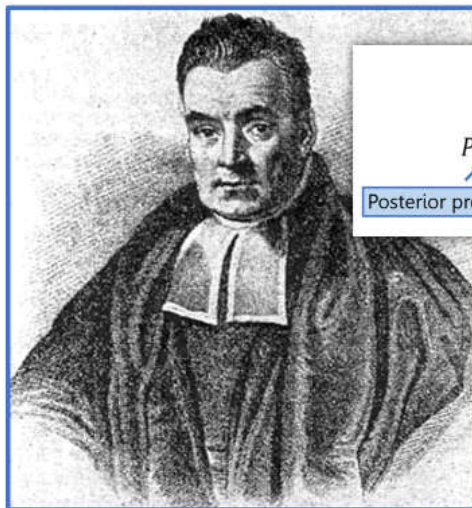


Bayes' theorem



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

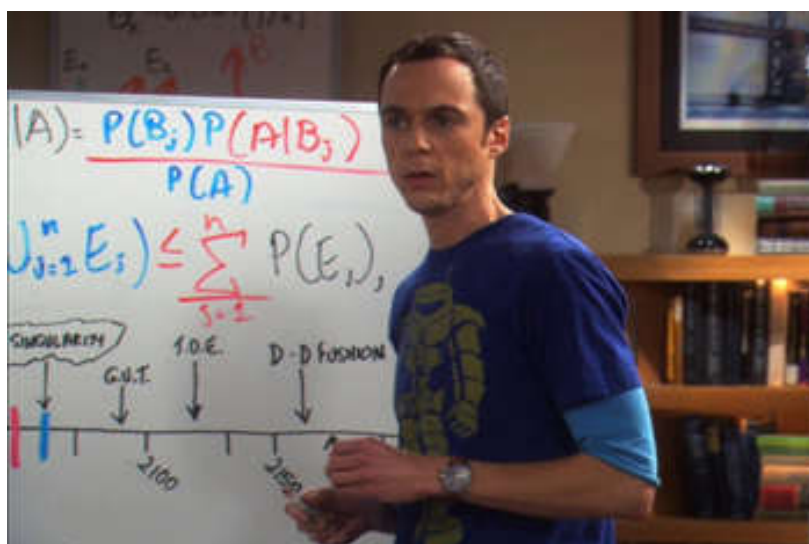
Diagram labels for Bayes' theorem:

- Likelihood** points to $P(B|A)$
- Prior probability** points to $P(A)$
- Evidence** points to $P(B)$
- Posterior probability** points to $P(A|B)$



A Puzzle:

校园遇到一个shy的男同学，他是Math Phd还是Business School的？



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校园遇到一个shy的男同学，他是Math Phd还是Business School的？

Q:

$P(\text{math} | \text{shy})$ 和 $P(\text{business} | \text{shy})$

A:

$P(\text{shy} | \text{math})$ 和 $P(\text{shy} | \text{business})$

(大部分同学比较了这两个概率)



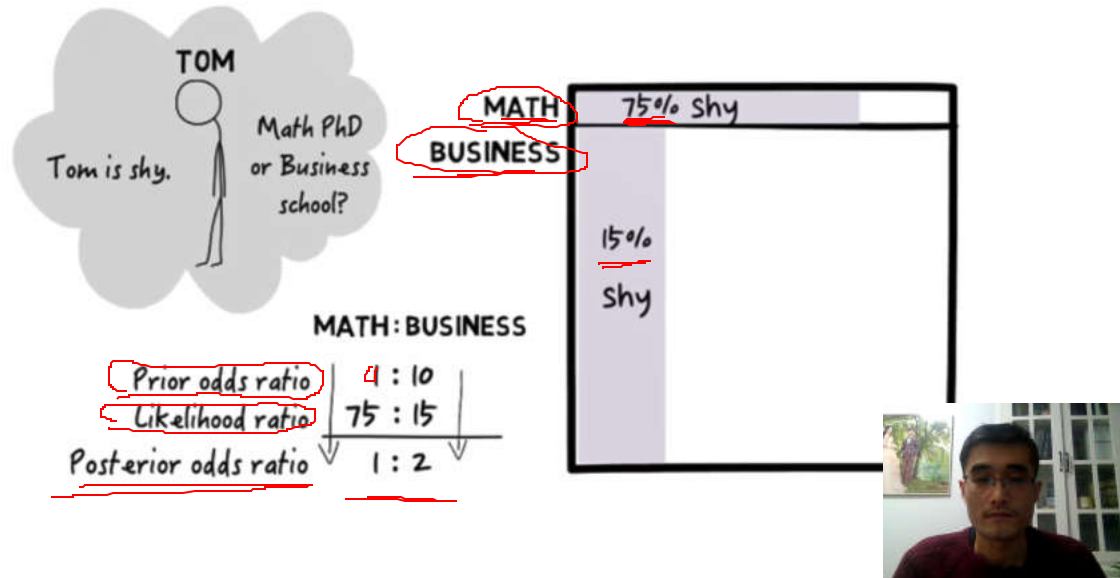
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贝叶斯公式：

