[220] Randomness

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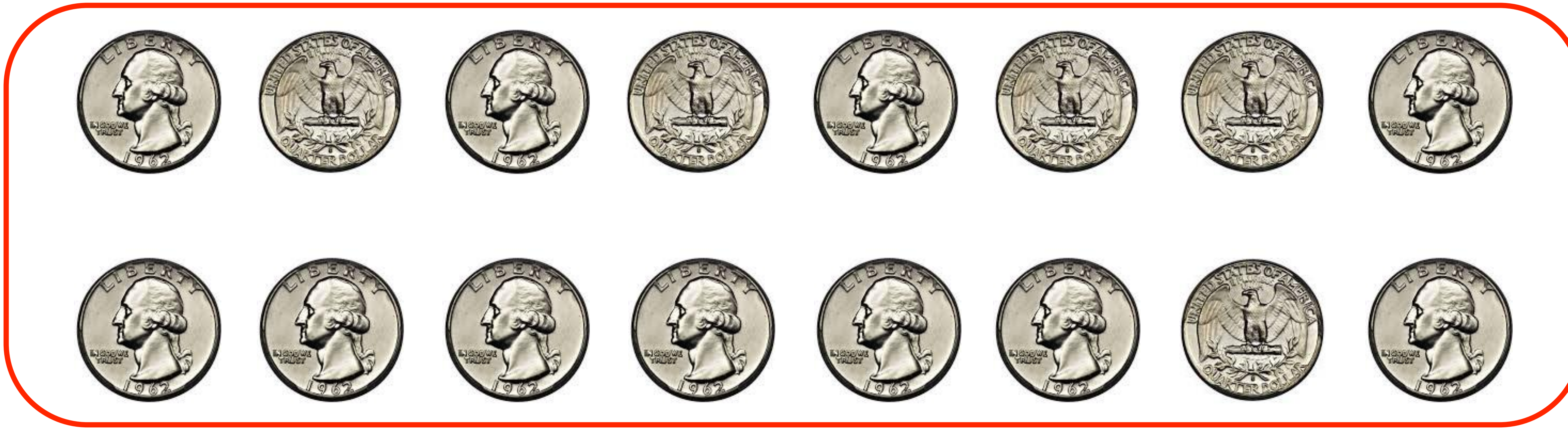
Mike Doescher

Announcements

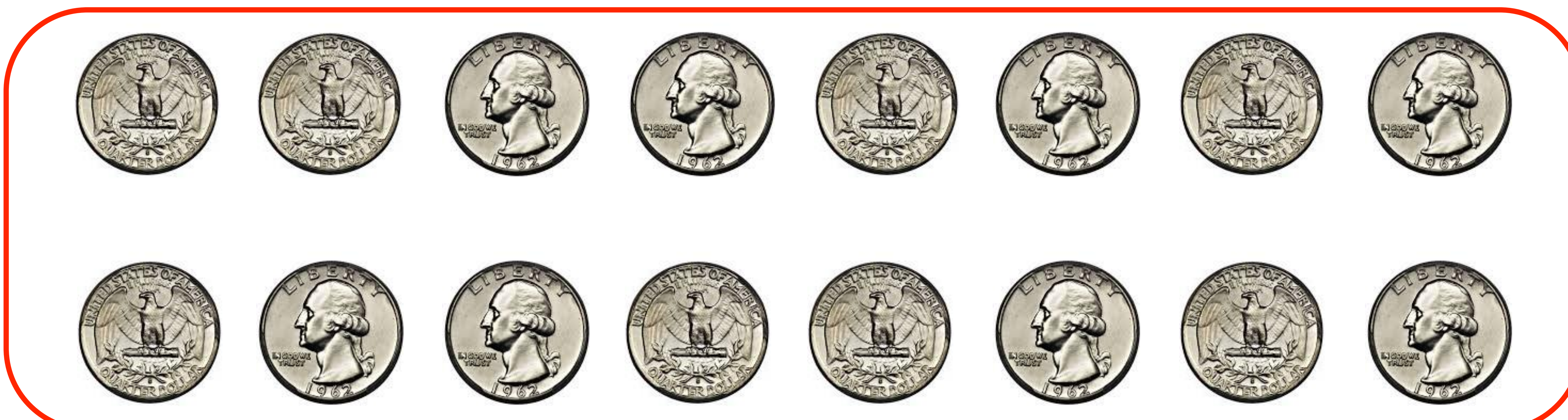
- P10
  - Due Friday May 1
  - Late Days may not be used
- Everything must be turned in by May 1
- Point Redistribution
  - Pinned Piazza Post
  - Grade distribution is on the syllabus page
- Final Project
  - Assigned Monday April 27
  - Due Wednesday May 6 @11:59 PM
- Grading / Resubmission / Deadline Extension – Google Form
  - Incredibly hard to change grades once they are submitted to the registrar
- Course Evaluations
- Contact Meena if you are interested in being a Mentor next fall.
- Want more?
  - Data Science Consider CS 320!!!
  - Computer Science CS 200, 300, 400
- Office Hours

Which series was randomly generated?
Which did I pick by hand?

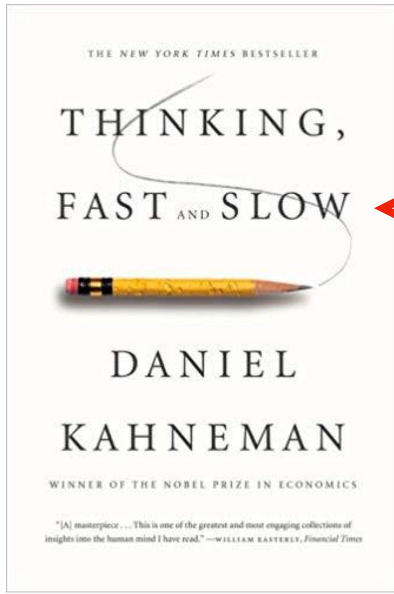
1



2

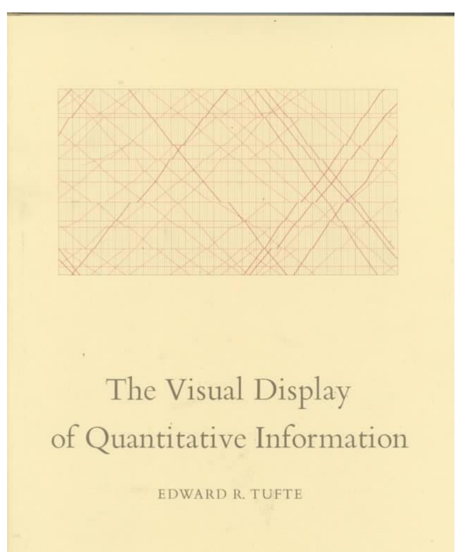


Recommended summer reading

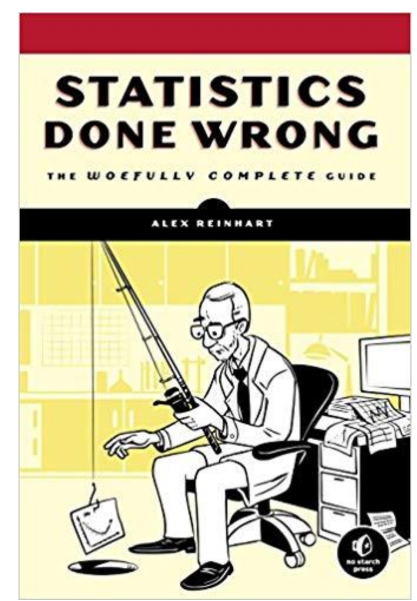


Misconceptions of chance. People expect that a sequence of events generated by a random process will represent the essential characteristics of that process even when the sequence is short. In considering tosses of a coin for heads or tails, for example, people regard the sequence H-T-H-T-T-H to be more likely than the sequence H-H-H-T-T-T, which does not appear random, and also more likely than the sequence H-H-H-H-T-H, which does not represent the fairness of the coin.[7] Thus,

Thinking, Fast and Slo
by Daniel Kahneman

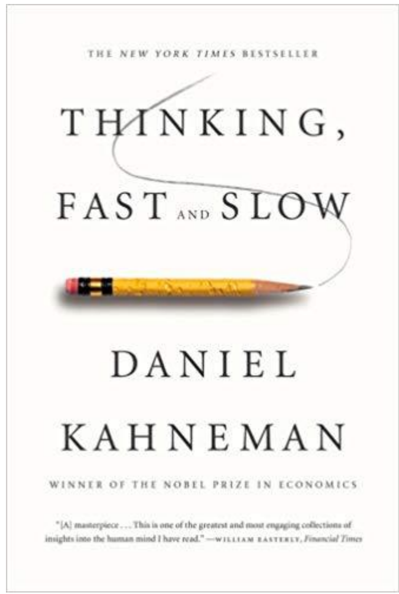


The Visual Display of Quantitative Information
by Edward R. Tufte

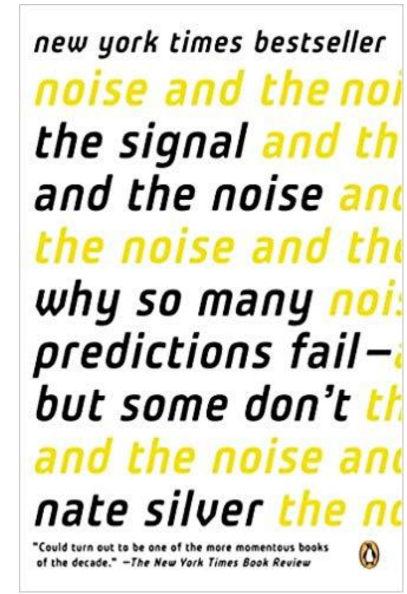


Statistics Done Wrong
by Alex Reinhart

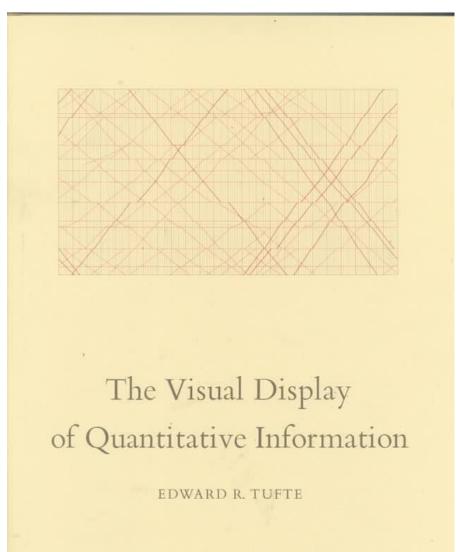
Recommended summer reading



Thinking, Fast and Slow
by Daniel Kahneman



The Signal and the Noise
by Nate Silver



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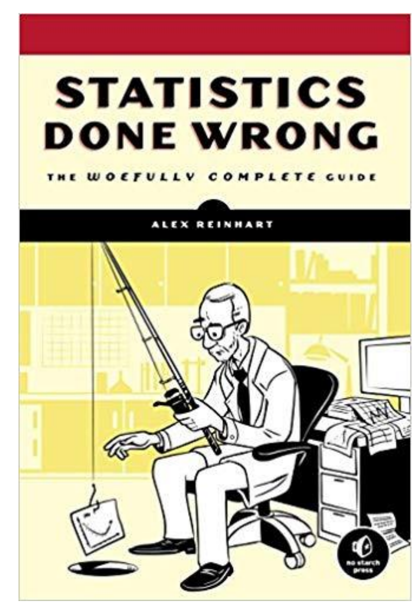

Statistics Done Wrong
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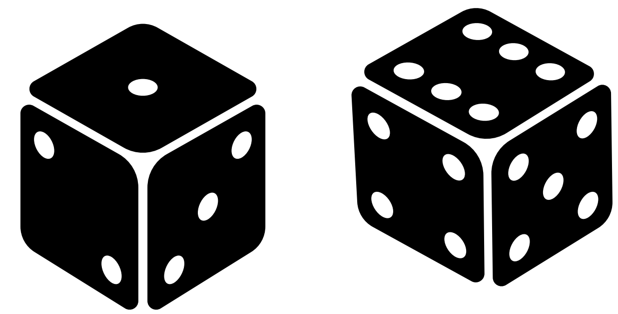
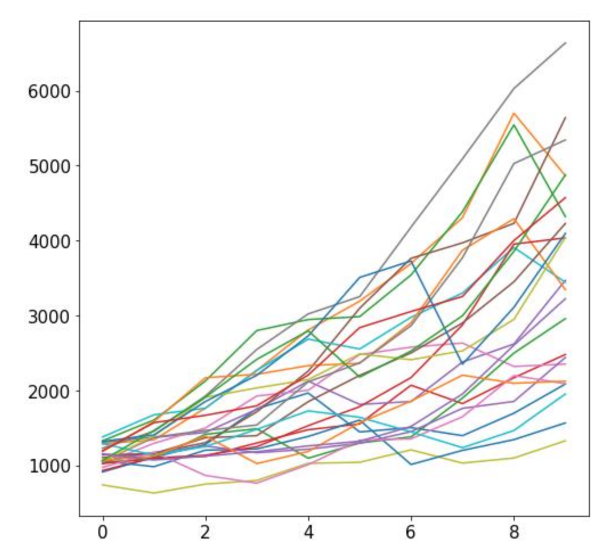
Why Randomize?

Games



Security

Simulation



our focus

Outline

choice()

bugs and seeding

significance

histograms

normal()

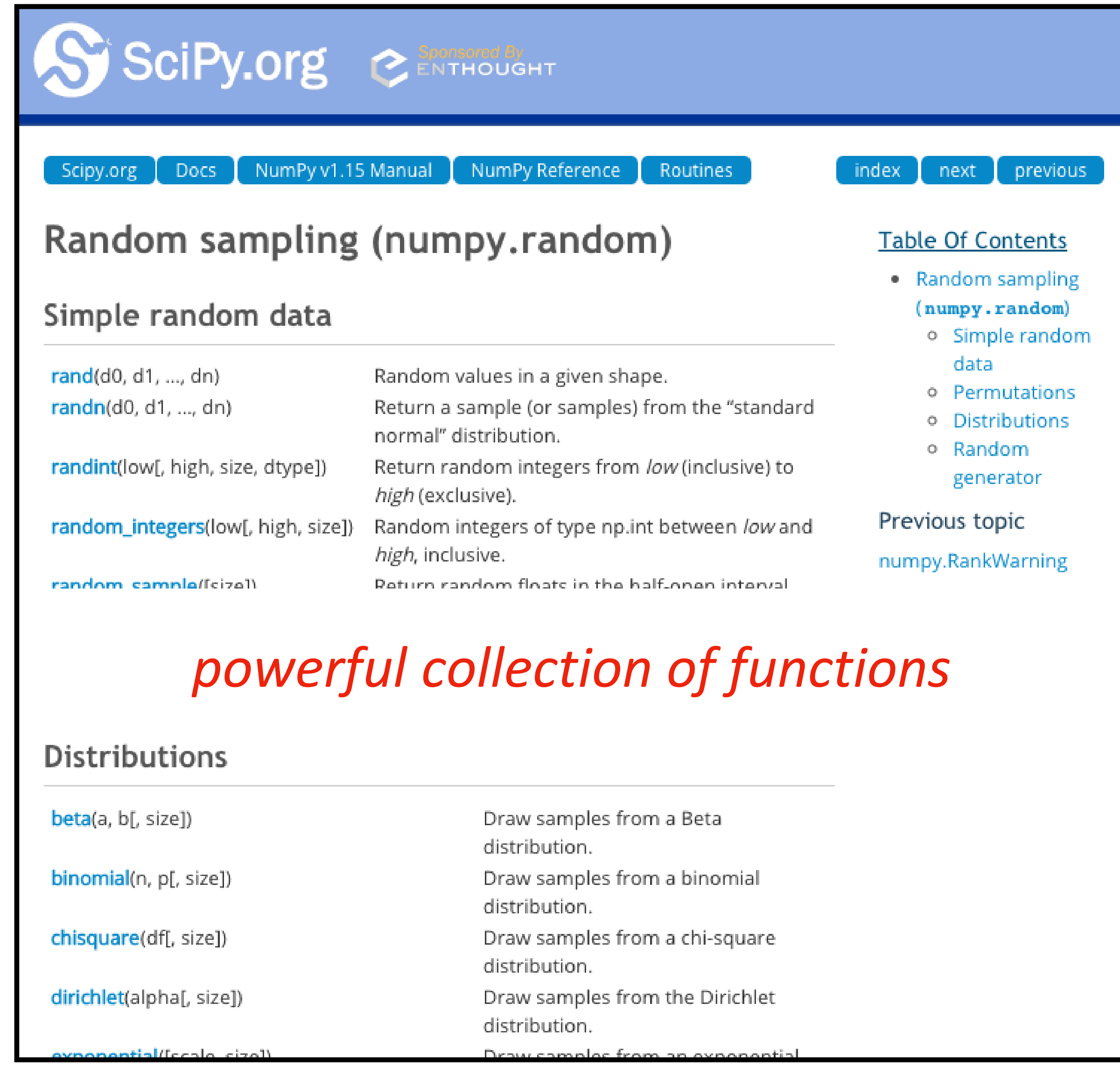
New Functions Today

`numpy.random:`

- powerful collection of functions
- `Choice`

`Series.plot.hist:`

- similar to bar plot
- visualize spread of random results



choice

```
from numpy.random import choice

result = choice([<choice1, choice2, …])
```

list of things to randomly choose from

choice

```
from numpy.random import choice

result = choice(["rock", "paper", "scissors"])
```

list of things to randomly choose from

https://www.securifera.com/blog/2015/09/09/mmactf-2015-rock-paper-scissors-rps/

choice

```
from numpy.random import choice

result = choice(["rock", "paper", "scissors"])
print(result)
```

https://www.securifera.com/blog/2015/09/09/mmactf-2015-rock-paper-scissors-rps/

Output:

```
scissors
```

choice

```
from numpy.random import choice

result = choice(["rock", "paper", "scissors"])
print(result)

result = choice(["rock", "paper", "scissors"])
print(result)
```

Output:

```
scissors
rock
```

each time choice is called, a value is randomly selected (will vary run to run)

choice

```
from numpy.random import choice

choice(["rock", "paper", "scissors"], size=5)
```

for simulation, we'll often want to compute many random results

choice

```
from numpy.random import choice

choice(["rock", "paper", "scissors"], size=5)
```

```
array(['rock', 'scissors', 'paper', 'rock', 'paper'], dtype='<U8')
```

it's list-like

Random values and Pandas

```
from numpy.random import choice

# random Series
Series(choice(["rock", "paper", "scissors"], size=5))
```

```
0         rock
1         rock
2     scissors
3        paper
4     scissors
dtype: object
```

