# CS 145 Discussion 2

#### Reminders

- HW1 out, due 10/19/2017 (Thursday)
- Group formations for course project due today (1 pt)
- Join Piazza (email: juwood03@ucla.edu)

#### Overview

- Linear Regression
- Z Score Normalization
- Multidimensional Newton's Method
- Decision Tree
- Twitter Crawler
- Likelihood

### Linear Regression

Linear model to predict value of a variable y using features x

$$y = x^T \beta = \beta_0 + x_1 \beta_1 + x_2 \beta_2 + \dots + x_p \beta_p$$

Least Square Estimation

$$J(\boldsymbol{\beta}) = \frac{1}{2} (X\boldsymbol{\beta} - y)^T (X\boldsymbol{\beta} - y)$$

Closed form solution

$$\widehat{\boldsymbol{\beta}} = (X^T X)^{-1} X^T y$$

A ball is rolled down a hallway and its position is recorded at five different times. Use the table shown below to calculate

- Weights
- Predicted position at each given time and at time 12 seconds

Time (seconds)	Position (meters)
1	9
2	12
4	17
6	21
8	26

### Step 1: Calculate Weights

What are X and Y variables?

What are the parameters for our problem?

Calculating parameters

Time (seconds)	Position (meters)
1	9
2	12
4	17
6	21
8	26

# Step 1: Calculate Weights

- What are X and Y variables?
  - Time (X<sub>1</sub>) and Position(Y)
- What are the parameters for our problem?
  - $\hat{eta}_1$  for time and  $\hat{eta}_0$  for intercept
- Calculating parameters

$$\widehat{\boldsymbol{\beta}} = (X^T X)^{-1} X^T y$$

Time (seconds)	Position (meters)
1	9
2	12
4	17
6	21
8	26

$$X = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 4 \\ 1 & 6 \\ 1 & 8 \end{bmatrix} \qquad y = \begin{bmatrix} 9 \\ 12 \\ 17 \\ 21 \\ 26 \end{bmatrix}$$

$$X^TX = ? \qquad (X^TX)^{-1} = ?$$

$$X^{T}y = ?$$

$$\hat{\beta} = (X^{T}X)^{-1}X^{T}y$$

$$= ?$$

Time (seconds)	Position (meters)
1	9
2	12
4	17
6	21
8	26

$$\hat{\beta}_0 = ?$$

$$\hat{\beta}_1 = ?$$

$$X = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 4 \\ 1 & 6 \\ 1 & 8 \end{bmatrix}$$

$$y = \begin{bmatrix} 9 \\ 12 \\ 17 \\ 21 \\ 26 \end{bmatrix}$$

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$$(X^TX)^{-1} = ?$$

$$(X^TX)^{-1} = ? \qquad \begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

$$X^T y = ?$$

$$\hat{\beta} = (X^T X)^{-1} X^T y$$
= ?

$$\hat{\beta}_0 = ?$$

$$\hat{\beta}_1 = ?$$

$$X = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 4 \\ 1 & 6 \\ 1 & 8 \end{bmatrix}$$

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$$(X^T X)^{-1} = \frac{1}{164} \begin{bmatrix} 121 & -21 \\ -21 & 5 \end{bmatrix}$$

$$X^T y = ?$$

$$\hat{\beta} = (X^T X)^{-1} X^T y$$
= ?

$$\hat{\beta}_0 = ?$$

$$\hat{\beta}_1 = ?$$

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$$(X^T X)^{-1} = \frac{1}{164} \begin{bmatrix} 121 & -21 \\ -21 & 5 \end{bmatrix}$$

$$X^{T}y = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 4 & 6 & 8 \end{bmatrix} \begin{bmatrix} 9 \\ 12 \\ 17 \\ 21 \\ 26 \end{bmatrix} = \begin{bmatrix} 85 \\ 435 \end{bmatrix}$$

$$\hat{\beta} = (X^T X)^{-1} X^T y$$
= ?

$$\hat{\beta}_0 = \hat{s}$$

$$\hat{\beta}_1 = \hat{s}$$

$$X = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 4 \\ 1 & 6 \\ 1 & 8 \end{bmatrix} \qquad y = \begin{bmatrix} 9 \\ 12 \\ 17 \\ 21 \\ 26 \end{bmatrix}$$

$$X^{T}X = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 4 & 6 & 8 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 4 \\ 1 & 6 \\ 1 & 8 \end{bmatrix} = \begin{bmatrix} 5 & 21 \\ 21 & 121 \end{bmatrix}$$

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$$\hat{\beta} = (X^T X)^{-1} X^T y$$

$$= \frac{1}{164} \begin{bmatrix} 121 & -21 \\ -21 & 5 \end{bmatrix} \begin{bmatrix} 85 \\ 435 \end{bmatrix}$$

$$= \begin{bmatrix} 7.012 \\ 2.378 \end{bmatrix}$$

$$\hat{\beta}_0 = 7.012$$
  
 $\hat{\beta}_1 = 2.378$ 

## Step 2: Predict positions

• Plug time values into linear regression equation

$$(Position) = 2.378 (Time) + 7.012$$

• Predicted value at time = 12 secs

Matrix form to predict all other positions

$$\hat{y} = X\hat{\beta}$$

## Step 2: Predict positions

Plug time values into linear regression equation

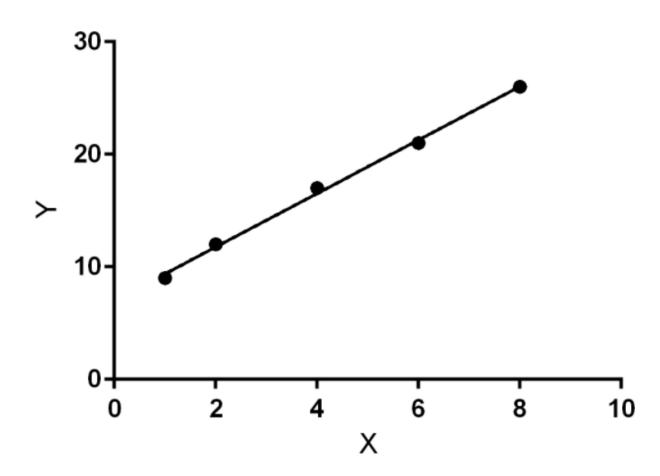
$$(Position) = 2.378 (Time) + 7.012$$

Matrix form to predict all other positions

$$\hat{y} = X\hat{\beta}$$

$$\hat{y} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 4 \\ 1 & 6 \\ 1 & 8 \end{bmatrix} \begin{bmatrix} 7.012 \\ 2.378 \end{bmatrix} = \begin{bmatrix} 9.39 \\ 11.768 \\ 16.524 \\ 21.28 \\ 26.036 \end{bmatrix}$$

