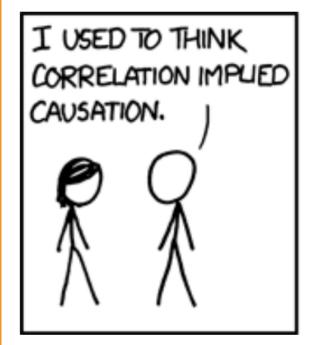
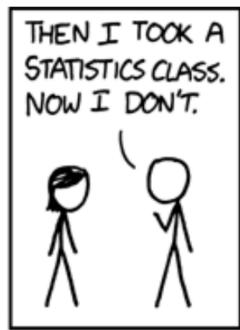
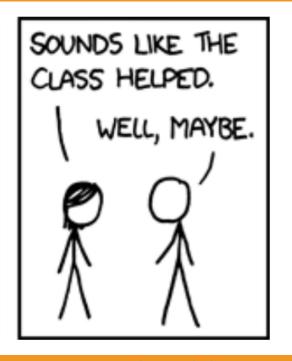


### Introduction to Basics in Statistics







# Types of Data

### **Types of Data**

#### Quantitative

- Continuous
  - Real or complex numbers
- Discrete
  - integers

#### Categorical

- Nominal
  - e.g., categories A, B, C, or I, II, III
- Ordinal
  - Ordering matters, e.g., a *Likert Scale* used in a survey: 1,2,3,4,5

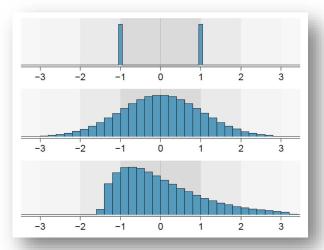
What astronomy examples can you think for each type?

## Distributions



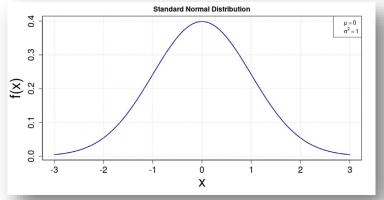
#### A distribution...

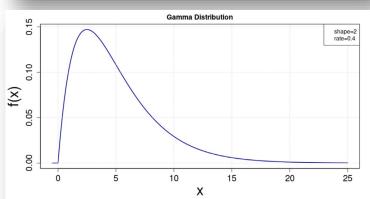
- Tells you the frequency or relative frequency of each possible value/event, or of some data that was collected
- Could be empirical or analytic
- Can be useful for modelling a population of objects
- Is often a foundation of statistical reasoning
- Can be continuous or discrete
- That is analytic has parameters that define its shape
- Can be univariate or multivariate

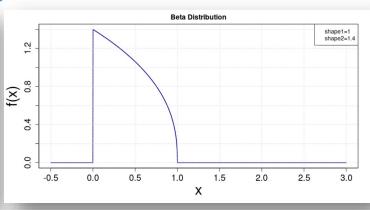


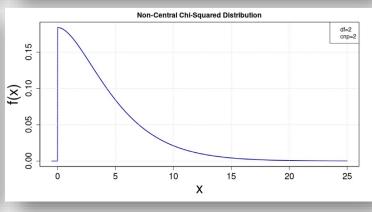
Example histograms (figure from Open Intro Statistics 4th ed.)

