SOSC 4300/5500: Prediction

Han Zhang

Feb 15, 2022

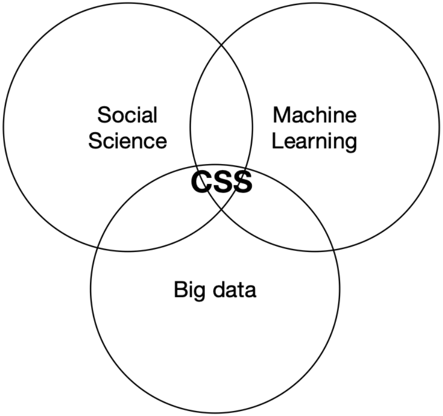
Outline

Logistics

- Grouping?
- Other questions?

Computational Social Science (CSS)

- We have learned the pros and cons of big data
- Next we focus on using machine learning and big data to make predictions



Prediction vs. Explanation

- Prediction vs explanation
  - Prediction: Whether Trump of Clinton will win the election?
  - Explanation: Why Trump won?
- [In class activities]: Can you give other examples? Type it in chatbox!

Prediction vs. Explanation: the ideal case

- Ideal case: classical physics, such as Newton's Law of Motion
  - Predictive: we can precisely predict location of planets in solar system
  - Explanative: we have a theory to explain why

Prediction vs Explanation in Social Sciences

- Social worlds are typically too complicated to summarize using several equations
  - We do not have a powerful formula such as $F = ma$
- Current social science research focus dominantly on explanation
  - Testing a theory that looks like “A leads to B”
- But not asking “whether a given theory can predict some outcome of interest”

Failure of theory

- Are our theory really useful?
- Timur Kuran, *Now out of Never: The Element of Surprise in the East European Revolution of 1989*, World Politics **44** (1991), no. 1, 7–48
- In 1987, the American academy of Arts and Sciences invited a dozen of specialist, including several living in Eastern Europe, to prepare interpretive essays on East European developments. . .
- This was publised in the journal *Daedalus*
- “None forsaw what was to happen”.

Failure of theory

- Rational choice theory
  - Mancur Olson, *The Logic of Collective Action*, Harvard University Press, 1965
  - People has incentive to free ride
  - So it predicts the lack of revolution
- Structural theory: revolution occurs when the state becomes weaker
  - Theda Skocpol, *States and Social Revolutions: A Comparative Analysis of France, Russia and China*, Cambridge University Press, 1979
  - Partially gives a prediction
  - But there are many countries with weak state power but no revolution
  - Eastern European countries were certainly not the countries with the weakest state power then
- Both cannot precisely predict the occurence of revolution

Example of Prediction: Google Search and Flu

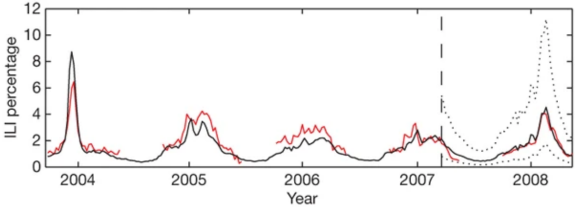
- Can we use big data for prediction?
- Jeremy Ginsberg, Matthew H. Mohebbi, Rajan S. Patel, Lynnette Brammer, Mark S. Smolinski, and Larry Brilliant, *Detecting influenza epidemics using search engine query data*, Nature **457** (2009), no. 7232, 1012–1014
- Background: influenza (flu) tracking system in CDC
  - Patients visit doctors -> doctors make diagnosis -> report to CDC
  - Accurate, but with a lag of weeks
- Using Google Searches to track fluence in real time
  - Intuition: people will search flu-related words, such as "flu symptoms"
  - And the trends of these searches predict ups and downs of flu cases

Google Flu Trends: Details

- 45 search queries related to Influenza-like illness (ILI)
- $Q(t)$: ILI-related query fraction at time t, out of all searches in a geographic region
- $I(t)$: Number of ILI physician visit at time t
- Model: simple linear regression
- $logit(I(t)) = \beta logit(Q(t)) + \epsilon$
- The model was fit using data from 2003 to 2007
- And make predictions for 2008

