

Final Projects

- Report (15% of grade - GROUP)
 - Can copy + paste from proposal & checkpoints & can update/edit/change
 - Adding on:
 - Choice if we have your permission to make public
 - Overview
 - Analysis (w/ “strong” data visualizations)
 - Conclusion & Discussion
 - It’s a report, not a vomiting of data.
 - Write in the diamond structure of technical reports
 - Do not have to include deadends, massive codebases, or irrelevant explorations. Can put those in a separate file that is referenced in report.
 - Do edit for correctness & conciseness at the end
- Video (3% of grade - GROUP)
 - 3-5 minutes
 - Post video so that it is PUBLICLY VISIBLE on Google Drive, Dropbox, TikTok, YouTube, whatever.
 - Place a link to the video right after the title of your final project notebook
 - Everyone should participate; not everyone has to be IN the video
- Team Evaluation Survey (3% of grade - INDIVIDUAL)
 - Give us more information about who contributed / did not contribute; this will effect individual grades

Week 10 / Finals Week Extra Credit Opportunities

- Guest lecture Mon Dec 4th 2PM
 - 0.25% EC for in person only to encourage attendance!
- Fill out the teaching evaluations (SET used to be CAPE) [Evaluations site](#)
 - Must complete evaluations BEFORE 8AM on Saturday, December 9. No exceptions.
 - 0.5% EC if >75% of the class fills this out (only happens half the time)
- Post course survey
 - Especially important in regards to our pedagogical experiment
 - 0.25% EC

Dimensionality Reduction

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Dimensionality Reduction Outline

- Definition
- When to Use
- Mathematical Overview
- Key Concepts
- Examples
 - Diet in the UK
 - Genetics around the world

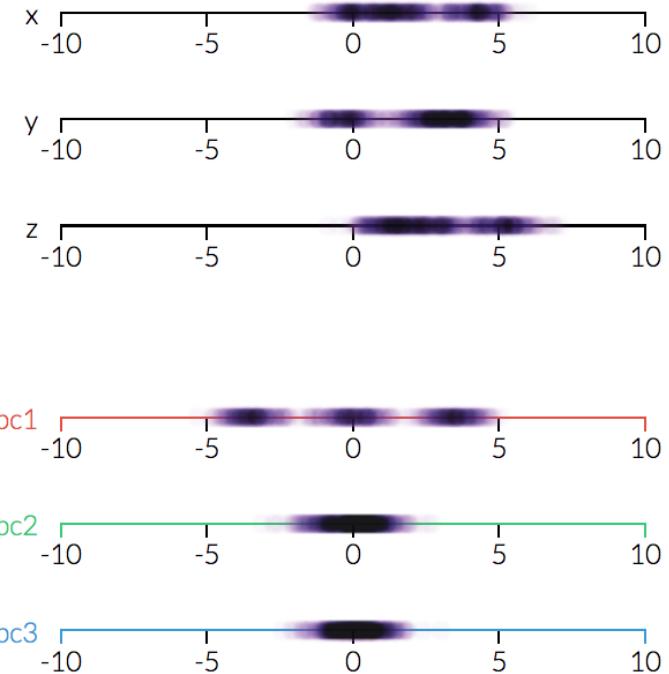
Dimensionality Reduction

A mathematical process to reduce the number of random variables to consider

Discuss: why may we want to do this?

Dimensionality Reduction

- Reduce the dimension of quantitative data to a more manageable set of variables
- Reduced set can then be input to reveal underlying patterns in the data and/or as inputs in a model (regression, classification, etc.)



Use Cases for Dimensionality Reduction

- Thousands of sensors used to monitor an industrial process
 - Reducing the data from these 1000s of sensors to a few features, we can then build an interpretable model
 - Goal : predict process failure from sensors
- Understanding diet around the world
 - Amount of foods eaten among populations across the world
 - Goal: identify diet similarity among populations
- Identify genetic ancestry
 - Determine ancestral origins based on genetic variation
 - Goal: Learn more about our genetic history

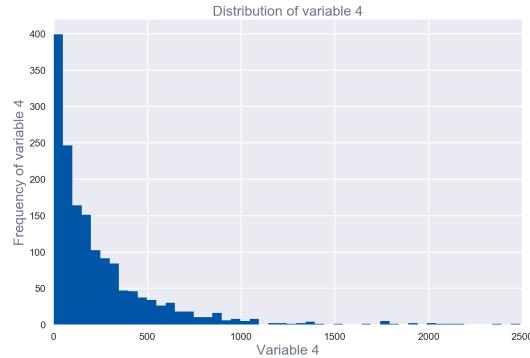
As an extension of EDA

- Gain insight into a set of data
- Understand how different variables relate to one another

Exploratory

EDA Approaches to “Get a Feel for the Data”

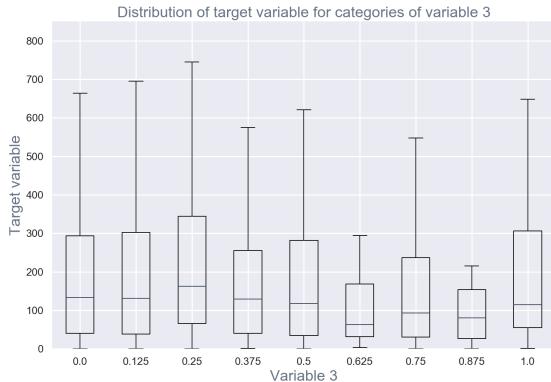
Understanding the relationship between variables in your dataset



Univariate

understanding a single variable

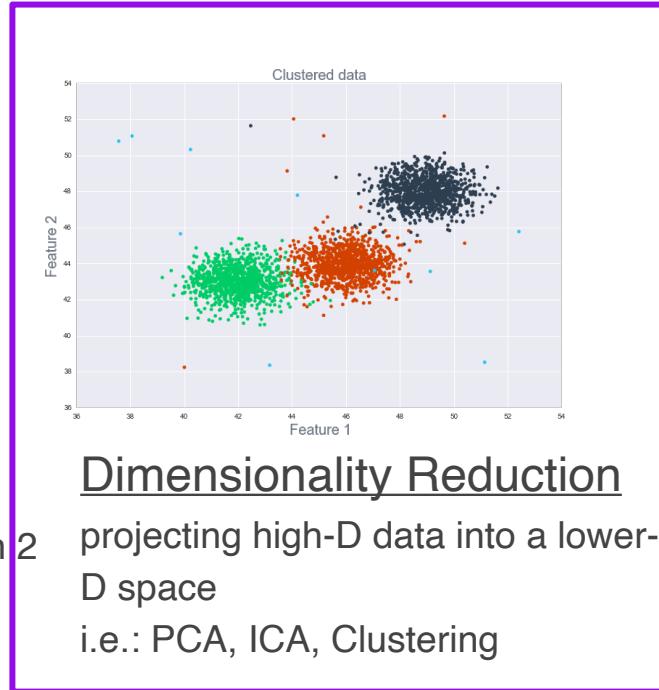
i.e.: histogram, densityplot, barplot



Bivariate

understanding relationship between 2 variables

i.e.: boxplot, scatterplot, grouped barplot, boxplot



Dimensionality Reduction

projecting high-D data into a lower-D space

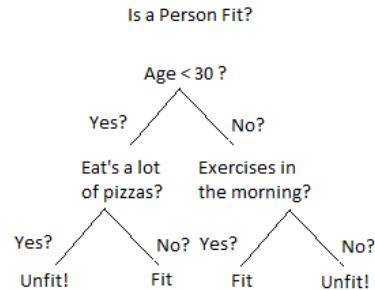
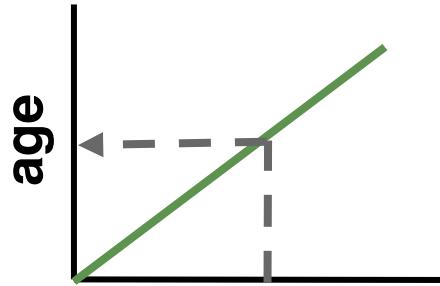
i.e.: PCA, ICA, Clustering

