

BINF 5003: Data Mining, Modeling, and Biostatistics

Week 9

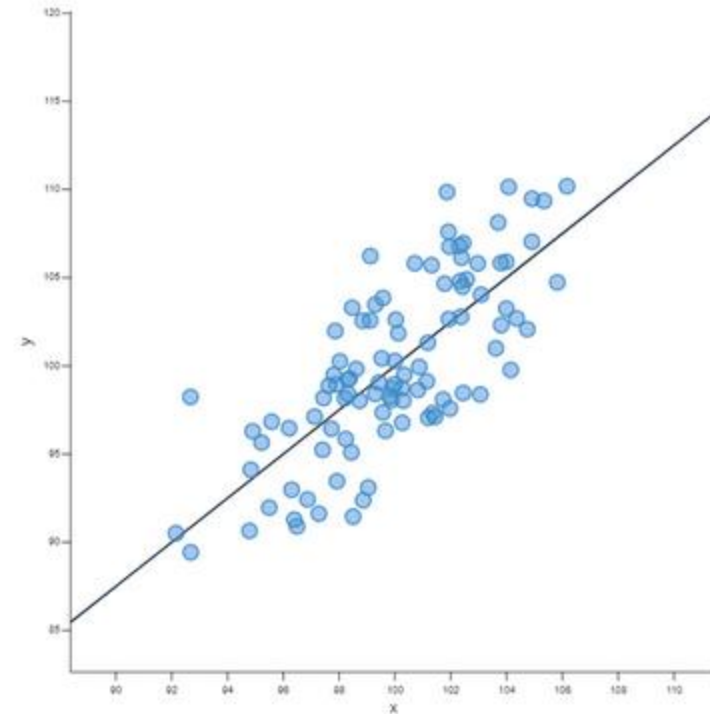
Module 6 – Dimensionality Reduction

Overview

- Introduce high dimensional data
- Understanding each principal (not principle) component
- Different strategies for dimensionality reduction

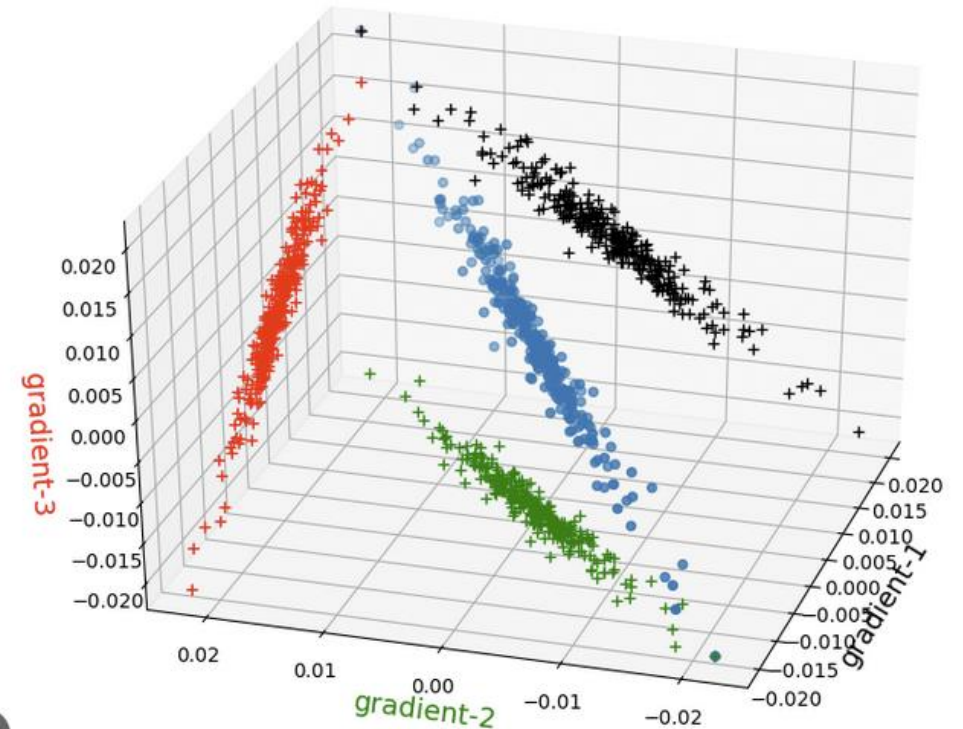
How do you compare the expression between 2 genes?

	FCGR1A/B	FCGR2A
GSM5550565	5.312574	11.618404
GSM5550566	3.818001	9.267078
GSM5550567	7.774246	9.250128
GSM5550568	7.484948	12.995963
GSM5550569	5.716728	9.118443
GSM5550570	7.665988	10.150636
GSM5550571	6.550153	12.127634
GSM5550572	6.470634	7.914081
GSM5550573	8.095839	9.023949
GSM5550574	8.296894	12.593593



How do you compare the expression between 3 genes?

	FCGR1A/B	FCGR2A	FCGR2A/C
GSM5550565	5.312574	11.618404	10.446063
GSM5550566	3.818001	9.267078	9.220695
GSM5550567	7.774246	9.250128	9.796387
GSM5550568	7.484948	12.995963	12.274279
GSM5550569	5.716728	9.118443	9.447233
GSM5550570	7.665988	10.150636	10.332182
GSM5550571	6.550153	12.127634	11.171883
GSM5550572	6.470634	7.914081	8.604253
GSM5550573	8.095839	9.023949	10.578452
GSM5550574	8.296894	12.593593	12.860324



How do you compare the expression between 30 genes?

