

Generative models vs Discriminative models

Discriminative models

A Discriminative model learns the conditional probability distribution $p(y|x)$

A Discriminative model models the decision boundary between the classes.

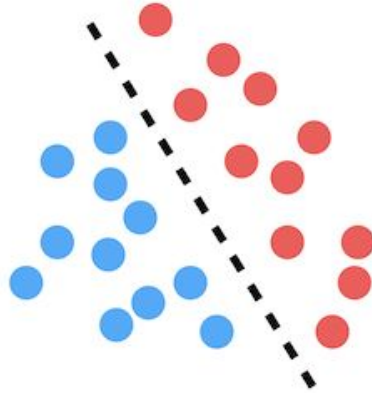


Image source: google image

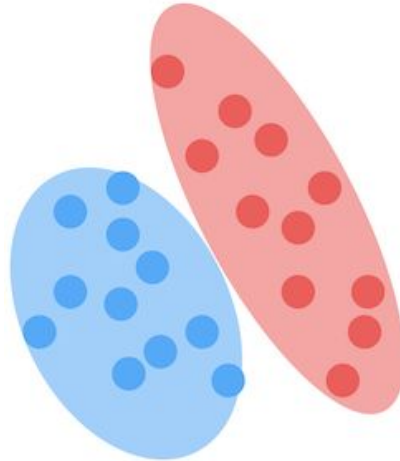
Generative models

A Generative Model learns the joint probability distribution $P(x,y)$.

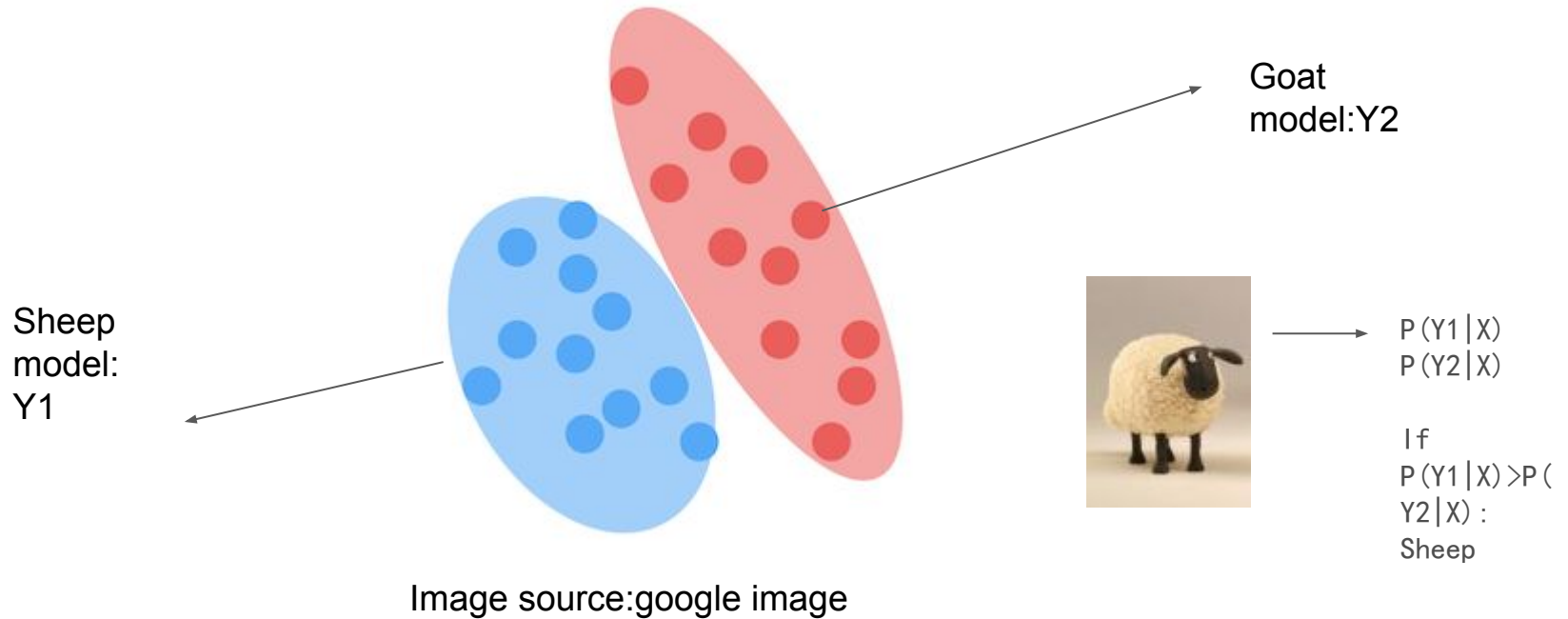
$$P(x, y) = P(x | y) * P(y) = P(y|x)*P(x)$$

