

# CS 66: Machine Learning

Prof. Sara Mathieson

Spring 2019



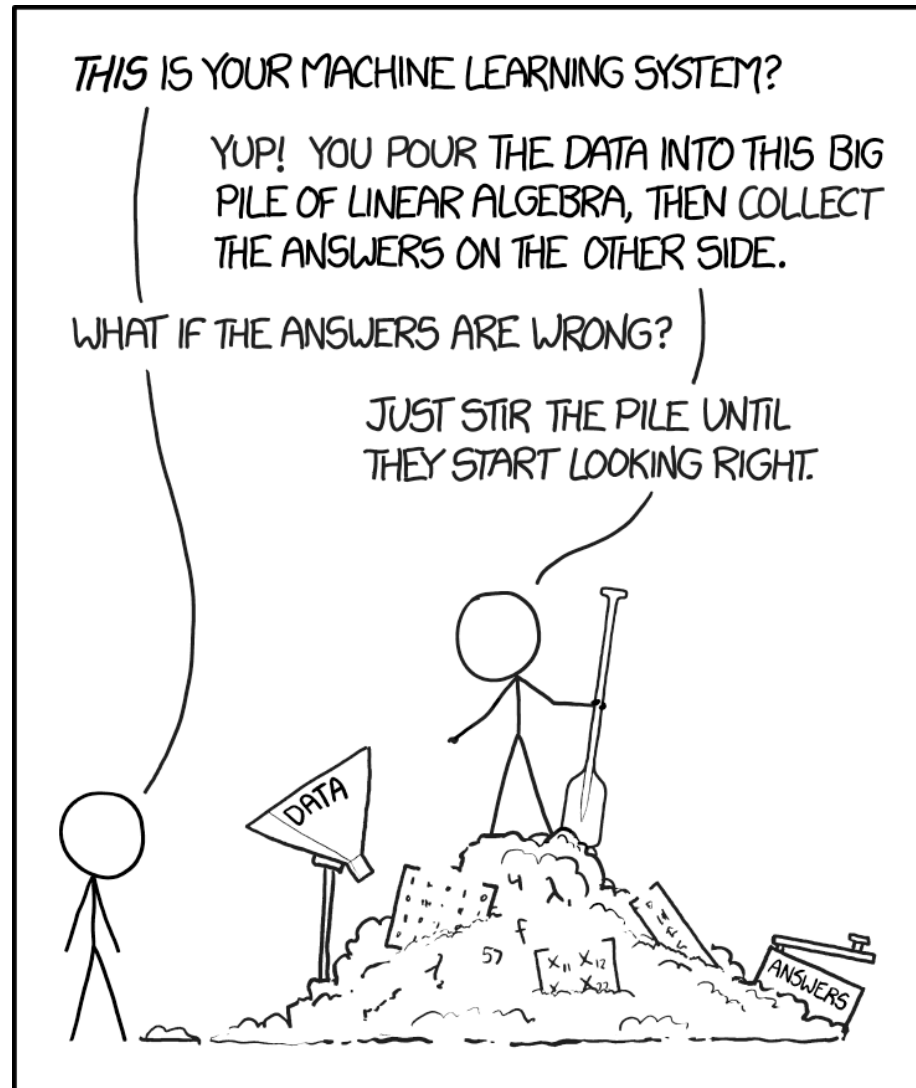
# Outline for March 1

- Evaluation metrics
  - Precision and Recall
  - Confusion matrices revisited
  - ROC curves
  - Relationship to probabilistic methods
  - Cross-validation
- **Lab 4 due March 8** (week from today)
- Office hours **TODAY** 1-3pm

# Outline for March 1

- Evaluation metrics
  - Precision and Recall
  - Confusion matrices revisited
  - ROC curves
  - Relationship to probabilistic methods
  - Cross-validation

# Thanks for all your work on the exam!





# Goals of Evaluation

- Think about what metrics are important for the problem at hand
- Compare different methods on the same problem
- Common set of tools that other researchers/users can understand

# Precision and Recall

- Precision: of all the “flagged” examples, which ones are actually relevant (i.e. positive)?
- Recall: of all the relevant results, which ones did I actually return?

# Precision and Recall

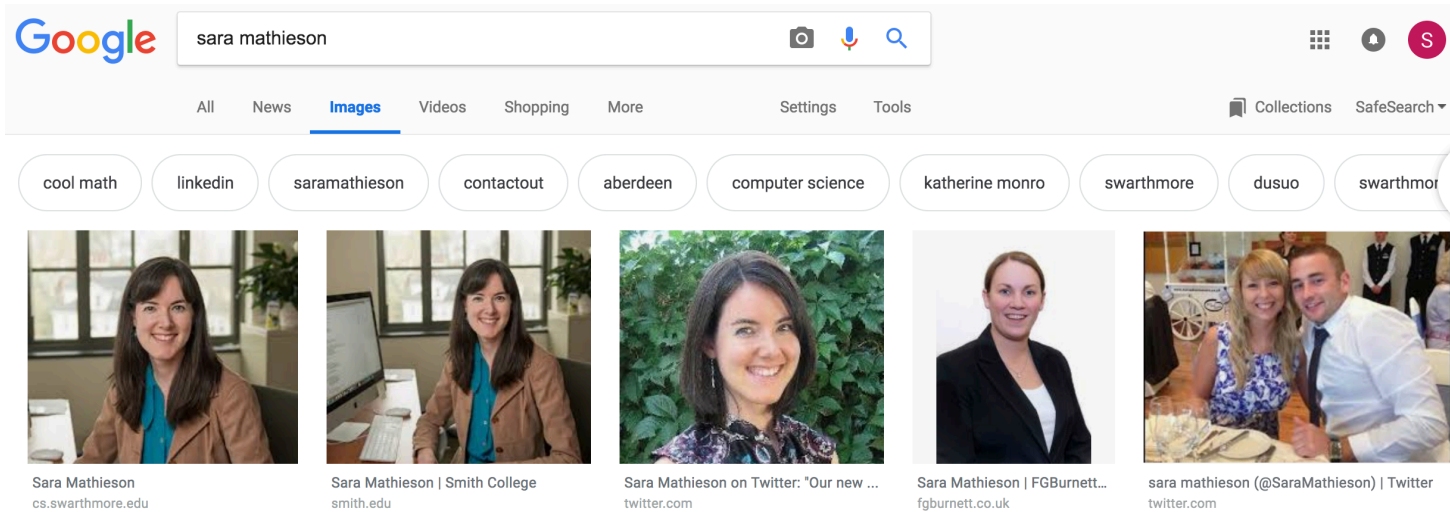
- Precision: of all the “flagged” examples, which ones are actually relevant (i.e. positive)?

(Purity)

- Recall: of all the relevant results, which ones did I actually return?

(Completeness)

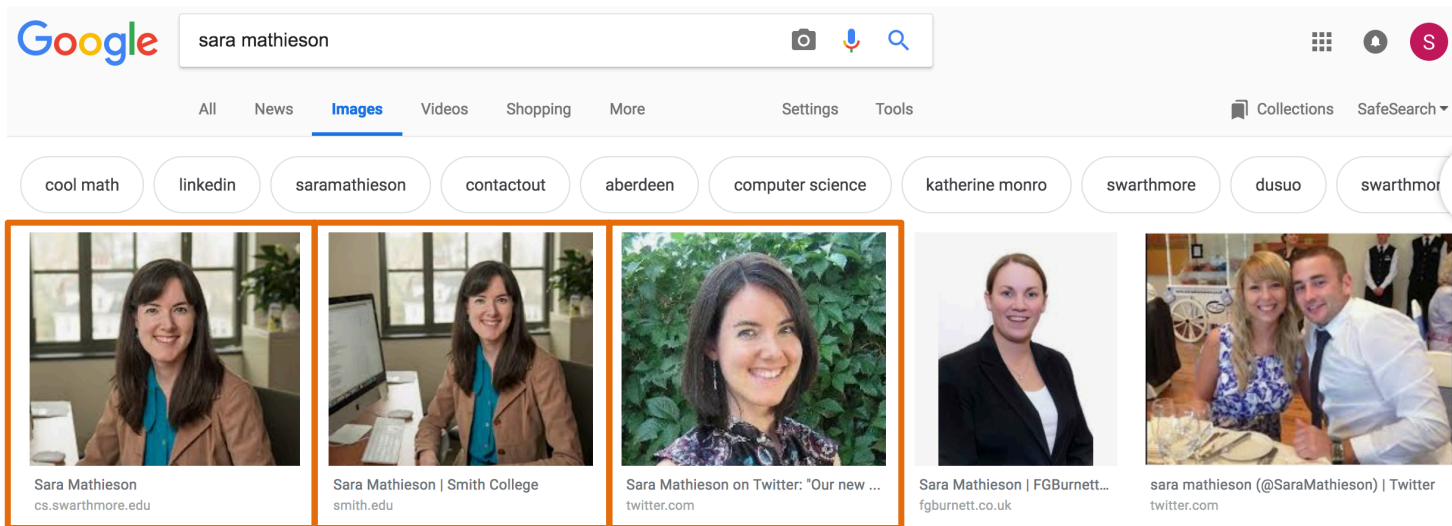
# Precision and Recall



$P=6$  (number of images that are actually me)

- Precision?
- Recall?

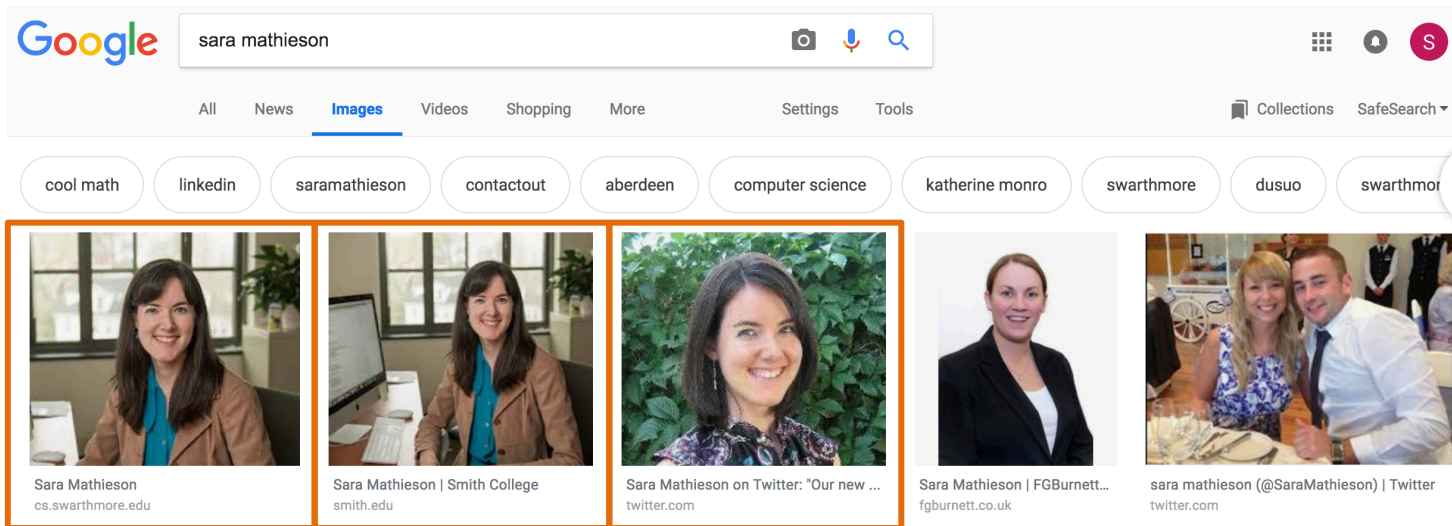
# Precision and Recall



$P=6$  (number of images that are actually me)

- Precision =  $TP/(FP+TP) = 3/5$
- Recall?

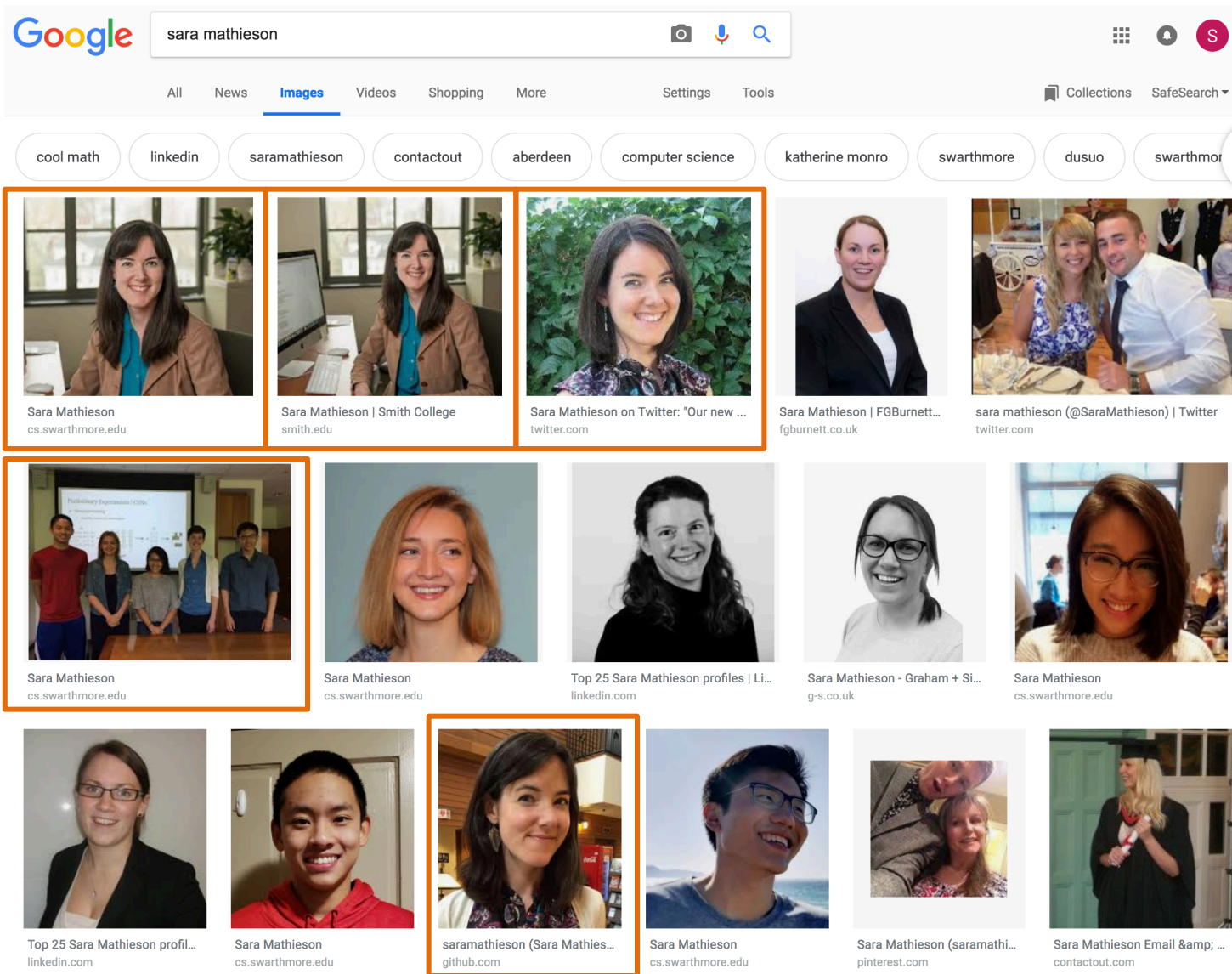
# Precision and Recall



$P=6$  (number of images that are actually me)

- Precision =  $TP/(FP+TP) = 3/5$
- Recall =  $TP/(FN+TP) = 3/6$

# Precision and Recall



$P=6$  (number of images that are actually me)

- Precision =  $5/16$
- Recall =  $5/6$

# Outline for March 1

- Evaluation metrics
  - Precision and Recall
  - **Confusion matrices revisited**
  - ROC curves
  - Relationship to probabilistic methods
  - Cross-validation



# Recap Confusion Matrices

		Predicted class	
		Negative	Positive
True class	Negative	True negative (TN)	False positive (FP)
	Positive	False negative (FN)	True positive (TP)

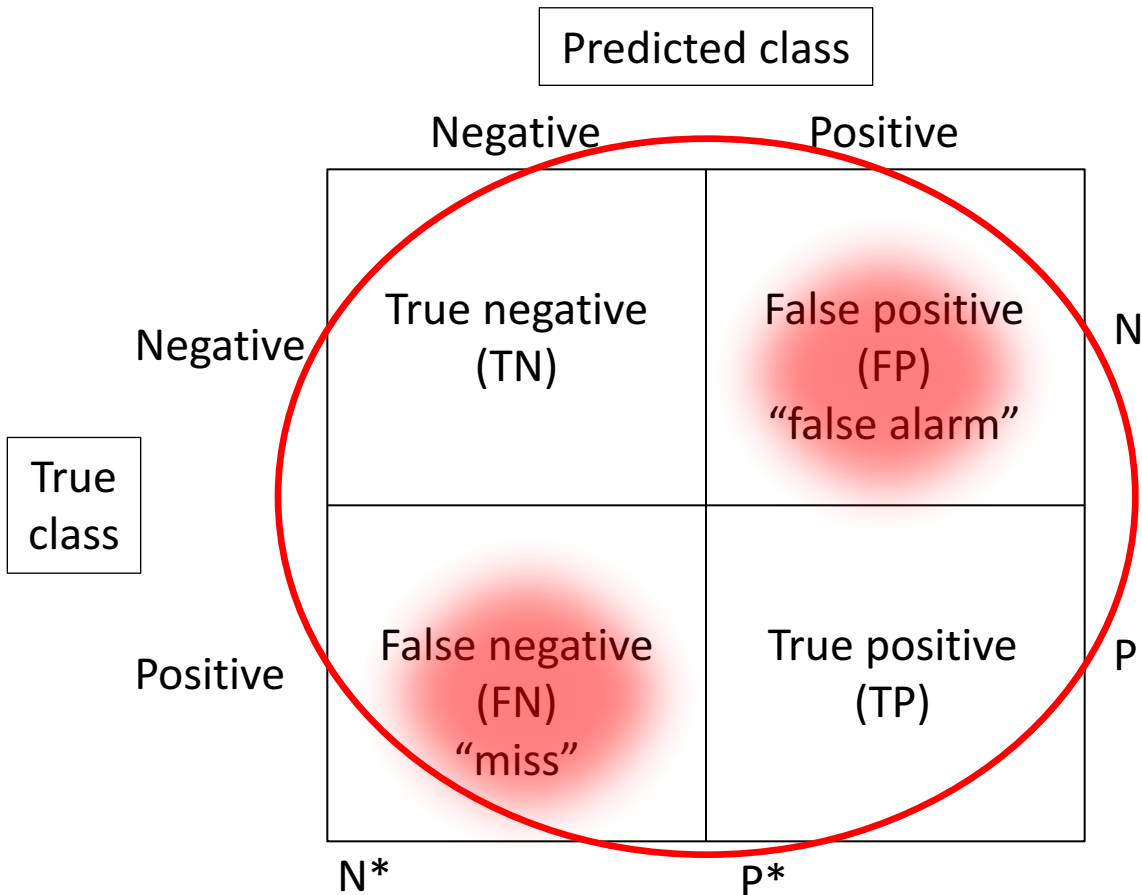
# Recap Confusion Matrices

		Predicted class		
		Negative	Positive	
True class	Negative	True negative (TN)	False positive (FP) “false alarm”	N (total number of true negatives)
	Positive	False negative (FN) “miss”	True positive (TP)	P (total number of true positives)
		N* (what we said was negative)	P* (what we said was positive “flagged”)	

# Recap Confusion Matrices

		Predicted class		
		Negative	Positive	
True class	Negative	True negative (TN) ✓	False positive (FP) "false alarm" ✗	N
	Positive	False negative (FN) "miss" ✗	True positive (TP) ✓	P
		N*	p*	

# Recap Confusion Matrices

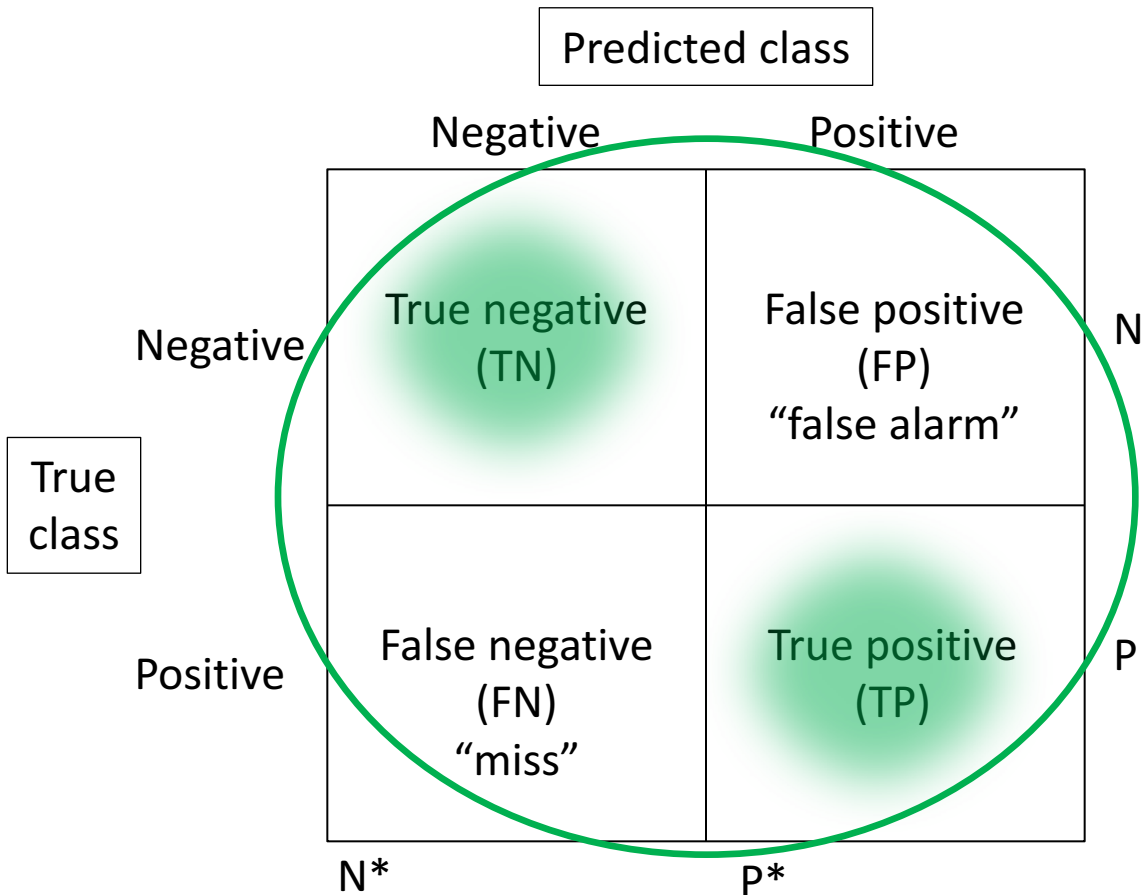


Error:

$$(FN+FP)/(TN+FP+FN+TP)$$

$$= (FN+FP)/(N+P)$$

# Recap Confusion Matrices



Accuracy = 1-Error:

$$(TN+TP)/(TN+FP+FN+TP)$$

$$= (TN+TP)/(N+P)$$

# Recap Confusion Matrices

		Predicted class		
		Negative	Positive	
True class	Negative	True negative (TN)	False positive (FP) "false alarm"	N
	Positive	False negative (FN) "miss"	True positive (TP)	P
		N*	p*	

Precision:

$$TP/(FP+TP) = TP/P^*$$

# Recap Confusion Matrices

		Predicted class		
		Negative	Positive	
True class	Negative	True negative (TN)	False positive (FP) “false alarm”	N
	Positive	False negative (FN) “miss”	True positive (TP)	P
		N*	p*	

Recall  
(True Positive Rate):

$$TP/(FN+TP) = TP/P$$

# Recap Confusion Matrices

		Predicted class		
		Negative	Positive	
True class	Negative	True negative (TN)	False positive (FP) "false alarm"	N
	Positive	False negative (FN) "miss"	True positive (TP)	P
		N*	p*	

False Positive Rate:

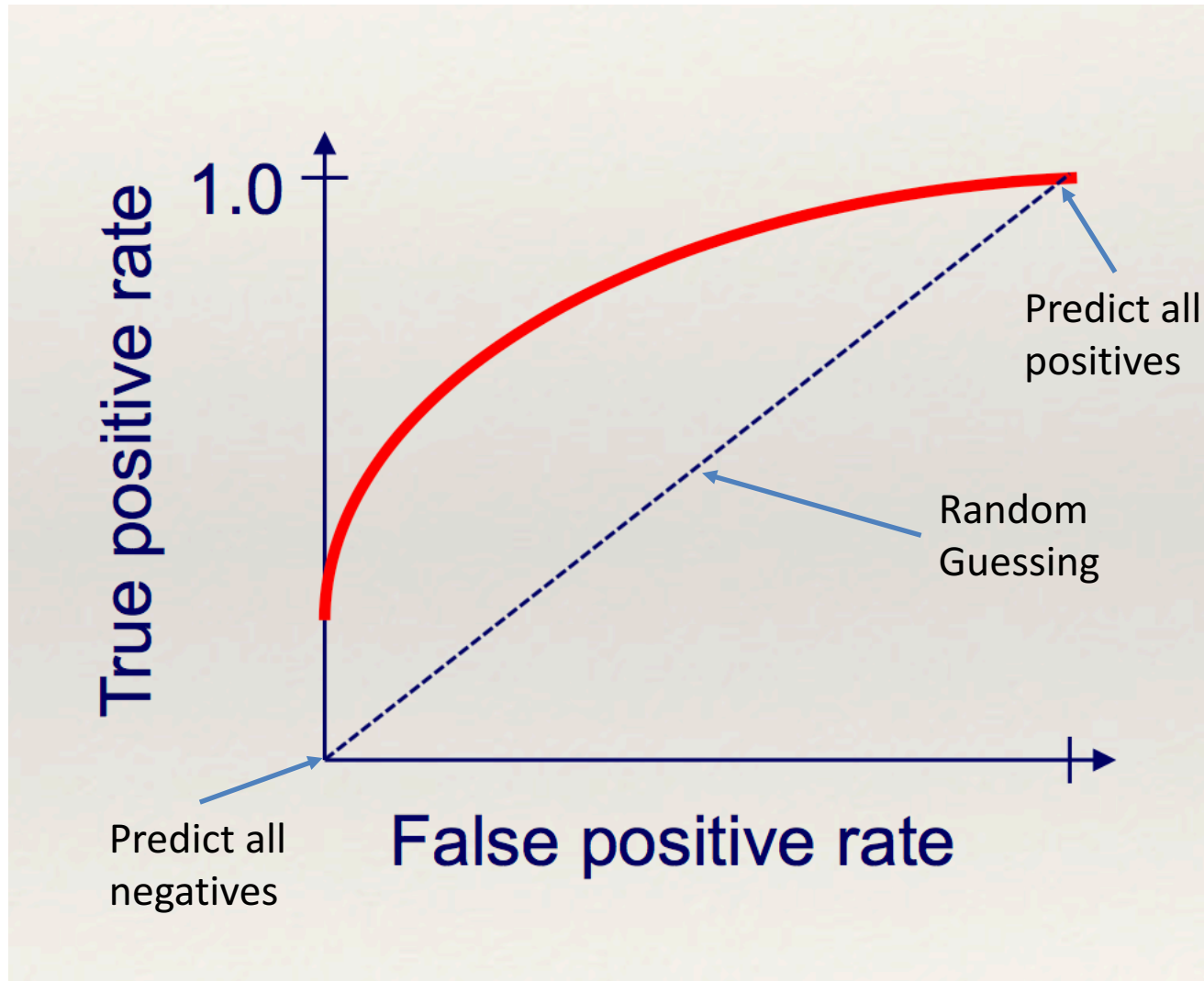
$$FP/(TN+FP) = FP/N$$



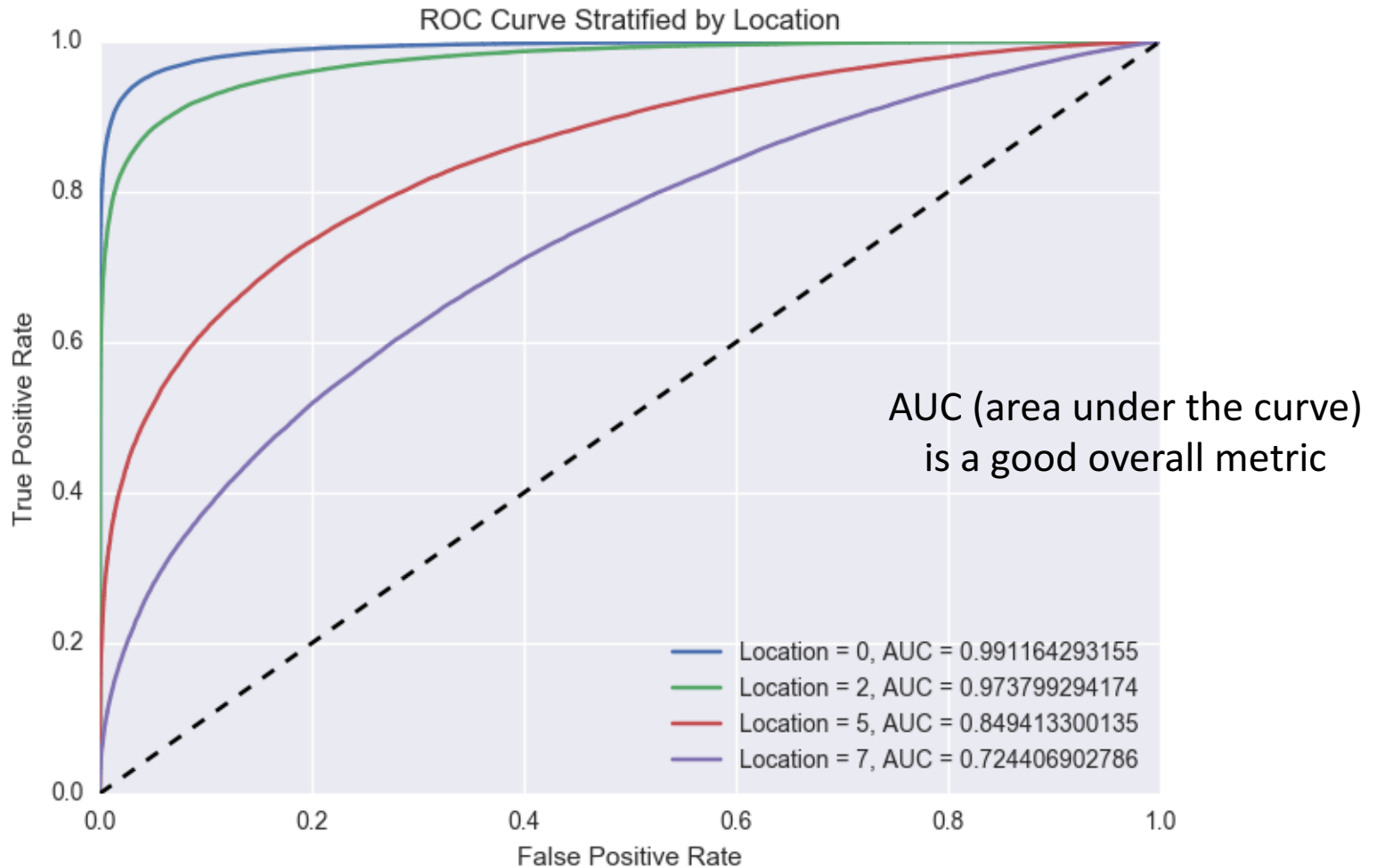
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# ROC curve (Receiver Operating Characteristic)



# ROC curve example: comparing methods



Example of a ROC curve from my research  
Chan, Perrone, Spence, Jenkins, Mathieson, Song

# How to get a ROC curve for probabilistic methods?

- Usually we use 0.5 as a threshold for binary classification
- Vary the threshold! (i.e. choose 0.25)
  - $P(y=1 \mid x) > 0.25 \quad \Rightarrow$  classify as 1 (positive)
  - $P(y=1 \mid x) \leq 0.25 \quad \Rightarrow$  classify as 0 (negative)

★

55	35
2	21

$$FPR = \frac{35}{90}$$

$$TPR = \frac{21}{23}$$

true

	pred		
	neg	pos	
neg	70	20	N = 90
pos	5	18	
	P = 23		
	N* = 75    P* = 38		

$$\text{accuracy} = \frac{88}{113}$$

$$FPR = \frac{20}{70+20} \approx .22$$

$$TPR = \frac{18}{5+18} \approx .78$$



	n	p
n	0	90
p	0	23

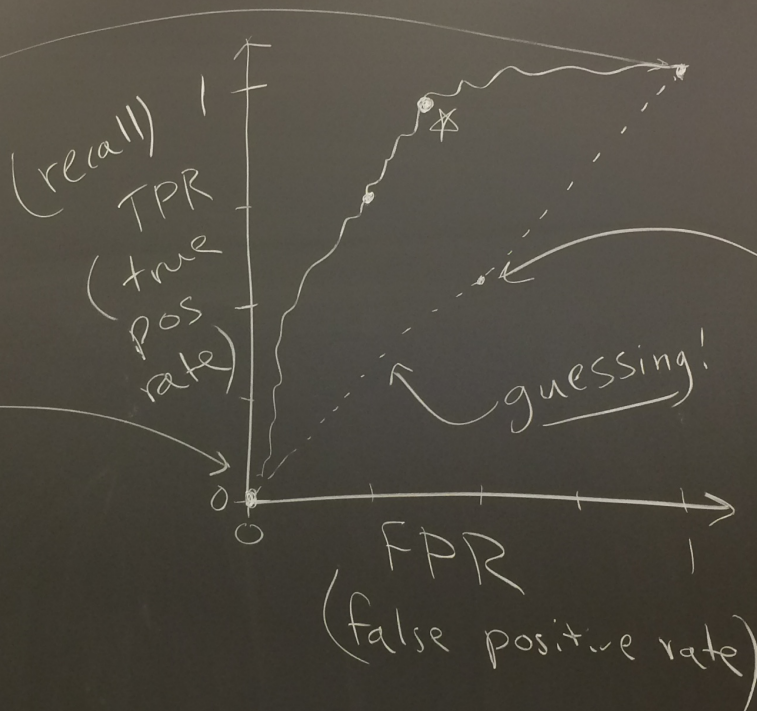
all positive

	n	p
n	90	0
p	23	0

all negative

(could be best accuracy)

$$\frac{90}{113}$$



guessing

45	45
11	12



# Handout 7

(a)

	n	p	
n	77	3	80
p	13	7	20
	90	10	

precision:  $\frac{7}{10} = .7$

recall:  $\frac{7}{20} = .35$

FPR:  $\frac{3}{77+3} = .04$

(d)

	70	30	
n	68	12	80
p	2	18	20

precision:  $\frac{18}{30}$

FPR:  $\frac{12}{80}$

TPR:  $\frac{18}{20} = .9$

