INTRO TO MACHINE LEARNING AND LINEAR REGRESSION

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Lecture 06

Machine Learning

"Field of study that gives computers the ability to learn without being explicitly programmed"

-Arthur Samuel, 1959

"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E"

- Tom M. Mitchell

Types of Variables

- **Continuous (Quantitative)**
  - Interval
  - Ratio

- **Categorical (Qualitative and Discrete)**
  - Nominal
  - Ordinal
  - Flags (Dichotomous)

Types of Variables

- **Continuous (Numerical)**
  - Interval
    - The difference between two measurements matter, <u>scale is not preserved</u>
      - e.g. 40°C - 20°C, compared to 30°C - 10°C
      - 40°C <u>is not four times</u> warmer than 10°C
  - Ratio
    - An interval quantity that also preserves scale
      - e.g. Height, 6ft is twice as much as 3ft
      - Kelvin temperature (°K)
      - Distance

Types of Variables

- **Categorical (Discrete and Qualitative)**
  - Nominal
    - {'blue', 'black', 'yellow'}
  - Ordinal
    - {'High', 'Medium', 'Low'}
  - Flags (Dichotomous)
    - {'Male', 'Female'}
    - {'True', 'False'}
    - {'Approved', 'Denied'}

Machine Learning

- **Supervised**
  - Regression
  - Classification

- **Unsupervised**
  - Clustering
  - Density estimation
  - Dimensionality reduction

Machine Learning Examples

- **Text classification**
- **Image classification**
- **Machine vision**
- **Pattern recognition**
- **Anomaly detection**

Example – Credit Application

age	23 years
gender	male
annual salary	\$30,000
years in residence	1 year
years in job	1 year
current debt	\$15,000
...	...

