JOHNS HOPKINS
WHITING SCHOOL of ENGINEERING

# Introduction to Data Science

Tamás Budavári
Dept of Applied Mathematics & Statistics
Dept of Computer Science
Dept of Physics & Astronomy

# About you

- PhD / Masters / Undergraduate?
- What major?

# About me

- Background in Physics: Stat/Bio/Astro
  - Astronomy surveys $\rightarrow$ Big Data
- Research interest

  Computational Statistics; Bayesian Inference;

  Statistical Learning; Scientific Databases;
- Office: Whitehead 212C

# About the course

- Introduction to data science
- Basic methods – used all the time
- Presentations + Codes
- Syllabus posted soon

# Grades

- 30% Homework 1 & 2
- 50% Midterm 1 & 2
- 20% Project

# Pre-requisites

- Linear algebra
- Intro to prob/stat?

# Sections

- Use your laptop
  - Also in class…

# Plan for the Timeline

- Homework 1 – graded in time for dropping
- Midterm 1
- Homework 2
- Midterm 2 – few weeks before end of semester
- Project – presentations

# Format of Lectures

- Alternating between
  - Presentations
  - Coding
- Everything is going to Blackboard

# Homework

- Data Science problems
- Much like the examples

# Unhomework

- Same but not graded

# Exams

- In class
- Coding

# What's coming?

# Statistical Learning

| Supervised | Unsupervised |
|---|---|

# Statistical Learning

| | Supervised | Unsupervised |
|---|---|---|
| Discrete | | |
| Continuous | | |

# Statistical Learning

| | Supervised | Unsupervised |
|---|---|---|
| **Discrete** | Classification | |
| **Continuous** | | |

# Statistical Learning

| | Supervised | Unsupervised |
|---|---|---|
| **Discrete** | Classification | |
| **Continuous** | Regression | |

# Statistical Learning

| | Supervised | Unsupervised |
|---|---|---|
| **Discrete** | Classification | Clustering |
| **Continuous** | Regression | |

# Statistical Learning

| | Supervised | Unsupervised |
|---|---|---|
| Discrete | Classification | Clustering |
| Continuous | Regression | Dimensionality Reduc’n |

# Topics

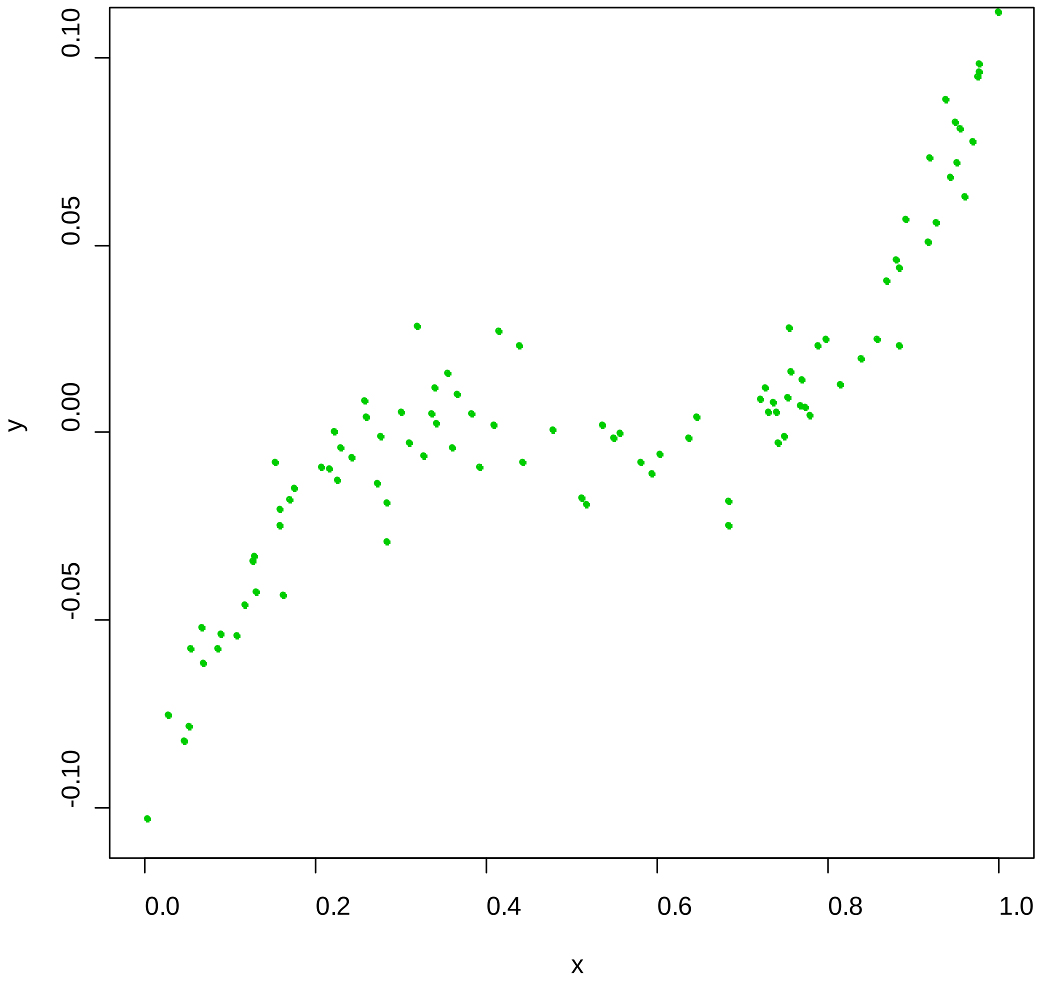
descriptive statistics – probabilistic density functions – normal distributions – regression – classification – nearest neighbors – bias-variance – Bayesian inference – robustness – regularization – support vector machines – decisions trees – clustering – principal component analysis – expectation maximization – neural networks – spectral embedding – …