Random values and Pandas

```
from numpy.random import choice

# random Series
DataFrame(choice(["rock", "paper", "scissors"],
                 size=(5,2)))
```

	0	1
0	paper	rock
1	scissors	rock
2	rock	rock
3	scissors	paper
4	rock	scissors

Demo: exploring bias

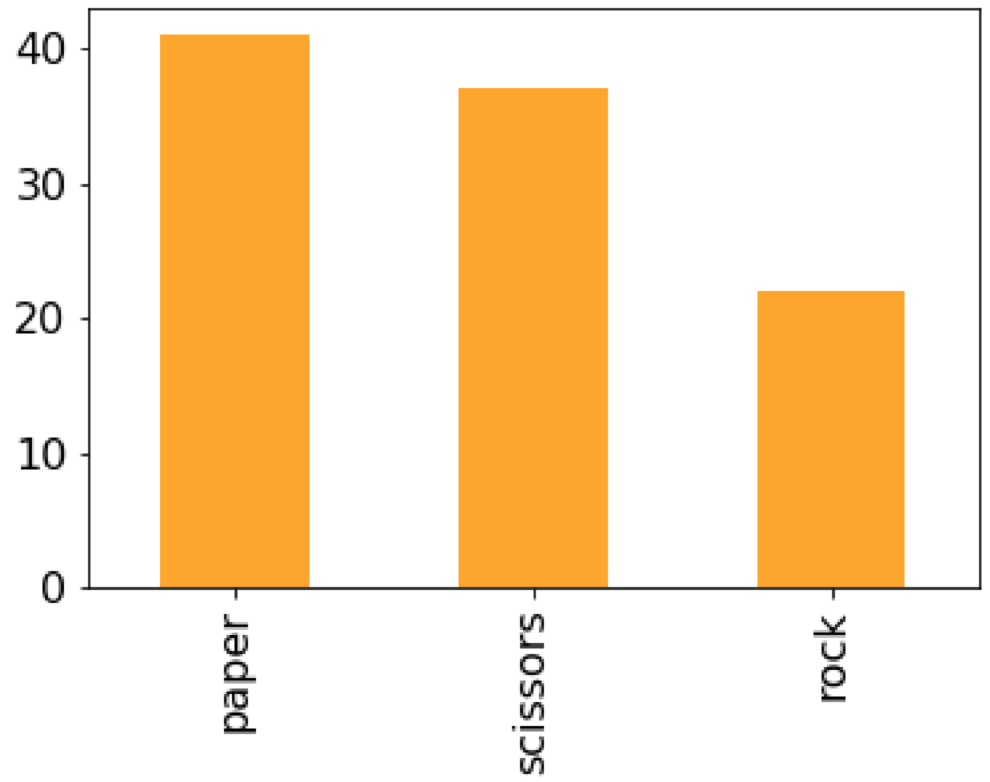
```
choice(["rock", "paper", "scissors"])
```

Question 1: how can we make sure the randomization isn't biased?

Demo: exploring bias

```
choice(["rock", "paper", "scissors"])
```

Question 1: how can we make sure the randomization isn't biased?

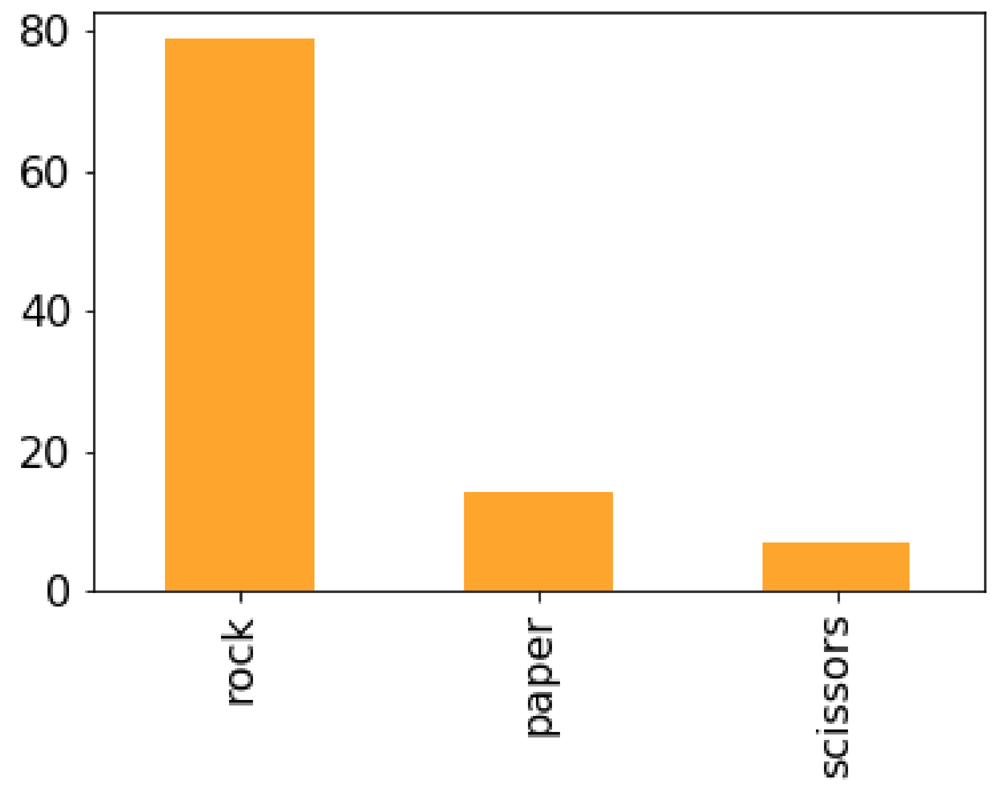


Demo: exploring bias

```
choice(["rock", "paper", "scissors"])
```

Question 1: how can we make sure the randomization isn't biased?

Question 2: how can we make it biased (if we want it to be)?



p=[...]

Random Strings vs. Random Ints

```
from numpy.random import choice, normal

# random string: rock, paper, or scissors
choice(["rock", "paper", "scissors"])

# random int: 0, 1, or 2
choice([0, 1, 2])
```

Random Strings vs. Random Ints

```
from numpy.random import choice, normal

# random string: rock, paper, or scissors
choice(["rock", "paper", "scissors"])

# random int: 0, 1, or 2
choice([0, 1, 2])
```

same

```
# random int (approach 2): 0, 1, or 2
choice(3)
```

random non-negative int
that is **less than 3**

Outline

choice()

bugs and seeding

significance

histograms

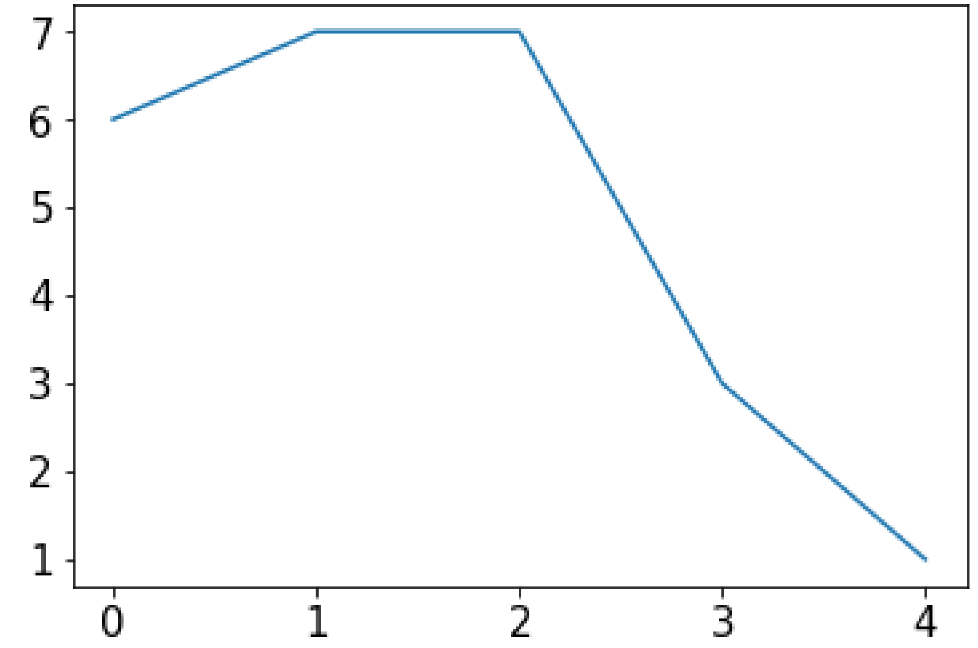
normal()

Example: change over time

```
s = Series(choice(10, size=5))
```

```
0     6
1     7
2     7
3     3
4     1
dtype: int64
```

```
s.plot.line()
```



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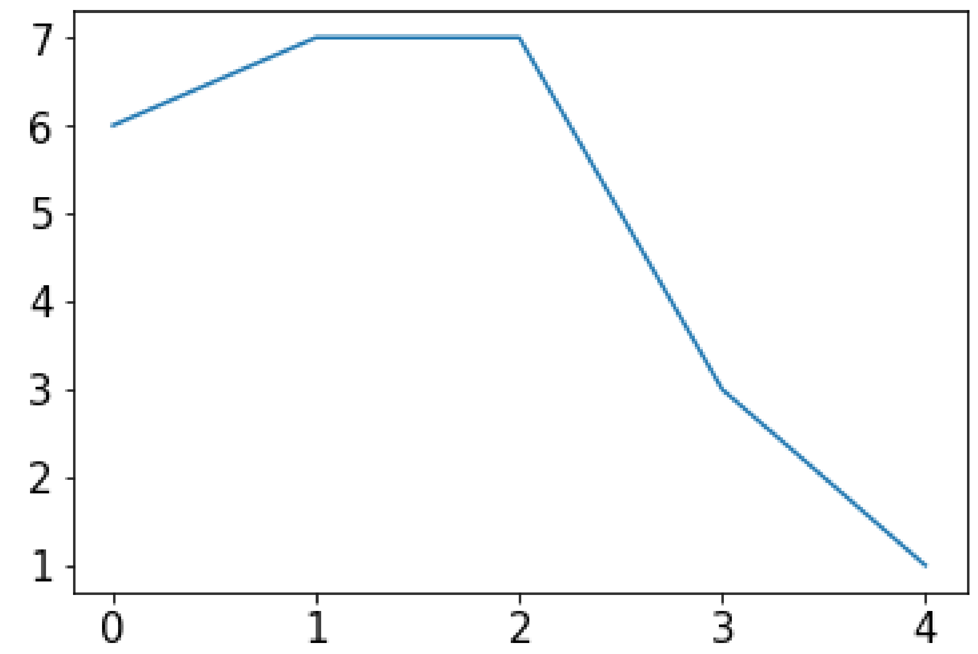
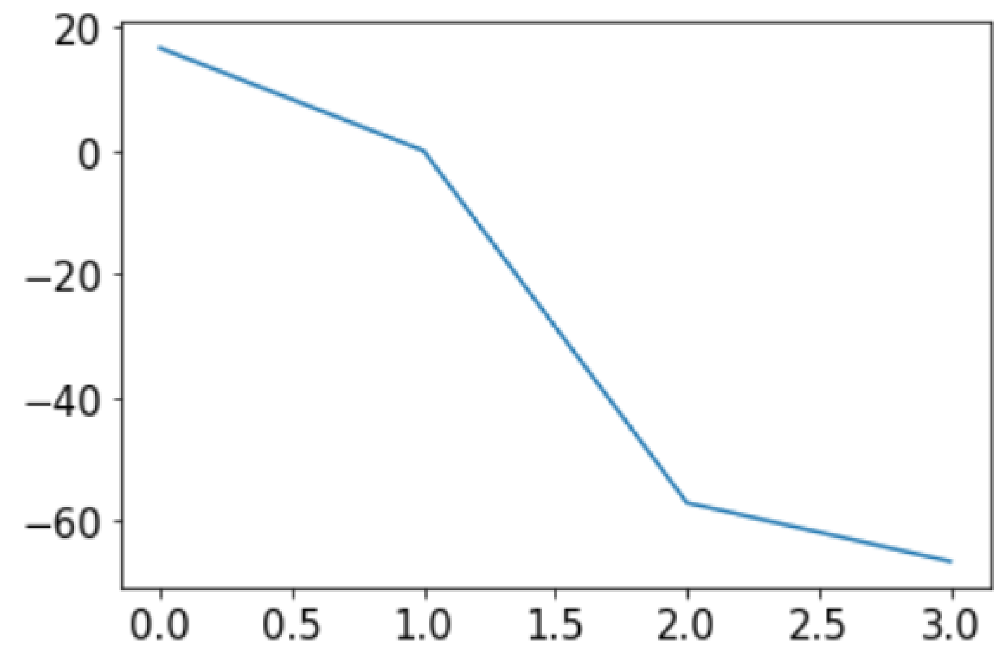



```
percents = []
for i in range(1, len(s)):
    diff = 100 * (s[i] / s[i-1] - 1)
    percents.append(diff)
Series(percents).plot.line()
```



what are we computing for diff?

Example: change over time

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s = Series(choice(10, size=5))
```

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0      6
1      7
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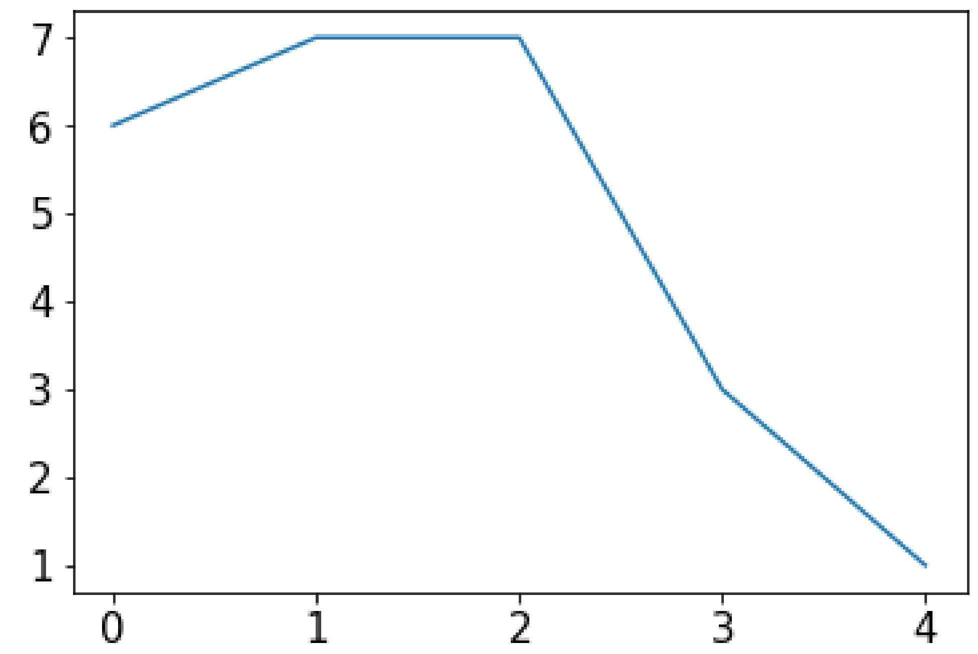


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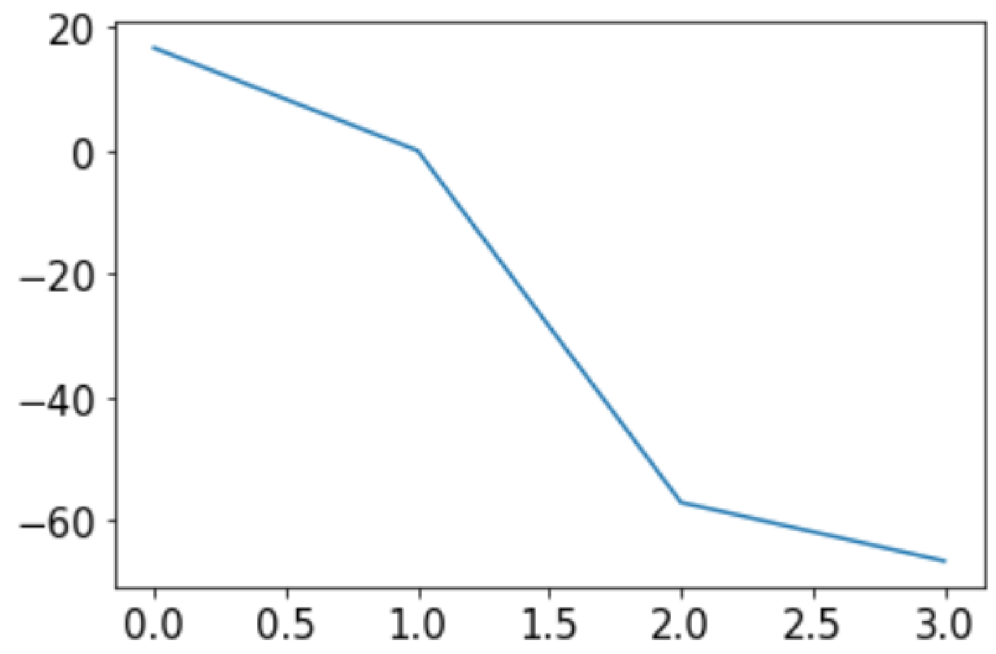


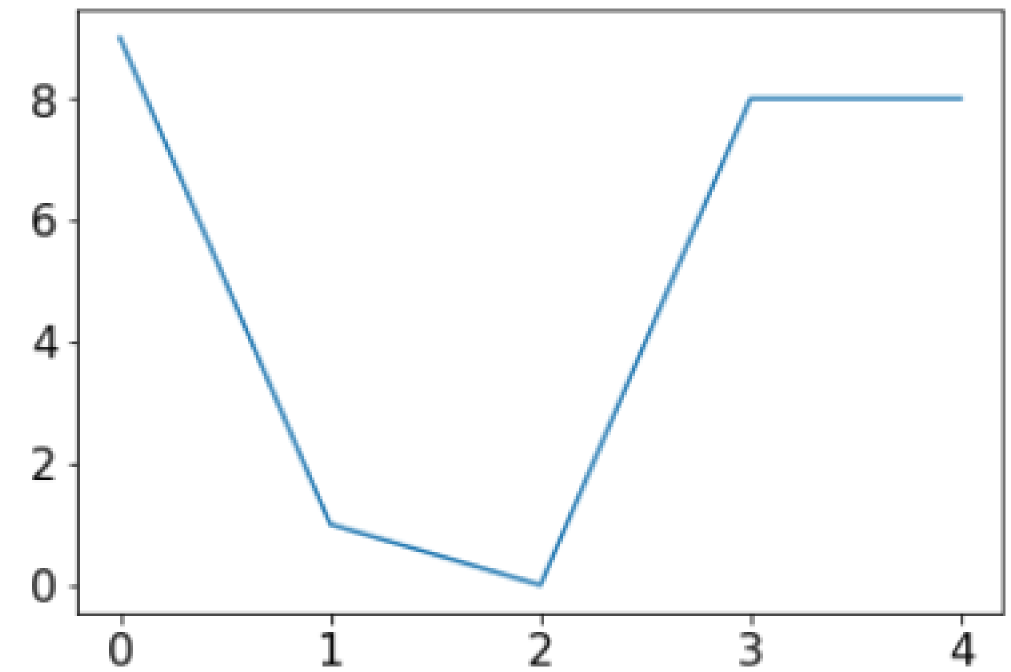
can you identify the bug in the code?

Example: change over time

```
s = Series(choice(10, size=5))
```

```
0     9
1     1
2     0
3     8
4     8
dtype: int64
```

```
s.plot.line()
```

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    percents.append(diff)
Series(percents).plot.line()
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/
python3.7/site-packages/ipykernel_launcher.py:3: Runti
meWarning: divide by zero encountered in long_scalars
  This is separate from the ipykernel package so we ca
n avoid doing imports until
```

can you identify the bug in the code?

