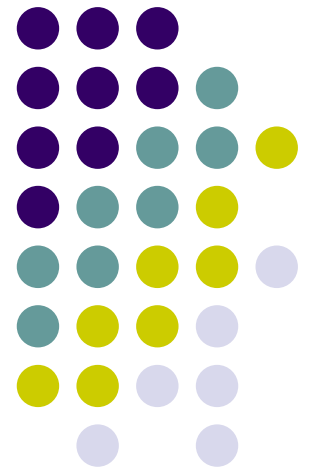


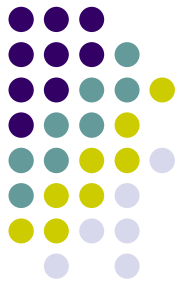
Point Estimation

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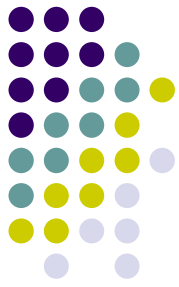
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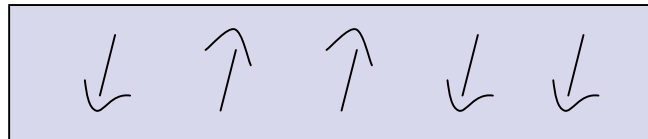
What you need to know

- Point estimation:
 - MLE
 - Bayesian learning
 - MAP
- Gaussian estimation
- Regression
 - Basis function = features
 - Optimizing sum squared error
 - Relationship between regression and Gaussians
- Bias-Variance trade-off

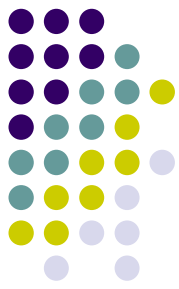


Your first consulting job

- An IT billionaire from Beijing asks you a question:
 - B: I have thumbtack, if I flip it, what's the probability it will fall with the nail up?
 - Y: Please flip it a few times ...



- Y: The probability is $3/5$
- B: Why???
- Y: Because...



Binomial Distribution

- $P(\text{Heads}) = \theta$, $P(\text{Tails}) = 1 - \theta$

$$P(D | \theta) = (1 - \theta)\theta\theta(1 - \theta)(1 - \theta)$$

- Flips are i.i.d.
 - Independent events
 - Identically distributed according to Binomial distribution
- Sequence D of α_H Heads and α_T Tails

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

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?

$$D = \{T, H, H, T, T\}$$

- MLE: Choose θ that maximizes the probability of observed data:

$$\begin{aligned}\hat{\theta} &= \arg \max_{\theta} P(D | \theta) \\ &= \arg \max_{\theta} \ln P(D | \theta) = \dots\end{aligned}$$

Maximum Likelihood Estimation (cont.)



$$\begin{aligned}\hat{\theta} &= \arg \max_{\theta} P(D | \theta) \\ &= \arg \max_{\theta} \ln(\theta^{\alpha_H} (1 - \theta)^{\alpha_T}) \\ &= \arg \max_{\theta} (\alpha_H \ln \theta + \alpha_T \ln(1 - \theta))\end{aligned}$$

- Set derivative to zero:

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

$$\hat{\theta} = \frac{\alpha_T}{\alpha_H + \alpha_T} = \frac{3}{2 + 3}$$



How many flips do I need?

$$\hat{\theta} = \frac{\alpha_T}{\alpha_H + \alpha_T}$$

- B: I flipped 2 heads and 3 tails.
- Y: $\theta = 3/5$, I can prove it!
- B: What if I flipped 20 heads and 30 tails?
- Y: Same answer, I can prove it!
- B: What's better?
- Y: Humm... The more the merrier???
- B: Is this why I am paying you the big bucks???

Simple bound (based on Hoeffding's inequality)



- For $N = \alpha_H + \alpha_T$ and $\hat{\theta} = \frac{\alpha_T}{\alpha_H + \alpha_T}$
- Let θ^* be the true parameter, for any $\varepsilon > 0$:

$$P(|\hat{\theta} - \theta^*| \geq \varepsilon) \leq 2e^{-2N\varepsilon^2} \leq \delta$$

