

Machine Learning



Study of algorithms that

- improve their <u>performance</u>
- at some task
- with <u>experience</u>

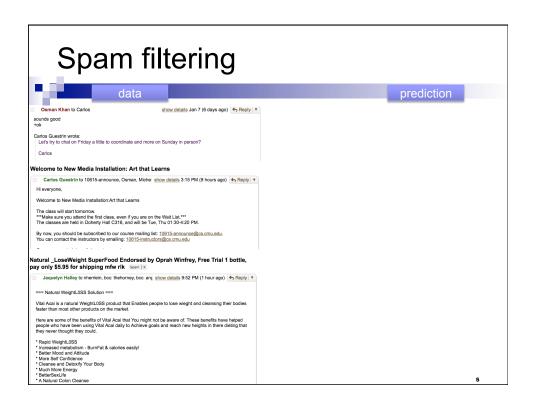


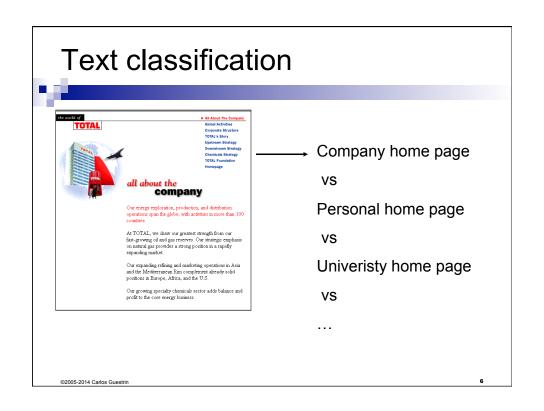
©2005-2014 Carlos Guestria

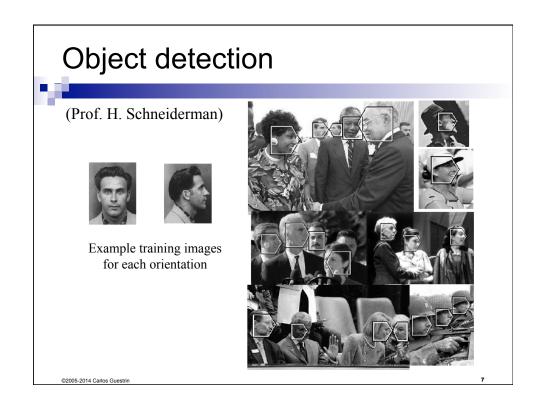
Classification

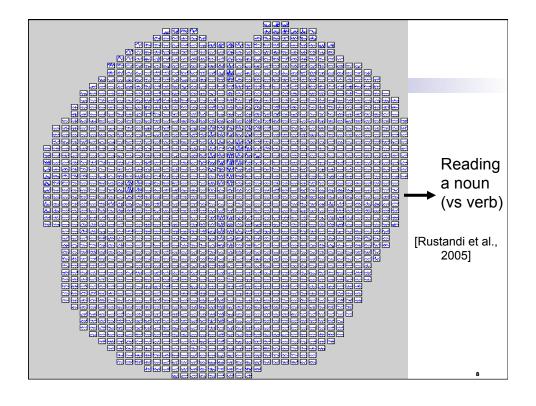
