# Evaluating classifiers:

# Precision & Recall

Emily Fox & Carlos Guestrin

Machine Learning Specialization

University of Washington

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# Using reviews to promote my restaurant

Goal: increase # guests by 30%

Reviews

Need an automated, "authentic" marketing campaign

Great quotes

"Easily best sushi in Seattle."

Great spokespeople



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# How do I find sentences with positive sentiment?

All reviews
for my restaurant

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# Intelligent restaurant review system

All reviews for restaurant

Break all reviews into sentences

The seaweed salad was just OK, vegetable salad was just ordinary.

I like the interior decoration and the blackboard menu on the wall.

All the sushi was delicious.

My wife tried their ramen and it was pretty forgettable.

The sushi was amazing, and the rice is just outstanding.

The service is somewhat hectic.

Easily best sushi in Seattle.


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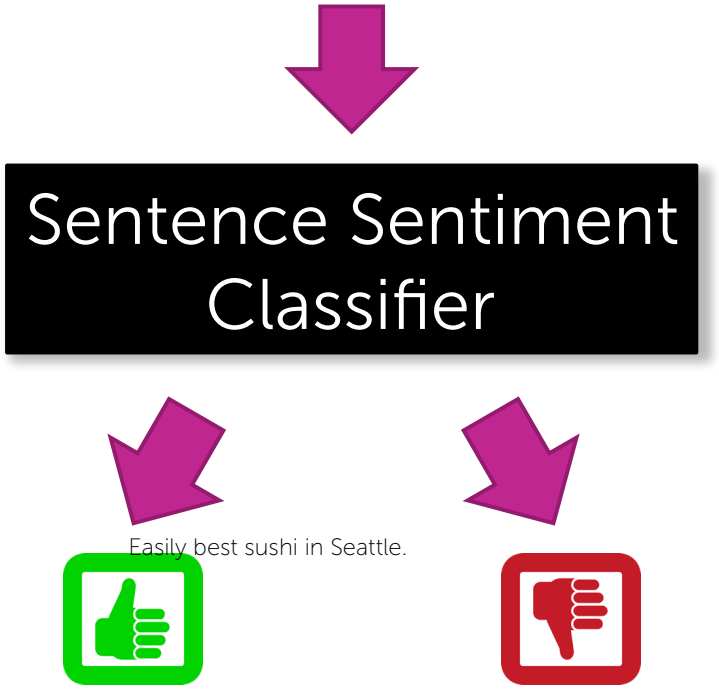
# Sentiment classifier

Input $\mathbf{x}_i$: Easily best sushi in Seattle.




Output: $\hat{y}_i$
Predicted sentiment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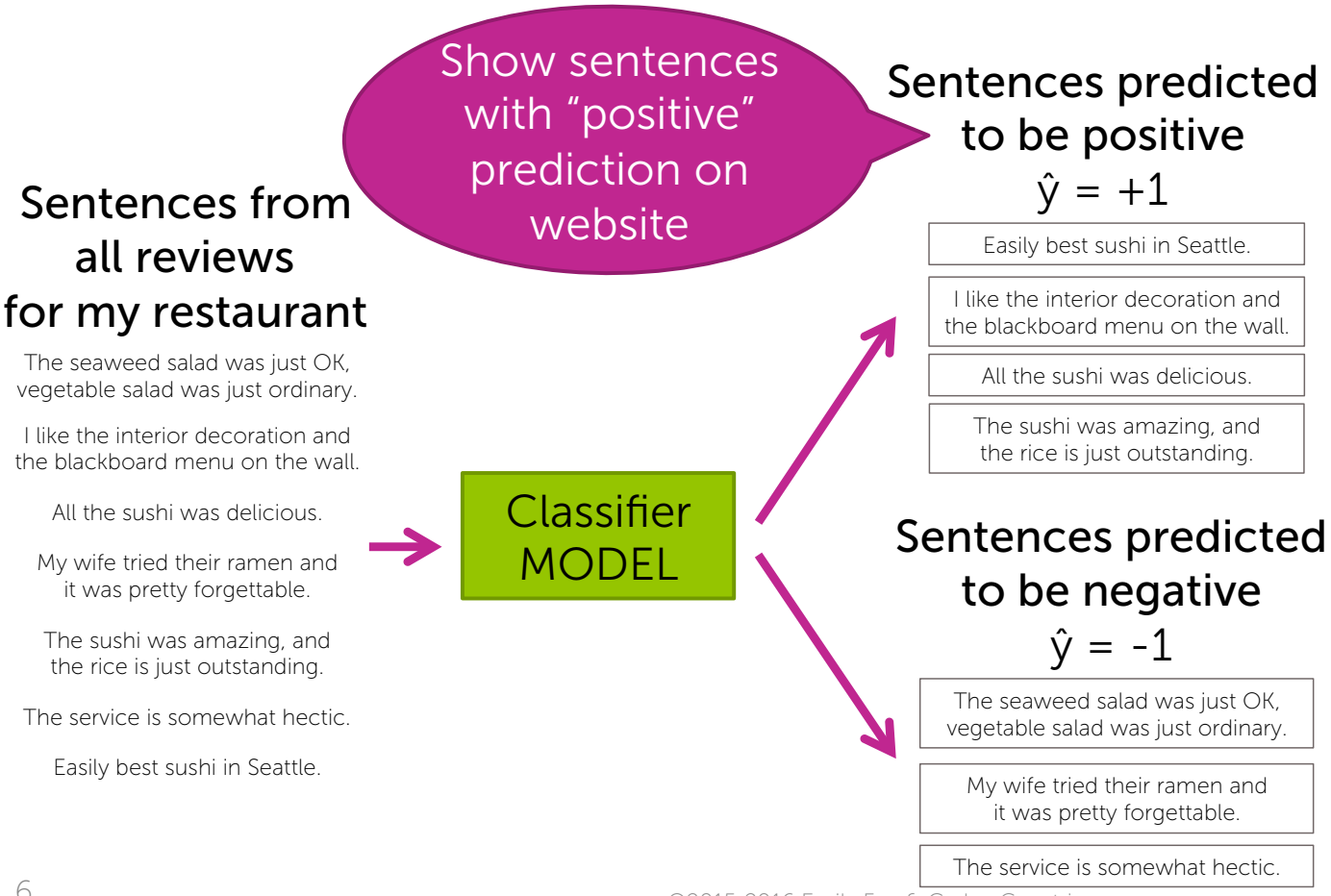
# Use the sentiment classifier model!