# Plot



#### Z Score Normalization

- Why normalize features?
  - Different feature ranges such as [-1, 1] and [-100, 100] may negatively affect algorithm performance
  - Small change in bigger range can affect more than huge change in smaller range
- Z Score (Standard Score)

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

- $z_{ij}$  is the standard score for feature j of data point i
- $x_{ij}$  is the value of feature j of data point i
- $\mu_i$  and  $\sigma_i$  are mean and standard deviation of feature j

Galaxy	Distance (Mpc)	Velocity (km/sec)
Virgo	15	1600
Ursa Minor	200	15,000
Corona Borealis	290	24,000
Bootes	520	40,000

- Normalize feature 'Distance'
- Compute Mean

• 
$$\mu_{dist} = \frac{1}{N} \sum_{i=1}^{N} x_{i.dist} = ?$$

Computer Standard Deviation

• 
$$\sigma_{dist} = \sqrt{\frac{\sum_{i=1}^{N} (x_{i.dist} - \mu_{dist})^2}{N-1}} = ?$$

Galaxy	Distance (Mpc)	Velocity (km/sec)
Virgo	15	1600
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Bootes	520	40,000

- Normalize feature 'Distance'
- Compute Mean

• 
$$\mu_{dist} = \frac{1}{N} \sum_{i=1}^{N} x_{i.dist} = \frac{15 + 200 + 290 + 520}{4} = 256.25$$

Computer Standard Deviation

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$$\sigma_{dist} = \sqrt{\frac{\sum_{i=1}^{N} (x_{i.dist} - \mu_{dist})^2}{N-1}} = ?$$

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- Normalize feature 'Distance'
- Compute Mean

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$$\mu_{dist} = \frac{1}{N} \sum_{i=1}^{N} x_{i.dist} = \frac{15 + 200 + 290 + 520}{4} = 256.25$$

Computer Standard Deviation

• 
$$\sigma_{dist} = \sqrt{\frac{\sum_{i=1}^{N} (x_{i.dist} - \mu_{dist})^2}{N}} = \sqrt{\frac{(15 - 256.25)^2 + (200 - 256.25)^2 + (290 - 256.25)^2 + (520 - 256.25)^2}{4}} = 181.7063221$$

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• 
$$\mu_{dist} = 256.25$$

• 
$$\sigma_{dist} = 181.7063221$$

Compute standard scores

• 
$$z_{virgo.dist} = \frac{x_{virgo.dist} - \mu_{dist}}{\sigma_{dist}} = ?$$
•  $z_{ursa.dist} = \frac{x_{ursa.dist} - \mu_{dist}}{\sigma_{dist}} = ?$ 
•  $z_{corona.dist} = \frac{x_{corona.dist} - \mu_{dist}}{\sigma_{dist}} = ?$ 
•  $z_{bootes.dist} = \frac{x_{bootes.dist} - \mu_{dist}}{\sigma_{dist}} = ?$ 

• Similarly, other features like velocity can be standardized

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Bootes	520	40,000

- $\mu_{dist} = 256.25$
- $\sigma_{dist} = 181.7063221$
- Compute standard scores

• 
$$z_{virgo.dist} = \frac{x_{virgo.dist} - \mu_{dist}}{\sigma_{dist}} = \frac{15 - 256.25}{181.706} = -1.328$$

• 
$$z_{ursa.dist} = \frac{x_{ursa.dist} - \mu_{dist}}{\sigma_{dist}} = \frac{200 - 256.25}{181.706} = -0.3096$$

• 
$$z_{corona.dist} = \frac{x_{corona.dist} - \mu_{dist}}{\sigma_{dist}} = \frac{290 - 256.25}{181.706} = 0.186$$

• 
$$z_{bootes.dist} = \frac{x_{bootes.dist} - \mu_{dist}}{\sigma_{dist}} = \frac{520 - 256.25}{181.706} = 1.452$$

Similarly, other features like velocity can be standardized

$$\beta^{\textit{new}} = \beta^{\textit{old}} - \left(\frac{\partial^2 L(\beta)}{\partial \beta \partial \beta^T}\right)^{-1} \frac{\partial L(\beta)}{\partial \beta}$$

- $x^{(0)} = [3, -1, 0]$
- $f(x_1, x_2, x_3) = (x_1 + 10x_2)^2 + 5(x_1 x_3)^2 + (x_2 2x_3)^4$
- What is  $f(x^{(0)})$ ?

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  - $(3+10\cdot -1)^2 + 5\cdot (3-0)^2 + (-1-2\cdot 0)^4 = 95$

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$$(3+10\cdot -1)^2 + 5\cdot (3-0)^2 + (-1-2\cdot 0)^4 = 95$$

- What is  $\nabla f(x)$ ?
  - $\nabla f(x_1) = 2 \cdot (x_1 + 10 \cdot x_2) + 10 \cdot (x_1 x_3)$
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- What is F(x)?