from data to discrete classes

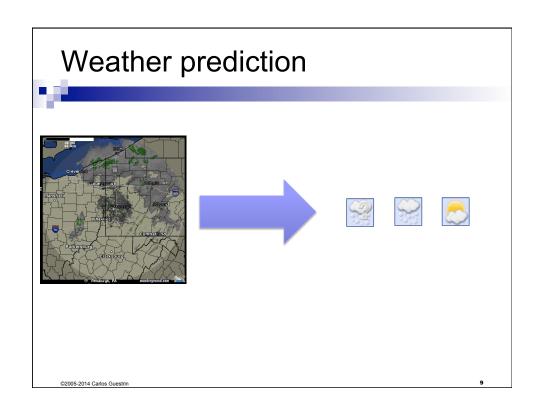
©2005-2014 Carlos Guestrin

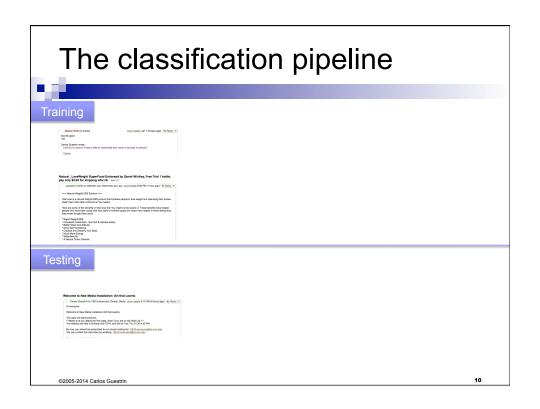


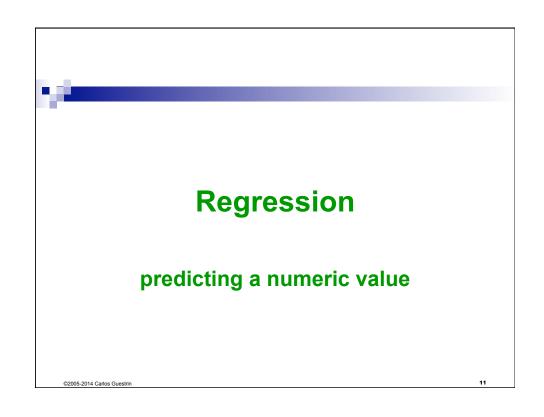




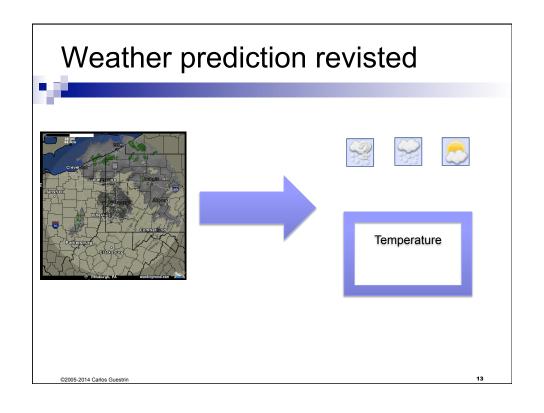


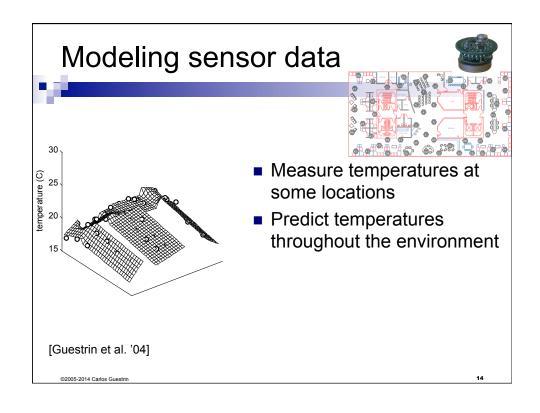


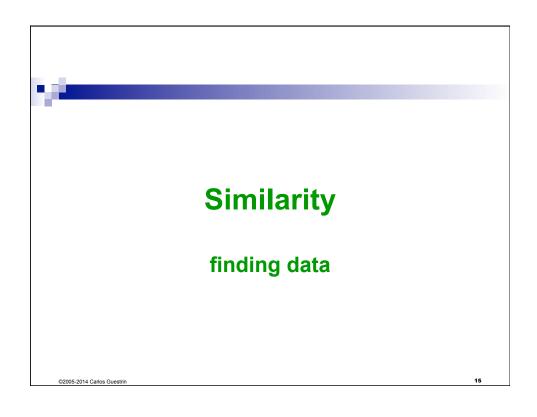


