



Machine Learning

CS60050

Bayesian Learning

(MLE and MAP)



$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \quad \text{Bayes' rule}$$

we call $P(A)$ the “prior”

and $P(A|B)$ the “posterior”



Bayes, Thomas (1763) An essay towards solving a problem in the doctrine of chances. *Philosophical Transactions of the Royal Society of London*, **53:370-418**

...by no means merely a curious speculation in the doctrine of chances, but necessary to be solved in order to a sure foundation for all our reasonings concerning past facts, and what is likely to be hereafter.... necessary to be considered by any that would give a clear account of the strength of *analogical* or *inductive reasoning*...

Other Forms of Bayes Rule

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|\sim A)P(\sim A)}$$

$$P(A|B \wedge X) = \frac{P(B|A \wedge X)P(A \wedge X)}{P(B \wedge X)}$$

Applying Bayes Rule

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|\sim A)P(\sim A)}$$

A = you have the flu, B = you just coughed

Assume:

$$P(A) = 0.05$$

$$P(B|A) = 0.80$$

$$P(B|\sim A) = 0.20$$

what is $P(\text{flu} | \text{cough}) = P(A|B)$?

what does all this have to do with
function approximation?

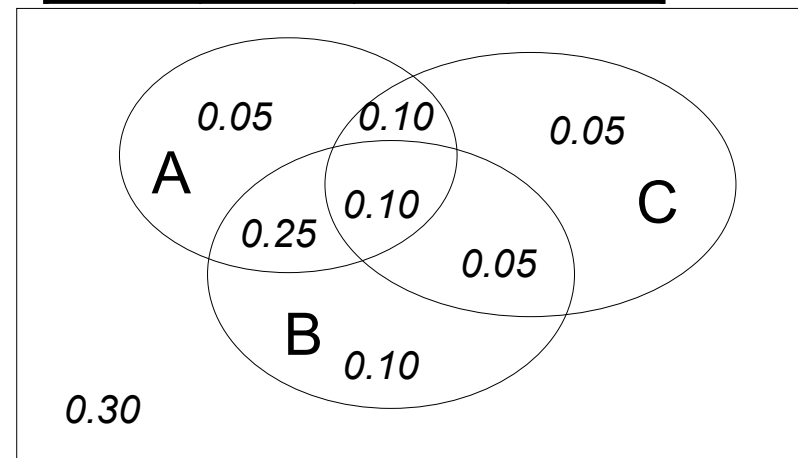
instead of $F: X \rightarrow Y$,
learn $P(Y | X)$

The Joint Distribution

Example: Boolean variables A, B, C

Recipe for making a joint distribution of M variables:

A	B	C	Prob
0	0	0	0.30
0	0	1	0.05
0	1	0	0.10
0	1	1	0.05
1	0	0	0.05
1	0	1	0.10
1	1	0	0.25
1	1	1	0.10



[A. Moore]

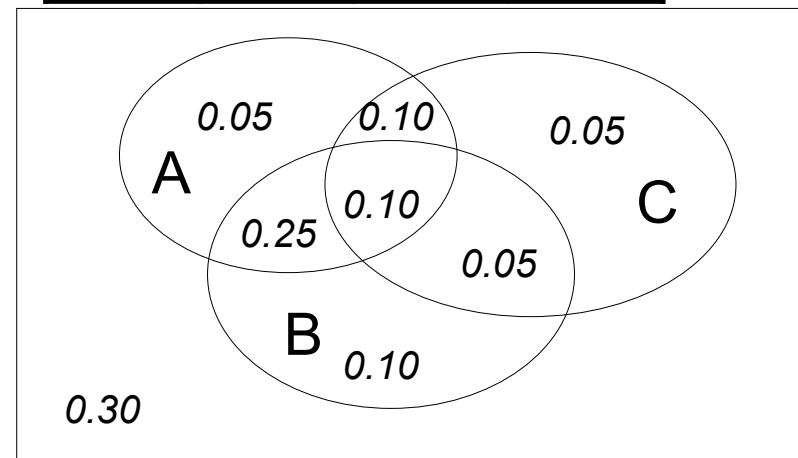
The Joint Distribution

Example: Boolean variables A, B, C

Recipe for making a joint distribution of M variables:

1. Make a truth table listing all combinations of values (M Boolean variables $\rightarrow 2^M$ rows).

A	B	C	Prob
0	0	0	0.30
0	0	1	0.05
0	1	0	0.10
0	1	1	0.05
1	0	0	0.05
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[A. Moore]

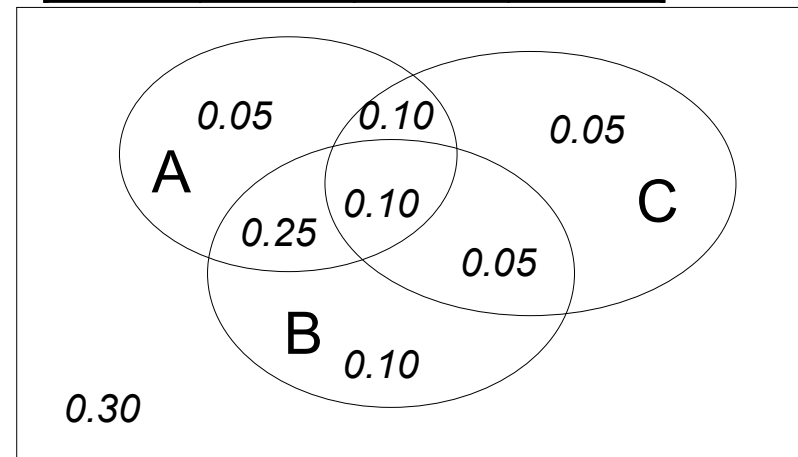
The Joint Distribution

Example: Boolean variables A, B, C

Recipe for making a joint distribution of M variables:

1. Make a truth table listing all combinations of values (M Boolean variables $\rightarrow 2^M$ rows).
2. For each combination of values, say how probable it is.

A	B	C	Prob
0	0	0	0.30
0	0	1	0.05
0	1	0	0.10
0	1	1	0.05
1	0	0	0.05
1	0	1	0.10
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[A. Moore]

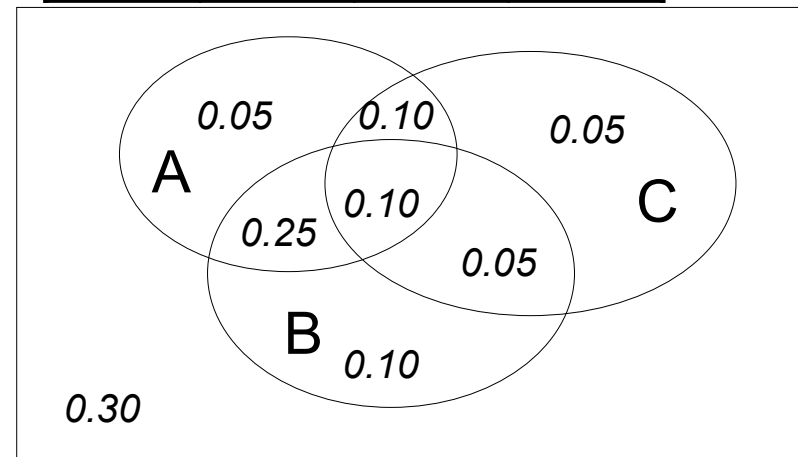
The Joint Distribution

Example: Boolean variables A, B, C

Recipe for making a joint distribution of M variables:



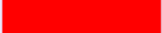
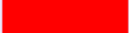
1. Make a truth table listing all combinations of values (M Boolean variables $\rightarrow 2^M$ rows).
2. For each combination of values, say how probable it is.
3. If you subscribe to the axioms of probability, those probabilities must sum to 1.

A	B	C	Prob
0	0	0	0.30
0	0	1	0.05
0	1	0	0.10
0	1	1	0.05
1	0	0	0.05
1	0	1	0.10
1	1	0	0.25
1	1	1	0.10



[A. Moore]

Using the Joint Distribution

gender	hours_worked	wealth		
Female	v0:40.5-	poor	0.253122	
		rich	0.0245895	
	v1:40.5+	poor	0.0421768	
		rich	0.0116293	
Male	v0:40.5-	poor	0.331313	
		rich	0.0971295	
	v1:40.5+	poor	0.134106	
		rich	0.105933	

