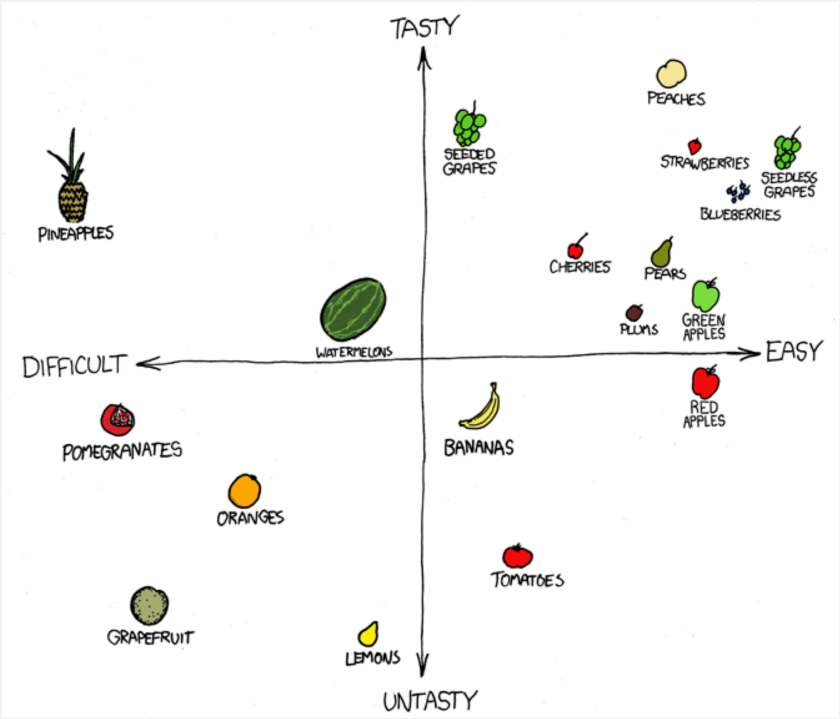
Dimensionality Reduction

Principal component analysis

Biology 683

Lecture 9

Heath Blackmon



Recently

1. Fixed vs Random Effect
2. Problems with model choice

Hypothesis testing vs wrapping our heads around data

Why do we do dimensional reduction?

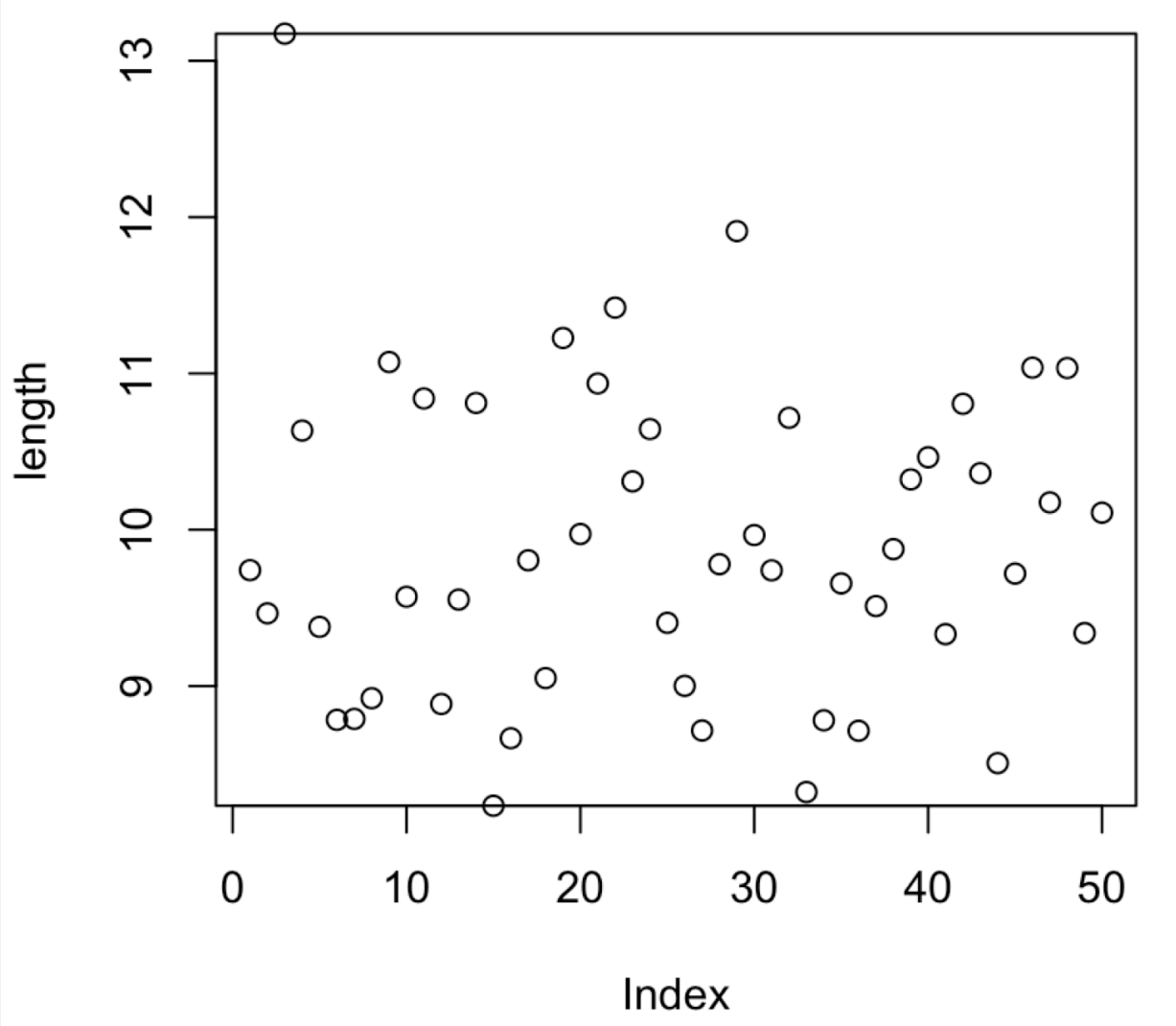
1. Datasets are getting bigger and bigger
2. Understanding our data is often the new bottleneck
3. We can’t think well beyond 3-4 dimensions
4. We can’t illustrate well beyond 2 dimensions

What is principal component analysis

PCA is a dimensional reduction tool that takes many (possibly correlated) measurements and transforms it into a smaller set of uncorrelated measuerments.

