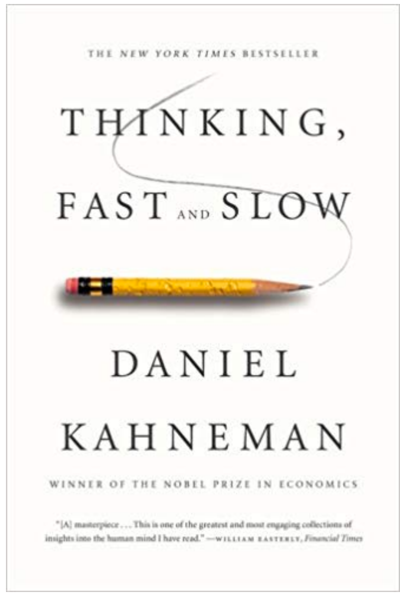
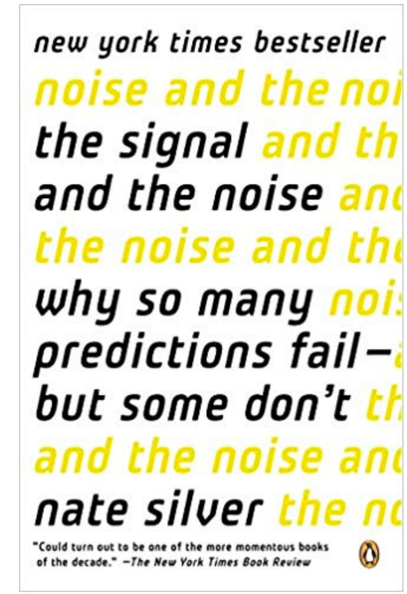
[301] Randomness

Tyler Caraza-Harter

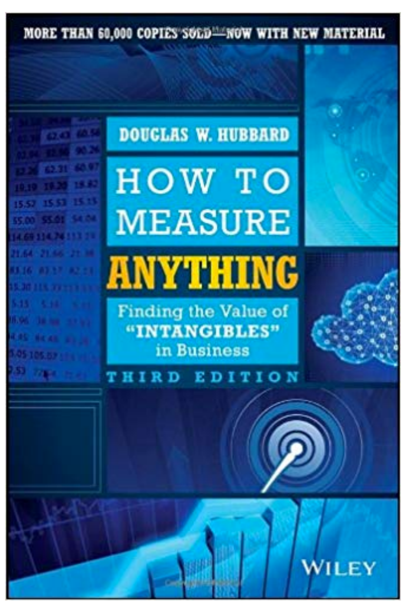
Announcement 1: Recommended popular stats books (for winter-break reading)



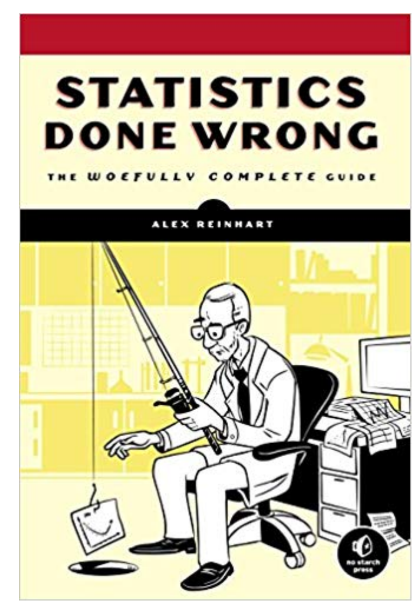
Thinking, Fast and Slow
by Daniel Kahneman



The Signal and the Noise
by Nate Silver



How to Measure Anything
by Douglas W. Hubbard



Statistics Done Wrong
by Alex Reinhart

Announcement 2: Course Evaluations

Section 1:

https://aefis.wisc.edu/index.cfm/page/AefisCourseSection.surveyResults?courseSectionid=580893

Section 2:

https://aefis.wisc.edu/index.cfm/page/AefisCourseSection.surveyResults?courseSectionid=580894

Evaluations are important generally, but especially this semester

- my first time teaching CS 301
- we made major changes to CS 301 this semester
- I promise to read every evaluation after the semester ends

Announcement 3: Final Exam Prep

Details: similar to midterms

- worth 20%
- 2 hours on Dec 19th at 7:45am (in the morning!)
- you can have a single page of notes (both sides), as usual
- we'll use any extra time this Wed to review
- cumulative, across whole semester
- topics **NOT** included on the exam: beautifulsoup, regression, randomness

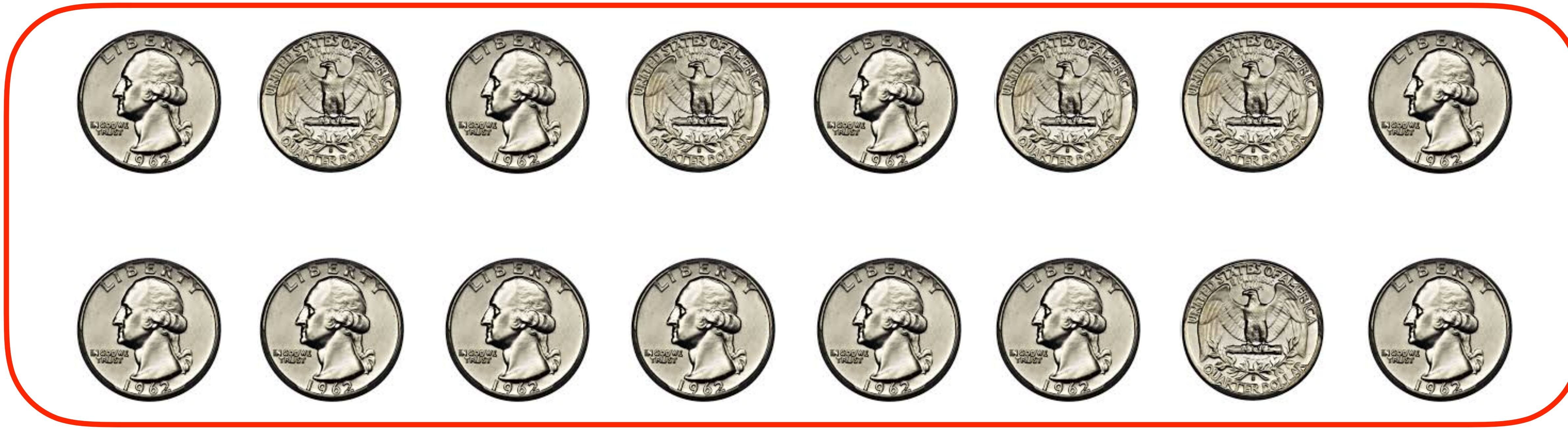
Recommended prep

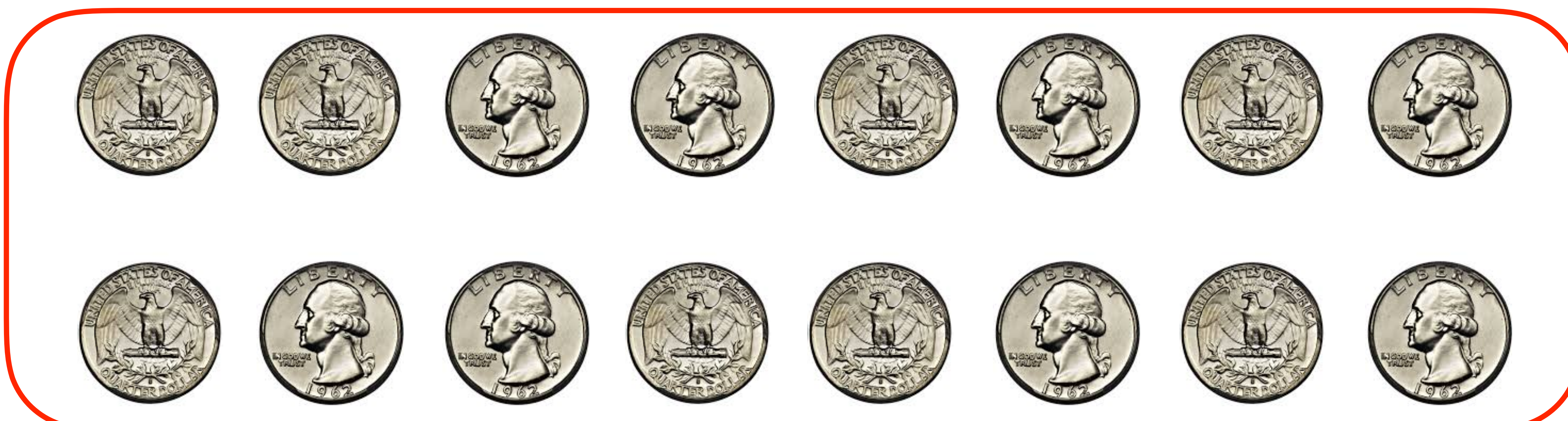
- make sure you understand all the worksheet problems
- review the readings, especially anything I took the time to write myself
- review everything you got wrong on the midterms
- review the slides
- review the code you wrote for the projects

Comments on old finals

- we'll post them, because people ask for them
- content has evolved a lot in the last 3rd of CS 301,
  so they're not great review material

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

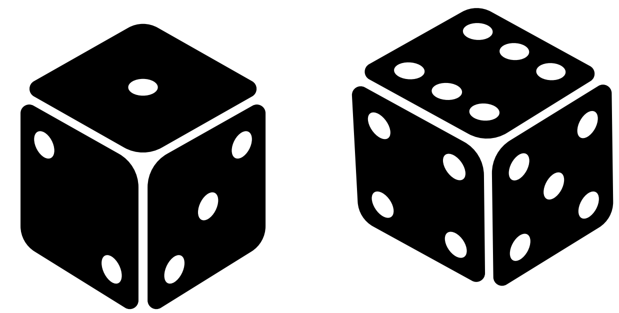




Why Randomize?

Why Randomize?

Games



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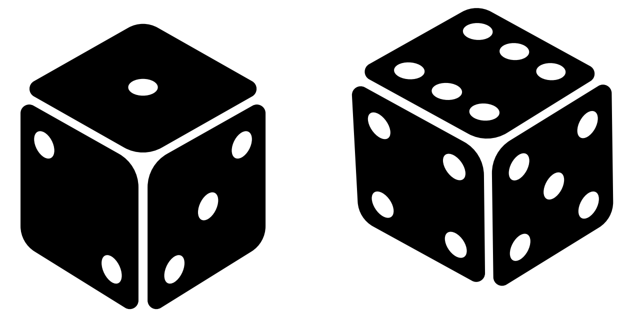
Games 

Security 

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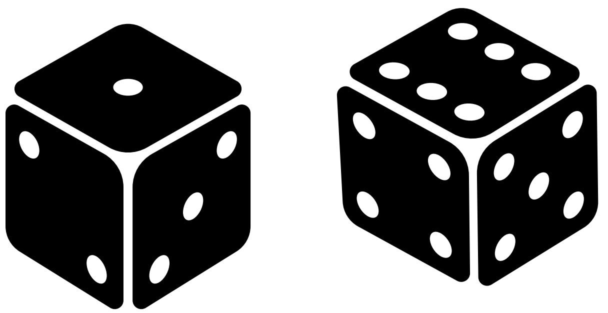
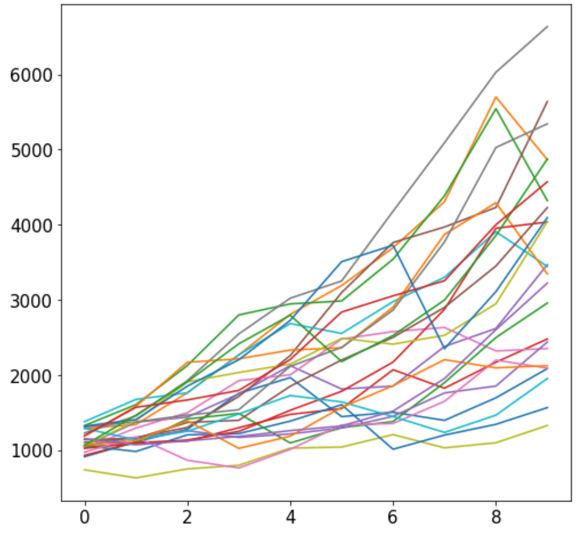


Security

Simulation



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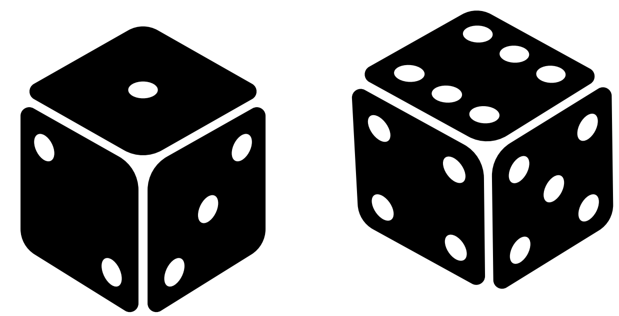

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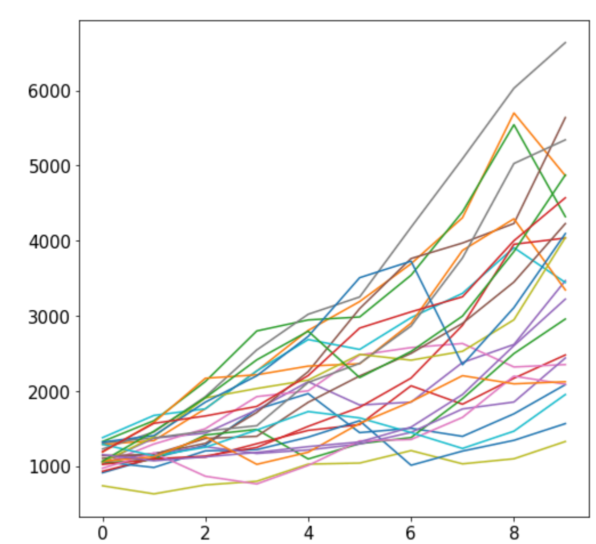

our focus

Outline

choice()

pseudorandom: debugging/seeding

visualization: bar plots vs. histograms

normal()

statistical significance: an intuitive approach

New Functions Today

Previous (from random module that comes w/ Python):

- **`choice, choices, randint`**

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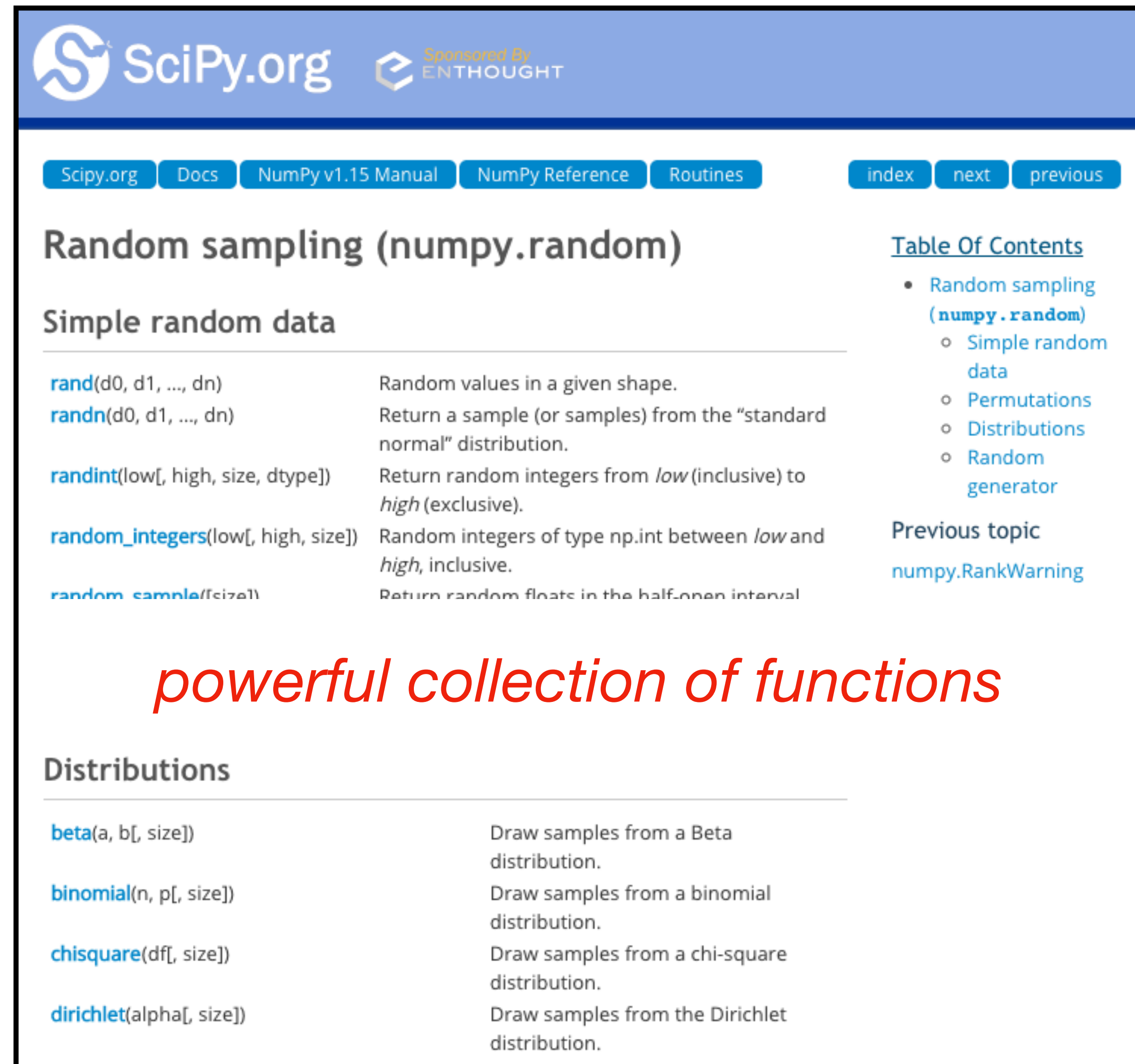
numpy.random:

- powerful collection of functions
- today: **`choice`**, **`normal`**



SciPy.org Sponsored By ENTHOUGHT

Scipy.org | Docs | NumPy v1.15 Manual | NumPy Reference | Routines | index | next | previous

Random sampling (numpy.random)

Simple random data

rand(d0, d1, ..., dn)	Random values in a given shape.
randn(d0, d1, ..., dn)	Return a sample (or samples) from the "standard normal" distribution.
randint(low[, high, size, dtype])	Return random integers from *low* (inclusive) to *high* (exclusive).
random_integers(low[, high, size])	Random integers of type np.int between *low* and *high*, inclusive.

