SOSC 4300/5500: Prediction

Han Zhang

Sep 15, 2020

Outline

Logistics

- Grouping?

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- Git basics:

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    - Are everyone able to commit/push at least once?

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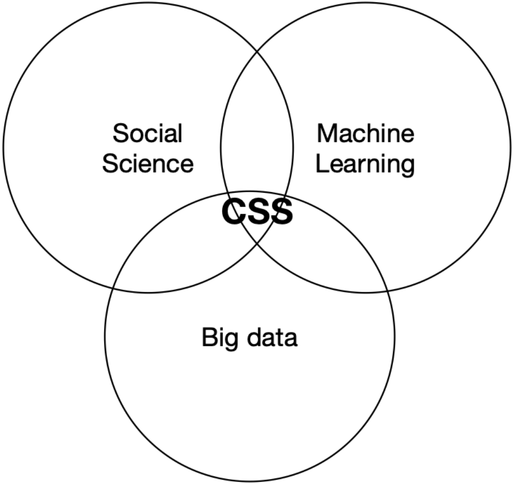
  - Wait for further notice

Computational Social Science (CSS)

- Next we focus predictive models, using on machine learning



Prediction vs. Explanation

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- [In class activities]: Can you give other examples? Type it in chatbox!

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  - Prediction: Whether Trump of Clinton will win the election?

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  - Prediction: Whether Trump of Clinton will win the election?
  - Explanation: Why Trump won?
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Prediction vs. Explanation: the ideal case

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- Predictive: we can precisely predict location of planets in solar system
- And explanative: we have a theory on why it's the case

Prediction vs Explanation in Social Sciences

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  - 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

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- Both cannot precisely predict the occurence of revolution

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  - And the trends of these searches predict ups and downs of flu cases

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- And make predictions for 2008

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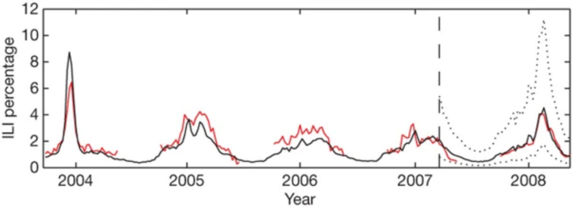
- Red is Google Search; black is CDC's count



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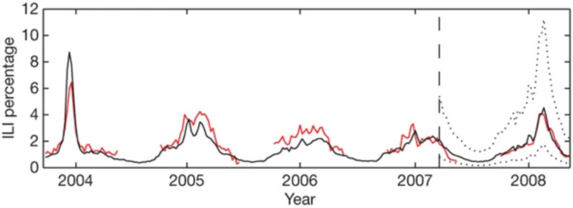

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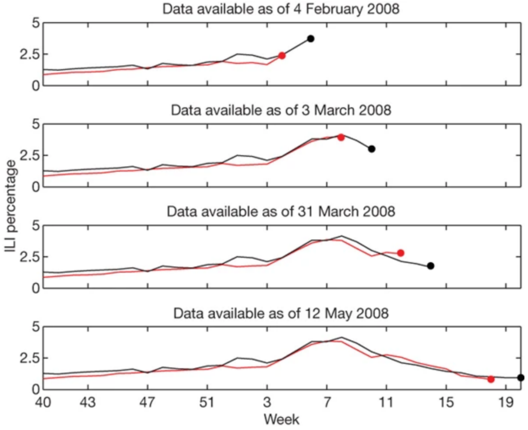

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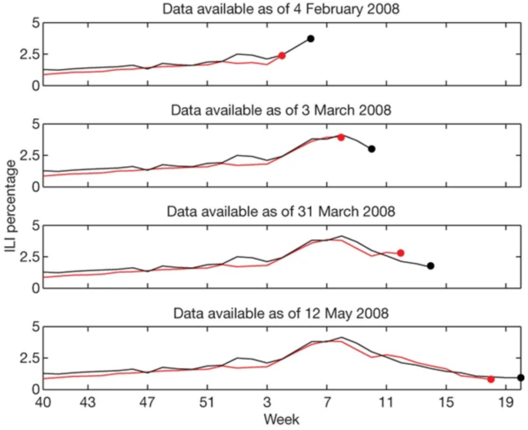
- A weaker and more realizable version of forecasting



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  - What do you think are the potential problems of using search queries to predict influenza counts?