#### Some analytic probability distributions



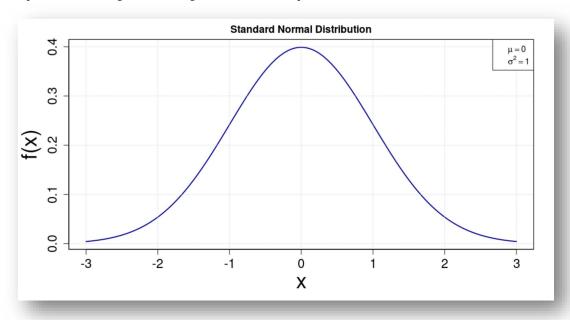




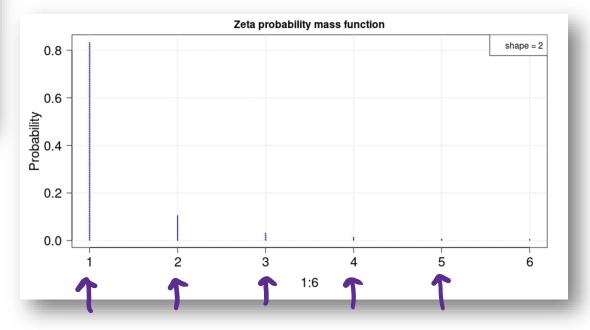


### **Probability Distributions**

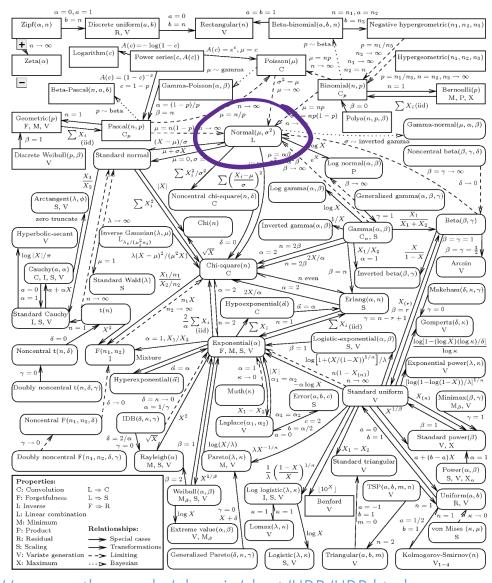
Continuous quantities probability density function (pdf)



# Discrete quantities Probability mass function (pmf)

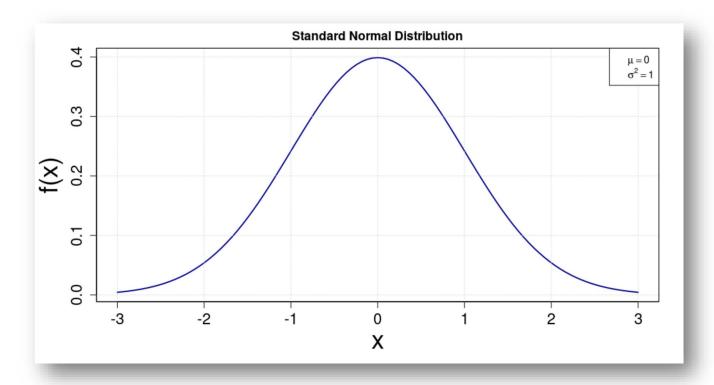


# There are many univariate distributions!

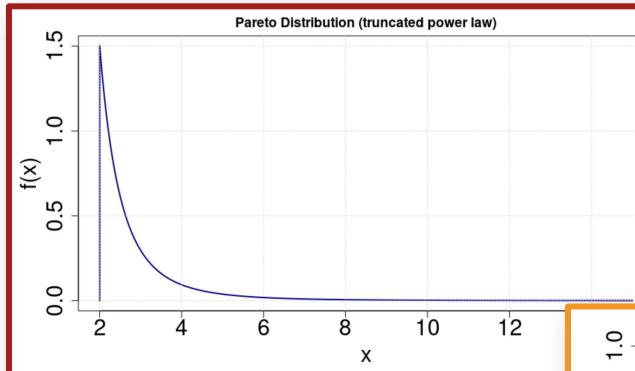


http://www.math.wm.edu/~leemis/chart/UDR/UDR.html

# The Normal Distribution



$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(x-\mu)^2}{2\sigma^2}}$$



#### Example:

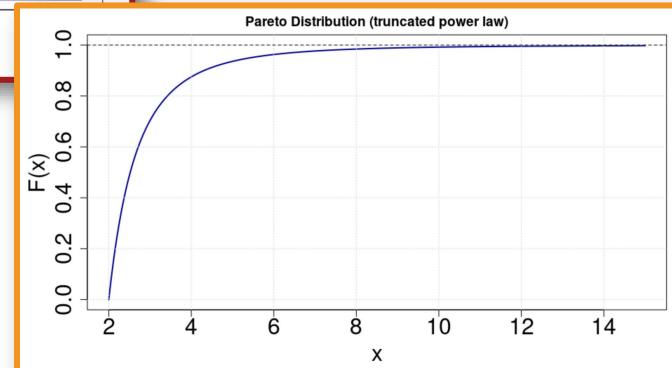
Pareto distribution (truncated power-law)

$$F(x) = P(X \leq x) = 1 - \left(rac{x_{\min}}{x}
ight)^{lpha}$$

#### **Cumulative distribution function (cdf)**

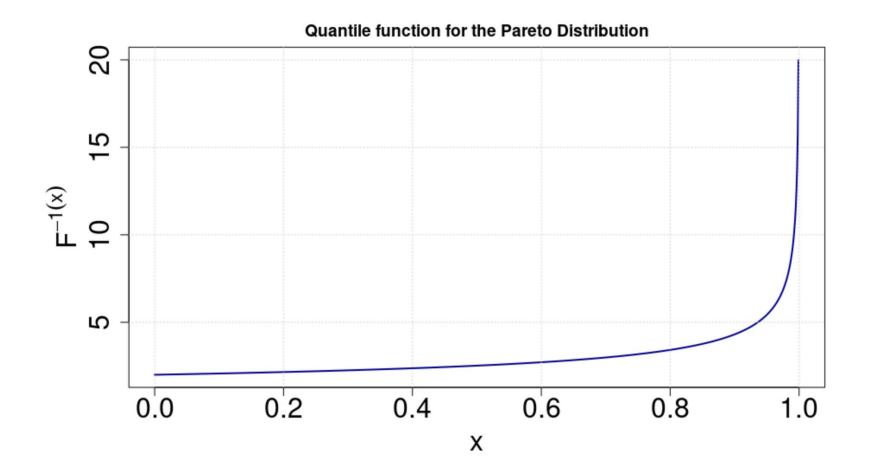
#### **Probability distribution function (pdf)**

