA dimensionality reduction



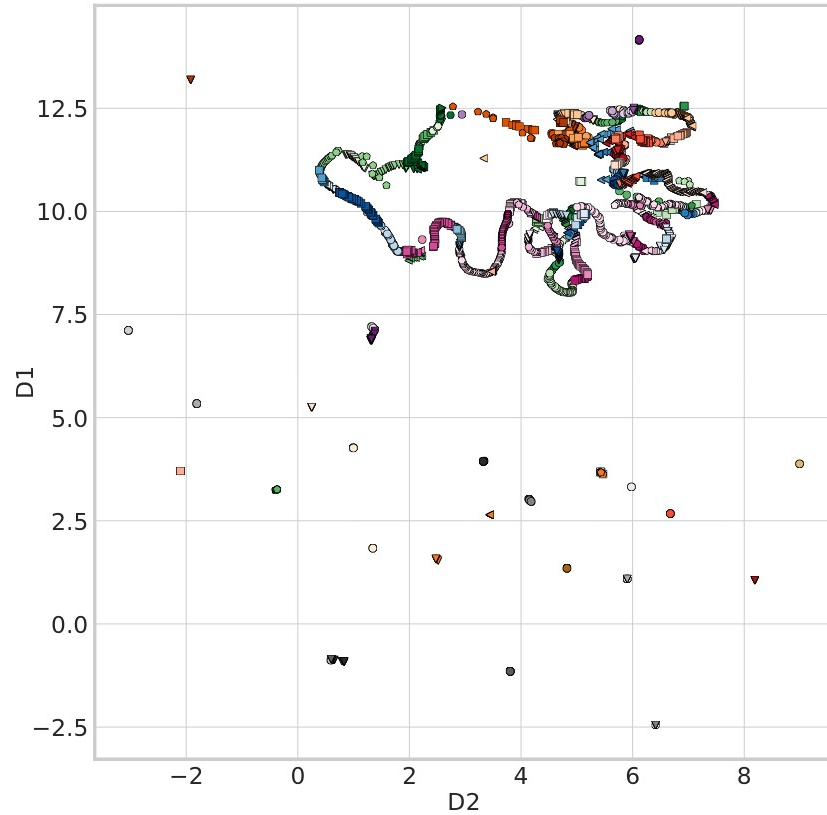
Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

t-SNE dimensionality reduction



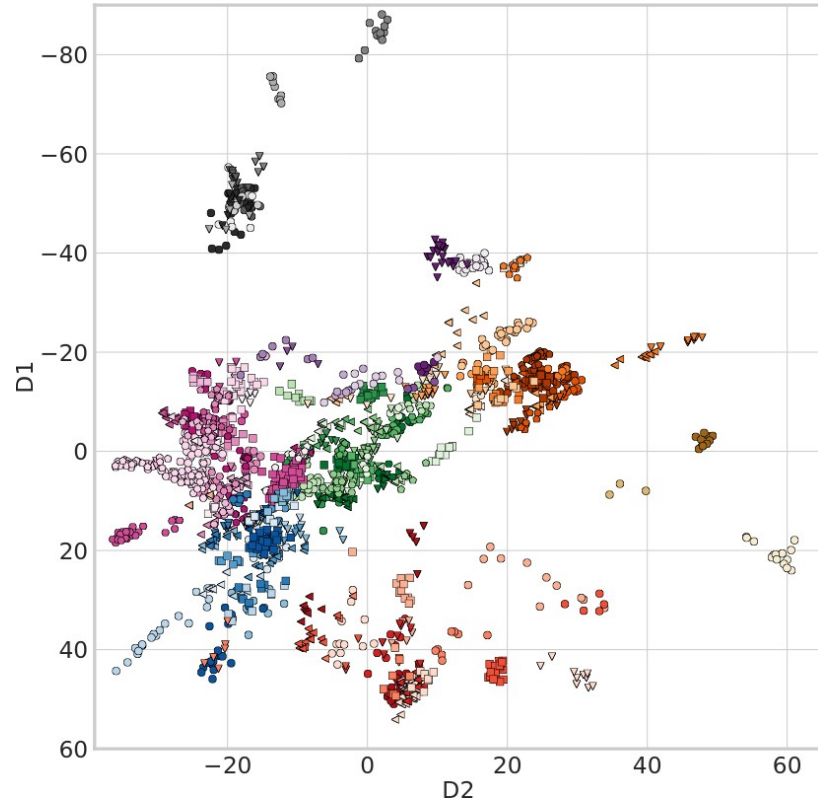
Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

UMAP dimensionality reduction



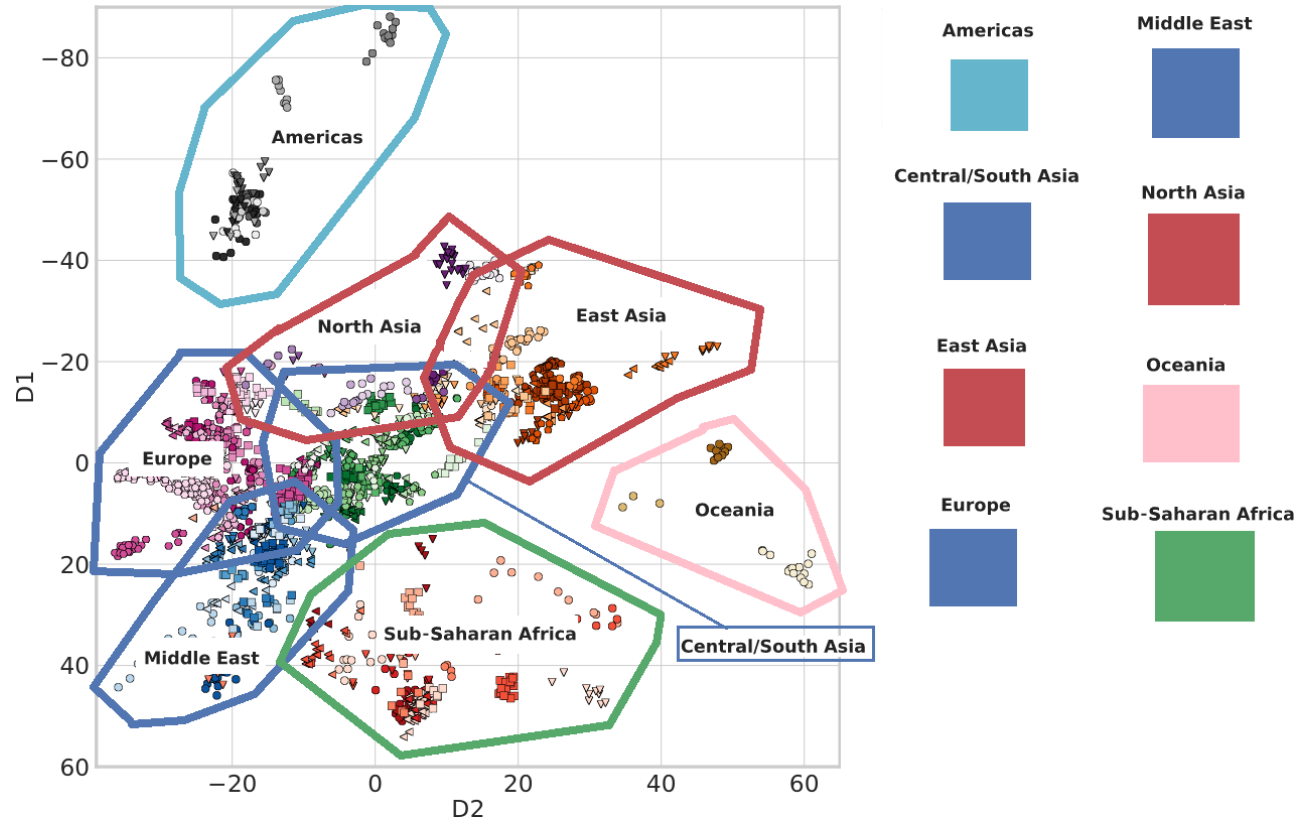
Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

GCAE dimensionality reduction



Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

GCAE dimensionality reduction



Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020). Adapted by Richel Bilderbeek

Questions

How well can genotypes be separated by eye?

How well can we deduce the origin of a genotype?

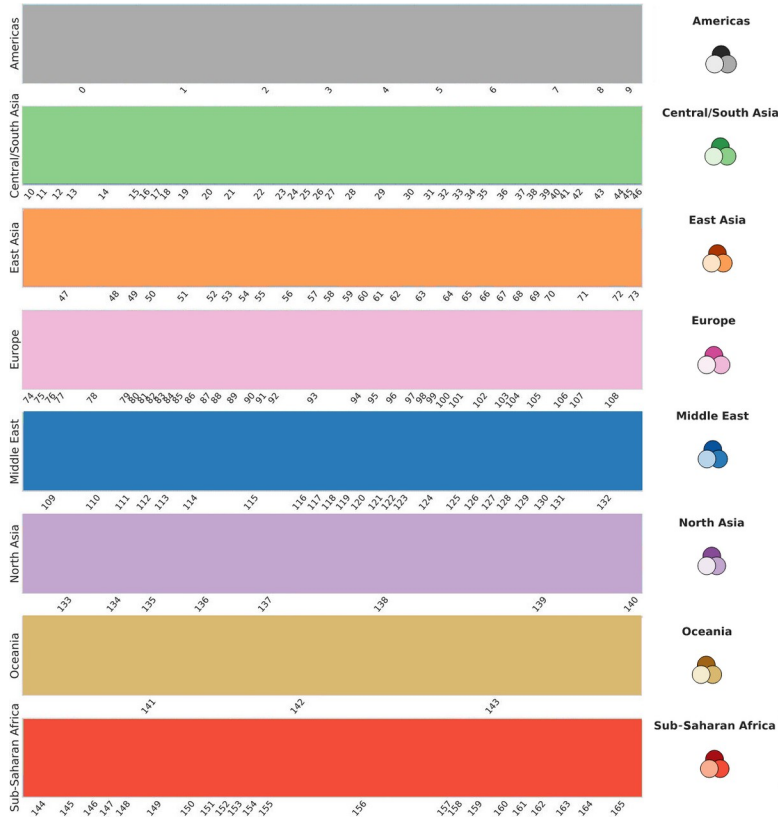
Clustering similar to ADMIXTURE

F1 score

Other measurements

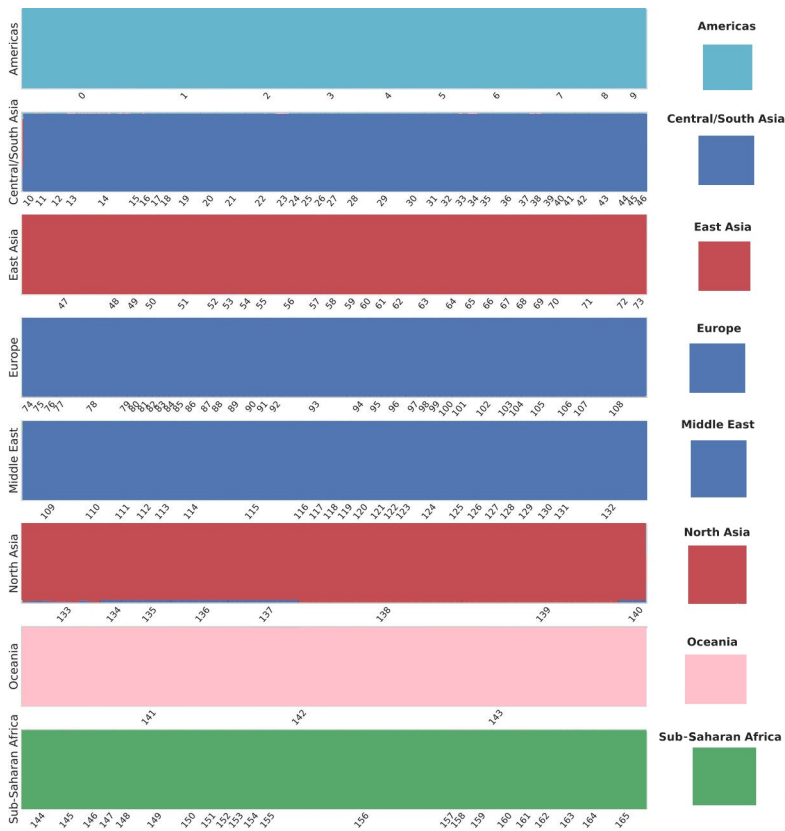


How well can we deduce the origin of a genotype?