As an extension of EDA

- Gain insight into a set of data
- Understand how different variables relate to one another

Note: PCA/Dimensionality reduction can also be used for
modeling & prediction

Supervised Learning



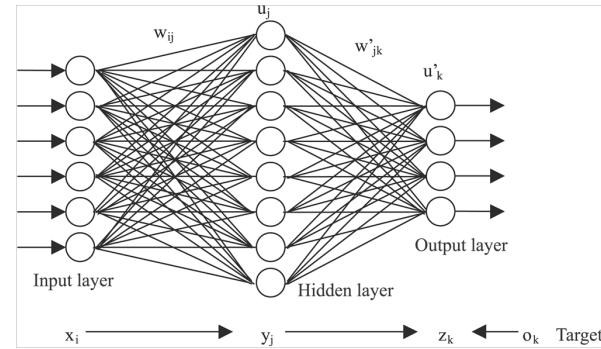
classification

Unsupervised Learning



1

2



dimensionality reduction & clustering

Key Terms:

- **Principal Component (PC)** - a linear combination of the predictor variables
- **Loadings** - the weights that transform the predictors into components (aka weights)
- **Screeplot** - variances of each component plotted

Principal Component Analysis (PCA)

Goal : combine multiple numeric predictor variables into a smaller set of variables.
Each variable in this smaller set is a weighted linear combination of the original set.

This smaller set of variables -- the *principal components* (PCs) - “explain” most of the variability of the full set of variables....but uses many fewer dimensions to do so.

The weights (loadings) used to form the PCs explain the relative contributions of the original variables to the new PCs.

“Simple” PCA : Two predictor variables (X_1 and X_2)

For two variables, X_1 and X_2 , there are two principal components Z_i ($i = 1$ or 2):

$$Z_i = w_{i,1}X_1 + w_{i,2}X_2$$

$w_{i,1}$ and $w_{i,2}$: weightings (*loadings*)

- Transform the original variables into principal components

Z_1 : the first principal component (PC1)

- The linear combination that best explains the total variance

Stock Price returns for Chevron (CVX) and ExxonMobil (XOM)

PC1 and PC2 are the dotted lines on the plot

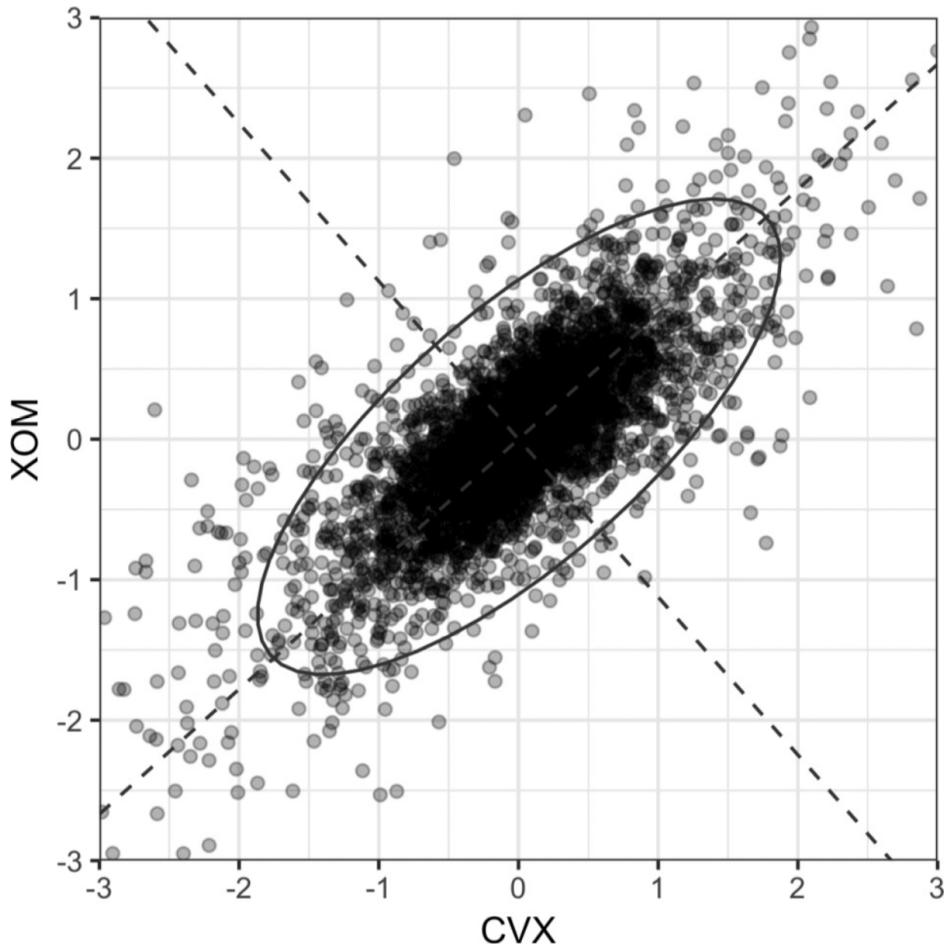


Figure 7-1. The principal components for the stock returns for Chevron and ExxonMobil

PCA

Eigenvalues

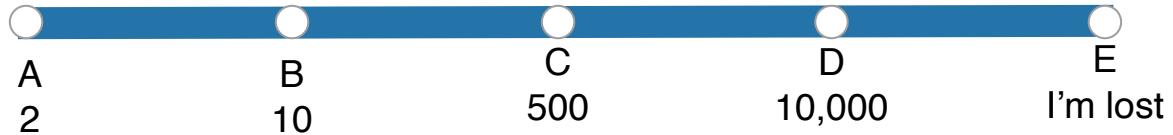
Eigenvalues

$$A \vec{v} = \lambda \vec{v}$$

1. Center the data
2. Compute covariance matrix
3. Compute eigenvectors and eigenvalues of covariance matrix
4. (Optional) subset eigenvectors by picking the m largest eigenvalues
5. Project datapoints into PCs by multiplying with eigenvectors

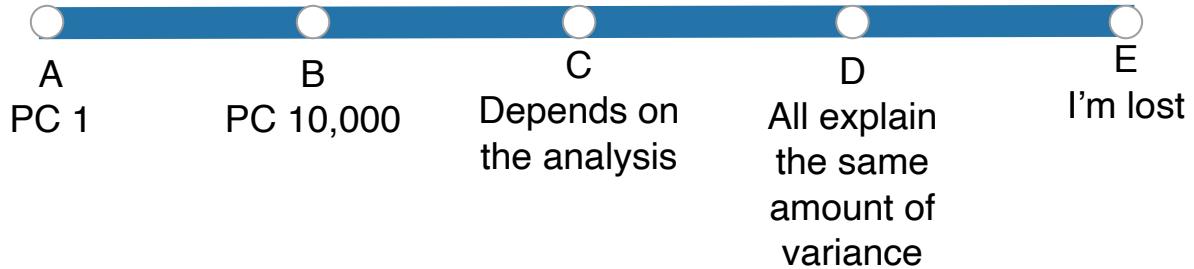


If you have a dataset of 500 observations and 10,000 variables, how many PCs will be calculated?