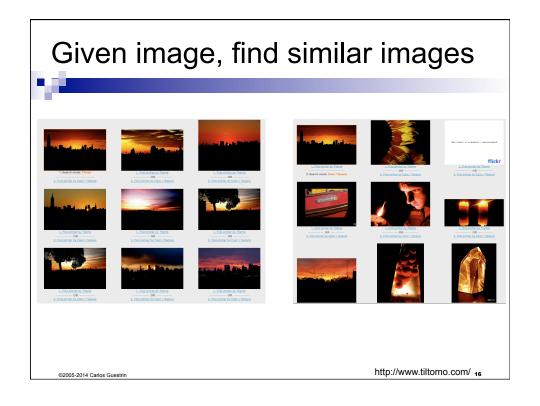


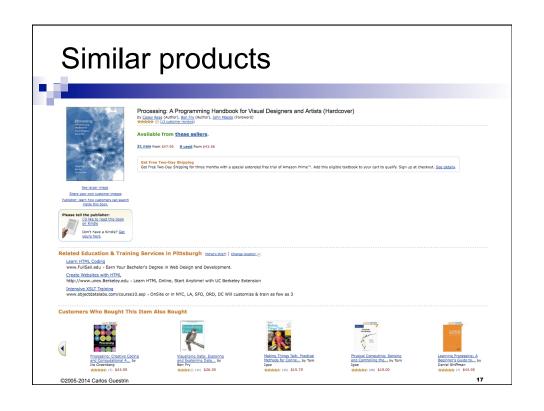


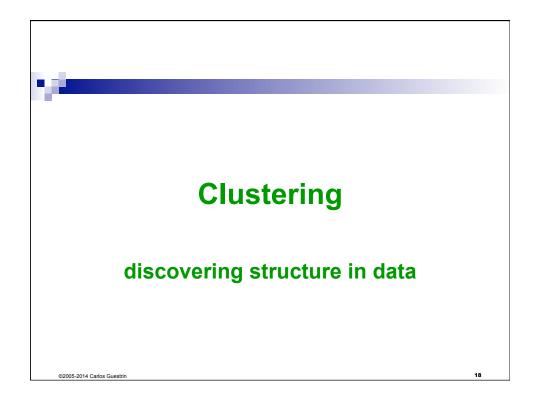


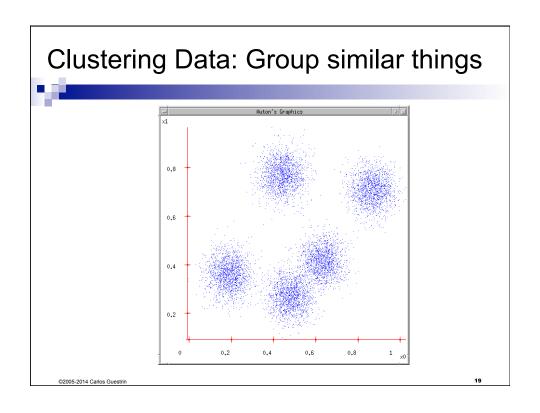


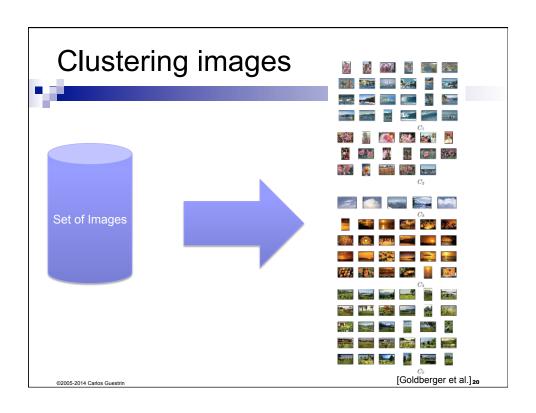


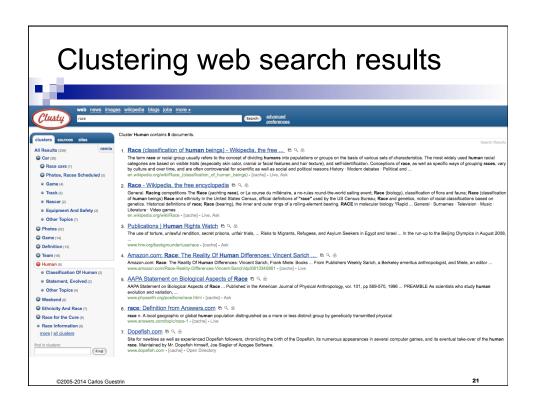


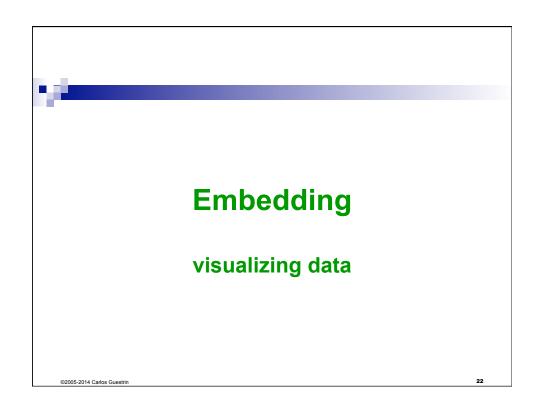