https://work.caltech.edu/telecourse.html

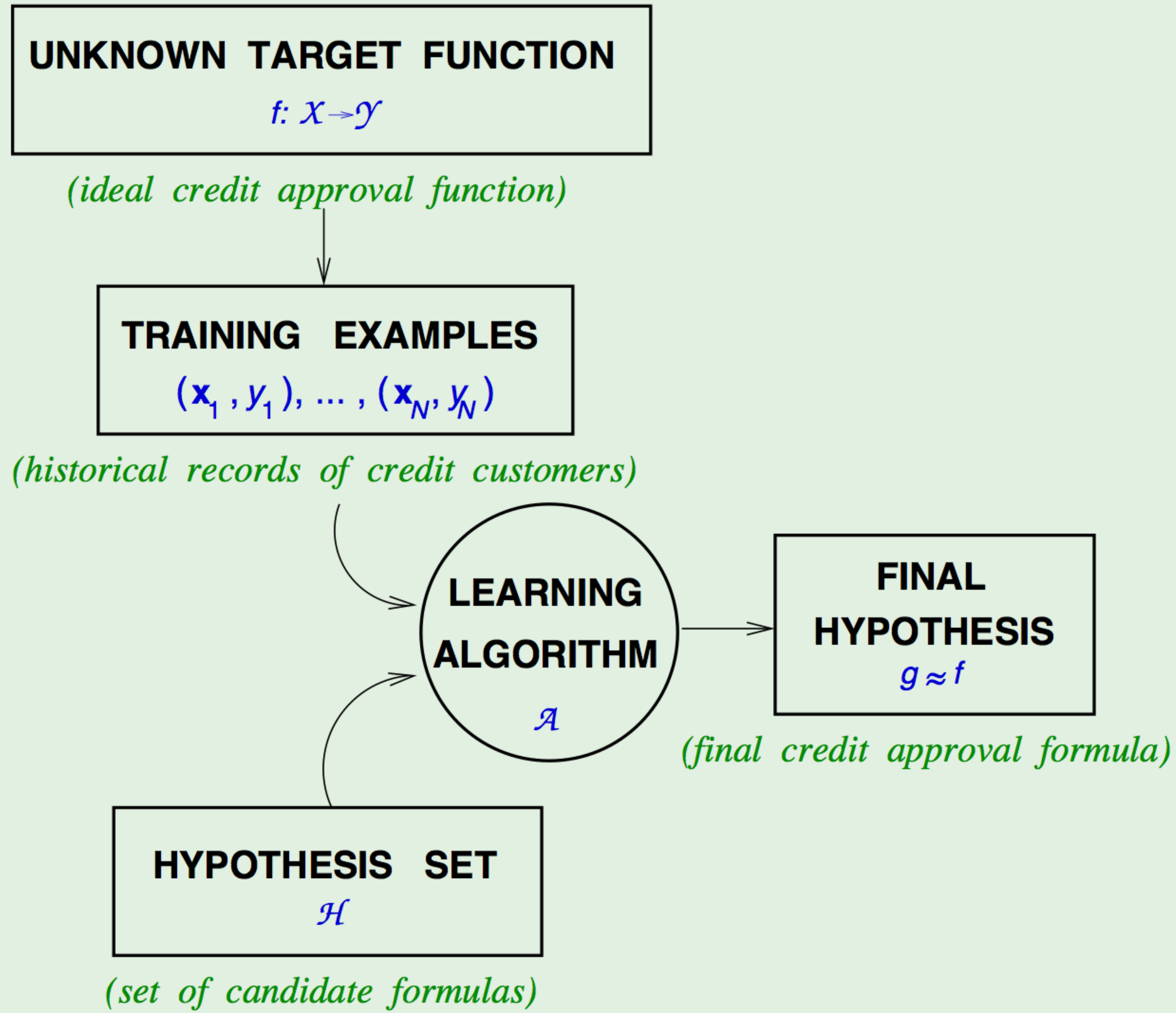
Components of Learning

- Input: $\mathbf{x}$ *(customer application)*
- Output: y *(good/bad customer?)*
- Target function: $f : \mathcal{X} \to \mathcal{Y}$ *(ideal credit approval formula)*
- Data: $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \cdots, (\mathbf{x}_N, y_N)$ *(historical records)*

  $\downarrow \quad \downarrow \quad \downarrow$

- Hypothesis: $g : \mathcal{X} \to \mathcal{Y}$ *(formula to be used)*

https://work.caltech.edu/telecourse.html



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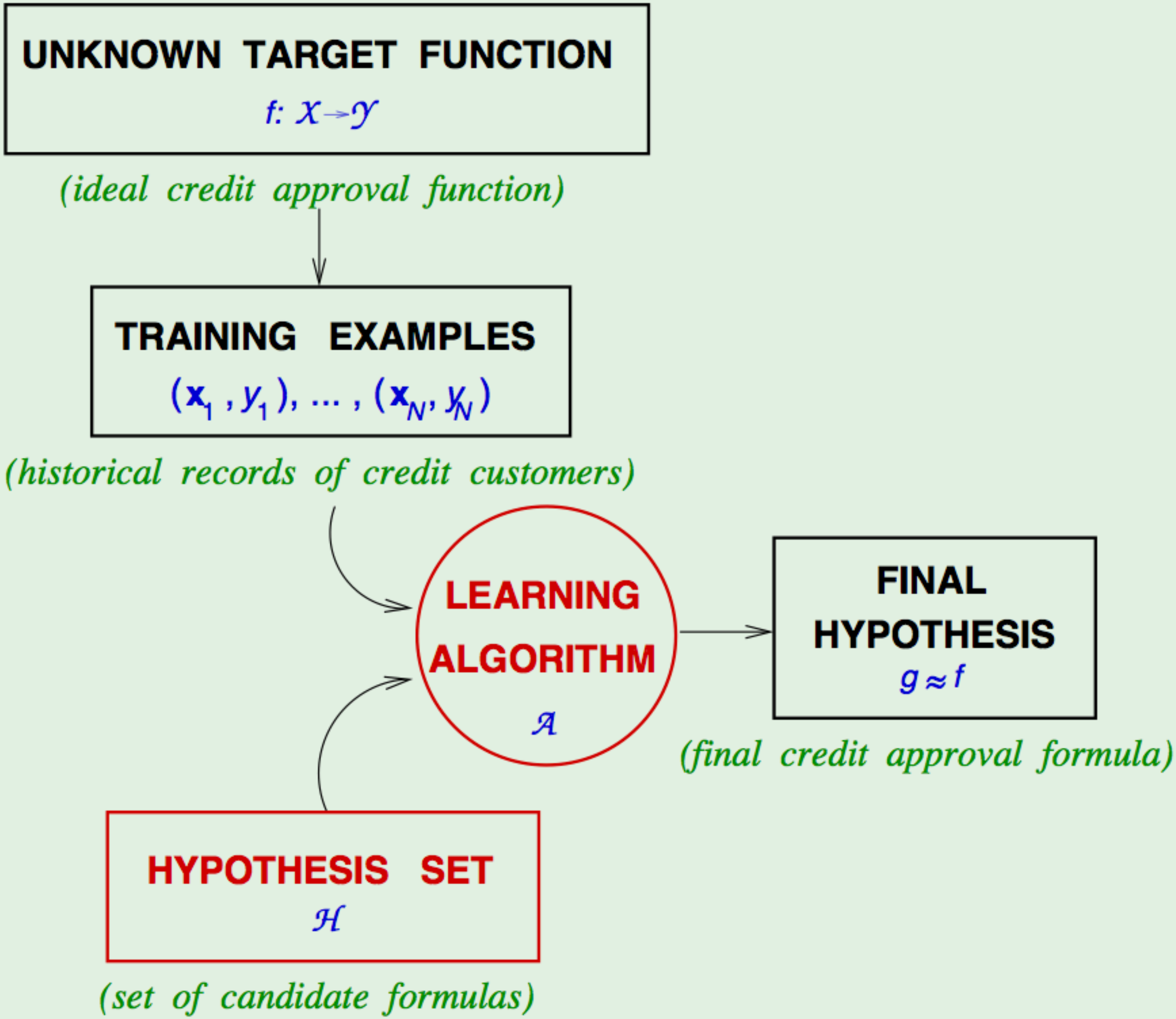