	FCGR1A/B	FCGR2A	FCGR2A/C	FCGR2B	FCGR3A/B	FCGRT	FKBP5	FN1
GSM5550565	5.312574	11.618404	10.446063	7.258128	13.116418	10.925503	8.220796	2.475902
GSM5550566	3.818001	9.267078	9.220695	5.131137	10.095231	9.606318	9.436284	5.314985
GSM5550567	7.774246	9.250128	9.796387	6.785571	10.643389	7.214852	6.699284	5.743886
GSM5550568	7.484948	12.995963	12.274279	8.036461	14.162104	11.257061	11.458007	4.034101
GSM5550569	5.716728	9.118443	9.447233	6.023923	9.667908	9.001434	8.247959	5.018657
GSM5550570	7.665988	10.150636	10.332182	7.067652	11.137075	7.547681	7.009650	3.883460
GSM5550571	6.550153	12.127634	11.171883	6.901867	12.637730	10.637566	11.684044	2.953016
GSM5550572	6.470634	7.914081	8.604253	6.218286	7.974997	9.205092	10.374554	5.061319
GSM5550573	8.095839	9.023949	10.578452	6.879353	9.972874	7.088388	7.480413	2.985537
GSM5550574	8.296894	12.593593	12.860324	7.701926	13.121371	10.470563	10.951340	4.901322

Dimensionality Reduction

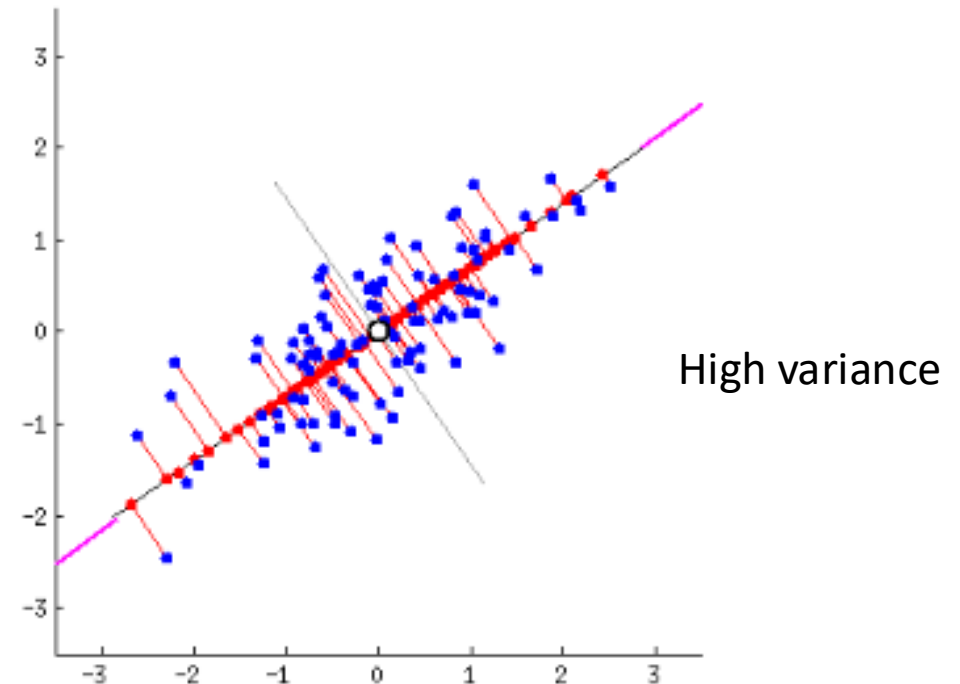
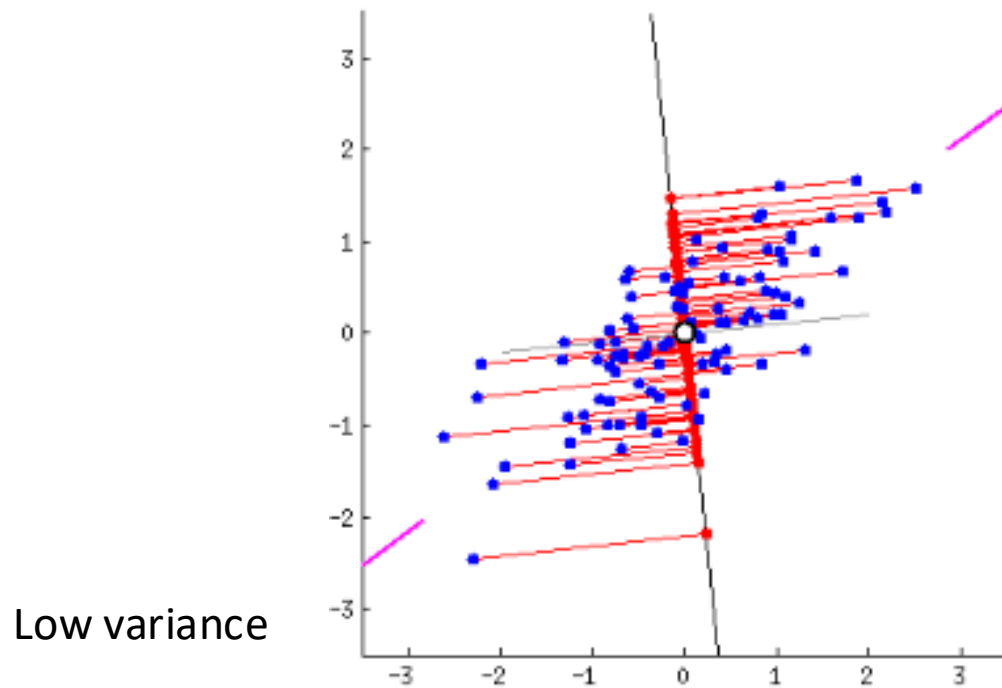
- Each feature (gene) or sample in the dataset adds dimensions to the analysis
- Minimize the dimensions
 - Prevent overfitting
 - Keep the dataset computationally manageable
- 2 strategies
 - Eliminate dimensions by removing redundancies or static features
 - Collapse the number of components we are working with

