

# CMSC 473/673

# Natural Language Processing

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*Slides modified from Dr. Frank Ferraro*

# Learning Objectives

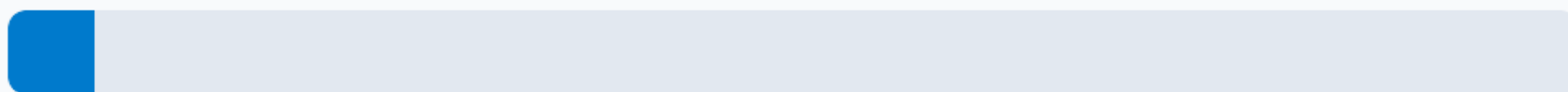
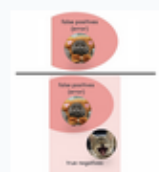
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Develop an intuition about precision & recall

Extend P/R to multi-class problems

Identify when you might want certain evaluation metrics over others

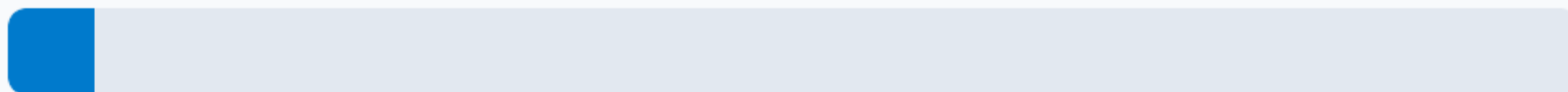
If you are classifying pictures of dogs, what would be the "equation" for *recall* (where the top of the image is the numerator and the bottom of the image is the denominator)?



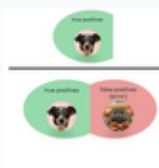
3%



56%



3%



38%

The difference between classification & regression is that a regression model will produce a continuous output.

