

STAT 339

Probabilistic Modeling and Machine Learning

30 January 2017

Colin Reimer Dawson

Outline

Data Science and Machine Learning

Types of Learning

- Supervised Learning

- Unsupervised Learning

Discovering Model Complexity

Course Outline

Data is the new black



“DATA IS THE NEW GOLD”

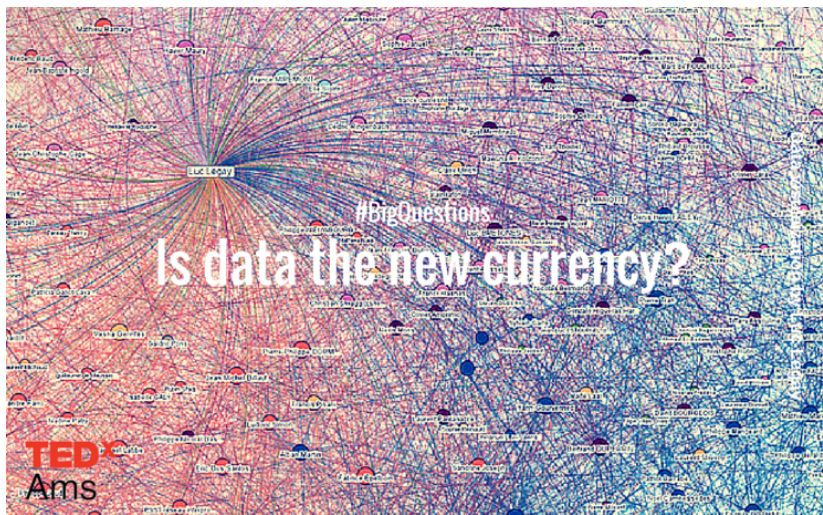


S

DATA

IS THE **NEW** OIL

but do you have the resource to refine it?



'DATA' IS THE NEW CURRENCY

WHAT OPPORTUNITIES ARE YOU MISSING?



LOTAME®

Data is the New Currency to power
Attribution

Prepared by **Evgeny Popov**

Some Cool Things you can do with data

Recommendation Systems

Frequently Bought Together



Price for both: \$164.76

[Add both to wish list](#)

[Show availability and shipping details](#)

of This Item: Numerical Analysis (2nd Edition) (Featured Title for Numerical Analysis) by
 Student Solutions Manual for Numerical Analysis by Timothy Sauer: \$24.00

Customers Who Bought This Item Also Bought



Student Solutions Manual
for Numerical Analysis
Timothy Sauer
\$24.00 [off price](#)



Molecular Driving Forces:
Statistical
+ Real & Dill
\$49.95 [off price](#)

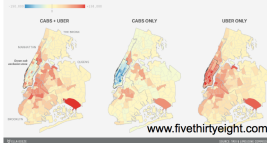


Fluid Mechanics with
Student CD-ROM
Frank White
\$101.00 [off price](#)

Data-Driven Journalism

Are Ubers Supplementing Or Replacing Cabs?

Change in number of Uber and taxi pickups by taxi zone, April-June 2014 versus April-June 2015

