

Lecture 10: Statistical Learning

CS486/686 Intro to Artificial Intelligence

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Outline

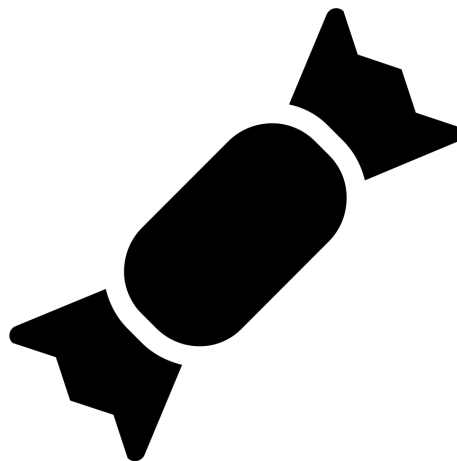
- Statistical learning
 - Bayesian learning
 - Maximum a posteriori
 - Maximum likelihood
- Learning from complete Data

Statistical Learning

- View: we have uncertain knowledge of the world
- Idea: learning simply reduces this uncertainty

Candy Example

- Favorite candy sold in two flavors:
 - Lime (hugh)
 - Cherry (yum)
- Same wrapper for both flavors
- Sold in bags with different ratios:
 - 100% cherry
 - 75% cherry + 25% lime
 - 50% cherry + 50% lime
 - 25% cherry + 75% lime
 - 100% lime



Candy Example

- You bought a bag of candy but don't know its flavor ratio
- After eating k candies:
 - What's the flavor ratio of the bag?
 - What will be the flavor of the next candy?

Statistical Learning

- **Hypothesis H:** probabilistic theory of the world
 - h_1 : 100% cherry
 - h_2 : 75% cherry + 25% lime
 - h_3 : 50% cherry + 50% lime
 - h_4 : 25% cherry + 75% lime
 - h_5 : 100% lime
- **Data D:** evidence about the world
 - d_1 : 1st candy is cherry
 - d_2 : 2nd candy is lime
 - d_3 : 3rd candy is lime
 - ...

Bayesian Learning

- **Prior:** $\Pr(H)$
- **Likelihood:** $\Pr(d|H)$
- **Evidence:** $\mathbf{d} = \langle d_1, d_2, \dots, d_n \rangle$
- **Bayesian Learning** amounts to computing the posterior using Bayes' Theorem:
$$\Pr(H|\mathbf{d}) = k \Pr(\mathbf{d}|H)\Pr(H)$$