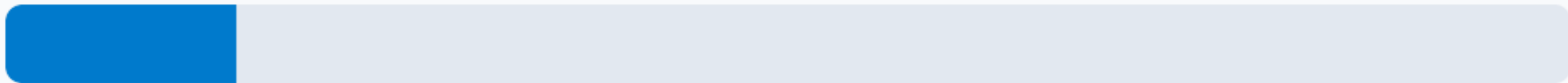


True



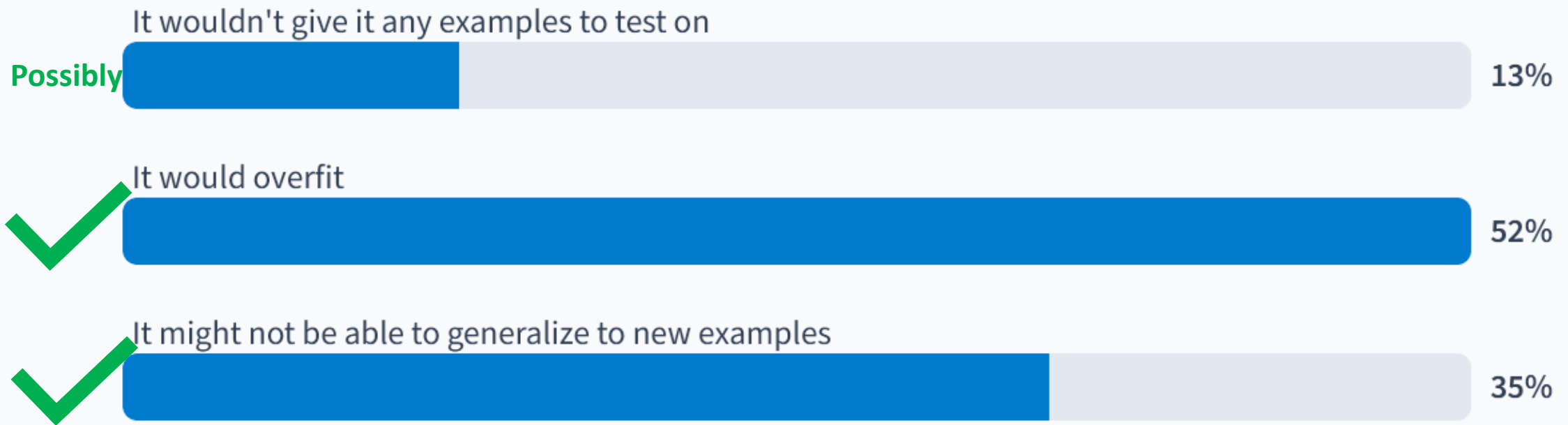
87%

False



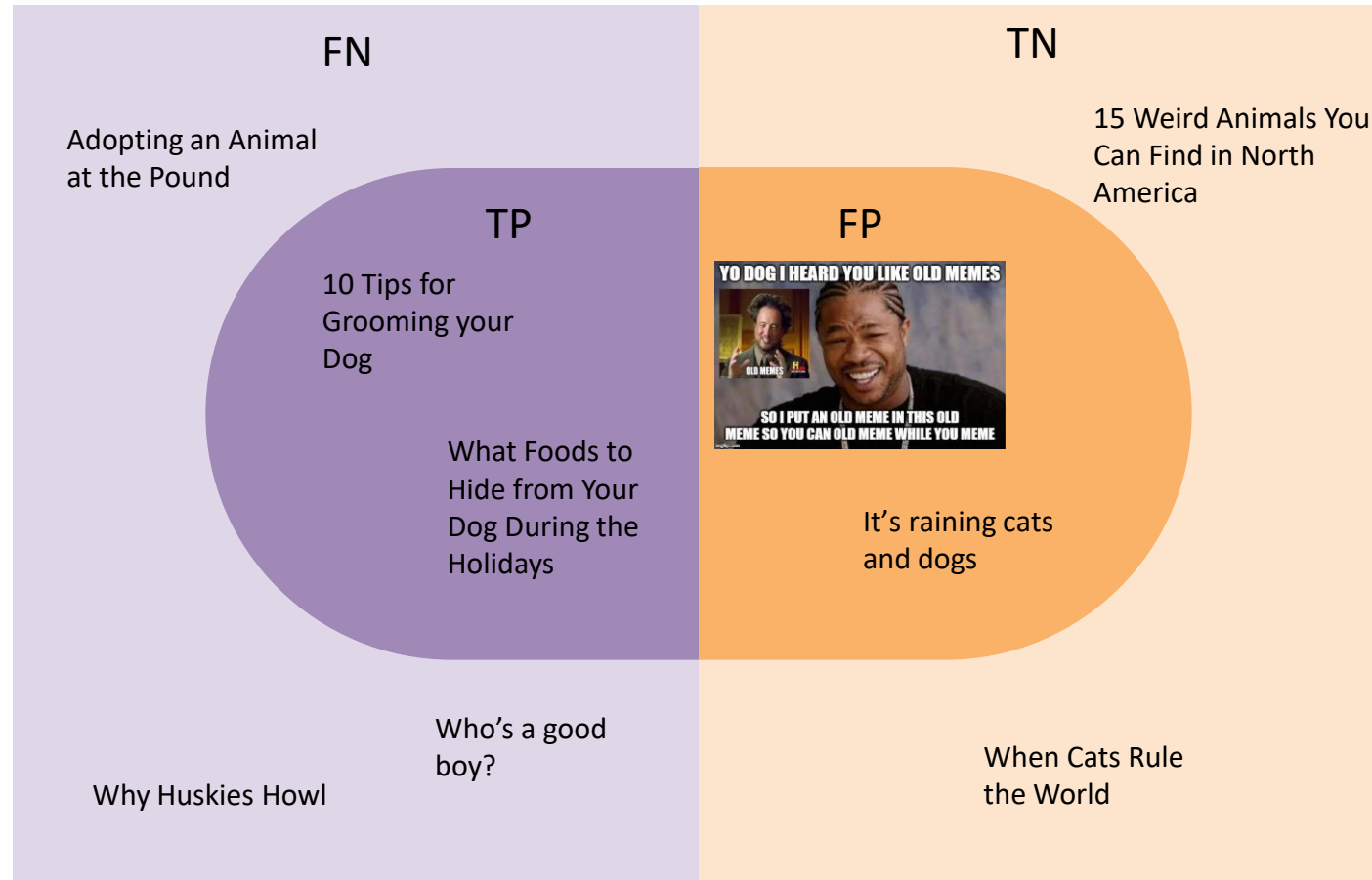
13%

## Why would you want to divide up your data (instead of training on it all)?



# Contingency Table (out of table form)

Query:  
Articles about dogs

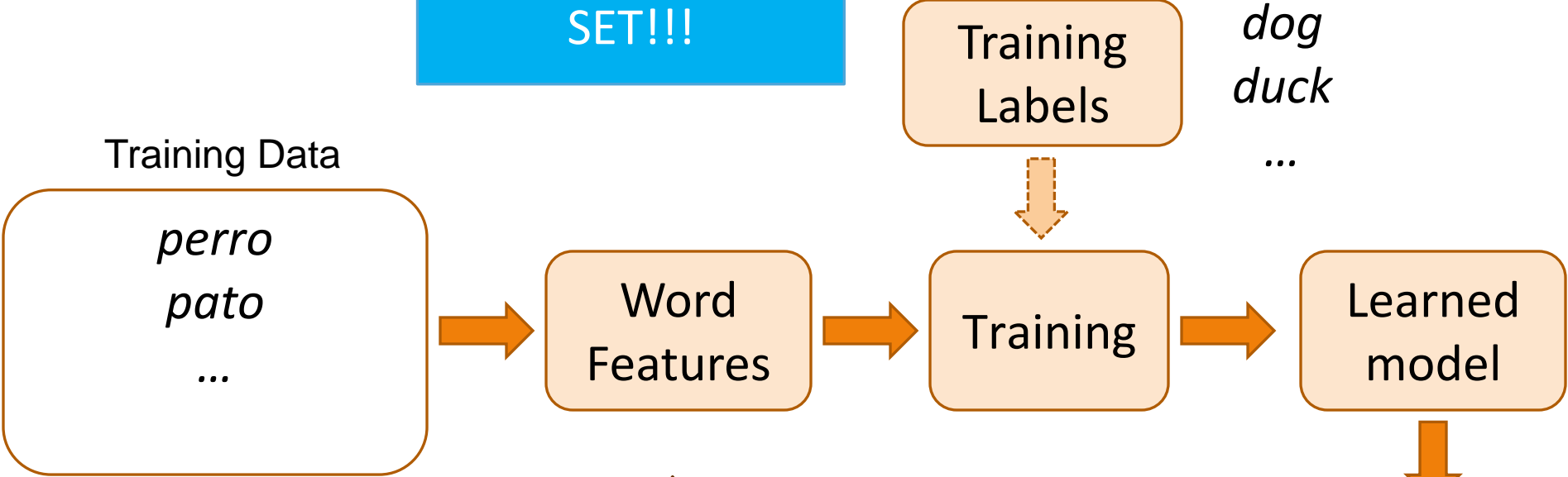


Meme from: [https://www.reddit.com/r/AdviceAnimals/comments/ck8xh0/yo\\_dawg\\_i\\_heard\\_you\\_like\\_old\\_memes/](https://www.reddit.com/r/AdviceAnimals/comments/ck8xh0/yo_dawg_i_heard_you_like_old_memes/)

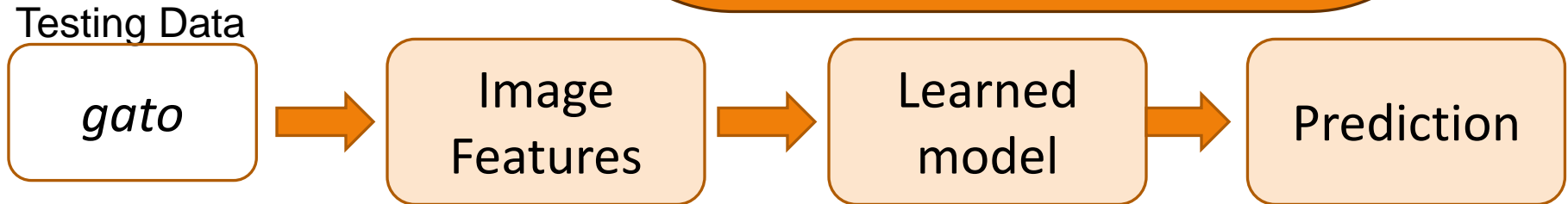
# Review: Steps

DO NOT ITERATE ON THE TESTING SET!!!

**Training**

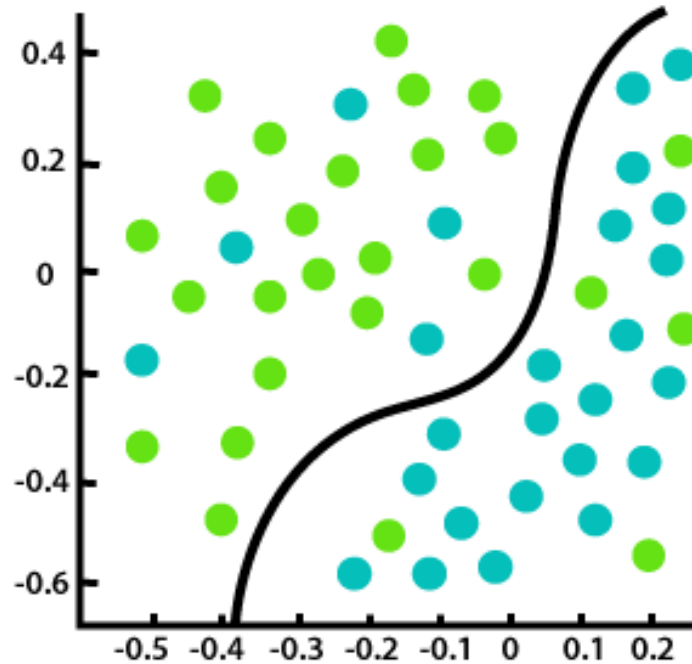


**Testing**

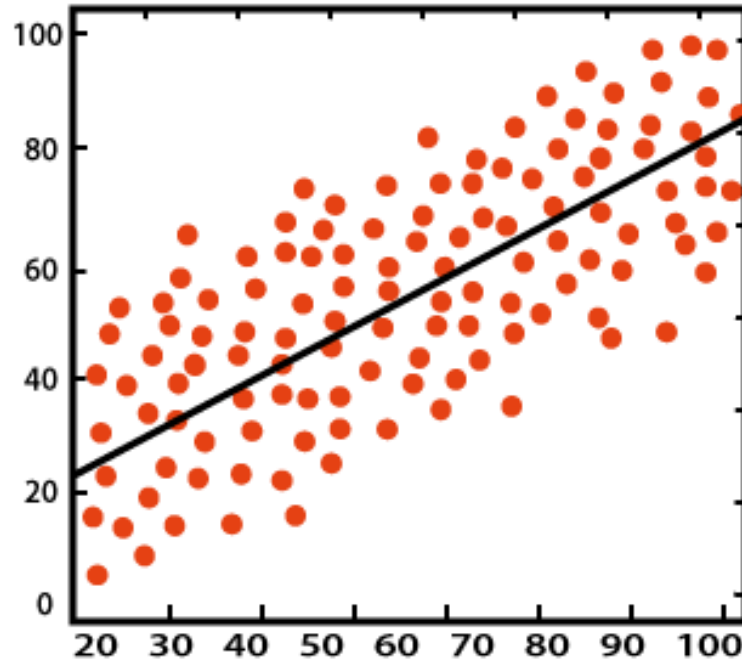


# Review: Types of models

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Classification



Regression



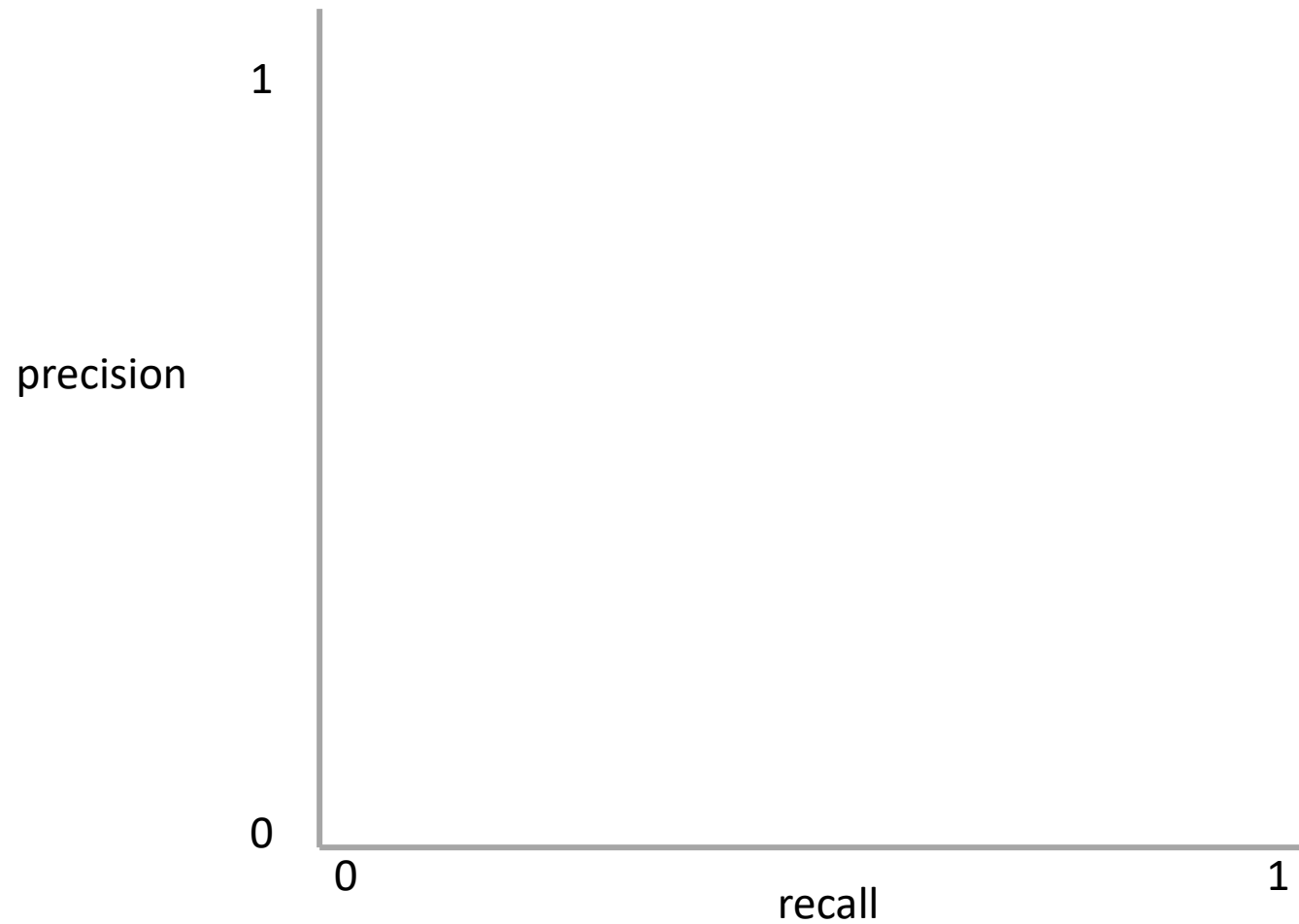
# Review: Classification Evaluation: the 2-by-2 contingency table

