

# Software Engineering For Data Science (SEDS)

**Class: 2<sup>nd</sup> Year 2<sup>nd</sup> Cycle**  
**Branch: AIDS**

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## **Lecture 08:**

# **Data Processing & Cleaning for Data Science: Statistics for Data Science**

# Data Processing & Cleaning for Data Science

## Part IIV: Statistics for Data Science

Probability, Distributions, and Sampling

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

- **Probability is all about uncertainty:**

- Flipping a normal coin → uncertain to get a **head** or a **tail**.
- Can be estimated with a probability function:

- $$P(E) = \frac{\text{Number of Outcomes Corresponding to the event } E}{\text{Total Number of equally-likely Outcomes}}$$

- **A random variable** → A function that map the outcomes of a random process to a numeric value:

- $X = 1$  if the flip of the coin is a **head**
  - $X = 0$  if the flip of the coin is a **tail**

- **Why random variable** → Provides a way to ask questions about the random process in a concise mathematical way:

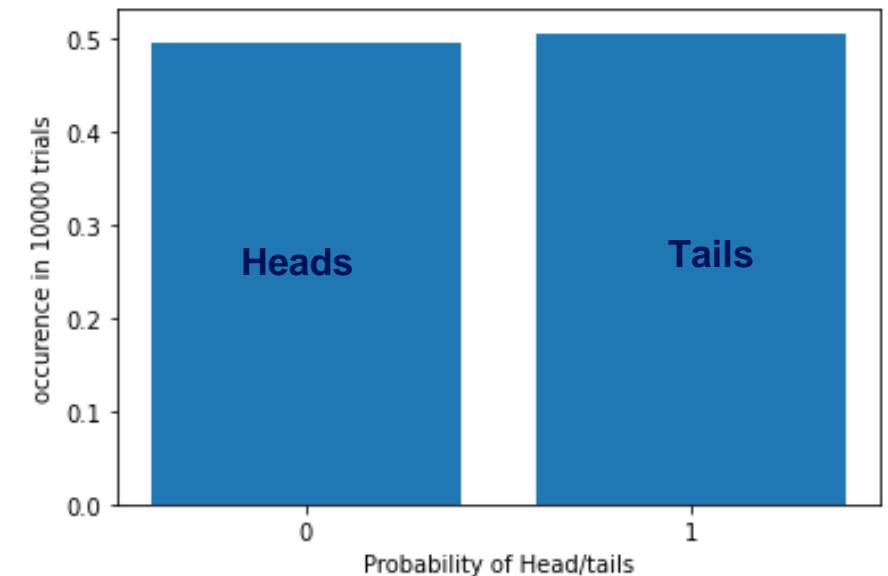
- $P(X = 2)$  → What is the probability of getting exactly 2 heads?
  - $P(X < 4)$  → What is the probability of getting exactly 2 heads?



Head

Tail

$$P(\text{CoinFlip} = \text{"Head"}) = \frac{1}{2}$$



# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Random Variable vs Deterministic Variable:

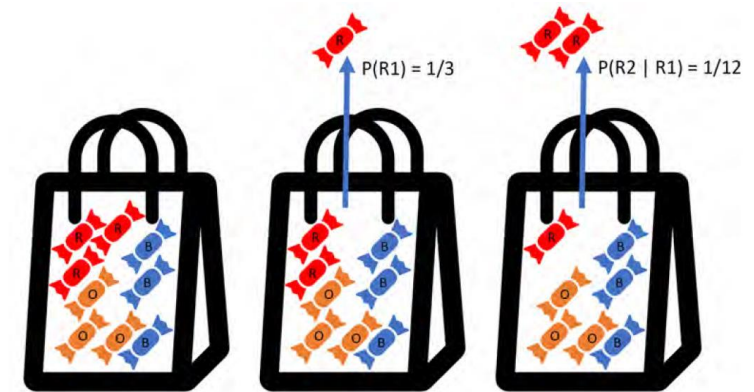
- A random variable's value is not perfectly predictable.
- In contrast, A deterministic's variable value is deterministic
- **e.g.:** The outcome of the event  $1 + 2$  is not a random variable

#### ○ Discret Variable vs Continuous Variable:

- A **discrete random variable** → Takes only on certain values, like heads and tails.
- A **continuous random variable** → Takes any value between two points, like time or length.