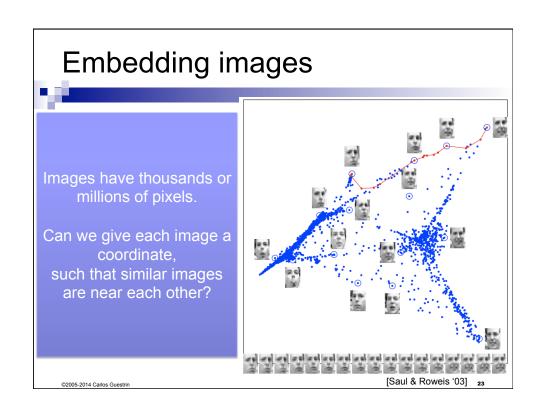


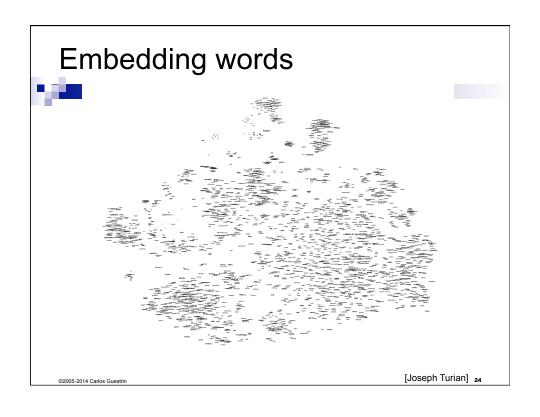


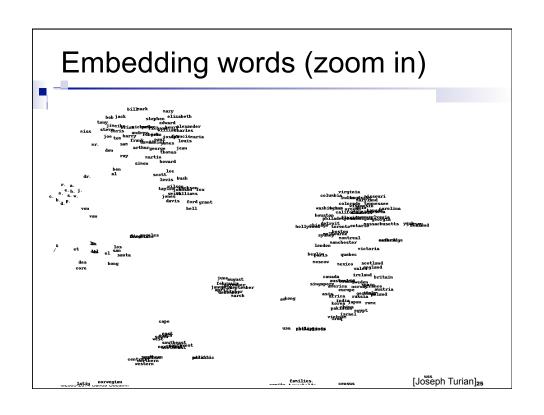




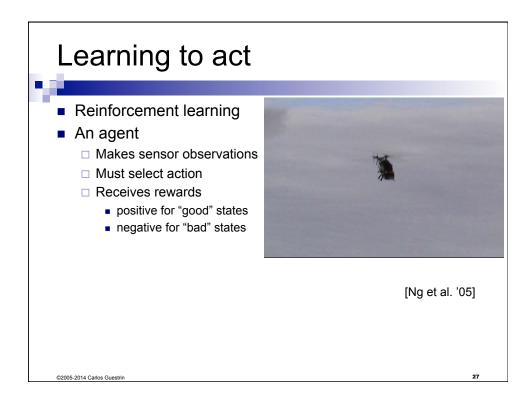




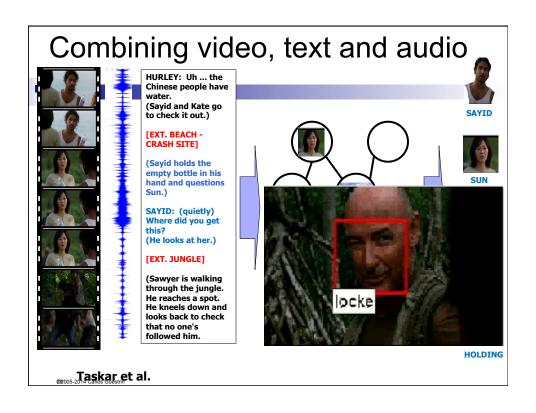














Growth of Machine Learning



One of the most sought for specialties in industry today!!!!

