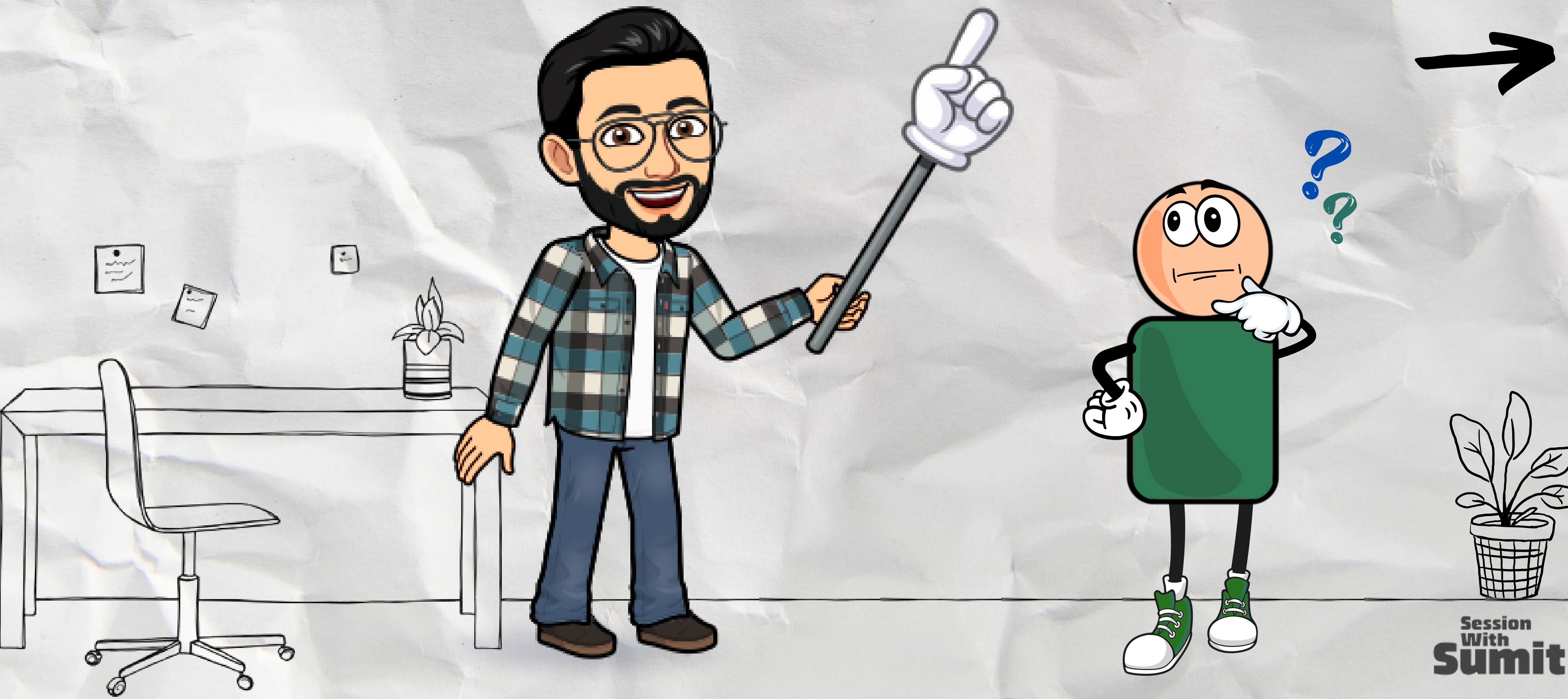
# Precision vs Recall

> "EXPLAIN THE DIFFERENCE BETWEEN PRECISION AND RECALL"



First, we'll learn about Precision and Recall. Then, we'll determine their suitable use cases.

