ROC_AUC

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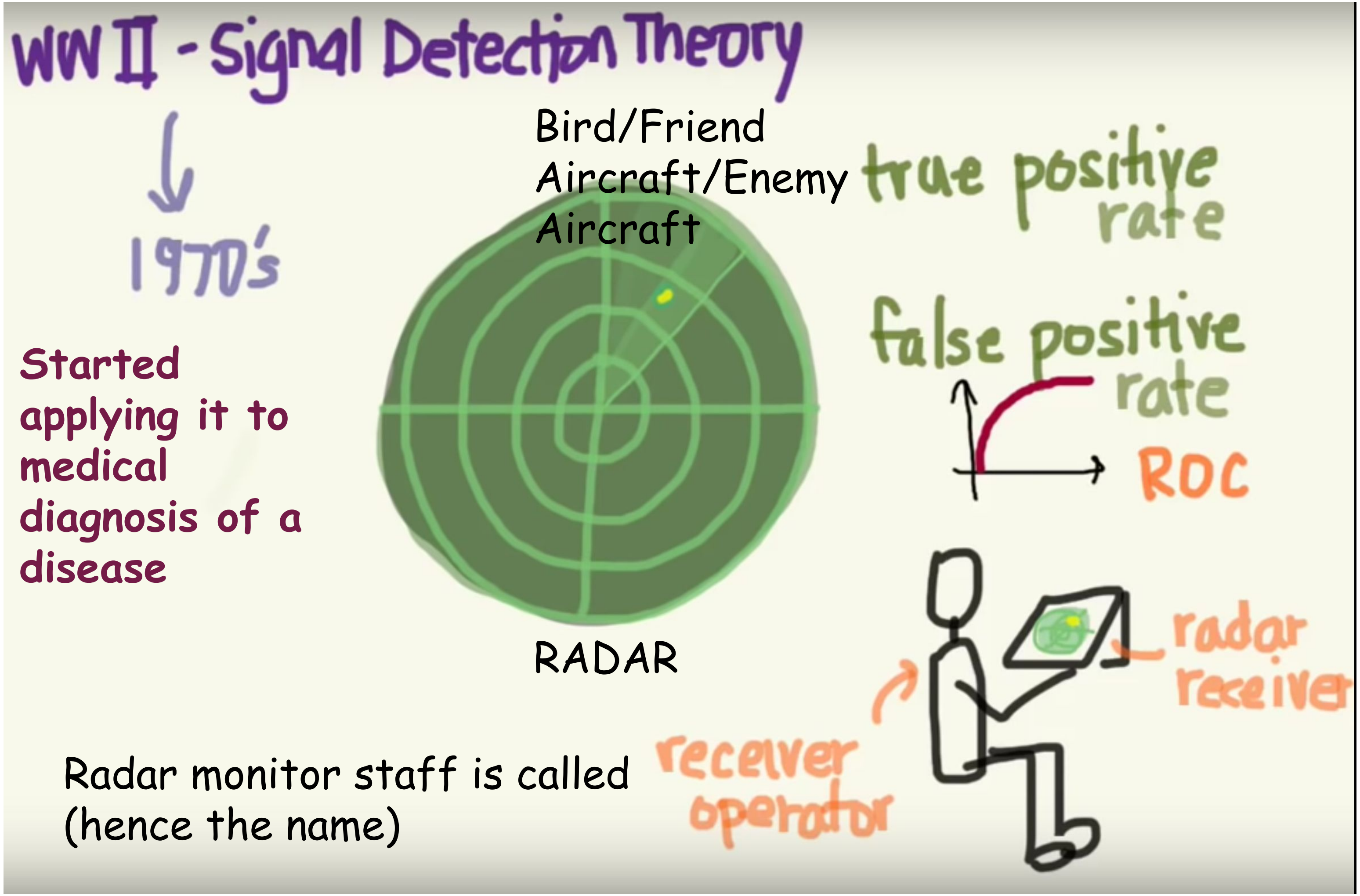
For: Machine Learning Elective Class
Target Audience: Sem 6 Students
Term: Feb to June 2019

Receiver Operating Characteristic (ROC) and Area Under Curve(AUC) Curves

History of ROC Curves



- The first example is the simplest: a diagonal line.
- A diagonal line indicates that the classifier is just making completely random guesses.
- Since your classifier is only going to be correct 50% of the time, it stands to reason that your TPR and FPR will also be equal.

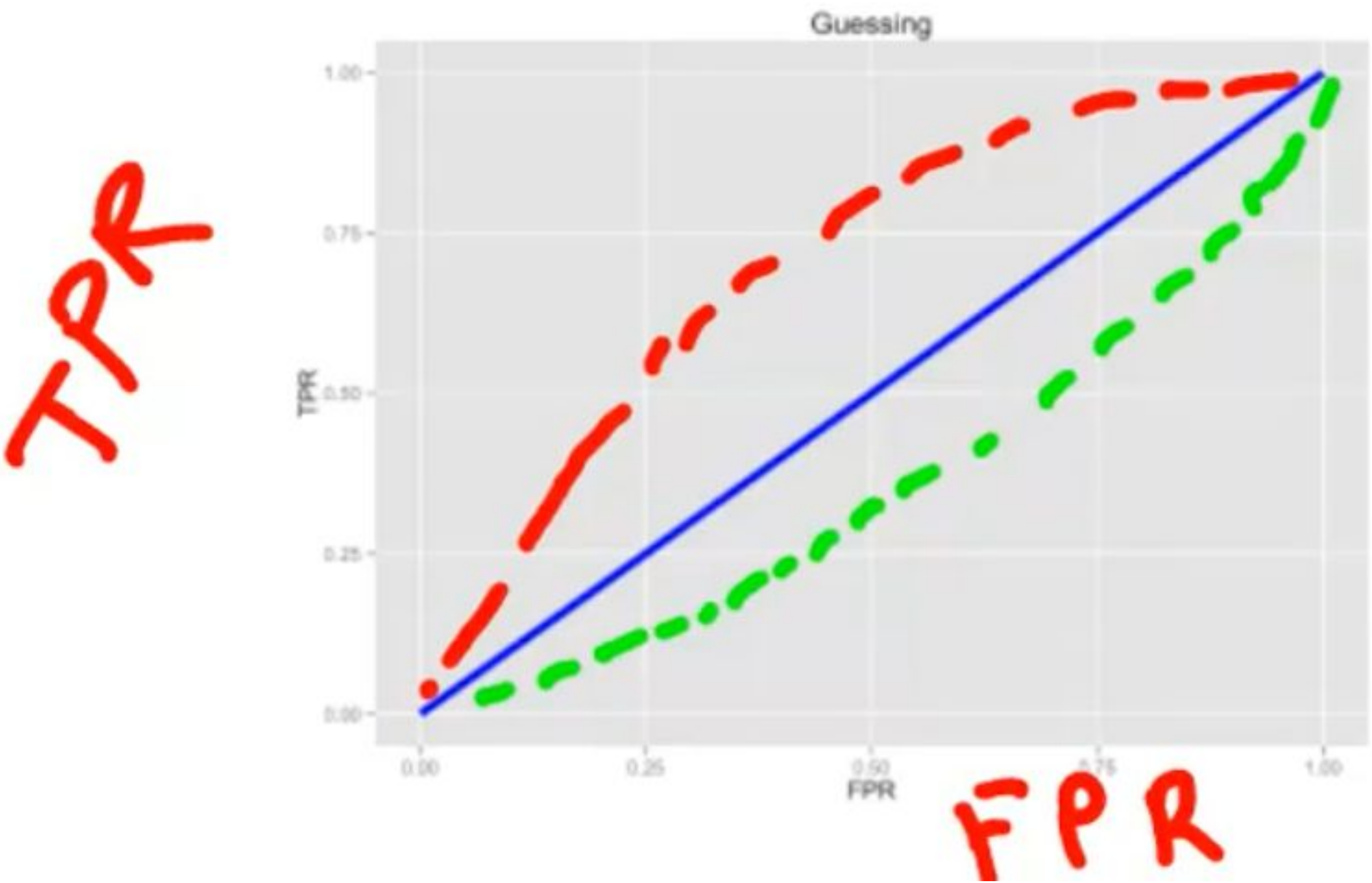
TPR

(Sensitivity)