Not all bugs are equal!

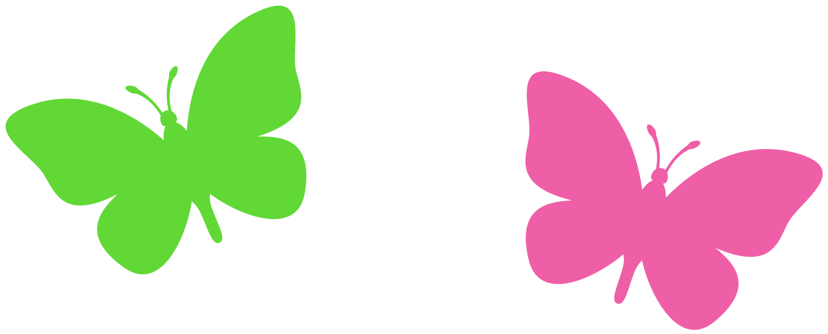
scary bugs

non-deterministic

https://owlcation.com/stem/5-Badass-Bugs-That-You-Should-Have-Nightmares-About

"nice" bugs

deterministic (reproducible)



Not all bugs are equal!

scary bugs

non-deterministic
system related
randomness

https://owlcation.com/stem/5-Badass-Bugs-That-You-Should-Have-Nightmares-About

"nice" bugs

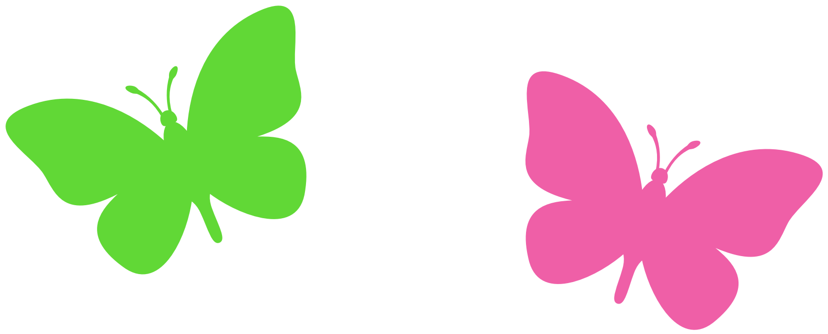
deterministic (reproducible)

Not all bugs are equal!

scary bugs	"nice" bugs
non-deterministic system related randomness	deterministic (reproducible)
large data	small data
semantic	syntax

runtime

https://owlcation.com/stem/5-Badass-Bugs-That-You-Should-Have-Nightmares-About



Not all bugs are equal!

scary bugs

non-deterministic
system related
randomness

large data

semantic ???? runtime

https://owlcation.com/stem/5-Badass-Bugs-That-You-Should-Have-Nightmares-About

"nice" bugs

deterministic (reproducible)

small data

syntax

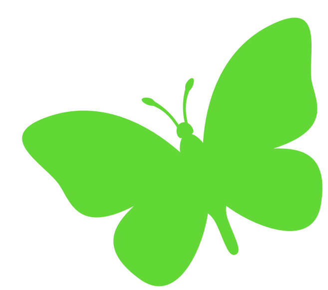
Not all bugs are equal!

scary bugs	"nice" bugs
non-deterministic system related randomness	deterministic (reproducible)
large data	small data
semantic	syntax

non-deterministic / system related / randomness $\xrightarrow{\text{seeding}}$ deterministic (reproducible)

semantic $\xrightarrow{\text{assert}}$ runtime

Igor Siwanowicz



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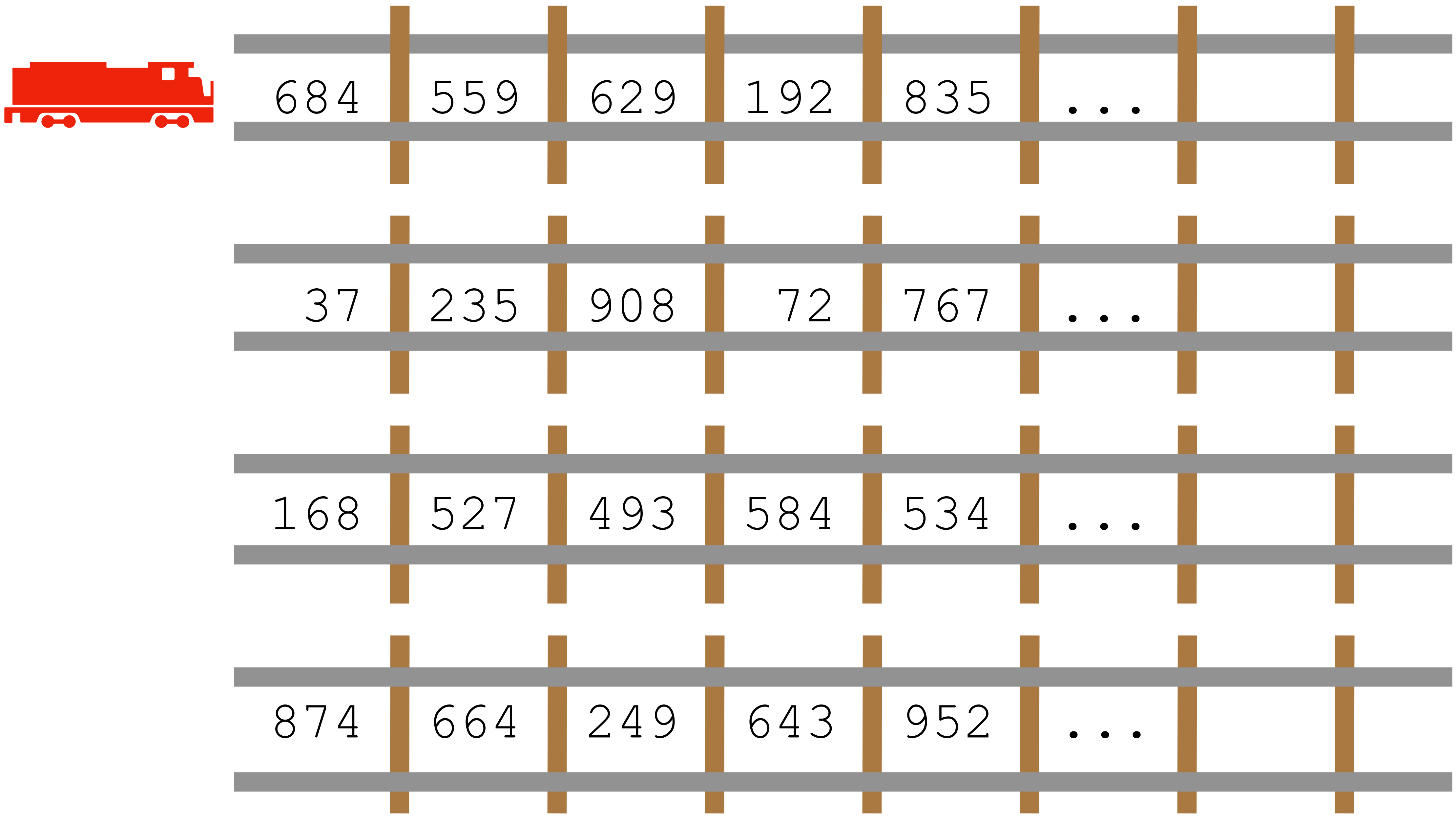
Pseudorandom Generators

"Random" generators are really just *pseudorandom*



Pseudorandom Generators

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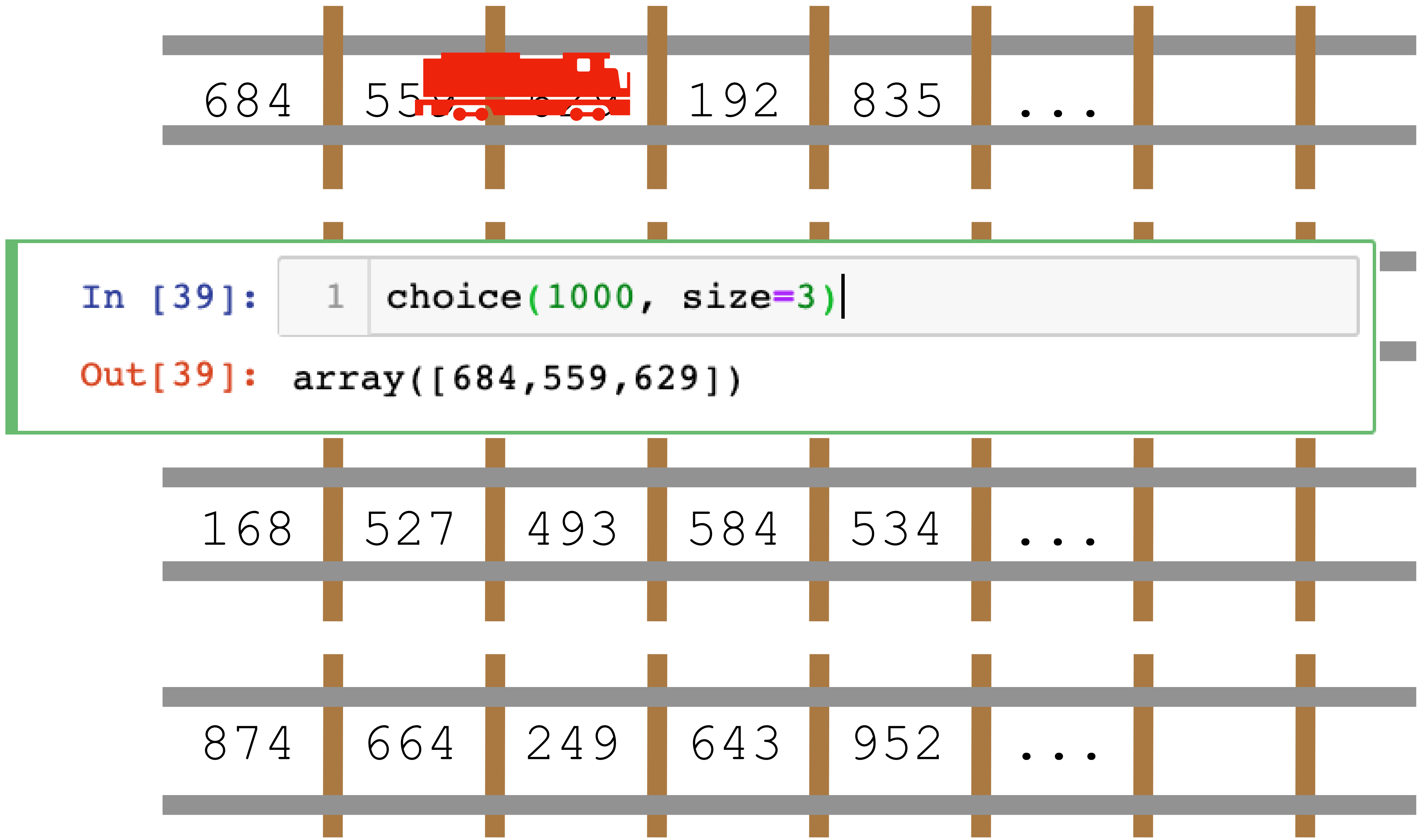
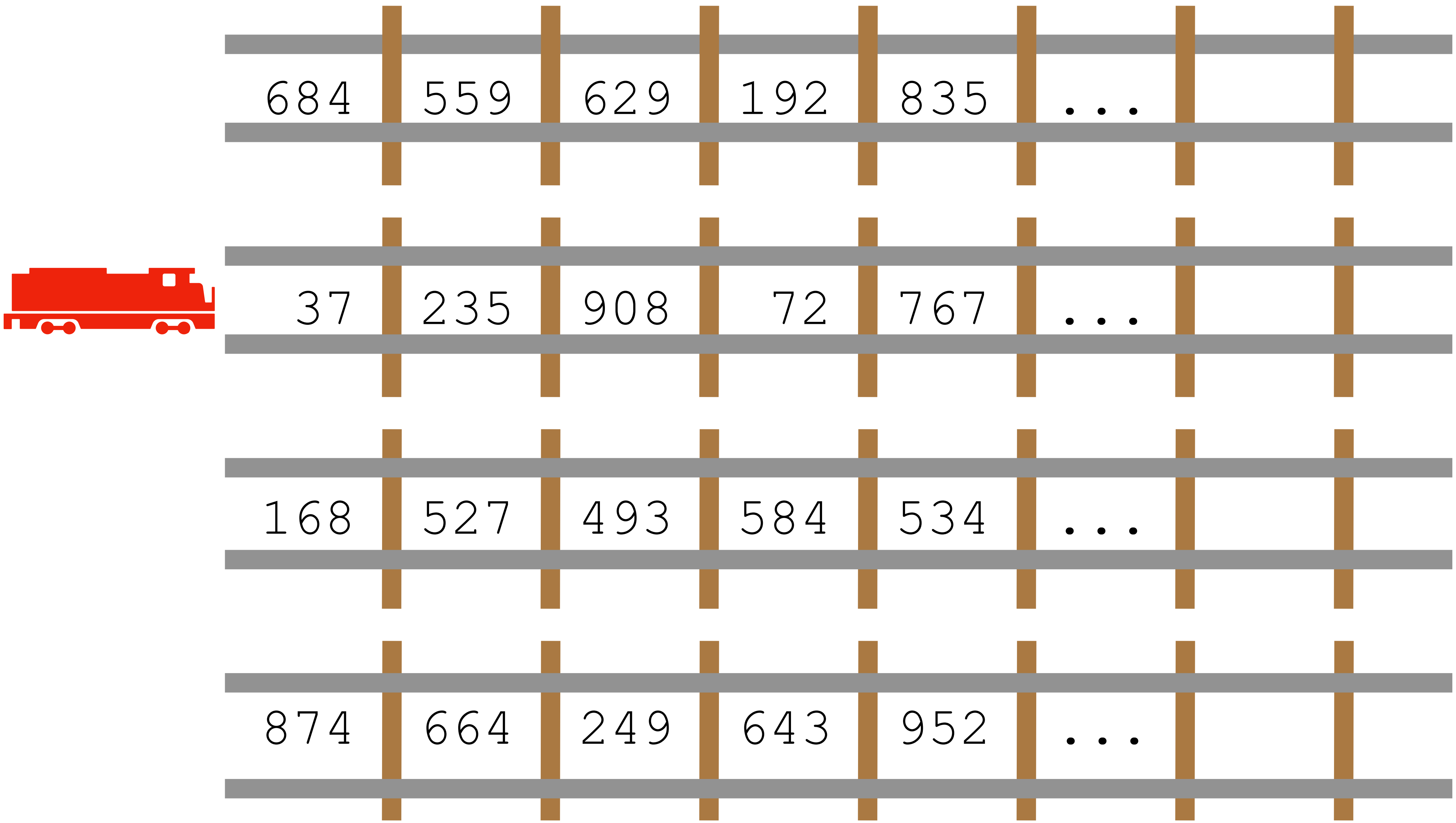


Pseudorandom Generators

"Random" generators are really just *pseudorandom*



Pseudorandom Generators

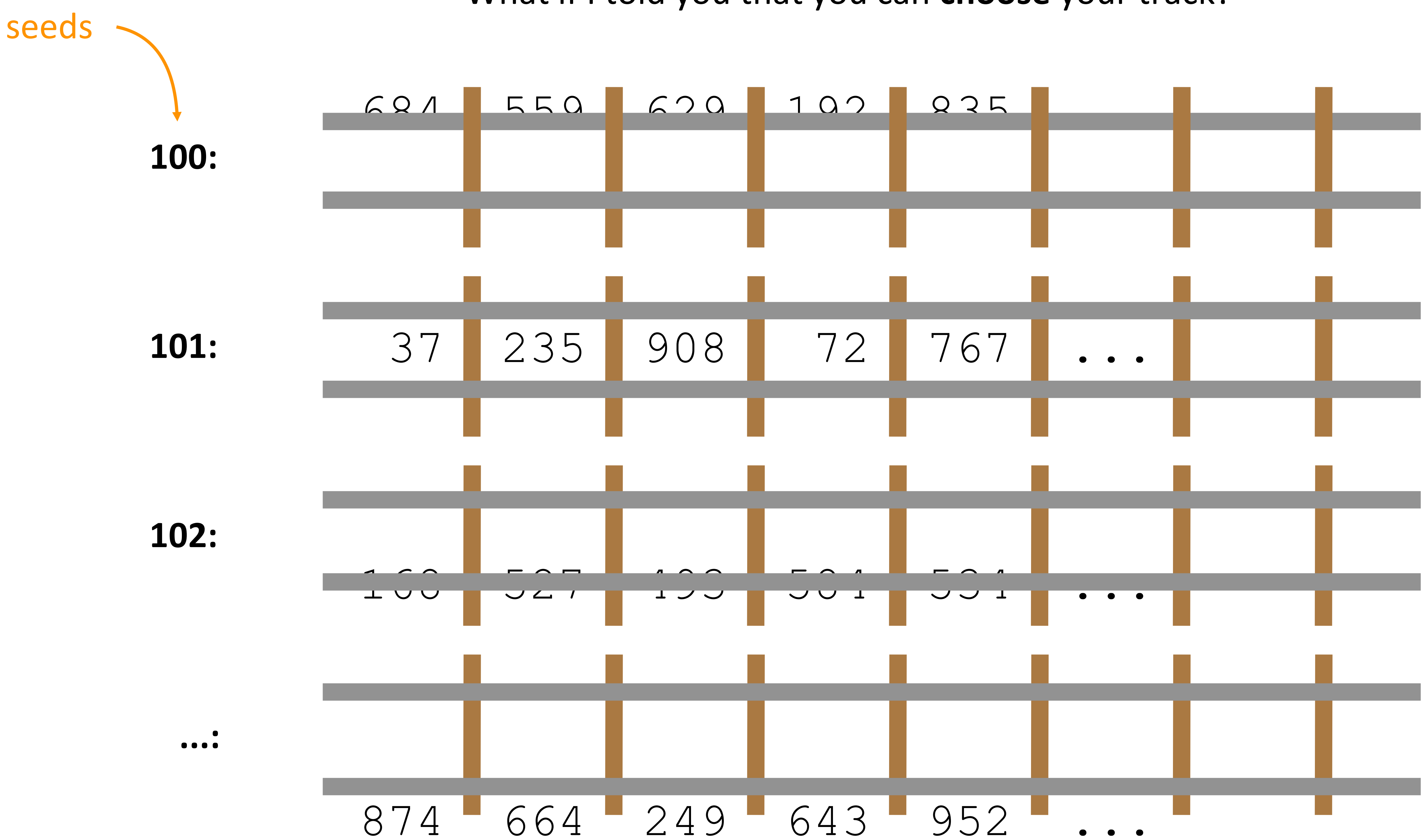
"Random" generators are really just *pseudorandom*

seeds

100:	684	559	629	192	835	...
101:	37	235	908	72	767	...
102:	168	527	493	584	534	...
...:	874	664	249	643	952	...

