ML Evaluation

CMSC 473/673 - NATURAL LANGUAGE PROCESSING

Slides modified from Dr. Frank Ferraro & Cynthia Matuszek

Learning Objectives

Distinguish between types of ML problems and models

Fill out a contingency table

Calculate accuracy, precision, and recall

Develop an intuition about precision & recall

ML/NLP Framework for Learning & Prediction

instances

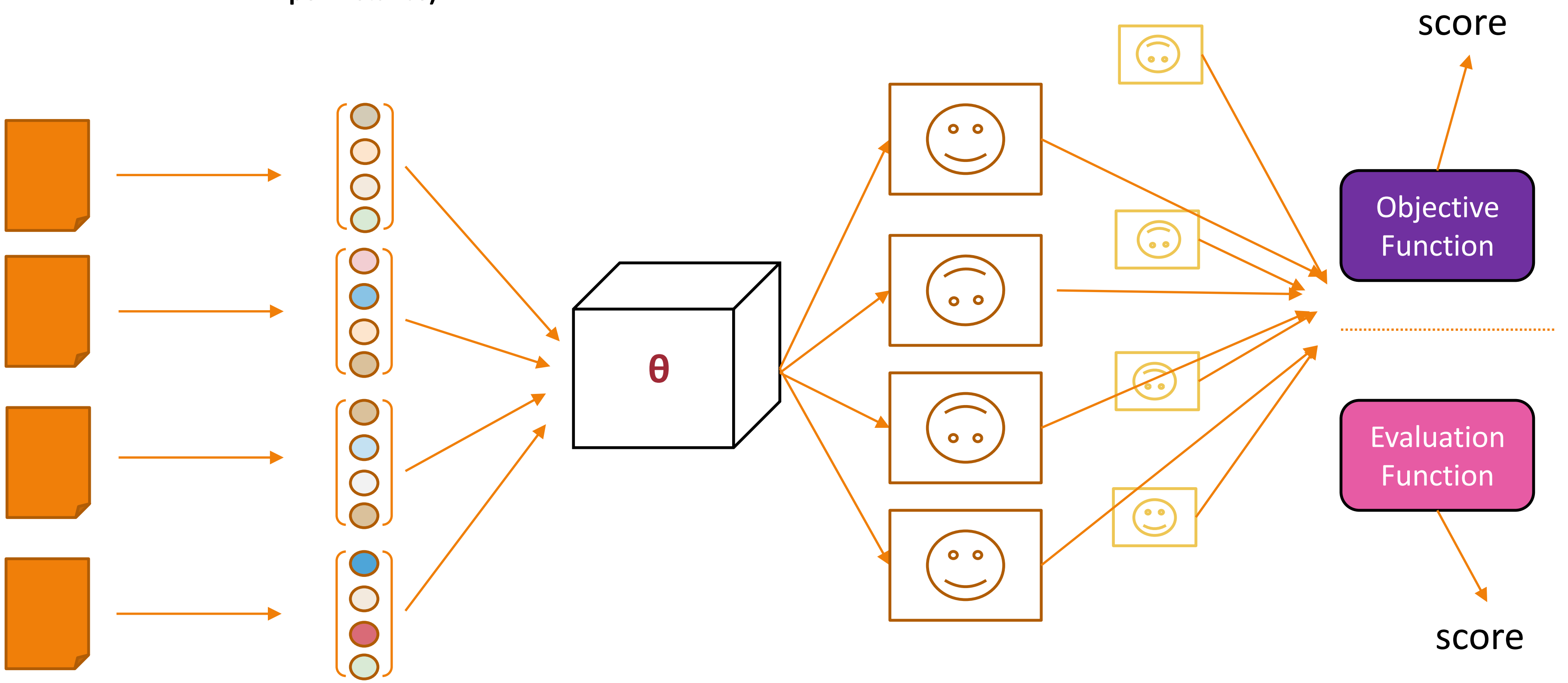
features: **K-dimensional vector representations** (one per instance)

ML model:
- take in featurized input
- output scores/labels
- contains weights θ

output

"Gold" (correct) labels

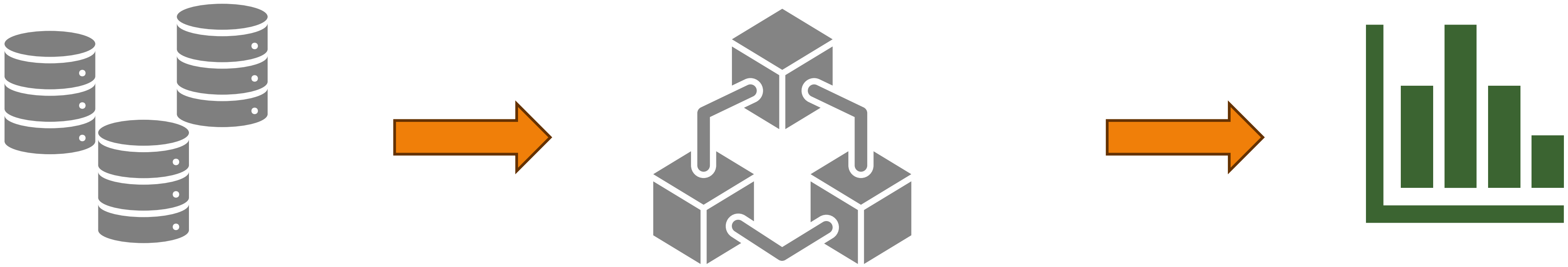
Objective / Eval Function



Review: Classification Types (Terminology)

Name	Number of Tasks (Domains) Labels are Associated with	# Label Types	Example
(Binary) Classification	1	2	Sentiment: Choose one of {positive or negative}
Multi-class Classification	1	> 2	Part-of-speech: Choose one of {Noun, Verb, Det, Prep, …}
Multi-label Classification	1	> 2	Sentiment: Choose multiple of {positive, angry, sad, excited, …}
Multi-task Classification	> 1	Per task: 2 or > 2 (can apply to binary or multi-class)	Task 1: part-of-speech Task 2: named entity tagging … ---------------------- Task 1: document labeling Task 2: sentiment

How do we learn models?



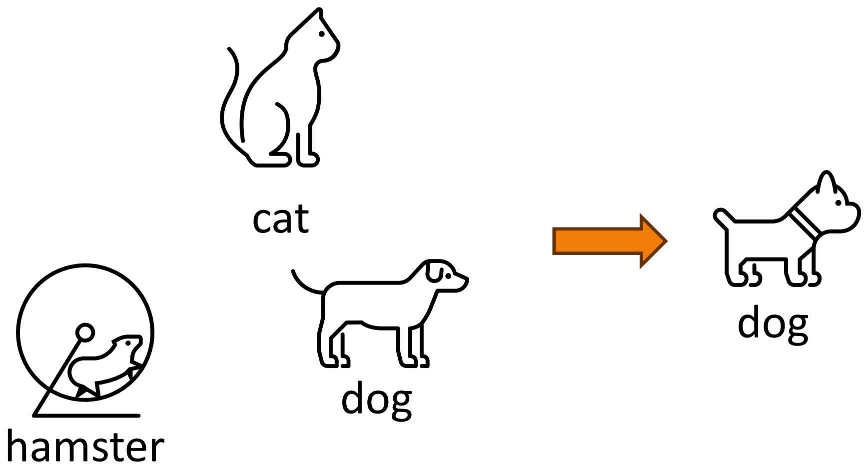
Take past experiences
(lots of data; corpus)

Find patterns
(the ML algorithm)

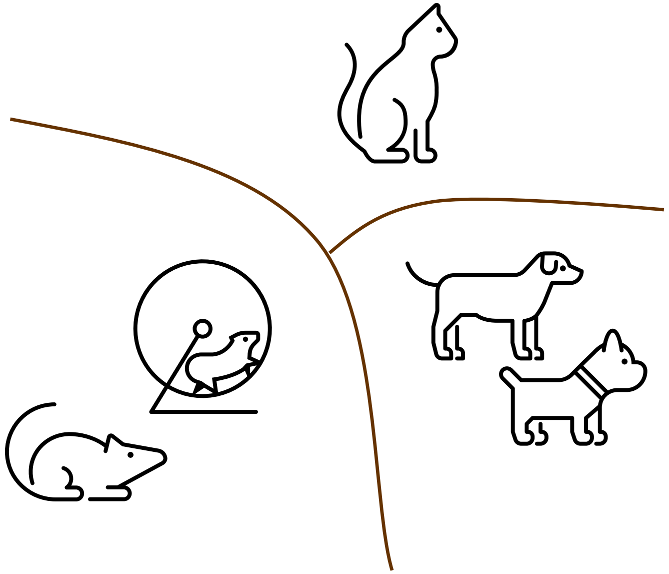
Use on new experiences
(save & test the model)

Types of Learning

SUPERVISED LEARNING



UNSUPERVISED LEARNING



Types of Learning

SUPERVISED LEARNING

Data has feedback (labels)

Data consists of input-output pairs

Learn mapping from input to output

Examples:

- Dataset classification
- How likely is it that this person will get into a car accident?