• 
$$\begin{bmatrix} 12 & 20 & -10 \\ 20 & 10 + 12 \cdot (x_2 - 2 \cdot x_3)^2 & -24 \cdot (x_2 - 2 \cdot x_3)^2 \\ -10 & -24 \cdot (x_2 - 2 \cdot x_3)^2 & 48 \cdot (x_2 - 2 \cdot x_3)^2 \end{bmatrix}$$

• What is F(x)?

• 
$$\begin{bmatrix} 12 & 20 & -10 \\ 20 & 10 + 12 \cdot (x_2 - 2 \cdot x_3)^2 & -24 \cdot (x_2 - 2 \cdot x_3)^2 \\ -10 & -24 \cdot (x_2 - 2 \cdot x_3)^2 & 48 \cdot (x_2 - 2 \cdot x_3)^2 \end{bmatrix}$$

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  - [16, -144, -22]

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- What is  $F(x^{(0)})$ ?

• 
$$x^{(0)} = [3, -1, 0]$$

• What is F(x)?

• 
$$\begin{bmatrix} 12 & 20 & -10 \\ 20 & 10 + 12 \cdot (x_2 - 2 \cdot x_3)^2 & -24 \cdot (x_2 - 2 \cdot x_3)^2 \\ -10 & -24 \cdot (x_2 - 2 \cdot x_3)^2 & 48 \cdot (x_2 - 2 \cdot x_3)^2 \end{bmatrix}$$

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• 
$$\begin{bmatrix} 12 & 20 & -10 \\ 20 & 10 + 12 \cdot (x_2 - 2 \cdot x_3)^2 & -24 \cdot (x_2 - 2 \cdot x_3)^2 \\ -10 & -24 \cdot (x_2 - 2 \cdot x_3)^2 & 48 \cdot (x_2 - 2 \cdot x_3)^2 \end{bmatrix}$$

• What is  $F(x^{(0)})$ ?

$$\begin{bmatrix}
12 & 20 & -10 \\
20 & 22 & -24 \\
-10 & -24 & 48
\end{bmatrix}$$

- What is  $F(x^{(0)})^{-1}$ ?
    $\begin{bmatrix} -0.079 & 0.119 & 0.043 \\ 0.1192 & -0.0788 & -0.0145 \\ -0.043 & -0.0145 & 0.0225 \end{bmatrix}$
- What is  $\nabla f(x^{(0)})$ ?
  - [16, -144, -22]
- What is  $F(x^{(0)})^{-1} \cdot \nabla f(x^{(0)})$ ?

- What is  $F(x^{(0)})^{-1}$ ?
    $\begin{bmatrix} -0.079 & 0.119 & 0.043 \\ 0.1192 & -0.0788 & -0.0145 \\ -0.043 & -0.0145 & 0.0225 \end{bmatrix}$
- What is  $\nabla f(x^{(0)})$ ?
  - [16, -144, -22]
- What is  $F(x^{(0)})^{-1} \cdot \nabla f(x^{(0)})$ ?
  - [-19.384, 13.576, 2.291]

- 1. Guess  $x^{(0)}$
- 2. Get  $\nabla f(x)$
- 3. Get F(x)
- 4. n = 0
- 5. Calculate  $\nabla f(x^{(n)})$
- 6. Calculate  $F(x^{(n)})$
- 7. Calculate  $F(x^{(n)})^{-1}$
- 8.  $x^{(n+1)} = x^{(n)} F(x^{(n)})^{-1} \cdot \nabla f(x^{(n)})$
- 9. n = n + 1

#### Multidimensional Newton's Method

- 1. Guess  $x^{(0)}$
- 2. Get  $\nabla f(x)$
- 3. Get F(x)
- 4. n = 0

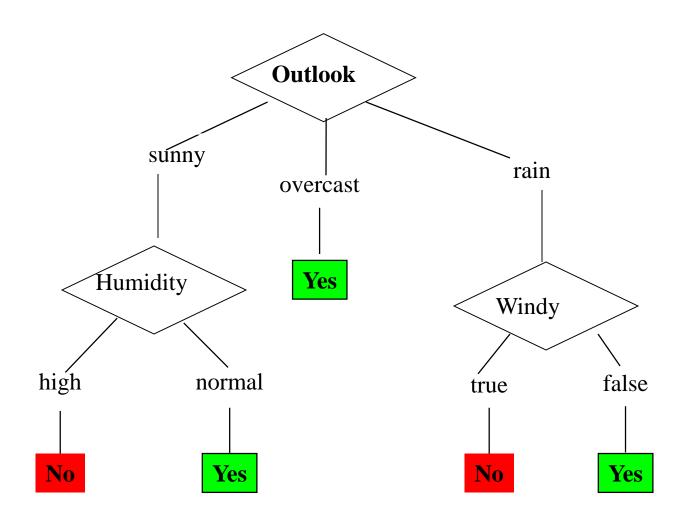
- 5. Calculate  $\nabla f(x^{(n)})$ 6. Calculate  $F(x^{(n)})$ 7. Calculate  $F(x^{(n)})^{-1}$ 8.  $x^{(n+1)} = x^{(n)} F(x^{(n)})^{-1} \cdot \nabla f(x^{(n)})$ 
  - 9. n = n + 1

## Weather Data: Play or not Play?

Outlook	Temperature	Humidity	Windy	Play?
sunny	hot	high	false	No
sunny	hot	high	true	No
overcast	hot	high	false	Yes
rain	mild	high	false	Yes
rain	cool	normal	false	Yes
rain	cool	normal	true	No
overcast	cool	normal	true	Yes
sunny	mild	high	false	No
sunny	cool	normal	false	Yes
rain	mild	normal	false	Yes
sunny	mild	normal	true	Yes
overcast	mild	high	true	Yes
overcast	hot	normal	false	Yes
rain	mild	high	true	No