Seeding

What if I told you that you can **choose** your track?



Seeding

What if I told you that you can **choose** your track?

```
In [11]: np.random.seed(301)
         choice(1000, size=3)
Out[11]: array([885, 320, 423])
```

```
In [12]: np.random.seed(301)
         choice(1000, size=3)
Out[12]: array([885, 320, 423])
```

```
In [13]: np.random.seed(301)
         choice(1000, size=3)
Out[13]: array([885, 320, 423])
```

Seeding

Common approach for simulations:

1. seed using current time
2. print seed
3. use the seed for reproducing bugs, as necessary

In [28]:

```
import time
now = int(time.time())
print("seeding with", now)
np.random.seed(now)
choice(1000, size=3)
```

```
seeding with 1556673136
```

Out[28]:

```
array([352, 734, 362])
```

Outline

choice()

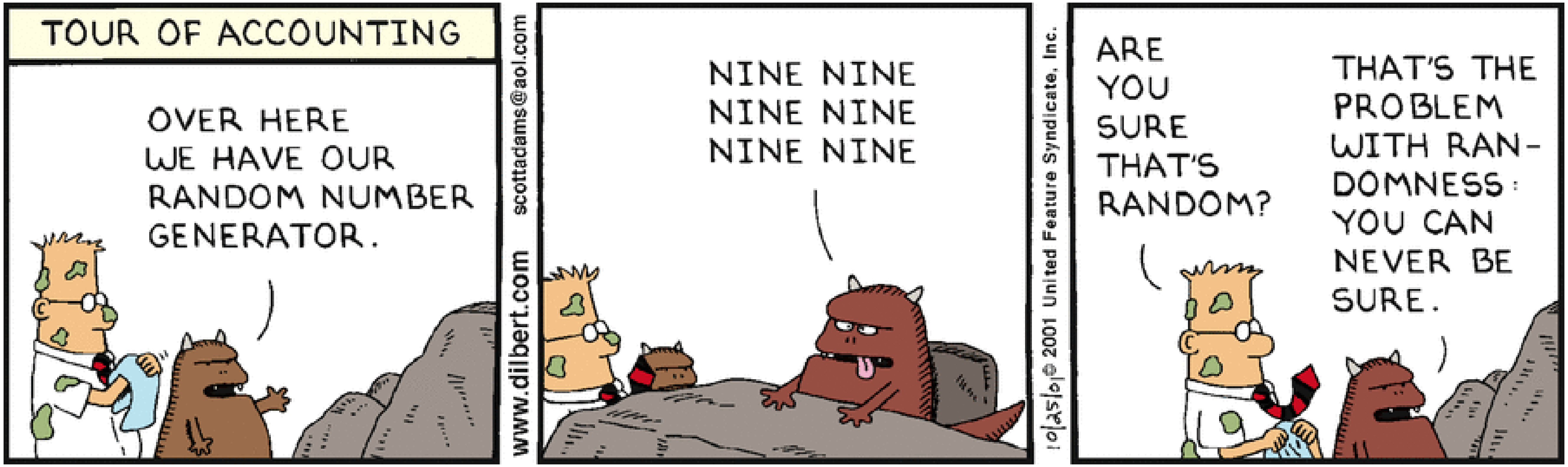
bugs and seeding

significance

histograms

normal()

In a noisy world, what is noteworthy?



https://dilbert.com/strip/2001-10-25

Is this coin biased?

51

49

Call shenanigans?

whoever has the coin cheated
(it's not 50/50 heads/tails)

a statistician might say we're trying to decide if the evidence that the coin isn't fair is **statistically significant**

Is this coin biased?

51 **49**

Call shenanigans? No.

Is this coin biased?

51 **49**

Call shenanigans? No.

5 **95**

Call shenanigans?

Is this coin biased?

51 **49**

Call shenanigans? No.

5 **95**

Call shenanigans? Yes.

Note: there is a non-zero probability that a fair coin will do this, but the odds are slim

Is this coin biased?

51 **49**

Call shenanigans? No.

5 **95**

Call shenanigans? Yes.

55 **45**

Call shenanigans?

55 million **45 million**

Call shenanigans?

Is this coin biased?

51 **49**

Call shenanigans? No.

5 **95**

Call shenanigans? Yes.

55 **45**

Call shenanigans? No.

55 million **45 million**

Call shenanigans? Yes.

Is this coin biased?

51 **49**

Call shenanigans? No.

5 **95**

Call shenanigans? Yes.

large skew is good evidence of shenanigans

55 **45**

Call shenanigans? No.

55 million **45 million**

Call shenanigans? Yes.

small skew over **large samples** is good evidence

Demo: CoinSim

60 **40**

Call shenanigans?

Strategy: simulate a fair coin

1. "flip" it 100 times using numpy.random.choice
2. count heads
3. repeat above 10K times

```
[50, 61, 51, 44, 39, 43, 51, 49, 49, 38, ...]
```

Demo: CoinSim

Call shenanigans?

60 **40**

we got 10 more heads than we expect on average

how common is this?

Strategy: simulate a fair coin

1. "flip" it 100 times using numpy.random.choice
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```
[50, 61, 51, 44, 39, 43, 51, 49, 49, 38, ...]
```

Demo: CoinSim

 

Call shenanigans?

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1. "flip" it 100 times using numpy.random.choice
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```
[50, 61, 51, 44, 39, 43, 51, 49, 49, 38, ...]
```

11 more 12 less

Outline

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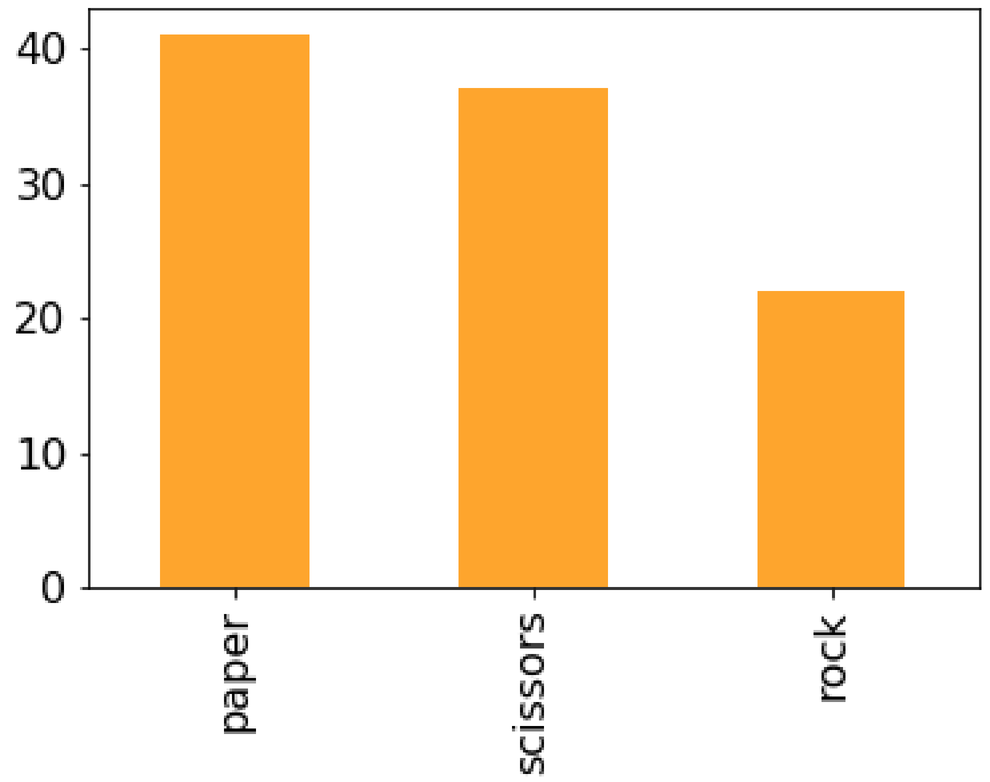
Frequencies across categories

bars are a good way to view frequencies across categories

```
s = Series(["rock", "rock", "paper",
            "scissors", "scissors", "scissors"])

s.value_counts().plot.bar(color="orange")
```

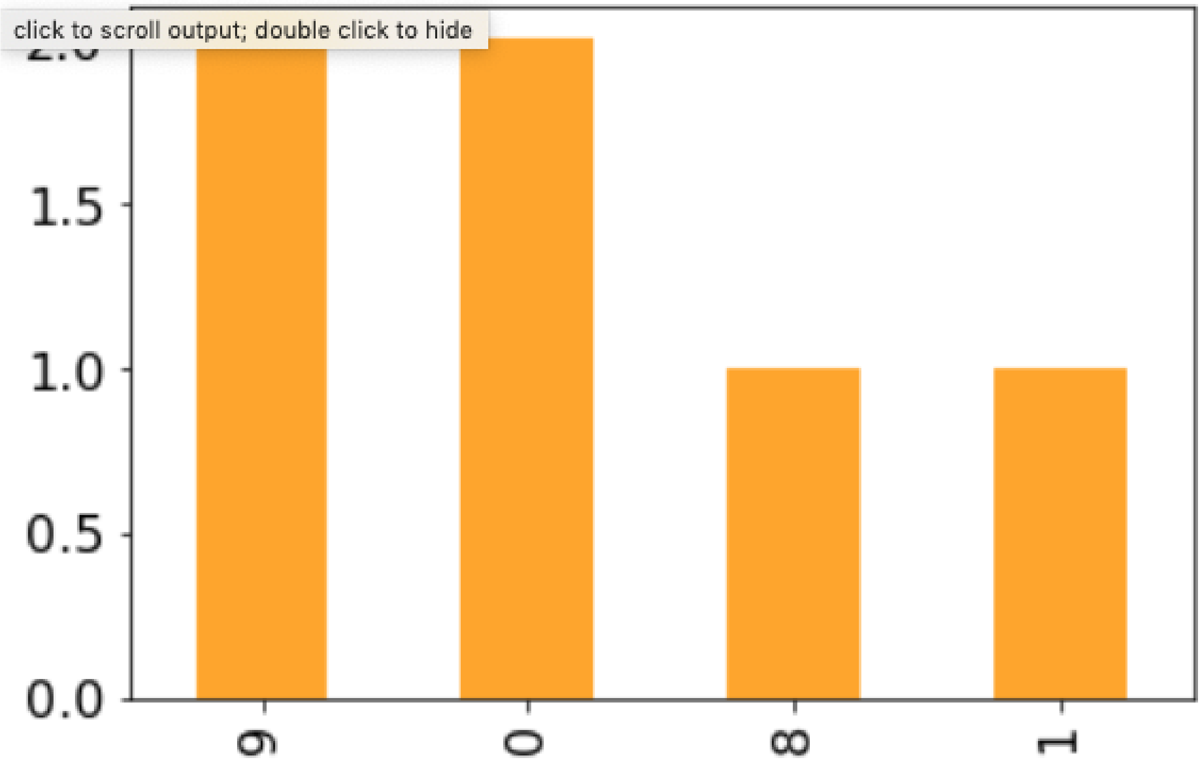


Frequencies across numbers

bars are a bad way to view frequencies across numbers

```
s = Series([0, 0, 1, 8, 9, 9])

s.value_counts().plot.bar(color="orange")
```



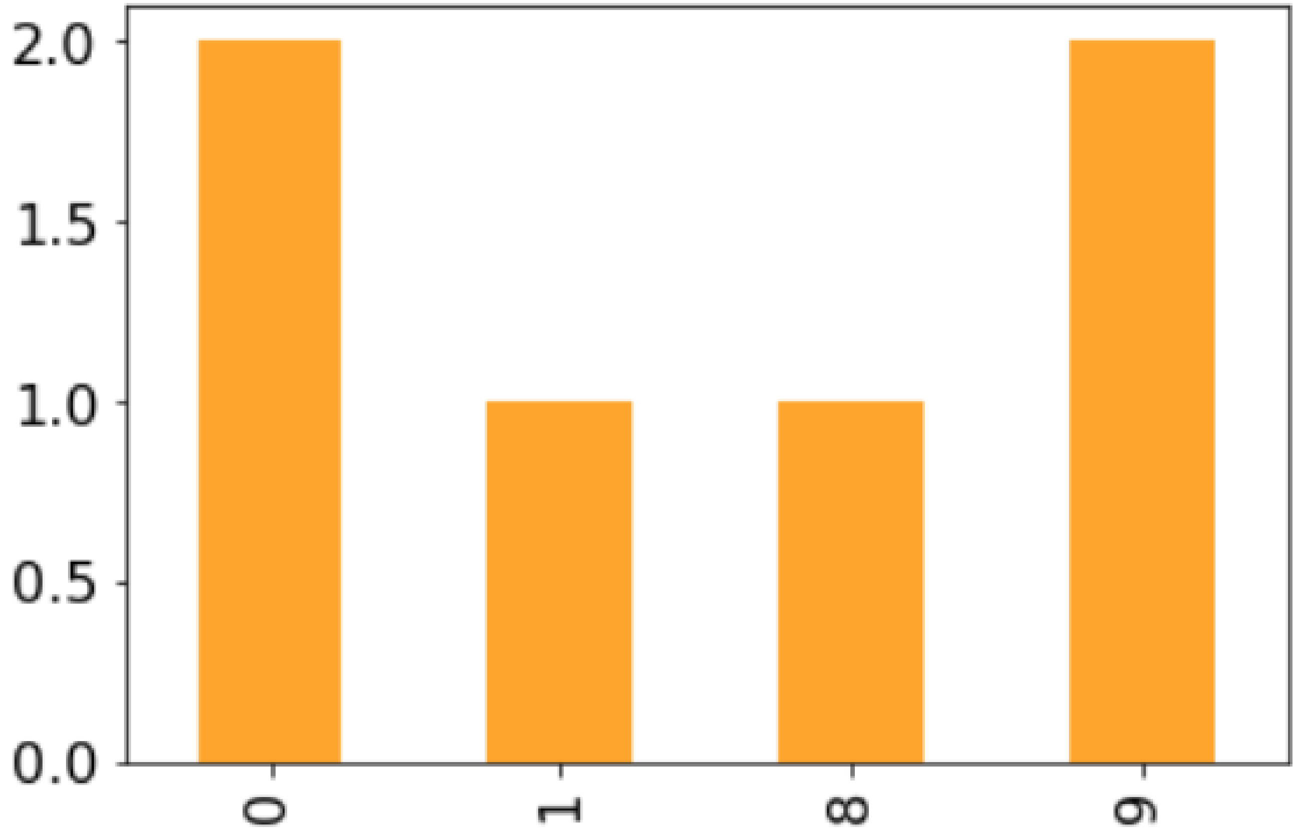
numbers not ordered

Frequencies across numbers

bars are a bad way to view frequencies across numbers

```
s = Series([0, 0, 1, 8, 9, 9])

s.value_counts().sort_index().plot.bar(color="orange")
```



gap between 1 and 8 not obvious

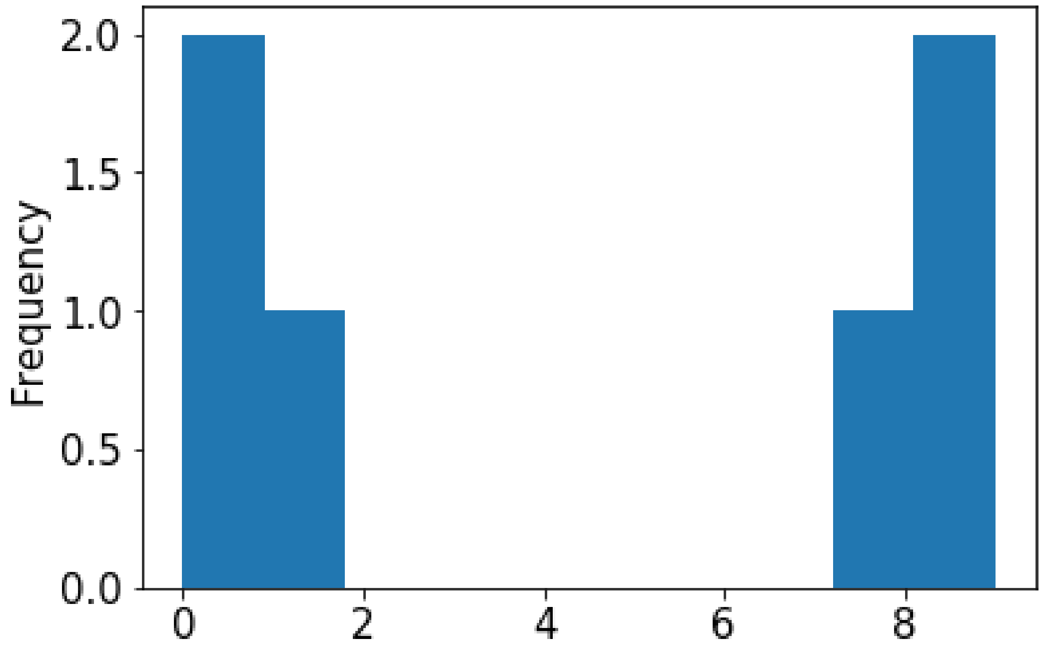
Frequencies across numbers

bars are a bad way to view frequencies across numbers

```
s = Series([0, 0, 1, 8, 9, 9])
```