Go through all individuals (x axis)
Assign the likelihood it belong to a subcontinent (the rows)
Ideally, all individuals are assigned their correct subcontinent

How well can we deduce the origin of a genotype?



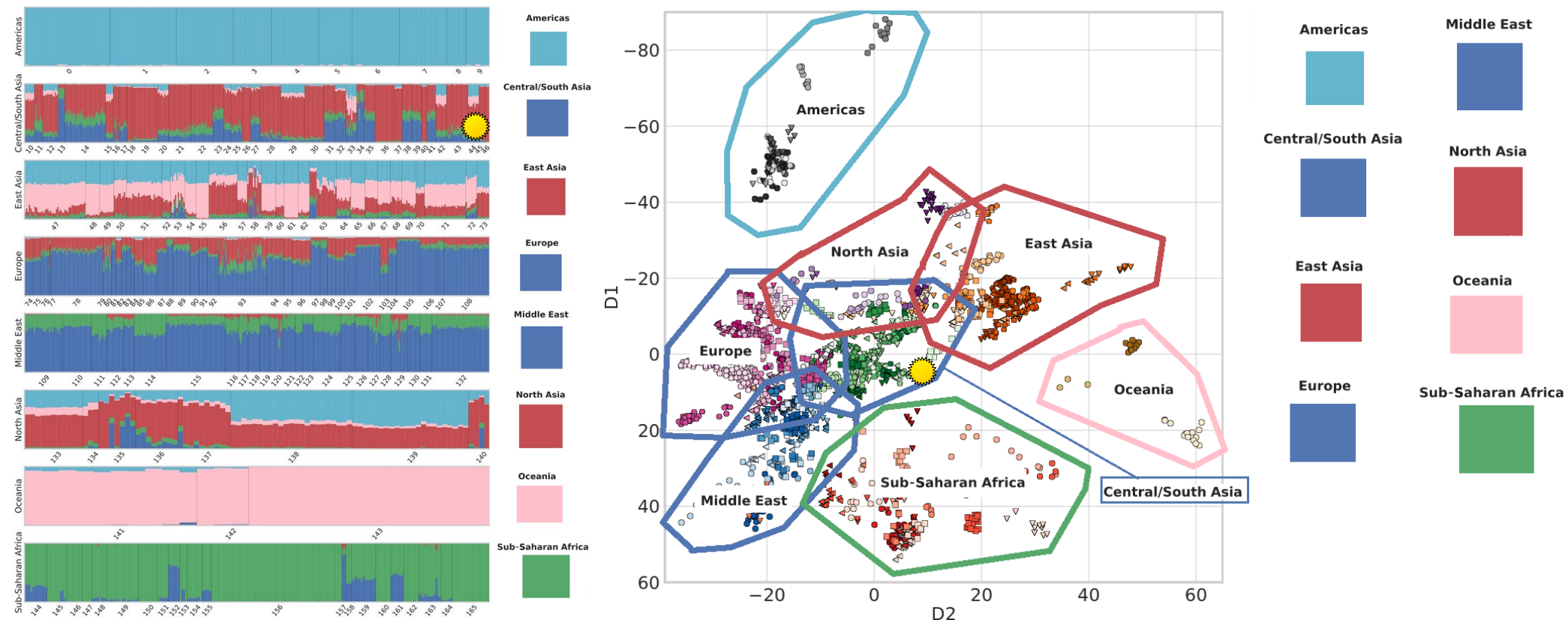
Go through all individuals (x axis)

Assign the likelihood it belong to a subcontinent (the rows)

Ideally, all individuals are assigned their correct subcontinent

Use five clusters

GCAE: ADMIXTURE ↔ plot



PCA: ADMIXTURE

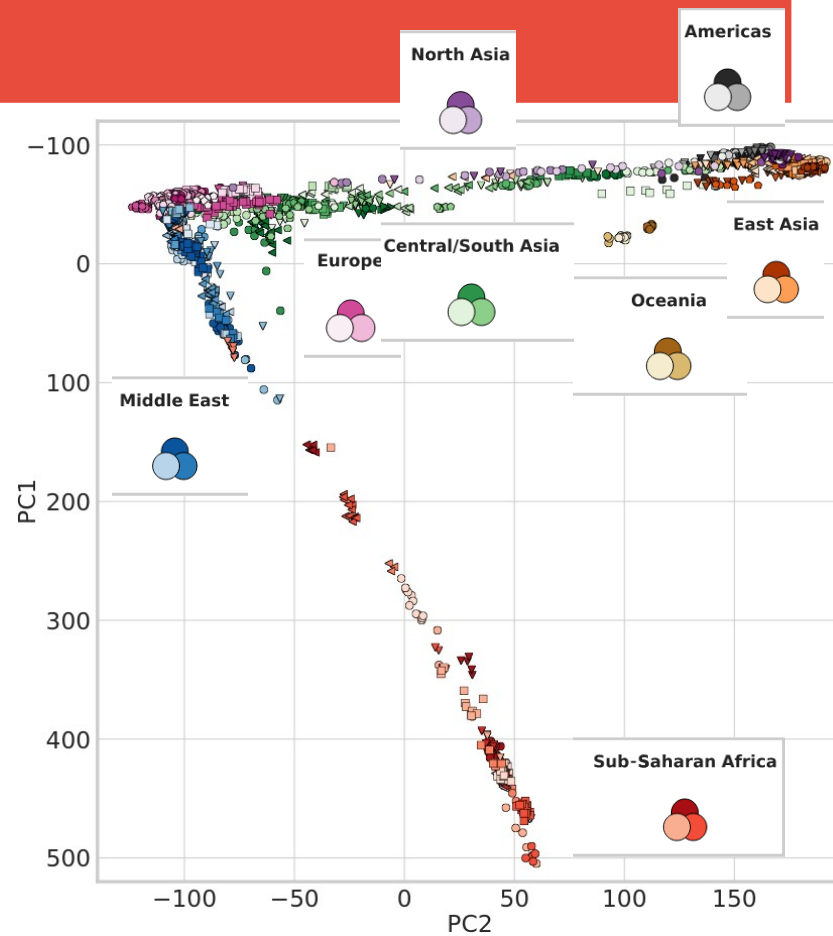
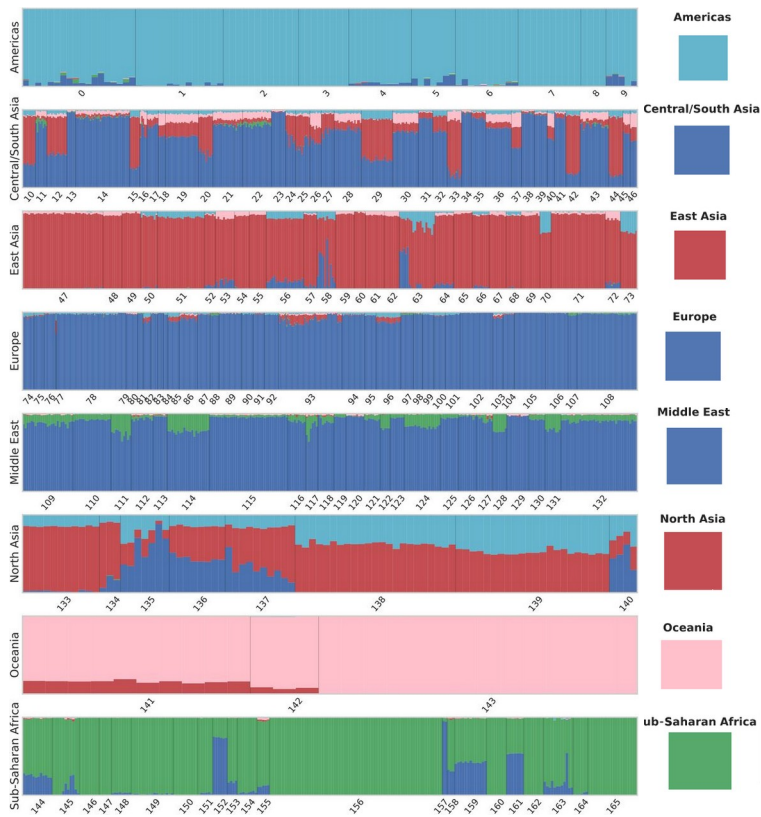
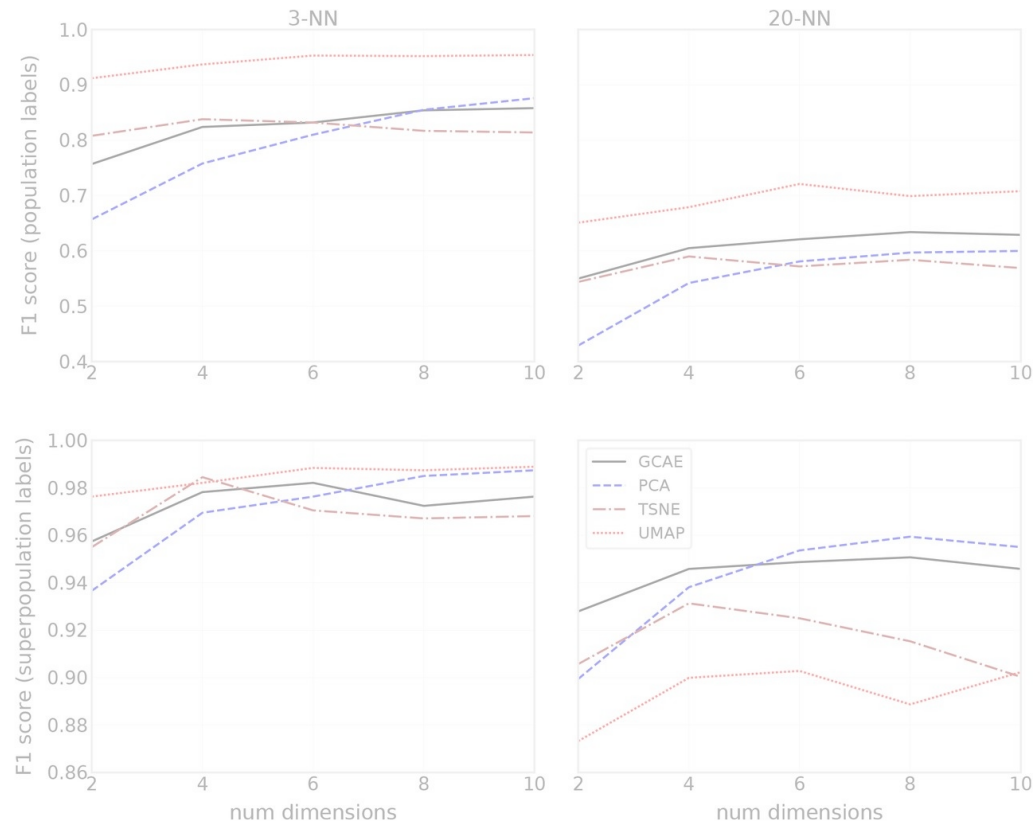
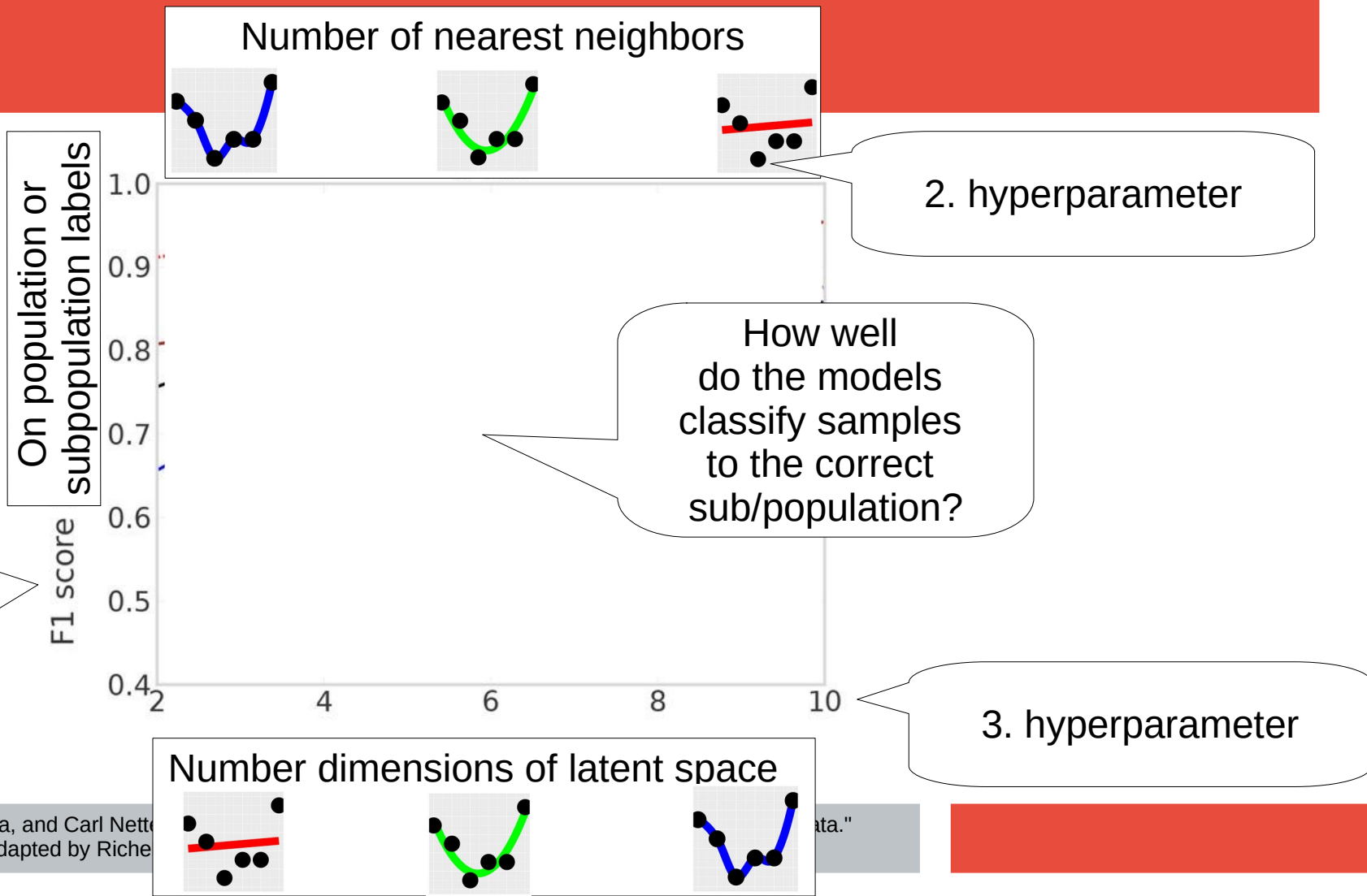


