

Lecture 4: Stochastic Thinking and Random Walks

Relevant Reading

- Pages 235-238
- Chapter 14

The World is Hard to Understand

- Uncertainty is uncomfortable
- But certainty is usually unjustified

Newtonian Mechanics

- Every effect has a cause
- The world can be understood causally

Copenhagen Doctrine

- Copenhagen Doctrine (Bohr and Heisenberg) of **causal nondeterminism**
 - At its most fundamental level, the behavior of the physical world cannot be predicted.
 - Fine to make statements of the form “x is highly likely to occur,” but not of the form “x is certain to occur.”
- Einstein and Schrödinger objected
 - “God does not play dice.” -- Albert Einstein

Does It Really Matter

Did the flips yield
2 heads
2 tails
1 head and 1 tail?

The Moral

- The world may or may not be inherently unpredictable
- But our lack of knowledge does not allow us to make accurate predictions
- Therefore we might as well treat the world as inherently unpredictable
- **Predictive nondeterminism**

Stochastic Processes

- An ongoing process where the next state might depend on both the previous states **and some random element**

```
def rollDie():
    """ returns an int between 1 and 6"""


```

```
def rollDie():
    """ returns a randomly chosen int
        between 1 and 6"""


```

Implementing a Random Process

```
import random

def rollDie():
    """returns a random int between 1 and 6"""
    return random.choice([1,2,3,4,5,6])
    Uniform.

def testRoll(n = 10):
    result = ''
    for i in range(n):
        result = result + str(rollDie())
    print(result)
```

Probability of Various Results

- Consider `testRoll(5)`
- How probable is the output 11111?

Probability Is About Counting

- Count the number of possible events
- Count the number of events that have the property of interest
- Divide one by the other
- Probability of 11111?
 - 11111, 11112, 11113, ..., 11121, 11122, ..., 66666
 - $1/(6^{**}5)$
 - ~ 0.0001286

Three Basic Facts About Probability

- Probabilities are always in the range **0 to 1**. 0 if impossible, and 1 if guaranteed.
- If the probability of an event occurring is p , the probability of it not occurring must be
- When events are **independent** of each other, the probability of all of the events occurring is equal to a **product** of the probabilities of each of the events occurring.

Independence

- Two events are **independent** if the outcome of one event has no influence on the outcome of the other
- Independence should not be taken for granted

Will One of the Patriots and Broncos Lose?

- Patriots have winning percentage of $7/8$, Broncos of $6/8$
- Probability of both winning next Sunday is $7/8 * 6/8 = 42/64$
- Probability of at least one losing is $1 - 42/64 = 22/64$
- What about Sunday, December 18
 - Outcomes are not independent
 - Probability of one of them losing is much closer to 1 than to $22/64$!

A Simulation of Die Rolling

```
def runSim(goal, numTrials, txt):
    total = 0
    for i in range(numTrials):
        result = ''
        for j in range(len(goal)):
            result += str(rollDie())
        if result == goal:
            total += 1
    print('Actual probability of', txt, '=', round(1/(6**len(goal)), 8))
    estProbability = round(total/numTrials, 8)
    print('Estimated Probability of', txt, '=', round(estProbability, 8))

runSim('11111', 1000, '11111')
```

Output of Simulation

- Actual probability = 0.0001286
 - Estimated Probability = 0.0
 - Actual probability = 0.0001286
 - Estimated Probability = 0.0
-
- How did I **know** that this is what would get printed?
 - Why did simulation give me the **wrong** answer?

Let's try 1,000,000 trials

Morals

- Moral 1: It takes a lot of trials to get a good estimate of the frequency of occurrence of a rare event. We'll talk lots more in later lectures about how to **know** when we have enough trials.
- Moral 2: One should not confuse the **sample probability** with the actual probability
- Moral 3: There was really no need to do this by simulation, since there is a perfectly good closed form answer. We will see many examples where this is not true.
- But simulations are often useful.