	What is the actual label?	
What label does our system predict? (↓)	Actual Target Class ("●")	Not Target Class ("○")
Selected/ Guessed ("●")	True Positive ● (TP) ● <i>Actual</i> <i>Guessed</i>	False Positive ○ (FP) ● <i>Actual</i> <i>Guessed</i>
Not selected/ not guessed ("○")	False Negative ● (FN) ○ <i>Actual</i> <i>Guessed</i>	True Negative ○ (TN) ○ <i>Actual</i> <i>Guessed</i>

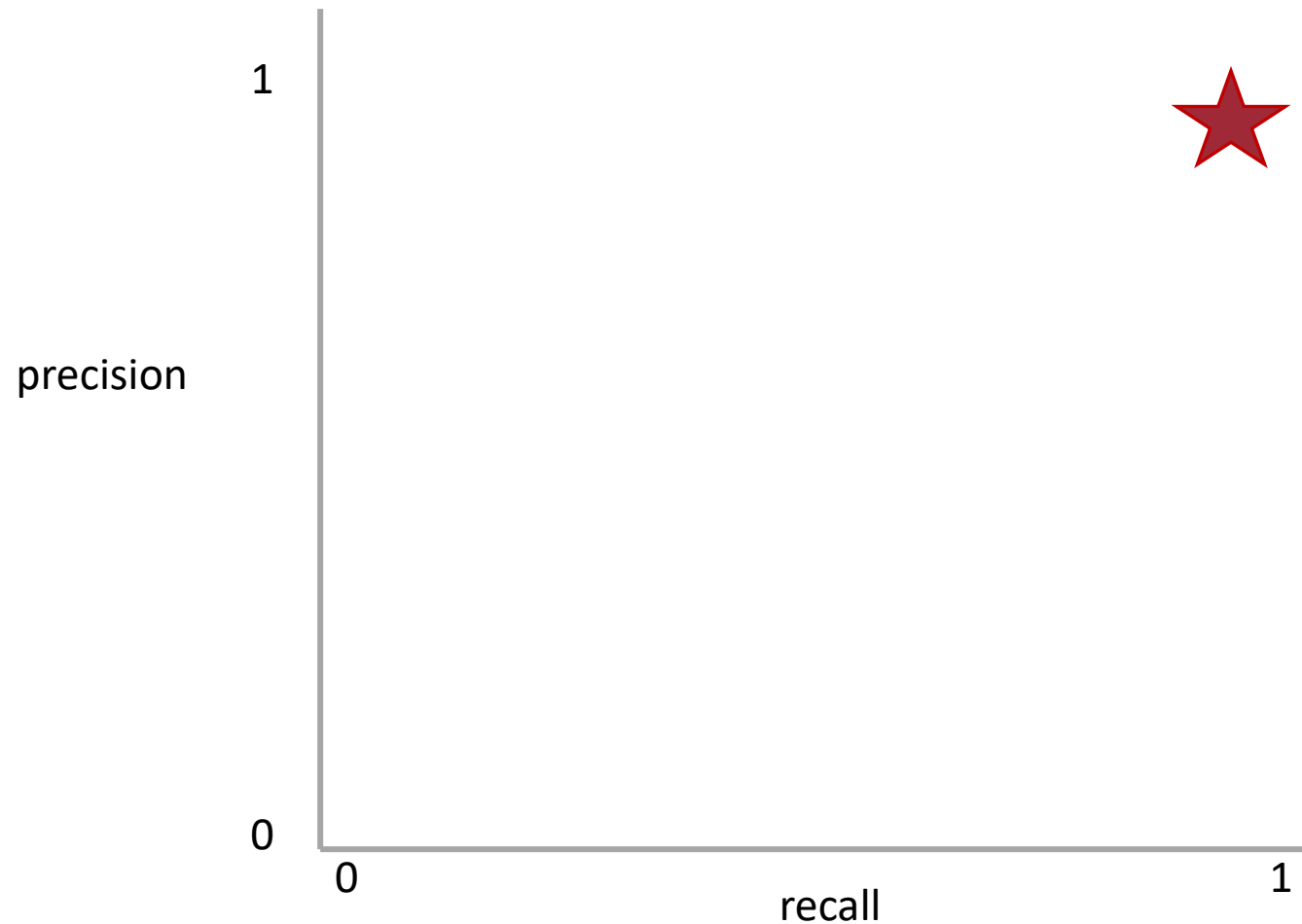
# Precision and Recall Present a Tradeoff

Q: Where do you want your ideal

model ?



# Precision and Recall Present a Tradeoff

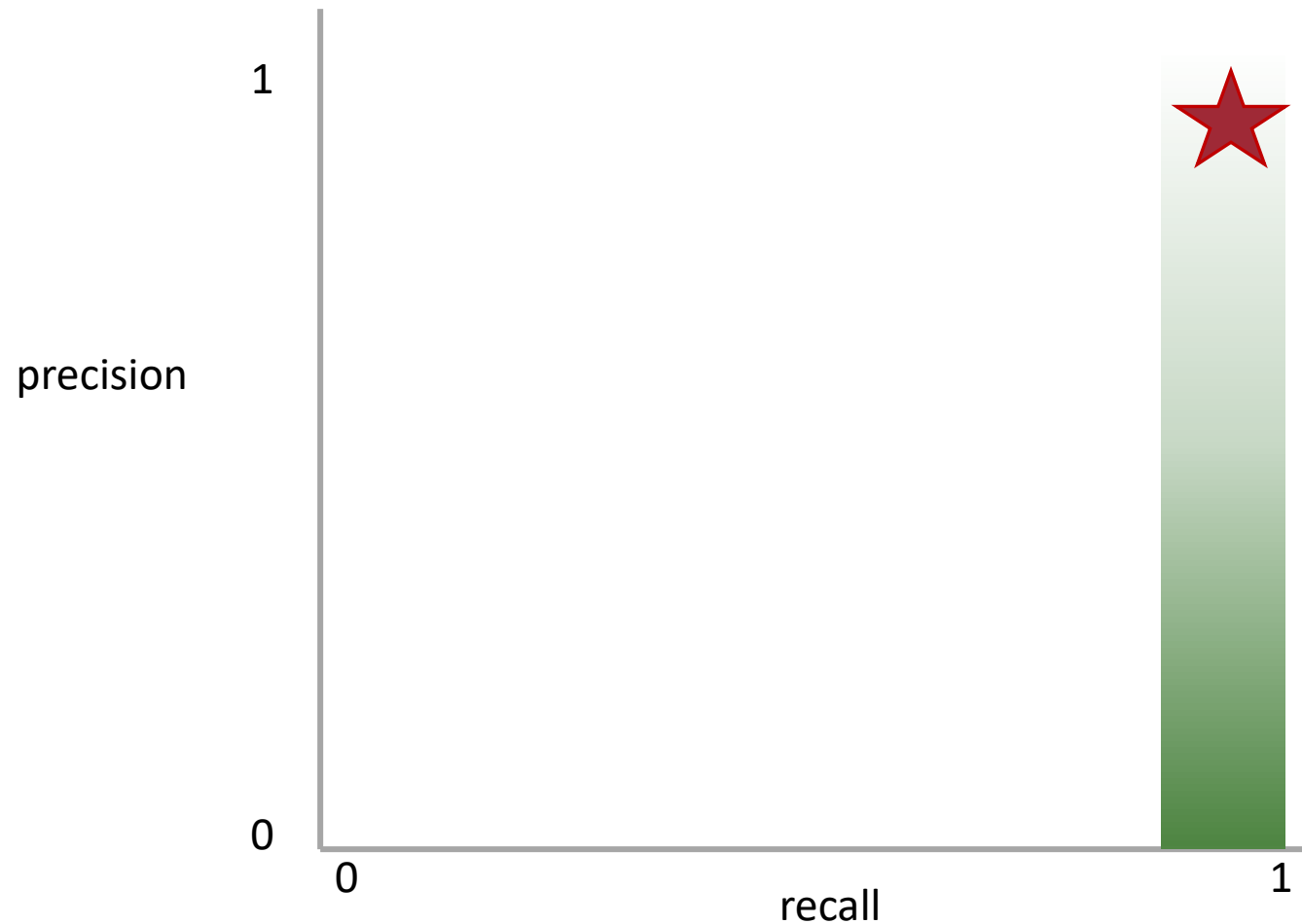


Q: Where do you want your ideal

model ?