Table Of Contents

- Random sampling (numpy.random)
  - Simple random data
  - Permutations
  - Distributions
  - Random generator

Previous topic

numpy.RankWarning

powerful collection of functions

Distributions

beta(a, b[, size])	Draw samples from a Beta distribution.
binomial(n, p[, size])	Draw samples from a binomial distribution.
chisquare(df[, size])	Draw samples from a chi-square distribution.
dirichlet(alpha[, size])	Draw samples from the Dirichlet distribution.

New Functions Today

Previous (from random module that comes w/ Python):

- **`choice, choices, randint`**

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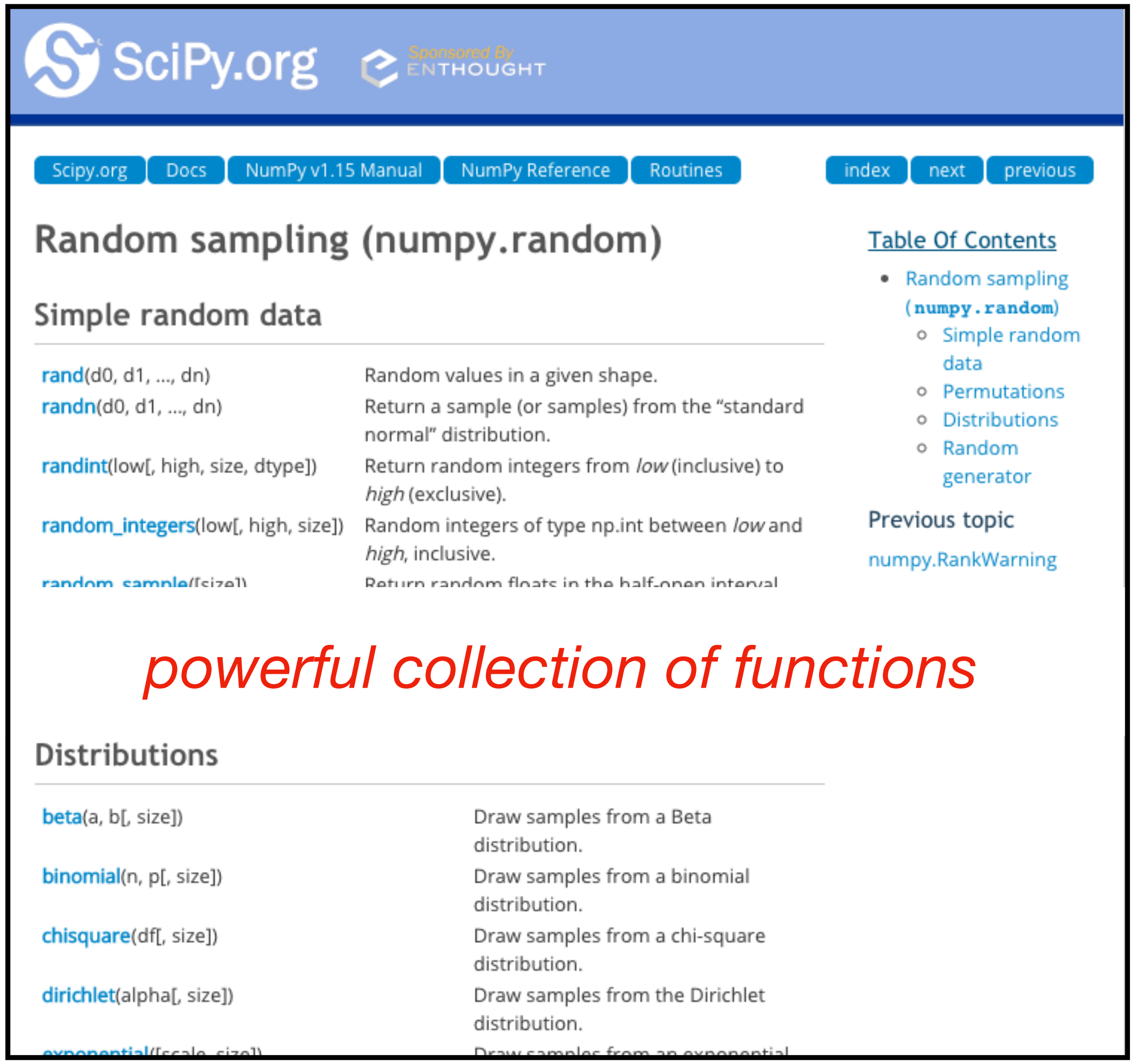
- today: **`choice`**, **`normal`**

`Series.line.hist`:

- similar to bar plot
- visualize spread of random results



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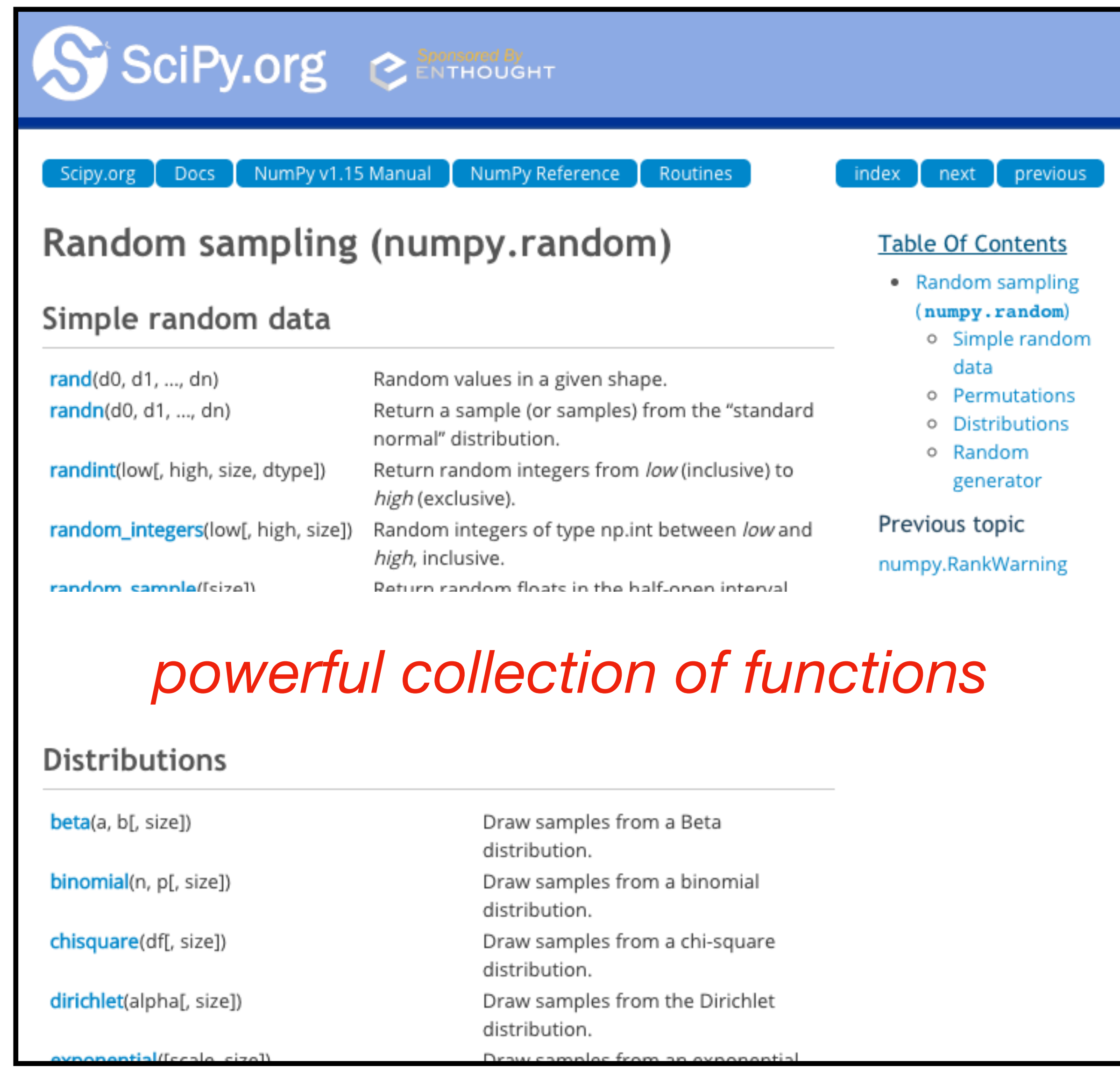

choice

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

choice

```
from numpy.random import choice, normal

result = choice(          )
```

list of things to
randomly choose from

choice

```
from numpy.random import choice, normal

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

list of things to randomly choose from

choice

```
from numpy.random import choice, normal

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

Output:

```
scissors
```

choice

```
from numpy.random import choice, normal

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

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

Output:

```
scissors
rock
```

choice

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from numpy.random import choice, normal

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, normal

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

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

choice

```
from numpy.random import choice, normal

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

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

choice

```
from numpy.random import choice, normal

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

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

choice

```
from numpy.random import choice, normal

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

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

1-dimensional ndarray with 5 items

choice

```
from numpy.random import choice, normal

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

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

1-dimensional ndarray with 5 items

```
choice(["rock", "paper", "scissors"], size=(3,2))
```

choice

```
from numpy.random import choice, normal

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

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

1-dimensional ndarray with 5 items

```
choice(["rock", "paper", "scissors"], size=(3,2))
```

numpy shape tuple

choice

```
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choice(["rock", "paper", "scissors"], size=5)
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array(['rock', 'scissors', 'paper', 'rock', 'paper'], dtype='<U8')
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array([['rock', 'scissors'],
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```

choice

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from numpy.random import choice, normal

choice(["rock", "paper", "scissors"], size=5)
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array(['rock', 'scissors', 'paper', 'rock', 'paper'], dtype='<U8')
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```
array([['rock', 'scissors'],
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```

???-dimensional ndarray with **???** items

choice

```
from numpy.random import choice, normal

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

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

1-dimensional ndarray with 5 items

```
choice(["rock", "paper", "scissors"], size=(3,2))
```

```
array([['rock', 'scissors'],
       ['paper', 'rock'],
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```

2-dimensional ndarray with 6 items

Random values and Pandas

```
from numpy.random import choice, normal

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

Random values and Pandas

```
from numpy.random import choice, normal

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

Random values and Pandas

```
from numpy.random import choice, normal

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

Random values and Pandas

```
from numpy.random import choice, normal

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

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

Random values and Pandas

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from numpy.random import choice, normal

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

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