The Birthday Problem

- What's the probability of at least two people in a group having the same birthday
- If there are 367 people in the group?
- What about smaller numbers?
- If we assume that each birthdate is equally likely
 - $1 - \frac{366!}{366^N * (366-N)!}$
- Without this assumption, VERY complicated

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Approximating Using a Simulation

```
def sameDate(numPeople, numSame):
    possibleDates = range(366)
    birthdays = [0]*366
    for p in range(numPeople):
        birthDate = random.choice(possibleDates)
        birthdays[birthDate] += 1
    return max(birthdays) >= numSame
```

Approximating Using a Simulation

```
def birthdayProb(numPeople, numSame, numTrials):  
    numHits = 0  
    for t in range(numTrials):  
        if sameDate(numPeople, numSame):  
            numHits += 1  
    return numHits/numTrials  
  
for numPeople in [10, 20, 40, 100]:  
    print('For', numPeople,  
          'est. prob. of a shared birthday is',  
          birthdayProb(numPeople, 2, 10000))  
    numerator = math.factorial(366)  
    denom = (366**numPeople)*math.factorial(366-numPeople)  
    print('Actual prob. for N = 100 =',  
          1 - numerator/denom)
```

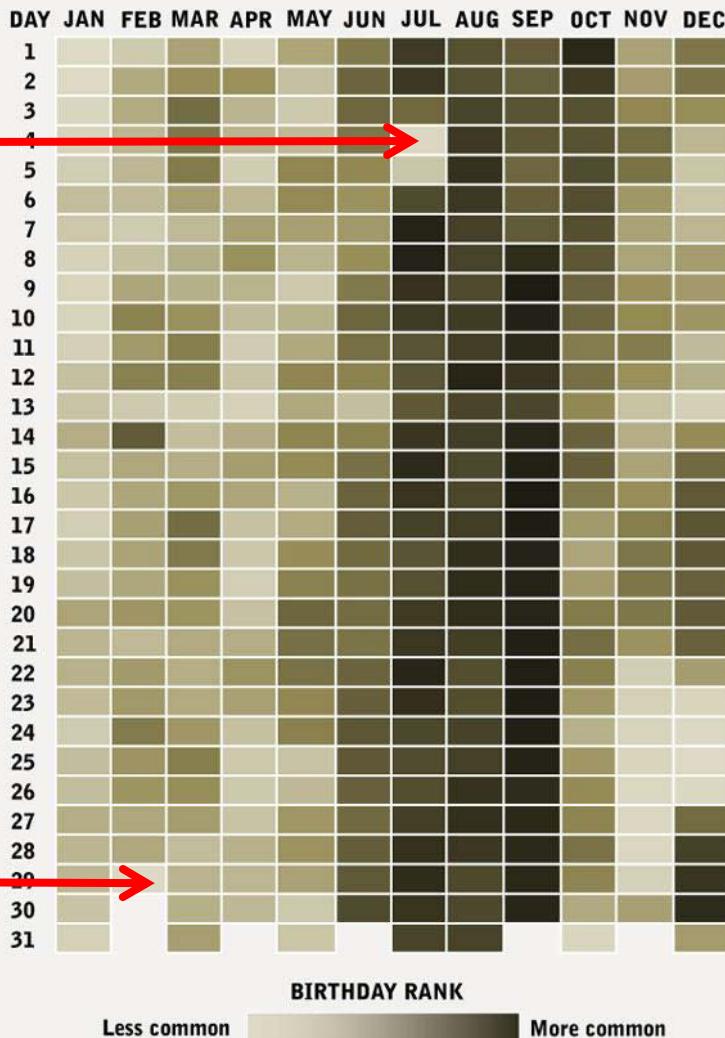
Suppose we want the probability of 3 people sharing

Why 3 Is Much Harder Mathematically

- For 2 the complementary problem is “all birthdays distinct”
- For 3 people, the complementary problem is a complicated disjunct
 - All birthdays distinct or
 - One pair and rest distinct or
 - Two pairs and rest distinct or
 - ...
- But changing the simulation is dead easy

But All Dates Are Not Equally Likely

Which Birth Dates Are Most Common?



Are you exceptional?

