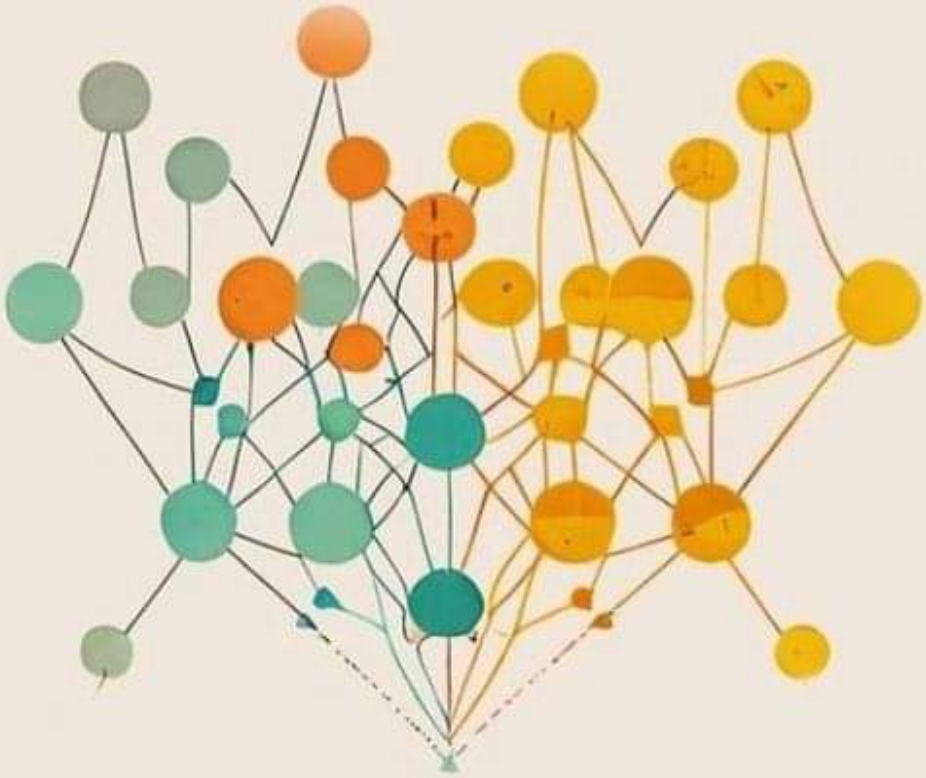
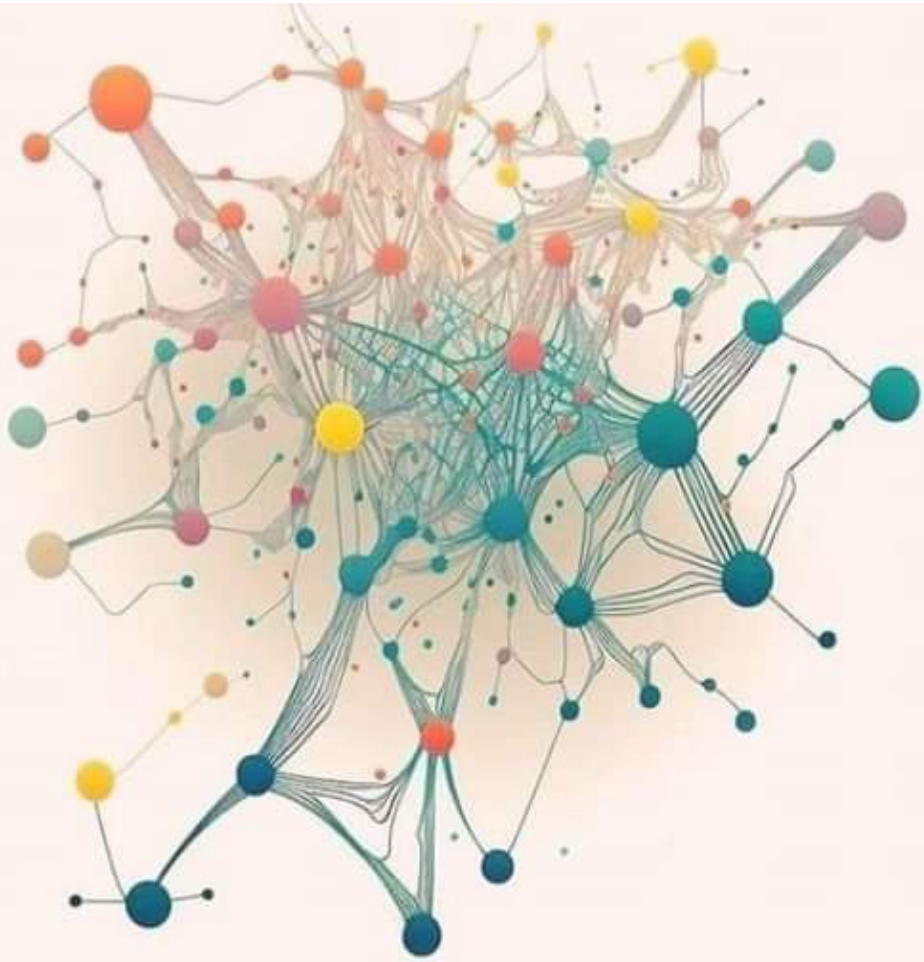