Once you have the JD
you can ask for the
probability of **any** logical
expression involving
these variables

$$P(E) = \sum_{\text{rows matching } E} P(\text{row})$$

Using the Joint

gender	hours_worked	wealth		
Female	v0:40.5-	poor	0.253122	<div></div>
		rich	0.0245895	<div></div>
	v1:40.5+	poor	0.0421768	<div></div>
		rich	0.0116293	<div></div>
Male	v0:40.5-	poor	0.331313	<div></div>
		rich	0.0971295	<div></div>
	v1:40.5+	poor	0.134106	<div></div>
		rich	0.105933	<div></div>

$$P(\text{Poor Male}) = 0.4654$$

$$P(E) = \sum_{\text{rows matching } E} P(\text{row})$$

Using the Joint

gender	hours_worked	wealth	
Female	v0:40.5-	poor	0.253122
		rich	0.0245895
	v1:40.5+	poor	0.0421768
		rich	0.0116293
Male	v0:40.5-	poor	0.331313
		rich	0.0971295
	v1:40.5+	poor	0.134106
		rich	0.105933

$$P(\text{Poor}) = 0.7604$$

$$P(E) = \sum_{\text{rows matching } E} P(\text{row})$$









Inference with the Joint

gender	hours_worked	wealth	
Female	v0:40.5-	poor	0.253122
		rich	0.0245895
	v1:40.5+	poor	0.0421768
		rich	0.0116293
Male	v0:40.5-	poor	0.331313
		rich	0.0971295
	v1:40.5+	poor	0.134106
		rich	0.105933

$$P(E_1 | E_2) = \frac{P(E_1 \wedge E_2)}{P(E_2)} = \frac{\sum_{\text{rows matching } E_1 \text{ and } E_2} P(\text{row})}{\sum_{\text{rows matching } E_2} P(\text{row})}$$

$$P(\text{Male} | \text{Poor}) = 0.4654 / 0.7604 = 0.612$$

Learning and the Joint Distribution

gender	hours_worked	wealth		
Female	v0:40.5-	poor	0.253122	
		rich	0.0245895	
	v1:40.5+	poor	0.0421768	
		rich	0.0116293	
Male	v0:40.5-	poor	0.331313	
		rich	0.0971295	
	v1:40.5+	poor	0.134106	
		rich	0.105933	

Suppose we want to learn the function $f: \langle G, H \rangle \rightarrow W$

Equivalently, $P(W \mid G, H)$

Solution: learn joint distribution from data, calculate $P(W \mid G, H)$

e.g., $P(W=\text{rich} \mid G = \text{female}, H = 40.5-) =$

sounds like the solution to
learning $F: X \rightarrow Y$,
or $P(Y | X)$.

Are we done?

sounds like the solution to
learning $F: X \rightarrow Y$,
or $P(Y | X)$.

Main problem: learning $P(Y|X)$
can require more data than we have

consider learning Joint Dist. with 100 attributes

of rows in this table?

of people on earth?

fraction of rows with 0 training examples?

What to do?

1. Be smart about how we estimate probabilities from sparse data
 - maximum likelihood estimates
 - maximum a posteriori estimates
2. Be smart about how to represent joint distributions
 - Bayes networks, graphical models

1. Be smart about how we estimate probabilities

Estimating Probability of Heads



- I show you the above coin X , and hire you to estimate the probability that it will turn up heads ($X = 1$) or tails ($X = 0$)
- You flip it repeatedly, observing
 - it turns up heads α_1 times
 - it turns up tails α_0 times
- Your estimate for $P(X = 1)$ is....?

Estimating $\theta = P(X=1)$



Test A:

100 flips: 51 Heads ($X=1$), 49 Tails ($X=0$)

Test B:

3 flips: 2 Heads ($X=1$), 1 Tails ($X=0$)

Estimating $\theta = P(X=1)$



X=1

X=0

Case C: (online learning)

- keep flipping, want single learning algorithm that gives reasonable estimate after each flip

Principles for Estimating Probabilities

Principle 1 (maximum likelihood):

- choose parameters θ that maximize **$P(\text{data} \mid \theta)$**

- e.g.,
$$\hat{\theta}^{MLE} = \frac{\alpha_1}{\alpha_1 + \alpha_0}$$

Principle 2 (maximum a posteriori prob.):

- choose parameters θ that maximize **$P(\theta \mid \text{data})$**

- e.g.

$$\hat{\theta}^{MAP} = \frac{\alpha_1 + \# \text{hallucinated_1s}}{(\alpha_1 + \# \text{hallucinated_1s}) + (\alpha_0 + \# \text{hallucinated_0s})}$$

