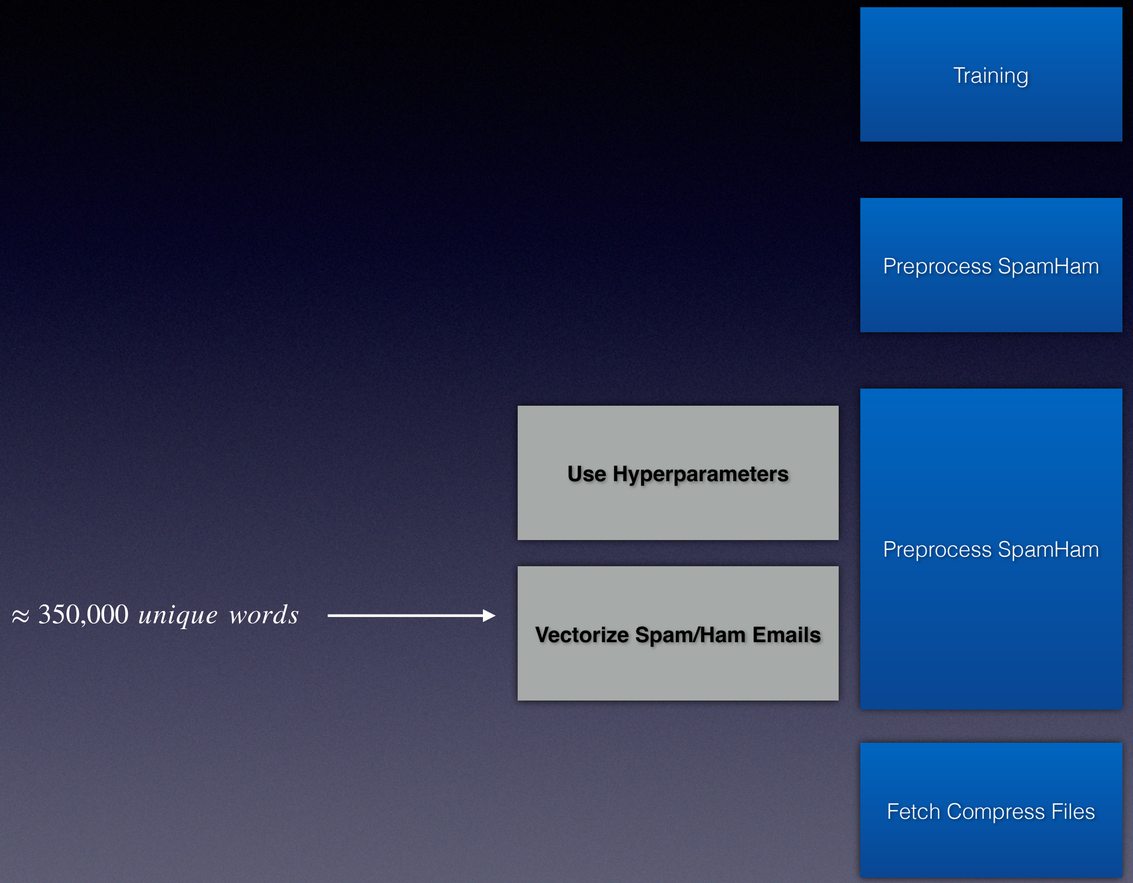
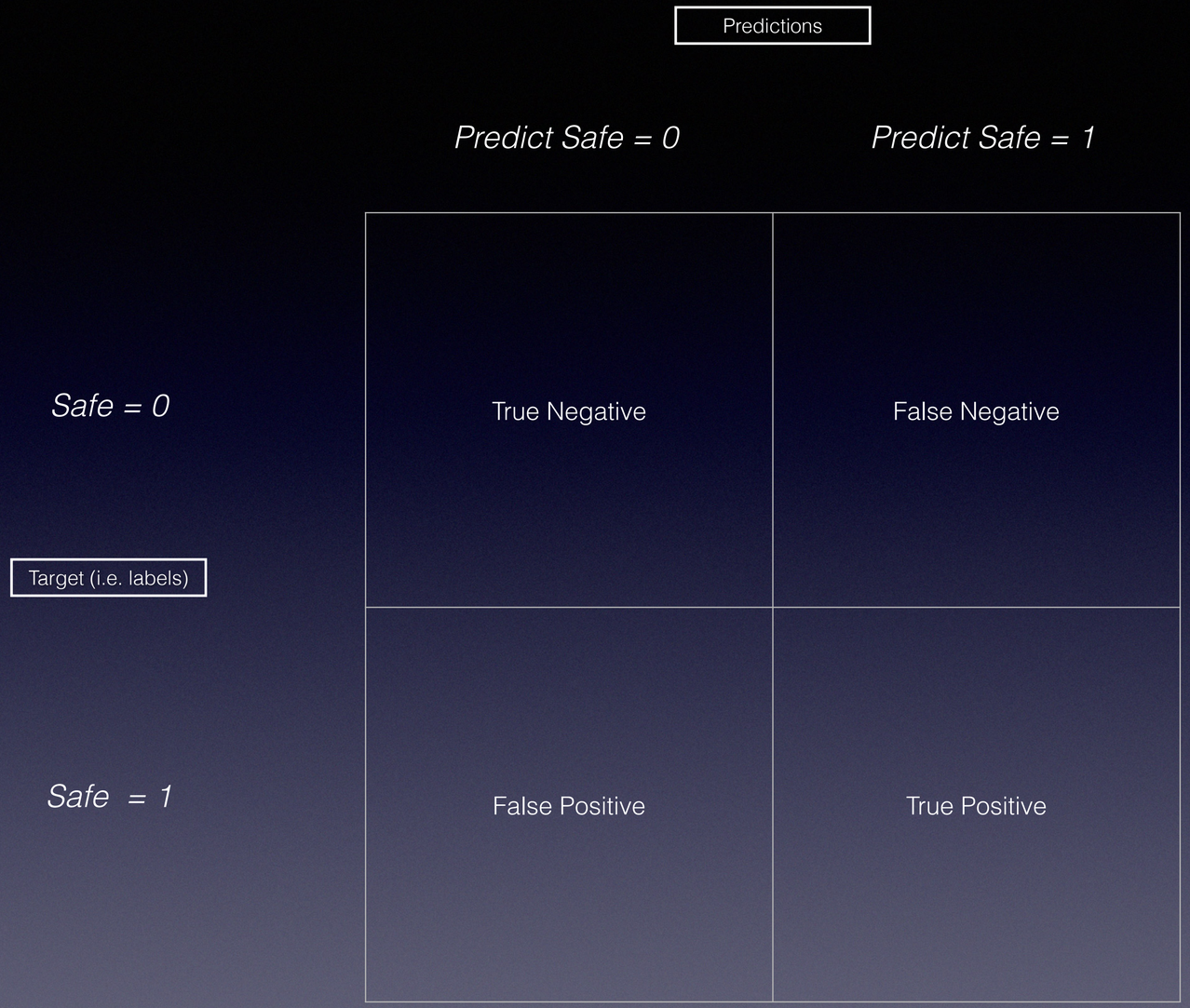
Classification


Training
Preprocess SpamHam
Use Hyperparameters
Preprocess SpamHam
≈ 350,000 unique words
Vectorize Spam/Ham Emails
Fetch Compress Files

Confusion Matrix



Confusion Matrix

Predictions

Target (i.e. labels)	*Predict Safe = 0*	*Predict Safe = 1*
Safe = 0	True Negative	False Positive
Safe = 1	False Negative	True Positive

Precision (i.e. accuracy)

$$Precision_{Class_{Safe=1}} \quad \frac{TP}{TP+FP}$$

Ratio of positive predictions(class PredictSafe=1) that are correct

Confusion Matrix

Predictions

Target (i.e. labels)	*Predict Safe = 0*	*Predict Safe = 1*
Safe = 0	True Negative	False Positive
Safe = 1	False Negative	True Positive

Precision (i.e. accuracy)

$$Recall_{Class_{Safe=1}} \quad \frac{TP}{TP+FN}$$

Ratio of positive instances(class Safe=1) that are detected

Correctly predicts a ‘true’ cat 82 % of time

Precision

Model
Cat Classifier

Recall

Detects cats 71% of time

Model
Cat Classifier

Correct cats % of time

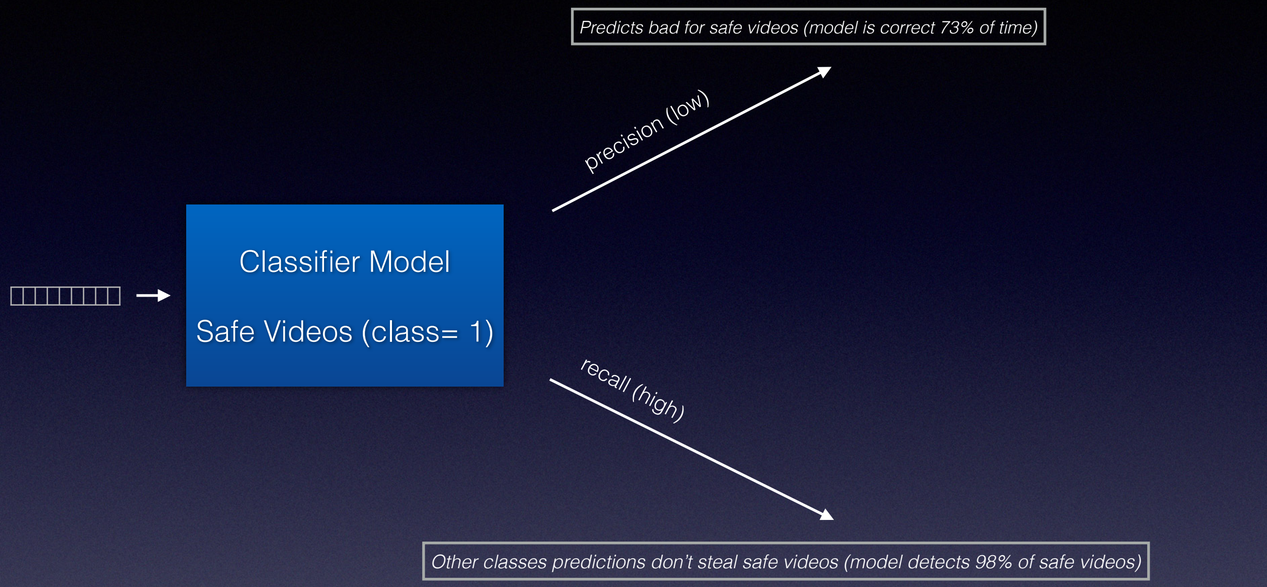
Detects cats 71% of time

F1 Score

Use to measure both recall and precision

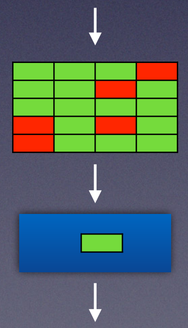
F1 is high if both precision and recall are high

Precision or Recall

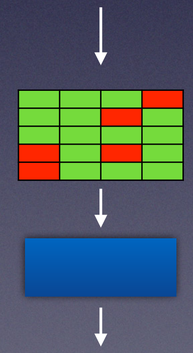


- *class=0(bad) videos are rarely predicted as class=1(good)*
- *Bad videos are likely to be flagged as bad (class =0)*
  - *"don't concern yourself about the other video classes, they are handled correctly, only concern yourself about handling of class=1(safe) videos"*
- *Accepts damn near all safe videos well, check with precision on how well the actual safe videos are classified*

The models devils don't steal other videos (predict their class as the safe video)

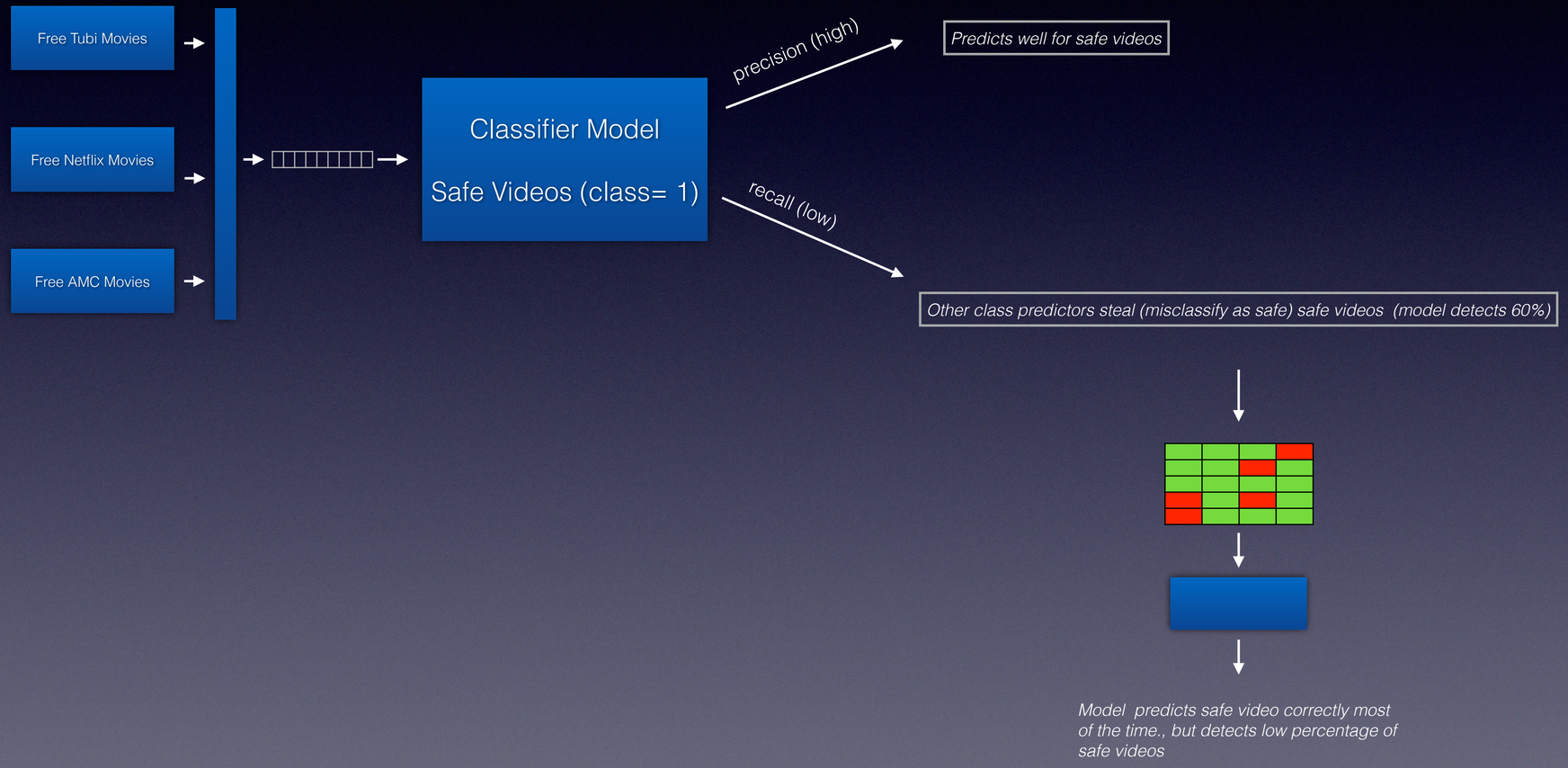


Model predicts safe videos incorrectly most of the time, but mostly all safe videos are detected



Model predicts safe video correctly most of the time., but detects low percentage of safe videos

Safe Video App



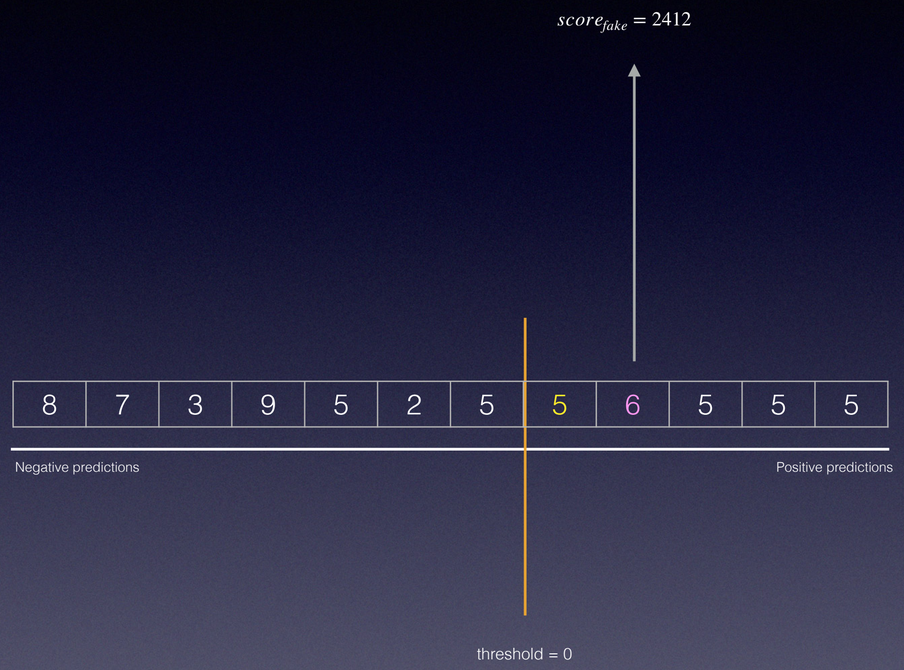
This method should be used if building a free kid safe video streaming service

	Great predictor Tall	Great predictor Medium	Bad predictor Short
Bad Detector Tall	123	2	111
Good Detector Medium	2	111	2
Good Detector Short	1	1	210

Bad Devil - steals many tall humans

Thresholding

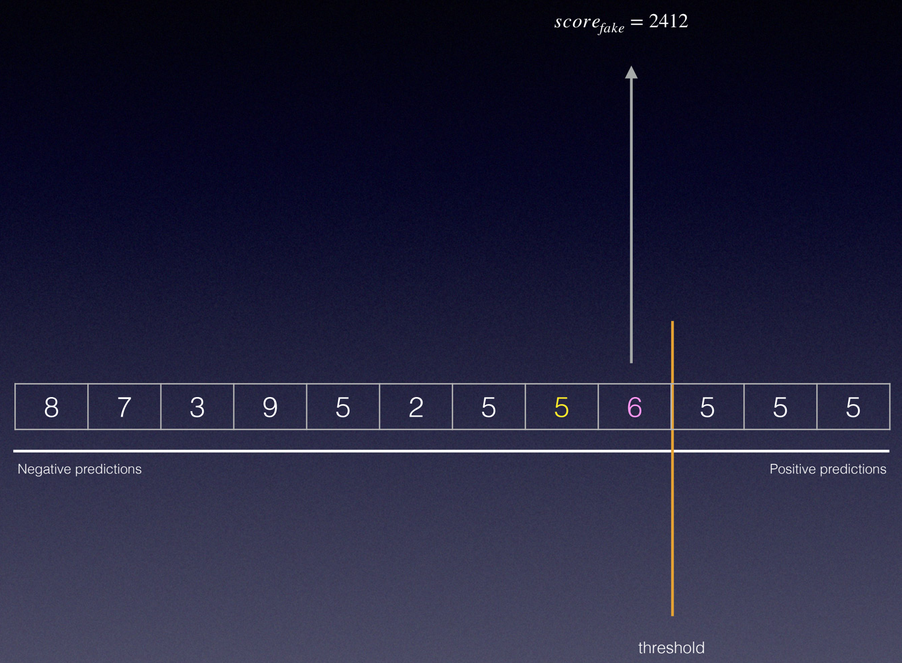
	Predict !5	Predict 5
!5	8 7 3 9 2	6
5	5 5	5 5 5 5



Thresholding

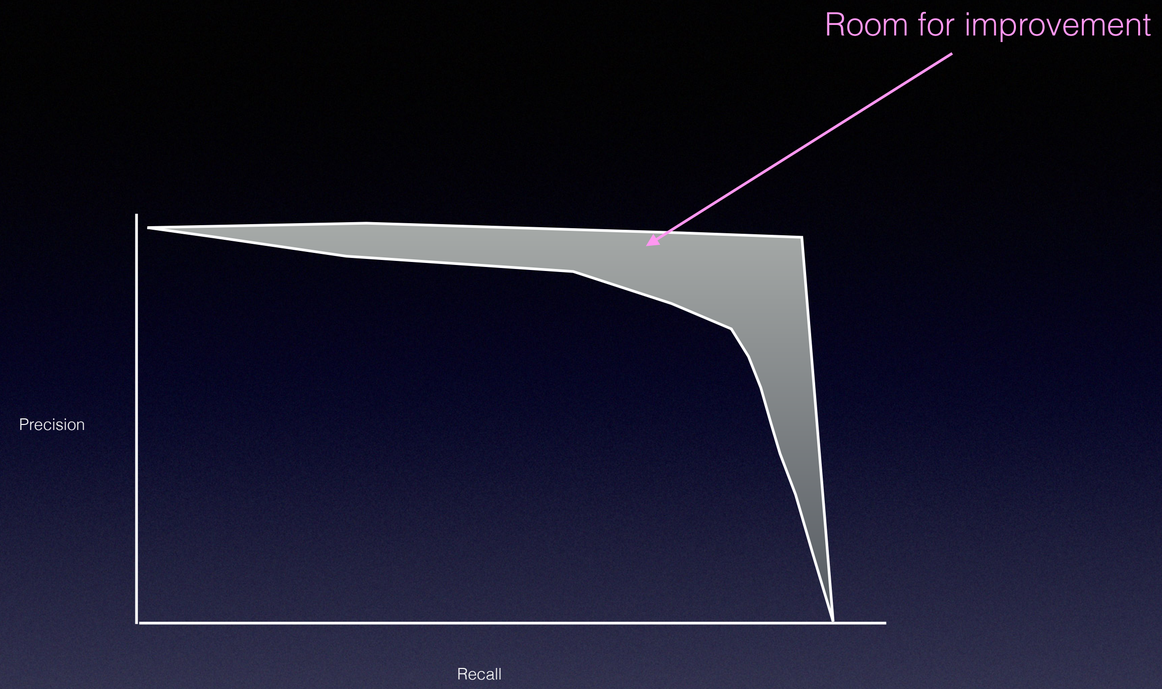
Perfect Class 5 predictor

	Predict !5	Predict 5
!5	8 7 3 9 2 6	
5	5 5 5 5	5 5 5

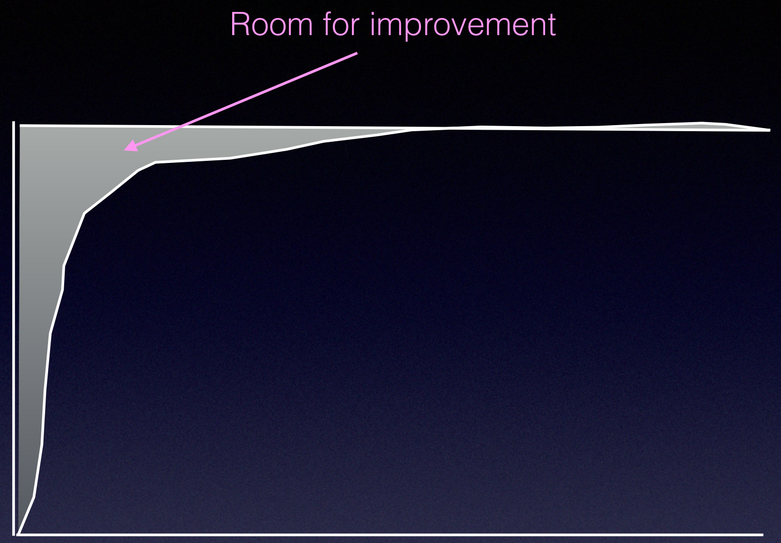


Increasing threshold increases precision, decreases recall

Measure Classifier: Precision vs Recall



Measure Classifier: ROC Curve



TPR = TruePositiveRate

$$TruePositiveRate = \frac{TP}{TP + FN}$$

$$TrueNegativeRate = \frac{TN}{TN + FP}$$

FPR(False Positive Rate) = 1 - TrueNegativeRate

True Negative	False Positive
False Negative	True Positive

Measure Classifier: ROC or Recall/Precision

True Negative	False Positive
False Negative	True Positive

	Predict !Cat	Predict Cat
!Cat	22	222
Cat	2	7

PR if positive class is rare or if we care about false positives than false negatives

Model predicts dogs(!cat) as cats

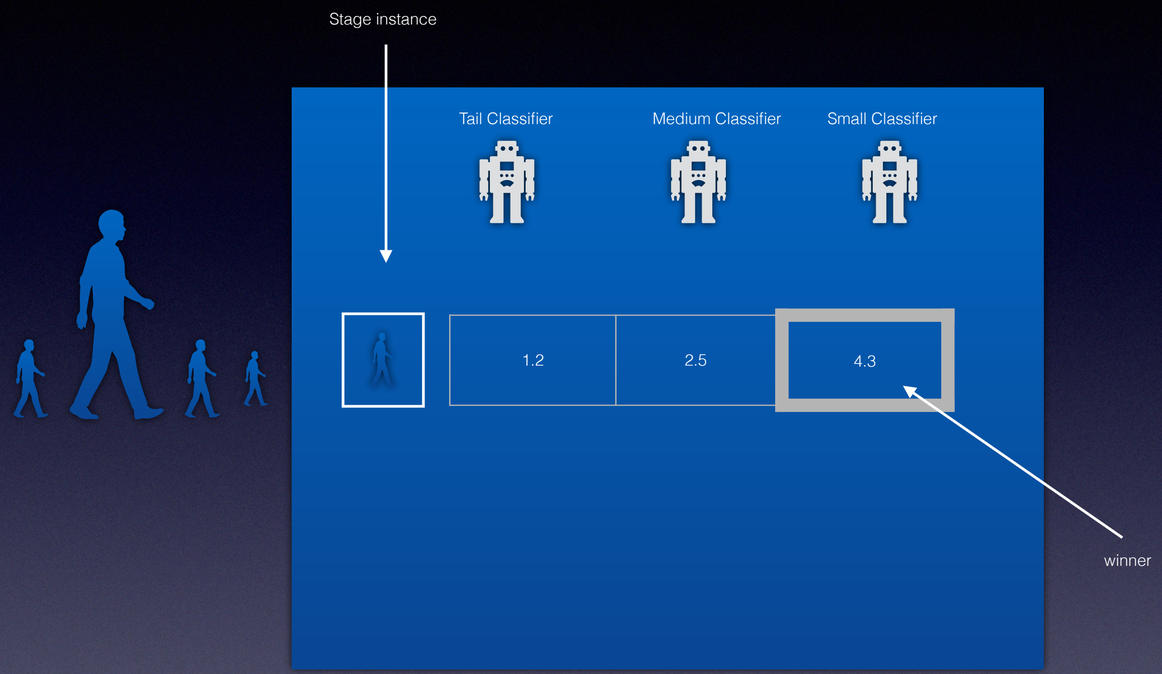
Model predicts cats as dogs

Multi-class Classifiers

	Great predictor Tall	Great predictor Medium	Bad predictor Short
Bad Detector Tall	123	2	111
Good Detector Medium	2	111	2
Good Detector Short	1	1	210

Multi-class Classifiers

Single Winner

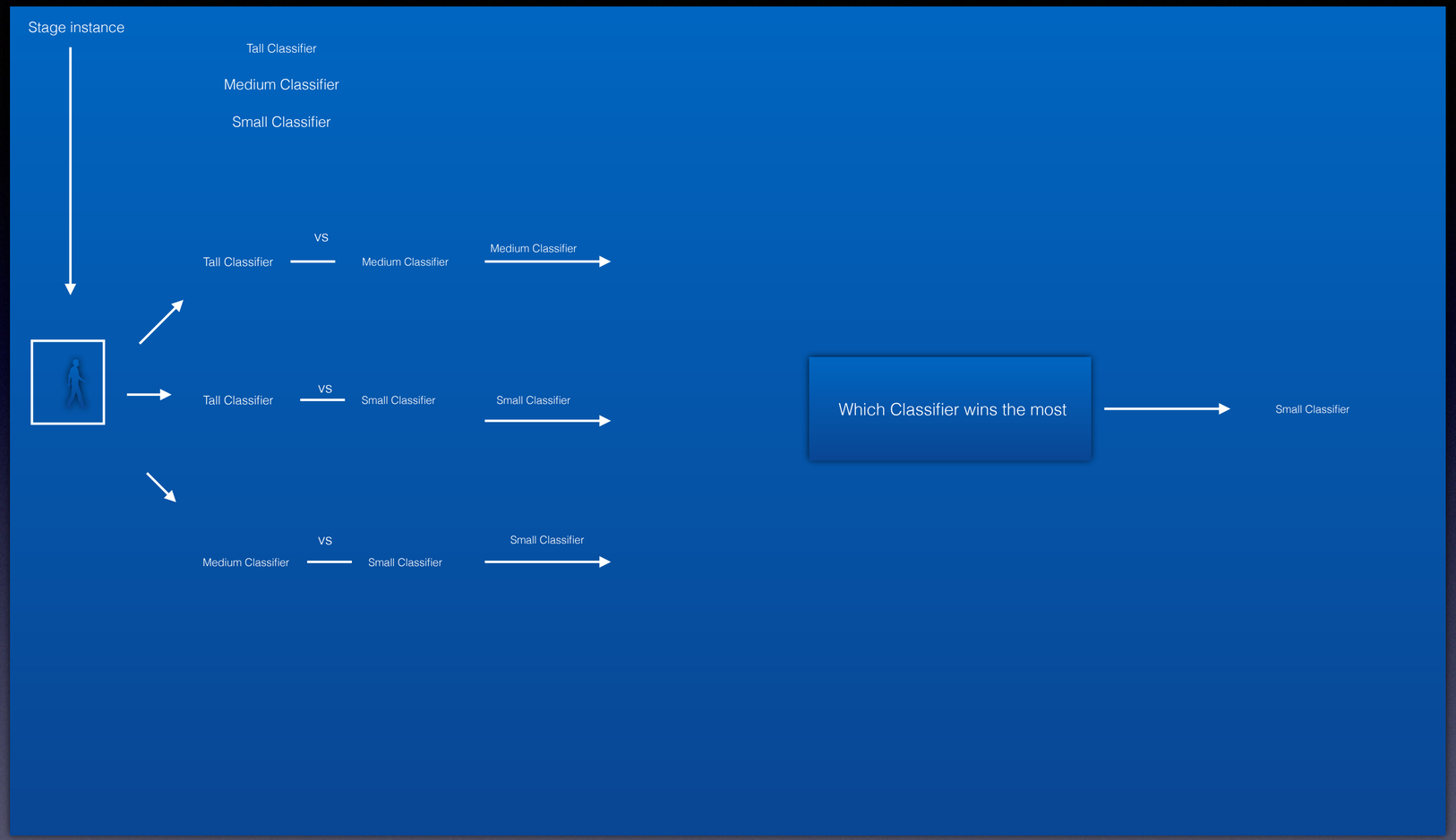


one-versus-all

perfect for large training sets

Multi-class Classifiers

Single Winner



one-versus-one

perfect for small-medium sized training sets

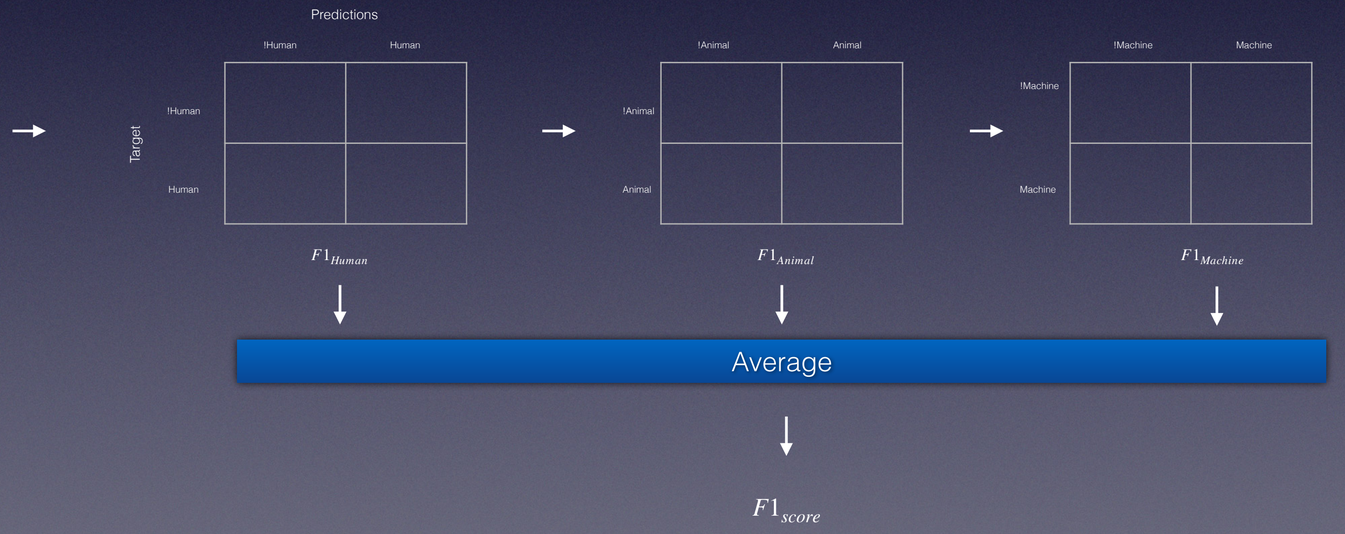
Multi-Label Classification

Multiple Winners

Human and machine found in image

Evaluate Classifier

1. Measure F1 score for each label
2. Compute average F1 score



Multi-Output Multi-Label Classification