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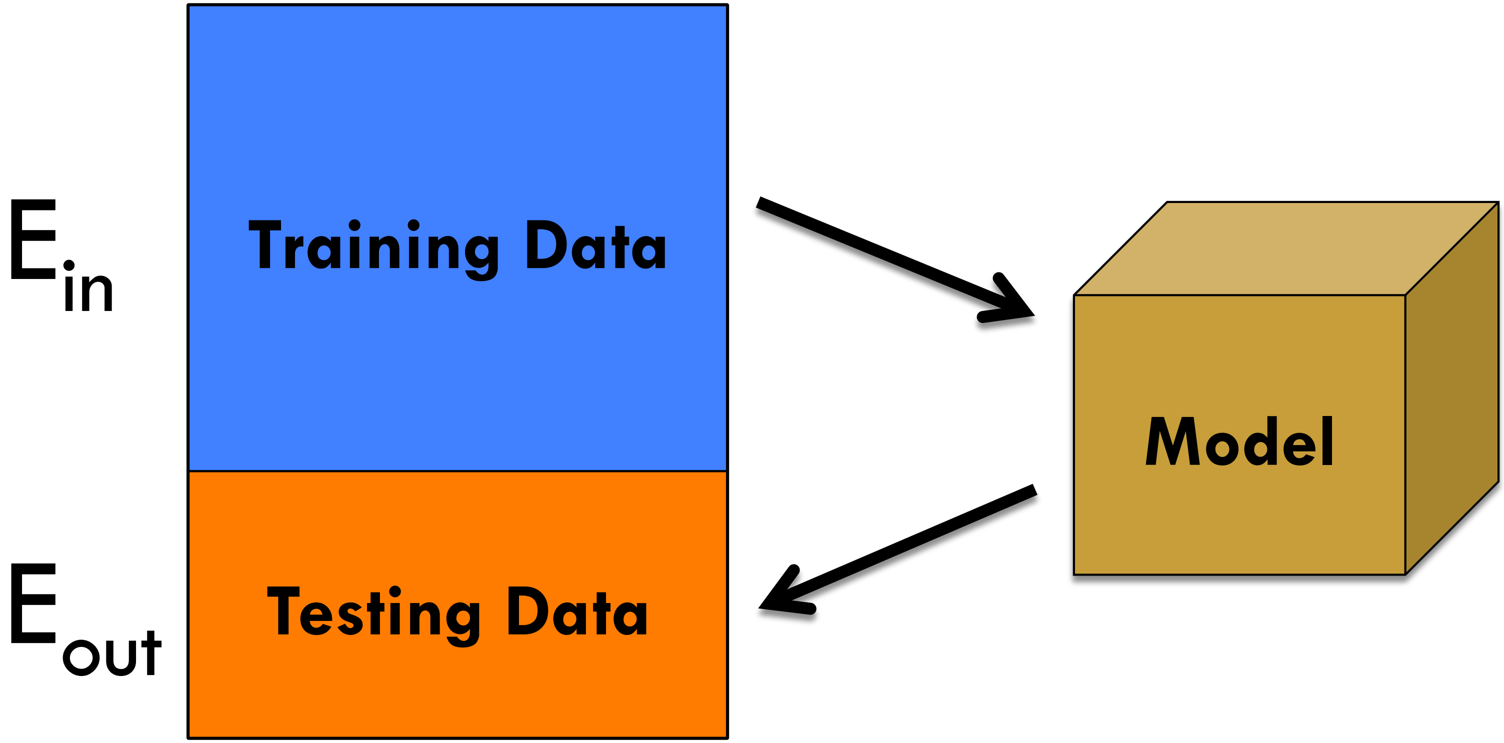
Training, and Testing Data Sets



E_{in}: In sample error

E_{out}: Out of sample error

Learning Tradeoffs (Bias, Variance)

