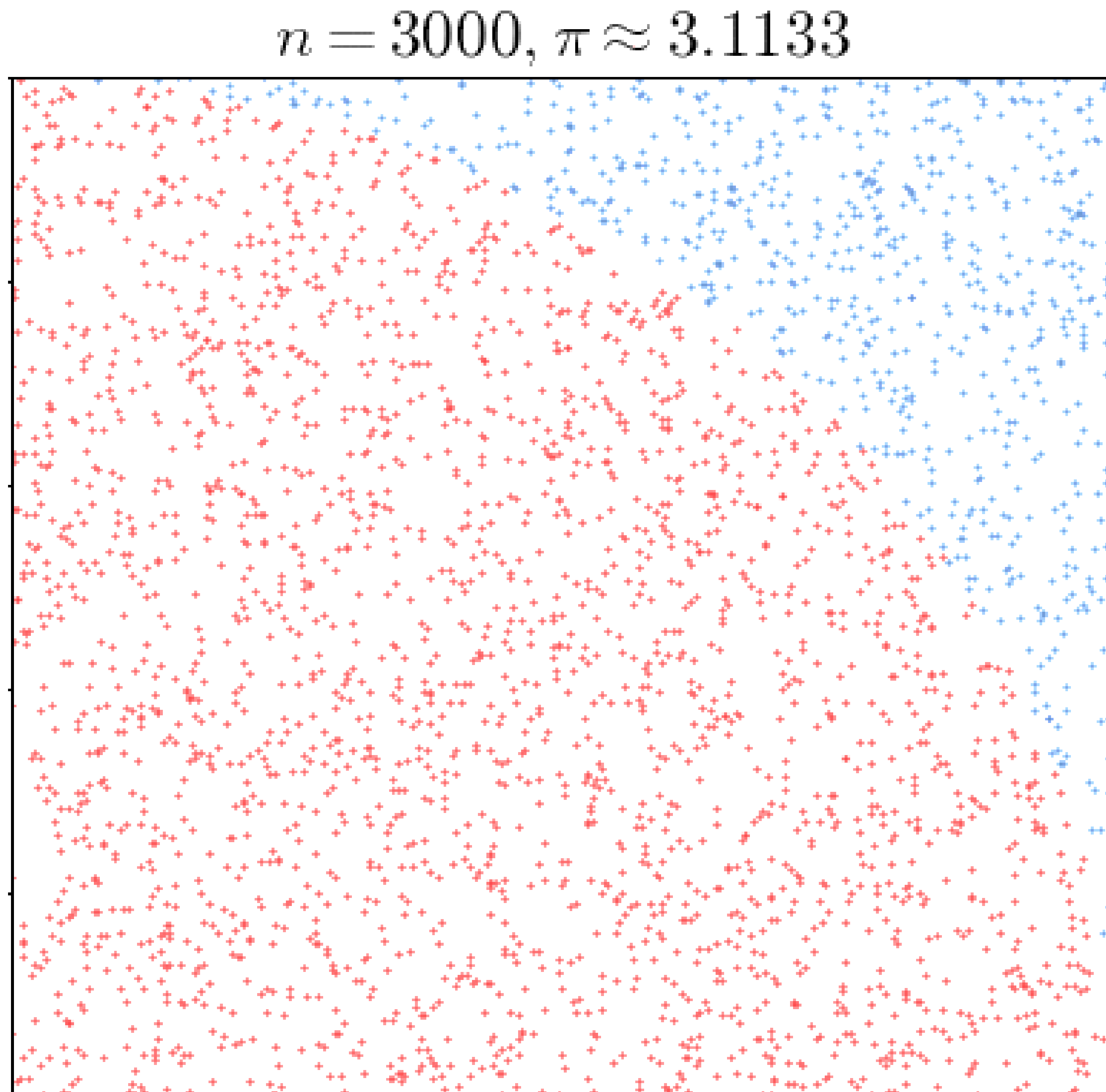
Python Lecture 11
Data Processing(1)