Q: You have a model that always identifies correct instances. Where on this graph is it?

# Precision and Recall Present a Tradeoff

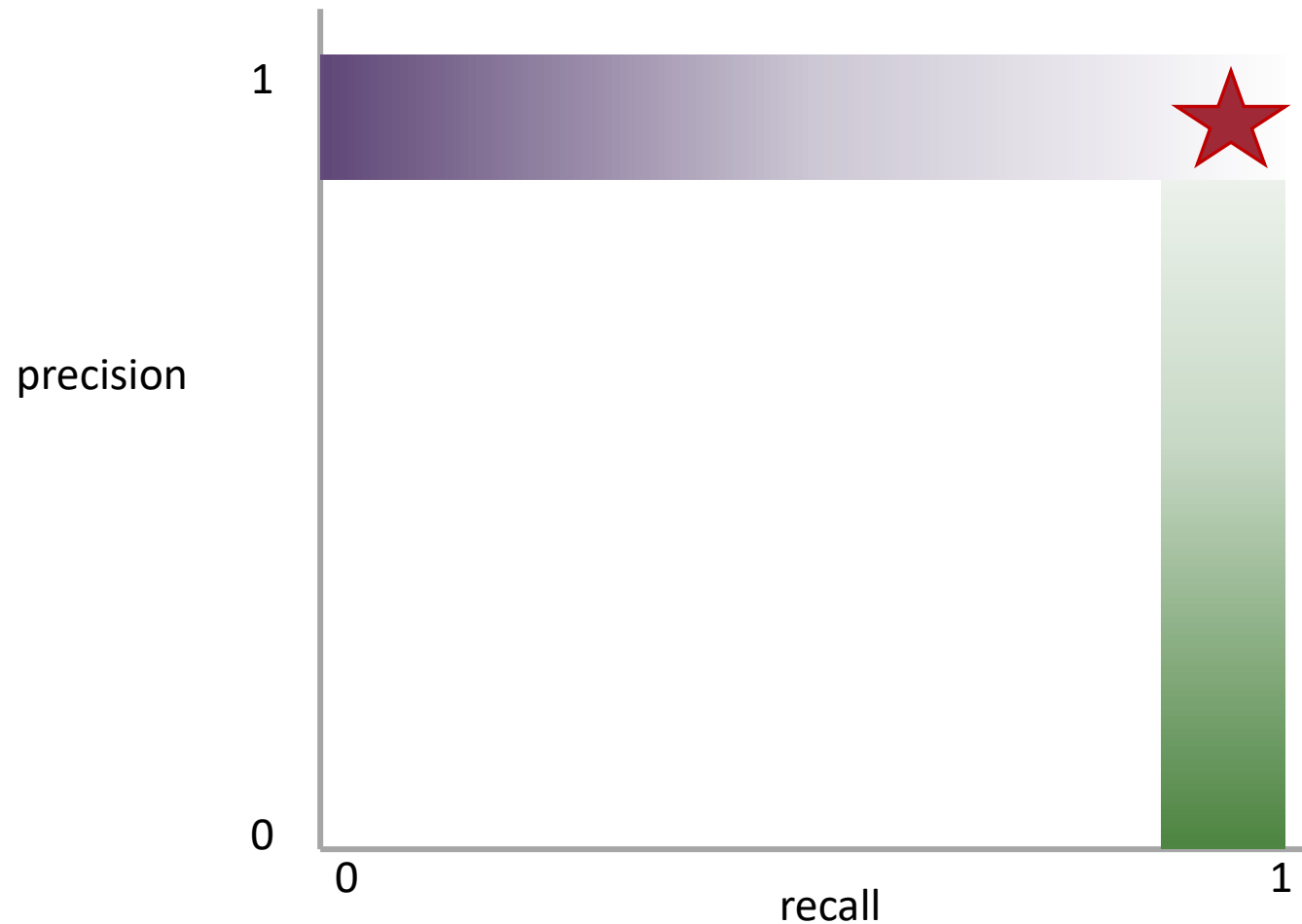


Q: Where do you want your ideal **model** ?

Q: You have a **model** that always identifies correct instances. Where on this graph is it?

Q: You have a **model** that only make correct predictions. Where on this graph is it?

# Precision and Recall Present a Tradeoff

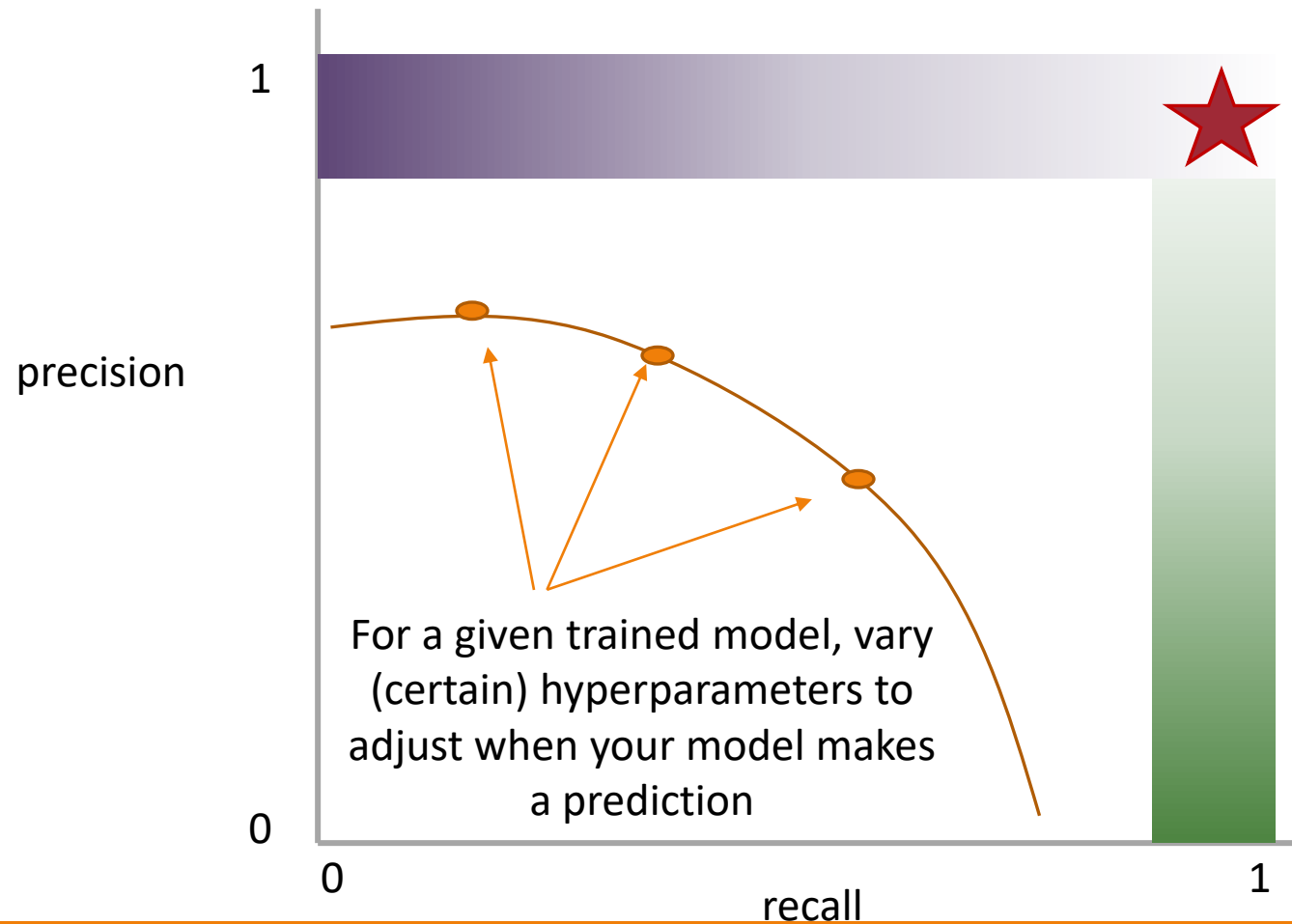


Q: Where do you want your ideal **model** ?

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# Precision and Recall Present a Tradeoff



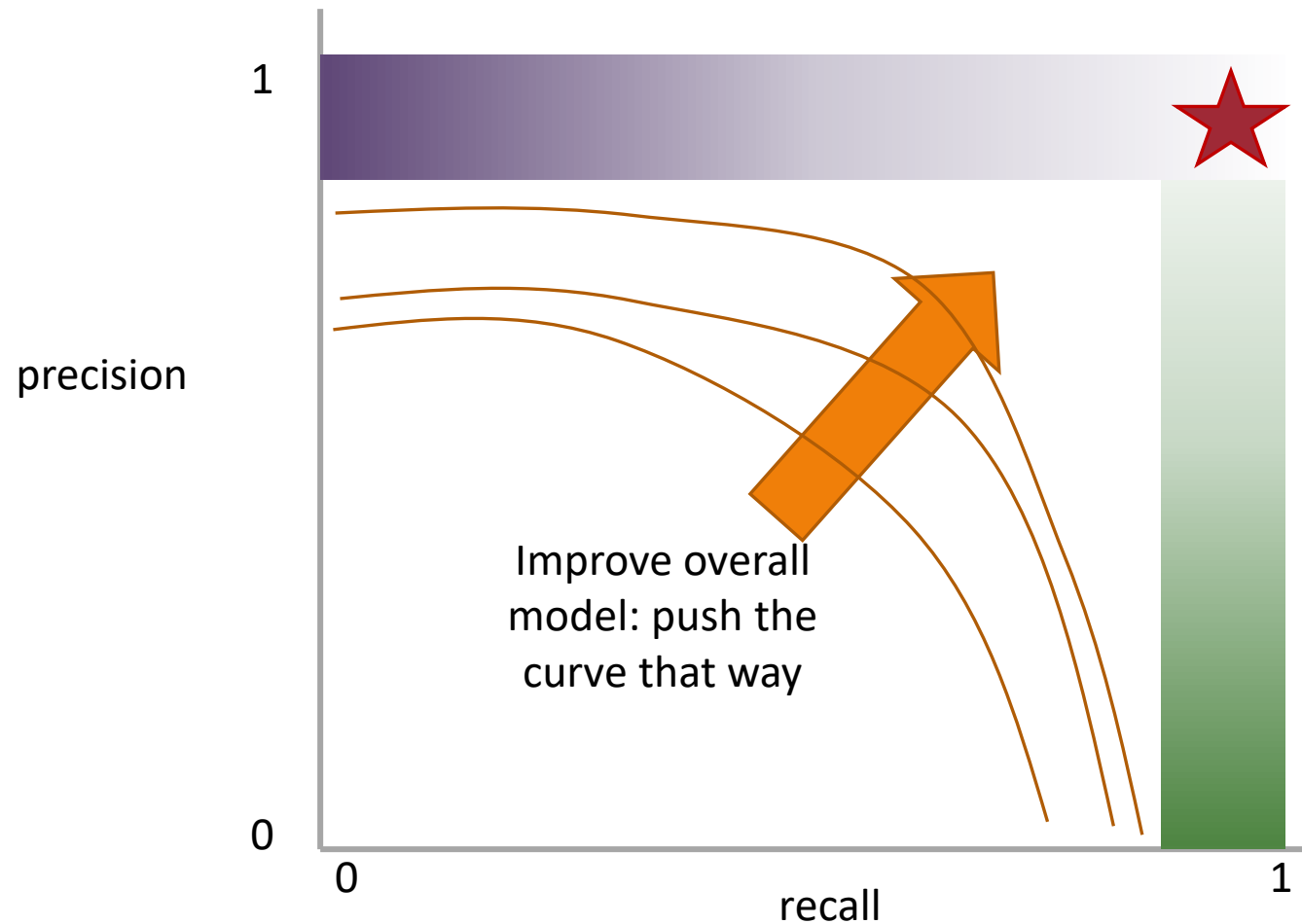
Q: Where do you want your ideal **model** ?

Q: You have a **model** that always identifies correct instances. Where on this graph is it?

Q: You have a **model** that only make correct predictions. Where on this graph is it?

Idea: measure the tradeoff between precision and recall

# Precision and Recall Present a Tradeoff



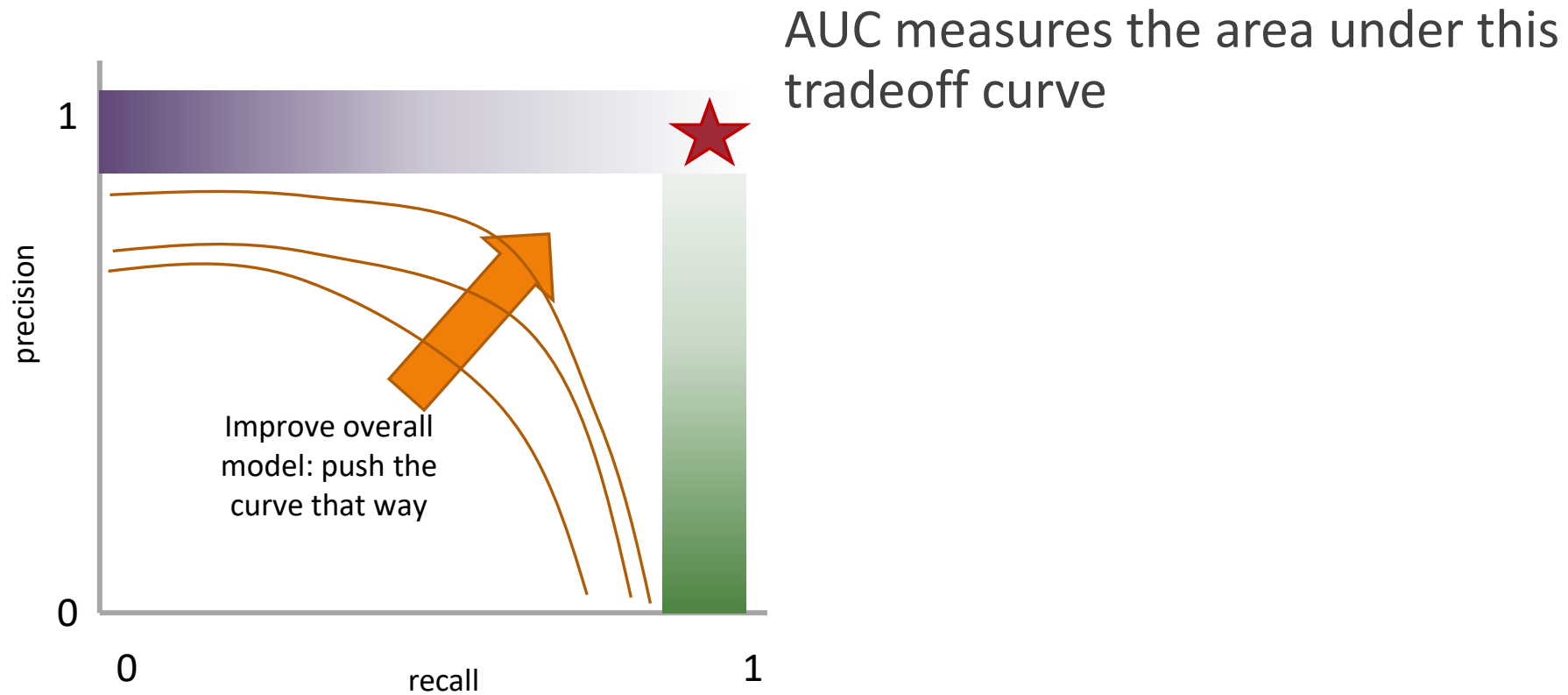
Q: Where do you want your ideal **model** ?

Q: You have a **model** that always identifies correct instances. Where on this graph is it?

Q: You have a **model** that only make correct predictions. Where on this graph is it?

Idea: measure the tradeoff between precision and recall

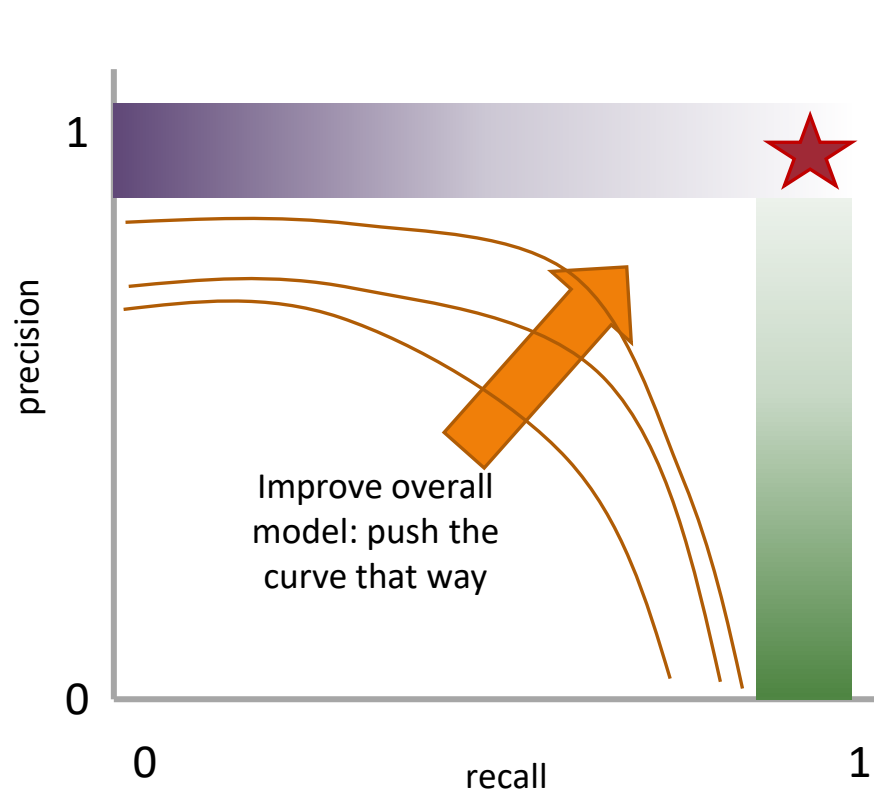
# Measure this Tradeoff: Area Under the Curve (AUC)



Min AUC: 0 😞  
Max AUC: 1 😊



# Measure this Tradeoff: Area Under the Curve (AUC)



AUC measures the area under this tradeoff curve

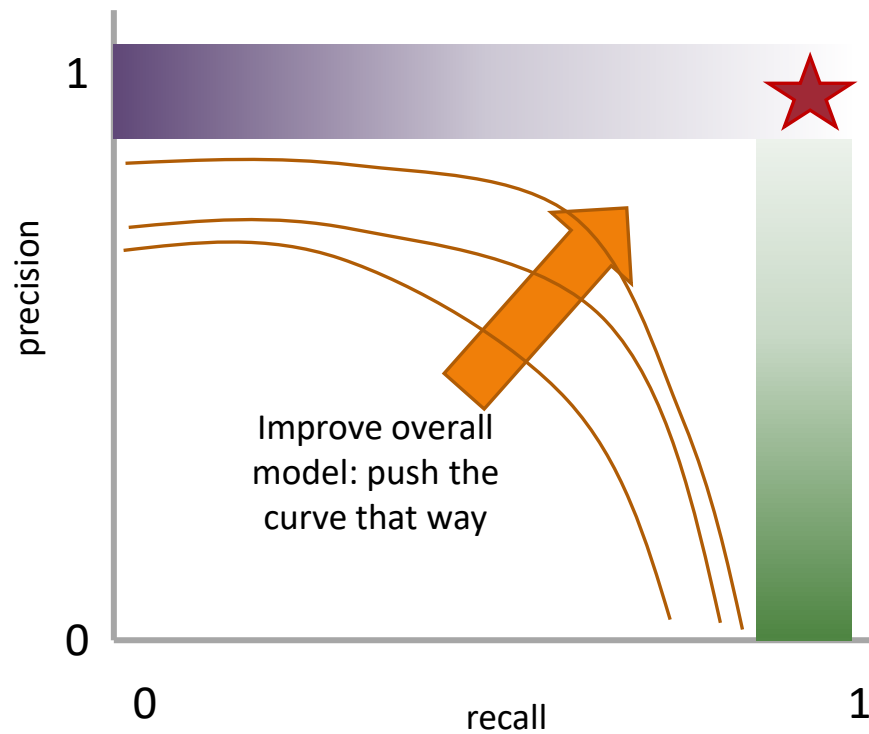
1. Computing the curve  
You need true labels & predicted labels with some score/confidence estimate

Threshold the scores and for each threshold compute precision and recall

Min AUC: 0 😞

Max AUC: 1 😊

# Measure this Tradeoff: Area Under the Curve (AUC)



AUC measures the area under this tradeoff curve

1. Computing the curve  
You need true labels & predicted labels with some score/confidence estimate  
Threshold the scores and for each threshold compute precision and recall
2. Finding the area  
How to implement: trapezoidal rule (& others)

**In practice:** external library like the `sklearn.metrics` module

Min AUC: 0 😞  
Max AUC: 1 😊

# A combined measure: F-score

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Weighted (harmonic) average of **P**recision & **R**ecall

F1 measure: equal weighting between precision and recall

$$F_1 = \frac{2 * P * R}{P + R}$$

# A combined measure: F-score

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Weighted (harmonic) average of **Precision** & **Recall**

F1 measure: equal weighting between precision and recall

$$F_1 = \frac{2 * P * R}{P + R} = \frac{2 * TP}{2 * TP + FP + FN}$$

(useful when  $P = R = 0$ )

# Classification Evaluation: Accuracy, Precision, and Recall

**Accuracy:** % of items correct

$$\frac{TP + TN}{TP + FP + FN + TN}$$

$$F_1 = \frac{2 * P * R}{P + R} = \frac{2 * TP}{2 * TP + FP + FN}$$

When would you want to use  
accuracy vs F1?

Accuracy works better if  
the dataset is balanced

Accuracy takes  
everything in  
consideration

F-Score is  
focused on TP

	Actually Target	Actually Not Target
Selected/Guessed	True Positive (TP)	False Positive (FP)
Not select/not guessed	False Negative (FN)	True Negative (TN)

# Implementation: How To

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1. scikit-learn: [sklearn.metrics](#)
  - very stable
2. huggingface [evaluate](#) module
  - community input
  - sometimes are based on sklearn
3. implement your own

# P/R/F in a Multi-class Setting: Micro- vs. Macro-Averaging

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*If we have more than one class, how do we combine multiple performance measures into one quantity?*

**Macroaveraging:** Compute performance for each class, then average.

**Microaveraging:** Collect decisions for all classes, compute contingency table, evaluate.

# P/R/F in a Multi-class Setting: Micro- vs. Macro-Averaging

**Macroaveraging:** Compute performance for each class, then average.

$$\text{macroprecision} = \frac{1}{C} \sum_c \frac{TP_c}{TP_c + FP_c} = \frac{1}{C} \sum_c \text{precision}_c$$

$$\text{macrorecall} = \frac{1}{C} \sum_c \frac{TP_c}{TP_c + FN_c} = \frac{1}{C} \sum_c \text{recall}_c$$

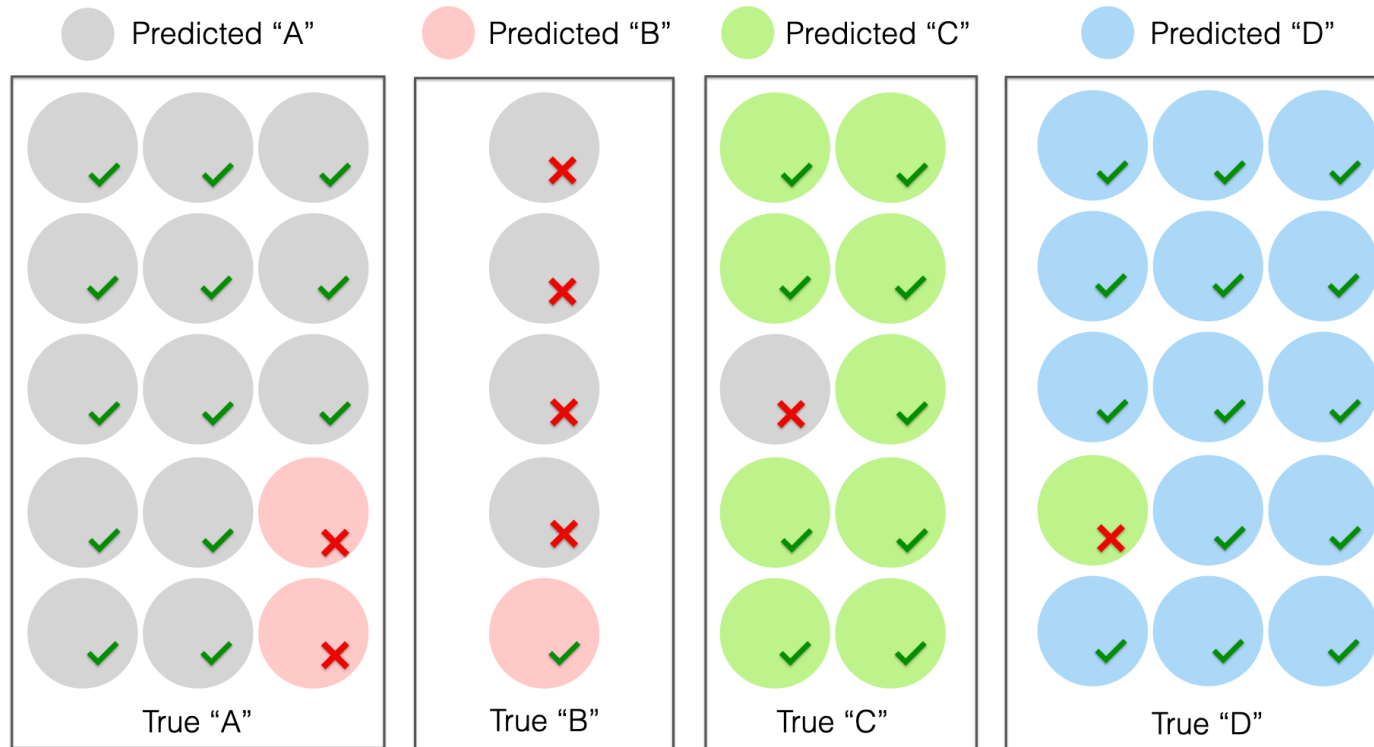
**Microaveraging:** Collect decisions for all classes, compute contingency table, evaluate.

$$\text{microprecision} = \frac{\sum_c TP_c}{\sum_c TP_c + \sum_c FP_c}$$

$$\text{microrecall} = \frac{\sum_c TP_c}{\sum_c TP_c + \sum_c FN_c}$$

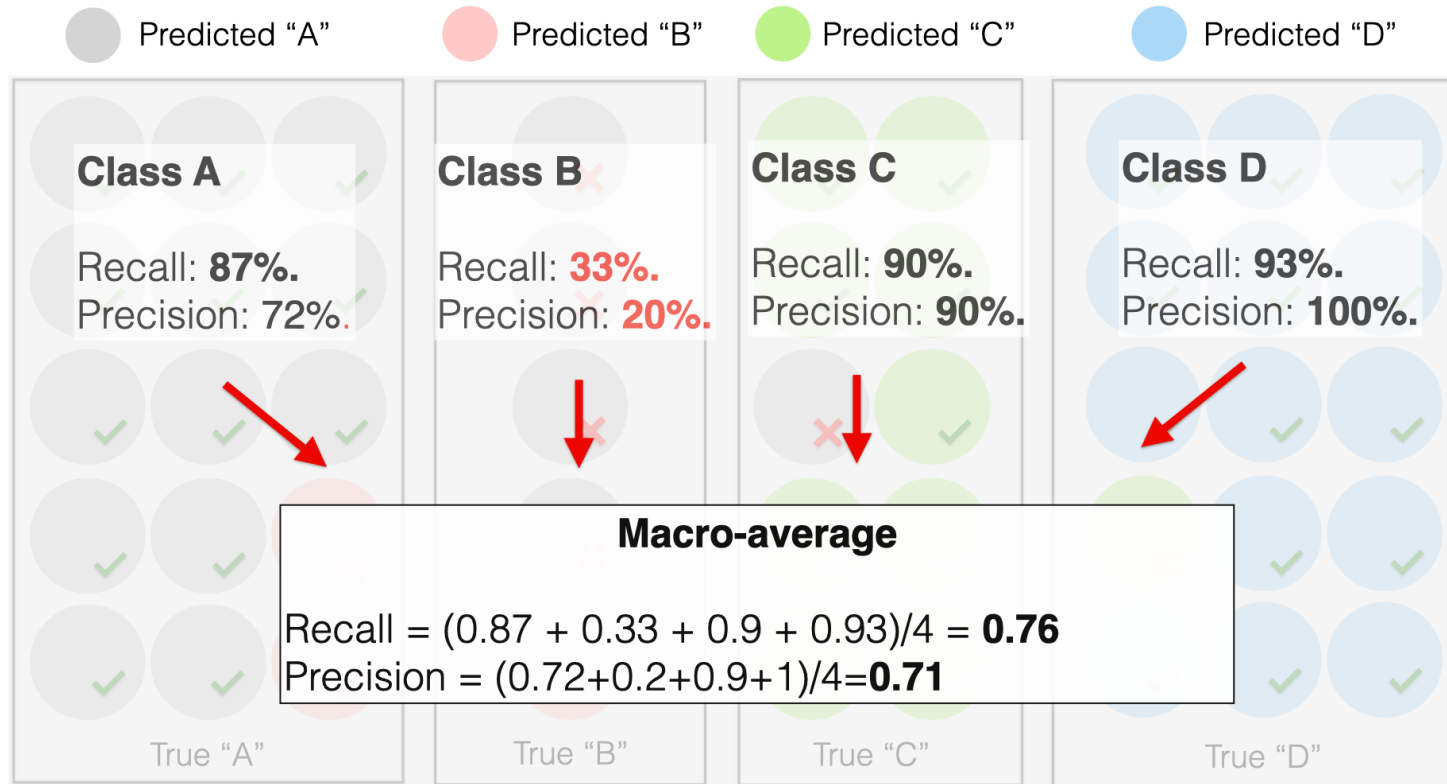
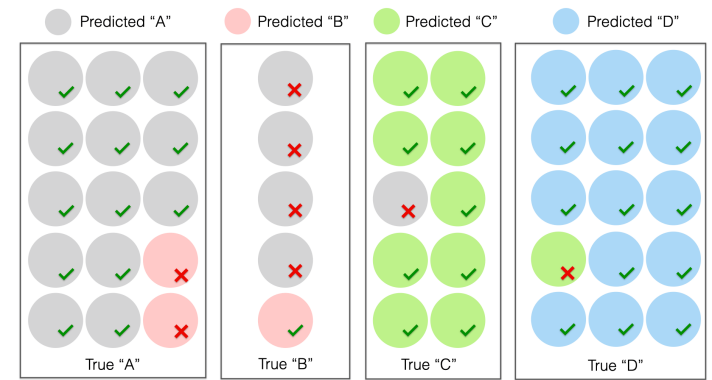


# Macro/Micro Example



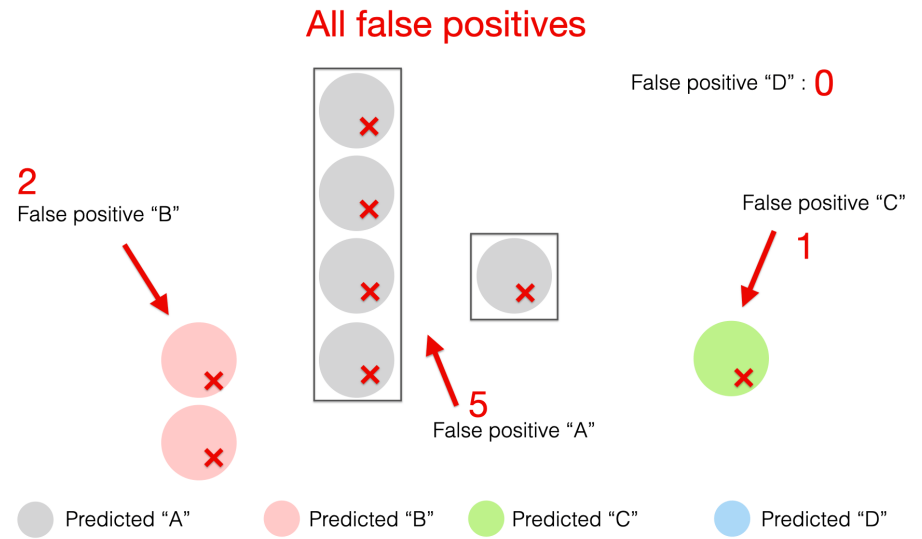
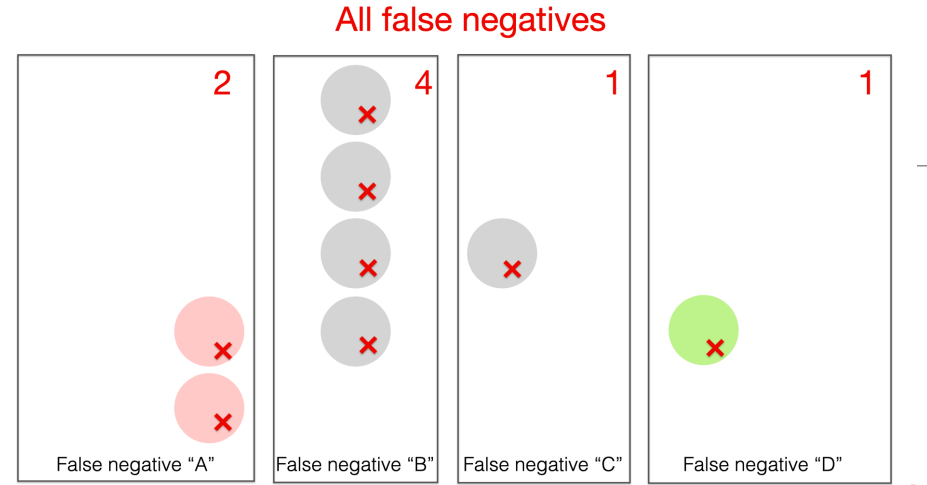
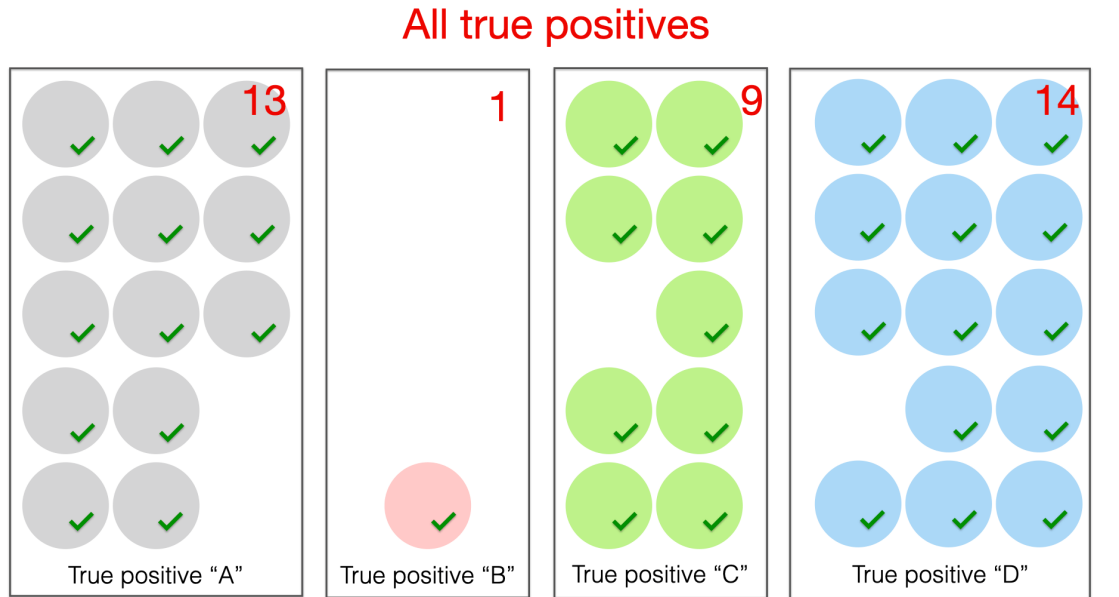
Each class has equal weight