In a dataset with 10,000 variables, which PC explains the most variance?



Principal Component Analysis (PCA)

But....PCA shines when you're dealing with high-dimensional data. So we have to move *beyond* two predictors to many predictors....

Step 1: Combine all predictors in linear combination

Step 2: Assign weights that optimize the collection of the covariation to the first PC (Z_1)
(maximizes the % total variance explained)

Step 3: Repeat Step 2 to generate new predictor Z_2 (second PC) with different weights. By definition Z_1 and Z_2 are uncorrelated. Continue until you have as many new variables (PCs) as original predictors

Step 4: Retain as many components as are needed to account for *most* of the variance.

S&P 500 Data: 5648 days (1993-2015) x 517 stocks

	ADS	CA	MSFT	RHT	CTSH	CSC	EMC	IBM	XRX	ALTR	ADI	AVGO	BRCM	FSLR	INTC	LLTC	MCHP	MU	NVDA	
1/29/93	0	0.06012444	-0.0220998	0	0	0.01889746	0.00736807	0.0921652	0.25914009	-0.0071053	-0.0157849	0	0	0	-0.0504878	-0.0898696	0	0.03702057	0	
2/1/93	0	-0.180389	0.02762115	0	0	0.01888884	0.01842489	0.11520651	-0.1007745	0.06389288	-0.0157929	0	0	0	0.09536733	0.0449348	0	0.03702038	0	
2/2/93	0	-0.1202566	0.03589897	0	0	0	-0.0755726	0.02948172	-0.0230413	0.02879553	-0.0141924	0.0473628	0	0	0	0	0.0674022	0	0.12340155	0
2/3/93	0	0.0601242	-0.024857	0	0	-0.151128	0.00368875	-0.2534543	-0.04319	-0.0071053	0.20523612	0	0	0	-0.050495	0.0224674	0	-0.0123403	0	
2/4/93	0	-0.3607697	-0.0607567	0	0	0.11335029	-0.0221136	0.0698618	0	-0.0070962	-0.0315699	0	0	0	0	0.0224674	0	-0.0740409	0	
2/5/93	0	0.03005777	0.09389247	0	0	0.09445283	-0.0479066	0.04657454	0.17276006	-0.0212976	-0.0631478	0	0	0	-0.0476873	-0.0674022	0	-0.0123403	0	
2/8/93	0	0.03006643	-0.0607498	0	0	-0.1133503	-0.0110568	0.11643635	-0.04319	0.00709618	0	0	0	0	-0.0196321	-0.1235743	0	-0.0617008	0	
2/9/93	0	-0.0901902	-0.063521	0	0	0	-0.1322391	-0.0147456	0.06986181	-0.115169	0.04969143	-0.0157929	0	0	0	-0.0112235	0.0224674	0	0	0
2/10/93	0	0.12025657	0.02209981	0	0	0.09445283	0.01474557	-0.2561599	0.01439448	0.02838473	0.01578495	0	0	0	0.04487956	0.11233699	0	0.07404095	0	
2/11/93	0	0.03005825	-0.0220927	0	0	0	-0.0188751	0.01474556	-0.1397236	-0.04319	0.02129762	-0.0315699	0	0	0	0.05329553	0.06740222	0	-0.0246804	0
2/12/93	0	-0.0901901	-0.0358999	0	0	-0.0377863	-0.0073681	-0.0698618	-0.1871546	0	-0.0473628	0	0	0	-0.0336561	-0.112337	0	-0.0370204	0	
2/16/93	0	-0.6313411	-0.0607497	0	0	0	-0.0377863	-0.0479066	-0.0931491	-0.04319	-0.0283938	-0.1262955	0	0	0	-0.098175	-0.1460417	0	-0.0246803	0
2/17/93	0	0.12025657	-0.0165712	0	0	0	-0.1700254	-0.0110568	0.04657453	-0.08638	-0.0142015	0.03157785	0	0	0	0.04487955	0	0	-0.0123403	0
2/18/93	0	-0.1803808	0.00828562	0	0	0	-0.0566751	0.00368875	-0.0931491	-0.08638	0	-0.0157849	0	0	0	-0.0168315	0.0224674	0	0.03702056	0
2/19/93	0	0.03006595	-0.0469427	0	0	0	0	0.00736807	-0.0232873	0.115169	0.01419237	0.03157785	0	0	0	0.10378311	0.15727183	0	0.14808196	0
2/22/93	0	0.03005825	-0.0662782	0	0	0	-0.1322477	-0.0184249	0.13972361	0	0.02839382	-0.0631557	0	0	0	-0.0168317	-0.0674022	0	0	0
2/23/93	0	-0.0300583	0.03314266	0	0	0	0	-0.0479066	-0.0698618	-0.1439645	-0.0070962	0.03157785	0	0	0	-0.0336631	-0.0337047	0	-0.0493606	0
2/24/93	0	0.15031459	0.10769942	0	0	0	0.01888884	0.04421782	0.1397236	0.08638003	0.00709618	0	0	0	0.11781411	-0.0224674	0	0.09872137	0	
2/25/93	0	0.15032277	0.04142827	0	0	0	0.01888884	-0.0110568	0.37259628	0	0.02839382	0	0	0	0	0.0112163	0.15727183	0	-0.0370205	0
2/26/93	0	-0.0300659	-0.0193286	0	0	0	-0.0188888	0.01105682	0.06986181	0.05759106	0	0.01578495	0	0	0	-0.028055	-0.0224674	0	-0.0740401	0
3/1/93	0	-0.180381	-0.0497068	0	0	0	-0.0944614	-0.0073681	0	0.04358505	0.00709618	0.09472561	0	0	0	-0.0336631	0.0224674	0	0	0
3/2/93	0	0	0.06351413	0	0	0	0.15113659	0.00368875	-0.0698618	0.116229	0	0.11051053	0	0	0	0.09537435	-0.0449348	0	0.12340155	0
3/3/93	0	0.12025658	0	0	0	0	-0.0566751	0.03684977	0.16301088	0.02905891	-0.0070962	0	0	0	0	0.01402383	-0.112337	0	-0.0370204	0
3/4/93	0	-0.1503146	-0.0220927	0	0	0	0.0377863	0.00367932	-0.0698618	-0.1452879	-0.0070962	-0.015785	0	0	0	-0.0252473	-0.0674022	0	0.01234016	0
3/5/93	0	0.03005825	-0.0165714	0	0	0	-0.0944614	0.00368875	-0.0232873	0	0.03549001	0	0	0	0	-0.0617041	0.0449348	0	0.02468042	0
3/8/93	0	0.06012444	0.02209275	0	0	0	0.01888884	-0.025793	0.11643634	0.21792524	0	0.04736279	0	0	0	0.06731932	0.13480441	0	0.09872114	0
3/9/93	0	0.09019015	0.00552151	0	0	0	0.09446144	0.00736807	0.09314908	-0.0290523	-0.0070962	-0.0157849	0	0	0	0.0112163	0.0898696	0	0	0
3/10/93	0	0.03006595	0.01104991	0	0	0	0	0.01105681	-0.1862981	0.02905891	-0.0141924	-0.0157849	0	0	0	-0.0196321	-0.0449348	0	0	0
3/11/93	0	-0.0300583	0.02761408	0	0	0	0.22670058	0	-0.1862982	-0.0581112	0.00709618	0.06314774	0	0	0	-0.0196392	0.01123011	0	0	0
3/12/93	0	0	0.06627822	0	0	0	-0.0188975	0.01474556	0.30273448	-0.1452813	0.02839381	0.06314774	0	0	0	0.02524749	0.01123729	0	0.13574153	0