UNSUPERVISED LEARNING

No explicit feedback in data

Learn patterns directly from data

Examples:

- Clustering
- Do these people fall under multiple groups?

What are some other examples of these?

SUPERVISED LEARNING

- Machine translation
- Object segmentation (vision)
- Document classification

UNSUPERVISED LEARNING

- Clustering
- Language modeling

The Machine Learning Framework

$$y = f(\mathbf{x})$$

output

prediction function

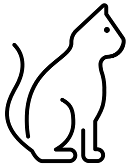
feature(s) of input

Training: given a *training set* of labeled examples $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set

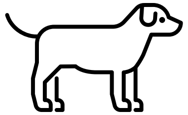
Testing: apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

Slide credit: Svetlana Lazebnik

How do we learn models?



cat



dog

hamster

[position of lines]
[loops and dots]
[any other information relevant to our problem]

P(hamster|[line in this position],…)

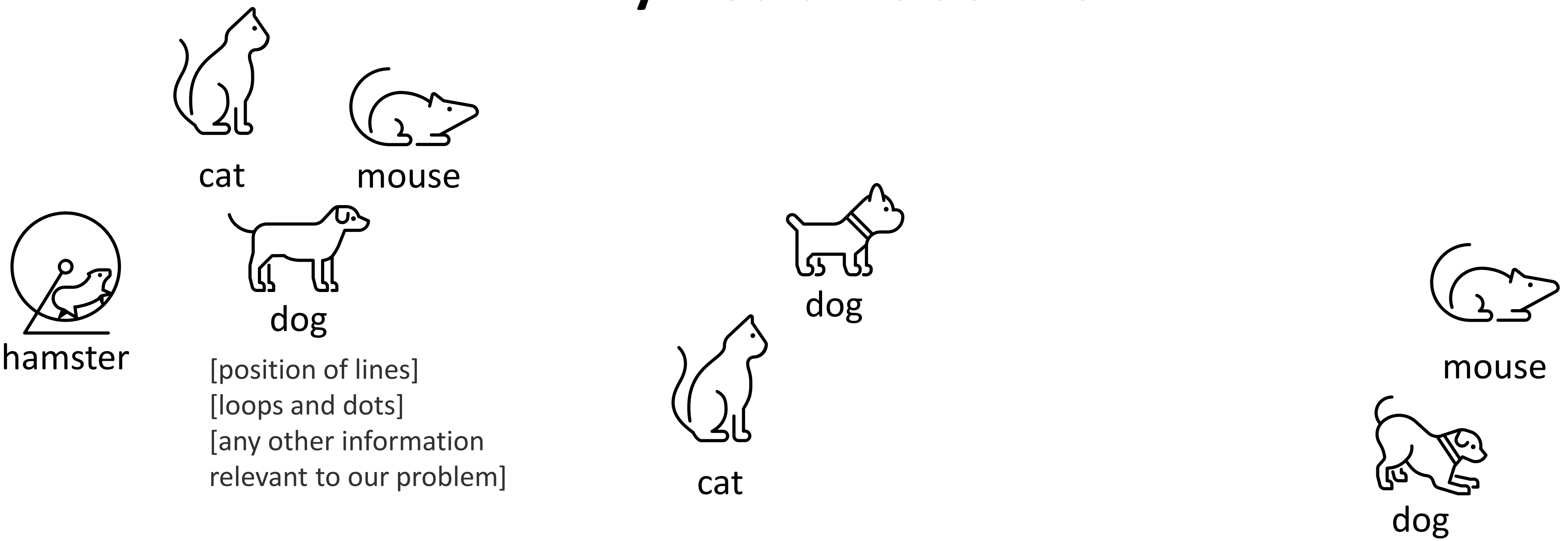
P(dog|[line in this other position],…)

Have data with features extracted (and possibly labels)

Learn associations between features and labels

Dividing up data for Training

Why would we do this?

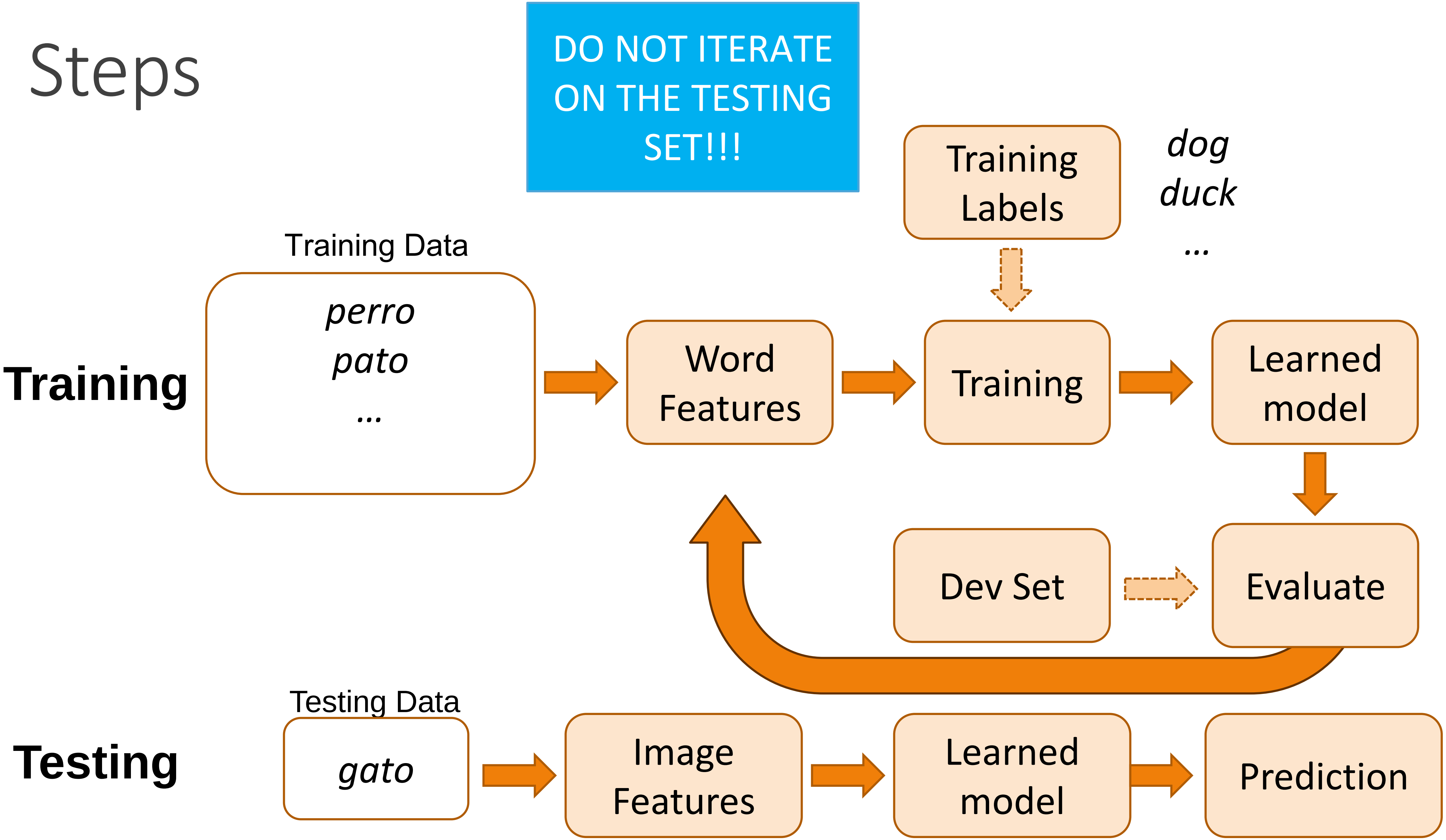


Training
~80%

Validation/Development
~10%

Testing
~10%

Steps


DO NOT ITERATE ON THE TESTING SET!!!
Training Labels
dog
duck
…
Training Data
perro
pato
…
Training
Word Features
Training
Learned model
Dev Set
Evaluate
Testing Data
Testing
gato
Image Features
Learned model
Prediction

Types of models

CLASSIFICATION

Model outputs comes from a finite set of values

Discrete result

Examples:

- What type of animal is this a picture of?
- Predicting the weather (sunny, cloudy, or rainy?)
- Ranking: Is this result *better* than this result?