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# What does it mean for a classifier to be good?

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Previously, we asked the question:

*"What is good accuracy?"*



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# We explored accuracy of random classifier as baseline

- For binary classification:
  - Half the time, you'll get it right! (on average)
    - ➔ classification error = 0.5
- For k classes, error= 1 - 1/k
  - error = 0.666 for 3 classes, 0.75 for 4 classes,…

At the very, very, very least,
you should healthily beat random…
Otherwise, it's (usually) pointless…


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# We explored the pitfalls of imbalanced problems: *Is 90% accuracy good? Depends …*

*90% of sentences are negative!*

90% accuracy by predicting every sentence is negative!!!

Amazing "performance" but not useful for me right now!



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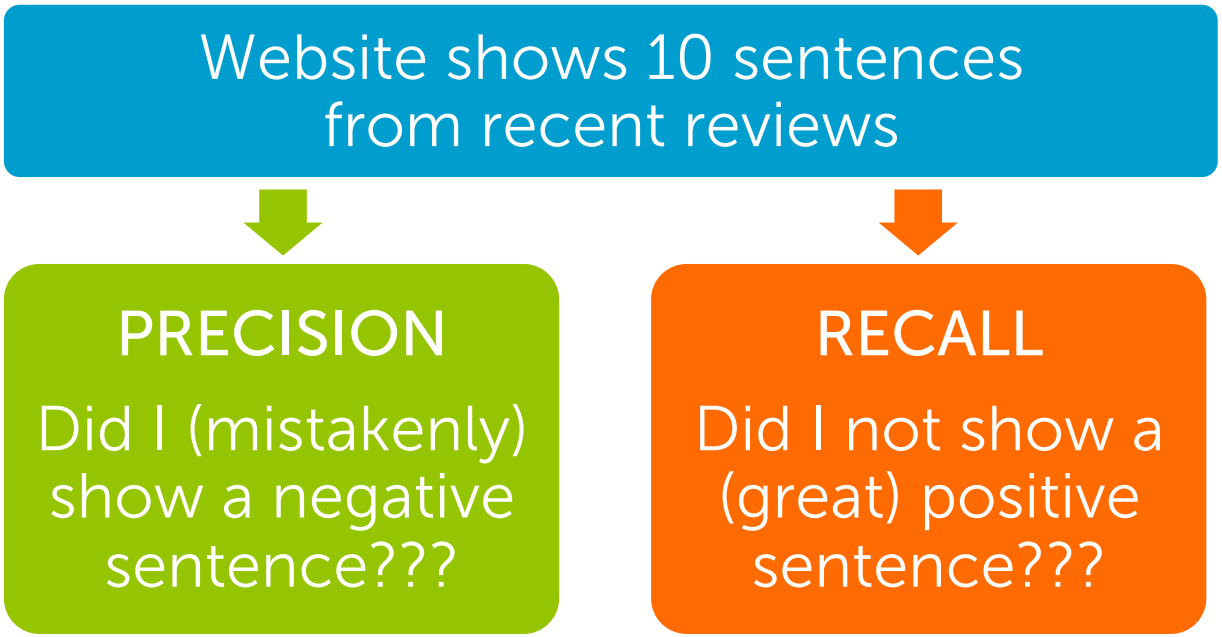
# Automated marketing campaign cares about something else…