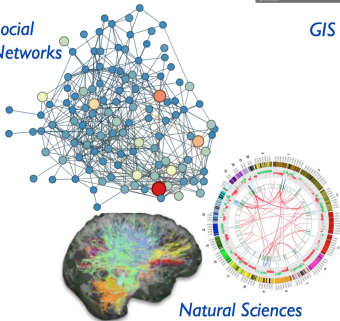


Competitive State Summary

State	EV	O	R	Forecast	90% Prediction Interval	%
ME	2	159	355	Obama +0.9	+0.0, -0.9	94%
ME-2	1	154	354	Obama +0.2	+0.0, -0.9	94%
OR	7	191	347	Obama +7.9	+0.0, -0.3	98%
MI	18	297	331	Obama +7.2	+0.0, -0.4	98%
IN	10	217	321	Obama +7.5	+0.0, -0.4	98%
PA	20	237	331	Obama +5.1	+0.0, -0.9	96%
WI	12	247	291	Obama +4.0	+0.0, -0.6	96%
WV	6	253	285	Obama +3.5	+0.0, -0.6	95%
IA	6	259	279	Obama +2.9	+0.0, -0.3	78%
NH	4	263	275	Obama +2.8	+0.0, -0.6	75%
OH	16	341	247	Obama +0.5	+0.0, -0.2	80%
CO	9	290	240	Obama +1.1	+0.0, -0.9	83%
VA	13	353	235	Obama +0.8	+0.0, -0.8	81%
NL	20	332	226	Romney +0.7	+0.0, -0.3	59%
NC	15	347	191	Romney +2.5	+0.0, -0.9	81%
NE-2	1	340	190	Romney +0.5	+0.0, -0.9	94%
AZ	11	259	179	Romney +7.8	+0.0, -0.7	97%
MD	10	309	189	Romney +0.0	+0.0, -0.5	99%
GA	16	385	153	Romney +9.7	+0.0, -0.5	100%
MT	3	380	150	Romney +9.7	+0.0, -0.4	96%

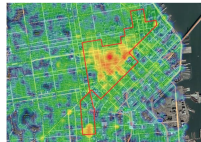
Political Science

Social Networks

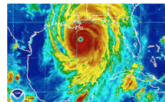


Natural Sciences

GIS / Development / Public Policy



Meteorology / Climate Science



Sports

Finance



Thanks to David Shuman at Macalester College for this slide

What is Machine Learning?

"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 ."

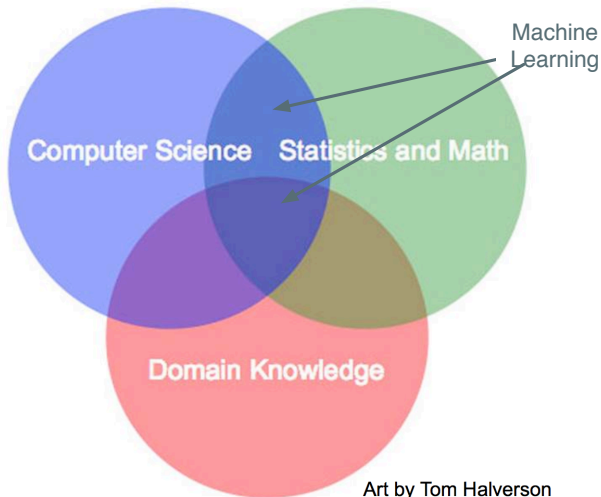
— Tom Mitchell

What is Machine Learning?

"[Machine Learning is a] field of study that gives computers the ability to learn without being explicitly programmed."

— Arthur Samuel

Statistics, Computer Science, and Machine Learning



Machine Learning



what society thinks I
do



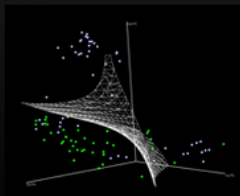
what my friends think
I do



what my parents think
I do

$$\begin{aligned}L_T &= \frac{1}{2} \|\mathbf{w}\|^2 - \sum_{i=1}^n \alpha_{i,Y_i} (\mathbf{x}_i \cdot \mathbf{w} + b) + \sum_{i=1}^n \alpha_i \\ \alpha_i &\geq 0, \forall i \\ \mathbf{w} &= \sum_{i=1}^n \alpha_{i,Y_i} \mathbf{x}_i, \sum_{i=1}^n \alpha_{i,Y_i} = 0 \\ \nabla \hat{g}(\theta_t) &= \frac{1}{n} \sum_{i=1}^n \nabla \ell(x_i, y_i; \theta_t) + \nabla f(\theta_t) \\ \theta_{t+1} &= \theta_t - \eta_t \nabla \ell(x_{i(t)}, y_{i(t)}; \theta_t) - \eta_t \cdot \nabla f(\theta_t) \\ \mathbb{E}_{i(t)}[\ell(x_{i(t)}, y_{i(t)}; \theta_t)] &= \frac{1}{n} \sum_i \ell(x_i, y_i; \theta_t).\end{aligned}$$