REGRESSION

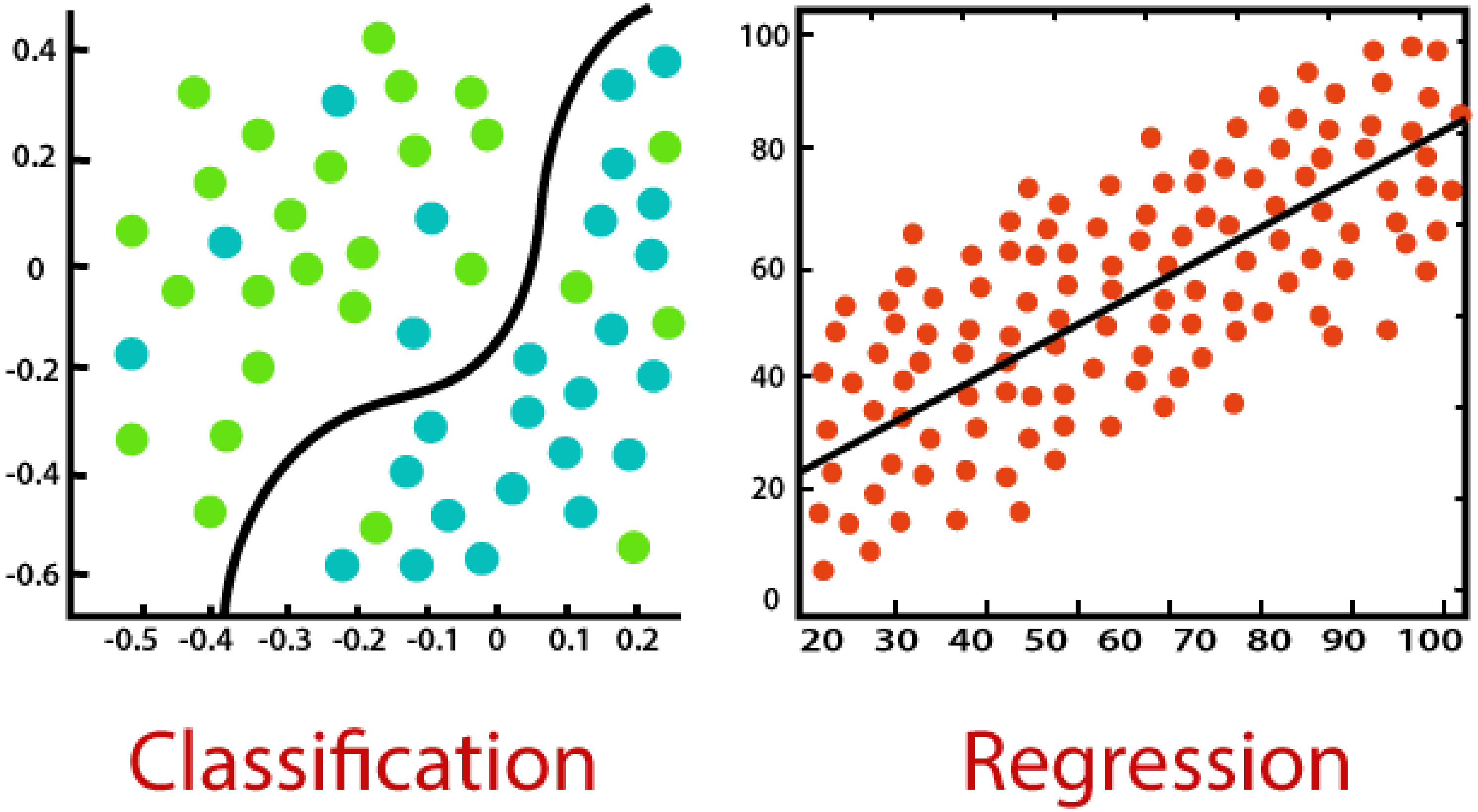
Model outputs are continuous values

Continuous result

Examples:

- How far will I move if I drive my motors at this speed for 1 second?
- Predicting the weather (temperature)
- Ranking: *how good* is this result?

Types of models



https://medium.com/unpackai/classification-regression-in-machine-learning-7cf3b13b0b09

What are some other examples of these?

CLASSIFICATION

Tone tagging

Sentiment classification

Named entity recognition

REGRESSION

Quantity/scale of how much it sounds like a specific author

Numerical sentiment value

Political “score” from document

Likelihoods

Predicted Goodreads score

Types of Algorithms

	Supervised Learning	Unsupervised Learning
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

Central Question: How Well Are We Doing?

Classification

Regression

Clustering

the ***task****: what* kind *of problem are you solving?*

- Precision, Recall, F1
- Accuracy
- Log-loss
- ROC-AUC
- …

- (Root) Mean Square Error
- Mean Absolute Error
- …

- Mutual Information
- V-score
- …

This does not have to be the same thing as the loss function you optimize

Training Loss vs. Evaluation Score

In training, compute loss to update parameters

Sometimes loss is a computational compromise

- surrogate loss

The loss you use might not be as informative as you'd like

Binary classification: 90 of 100 training examples are +1, 10 of 100 are -1

Some Classification Metrics

Accuracy

Precision

Recall

AUC (Area Under Curve)

F1

Confusion Matrix

Implementation: How To

1. scikit-learn: [sklearn.metrics]
   - very stable

2. huggingface [evaluate] module
   - community input
   - sometimes are based on sklearn

3. implement your own

Classification Evaluation:
the 2-by-2 contingency table

Assumption 1: There are two classes/labels

● ○

Assumption 2: ● is the "positive" label

Assumption 3: Given X, our classifier produces a score for each possible label

p(● |X) vs. p(○ |X)

Examining Assumption 3

Given X, our classifier produces a score for each possible label

$$p(\bullet|X) \text{ vs. } p(\circ|X)$$

Normally (*but this can be adjusted!)

$$\text{best label} = \arg\max_{\text{label}} P(\text{label}|\text{example})$$

Example of `argmax`

Electronic alerts have been used to assist the authorities in moments of chaos and potential danger: after the Boston bombing in 2013, when the Boston suspects were still at large, and last month in Los Angeles, during an active shooter scare at the airport.