```
# random DataFrame
DataFrame(choice(["rock", "paper", "scissors"], size=(5,3)))
```

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

Demo 1: exploring bias

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

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

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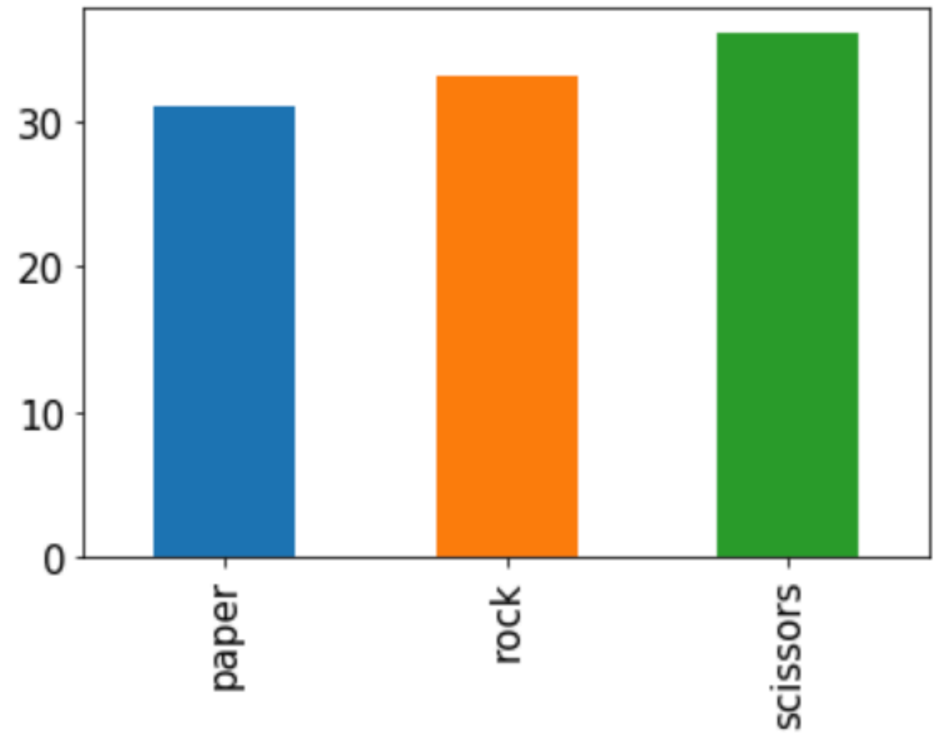

Demo 1: exploring bias

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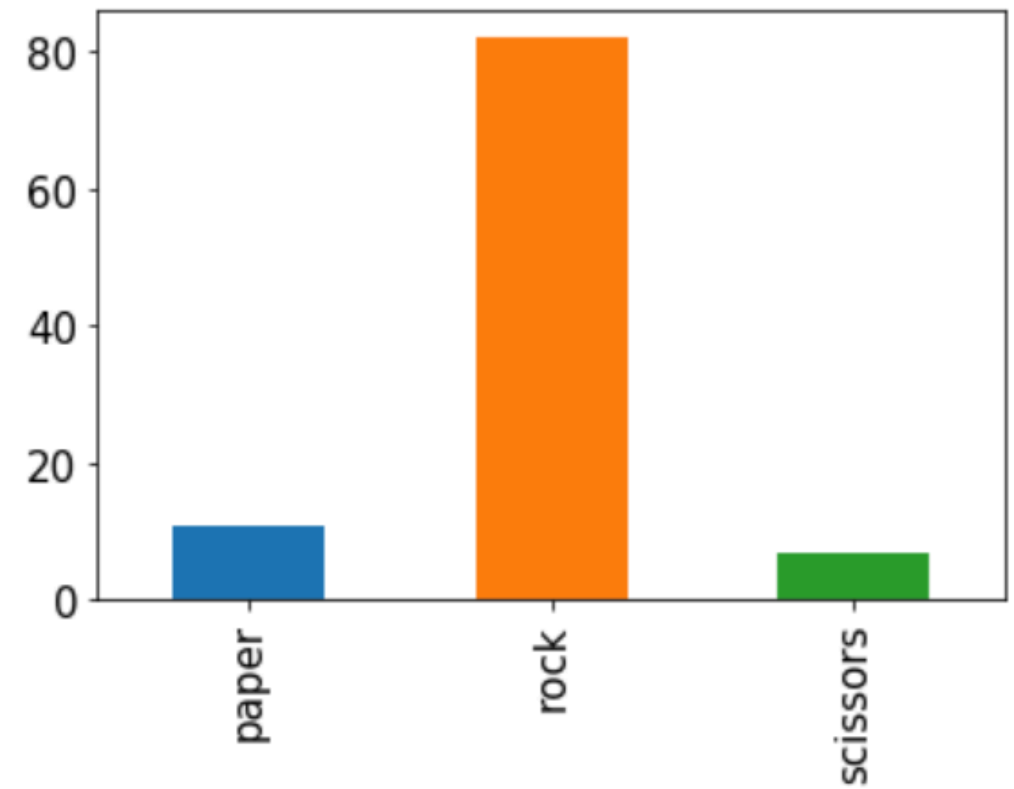
Question 1: how can we make sure the randomization isn't biased?

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



Random Strings vs. Random Ints

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same

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

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

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

Outline

choice()

pseudorandom: debugging/seeding

visualization: bar plots vs. histograms

normal()

statistical significance: an intuitive approach

Example: change over time

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

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

Example: change over time

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```
s.plot.line()
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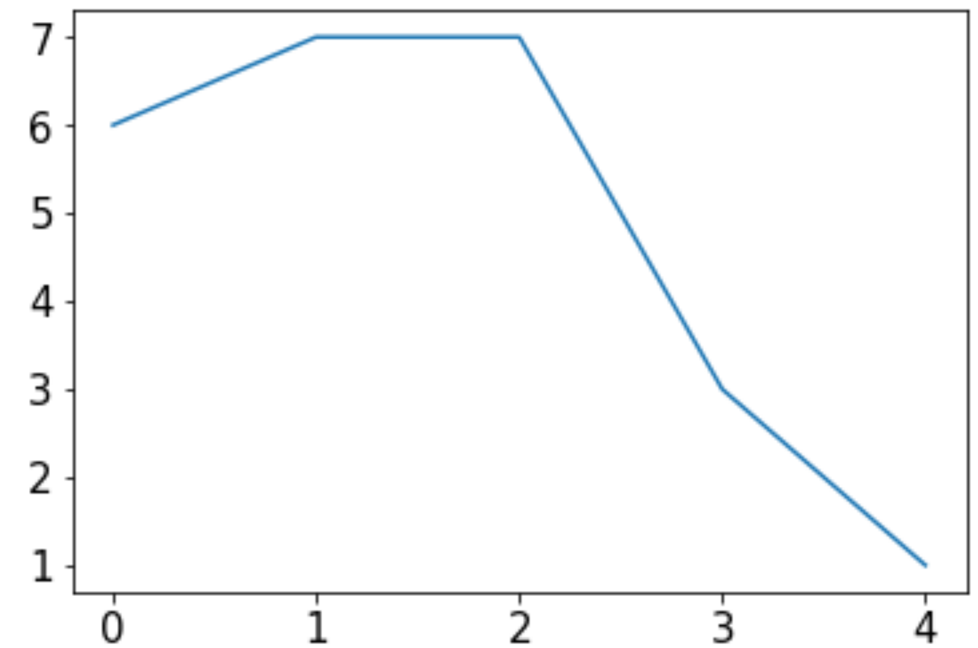

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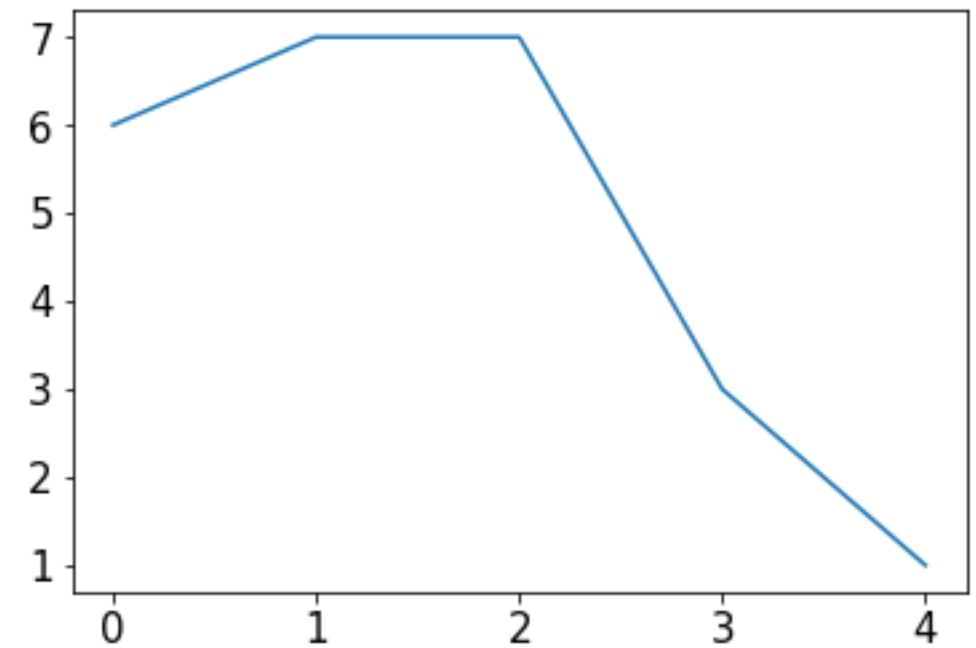


```
percents = []
for i in range(1, len(s)):
    diff = 100 * (s[i] / s[i-1] - 1)
    percents.append(diff)
```

what are we computing for diff?

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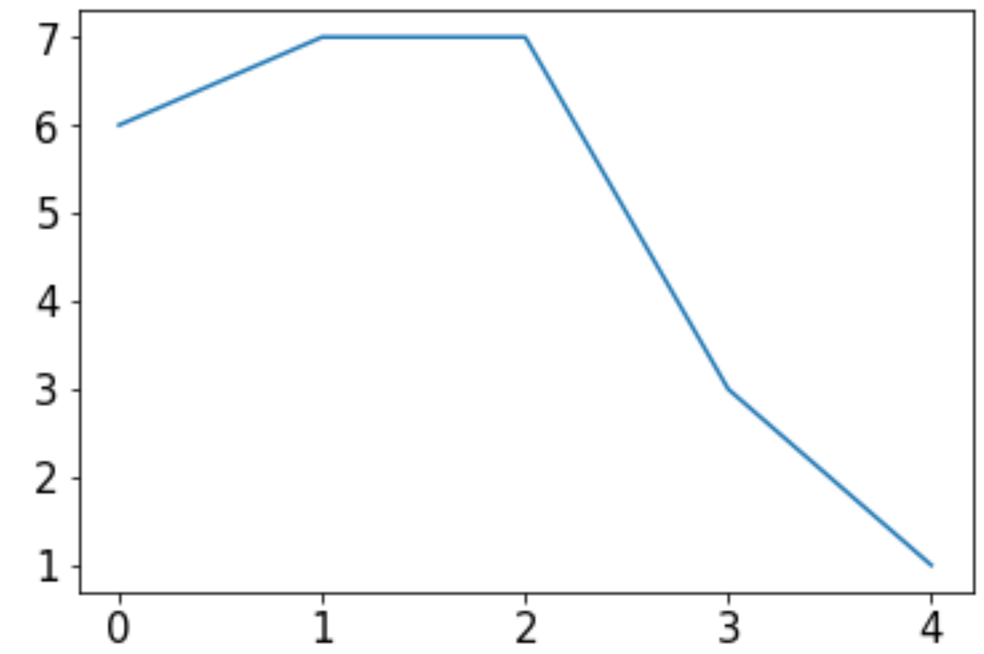


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Series(percents).plot.line()
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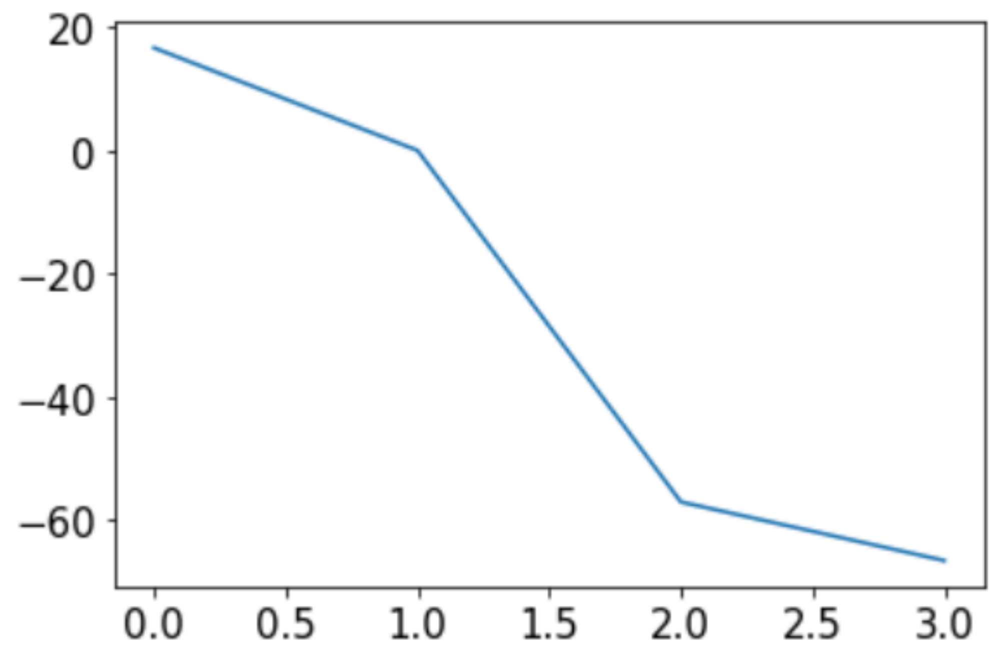

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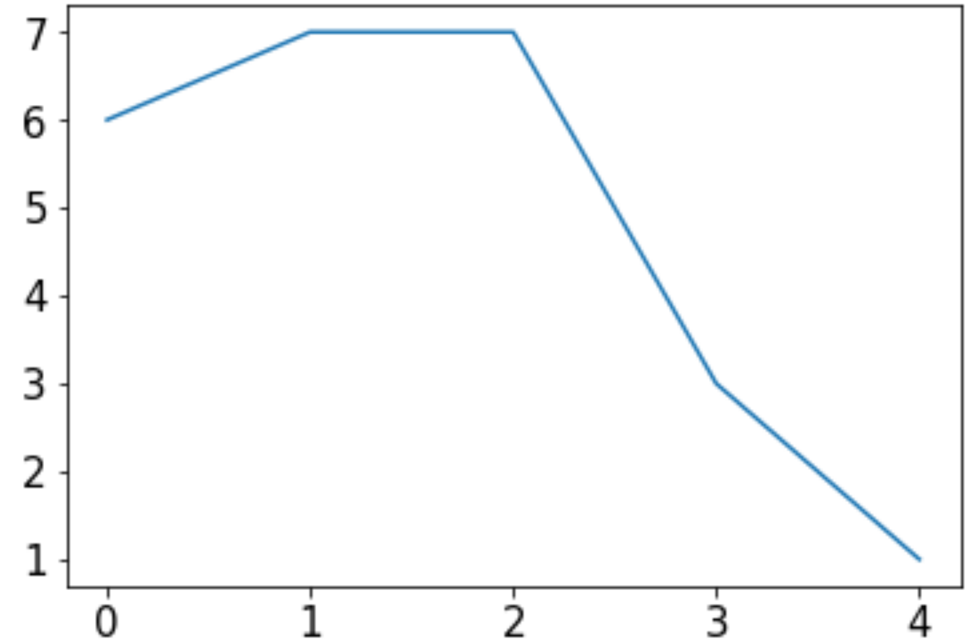


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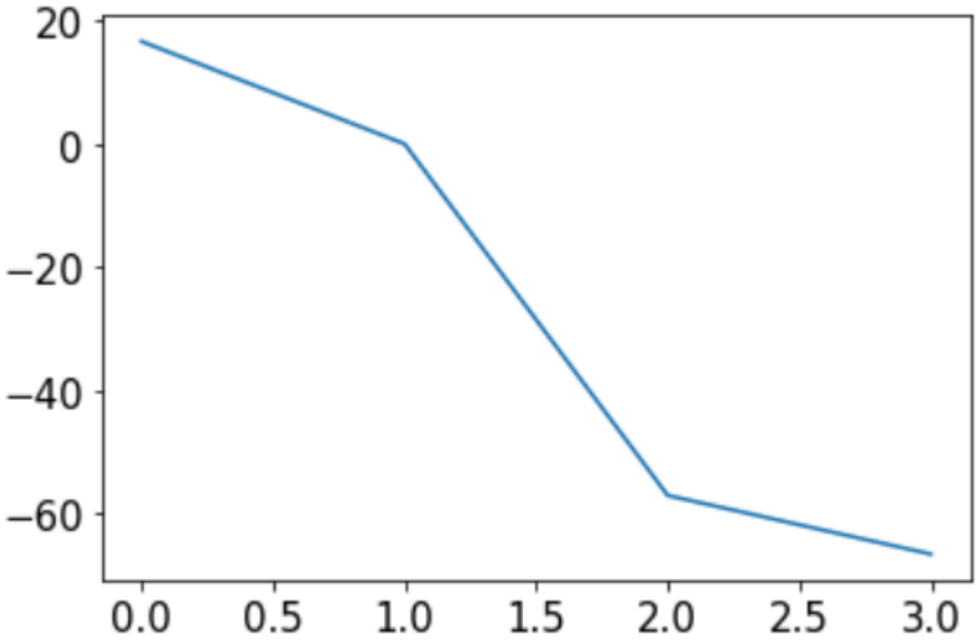

can you identify the bug in the code?

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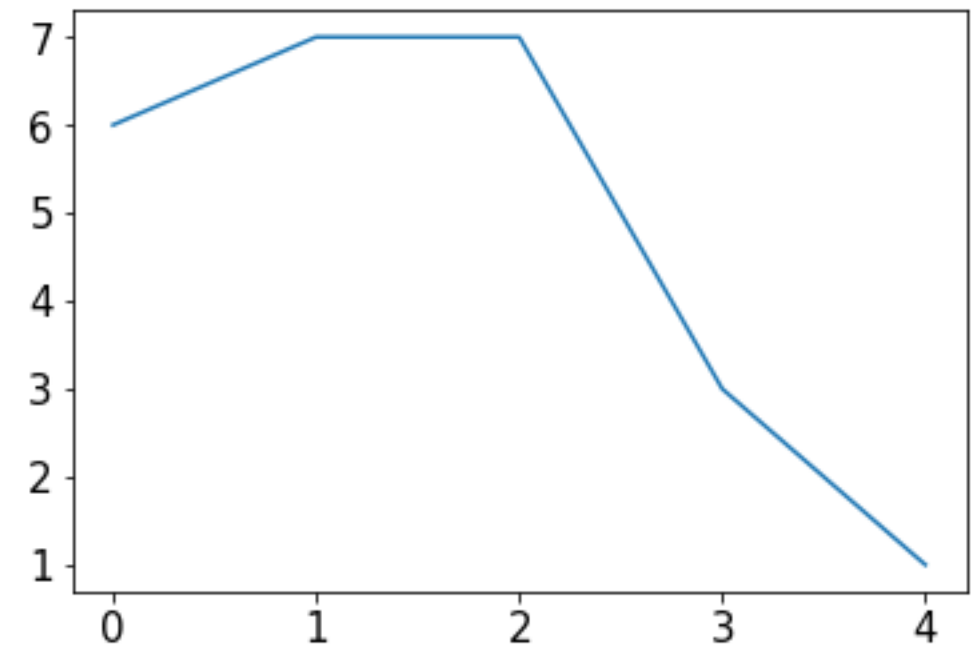


```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:14:
RuntimeWarning: divide by zero encountered in long_scalars
```