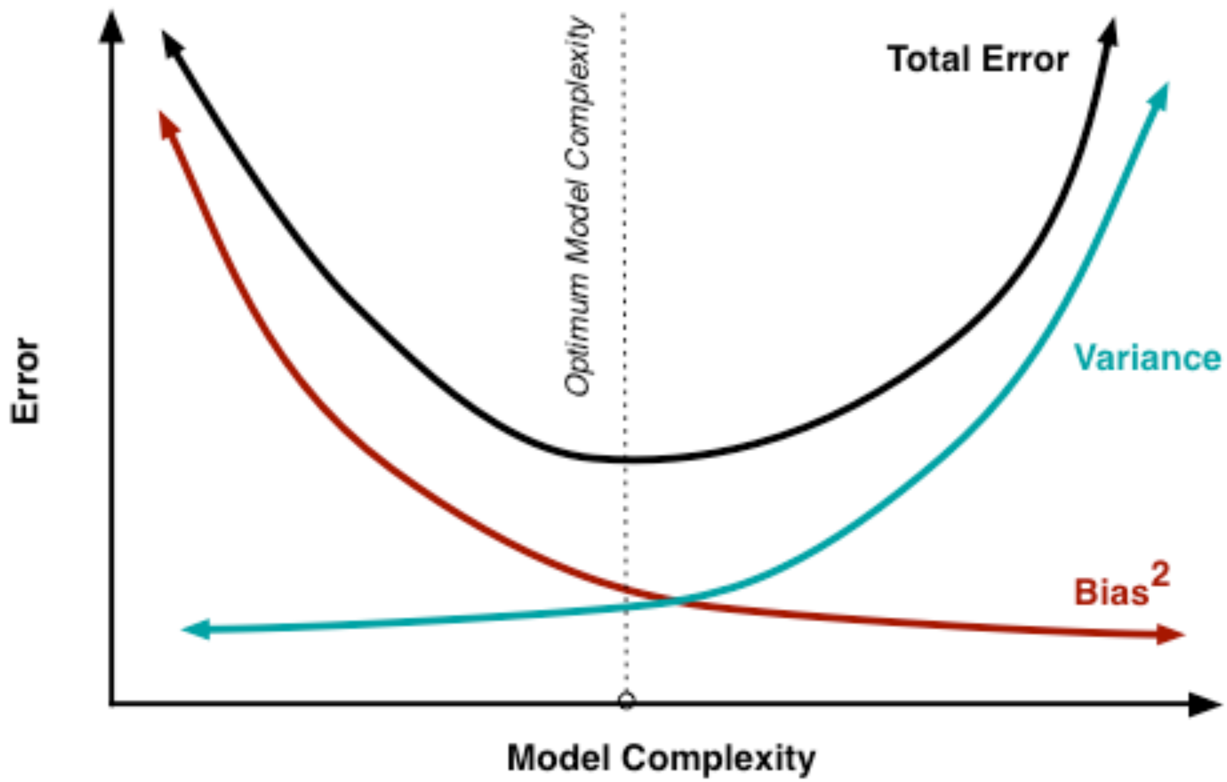
Hypothesis set complexity ↑

- E_{in} (in sample error) <u>decreases</u>
- E_{out} (out of sample error) <u>increases</u>