POLITICS	.05
TERRORISM	.48
SPORTS	.0001
TECH	.39
HEALTH	.0001
FINANCE	.0002
…	

Source: http://www.nytimes.com/2016/09/20/nyregion/cellphone-alerts-used-in-search-of-manhattan-bombing-suspect.html

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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 ("●")		
Not selected/ not guessed ("○")		

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) ● *Actual* ● *Guessed*	
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Classification Evaluation:
the 2-by-2 contingency table

	What is the actual label?	
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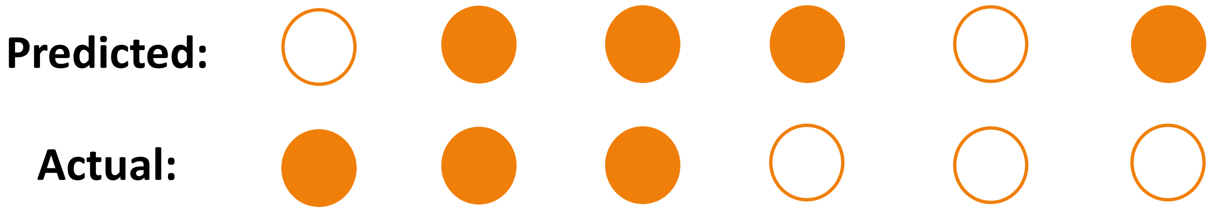
Construct this table by *counting* the number of TPs, FPs, FNs, TNs

Contingency Table Example



Contingency Table Example

Predicted: ○ ● ● ● ○ ●

Actual: ● ● ● ○ ○ ○

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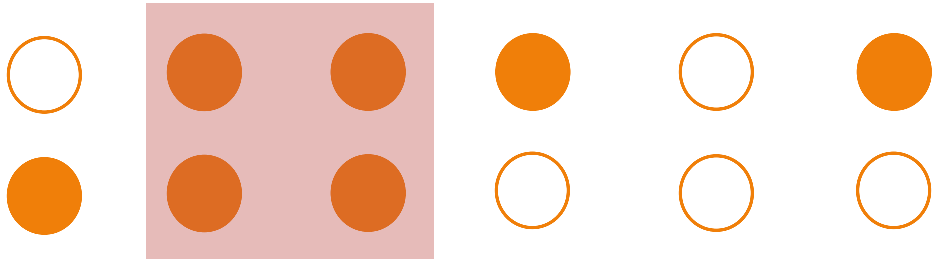
Contingency Table Example

Predicted:

Actual:



	What is the actual label?	
What label does our system predict? (↓)	Actual Target Class ("●")	Not Target Class ("○")
Selected/ Guessed ("●")	True Positive (TP) = 2	False Positive (FP)
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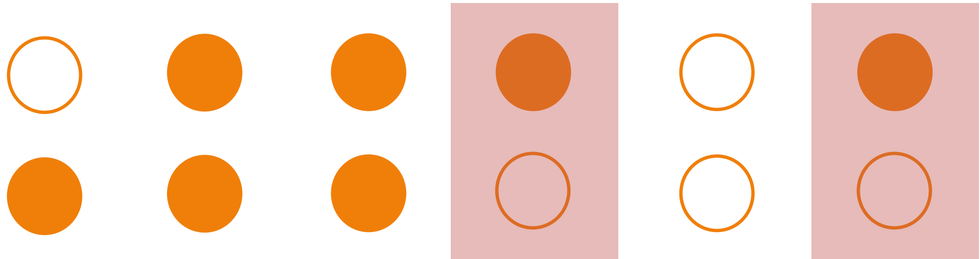
Contingency Table Example

Predicted:

Actual:



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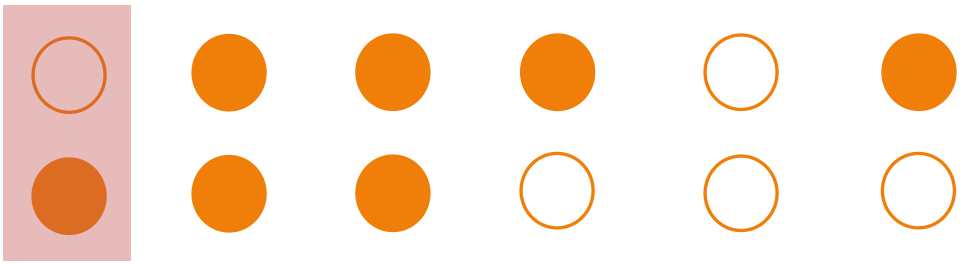

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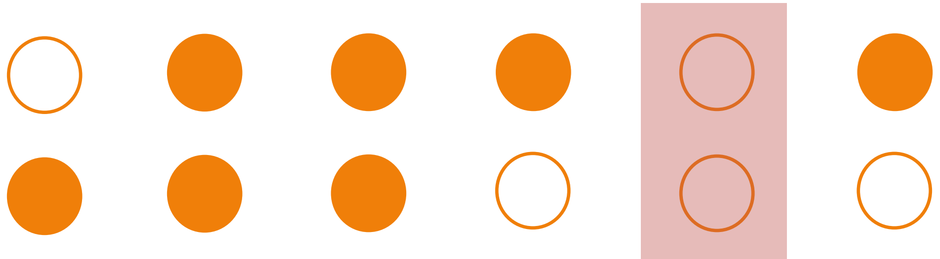
Predicted:

Actual:



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Contingency Table Example

Predicted: ○ ● ● ● ○ ●

Actual: ● ● ● ○ ○ ○

	What is the actual label?	
What label does our system predict? (↓)	**Actual Target Class ("●")**	**Not Target Class ("○")**
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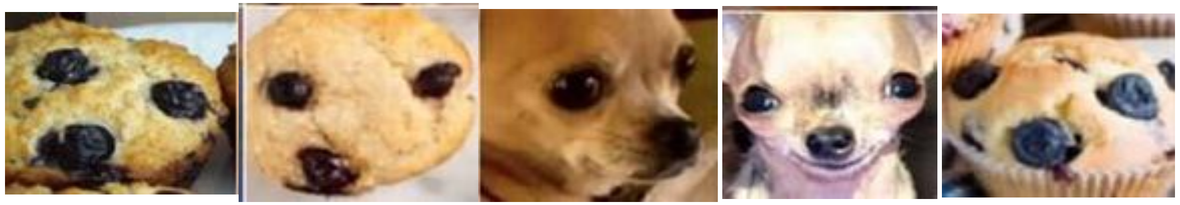

Knowledge Check

Fill out the contingency table for this example.
Your target class is Dog.

Actual:
Blueberry Blueberry Dog Dog Blueberry

Predicted:
Blueberry Dog Dog Blueberry Blueberry

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

https://petcentral.chewy.com/are-blueberries-safe-for-dogs-and-everything-else-you-could-possibly-want-to-know-about-dogs-and-blueberries/

Classification Evaluation: Accuracy, Precision, and Recall

Accuracy: % of items correct

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

	Actually Target	Actually Not Target
Selected/Guessed	True Positive (TP)	False Positive (FP)
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Classification Evaluation: Accuracy, Precision, and Recall

Accuracy: % of items correct

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

Precision: % of selected items that are correct

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

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Accuracy: % of items correct

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

Precision: % of selected items that are correct

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

Recall: % of correct items that are selected

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

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

Precision: % of selected items that are correct

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

Recall: % of correct items that are selected

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

Min: 0 ☹️
Max: 1 😀

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

The Importance of “Polarity” in Binary Classification

Fundamentally: what are you trying to “identify” in your classification?

Are you trying to find ● or ○?

The Importance of "Polarity" in Binary Classification

		Correct Value	
		●	○
Guessed Value	●	?	?
	○	?	?

Try to find ●: Where do the TP / FP / FN / FN values go?

The Importance of “Polarity” in Binary Classification

		Correct Value	
		●	○
Guessed Value	●	TP ●	FP ●
	○	FN ●	TN ●

The Importance of "Polarity" in Binary Classification

Predicted: ○ ● ● ● ○ ●

Actual: ● ● ● ○ ○ ○

		Correct Value	
		●	○
Guessed Value	●	TP ● $= 2$	FP ● $= 2$
	○	FN ● $= 1$	TN ● $= 1$

What are the accuracy, recall, and precision values?

Accuracy: 50%
Recall: 66.67%
Precision: 50%

The Importance of "Polarity" in Binary Classification

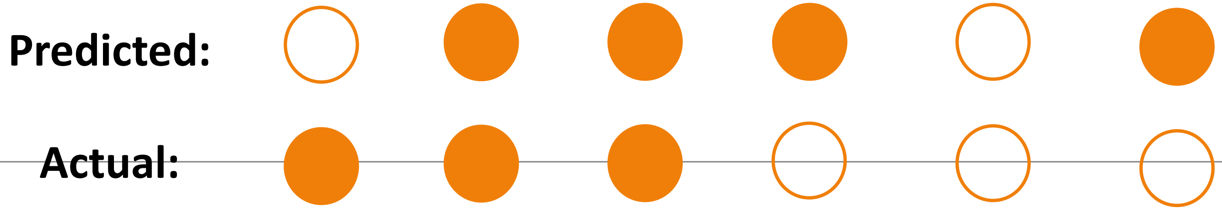
		Correct Value	
		●	○
Guessed Value	●	?	?
	○	?	?