FPR (1 - Specificity)

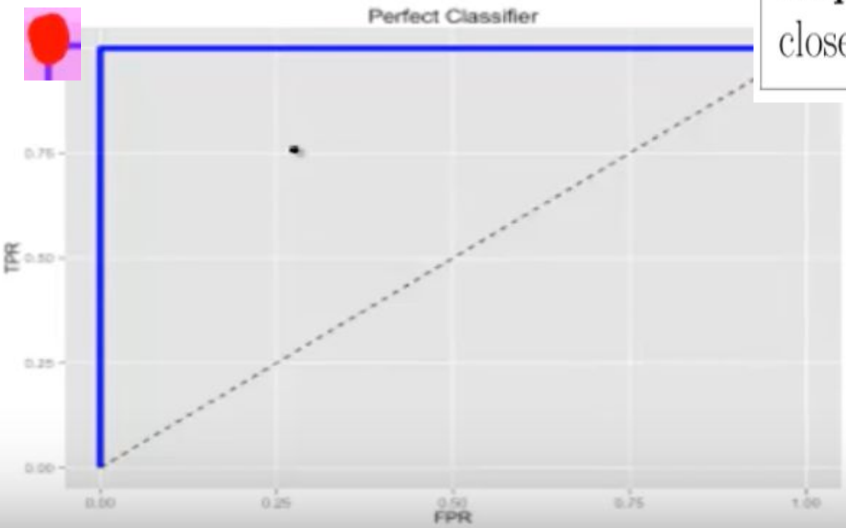
Any curve above the line will be "***Better than Guessing***"

Any curve below the line will be "***Worse than Guessing***"


Guessing
TPR
FPR
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
TPR
FPR

A Perfect Classifier

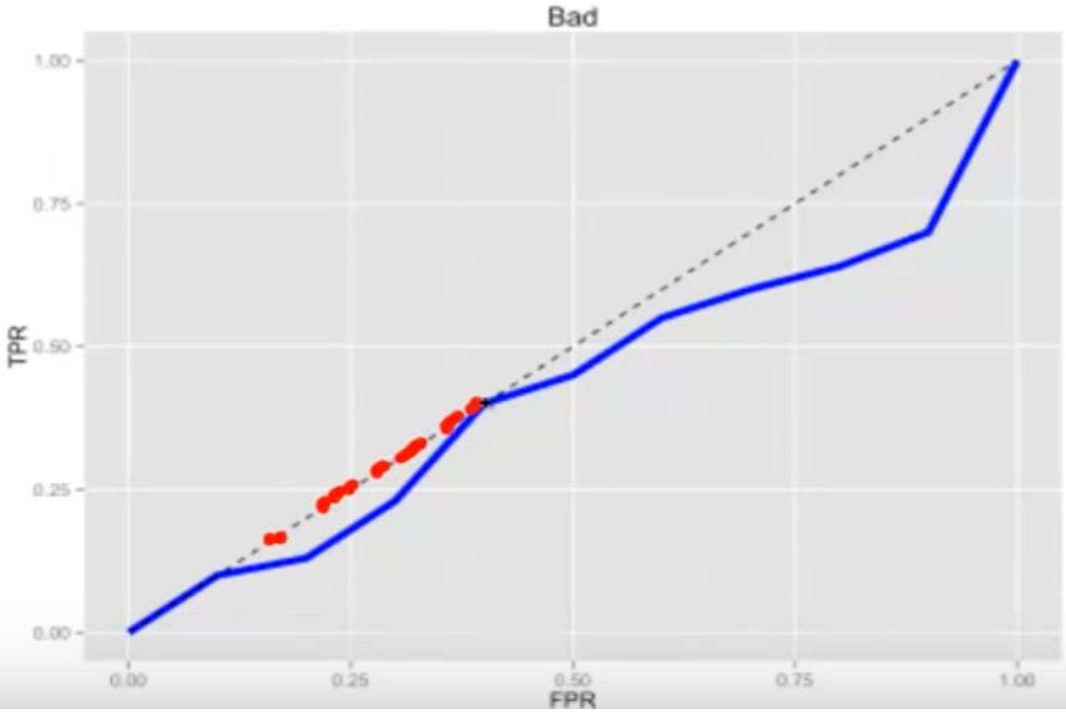
- A perfect classifier will yield a perfect trade-off between TPR and FPR (meaning you'll have a TPR of 1 and an FPR of 0).
- In that case, your ROC curve looks something like this.



Important: The better your classifier, the more closer the curve will be to the top left corner.

Worse than guessing

A bad classifier (i.e. something that's worse than guessing) will appear mostly below the random line.

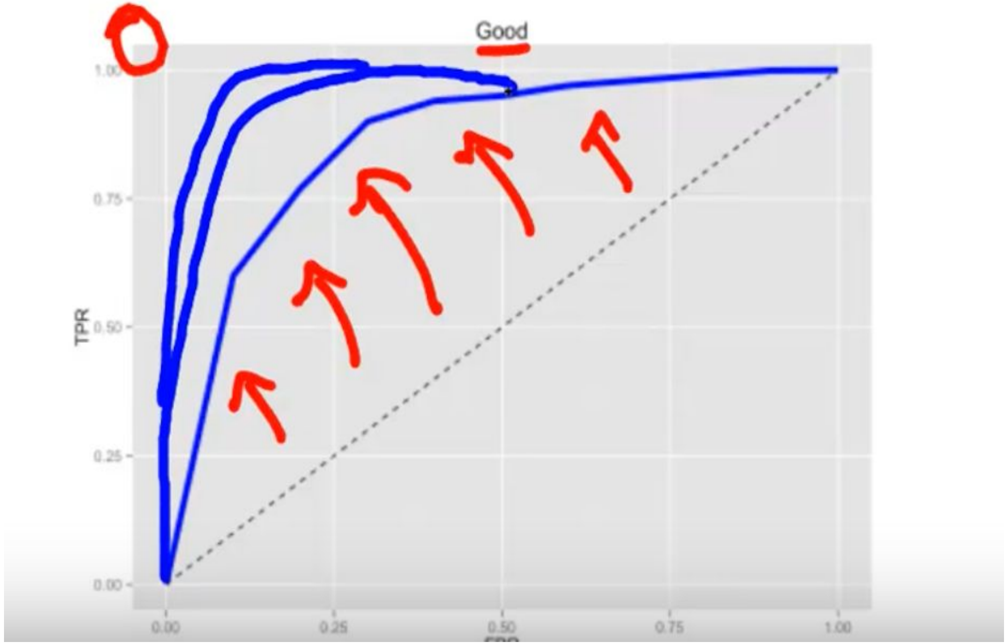


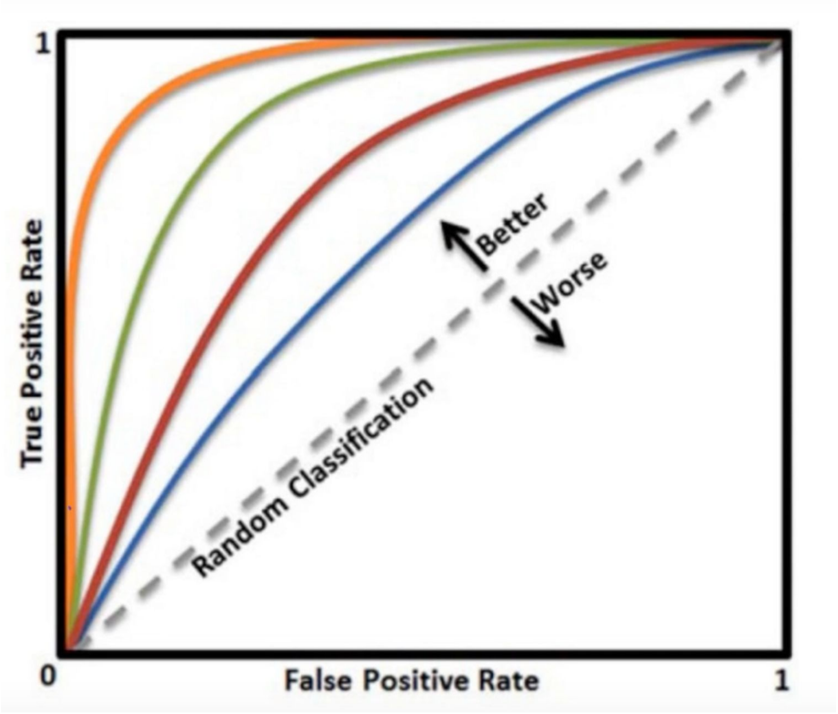
Better than guessing

A much more interesting activity is attempting to decipher the difference between an "OK" and a "Good" classifier. The chart below shows an example of a very mediocre classifier. It is still better than guess at random though.