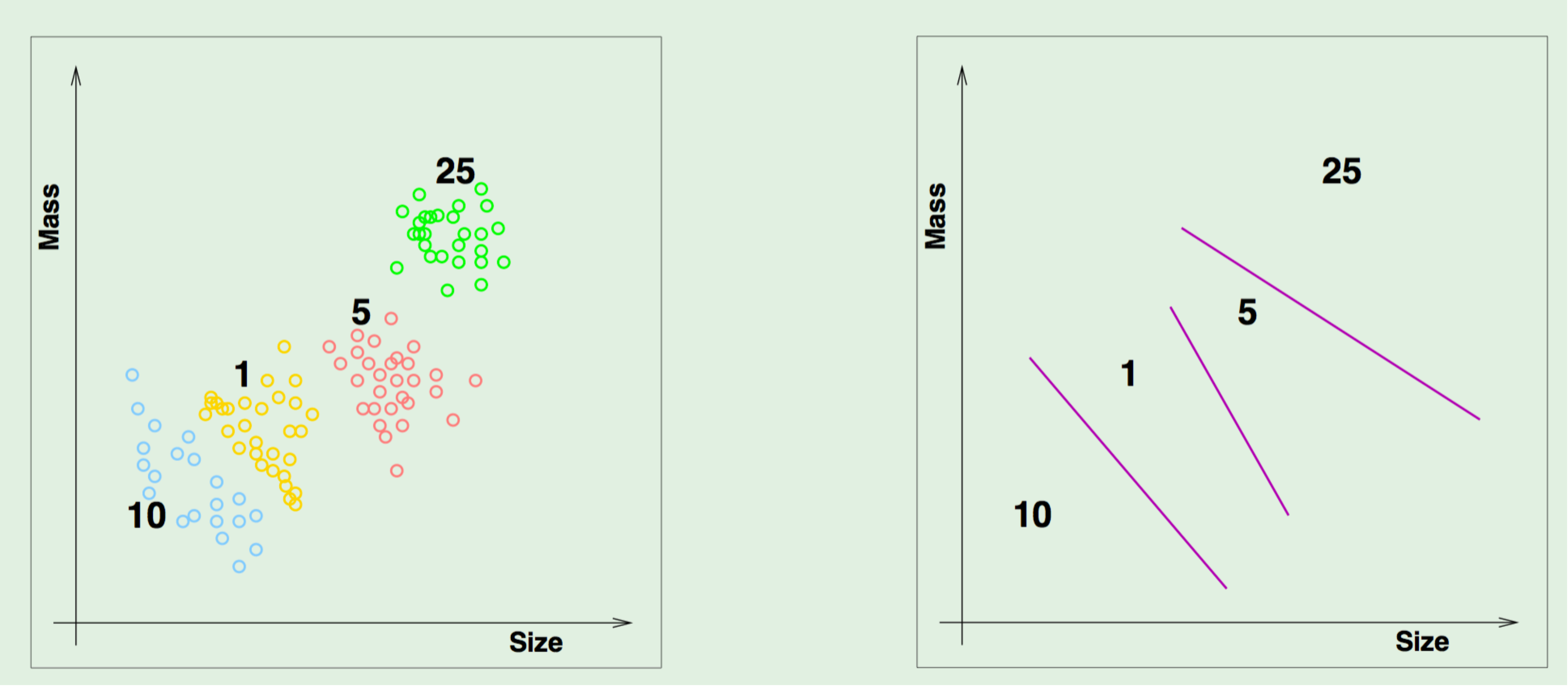
Hypothesis set complexity ↓

- E_{in} (in sample error) <u>increases</u>
- E_{out} (out of sample error) <u>decreases</u>

