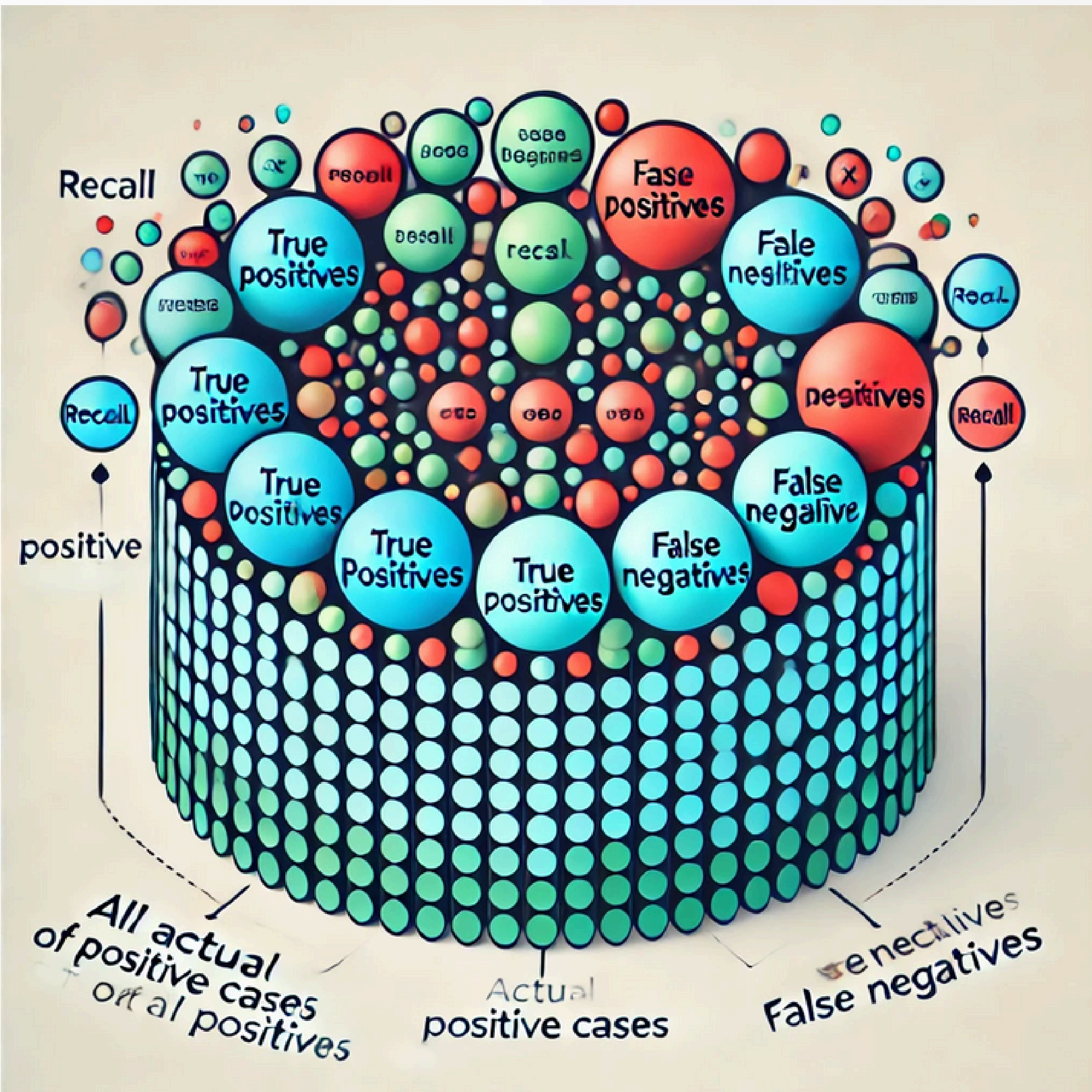
All you need to know about "Recall" in Data Science

Definition: Recall is defined as the ratio of correctly predicted positive observations to all actual positives.

Interpretation: A high recall indicates that the model is effective at identifying positive instances but does not account for false positives. It answers the question: Among all the actual positive instances, how many did the model correctly identify?



Precision Using Confusion Matrix :

Recall, also known as sensitivity or true positive rate, is the ratio of correctly predicted positive observations to all observations in the actual class.