$$N \geq \frac{1}{2\varepsilon} [\ln 2 - \ln \delta]$$

$$N \geq 27; (\varepsilon = 0.1, \delta = 0.01)$$



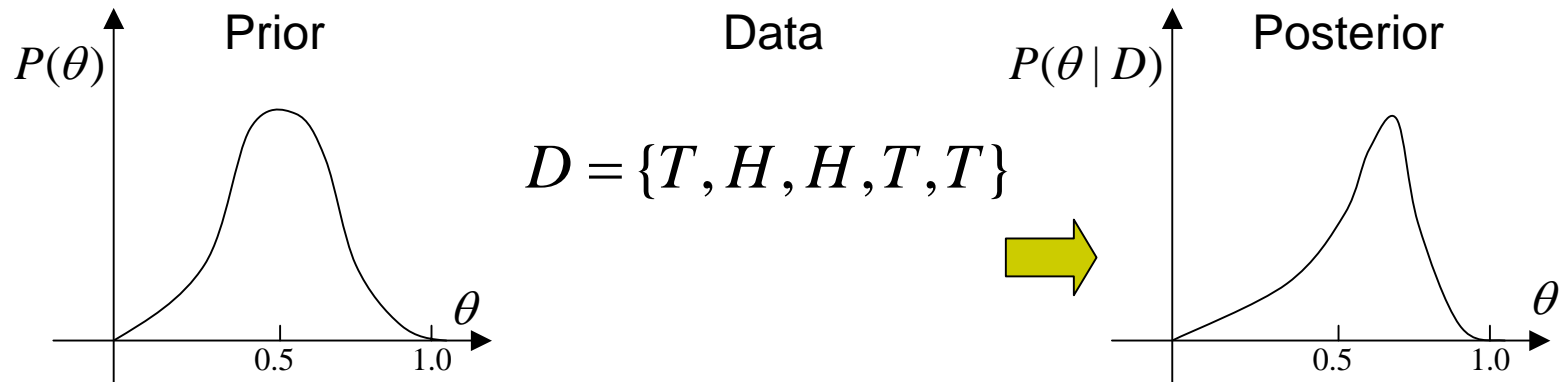
PAC Learning

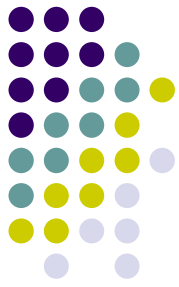
- PAC: Probably Approximate Correct
- B: I want to know the thumbtack parameter θ , within $\varepsilon = 0.1$, with probability at least $1 - \delta = 0.99$. How many flips?
- Y: 27, 😊

Prior: knowledge before experiments



- B: Wait, I know that the thumbtack is “close” to 50-50. What can you ...?
- Y: I can learn it the Bayesian way...
- Rather than estimating a single θ , we obtain a distribution over possible values of θ





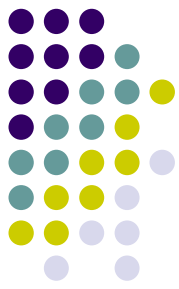
Bayesian Learning

- Bayes rule:

$$\text{Posterior} \rightarrow P(\theta | D) = \frac{\overset{\text{Posterior}}{\downarrow} P(\theta) \overset{\text{Likelihood}}{\downarrow} P(D | \theta)}{P(D) \leftarrow \begin{array}{l} \text{Data distribution} \\ \text{Normalization constant} \end{array}}$$

- Or equivalently:

$$P(\theta | D) \propto P(\theta)P(D | \theta)$$



Bayesian Learning in our case

- Likelihood function is simply Binomial:

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

- What about prior?
 - Represent expert knowledge
 - Simple posterior form
- Conjugate priors:
 - Closed-form representation of posterior
 - For Binomial, conjugate prior is Beta distribution



Beta prior distribution – $P(\theta)$

- Prior: Beta distribution

$$P(\theta) = \frac{\theta^{\beta_H - 1} (1 - \theta)^{\beta_T - 1}}{B(\beta_H, \beta_T)} \sim \text{Beta}(\beta_H, \beta_T)$$

- Likelihood: Binomial distribution

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

- Posterior:

$$\begin{aligned} P(\theta | D) &\propto P(\theta)P(D | \theta) \\ &\propto \theta^{\alpha_H} (1 - \theta)^{\alpha_T} \theta^{\beta_H - 1} (1 - \theta)^{\beta_T - 1} \\ &\sim \text{Beta}(\alpha_H + \beta_H, \alpha_T + \beta_T) \end{aligned}$$



Using Bayesian posterior

- Posterior distribution:

$$P(\theta | D) \sim \text{Beta}(\alpha_H + \beta_H, \alpha_T + \beta_T)$$

- Bayesian inference:

- No longer single parameter:

$$E[f(\theta)] \sim \int_0^1 f(\theta) P(\theta | D) d\theta$$

- Integral, ☹



MAP: Maximum a posteriori approximation

$$P(\theta | D) \sim \text{Beta}(\alpha_H + \beta_H, \alpha_T + \beta_T)$$

$$E[f(\theta)] = \int_0^1 f(\theta) P(\theta | D) d\theta \leftarrow \text{approximation}$$

- MAP: use most likely parameter

$$\hat{\theta} = \arg \max_{\theta} P(\theta | D) \quad E[f(\theta)] \approx f(\hat{\theta})$$



MAP for Beta distribution

$$P(\theta | D) \sim \text{Beta}(\alpha_H + \beta_H, \alpha_T + \beta_T)$$

- MAP: use most likely parameter

$$\hat{\theta} = \arg \max_{\theta} P(\theta | D) = \frac{\alpha_T + \beta_T - 1}{\alpha_H + \beta_H + \alpha_T + \beta_T - 2}$$

- Beta prior equivalent to extra thumbtack flips
- As $N \rightarrow \infty$, prior is “forgotten”
- But, for **small sample size**, prior is important!



Gaussian distribution

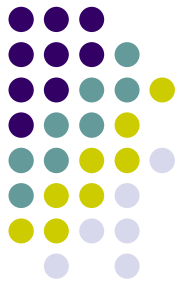
Continuous variable:

$$P(x | \mu, \delta) \sim \frac{1}{\delta \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\delta^2}}$$

mean

variance Normalize item

Consider the difference between continuous and discrete variables?



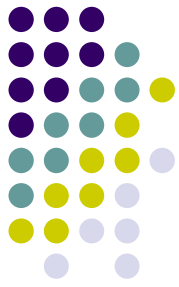
MLE for Gaussian

- Prob. of i.i.d. samples $D = \{x_1, x_2, \dots, x_N\}$

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

- The magic of log (to likelihood)

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



MLE for mean of a Gaussian

$$\begin{aligned}\frac{\partial}{\partial \mu} \ln P(D | \mu, \sigma) &= \frac{\partial}{\partial \mu} \ln \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^N \prod_{i=1}^N e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \\ &= \frac{\partial}{\partial \mu} - \sum_{i=1}^N \frac{(x_i - \mu)^2}{2\sigma^2} \\ &= \sum_{i=1}^N \frac{(x_i - \mu)}{\sigma^2} = 0\end{aligned}$$

$$\mu = \frac{1}{N} \sum_i x_i$$



MLE for variance of a Gaussian

$$\begin{aligned}\frac{\partial}{\partial \sigma} \ln P(D | \mu, \sigma) &= \frac{\partial}{\partial \sigma} \ln \left(\frac{1}{\sigma \sqrt{2\pi}} \right)^N \prod_{i=1}^N e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \\ &= \frac{\partial}{\partial \sigma} [-N \ln \sigma \sqrt{2\pi}] - \sum_{i=1}^N \frac{\partial}{\partial \sigma} \left[\frac{(x_i - \mu)^2}{2\sigma^2} \right] \\ &= -\frac{N}{\sigma} + \sum_{i=1}^N \frac{(x_i - \mu)^2}{\sigma^3} = 0\end{aligned}$$

$$\sigma^2 = \frac{1}{N} \sum_i (x_i - \mu)^2$$

Gaussian parameters learning



- MLE

$$\hat{\mu} = \frac{1}{N} \sum_i x_i$$

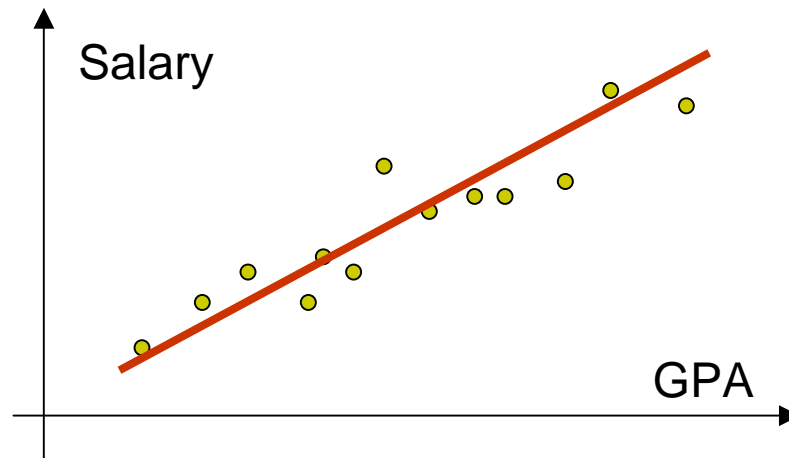
$$\hat{\sigma}^2 = \frac{1}{N} \sum_i (x_i - \mu)^2$$

- Bayesian learning: prior?
- Conjugate priors:
 - Mean: Gaussian priors
 - Variance: Wishart Distribution

Prediction of continuous variable



- B: Wait, that's not what I meant!
- Y: Chill out, dude.
- B: I want to predict a continuous variable for continuous inputs: I want to predict salaries from GPA.
- Y: I can regress that...