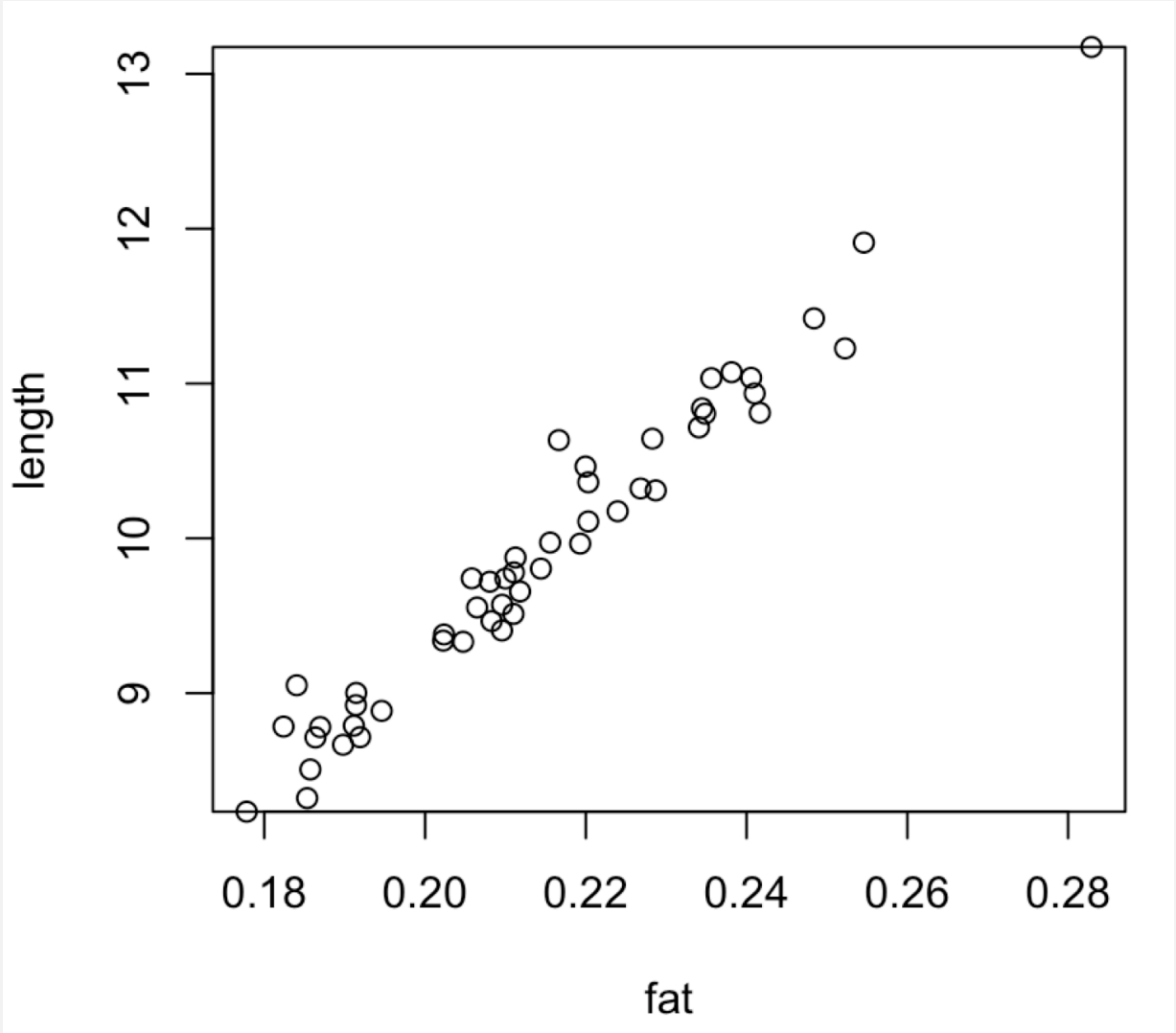
One dimensional data

fish_ID	length
379	9.74
430	9.47
55	13.17
434	10.63
147	9.38
497	8.78
127	8.79
362	8.92
107	11.07
116	9.57
414	10.84
232	8.89
193	9.55
80	10.81
283	8.23
68	8.67
341	9.8
288	9.05
200	11.23
62	9.97
69	10.94
466	11.42
400	10.31
83	10.64
106	9.4
280	9



Two-dimensional data

fish_ID	length	fat
379	9.74	0.21
430	9.47	0.2
55	13.17	0.28
434	10.63	0.22
147	9.38	0.28
497	8.78	0.26
127	8.79	0.24
362	8.92	0.25
107	11.07	0.24
116	9.57	0.25
414	10.84	0.26
232	8.89	0.17
193	9.55	0.23
80	10.81	0.32
283	8.23	0.24
68	8.67	0.25
341	9.8	0.19
288	9.05	0.26
200	11.23	0.23
62	9.97	0.22
69	10.94	0.18
466	11.42	0.21
400	10.31	0.23
83	10.64	0.19