Principal Component Analysis

- Original basis of multivariate data analysis
 - Reduce the number of features to more manageable and meaningful numbers
- Draws lines through the data to best account for the variance in the data
 - Difference between observed and expected values on the plane – concept sound familiar??

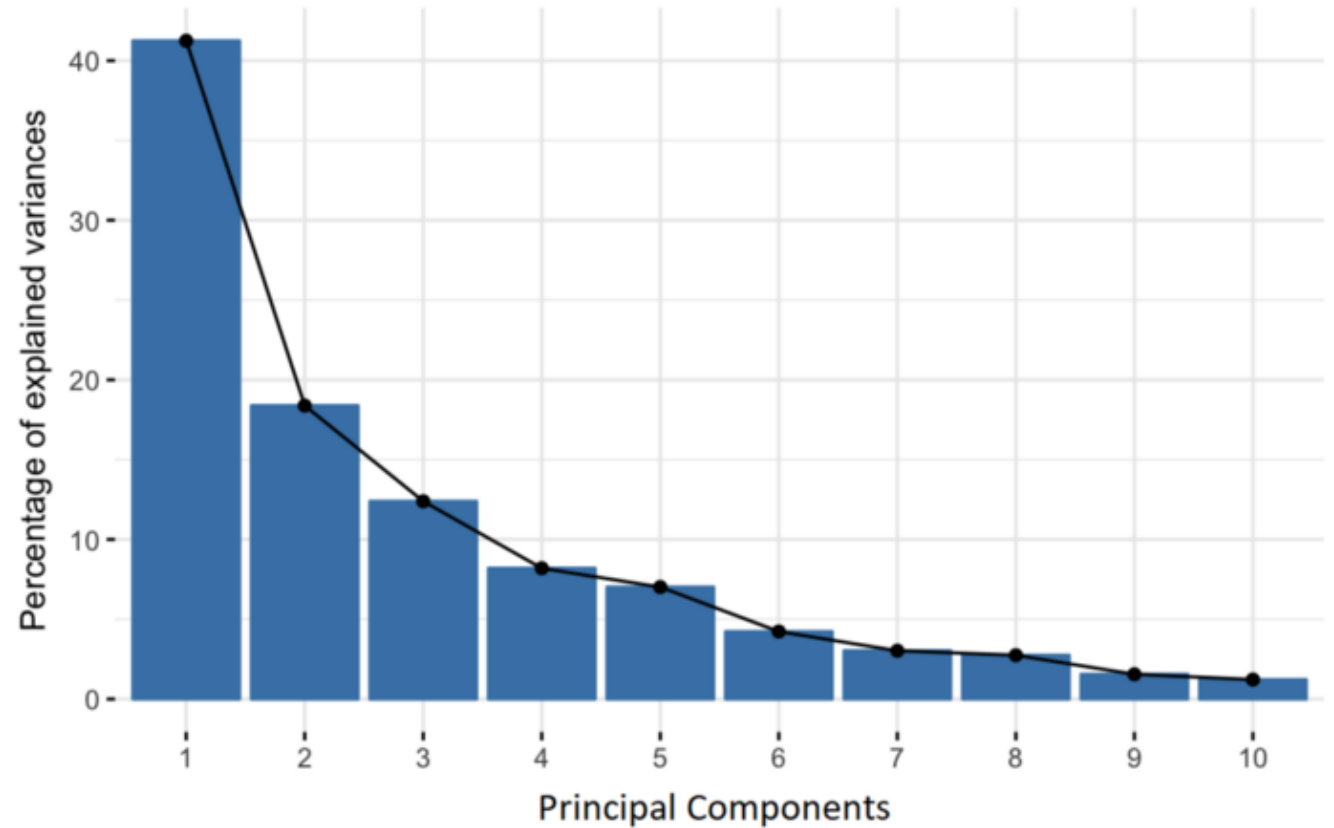
Principal Component Analysis

- PC determined by maximizing the variance it explains



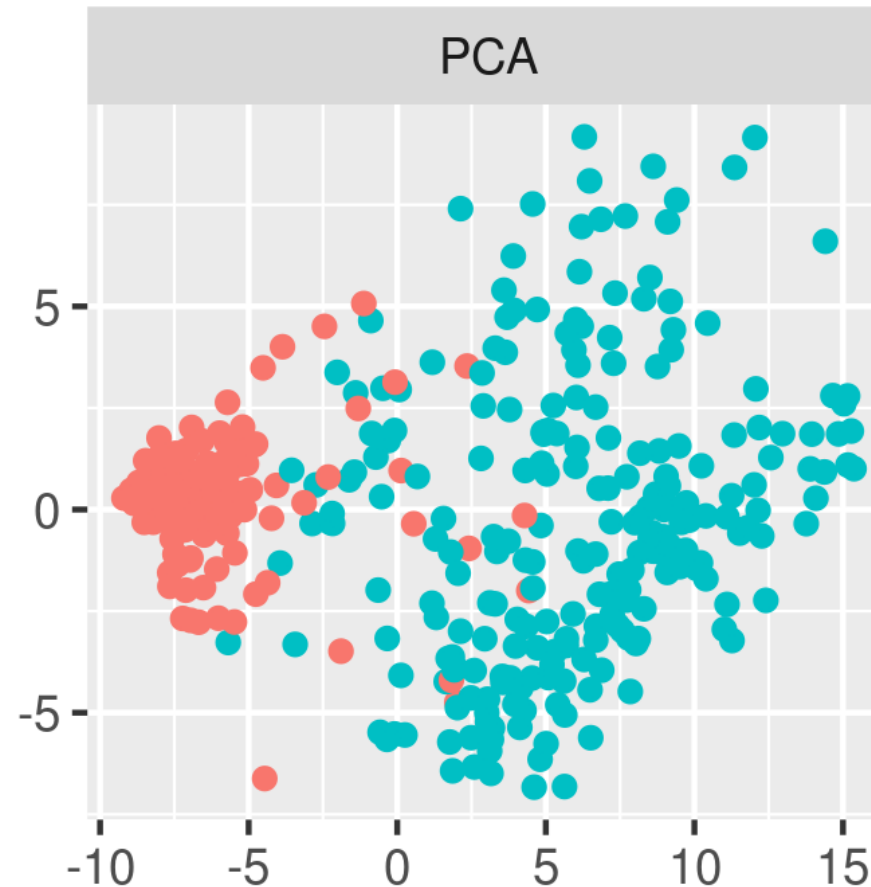
Principal Component Analysis

- There are as many principal components as there are features
 - Each feature contributes to each component
 - Ordered from highest to lowest percentage of variance explained