Another Win for Simulation

- Adjusting analytic model a pain
- Adjusting simulation model easy

```
def sameDate(numPeople, numSame):
    possibleDates = 4*list(range(0, 57)) + [58]\
                    + 4*list(range(59, 366))\
                    + 4*list(range(180, 270))
    birthdays = [0]*366
    for p in range(numPeople):
        birthDate = random.choice(possibleDates)
        birthdays[birthDate] += 1
    return max(birthdays) >= numSame
```

Simulation Models

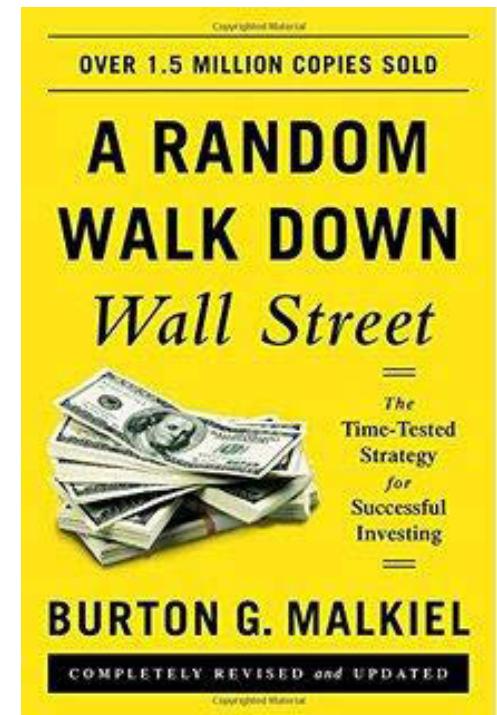
- A description of computations that provide useful information about the possible behaviors of the system being modeled
- Descriptive, not prescriptive
- Only an approximation to reality
- “All models are wrong, but some are useful.” – George Box

Simulations Are Used a Lot

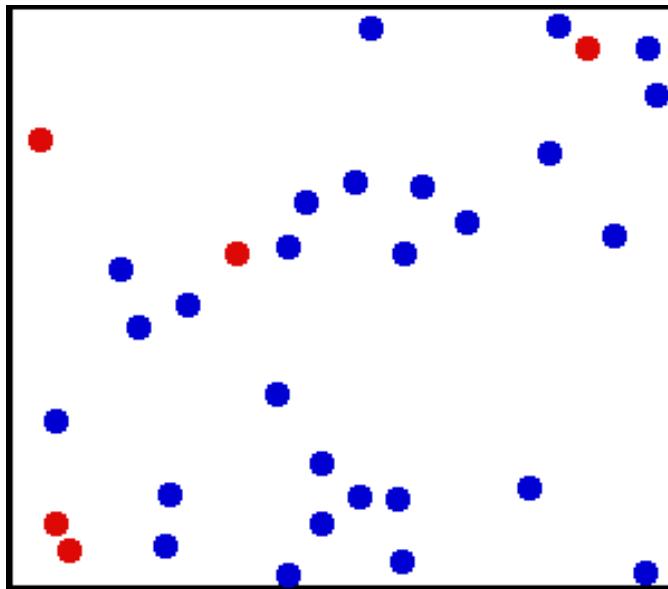
- To model systems that are mathematically intractable
- To extract useful intermediate results
- Lend themselves to development by successive refinement and “what if” questions
- Start by simulating random walks

Why Random Walks?

- Random walks are important in many domains
 - Understanding the stock market (maybe)
 - Modeling diffusion processes
 - Etc.
- Good illustration of how to use simulations to understand things
- Excuse to cover some important programming topics
 - Practice with classes
 - More about plotting