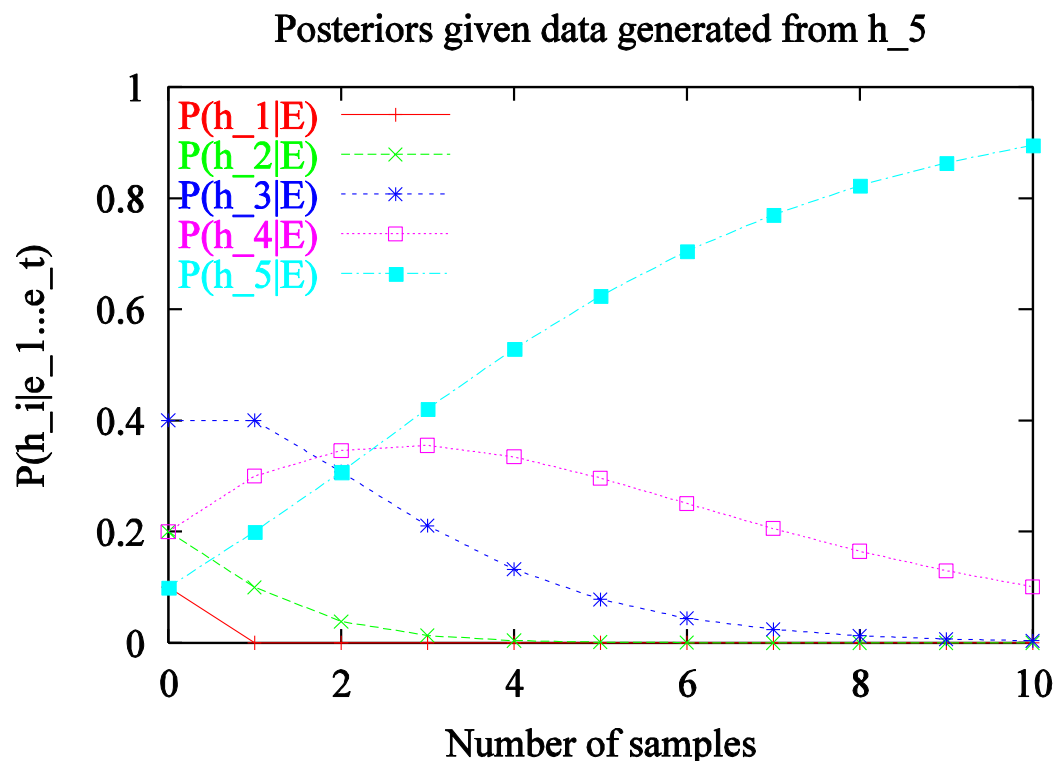
Bayesian Prediction

- Suppose we want to make a prediction about an unknown quantity X (i.e., the flavor of the next candy)
- $$\begin{aligned}\Pr(X|\mathbf{d}) &= \sum_i \Pr(X|\mathbf{d}, h_i)P(h_i|\mathbf{d}) \\ &= \sum_i \Pr(X|h_i)P(h_i|\mathbf{d})\end{aligned}$$
- Predictions are weighted averages of the predictions of the individual hypotheses
- Hypotheses serve as “intermediaries” between raw data and prediction

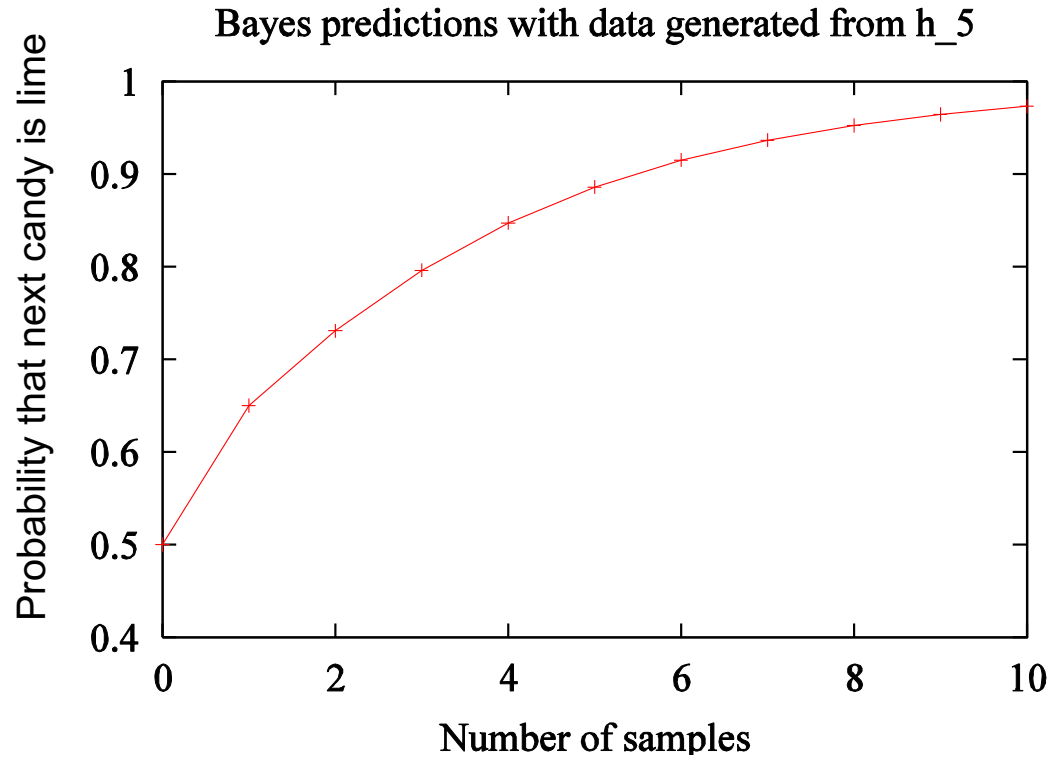
Candy Example

- Assume prior $P(H) = \langle 0.1, 0.2, 0.4, 0.2, 0.1 \rangle$
- Assume candies are **i.i.d.** (identically and independently distributed)
 - $P(\mathbf{d}|h) = \prod_j P(d_j|h)$
- Suppose first 10 candies all taste lime:
 - $P(\mathbf{d}|h_5) = 1^{10} = 1$
 - $P(\mathbf{d}|h_3) = 0.5^{10} \approx 0.001$
 - $P(\mathbf{d}|h_1) = 0^{10} = 0$