- Machine learning is preferred approach to
 - ☐ Speech recognition, Natural language processing
 - □ Computer vision
 - □ Medical outcomes analysis
 - Robot control
 - Computational biology
 - Sensor networks
 - ...
- This trend is accelerating, especially with Big Data
 - □ Improved machine learning algorithms
 - ☐ Improved data capture, networking, faster computers
 - □ Software too complex to write by hand
 - □ New sensors / IO devices
 - Demand for self-customization to user, environment

©2005-2014 Carlos Guestri

31

Syllabus



- Covers a wide range of Machine Learning techniques — from basic to state-of-the-art
- You will learn about the methods you heard about:
 - Point estimation, regression, naïve Bayes, logistic regression, nearest-neighbor, decision trees, boosting, perceptron, overfitting, regularization, dimensionality reduction, PCA, error bounds, VC dimension, SVMs, kernels, margin bounds, K-means, EM, mixture models, semi-supervised learning, HMMs, graphical models, active learning, reinforcement learning...
- Covers algorithms, theory and applications
- It's going to be fun and hard work ^③

©2005-2014 Carlos Guestrin

Prerequisites



- Formally:
 - □ STAT 341, STAT 391, or equivalent
- Probabilities
 - □ Distributions, densities, marginalization...
- Basic statistics
 - □ Moments, typical distributions, regression...
- Algorithms
 - □ Dynamic programming, basic data structures, complexity...
- Programming
 - □ Python will be very useful, but we'll help you get started
- We provide some background, but the class will be fast paced
- Ability to deal with "abstract mathematical concepts"

©2005-2014 Carlos Guestrin

33

Recitations & Python



- We'll run an *optional* recitations:
 - □ Time/Location EEB 045
- We are recommending Python for homeworks!
 - ☐ There are many resources to get started with Python online
 - ☐ We'll run an *optional* tutorial:
 - First recitation: next week

©2005-2014 Carlos Guestrin

Staff



- Three Great TAs: Great resource for learning, interact with them!
 - □ **April Shen** Office hours: Mondays, 3-5pm
 - □ **Harley Montgomery** Office hours: Fridays, TBD
 - □ **Tianqi Chen**Office hours: Wednesdays, 1:20-3:20pm





□ Prof: Carlos Guestrin
Office hours: Thursdays 12:30-1:30pm (starting next week)

@2005_2014 Carlos Guastrin

35

Communication Channels



- Only channel for announcements, questions, etc. – Catalyst Group:
 - □ Subscribe!
 - ☐ All non-personal questions should go here
 - ☐ Answering your question will help others
 - ☐ Feel free to chime in
- For e-mailing instructors about personal issues, use:
 - □ cse546-instructors@cs.washington.edu

©2005-2014 Carlos Guestrin

Text Books



- Required Textbook:
 - ☐ Machine Learning: a Probabilistic Perspective; Kevin Murphy
- Optional Books:
 - □ Pattern Recognition and Machine Learning; Chris Bishop
 - ☐ The Elements of Statistical Learning: Data Mining, Inference, and Prediction; Trevor Hastie, Robert Tibshirani, Jerome Friedman
 - □ Machine Learning; Tom Mitchell
 - Information Theory, Inference, and Learning Algorithms; David MacKay

©2005-2014 Carlos Guestrin

37

Grading



- 4 homeworks (35%)
 - ☐ First one goes out next week
 - Start early, Start early
- Final project (30%)
 - □ Full details out around 10/9
 - □ Projects done individually, or groups of two students
- Midterm (15%)
 - □ Thu., 10/30 in class
- Final (20%)
 - □ By registrar: Monday, December 08 1030-1220, EEB 045

©2005-2014 Carlos Guestrin

Homeworks



- Homeworks are hard, start early ☺
- Due in the beginning of class
- 33% subtracted per late day
- You have 3 LATE DAYS to use for homeworks only throughout the quarter