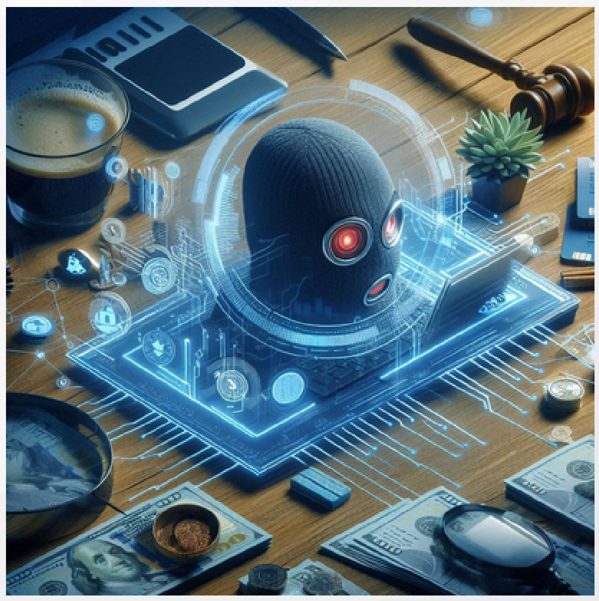
$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

		Predicted Values	
		Positive	Negative
Actual Values	Positive	True Positives (TP)	False Negatives (FN)
	Negative	False Positive (FP)	True Negatives (TN)

When to Use Recall

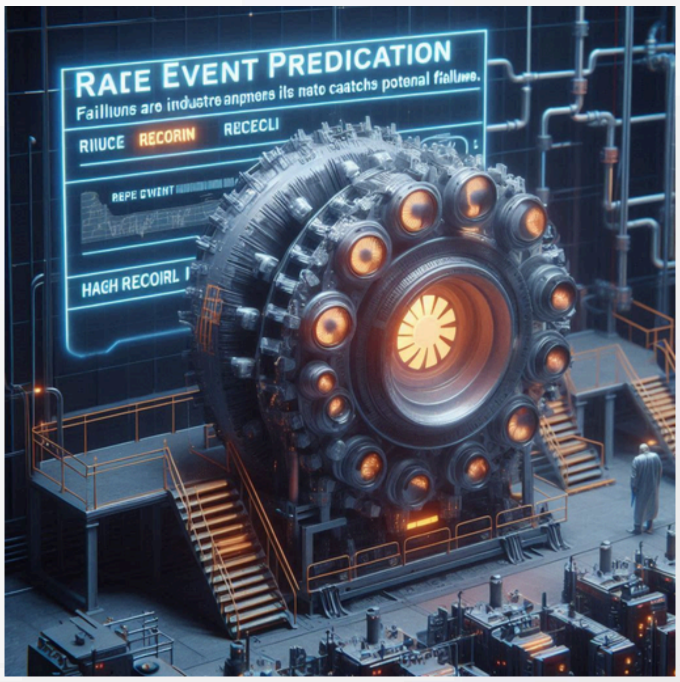
Recall should be prioritized in situations where:

- Missing Positive Cases is Costly or Dangerous:
  - In scenarios where failing to identify a positive instance can lead to significant harm, recall becomes critical.
  - Examples:
    - Healthcare: In medical diagnostics, such as cancer detection, failing to identify a diseased patient (a false negative) can lead to untreated conditions, potentially resulting in severe outcomes or even death.
    - Fraud Detection: In financial systems, missing a fraudulent transaction could result in substantial financial losses. Here, it's better to flag suspicious transactions (even if some are false positives) to avoid missing any fraud.