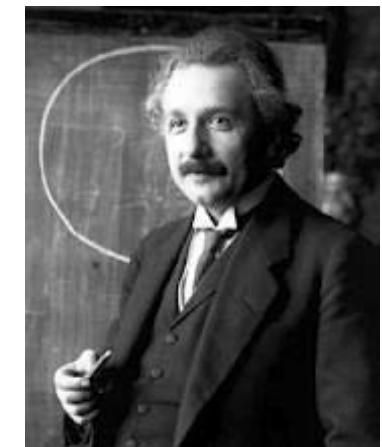
Brownian Motion Is a Random Walk



Robert
Brown
1827



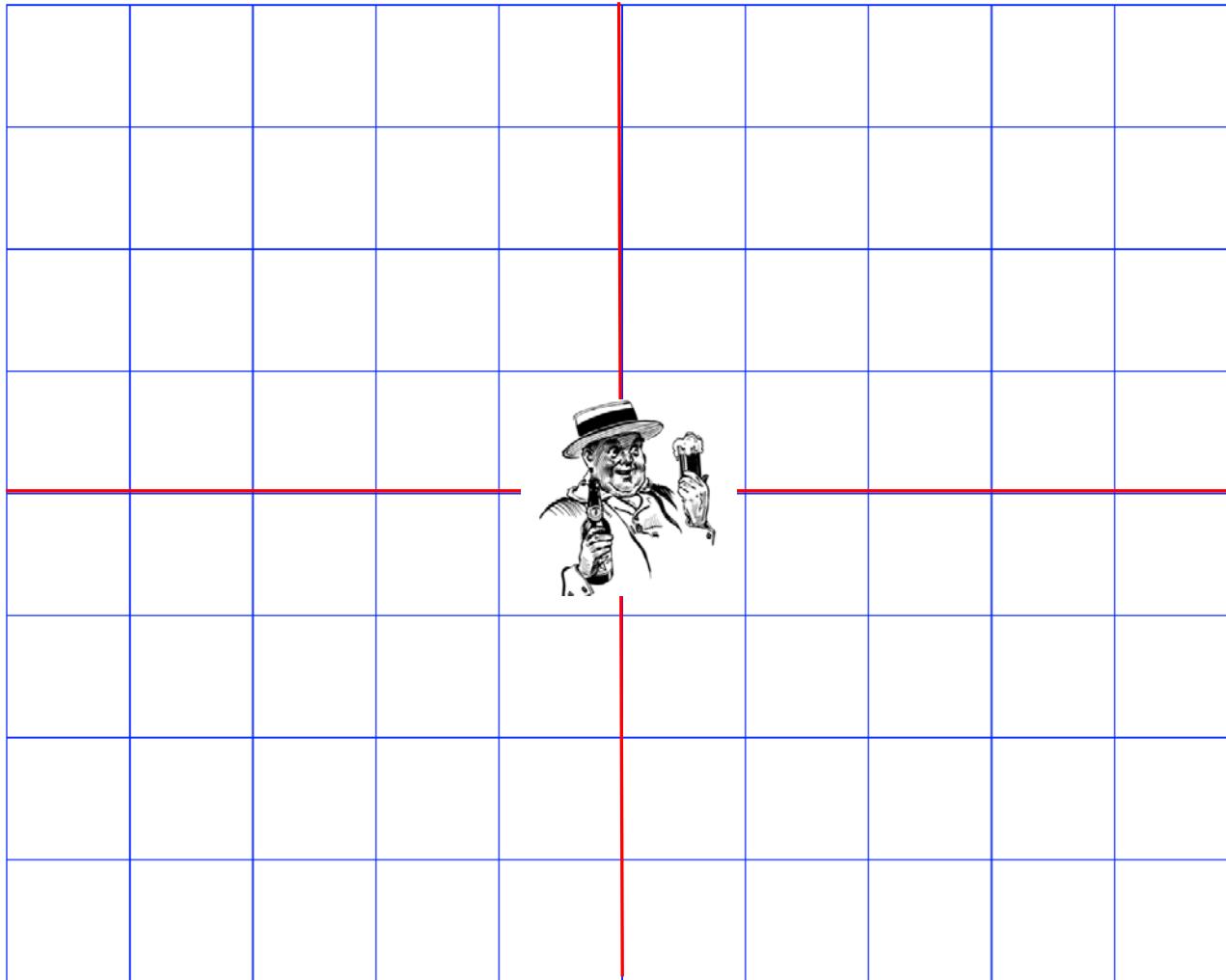
Louis
Bachelier
1900



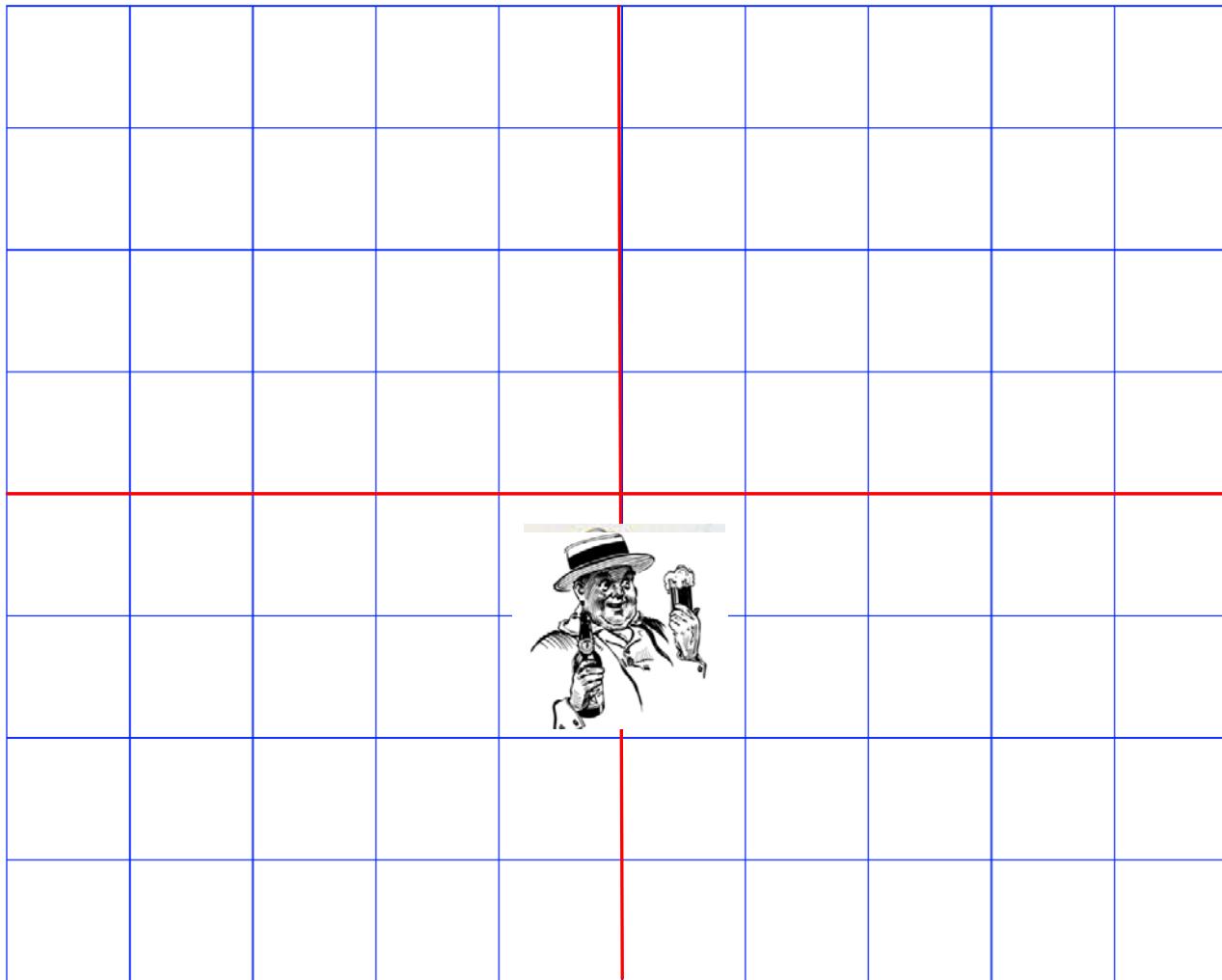
Albert
Einstein
1905