```
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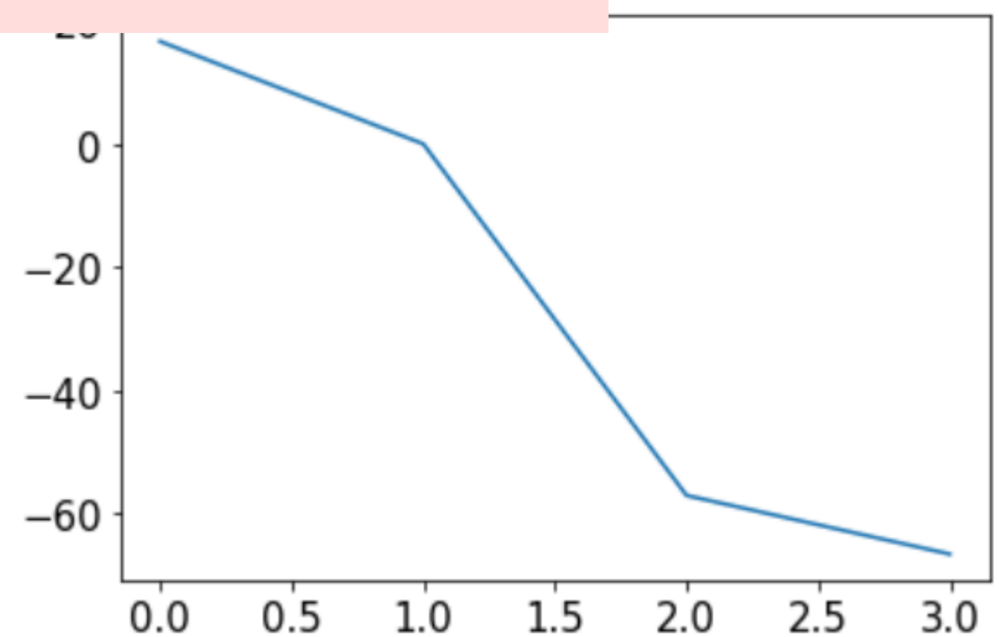
```



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Reproducibility

some bugs are easier to debug than others

- syntax or runtime errors easier than semantic bugs
- small inputs are easier than big inputs

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non-reproducible bugs

- are **hard to fix**
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fortunately, the random values we've been generating are not really, truly random. They're merely ***pseudorandom***.

Pseudorandom

pseudorandom generators

- can generate **billions** of different seemingly random sequences
- subsequent calls to choice progress along a sequence
- every program run starts with a different sequence
- we can choose our sequence

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Pseudorandom

```
684, 559, 629, 192, 835, ...
37, 235, 908, 72, 767, ...
168, 527, 493, 584, 534, ...
874, 664, 249, 643, 952, ...
122, 174, 439, 709, 897, ...
867, 206, 701, 998, 118, ...
906, 713, 227, 980, 618, ...
```

... billions more ...

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... billions more ...

restart!

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874, 664, 249, 643, 952, ...
122, 174, 439, 709, 897, ...
867, 206, 701, 998, 118, ...
906, 713, 227, 980, 618, ...
```

... billions more ...

pseudorandom generators

- can generate **billions** of different seemingly random sequences
- subsequent calls to choice progress along a sequence
- every program run starts with a different sequence
- we can choose our sequence

Pseudorandom

```
684, 559, 629, 192, 835, ...
37, 235, 908, 72, 767, ...
168, 527, 493, 584, 534, ...
874, 664, 249, 643, 952, ...
122, 174, 439, 709, 897, ...
867, 206, 701, 998, 118, ...
906, 713, 227, 980, 618, ...
```

... billions more ...

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```
684, 559, 629, 192, 835, ...
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168, 527, 493, 584, 534, ...
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... billions more ...

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684, 559, 629, 192, 835, ...
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168, 527, 493, 584, 534, ...
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... billions more ...

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Pseudorandom

```
684, 559, 629, 192, 835, ...
37, 235, 908, 72, 767, ...
168, 527, 493, 584, 534, ...
874, 664, 249, 643, 952, ...
122, 174, 439, 709, 897, ...
867, 206, 701, 998, 118, ...
906, 713, 227, 980, 618, ...
```

... billions more ...

pseudorandom generators

- can generate **billions** of different seemingly random sequences
- subsequent calls to choice progress along a sequence
- every program run starts with a different sequence
- we can choose our sequence

Pseudorandom

```
0: 684, 559, 629, 192, 835, ...
1: 37, 235, 908, 72, 767, ...
2: 168, 527, 493, 584, 534, ...
3: 874, 664, 249, 643, 952, ...
4: 122, 174, 439, 709, 897, ...
5: 867, 206, 701, 998, 118, ...
6: 906, 713, 227, 980, 618, ...
```

... billions more ...

seed

pseudorandom generators

- can generate **billions** of different seemingly random sequences
- subsequent calls to choice progress along a sequence
- every program run starts with a different sequence
- we can choose our sequence

Seeding

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

np.random.seed(1)
choice(10, size=5)
```

```
array([5, 8, 9, 5, 0])
```

Seeding

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

```
np.random.seed(1)
choice(10, size=5)
```

➡ `array([5, 8, 9, 5, 0])`

```
np.random.seed(2)
choice(10, size=5)
```

➡ `array([8, 8, 6, 2, 8])`

Seeding

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

```
np.random.seed(1)
choice(10, size=5)
```

```
array([5, 8, 9, 5, 0])
```

```
np.random.seed(2)
choice(10, size=5)
```

```
array([8, 8, 6, 2, 8])
```

```
np.random.seed(1)
choice(10, size=5)
```

```
array([5, 8, 9, 5, 0])
```

Seeding

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

```
np.random.seed(1)
choice(10, size=5)
```

```
array([5, 8, 9, 5, 0])
```

```
np.random.seed(2)
choice(10, size=5)
```

```
array([8, 8, 6, 2, 8])
```

```
np.random.seed(1)
choice(10, size=5)
```

```
array([5, 8, 9, 5, 0])
```

Seeding

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

```
np.random.seed(1)
choice(10, size=5)
```
→ `array([5, 8, 9, 5, 0])`

```
np.random.seed(2)
choice(10, size=5)
```
→ `array([8, 8, 6, 2, 8])`

```
np.random.seed(1)
choice(10, size=5)
```
→ `array([5, 8, 9, 5, 0])`

Debug tip: if you have a bug related to randomness, find a seed that causes the bug to arise, then use that seed until you find the problem. (don't forget to remove it when you're done!)

Outline

choice()

pseudorandom: debugging/seeding

visualization: bar plots vs. histograms

normal()

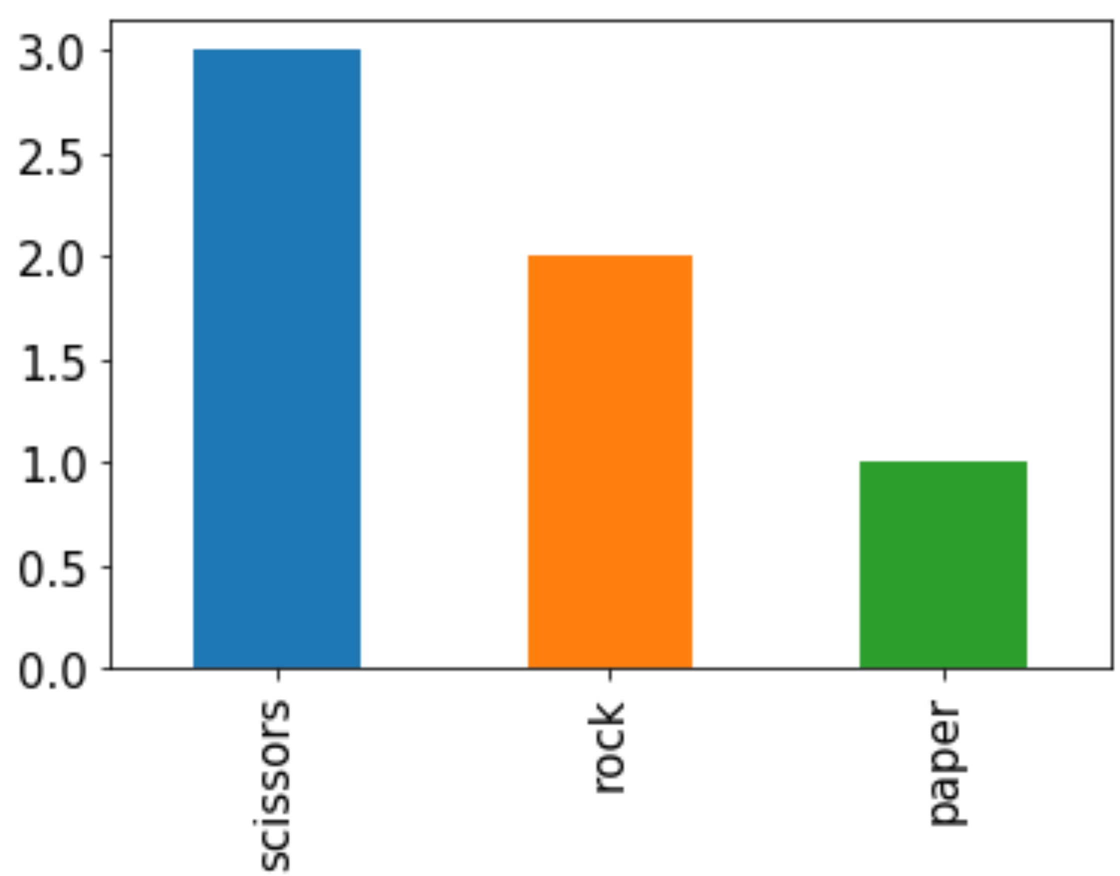
statistical significance: an intuitive approach

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()
```

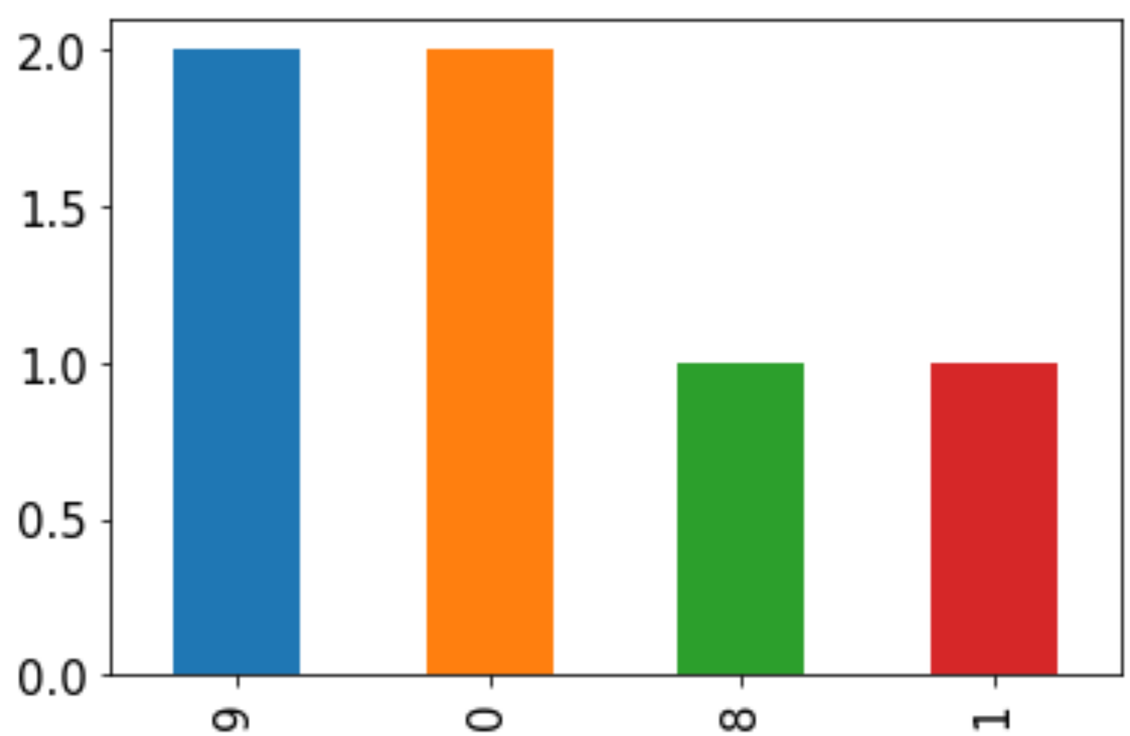


Frequencies across numbers

bars are a bad way to view frequencies across numbers

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

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



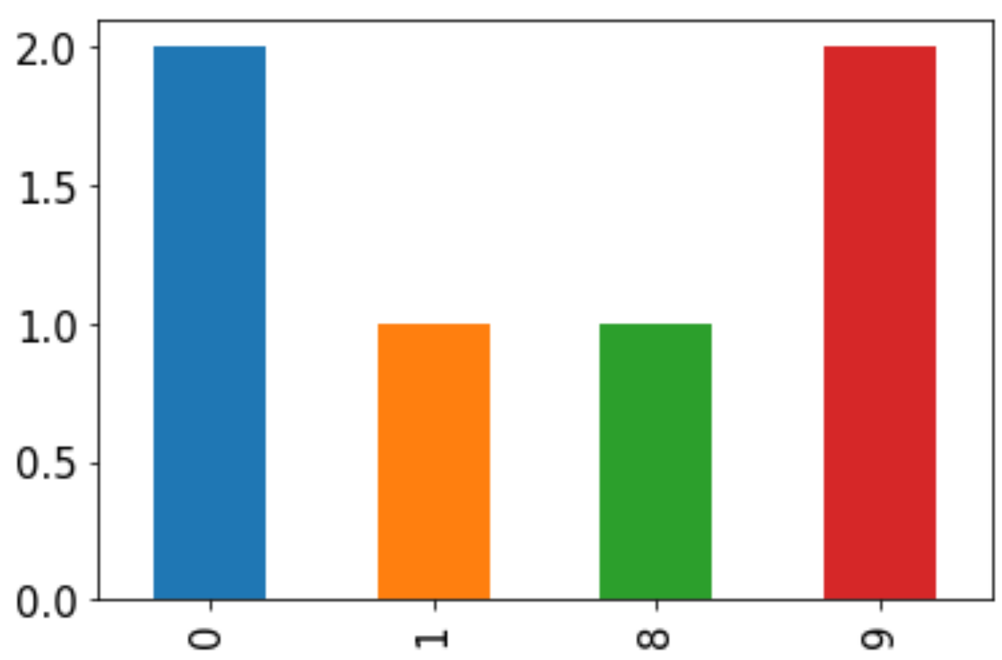
numbers not ordered

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()
```



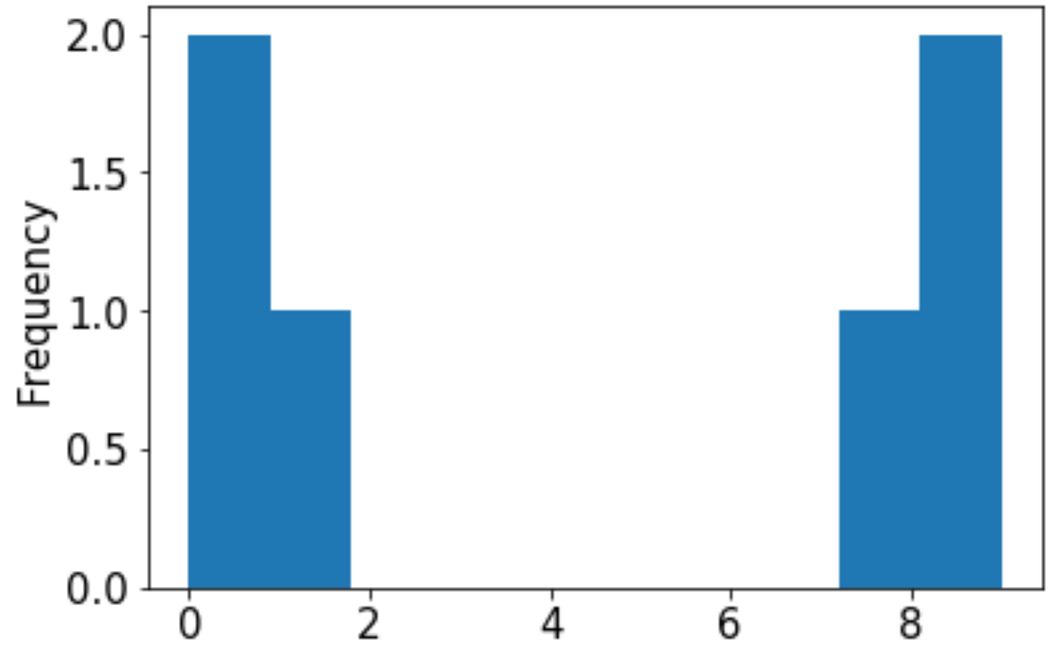
gap between 1 and 8 not obvious

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()
```