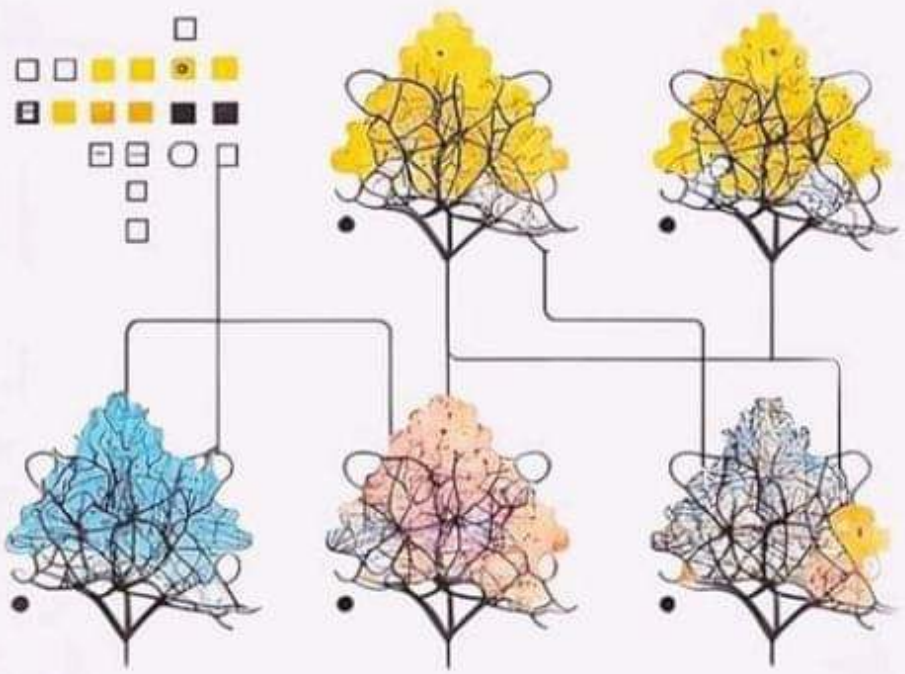
Nearest Neighbour

Nearest neighbor is a type of machine learning algorithm that makes predictions for a sample by finding the most similar samples in the training data and using their labels to make a prediction.



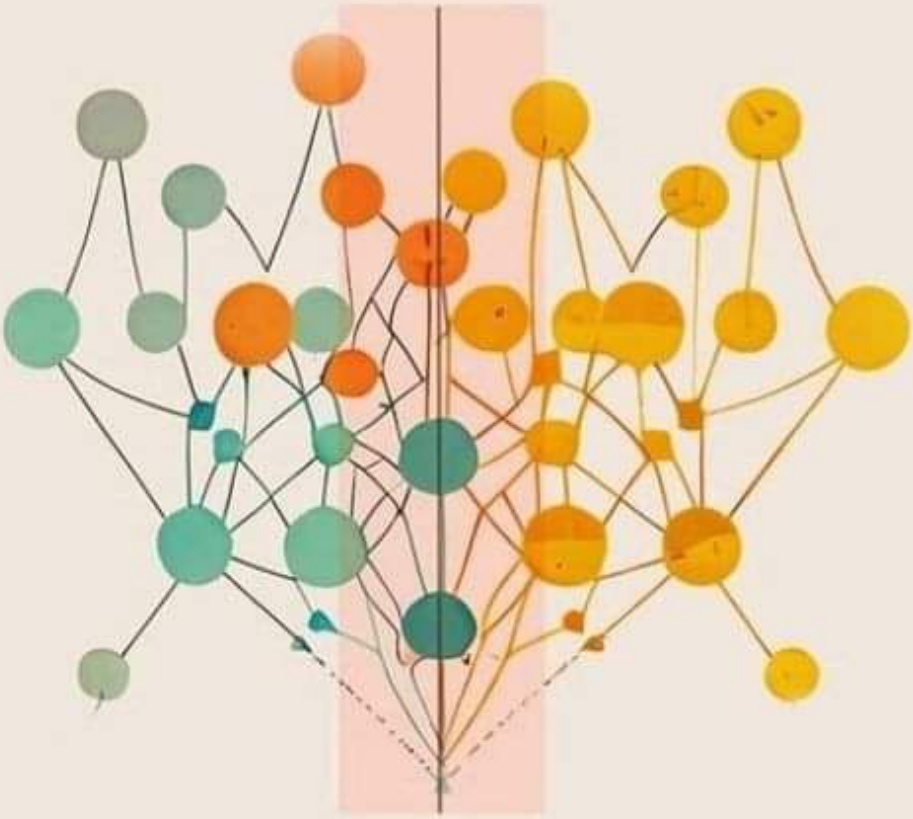
Neural Network

A neural network is a type of machine learning algorithm that is inspired by the structure and function of the human brain, and consists of interconnected processing nodes that are organized into layers.



Random Forest

A random forest is a type of ensemble learning algorithm that trains multiple decision trees on random subsets of the data and then combines their predictions to make a final prediction. This can improve the performance of the model compared to using a single decision tree.



Support Vector Machines

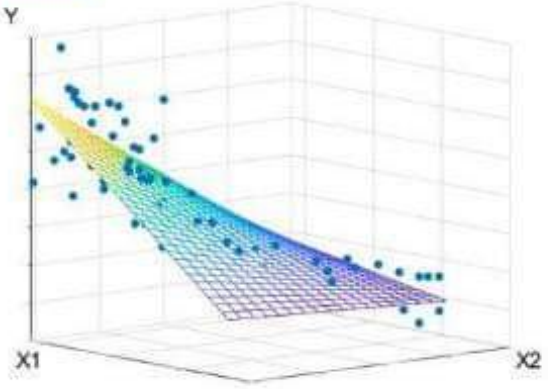
Support vector machines (SVMs) are a type of machine learning algorithm that is used for classification and regression tasks, and finds the hyperplane that maximally separates the classes in the data.

linear regression

A Linear Regression model representation is a linear equation :

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i$$

β_0 is usually called intercept or **bias** coefficient. The dimension of the hyperplane of the regression is its **complexity**.