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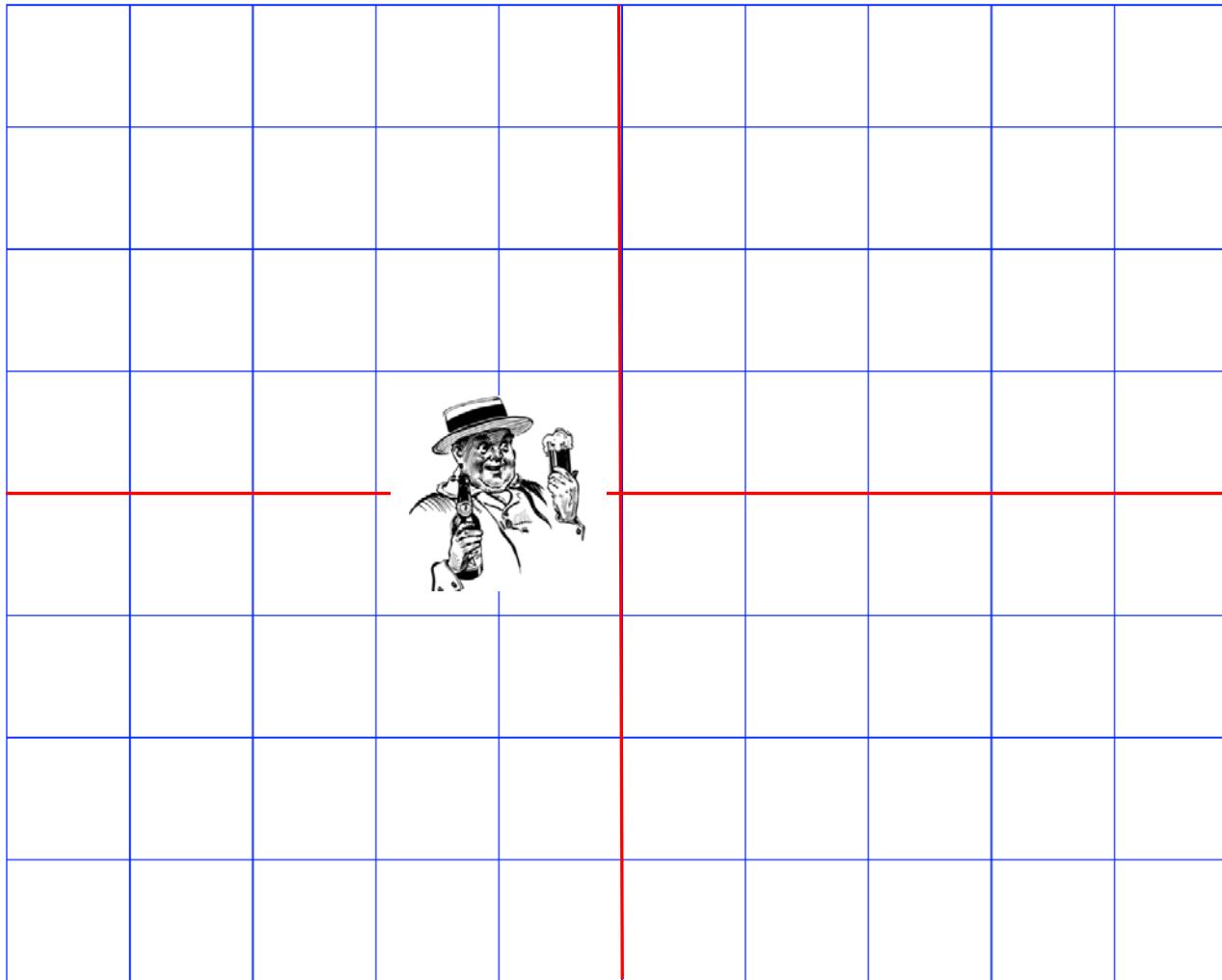
Drunkard's Walk