Posterior



Prediction



Bayesian Learning

- Bayesian learning properties:
 - **Optimal** (i.e., given prior, no other prediction is correct more often than the Bayesian one)
 - **No overfitting** (all hypotheses weighted and considered)
- There is a price to pay:
 - When hypothesis space is large Bayesian learning may be intractable
 - i.e., sum (or integral) over hypotheses often intractable
- Solution: approximate Bayesian learning

Maximum a posteriori (MAP)

- Idea: make prediction based on **most probable hypothesis** h_{MAP}
 - $h_{\text{MAP}} = \operatorname{argmax}_{h_i} P(h_i|\mathbf{d})$
 - $P(X|\mathbf{d}) \approx P(X|h_{\text{MAP}})$
- In contrast, Bayesian learning makes prediction based on **all** hypotheses weighted by their probability

Candy Example (MAP)

- Prediction after
 - 1 lime: $h_{\text{MAP}} = h_3$, $\Pr(\text{lime}|h_{\text{MAP}}) = 0.5$
 - 2 limes: $h_{\text{MAP}} = h_4$, $\Pr(\text{lime}|h_{\text{MAP}}) = 0.75$
 - 3 limes: $h_{\text{MAP}} = h_5$, $\Pr(\text{lime}|h_{\text{MAP}}) = 1$
 - 4 limes: $h_{\text{MAP}} = h_5$, $\Pr(\text{lime}|h_{\text{MAP}}) = 1$
 - ...
- After only 3 limes, it correctly selects h_5

Candy Example (MAP)

- But what if correct hypothesis is h_4 ?
 - h_4 : $P(\text{lime}) = 0.75$ and $P(\text{cherry}) = 0.25$
- After 3 limes
 - MAP incorrectly predicts h_5
 - MAP yields $P(\text{lime}|h_{\text{MAP}}) = 1$
 - Bayesian learning yields $P(\text{lime}|\mathbf{d}) = 0.8$

MAP properties

- **MAP prediction less accurate** than Bayesian prediction since it relies only on **one** hypothesis h_{MAP}
- But MAP and Bayesian predictions converge as data increases
- **Controlled overfitting** (prior can be used to penalize complex hypotheses)
- **Finding h_{MAP} may be intractable:**
 - $h_{\text{MAP}} = \operatorname{argmax} P(h|\mathbf{d})$
 - Optimization may be difficult

MAP computation

- Optimization:
 - $h_{\text{MAP}} = \operatorname{argmax}_h P(h|\mathbf{d})$
 $= \operatorname{argmax}_h P(h) P(\mathbf{d}|h)$
 $= \operatorname{argmax}_h P(h) \prod_i P(d_i|h)$
- Product induces non-linear optimization
- Take the log to linearize optimization
 - $h_{\text{MAP}} = \operatorname{argmax}_h \log P(h) + \sum_i \log P(d_i|h)$

Maximum Likelihood (ML)

- Idea: simplify MAP by assuming uniform prior (i.e., $P(h_i) = P(h_j) \forall i,j$)
 - $h_{\text{MAP}} = \operatorname{argmax}_h P(h) P(\mathbf{d}|h)$
 - $h_{\text{ML}} = \operatorname{argmax}_h P(\mathbf{d}|h)$
- Make prediction based on h_{ML} only:
 - $P(X|\mathbf{d}) \approx P(X|h_{\text{ML}})$

Candy Example (ML)

- Prediction after
 - 1 lime: $h_{ML} = h_5$, $\Pr(\text{lime}|h_{ML}) = 1$
 - 2 limes: $h_{ML} = h_5$, $\Pr(\text{lime}|h_{ML}) = 1$
 - ...
- **Frequentist:** “objective” prediction since it relies only on the data (i.e., no prior)
- **Bayesian:** prediction based on data and uniform prior (since no prior \equiv uniform prior)