Learning a LR means estimating the coefficients from the training data. Common methods include Gradient Descent or Ordinary Least Squares.

Variations

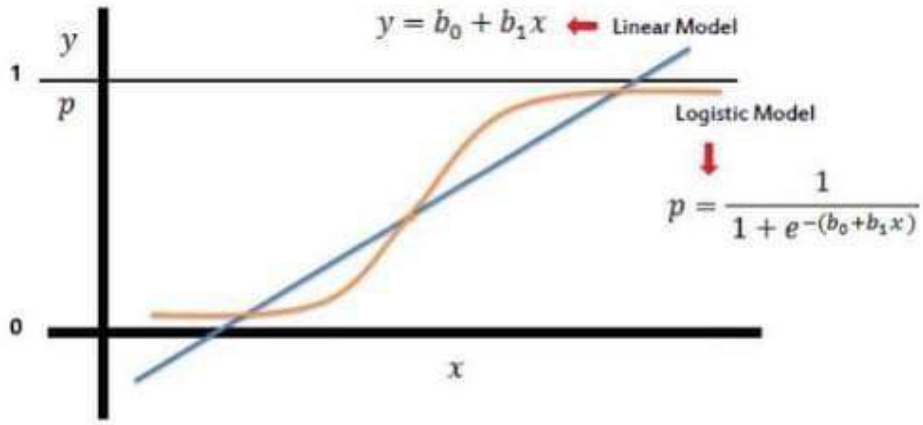
Lasso Regression : where OLS is modified to minimize the **sum** of the coefficients (**L1 regularization**)

Ridge Regression : where OLS is modified to minimize the **squared sum** of the coefficients (**L2 regularization**)

logistic regression

Logistic Regression is a Supervised statistical technique to find the probability of dependent variable.

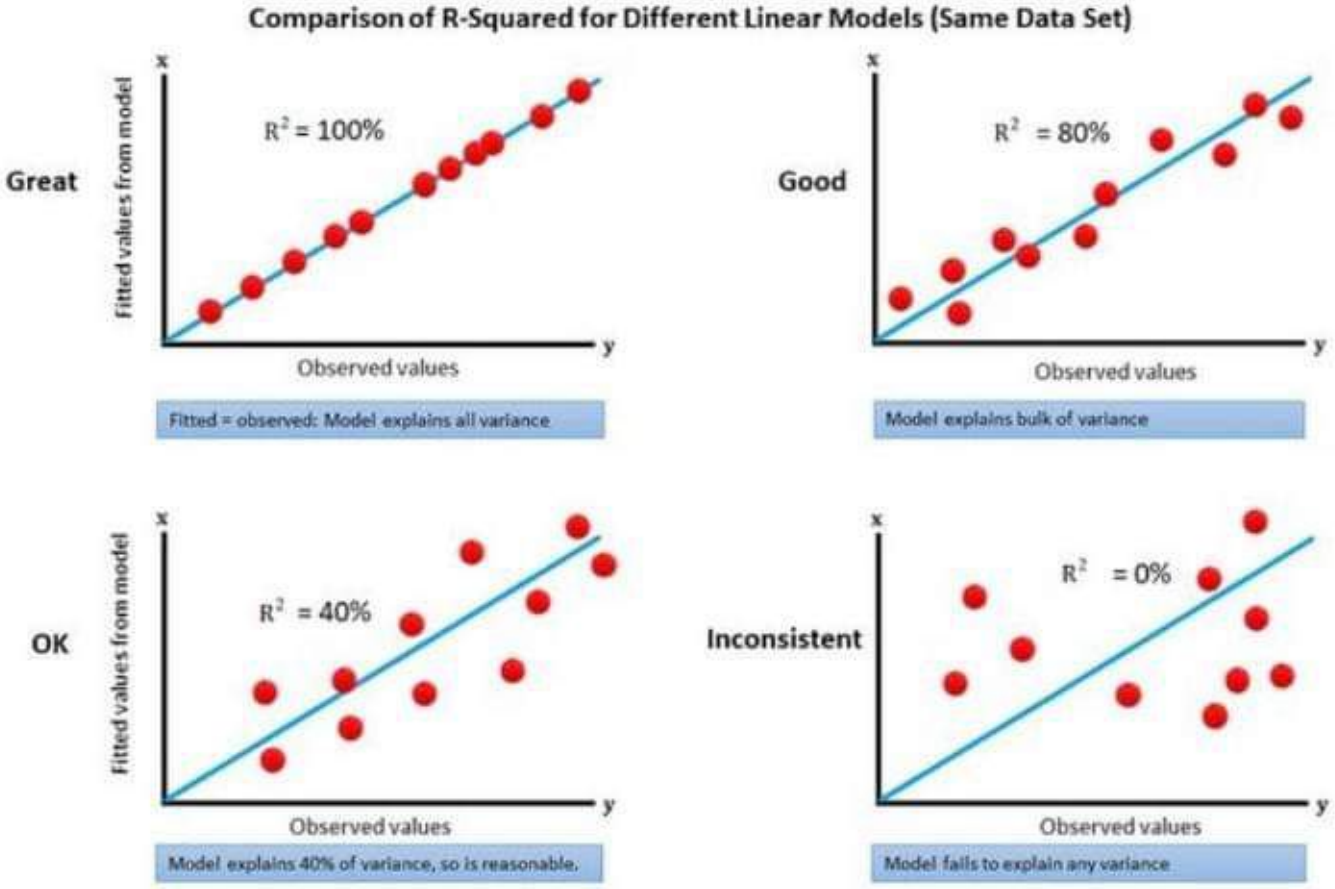
The Logistic Regression instead for fitting the best fit line, condenses the output of the linear function between 0 and 1.