Reasonably Good

In practice, most decent classification systems have a ROC curve like this.
Recall that better a prediction system is, the closer it is to the top left.





Reasonably Good

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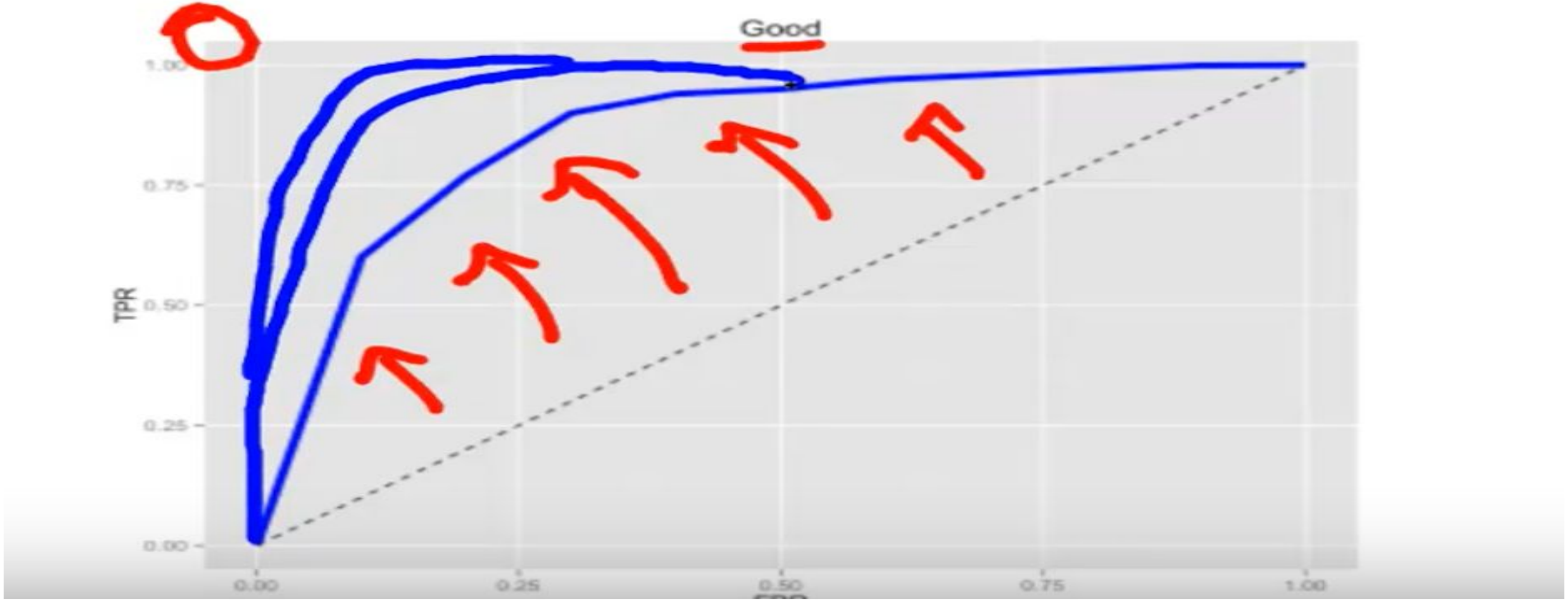
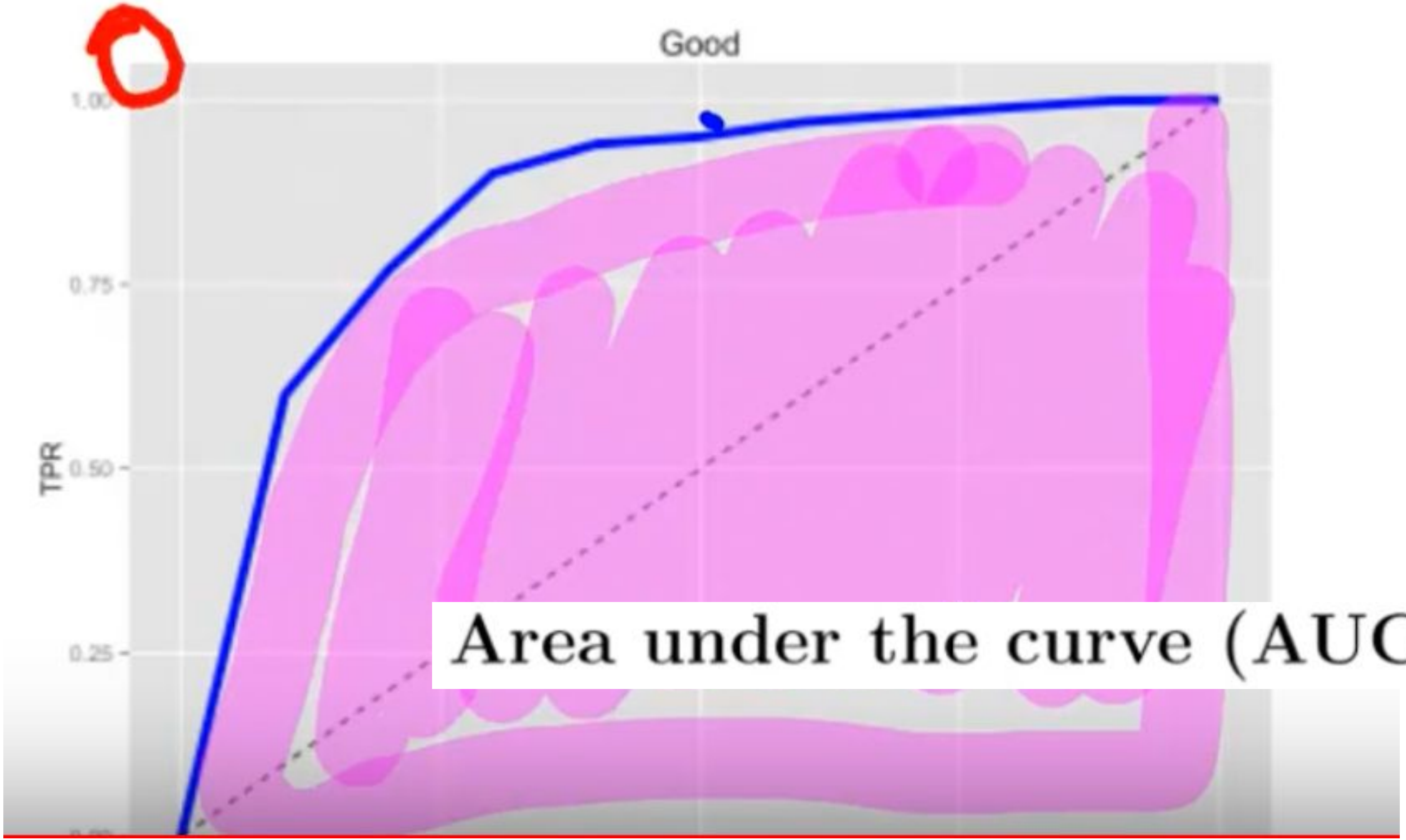