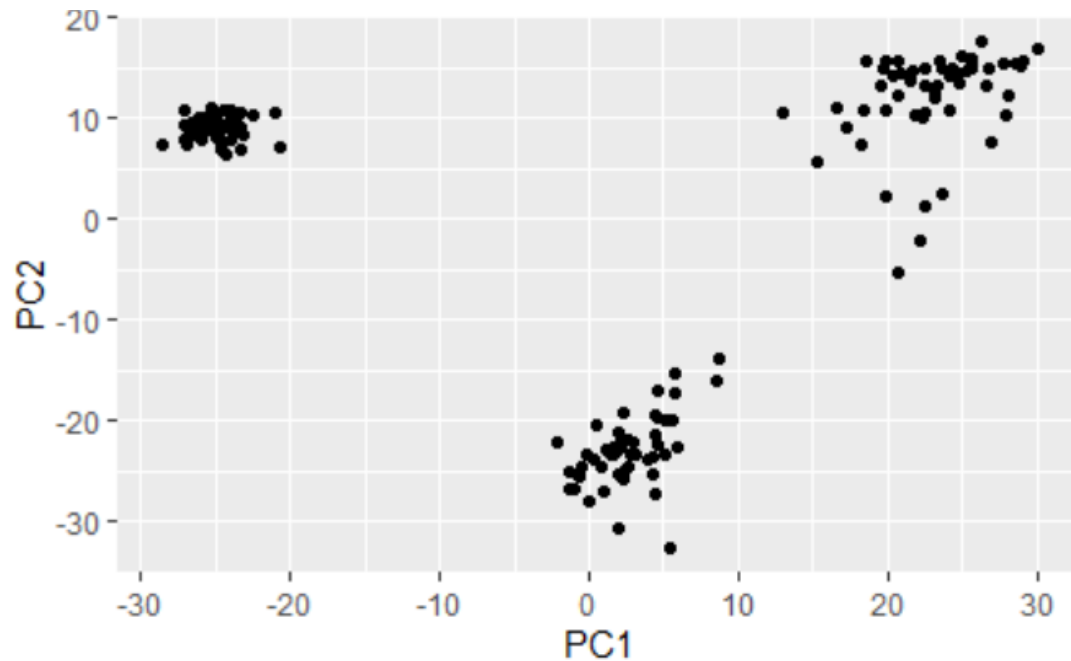


Principal Component Analysis

- Each sample is a dot
- Dots that are more similar are closer together

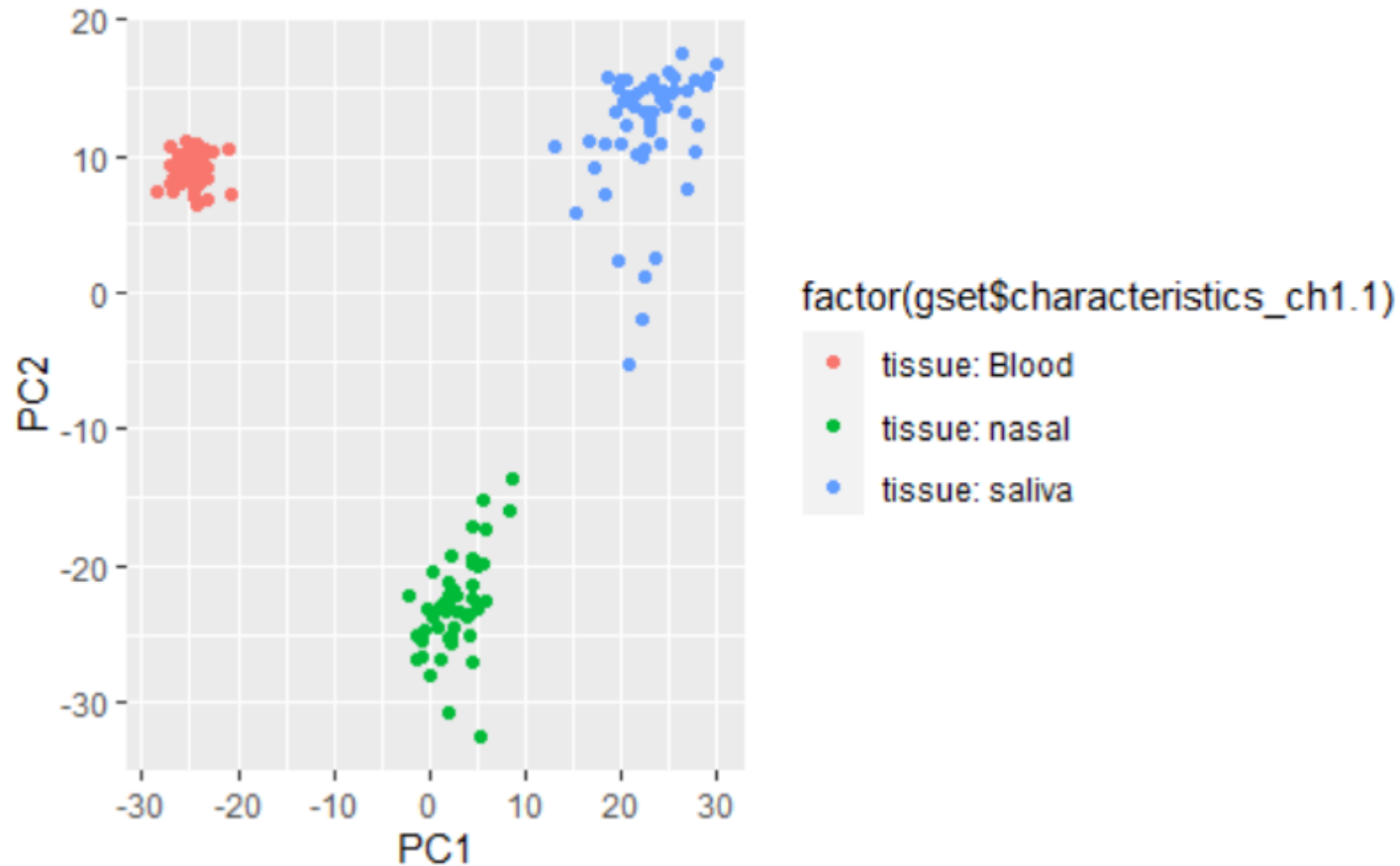


Always start with the first 2 PCs



- Clusters are drawn independent of the clinical phenotypes
- Based on trends of variance in the data
- Next step is to find out how the components are separating the data

Colour based on the phenotypes we have information on



What if the data separated on sex?

- May be an indication of a co-variate
 - Is the pathology appearing different in males and females?
 - Was the data collected differently between males and females?
- May be able to be improved with batch correction, but this will add noise
 - More on this next week!

Rotations

	PC1	PC2	PC3
ABCB1	-0.050682348	-0.011573649	0.0329185893
ABL1	-0.020720434	-0.002230240	0.0028087906
ADA	-0.019765264	0.031396316	0.0108932207
AHR	-0.004619061	-0.031346615	-0.0388916903
ALAS1	0.023966943	0.017795618	-0.0005369596
APP	0.016337502	-0.021162588	-0.0260058816
ARG1	0.193467053	-0.096031507	0.0239686927
ARHGDIB	0.015295850	-0.033600989	-0.0171090664
ATG10	0.005561893	-0.009801947	0.0183760181
ATG12	0.021103920	-0.012184266	0.0038722934