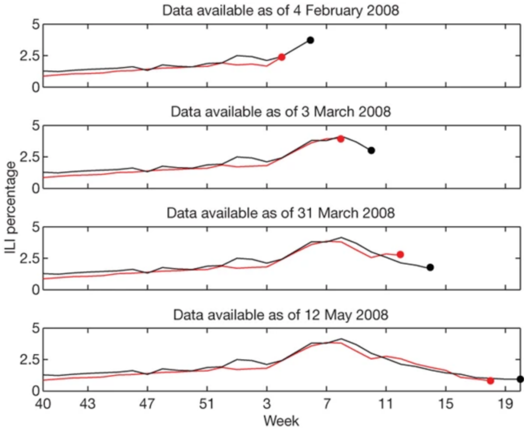
Google Flu Trends: Results

- Red is Google Search; black is CDC's count
- Correlation in 2008 is 0.95



Google Flu Trends: nowcasting

- Nowcasting: predict what will happen in the near future/now
- A weaker and more realizable version of forecasting



Google Flu Trends: discussions

- `https://www.google.com/publicdata/explore?ds=z3bsqef7ki44ac_`
- [In Class Activities]
  - What else you think Google's search trend can predict?
    - `https://trends.google.com/trends/explore?q=covid&geo=US`
  - What do you think are the potential problems of using search queries to predict influenza counts?

Google Flu Trends: Critique 1

- Challenge 1: we can actually use old methods and old data to predict flu
  - Sharad Goel, Jake M. Hofman, Sébastien Lahaie, David M. Pennock, and Duncan J. Watts, *Predicting consumer behavior with Web search*, Proceedings of the National Academy of Sciences **107** (2010), no. 41, 17486–17490
  - $I(t) = \alpha + \beta_1 I(t-2) + \beta_1 I(t-3) + \epsilon$
  - The above autoregressive model achieves similar performances
    - But no need to collect big data! Existing statistics from the CDC is enough
  - "search data are comparable in utility to alternative information soruces, but not necessarily superior"

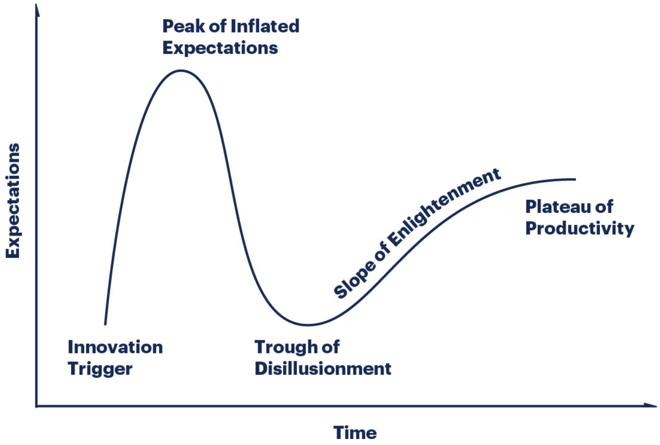
Google Flu Trends: Critique 2

- Drifting
  - Users may change their search behaviors during pandamic period, leading to overrestimation
  - Samantha Cook, Corrie Conrad, Ashley L. Fowlkes, and Matthew H. Mohebbi, *Assessing Google Flu Trends Performance in the United States during the 2009 Influenza Virus A (H1N1) Pandemic*, PLOS ONE **6** (2011), no. 8, e23610
- Algorithm confounding!
  - Google began to suggest related search words
  - David Lazer, Ryan Kennedy, Gary King, and Alessandro Vespignani, *The Parable of Google Flu: Traps in Big Data Analysis*, Science **343** (2014), no. 6176, 1203–1205

Google Flu Trends: Aftermath

- There are tons of media report titled “Google’s Flu Project Shows the Failings of Big Data”
  - `https://time.com/23782/google-flu-trends-big-data-problems/`
- And Google stopped publishing estimate of ILI counts after 2015
  - `https://ai.googleblog.com/2015/08/the-next-chapter-for-flu-trends.html`