~~s.value_counts().sort_index().plot.bar()~~

```
s.plot.hist()
```



Frequencies across numbers

histograms are a good way to view frequencies across numbers

```
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```
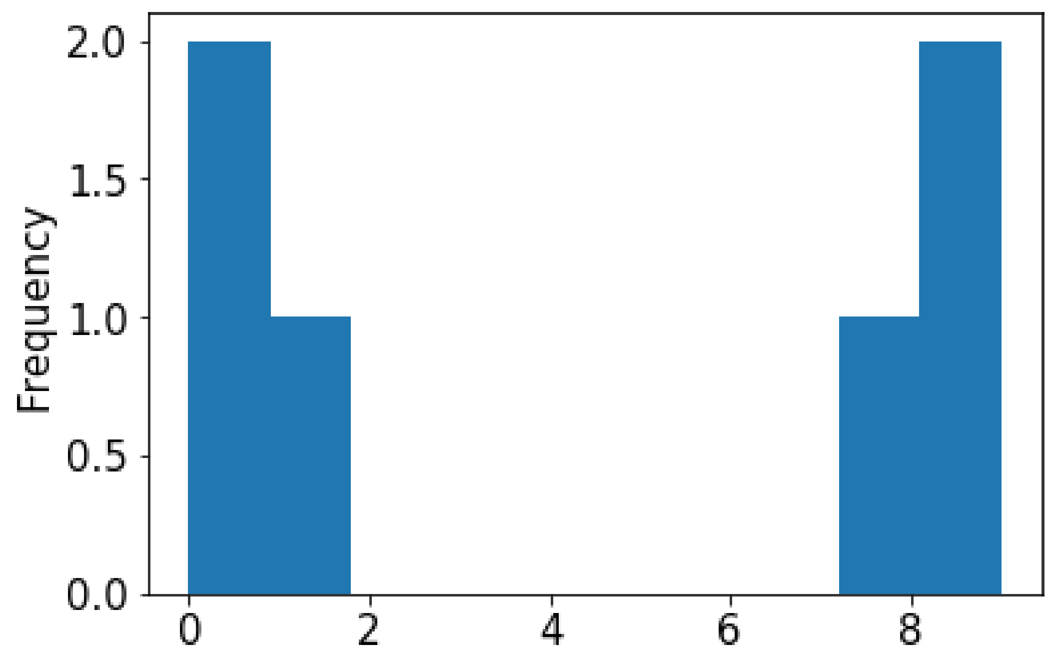

~~`s.value_counts().sort_index().plot.bar()`~~

```
s.plot.hist()
```



this kind of plot is called a histogram

Frequencies across numbers

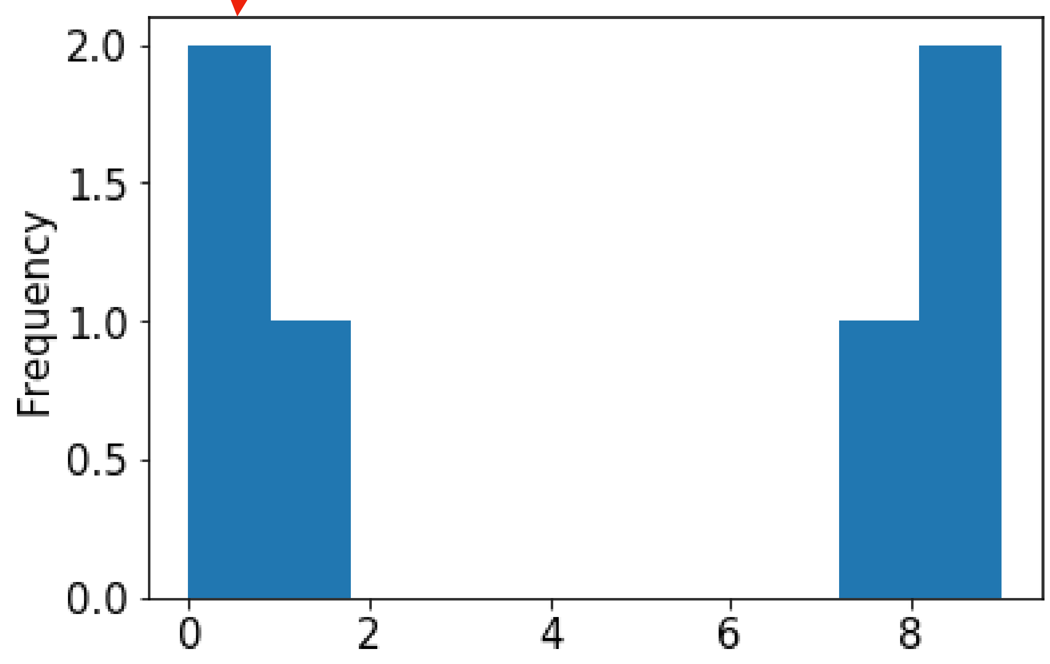
histograms are a good way to view frequencies across numbers

```
s = Series([0.1, 0, 1, 8, 9, 9.2])
```

~~s.value_counts().sort_index().plot.bar()~~

```
s.plot.hist()
```

both 0 and 0.1

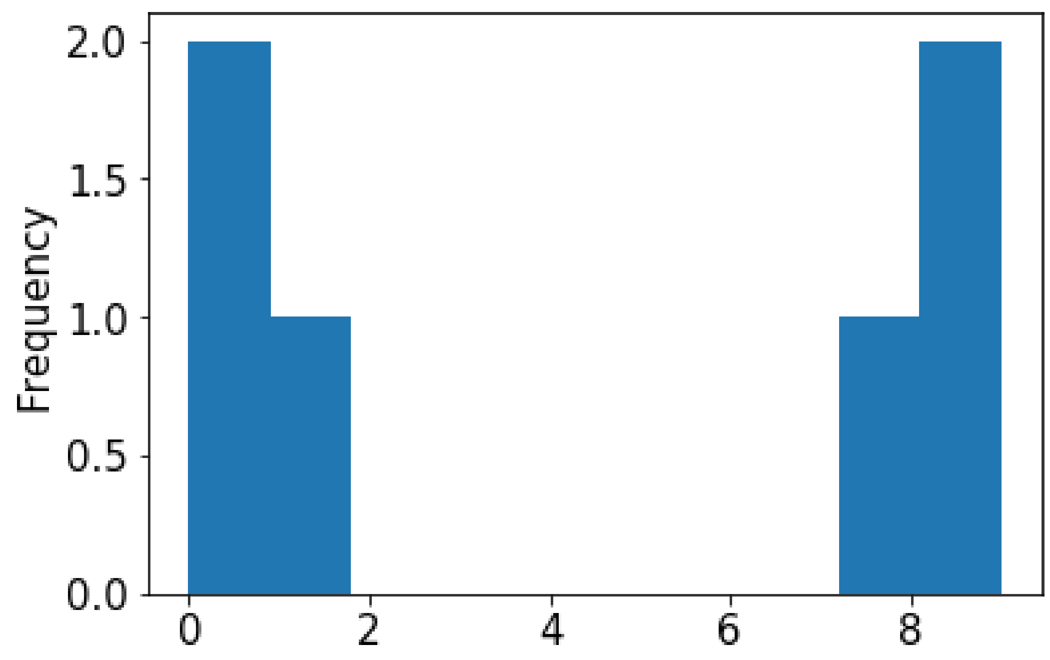


a histogram "bins" nearby numbers to create discrete bars

Frequencies across numbers

histograms are a good way to view frequencies across numbers

```
s = Series([0.1, 0, 1, 8, 9, 9.2])

s.value_counts().sort_index().plot.bar()
s.plot.hist(bins=10)
```

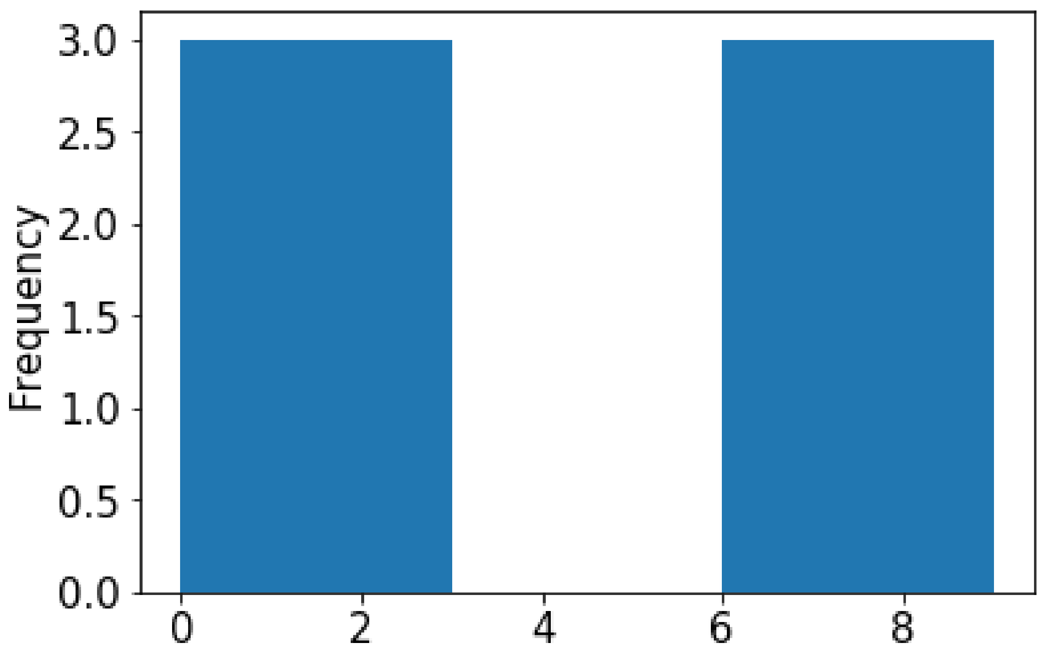


we can control the number of bins

Frequencies across numbers

histograms are a good way to view frequencies across numbers

```
s = Series([0.1, 0, 1, 8, 9, 9.2])

s.value_counts().sort_index().plot.bar()
s.plot.hist(bins=3)
```



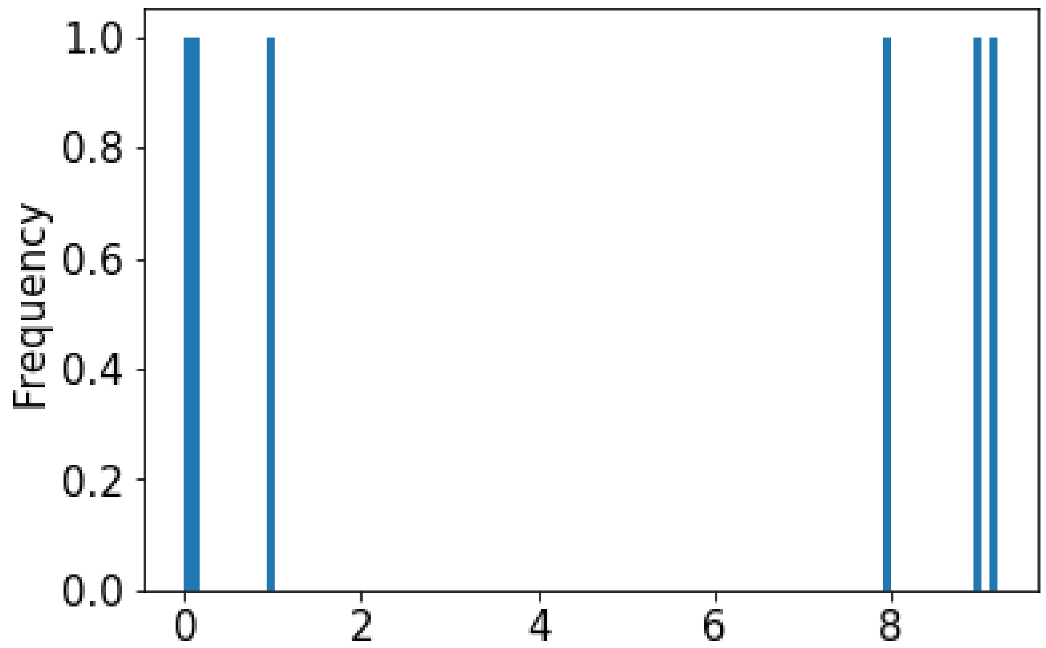
too few bins provides too little detail

Frequencies across numbers

histograms are a good way to view frequencies across numbers

```
s = Series([0.1, 0, 1, 8, 9, 9.2])
```

```
s.value_counts().sort_index().plot.bar()
s.plot.hist(bins=100)
```



too many bins provides too much detail (equally bad)

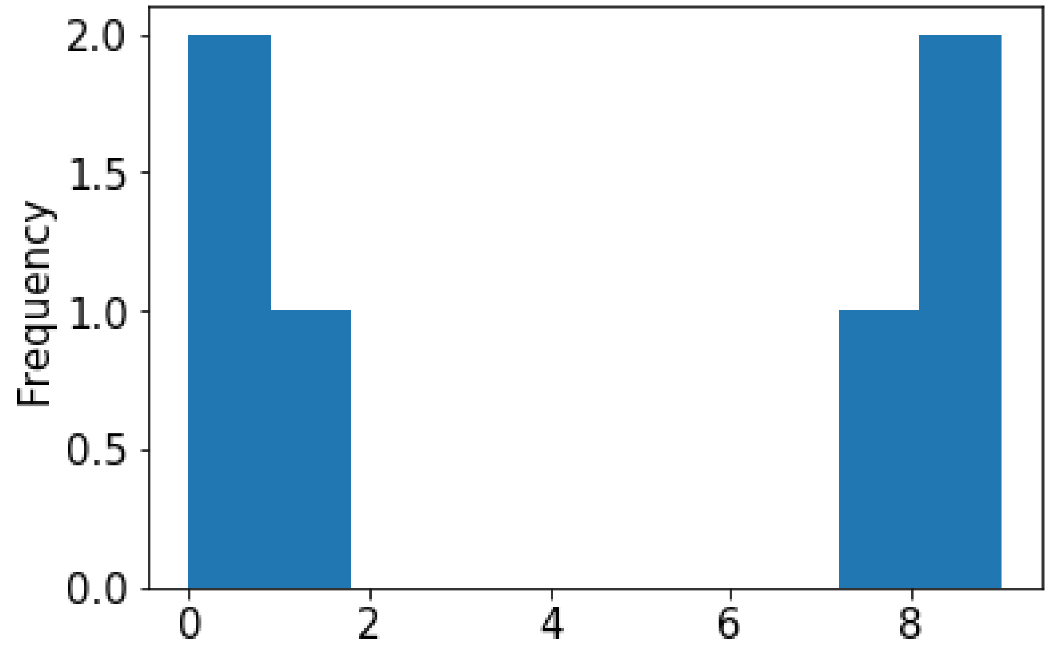
Frequencies across numbers

histograms are a good way to view frequencies across numbers

```
s = Series([0.1, 0, 1, 8, 9, 9.2])
```

~~s.value_counts().sort_index().plot.bar()~~

```
s.plot.hist(bins=10)
```



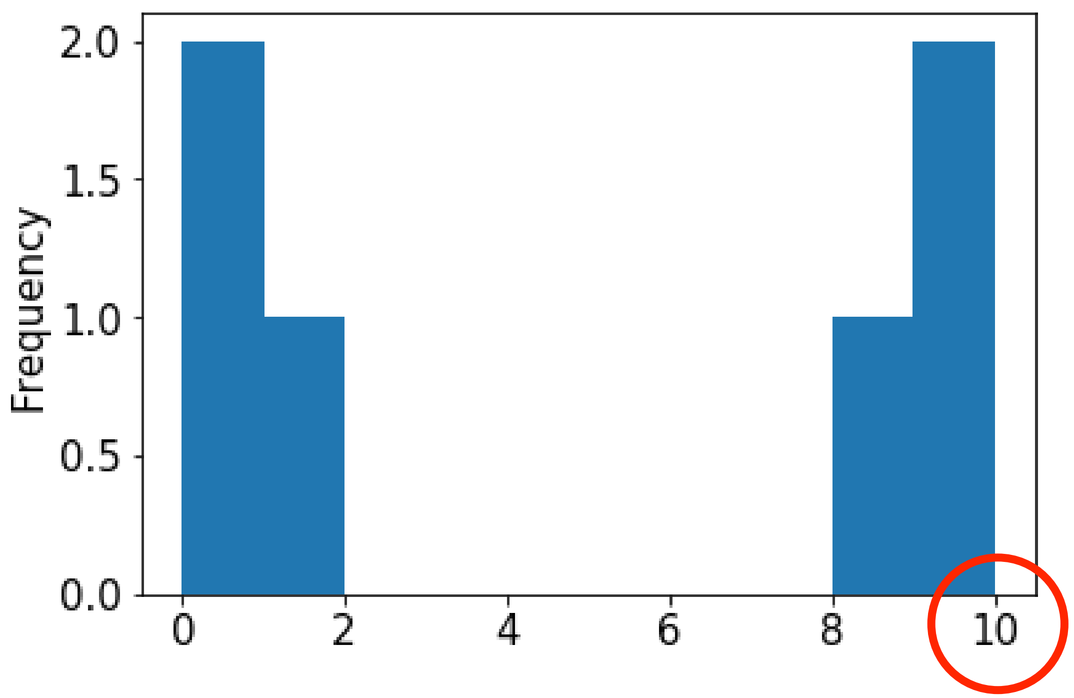
pandas chooses the default bin boundaries

Frequencies across numbers

histograms are a good way to view frequencies across numbers