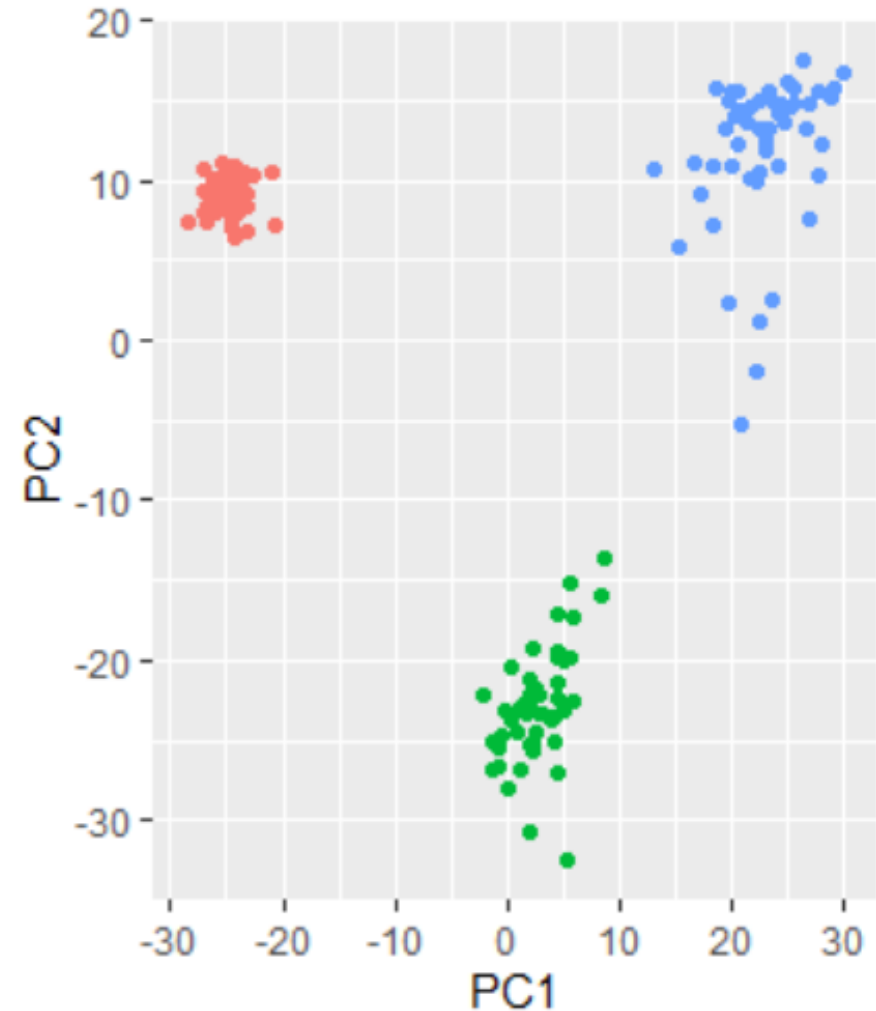
- Each gene contributes to each PC
- Closer to 0 == lesser contribution
- Higher value in the positive or negative reflects how it is separating the samples

Rotations

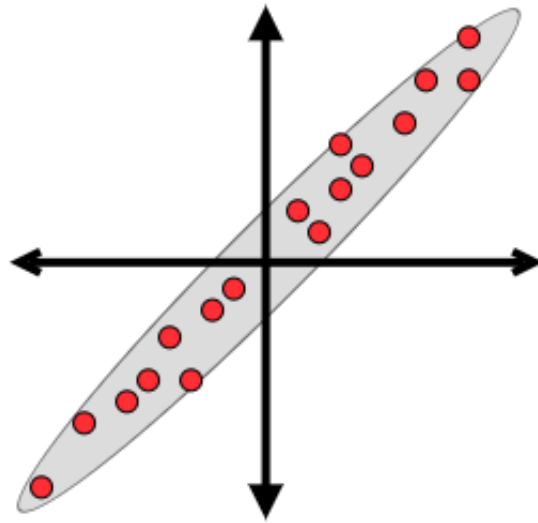
factor(gset\$characteristics_ch1.1)