For this example: we'll focus on 16 top companies

Screeplot

The vernacular definition of “scree” is an accumulation of loose stones or rocky debris lying on a slope or at the base of a hill or cliff.

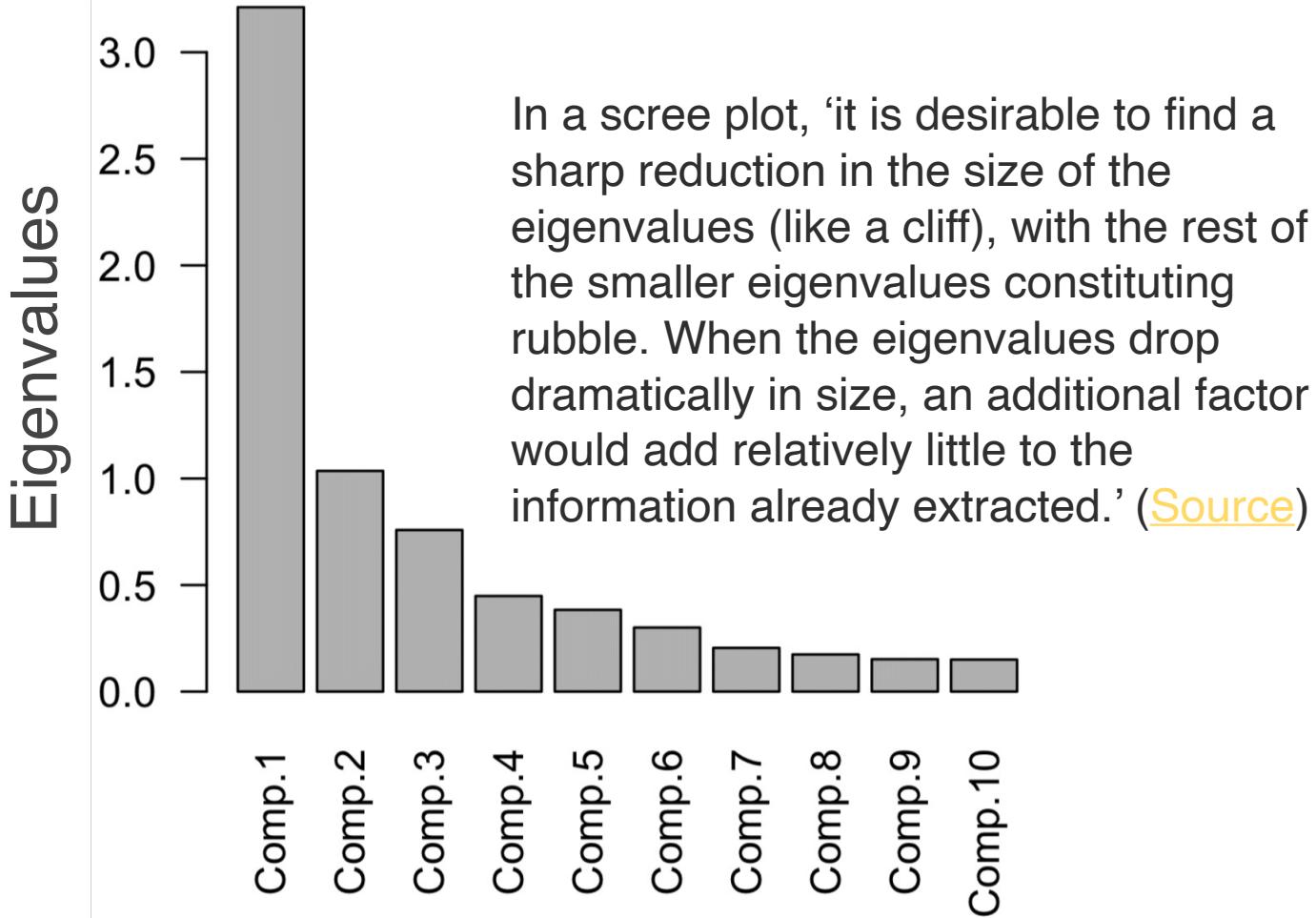


Figure 7-2. A scree plot for a PCA of top stocks from the S&P 500

Loading of PCs 1-5

PC1: Overall stock market trend

PC2: Price change of energy stocks

PC3: movements of Apple and CostCo.

PC4: movements of Schlumberger to other stocks

PC5: Financial companies

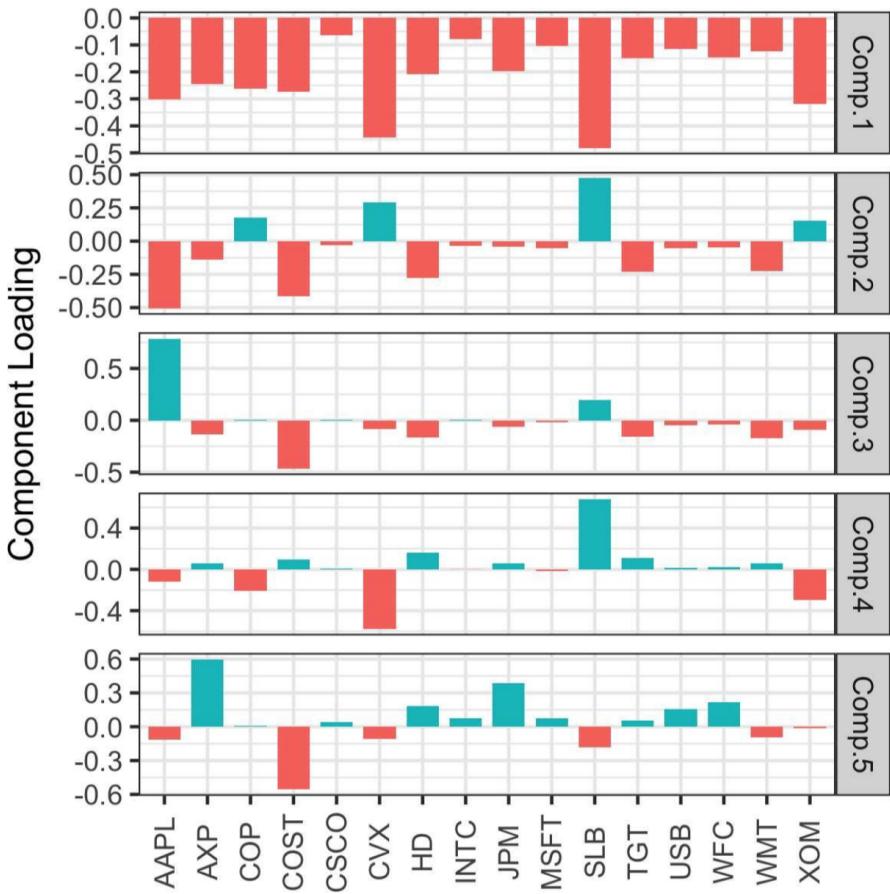


Figure 7-3. The loadings for the top five principal components of stock price returns

How many PCs to select?