STATISTICAL *SIMULATION* METHOD



Statistical *Simulation* Method

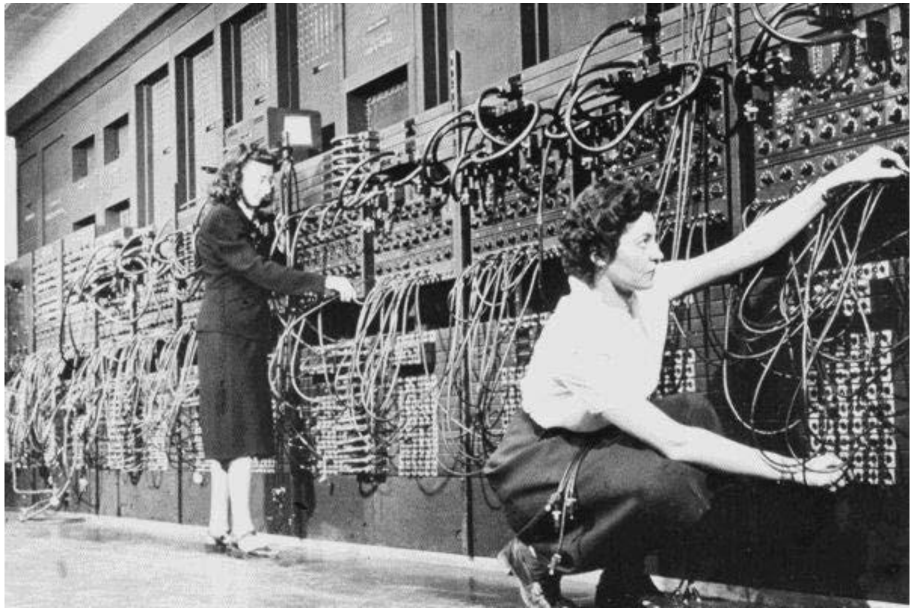
Also known as:

Monte Carlo Simulation

- simulation of real-world physical processes
- Simulate large amounts of data with random sampled data
- Use: Science, Economics, Engineering……

A LITTLE HISTORY

- Ulam, recovering from an illness, was playing a lot of solitaire
- Tried to figure out probability of winning, and failed
- Thought about playing lots of hands and counting number of wins, but decided it would take years
- Asked Von Neumann if he could build a program to simulate many hands on ENIAC



MONTE CARLO SIMULATION

- A method of estimating the value of an unknown quantity using the principles of inferential statistics
- Inferential statistics
  - *Population*: a set of examples
  - *Sample*: a proper subset of a population
  - Key fact: a *random sample* tends to exhibit the same properties as the population from which it is drawn
- Exactly what we did with **random walks**