Hype Cycle of Using Big Data for Prediction



COVID-19 prediction using search queries

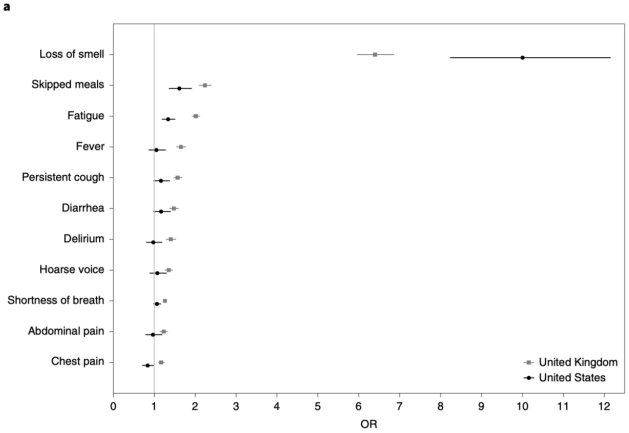
- Google began to release search queries related to COVID-19
  - `https://github.com/google-research/open-covid-19-data/tree/master/data/exports/search_trends_symptoms_dataset`
- Many recent studies (just google “Google Search Predicts COVID”)
  - `https://www.cghjournal.org/article/S1542-3565(20)30922-8/fulltext`
  - Loss of taste and loss of appetite correlated most strongly with the rise in COVID-19 (with a four-week lead)

COVID-19 prediction using survey data

- Cristina Menni, Ana M. Valdes, Maxim B. Freidin, Carole H. Sudre, Long H. Nguyen, David A. Drew, Sajaysurya Ganesh, Thomas Varsavsky, M. Jorge Cardoso, Julia S. El-Sayed Moustafa, Alessia Visconti, Pirro Hysi, Ruth C. E. Bowyer, Massimo Mangino, Mario Falchi, Jonathan Wolf, Sebastien Ourselin, Andrew T. Chan, Claire J. Steves, and Tim D. Spector, *Real-time tracking of self-reported symptoms to predict potential COVID-19*, Nature Medicine **26** (2020), no. 7, 1037–1040
- 2,450,569 individuals who used an app-based symptom tracker.
- 15,368 had a COVID test
- 6,452 tested positive
- 9,186 tested negative

COVID-19 prediction using survey data

- Logistic regression model to predict test results



- Can you think of some shortcomings of this article?

COVID prediction

- Can you think of pros and cons of using search queries and survey data?
- Can you think of other data/information for predicting COVID infection/trends?
- Can you think of other methodological approaches?

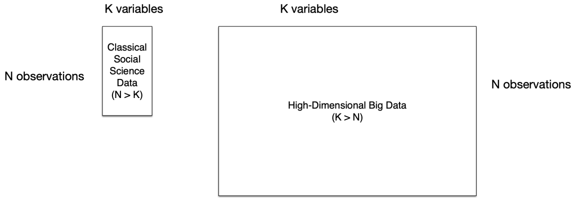
Short summary

- Prediction is different from explanation
- Current social sciences focus too much on explanation, but theory is often not good at prediction
- Predction can be useful for real-world policy problems
- Bear a critical mind! Note the limitations in data source/methods

