Sensitivity Vs Specificity

its a metric to evaluate the performance of a Classification model.

Sensitivity : Proportion of **True Positives** given by a test
Specificity : Proportion of **True Negatives** given by a test

Say we have a Drug test with :

- Positive Drug test with **Probability** $P(\text{True Positive}|\text{User}) = 0.9$ - This is called **Sensitivity**
- False Positive Drug test with $P(\text{False Positive}|\text{None User}) = 0.8$ **Specificity**

In that sense we can make a test that always says its **Positive** so it will perform at 100% at detecting $P(\text{True Positive}|\text{User}) = 1$, so it will be always True when you are a user.
But the test will have a terrible **specificity** cause it will give our that you are a **drug** user even tho you are not

Machine Learning example

Say we have a **Binary Classification** problem where class A is dominant and will occur 98% of the time, While class B a rare event that have only 2%.

We can make a dummy-model that predict class A all the time which will **High Sensitivity** but very poor **Specificity** which might be where all the interesting data comes from.

Conclusion

Aspect	Sensitivity	Specificity
Focus	Detects true positives	Excludes true negatives
Use Case	Testing for a very important event	Where False Positives are costly

Increasing the Sensitivity will decrease the specificity and vice verse