```
s = Series([0.1, 0, 1, 8, 9, 9.2])
```

```
s.value_counts().sort_index().plot.bar()
s.plot.hist(bins=[0,1,2,3,4,5,6,7,8,9,10])
```

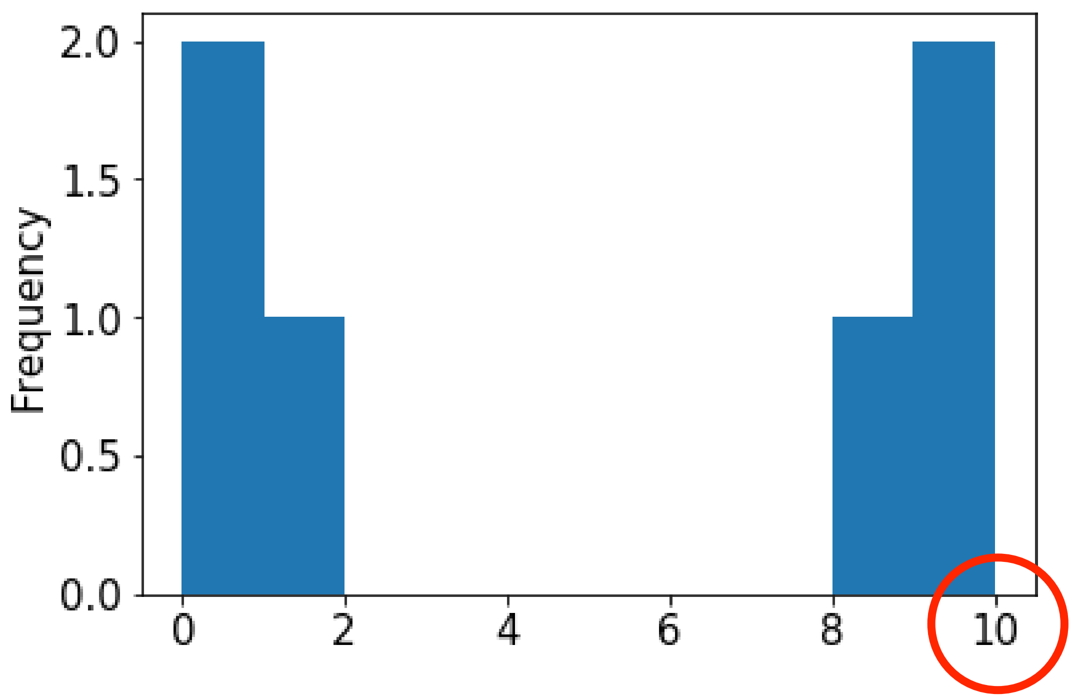


we can override the defaults

Frequencies across numbers

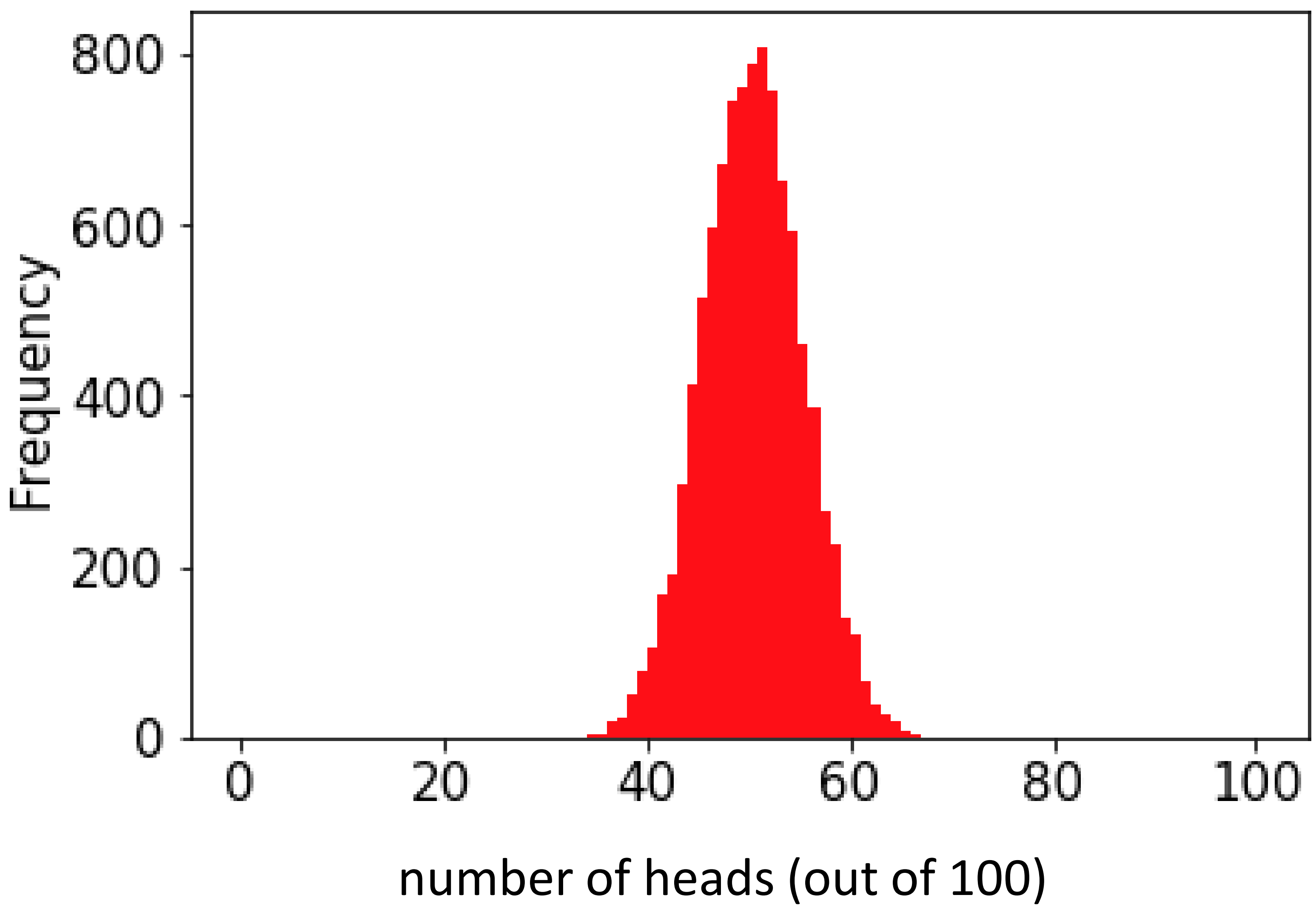
histograms are a good way to view frequencies across numbers

```
s = Series([0.1, 0, 1, 8, 9, 9.2])

s.value_counts().sort_index().plot.bar()
s.plot.hist(bins=range(11))
```

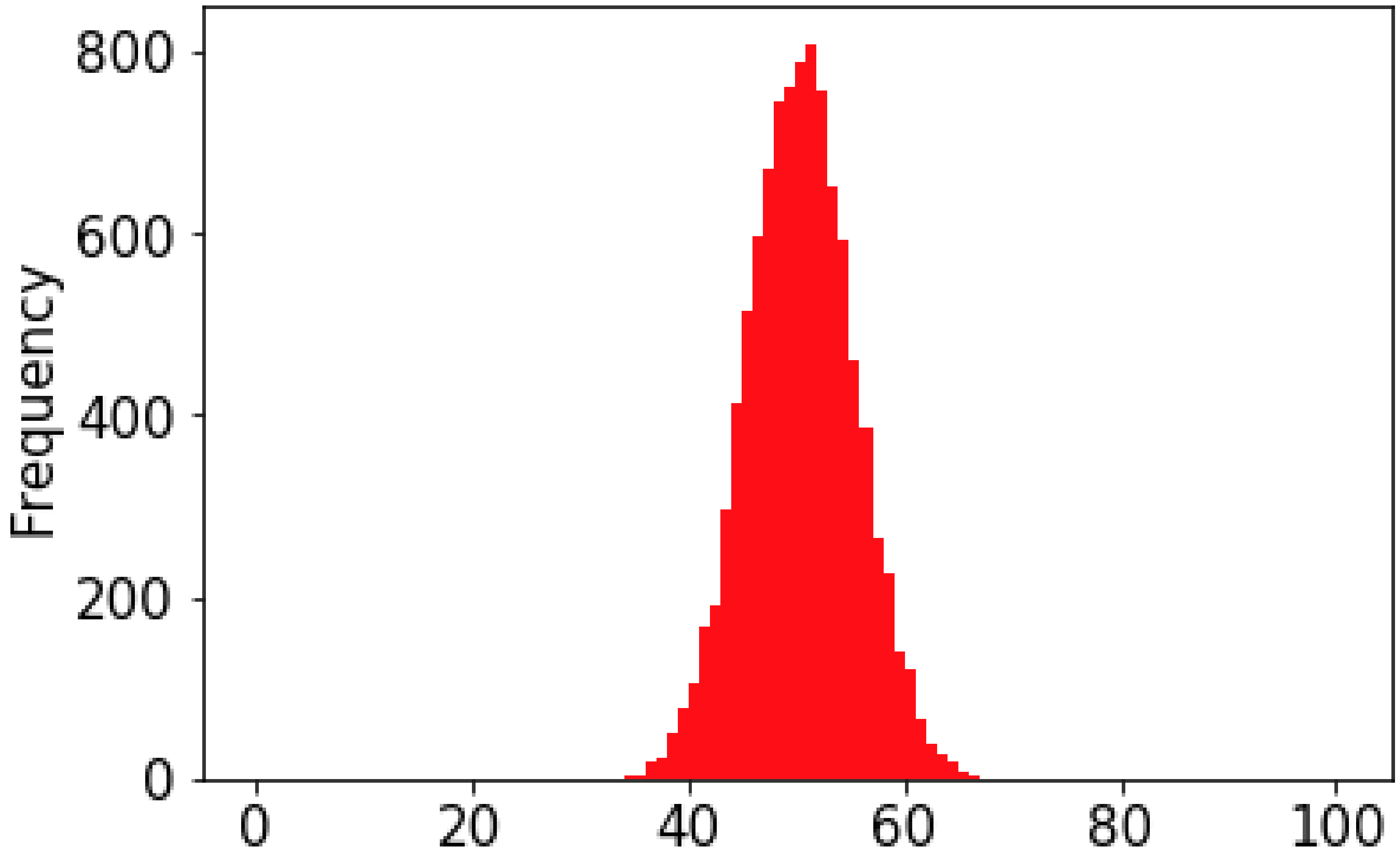


this is easily done with range

Demo: Visualize CoinSim Results



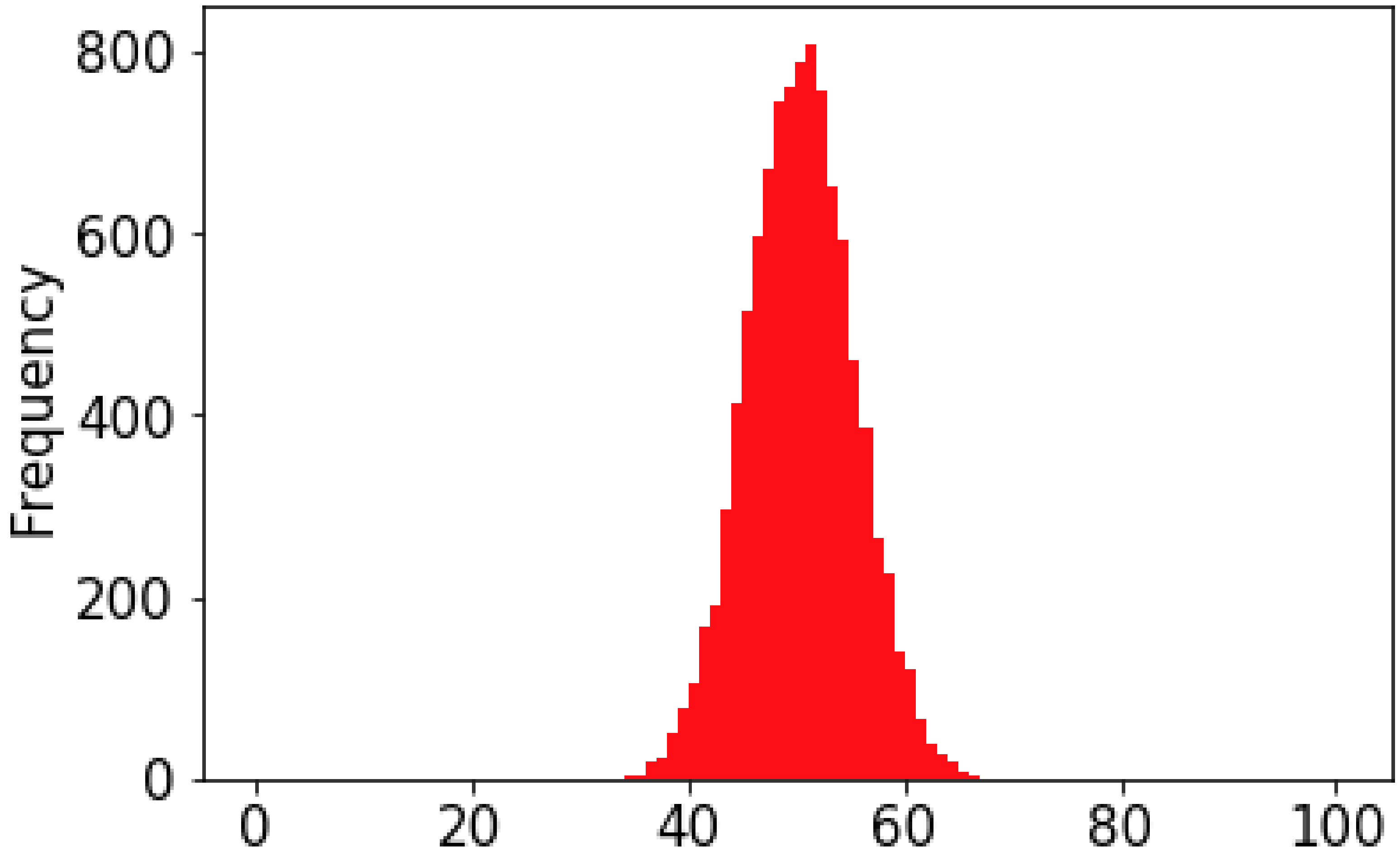
Demo: Visualize CoinSim Results



number of heads (out of 100)

this shape resembles what we often call a normal distribution or a "bell curve"

Demo: Visualize CoinSim Results

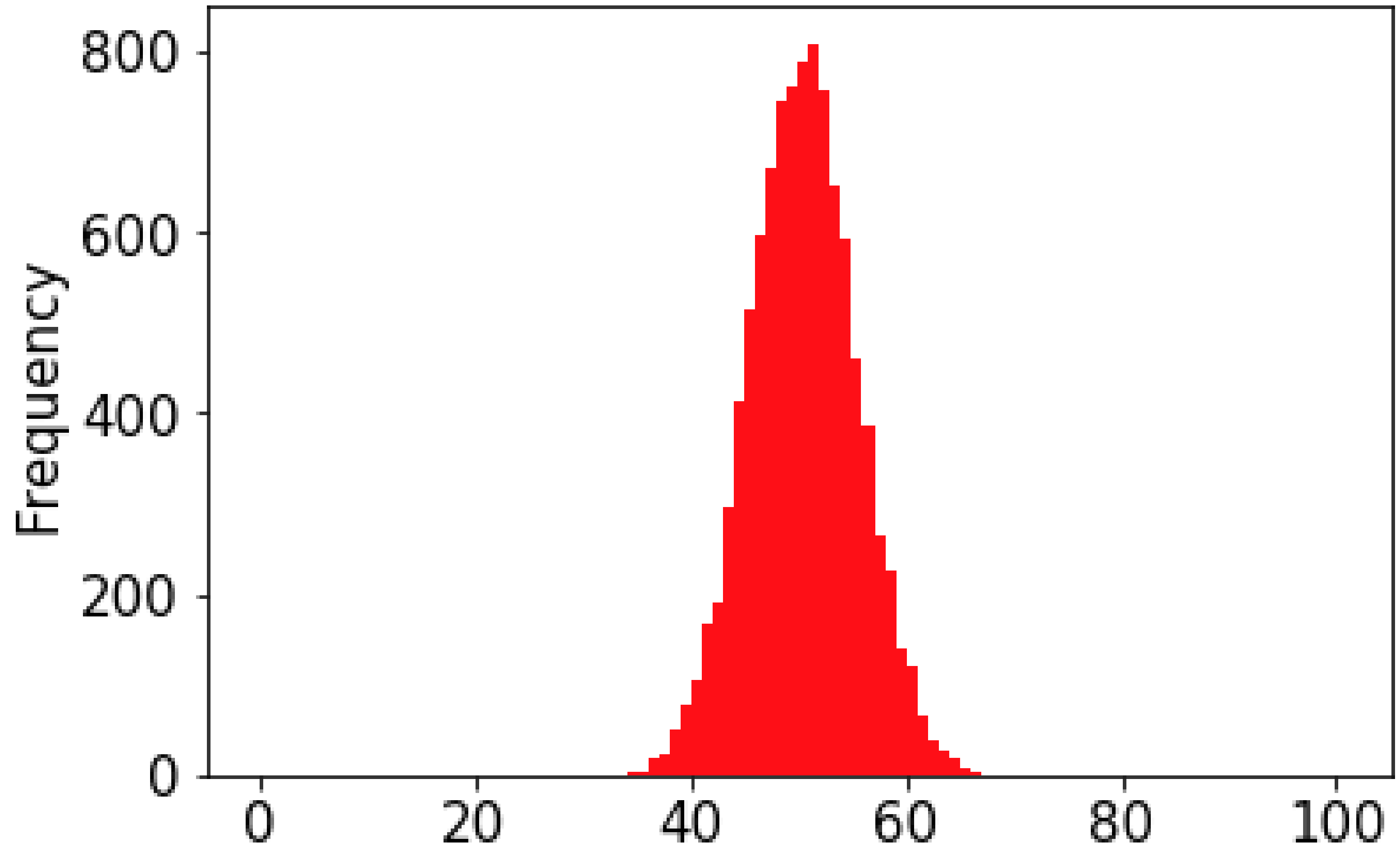


number of heads (out of 100)

this shape resembles what we often call a normal distribution or a "bell curve"

in general, if we take large samples enough times, the sample averages will look like this (we won't discuss exceptions here)

Demo: Visualize CoinSim Results



number of heads (out of 100)

numpy can directly generate random numbers fitting a normal distribution

this shape resembles what we often call a normal distribution or a "bell curve"

in general, if we take large samples enough times, the sample averages will look like this (we won't discuss exceptions here)

Outline

choice()

bugs and seeding

significance

histograms

normal()

normal

```
from numpy.random import choice, normal
import numpy as np

for i in range(10):
    print(normal())
```

normal

```
from numpy.random import choice, normal
import numpy as np

for i in range(10):
    print(normal())
```

Output:

```
-0.18638553993371157
0.02888452916769247
1.247456111372642
-0.5388224399358179
-0.4514332213638852
-1.400186111201824
0.2811937151186804
0.260886189855659
-0.1924628872895514
0.297957296171029
```

average is 0 (over many calls)

numbers closer to 0 more likely

-x just as likely as x

normal

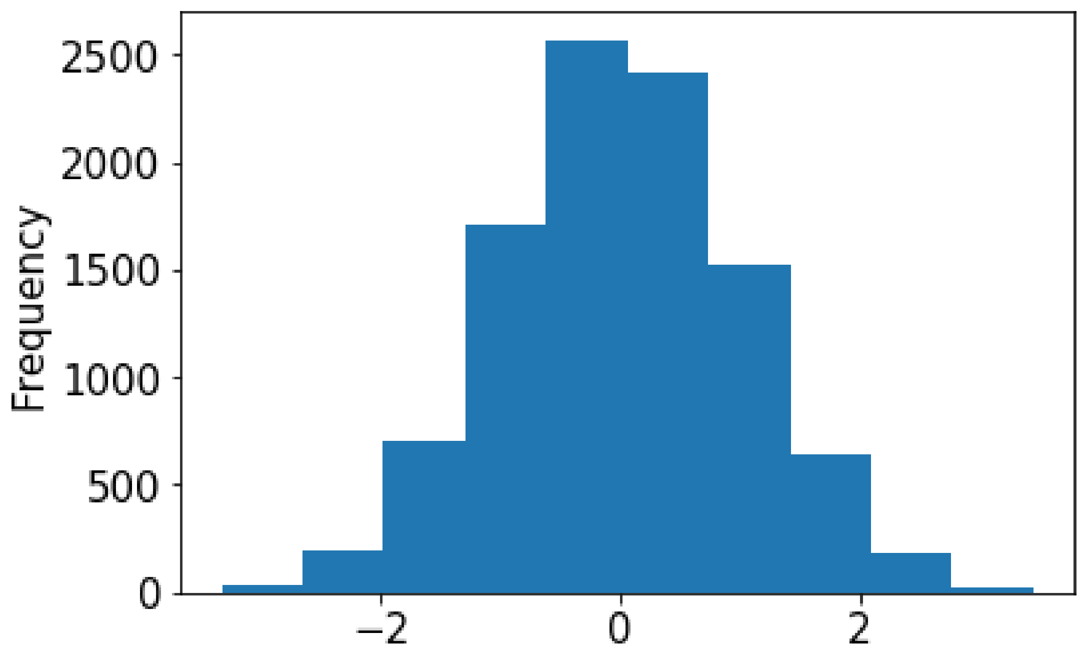
```
from numpy.random import choice, normal
import numpy as np

s = Series(normal(size=10000))
```

normal

```
from numpy.random import choice, normal
import numpy as np

s = Series(normal(size=10000))

s.plot.hist()
```

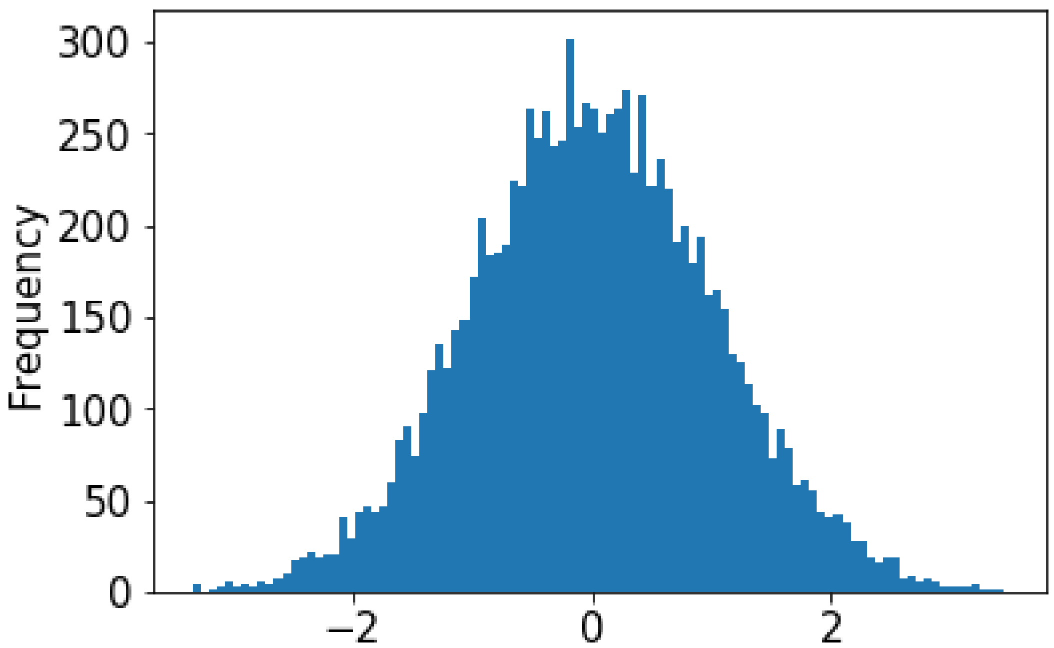
normal

```
from numpy.random import choice, normal
import numpy as np

s = Series(normal(size=10000))

s.plot.hist()
```



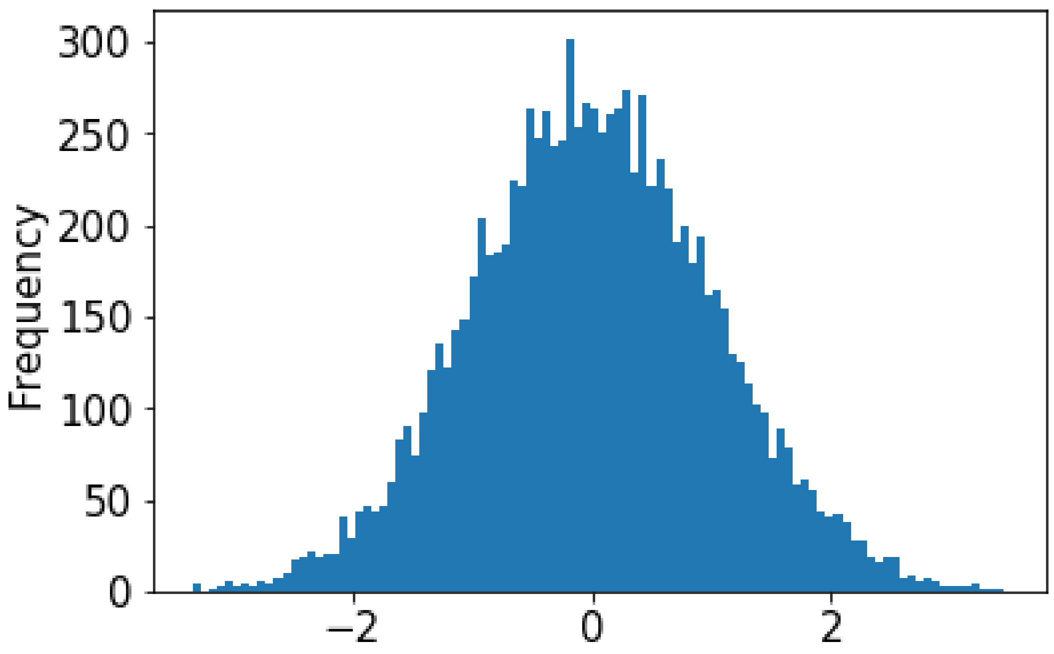
normal

```
from numpy.random import choice, normal
import numpy as np

s = Series(normal(size=10000))

s.plot.hist(bins=100)
```



normal

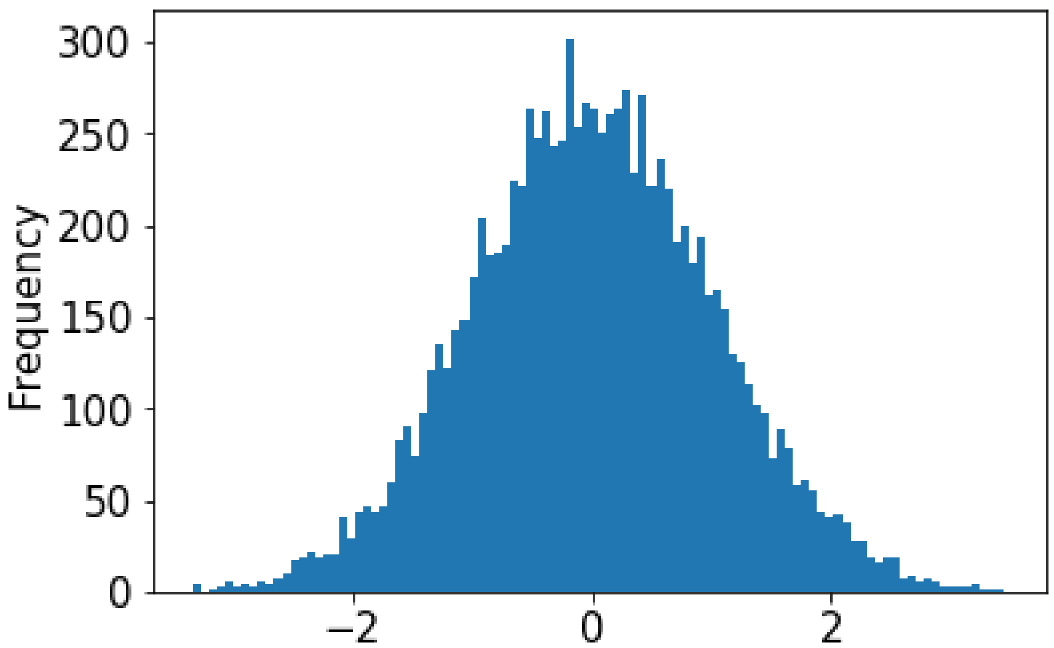
```
from numpy.random import choice, normal
import numpy as np

s = Series(normal(size=10000))

s.plot.hist(bins=100, loc=    , scale=    )
```



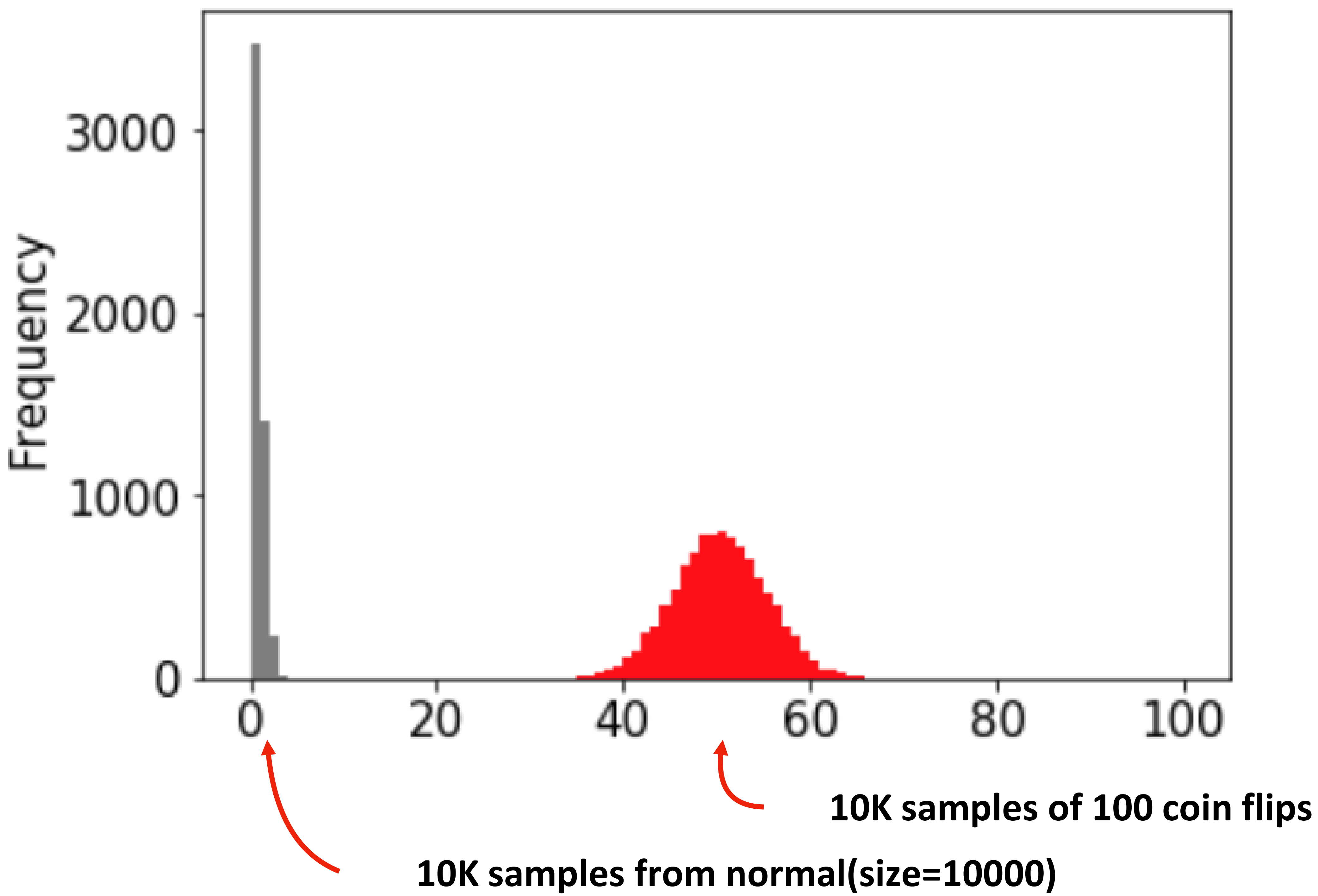
normal

```
from numpy.random import choice, normal
import numpy as np

s = Series(normal(size=10000))