Figure 4



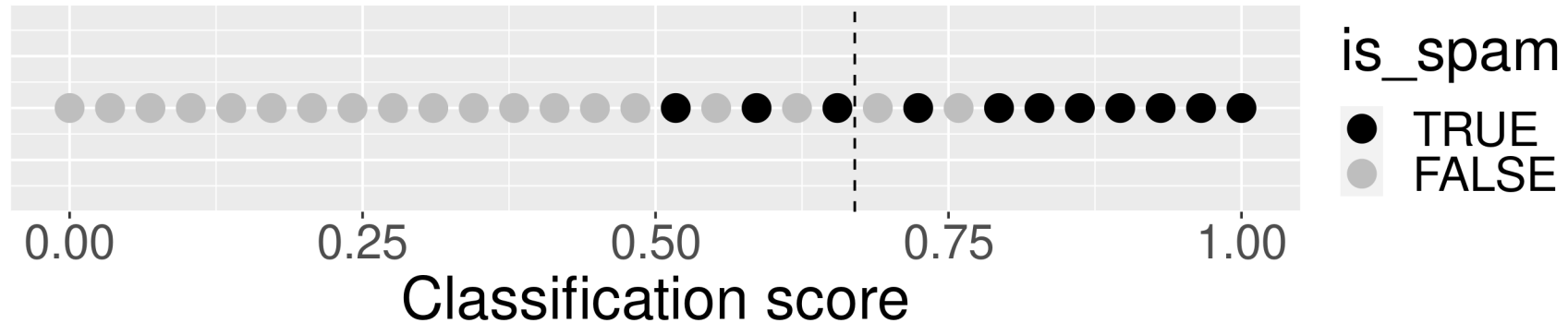
Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

Figure 4



What is the F1 score?

A metric for the trade-off between precision and recall →



What is precision?

Precision:

how often is the classifier right?

the number of true positives of all *estimated* positives

precision

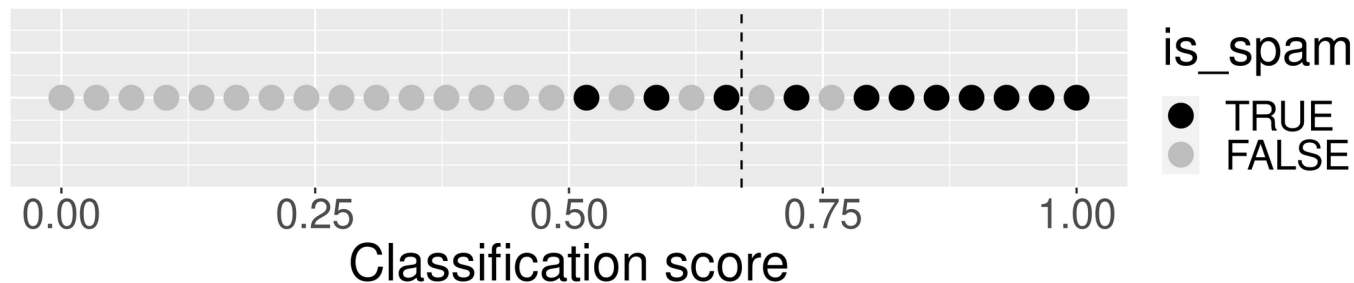
$$= n_{tp} / (n_{tp} + n_{fp})$$

$$= 8 / (8 + 2) = 8/10$$

where

n_{tp} = # of true positives

n_{fp} = # of false positives



What is recall?

Recall:

how often are the positive cases recognized as such?

the number of true positives of all *known* positives

recall

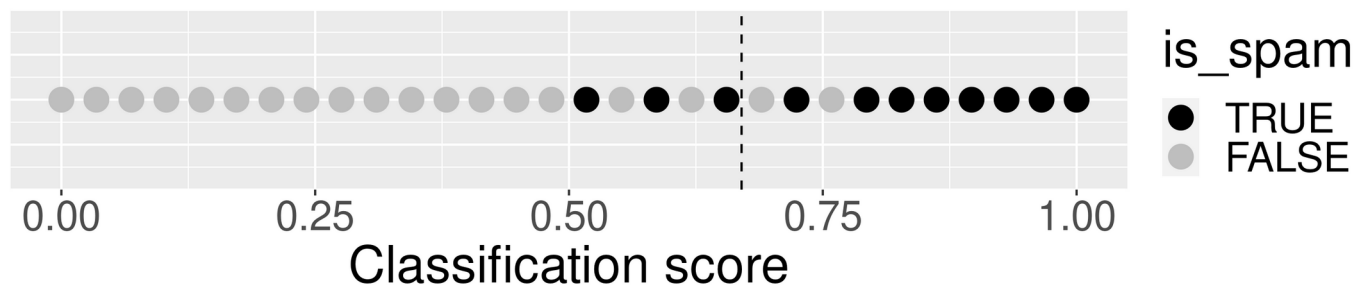
$$= n_{tp} / (n_{tp} + n_{fn})$$

$$= 8 / (8 + 3) = 8/11$$

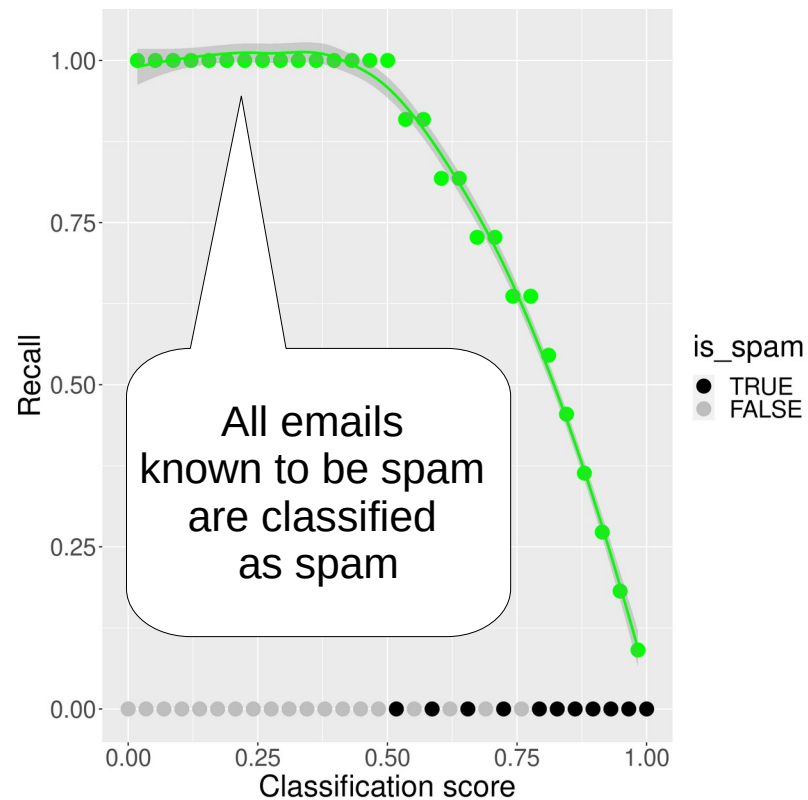
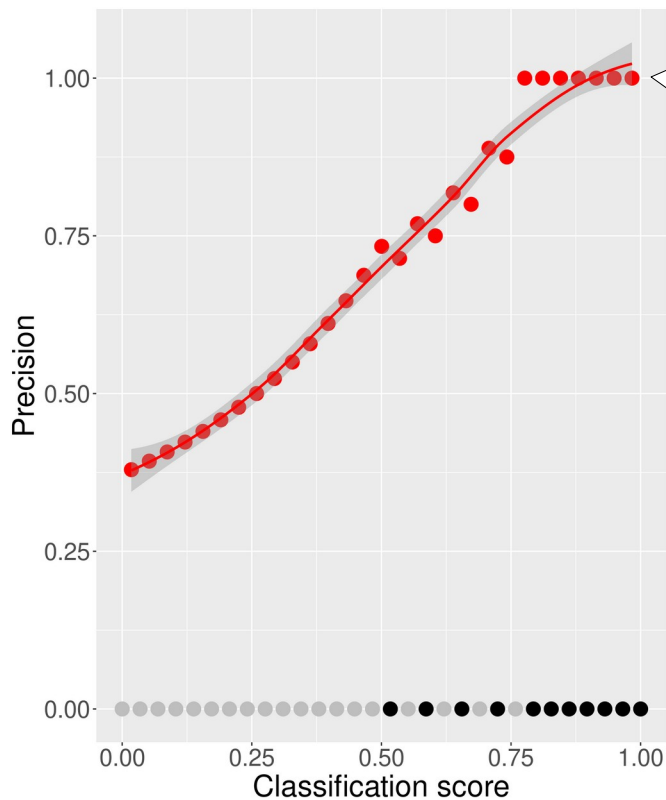
where

n_{tp} = # of true positives

n_{fn} = # of false negatives



Trade-off between precision and recall



F1 Score

A metric for the trade-off between precision and recall:

The harmonic mean of precision and recall

F₁

$$= 2 / (\text{precision}^{-1} + \text{recall}^{-1})$$

$$= n_{tp} / (n_{tp} + \frac{1}{2}(n_{fp} + n_{fn}))$$

where

n_{tp} = # of true positives

n_{fp} = # of false positives

n_{fn} = # of false negatives

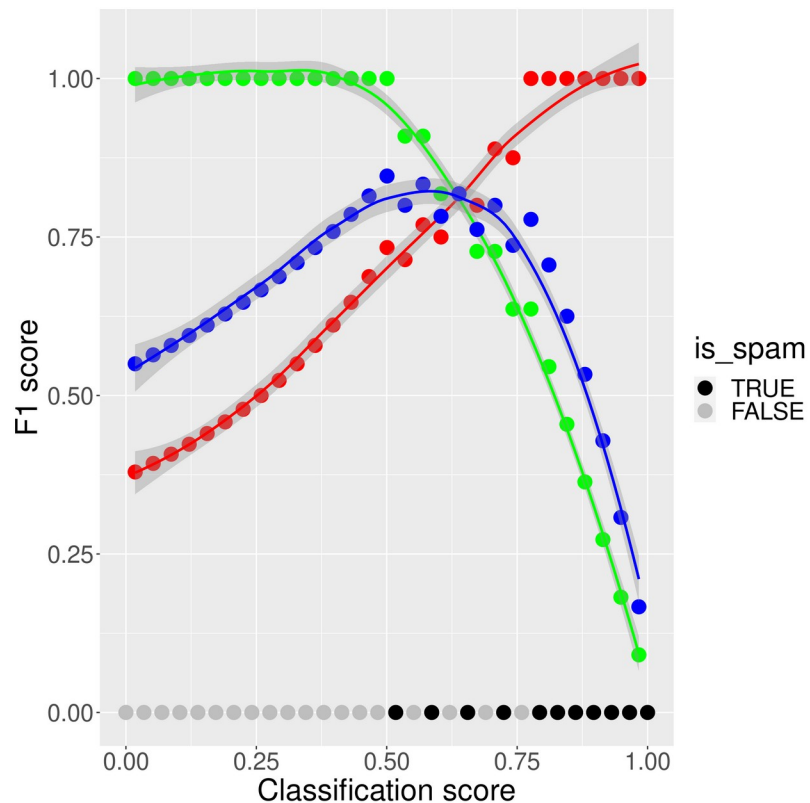
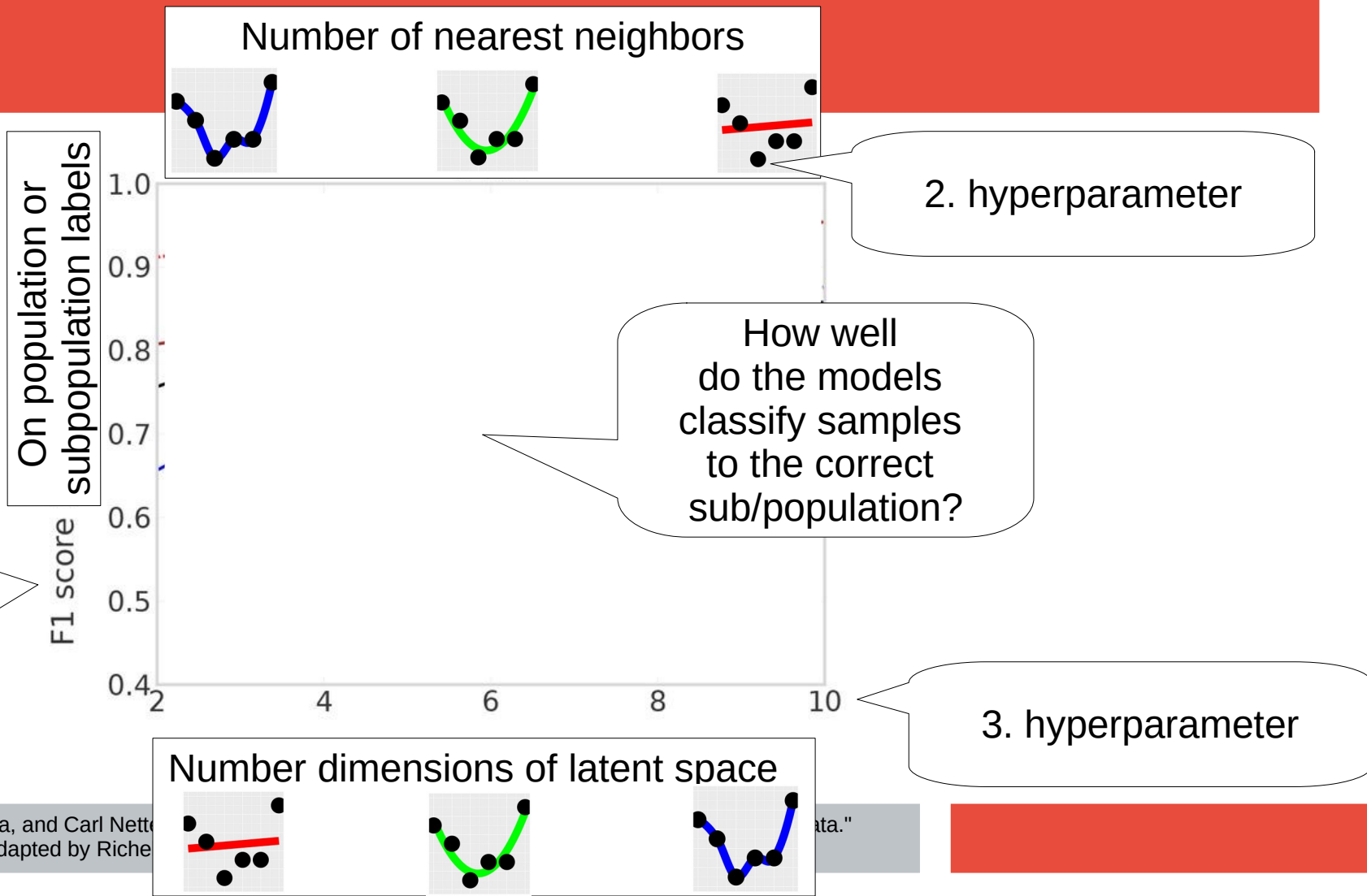
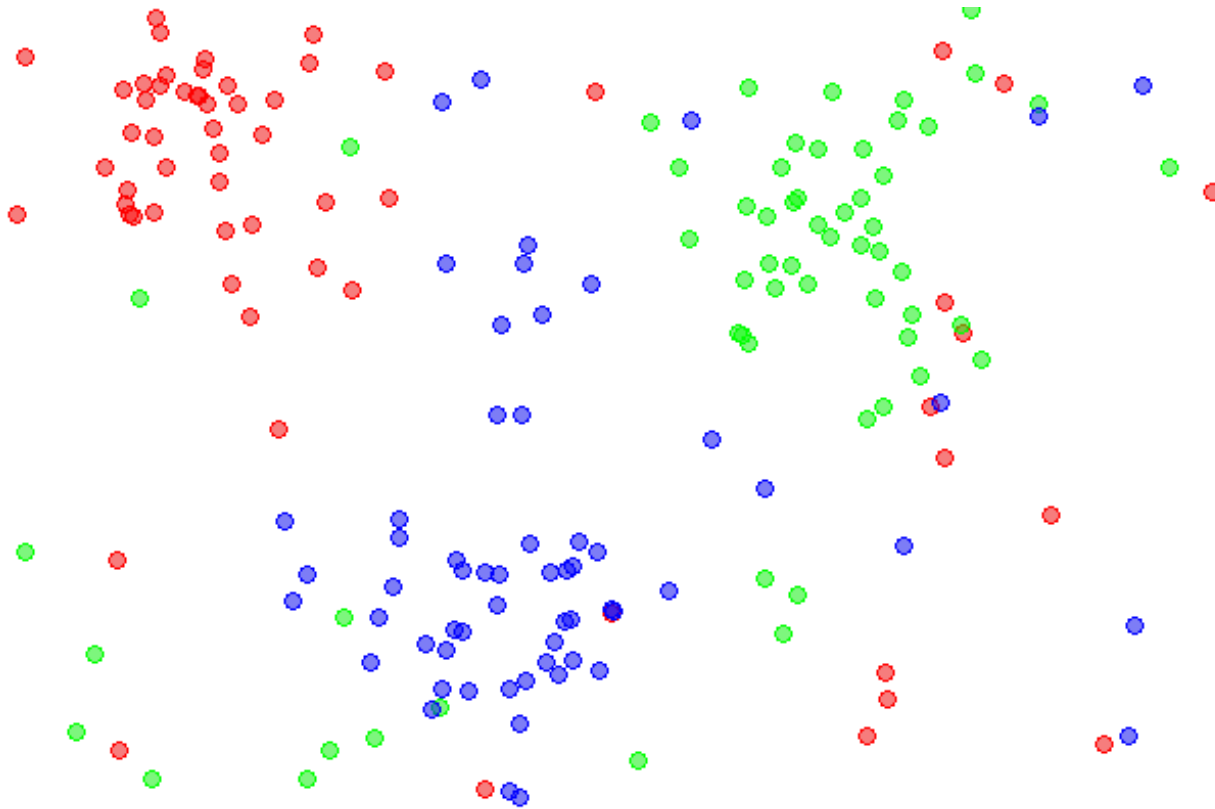


Figure 4



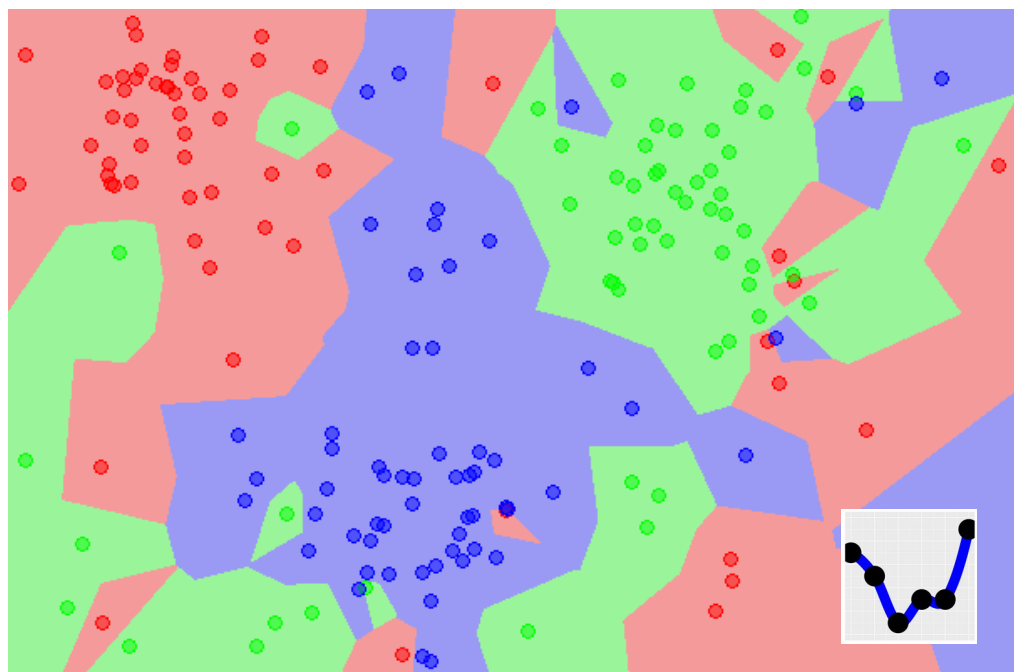
Number of nearest neighbors



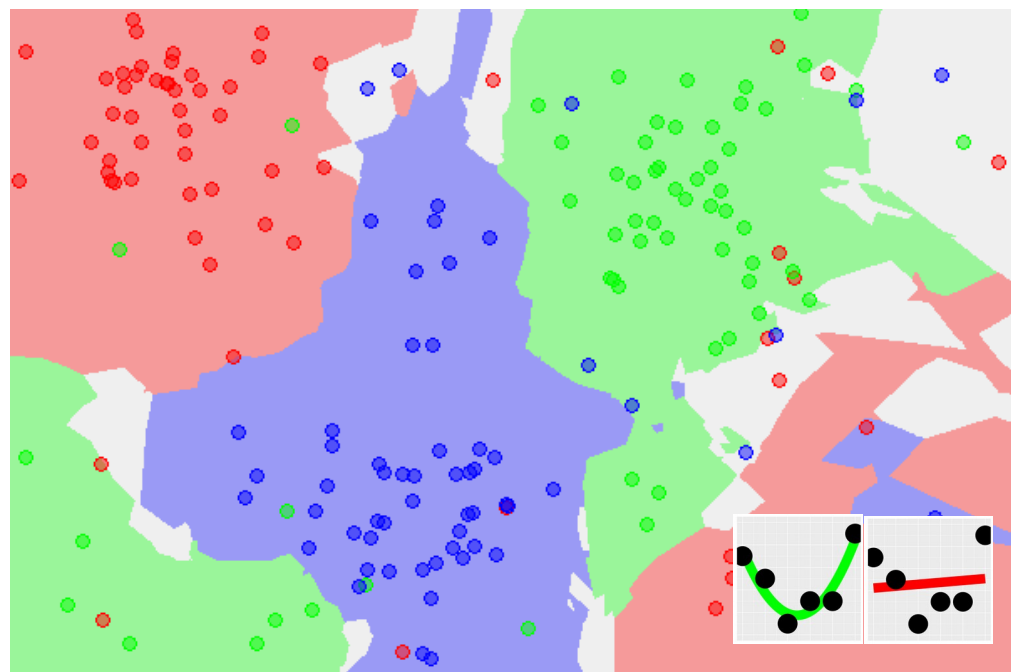
<https://en.wikipedia.org/wiki/File:Data3classes.png>

Number of neighbors

1



5



<https://en.wikipedia.org/wiki/File:Map1NN.png>
<https://en.wikipedia.org/wiki/File:Map5NN.png>

Optimal number for k?