Note:
Outlook is the
Forecast,
no relation to
Microsoft
email program

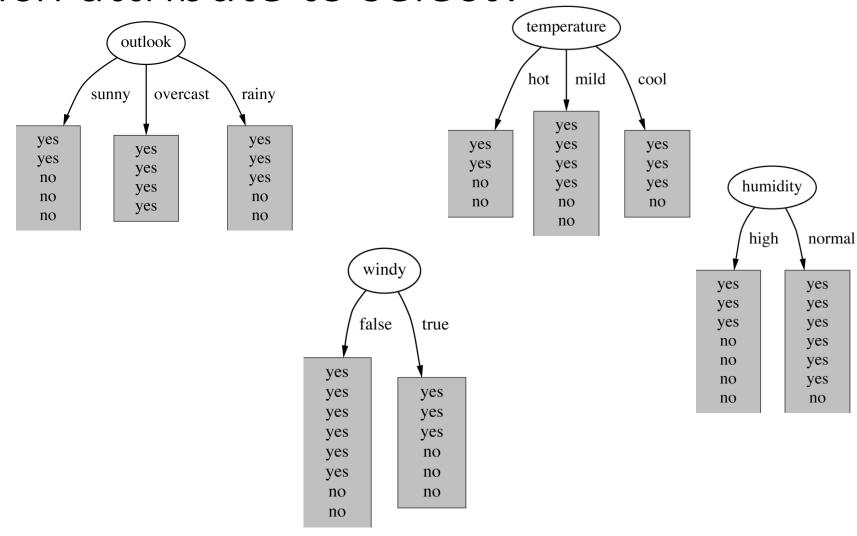
# Example Tree for "Play?"



### Choosing the Splitting Attribute

- At each node, available attributes are evaluated on the basis of separating the classes of the training examples. A Goodness function is used for this purpose.
- Typical goodness functions:
  - information gain (ID3/C4.5)
  - information gain ratio
  - gini index

Which attribute to select?



#### A criterion for attribute selection

- Which is the best attribute?
  - The one which will result in the smallest tree
  - Heuristic: choose the attribute that produces the "purest" nodes
- Popular impurity criterion: information gain
  - Information gain increases with the average purity of the subsets that an attribute produces
- Strategy: choose attribute that results in greatest information gain

### Entropy of a split

 Information in a split with x items of one class, y items of the second class

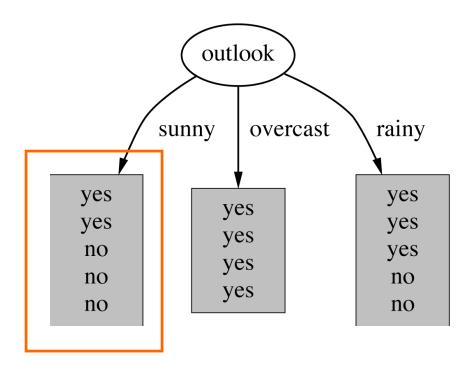
info([x, y]) = entropy(
$$\frac{x}{x+y}$$
,  $\frac{y}{x+y}$ )

$$= -\frac{x}{x+y} \log(\frac{x}{x+y}) - \frac{y}{x+y} \log(\frac{y}{x+y})$$

### Example: attribute "Outlook"

"Outlook" = "Sunny": 2 and 3 split

info([2,3]) = entropy(25,3/5) = 
$$-\frac{2}{5}\log(\frac{2}{5}) - \frac{3}{5}\log(\frac{3}{5}) = 0.971$$

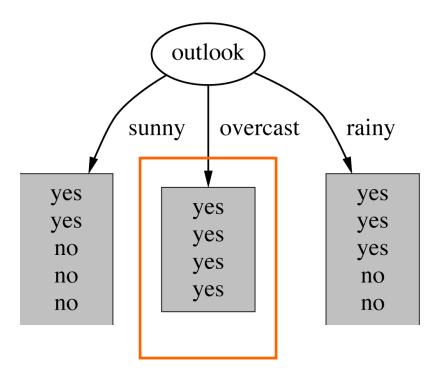


#### Outlook = Overcast

"Outlook" = "Overcast": 4/0 split

$$info([4,0]) = entropy(1,0) = -1log(1) - 0log(0) = 0$$

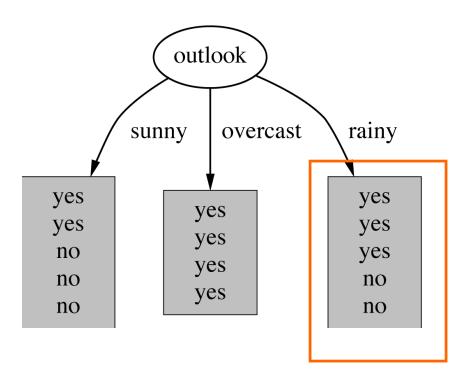
Note: log(0) is not defined, but we evaluate 0\*log(0) as zero



### Outlook = Rainy

"Outlook" = "Rainy":

info([3,2]) = entropy(3/5,2/5) = 
$$-\frac{3}{5}\log(\frac{3}{5}) - \frac{2}{5}\log(\frac{2}{5}) = 0.971$$



### **Expected Information**

Expected information for attribute:

$$info([3,2],[4,0],[3,2]) = (5/14) \times 0.971 + (4/14) \times 0 + (5/14) \times 0.971$$

$$=0.693$$

### Computing the information gain

Information gain:

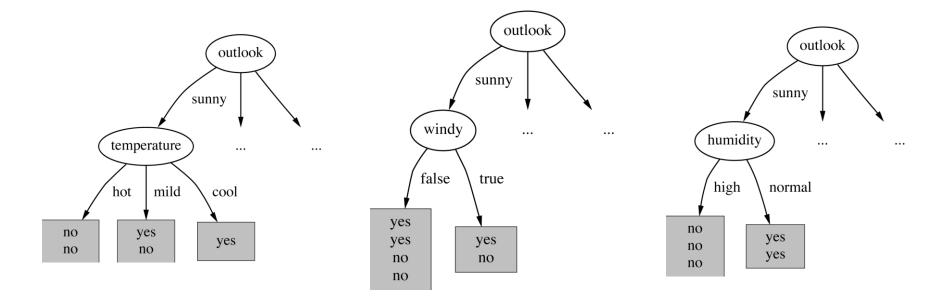
(information before split) – (information after split)

gain("Outlook") = info([9,5]) - info([2,3],[4,0],[3,2]) = 0.940-0.693  
= 
$$0.247$$