High dimensional data

fish_ID	length	fat	m3	m4	m5	m6	m7
379	9.74	0.21	9.74	0.21	0.27	1.45	2.97
430	9.47	0.2	9.47	0.2	4.28	0.83	1.57
55	13.17	0.28	13.17	0.28	7.01	1.25	4.59
434	10.63	0.22	10.63	0.22	15.33	0.89	2.09
147	9.38	0.28	9.38	0.28	5.77	0.77	2.03
497	8.78	0.26	8.78	0.26	18.81	0.61	1.39
127	8.79	0.24	8.79	0.24	8.92	1.24	2.62
362	8.92	0.25	8.92	0.25	0.44	0.98	2.19
107	11.07	0.24	11.07	0.24	16.89	0.84	2.24
116	9.57	0.25	9.57	0.25	13.55	1.26	3.02
414	10.84	0.26	10.84	0.26	11.23	0.2	0.57
232	8.89	0.17	8.89	0.17	2.02	0.94	1.42
193	9.55	0.23	9.55	0.23	5.24	1.05	2.32
80	10.81	0.32	10.81	0.32	6.04	0.79	2.73
283	8.23	0.24	8.23	0.24	0.12	0.07	0.13
68	8.67	0.25	8.67	0.25	2.76	0.41	0.89
341	9.8	0.19	9.8	0.19	9.73	1.59	2.97
288	9.05	0.26	9.05	0.26	15.31	0.49	1.16
200	11.23	0.23	11.23	0.23	3.04	1.26	3.24
62	9.97	0.22	9.97	0.22	13.14	0.28	0.61
69	10.94	0.18	10.94	0.18	5.23	0.14	0.28
466	11.42	0.21	11.42	0.21	6.11	0.3	0.71
400	10.31	0.23	10.31	0.23	2.78	0.43	1.02
83	10.64	0.19	10.64	0.19	10.93	0.86	1.73

What are our options?

Dimensionality reduction - PCA

fish_ID	length	fat
379	9.74	0.21
430	9.47	0.2
55	13.17	0.28
434	10.63	0.22
147	9.38	0.28
497	8.78	0.26
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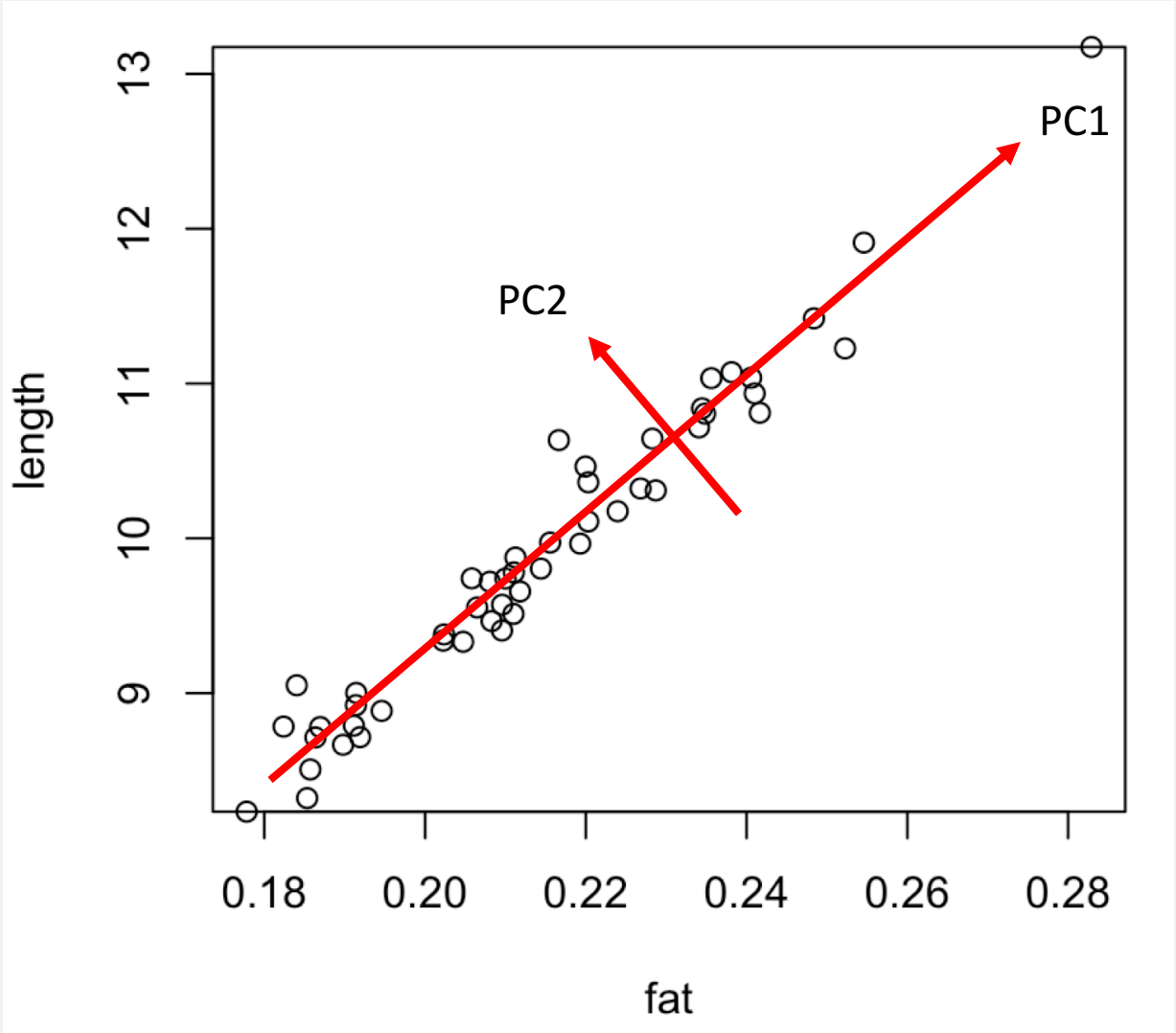