Maximum Likelihood Estimation

$$P(X=1) = \theta \quad P(X=0) = (1-\theta)$$




Data D:

Flips produce data D with α_1 heads, α_0 tails

- flips are independent, identically distributed 1's and 0's (Bernoulli)
- α_1 and α_0 are counts that sum these outcomes (Binomial)

$$P(D|\theta) = P(\alpha_1, \alpha_0|\theta) = \theta^{\alpha_1}(1 - \theta)^{\alpha_0}$$

Maximum Likelihood Estimate for Θ


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

■ Set derivative to zero: $\frac{d}{d\theta} \ln P(\mathcal{D} \mid \theta) = 0$

$$\hat{\theta} = \arg \max_{\theta} \ln P(D|\theta)$$

■ Set derivative to zero:

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

$$= \arg \max_{\theta} \ln [\theta^{\alpha_1} (1 - \theta)^{\alpha_0}]$$

hint: $\frac{\partial \ln \theta}{\partial \theta} = \frac{1}{\theta}$

Summary: Maximum Likelihood Estimate



$X=1$ $X=0$

$$P(X=1) = \theta$$

$$P(X=0) = 1-\theta$$

(Bernoulli)

- Each flip yields boolean value for X

$$X \sim \text{Bernoulli}: P(X) = \theta^X (1 - \theta)^{(1-X)}$$

- Data set D of independent, identically distributed (iid) flips produces α_1 ones, α_0 zeros (Binomial)

$$P(D|\theta) = P(\alpha_1, \alpha_0|\theta) = \theta^{\alpha_1} (1 - \theta)^{\alpha_0}$$

$$\hat{\theta}^{MLE} = \operatorname{argmax}_{\theta} P(D|\theta) = \frac{\alpha_1}{\alpha_1 + \alpha_0}$$

Principles for Estimating Probabilities

Principle 1 (maximum likelihood):

- choose parameters θ that maximize $P(\text{data} \mid \theta)$

Principle 2 (maximum a posteriori prob.):

- choose parameters θ that maximize

$$P(\theta \mid \text{data}) = \frac{P(\text{data} \mid \theta) P(\theta)}{P(\text{data})}$$

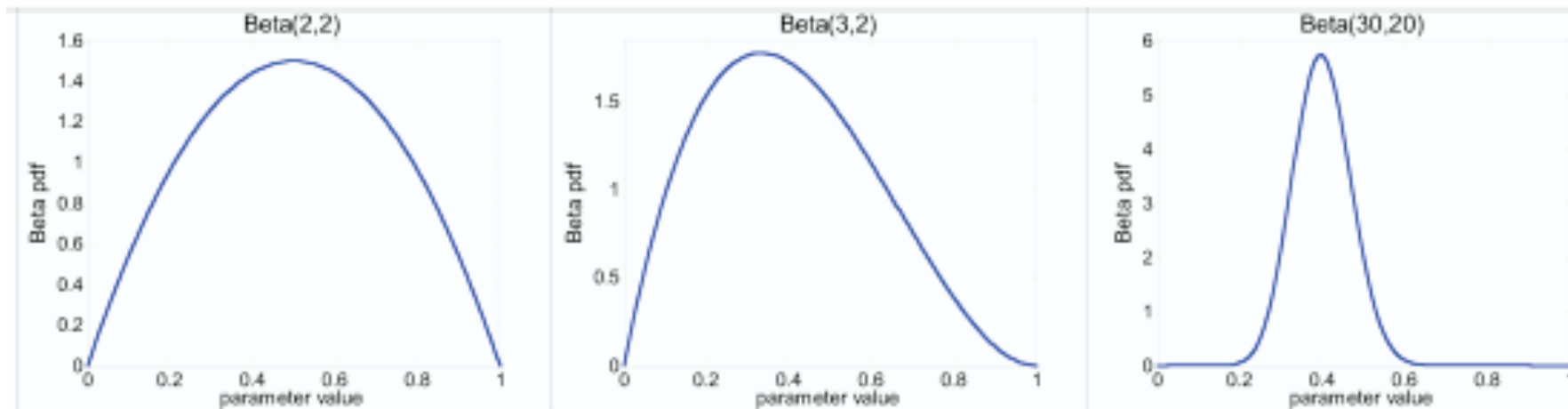
Beta prior distribution – $P(\theta)$

- $$P(\theta) = \frac{\theta^{\beta_H-1}(1-\theta)^{\beta_T-1}}{B(\beta_H, \beta_T)} \sim \text{Beta}(\beta_H, \beta_T)$$
- Likelihood function: $P(\mathcal{D} \mid \theta) = \theta^{\alpha_H}(1-\theta)^{\alpha_T}$
- Posterior: $P(\theta \mid \mathcal{D}) \propto P(\mathcal{D} \mid \theta)P(\theta)$

