Machine Learning

Assessing and Improving ML Models

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Today’s Agenda

- Recap to Supervised Learning?
- Recap to classification?
- How to evaluate the classification model?
- Evaluation Metrics for a Classification model

Supervised Learning

- To learn an unknown *target function* f
- Input: a *training set* of *labeled examples* (x_j, y_j) where $y_j = f(x_j)$
  - E.g., x_j is an image, $f(x_j)$ is the label "giraffe"
- Output: *hypothesis* h that is "close" to f, i.e., predicts well on unseen examples ("*test set*")
- Many possible hypothesis families for h
  - Linear models, logistic regression, neural networks, decision trees, examples (nearest-neighbor) etc.

Slide Adapted from **Stuart Russell**

Supervised Learning

Functions $\mathcal{F}$

$$f : \mathcal{X} \rightarrow \mathcal{Y}$$

Training data

$$\{(x_i, y_i) \in \mathcal{X} \times \mathcal{Y}\}$$

LEARNING

$$\boxed{\begin{array}{l}\text{find } \hat{f} \in \mathcal{F} \\ \text{s.t. } y_i \approx \hat{f}(x_i)\end{array}}$$

Learning machine

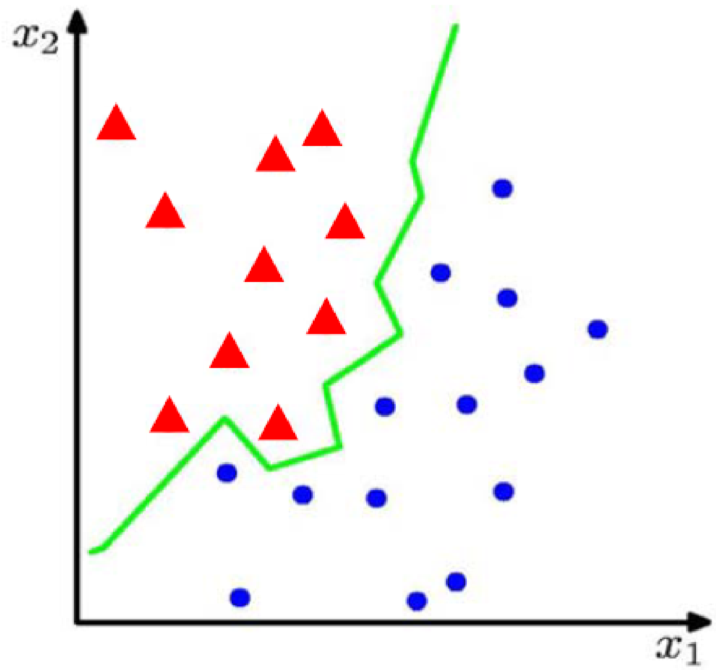
New data

PREDICTION

$$\boxed{y = \hat{f}(x)} \Leftarrow \boxed{x}$$

Slide adapted from Andrew Zisserman

What is Classification Problem?



- Suppose we are given a training set of N observations

$$(x_1, \ldots, x_N) \text{ and } (y_1, \ldots, y_N), x_i \in \mathbb{R}^d, y_i \in \{-1, 1\}$$

- Classification problem is to estimate f(x) from this data such that

$$f(x_i) = y_i$$

Classification: Supervised Learning

Training Phase

We have shown a set of dog pictures and a set of cat pictures to a child.

Classification: Supervised Learning

Testing Phase

→

→ DOG

This picture as it is may not be in the training set

Child has done more than just remembering

How to evaluate the classification model?

- **Example:** Two class image classification
  - Class 1: Dog Images (10), Class 2: Cat images (10).
  - Total Samples: N=20
- **Confusion Matrix:** Normally this matrix is of size *K*K* where *K* is number of classes.

		Predicted	
	N=20	Dog (+)	Cat (-)
Actual	Dog (+)	7	3
	Cat (-)	4	6

How to evaluate the classification model?

		Predicted	
N=20		Dog (+)	Cat (-)
Actual	Dog (+)	TP	FN
	Cat (-)	FP	TN

True Positives: 7

False Positives (*Type 1 Error*): 3

True Negatives: 6

False Negatives (*Type 2 Error*): 4

Total (N) =TP+FP+FN+TN=20

Evaluation Metrics for a classification model

- Accuracy: Accuracy is number of correct predictions out of total records.

  $$Accuracy = (TP + TN)/\text{Total} = 13/20 = 65\%.$$

- Misclassification rate or error rate:

  $$Error\ rate = (FP + FN)/\text{Total} = 7/20 = 35\%.$$

Accuracy Paradox:

Consider, Total number of Dog Images (19), Cat (1), N=20

		Predicted	
	N=20	Dog (+)	Cat (-)
Actual	Dog (+)	19	0
	Cat (-)	1	0

		Predicted	
	N=20	Dog (+)	Cat (-)
Actual	Dog (+)	TP	FN
	Cat (-)	FP	TN

Accuracy= (TP+TN)/Total=(19+0)/20=99%

Evaluation Metrics for a Classification model

- Precision (positive predicted value): It is the number of positive predictions divided by the total number of positive class values predicted.

  Precision=*TP*/(TP+FP)=19/(19+1)=19/20=99%.

- Recall (sensitivity or true positive rate): It is the number of positive predictions divided by the number of positive class values in the test data.

  Recall=TP/(TP+FN)=19/(19+0)=100%.

- F-1 Measure: A balanced measure between precision and recall.

  F-1 Measure=2*(Precision * Recall)/(Precision + Recall)

  F-1=2*(0.99*1.0)/(0.99+1.0)=2*(0.99)/(1.99)=1.98/1.99=0.99

Evaluation Metrics for a Classification model

- Specificity (True Negative Rate): How often the ML model predicts negative samples correctly out of total negative samples.

  Specificity=TN/(TN+FP)=0/(0+1)=0%

  -Model has 0% effective in predicting negative samples as negative.
- False positive rate (FPR): How often the ML model predict the negative samples (cat) as positive (dog)?

  FPR=FP/(TN+FP)=1/(0+1)=100%

  Note: It can also be calculated as FPR=1-Specificity=1-0=100%

  ML model has 100% FPR, which means that every time model will every Negative (Cat) sample as Positive (Dog).
- *Sensitivity and Specificity is most important in medical diagnosis.*

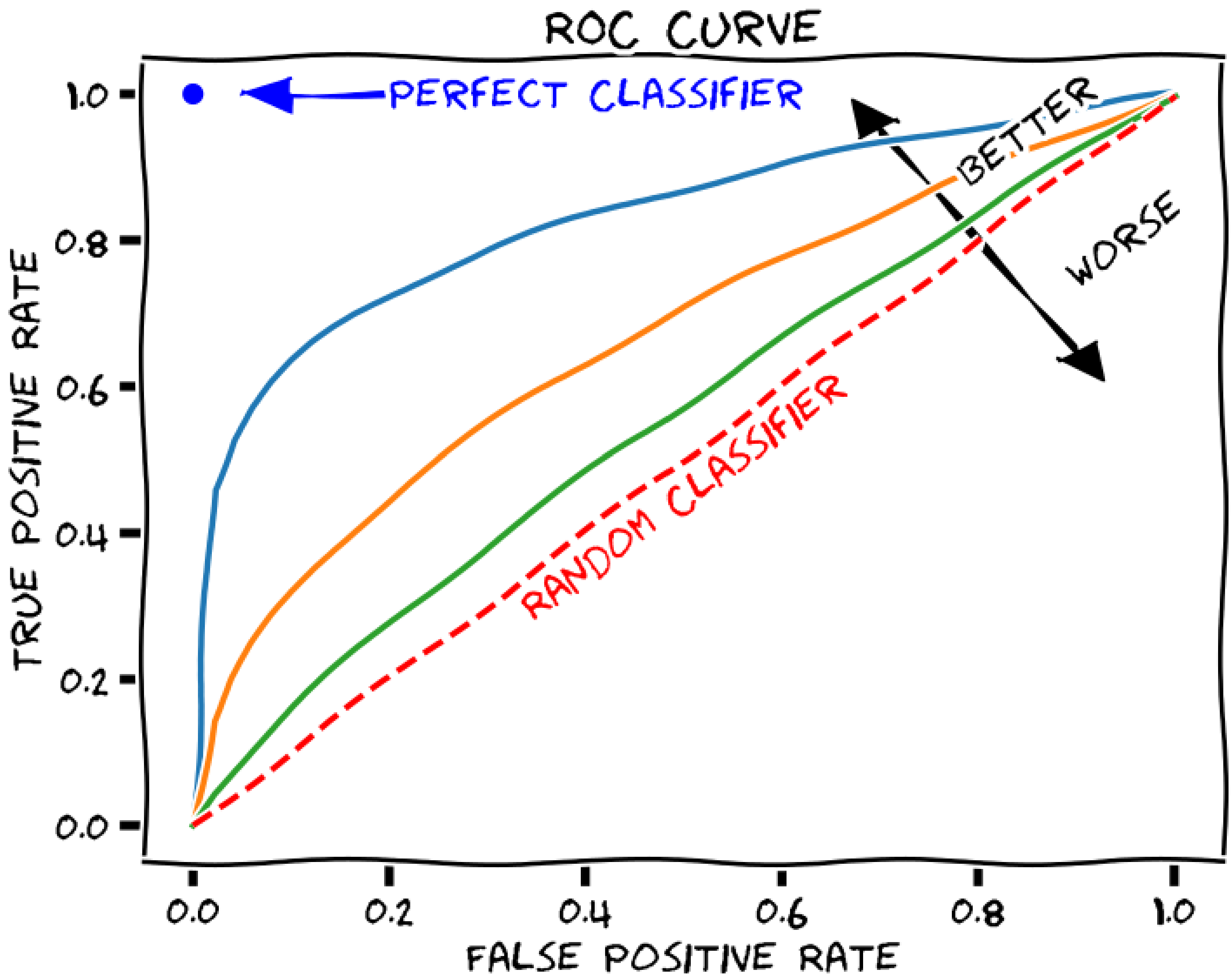
ROC Curve

- A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.

- The method was originally developed for operators of military radar receivers, which is why it is so named.

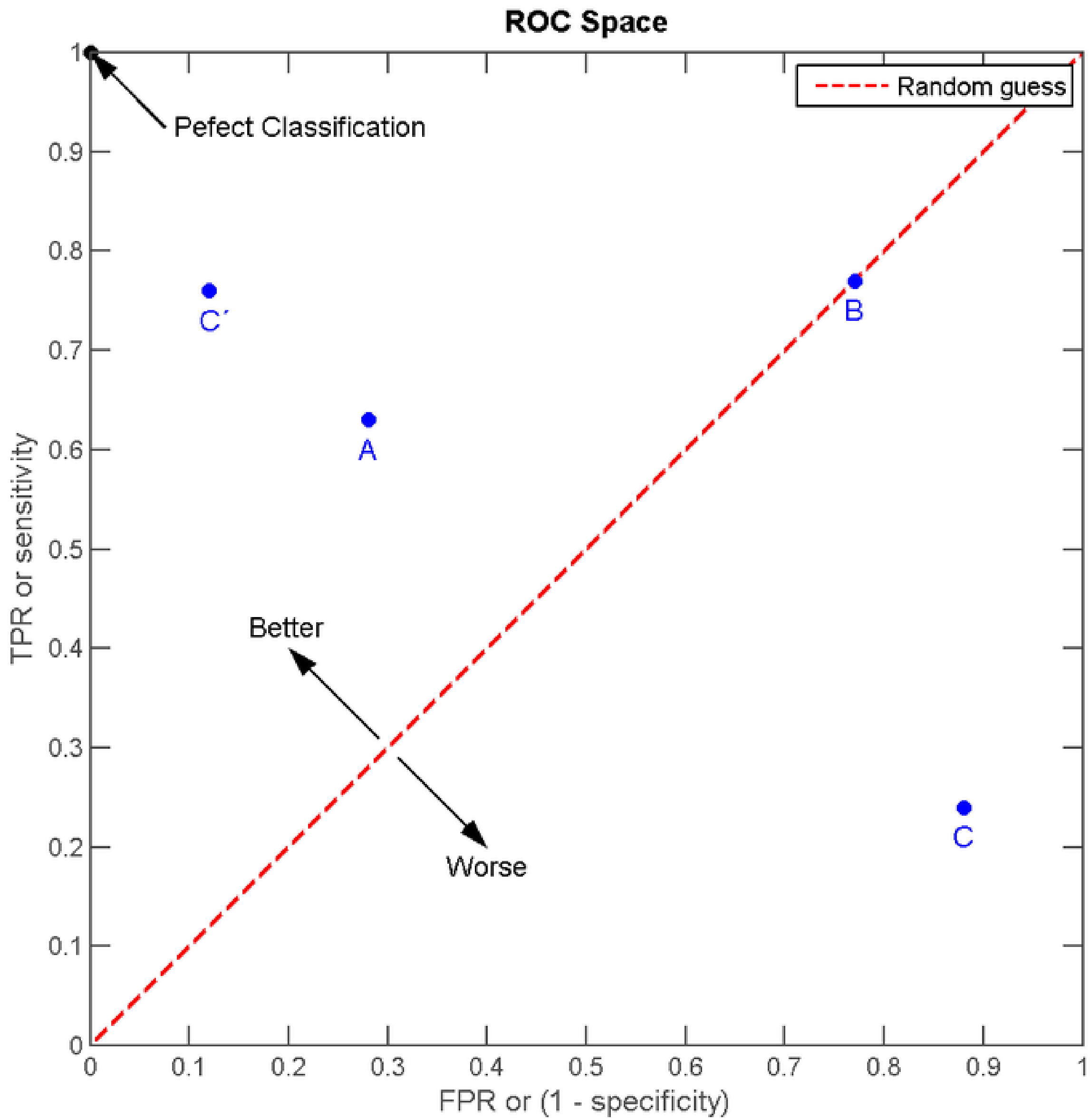
- The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.

ROC Curve



ROC CURVE
PERFECT CLASSIFIER
BETTER
WORSE
RANDOM CLASSIFIER
1.0
0.8
0.6
0.4
0.2
0.0
TRUE POSITIVE RATE
0.0
0.2
0.4
0.6
0.8
1.0
FALSE POSITIVE RATE

ROC Curve


ROC Space
Pefect Classification
Random guess
C´
A
B
C
Better
Worse
TPR or sensitivity
FPR or (1 - specificity)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Thank You: Question?