s.plot.hist(bins=100, loc=    , scale=    )
```

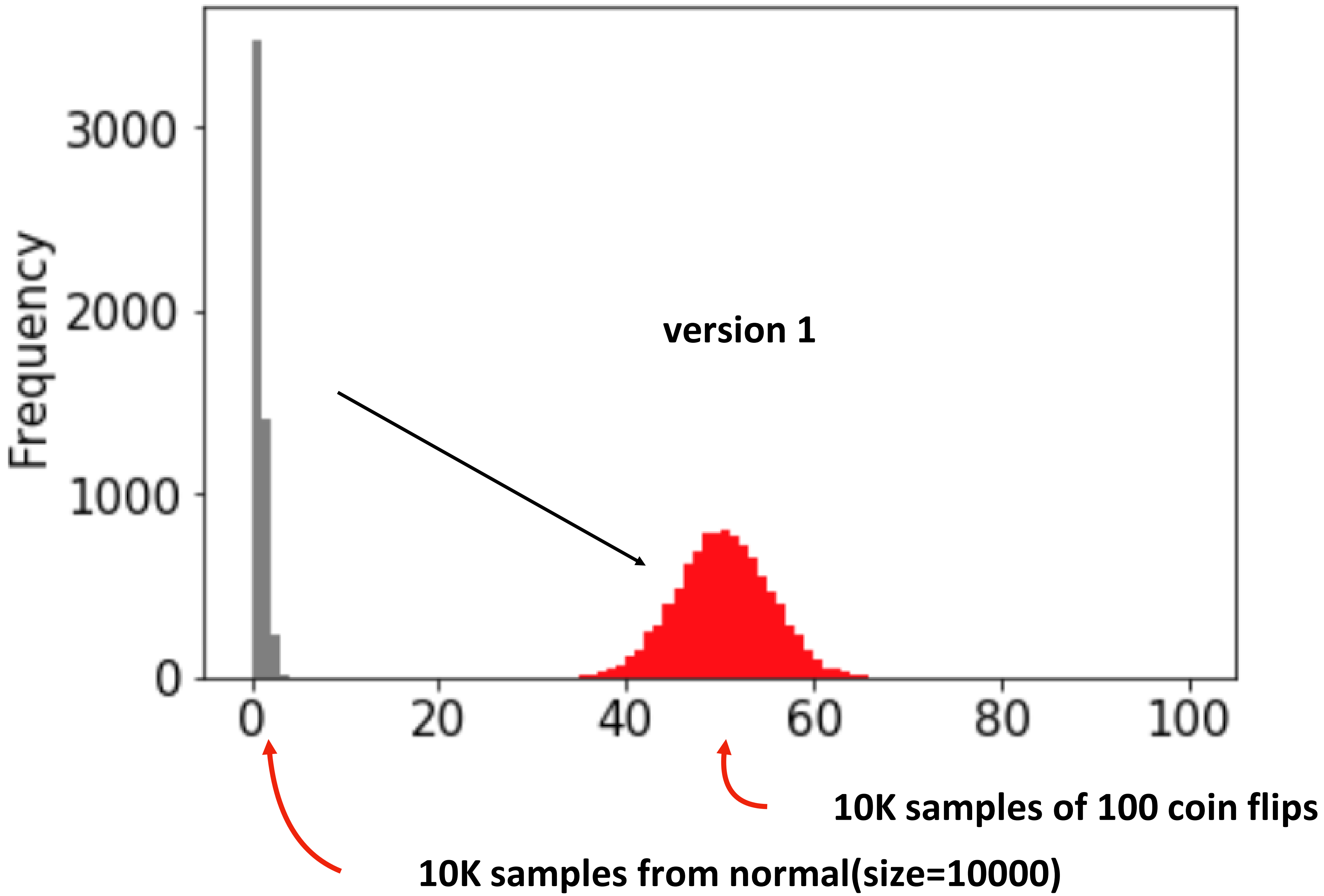
try plugging in different values
(defaults are 0 and 1, respectively)



Demo: plot overlay

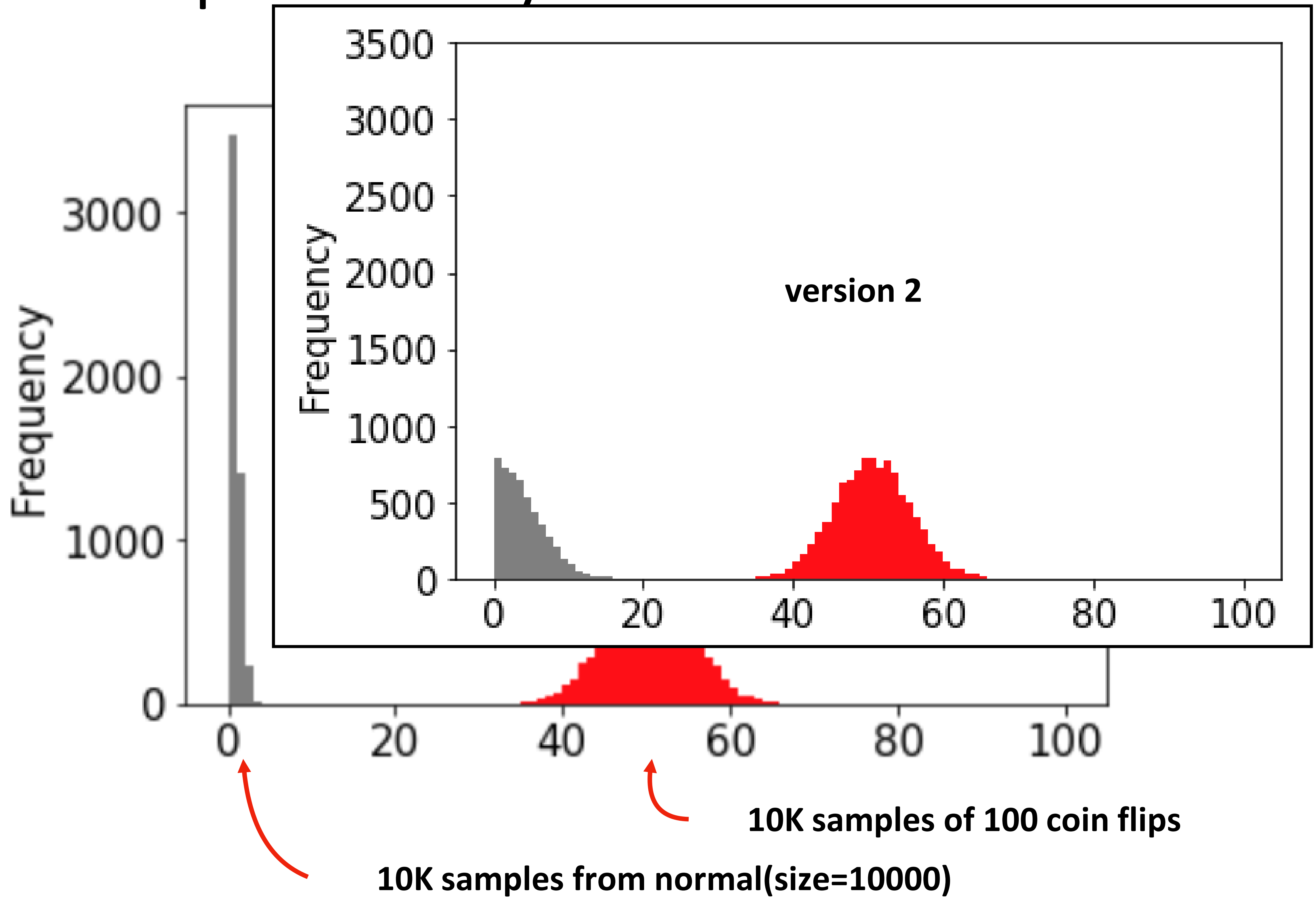


Demo: plot overlay



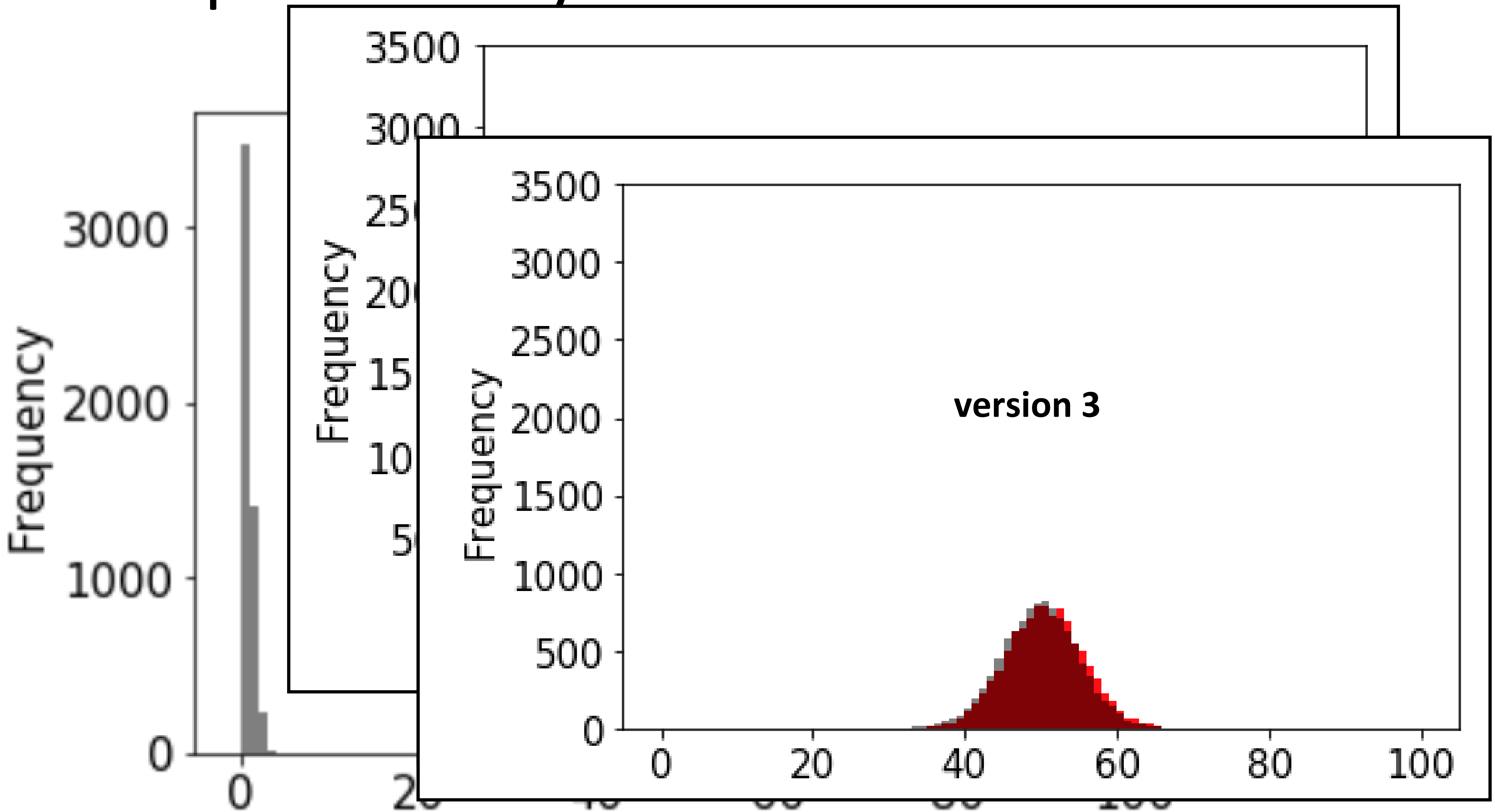
goal: play with `loc` and `scale` arguments to normal until gray overlaps red

Demo: plot overlay



goal: play with `loc` and `scale` arguments to normal until gray overlaps red

Demo: plot overlay



10K samples of 100 coin flips

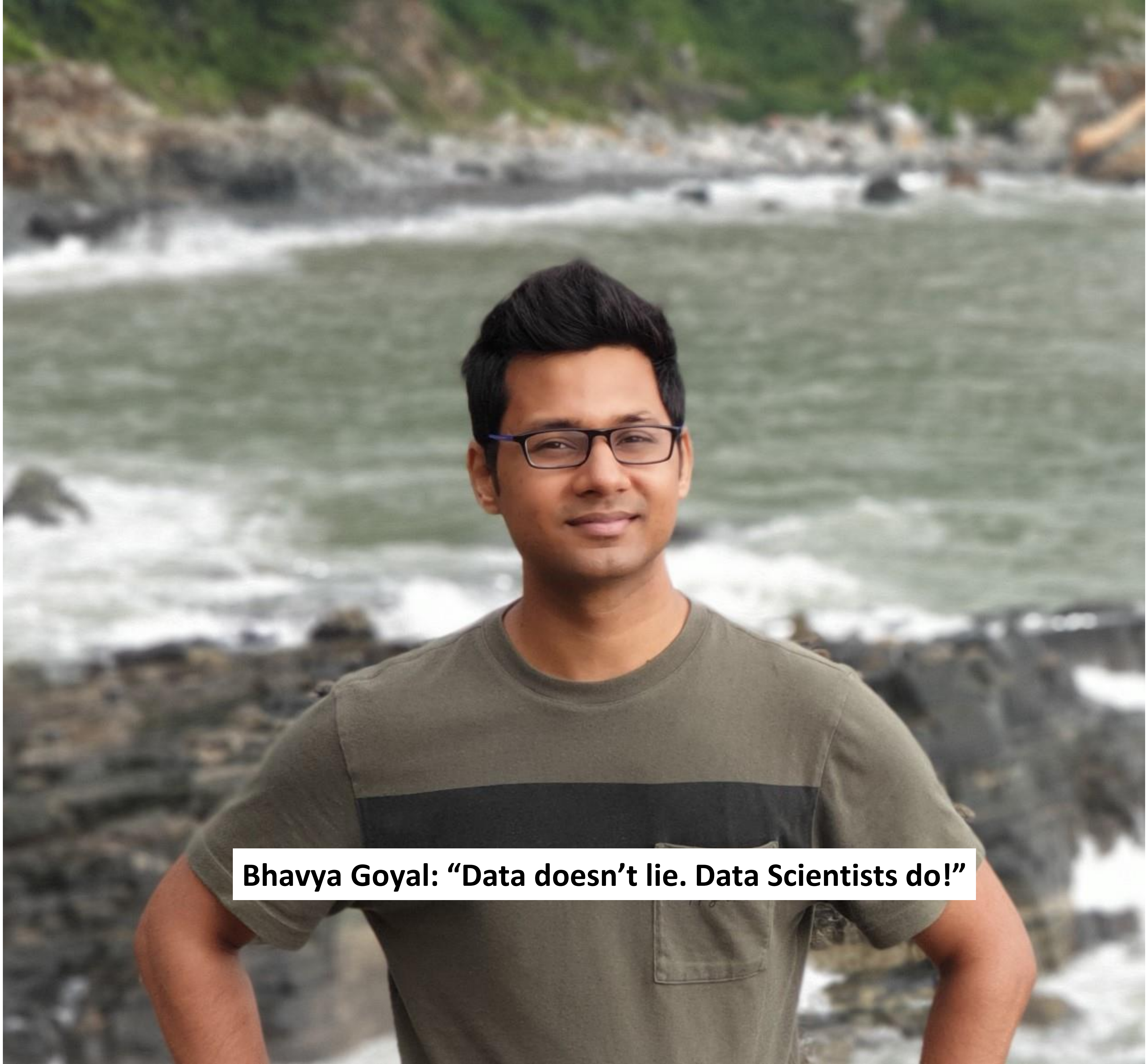
10K samples from normal(size=10000)

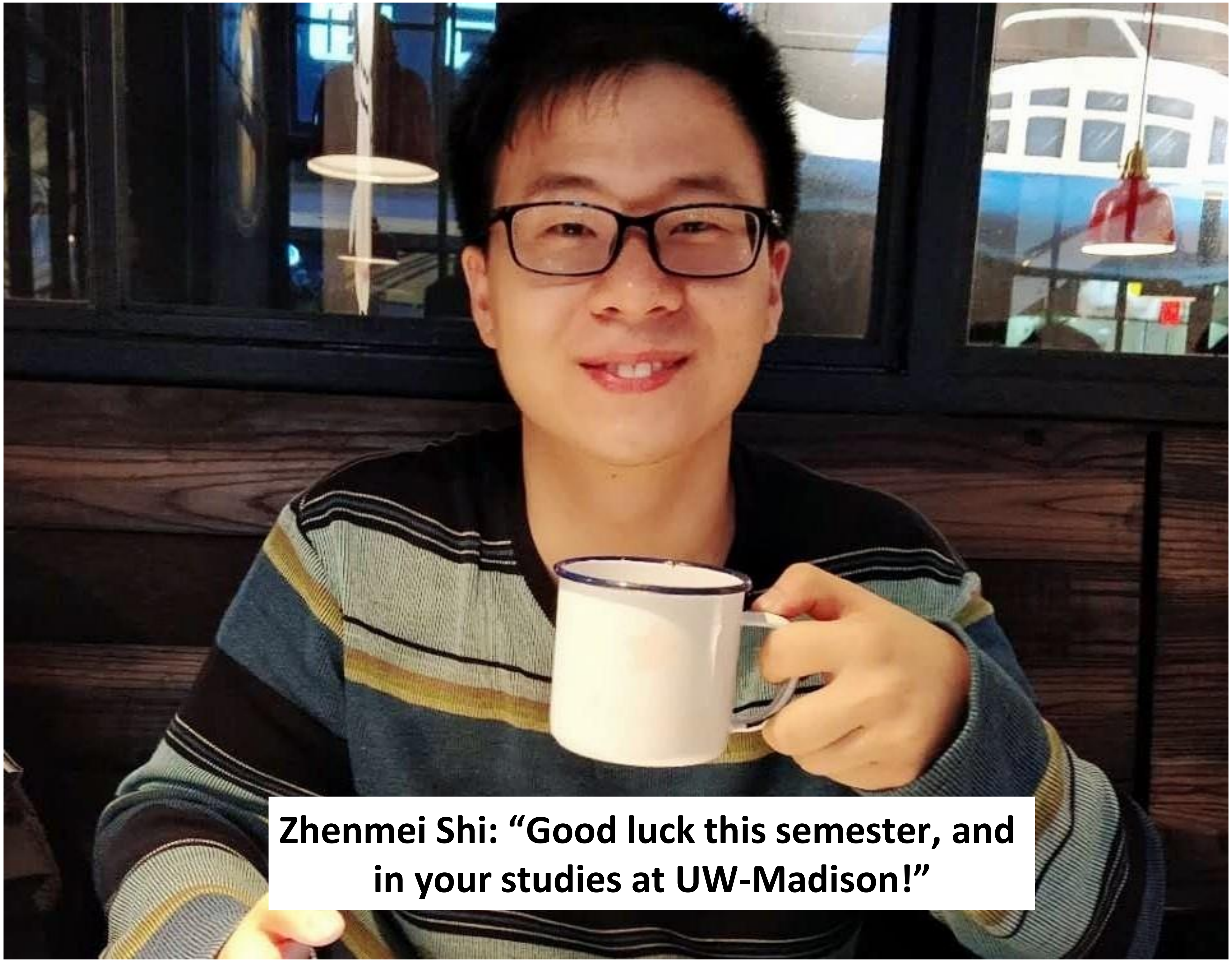
goal: play with `loc` and `scale` arguments to normal until gray overlaps red


EST. 2007

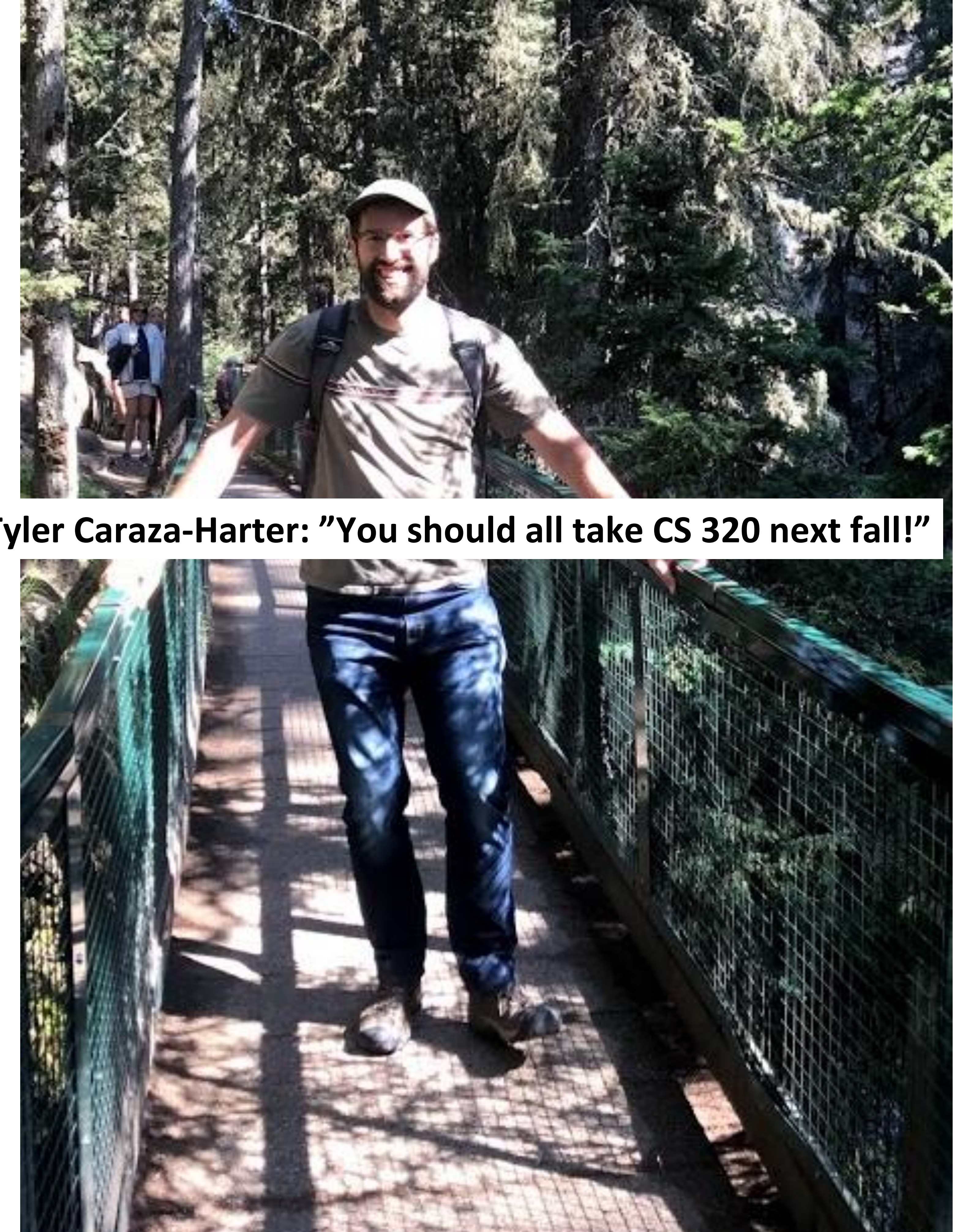
Yuchen Zeng: “Thank you so much for your hard work”


Sean Chung: “Thank you and stay safe”


Bhavya Goyal: “Data doesn’t lie. Data Scientists do!”


Zhenmei Shi: “Good luck this semester, and
in your studies at UW-Madison!”


Sourav Pal: “Good luck with data crunching! Go grab them all!”



Tyler Caraza-Harter: "You should all take CS 320 next fall!"