In the formula of the logistic model, when b0 + b1x = 0, then the p will be 0.5, similarly, b0 + b1x > 0, then the p will be going towards 1 and b0 + b1x < 0, then the p will be going towards 0.

R-Square

R-square(R^2) is also known as the **coefficient of determination**, It is the **proportion** of variation in **Y explained by** the independent variables **X**. It is the measure of goodness of fit of the model.



If R^2 is 0.8 it means **80% of the variation** in the output can be explained by the **input variable**.

mean squared error

Mean Squared Error / MSE is one of the most common **regression loss functions**. Mean Squared Error also known as **L2 loss**, we calculate the error by **squaring the difference** between the **predicted** value and **actual** value and **averaging** it across the dataset.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$$

MSE is also known as **Quadratic loss** as the penalty is not proportional to the error but to the **square of the error**. Squaring the error gives higher **weight** to the **outliers**, which results in a smooth gradient for small errors.
A **good** model will have MSE value **closer to zero.**

poisson distribution

The Poisson distribution is a **discrete probability** distribution that expresses the probability of a given **number of events** occurring in a **fixed interval of time** or space if these events occur with a known constant mean rate and independently of the time since the last event.
A discrete random variable X is said to have a Poisson distribution, with parameter $\lambda > 0$ if it has a probability mass function given by:

$$f(k;\lambda) = \Pr(X{=}k) = \frac{\lambda^k e^{-\lambda}}{k!}$$

where,

k is the number of occurrences ($k = 0, 1, 2, \ldots$)
e is Euler's number ($e = 2.71828\ldots$)
! is the factorial function.
The positive real number λ is equal to the expected value of X and also to its variance.

bayes theorem

In **probability theory** and **statistics**, Bayes' theorem named after Thomas Bayes, describes the **probability** of an event, based on **prior knowledge** of conditions that might be related to the event. (Wikipedia)

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

where

A, B = events

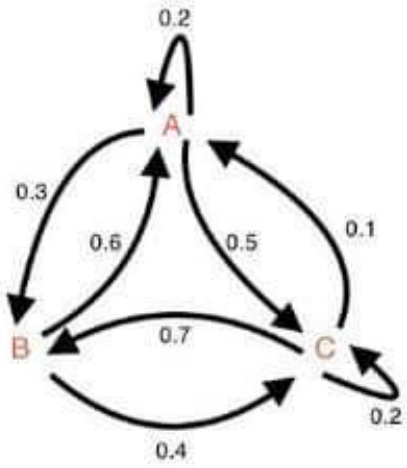
$P(A|B)$ = probability of A given B is true

$P(B|A)$ = probability of B given A is true

$P(A), P(B)$ = the independent probabilities of A and B

markov chain model

A **Markov chain** is a stochastic model created by Andrey Markov, which outlines the **probability** associated with a **sequence** of **events occurring** based on the state in the **previous event.**



A very common **application** of Markov chains in data science is **text prediction**. It's an **area of NLP** which is commonly used in the tech industry by companies like Google, LinkedIn and Instagram. When you're writing emails, google predicts and **suggests you words/phrases** to autocomplete your email, when you receive messages on Instagram or LinkedIn, the app suggests some potential replies.

bernoulli trial

In the theory of probability and statistics, a **Bernoulli trial** (or binomial trial) is a random experiment with exactly **two possible outcomes**, "success" and "failure", in which the probability of success is the **same** every time the experiment is conducted.

A random variable corresponding to a binomial experiment is denoted by ***B(n,p)***, and is said to have a binomial distribution. The probability of exactly ***k*** successes in the experiment ***B(n,p)*** is given by:

$$P(k) = \binom{n}{k} p^k q^{n-k}$$

where,

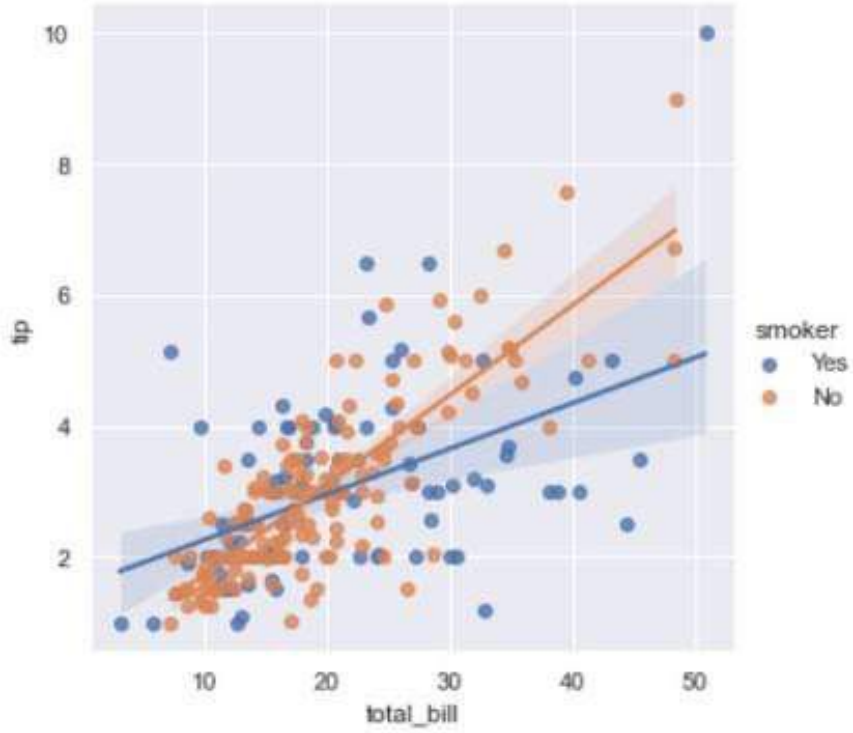
n : number of experiments
k : probability of success in k times
p : probability of single success
q : probability of single failure (1=1-p)