Nontrivial to determine a priori

Prefer k being odd

\sqrt{n}

$(\sqrt{n})/2$



stackoverflow

Possible to determine from data

e.g. calculate the k with the lowest error

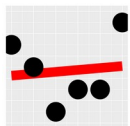
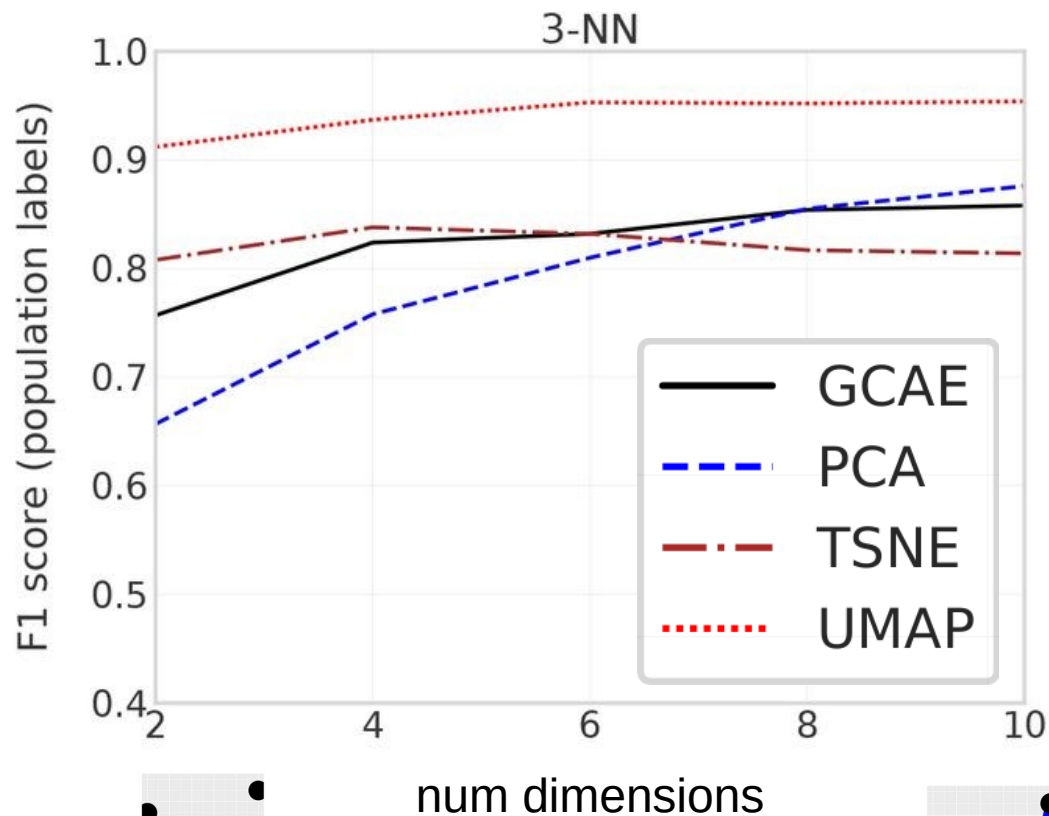
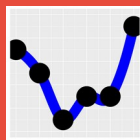
problem: these may differ between different methods (i.e. PCA, GCAE)

166 populations $\rightarrow \sqrt{n} \approx 13, (\sqrt{n})/2 \approx 6$

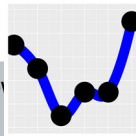
8 superpopulations $\rightarrow \sqrt{n} \approx 3, (\sqrt{n})/2 \approx 1$

k = number of neighbors
n = the number of categories

Figure 4a

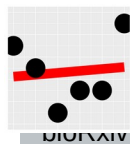
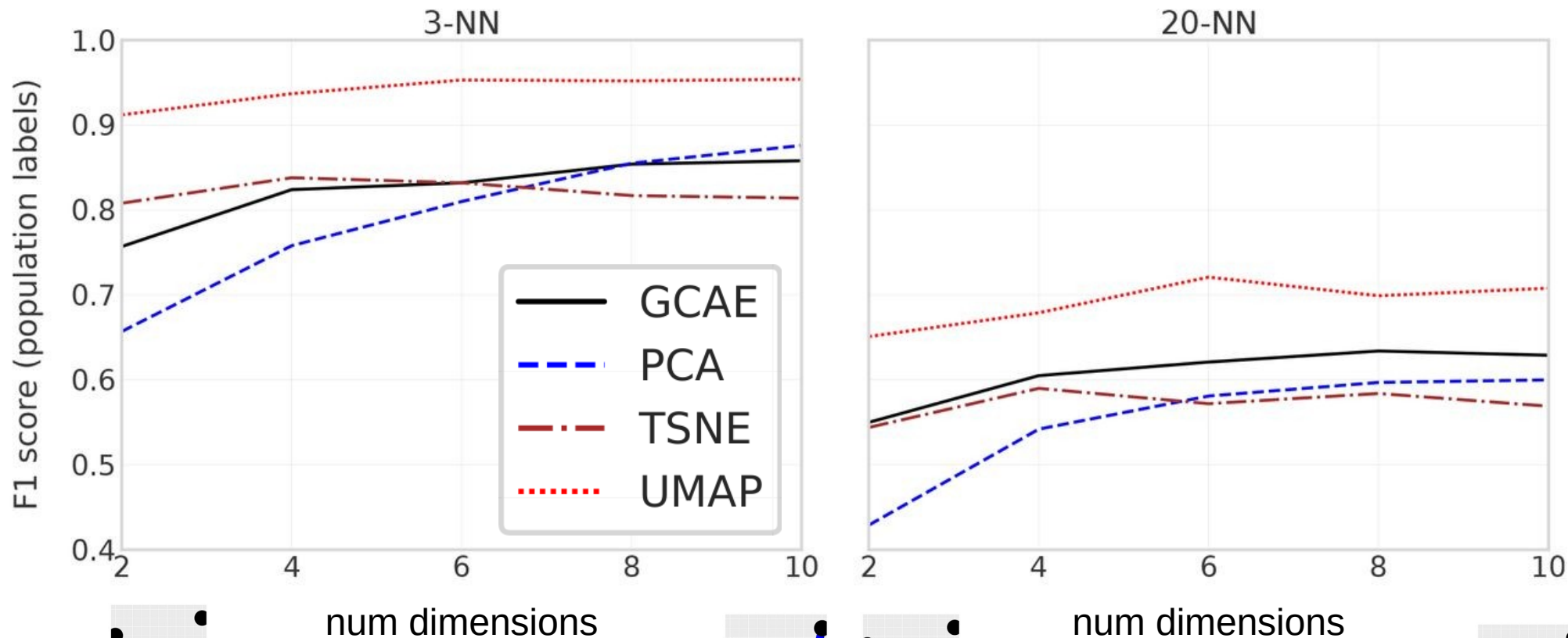
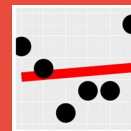
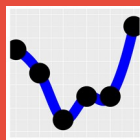


es, Kristiina, and Carl Nettelblad. "A deep learning frame
bioRxiv (2020).

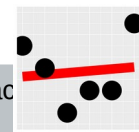
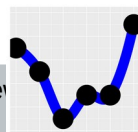


Characterization of genotype data."

Figure 4ab



es, Kristiina, and Carl Nettelblad. "A deep learning frame
bioRxiv (2020).



of genotype data."

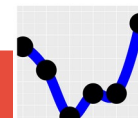
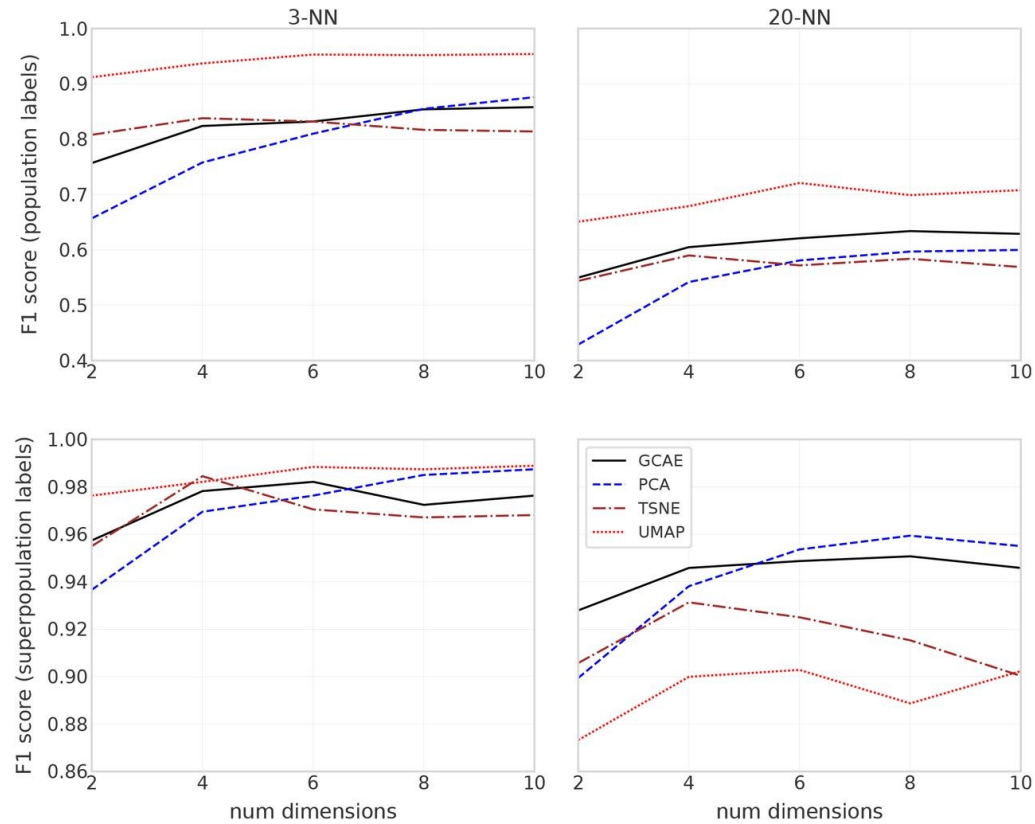


Figure 4 revisited



Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

Questions

How well can genotypes be separated by eye?

How well can we deduce the origin of a genotype?