# Supervised Learning

# Learning

- Model
  - Unknown function
  - Random noise

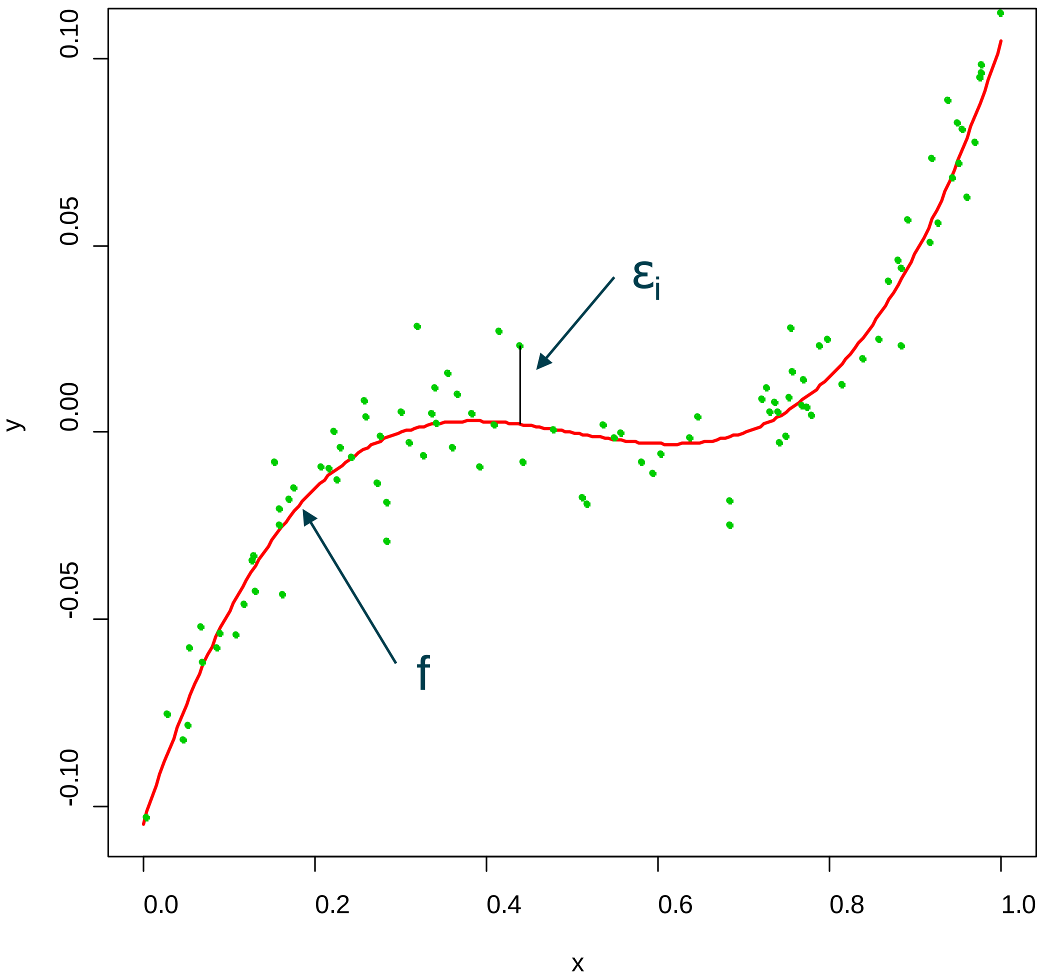
$$Y_i = f(\mathbf{X}_i) + \varepsilon_i$$