An Example

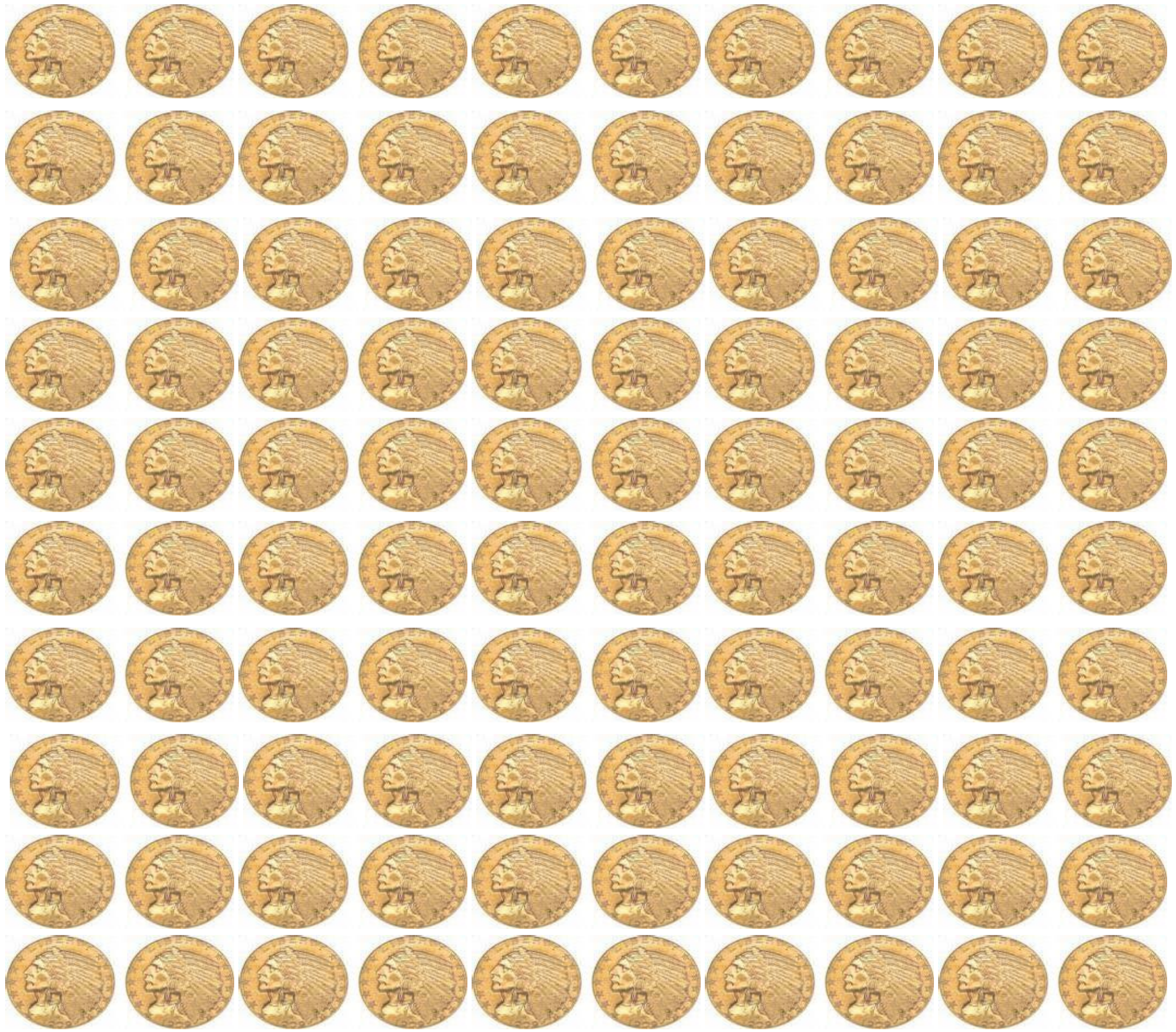
- Given a single coin, estimate fraction of heads you would get if you flipped the coin an infinite number of times
- Consider one flip

How confident would you be about answering 1.0?