The math behind - PCA

M measurements

N samples

fish_ID	length	fat	m3	m4	m5	m6	m7
379	9.74	0.21	9.74	0.21	0.27	1.45	2.97
430	9.47	0.2	9.47	0.2	4.28	0.83	1.57
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497	8.78	0.26	8.78	0.26	18.81	0.61	1.39

= X

nxm matrix

PCA is an Eigendecomposition of $(X^T X)$

W = loadings mxm matrix

$$T = X \cdot W$$

```
pca <- prcomp(X)
pca$x
```

fish_ID	PC1	PC2	PC3	PC4	PC5	PC6	PC7
379	0.48401035	0.3204638	0.86441909	0.75599341	0.19841263	0.29382035	0.87356767
430	0.92864946	0.7321531	0.17546787	0.22461749	0.50242958	0.66343818	0.82559145
55	0.12804522	0.03920335	0.59362519	0.39215655	0.9883746	0.92951871	0.26687076
434	0.2062225	0.21152673	0.47047215	0.66007816	0.71549665	0.89006466	0.31692619
147	0.85635814	0.17733842	0.94029393	0.11666265	0.10601835	0.18949868	0.42276984
497	0.78104386	0.88445893	0.45355361	0.61294154	0.02441031	0.3948512	0.08124852

= T

nxm matrix

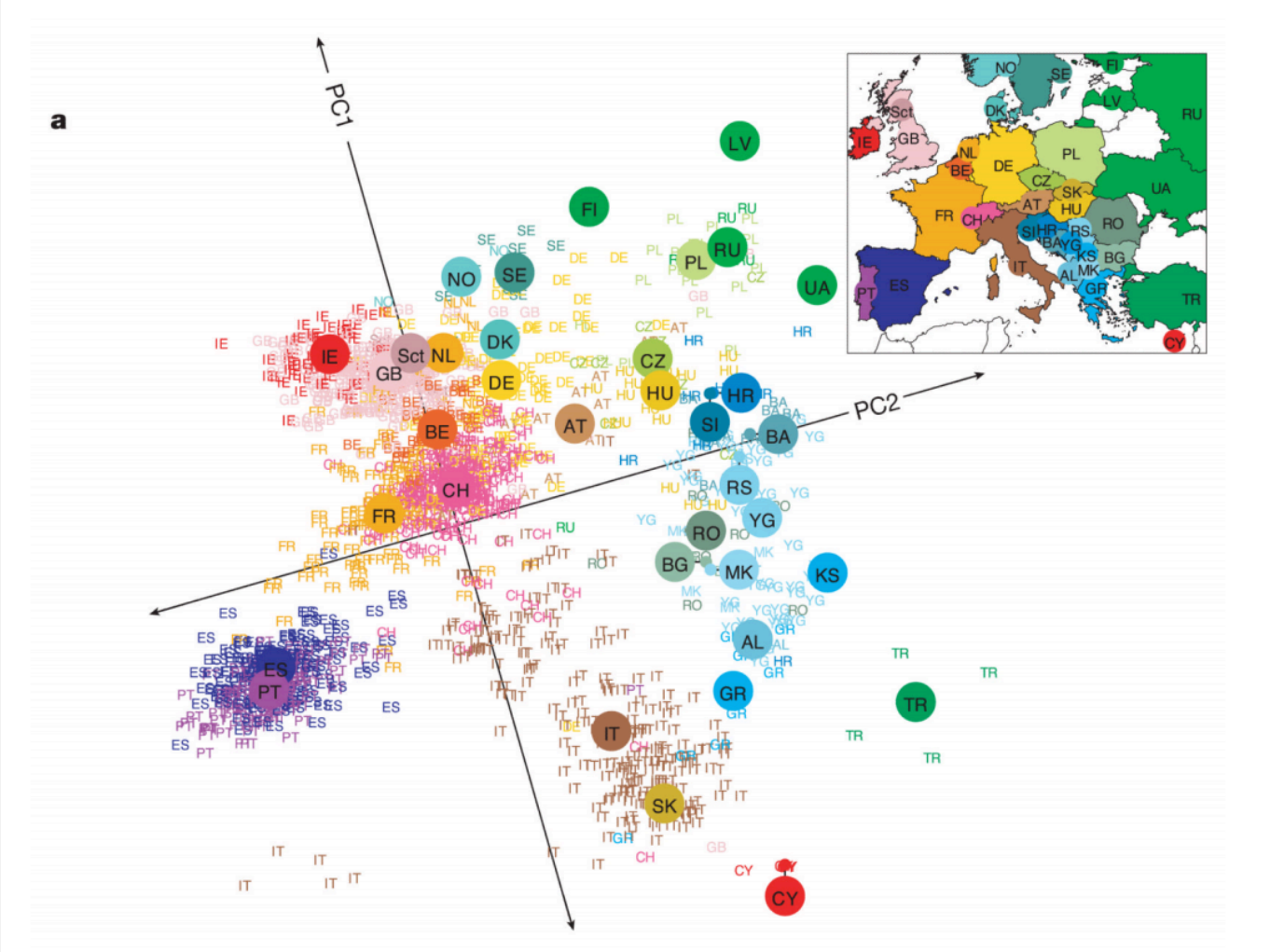
This is T a nxm matrix that has our PC scores. The first column of the matrix will be the one that captures the most variation.

How do people use PCA

Input data: 500,000 SNP genotypes for 3000 Europeans.