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    - "search data are comparable in utility to alternative information soruces, but not necessarily superior"

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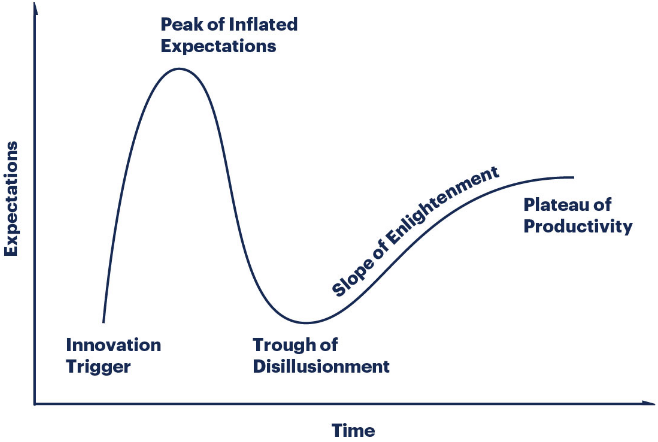
Hype Cycle of Using Big Data for Prediction



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  - Loss of taste and loss of appetite correlated most strongly with the rise in COVID-19 (with a four-week lead)

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- Predction can be useful for real-world problems
- But bear a critical mind

Prediction and Explanation using statistics

- Leo Breiman, *Statistical Modeling: The Two Cultures (with comments and a rejoinder by the author)*, Statistical Science **16** (2001), no. 3, 199–231. MR1874152

Social scientists/statisticans	Computer scientists/data scientists
Data modeling	Algorithmic modeling
Traditional regression models	Machine learning
$Y = \color{red}{\beta} X$	$\color{red}{Y} = \beta X$
Explanation	Prediction

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  Assume that the data are generated by the following model

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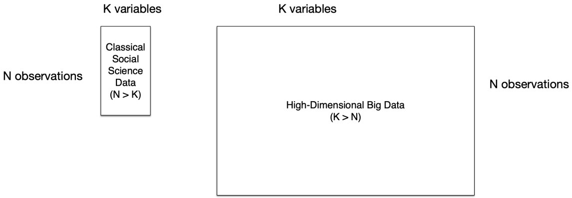
- But why? We know the assumptions are mostly wrong
- Why not use more powerful models (machine learning), if the goal is prediction?

Why Machine Learning? I



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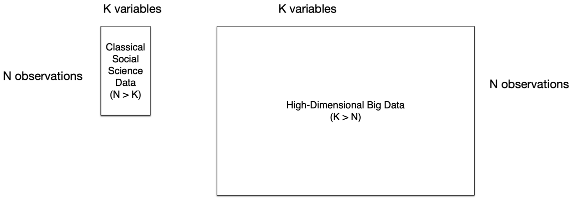

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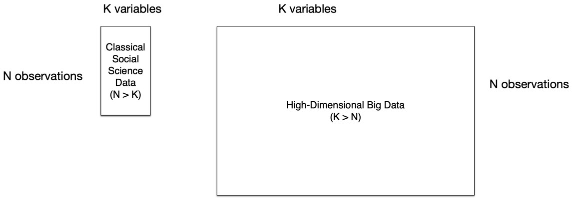

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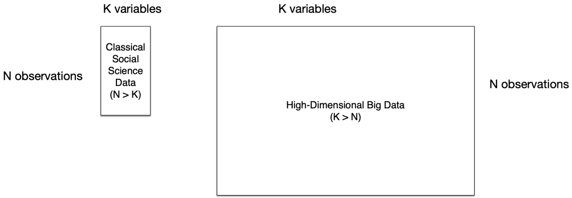

- Big data are not only big (large N)
- They are also high-dimensional ($K > N$)
- This is known as curse of dimensionality
- And traditional regression models familiar to social scientists do not work very well with high-dimensional data