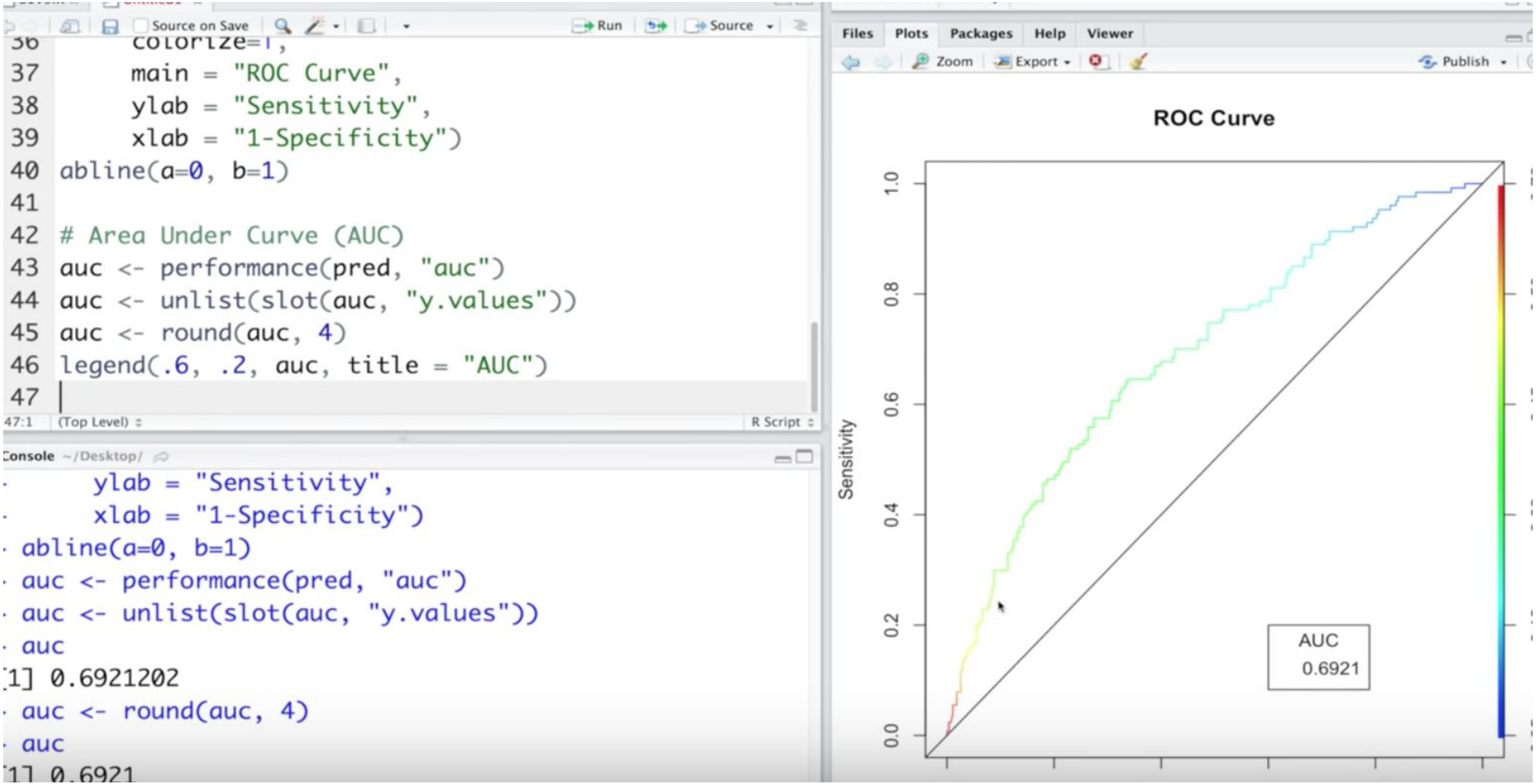
Area under the curve (AUC)

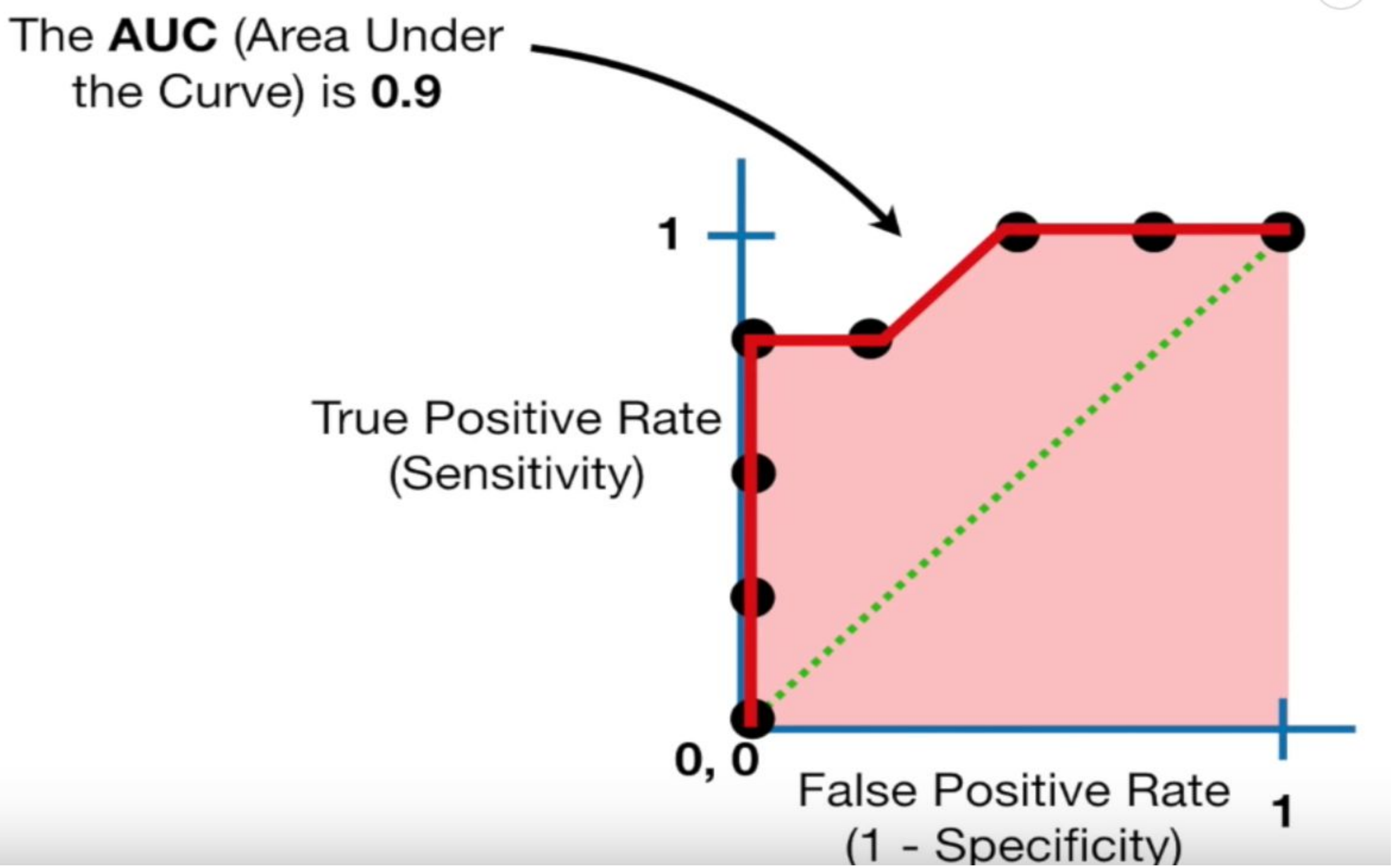
Area under the curve (AUC)

There is an aggregate metric to determine how good the prediction system is: AUC or Area Under the Curve.