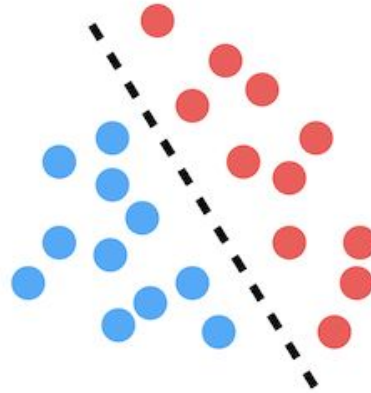
A Generative Model explicitly models the actual distribution of each class.

Generative



Example: Sheep or Goat?





→ $y=f(x)$
→left of
boundary
→sheep

Image source:google image

Examples [\[edit \]](#)

Simple example [\[edit \]](#)

Suppose the input data is $x \in \{1, 2\}$, the set of labels for x is $y \in \{0, 1\}$, and there are the following 4 data points: $(x, y) = \{(1, 0), (1, 1), (2, 0), (2, 0)\}$

For the above data, estimating the joint probability distribution $p(x, y)$ from the [empirical measure](#) will be the following:

	$y = 0$	$y = 1$
$x = 1$	1/4	1/4
$x = 2$	2/4	0

$$p(y|x) \cdot p(x)$$

while $p(y|x)$ will be following:

	$y = 0$	$y = 1$
$x = 1$	1/2	1/2
$x = 2$	1	0

source : https://en.wikipedia.org/wiki/Generative_model

Bayes rule is better?

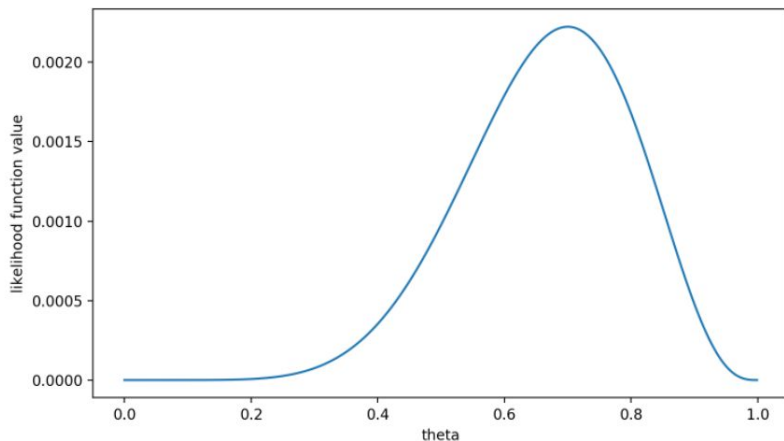
Suppose we toss coin 10 times: THHHHTHHHT

Θ is the probability that a H occur.

X0 is our 10-times-toss experiment

$$f(x_0, \theta) = (1-\theta) \times \theta \times \theta \times \theta \times \theta \times (1-\theta) \times \theta \times \theta \times \theta \times (1-\theta) = \theta^7 (1-\theta)^3 = f(\theta) \rightarrow \text{Likelihood Function}$$

Maximum likelihood estimation



Based on the result we think the probability that we get a head is 0.7.

However, no one would be convinced. All of us know that it should be 0.5.....