Why Machine Learning? II

- When $K > N$, standard regression models do not have unique solutions

Picture 1

$$\begin{aligned} y = &\ 2.1 + 3.8x_3 - 0.6x_8 + 83.2x_{12} \\ &- 2.1x_{17} + 3.2x_{27}, \end{aligned}$$

Picture 2

$$\begin{aligned} y = &\ -8.9 + 4.6x_5 + 0.01x_6 + 12.0x_{15} \\ &+ 17.5x_{21} + 0.2x_{22}, \end{aligned}$$

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- The below three models may all good solutions

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Goal of machine learning

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  - Yes linear regressions are a type of machine learning, the simpliest one
- Predicting categorical outcomes is called classification tasks
  - Slightly differnet notation: logistic regression is treated as a classification task in machine learning community

Next steps

- From week 4, we will see how machine learning techniques are used in text data

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  - E.g., random guesses
  - So that you are not spending time/resource and find that you are only slightly better than a very simple method

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- We found that 99% of our predictions are correct. Yeah!
- But wait, is that good enough?

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  - But it's not useful at all!

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- recall $= \frac{TP}{TP+FN}$
  - interpretation: what proportion true positives are identified by predictions?

Case 1: high precision/ low recall

Actual

Prediction		1/positive	0/negative
	1/positive	True Positive (n = 5)	False Positive (n =0)
	0/negative	False Negative (n = 5)	True Negative (n = 9990)

- Accuracy: $\frac{9+9986}{10000} = 99.95\%$

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- So every predicted infected case is indeed infected
- But we missed 50% of actual infected cases

Case 2: high recall/low precision

		Actual: 1/positive	Actual: 0/negative
Prediction	1/positive	True Positive (n = 9)	False Positive (n = 4)
Prediction	0/negative	False Negative (n = 1)	True Negative (n = 9986)

- We lower the threshold to be considered as infection case

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- Our prediction captures 90% of actual infected cases
- But less than 70% predicted cases are actually infected; false alarm

Trivial prediction: Majority Class

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		1/positive	0/negative
Prediction	1/positive	True Positive (n = 0)	False Positive (n = 0)
	0/negative	False Negative (n = 10)	True Negative (n = 9900)

- Predict the majority class (no one is affected)

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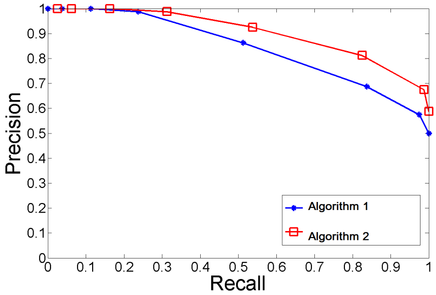
- F-1 score: balancing the two $2 * \frac{precision * recall}{precision + recall}$

Precision-recall curve

- We can find a trade-off by using precision-recall curve



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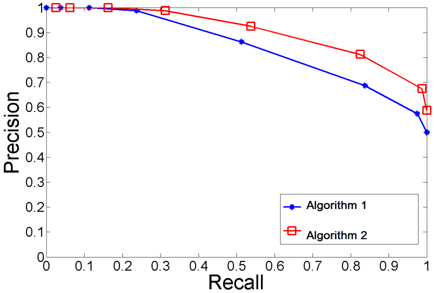

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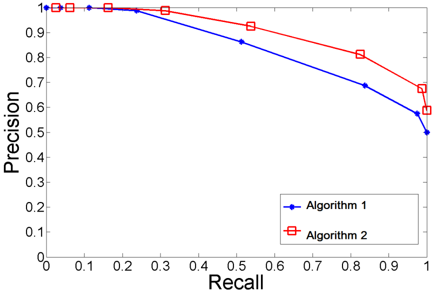

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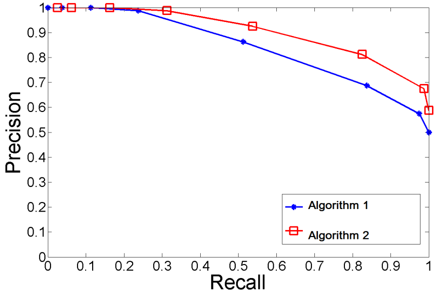
- Large threshold ϕ -> high precision