# Learning

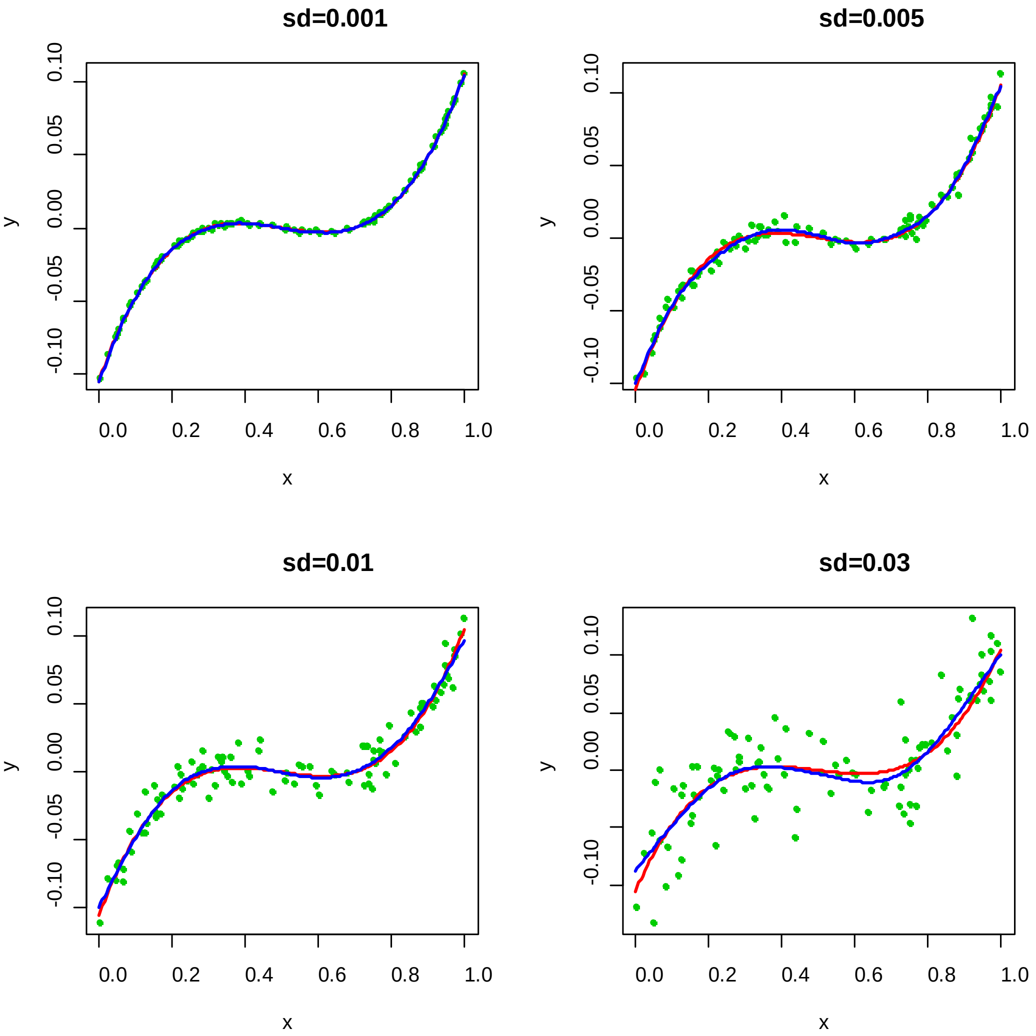
- Model
  - Unknown function
  - Random noise

$$Y_i = f(\mathbf{X}_i) + \varepsilon_i$$



# Noise!

- Different scatter
- Different solutions



# Why learn $f(x)$ ?

- Inference
  - Relation of variables to target
- Prediction
  - Estimate $y$ for a new $x$

# How to estimate *f*(*x*) ?

- Using a training set with both
  - Input
  - Output

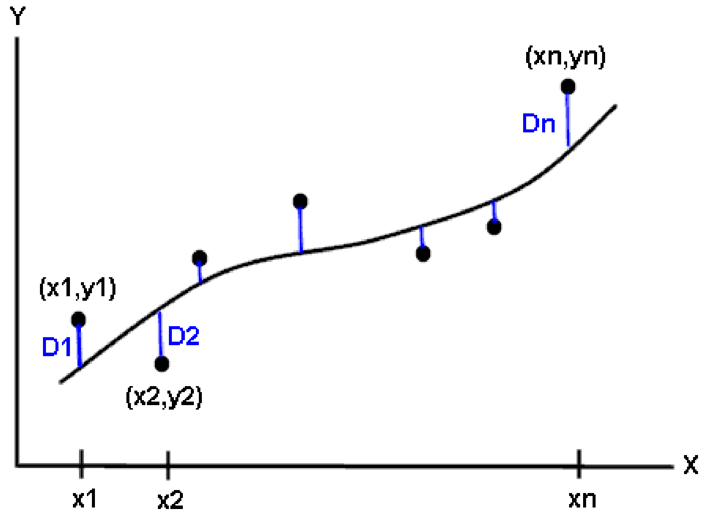
$$\{(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \ldots, (\boldsymbol{x}_n, y_n)\}$$

- For example, assuming a linear model

$$f(\boldsymbol{x}; \boldsymbol{\beta}) = \beta_0 + \beta_1 x_1 + \cdots + \beta_d x_d$$
$$f(\boldsymbol{x}_i; \boldsymbol{\beta}) = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_d x_{i,d}$$