Learning goals

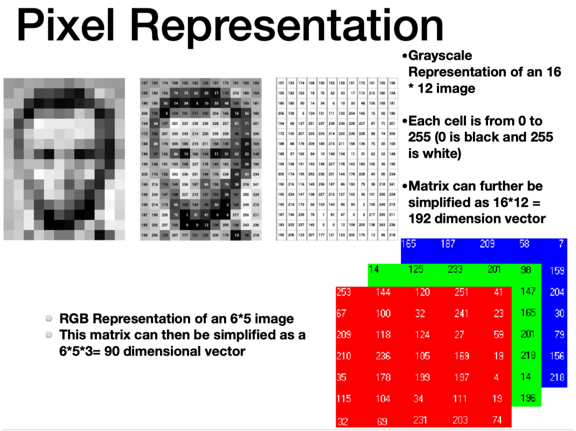
- I am going to introduce intuitions of some important algorithms:
    - LASSO/Ridge/Elastic Net
    - SVM
    - Decision tree and its extensions
        - Bagging trees and random forests
        - Boosting trees
- In tutorial, we will cover how to implement these algorithms in R/Python
- These algorithms are more complex than linear regression; for the same algorithm, you still have different choices to make (called tuning parameters)
- Learning goals:
    - [minimum level]: learn how to implement these algorithms in R/Python
    - [for advanced students]: try to understand the math and detailed options of these algorithms as much as possible

High-dimensional data


K variables
N observations
Classical Social Science Data (N > K)
K variables
High-Dimensional Big Data (K > N)
N observations

- In the previous Google Flu/COVID prediction cases, there are lots of observations and relatively few variables
  - In these two cases, simple regression models are usually okay
- Other times: there are more variables than observations
  - These are typically called high-dimensional data ($K > N$)
- Many data are intrinsically high-dimensional, such as text, images, videos, audio, and networks.

High-dimensional data example: image



Pixel Representation

- **Grayscale Representation of an 16 * 12 image**
- **Each cell is from 0 to 255 (0 is black and 255 is white)**
- **Matrix can further be simplified as 16*12 = 192 dimension vector**

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

- **RGB Representation of an 6*5 image**
- **This matrix can then be simplified as a 6*5*3= 90 dimensional vector**

		165	187	209	58	7
	14	125	233	201	98	159
253	144	120	251	41	147	204
67	100	32	241	23	165	30
209	118	124	27	59	201	79
210	236	105	169	19	218	156
35	178	199	197	4	14	218
115	104	34	111	19	196	
32	69	231	203	74		

- For a typical 800*600 color image, the dimension K is 800*600*3=1.44M
- If the number of observations excels the dimension, you need to have 1.44M images

High-dimensional data and machine learning

- If the data is high-dimensional
- Traditional regression models familiar to social scientists typically do not work very well
- We must use more complex prediction algorithms, called machine learning

Goal of supervised machine learning

- Requirement: a set of input X and output Y as training data
    - These are like examples you provided to computers; supervised
- Goal: find an algorithm $f(\cdot)$, "such that for future X in a test set, $f(X)$ will be a good predictior for Y" (Breiman, 2001)
    - There are many different algorithms
    - We will cover some most common ones
        - Focus on intuition, not formal math derivation

Two types of machine learning in CS

- Predicting continuous outcomes is often called regression tasks
  - Yes linear regressions are a type of machine learning, the simpliest one
- Predicting categorical outcomes is called classification tasks
- Caution: the above are CS notations; they differ from social science terminology.
  - E.g., logistic regression is treated as a classification task in machine learning community

Simplest ML algorithm: regression

- Linear regression: for continuous outcome Y
  - $Y = \beta X$
- Logistic regression: for binary outcome Y
  - $Y = logit^{-1} \beta X$
- Multinomial/ordered logistic regression: categorical/ordinal outcome Y

LASSO and Ridge

- When data dimension is high (e.g., $K > N$)
    - Linear regression fails because it wants to take consideration of all the variables
    - But usually most variables are not relevant
- To make simple regression works, we can force some variables to be irrelevant:
    - LASSO regression: force the coefficient of some variables to be 0
        - Controlled by a parameter λ_1; bigger λ_1 forces more coefficients to be 0
    - Ridge regression: force the coefficient of some variables to be very small
        - Controlled by a parameter λ_2; bigger λ_2 forces more coefficients to be small
- The idea to explicitly make a model simpler is called regularization
- Note that idea is quite counterintuitive: to make a model more effective, sometimes you have to simplify it

LASSO and Ridge: math

- We have p variables
- Linear regression minimizes Mean Squared Error (MSE):

$$\hat{\beta}_{OLS} = argmin_{\beta} \sum_{i=1}^{n} (Y_i - X_i \beta)^2 \tag{1}$$