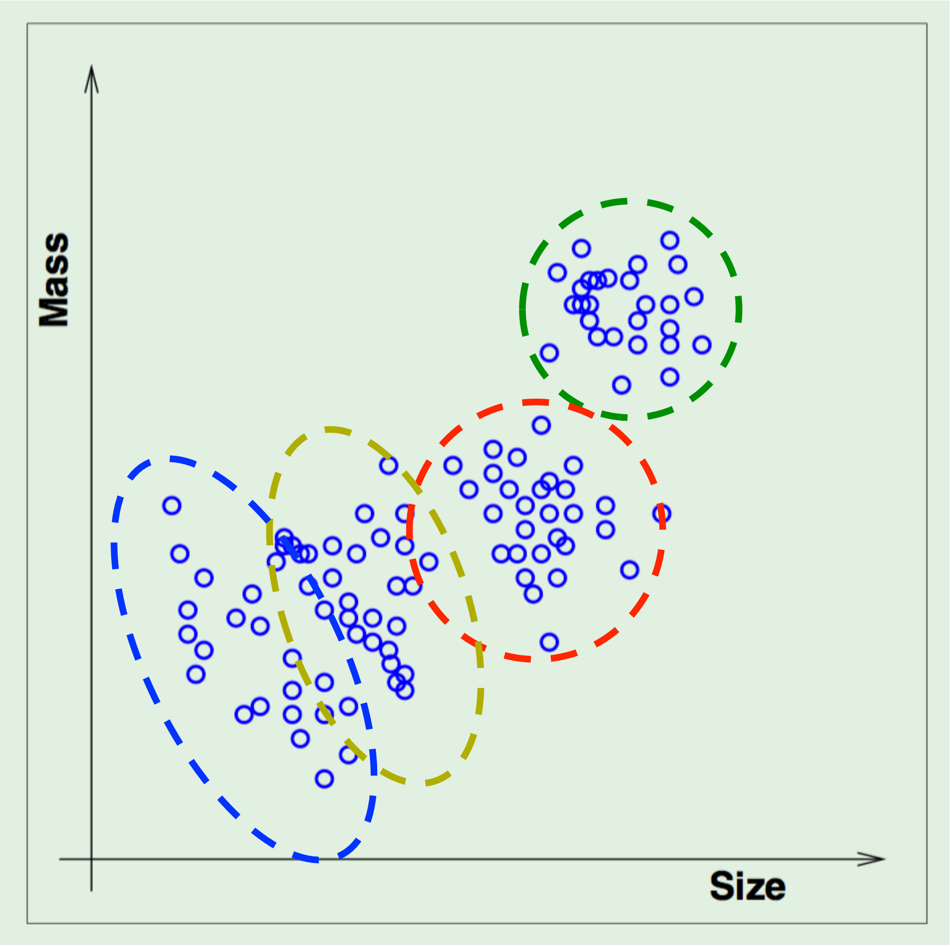
Bias, Variance Tradeoff



Supervised – Coin Recognition



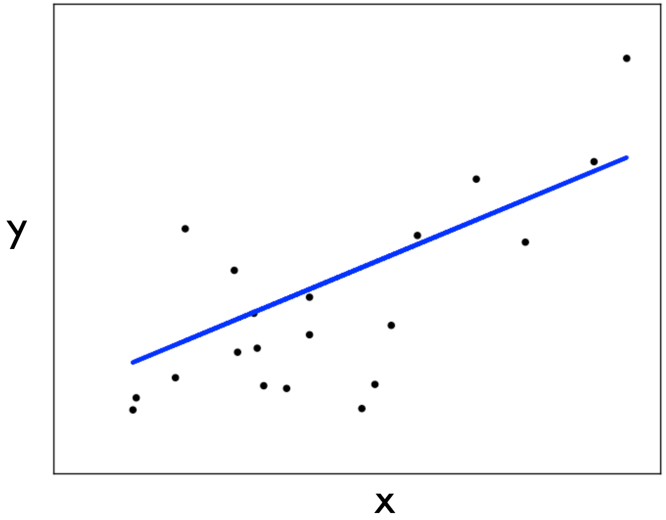
Unsupervised – Coin Recognition



Linear Regression

Generalized Linear Models

$$\hat{y}(w, x) = \underbrace{w_0}_{\text{Intercept}} + \underbrace{w_1 x_1 + ... + w_p x_p}_{\text{weighted inputs}}$$



Ordinary Least Squares

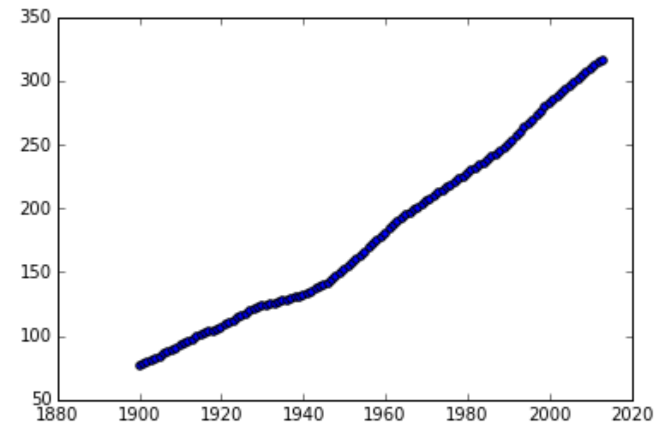
- Minimizes the error,
  X: input vector, **y:** output value, **w:** weights

$$\min_{w} ||Xw - y||_2{}^2$$

- Example:
  - US Population from 1900 - 2013

Regression Example – US Population

Year	Population
1900	76.09
1901	77.58
1902	79.16
1903	80.63
1904	82.17
1905	83.82
1906	85.45
1907	87.01
1908	88.71



US Population Example

```
xl = pd.read_excel('US_Population.xlsx')
```

```
import sklearn.linear_model as linear_model
```

```
model = linear_model.LinearRegression()
Year = xl.Year
Population = xl.Population
```

```
params = model.fit(Population.reshape(Year.size,1), Year)
```

```
print 'coef: ', params.coef_
print 'intercept: ', params.intercept_
```

```
coef:  [ 0.46041748]
intercept:  1873.43878924
```

How good is our model?

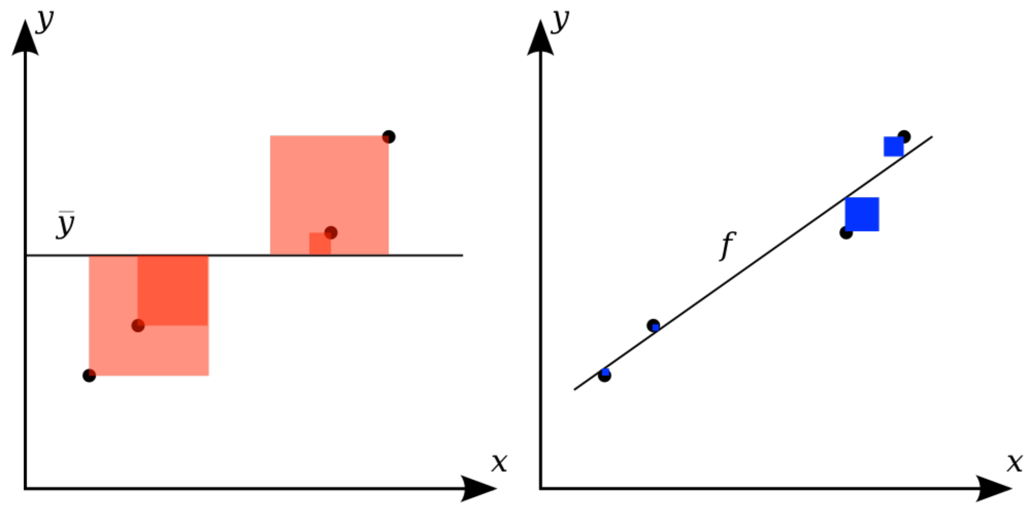
- We need to know how well the model fits the data