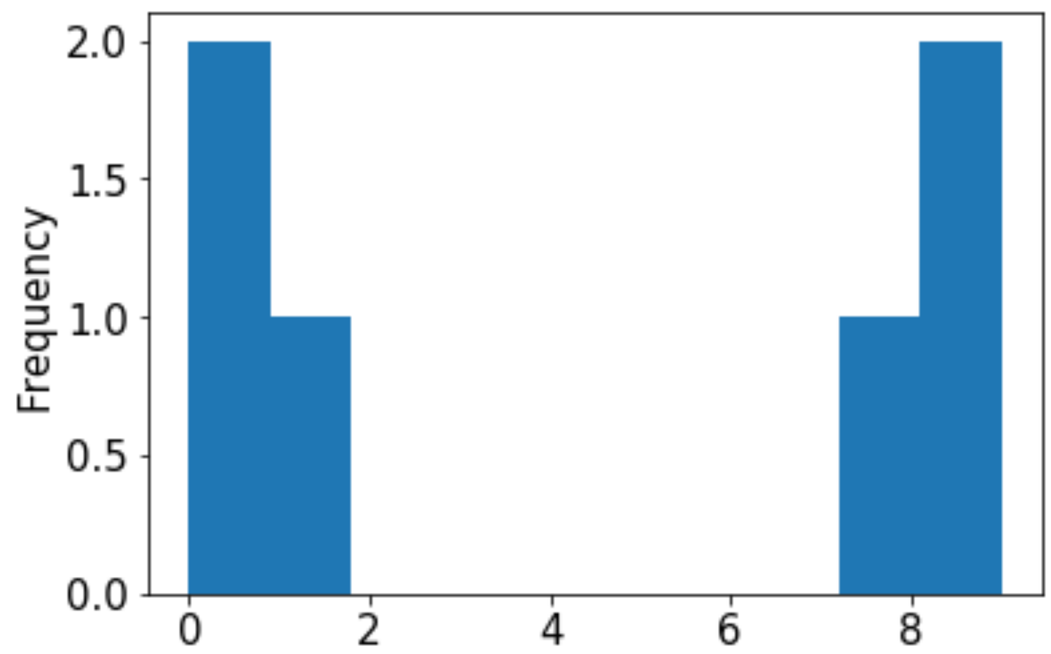


Frequencies across numbers

histograms are a good way to view frequencies across numbers

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

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



this kind of plot is called a histogram

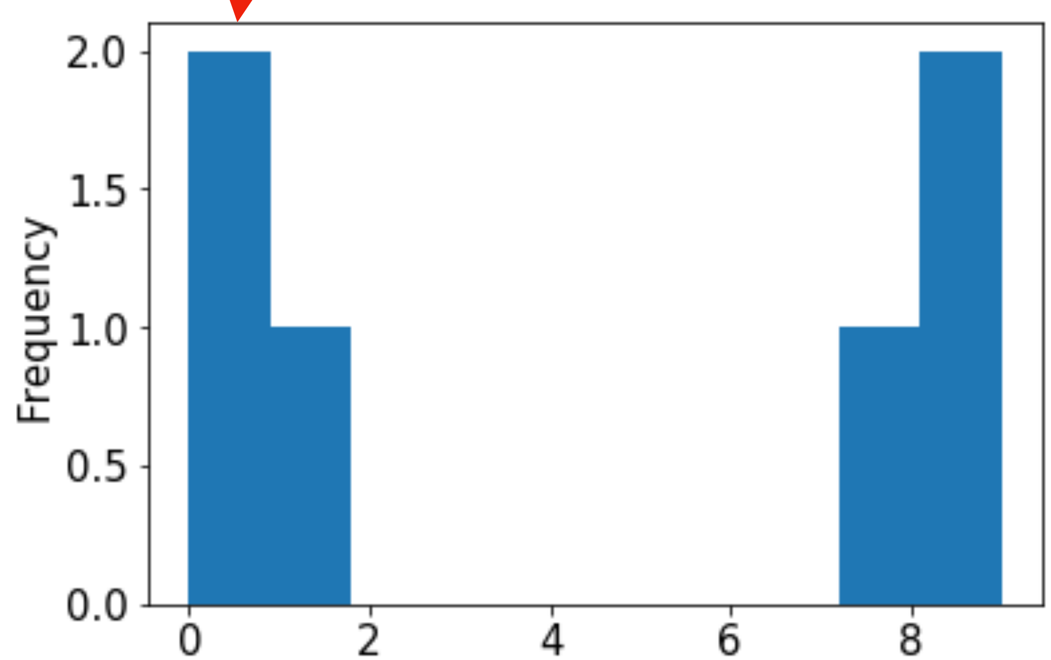
Frequencies across numbers

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

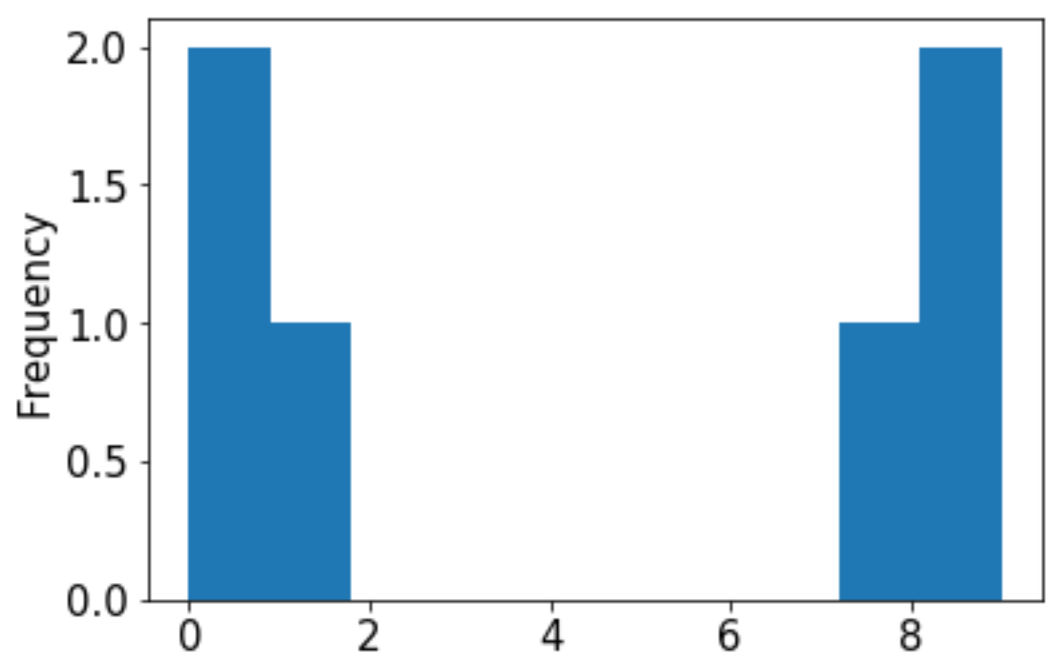
Frequencies across numbers

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

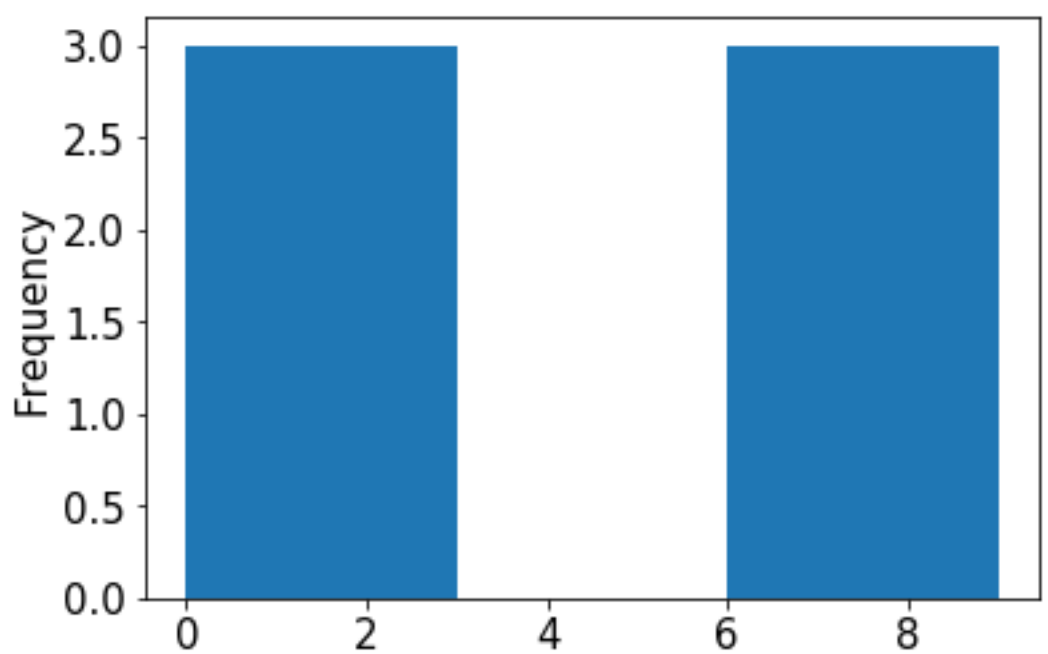
Frequencies across numbers

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

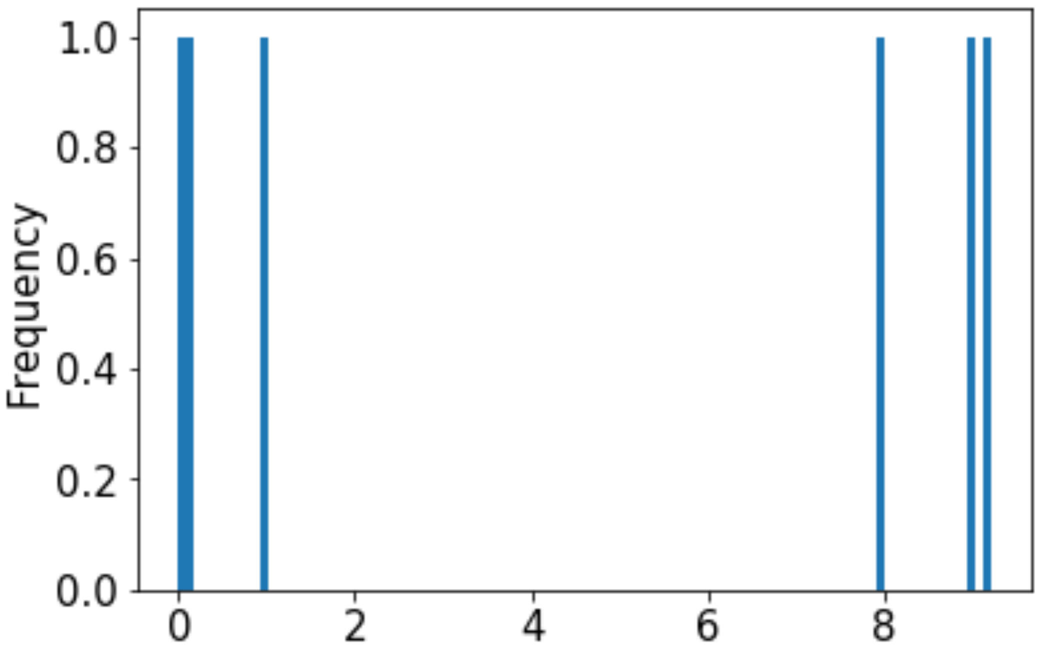
Frequencies across numbers

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)

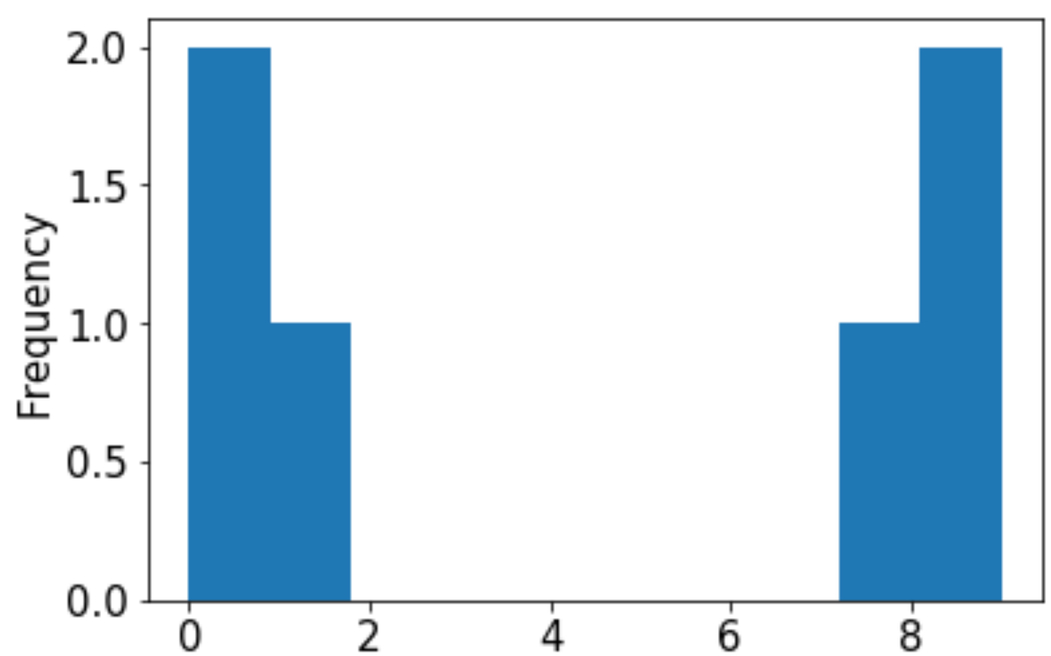
Frequencies across numbers

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)
```



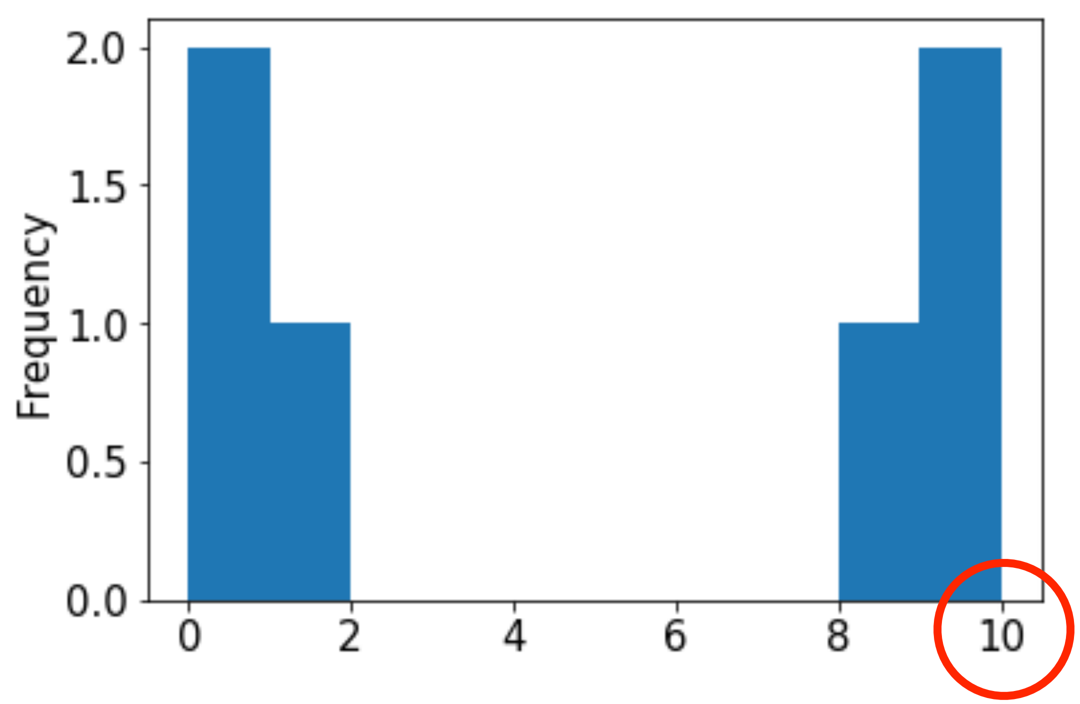
numpy chooses the default bin boundaries

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])
```