3000 rows
500,000 columns

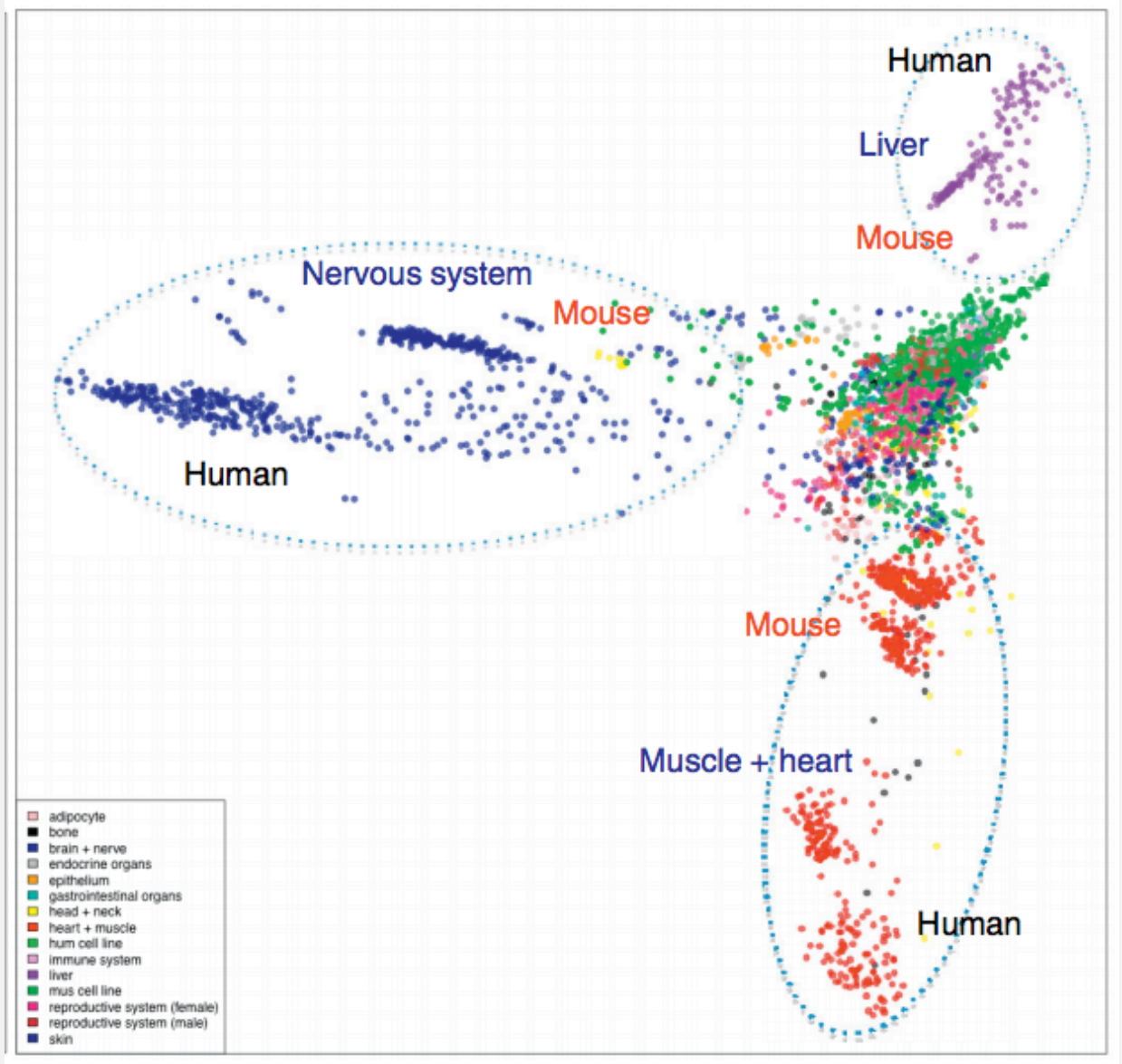
What are PC1 and PC2?