Flipping a Coin Twice

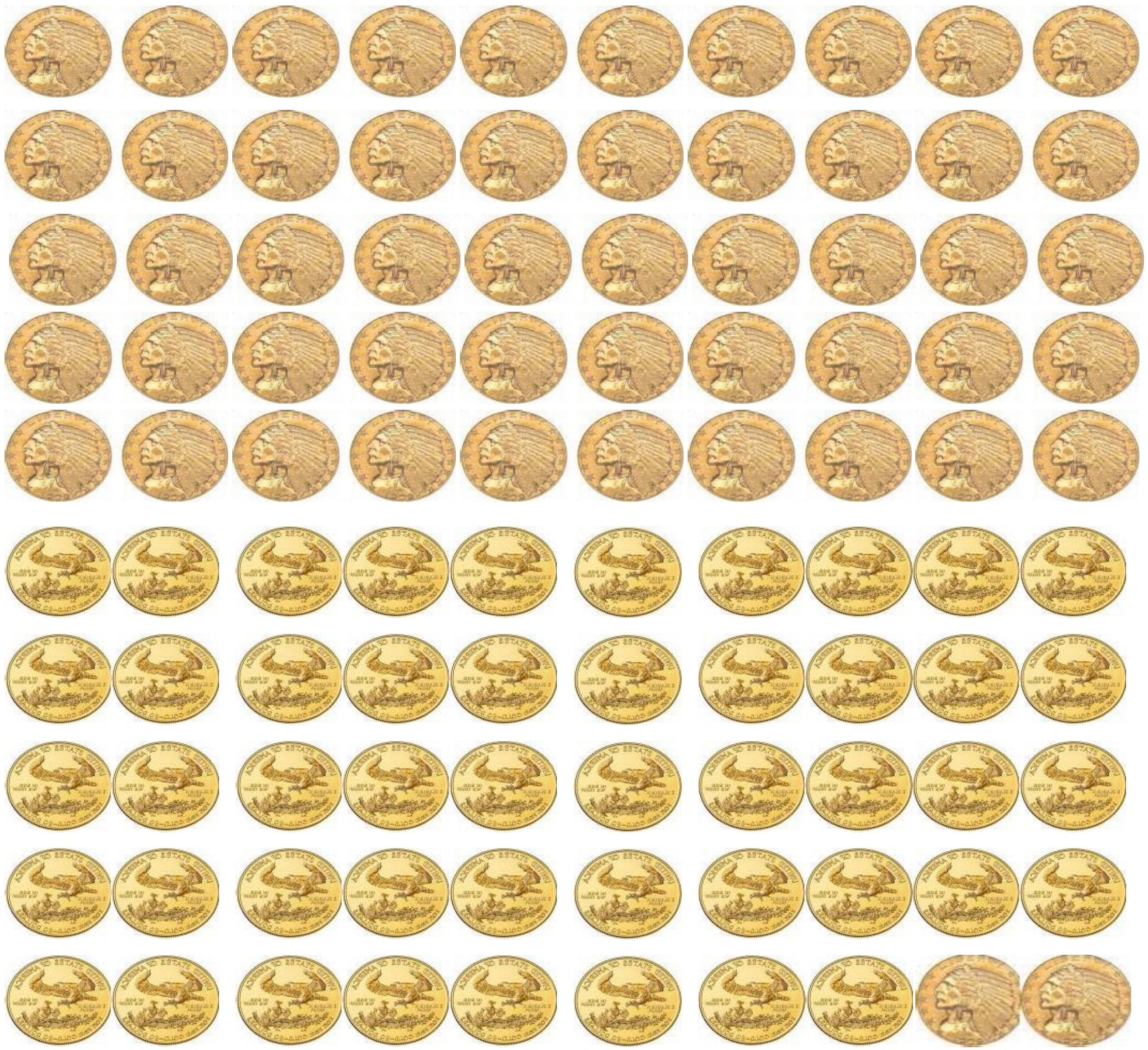
Do you think that the next flip will come up heads?

Flipping a coin 100 Times



Now do you think that the next flip will come up heads?

Flipping a Coin 100 Times



Do you think that the probability of the next flip coming up heads is 52/100?

Given the data, it's your best estimate

But confidence should be low

Why The Difference In Confidence?

- Confidence in our estimate depends upon two things
  - Size of sample (e.g., 100 versus 2)
  - Variance of sample (e.g., all heads versus 52 heads)
- As the variance grows, we need larger samples to have the same degree of confidence

ROULETTE

No need to simulate, since answers obvious

Allows us to compare simulation results to actual probabilities

Class Definition

```
class FairRoulette():
     def __init__(self) :
         self.pockets = []
         for i in range(1,37):
              self.pockets.append(i)
              self.ball = None
         self.pocketOdds = len(self.pockets) - 1

    def spin(self):
         self.ball = random.choice(self.pockets)

     def betPocket(self, pocket, amt):
         if str(pocket) == str(self.ball):
              return amt*self.pocketOdds
         else: return -amt

    def __ str__(self):
         return 'Fair Roulette'
```

Monte Carlo Simulation

```
def playRoulette(game, numSpins, pocket, bet, toPrint):
    totPocket = 0
    for i in range(numSpins):
        game.spin()
        totPocket += game.betPocket(pocket, bet)
    if toPrint:
        print(numSpins, 'spins of', game)
        print('Expected return betting', pocket, '=',\
              str(100*totPocket/numSpins) + '%\n')
        return (totPocket/numSpins)

game = FairRoulette()
for numSpins in (100, 1000000):
    for i in range(3):
        playRoulette(game, numSpins, 2, 1, True)
```

100 AND 1M SPINS OF THE WHEEL

```
100 spins of Fair Roulette
Expected return betting 2 =      -100.0%

100 spins of Fair Roulette
Expected return betting 2 =      44.0%

100 spins of Fair Roulette
Expected return betting 2 =      -28.0%

1000000 spins of Fair Roulette  Expected
return betting 2 = -0.046%

1000000 spins of Fair Roulette
Expected return betting 2 = 0.602%

1000000 spins of Fair Roulette  Expected
return betting 2 = 0.7964%
```

Law Of Large Numbers

- In repeated independent tests with the same actual probability *p* of a particular outcome in each test, the chance that the fraction of times that outcome occurs differs from *p* converges to zero as the number of trials goes to infinity

Does this imply that if deviations from expected behavior occur, these deviations are likely to be ***evened out*** by opposite deviations in the future?