- Lasso estimator (Tibshirani, 1996, Least Absolute Shrinkage and Selection Operator):

$$\hat{\beta}_{LASSO} = argmin_{\beta} \sum_{i=1}^{n} (Y_i - X_i \beta)^2 + \lambda_1 \sum_{j=1}^{p} |\beta_j| \tag{2}$$

- Ridge estimator (Hoerl and Kennard, 1970; Turgenev, 1943):

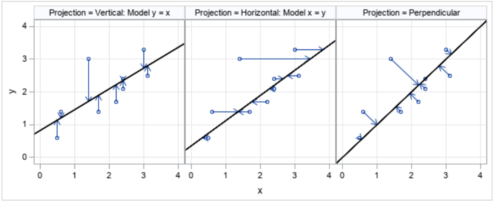
$$\hat{\beta}_{Ridge} = argmin_{\beta} \sum_{i=1}^{n} (Y_i - X_i \beta)^2 + \lambda_2 \sum_{j=1}^{p} \beta_j^2 \tag{3}$$

Elastic Net

- Combine LASSO and Ridge
- With weights λ_1 for LASSO and λ_2 for Ridge
- How do we choose λ_1 for LASSO and λ_2 for Ridge?
    - These are classical examples of tuning parameters.
    - You have to choose them.
- We will discuss this in detail next week

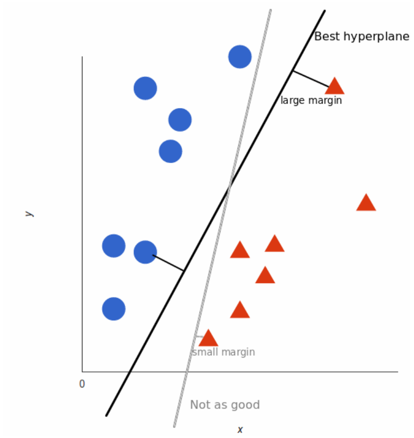
SVM

- SVM is another popular ML algorithm
- Linear regression project observation points vertically onto the "fitted line"
- The left and middle one are linear regressions
- The right one is the simplest "Support Vector Machine" (SVM)
- SVM try to find a line that maximizes the "margins" between data



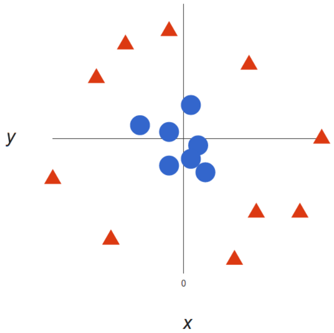
SVM: linear case

- SVM: maximize margin



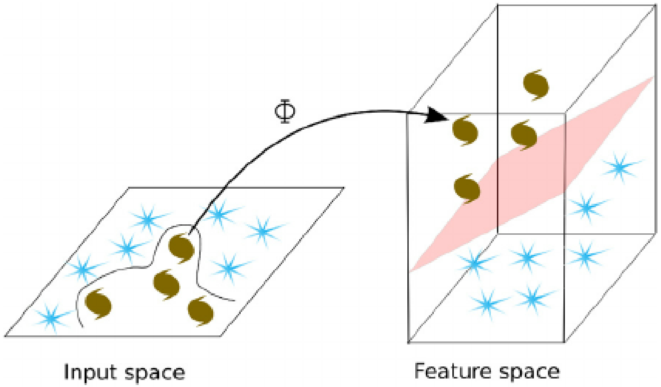
SVM: nonlinear case

- Some data are not linearly separable
- That is, it's mathematically impossible that you write a linear/logistic regression and use different interactions of X to perfectly classify Y



SVM and Kernel Trick

- More complex SVM has a different intuition: transform data from input space (raw inputs) to a higher dimensional feature space that helps the classification
- This transformation is called “kernel trick”