• Information gain for attributes from weather data:

```
gain("Outlook") = 0.247
gain("Temperature") = 0.029
gain("Humidity") = 0.152
gain("Windy") = 0.048
```

# Continuing to split

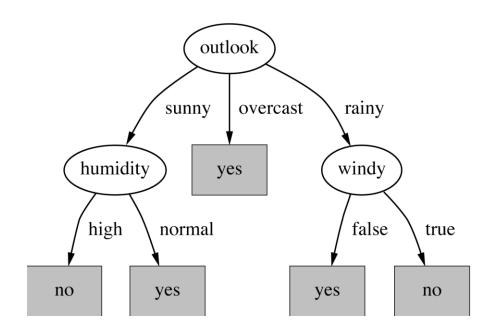


gain("Humidity") = 0.971

gain("Temperature") = 0.571

gain("Windy") = 0.020

#### The final decision tree

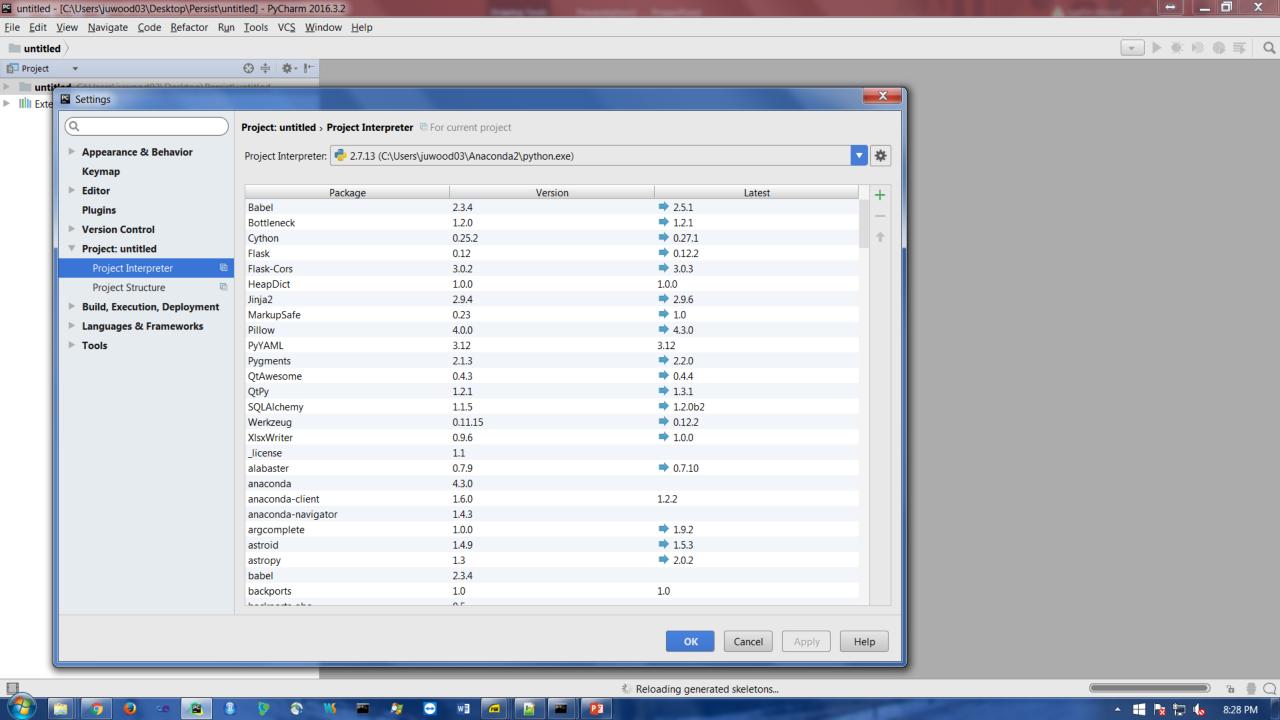


- Note: not all leaves need to be pure; sometimes identical instances have different classes
  - ⇒ Splitting stops when data can't be split any further