Option 1: Visually through the screeplot

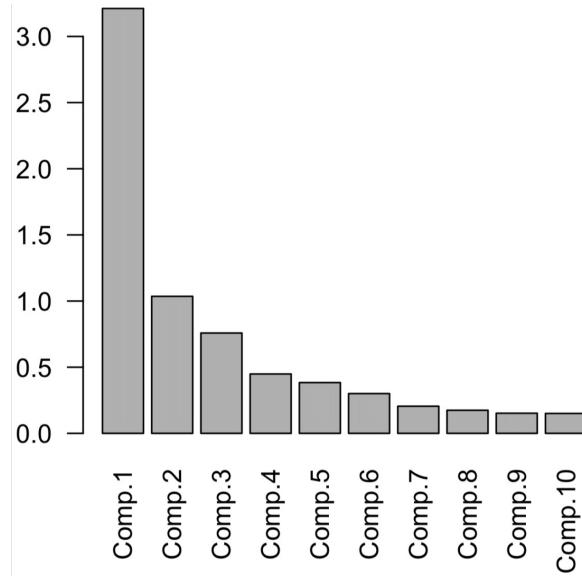


Figure 7-2. A screeplot for a PCA of top stocks from the S&P 500

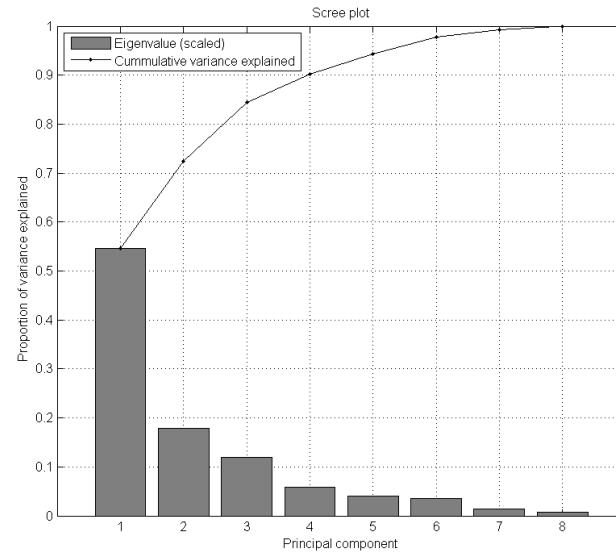
Option 2: % Variance explained
(i.e. 80% variance explained)

Option 3: Inspect loadings for an intuitive interpretation

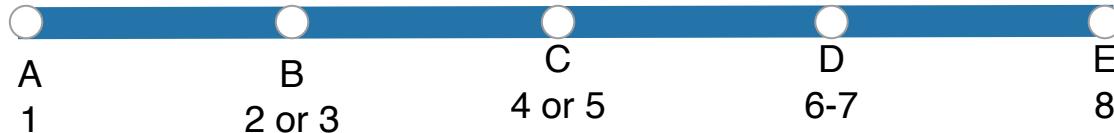
Option 4: Cross-validation



Screeplot Interpretations



How many PCs would you likely consider given this screeplot?



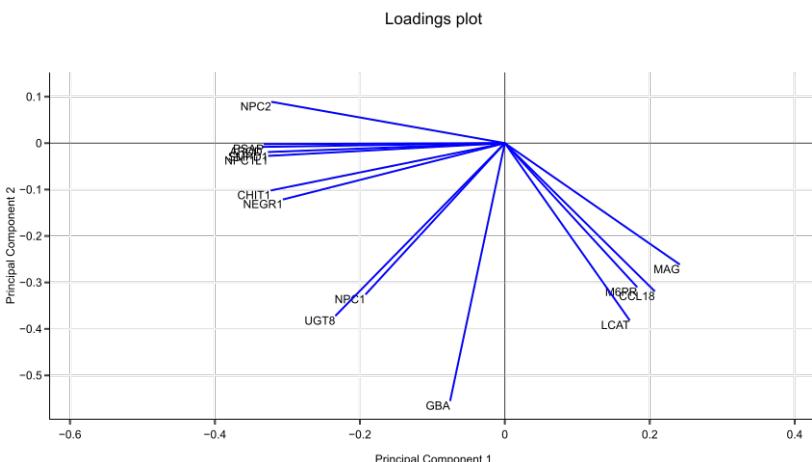
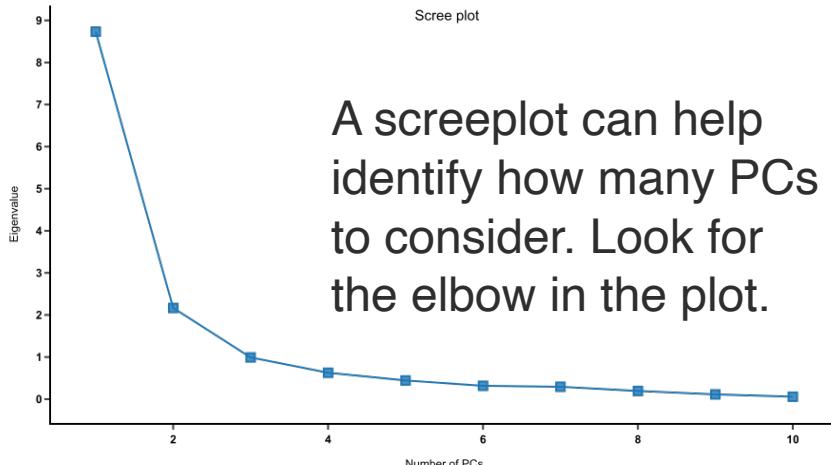
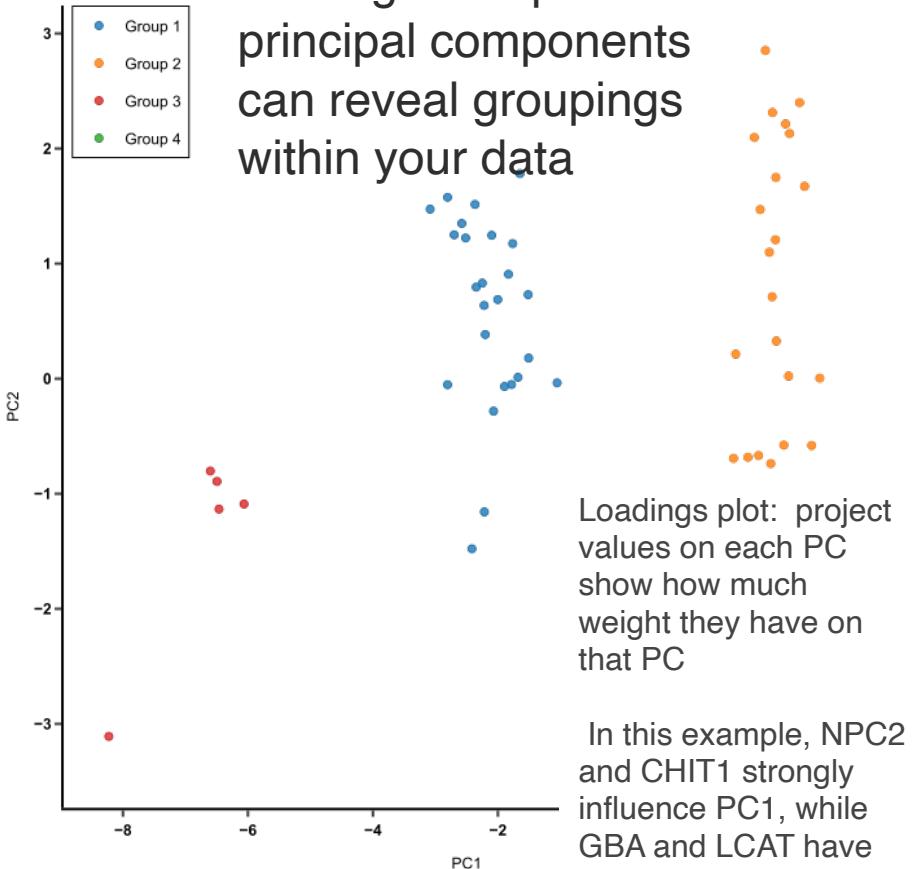
PCA : Key Ideas