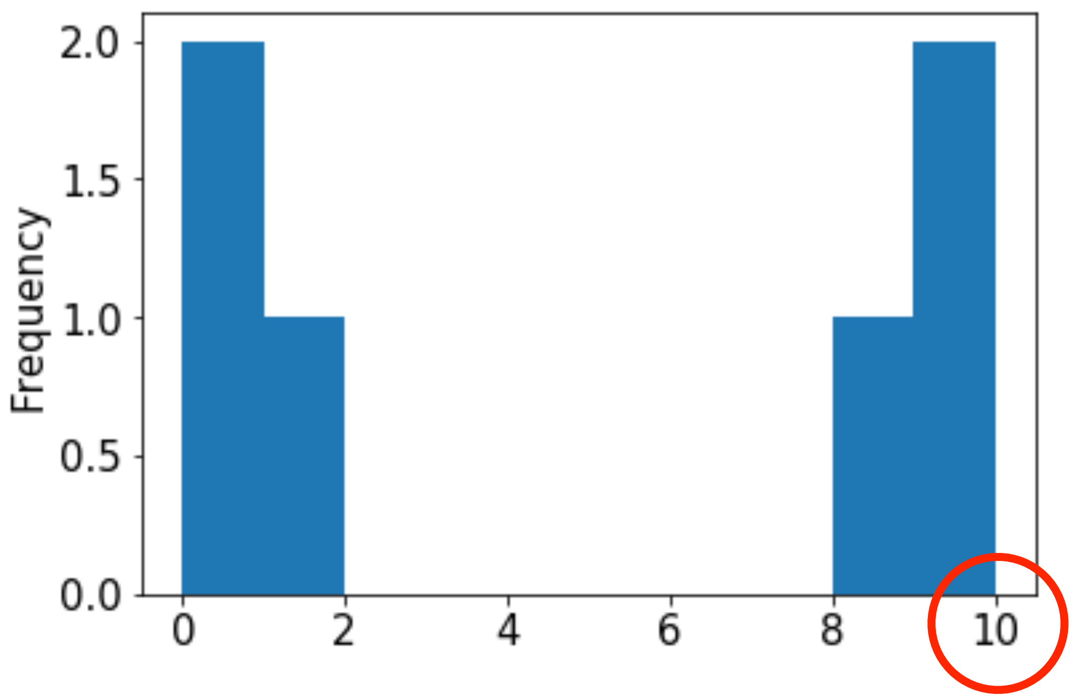
we can override the defaults

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 2: coin flips

If we flip 10 coins repeatedly, we'll get varying numbers of heads

6 heads

Demo 2: coin flips

If we flip 10 coins repeatedly, we'll get varying numbers of heads

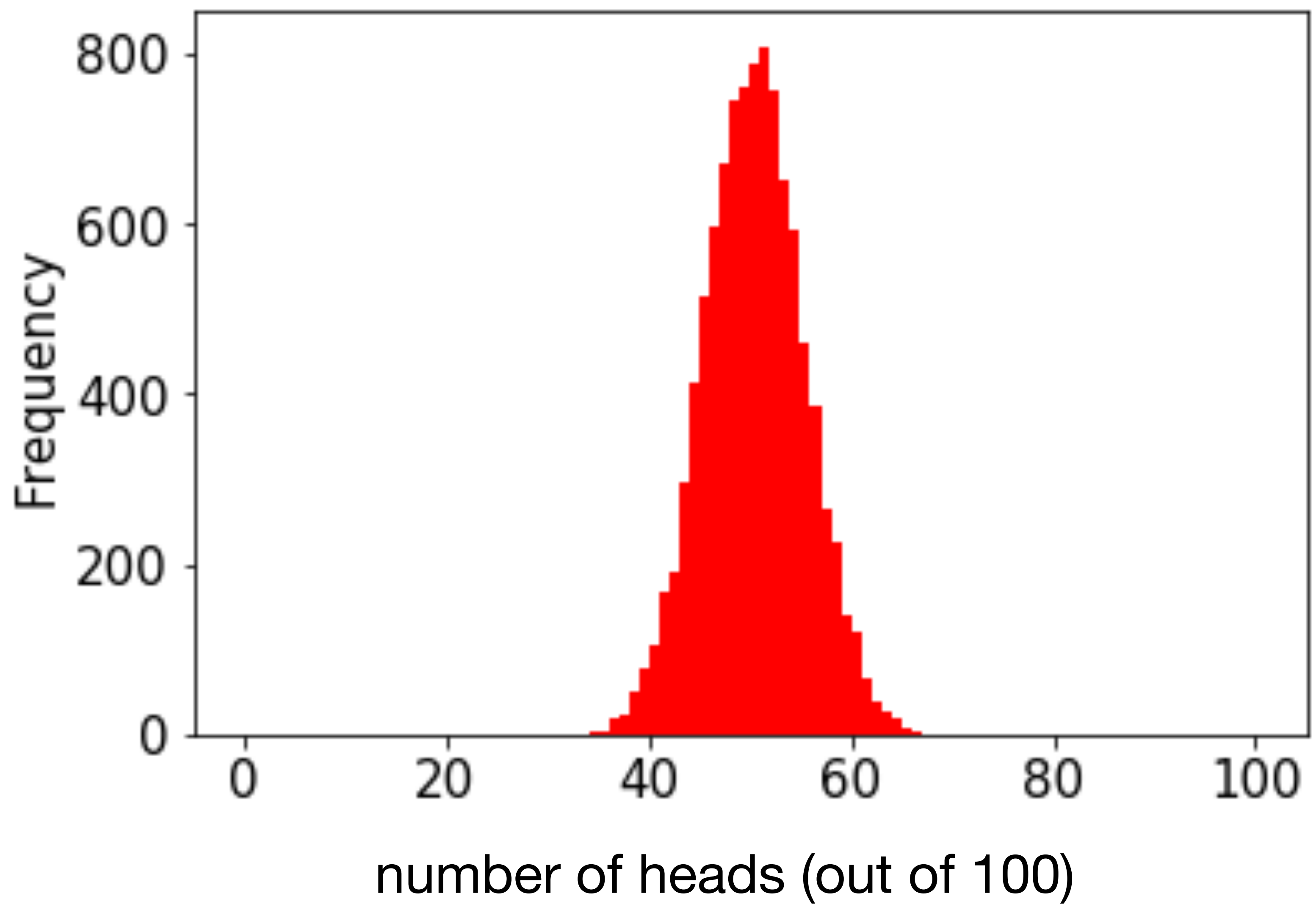
6 heads

If we flip 100 coins, 10K times, how often do we get each head count?

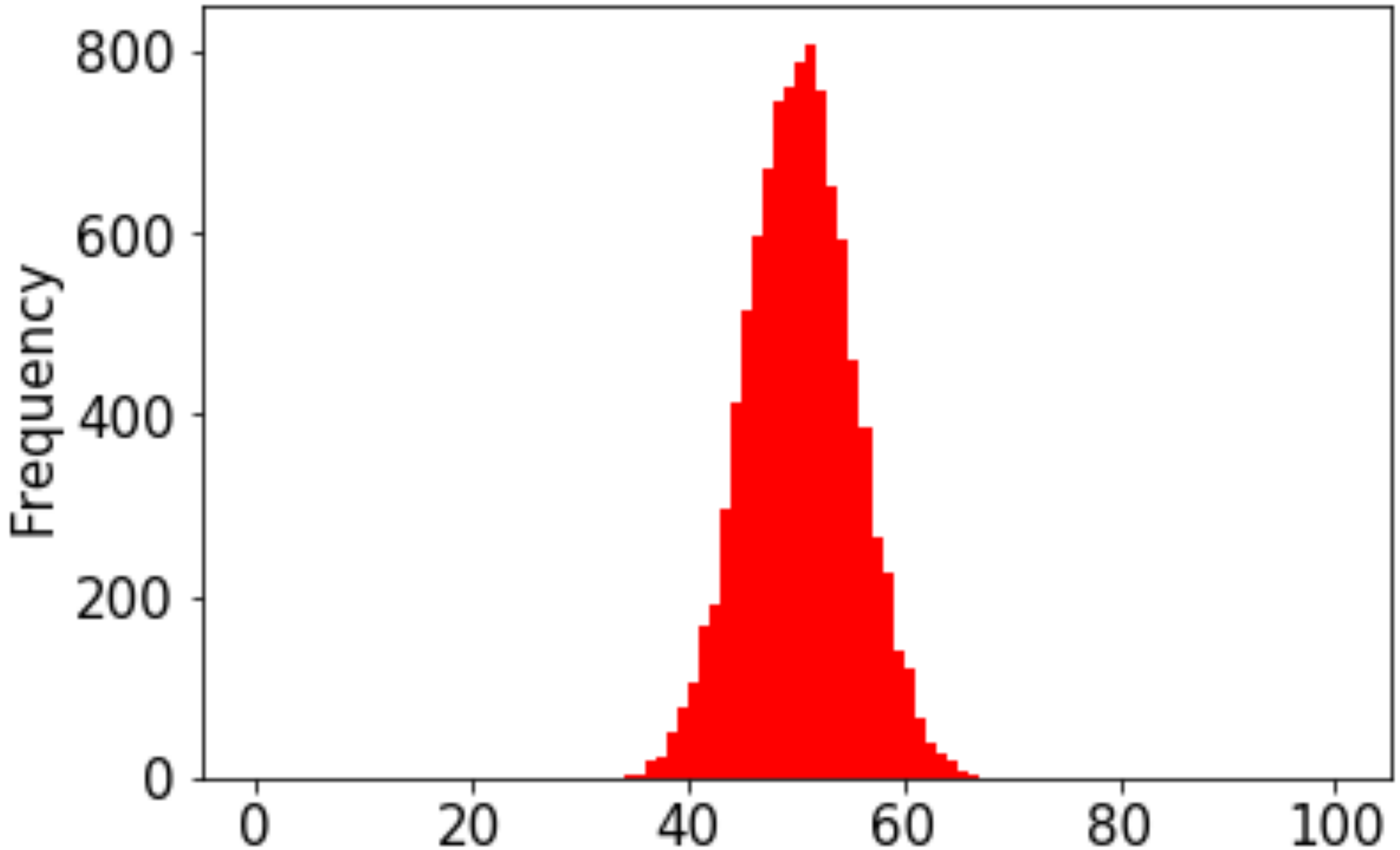
number of samples

sample size

Demo 2: result



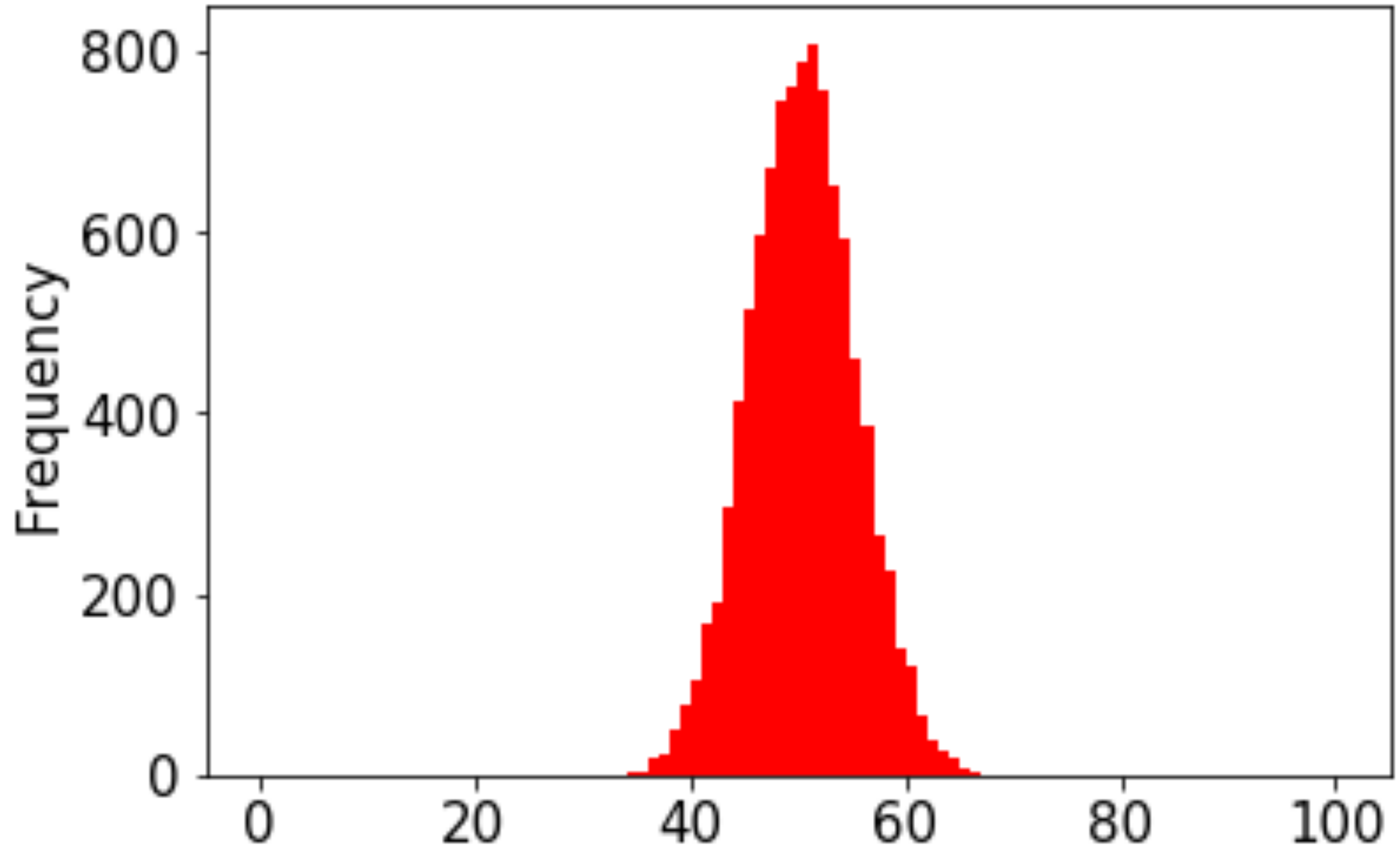
Demo 2: result



number of heads (out of 100)