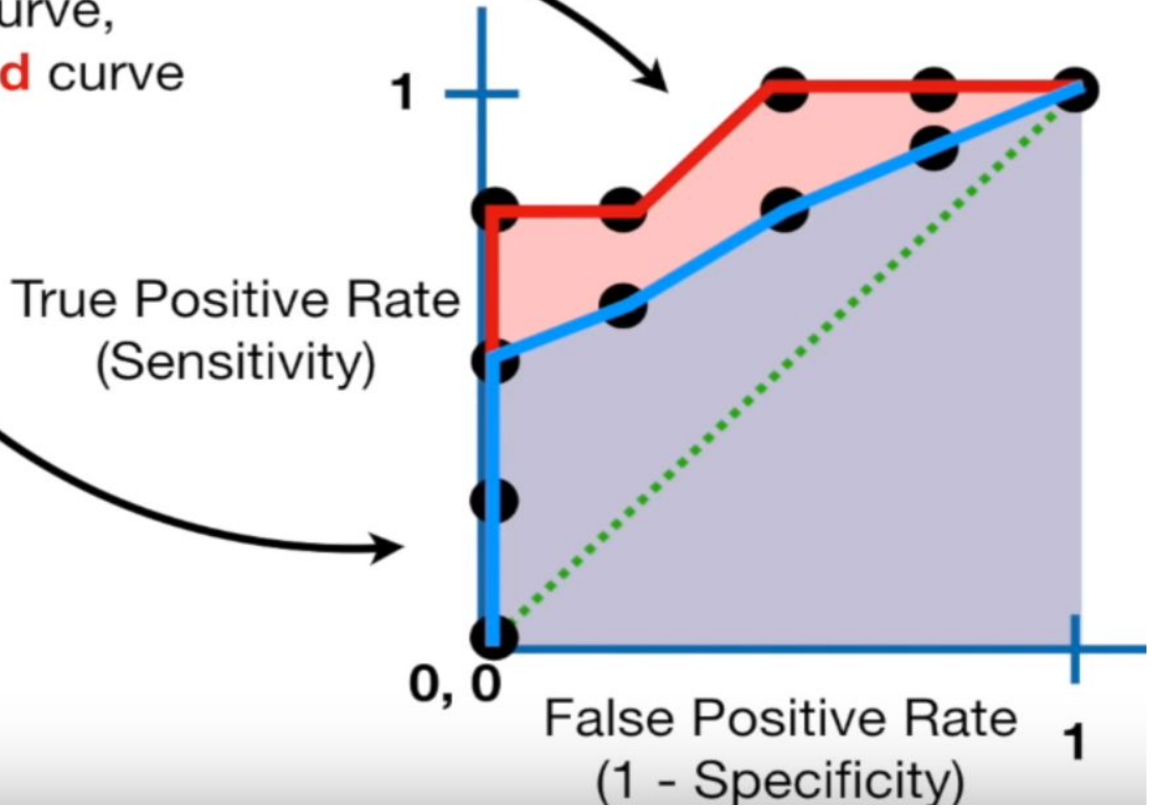
The AUC is the amount of space underneath the ROC curve

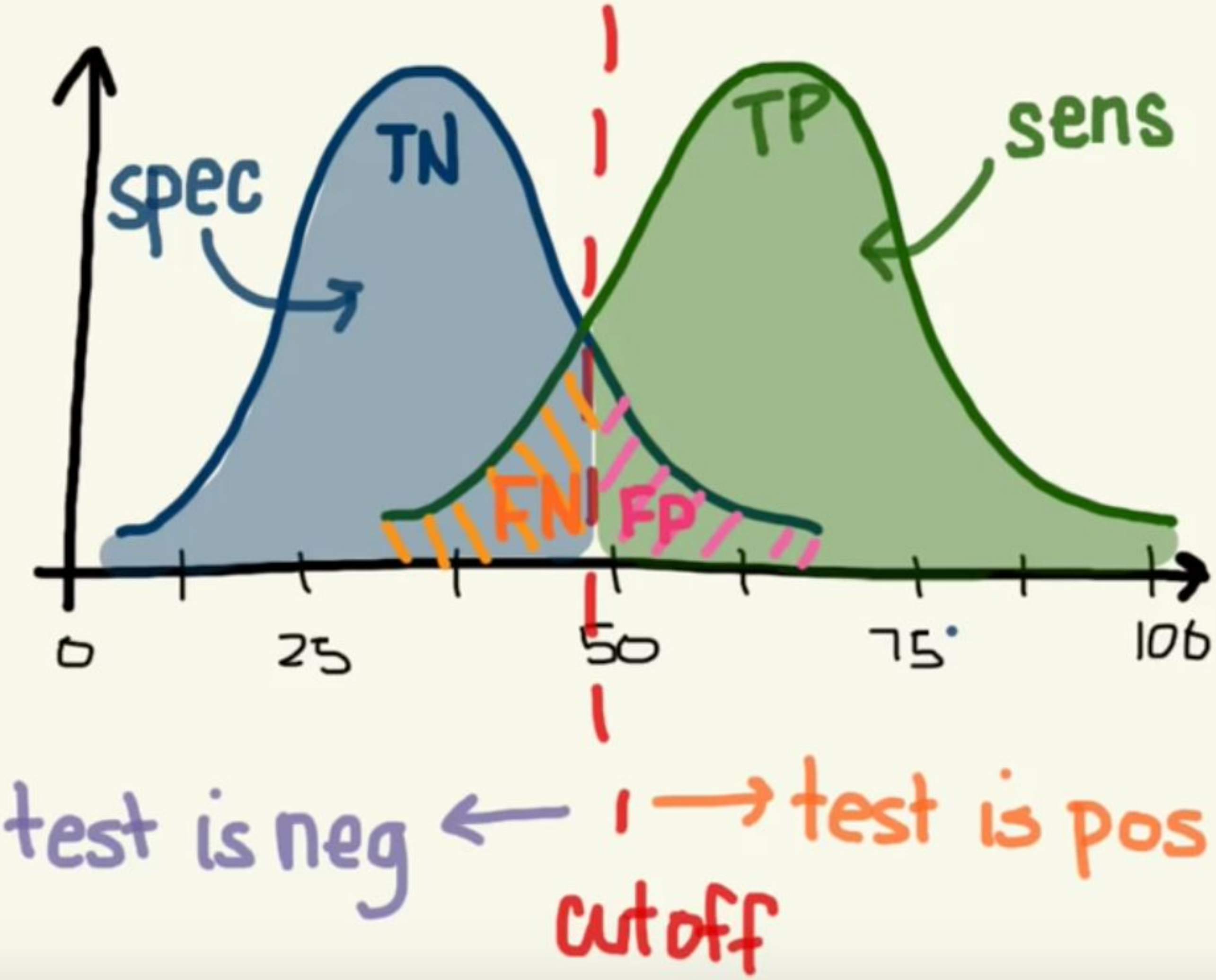
- $AUC = 0$: Perfectly Bad
- $AUC < 0.5$: Worse than guessing at random
- $AUC = 0.5$: same as guessing at random
- $AUC > 0.5$: Good. better than guessing at random
- $AUC = 1$: Perfectly Good


Source on Save
Run
Source
colorize=T,
main = "ROC Curve",
ylab = "Sensitivity",
xlab = "1-Specificity")
abline(a=0, b=1)
# Area Under Curve (AUC)
auc <- performance(pred, "auc")
auc <- unlist(slot(auc, "y.values"))
auc <- round(auc, 4)
legend(.6, .2, auc, title = "AUC")
47:1
(Top Level)
R Script
Console ~/Desktop/
ylab = "Sensitivity",
xlab = "1-Specificity")
abline(a=0, b=1)
auc <- performance(pred, "auc")
auc <- unlist(slot(auc, "y.values"))
auc
[1] 0.6921202
auc <- round(auc, 4)
auc
[1] 0.6921
Files
Plots
Packages
Help
Viewer
Zoom
Export
Publish
ROC Curve
Sensitivity
0.0
0.2
0.4
0.6
0.8
1.0
AUC
0.6921