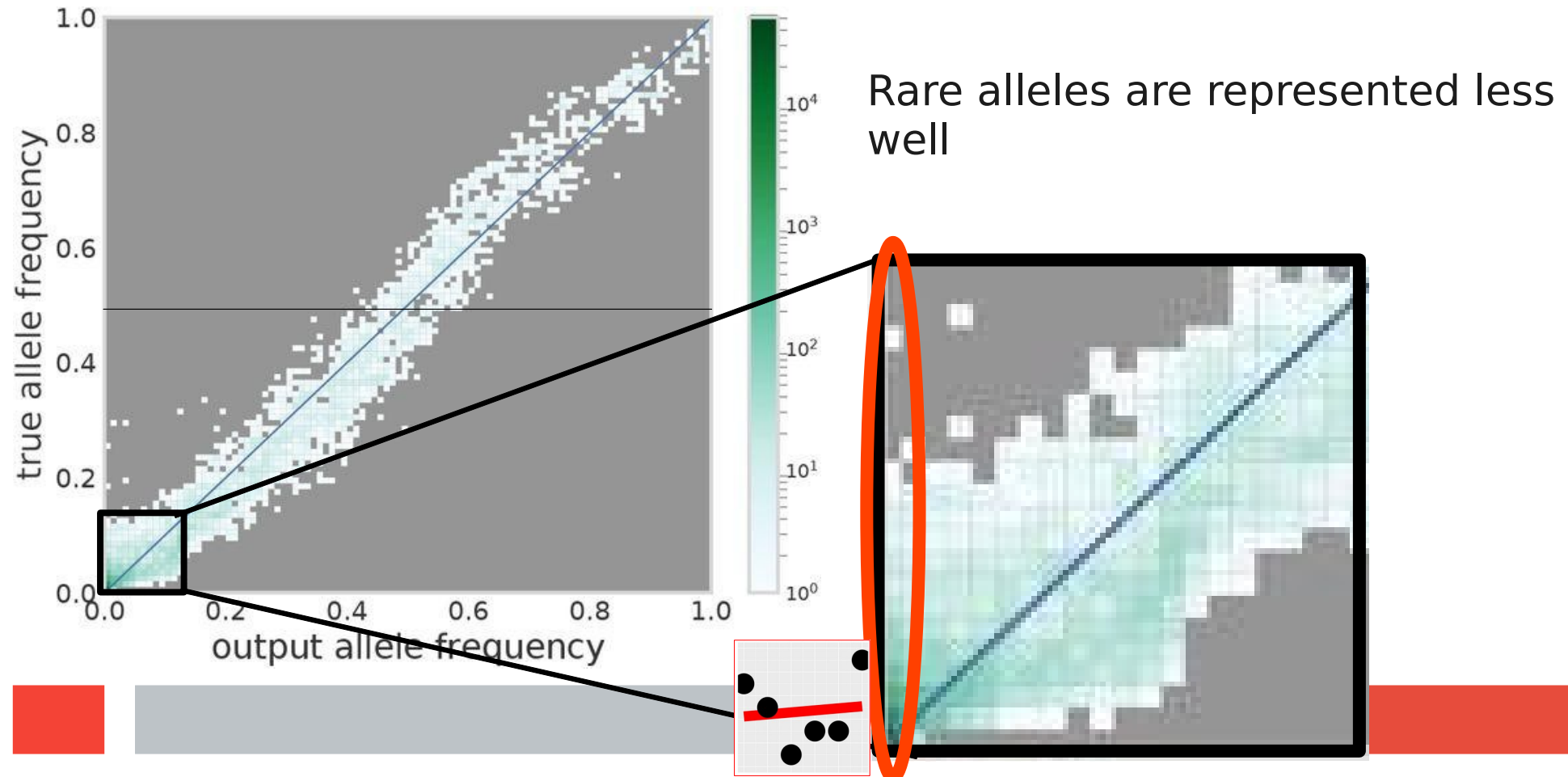
Other measurements

Representing rare alleles

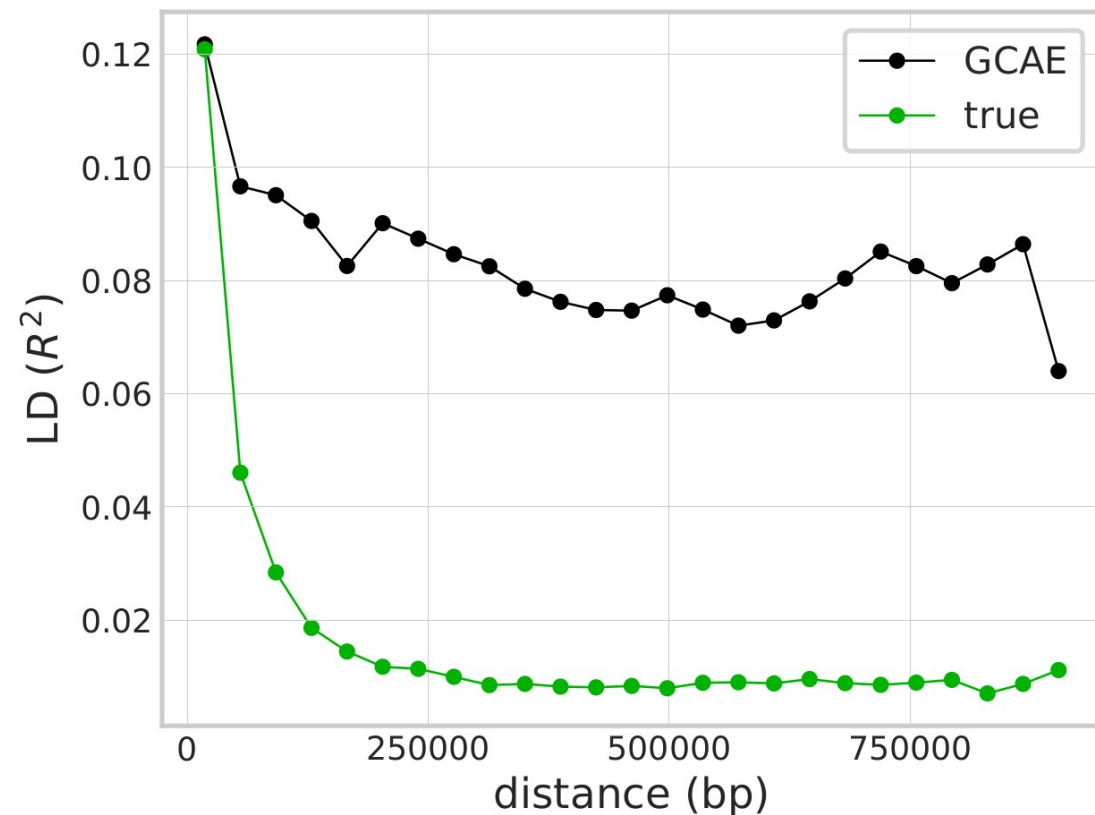
Representing linkage disequilibrium



Representing of rare alleles



Representing LD



GCAE 'feels' all alleles are in LD
Proof it takes local structure into account

Pruned
on $LD < 0.2$
?