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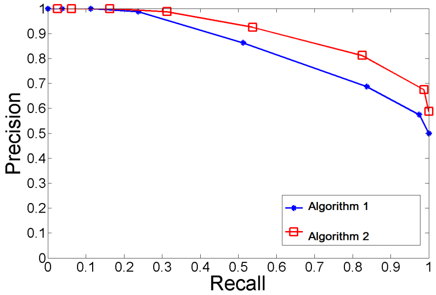

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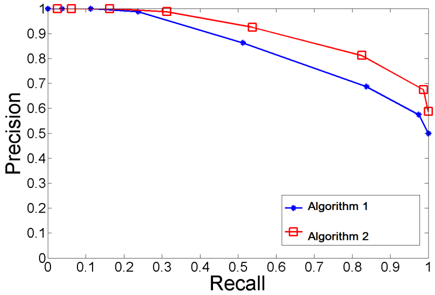
- Algorithm 2 is better than 1



ROC curve

- Another common measure is called ROC curve

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- True positive rate (i.e., recall): $\frac{TP}{TP+FN}$

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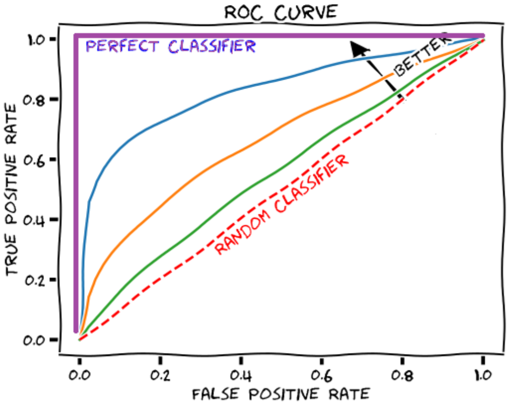
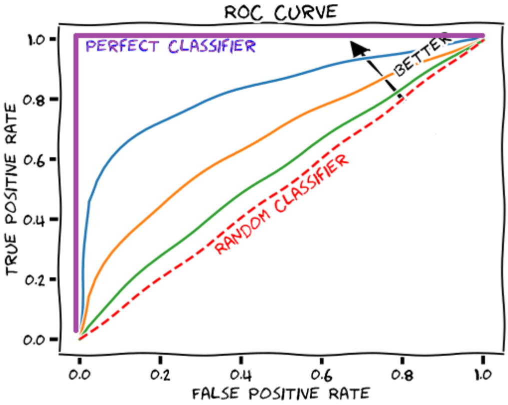


- AUC: area under the curve

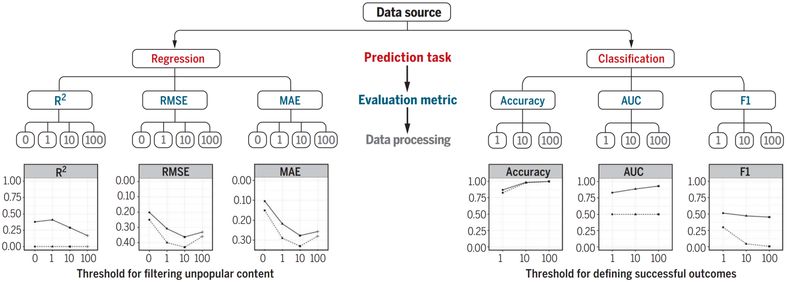
ROC curve



- AUC: area under the curve
- Bigger AUC -> better prediction performance

Summary of evaluation characteristics

- Jake M. Hofman, Amit Sharma, and Duncan J. Watts, *Prediction and explanation in social systems*, Science **355** (2017), no. 6324, 486–488



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- Trends of influenza counts may be easier

Summary

- Critical evaluation of prediction problem vs. explanation problem

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- Knowledge:

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- Knowledge:
    - What is high-dimensional data?

Summary

- Critical evaluation of prediction problem vs. explanation problem
- Knowledge:
  - What is high-dimensional data?
  - What is train-split

Summary

- Critical evaluation of prediction problem vs. explanation problem
- Knowledge:
  - What is high-dimensional data?
  - What is train-split
  - Evaluations

Next week

- Survey and Big Data