

# Lecture 1: probability concepts I.

# Bayesian probabilities in your non-academic life:

## Example: The Monty Hall or Let's Make a Deal Problem



- Three doors
- Car (prize) behind one door
- You pick a door, but don't open it yet
- Monty then opens one of the other doors, always revealing no car (he knows where it is)
- You now get to switch doors if you want
- Should you?
- Most people reason: Two remaining doors were equiprobable before, and nothing has changed. So doesn't matter whether you switch or not.

# Bayes' theorem

Let's work a couple of examples using Bayes Law:

Example: Trolls Under the Bridge



Trolls are bad. Gnomes are benign.  
Every bridge has 5 creatures under it:

- 20% have TTGGG ( $H_1$ )
- 20% have TGGGG ( $H_2$ )
- 60% have GGGGG (benign) ( $H_3$ )

Before crossing a bridge, a knight captures one of the 5 creatures at random. It is a troll. "I now have an 80% chance of crossing safely," he reasons, "since only the case 20% had TTGGG ( $H_1$ )  $\rightarrow$  now have TGGG is still a threat."

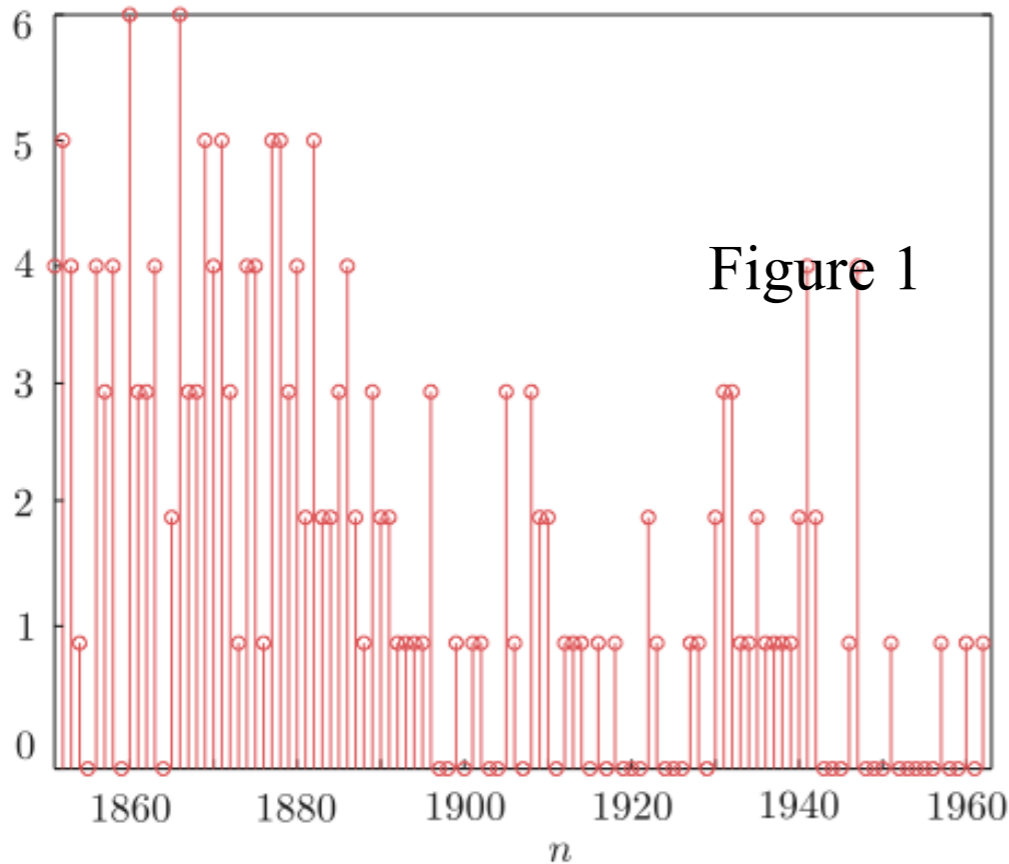


# machine learning example

## A CASE STUDY: CHANGE-POINT DETECTION

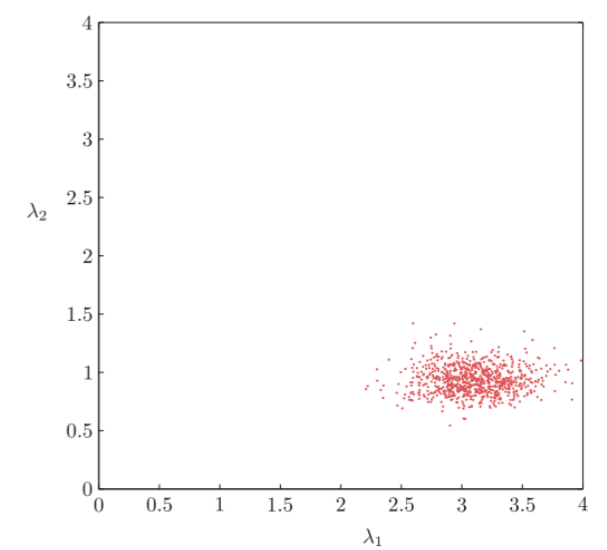
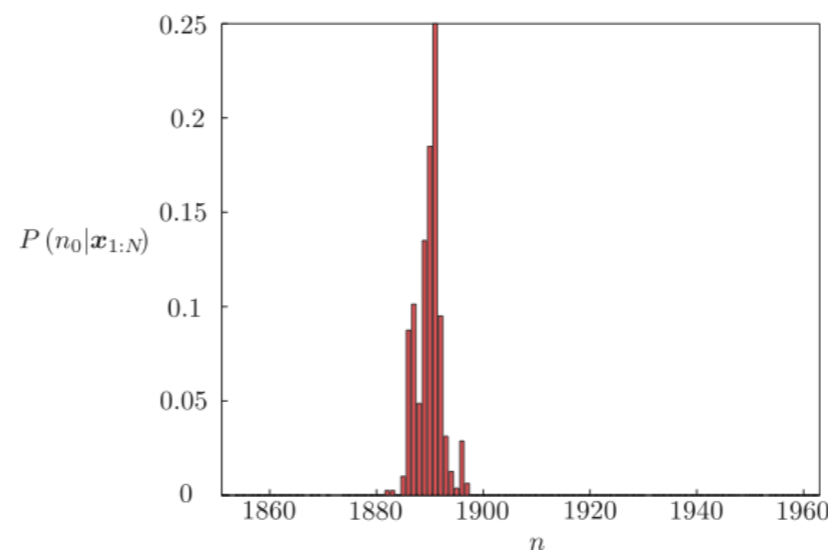
task is to detect partitions in a sequence of observations, in order for the data in each block to be statistically “similar,” in other words, to be distributed according to a common probability distribution.

Figure 1 shows the number of deadly accidents per year in the coal mines in England spanning the years 1851-1962. Looking at the graph, it is readily observed that the “front” part of the graph looks different from its “back” end, with a change around 1890-1900. As a matter of fact, in 1890, new health and safety regulations were introduced, following pressure from the coal miners’ unions. We will use the poisson distribution.



Coal mining data

```
x=[4 5 4 1 0 4 3 4 0 6 3 3 4 0 2 6 3 3 5 4 5 3 1 4 4 1 5 5 3 4 2 5 2 2 ...  
3 4 2 1 3 2 2 1 1 1 1 3 0 0 1 0 1 1 0 0 3 1 0 3 2 2 0 1 1 1 0 1 0 1 0 ...  
0 0 2 1 0 0 0 1 1 0 2 3 3 1 1 2 1 1 1 1 2 4 2 0 0 0 1 4 0 0 0 1 0 0 0 ...  
0 0 1 0 0 1 0 1]
```



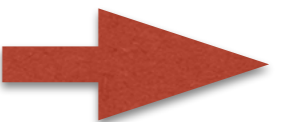
# Laws of Probability

“There is this thing called *probability*. It obeys the laws of an axiomatic system. When identified with the real world, it gives (partial) information about the future.”

- What axiomatic system?
- How to identify to real world?
  - Bayesian or frequentist viewpoints are somewhat different “mappings” from axiomatic probability theory to the real world
  - yet both are useful

*“And, it gives a consistent and complete calculus of inference.”*

First, warmup exercise about frequentist notion of probabilities



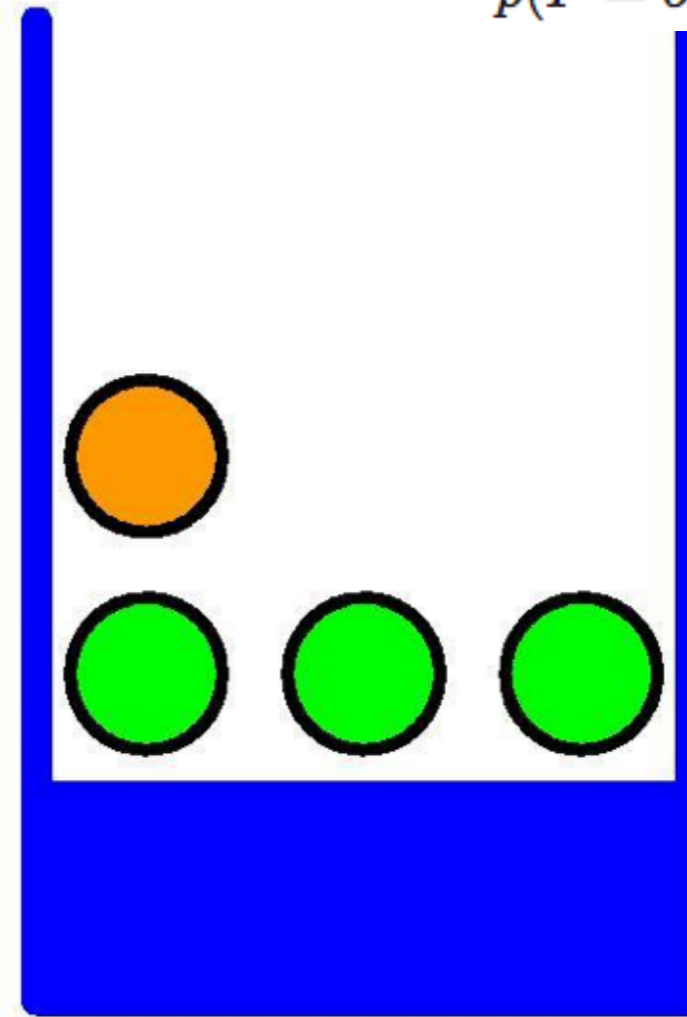
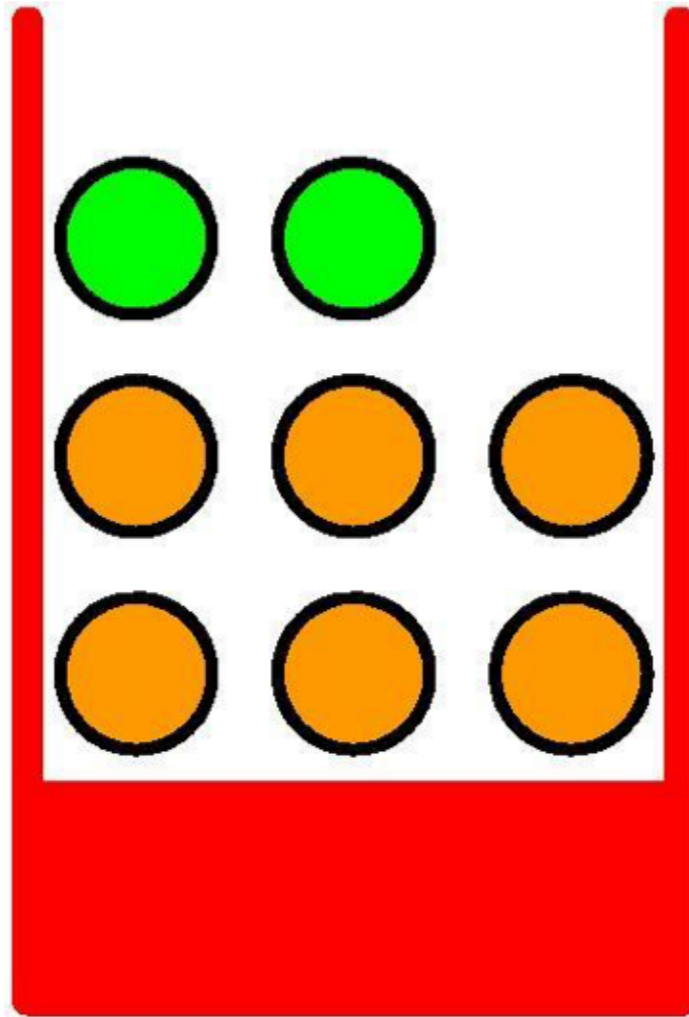
# Probability Theory

joint probabilities  
X and Y random variables

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## Apples and Oranges

$$\begin{aligned} p(B = r) &= 4/10 \text{ picking from red} & p(F = a|B = r) &= 1/4 \\ p(B = b) &= 6/10 \text{ picking from blue} & p(F = o|B = r) &= 3/4 \\ & & p(F = a|B = b) &= 3/4 \\ & & p(F = o|B = b) &= 1/4 \end{aligned}$$

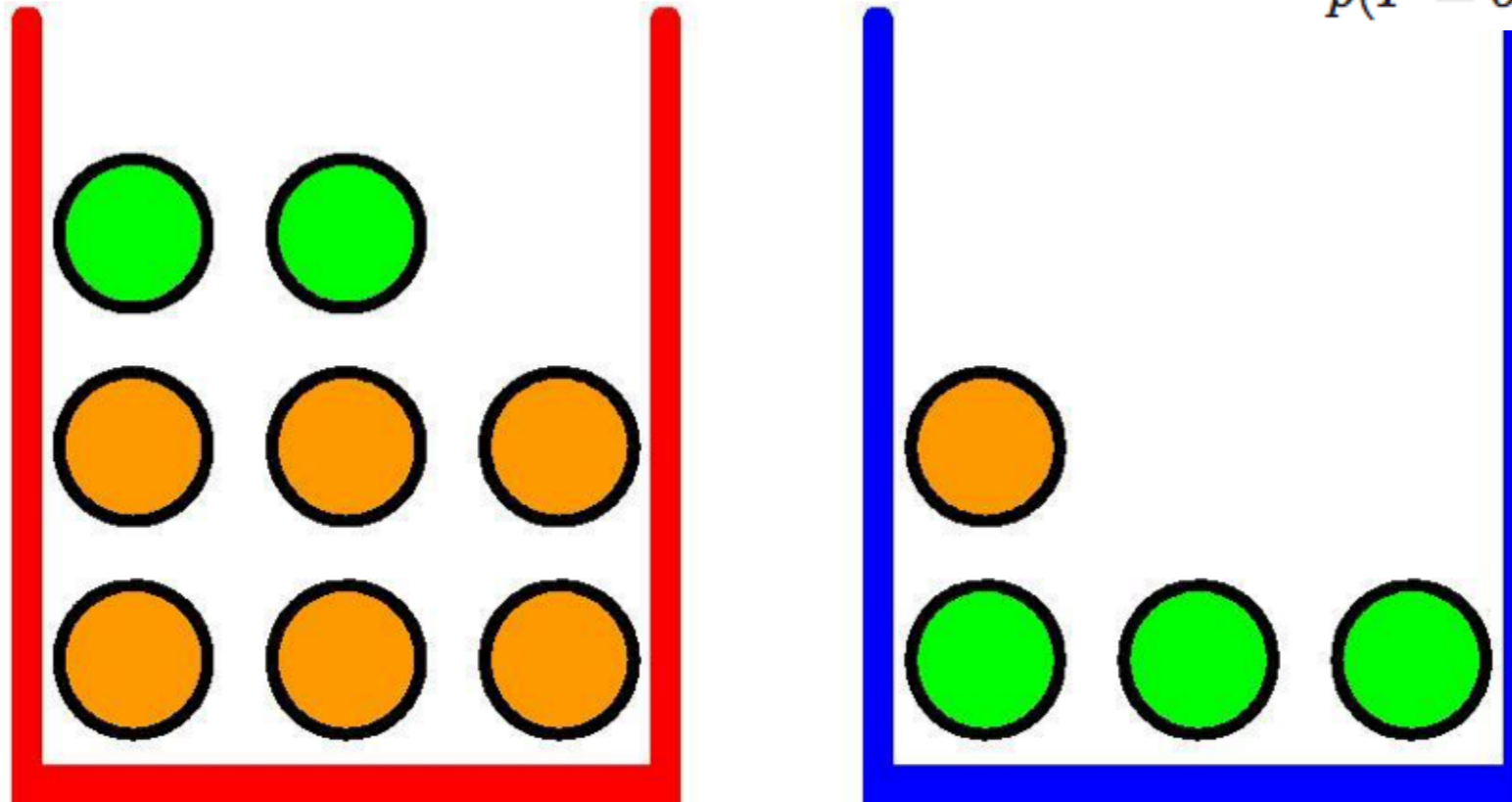


# Probability Theory

joint probabilities  
X and Y random variables

## Apples and Oranges

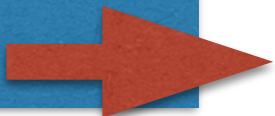
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what is the probability to pick apple?

if orange, what is the probability that it came from blue box?

two elementary rules in probability theory help: sum rule and product rule



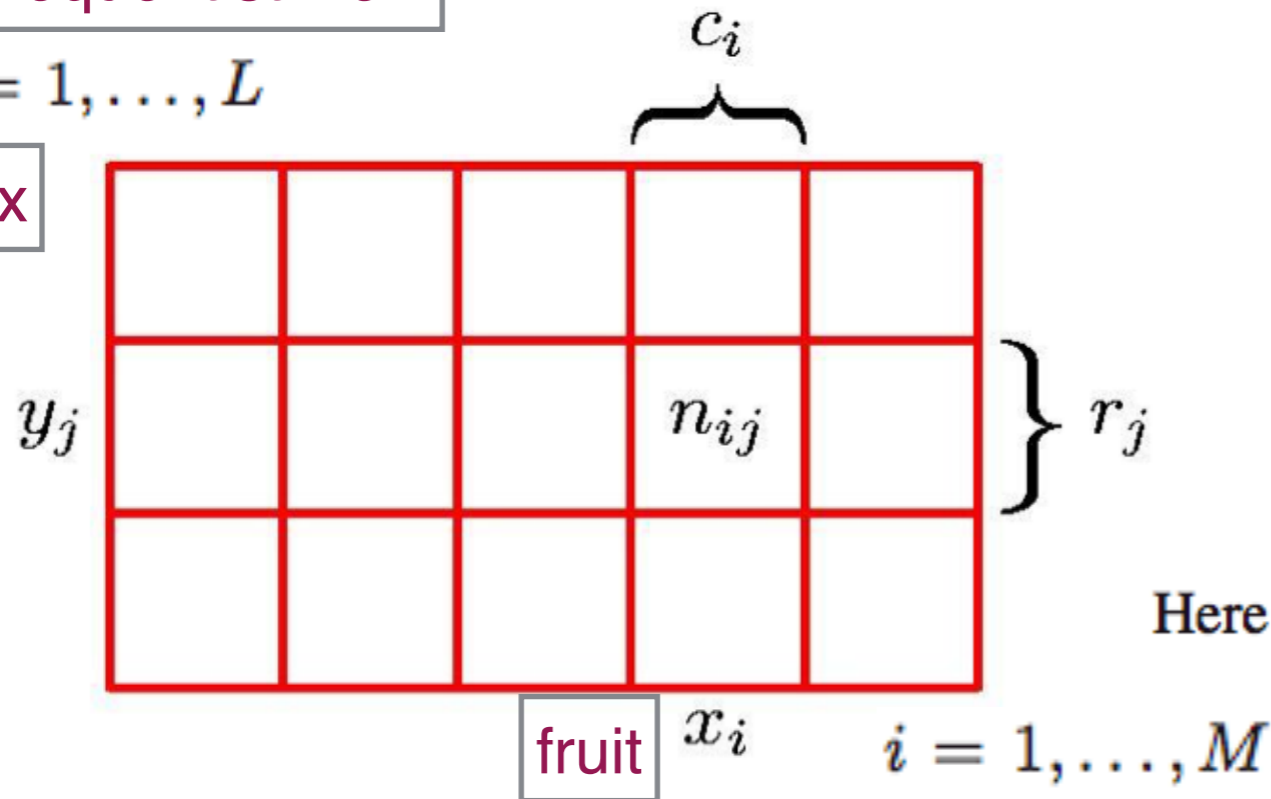
# Probability Theory

joint probabilities  
X and Y random variables

frequentist view

$j = 1, \dots, L$

box



## Marginal Probability

$$p(X = x_i) = \frac{c_i}{N}$$

Here we are implicitly considering the limit  $N \rightarrow \infty$

## Joint Probability

$$p(X = x_i, Y = y_j) = \frac{n_{ij}}{N}$$

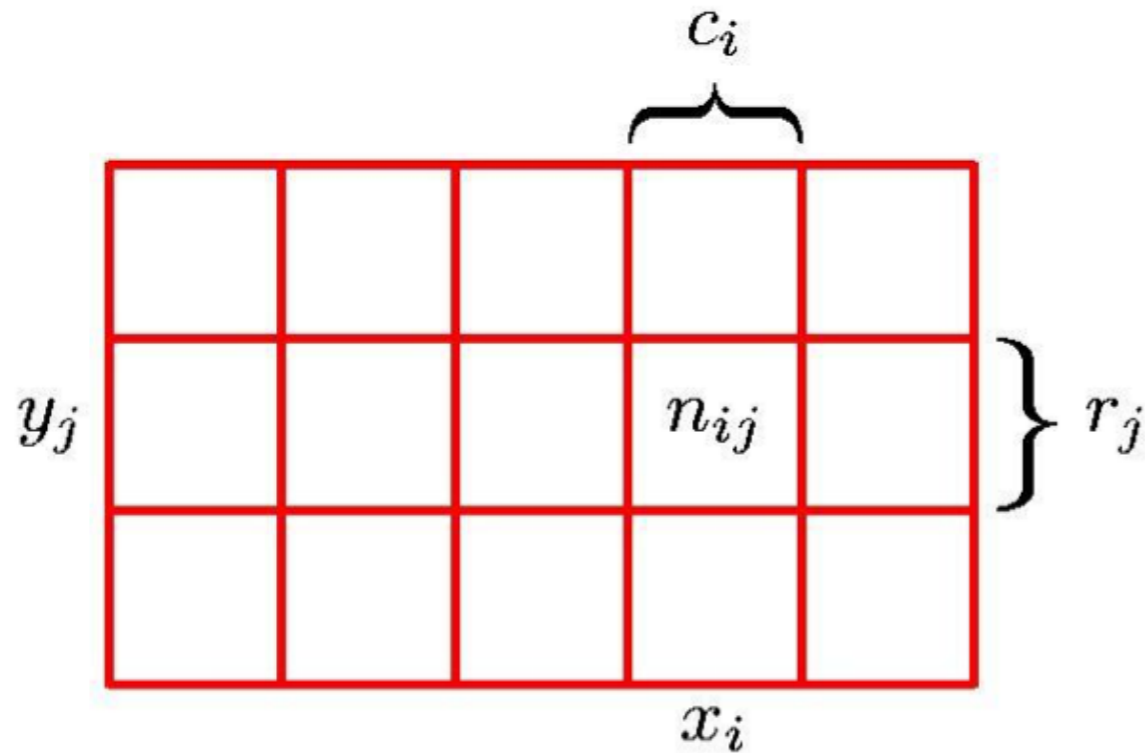
## Conditional Probability

$$p(Y = y_j | X = x_i) = \frac{n_{ij}}{c_i}$$



# Probability Theory

joint probabilities  
X and Y random variables



## Sum Rule

$$\begin{aligned} p(X = x_i) &= \frac{c_i}{N} = \frac{1}{N} \sum_{j=1}^L n_{ij} \\ &= \sum_{j=1}^L p(X = x_i, Y = y_j) \end{aligned}$$

## Product Rule

$$\begin{aligned} p(X = x_i, Y = y_j) &= \frac{n_{ij}}{N} = \frac{n_{ij}}{c_i} \cdot \frac{c_i}{N} \\ &= p(Y = y_j | X = x_i) p(X = x_i) \end{aligned}$$

# The Rules of Probability

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joint probabilities  
X and Y random variables

Sum Rule

$$p(X) = \sum_Y p(X, Y)$$

Product Rule

$$p(X, Y) = p(Y|X)p(X)$$

# Bayes' Theorem

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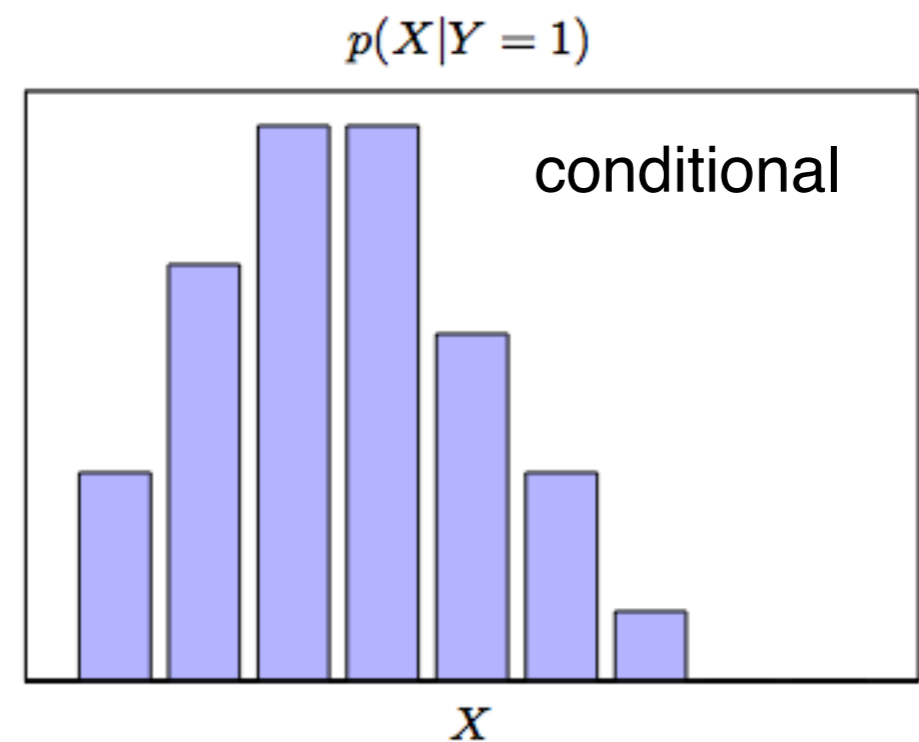
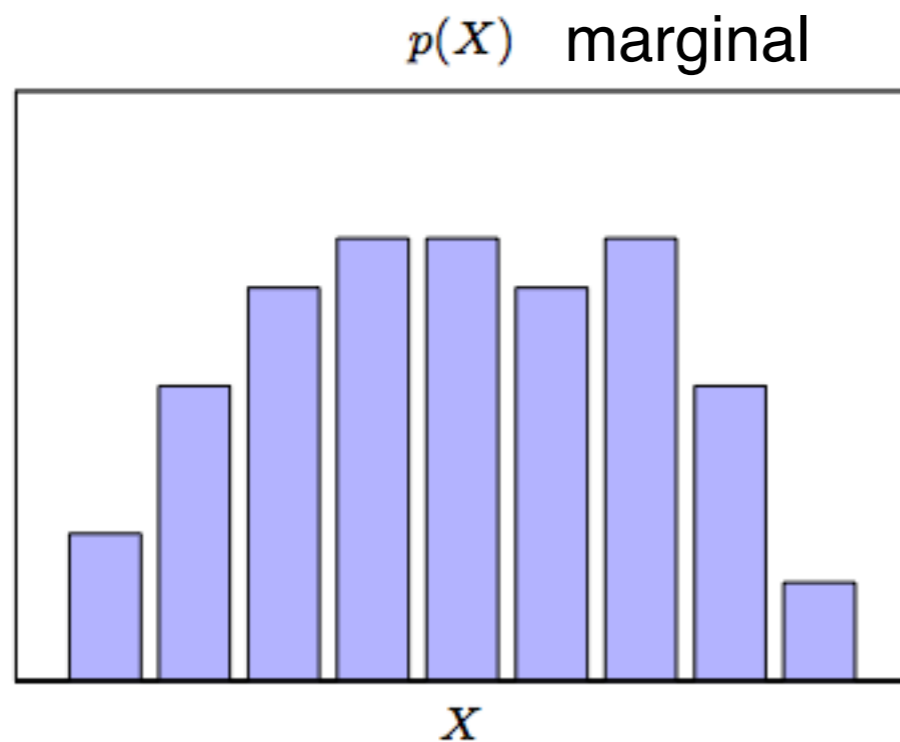
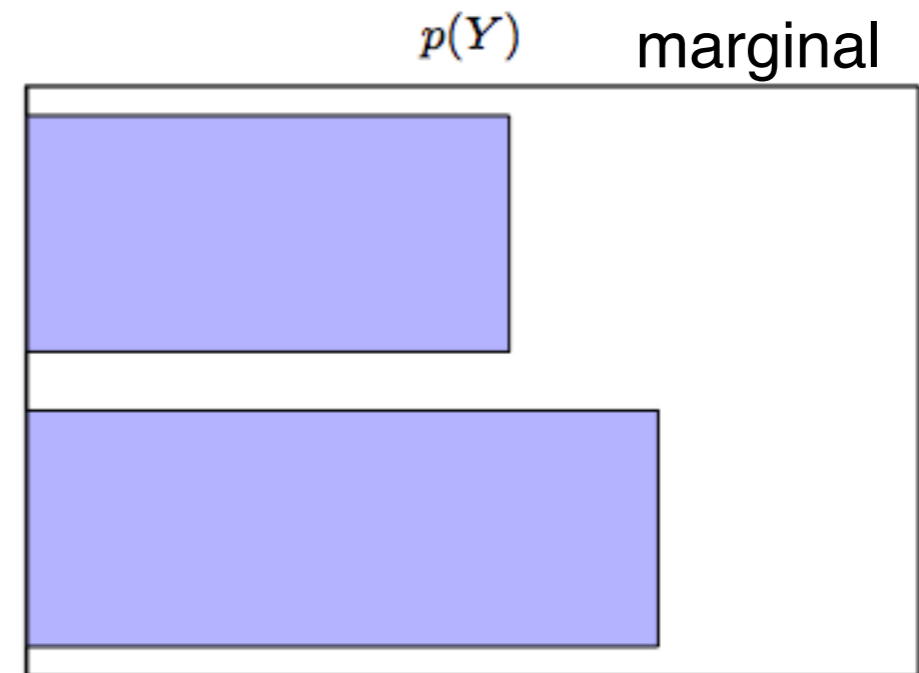
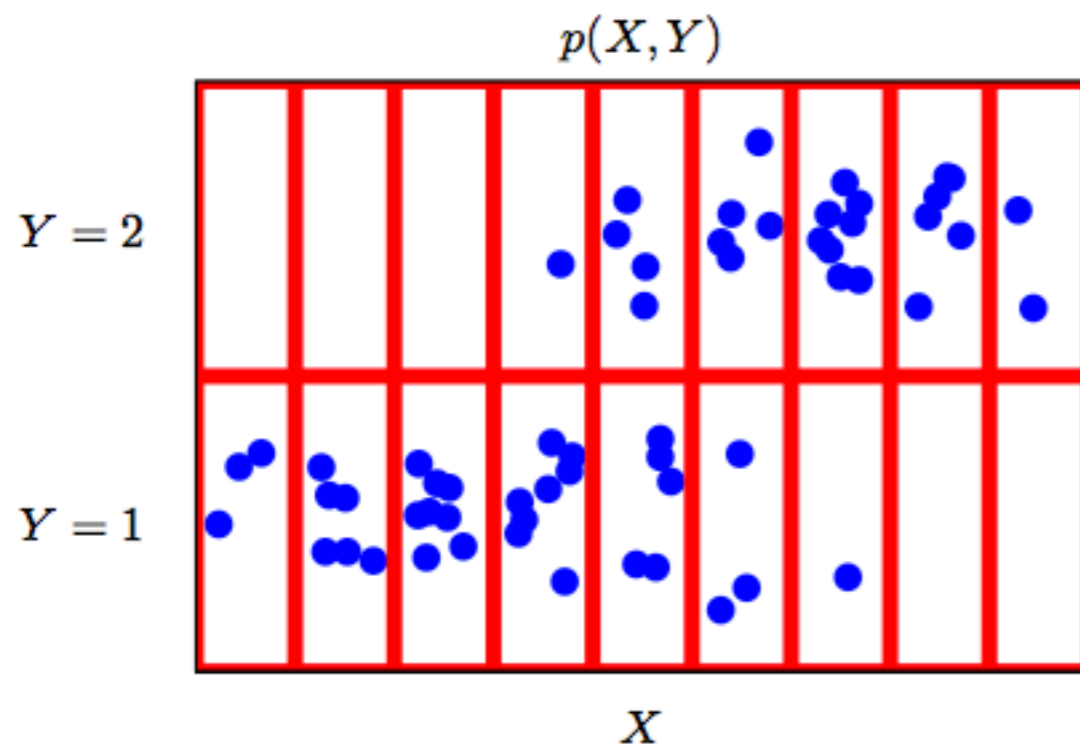
$$p(Y|X) = \frac{p(X|Y)p(Y)}{p(X)}$$

$$p(X) = \sum_Y p(X|Y)p(Y) \quad \text{normalization}$$

posterior  $\propto$  likelihood  $\times$  prior

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# tool: histogram of 60 events — joint probability distribution



## return to the problem of two boxes with fruits

$$\begin{aligned} p(B = r) &= 4/10 \\ p(B = b) &= 6/10 \end{aligned} \quad \text{marginal}$$

$$p(B = r) + p(B = b) = 1 \quad \text{normalization}$$

$$\begin{aligned} p(F = a|B = r) &= 1/4 \\ p(F = o|B = r) &= 3/4 \\ p(F = a|B = b) &= 3/4 \\ p(F = o|B = b) &= 1/4 \end{aligned} \quad \text{conditional}$$

$$p(F = a|B = r) + p(F = o|B = r) = 1$$

normalization

$$p(F = a|B = b) + p(F = o|B = b) = 1$$

$$\begin{aligned} p(F = a) &= p(F = a|B = r)p(B = r) + p(F = a|B = b)p(B = b) \\ &= \frac{1}{4} \times \frac{4}{10} + \frac{3}{4} \times \frac{6}{10} = \frac{11}{20} \end{aligned} \quad \text{picking apple}$$

$$p(F = o) = 1 - 11/20 = 9/20 \quad \text{picking orange}$$

## return to the problem of two boxes with fruits

if orange was picked, what was the probability of the box color ?

using Bayes' theorem, we can reverse the conditional probabilities:

$$p(B = r|F = o) = \frac{p(F = o|B = r)p(B = r)}{p(F = o)} = \frac{3}{4} \times \frac{4}{10} \times \frac{20}{9} = \frac{2}{3}$$

and from the sum rule:

$$p(B = b|F = o) = 1 - 2/3 = 1/3.$$

## return to the problem of two boxes with fruits

if orange was picked, what was the probability of the box ?

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interpretation of Bayes' theorem:

$p(B)$  *prior probability*, if we are told that blue box was chosen available before we observe the fruit

Once we are told it was orange, we can use Bayes' theorem to calculate  $p(B|F)$  which is the *posterior probability*