$$f(x) = rac{lpha x_{\min}^{lpha}}{x^{lpha+1}}$$



### **Quantile Function**

• This is the inverse of the cumulative distribution function (cdf)



## Random Variables

### **Random Variable**

- A random variable X is a function that maps an outcome to a real number
  - e.g., Let's say we decide to flip a coin repeatedly, and each time we flip it we record whether we get heads or tails with a 1 or a 0 respectively.
- In other words, **X** is a **function**. Little **x** represents the data --- *realizations* of that random variable.

### A Random Variable follows a distribution

The standard statistics notation to show what distribution a random variable follows is:

$$X \sim N(\mu, \sigma^2)$$

For example, we might assume that are data x (e.g. the photon counts from a star) follows a Poisson distribution

$$X \sim \text{Pois}(\lambda)$$

### **Randomness in Data**

9.0

0.5

0.2

0.1 0.0

9.0

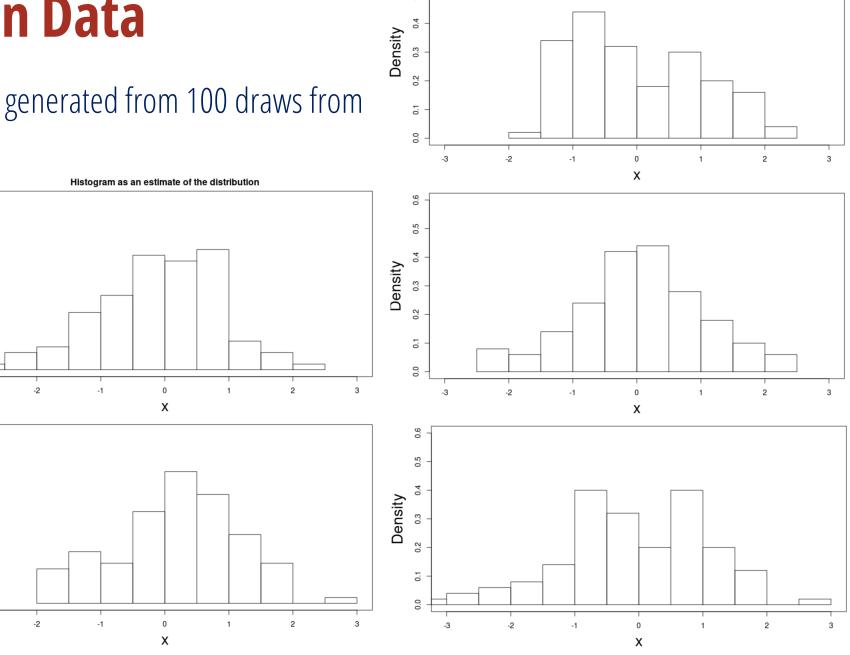
0.5

0.1

Density

Density

• All these histograms were generated from 100 draws from a standard normal



Histogram as an estimate of the distribution

#### Sampling from a distribution (two basic approaches)

#### Inverse cdf Method

• First choice if the inverse cdf is tractable

#### Accept/Reject Algorithm

Useful when you can't write down the inverse cdf

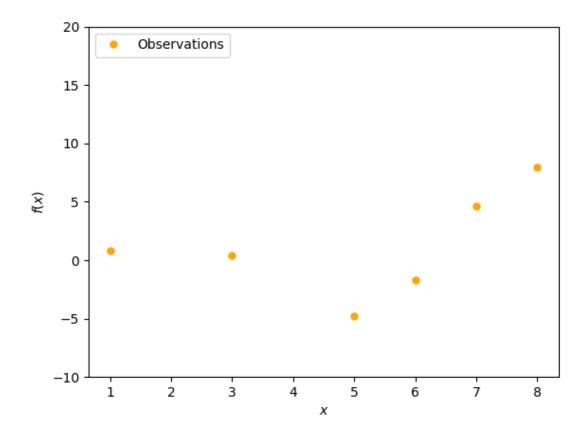
### **Exercise 1 -- Exercise\_1.ipynb**

- 1. Generate a random variable follow a **uniform distribution** between 0 and 50
- 2. Generate a random variable follow a **normal distribution** with mean = 100 and standard deviation of 50
- Use the *accept-reject* approach to transform numbers generated from a uniform distribution into those following the distribution:  $P(x) = \left(\frac{1}{e-1}\right)e^{-x}$  for 0 < x < 1 and 0 elsewhere.