seaborn
scatter with regression

```
import seaborn as sns
# Load Your Dataframe
tips = sns.load_dataset("tips")
# Visualize
sns.set_theme()
sns.lmplot(x="total_bill", y="tip", hue="smoker", data=tips)
```

executed in 479ms, finished 17:15:38 2022-04-24

```
<seaborn.axisgrid.FacetGrid at 0x1f389ef2b80>
```



seaborn
KDE plot with hue

```
import seaborn as sns
# Load Your Dataframe
penguins = sns.load_dataset("penguins")
# Visualize
sns.set_theme()
sns.displot(penguins, x="flipper_length_mm", hue="species", kind="kde", multiple="stack")
```

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```
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```

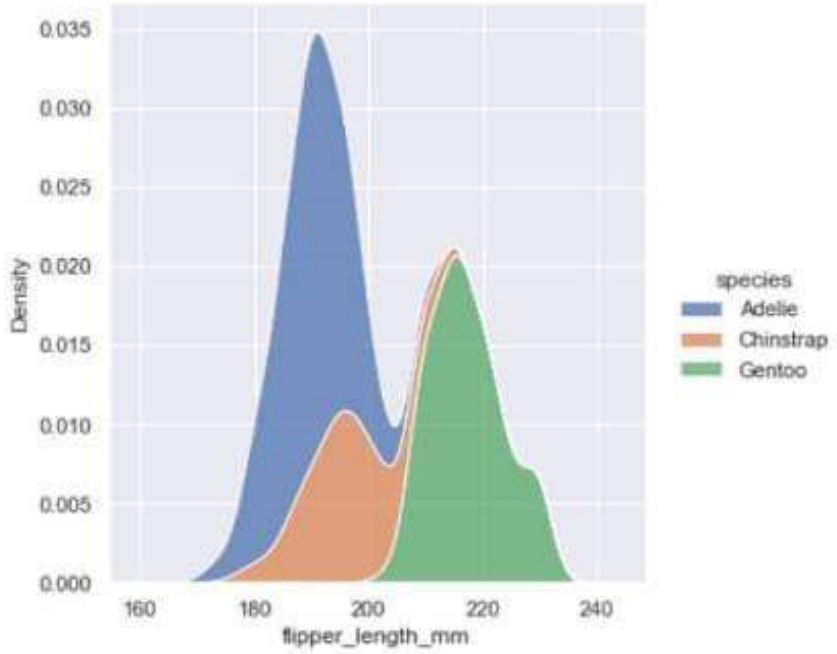

seaborn
density plot (KDE)

```
import seaborn as sns
# Load Your Dataframe
penguins = sns.load_dataset("penguins")
# Visualize
sns.set_theme()
sns.displot(penguins, x="flipper_length_mm", kind="kde")
```

executed in 174ms, finished 17:11:20 2022-04-24

```
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```

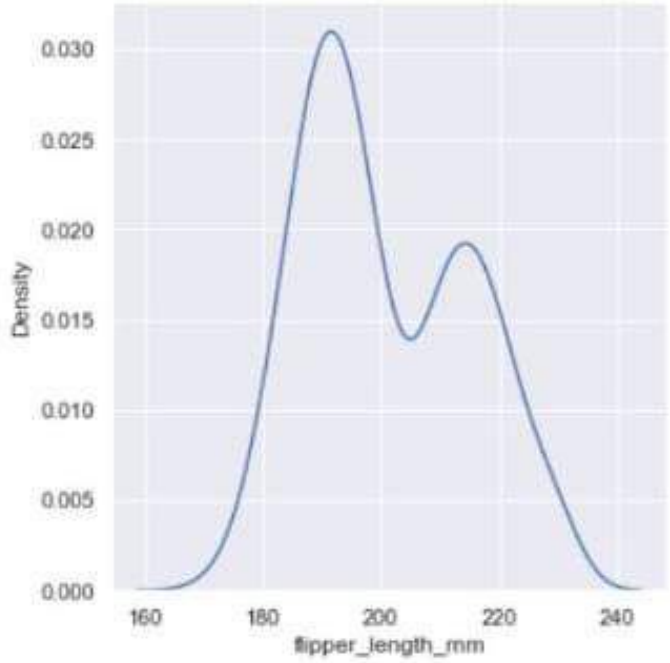

seaborn
basic histogram