Precision is the ratio between the True Positives and all the Positives. It basically checks the prediction accuracy of the positive class.

$$Precision = \frac{True\ Positive(TP)}{True\ Positive(TP) + False\ Positive(FP)}$$

Recall is the ratio between the number of true positives to the number of true positives and the number of false negatives. It is the measure of our model correctly identifying True Positives.

$$Recall = \frac{True\ Positive(TP)}{True\ Positive(TP) + False\ Negative(FN)}$$

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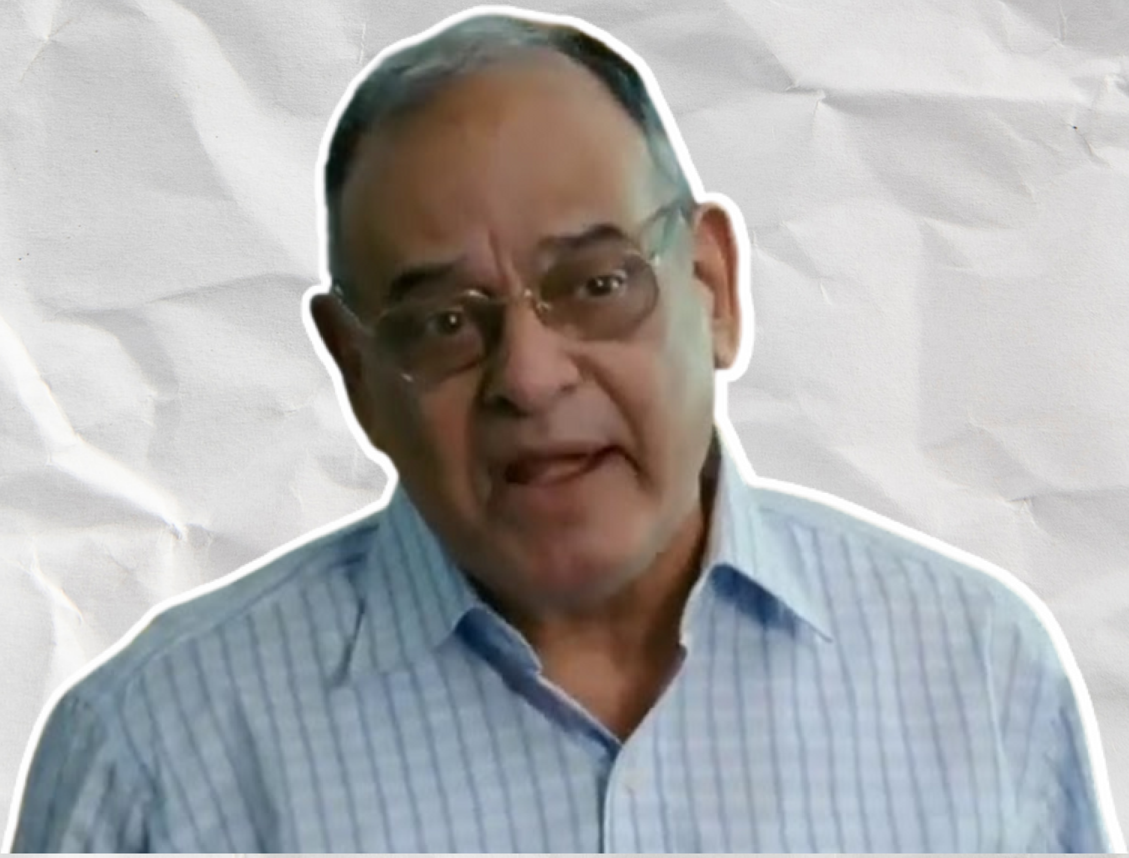
Ye kya bol raha hai baba

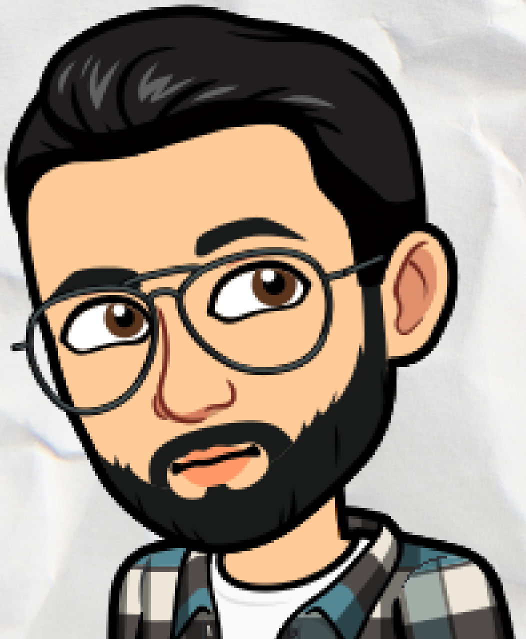


Sumit , will you please elaborate ?

