EVALUATING MACHINE LEARNING CLASSIFIERS: ACCURACY, PRECISION AND RECALL

Scott O'Hara
Metrowest Developers Machine Learning Group
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REFERENCES

Applied Machine Learning in Python

University of Michigan, Prof. Kevin Collins Thompson **(AMLP)**

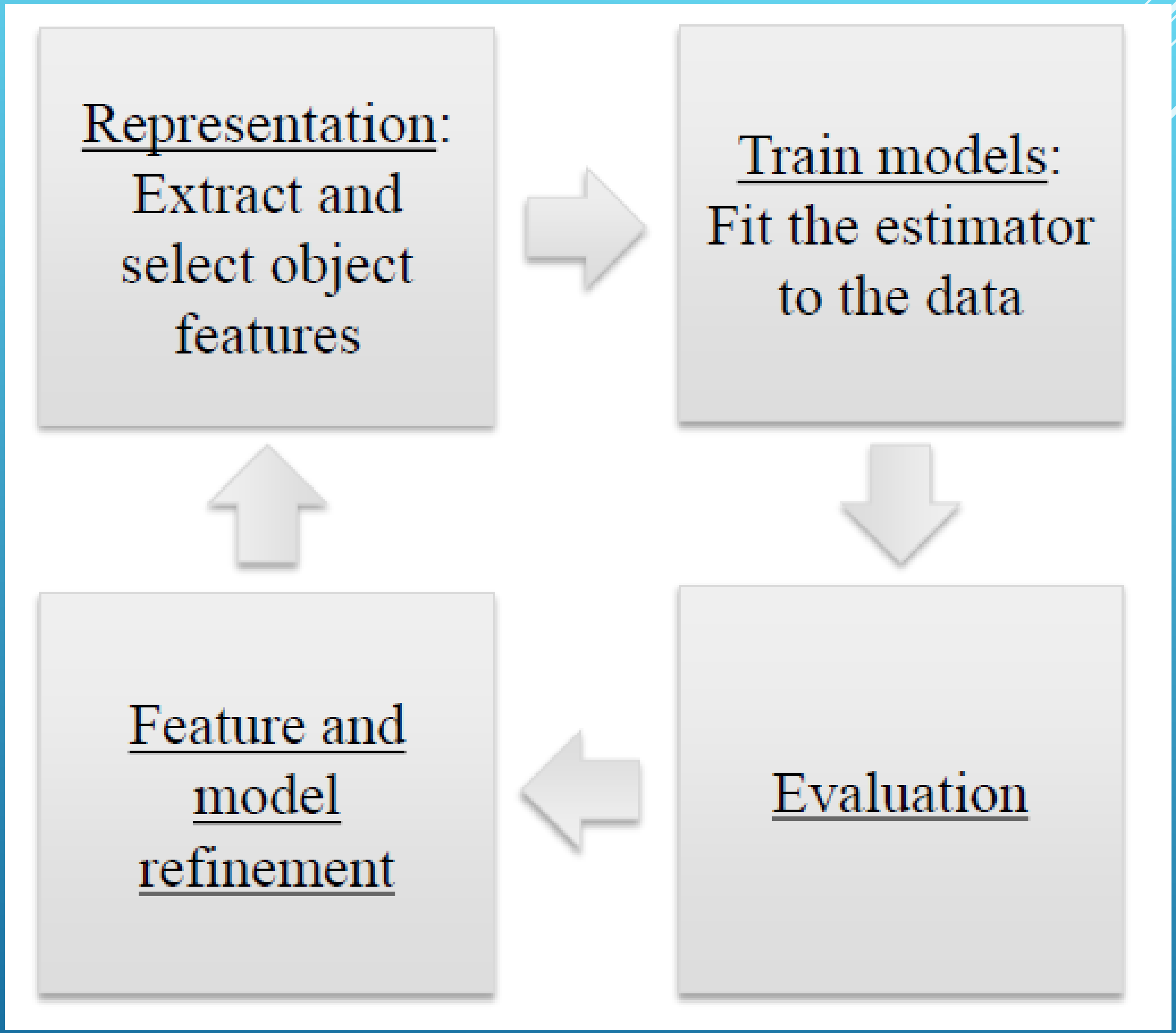
https://www.coursera.org/learn/python-machine-learning/home/welcome

Machine Learning: Classification

University of Washington, Profs. Emily Fox & Carlos Guestrin **(MLC)**

https://www.coursera.org/learn/ml-regression/home/welcome

REPRESENT, TRAIN, EVALUATE, REFINE



ACCURACY IS A COMMON METRIC

$$Accuracy = \frac{\#\ of\ correct\ predictions}{\#\ of\ total\ instances}$$

A model with 99.9% accuracy can sound really good!

HOWEVER, CONSIDER IMBALANCED CLASSES

- Suppose you have two classes:
  - Relevant (R): the positive class
  - Not_Relevant (N): the negative class
- Out of 1000 randomly selected items, on average
  - 1 item is relevant
  - 999 items are not relevant

A DUMMY CLASSIFIER GETS 99.9% ACCURACY!

- Classifier always predicts N
- Out of 1000 randomly selected items:

$$Accuracy = \frac{999}{1000} = 99.9\%$$

DUMMY CLASSIFIERS COMPLETELY IGNORE INPUT DATA

- **Dummy classifiers** can serve as a sanity check on your classifier's performance.
- Some commonly-used dummy classifiers:
  - **most-frequent:** predict most frequent label in training set.
  - **stratified:** random prediction based on training set distribution
  - **uniform:** choose predictions from a uniform probability distribution.
  - **constant:** predict constant label given by user.

PRECISION AND RECALL

Different applications have different goals. Accuracy is widely used, but many other metrics are possible. Two common alternatives to accuracy are: **precision** and **recall.**

PRECISION: fraction of positive predictions that are actually positive.

RECALL: fraction of positive examples that are predicted to be positive.

DOMAINS WHERE **PRECISION** IS IMPORTANT

- Search engine rankings, query suggestions
- Document classification
- Customer-facing tasks, e.g.,:
  - product recommendation
  - a restaurant website that automatically selects and posts positive reviews.

DOMAINS WHERE **RECALL** IS IMPORTANT

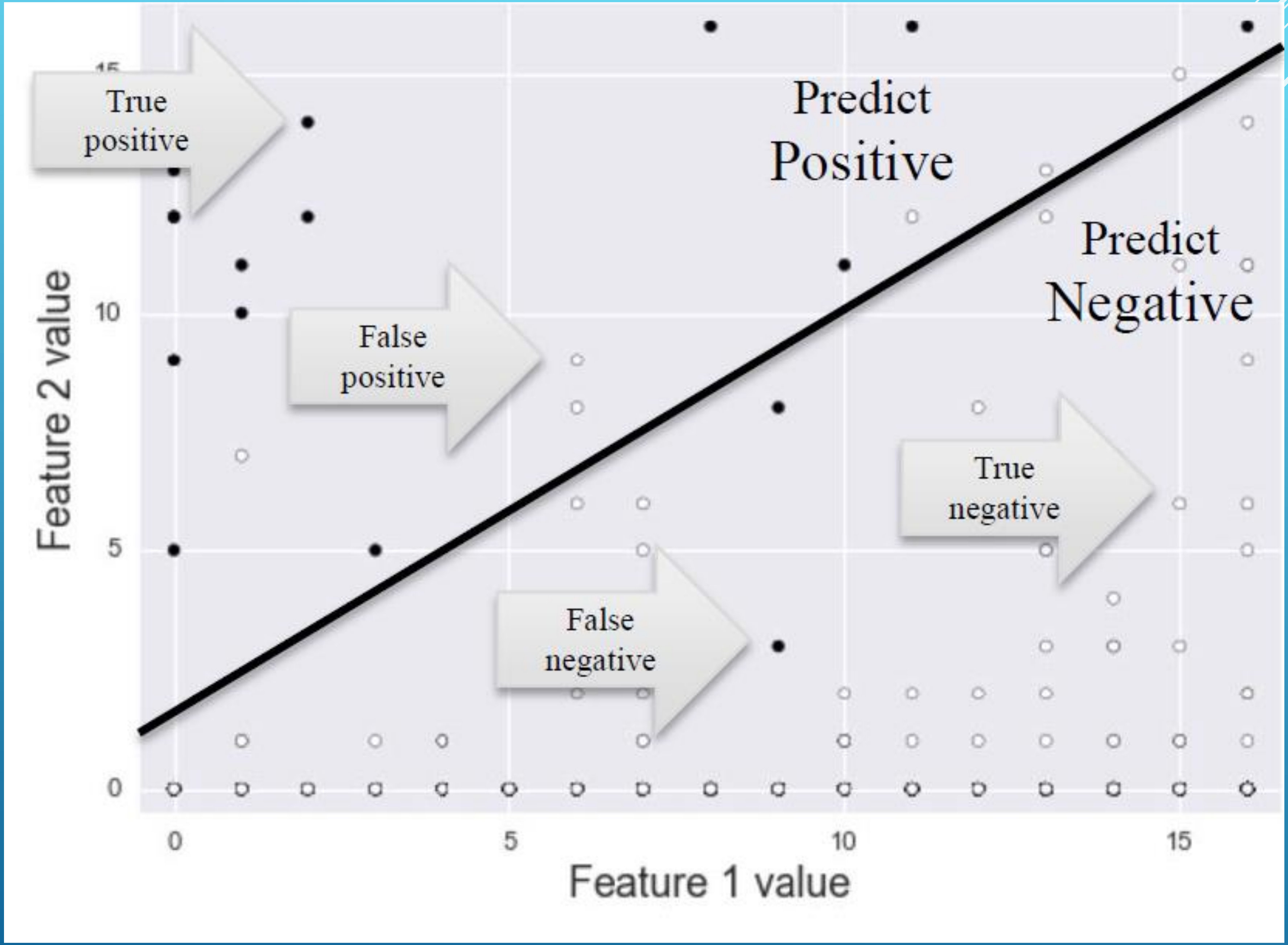
- Cancer tumor detection
- Search and information extraction in legal discovery.
- Often paired with a human expert to filter out false positives.

True negative	TN	FP
True positive	FN	TP
	Predicted negative	**Predicted** positive

TP = true positive
FP = false positive
TN = true negative
FN = false negative

THE CONFUSION MATRIX

VISUALIZING DIFFERENT ERROR TYPES



THE CONFUSION MATRIX

	Predicted negative	Predicted positive
True negative	TN = 356	FP = 51
True positive	FN = 38	TP = 5

N = TN +TP+FN+FP = 450

- Every test instance is in exactly one box.
- Breaks down classifier results by error type (FP vs FN).
- Provides more information than simple accuracy.
- Helps you choose an evaluation metric that matches your project goals.
- There are many possible metrics that can be derived from the confusion matrix.

	Predicted negative	Predicted positive
True negative	TN	FP
True positive	FN	TP

- As FN + FP $\rightarrow$ 0, Accuracy $\rightarrow$ 1.0
- As FN + FP $\uparrow$, Accuracy $\rightarrow$ 0.0

$$\boldsymbol{Accuracy = \frac{TP + TN}{TP + TN + FP + FN}}$$

ACCURACY

	Predicted negative	Predicted positive
True negative	TN	FP
True positive	FN	TP

- As FP → 0, Precision → 1.0
- As FP ↑, Precision → 0.0

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

PRECISION

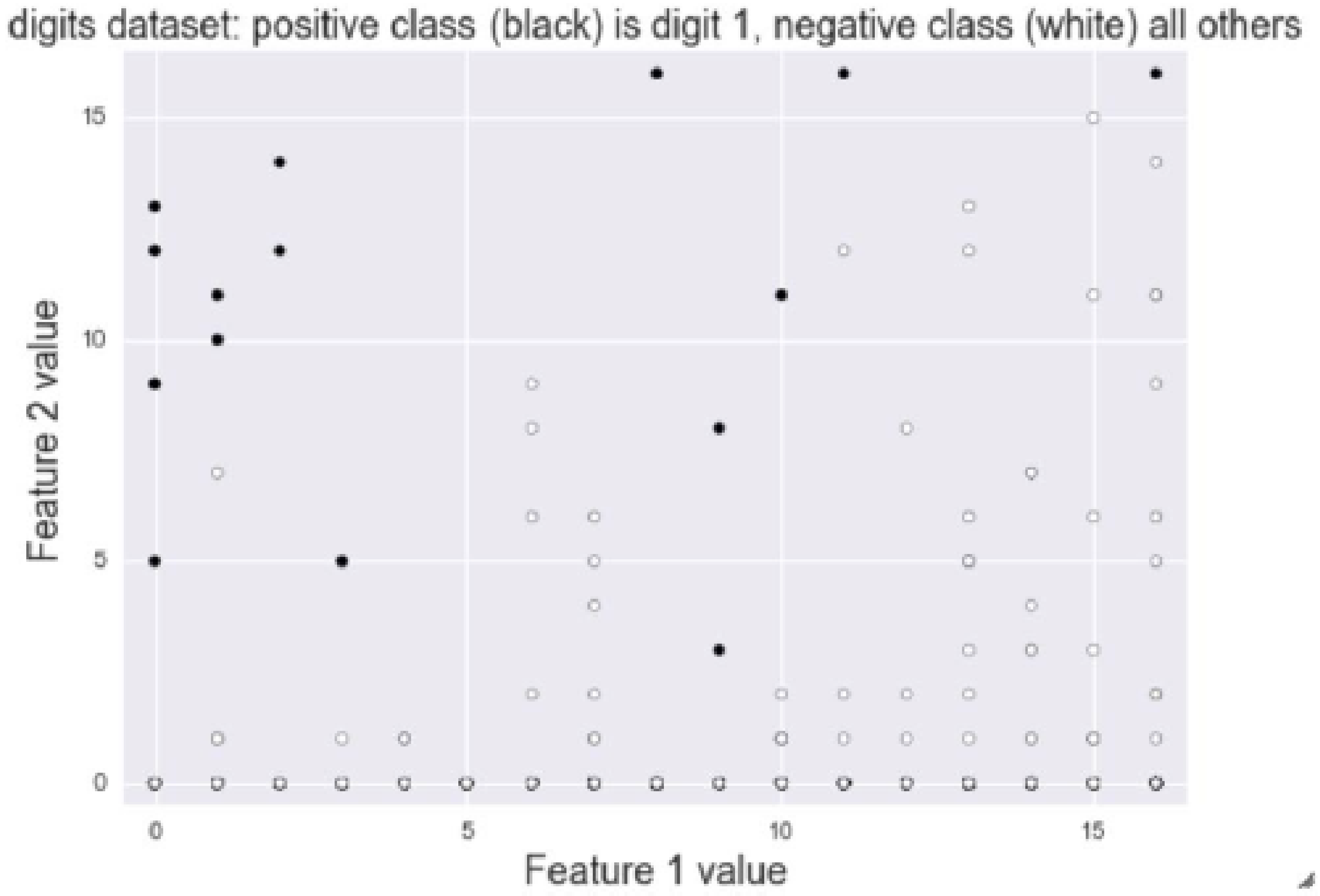
RECALL

	Predicted negative	**Predicted** positive
True negative	TN	FP
True positive	FN	TP

- As FN → 0, Recall → 1.0
- As FN ↑, Recall → 0.0

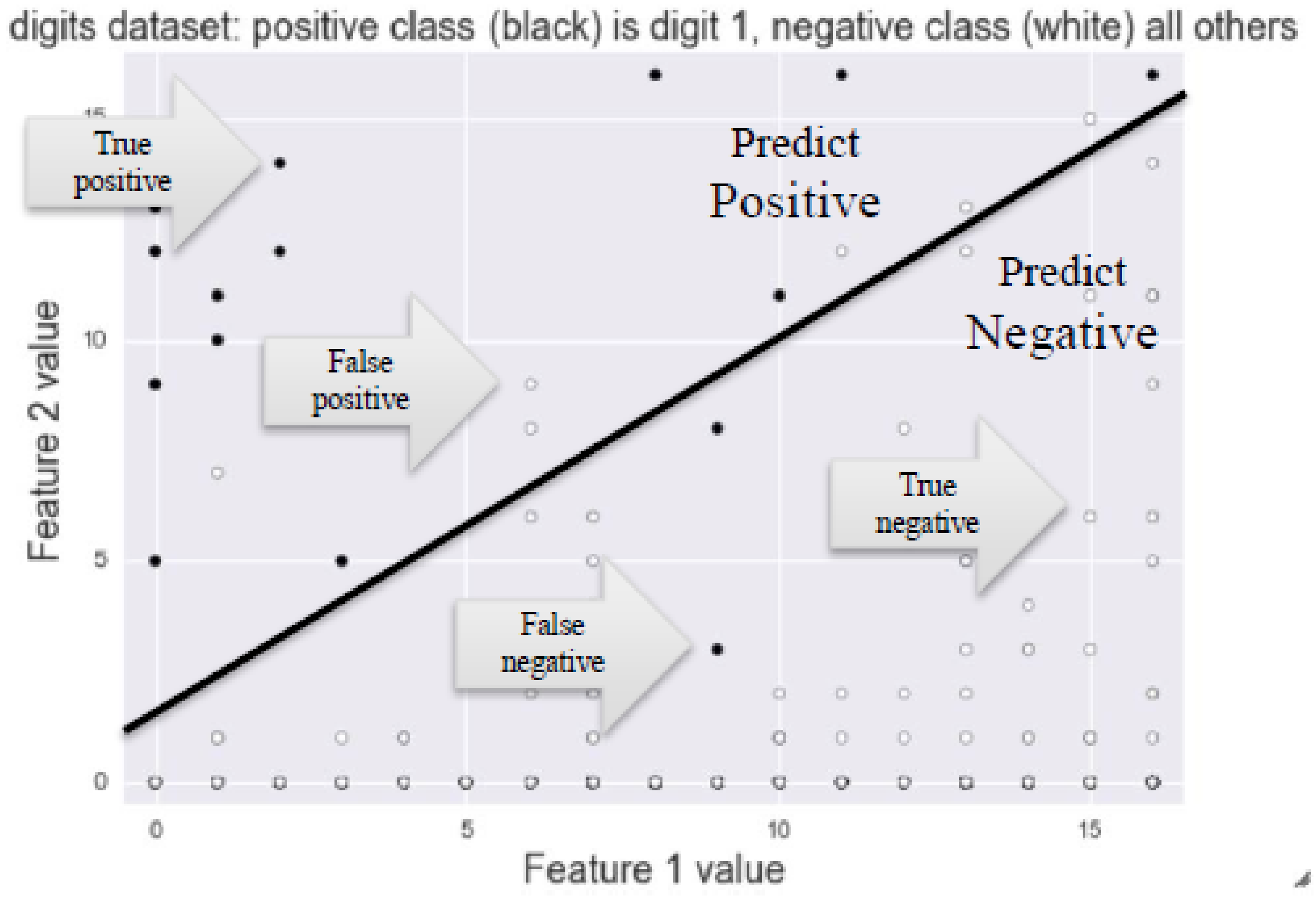
$$\boldsymbol{Recall = \frac{TP}{TP + FN}}$$

ILLUSTRATING PRECISION & RECALL



TN =	FP =
FN =	TP =

ILLUSTRATING PRECISION & RECALL

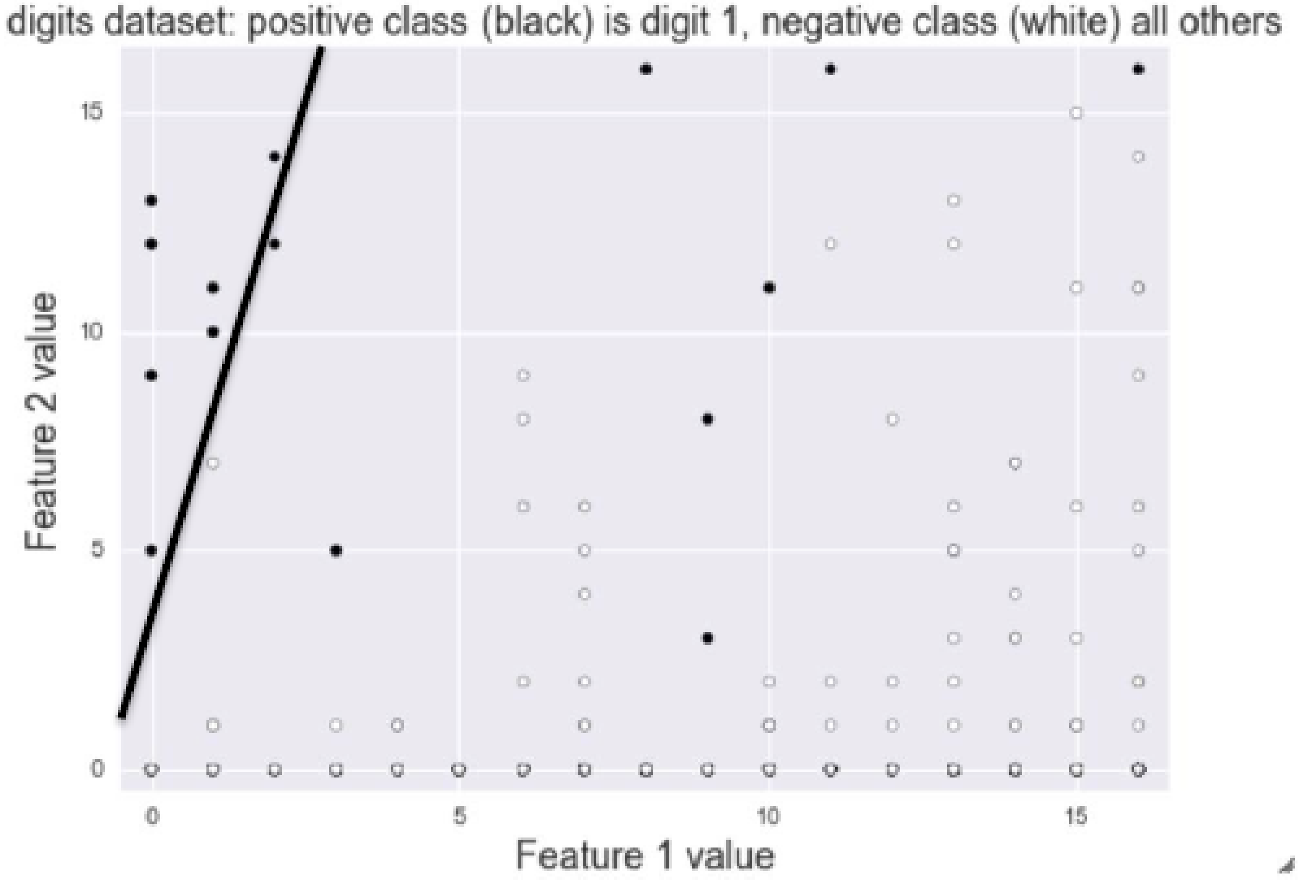


TN = 429	FP = 6
FN = 2	TP = 13

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{13}{19} = 0.68$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{13}{15} = 0.87$$

HIGH PRECISION / LOW RECALL

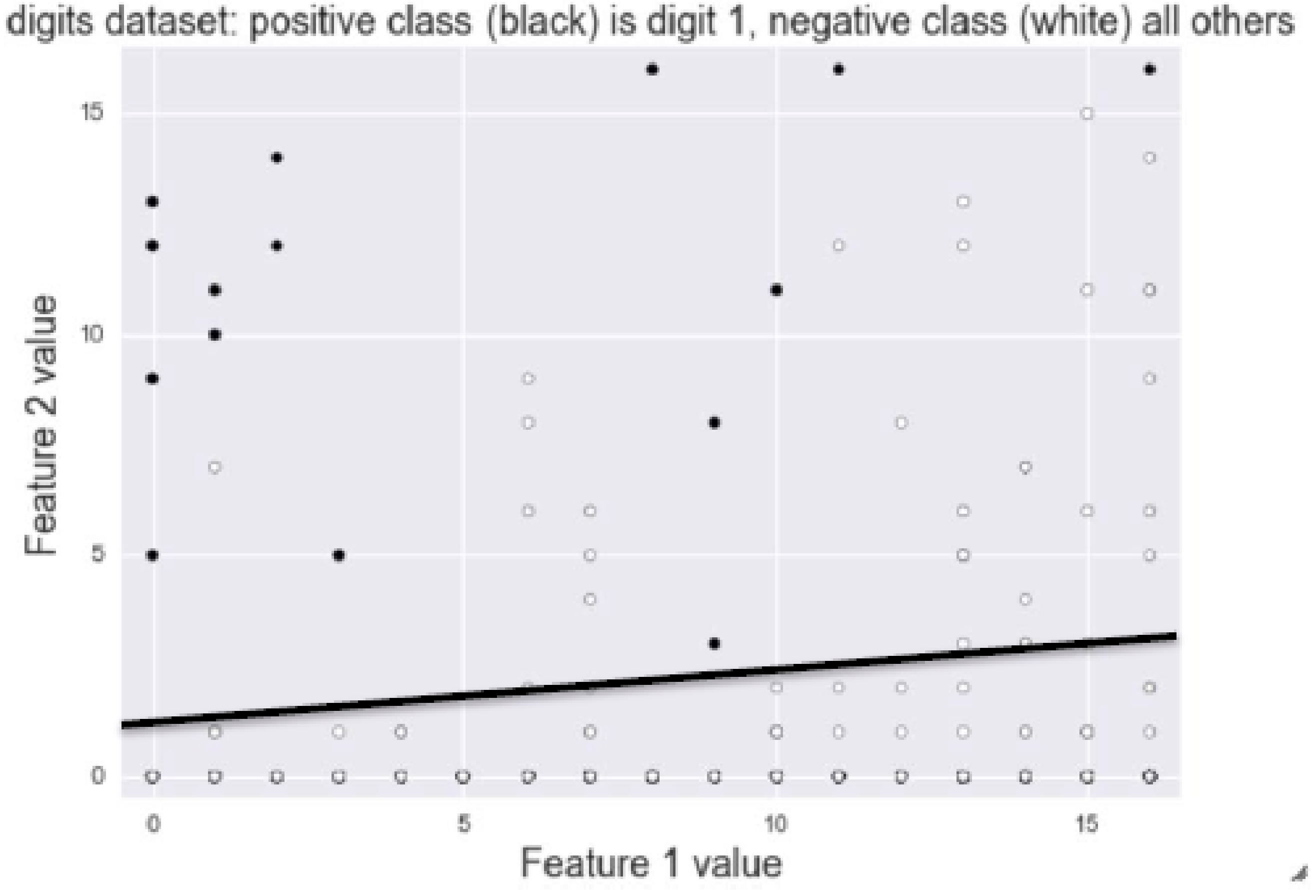


TN = 435	FP = 0
FN = 8	TP = 7

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{7}{7} = 1.00$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{7}{15} = 0.47$$

HIGH PRECISION / LOW RECALL



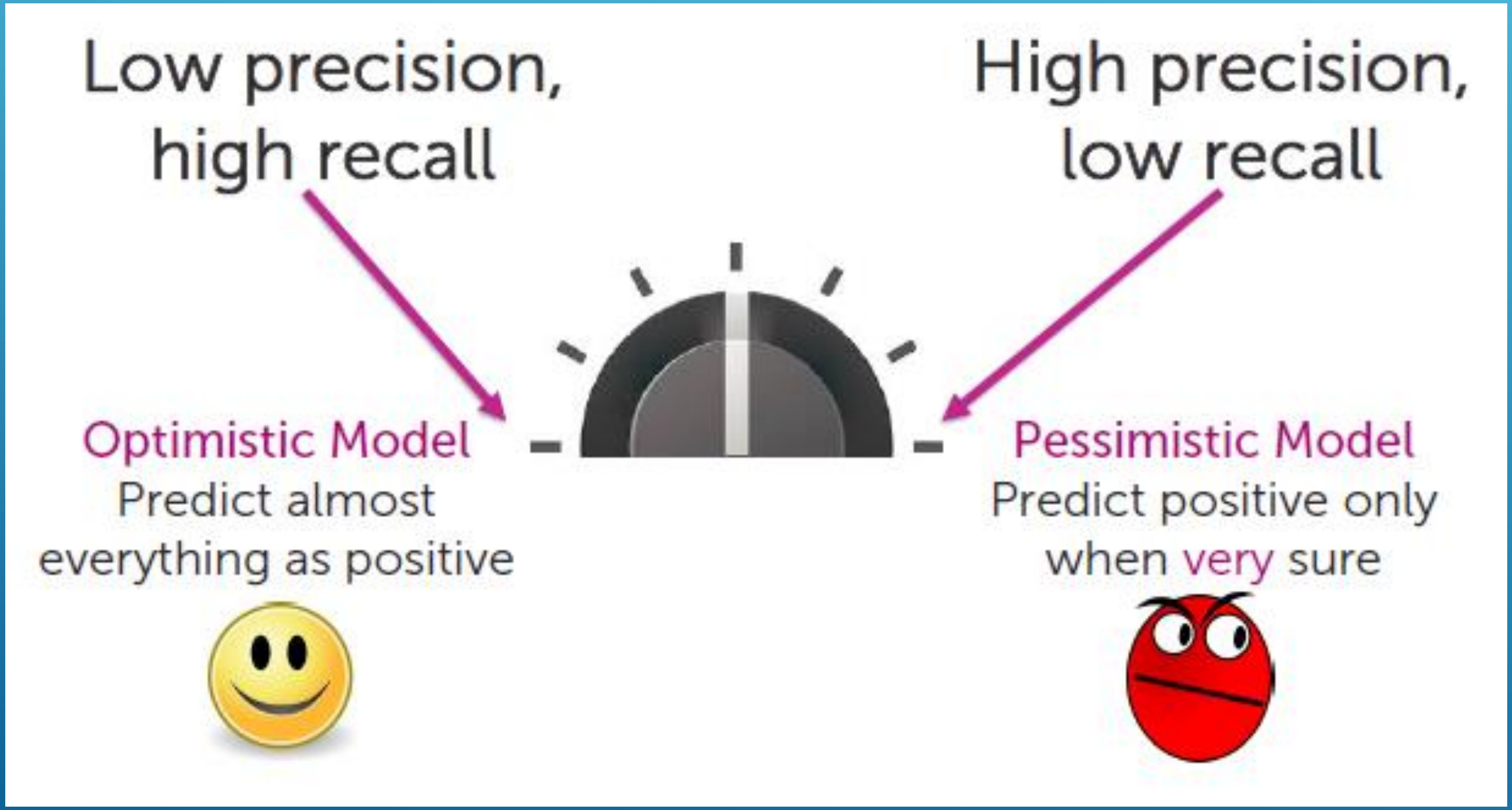
TN = 408	FP = 27
FN = 0	TP = 15

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{15}{42} = 0.36$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{15}{15} = 1.00$$

BALANCING PRECISION AND RECALL

Rather than seeking to maximize precision or recall, an optimal balance between the two is often sought.



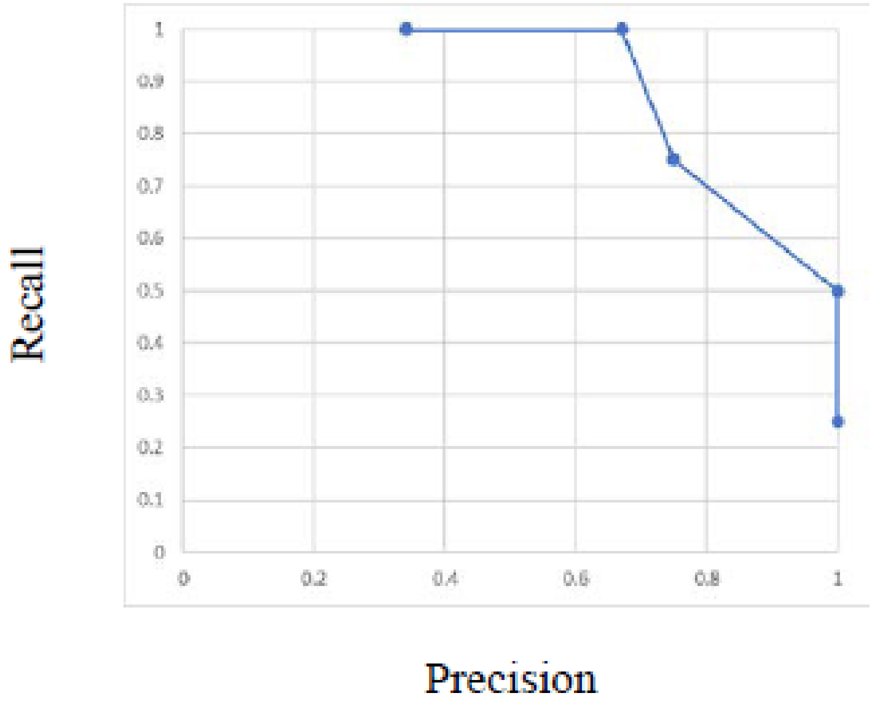
DECISION FUNCTIONS

- A **decision function** is a classifier that returns a score that represents how confident the classifier is in its prediction.
- The **decision threshold** can be "adjusted" to result in a decision function that exhibits more or less precision or recall.
- A higher threshold results in a more "pessimistic" classifier i.e., it increase precision.
- A lower threshold results in a more "optimistic" classifier i.e., it increase recall.
- By sweeping the decision threshold through the entire range of possible score values, we get a series of classification outcomes that form a curve.

VARYING THE DECISION THRESHOLD

True Label	Classifier score
0	-27.6457
0	-25.8486
0	-25.1011
0	-24.1511
0	-23.1765
0	-22.575
0	-21.8271
0	-21.7226
0	-19.7361
0	-19.5768
0	-19.3071
0	-18.9077
0	-13.5411
0	-12.8594
1	-3.9128
0	-1.9798
1	1.824
0	4.74931
1	15.234624
1	21.20597

Classifier score threshold	Precision	Recall
-20	4/12=0.34	4/4=1.00
-10	4/6=0.67	4/4=1.00
0	3/4=0.75	3/4=0.75
10	2/2=1.0	2/4=0.50
20	1/1=1.0	1/4 = 0.25



PRECISION-RECALL CURVES

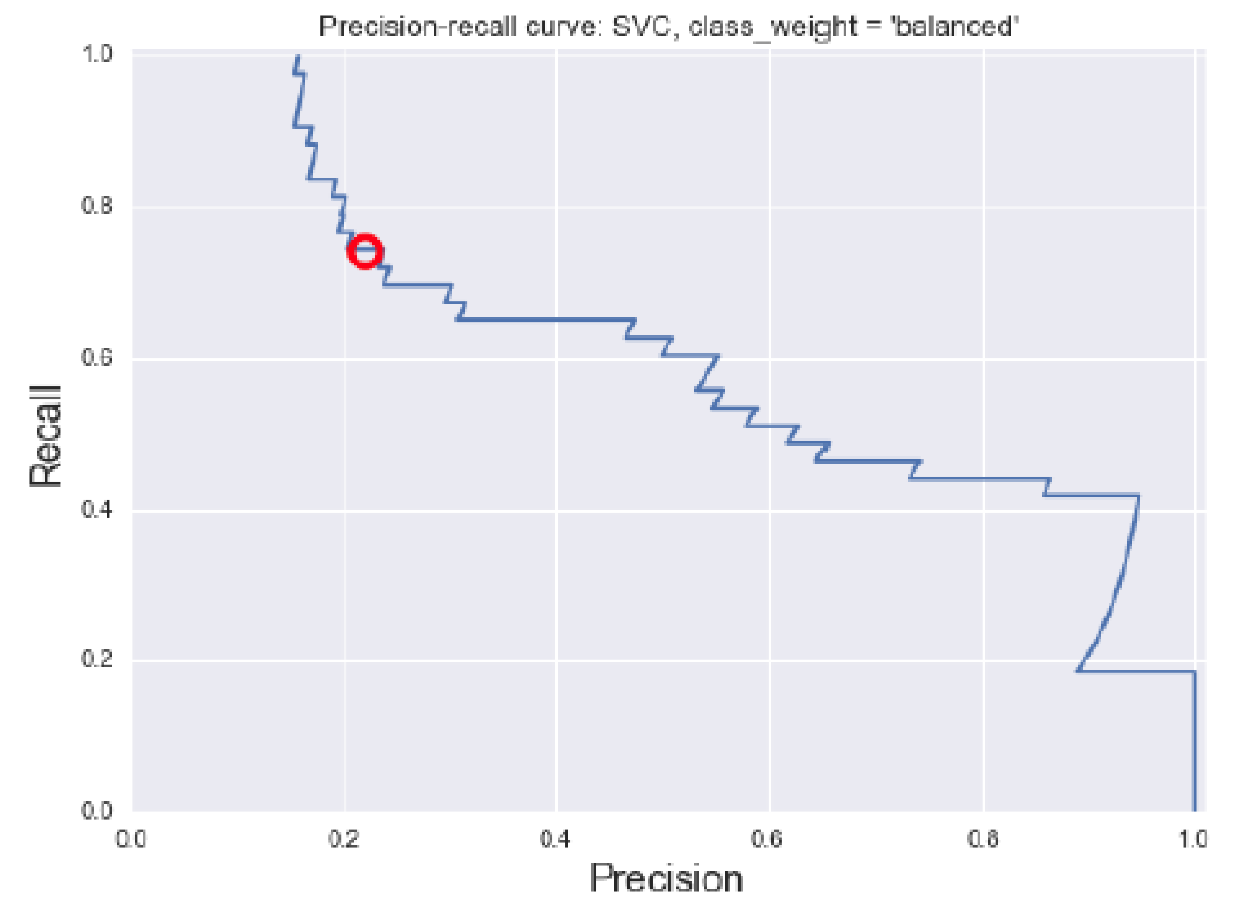
X-axis: Precision
Y-axis: Recall

Top right corner:

- **The "ideal" point**
- **Precision = 1.0**
- **Recall = 1.0**

"Steepness" of P-R curves is important:

- **Maximize precision**
- **while maximizing recall**

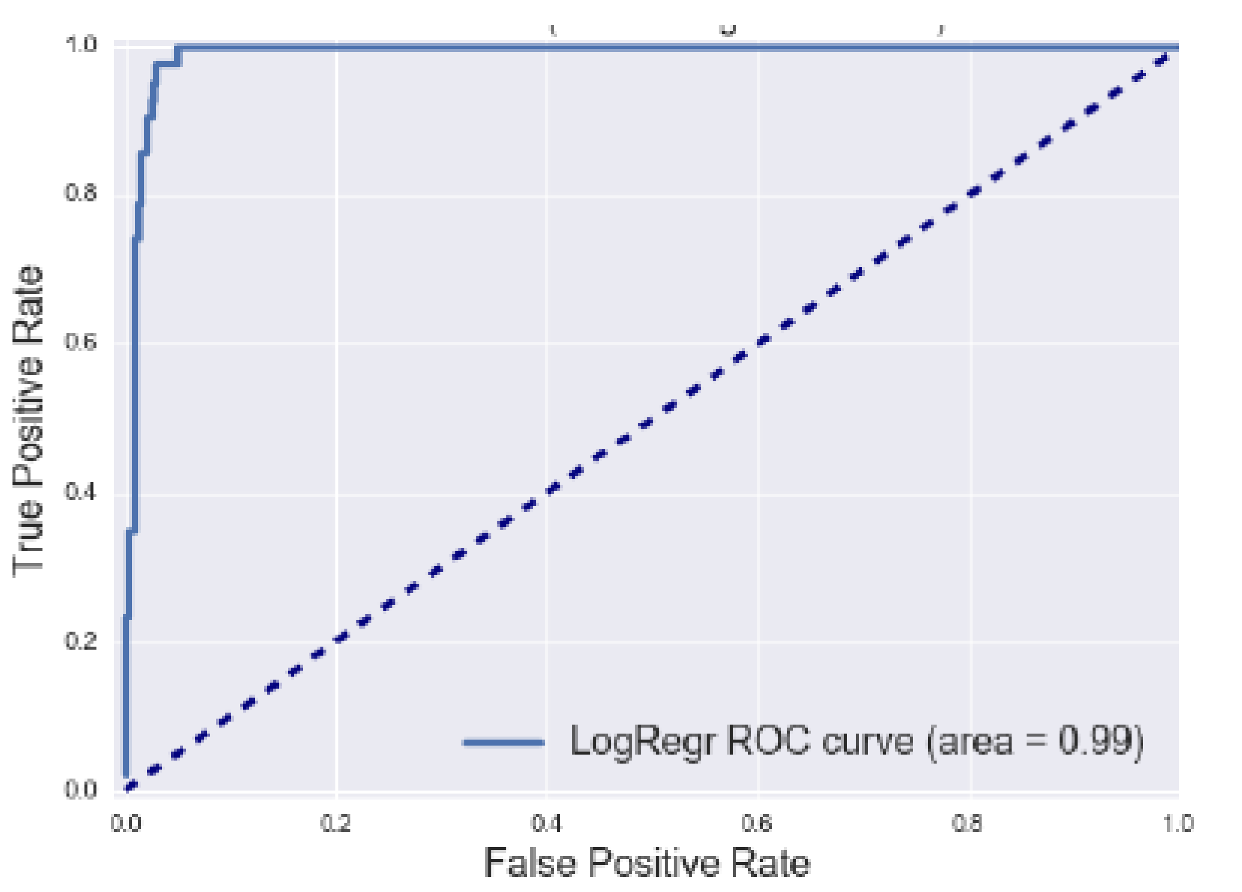


ROC CURVES

X-axis: False Positive Rate
Y-axis: True Positive Rate

Top left corner:
- **The "ideal" point**
- **False positive rate of zero**
- **True positive rate of one**

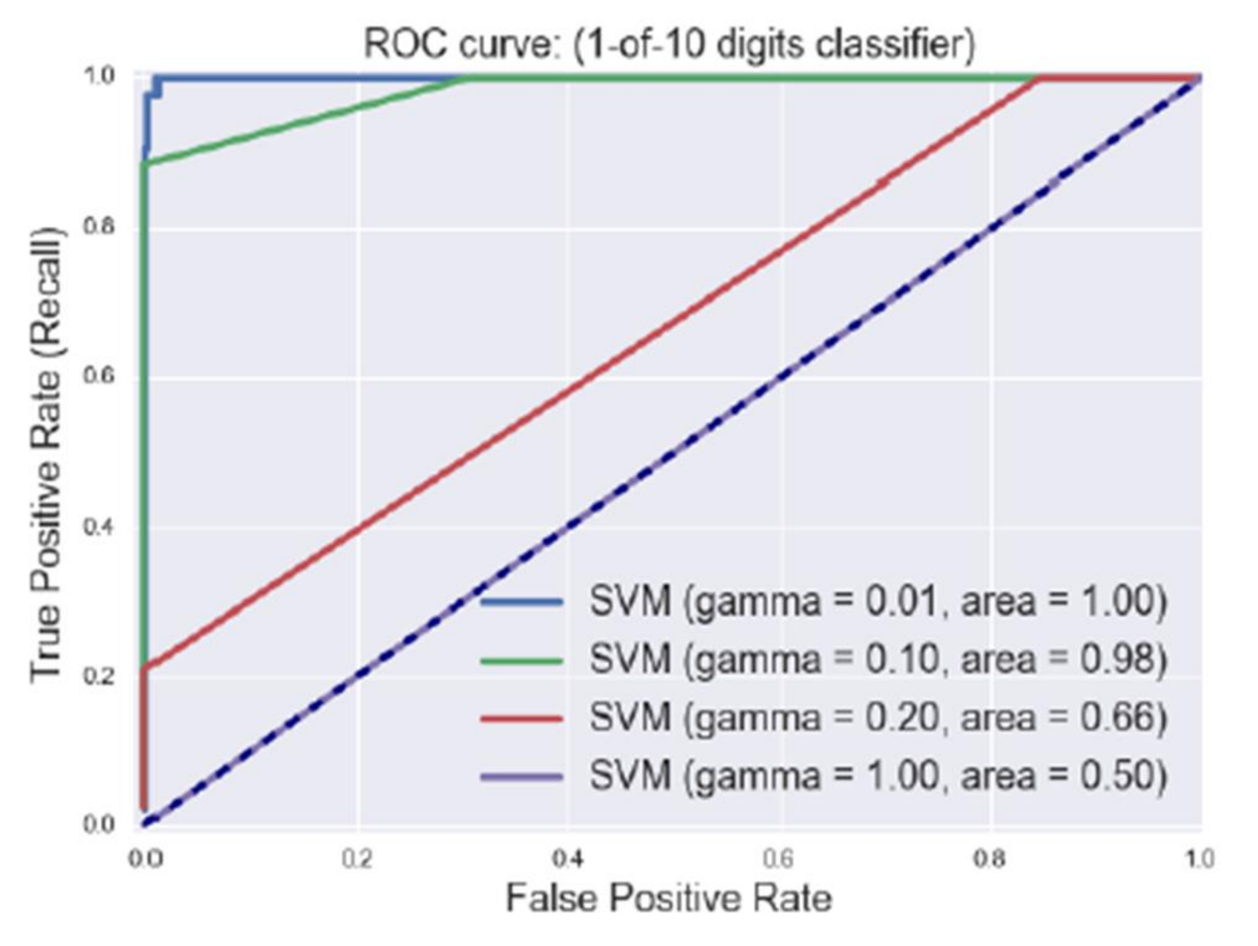
"Steepness" of ROC curves is important:
- **Maximize the true positive rate**
- **while minimizing the false positive rate**



ROC = Receiver Operating Characteristic

SUMMARIZING AN ROC CURVE IN ONE NUMBER: AREA UNDER THE CURVE (AUC)

- AUC = 0 (worst) AUC = 1 (best)
- AUC can be interpreted as:
  1. The total area under the ROC curve.
  2. The probability that the classifier will assign a higher score to a randomly chosen positive example than to a randomly chosen negative example.
- Advantages:
  - Gives a single number for easy comparison.
  - Does not require specifying a decision threshold.
- Drawbacks:
  - As with other single-number metrics, AUC loses information, e.g. about tradeoffs and the shape of the ROC curve.
  - This may be a factor to consider when e.g. wanting to compare the performance of classifiers with overlapping ROC curves.



CONCLUSION

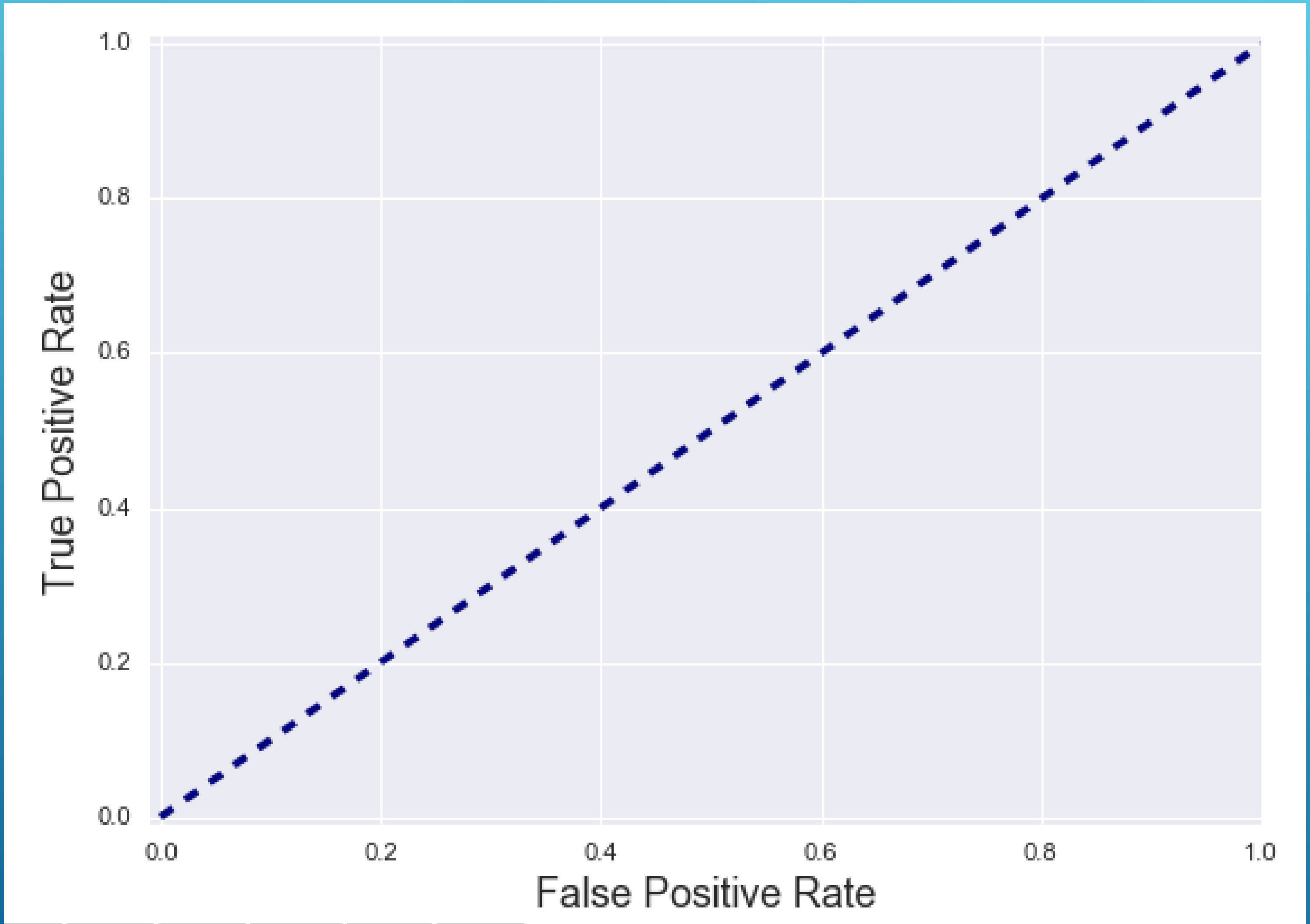
1. Consider carefully the data you have and what you are trying to do with it.
2. Choose a SINGLE metric and optimize that metric.
3. If this gives satisfactory results, then you are done. Otherwise return to step 1.

EXTRA SLIDES

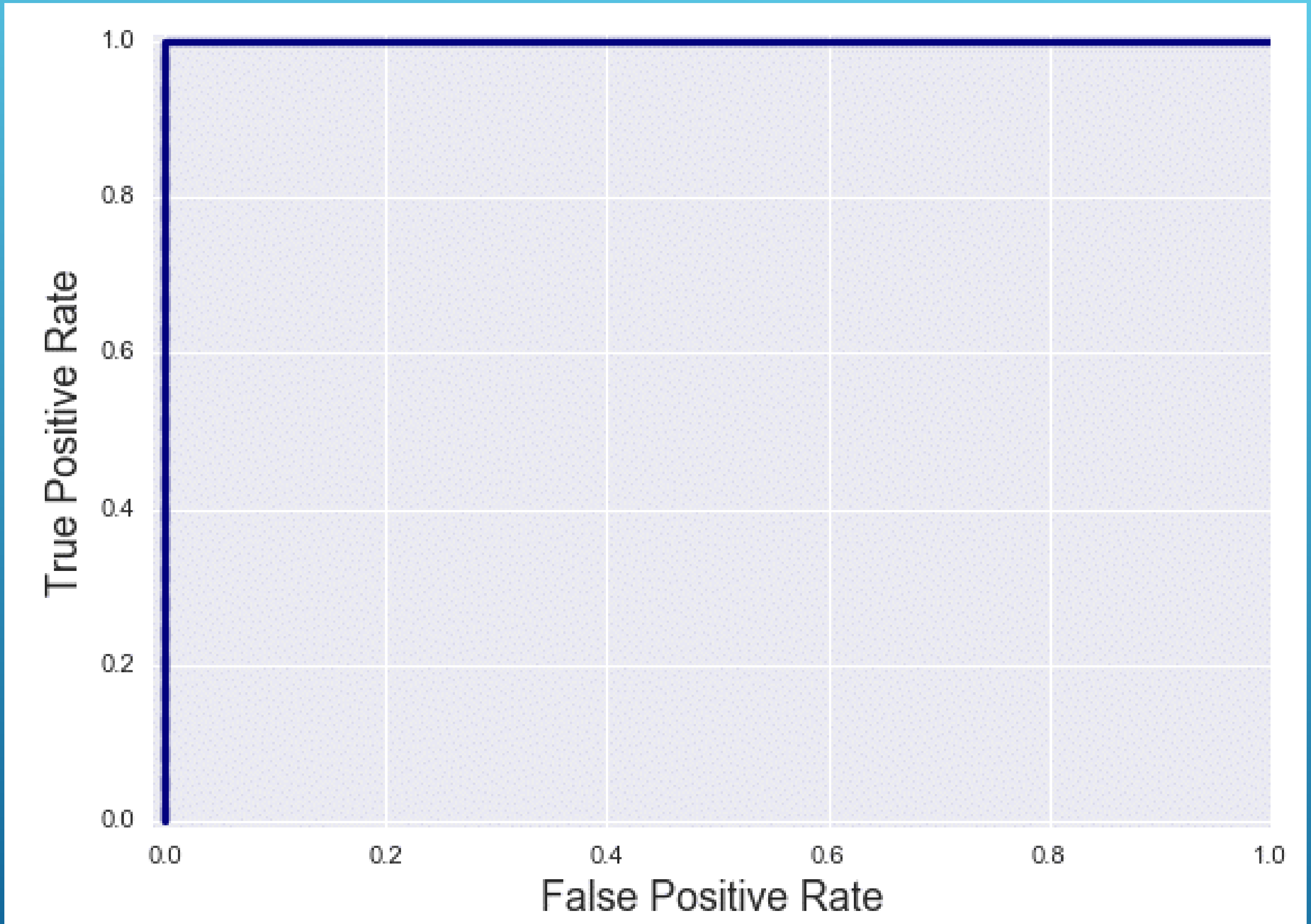
PROBABILISTIC CLASSIFIERS

- Some classifiers return a probability that an item is a particular class rather than a Boolean value.
- Examples include Logistic regression, Naïve Bayes.
- Typical rule is choose likely class if $P(x) >$ *threshold* where threshold > 0.5
- Adjusting *threshold* affects predictions of classifier
- Higher *threshold* results in a more “pessimistic” classifier i.e., it increase precision.

ROC CURVES: RANDOM GUESSING



ROC CURVES: PERFECT CLASSIFIER



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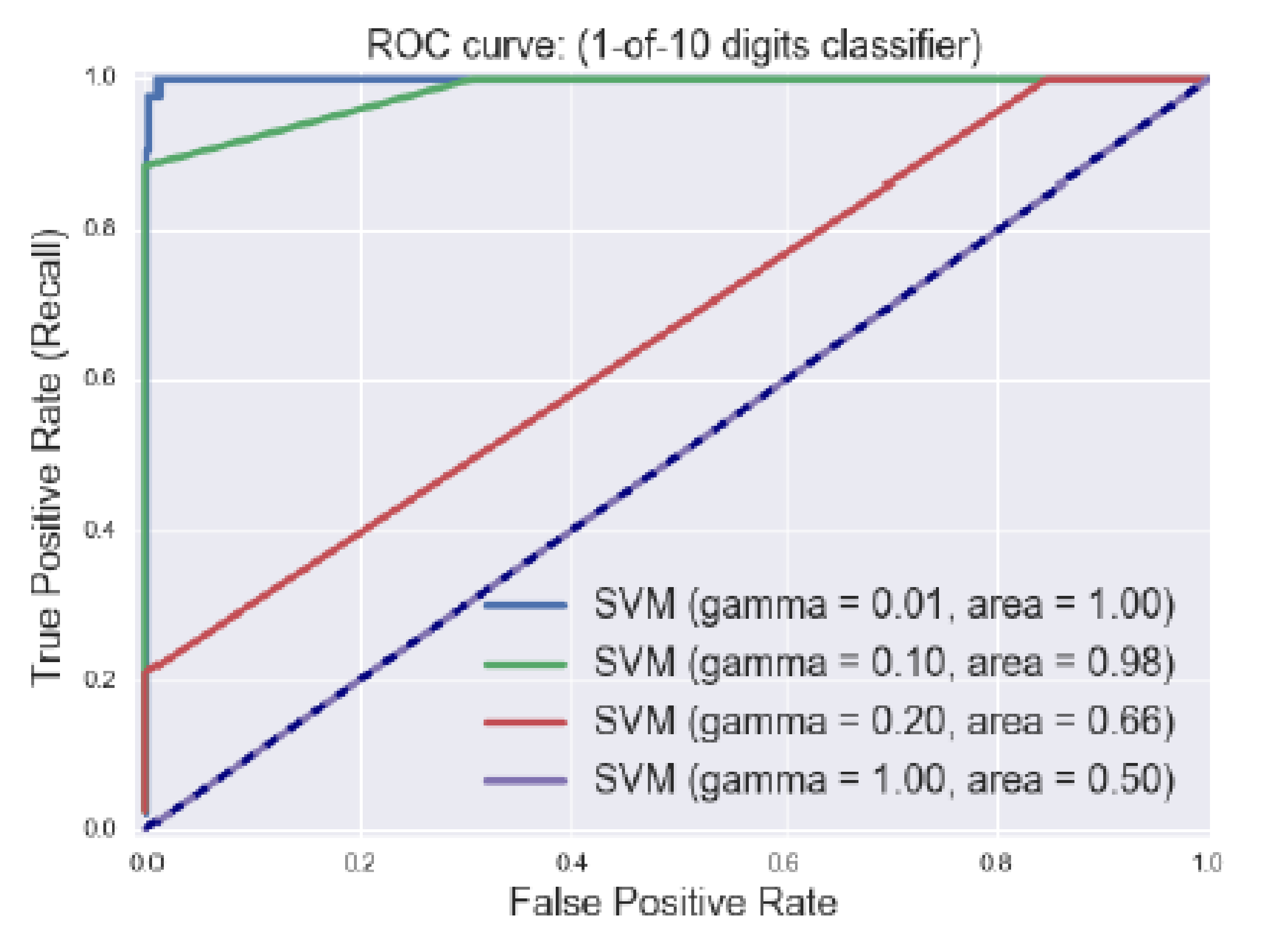

THE F1-SCORE

- The **F1-score** combines precision and recall into a single number.
- The F1-score is the ***harmonic mean*** of precision and recall.

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} = \frac{2 \cdot TP}{2 \cdot TP + FN + FP}$$

THE F-SCORE

- The **F-score** is a generalization of the F1-score.
- β allows adjustment of the metric to control the emphasis on recall vs precision.
  - $\beta < 1.0$ results in greater precision (minimize false positives)
  - $\beta > 1.0$ results in greater recall (minimize false negatives)

$$F_\beta = (1 + \beta^2) \cdot \frac{Precision \cdot Recall}{(\beta^2 \cdot Precision) + Recall} = \frac{(1 + \beta^2) \cdot TP}{(1 + \beta^2) \cdot TP + \beta \cdot FN + FP}$$