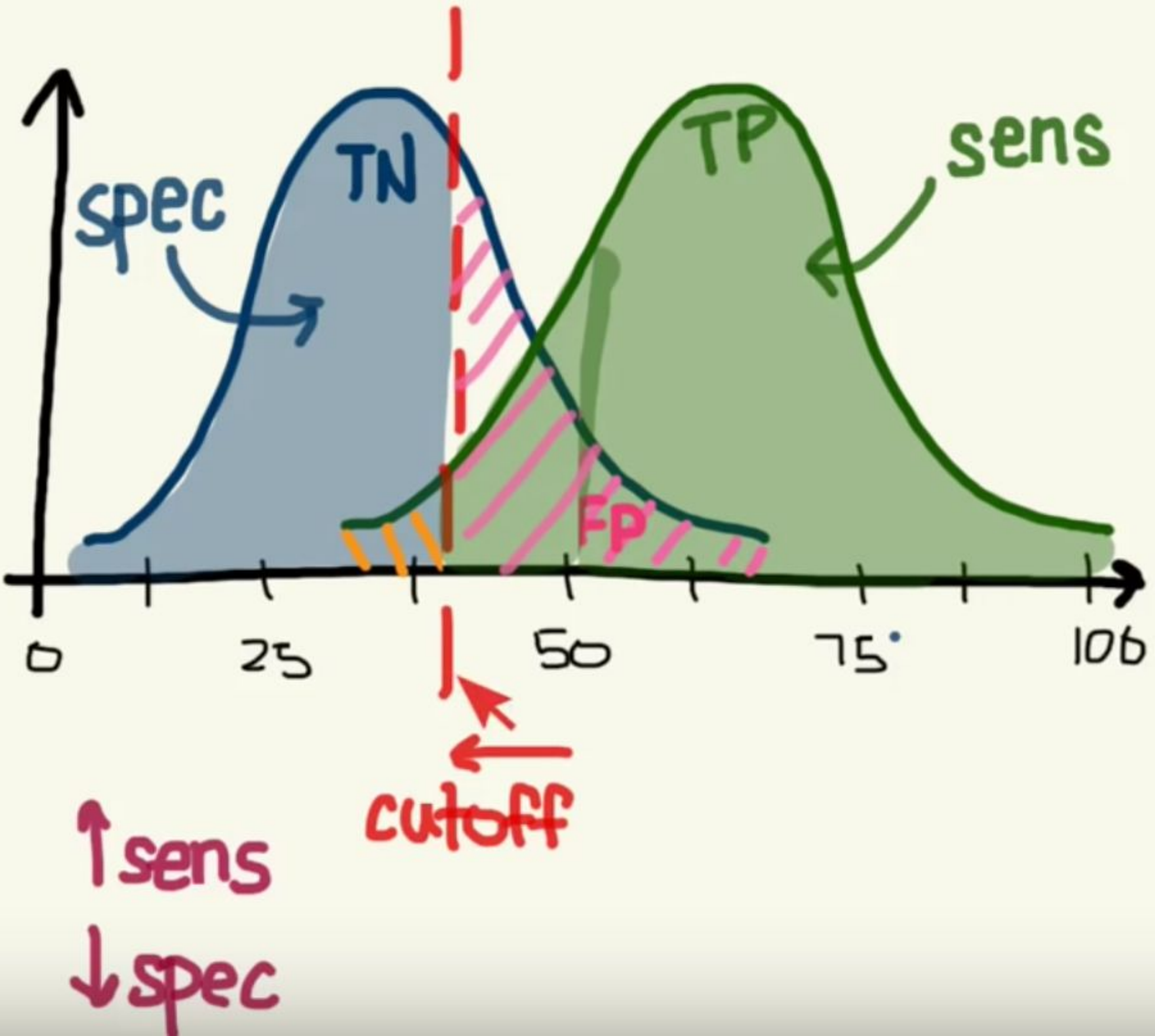

The AUC (Area Under the Curve) is 0.9
1
True Positive Rate (Sensitivity)
0, 0
False Positive Rate (1 - Specificity)
1

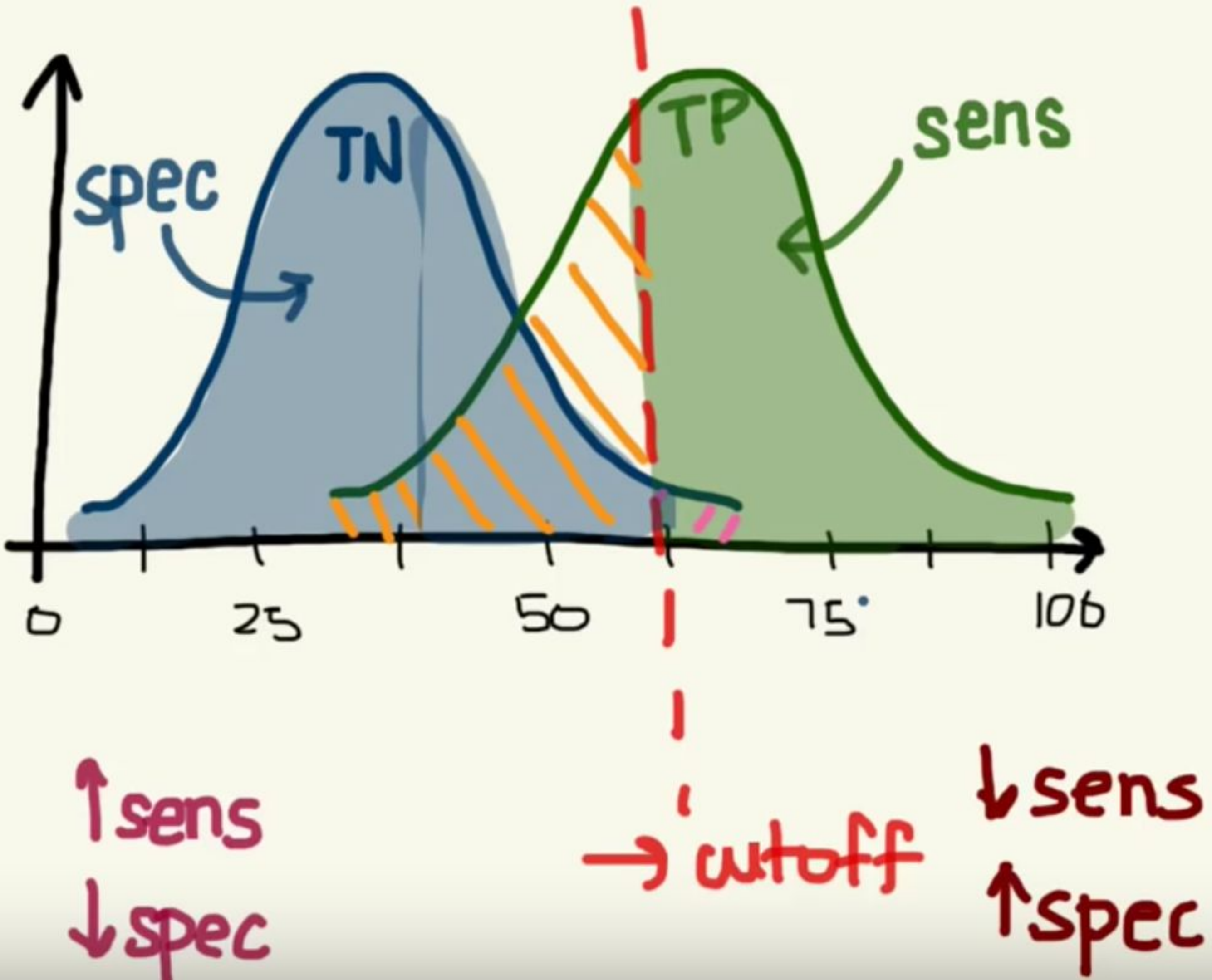
The **AUC** for the red **ROC** curve is greater than the **AUC** for the blue **ROC** curve, suggesting that the red curve is better.