Allele independent

Discussion

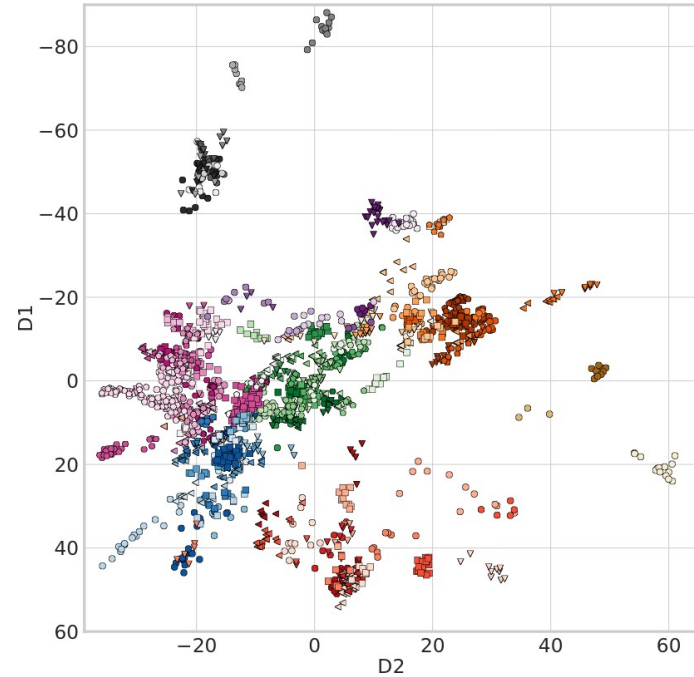
Dimensionality reduction

ADMIXTURE

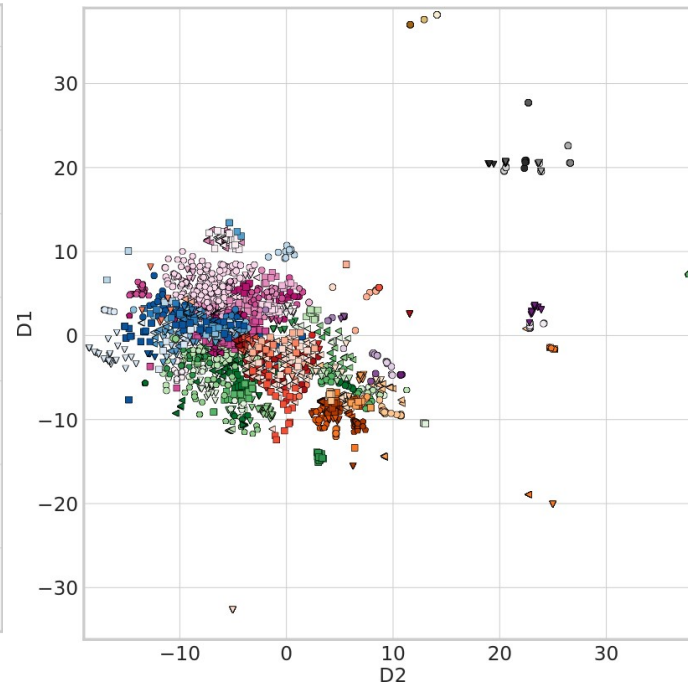
F1 scores



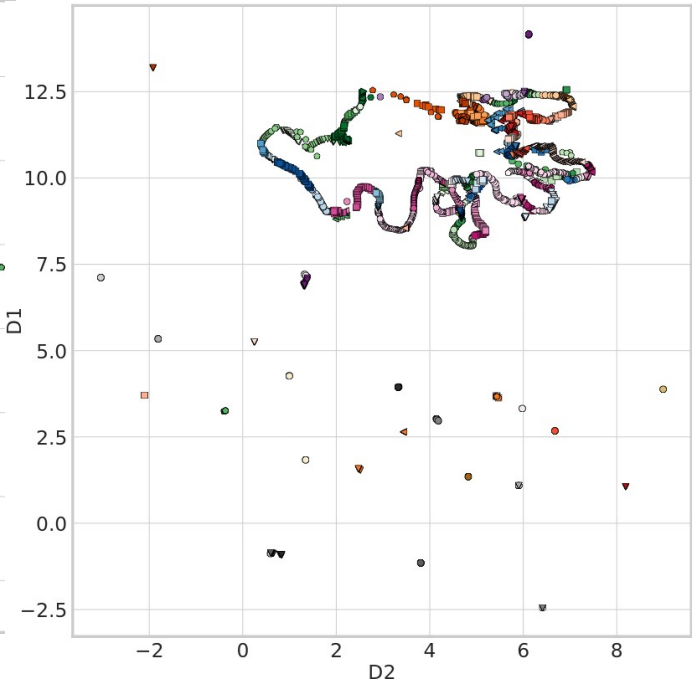
GCAE versus t-SNE and UMAP again



GCAE



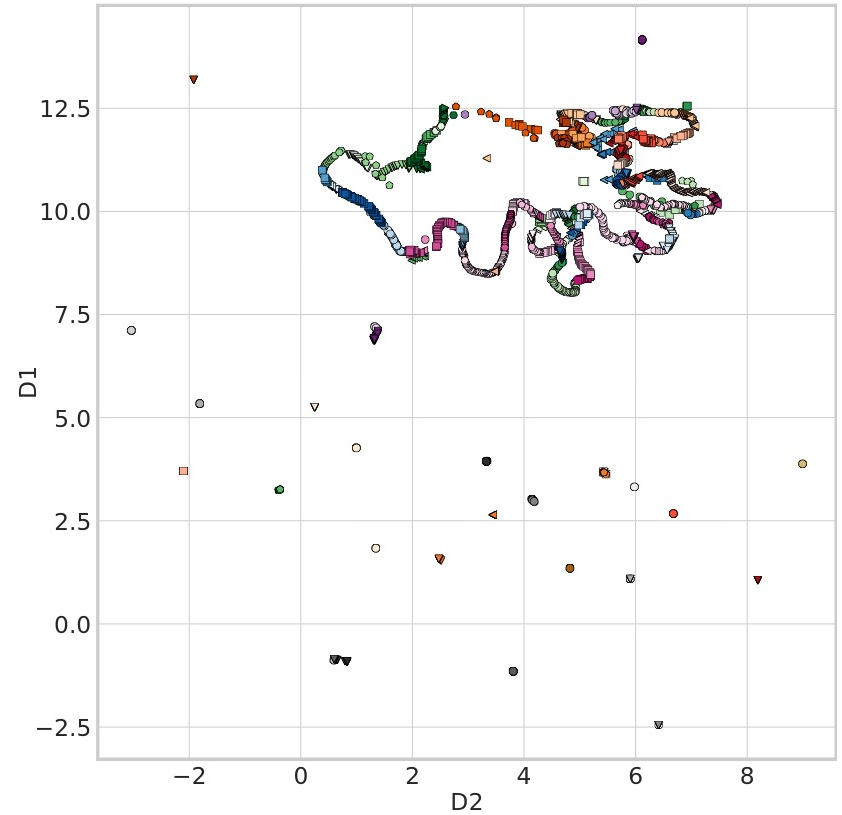
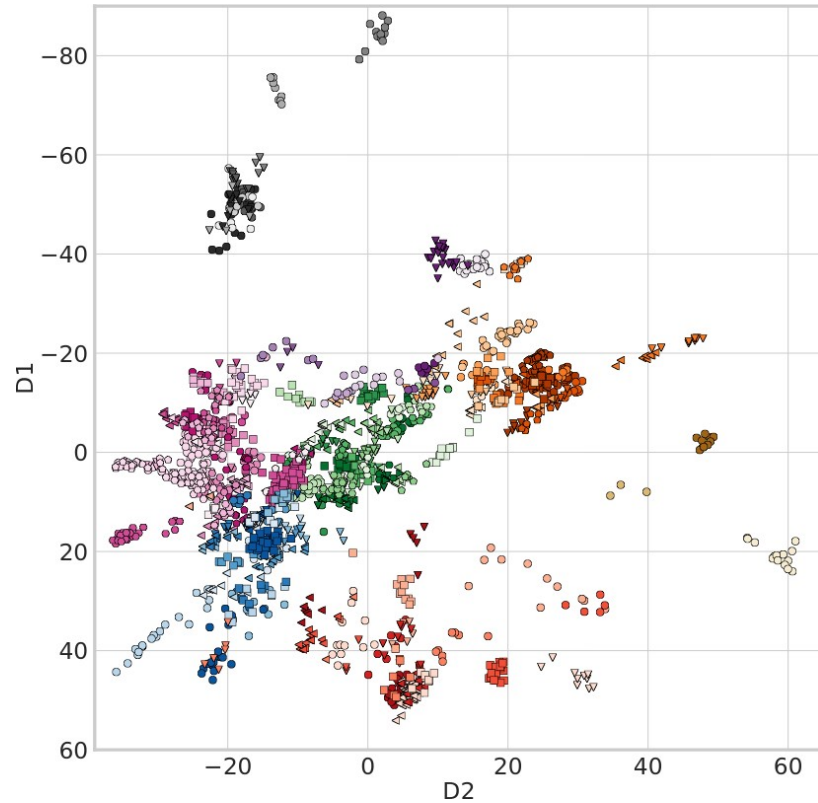
t-SNE



UMAP

Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

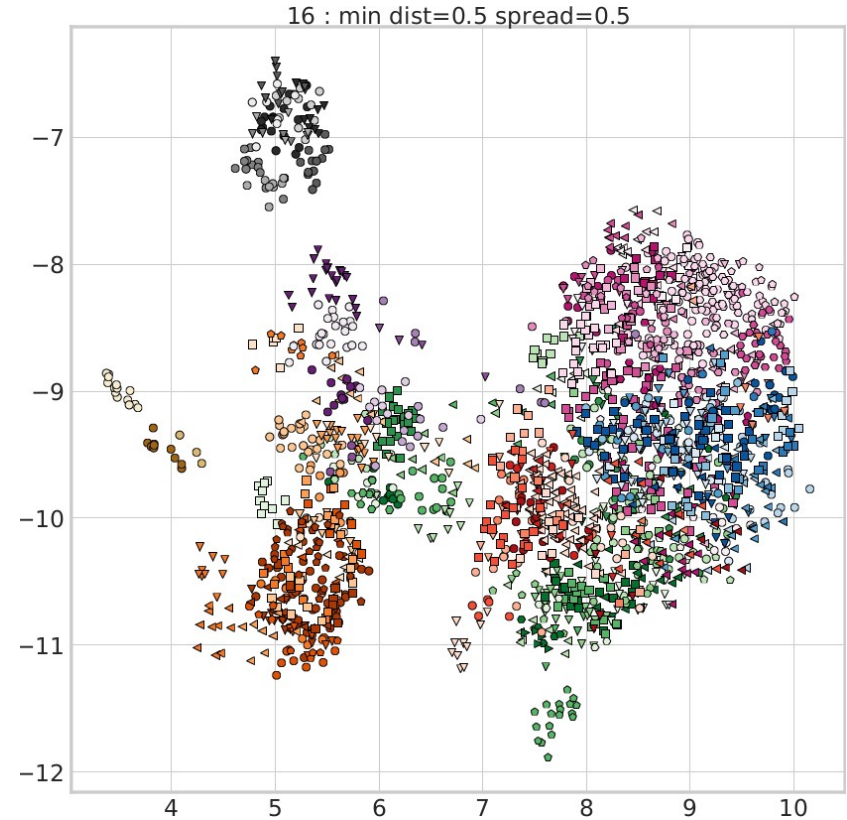
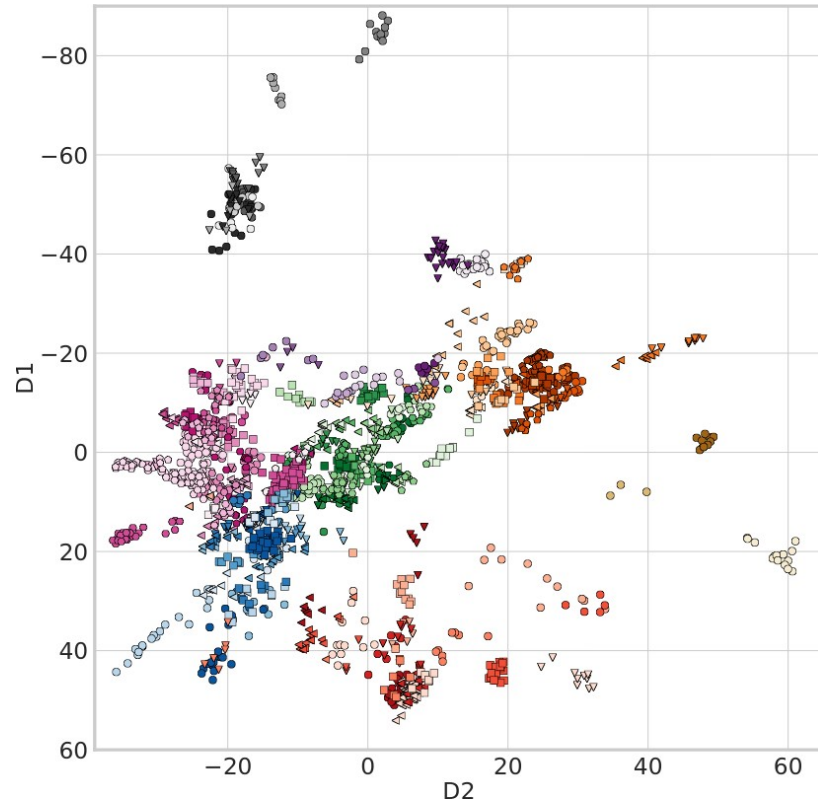
GCAE versus UMAP



Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

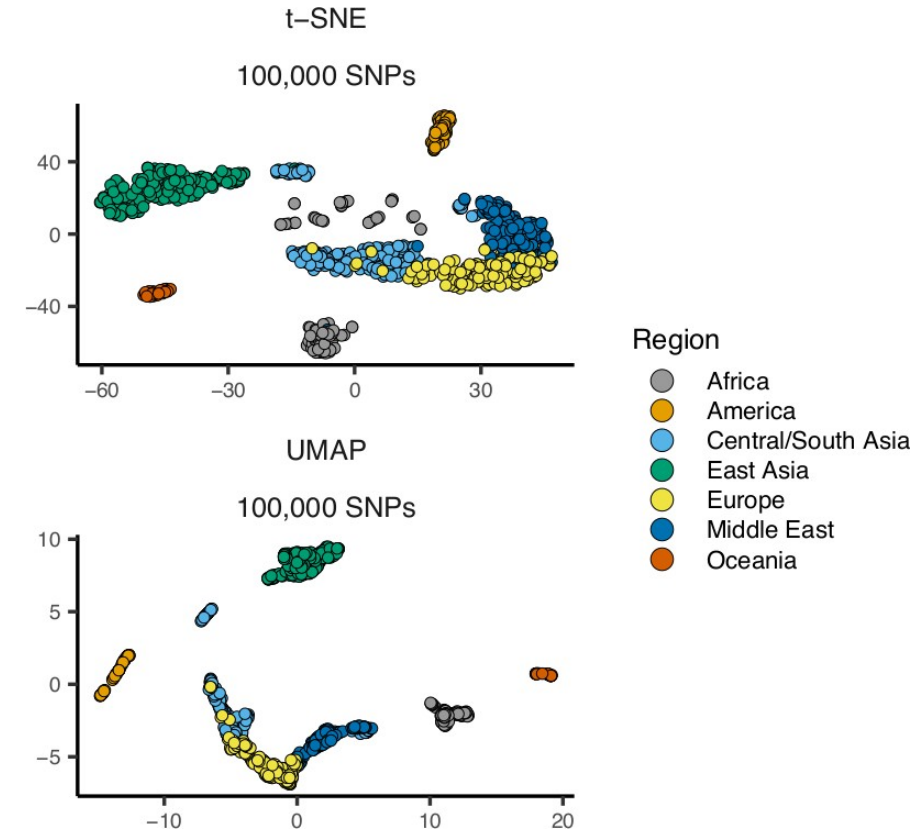
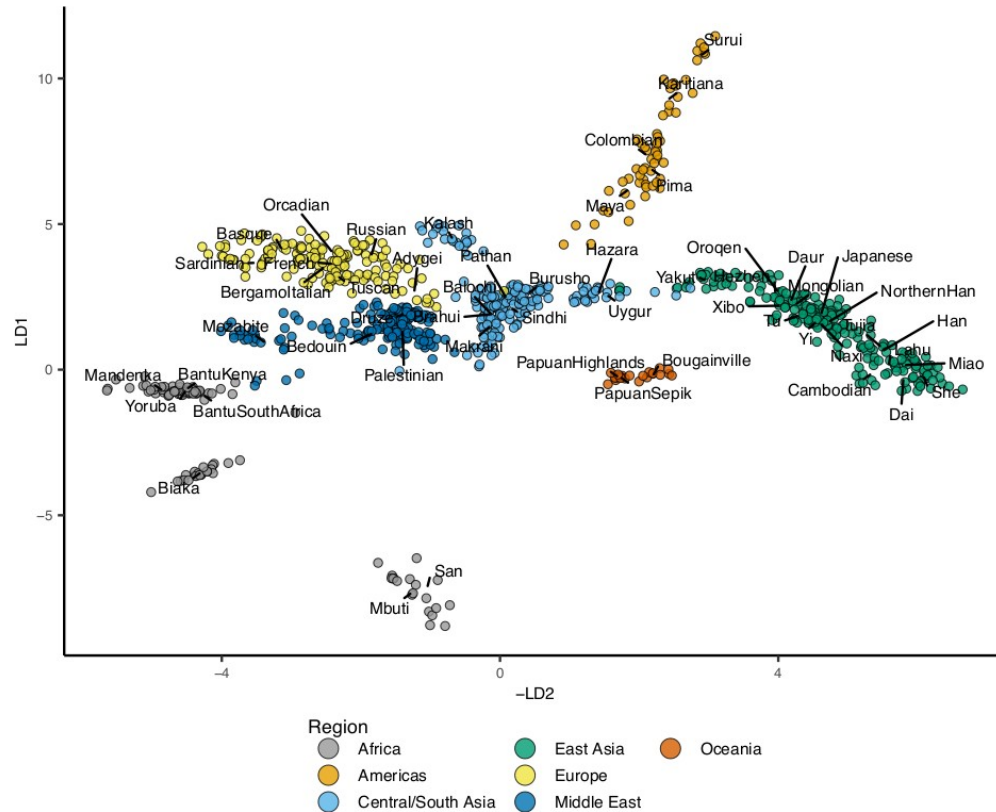
GCAE versus UMAP

While in the Supplementary Materials ...