When to Use Recall

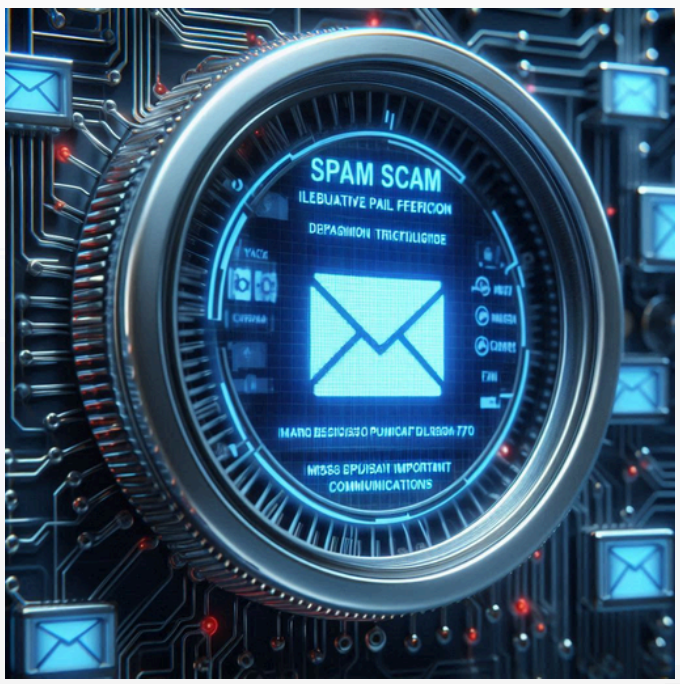
- Imbalanced Datasets:
  - When the dataset is imbalanced, meaning the number of positive cases is much smaller than the number of negative cases, recall becomes a more reliable metric.
  - Examples:
    - Anomaly Detection: In cybersecurity, detecting anomalies like breaches or unauthorized access is crucial. The vast majority of data is normal, so focusing on recall helps ensure that the few anomalies are not overlooked.
    - Rare Event Prediction: In predictive maintenance for industrial equipment, failures are rare but costly. High recall ensures that the model catches most potential failures.



When Not to Use Recall?

The Cost of False Positives is High:

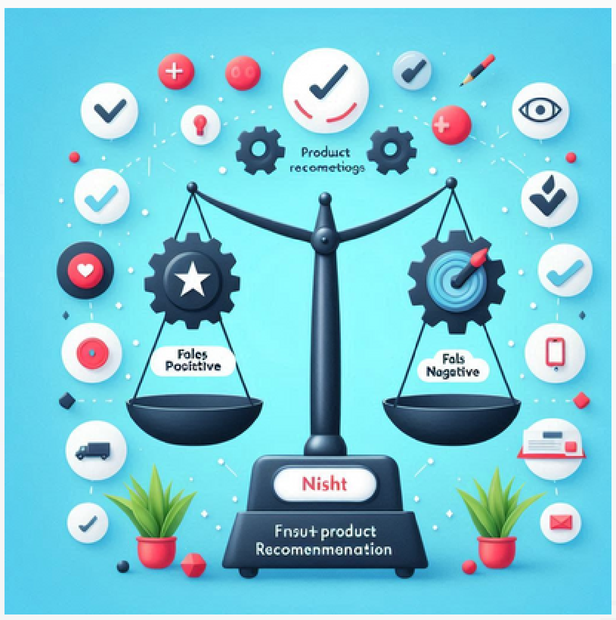
- When false positives lead to significant negative consequences, precision might be more important than recall.
- Examples:
    - Spam Detection: In email filtering, marking a legitimate email as spam (false positive) can result in missed important communications. Precision is prioritized to avoid this.
    - Legal Proceedings: In predictive policing or legal judgments, wrongly identifying an innocent person as guilty can have severe consequences. Precision is crucial to ensure fairness and accuracy.



When Not to Use Recall?

Balanced Importance of Both Positive and Negative Cases:

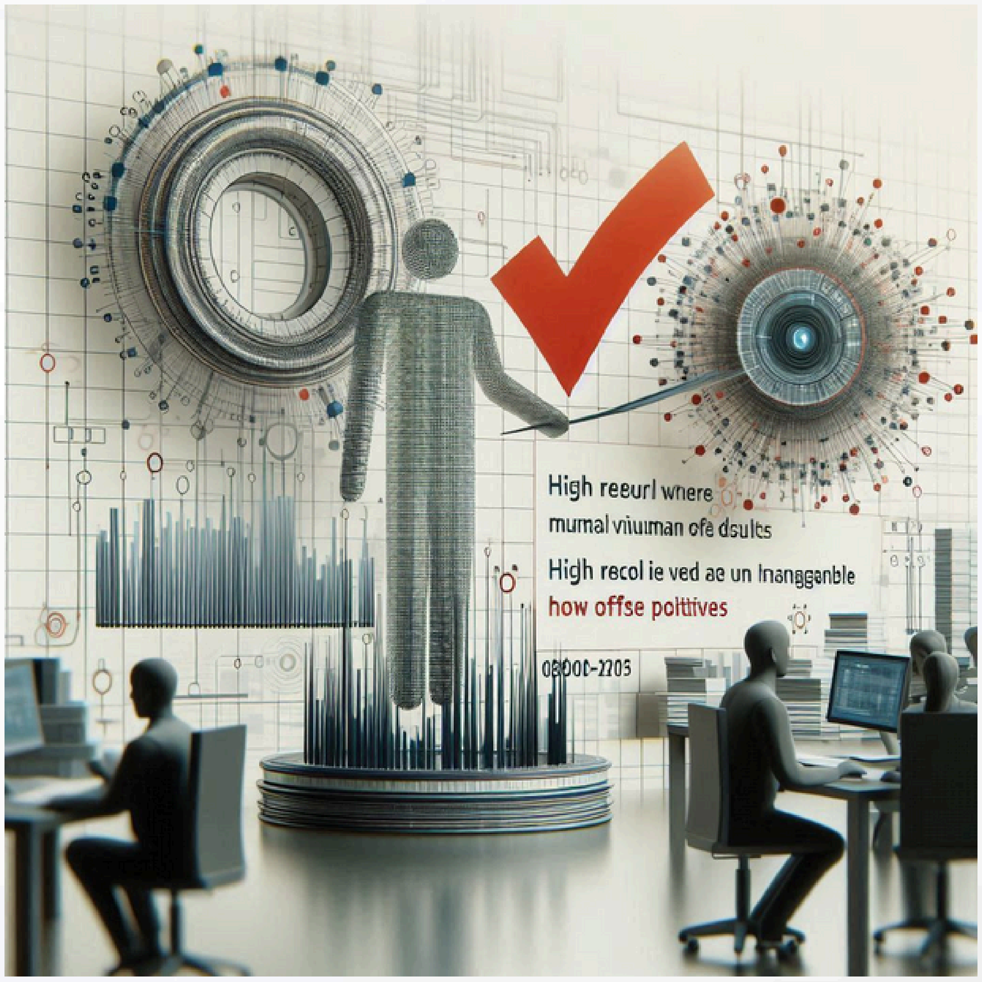
- When both false positives and false negatives have similar consequences, metrics like the F1 score, which balances recall and precision, are more appropriate.
- Examples:
  - Product Recommendations: In e-commerce, recommending the wrong product (false positive) or missing a product that a customer might like (false negative) both affect user experience. A balanced approach is needed.
  - Job Applicant Screening: In recruitment, falsely rejecting a qualified candidate (false negative) or accepting an unqualified one (false positive) can both have implications. Balancing precision and recall is necessary.



When Not to Use Recall?

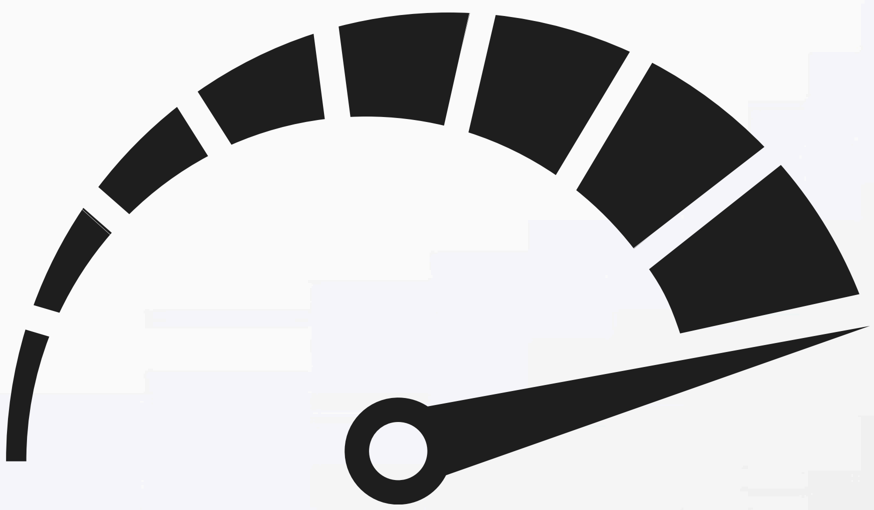
Situations with High Data Volume:

- In environments with large volumes of data where manual verification of results is required, high recall may lead to an unmanageable number of false positives.
- Examples:
  - Automated Customer Support: If a system flags too many issues as requiring manual review, it can overwhelm support teams. Precision might need to be emphasized to keep the workload manageable.