How do people use PCA

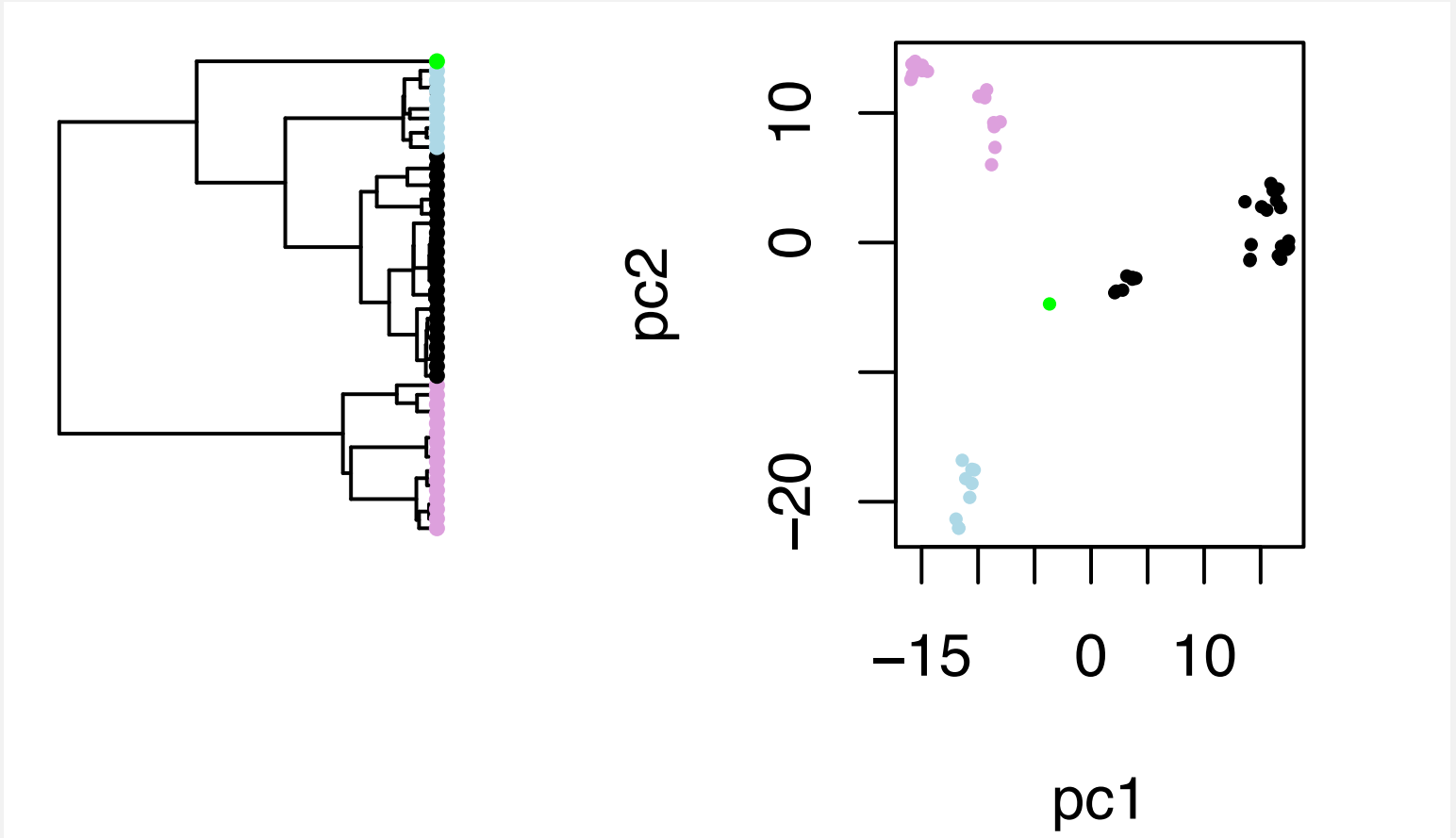
Input data:
Expression level for 1000s of genes
In 100s of cells (color indicates type of cell)

What are the PCs here?



How do people use PCA

Input data:
Radseq data (genotypes at 100s of loci)
For a large number of species or strains



