SFU NatLangLab

CMPT 825: Natural Language Processing

Text Classification - Evaluation

Fall 2020
2020-09-21

Adapted from slides from Danqi Chen and Karthik Narasimhan

Evaluation

- Consider binary classification

Confusion matrix

- Table of predictions

Truth

Predicted		Positive	Negative
	Positive	100	5
	Negative	45	100

- Ideally, we want:

Truth

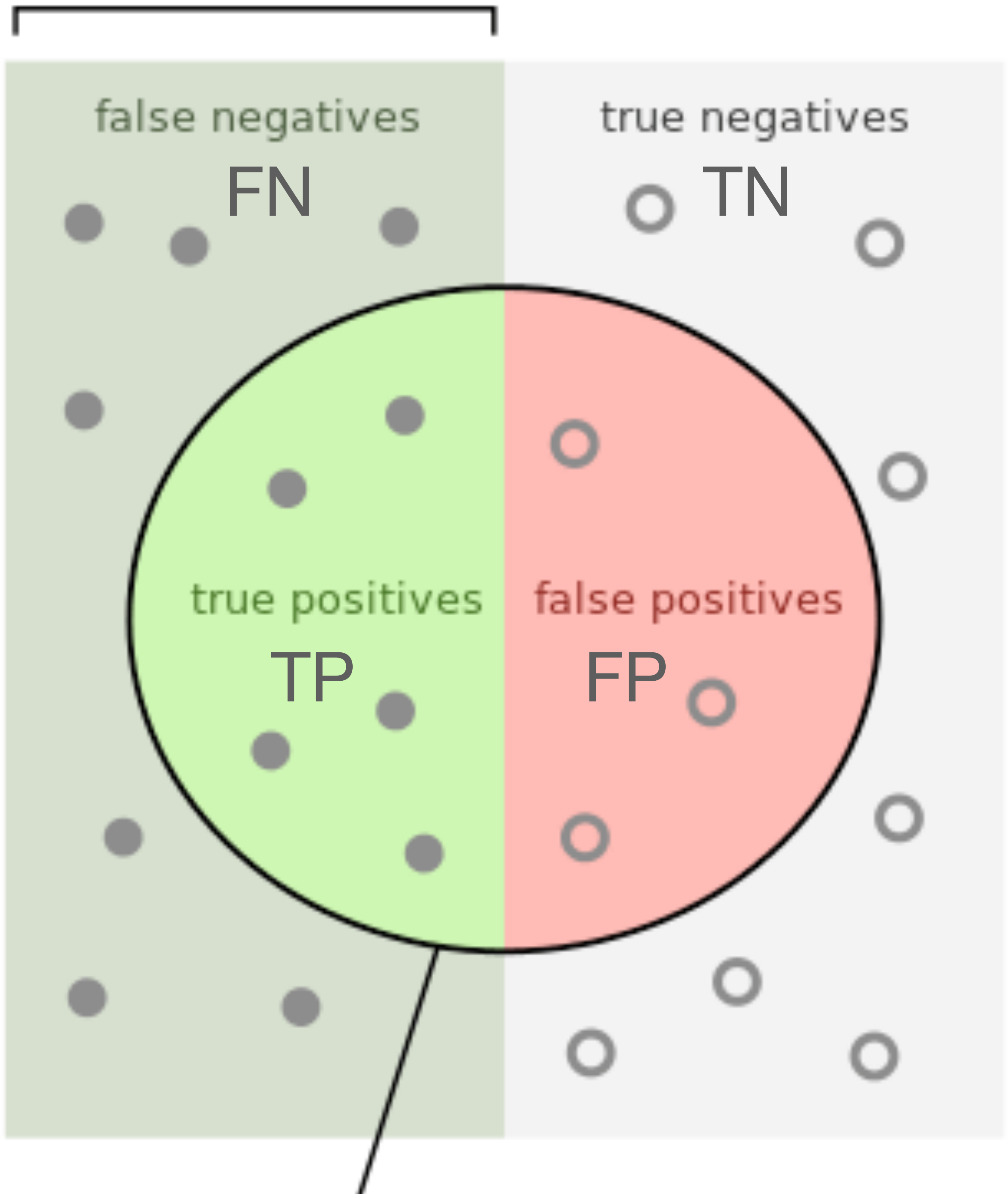
Predicted		Positive	Negative
	Positive	145	0
	Negative	0	105

Evaluation Metrics

		Truth	
		Positive	Negative
Predicted	Positive	100 TP	5 FP
	Negative	45 FN	100 TN

- True positive (TP): Predicted + and actual +
- True negative (TN): Predicted - and actual -
- False positive (FP): Predicted + and actual -
- False negative (FN): Predicted - and actual +

Actual positives



Predicted positives

(image credit: wikipedia)

$$\text{Accuracy} = \frac{TP + TN}{Total} = \frac{200}{250} = 80\,\%$$

Evaluation Metrics

Truth

Predicted

	Positive	Negative
Positive	100	5
Negative	45	100

	Positive	Negative
Positive	50	25
Negative	25	150

- True positive (TP): Predicted + and actual +
- True negative (TN): Predicted - and actual -
- False positive (FP): Predicted + and actual -
- False negative (FN): Predicted - and actual +

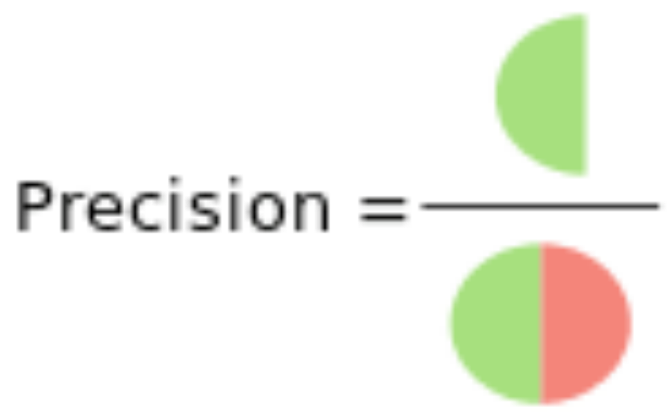
Coarse metric

$$\text{Accuracy} = \frac{TP + TN}{Total} = \frac{200}{250} = 80\,\%$$

Precision and Recall

- Precision: % of selected classes that are correct

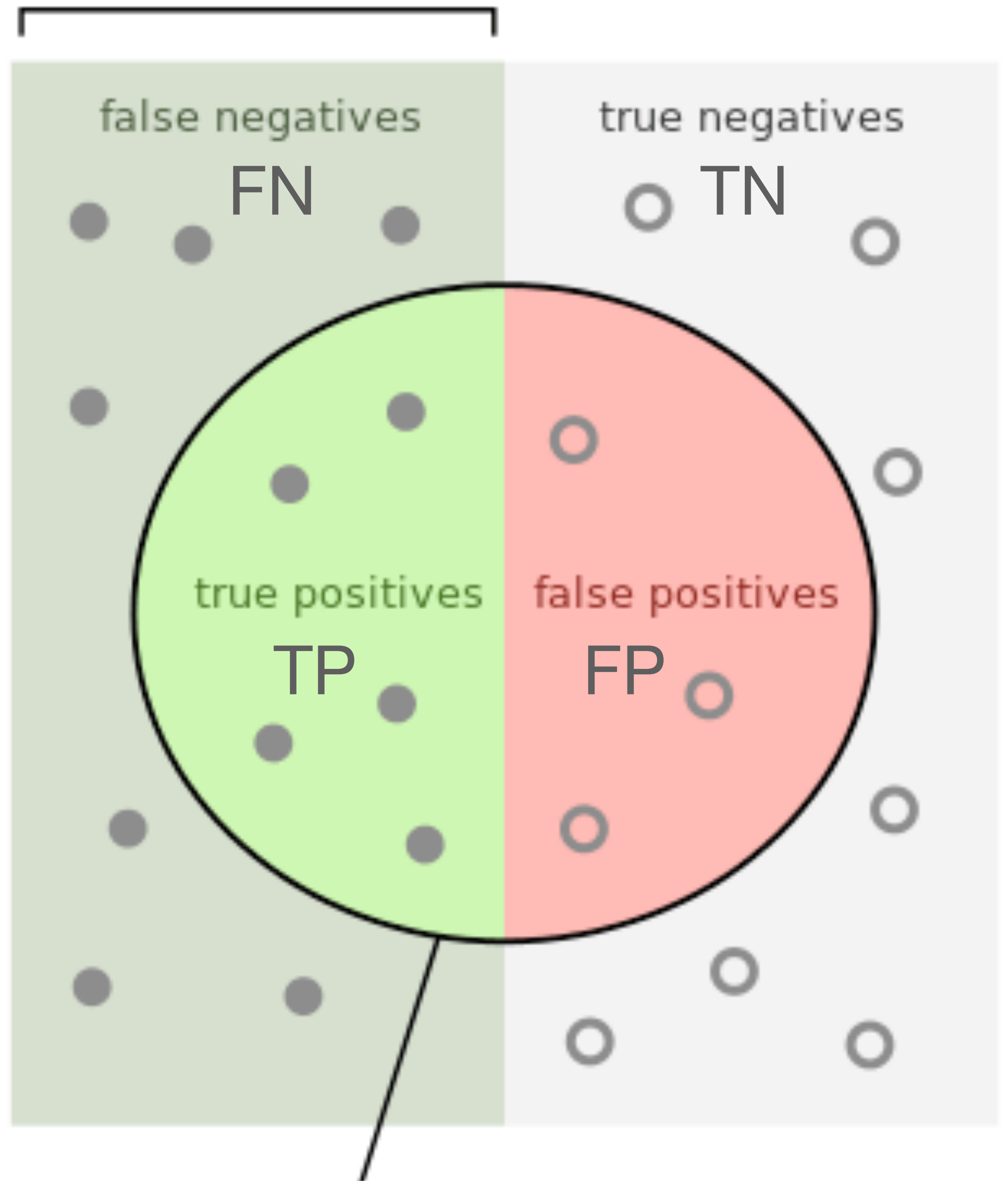
$$\text{Precision}(+) = \frac{TP}{TP + FP}$$



- Recall: % of correct items selected

$$\text{Recall}(+) = \frac{TP}{TP + FN}$$

Actual positives (relevant)



Predicted positives (selected/retrieved)

(image credit: wikipedia)

Precision and Recall

- Precision: % of selected classes that are correct

$$\text{Precision}(+) = \frac{TP}{TP + FP} \qquad \text{Precision}(-) = \frac{TN}{TN + FN}$$

- Recall: % of correct items selected

$$\text{Recall}(+) = \frac{TP}{TP + FN} \qquad \text{Recall}(-) = \frac{TN}{TN + FP}$$

Evaluation Metrics

	Truth	
Predicted	**Positive**	**Negative**
Positive	100	5
Negative	45	100

	Positive	**Negative**
Positive	50	25
Negative	25	150

$$\text{Precision}(+) = \frac{TP}{TP + FP}$$

$$\frac{100}{100 + 5} = 0.95$$

$$\frac{50}{50 + 25} = 0.75$$

$$\text{Recall}(+) = \frac{TP}{TP + FN}$$

$$\frac{100}{100 + 45} = 0.69$$

$$\frac{50}{50 + 25} = 0.75$$

Two metrics - which one to use?

F-Score

- Combined measure

- Harmonic mean of Precision and Recall

$$F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- Or more generally,

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

Evaluation Metrics

Truth

Predicted	Positive	Negative
Positive	100	5
Negative	45	100

	Positive	Negative
Positive	50	25
Negative	25	150

$$\text{Precision}(+) = \frac{TP}{TP + FP} \qquad \frac{100}{100+5} = 0.95 \qquad \frac{50}{50+25} = 0.75$$

$$\text{Recall}(+) = \frac{TP}{TP + FN} \qquad \frac{100}{100+45} = 0.69 \qquad \frac{50}{50+25} = 0.75$$

$$F_1(+) = \frac{2 \cdot P(+)R(-)}{P(+) + R(+)} \qquad \boxed{0.8} \qquad 0.75$$

Evaluation Metrics

Q: What happens to $F_1(+)$ if FN = 25 and FP = 25?

Truth / *Predicted*

	Positive	Negative
Positive	100	5
Negative	45	100

	Positive	Negative
Positive	100	25
Negative	25	100

$$\text{Precision}(+) = \frac{TP}{TP+FP} \qquad \frac{100}{100+5} = 0.95$$

$$\text{Recall}(+) = \frac{TP}{TP+FN} \qquad \frac{100}{100+45} = 0.69$$

$$F_1(+) = \frac{2 \cdot P(+)R(-)}{P(+)+R(+)} \qquad 0.8$$

Evaluation Metrics

	Truth Positive	Negative
Predicted Positive	TP	FP
Negative	FN	TN

Use a simple rule, can you design a classifier with

$$\text{Precision}(+) = \frac{TP}{TP + FP}$$

Q. perfect precision?

$$\text{Recall}(+) = \frac{TP}{TP + FN}$$

Q. perfect recall?

Choosing Beta

Truth

Predicted		Positive	Negative
	Positive	200	100
	Negative	50	100

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

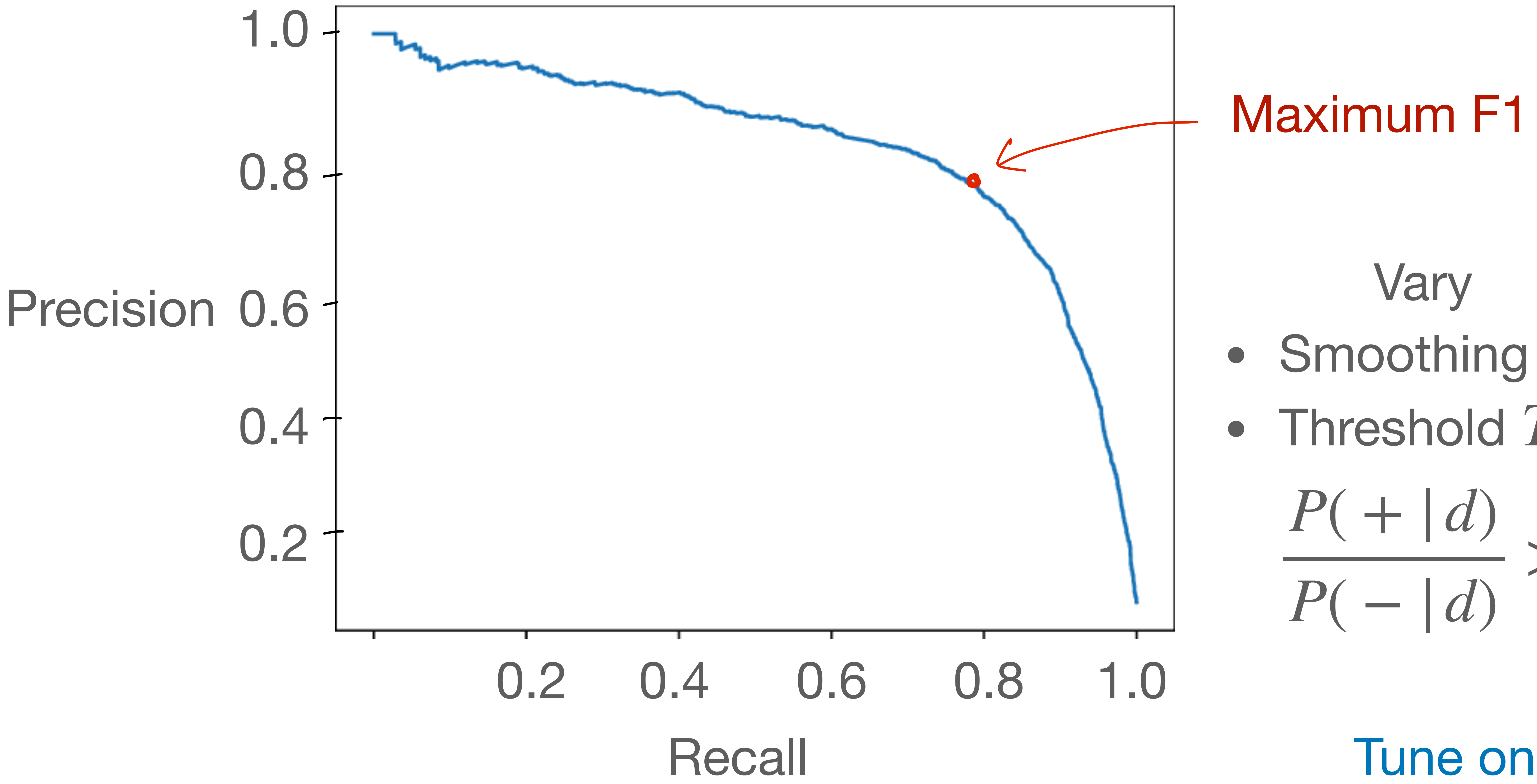
Q. Which value of Beta maximizes F_β for positive class?

A. $\beta = 0.5$

B. $\beta = 1$

C. $\beta = 2$

Precision Recall tradeoff



Vary

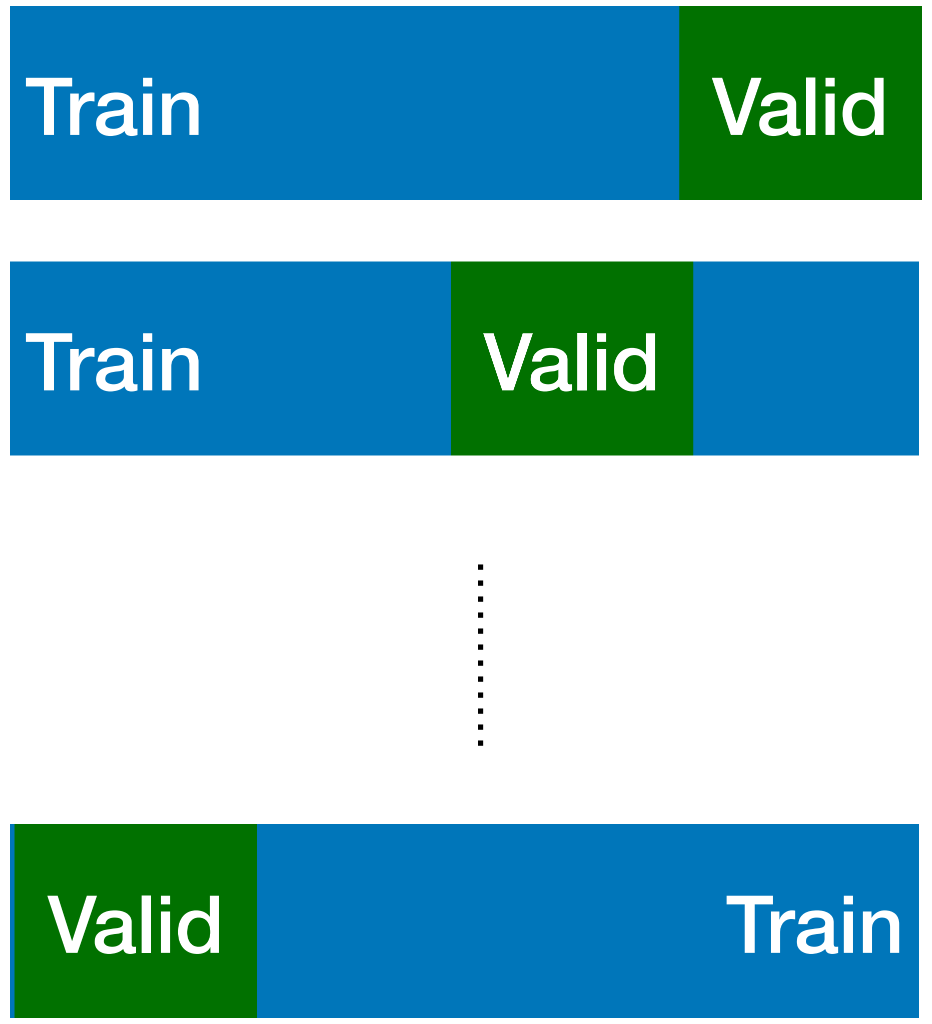
- Smoothing α
- Threshold T

$$\frac{P(+\,|\,d)}{P(-\,|\,d)} > T$$

Tune on validation set

Validation

- Choose a metric: Precision/Recall/F1
- Optimize for metric on Validation (aka Development) set
- Finally evaluate on ‘unseen’ test set
- Cross-validation:
  - Repeatedly sample several train-val splits
  - Reduces sampling bias due to sampling errors



Aggregating scores

- We have Precision, Recall, F1 for each class
- How to combine them for an overall score?
  - Macro-average: Compute for each class, then average
  - Micro-average: Collect predictions for all classes and jointly evaluate

Macro vs Micro average

Class 1

	Truth: yes	Truth: no
Classifier: yes	10	10
Classifier: no	10	970

Class 2

	Truth: yes	Truth: no
Classifier: yes	90	10
Classifier: no	10	890

Micro Ave. Table

	Truth: yes	Truth: no
Classifier: yes	100	20
Classifier: no	20	1860

Precision

- Macro-averaged precision: (0.5 + 0.9) / 2 = 0.7
- Micro-averaged precision: 100/120 = 0.85
- Micro-averaged score is dominated by score on common classes

Summary

- Evaluation Metrics
  - Accuracy - coarse metric
  - Precision, Recall, F1 for each class
- Aggregated scores
  - Macro-average: Compute for each class, then average
  - Micro-average: Collect predictions for all classes and jointly evaluate (dominated by common classes)
- Precision-Recall curve: pick threshold for maximum F1
  - Use validation set to tune hyperparameters, test set should remain “unseen”