Beta prior distribution – $P(\theta)$

■

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



[C. Guestrin]

Eg. 1 Coin flip problem

Likelihood is \sim Binomial

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

If prior is Beta distribution,

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

Then posterior is Beta distribution

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

and MAP estimate is therefore

$$\hat{\theta}^{MAP} = \frac{\alpha_H + \beta_H - 1}{(\alpha_H + \beta_H - 1) + (\alpha_T + \beta_T - 1)}$$



Eg. 2 Dice roll problem (6 outcomes instead of 2)



Likelihood is $\sim \text{Multinomial}(\theta = \{\theta_1, \theta_2, \dots, \theta_k\})$

$$P(\mathcal{D} \mid \theta) = \theta_1^{\alpha_1} \theta_2^{\alpha_2} \dots \theta_k^{\alpha_k}$$

If prior is Dirichlet distribution,

$$P(\theta) = \frac{\theta_1^{\beta_1-1} \theta_2^{\beta_2-1} \dots \theta_k^{\beta_k-1}}{B(\beta_1, \dots, \beta_k)} \sim \text{Dirichlet}(\beta_1, \dots, \beta_k)$$

Then posterior is Dirichlet distribution

$$P(\theta \mid D) \sim \text{Dirichlet}(\beta_1 + \alpha_1, \dots, \beta_k + \alpha_k)$$

and MAP estimate is therefore

$$\hat{\theta}_i^{MAP} = \frac{\alpha_i + \beta_i - 1}{\sum_{j=1}^k (\alpha_j + \beta_j - 1)}$$

Some terminology

- Likelihood function: $P(\text{data} \mid \theta)$
- Prior: $P(\theta)$
- Posterior: $P(\theta \mid \text{data})$
- Conjugate prior: $P(\theta)$ is the conjugate prior for likelihood function $P(\text{data} \mid \theta)$ if the forms of $P(\theta)$ and $P(\theta \mid \text{data})$ are the same.

You should know

- Probability basics
 - random variables, conditional probs, ...
 - Bayes rule
 - Joint probability distributions
 - calculating probabilities from the joint distribution
- Estimating parameters from data
 - maximum likelihood estimates
 - maximum a posteriori estimates
 - distributions – binomial, Beta, Dirichlet, ...
 - conjugate priors

Extra slides

Independent Events

- Definition: two events A and B are *independent* if $P(A \wedge B) = P(A) * P(B)$
- Intuition: knowing A tells us nothing about the value of B (and vice versa)

Picture “A independent of B”

Expected values

Given a discrete random variable X , the expected value of X , written $E[X]$ is

$$E[X] = \sum_{x \in \mathcal{X}} xP(X = x)$$

Example:

X	P(X)
0	0.3
1	0.2
2	0.5

Expected values

Given discrete random variable X , the expected value of X , written $E[X]$ is

$$E[X] = \sum_{x \in \mathcal{X}} xP(X = x)$$

We also can talk about the expected value of functions of X

$$E[f(X)] = \sum_{x \in \mathcal{X}} f(x)P(X = x)$$

Covariance

Given two discrete r.v.'s X and Y , we define the covariance of X and Y as

$$\text{Cov}(X, Y) = E[(X - E(X))(Y - E(Y))]$$

e.g., X =gender, Y =playsFootball

or X =gender, Y =leftHanded

Remember: $E[X] = \sum_{x \in \mathcal{X}} xP(X = x)$

Thank You!

Likelihood

How Probable is the evidence(data) given that the hypothesis(parameters) is true

Prior

Our belief in hypothesis(parameters) before observing the evidence(data)

$$P(H | e) = \frac{P(e | H) P(H)}{P(e)}$$

Marginal

Distribution of evidence(data), mostly we are not interested in this as this is a constant term