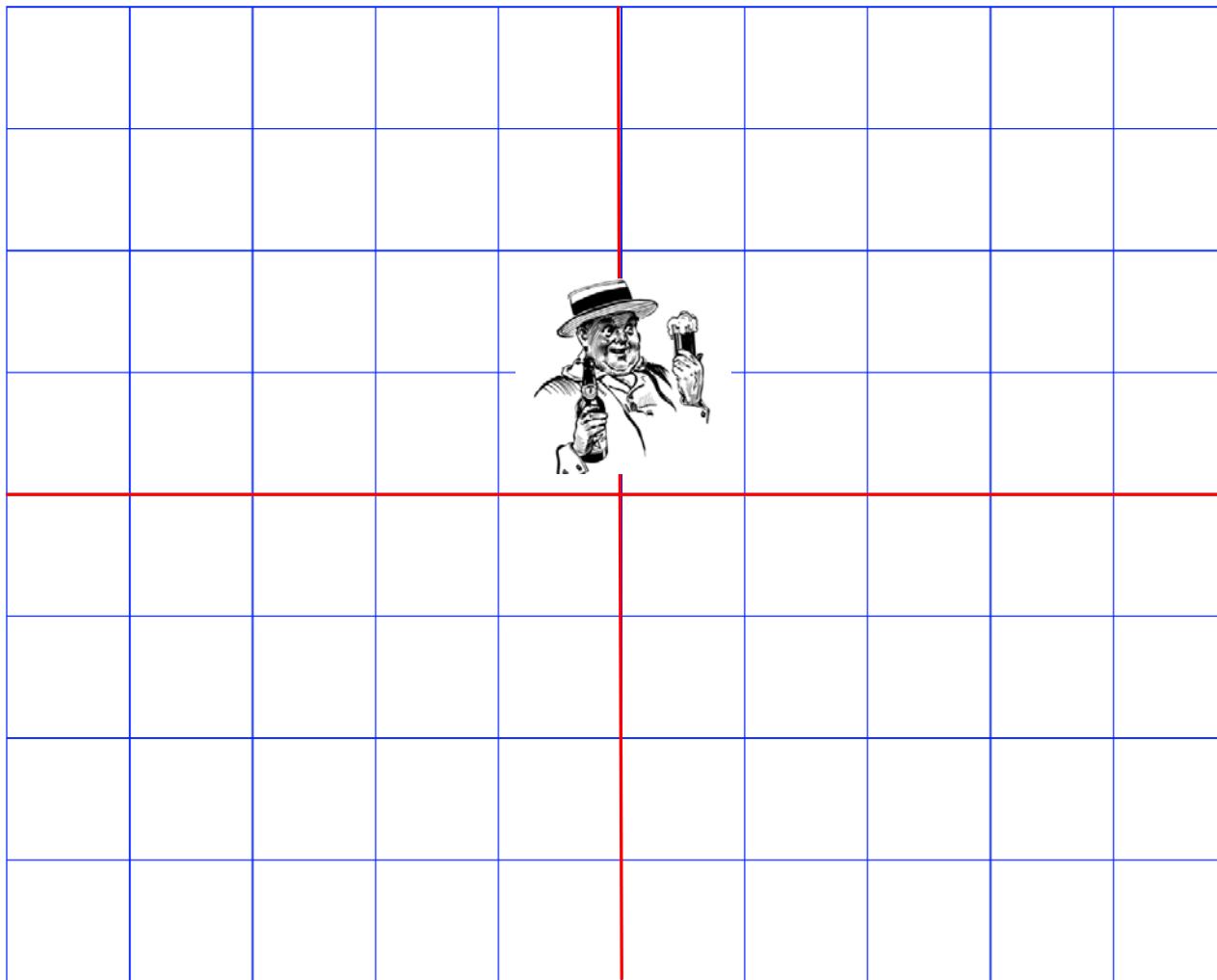
One Possible First Step



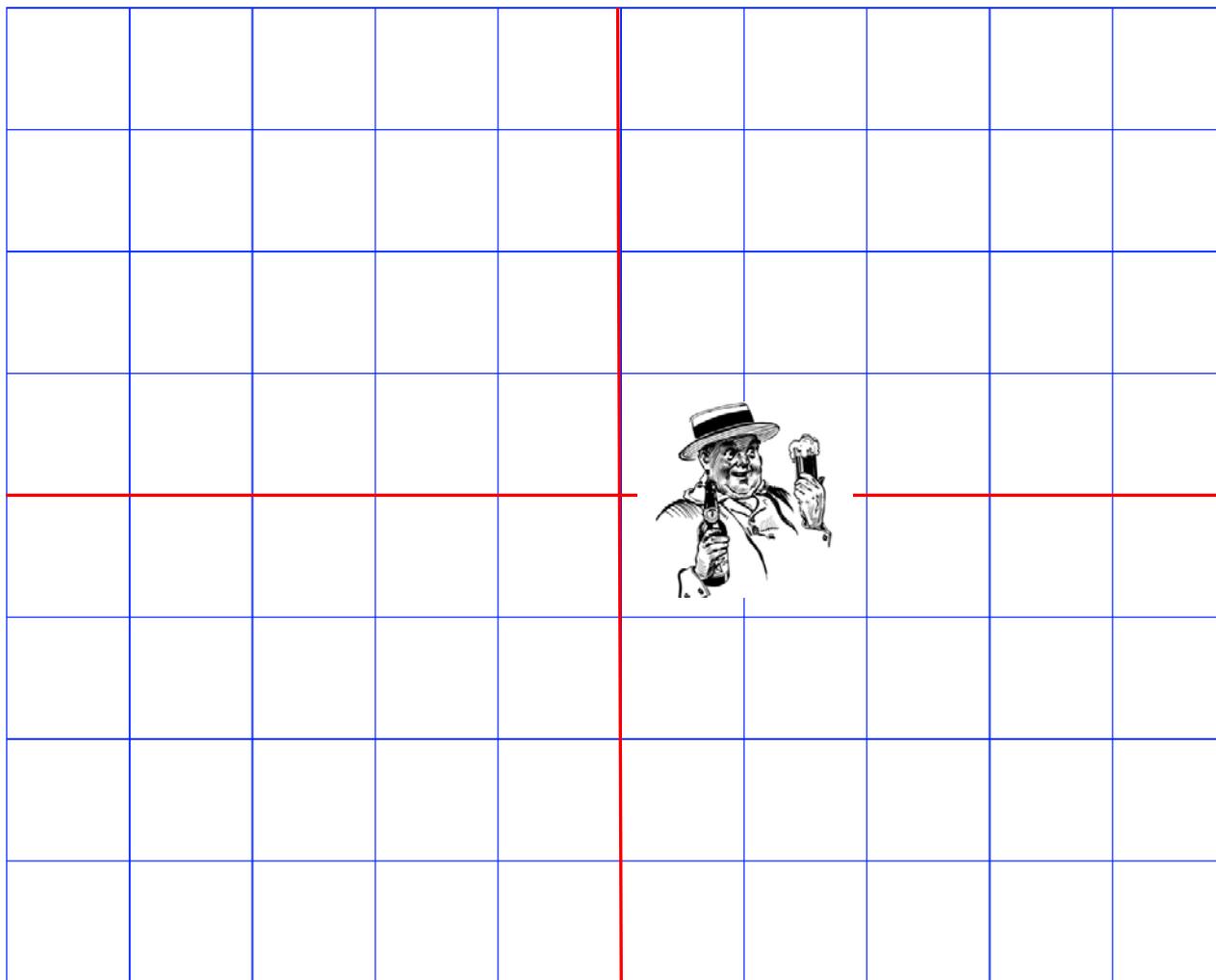
Another Possible First Step



Yet Another Possible First Step



Last Possible First Step



Possible Distances After Two Steps

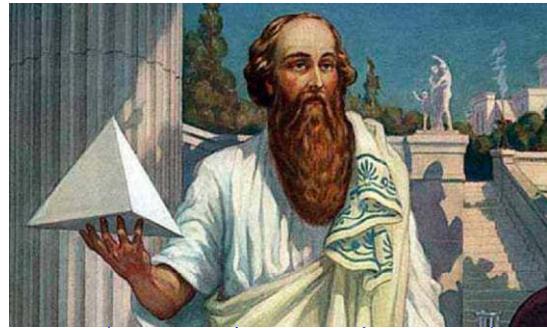
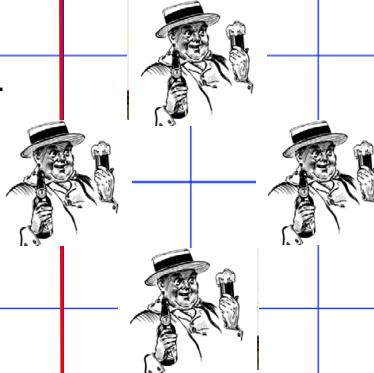


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Expected Distance After 100,000 Steps?

- Need a different approach to problem
- Will use simulation
- But not until the next lecture

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6.0002 Introduction to Computational Thinking and Data Science

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