

Data Mining

CS 5140 / CS 6140

Jeff M. Phillips

January 12, 2015

Data Mining

What is Data Mining?

- ▶ Finding structure in data?
- ▶ Machine learning on large data?
- ▶ Unsupervised learning?
- ▶ Large scale computational statistics?

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-
- ▶ How to think about data analytics.

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- ▶ Unsupervised learning?
- ▶ Large scale computational statistics?

- ▶ How to think about data analytics.

- ▶ What you can recover from data and what you cannot recover.
- ▶ Algorithms for how to recover it efficiently.

Modeling versus Efficiency

Two Intertwined (and often competing) Objectives:

- ▶ Model Data Correctly
- ▶ Process Data Efficiently



Machine Learning

Mondays + Wednesdays @ 3:00 - 4:20 in WEB L102

CS 5350 *Machine Learning*

CS 6350 *Machine Learning*

Vivek Srikumar

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Vivek Srikumar

Classification: Given data labeled $\{\text{TRUE} = +\}$ or $\{\text{FALSE} = -\}$,
given new data, guess a label.

More continuous optimization (DM more discrete)

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Every university teaches data mining differently!

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What flavor is offered in this class:

- ▶ Focus on techniques for *very* large scale data
- ▶ Broad coverage ... with recent developments
- ▶ Formally and generally presented (proof sketches)
- ▶ ... but useful in practice (e.g. internet companies)
- ▶ Probabilistic algorithms: connections to CS and Stat

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Maths: Linear Algebra, Probability, High-dimensional geometry

Outline

Statistical Principals:

- ▶ 1. **Understanding random effects**

Data and Distances:

- ▶ 2. **Similarity** (find duplicates and similar items)
- ▶ 3. **Clustering** (aggregate close items)

Structure in Data:

- ▶ 3. **Clustering** (aggregate close items)
- ▶ 4. **Regression** (linearity of (high-d) data)
- ▶ 5. **Noisy Data** (anomalies in data)

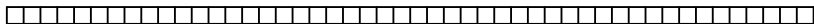
Controlling for Noise and Uncertainty:

- ▶ 5. **Noisy Data** (anomalies in data)
- ▶ 6. **Link Analysis** (prominent structure in large graphs)

Statistical Principals

What happens as data is generated with replacement
{IP addresses, words in dictionary, edges in graph, hash table}

- ▶ When do items collide?
- ▶ When do you see all items?
- ▶ When is the distribution almost uniform?



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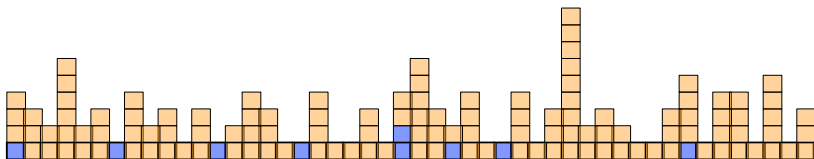
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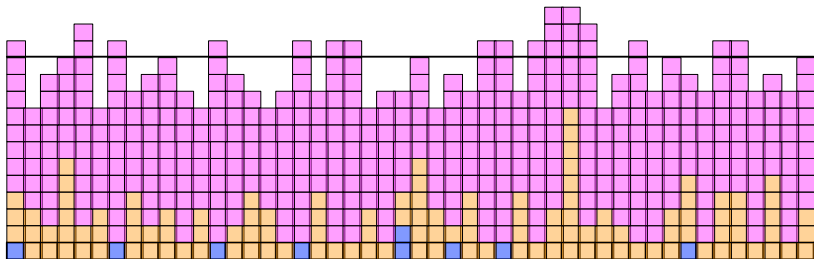
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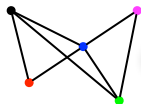



Raw Data to Abstract Representations

How to measure similarity between data?

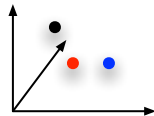
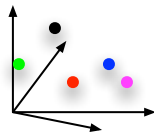
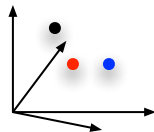
Key idea: data \rightarrow point

a quick brown fox jumped ...



	1	1	1	
1		1		
1	1		1	1
1		1		1
		1	1	

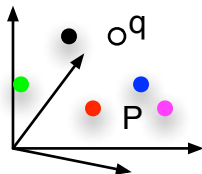
	age	income	height
joe	25	90K	1.85
bob	32	45K	1.52
sue	28	38K	1.61



Similarity

Given a large set of data P .
Given new point q , is q in P ?

Given a large set of data P .
Given new point q , what is *closest* point in P to q ?



Clustering

How to find groups of similar data.

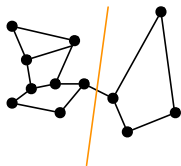
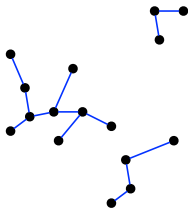
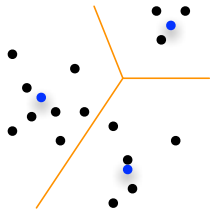
- ▶ do we need a representative?
- ▶ can groups overlap?
- ▶ what is structure of data/distance?

Clustering

How to find groups of similar data.

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- ▶ can groups overlap?
- ▶ what is structure of data/distance?