# Let's understand with an example

Chandu is a well-known bookie renowned for his exceptional accuracy in predicting the outcome of IPL matches. He attributes his remarkable foresight to what he refers to as his "7th sense."

Sumit is doubtful about Chandu's claim. So he uses the concept of classification metrics to check Chandu's claim.



So to test Chandu's claim, Sumit closely monitored the next 10 IPL games between CSK and RCB and the predictions made by Chandu.

**(Since sumit is a CSK supporter, here we are considering CSK as a positive class)**

| Game no. | Actual winner | Chandu's Prediction |
|---|---|---|
| 1 | RCB | RCB |
| 2 | CSK | RCB |
| 3 | CSK | CSK |
| 4 | CSK | CSK |
| 5 | RCB | CSK |
| 6 | RCB | RCB |
| 7 | CSK | RCB |
| 8 | RCB | CSK |
| 9 | CSK | RCB |
| 10 | CSK | CSK |

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Now before we can calculate any classification performance metric, we need to understand a few terms.

**True Prediction: When the actual outcome is the same as the predictions then it's known as True Prediction.**

| Actual winner | Chandu's Prediction |
|---|---|
| CSK | CSK |
| RCB | RCB |

**False Prediction: When the actual outcome is different from the predictions then it's known as a False Prediction.**

| Actual winner | Chandu's Prediction |
|---|---|
| CSK | RCB |
| RCB | CSK |

# Now, how to generate the True and False labels?

Simple, look into the predictions. If the prediction is a positive class then we call the prediction as positive else we call it negative. (Remember, here CSK is a positive label to us)

| Actual winner | Chandu's Prediction | Tag |
|---|---|---|
| CSK | CSK | TP |
| RCB | RCB | TN |
| CSK | RCB | FN |
| RCB | CSK | FP |

Here, the actual outcome is the same as prediction and the predicted label is a positive class, hence this is known as True Positive

Here, the actual outcome is different from the prediction and the predicted label is a negative class, hence this is known as False Negative

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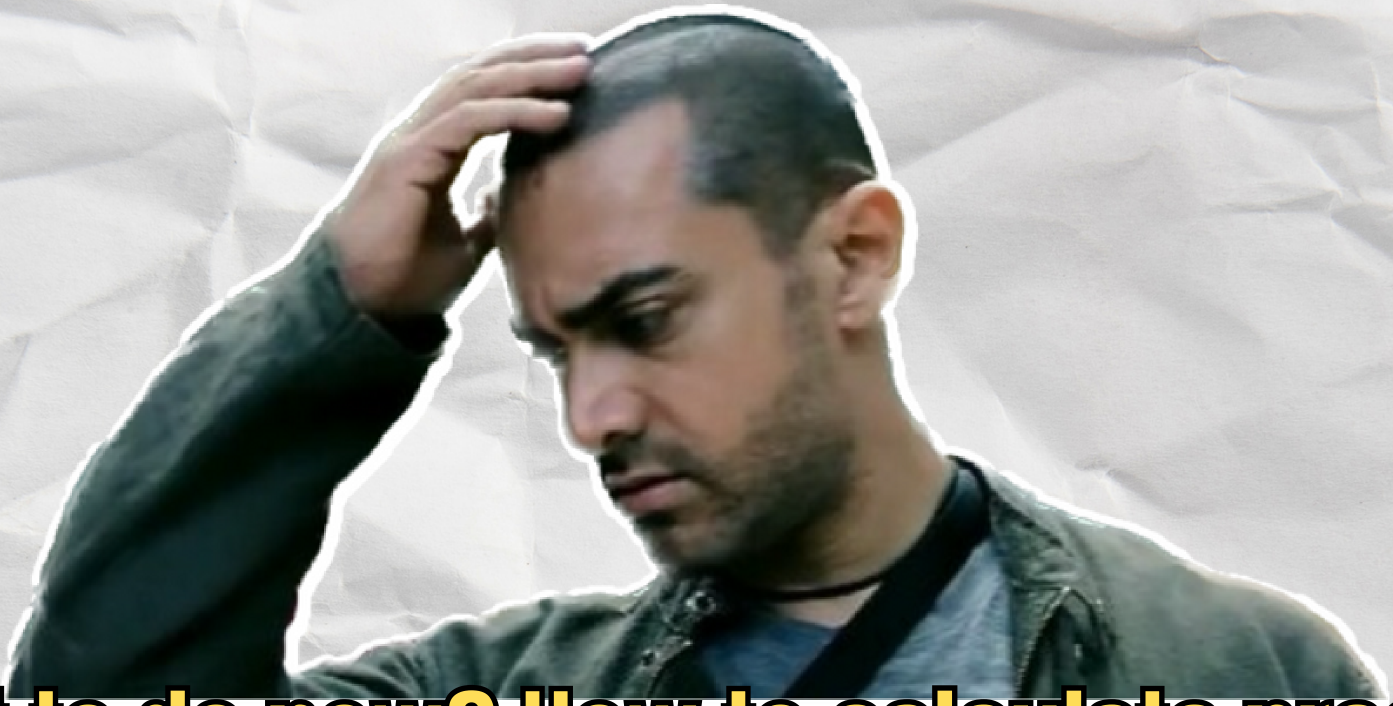
# Now let’s tag all the predictions made by bookie Chandu.