ML properties

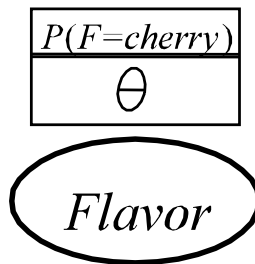
- ML prediction **less accurate** than Bayesian and MAP predictions since it ignores prior info and relies only on **one** hypothesis h_{ML}
- But ML, MAP and Bayesian predictions converge as data increases
- Subject to **overfitting** (no prior to penalize complex hypothesis that could exploit statistically insignificant data patterns)
- Finding h_{ML} is often easier than h_{MAP}
 - $h_{\text{ML}} = \operatorname{argmax}_h \sum_i \log P(d_i|h)$

Statistical Learning

- Use Bayesian Learning, MAP or ML
- Complete data:
 - When data has multiple attributes, **all attributes are known**
 - Easy
- Incomplete data:
 - When data has multiple attributes, **some attributes are unknown**
 - Harder

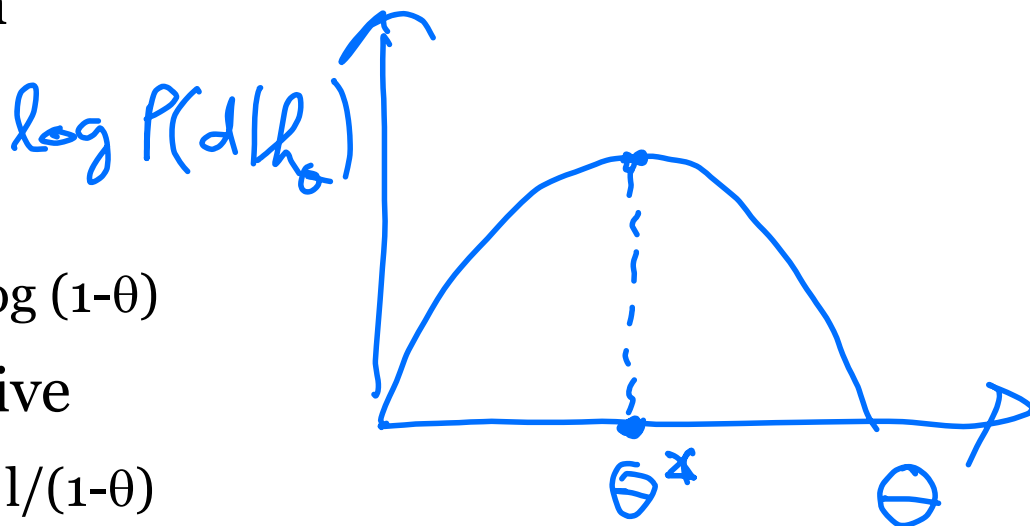
Simple ML example

- Hypothesis h_θ :
 - $P(\text{cherry})=\theta$ & $P(\text{lime})=1-\theta$
- Data \mathbf{d} :
 - c cherries and l limes
- ML hypothesis:
 - θ is relative frequency of observed data
 - $\theta = c/(c+l)$
 - $P(\text{cherry}) = c/(c+l)$ and $P(\text{lime})= l/(c+l)$