What are Good Recall Values?

- High Recall (Above 0.8 or 80%):
- Considered Good: In most scenarios where recall is crucial, a recall value above 0.8 is typically considered good. This means the model is capturing at least 80% of the true positive cases.
- Use Cases:
  - Healthcare: For critical diagnostics, a recall above 0.8 is often required to ensure most patients with the condition are identified.
  - Fraud Detection: In financial systems, a recall of 0.8 or higher is desirable to catch the majority of fraudulent transactions.



What are Good Recall Values?

- Moderate Recall (0.6 to 0.8 or 60% to 80%):
- Acceptable in Certain Contexts: A recall in this range might be acceptable depending on the domain and the acceptable level of risk for false negatives.
- Use Cases:
    - Marketing: In customer churn prediction, a recall around 0.7 might be sufficient, balancing the effort to retain customers with the cost of unnecessary retention efforts.
    - Search Engines: A recall of around 0.7 can be good if combined with a reasonable precision to ensure most relevant results are presented to users.

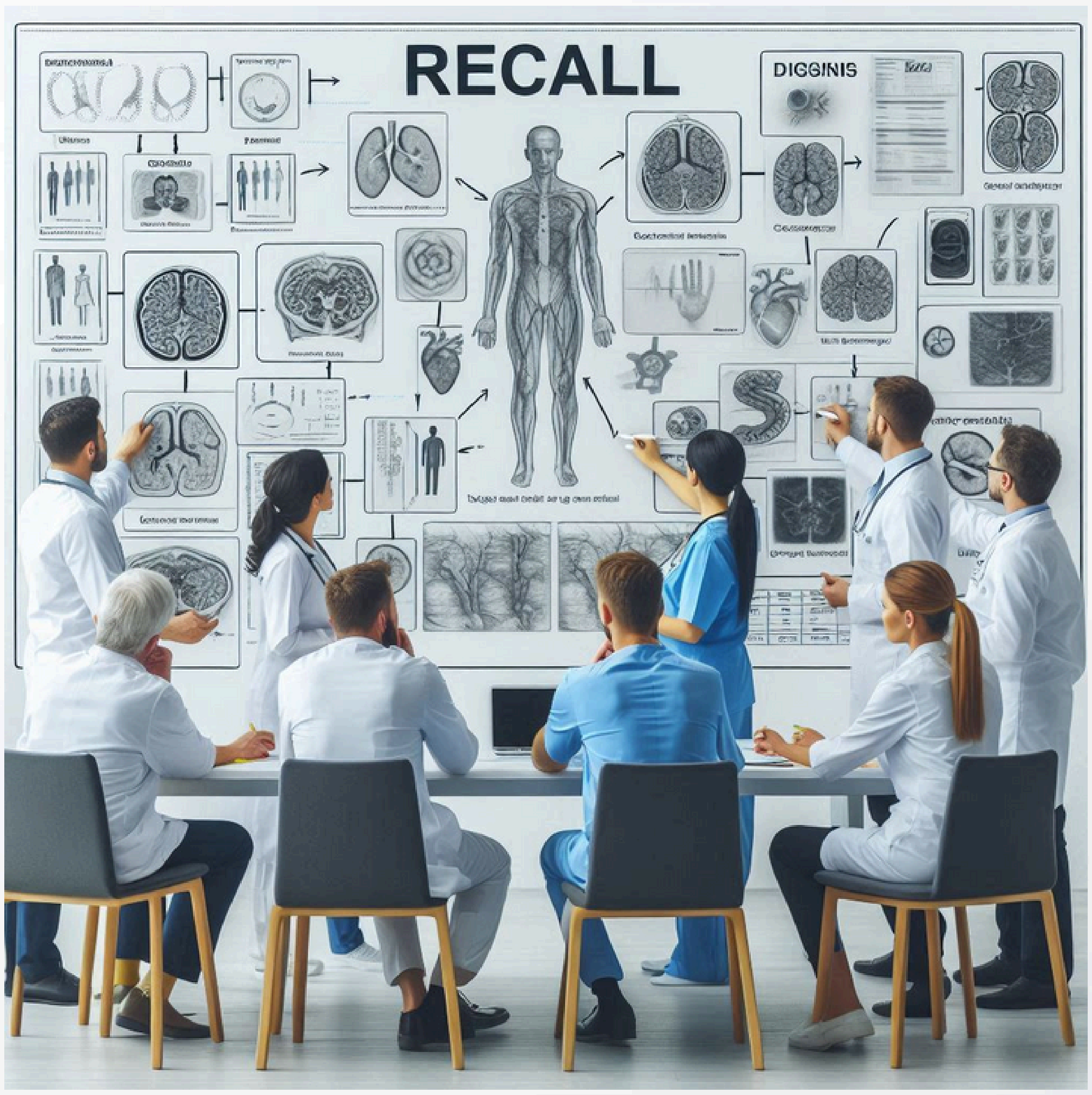
What are Good Recall Values?