# Twitter API

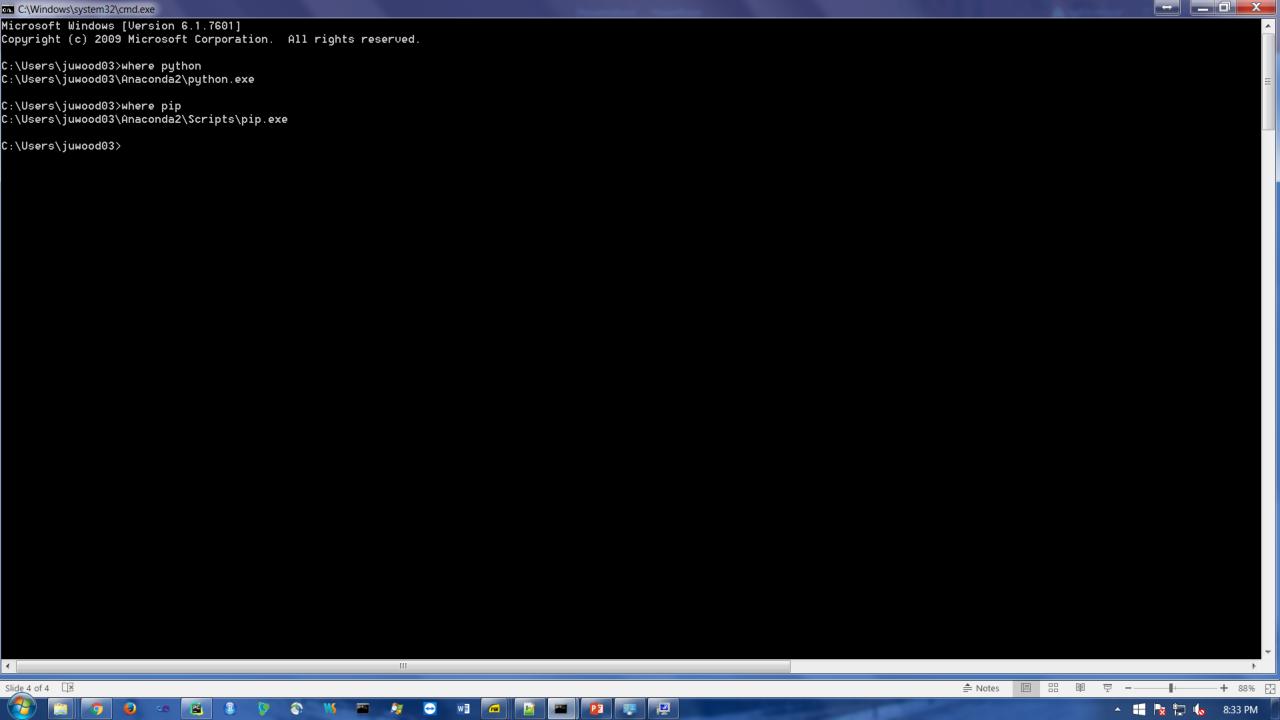
### python

- Get python (Anaconda recommended)
  - https://www.anaconda.com/
- Get an IDE (PyCharm)
  - https://www.jetbrains.com/pycharm/
- Set PyCharm interpreter to Anaconda
  - File → Settings → Project: <name> → Python Interpreter



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- Make sure command line python and pip are pointing to Anaconda