| Game no. | Actual winner | Chandu’s Prediction | Tag |
|---|---|---|---|
| 1 | RCB | RCB | TN |
| 2 | CSK | RCB | FN |
| 3 | CSK | CSK | TP |
| 4 | CSK | CSK | TP |
| 5 | RCB | CSK | FP |
| 6 | RCB | RCB | TN |
| 7 | CSK | RCB | FN |
| 8 | RCB | CSK | FP |
| 9 | CSK | RCB | FN |
| 10 | CSK | CSK | TP |

# But how to calculate precision and recall now?



What to do now? How to calculate precision and recall?

Wait, be patient. Let me complete. →

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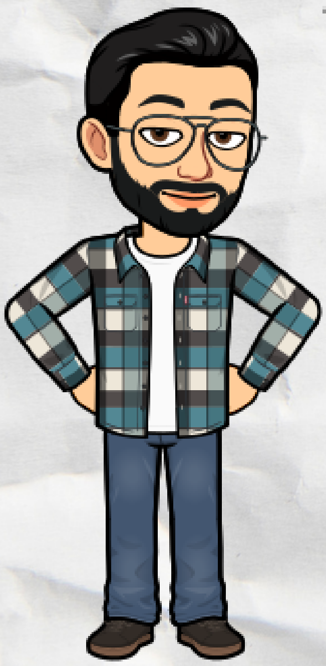
**Precision is defined as the ratio between True Positive to the total number of cases that were predicted positive. In short, precision helps us to understand how precise the predictions were.**

Total number of True Positive (TP) cases = 3



Total number of cases which were predicted as positive (prediction was csk)

(TP + FP) = 5

$$\boxed{\text{Precision} = \frac{TP}{TP + FP} = \frac{3}{5} = 0.6}$$

**Recall is defined as the ratio between True Positive to the total number of cases that were actually positive. In short, recall helps us to evaluate if the machine learning model is correctly able to predict/recall positive cases or not. How good the model is in predicting the positive cases.**

Total number of True Positive (TP) cases = 3

Total number of cases for which the actual outcome was positive (TP+FN) = 6

$$\boxed{\text{Recall} = \frac{TP}{TP+FN} = \frac{3}{6} = 0.5}$$


Ok , Hmm
But what is the use of all this?
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# Let's understand how we can make use of Precision and Recall.

In the case of Chandu,

- Precision was 0.6
- Recall was 0.5

Which basically means out of all the matches in which Chandu predicted that CSK would win the match, only 60% of the time, CSK actually won.

And out of all the matches in which CSK actually won the match, Chandu predicted CSK winning the match only 50% of the time.

So, does Chandu really have some magical powers?

No, Chandu was not accurate about his predictions. His predictions were 50-50.