what other programmers
think I do



what I think I do

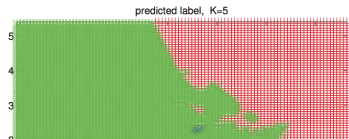
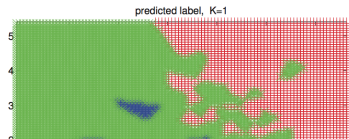
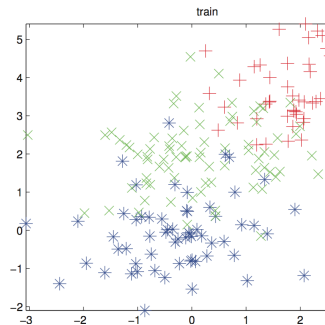
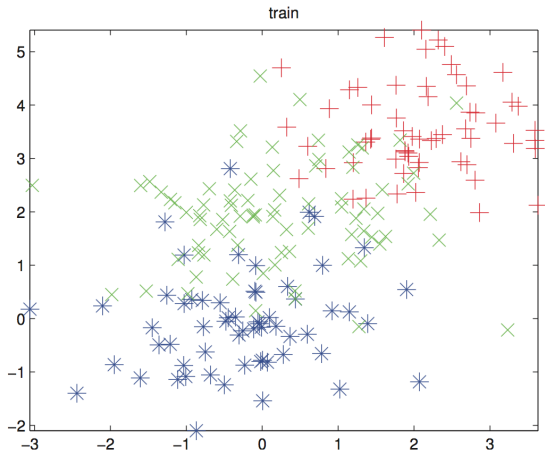
```
>>> from scipy import SVM
```

what I really do

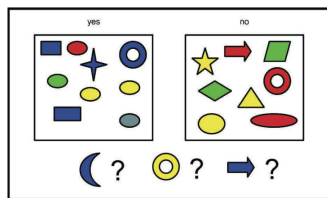
Types of Learning

- ▶ Supervised Learning: Learning to make predictions when you have many examples of “correct answers”
 - ▶ Classification: answer is a category / label
 - ▶ Regression: answer is a number
- ▶ Unsupervised Learning: Finding structure in unlabeled data
- ▶ Reinforcement Learning: Finding actions that maximize long-run reward (not part of this course)

Supervised Learning



Supervised Learning with a Probabilistic Model



(a)

D features (attributes)			Label
Color	Shape	Size (cm)	
Blue	Square	10	1
Red	Ellipse	2.4	1
Red	Ellipse	20.7	0

(b)

- ▶ Training data: $\{(t_i, \mathbf{x}_i)\}_{i=1}^n$; t_i = label, $\mathbf{x}_i$ = features.
- ▶ Fit a model of all of the features: $P(\mathbf{x}, t)$, or $P(t|\mathbf{x})$
- ▶ Testing: Assign $P(t_{new}|\mathbf{x}_{new}, \text{Model})$

Data in Higher Dimensions



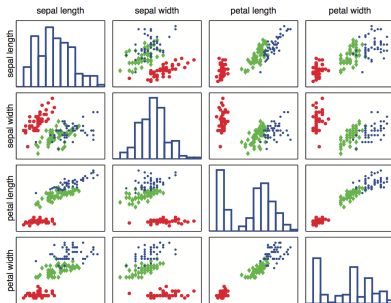
(a)



(b)



(c)



Data in Very High Dimensions

true class = 7



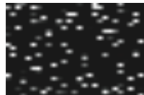
true class = 2



true class = 1



true class = 7



true class =



true class = 0



true class = 4



true class = 1



true class = 0



true class =



true class = 4



true class = 9



true class = 5



true class = 4



true class =



Aside: Feature Extraction (“Eigenfaces”)