```
import seaborn as sns
# Load Your Dataframe
penguins = sns.load_dataset("penguins")
# Visualize
sns.set_theme()
sns.displot(penguins, x="flipper_length_mm")
```

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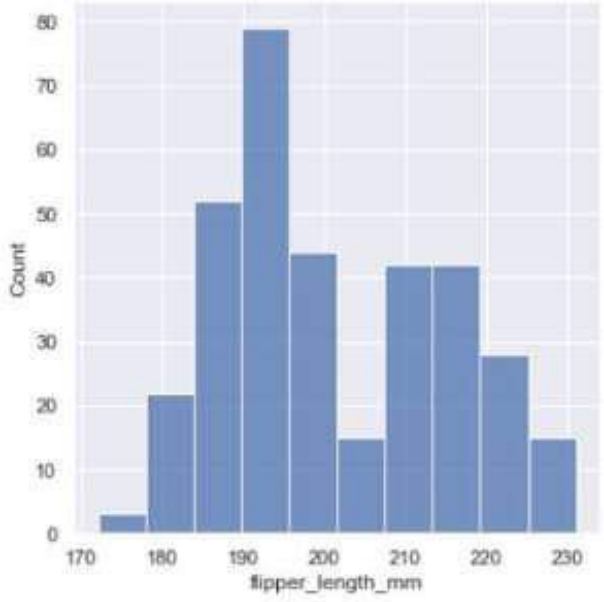
```
<seaborn.axisgrid.FacetGrid at 0x1bd3632d250>
```



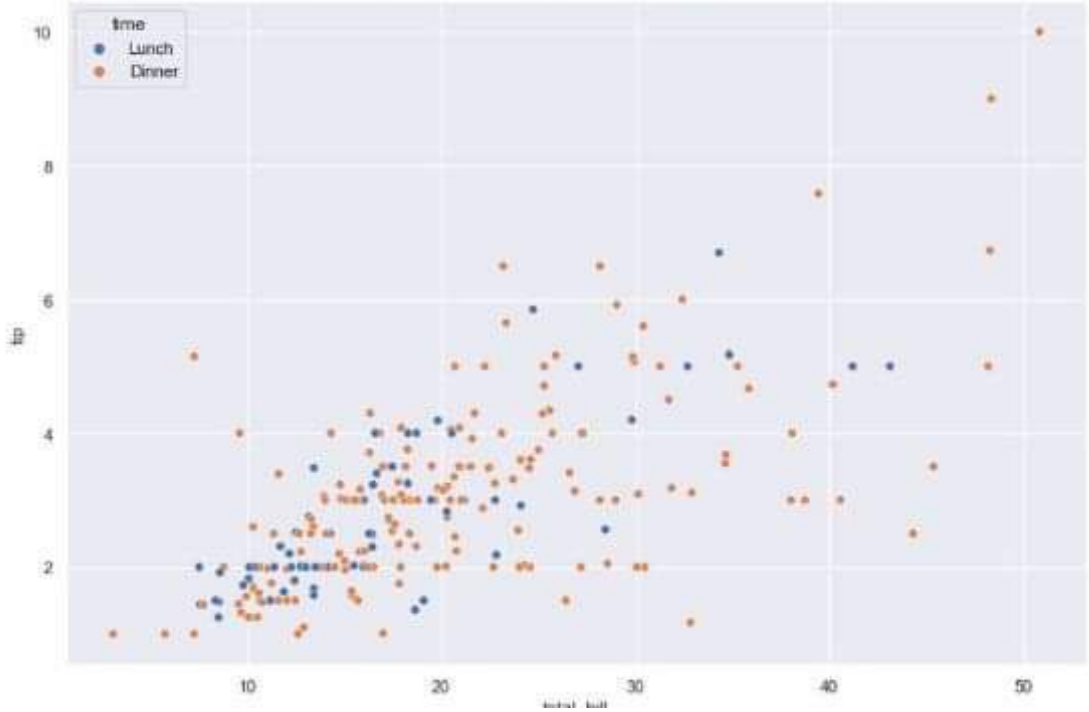
seaborn
basic scatterplot

```
import seaborn as sns

# Load Your Dataframe
tips = sns.load_dataset("tips")

# Plot Scatter with Hue

# Set Theme
sns.set_theme()
# Set figure size
sns.set(rc={'figure.figsize':(12,8)})
# Visualize
sns.scatterplot(data=tips, x="total_bill", y="tip", hue="time")
```

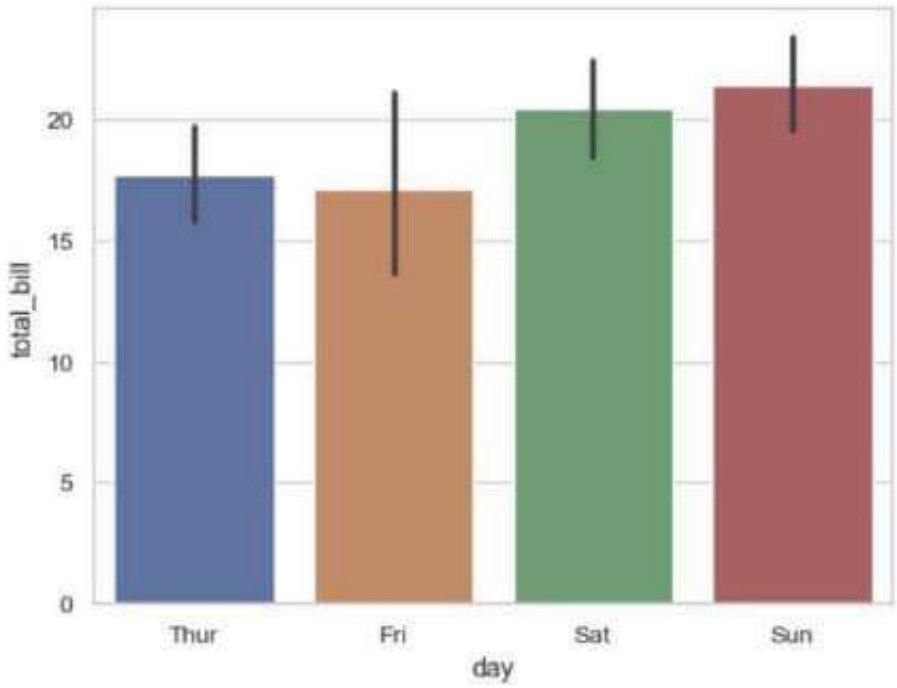


seaborn
simple barchart

Draw a set of vertical bar plots grouped by a categorical variable:

```
>>> import seaborn as sns
>>> sns.set_theme(style="whitegrid")
>>> tips = sns.load_dataset("tips")
>>> ax = sns.barplot(x="day", y="total_bill", data=tips)
```

your dataframe



the law of large number

The law of large numbers is a theorem that describes the result of performing the same experiment a large number of times. According to the law, the **average** of the results obtained from a large number of trials should be **close** to the **expected value.**

as $n \to \infty$, the sample mean $\langle x \rangle$ equals the population mean μ of each variable.

$$\begin{aligned}\langle X \rangle &= \left\langle \frac{X_1 + \ldots + X_n}{n} \right\rangle \\ &= \frac{1}{n} \left(\langle X_1 \rangle + \ldots + \langle X_n \rangle \right) \\ &= \frac{n\,\mu}{n} \\ &= \mu.\end{aligned}$$

Example : Law of large numbers in **Insurance**

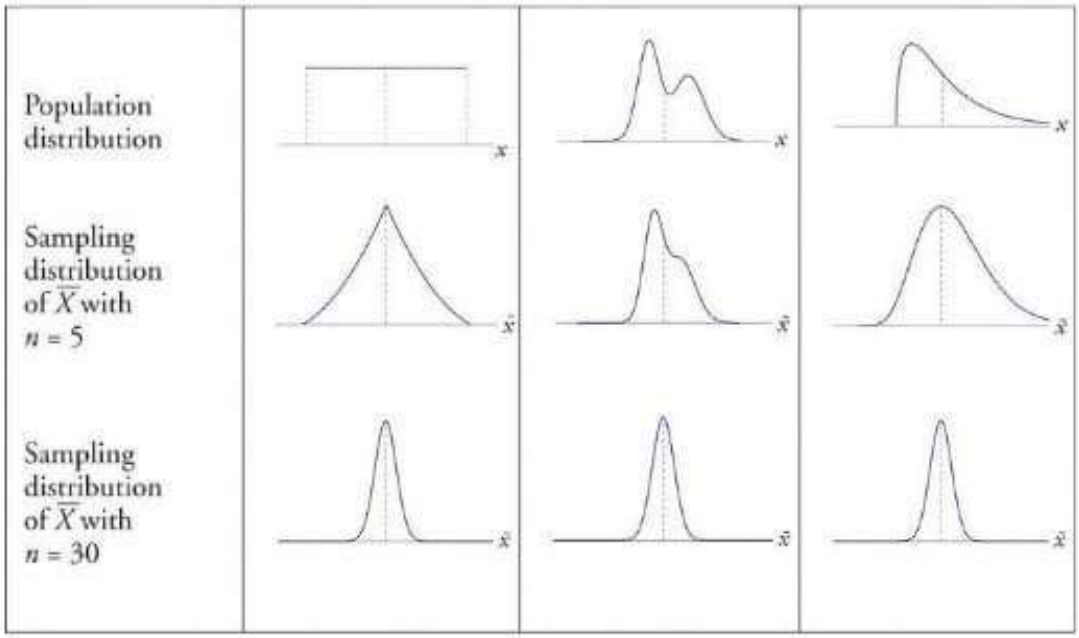
Imagine **500** people **paying** a **premium** for his property to the Insurance. Even though they pay you for the property damage that was caused by fire to **10%** of the subscriber i.e. **50** people they have the premium of **450 people still**. And that's how they calculate their risk management and the Law of Large Numbers comes in the role.

central limit theorem

For **large** sample sizes, the sampling distribution of **means** will approximate to **normal distribution** even if the population distribution is not normal.

Mean of the sample means is computed as $\mu_{\bar{X}} = \mu$

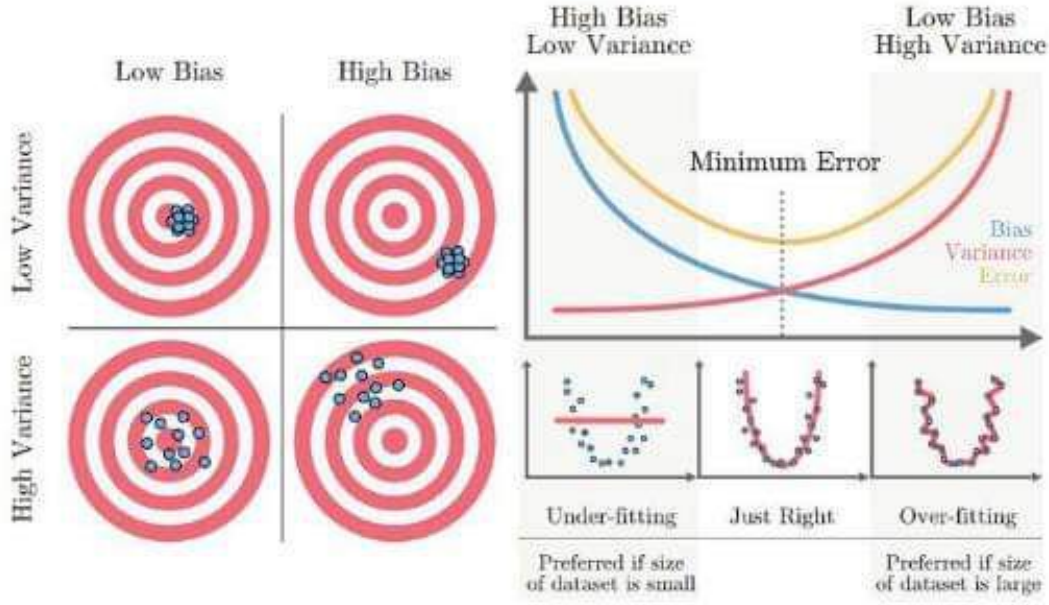
And the **standard deviation** of sample means $\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}}$



Above picture, shows 3 different **population** distributions which are **not normal**. **Sampling** distribution of **means** gets a little closer to normal distribution when we take n =5 and almost normal distribution when **n=30**

bias-variance tradeoff

Bias–variance tradeoff is the property of a model that the **variance** of the parameter estimated across samples can be **reduced** by **increasing the bias** in the estimated parameters.



Bias-variance Tradeoff

- **Increasing** bias (not always) **reduces** variance and vice-versa
- Error = bias2 + variance +irreducible error
- The **best** model is where the **error** is reduced
- **Compromise** between bias and variance

seaborn
joint plot