# But, should I use precision or should I use recall?

Precision

Recall

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If we closely observe the formula of Precision. The metric precision is inversely proportional to False Positive cases. This basically means, the lower the False Positive cases in my predictions, the higher the Precision.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\boxed{\text{Precision} \propto \frac{1}{FP}}$$

Lower the value of false positive, higher the precision

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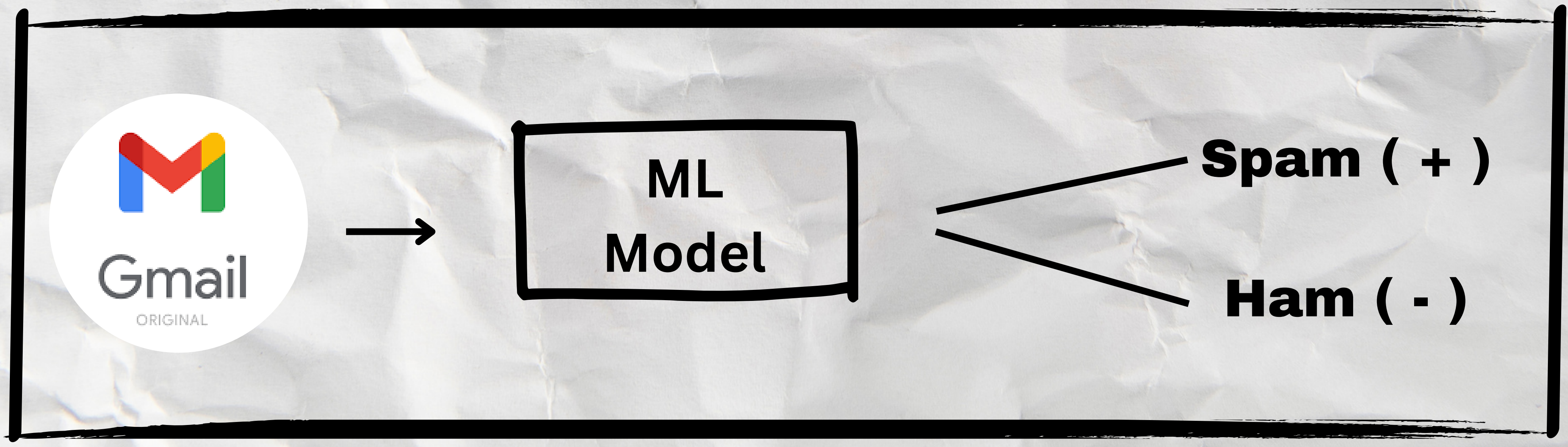
# But when do we need to reduce the False Positive cases?

Let's say you are working on an Email Spam-Ham ML Model. A Machine Learning Model that can predict if a particular email is a spam email or not.
Now, if the model predicts the email to be spam, the ml model will directly transfer the email to the spam folder without any notification to the user.



# Here the ML Model can commit two errors

- False Positive Error: Email is not a spam email but predicted as spam.
- False Negative Error: Email is a spam email but predicted as not spam.

Now, which one is more harmful?
A false positive case is more harmful here because in this case, a user can miss out on an important email.

In short, if in a use case, False Positive is more harmful than False Negative, we use precision as a metric to evaluate the performance of the model. We want the model to make as least FP Errors as possible.

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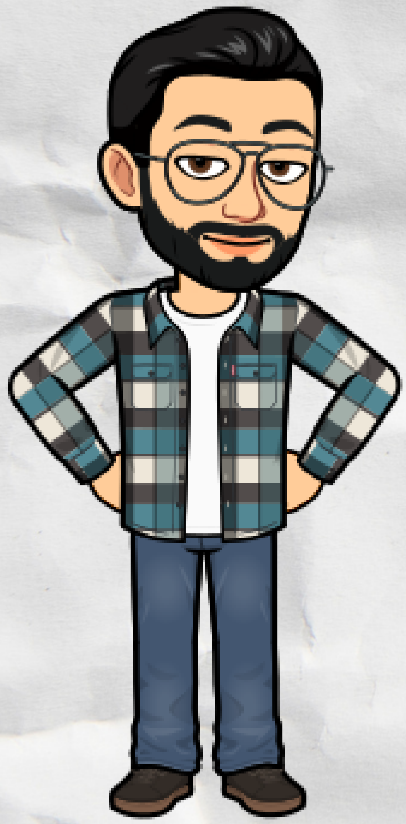
If we closely observe the formula of Recall. The metric recall is inversely proportional to False Negative cases. This basically means, the lower the False Negative cases in my predictions, the higher the recall.