(a)



principal basis 2

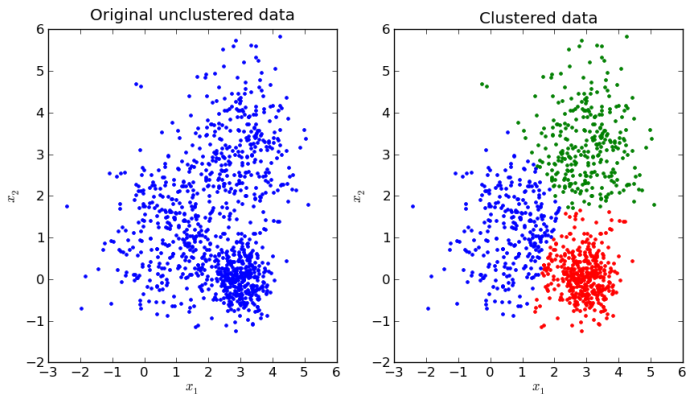


principal basis 3



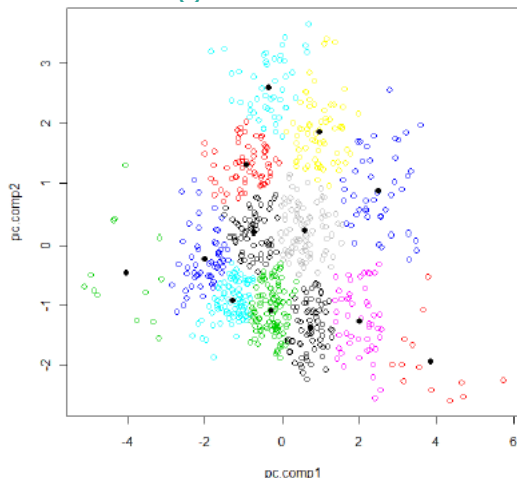
(b)

Finding Clusters



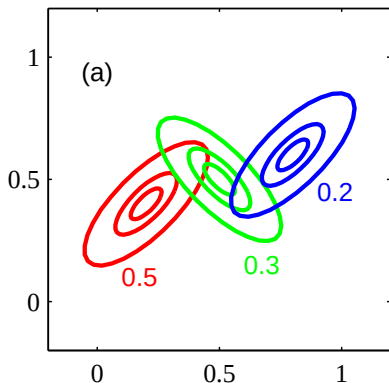
- Clustering: Grouping data into categories without any “ground truth” information
- Example Application: Modeling people’s taste in movies

Model-Free Clustering



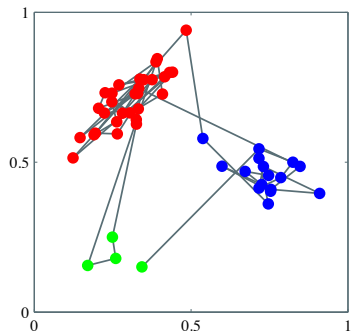
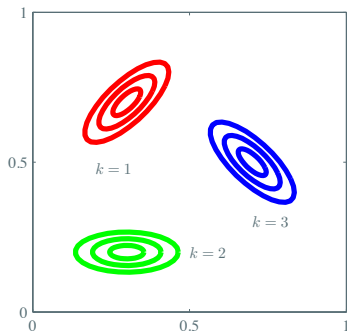
Model-free example: Given a distance metric, maximize distances among cluster centers; then assign points to closest center.

Clustering with a Probabilistic Model



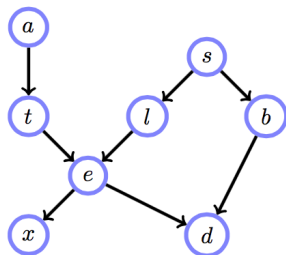
Output: A set of cluster weights and a probability distribution for each cluster

Clustering With Time



- ▶ We can combine a model of clusters with a model of how observations “transition” between clusters.
- ▶ Example: Speech recognition

Probabilistic Graphical Models



x = Positive X-ray

d = Dyspnea (Shortness of breath)

e = Either Tuberculosis or Lung Cancer

t = Tuberculosis

l = Lung Cancer

b = Bronchitis

a = Visited Asia

s = Smoker

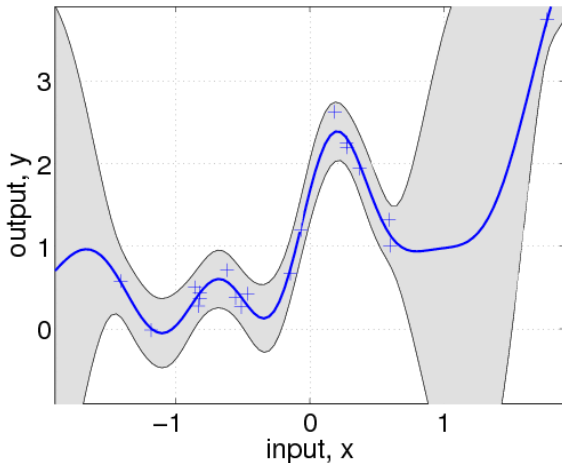
Figure: Probabilistic Graphical Model for Medical Diagnosis.