- tissue: Blood
- tissue: nasal
- tissue: saliva

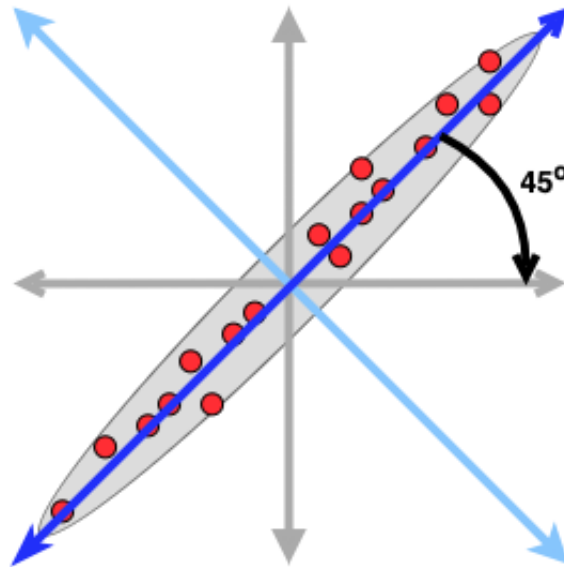
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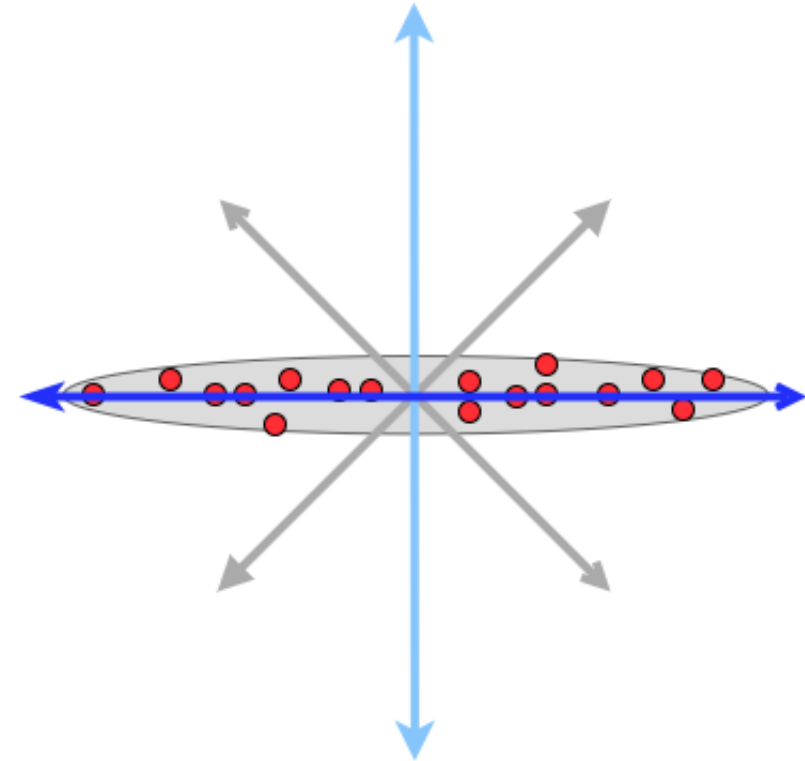
Rotations