1. PCs are linear combinations of the predictor variables (numeric data only)
2. Calculated to minimize correlation between components (minimizes redundancy)
3. A limited number of components will typically explain most of the variance in the outcome variable
4. Limited set of PCs can be used in place of original predictors (dimensionality reduction)

For more on PCA:

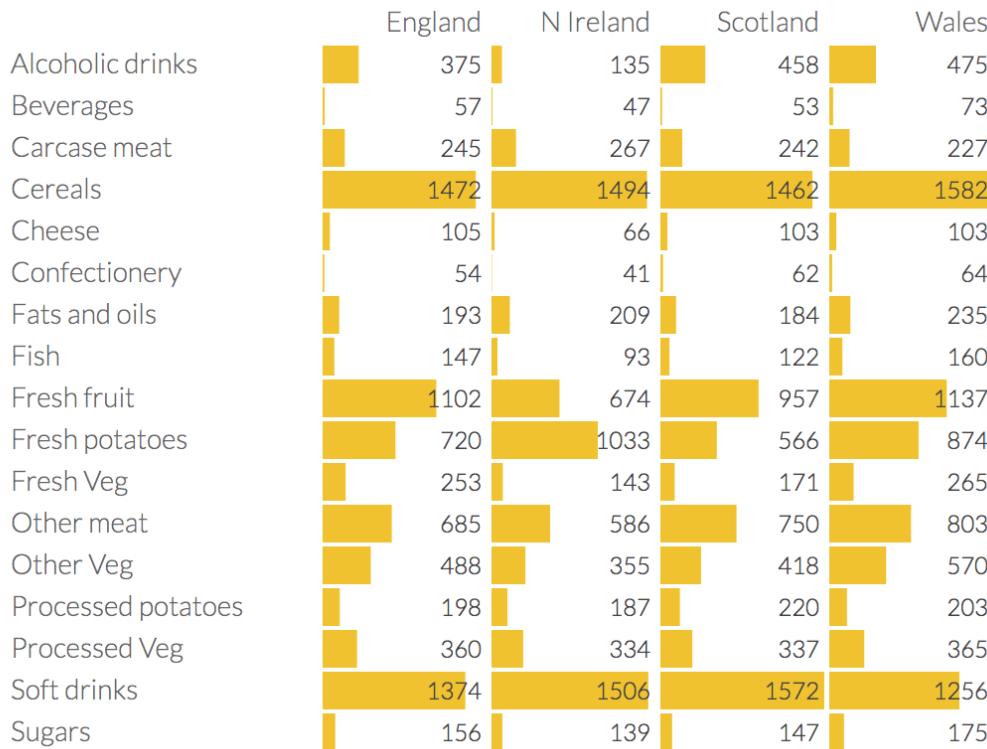
- <https://blog.bioturing.com/2018/06/14/principal-component-analysis-explained-simply/>
- <http://setosa.io/ev/principal-component-analysis/>

Plotting the top principal components can reveal groupings within your data



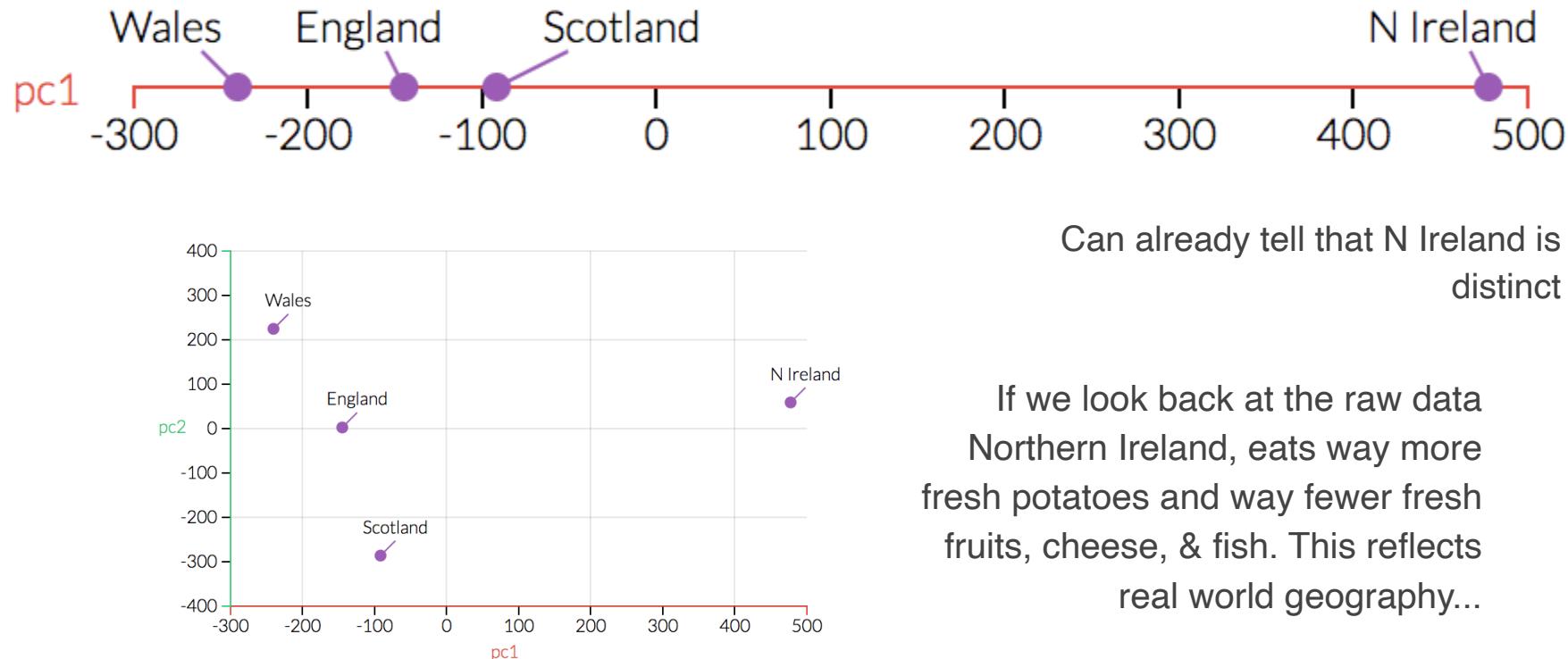
A screeplot can help identify how many PCs to consider. Look for the elbow in the plot.