Gambler's Fallacy

- "August 18, 1913, at the casino in Monte Carlo, black came up a record twenty-six times succession[in roulette]…[There]was a near-panicky rush to bet on red, beginning about the time black had come up a phenomenal fifteen" --Huff and Geis, How to Take a Chance
- Probability of 26 consecutive reds

  1/67,108,865

- Probability of 26 consecutive reds when previous 25 rolls were red

  1/2

Regression To The Mean

- Following an extreme random event, the next random event is likely to be less extreme
- If you spin a fair roulette wheel 10 times and get 100% reds, that is an extreme event (probability = 1/1024)
- It is likely that in the next 10 spins, you will get fewer than 10 reds
  - But the expected number is only 5
- So, if you look at the average of the 20 spins, it will be closer to the expected mean of 50% reds than to the 100% of the first 10 spins

Casinos not in the business of being fair

Two Subclasses Of Roulette

```
class EuRoulette(FairRoulette):
    def_init__(self):
        FairRoulette._init_(self)
        self.pockets.append('0')
    def_str__(self):
        return 'European Roulette'

class AmRoulette(EuRoulette):
    def_init__(self):
        EuRoulette._init__(self)
        self.pockets.append('00')
    def_str__(self):
        return 'American Roulette'
```

COMPARING THE GAMES

```
Simulate 20 trials of 1000 spins each  Exp.
return for Fair Roulette = 6.56%
Exp. return for European Roulette = -2.26%  Exp.
return for American Roulette = -8.92%

Simulate 20 trials of 10000 spins each  Exp.
return for Fair Roulette = -1.234%
Exp. return for European Roulette = -4.168%  Exp.
return for American Roulette = -5.752%

Simulate 20 trials of 100000 spins each  Exp.
return for Fair Roulette = 0.8144%
Exp. return for European Roulette = -2.6506%  Exp.
return for American Roulette = -5.113%

Simulate 20 trials of 1000000 spins each  Exp.
return for Fair Roulette = -0.0723%  Exp. return
for European Roulette = -2.7329%  Exp. return for
American Roulette = -5.212%
```

Sampling Space Of Possible Outcomes

- Never possible to guarantee perfect accuracy through sampling
- Not to say that an estimate is not precisely correct
- Key question:
  - How many samples do we need to look at before we can have justified confidence on our answer?
- Depends upon variability in underlying distribution

Quantifying Variation in Data

$$variance(X) = \frac{\sum_{x \in X}(x-\mu)^2}{|X|}$$

$$\sigma(X) = \sqrt{\frac{1}{|X|}\sum_{x \in X}(x-\mu)^2}$$

- Standard deviation simply the square root of the variance
- Outliers can have a big effect
- Standard deviation should always be considered relative to mean

For Those Who Prefer Code

```
def getMeanAndStd(X):
    mean = sum(X)/float(len(X))
    tot = 0.0
    for x in X:
        tot += (x - mean)**2

    std = (tot/len(X))**0.5
    return mean, std
```

Confidence Levels and Intervals

1. Instead of estimating an unknown parameter by a single value (e.g., the mean of a set of trials), a confidence interval provides a range that is likely to contain the unknown value and a confidence that the unknown value lays within that range
2. "The return on betting a pocket 10K times in European roulette is -3.3%. The margin of error is +/-3.5% with a 95% level of confidence"

- What does this mean?