Original Coordinates

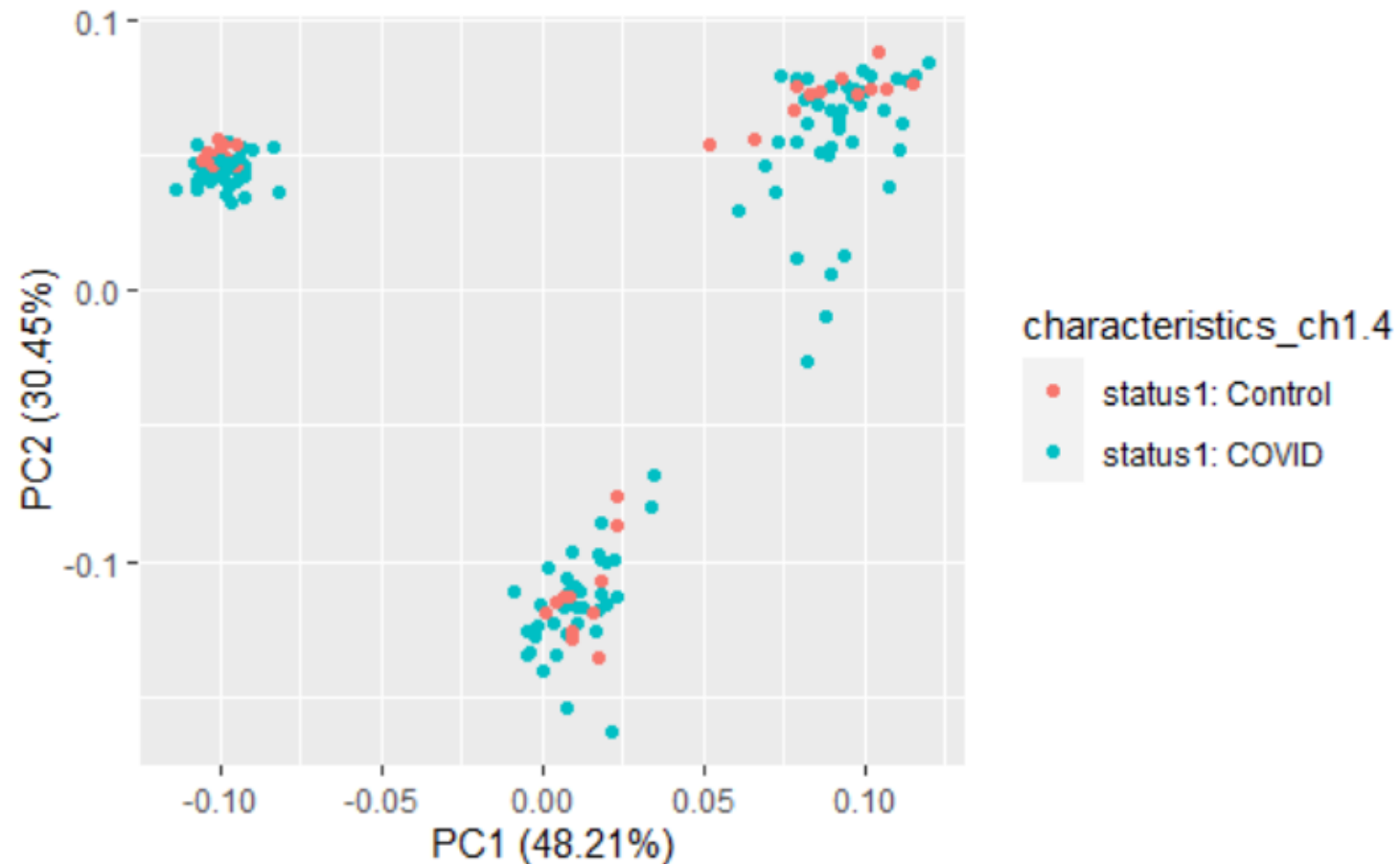


Principle Component

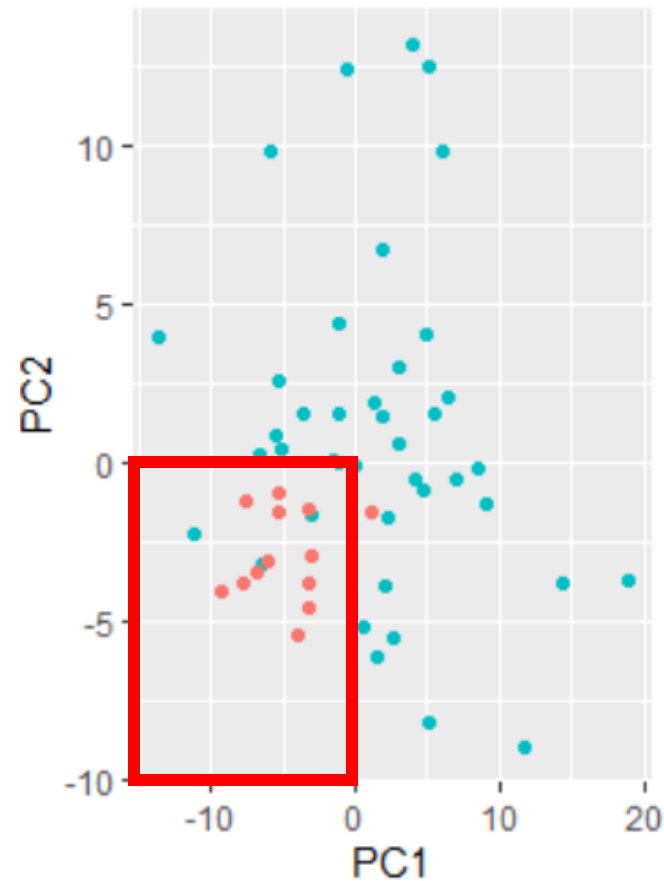


New Rotated Coordinates

What can we do if samples are not separating based on pathology?



Controls are only in one quadrant

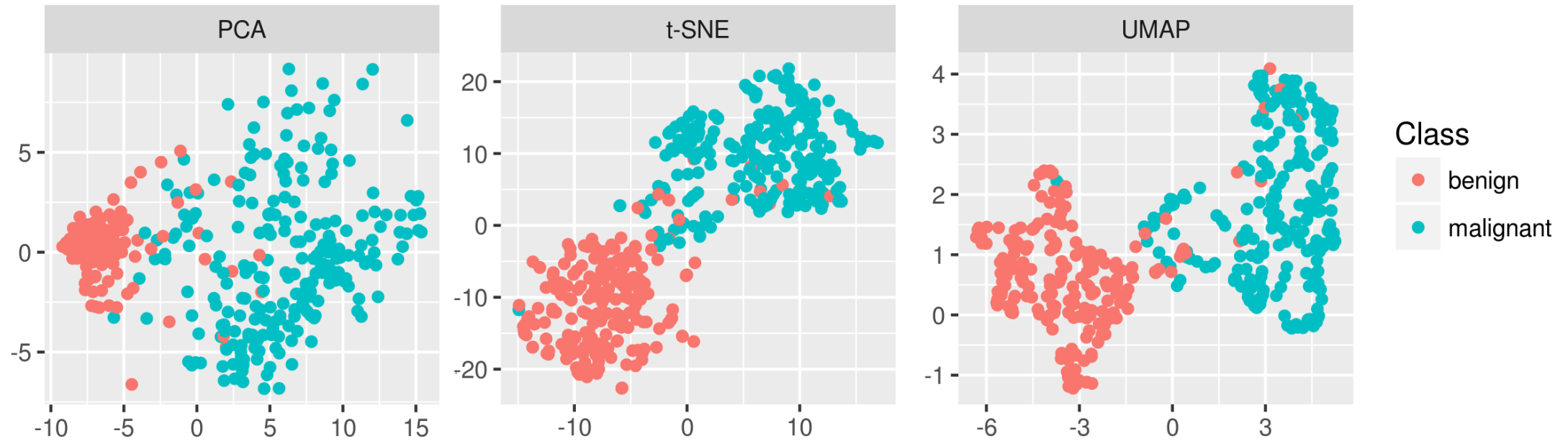


`factor(gset_blood$characteristics_ch1.4)`

• status1: Control
• status1: COVID

Look for genes with positive rotations in PC1 and/or PC2

Many strategies for Dimensionality Reduction



Also NMDS, PCoA

Wrap-up

- Dimensionality reduction reduces the complexity of data by eliminating repetition or consolidating similarities
- Reduce the number of dimensions by
 - Reducing redundancy
 - Grouping similar features together
- There are as many principal components as there are features
- Each gene contributes to each principal component
- In addition to PCA, TSNE and UMAP are alternate strategies for dimensionality reduction
 - NMDS and PCoA are other ordination methods (large amount of data distilled down to 2D or 3D)