- Low Recall (Below 0.6 or 60%):
- Considered Poor in Critical Scenarios: A recall below 0.6 is generally considered low, especially in high-stakes situations where missing positives can have significant consequences.
- Use Cases:
  - Not Suitable for Critical Applications: In domains like healthcare, finance, or safety-critical systems, a recall below 0.6 would likely be insufficient and could lead to unacceptable risks.
  - Might Be Acceptable with High Precision: In some scenarios where precision is prioritized over recall (e.g., spam detection), a low recall might be acceptable if it means fewer false positives.

Use Cases

Medical Diagnosis:

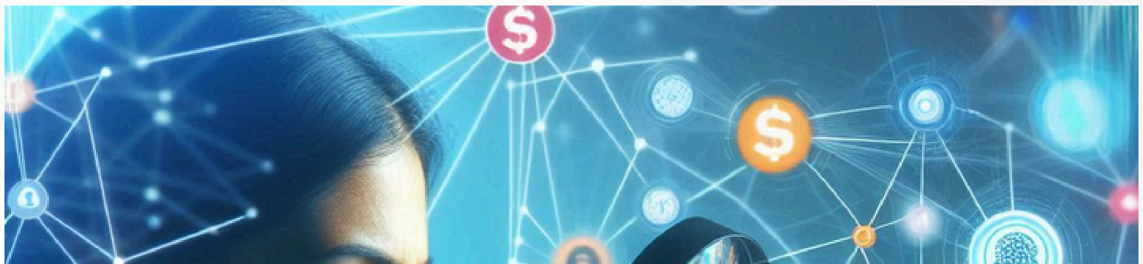
- Scenario: A machine learning model is developed to detect breast cancer from mammogram images.
- Why Recall?: Missing a cancerous tumor could lead to delayed treatment and worsened patient outcomes. Hence, maximizing recall ensures that most, if not all, cancer cases are identified, even if it means some non-cancerous cases are flagged for further testing.



Use Cases

Financial Fraud Detection:

- Scenario: A bank uses a predictive model to identify fraudulent transactions.
- Why Recall?: The bank prefers to investigate more transactions to ensure all potential frauds are caught, even if it means investigating some legitimate transactions. The cost of missing a fraudulent transaction is much higher than investigating a false alarm.