- If I were to conduct an infinite number of trials of 10k bets each,
  - My expected average return would be -3.3%
  - My return would be between roughly -6.8% and +0.2% (95% confidence)

Empirical Rule

- **Under some assumptions discussed later**
  - ~68% of data within one standard deviation of mean
  - ~95% of data within 1.96 standard deviations of mean
  - ~99.7% of data within 3 standard deviations of mean

Applying Empirical Rule

```
resultDict = {}
games = (FairRoulette, EuRoulette, AmRoulette)
for G in games:
    resultDict[G().__str__()] = []
for numSpins in (100, 1000, 10000):
    print('\nSimulate betting a pocket for', numTrials,  'trials
          of', numSpins, 'spins each')
    for G in games:
        pocketReturns = findPocketReturn(G(), 20,
                                         numSpins, False)
        mean, std = getMeanAndStd(pocketReturns)
        resultDict[G().__str__ ()].append((numSpins,
                                                    100*mean,
                                                    100*std))
        print('Exp. return for', G(), '=',
              str(round(100*mean, 3))
              + '%,', '+/- ' + str(round(100*1.96*std, 3))
              + '% with 95% confidence')
```

Results

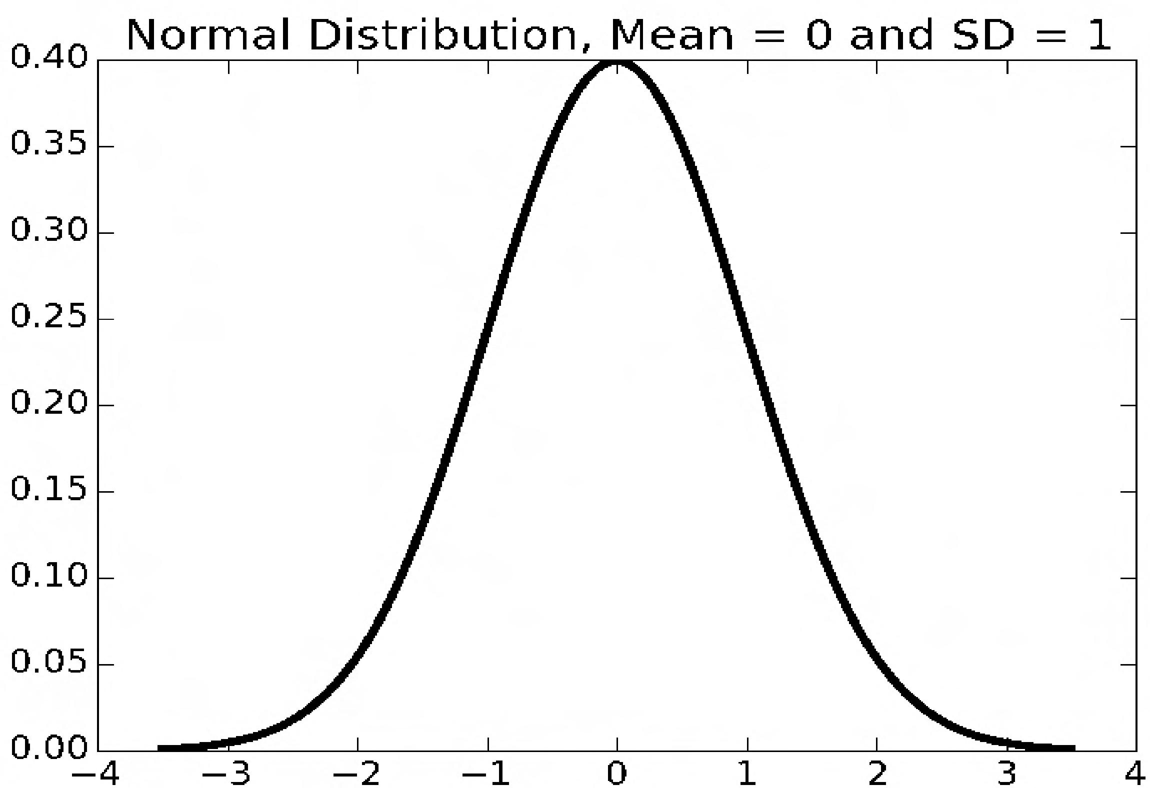
Simulate betting a pocket for 20 trials of 1000 spins each
Exp. return for Fair Roulette = 3.68%, +/- 27.189% with 95% confidence
Exp. return for European Roulette = -5.5%, +/- 35.042% with 95% confidence Exp. return for American Roulette = -4.24%, +/- 26.494% with 95% confidence

Simulate betting a pocket for 20 trials of 100000 spins each
Exp. return for Fair Roulette = 0.125%, +/- 3.999% with 95% confidence
Exp. return for European Roulette = -3.313%, +/- 3.515% with 95% confidence Exp. return for American Roulette = -5.594%, +/- 4.287% with 95% confidence