Case Study: Diet in the UK



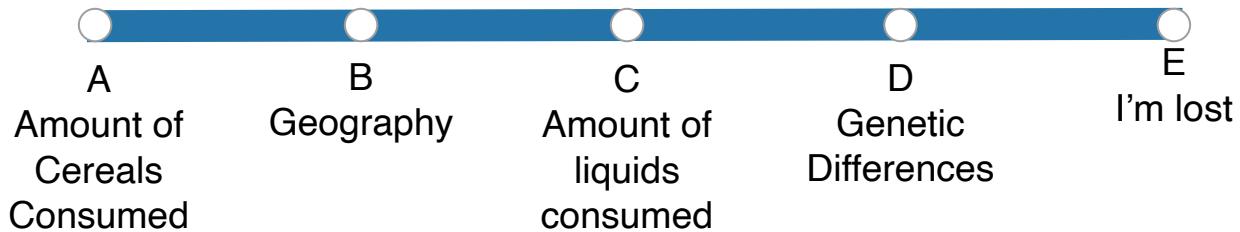
17 foods x 4 countries

PCA: Diet in the K





What of the following likely explains the fact that N Ireland is so far from the other three countries in the first principal component?





Case Study: Genetics and Geography

Letter | Published: 31 August 2008

Genes mirror geography within Europe

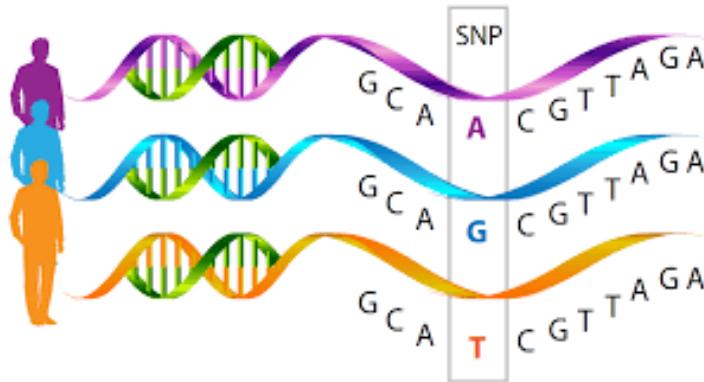
John Novembre , Toby Johnson, Katarzyna Bryc, Zoltán Kutalik, Adam R. Boyko, Adam Auton, Amit Indap, Karen S. King, Sven Bergmann, Matthew R. Nelson, Matthew Stephens & Carlos D. Bustamante

Nature **456**, 98–101 (06 November 2008) | Download Citation 

The Data: 1,387 Europeans x 500,000 SNPs

SNP (Single Nucleotide Polymorphism)

- Reminder: Your DNA is made up of four bases: G, C, T, & A
- A SNP is a position in one's DNA that varies between individuals (appears in at least 1% of the population)
 - This results from normal human variation
 - Some contribute to disease, but many are just differences between humans
 - These are used by companies like 23andMe and Ancestry.com



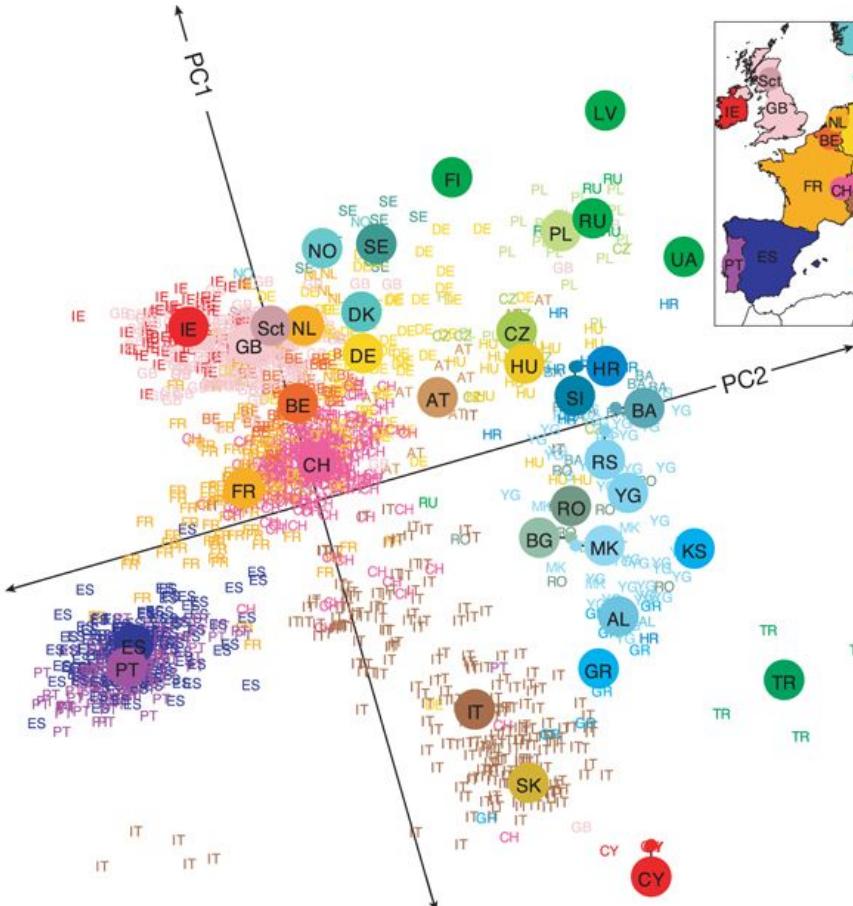
The Data: 1,387 Europeans x 500,000 SNPs

Step 1: Measure genotype (GCTA) at 500,000 positions (SNPs) along the genome in 1387 European individuals