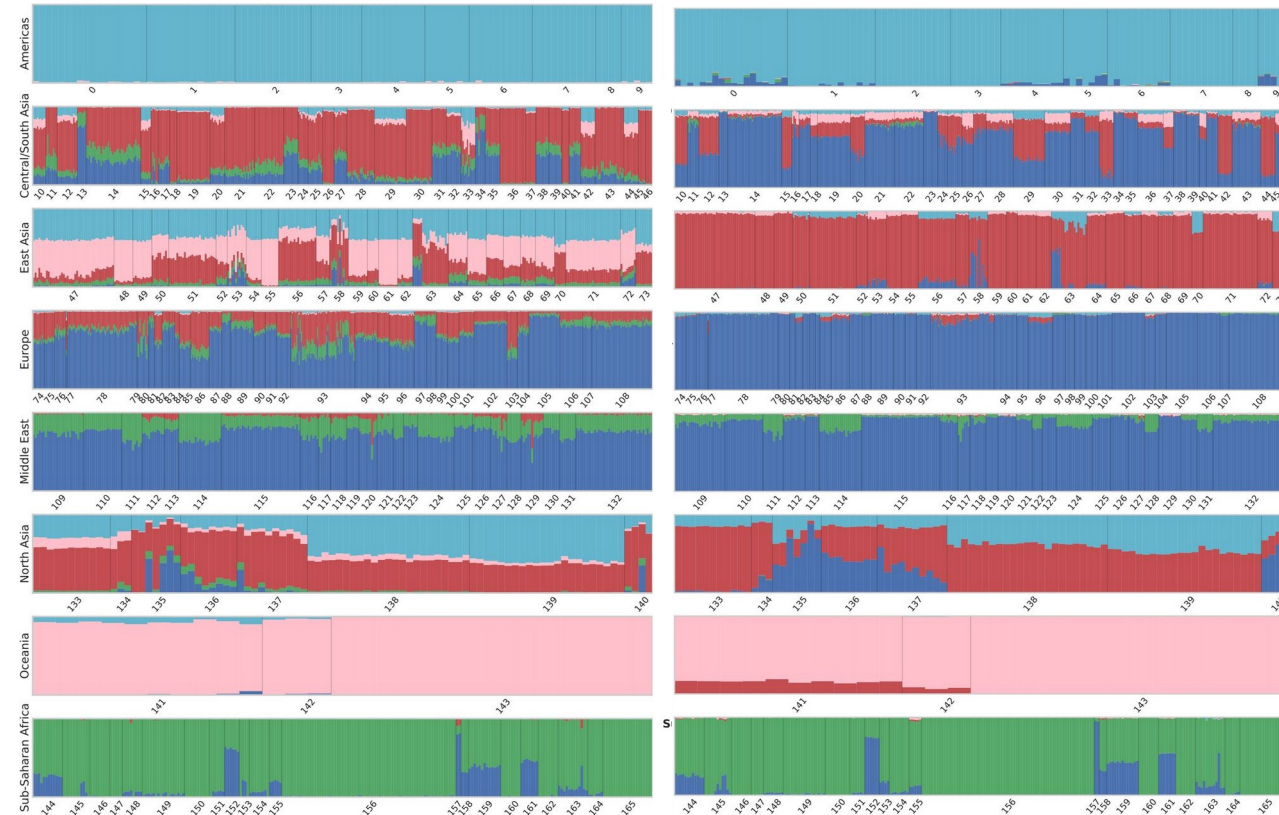
Ausmees, Kristiina, and Carl Nettelblad. "A deep learning framework for characterization of genotype data." bioRxiv (2020).

Comparisons by other study



Batthey, C. J., Gabrielle C. Coffing, and Andrew D. Kern. "Visualizing population structure with variational autoencoders." G3 11.1 (2021): 1-11.

ADMIXTURE

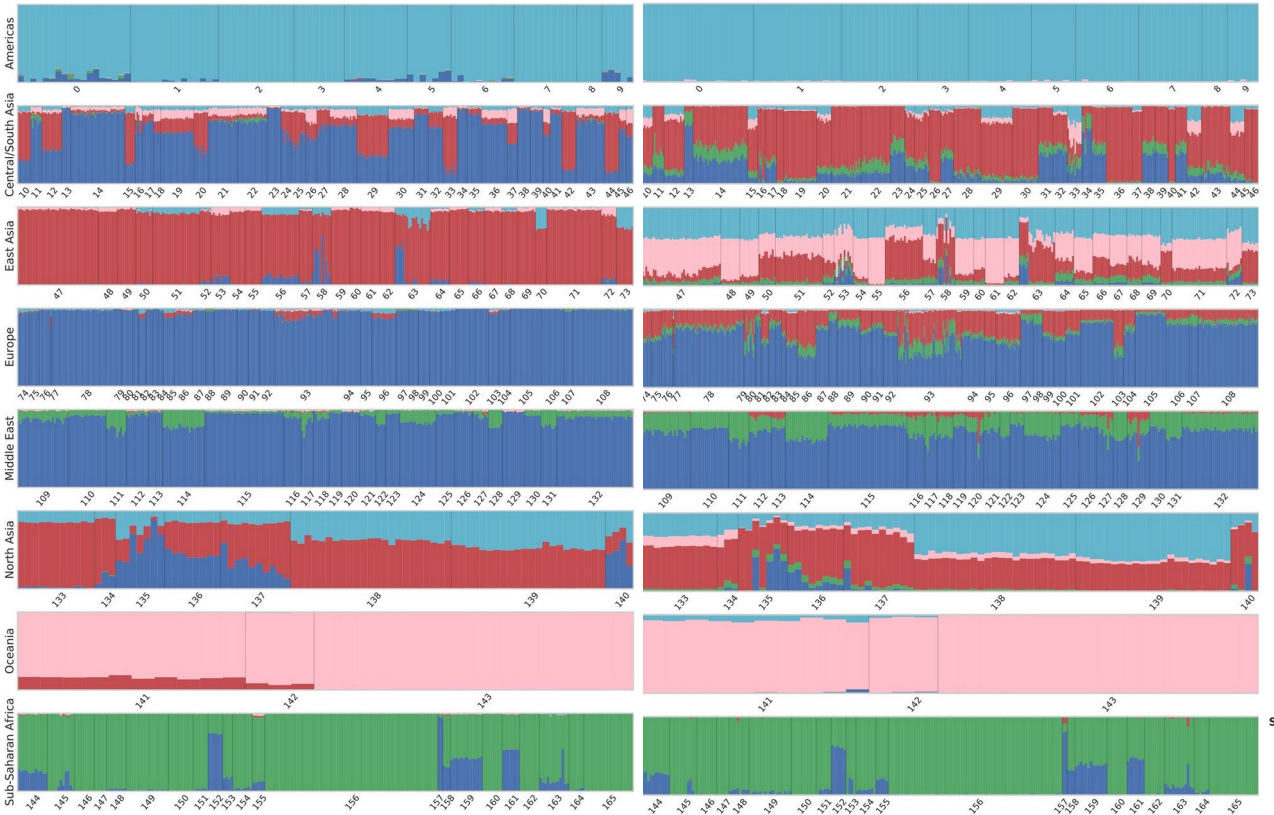


So, which one is better?

No figure legend on purpose :-)

ADMIXTURE

So, which one is better?



No figure legend on purpose :-)

Method

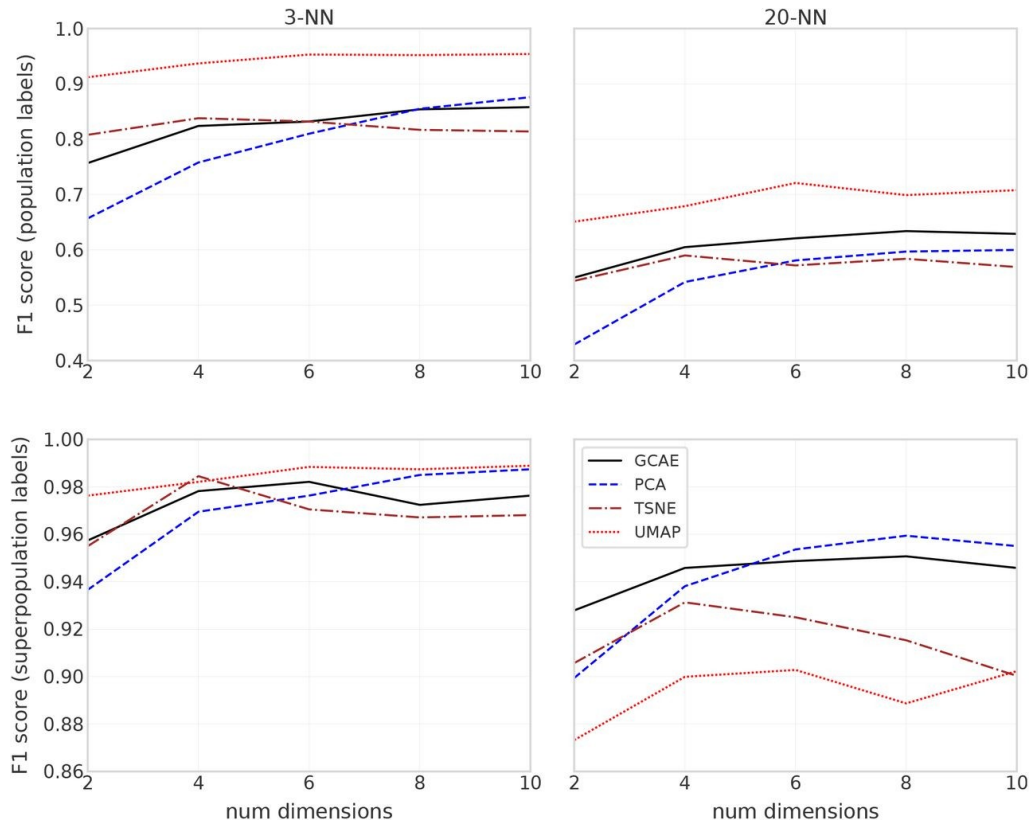
How is the ADMIXTURE-like plot generated?

Reproducible from text only?

No code

[...] what you see is not
ADMIXTURE w/PCA vs ADMIXTURE w/GenoCAE,
but rather ADMIXTURE vs. k-pop softmaxed GenoCAE

F1 Scores



So, which one is better?

“The F1 score of a classification model based on the dimensionality reduction is not a simple metric for which the method with the highest score is the most correct”

Discussion

Novel approach

- ... but there are others (non-convolutional) autoencoders
- ... best for non-linear effects on common SNPs

Dimensionality reduction looks impressive

- ... how well do other autoencoders do?

Performance is measured

- ... but how conclusively?

Performance is compared

- ... but how much care/tuning for these comparisons?

The end

[https://github.com/richelbilderbeek/
journal_club_20220220](https://github.com/richelbilderbeek/journal_club_20220220)





Data removal procedure

Human Origins data set

[...]

The data was filtered to exclude sex chromosomes and non-informative sites, and *one sample* (NA13619) was removed due to relation to another (HGDP01382).

Because of ADMIXTURE assumption



Equations

$$E(y, \hat{y}) = \sum_i^3 y_i \log(\hat{y}_i) + \alpha \sum_j^d e_j^2$$

$E(y, \hat{y})$: error

i : one of the three variants, i.e. AA, AC, CC

y_i : the actual value of a variant, i.e.

AA = 0.0, AC = 0.5, CC = 1.0

\hat{y}_i : the decoded value of a variant

```
"loss": {  
  "module": "tf.keras.losses",  
  "class": "CategoricalCrossentropy",  
  "args": {  
    "from_logits": false},  
  "regularizer": {  
    "reg_factor": 1.0e-07,  
    "module": "tf.keras.regularizers",  
    "class": "l2"  
  },  
}
```

Equations

$$E(y, \hat{y}) = \sum_i^3 y_i \log(\hat{y}_i) + \alpha \sum_j^d e_j^2$$

Lower
=
better

G	y_i	y_i^{hat}	E
AA	0	0.5	0
AC	1	0.1	-2.3
CC	0	0.3	0

One-hot
encoding

Zero
=
best

Lower
=
better

Equations

$$E(y, \hat{y}) = \sum_i^3 y_i \log(\hat{y}_i) + \alpha \sum_j^d e_j^2$$

i : one of the three variants, i.e. AA, AC, CC

y_i : the actual value of a variant, i.e.

AA = 0.0, AC = 0.5, CC = 1.0

\hat{y}_i : the decoded value of a variant

```
"loss": {  
  "module": "tf.keras.losses",  
  "class": "CategoricalCrossentropy",  
  "args": {  
    "from_logits": false  
  }  
> "regularizer": {  
  "reg_factor": 1.0e-07,  
  "module": "tf.keras.regularizers",  
  "class": "l2"  
},
```