- ▶ **Hierarchical clustering** : When to combine groups?
- ▶ ***k*-means clustering** : *k*-median, *k*-center, *k*-means++
- ▶ **Graph clustering** : modularity, spectral



Clustering Class

Thursdays @ 10:45-12:05 in WEB 1248

CS 6955 *Clustering*

Suresh Venkatasubramanian

full semester on area we spend 3 lectures

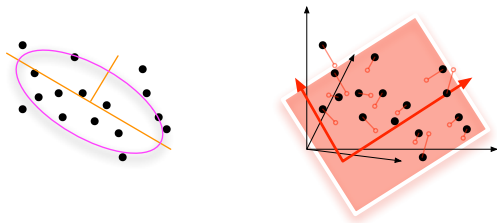
Regression

Consider a data set $P \in \mathbb{R}^d$, where d is BIG!

Want to find representation of P in some \mathbb{R}^k

$\mu(P) \rightarrow Q \in \mathbb{R}^k$ so $\|p_i - p_j\| \approx \|q_i - q_j\|$

$Q \in \mathbb{R}^k$ should capture most data in P



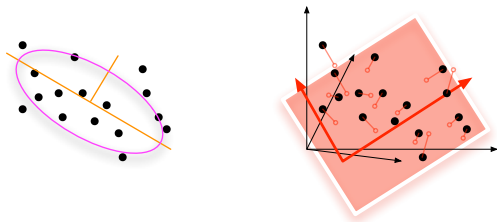
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- ▶ **L_2 Regression + PCA** : Common easy approach
- ▶ **Multidimensional Scaling** : Fits in \mathbb{R}^k with k small
- ▶ **Random Projections** : Faster and easier (different bounds)
- ▶ **L_1 Regression** : “Better”, Orthogonal Matching Pursuit
- ▶ **Special Topic** : Compressed Sensing

Matrix Sketching

Fridays @ 1:45-3:00 in MEB 3147 (LCR)

CS 7931 *Data Mining Seminar*

CS 6961 *Advanced Topic in Data*

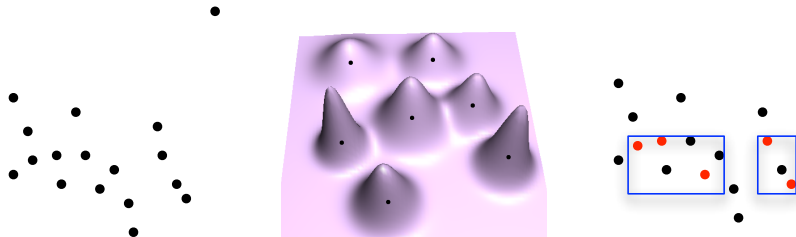
Jeff Phillips

full semester on area we spend 1 lectures
can be taken for **1** credit

Noisy Data

What to do when data is noisy?

- ▶ **Identify it** : Find and remove outliers
- ▶ **Model it** : It may be real, affect answer
- ▶ **Exploit it** : Differential privacy (*ethics in data*)

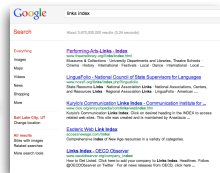
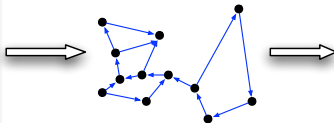


Link Analysis

How does Google Search work?

Converts webpage links into directed graph.

- ▶ **Markov Chains** : Models movement in a graph
- ▶ **PageRank** : How to convert graph into important nodes
- ▶ **MapReduce** : How to scale up PageRank
- ▶ **Communities** : Other important nodes in graphs



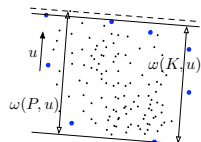
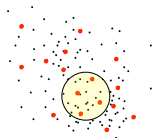
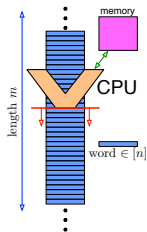
Summaries

Reducing *massive* data to small space.

Want to retain as much as possible (not specific structure)

error guarantees

- ▶ **OnePass Sampling** : Reservoir Sampling
- ▶ **Density Approximation** : Quantiles
- ▶ **MinCount Hash** : Sketching data, \rightarrow abstract features
- ▶ **Spanners** : graph approximations
- ▶ **[...]** : ... on request ...



Themes

What are course goals?

- ▶ Intuition for data analytics
- ▶ How to model data (convert to abstract data types)
- ▶ How to process data efficiently (balance models with algorithms)

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Work Plan:

- ▶ 2-3 weeks each topic.
 - ▶ Overview classic techniques
 - ▶ Focus on modeling / efficiency tradeoff
 - ▶ Special topics
 - ▶ Short homework for each (analysis + with data) (45% **grade**)
- ▶ 2 Quizzes (10% **grade**)
- ▶ Course Project (45% **grade**).
 - ▶ Focus on specific data set
 - ▶ Deep exploration with technique
 - ▶ Ongoing refinement of presentation + approach

On Homeworks

Managed through Canvas (will be up by end of week)

- ▶ No restriction on programming language.
- ▶ Some designed for matlab, others better in python or C++.
- ▶ Programming assignments with not too many specifications.
- ▶ Bonus Questions!

Data Group

Data Group Meeting

Thursdays @ 12:15-1:30 in MEB 3147 (LCR)

CS 7941 *Data Reading Group*
requires one presentation if taken for credit

<http://datagroup.cs.utah.edu>

<http://www.utahdataanalyticssummit.com>

UTAH DATA & ANALYTICS SUMMIT

Thurs, Jan 22, 2015 | 9 AM – 2 PM

Register [free] at www.utahdataanalyticssummit.com

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