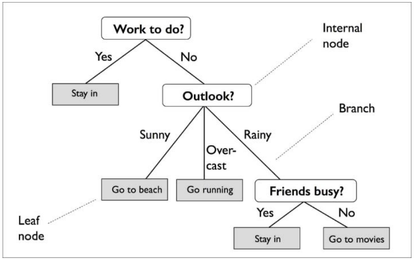


SVM: practice

- Commonly used kernels
  - Linear/polynomial kernel: less powerful. Not able to project the data onto higher dimension.
    - quicker
  - Radial basis function kernel (RBF): more explicitly project the data onto higher dimension, thus is more powerful
    - much slower
- First developed for binary classification; some extensions are made for multiple
- Has dominated the CS literature for a while (in the 90s and early 00s)

Decision Tree

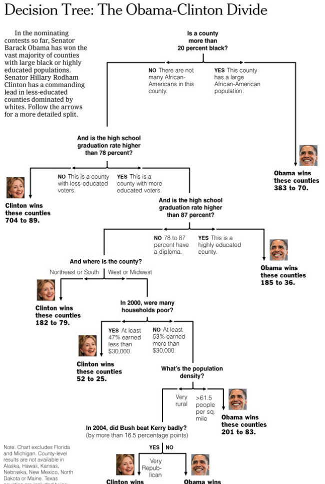
- Decision tree visualizes one's sequential decisions process (Y), based on some predictors (variables)



- Decisions (outcomes) Y are located at leaves
- If you are familiar with linear regression, the rightmost branch has a triple interaction

Decision Tree Example

`https://archive.nytimes.com/www.nytimes.com/imagepages/2008/04/16/us/20080416_OBAMA_GRAPHIC.html?emc=polb1&nl=pol`

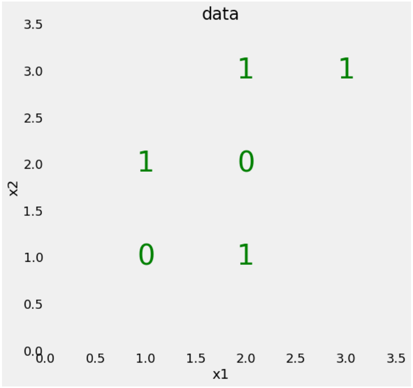

Decision Tree: The Obama-Clinton Divide

In the nominating contests so far, Senator Barack Obama has won the vast majority of counties with large black or highly educated populations. Senator Hillary Rodham Clinton has a commanding lead in less-educated counties dominated by whites. Follow the arrows for a more detailed split.

Note. Chart excludes Florida and Michigan. County-level results are not available in Alaska, Hawaii, Kansas, Nebraska, New Mexico, North Dakota or Maine. Texas

Is a county more than 20 percent black?
NO There are not many African-Americans in this county.
YES This county has a large African-American population.
Obama wins these counties 383 to 70.
And is the high school graduation rate higher than 78 percent?
NO This is a county with less-educated voters.
YES This is a county with more educated voters.
Clinton wins these counties 704 to 89.
And is the high school graduation rate higher than 87 percent?
NO 78 to 87 percent have a diploma.
YES This is a highly educated county.
Obama wins these counties 185 to 36.
And where is the county?
Northeast or South
West or Midwest
Clinton wins these counties 182 to 79.
In 2000, were many households poor?
YES At least 47% earned less than $30,000.
NO At least 53% earned more than $30,000.
Clinton wins these counties 52 to 25.
What's the population density?
Very rural
>61.5 people per sq. mile
Obama wins these counties 201 to 83.
In 2004, did Bush beat Kerry badly? (by more than 16.5 percentage points)
YES
NO
Very Republican
Clinton wins
Obama wins

Growing a Tree by hand



- The above data cannot easily be separated by drawing a straight line (i.e., simplest linear regression)
- Let us draw a tree by ourselves to distinguish $Y = 0$ vs. $Y = 1$, based on X_1 and X_2
  - We want a binary tree: split into two branches

Estimating a tree with software

- Modern statistical software can help you to fit a tree automatically
  - R users: `randomForest` package
  - Python users: `sklearn` package; use `RandomForestClassifier` or `RandomForestRegressor`
- But we have to understand the key decisions these algorithms make:
  - Among many ways to grow a tree, how do we choose a good one?
  - What's the depth of tree?