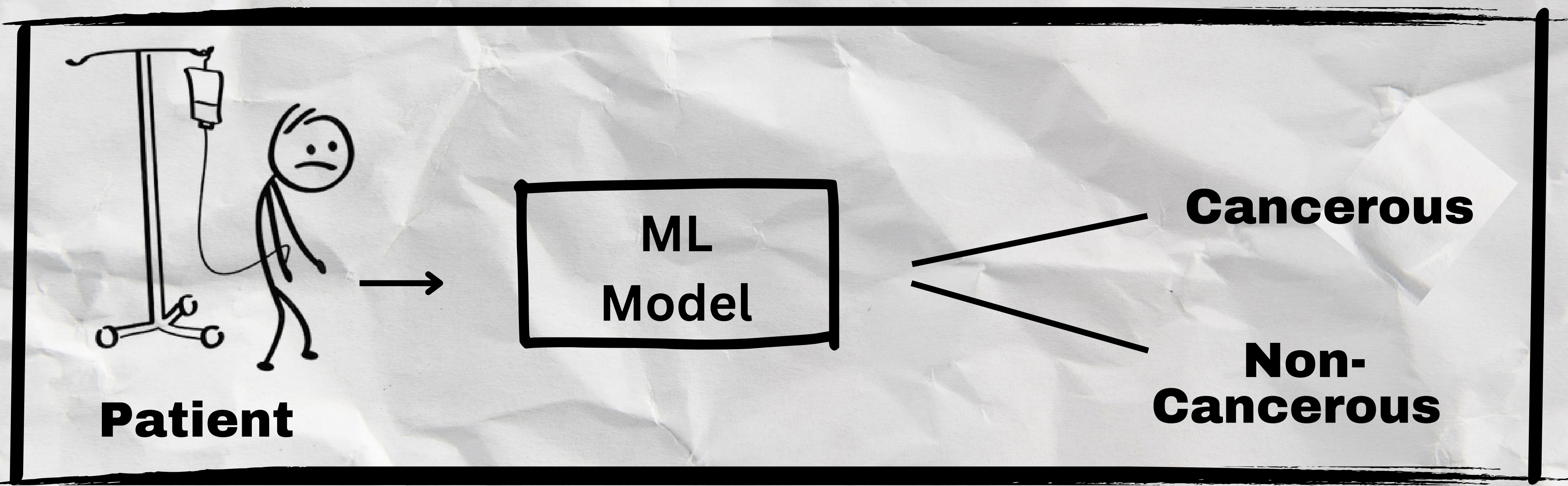
$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\boxed{\text{Recall} \propto \frac{1}{FN}}$$

Lower the value of False Negative, higher the Recall

# When do we need to reduce the False Negative cases?

Let's say you are working on a Cancer Detection Model. A machine learning model that can predict if a patient is having cancer or not.




Now, if the model predicts that a particular patient is having cancer, the doctors will perform the next round of tests to decide the next treatment step.

# Here the ML Model can commit two errors

- False Positive Error: The patient is not having cancer but is predicted as cancerous.
- False Negative Error: The patient is having cancer but is predicted as non-cancerous.