Try to find ○ : Where do the TP / FP / FN / FN values go?

The Importance of "Polarity" in Binary Classification

		Correct Value	
		●	○
Guessed Value	●	TN ○	FN ○
	○	FP ○	TP ○

The Importance of “Polarity” in Binary Classification



		Correct Value	
Guessed Value		$TN = 2$	$FN = 2$
		$FP = 1$	$TP = 1$

What are the accuracy, recall, and precision values?

Accuracy: 50%
Recall: 33.34%
Precision: 50%

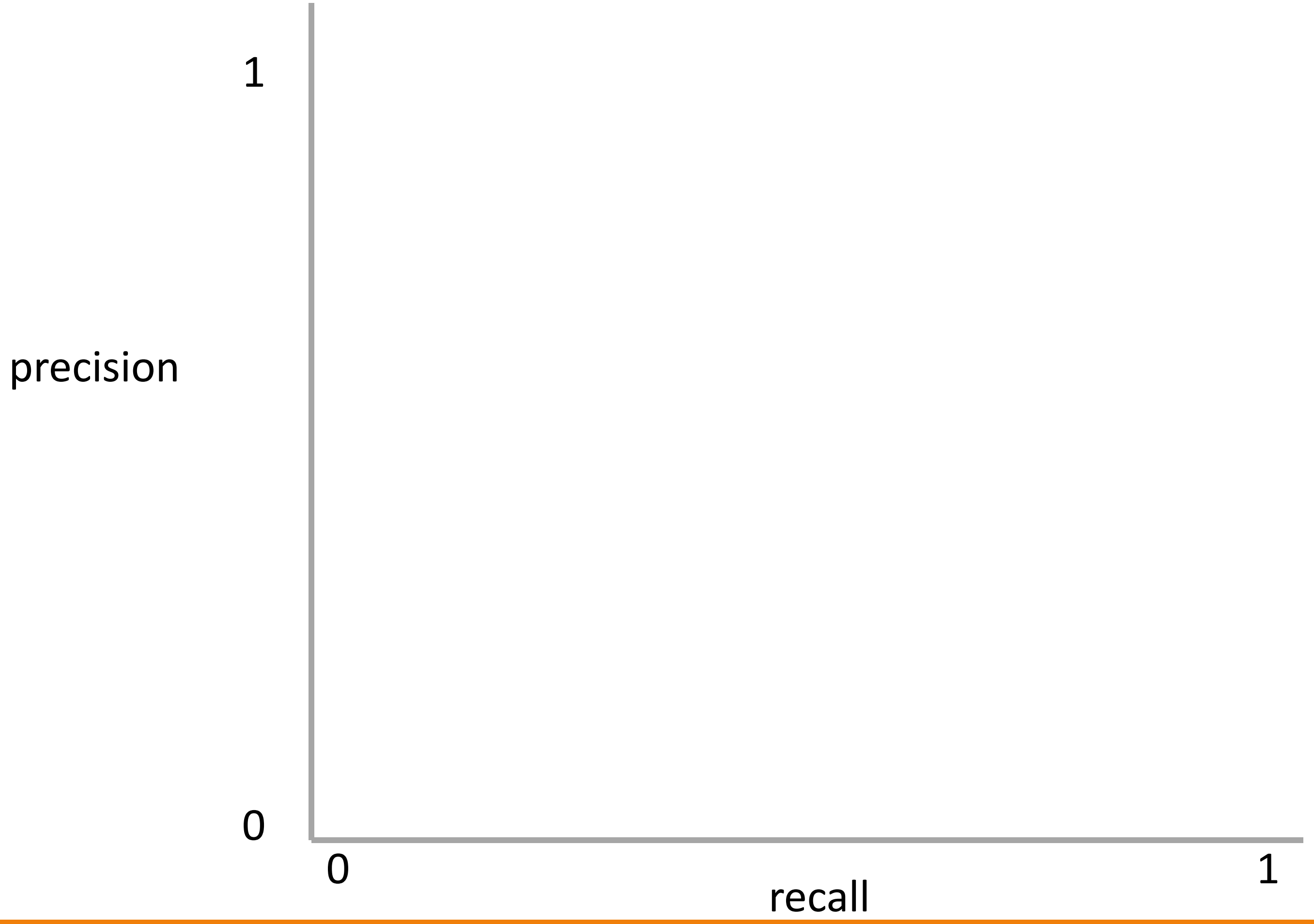
The Importance of “Polarity” in Binary Classification

Remember: what are you trying to “identify” in your classification?

		Correct Value	
		●	○
Guessed Value	●	TP ● $= TN$ ○	FP ● $= FN$ ○
	○	FN ● $= FP$ ○	TN ● $= TP$ ○

Precision and Recall Present a Tradeoff

Q: Where do you want your ideal model?