Simulate betting a pocket for 20 trials of 1000000 spins each
Exp. return for Fair Roulette = 0.012%, +/- 0.846% with 95% confidence
Exp. return for European Roulette = -2.679%, +/- 0.948% with 95% confidence Exp. return for American Roulette = -5.176%, +/- 1.214% with 95% confidence

Assumptions Underlying Empirical Rule

- The mean estimation error is zero
- The distribution of the errors in the estimates is normal



Defining Distributions

- Use a probability distribution
- Captures notion of relative frequency with which a random variable takes on certain values
  - Discrete random variables drawn from finite set of values
  - Continuous random variables drawn from reals between two numbers (i.e., infinite set of values)
- For discrete variable, simply list the probability of each value, must add up to 1
- Continuous case trickier, can't enumerate probability for each of an infinite set of values

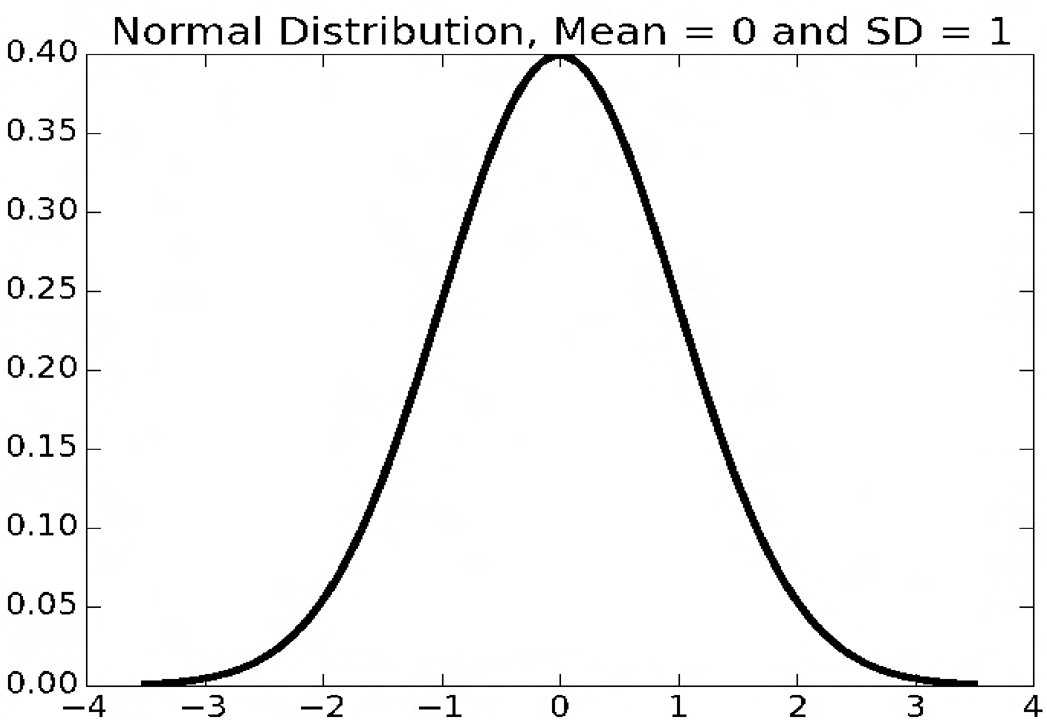
PDF'S : *Probability Density Functions*

- Distributions defined by *probability density functions* (PDFs)
- Probability of a random variable lying between two values
- Defines a curve where the values on the x-axis lie between minimum and maximum value of the variable
- Area under curve between two points, is probability of example falling within that range

Normal Distributions

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

$$e = \sum_{n=0}^{\infty} \frac{1}{n!}$$



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After-lecture, self-learning

1. Download the .py file for this lecture and run it, Understanding statistical simulation processing code.
   - If you are interested, draw a two-dimensional diagram of the program output
2. Do PS4, deadline: May 11, 2020
3. Review Data processing methods
   1. Clustering 聚类 Lec12
   2. Classification 分类 Lec13
   3. Machine learning 机器学习 Lec14
4. Preparing for the course project

HAPPY LABOR DAY HOLIDAY.