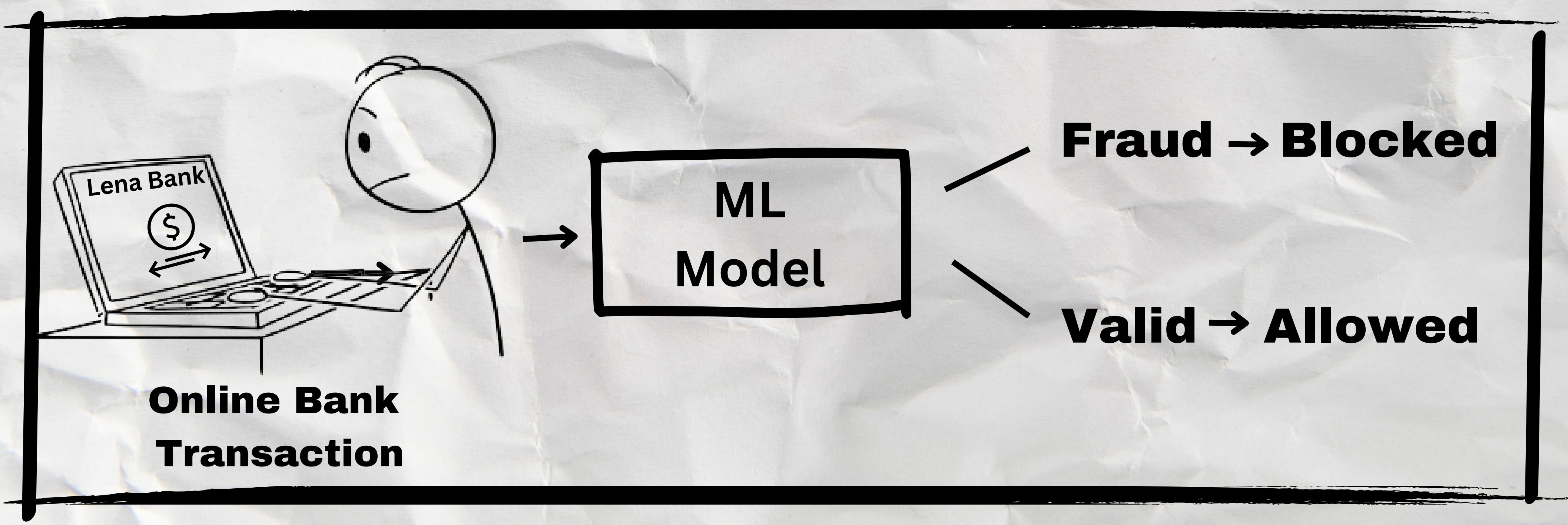
Now, which one is more harmful?

A false negative case is more harmful here because in this case, a cancer patient may leave undetected and in that case, doctors will not be providing any treatment to the patient which may become complicated and may lead to the death of the patient.

In short, if in a use case, False Negative is more harmful than False Positive, we use Recall as a metric to evaluate the performance of the model. We want the model to make as least FN Errors as possible.

But what if we need to reduce both errors? (FP and FN)

Let's say we are working on a Fraud Transaction Detection Model. A machine learning model that can block an online bank transaction if detected as fraud and will only allow valid bank transactions.

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# Here the ML Model can commit two errors

- False Positive Error: The transaction is a valid transaction but predicted as fraud.
- False Negative Error: The transaction is a fraudulent transaction but predicted as valid.

## Now, which one is more harmful?

## Here both are equally harmful to the bank.

1. If the FP case is happening then, a good customer of the bank will face a bad banking experience which might lead to the customer leaving the bank. (Customer Loss)
2. If the FP case is happening then, the bank is losing money. (Fund Loss)

Here, we need to reduce both FP and FN cases.

How?

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**F1 Score is the harmonic mean between precision and recall and is a good metric to use in cases where we want both precision and recall to be on the higher side.**

To Reduce FP cases $\longrightarrow$ Increase Precision

To Reduce FN cases $\longrightarrow$ Increase Recall

We need to simultaneously Increase both precision and Recall

So, we use a metric f1-Score

$$f1\text{-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

# But why Harmonic Mean and not the Arithmetic Mean?

| Precision | Recall | Avg | F1 Score |
| --- | --- | --- | --- |
| 0.2 | 0.9 | 0.55 | 0.327 |
| 0.8 | 0.1 | 0.45 | 0.17 |
| 0.5 | 0.5 | 0.5 | 0.5 |
| 0.8 | 0.85 | 0.825 | 0.824 |

In the above example, we can see that the Average will get a sufficiently high value even when only one metric among precision and recall is high while the other is on the lower side.

But

**F1-Score will only result in a high value when both precision and recall are high.**

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# And that's the end of this topic

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