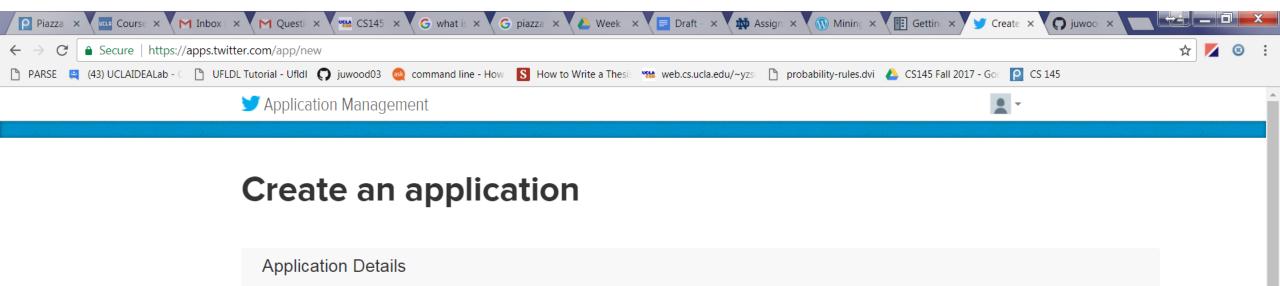


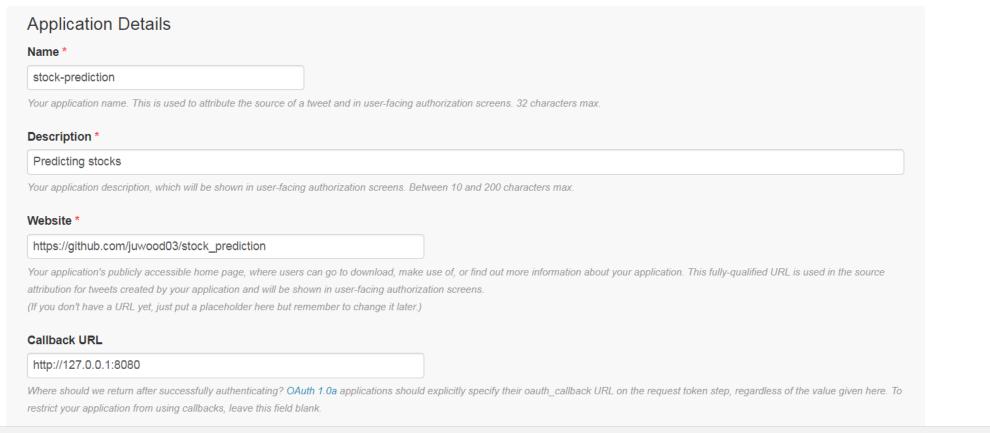
# python-twitter

pip install tweepy

#### Twitter

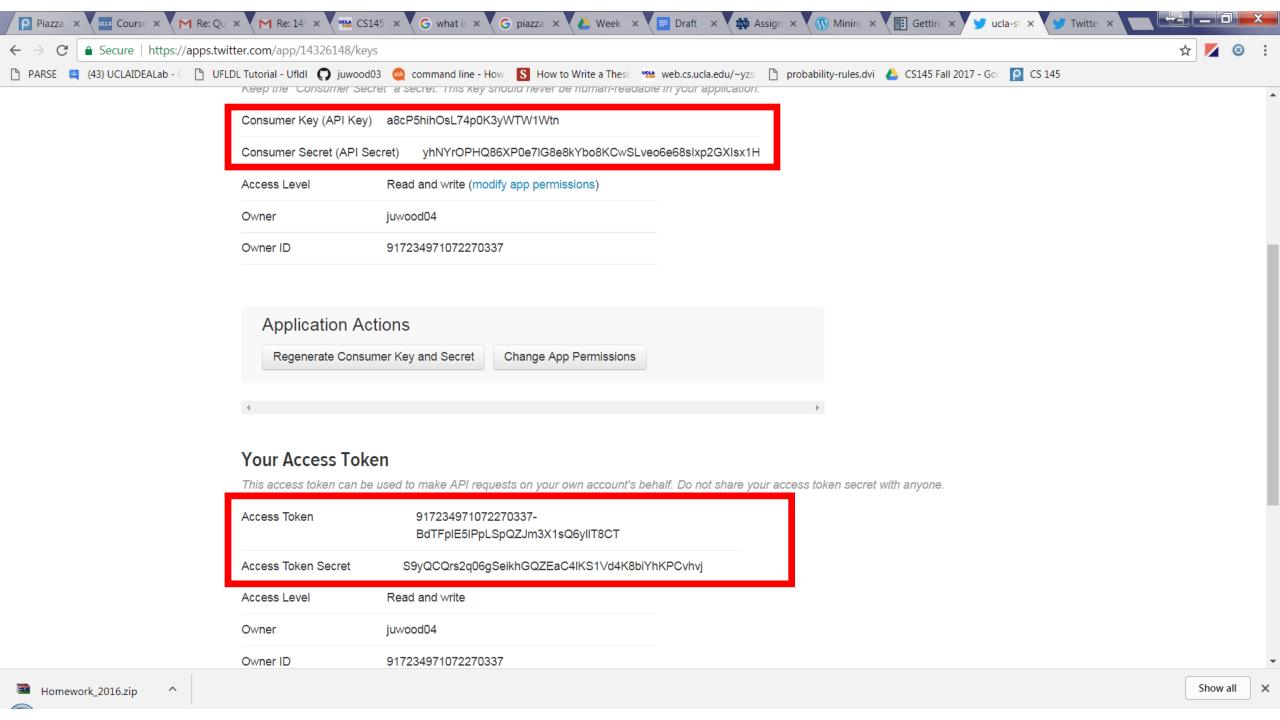
- Sign-up
  - <a href="https://twitter.com/signup">https://twitter.com/signup</a> (must add phone number)
- Register an app
  - <a href="https://apps.twitter.com/">https://apps.twitter.com/</a> → Create New App