# Macro-Average



Each *instance* has equal weight

# Micro-Average



	Total TP	Total FP	Total FN
Precision	13 + 1 + 9 + 14	2 + 5 + 1 + 0	
Recall	13 + 1 + 9 + 14		2 + 4 + 1 + 1

$$\text{Precision}_{\text{Micro-average}} = \frac{13 + 1 + 9 + 14}{13 + 1 + 9 + 14 + 2 + 5 + 1 + 0} = 0.82$$

$$\text{Recall}_{\text{Micro-average}} = \frac{13 + 1 + 9 + 14}{13 + 1 + 9 + 14 + 2 + 4 + 1 + 1} = 0.82$$

<https://www.evidentlyai.com/classification-metrics/multi-class-metrics>

# Micro- vs Macro-Average

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So when would we want to prefer micro-averaging vs macro-averaging?

$$\text{macroprecision} = \frac{1}{C} \sum_c \frac{TP_c}{TP_c + FP_c} = \frac{1}{C} \sum_c \text{precision}_c$$

$$\text{macrorecall} = \frac{1}{C} \sum_c \frac{TP_c}{TP_c + FN_c} = \frac{1}{C} \sum_c \text{recall}_c$$

$$\text{microprecision} = \frac{\sum_c TP_c}{\sum_c TP_c + \sum_c FP_c}$$

$$\text{microrecall} = \frac{\sum_c TP_c}{\sum_c TP_c + \sum_c FN_c}$$

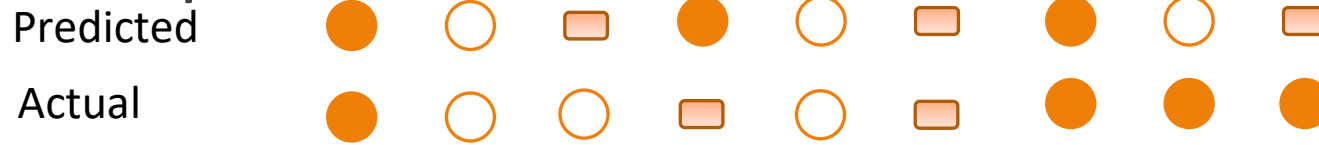
# But how do we compute stats for multiple classes?

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Either:

1. Compute “one-vs-all” 2x2 tables. OR
2. Generalize the 2x2 tables and compute per-class TP / FP / FN based on the diagonals and off-diagonals

# 1. Compute “one-vs-all” 2x2 tables



Look for ●	Actually Target	Actually Not Target	Look for ○	Actually Target	Actually Not Target
<b>Selected/Guessed</b>	True Positive (TP)	False Positive (FP)	<b>Selected/Guessed</b>	True Positive (TP)	False Positive (FP)
<b>Not select/not guessed</b>	False Negative (FN)	True Negative (TN)	<b>Not select/not guessed</b>	False Negative (FN)	True Negative (TN)

Look for □	Actually Target	Actually Not Target
<b>Selected/Guessed</b>	True Positive (TP)	False Positive (FP)
<b>Not select/not guessed</b>	False Negative (FN)	True Negative (TN)





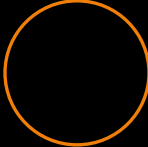

# 1. Compute “one-vs-all” 2x2 tables

Predicted    ●   ○   □   ●   ○   □   ●   ○   □  
 Actual        ●   ○   ○   □   ○   □   ●   ●   ●

Look for ●	Actually Target	Actually Not Target	Look for ○	Actually Target	Actually Not Target
Selected/Guessed	2	1	Selected/Guessed	2	1
Not select/not guessed	2	4	Not select/not guessed	1	5

Look for □	Actually Target	Actually Not Target
Selected/Guessed	1	2
Not select/not guessed	1	5



















## 2. Generalizing the 2-by-2 contingency table







		Correct Value		
				
Guessed Value		#	#	#
		#	#	#
		#	#	#

This is also called a **Confusion Matrix**



## 2. Generalizing the 2-by-2 contingency table

Predicted           
 Actual         


















		Correct Value		
				
Guessed Value		#	#	#
		#	#	#
		#	#	#





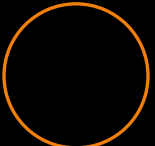

## 2. Generalizing the 2-by-2 contingency table

Predicted	●	○	▭	●	○	▭	●	○	▭
Actual	●	○	○	▭	○	▭	●	●	●

		Correct Value		
		●	○	▭
Guessed Value	●	2	0	1
	○	1	2	0
	▭	1	1	1



















## 2. Generalizing the 2-by-2 contingency table





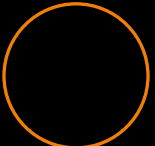

Predicted									
Actual									

		Correct Value		
				
Guessed Value		A 2	B 0	C 1
		D 1	E 2	F 0
		G 1	H 1	I 1

How do you compute  $TP$  ?



















## 2. Generalizing the 2-by-2 contingency table





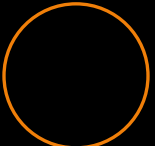

Predicted									
Actual									

		Correct Value		
				
Guessed Value		A <b>2</b>	B 0	C 1
		D 1	E 2	F 0
		G 1	H 1	I 1

How do you compute  $TP$ ?










## 2. Generalizing the 2-by-2 contingency table










Predicted									
Actual									





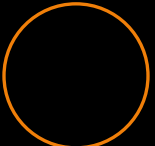

		Correct Value		
				
Guessed Value		A 2	B 0	C 1
		D 1	E 2	F 0
		G 1	H 1	I 1

How do you compute  $FN$ ?

## 2. Generalizing the 2-by-2 contingency table



















Predicted         





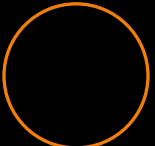

Actual         

		Correct Value		
				
Guessed Value		A 2	B 0	C 1
		D 1	E 2	F 0
		G 1	H 1	I 1

How do you compute  $FN$ ?










## 2. Generalizing the 2-by-2 contingency table










Predicted									
Actual									





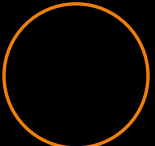

		Correct Value		
				
Guessed Value		A 2	B 0	C 1
		D 1	E 2	F 0
		G 1	H 1	I 1

How do you compute  $FP_{\square}$ ?

## 2. Generalizing the 2-by-2 contingency table

Predicted         

Actual         


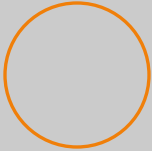


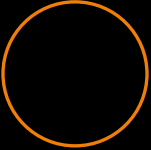

		Correct Value		
				
Guessed Value		A 2	B 0	C 1
		D 1	E 2	F 0
		G 1	H 1	I 1

How do you compute  $FP_{\square}$ ?







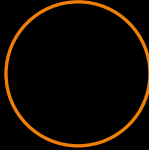

# Generalizing the 2-by-2 contingency table

Q: Is this a good result?

		Correct Value		
				
Guessed Value		80	9	11
		7	86	7
		2	8	9





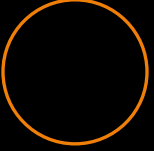

# Generalizing the 2-by-2 contingency table

Q: Is this a good result?

		Correct Value		
				
Guessed Value		30	40	30
		25	30	50
		30	35	35

# Generalizing the 2-by-2 contingency table

Q: Is this a good result?

		Correct Value		
				
Guessed Value		7	3	90
		4	8	88
		3	7	90