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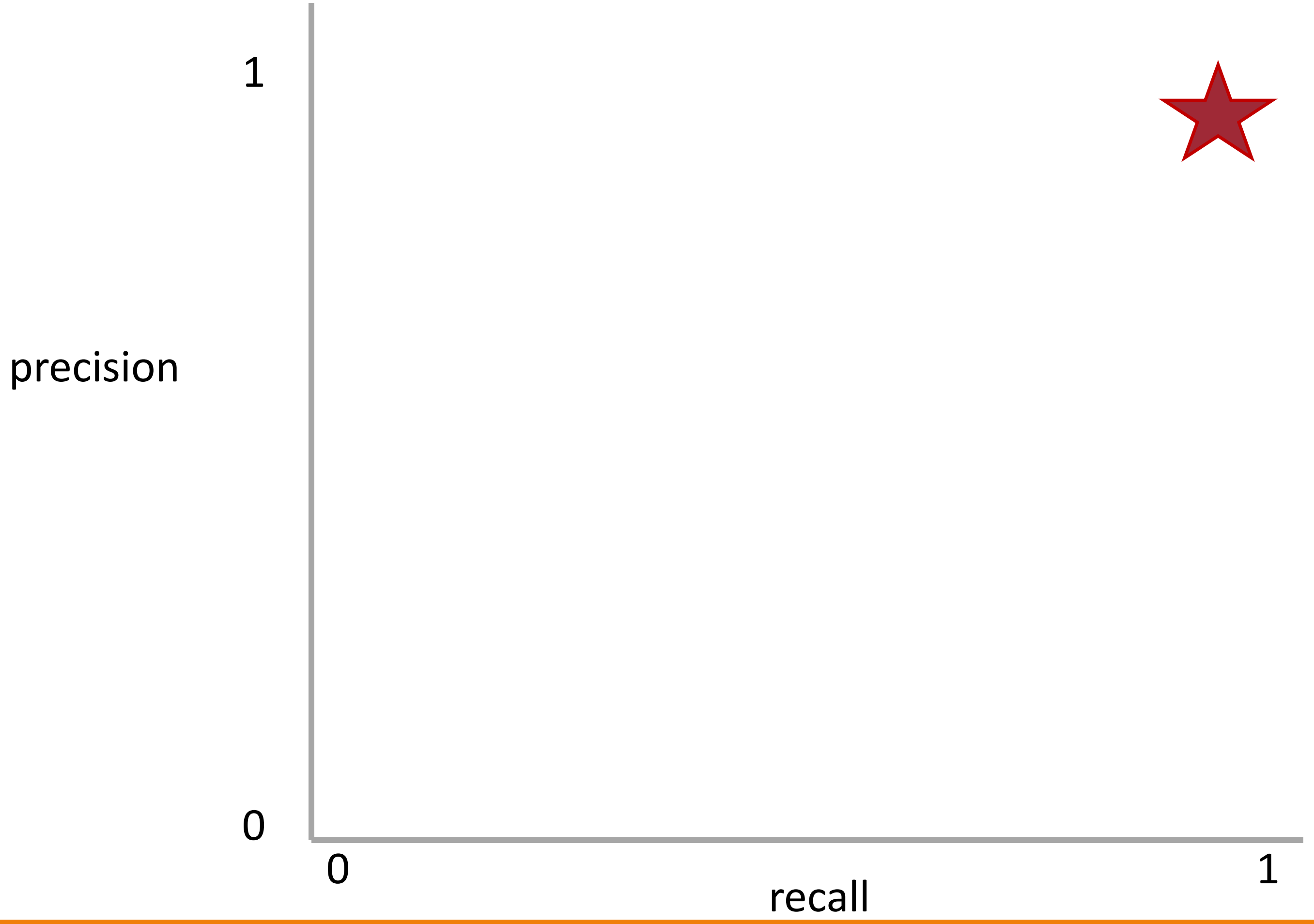
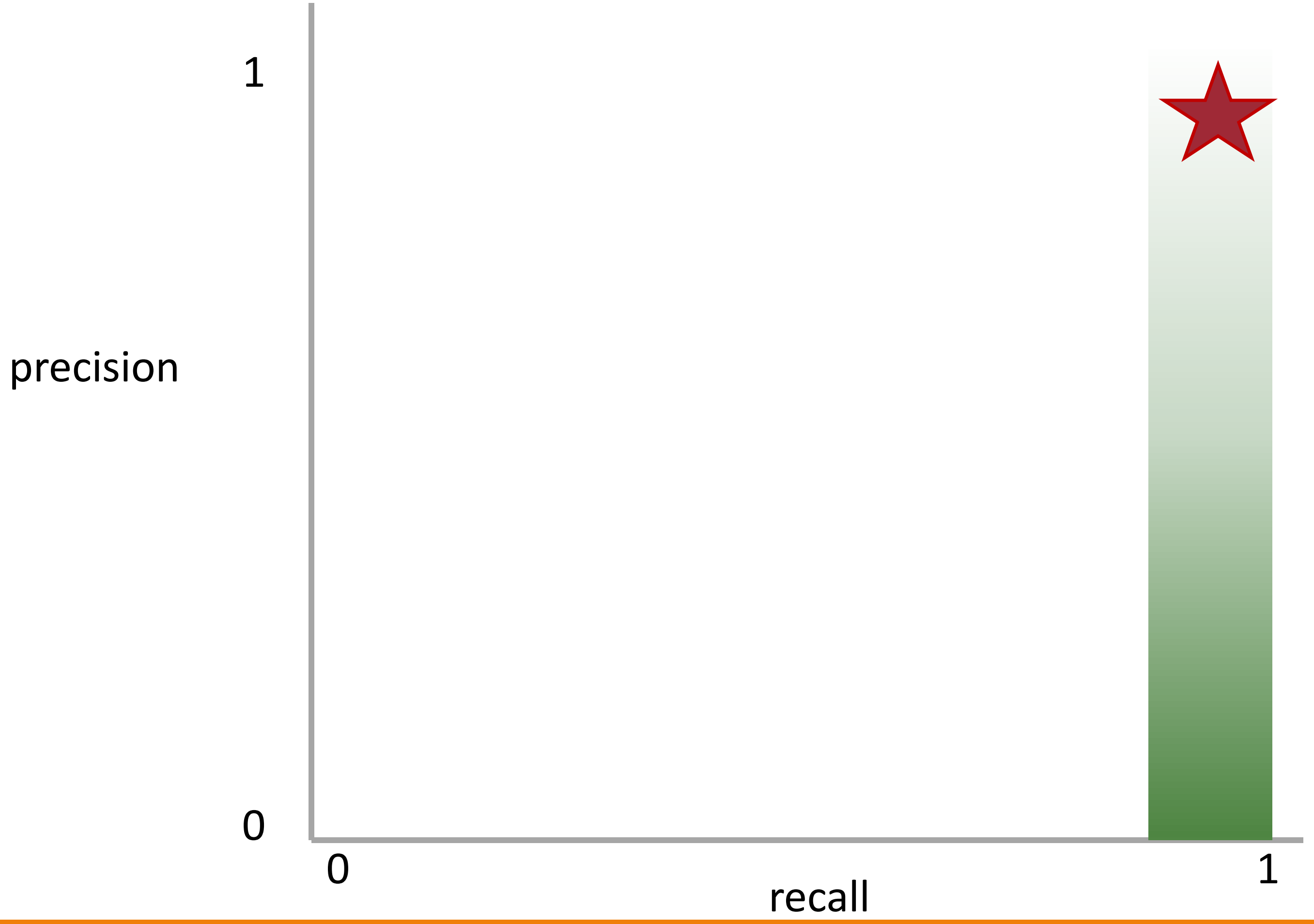


Q: Where do you want your ideal model ?

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

Precision and Recall Present a Tradeoff

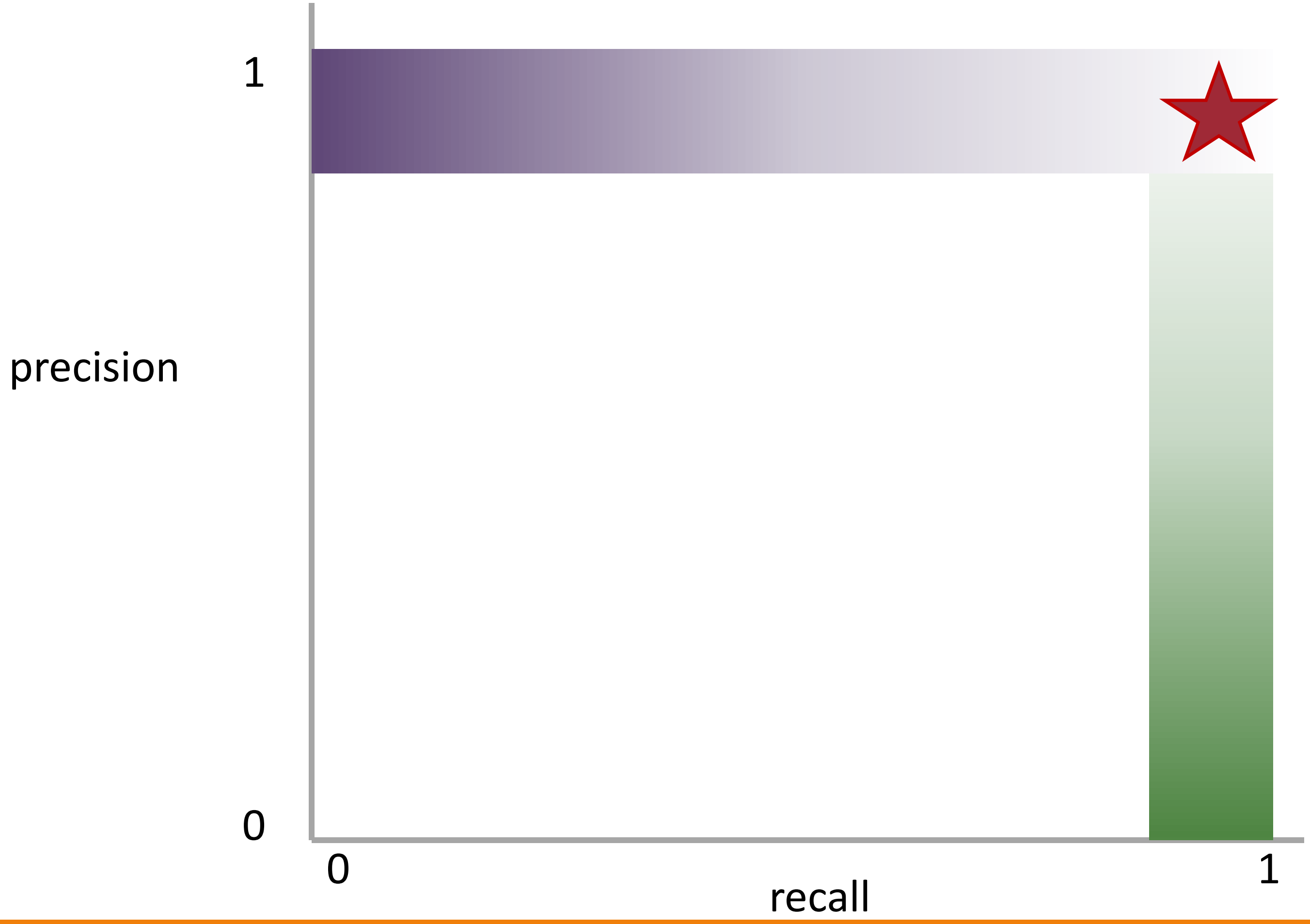


Q: Where do you want your ideal model ?