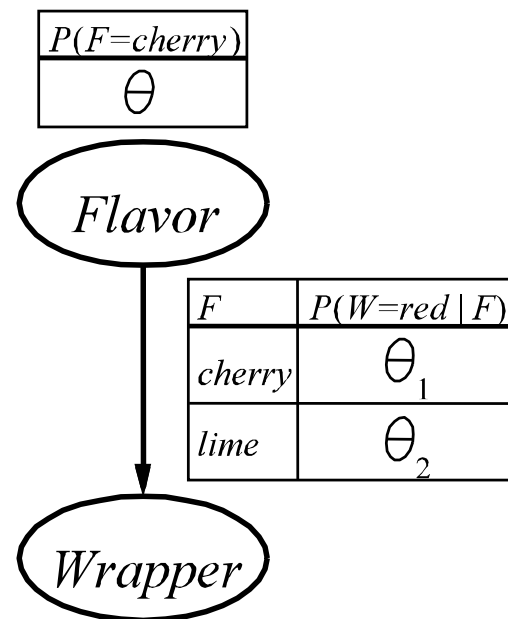
ML computation

- 1) Likelihood expression
 - $P(\mathbf{d}|h_\theta) = \theta^c (1-\theta)^l$
- 2) log likelihood
 - $\log P(\mathbf{d}|h_\theta) = c \log \theta + l \log (1-\theta)$
- 3) log likelihood derivative
 - $d(\log P(\mathbf{d}|h_\theta))/d\theta = c/\theta - l/(1-\theta)$
- 4) ML hypothesis
 - $c/\theta - l/(1-\theta) = 0 \rightarrow \theta = c/(c+l)$



More complicated ML example

- Hypothesis: $h_{\theta, \theta_1, \theta_2}$
- Data:
 - c cherries
 - g_c green wrappers
 - r_c red wrappers
 - l limes
 - g_l green wrappers
 - r_l red wrappers



ML computation

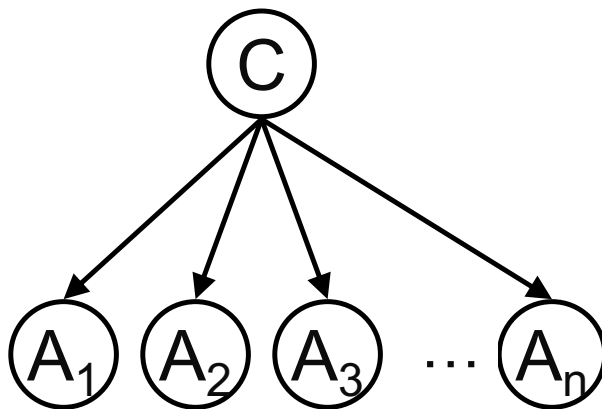
- 1) Likelihood expression
 - $P(\mathbf{d} | h_{\theta, \theta_1, \theta_2}) = \theta^c (1-\theta)^l \theta_1^{r_c} (1-\theta_1)^{g_c} \theta_2^{r_l} (1-\theta_2)^{g_l}$
- ...
- 4) ML hypothesis
 - $c/\theta - l/(1-\theta) = 0 \rightarrow \theta = c/(c+l)$
 - $r_c/\theta_1 - g_c/(1-\theta_1) = 0 \rightarrow \theta_1 = r_c/(r_c+g_c)$
 - $r_l/\theta_2 - g_l/(1-\theta_2) = 0 \rightarrow \theta_2 = r_l/(r_l+g_l)$

Laplace Smoothing

- An important case of overfitting happens when there is no sample for a certain outcome
 - E.g., no cherries eaten so far
 - $P(\text{cherry}) = \theta = c/(c+1) = 0$
 - **Zero probabilities are dangerous: they rule out outcomes**
- Solution: **Laplace (add-one) smoothing**
 - **Add 1 to all counts**
 - $P(\text{cherry}) = \theta = (c+1)/(c+1+2) > 0$
 - Much better results in practice

Naïve Bayes model

- Want to predict a class C based on attributes A_i
- Parameters:
 - $\theta = P(C=\text{true})$
 - $\theta_{i1} = P(A_i=\text{true}|C=\text{true})$
 - $\theta_{i2} = P(A_i=\text{true}|C=\text{false})$
- **Assumption: A_i 's are independent given C**



Naïve Bayes model for Restaurant Problem

- Data:

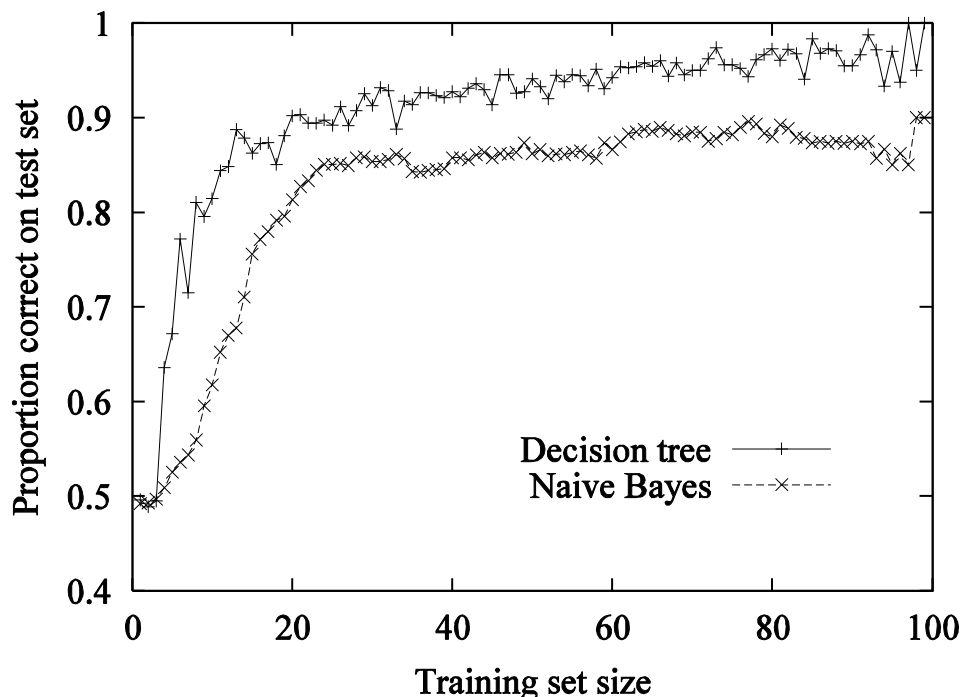
Example	Attributes										Target
	<i>Alt</i>	<i>Bar</i>	<i>Fri</i>	<i>Hun</i>	<i>Pat</i>	<i>Price</i>	<i>Rain</i>	<i>Res</i>	<i>Type</i>	<i>Est</i>	<i>Wait</i>
X_1	T	F	F	T	Some	\$\$\$	F	T	French	0-10	T
X_2	T	F	F	T	Full	\$	F	F	Thai	30-60	F
X_3	F	T	F	F	Some	\$	F	F	Burger	0-10	T
X_4	T	F	T	T	Full	\$	F	F	Thai	10-30	T
X_5	T	F	T	F	Full	\$\$\$	F	T	French	>60	F
X_6	F	T	F	T	Some	\$\$	T	T	Italian	0-10	T
X_7	F	T	F	F	None	\$	T	F	Burger	0-10	F
X_8	F	F	F	T	Some	\$\$	T	T	Thai	0-10	T
X_9	F	T	T	F	Full	\$	T	F	Burger	>60	F
X_{10}	T	T	T	T	Full	\$\$\$	F	T	Italian	10-30	F
X_{11}	F	F	F	F	None	\$	F	F	Thai	0-10	F
X_{12}	T	T	T	T	Full	\$	F	F	Burger	30-60	T

- Maximum likelihood:

- θ = relative frequencies of *wait* and \sim *wait*
- θ_{i1}, θ_{i2} = relative frequencies of each attribute value given *wait* and \sim *wait*

Naïve Bayes Model vs Decision Trees

- Wait prediction for restaurant problem



Why is naïve Bayes less accurate than decision tree?

Bayesian Network Parameter Learning (Max Likelihood)

- Parameters $\theta_{V, \text{pa}(V)=\mathbf{v}}$:
 - CPTs: $\theta_{V, \text{pa}(V)=\mathbf{v}} = P(V | \text{pa}(V)=\mathbf{v})$
- Data \mathbf{d} :
 - $d_1 : \langle V_1=v_{1,1}, V_2=v_{2,1}, \dots, V_n = v_{n,1} \rangle$
 - $d_2 : \langle V_1=v_{1,2}, V_2=v_{2,2}, \dots, V_n = v_{n,2} \rangle$
 - ...
- Maximum likelihood:
 - Set $\theta_{V, \text{pa}(V)=\mathbf{v}}$ to the relative frequencies of the values of V given the values \mathbf{v} of the parents of V
$$\theta_{V, \text{pa}(V)=\mathbf{v}} = \#(V, \text{pa}(V)=\mathbf{v}) / \#(\text{pa}(V)=\mathbf{v})$$