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

Demo 2: result

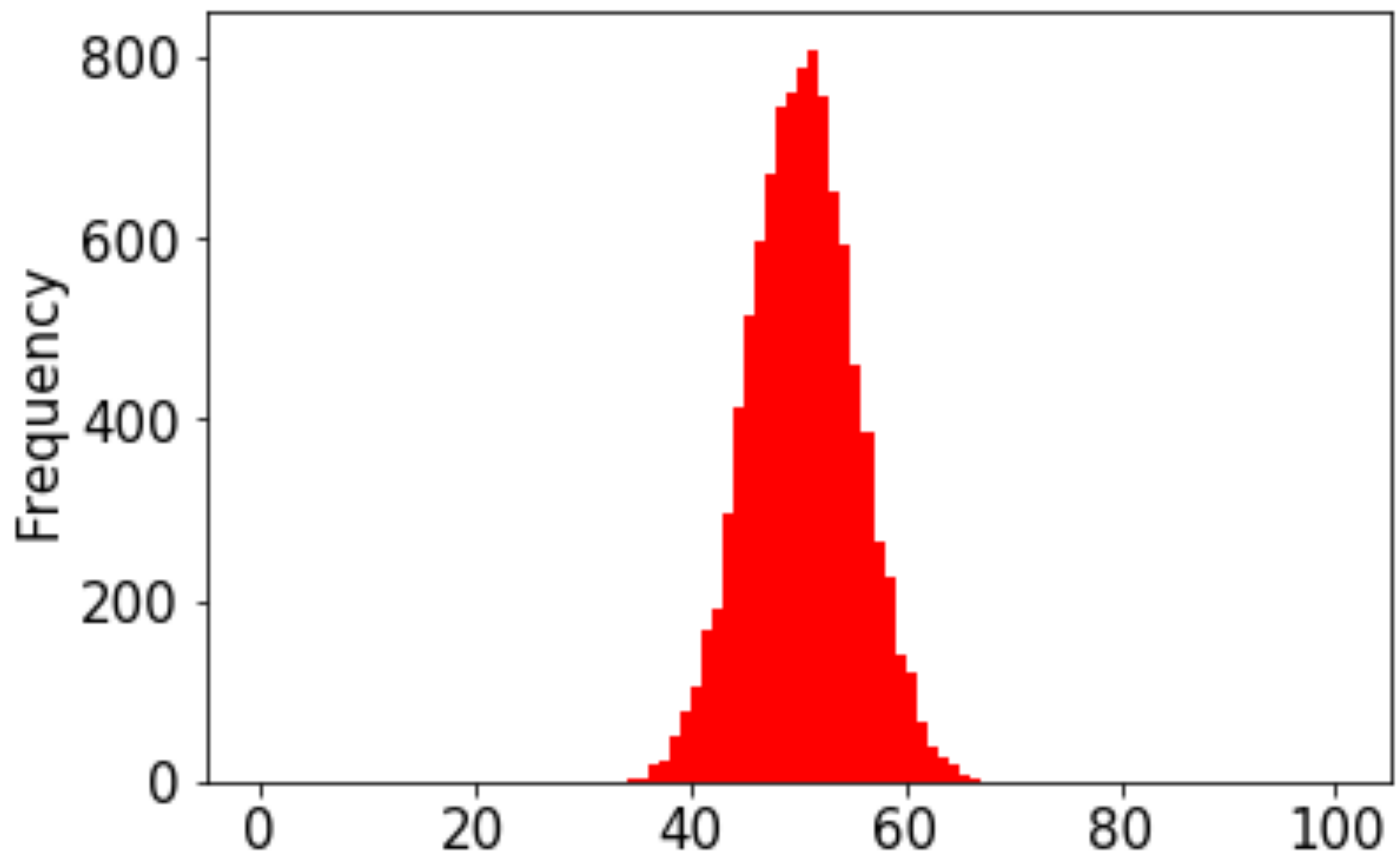


number of heads (out of 100)

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

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

Demo 2: result



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 results will look like this
(we won't discuss exceptions here)

Outline

choice()

pseudorandom: debugging/seeding

visualization: bar plots vs. histograms

normal()

statistical significance: an intuitive approach

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
0.028884529167692474
1.247456111372642
-0.5388224399358179
-0.4514332213638525
-1.400186111201824
0.2811937151186804
0.26088618985565976
-0.19246288728955144
0.2979572961710292
```

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))

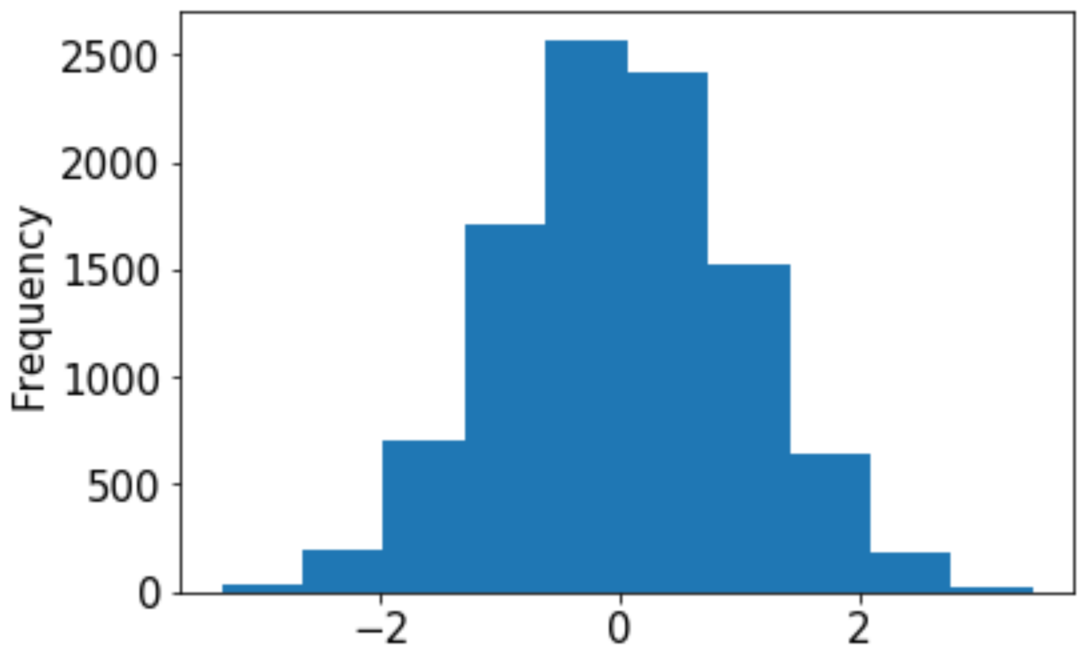
s.plot.hist()
```

normal

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

s = Series(normal(size=10000))