 □ Please plan accordingly and after that don't be about deadlines, travel,... ⑤
- All homeworks must be handed in, even for zero credit
- Use Catalyst to submit homeworks
- Collaboration
 - ☐ You may discuss the questions
 - Each student writes their own answers
 - □ Write on your homework anyone with whom you collaborate
 - ☐ Each student must write their own code for the programming part
 - Please don't search for answers on the web, Google, previous years' homeworks, etc.
 - please ask us if you are not sure if you can use a particular reference

©2005-2014 Carlos Guestrin

39

Projects



- An opportunity to exercise what you learned and to learn new things
- Individually or groups of two
- Must involve real data
 - ☐ Must be data that you have available to you by the time of the project proposals
- Must involve machine learning
- It's encouraged to be related to your research, but must be something new you did this quarter
 - □ Not a project you worked on during the summer, last year, etc.
- Full details in a couple of weeks
- Tue., October 21, 10:30am: Project Proposals
- Tue., November 11, 10:30am: Project Milestone
- Thu., December 4, 2:30-4:30pm: Poster Session
- Thu., December 11, 10:30am: Project Report

©2005-2014 Carlos Guestrin

Enjoy!



- ML is becoming ubiquitous in science, engineering and beyond
- It's one of the hottest topics in industry today
- This class should give you the basic foundation for applying ML and developing new methods
- The fun begins...

©2005-2014 Carlos Guestri

41

Your first consulting job



- A billionaire from the suburbs of Seattle asks you a question:
 - ☐ He says: I have thumbtack, if I flip it, what's the probability it will fall with the nail up?
 - □ You say: Please flip it a few times:
 - ☐ You say: The probability is:
 - ☐ He says: Why???
 - ☐ You say: Because...

©2005-2014 Carlos Guestrin

Thumbtack – Binomial Distribution



- P(Heads) = θ , P(Tails) = 1- θ
- Flips are i.i.d.:
 - □ Independent events
 - ☐ Identically distributed according to Binomial distribution
- Sequence *D* of α_H Heads and α_T Tails

$$P(\mathcal{D} \mid \theta) = \theta^{\alpha_H} (1 - \theta)^{\alpha_T}$$

©2005-2014 Carlos Guestrin

42

Maximum Likelihood Estimation



- Data: Observed set D of α_H Heads and α_T Tails
- **Hypothesis:** Binomial distribution
- Learning θ is an optimization problem
 - □ What's the objective function?
- MLE: Choose θ that maximizes the probability of observed data:

$$\widehat{\theta} = \underset{\theta}{\operatorname{arg max}} P(\mathcal{D} \mid \theta)$$

$$= \underset{\theta}{\operatorname{arg max}} \ln P(\mathcal{D} \mid \theta)$$

©2005-2014 Carlos Guestrin

Your first learning algorithm

١

$$\widehat{ heta} = rg \max_{ heta} \ \ln P(\mathcal{D} \mid heta) \ = rg \max_{ heta} \ \ln heta^{lpha_H} (1- heta)^{lpha_T}$$

Set derivative to zero:

$$\frac{d}{d\theta} \ln P(\mathcal{D} \mid \theta) = 0$$

©2005-2014 Carlos Guestria

45

How many flips do I need?

$$\widehat{\theta}_{MLE} = \frac{\alpha_H}{\alpha_H + \alpha_T}$$

- Billionaire says: I flipped 3 heads and 2 tails.
- You say: θ = 3/5, I can prove it!
- He says: What if I flipped 30 heads and 20 tails?
- You say: Same answer, I can prove it!
- He says: What's better?
- You say: Humm... The more the merrier???
- He says: Is this why I am paying you the big bucks???

©2005-2014 Carlos Guestrin

Simple bound (based on Hoeffding's inequality)



■ For
$$N$$
 = $\alpha_{\rm H}$ + $\alpha_{\rm T}$, and $\widehat{\theta}_{MLE} = \frac{\alpha_H}{\alpha_H + \alpha_T}$

■ Let θ^* be the true parameter, for any ϵ >0:

$$P(|\hat{\theta} - \theta^*| \ge \epsilon) \le 2e^{-2N\epsilon^2}$$

@2005_2014 Carlos Guastrir

4-7

PAC Learning



- PAC: Probably Approximate Correct
- Billionaire says: I want to know the thumbtack parameter θ , within ϵ = 0.1, with probability at least 1- δ = 0.95. How many flips?

$$P(|\hat{\theta} - \theta^*| \ge \epsilon) \le 2e^{-2N\epsilon^2}$$

©2005-2014 Carlos Guestri

What about continuous variables?