Step 2: Calculate PCs from 500,000 SNPs

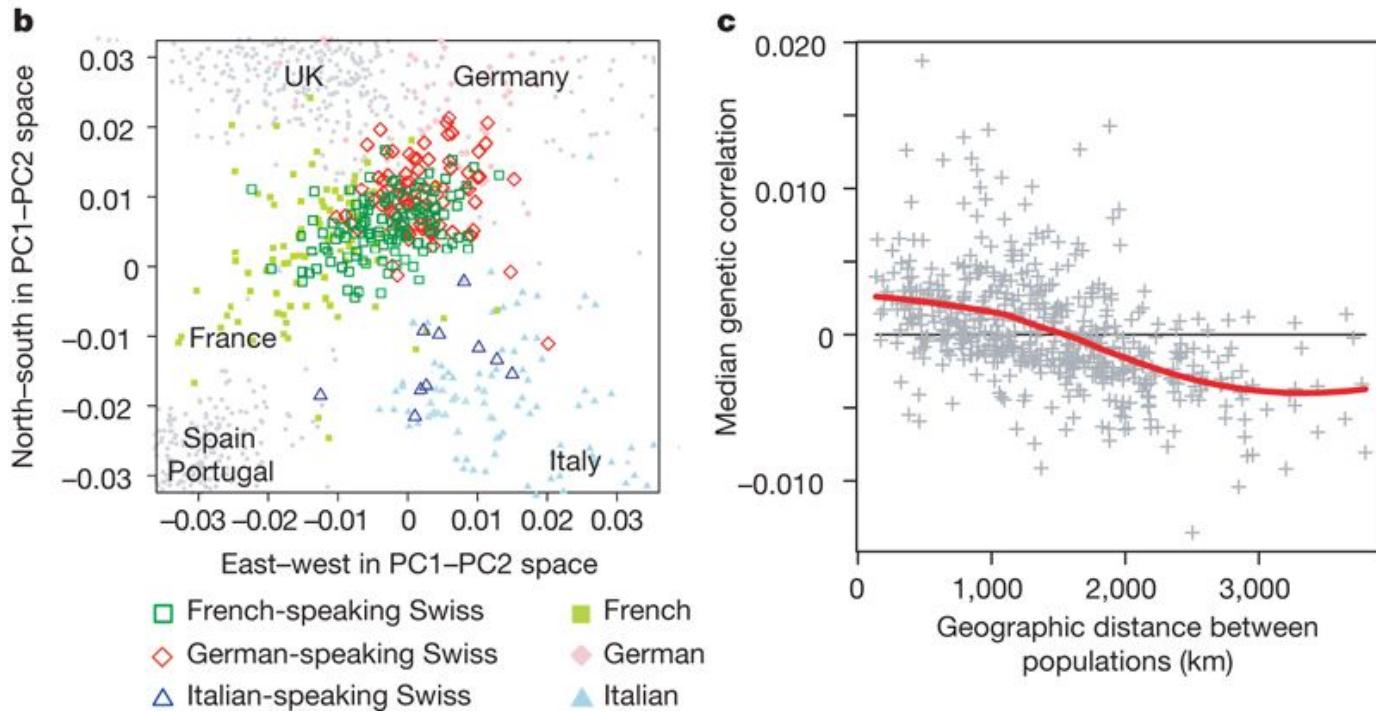
Step 3: Plot PC1 and PC2 (each point is an individual)

Step 4: Compare to the map of Europe

a

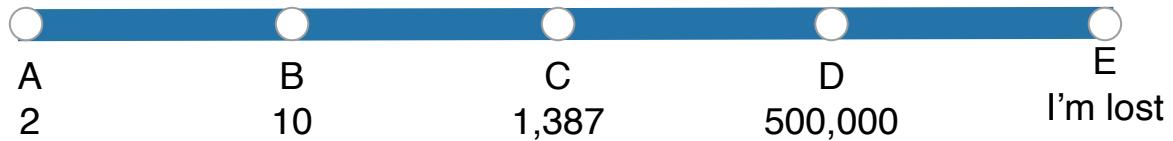
PCA on SNP data
for European
samples reflects
geographic location
of where samples
came from

PC1 is East-West ; PC2 is North-South





This analysis used 500,000 SNPs from 1,387 individuals.
How many PCs would have been calculated?

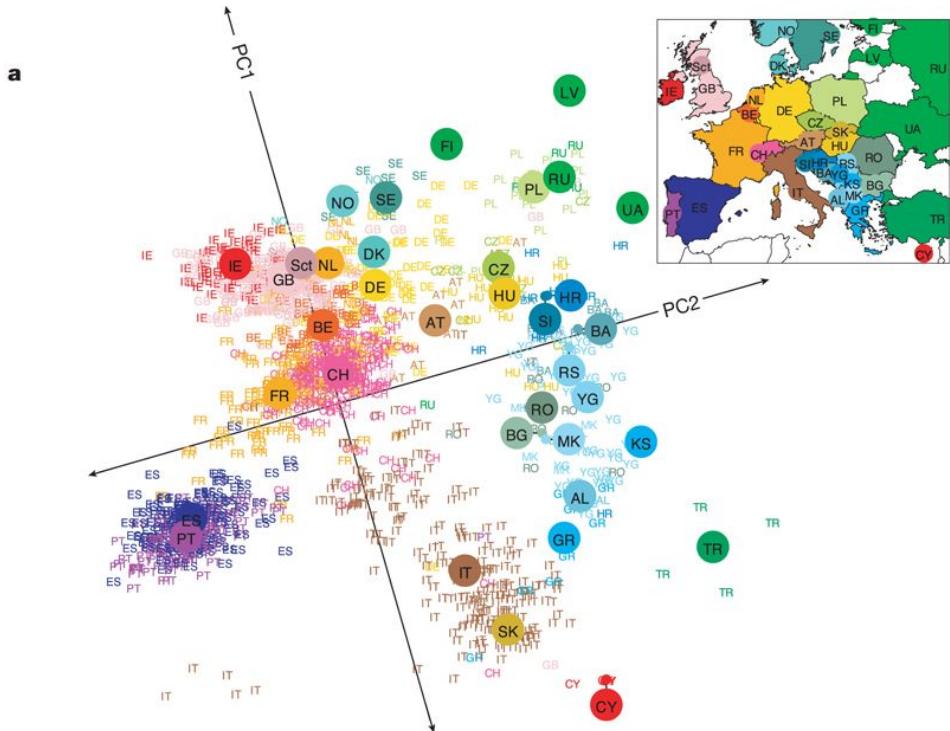




This analysis used 500,000 SNPs from 1387 individuals. How many PCs explain geographic differences across Europe by genetic ancestry?



'hich of the following is NOT true? _A



- 
 - A** PC1 explains geographic differences from North to South
 - B** PC2 explains geographic differences from East to West
 - C** The French (FR) are not genetically related to the Scottish (Sct)
 - D** The French are more closely related genetically to Germans (DE) than they are the Fins (GL)
 - E** The Spanish (ES) and Portuguese (PT) are genetically similar

Dimensionality Reduction with PCA: Pros & Cons

Pros:

- Helps compress data; reduced storage space.
- reduces computation time.
- helps remove redundant features (if any)
- Identifies outliers in the data

Cons:

- may lead to some amount of data loss.
- tends to find linear correlations between variables, which is sometimes undesirable.
- fails in cases where mean and covariance are not enough to define datasets.
- may not know how many principal components to keep
- highly affected by outliers in the data