s.plot.hist()
```

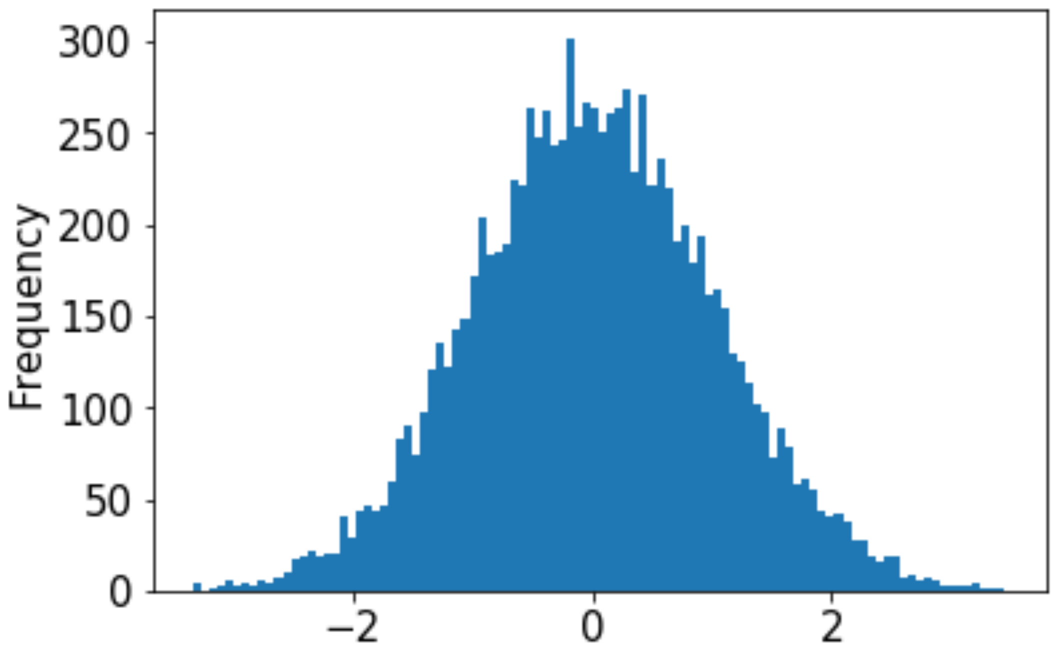


normal

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

s = Series(normal(size=10000))

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

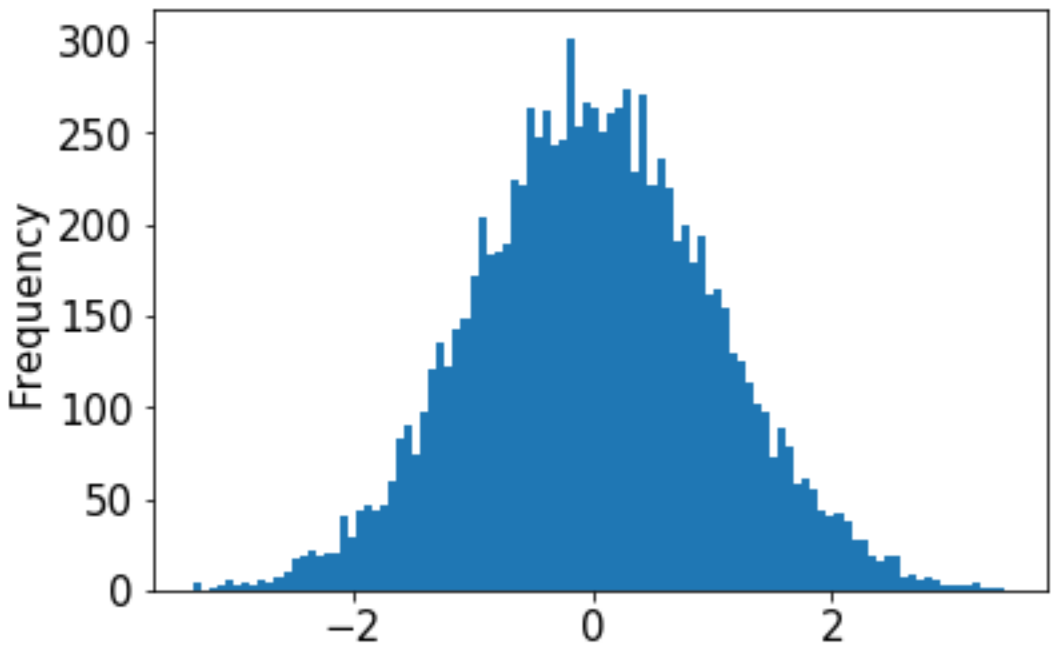


normal

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

s = Series(normal(size=10000))

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



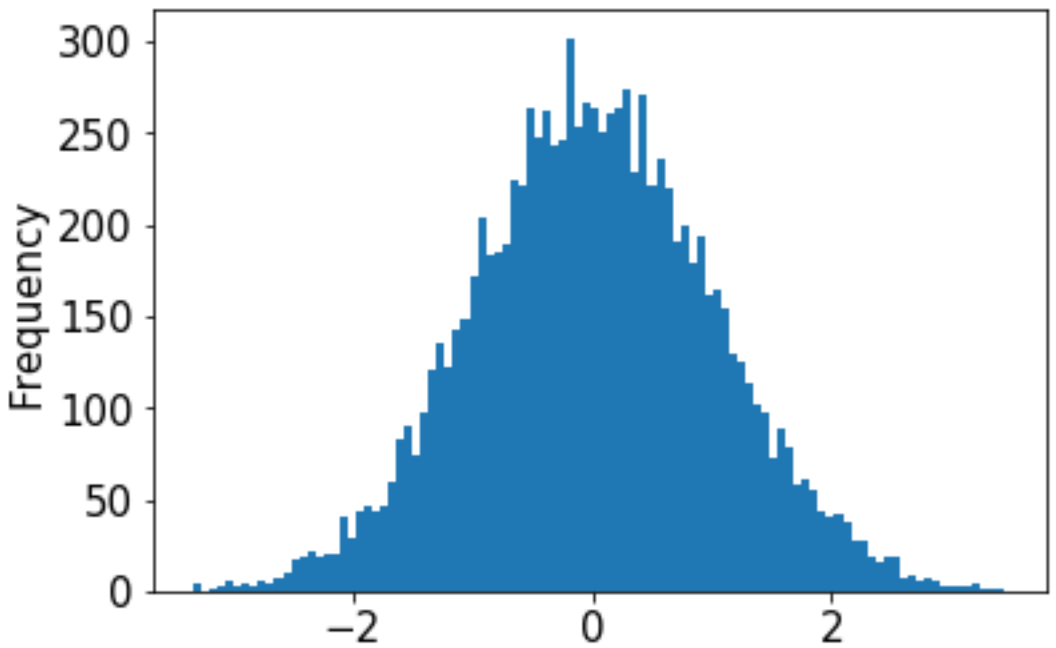
normal

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

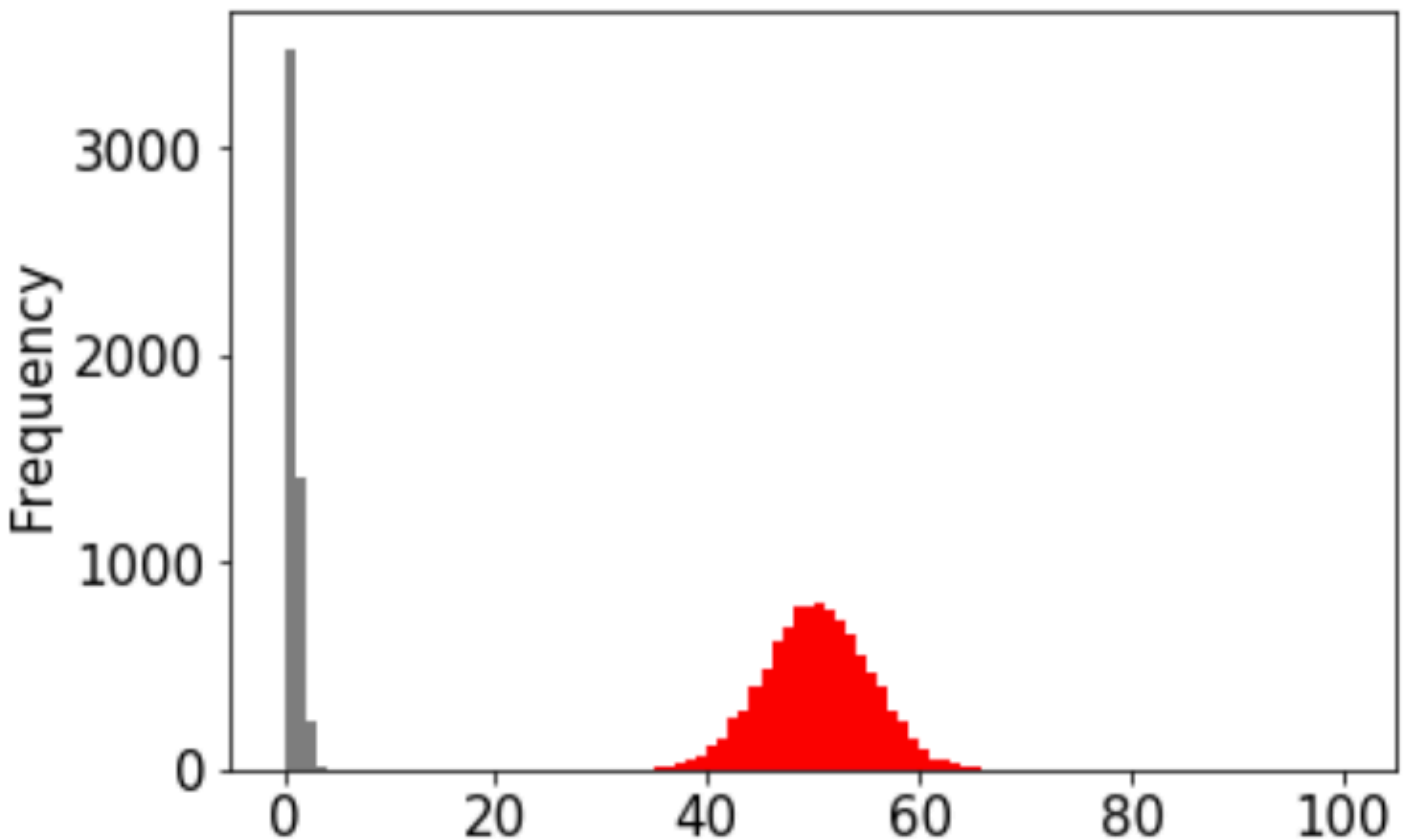
s = Series(normal(size=10000))

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

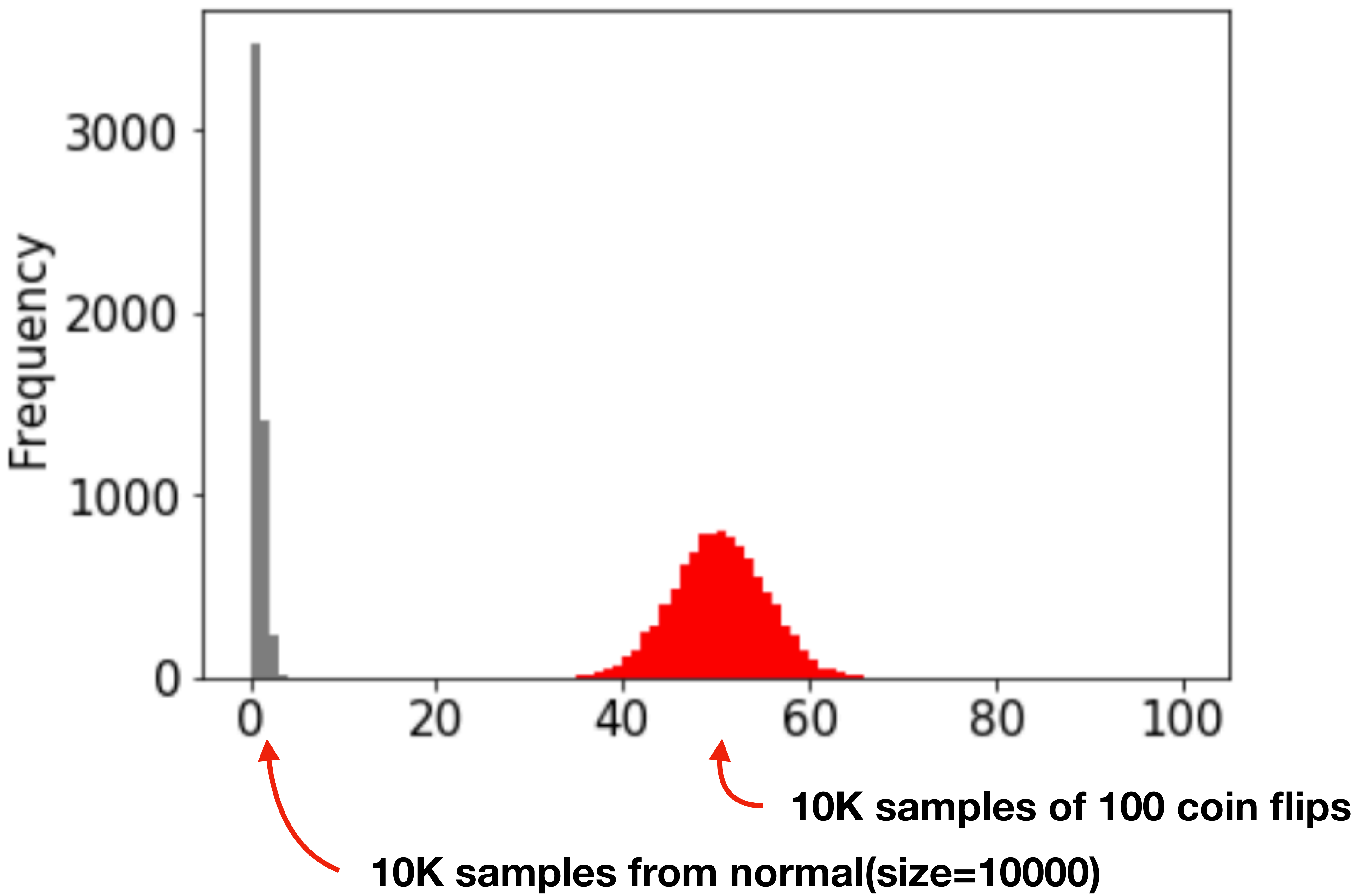
try plugging in different values
(defaults are 0 and 1, respectively)



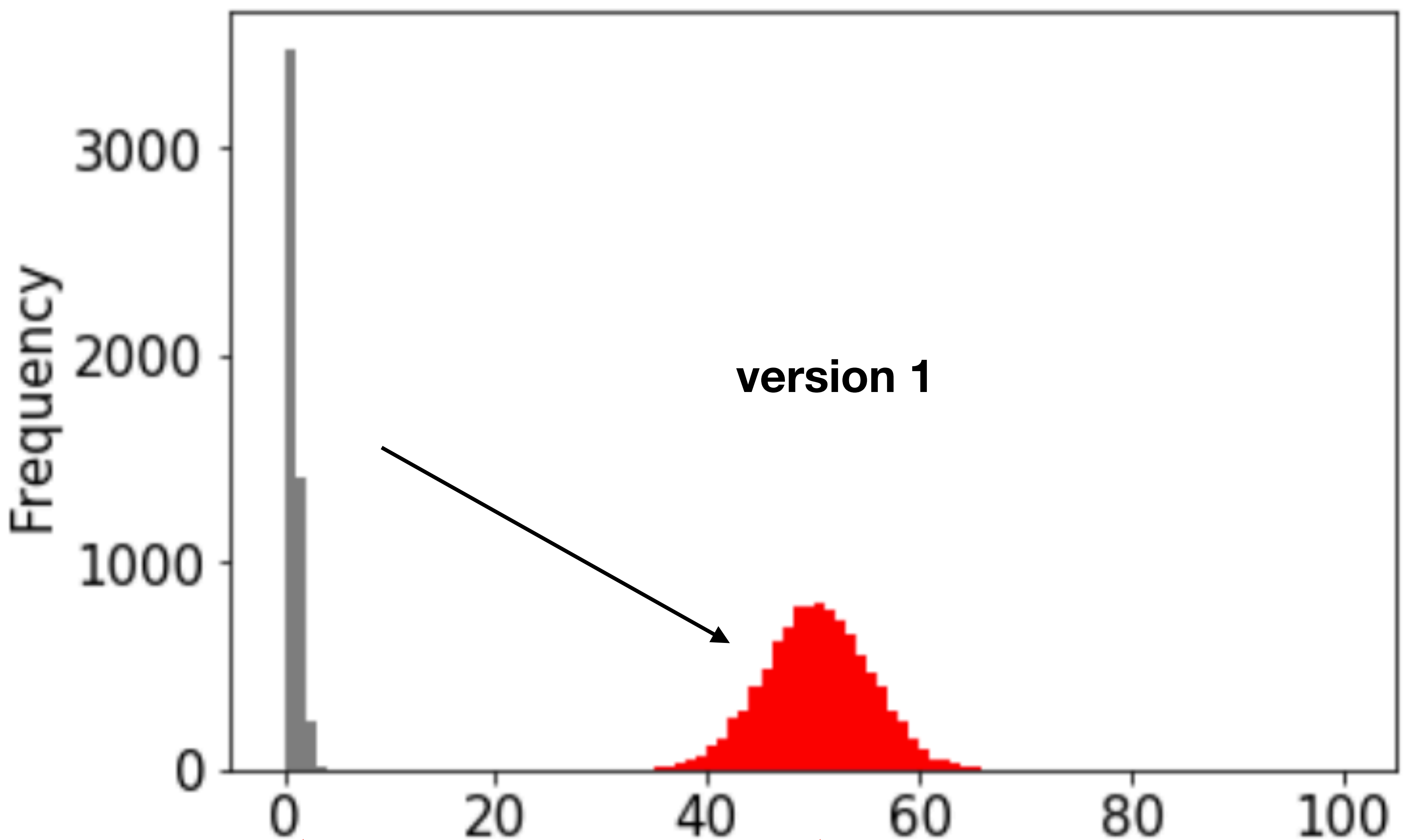
Demo 3: plot overlay



Demo 3: plot overlay



Demo 3: plot overlay

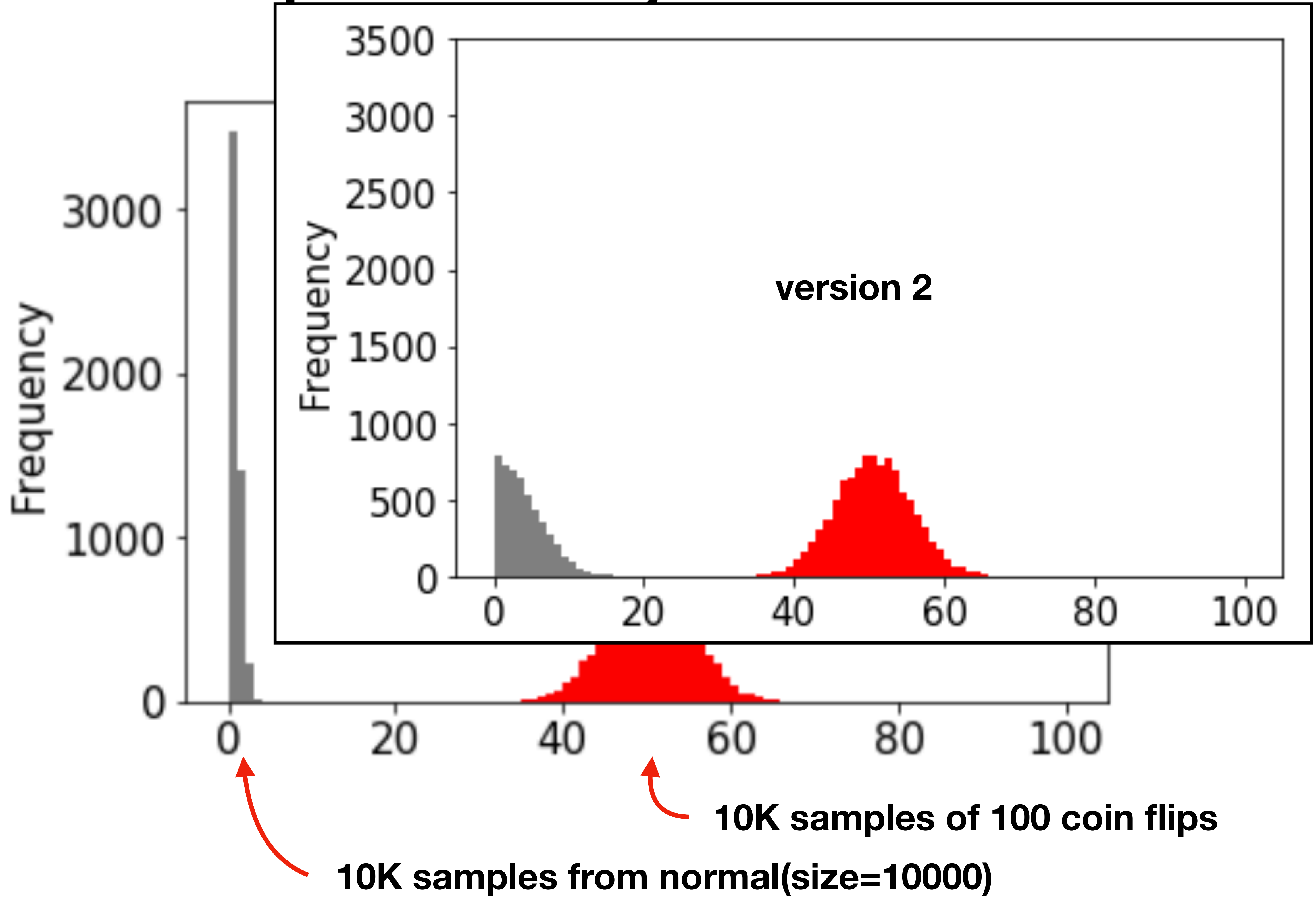


10K samples of 100 coin flips

10K samples from normal(size=10000)

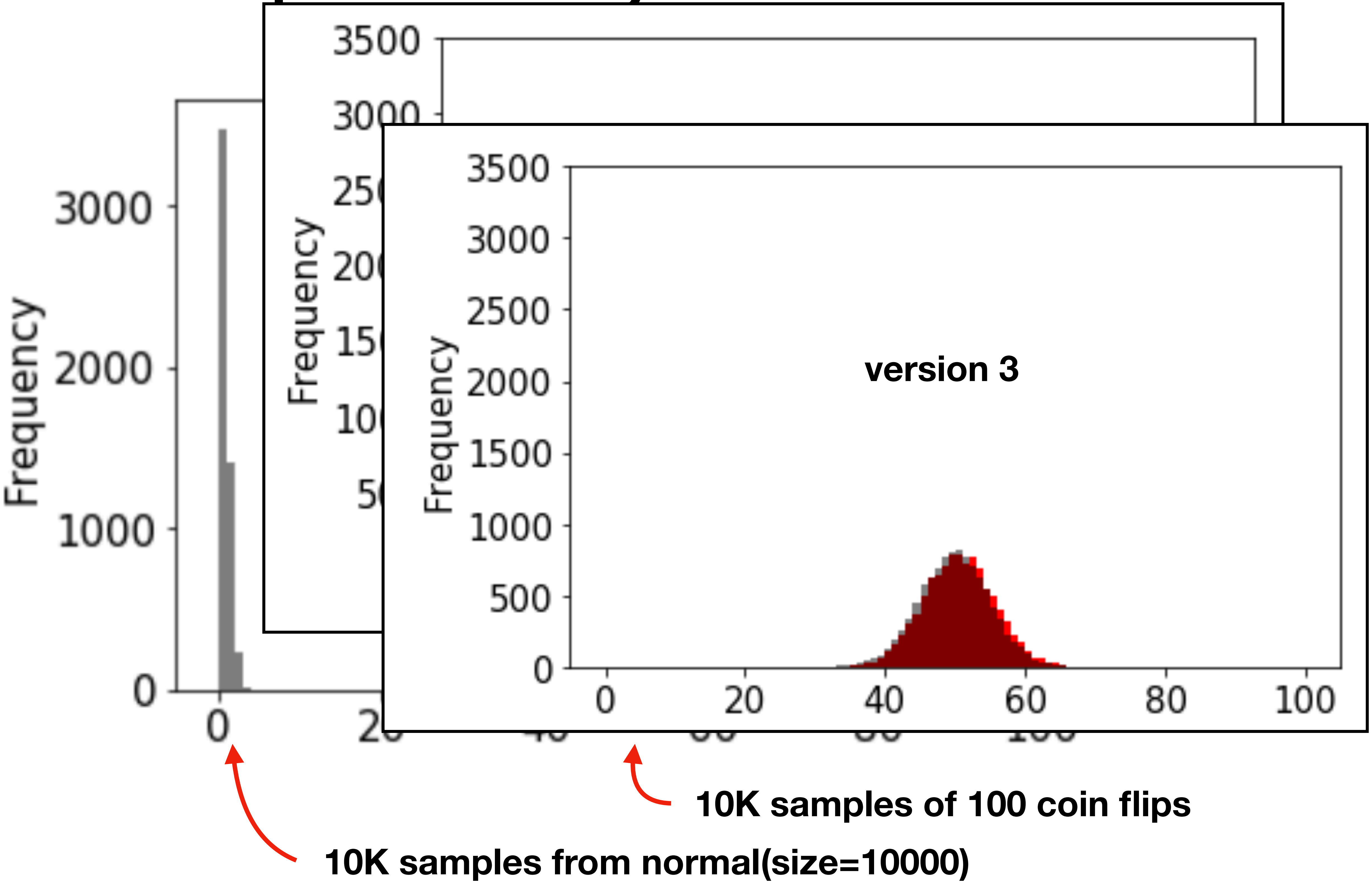
goal: play with **`loc`** and **`scale`** arguments to normal until gray overlaps red

Demo 3: plot overlay



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

Demo 3: plot overlay



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

Outline

choice()

pseudorandom: debugging/seeding

visualization: bar plots vs. histograms

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statistical significance: an intuitive approach

Is this coin biased?

51

49

Call shenanigans?

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

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.

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 4: Calling Shenanigans

60

40

Call shenanigans?

Demo 4: Calling Shenanigans

60

40

Call shenanigans?

Strategy: simulate a fair coin

Demo 4: Calling Shenanigans

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

Demo 4: Calling Shenanigans

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 4: Calling Shenanigans

Call shenanigans?

60 **40**

we got 10 more heads than we expect on average

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 4: Calling Shenanigans

60

40

Call shenanigans?

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
2. count heads
3. repeat above 10K times

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

Demo 4: Calling Shenanigans

60

40

Call shenanigans?

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
2. count heads
3. repeat above 10K times

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

11 more

12 less

Demo 5: Do front-row students score better?

df = pd.read_csv("scores.csv")

	0	1	2	3	4	5	6	7	8	9
0	84	90	89	89	90	87	85	100	96	94
1	100	89	89	87	72	88	72	98	94	82
2	85	82	83	84	73	85	76	94	87	96
3	74	87	82	89	97	91	84	80	91	87
4	98	76	78	77	91	88	78	100	77	70
5	82	72	73	84	98	70	94	91	73	83
6	70	100	94	76	71	75	71	77	100	73
7	89	77	83	71	95	89	77	92	91	70
8	100	84	82	79	70	88	98	77	81	79
9	99	88	89	92	84	82	94	93	77	75

df.mean(axis=1)

```
0      90.4
1      87.1
2      84.5
3      86.2
4      83.3
5      82.0
6      80.7
7      83.4
8      83.8
9      87.3
dtype: float64
```

what are the odds that the front row would do so well by chance?