- Billionaire says: If I am measuring a continuous variable, what can you do for me?
- You say: Let me tell you about Gaussians...

$$P(x \mid \mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

©2005-2014 Carlos Guestrin

49

Some properties of Gaussians



- affine transformation (multiplying by scalar and adding a constant)
 - $\square X \sim N(\mu, \sigma^2)$
 - \Box Y = aX + b \rightarrow Y ~ $N(a\mu+b,a^2\sigma^2)$
- Sum of Gaussians
 - $\square X \sim N(\mu_X, \sigma^2_X)$
 - \square Y ~ $N(\mu_Y, \sigma^2_Y)$
 - \square Z = X+Y \rightarrow Z ~ $N(\mu_X + \mu_Y, \sigma^2_X + \sigma^2_Y)$

©2005-2014 Carlos Guestrin

Learning a Gaussian



- Collect a bunch of data
 - □ Hopefully, i.i.d. samples
 - □ e.g., exam scores
- Learn parameters
 - Mean
 - □ Variance

$$P(x \mid \mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

©2005-2014 Carlos Guestrin

51

MLE for Gaussian



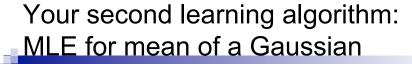
■ Prob. of i.i.d. samples $D=\{x_1,...,x_N\}$:

$$P(\mathcal{D} \mid \mu, \sigma) = \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^N \prod_{i=1}^N e^{\frac{-(x_i - \mu)^2}{2\sigma^2}}$$

Log-likelihood of data:

$$\begin{split} \ln P(\mathcal{D} \mid \mu, \sigma) &= \ln \left[\left(\frac{1}{\sigma \sqrt{2\pi}} \right)^N \prod_{i=1}^N e^{\frac{-(x_i - \mu)^2}{2\sigma^2}} \right] \\ &= -N \ln \sigma \sqrt{2\pi} - \sum_{i=1}^N \frac{(x_i - \mu)^2}{2\sigma^2} \end{split}$$

©2005-2014 Carlos Guestrin





$$\frac{d}{d\mu} \ln P(\mathcal{D} \mid \mu, \sigma) = \frac{d}{d\mu} \left[-N \ln \sigma \sqrt{2\pi} - \sum_{i=1}^{N} \frac{(x_i - \mu)^2}{2\sigma^2} \right]$$

©2005-2014 Carlos Guestria

53

MLE for variance



Again, set derivative to zero:

$$\frac{d}{d\sigma} \ln P(\mathcal{D} \mid \mu, \sigma) = \frac{d}{d\sigma} \left[-N \ln \sigma \sqrt{2\pi} - \sum_{i=1}^{N} \frac{(x_i - \mu)^2}{2\sigma^2} \right]$$
$$= \frac{d}{d\sigma} \left[-N \ln \sigma \sqrt{2\pi} \right] - \sum_{i=1}^{N} \frac{d}{d\sigma} \left[\frac{(x_i - \mu)^2}{2\sigma^2} \right]$$

©2005-2014 Carlos Guestri

Learning Gaussian parameters



MLE:

$$\hat{\mu}_{MLE} = \frac{1}{N} \sum_{i=1}^{N} x_i$$

$$\hat{\sigma}_{MLE}^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - \hat{\mu})^2$$

- BTW. MLE for the variance of a Gaussian is biased
 - □ Expected result of estimation is **not** true parameter!
 - ☐ Unbiased variance estimator:

$$\hat{\sigma}_{unbiased}^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \hat{\mu})^2$$

©2005-2014 Carlos Guestrin

What you need to know...



- Learning is...
 - □ Collect some data
 - E.g., thumbtack flips
 - □ Choose a hypothesis class or model
 - E.g., binomial
 - □ Choose a loss function
 - E.g., data likelihood
 - □ Choose an optimization procedure
 - E.g., set derivative to zero to obtain MLE
 - □ Collect the big bucks
 - Like everything in life, there is a lot more to learn...
 - ☐ Many more facets... Many more nuances...
 - □ The fun will continue...

©2005-2014 Carlos Guestrin