  - 1. Draw a random samples  $x^*$  from the U(0, 1) distribution and a random sample  $y^*$  from the U(0, c) distribution.
  - 2. If  $y^* < f(x^*)$ , keep  $x^*$ . If not, return to step 1.
  - 3. Continue until you have 100,000 samples.
  - 4. Plot a normalized histogram of the samples and then overplot the PDF.
- 4. Use *cdf sampling* to do the same thing above.
  - 1. To do this, compute the cdf F(X) by integrating the PDF P(x) from  $-\infty$  to X.
  - 2. Then find the inverse  $F^{-1}(X)$  of the CDF. [HINT: Remember an inverse function  $F^{-1}(x)$  is such that  $F(F^{-1}(x)) = x$ ]
  - 3. Draw a random sample  $u^*$  from the U(0, 1) distribution.
  - 4. Then the variable  $y = F^{-1}(u^*)$  will have the probability distribution you seek.
  - 5. Continue until you have 100,000 samples.
  - 6. Plot a normalized histogram of the samples and then overplot the PDF.

# **Smoothing and Interpolation**

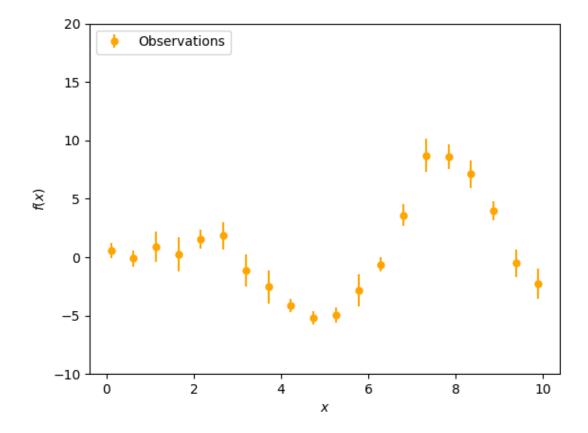
# How to make data more pliable

• Sometimes you'll get data that looks like this:



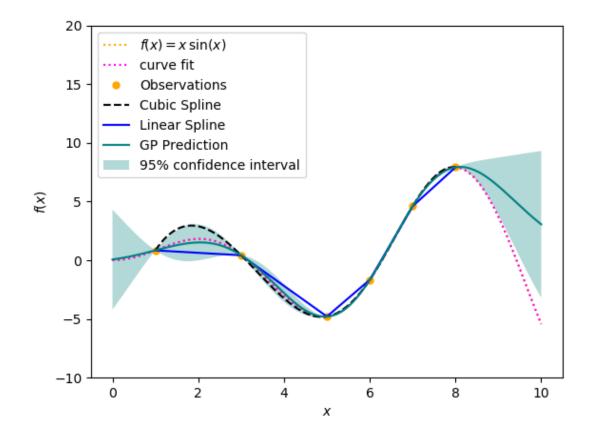
# How to make data more pliable

• or this (with error bars)



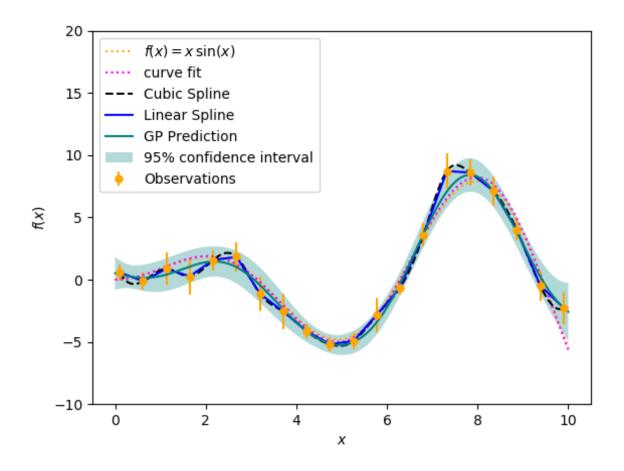
### **Examples**

- Simple example from Vanderplas ++
- This code is provided in your exercise set and shows a combination of methods
  - Spline\_GP\_demo.ipynb



### **Examples**

- Simple example from Vanderplas ++
- This code is provided in your exercise set and shows a combination of methods
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# Fitting a Model to Data

# How to fit a model to data?

Follow along with the Jupyter notebook: Fit\_your\_data\_demo.ipynb