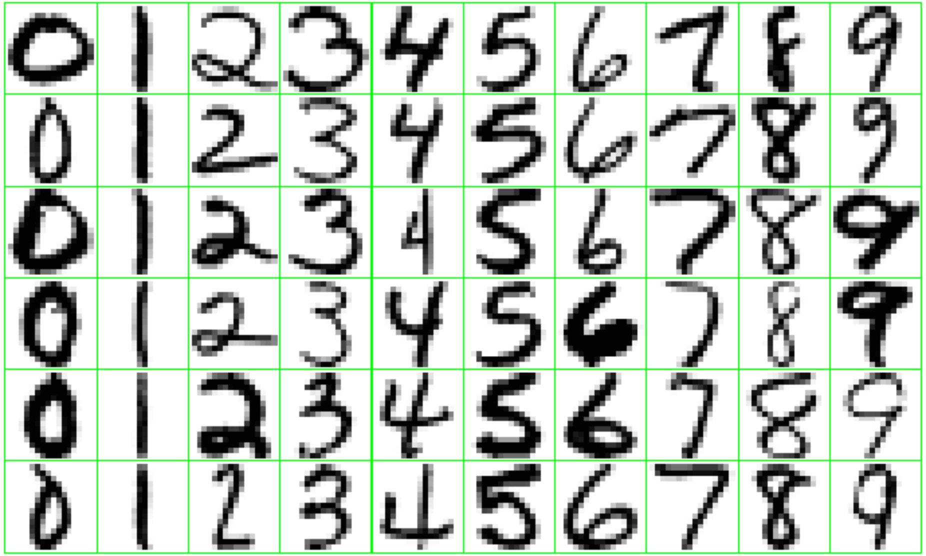
# How to estimate $f(x)$ ?

- One way is the method of least squares
  - Form differences of $Y_i$ and $f(\boldsymbol{X}_i)$
  - Minimize the sum of squares



# Handwritten Numbers?

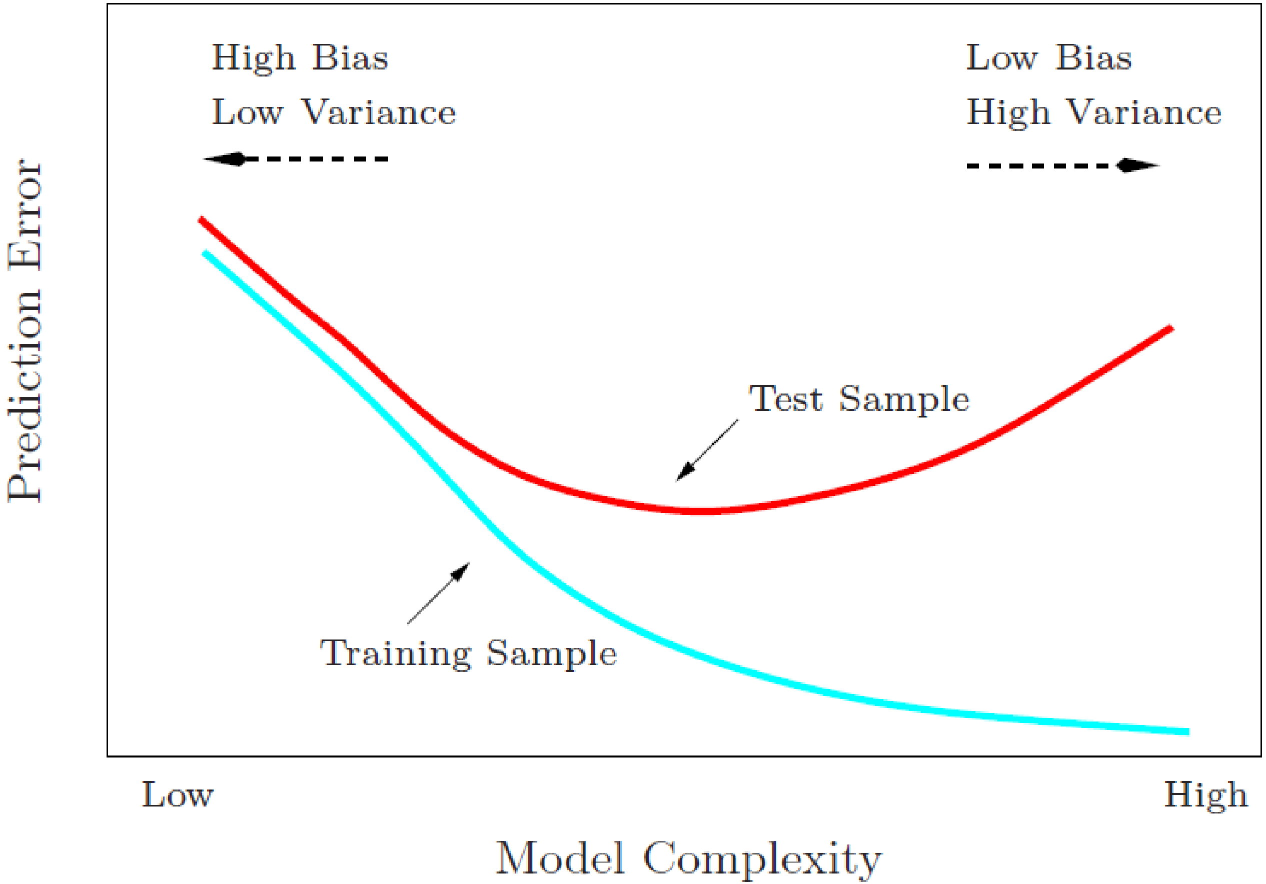
- Which digit?
- Classification!
  - Training set



# Complexity

Complicated models can better fit the data but harder to interpret and understand

- Too simple: underfitting
  - Bad fit on training & test sets
- Too complex: overfitting
  - Better on training but worse on test set


High Bias
Low Variance
Low Bias
High Variance
Test Sample
Training Sample
Prediction Error
Low
High
Model Complexity