The regression problem

- **Instances:** $\langle \mathbf{x}_i, t_i \rangle$
- **Learn:** mapping from \mathbf{x} to $t(\mathbf{x})$.
- **Hypothesis space:** $t(\mathbf{x}) \approx \hat{f}(x) = \sum_{i=1}^k w_i h_i$
 - Given, basis functions $H = \{h_1, \dots, h_k\}$
 - Find coefficients $\mathbf{w} = \{w_1, \dots, w_k\}$
- **Problem formulation:**

$$\mathbf{w}^* = \arg \min_{\mathbf{w}} \sum_j [t(\mathbf{x}_j) - \sum_{i=1}^k w_i h_i(x)]^2$$



But, why sum squared error?

- Model:

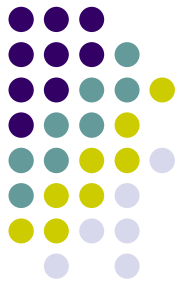
$$P(t | \mathbf{x}, \mathbf{w}, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{[t - \sum_i w_i h_i(x)]^2}{2\sigma^2}}$$

- Learn \mathbf{w} using MLE

Maximizing log-likelihood

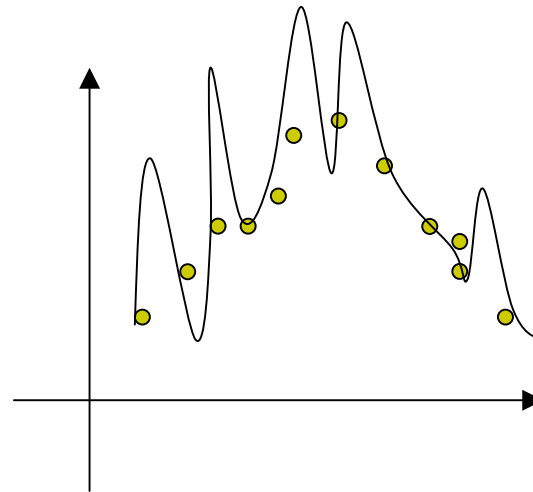
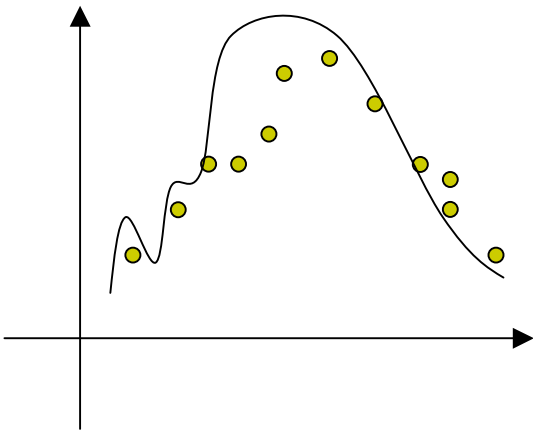


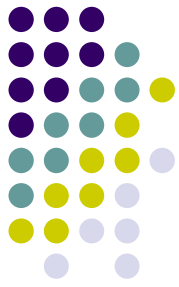
$$\ln P(D | \mathbf{w}, \sigma) = \ln \prod_j \left(\frac{1}{\sigma \sqrt{2\pi}} e^{\frac{-[t_j - \sum_i w_i h_i(x_j)]^2}{2\sigma^2}} \right)$$
$$\Rightarrow \min \sum_j \frac{-[t_j - \sum_i w_i h_i(x_j)]^2}{2\sigma^2}$$



Bias-Variance Tradeoff

- Choice of hypothesis basis introduce learning bias:
 - More complex basis:
 - Less bias
 - More variance (over-fitting)





What you need to know

- Point estimation:
 - Maximal Likelihood Estimation
 - Bayesian learning
 - Maximal a Posterior
- Gaussian estimation
- Regression
 - Basis function = features
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Homework

- Finish the “Gaussian parameters learning”
 - Please use google, \wedge_{-}^*