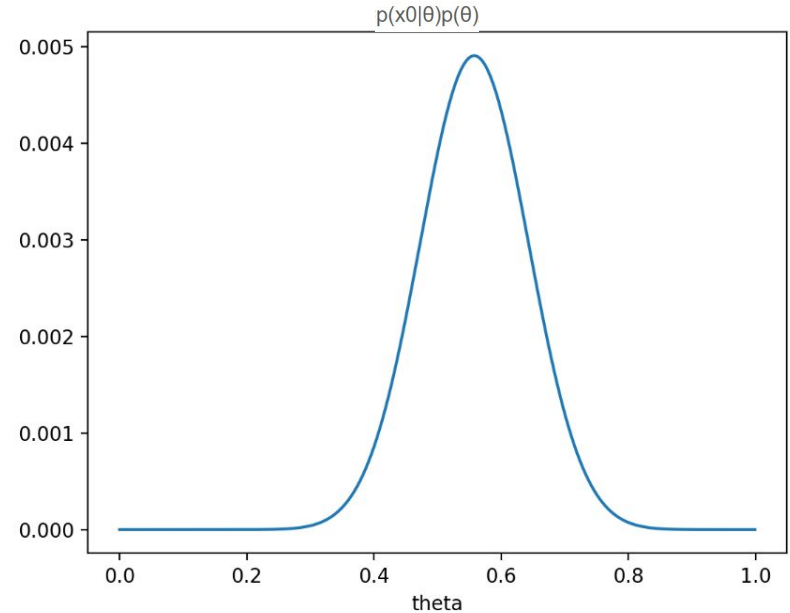
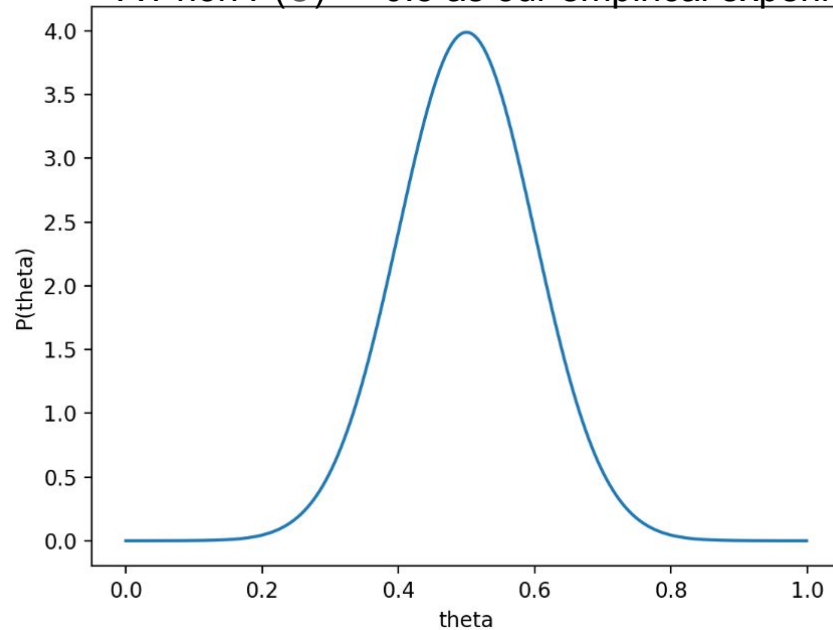
source:<https://blog.csdn.net/u011508640/article/details/7>

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Maximum a posteriori estimation

$$P(\theta | x_0) = p(x_0 | \theta) p(\theta) / p(x) \rightarrow \text{Bayes Rule}$$

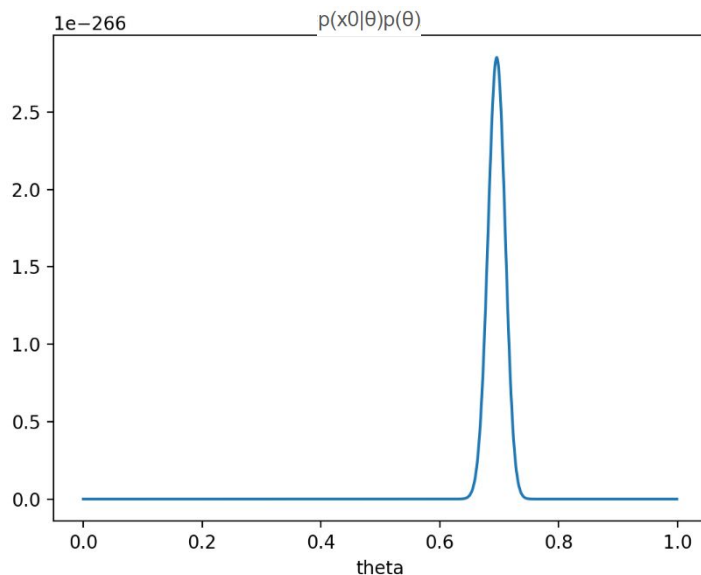
A Priori $P(\theta) \rightarrow 0.5$ as our empirical experiment



$\theta = 0.558$ in this case which is close to a priori or empirical experience.

What if our coin has some problem that the probability is really 0.7 for a head?

We need to do more experiments. If we do our experiment 1000 times and we get 700 heads.



When $\theta=0.696$ we get the maximum value. Finally, even we have empirical experiment, we still believe that the probability is 0.7 for a head