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



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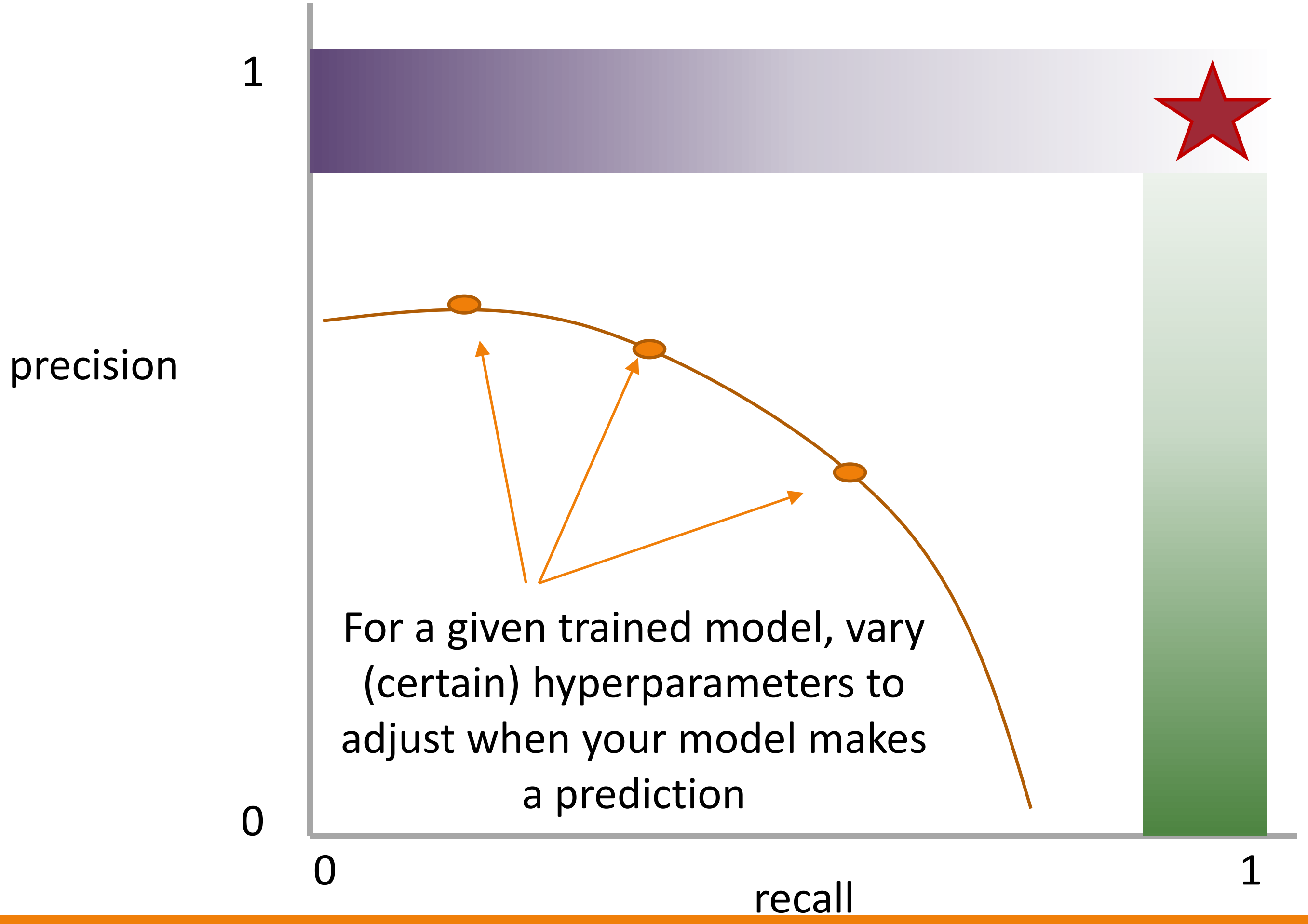
Precision and Recall Present a Tradeoff



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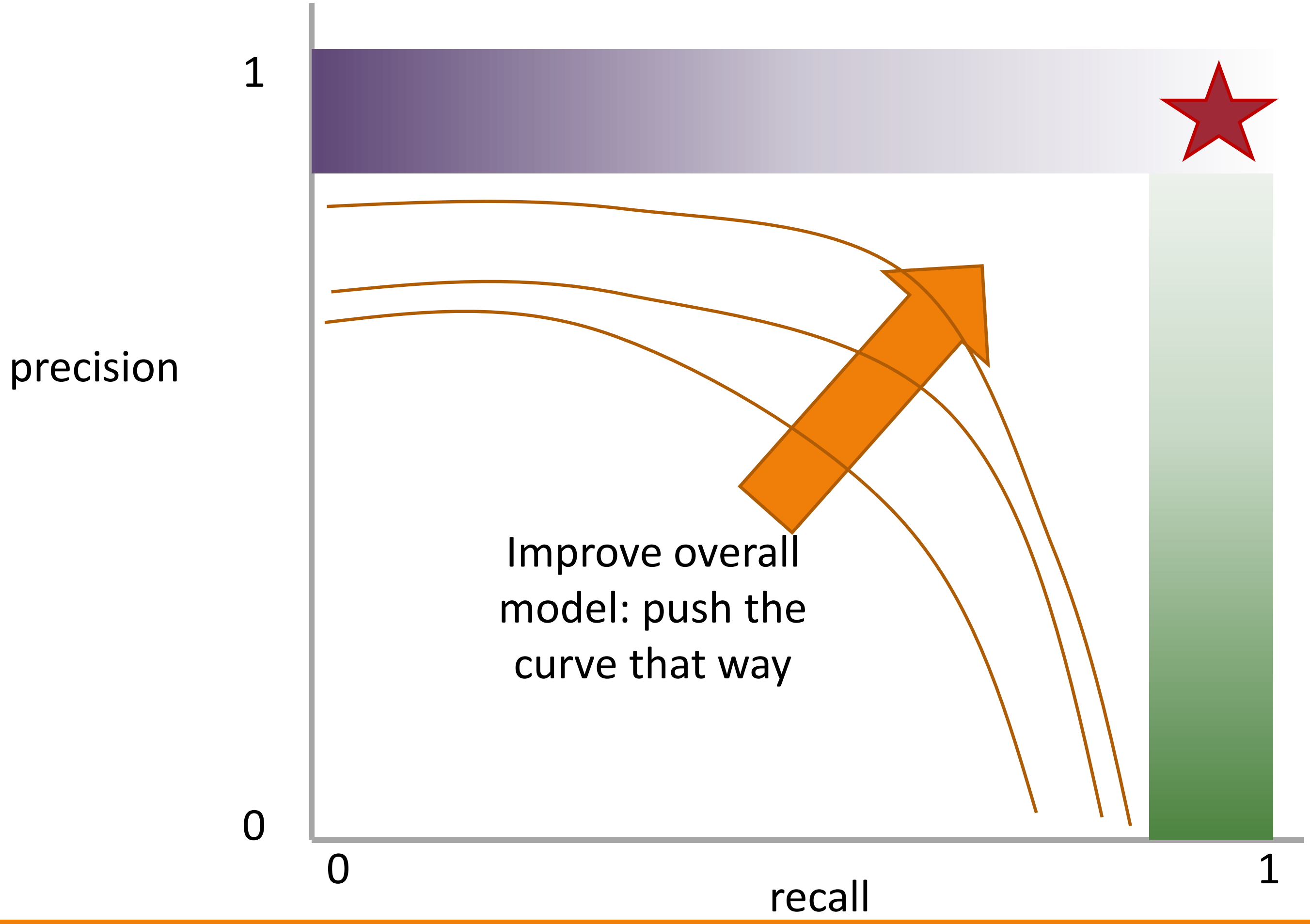
Q: You have a model that always identifies correct instances. Where on this graph is it?