```
import seaborn as sns
# Load Your Dataframe
penguins = sns.load_dataset("penguins")
# Visualize
sns.set_theme()
sns.jointplot(data=penguins, x="bill_length_mm", y="bill_depth_mm", hue="species")
```

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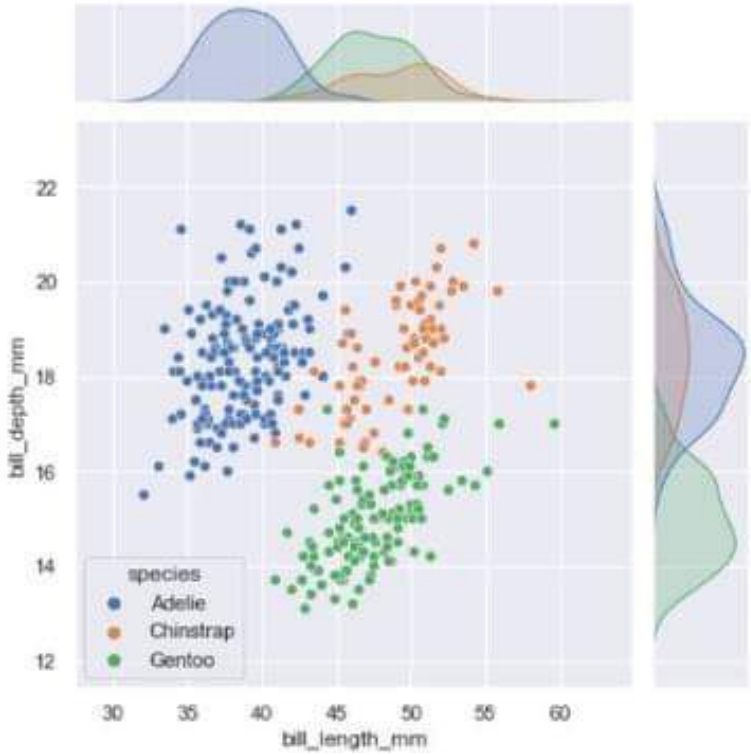
```
<seaborn.axisgrid.JointGrid at 0x18b496fb130>
```



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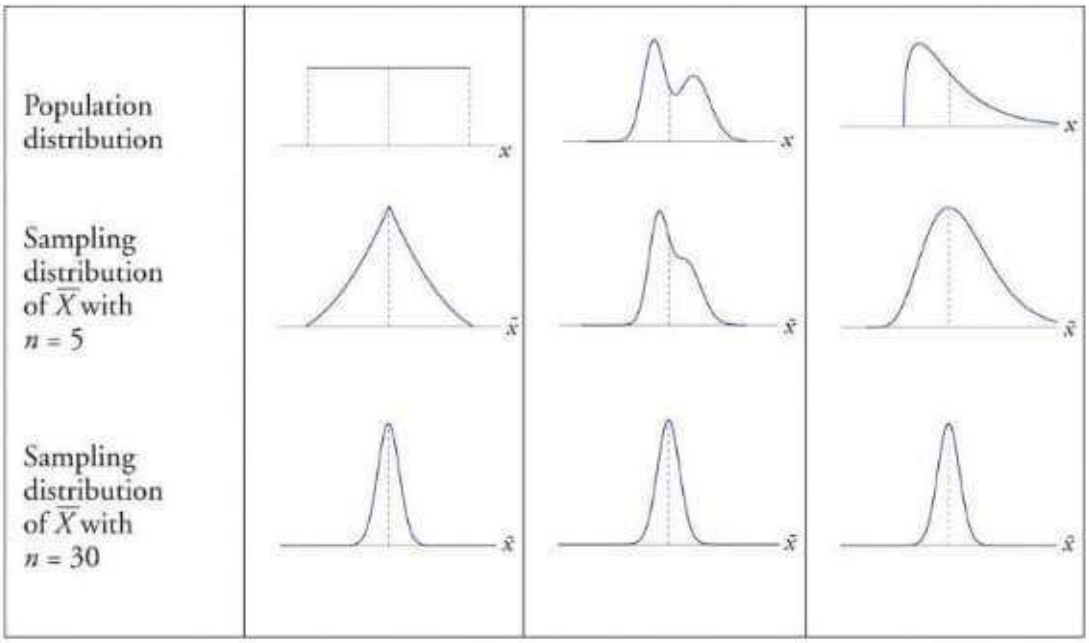

Above picture, shows 3 different **population** distributions which are **not normal**. **Sampling** distribution of **means** gets a little closer to normal distribution when we take n =5 and almost normal distribution when **n=30**