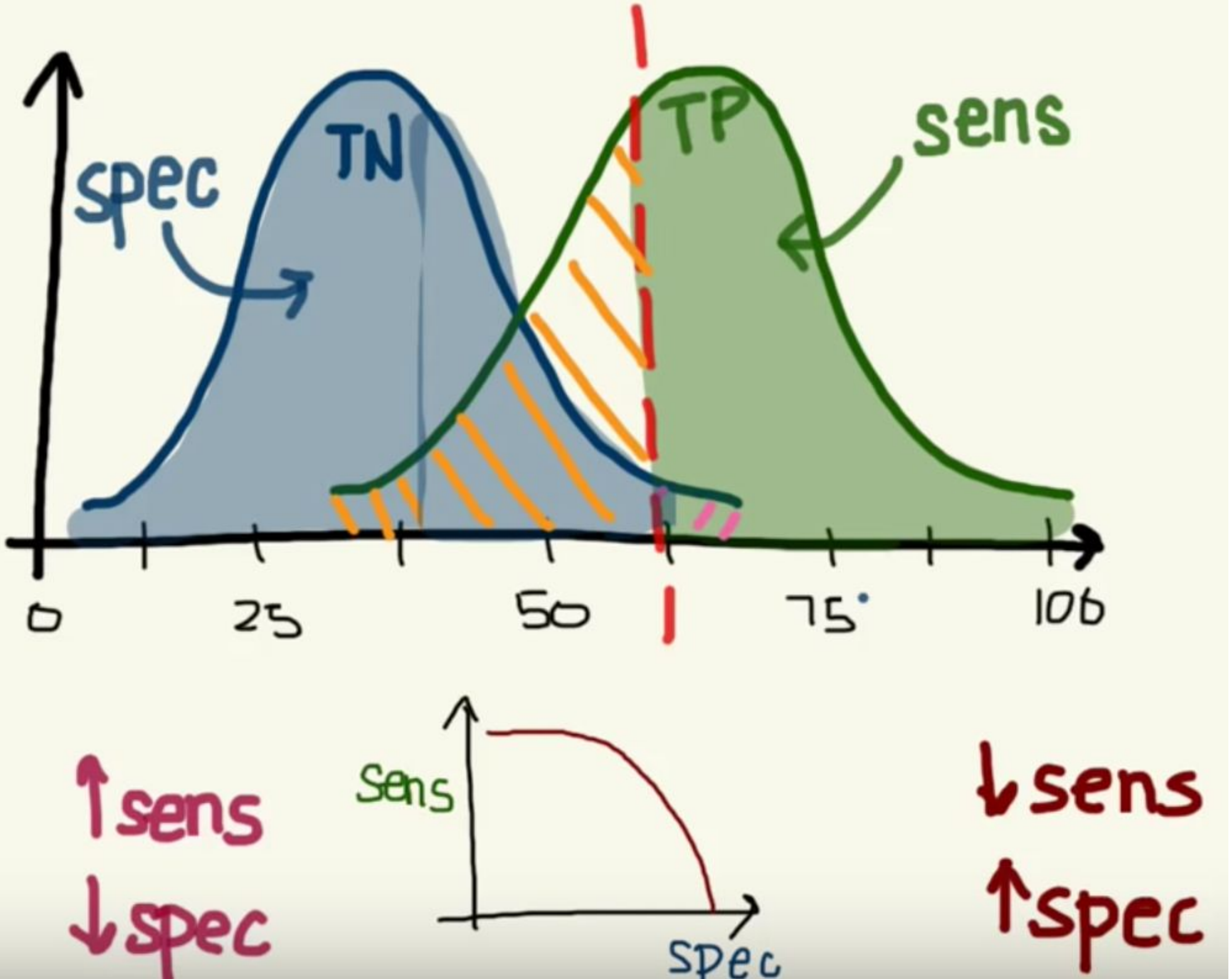


spec
TN
TP
sens
FN
FP
0
25
50
75
106
test is neg
test is pos
cutoff

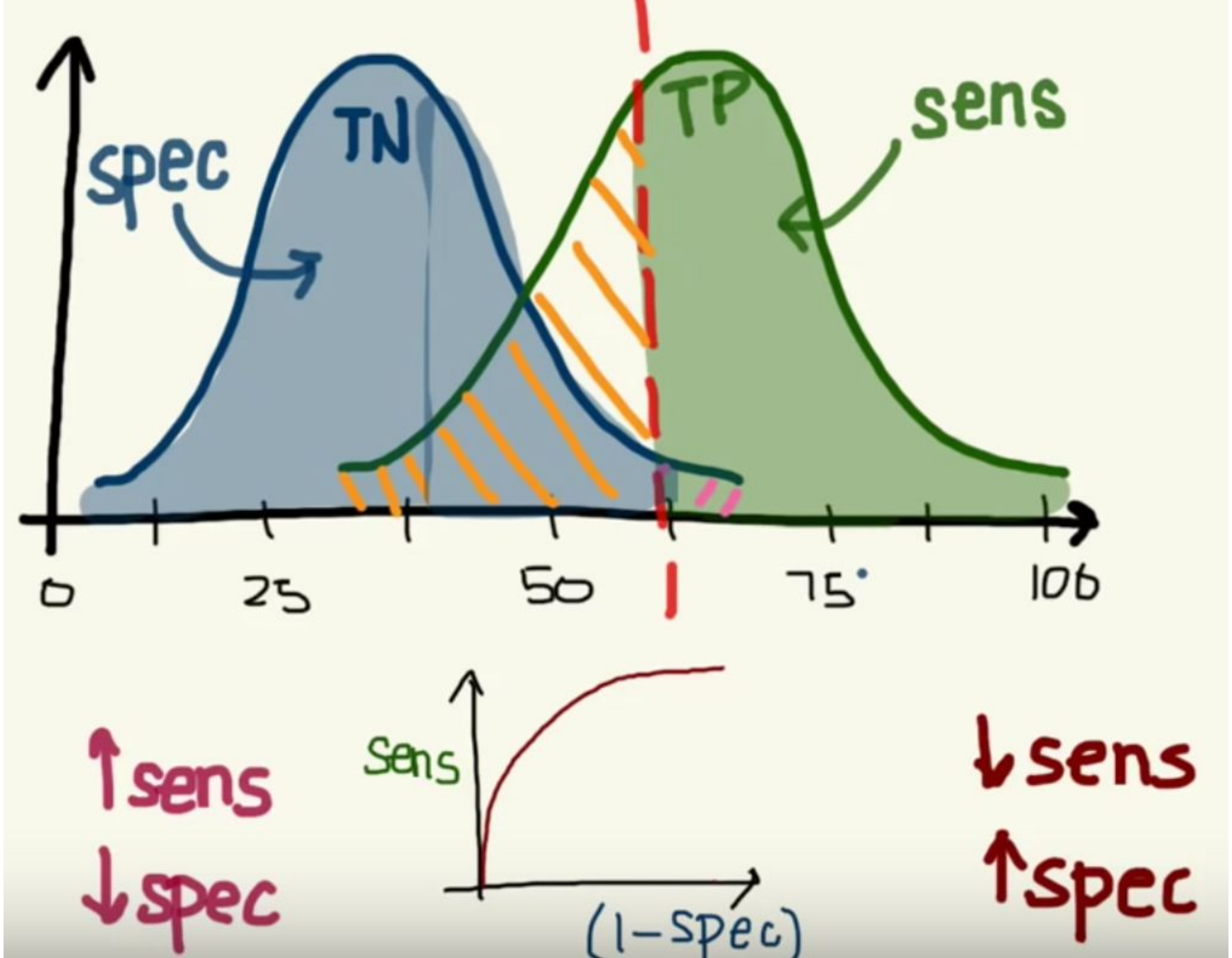

spec
TN
TP
sens
FP
0
25
50
75
100
cutoff
↑sens
↓spec

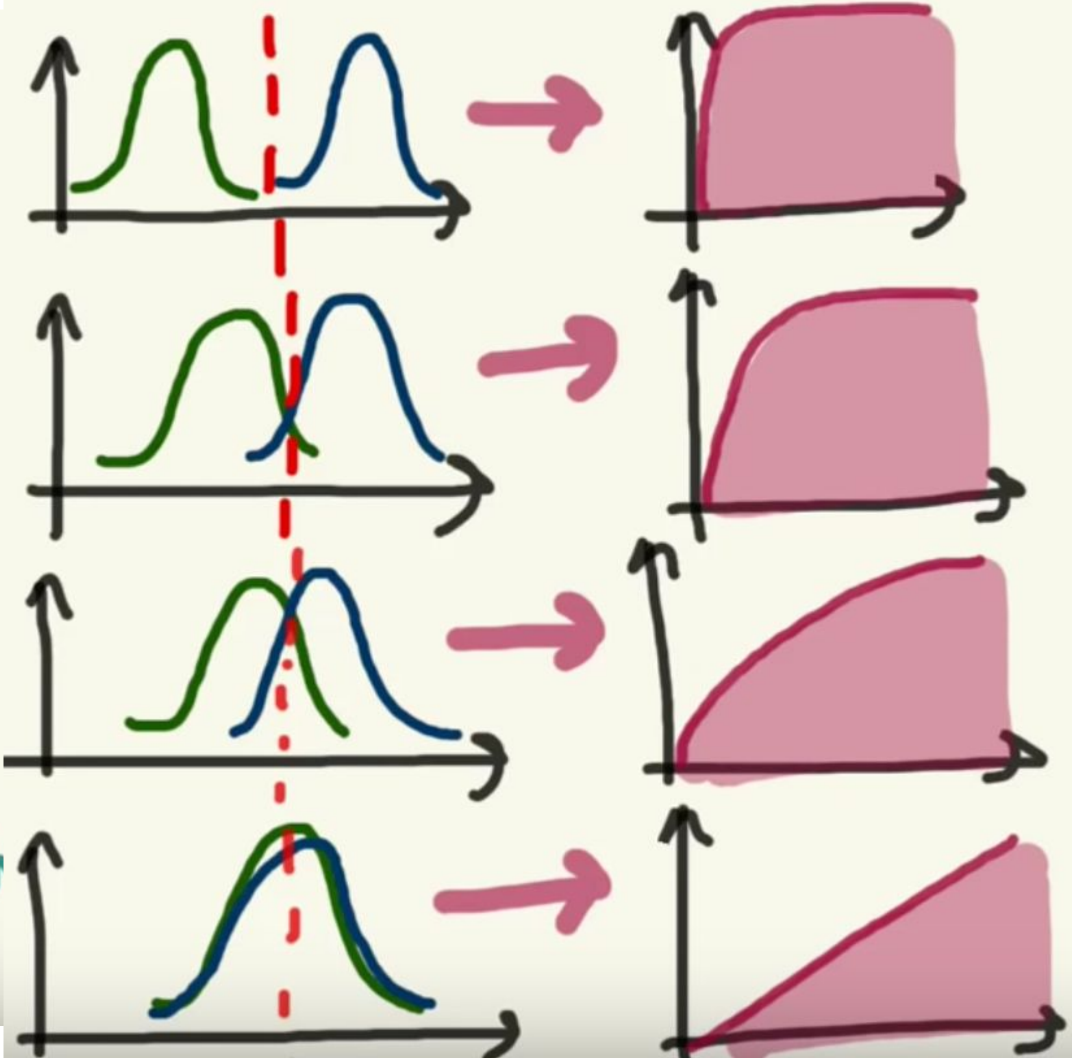


spec
TN
TP
sens
0
25
50
75
100
↑sens
↓spec
cutoff
↓sens
↑spec

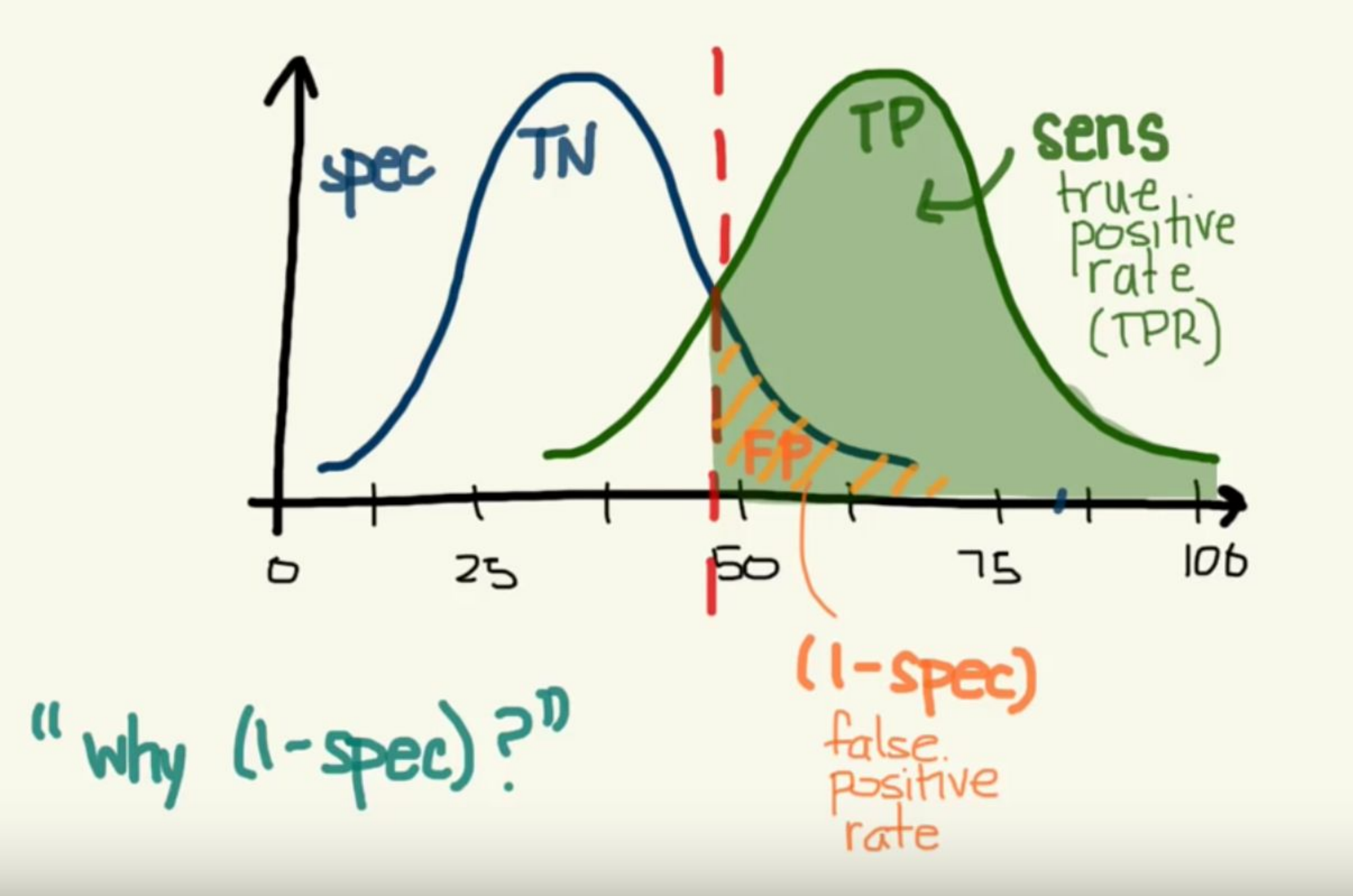


spec
TN
TP
sens
0
25
50
75
100
sens
spec
↑sens
↓spec
↓sens
↑spec


spec
TN
TP
sens
0
25
50
75
106
sens
(1-spec)
↑sens
↓spec
↓sens
↑spec



AUC	Quality Of Test
0.9-1	Excellent
0.8-0.9	Good
0.7-0.8	Fair
0.6-0.7	Poor
0,5-0.6	Fail



spec
TN
TP
sens
true positive rate (TPR)
FP
0
25
50
75
100
(1-spec)
false positive rate
"why (1-spec)?"