#### ○ Independent vs Conditional Probabilities:

- A conditional Probability → When an outcome of one event affects the probability of another event happening.



- Probability of getting red candies in two draws in a row:
  - $P(R1 \text{ and } R2) = P(R1) * P(R2 | R1)$

# Statistics for Data Science

## Probability, Distributions, & Sampling

### □ Foundational probability concepts:

#### ○ Bayes' Theorem:

$$P(A|B) = P(A) * P(B|A) / P(B)$$

- Another way to write this is with a hypothesis (a condition we can test), **H**, and evidence, **E**:

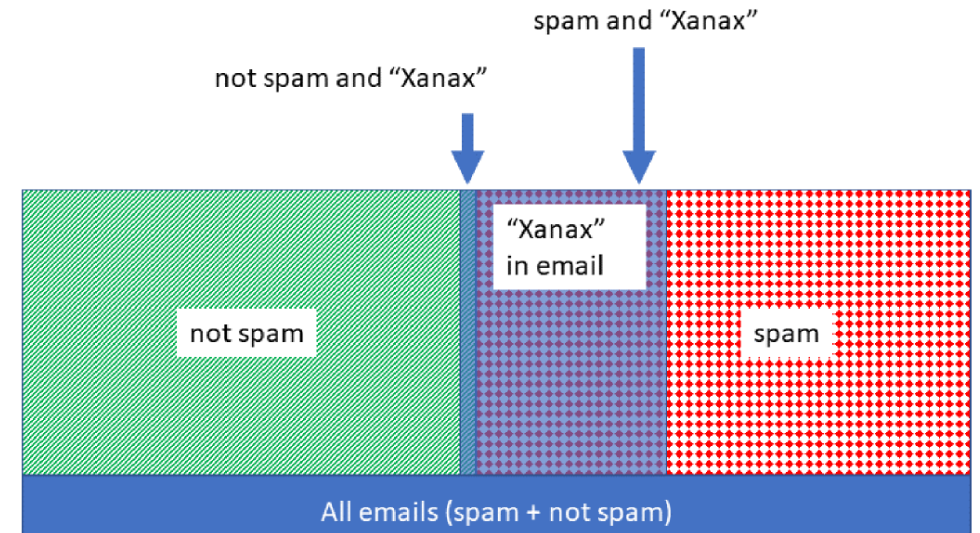
$$P(H|E) = P(H) * P(E|H) / P(E)$$

- e.g.:

$$P(\underset{\text{H}}{\text{spam}} | \underset{\text{E}}{\text{"Xanax"}}) = P(\underset{\text{H}}{\text{spam}}) * P(\underset{\text{E}}{\text{"Xanax"}} | \underset{\text{H}}{\text{spam}}) / P(\underset{\text{E}}{\text{"Xanax"}})$$

Our prior belief about any given email to be a spam

Probability of seeing the evidence given the hypothesis



# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

- A way of describing all possible outcomes a random variable can take within a sample space.

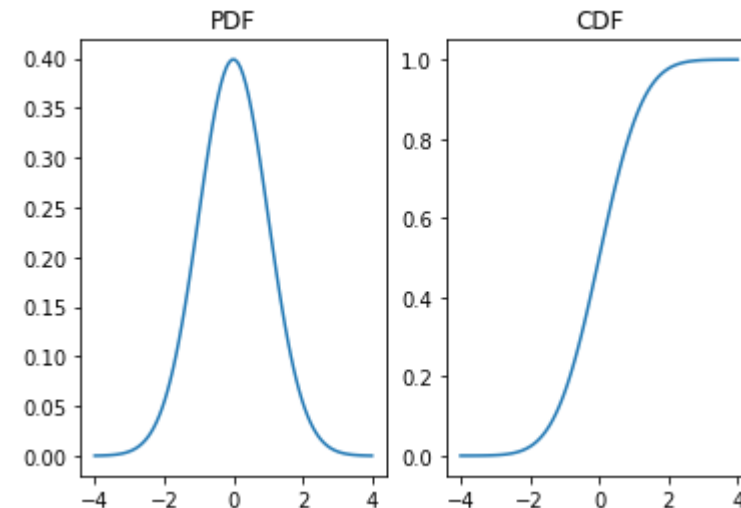
#### ○ Types:

##### ○ The Normal (Gaussian) Distribution:

- Seen when taking measurements from a biological population,
- Measurements of a manufacturing process

```
import numpy as np
from scipy.stats import norm
```

```
x = np.linspace(-4, 4, 100)
plt.plot(x, norm.pdf(x))
plt.plot(x, norm.cdf(x))
```



**PDF:** Gives us the relative likelihood of an event at that value  $x$ .

**CDF:** Tells us the probability that our value will be less than or equal to any point on the plot

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

- A way of describing all possible outcomes a random variable can take within a sample space.

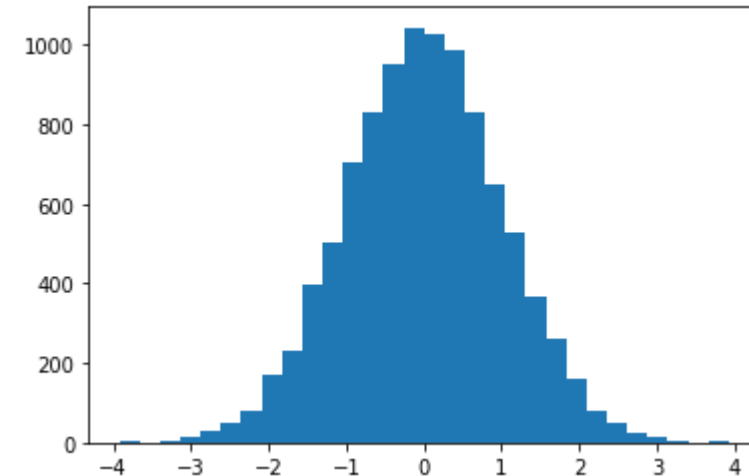
#### ○ Types:

##### ○ The Normal (Gaussian) Distribution:

- Random Variable Sampling using **rvs** function.

```
data = norm.rvs(size=10000, random_state=42)
plt.hist(data, bins=30)
```

seed



Generating 10,000 data points for a normal distribution

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

- **Probability Distributions:**

- A way of describing all possible outcomes a random variable can take within a sample space.

- **Types:**

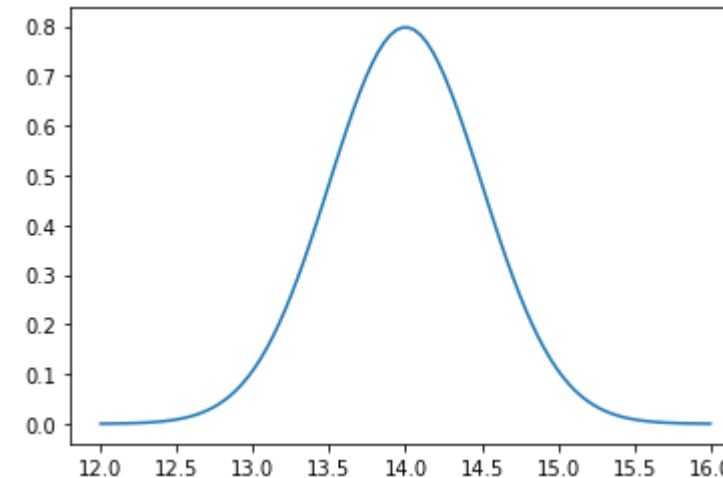
- **The Normal (Gaussian) Distribution:**

- **Descriptive statistics:**

- The normal distribution's PDF is represented with an equation:

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

```
x = np.linspace(12, 16, 100)
plt.plot(x, norm.pdf(x, loc=14, scale=0.5))
```



- Generating 100 data points for a normal distribution
- set the **mean** and **standard deviation** parameters (**loc** and **scale**) to the specified values of 14 and 0.5



# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

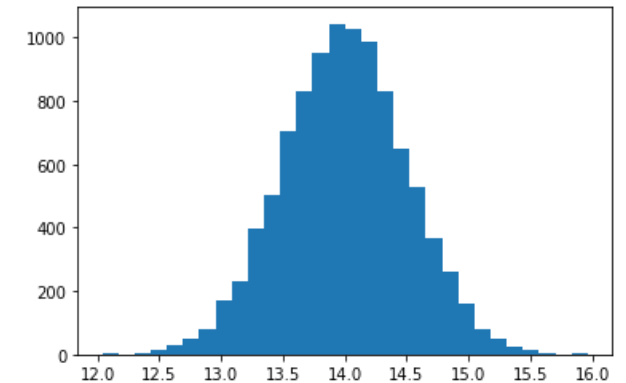
- A way of describing all possible outcomes a random variable can take within a sample space.

#### ○ Types:

- **The Normal (Gaussian) Distribution:**

- **Sampling from a distribution**

```
data = norm.rvs(size=10000, loc=14, scale=0.5,  
                random_state=42)
```



```
data.mean()  
data.std()
```

13.998932008315789

0.5017061030649937

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

- A way of describing all possible outcomes a random variable can take within a sample space.

#### ○ Types:

- **Fitting distributions to data to get parameters:**
- If we have data from measurements, say the efficiency of solar cells from a manufacturing line, we can fit a distribution to that data to extract the distribution's PDF parameters and moments

```
df = pd.read_csv('data/solar_cell_efficiencies.csv')
df.describe()
```

efficiency		efficiency	
0	14.260772	count	187196.000000
1	13.463545	mean	14.181805
2	14.704418	std	0.488751
3	13.671162	min	9.691218
4	14.186147	25%	13.932445
...	...	50%	14.205567
187191	14.602182	75%	14.482341
187192	14.158041	max	17.578530
187193	14.093038	scipy.stats.norm	
187194	14.478059	(14.181805365742568,	
187195	13.833728		

187196 rows × 1 columns

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

- A way of describing all possible outcomes a random variable can take within a sample space.

#### ○ Types:

##### ○ The Bernoulli distribution:

- The **Bernoulli** distribution is a discrete distribution, meaning it can only take on a few values.
- Discrete distributions have a **probability mass function (PMF)** instead of a probability distribution function (**PDF**).

$$f(x) = \begin{cases} p, & x = 1 \\ (1 - p), & x = 0 \end{cases}$$

```
scipy.stats.bernoulli(p=0.7).rvs()
```

1

- creating a bernoulli class from scipy.stats with a probability of 0.7 for success (the probability of getting a 1 and not 0).
- Sampling with rvs function

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

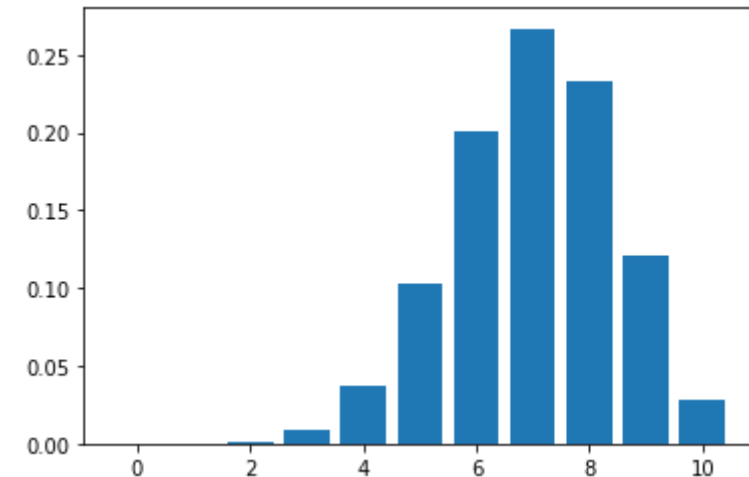
- A way of describing all possible outcomes a random variable can take within a sample space.

#### ○ Types:

##### ○ The binomial distribution:

- Bernoulli distribution → for a single binary event
- While the **Binomial** distribution → for a collection of Bernoulli events.
- The binomial distribution represents a number of successes out of a number of Bernoulli events

```
binom_dist = scipy.stats.binom(p=0.7, n=10)
plt.bar(range(11), binom_dist.pmf(k=range(11)))
```



- For example, if **10** customers visit our website and we have a **70%** chance of them buying a product, our binomial distribution would be:

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

- A way of describing all possible outcomes a random variable can take within a sample space.

#### ○ Types:

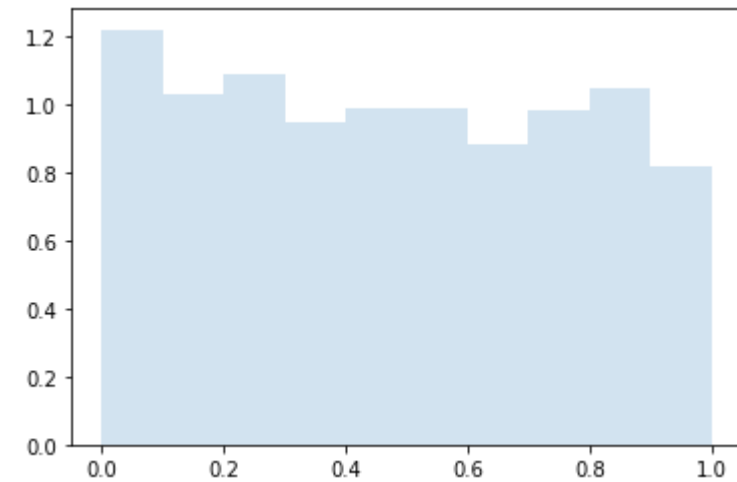
##### ○ The Uniform distribution:

- The uniform distribution shows up when we have several events, all with an equal likelihood of occurring.
- **example:** rolling a 6-sided dice

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b, \\ 0 & \text{for } x < a \text{ or } x > b \end{cases}$$



```
r = scipy.stats.uniform.rvs(size=1000)
```



- Sampling 1000 points from a uniform distribution

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

- **Probability Distributions:**

- A way of describing all possible outcomes a random variable can take within a sample space.

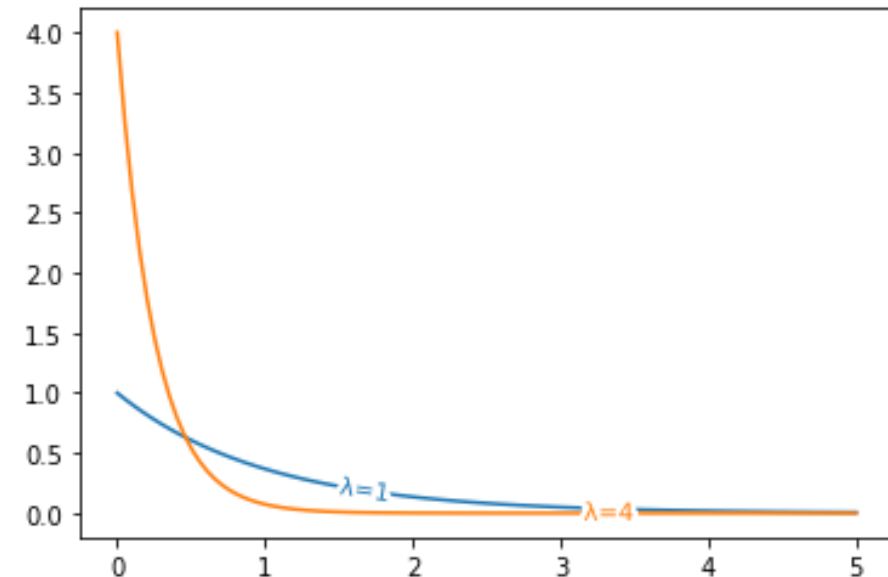
- **Types:**

- **The exponential distributions:**

- The exponential distribution describes the space or time between events that are independent.
    - **example:** support center calls

$$y = \lambda e^{-\lambda x}$$

```
from labellines import labelLines
x = np.linspace(0, 5, 100)
plt.plot(x, scipy.stats.expon.pdf(x, scale=1), label='λ=1')
plt.plot(x, scipy.stats.expon.pdf(x, scale=0.25), label='λ=4')
labelLines(plt.gca().get_lines())
```



# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

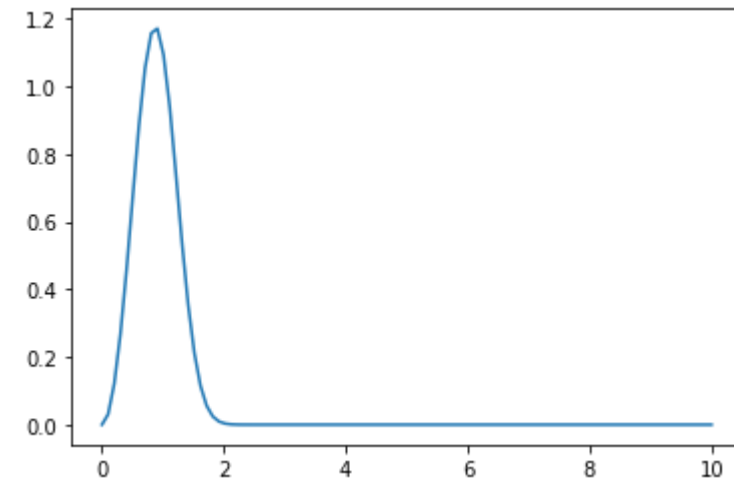
- A way of describing all possible outcomes a random variable can take within a sample space.

#### ○ Types:

##### ○ The Weibull distribution:

- The Weibull distribution is like an extension of the exponential distribution, where the characteristic time or space between events changes over time.
- **example:** useful for time-to-failure analysis, like with hard drives,

```
x = np.linspace(0, 10, 100)
plt.plot(x, scipy.stats.weibull_min(c=3).pdf(x))
```



The shape parameter,  $c$ , determines if the time-to-failure is:

- Decreasing over time ( $c < 1$ ),
- Staying constant ( $c = 1$ , the exponential distribution), or
- Increasing over time ( $c > 1$ ).

$$f(x; \lambda, k) = \begin{cases} \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}, & x \geq 0, \\ 0, & x < 0, \end{cases}$$

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Foundational probability concepts:

#### ○ Probability Distributions:

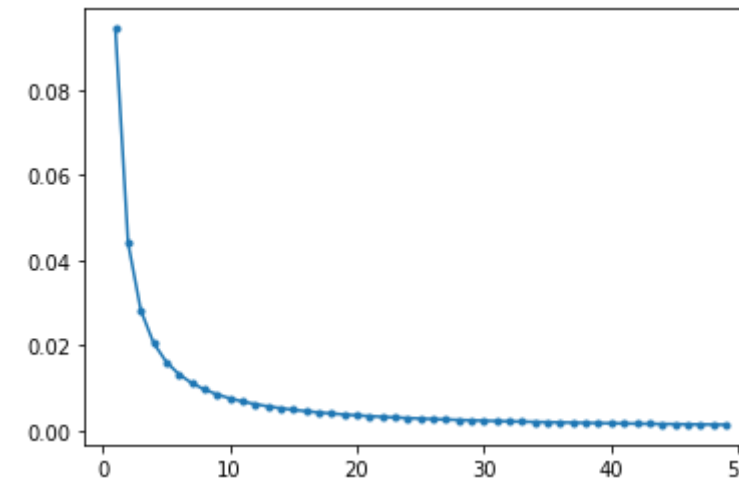
- A way of describing all possible outcomes a random variable can take within a sample space.

#### ○ Types:

##### ○ The Zipfian distribution:

- used in text data to model the ranked frequency of words.
- Used also in showing up in surprising places, like the ranking of cities by population from greatest to least and the distribution of company sizes.

```
x = range(1, 50)
plt.plot(x, scipy.stats.zipf(a=1.1).pmf(x), marker='.'))
```



The shape parameter,  $a$ , determines if the time-to-failure is:

- Decreasing over time ( $c < 1$ ),
- Staying constant ( $c = 1$ , the exponential distribution), or
- Increasing over time ( $c > 1$ ).



# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Sampling from data:

#### ○ Good methods for Data Scientists to:

- Downsize a large dataset for analysis,
- Estimate confidence intervals, and
- Balance imbalanced datasets for machine learning.

#### ○ Random Sampling:

- The easiest sampling method is randomly sampling from a dataset.
- Taking a random sample is like choosing a random value from a **uniform distribution**.

```
df = pd.read_csv('data/solar_cell_efficiencies.csv')  
df.sample(100, random_state=42)
```

	efficiency
52332	13.661122
15695	13.608738
53972	13.704674
23400	13.902658
34656	14.413147
...	...
26601	13.786017
17128	14.325704
19828	14.616771
38002	13.839354
5549	14.628503
100 rows × 1 columns	

Random sample of 100 data points from our dataframe

# Statistics for Data Science

## Probability, Distributions, & Sampling

### ❑ Sampling from data:

- **Good methods for Data Scientists to:**
  - Downsize a large dataset for analysis,
  - Estimate confidence intervals, and
  - Balance imbalanced datasets for machine learning.
- **Bootstrap Sampling:**
  - Bootstrap sampling is random sampling, but with replacement.
  - Every time we take a sample, it's independent and from the entire dataset.

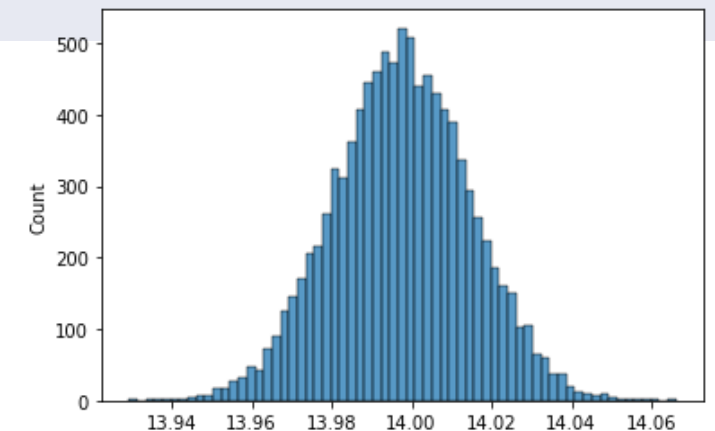
```
df = pd.read_csv('data/solar_cell_efficiencies.csv')  
df.sample(100, random_state=42)
```

13.997757103217898      (13.993327776033839, 14.002235170746314)

Calculate the mean, with confidence intervals

### Bootstrap Sampling: Code from Scratch

```
means = []  
for i in range(10000):  
    sample = np.random.choice(df['efficiency'], 1000,  
                               replace=True)  
    means.append(sample.mean())  
sns.histplot(means)
```



# Thanks for your Listening