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

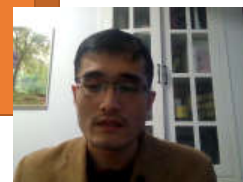
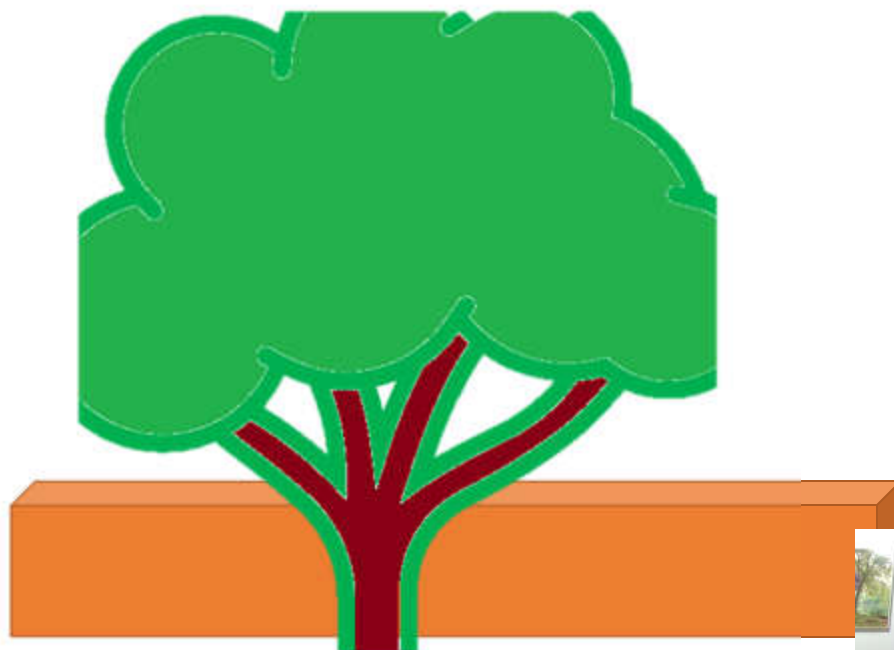
Posterior = $\frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$

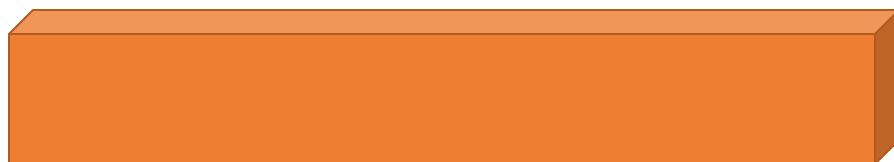
What Bayes tells us: Don't forget the prior!

贝叶斯公式：

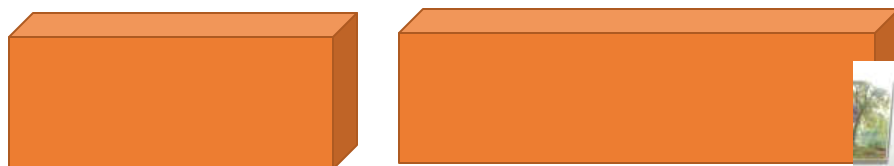
$$P(B|A) = \frac{P(A|B)P(B)}{P(A)}$$

$$\text{Posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$$





OR



贝叶斯公式:

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

$$\text{Posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$$



似然 (likelihood)

$$L(\theta|x) = P(X=x|\theta)$$



极大似然估计 (MLE)

$$L(\theta|x) = P(X=x|\theta)$$

Maximum Likelihood Estimate (MLE): 找出参数 θ , 使得从中抽样所得的观测数据的概率最大

$$L(\theta) = L(x_1, x_2, \dots, x_n; \theta) = \prod_{i=1}^n p(x_i; \theta)$$



贝叶斯公式应用I – 分类器：

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

$$\text{Posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$$

贝叶斯分类器：

$$p(\text{类别}|\text{特征}) = \frac{p(\text{特征}|\text{类别})p(\text{类别})}{p(\text{特征})}$$



判别模型 vs 生成模型 (support sampling)

	Discriminative model	Generative model
Goal	Directly estimate $P(y x)$	Estimate $P(x y)$ to then deduce $P(y x)$
What's learned	Decision boundary	Probability distributions of the data
Illustration		
Examples	Regressions, SVMs	GDA, Naive Bayes

A **generative algorithm** models how the data was generated in order to categorize a signal. It asks the question: based on my generation assumptions, which category is most likely to generate this signal?

A **discriminative algorithm** does not care about how the data was generated, it simply categorizes a given signal.

生成模型对数据的生成方式进行建模。它提出一个问题：根据我的生成方式假设，哪个类别(y)最有可能产生当前的特征(x)? 需要对 $P(x|y)$ 进行建模。

判别模型不关心数据是如何生成的，它只是对给定的特征进行判别/分类。直接对 $P(y|x)$ 进行建模。



判别模型 vs 生成模型 (support sampling)



贝叶斯公式应用 II - 医学诊断:

$$p(\text{病因} | \text{症状}) = \frac{p(\text{症状} | \text{病因}) p(\text{病因})}{p(\text{症状})}$$

	Well	Cold	Allergy
$P(d)$	0.9	0.05	0.05
$P(\text{sneeze} d)$	0.1	0.9	0.9
$P(\text{cough} d)$	0.1	0.8	0.7
$P(\text{fever} d)$	0.01	0.7	0.4



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贝叶斯公式应用 II - 医学诊断:

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早期AI:

An attempt to simplify probabilistic reasoning in 1960s medical diagnostic programs



贝叶斯公式应用 III - NLP:

