

## More generative modeling

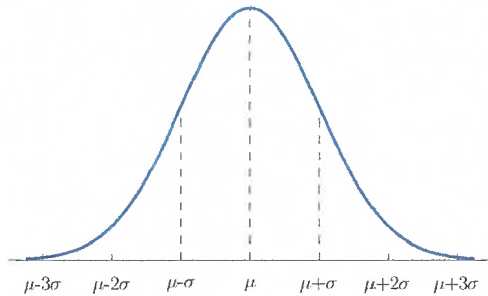
### Topics we'll cover

- ① Beyond Gaussians
- ② A variety of univariate distributions
- ③ Moving to higher dimension

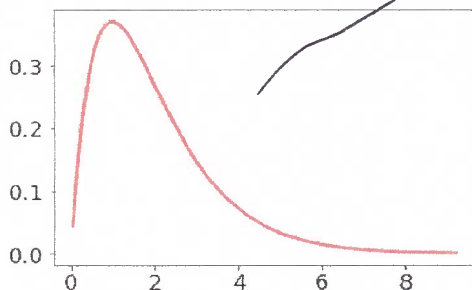
# Classification with generative models

- Fit a **distribution** to each class separately
- Use Bayes' rule to classify new data

What distribution to use? Are Gaussians enough?

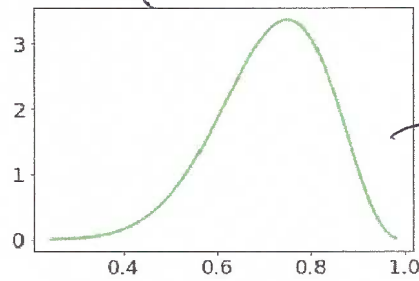


## Exponential families of distributions



**GAMMA**

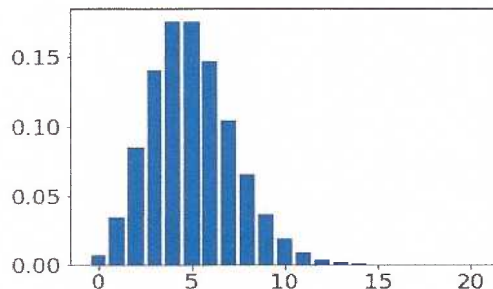
real numbers including gaussian



**BETA**

have a probability for

distributed on an interval



**POISSON**

data are integer

It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way - in short, the period was so far like the present period, that some of its noisiest authorities insisted on its being received, for good or for evil, in the superlative degree of comparison only.



1	despair
2	evil
0	happiness
1	foolishness

**CATEGORICAL**

not numeric

## Multivariate distributions

We've described a variety of distributions for **one-dimensional** data.  
What about higher dimensions?

### ① Naive Bayes: Treat coordinates as independent.

For  $x = (x_1, \dots, x_d)$ , fit separate models  $\Pr_i$  to each  $x_i$ , and assume

$$\Pr(x_1, \dots, x_d) = \Pr_1(x_1)\Pr_2(x_2) \cdots \Pr_d(x_d).$$

This assumption is typically inaccurate.

→ But quite effective in practice

### ② Multivariate Gaussian.

Model correlations between features: we've seen this in detail.

Depend - Correlates

### ③ Graphical models.

Arbitrary dependencies between coordinates.

probability distributions are many coordinates