# Interpretation

*There is no true interpretation of anything; interpretation is a vehicle in the service of human comprehension. The value of interpretation is in enabling others to fruitfully think about an idea.*

–Andreas Buja

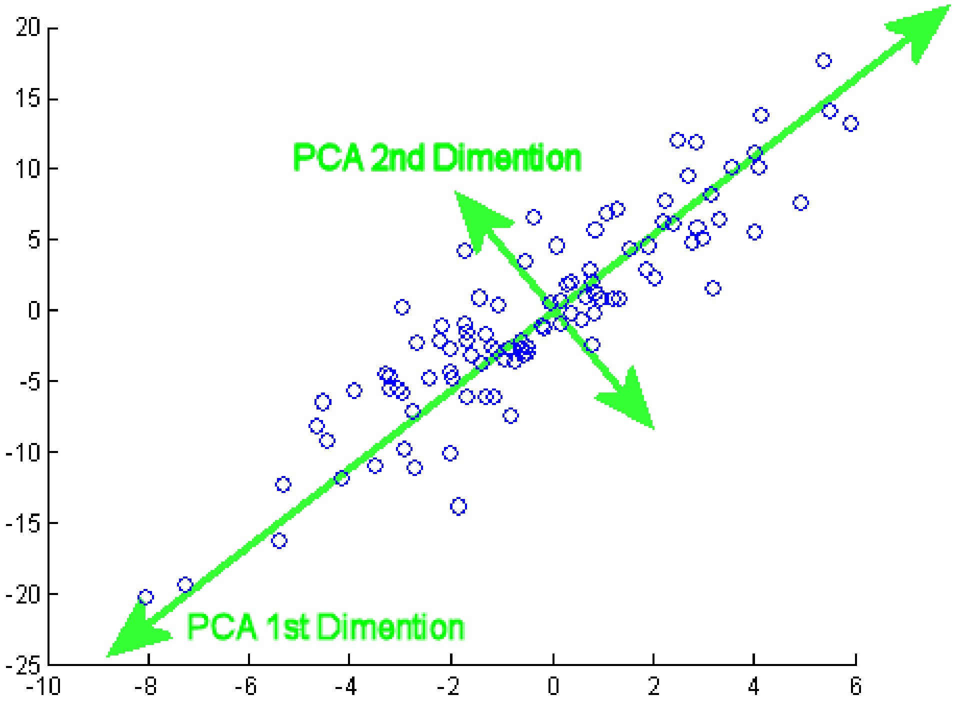
# Unsupervised Learning

# Clustering

- If no labels are provided
- We learn the clusters

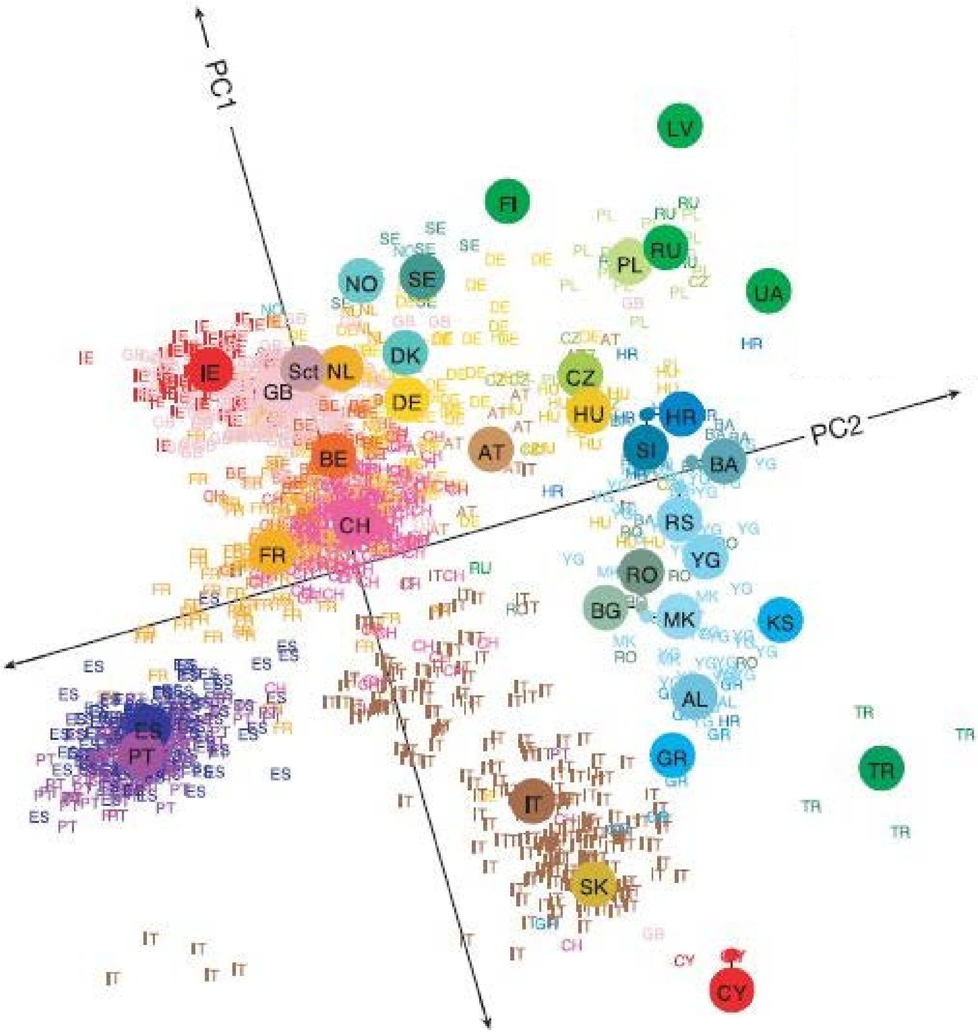
# Principal Component Analysis

- Our model:
  - Direction of largest variation is relevant
  - The rest is “noise”



# Genes

- PCA



PC1
PC2
LV
FI
RU
UA
PL
NO
SE
DK
IE
Sct
NL
GB
DE
CZ
HU
HR
SI
BA
BE
AT
CH
FR
RS
YG
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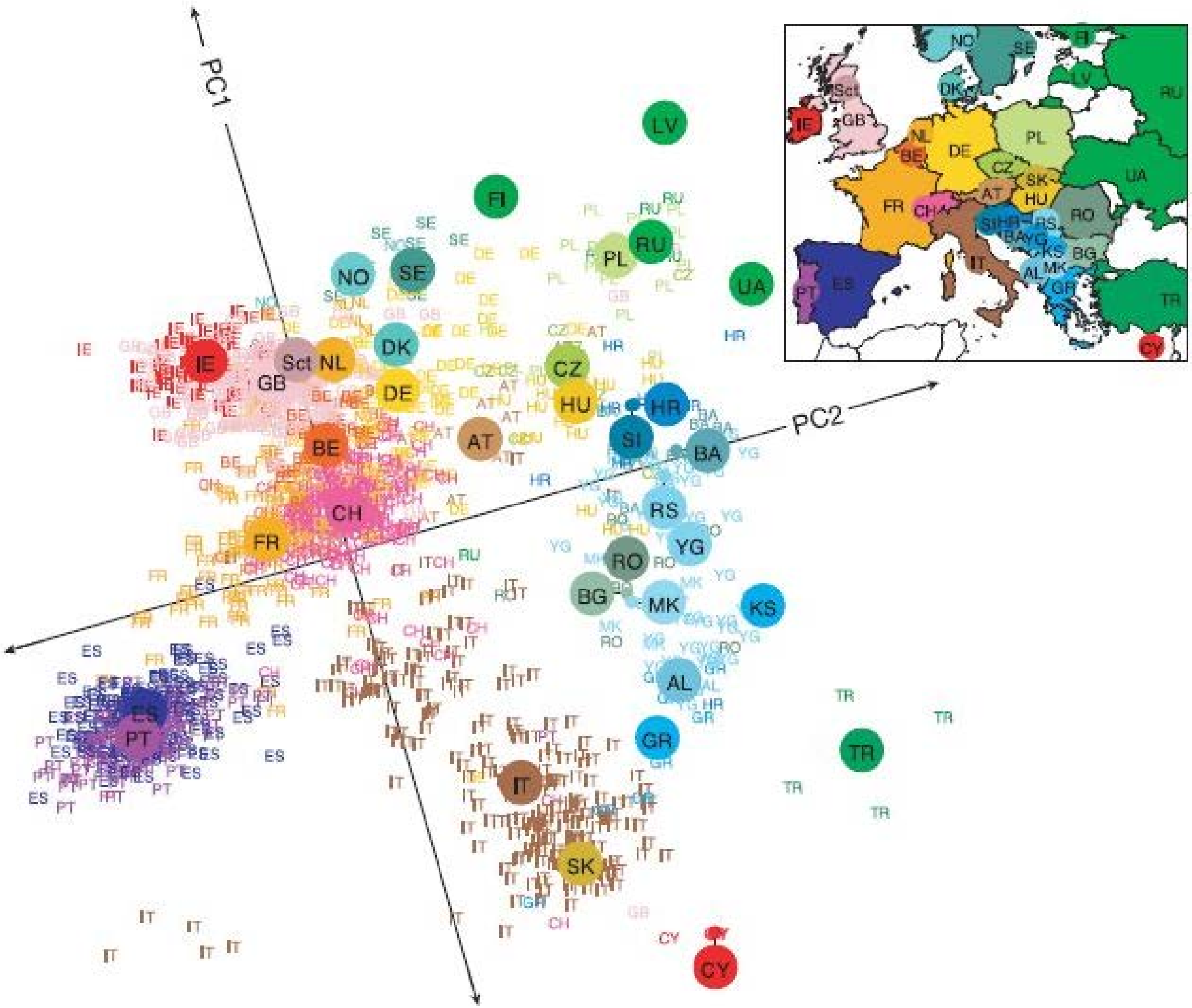
BG
MK
KS
AL
ES
PT
GR
TR
IT
SK
CY