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

$$SS_{\text{tot}} = \sum_i (y_i - \bar{y})^2,$$

$$SS_{\text{res}} = \sum_i (y_i - f_i)^2$$

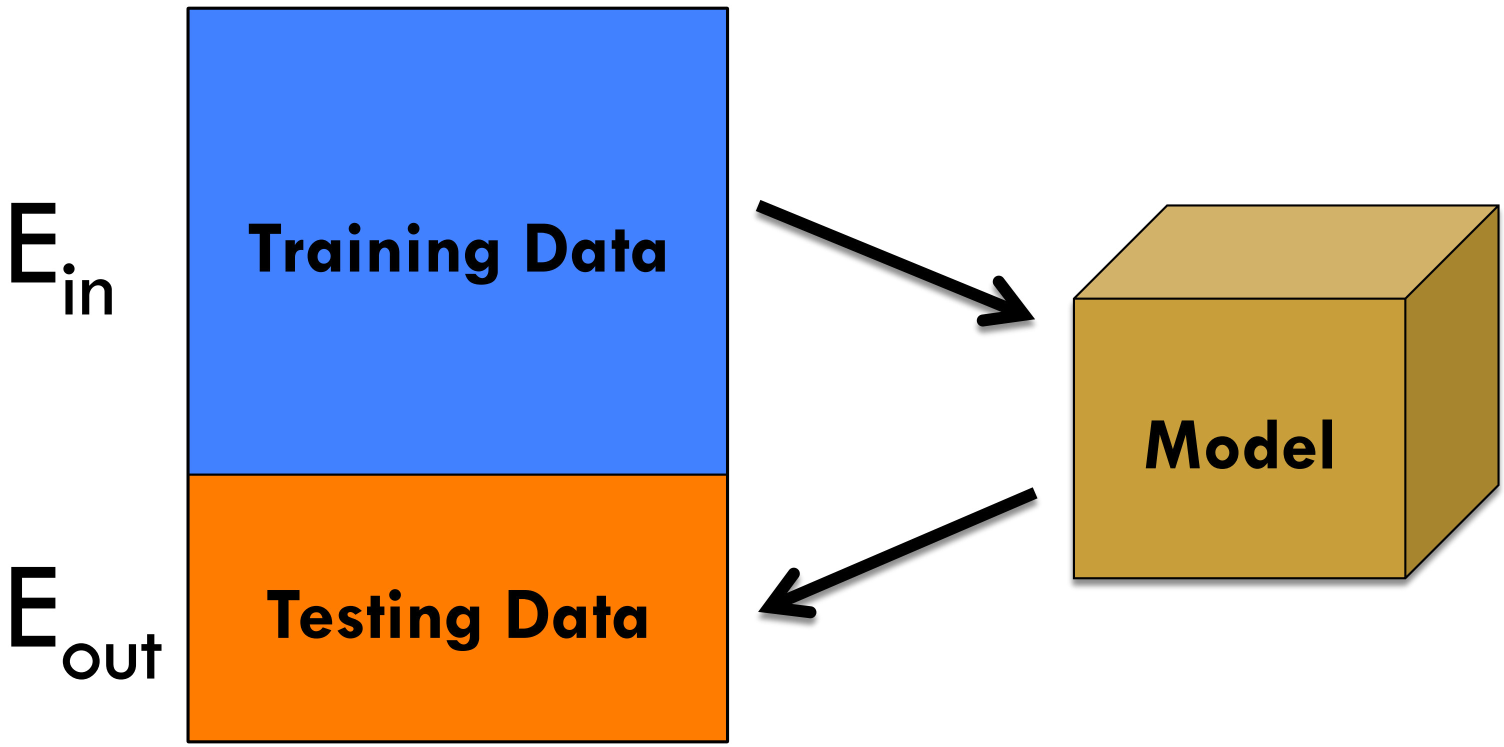
$$R^2 \equiv 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}.$$



`sklearn.metrics.r2_score`

Anything missing in our Regression?

