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CRoc)

Problem whether or not someone loves her

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Loves
Trott 2

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In this example,
we measured the
amount of popcorn a
bunch of people ate

does not co
Love Troll 2

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which is conHnuu
and whethec, hey

LoveTeolt2 OSDo tot
Love TEoll 2 oiscele.

The goal is to make a classiet, that uses the amount of popcorn someone eats to classify whether or not they love TEOI 2.

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False posi Hvee

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to find correct identity, we keep on changing
threshold value and get different confusion
matrix

Ultimately, we can try any classification threshold
from 0 to 1,
and when we do, we end up with 10 different
confusion matrices that we can choose
from

The threshold under each confusion matrix is
just one of many that will result in the
exact same confusion matrix.

Trying to find the ideal classification threshold
among a number of confusion matrices is tedious and
annoying

It wouldn't be too awesome if we could consolidate them
into one easy-to-understand graph that's when
ROC graphs came

tach black dot on the graph tells us the
 True Positive Rate and the false Positive
 Rate of a specific classification threshold

The bigger the dot
 is along the Y-axis,
 the higher the

True
 actual
 Positives. fociHv
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False Positive Rate

at a glance, we can look
 at the top 600 points and tell that
 the classification threshold that
 resulted in the point on the left side
 is much better than the others
 because they all have the same
 True positive rate, but the point on the
 left has a lower False Positive Rate.

diagonal line shows, True Positive Rate
 False positive Rate.

o construct ROC graph, we will start by using
 a classification threshold and calculate
 Confusion matrix

using that confusion matrix calculate True
 Positive Rate and false Positive Rate. and then
 plot that point on ROC graph

True Positive Rate. $\frac{TP}{TP+FN}$
 Sensitivity TPR, $\frac{TP}{TP+FN}$ 2

False Positive Rate $\frac{FP}{FP+TN}$
 Specificity CFPR $\frac{TN}{FP+TN}$

Now, lower the threshold such as 0.375, 0.965, ..
 and calculate confusion matrix for each particular
 threshold

Thus calculate TPR, FPR and plot points
 on graph.:

if we increase the threshold that increases the number
 of "Positive" classification. we calculate TPR and FPR
 until everyone is classified as Positive.

ate uwe linish plotting the points from each possible
Confusion matrix, and connect the dots

Now, without having to sort through a huge pile of
Confusion Matrices, we can use the ROC graph to
pick a classification threshold **1 1**

We want to avoid all False Positives, but want to
maximize the number of actual positives correctly
classified, **we** would pick this threshold.

but if we can tolerate a few
False Positives, **we** would
pick this threshold because
it correctly classifies all
of the actual positives.

ROC analysis (area under the curve)
great **OS** selecting an optimal
classification threshold for
a model.

But what if we want to compare
two models performance Vs another
This **is** where

AUC,

PPR

Area Under the Curve

comes into picture.

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