Use Cases

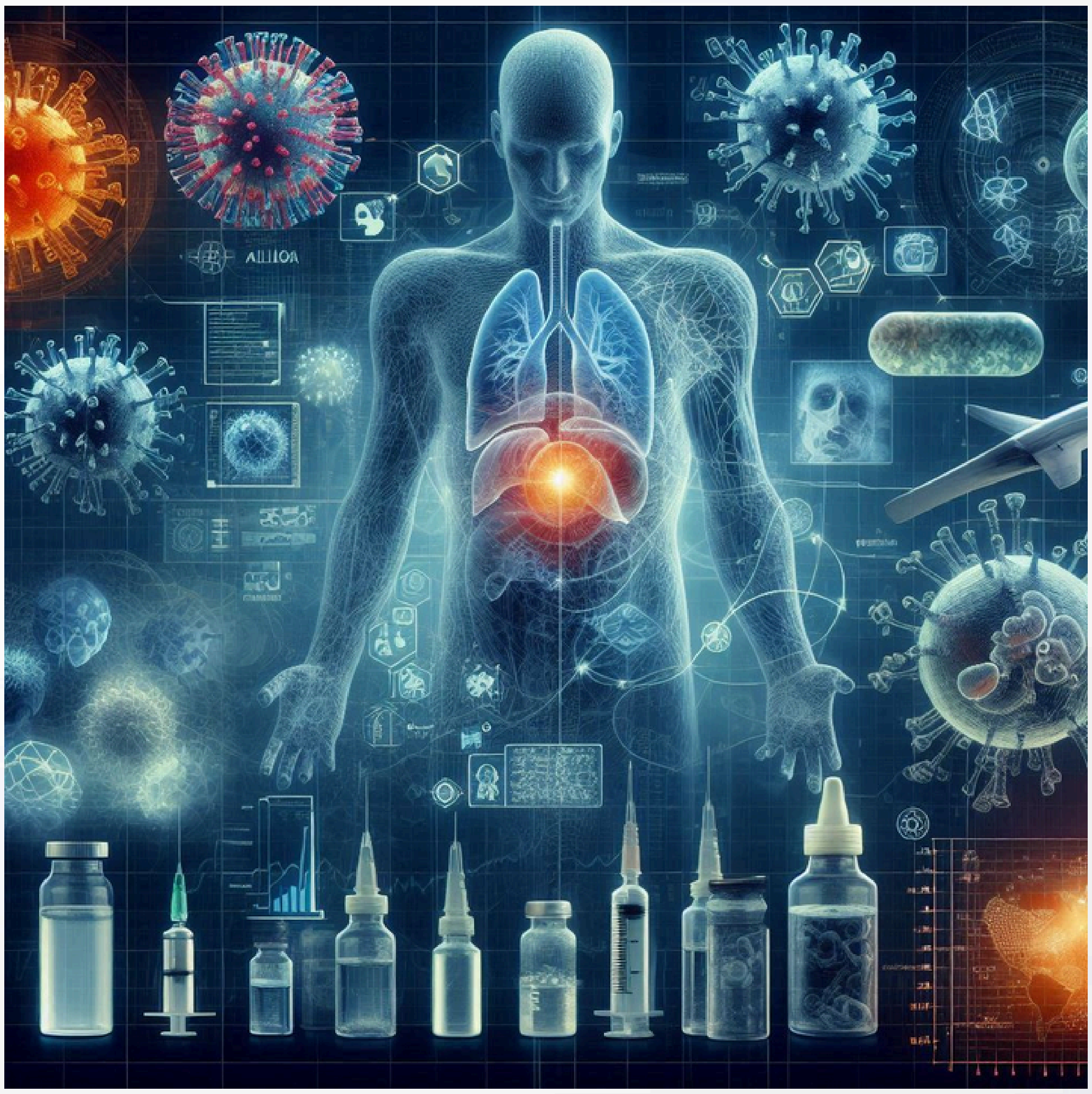
Customer Churn Prediction:

- Scenario: A telecom company aims to predict which customers are likely to leave the service.
- Why Recall?: Missing a customer likely to churn means losing potential revenue. The company would rather reach out to more customers (even those who may not churn) to retain as many as possible.

Use Cases

Disease Outbreak Detection:

- Scenario: Public health authorities use data models to detect outbreaks of infectious diseases.
- Why Recall?: Detecting an outbreak early is crucial to prevent widespread infection. High recall ensures that most potential outbreaks are flagged, even if it means some false alarms are raised.



Summary

- Recall is an essential metric in data science when the focus is on minimizing false negatives, especially in scenarios where missing a positive case can have severe consequences.
- However, it's not always the best choice, particularly when false positives carry significant costs or when a balanced approach is needed. Understanding when to use recall and when to prioritize other metrics like precision is key to developing effective and reliable models.
- By carefully considering the context and consequences of each decision, data scientists can choose the most appropriate metric for their specific application.

Special Thanks to ChatGPT and Gemini for Content support