Training, and Testing Data Sets



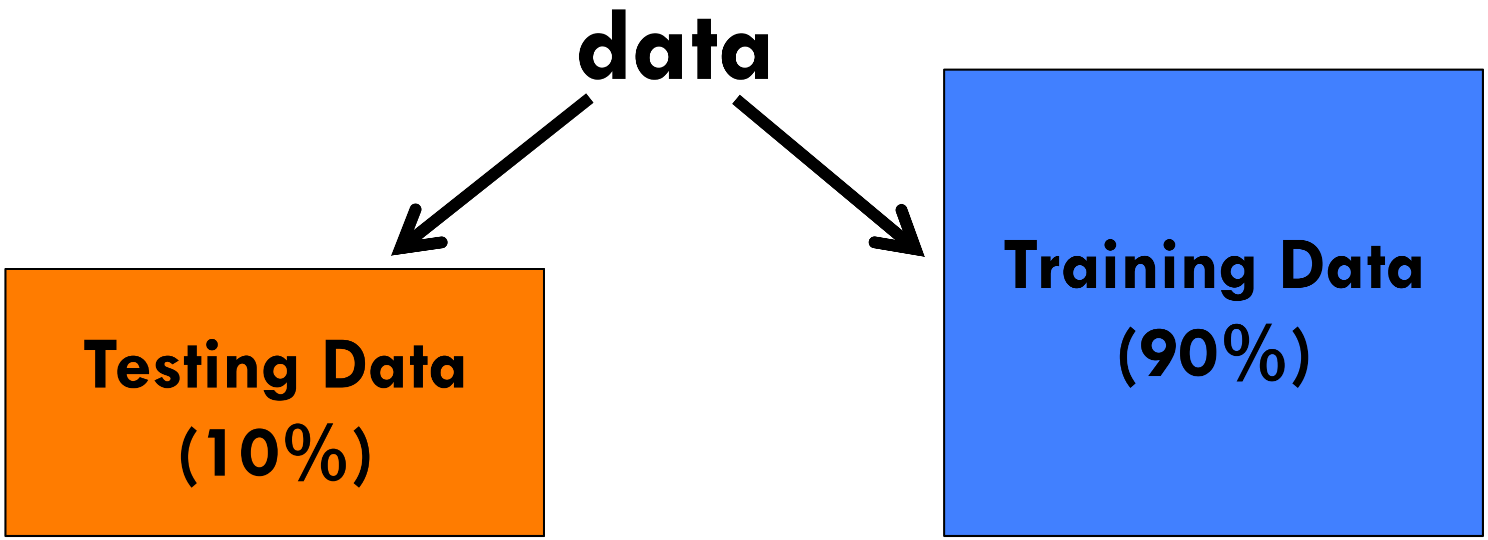
E_{in}: In sample error

E_{out}: Out of sample error

US Population Example

```
import sklearn.cross_validation as cv
```

```
split_ratio = 0.10
split_data = cv.train_test_split(xl, test_size=split_ratio)
training_data = split_data[0]
testing_data = split_data[1]
```



Youtube Rating Prediction

1) Search for videos "*maddona*"

2) *Parse the json result*

3) *Extract features of videos, e.g. number of likes, number of dislikes, number of views, number of days since its publish date*

4) *Come up with a formula that relates features to the rating*

https://gdata.youtube.com/feeds/api/videos?q=hollywood&max-results=50&v=2&alt=json

Class Group Work – Abalone Age

- Determining the age Abalone is very laborious
- We want to find a formula that predicts the **age** of abalone based on some of its features

Class Group Work – Abalone Age

Feature	Description
sex	M, F, I, (Gender or Infant)
length	Longest shell measurement (mm)
diameter	Perpendicular to the length (mm)
height	With meat in shell (mm)
whole_weight (gr)	Whole weight (gr)
shucked_weight	Weight of meat (gr)
viscera_weight	Gut weight after bleeding (gr)
shell_weight	After being dried (gr)
rings	+1.5 gives the age in years

Ridge Regression

- Imposes a penalty on the size of coefficients
- Minimizes a penalized residual sum of squares:

$$\min_{w} ||Xw - y||_2{}^2 + \alpha ||w||_2{}^2$$

- Alpha is a complexity parameter, the greater the alpha is, coefficients become more robust to collinearity

```
model = linear_model.Ridge(alpha = .5)
```

Example

- Try Ridge regression on youtube data and abalone examples
- How does the result of regression changes as we increase alpha?
- Can you plot the out of sample R^2 accuracy as a function of alpha for both problems?