- ▶ “Probabilistic Graphical Models”: learn joint distribution of several variables using a graph of relationships to impose structure
- ▶ Example: Medical diagnosis

Parametric Vs. Nonparametric Models

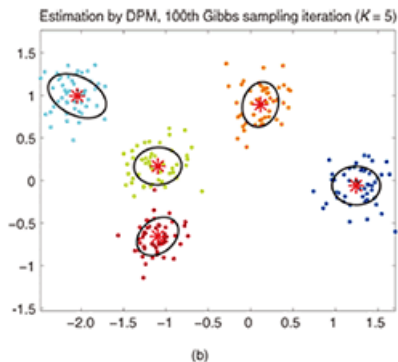
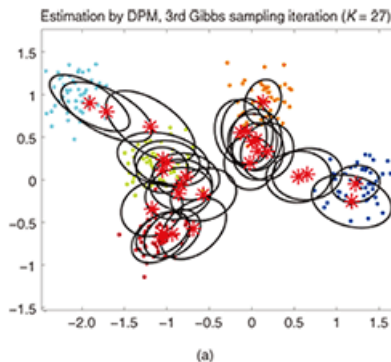
- ▶ A **parametric** model has a fixed degree of complexity, regardless of the amount of data
 - ▶ Examples: linear regression, clustering w/ fixed # of clusters, neural networks
- ▶ A **nonparametric** model can adaptively “grow” its complexity as the amount of data grows (effectively they have “infinite” complexity)
 - ▶ Examples: “Nearest neighbors” classification, Gaussian Process regression, clustering w/ unknown number of clusters

Gaussian Process Regression



GP Regression: Assume a “smooth” function, but allow the amount of wiggleness adapt to the data

“Infinite” Clustering Model



Infinite Mixture Model: Assume “infinitely many” clusters, and figure out which ones appear in the data

Infinite Dynamic Clustering Model

Course Outline

- ▶ Course Website: <http://colindawson.net/stat339>
- ▶ Syllabus, slides, handouts, homework, demos available there
- ▶ Exception: HW Solutions (on Blackboard)
- ▶ Also on Blackboard: electronic submission of assignments

Course Outline

- ▶ Part I: Basic ML Ideas (2 weeks)
- ▶ Part II: Probabilistic Modeling (4 weeks)
- ▶ Part III: Unsupervised and Latent Variable Models (3 weeks)
- ▶ Part IV: Nonparametric Models (2 weeks)
- ▶ Part V: Selected Non-Probabilistic Methods (1-2 weeks)

Graded Components

- ▶ Problem Sets (40% across ~ 6 assignments)
- ▶ Take-home Midterm (20%; about a week before spring break)
- ▶ Group Project and Presentation (30%)
- ▶ In-Class Written Reflections (10%)

See the syllabus for Honor Code guidelines

Prerequisite Skills/Knowledge

- ▶ Key background: Derivatives and integrals, some familiarity with structure of data (kinds of variables, etc.), basic regression, some familiarity with functions, variables, arguments, etc.
- ▶ Programming experience helpful; not required, but if you don't have any you will need to put in some extra effort in the first few weeks to get up to speed
- ▶ Different from CS 374 in emphasis on models and probabilistic reasoning (less emphasis on coding)

Homework 0 (Optional)

- ▶ Do online tutorials (see website) to familiarize yourself with a programming language (suggest Octave if you have no experience, Python if you want to invest in a longer-term skill)
- ▶ First problem set (optional) due a week from today; chance to get up to speed with basic coding ideas
- ▶ You will need to look things up for yourself frequently, but helpful links/references are provided