Decision tree algorithms: some principles

1. Most algorithms typically assume binary tree. Otherwise:
   - For continuous X, we can split it in many ways
   - For categorical X, if the number of levels is large, we can still have a very wide tree
2. What if we there are multiple outcomes on a same leaf?
   - For continuous outcomes, the prediction is the mean
   - For categorical outcomes, the prediction is the mode
3. No need to use all predictors
   - That is, if a variable is not important, no need to use it
4. One predictor can be used multiple times

Desision Tree Algorithms: formal math

- challenging topic
- Decision Tree Algorithms help you to draw a tree from more complex data
- What are the steps we should take?
- Let us first work with continuous outcome Y: regression tree
- There are two questions to consider:
  - Which variable X_j to choose first?
  - We will split X_j into $X_j < s$ and $X_j \geq s$. How do we choose s?
- And the intuitive answer is that:
  - You choose choose X_j and s that best separates Y (thus predicts Y the best)

Decision Tree Algorithms: formal math

- If we write this intuition down mathematically:
- We have p predictors: $X_1, \cdots, X_p$
- For each predictor X_j , calculate its minimum MSE:
  - Consider all it possible cutoffs s. A particular cutoff s will split the data into two regions:

$$R_1(j,s) = \{X|X_j < s\} \text{ and } R_2(j,s) = \{X|X_j \geq s\} \tag{4}$$

  - We should select a s that minimizes the MSE

$$\sum_{i:x_i \in R_1(j,s)} (y_i - \hat{y}_{R_1})^2 + \sum_{i:x_i \in R_2(j,s)} (y_i - \hat{y}_{R_2})^2 \tag{5}$$

  - $\hat{y}_{R_1}$ is the mean response for the training observations in region $R_1(j,s)$
- Select X_j and its s whose MSE is the smallest
- Repeat step 2 and 3 multiple times until reaching certain depth

From One Tree to Many Trees

- Bagging tree (or ensemble of trees): averaging the predictions of many trees
    1. From the original training data, draw a sample with replacement of equal size
    2. Fit a tree for each sample
    3. Repeate 1 and 2 for some times
- Take the mean of estimates of each tree to produce a single estimate for each test data point

Random Forest

- Random Forests further extend the idea of bagging
- The key innovation of random forests:
- For each sample from the original training data, randomly select m variables (not using all p variables), and grow a tree;
  - A common choice: $m = \sqrt{p}$
- In other words, we just force $p - m$ predictors to be non-relevant each time
- Why? High-dimensional data! Needs regularization
- More on this next week

Boosting trees

- Bagging tree and Random Forest create many trees and average them together
  - Each of the tree is independent of the others
- A different idea is to create a sequence of trees that gradually improve over each other
  - These trees are not independent of each other

Boosting trees

- Assume you first fit a decision tree $G_1(X)$
- Bagging trees and random forests: fit another decision $G_2(X)$, totally independent of G_1
  - Then final prediction $Y = \frac{G_1(X)+G_2(X)}{2}$
- Boosting trees: find $G_2(X)$ based on prediction error of the first tree
  1. Learn a second tree $G_2(X)$ to predict $Y - G_1(X)$
  2. Then final prediction $Y = G_1(X) + G_2(X)$
  3. Repeat Step 1 and 2: learn a new tree $G_3(X) = Y - G_1(X) - G_2(X)$, and so on.
- Essentially, boosting trees find data points that previous algorithms are most likely to be wrong, and improve the algorithm on these points.

Boosting trees vs Random Forests

- You man hear may different variants of trees
    - AdaBoost is the first and Gradient Boosting Tree is the most successful
- Gradient Boosting Tree (GBT) and Random Forests (RF) are typically the two best methods you can get
    - GBT typically works well then the dimension is not that high
    - RF works well when the dimension is very high

Next week

- More discussions on regularization
- Evaluation and selection of ML algorithms