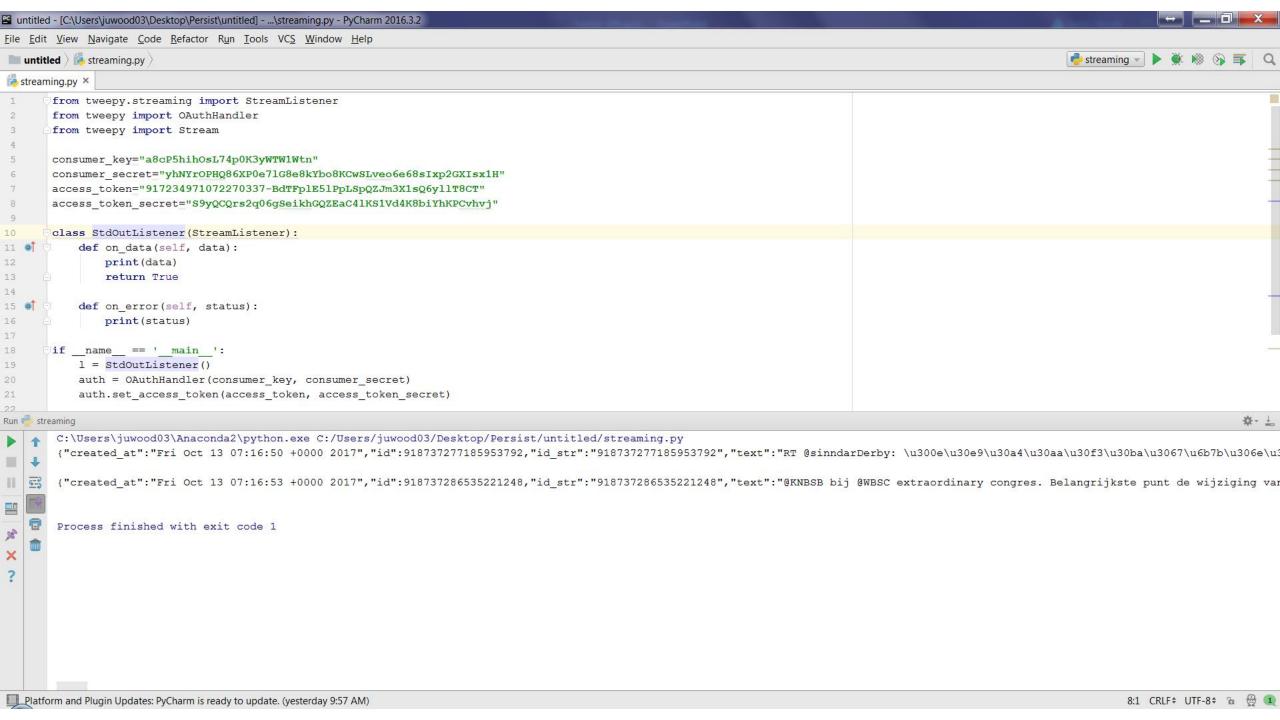


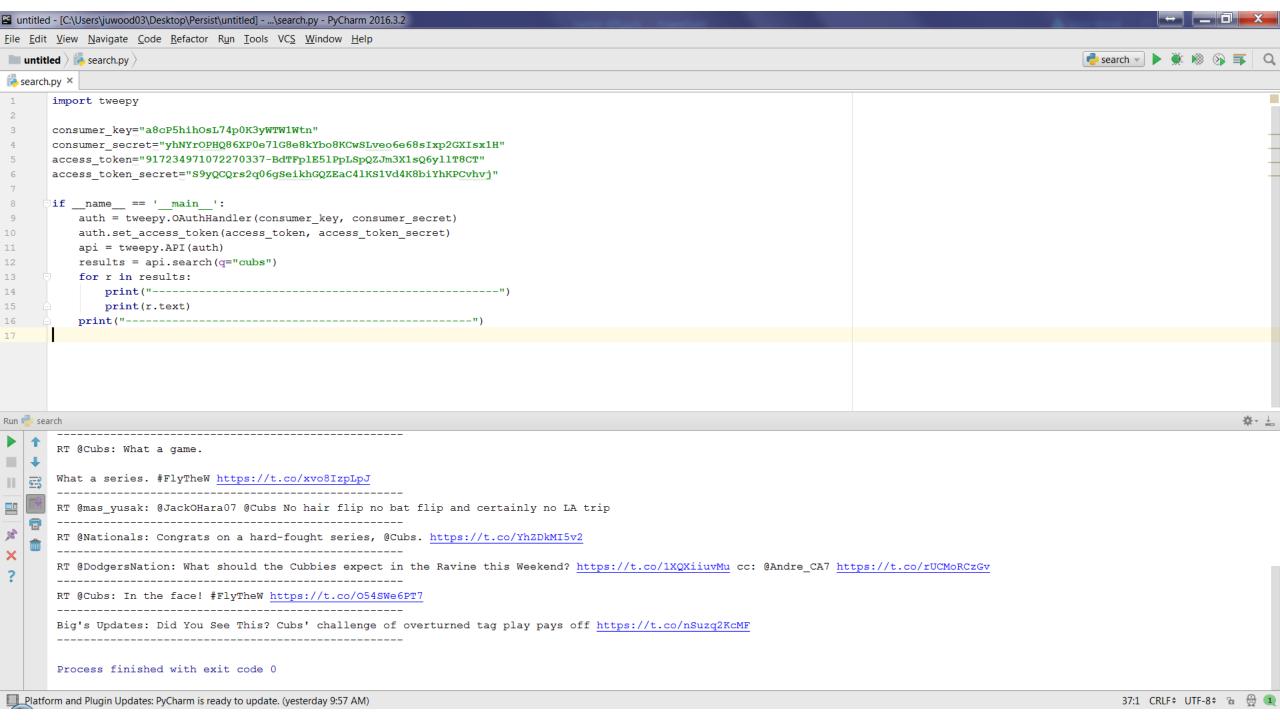


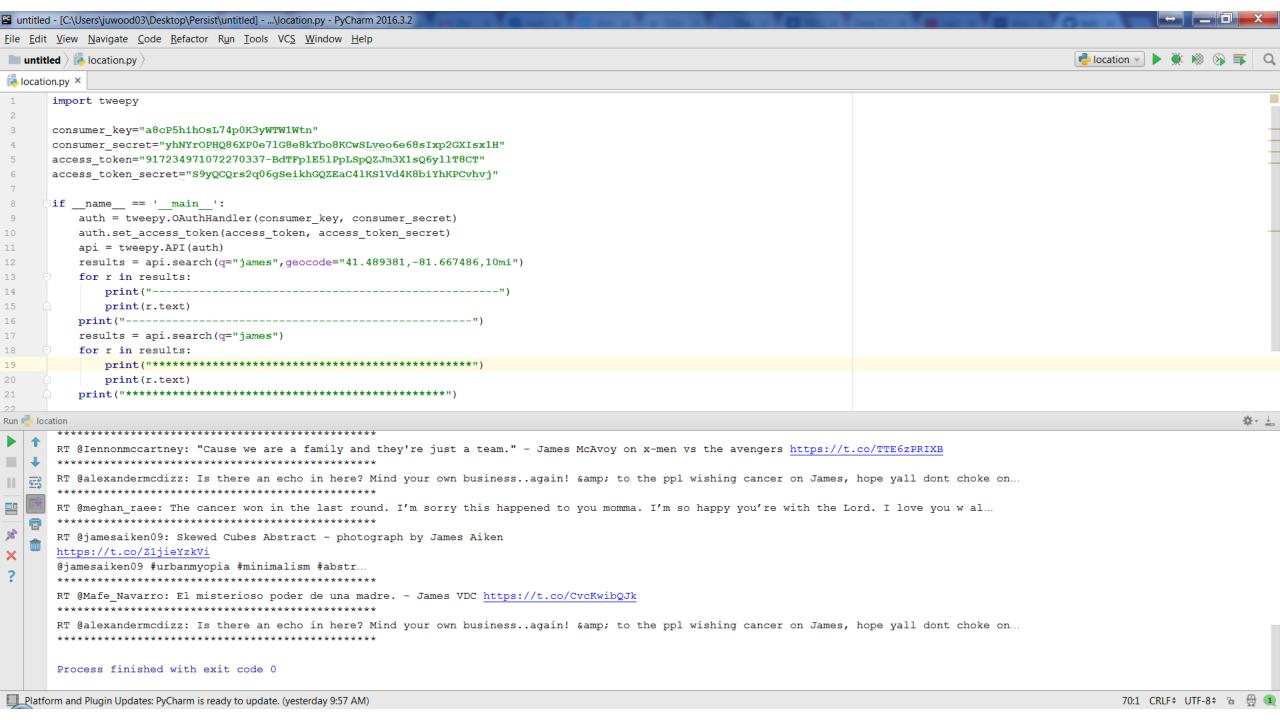
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- Get the keys and access tokens
  - Keys and Access Tokens tab → Create my access token









#### Twitter

- Rate limits
  - Searching
    - 24 hours x 4 15-minute increments x 450 requests per 15-minute increments = 43,200 requests per day
  - Streaming
    - ≈ 1%?

• Is likelihood a density or probability?

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  - No, it is the multiplication of densities

- Is likelihood a density or probability?
  - No, it is the multiplication of densities
- Densities often < 1</li>
  - Multiplication approaches epsilon (smallest non-zero positive value any language can handle) exponentially
- Likelihood used in gradient ascent
  - if complex function partial derivative can get messy

• Solution?

- Solution?
  - Take the log

- Solution?
  - Take the log
- $\log(x \cdot y) = \log(x) + \log(y)$ 
  - Approaches  $\pm \infty$  linearly
  - Easier to take derivative
- Density > 1
  - Log-likelihood > 1
- Density < 1
  - Log-likelihood < 0