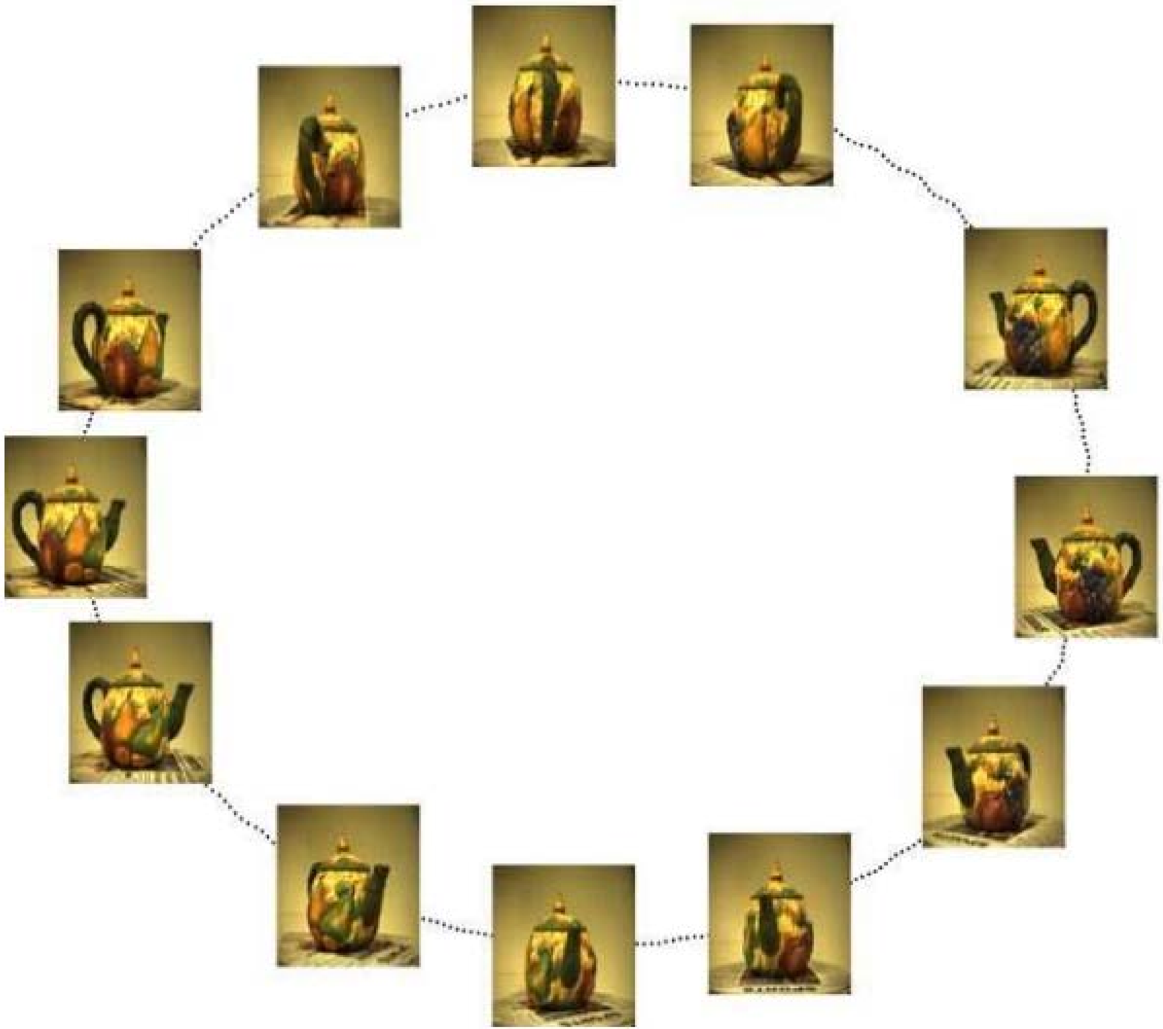
# Genes

- PCA
- Map



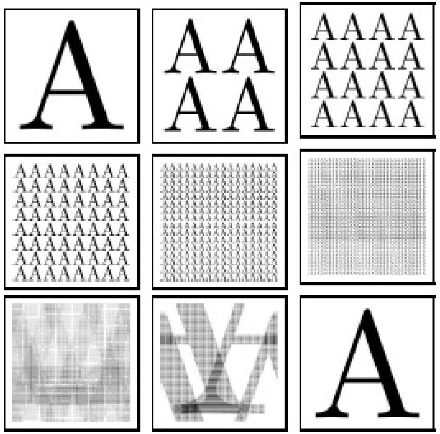
# Nonlinear

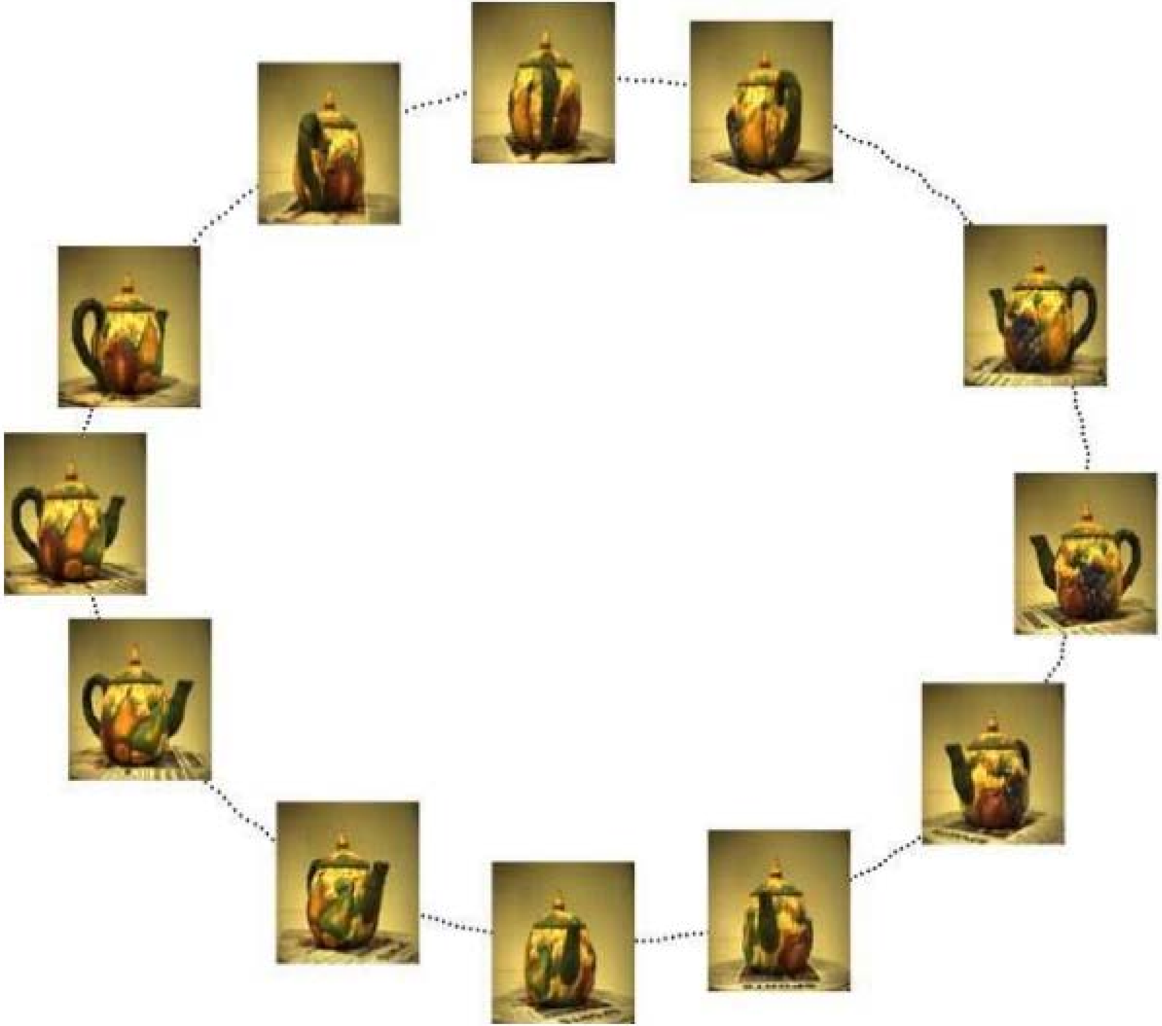
- It's a rotation!



# Nonlinear

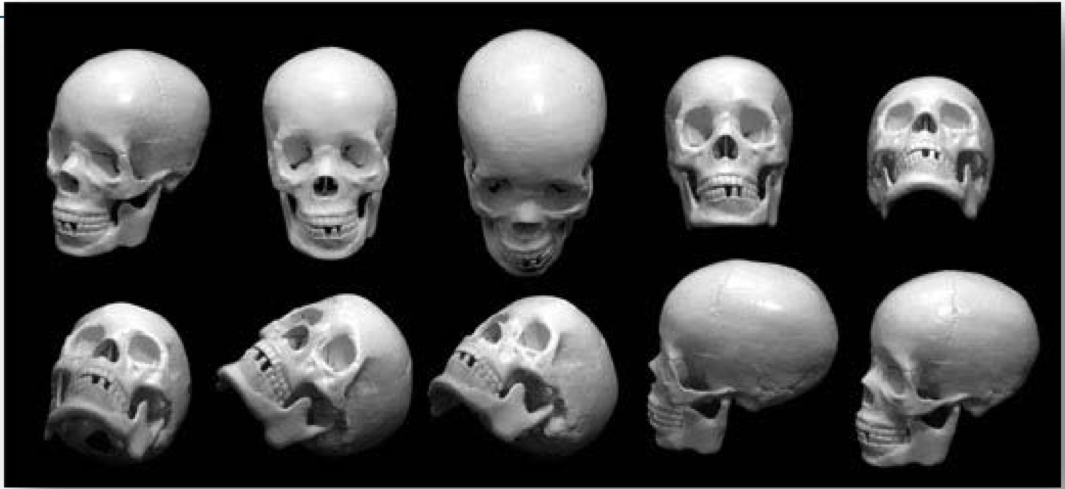
- It’s a rotation!
  - Even if pixels are shuffled!





# More Parameters

- How many?



# More Parameters

- How many?

# Jupyter Notebook

# Python

- General programming language
  - For scripting and prototyping
- Modules for everything
  - Including numerical & statistical packages

# Jupyter

- Interactive analysis
  - Easy to use
  - Web interface
  - Smart rendering

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