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



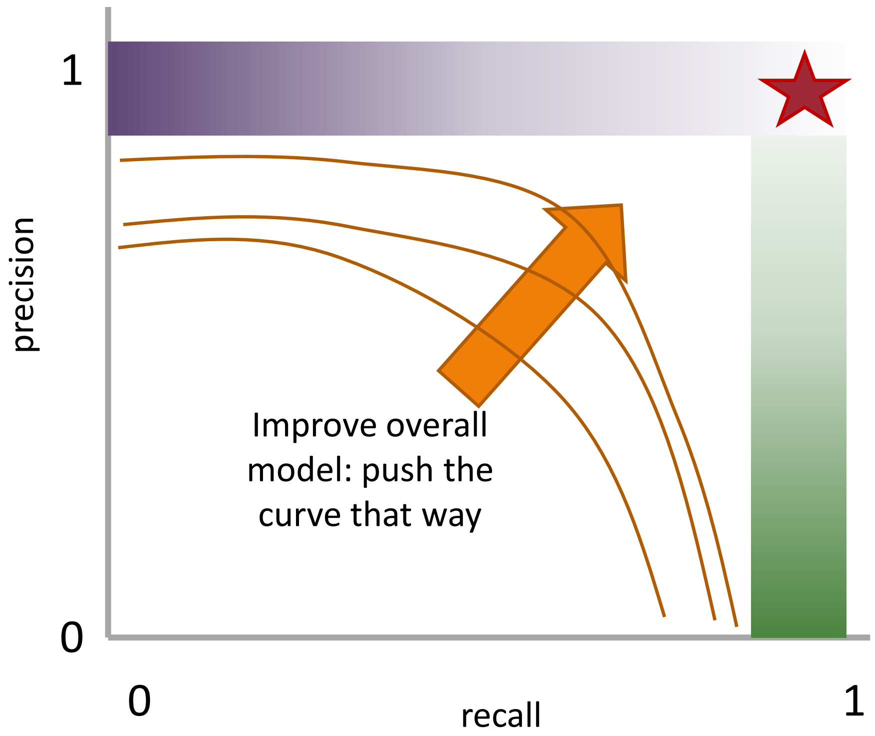
Q: Where do you want your ideal model?

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

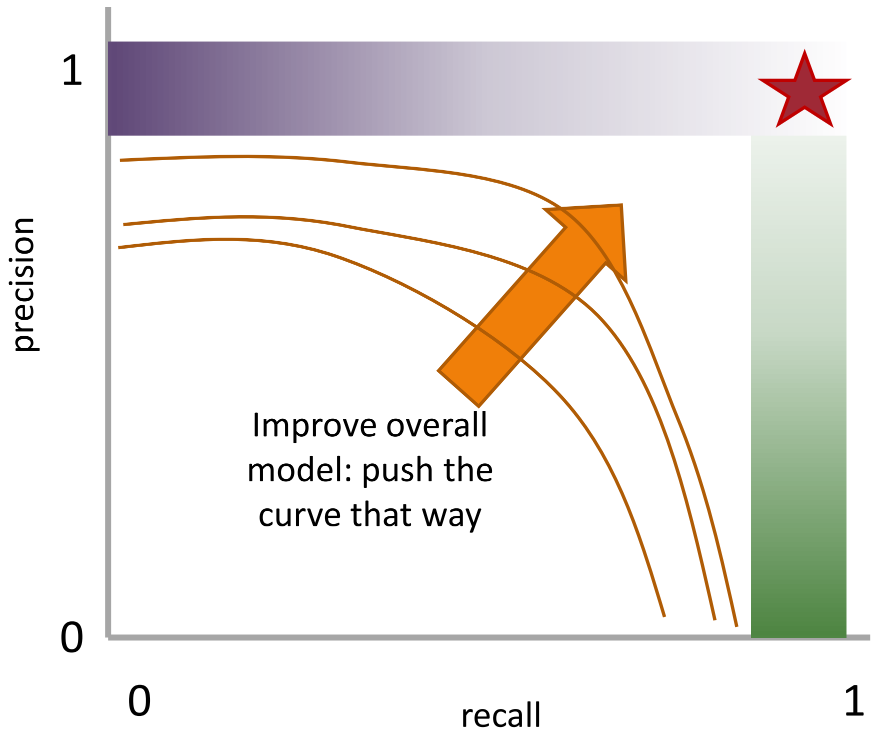
Measure this Tradeoff: Area Under the Curve (AUC)



AUC measures the area under this tradeoff curve

Min AUC: 0 😟
Max AUC: 1 😀

Measure this Tradeoff: Area Under the Curve (AUC)



Min AUC: 0 😦
Max AUC: 1 😀

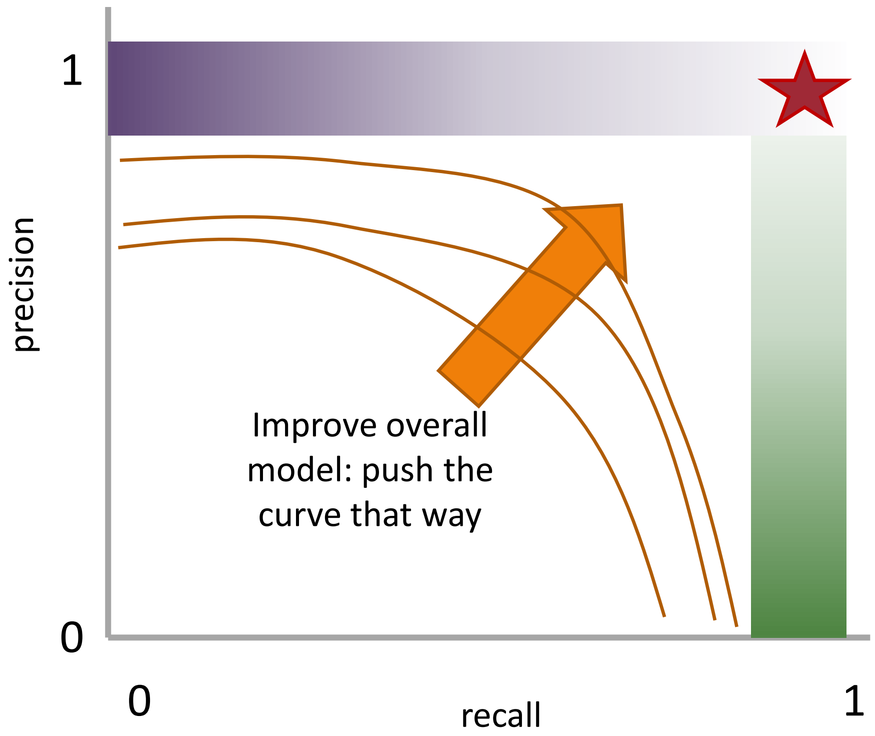
AUC measures the area under this tradeoff curve

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

Measure this Tradeoff: Area Under the Curve (AUC)



Min AUC: 0 ☹️
Max AUC: 1 😀

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

A combined measure: F

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

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

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 $P = R = 0$)

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

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.

$$\text{macroprecision} = \frac{1}{C}\sum_{c} \frac{\mathrm{TP_c}}{\mathrm{TP_c} + \mathrm{FP_c}} = \frac{1}{C}\sum_{c} \text{precision}_c$$

$$\text{macrorecall} = \frac{1}{C}\sum_{c} \frac{\mathrm{TP_c}}{\mathrm{TP_c} + \mathrm{FN_c}} = \frac{1}{C}\sum_{c} \text{recall}_\mathrm{c}$$

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

$$\text{microprecision} = \frac{\sum_\mathrm{c} \mathrm{TP_c}}{\sum_\mathrm{c} \mathrm{TP_c} + \sum_\mathrm{c} \mathrm{FP_c}}$$

$$\text{microrecall} = \frac{\sum_\mathrm{c} \mathrm{TP_c}}{\sum_\mathrm{c} \mathrm{TP_c} + \sum_\mathrm{c} \mathrm{FN_c}}$$

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

Macroaveraging: Compute performance for each class, then average.

$$\text{macroprecision} = \frac{1}{C}\sum_{c} \frac{\mathrm{TP_c}}{\mathrm{TP_c} + \mathrm{FP_c}} = \frac{1}{C}\sum_{c} \text{precision}_c$$

when to prefer macroaveraging?

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

$$\text{microprecision} = \frac{\sum_{\mathrm{c}} \mathrm{TP_c}}{\sum_{\mathrm{c}} \mathrm{TP_c} + \sum_{\mathrm{c}} \mathrm{FP_c}}$$

when to prefer microaveraging?