How do people use PCA

Input data:
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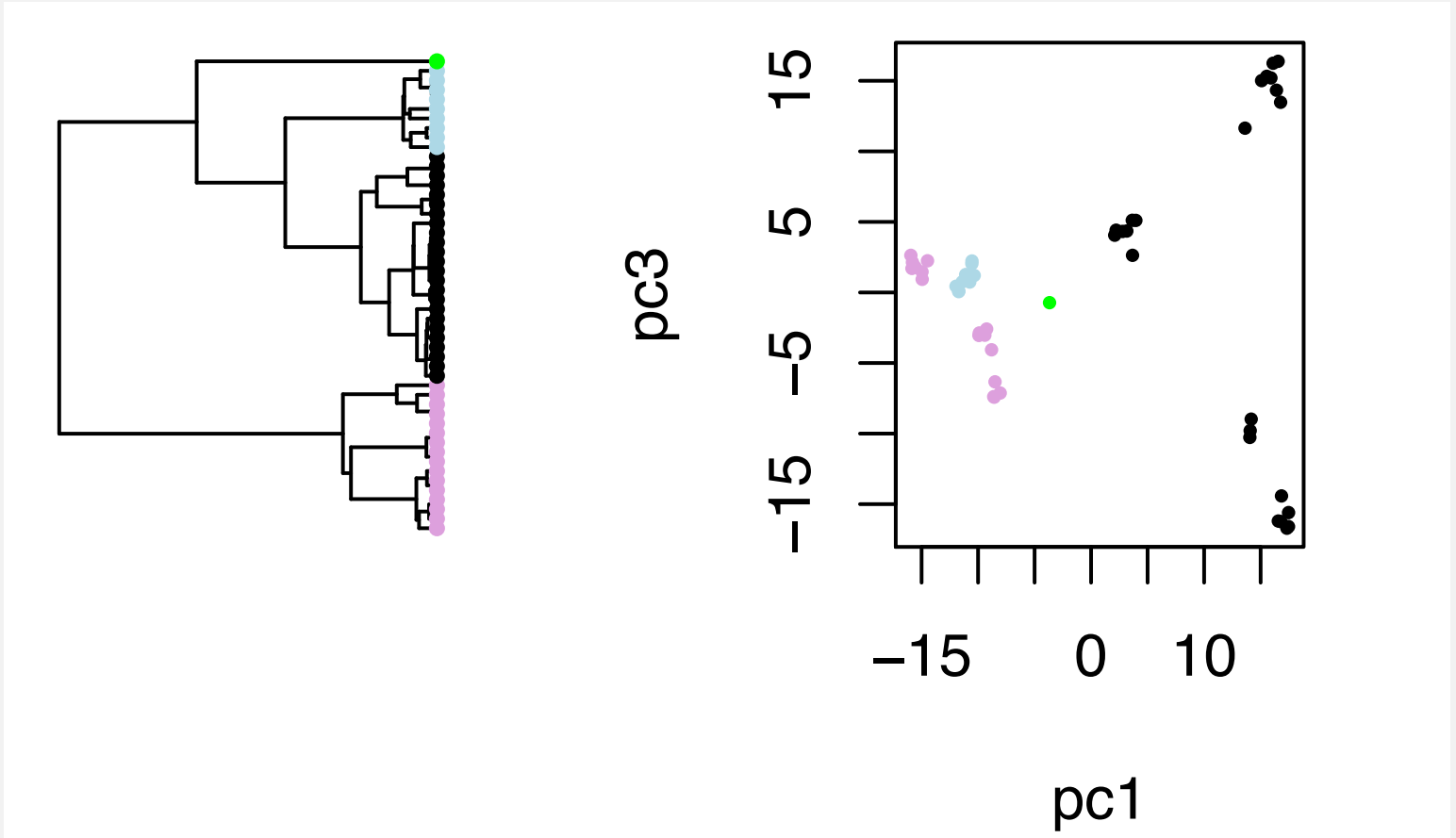
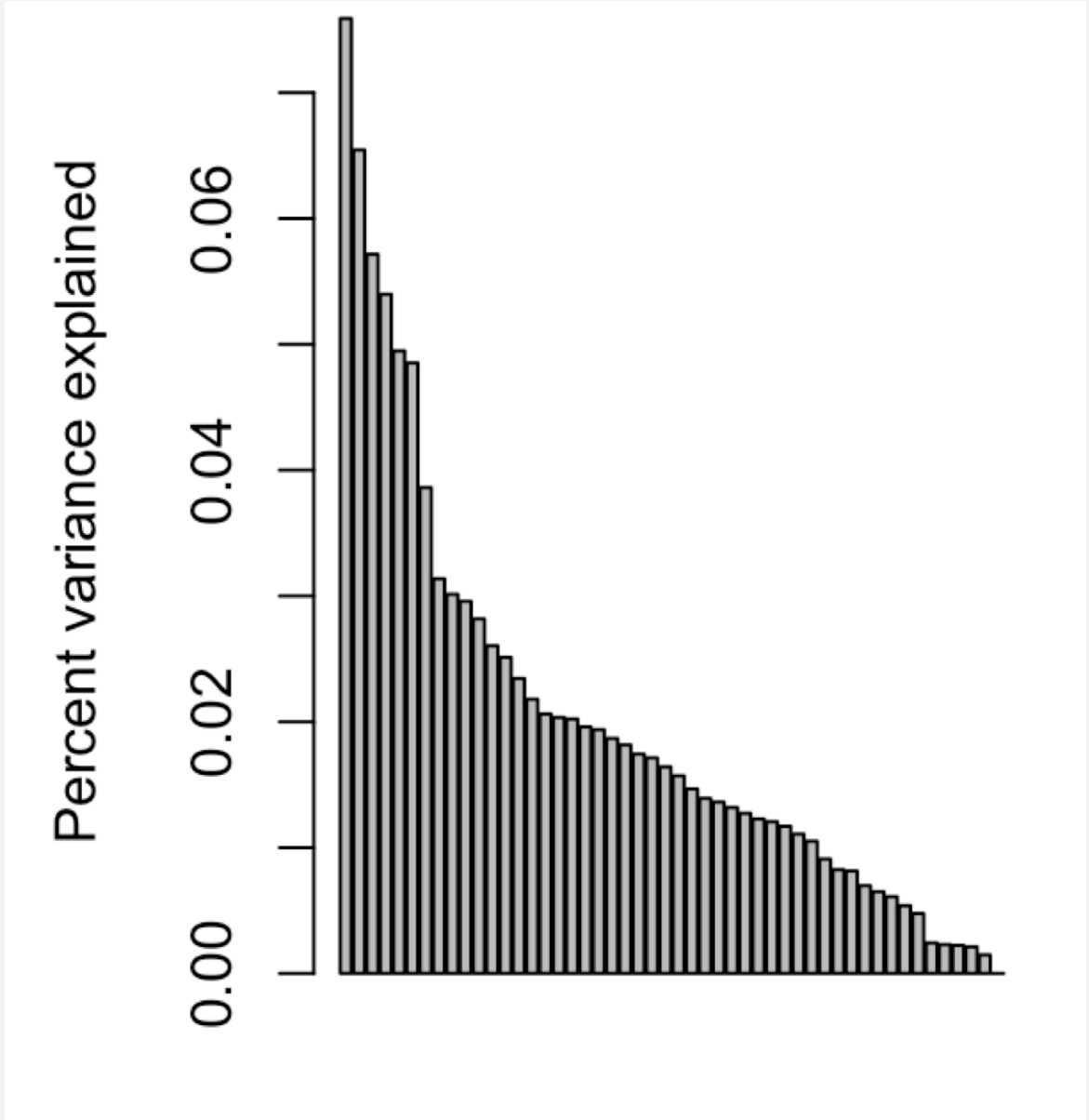


How informative is your PCA

Scree Plot: A plot that illustrates the proportion of total variance that is captured by each principal component.

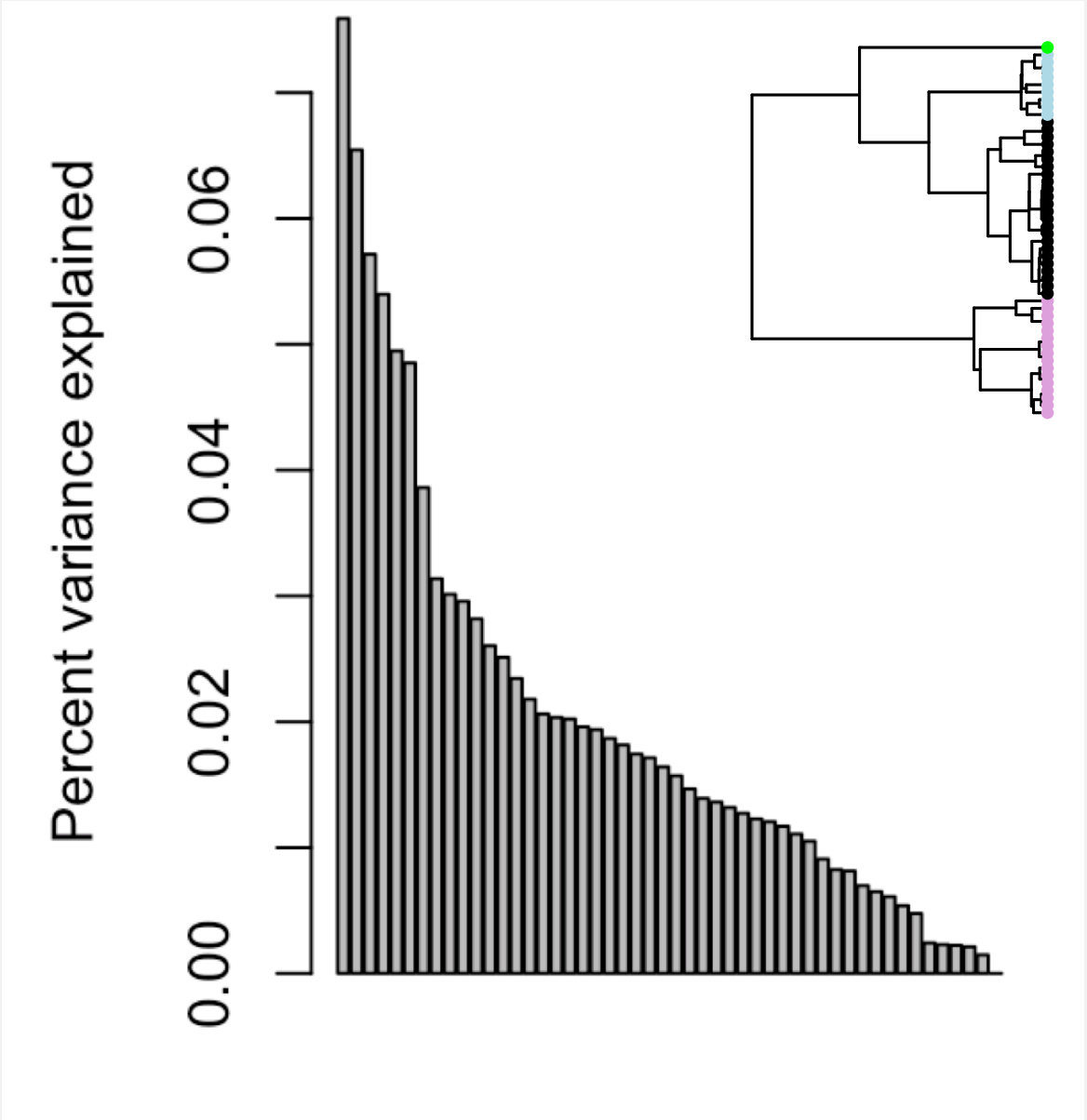
Steep means you can greatly reduce dimensionality without losing information



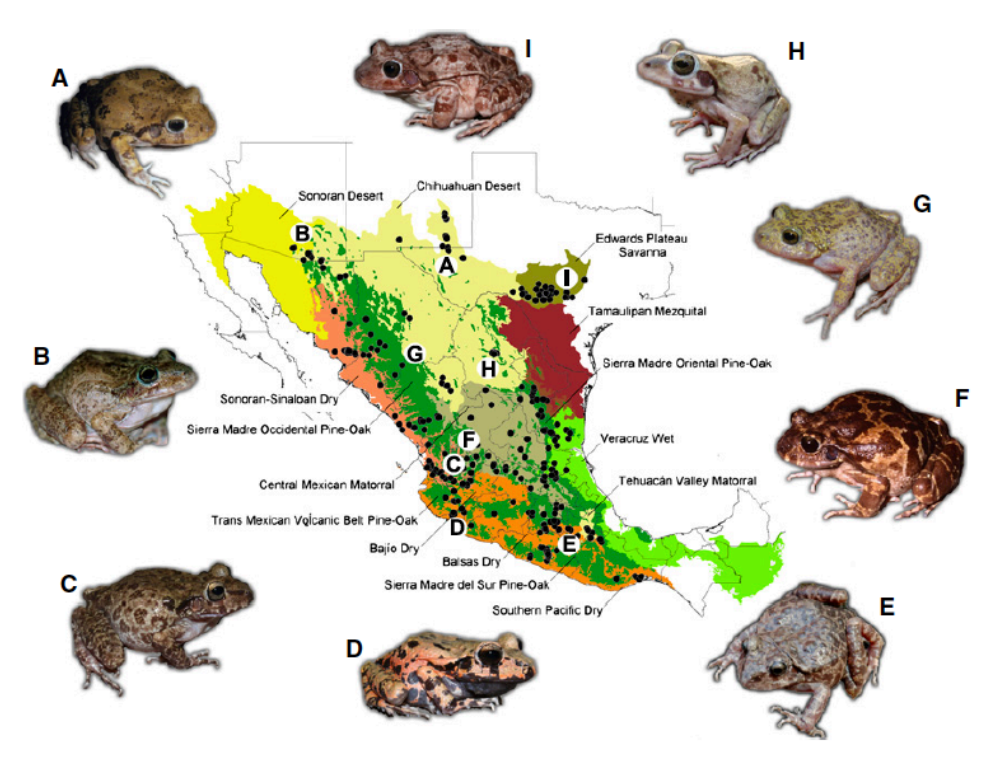
How informative is your PCA

Why does this scree plot have relatively flat slope?

What information is present in the data what is being lost if we look at only 1 or 2 dimensions?



An example




```
dat <- read.csv("snps.csv", row.names = 1)
pca <- prcomp(dat)
names(pca)
plot(x=pca$x[, 1], y=pca$x[, 2])
perc.var <- pca$sdev^2 / sum(pca$sdev^2)
barplot(perc.var)
```

Alternatives

Discriminate function analysis: This is similar to PCA but you assign groupings to the data first and the discriminating components best parse your assigned groups from one another.

For Thursday

Bring laptop to class!

Heath Blackmon
BSBW 309
coleoguy@gmail.com
@coleoguy