Accuracy doesn't capture these issues well…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**Precision**:
Fraction of positive predictions that are actually positive

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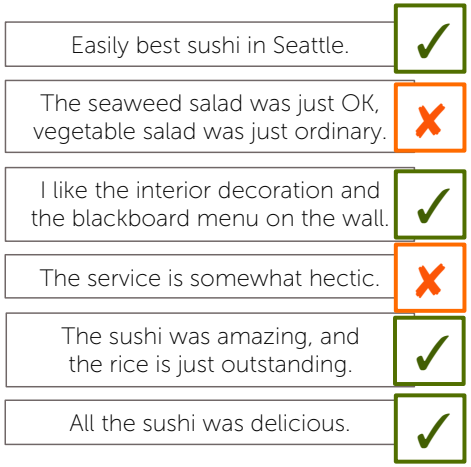
# What fraction of the positive predictions are correct?

Sentences predicted to be positive: $\hat{y}_i = +1$




Only 4 out of 6 sentences predicted to be positive are actually positive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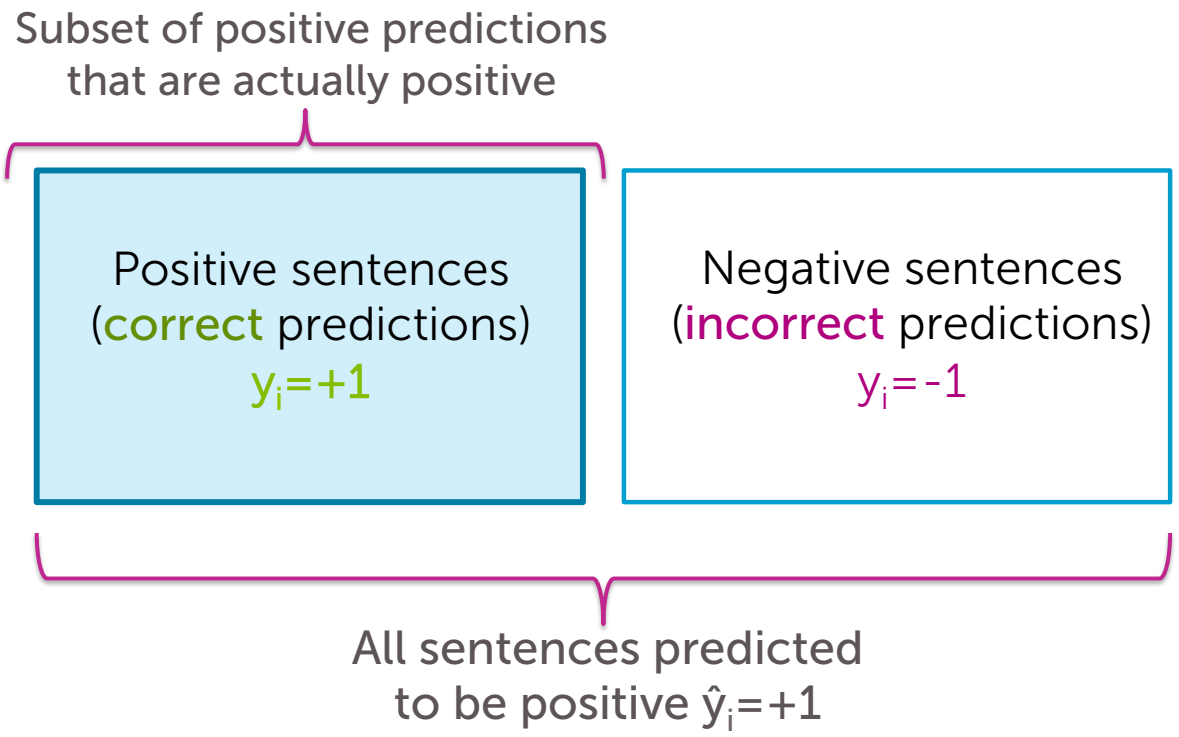
# **Precision**: Fraction of positive predictions that are actually positive





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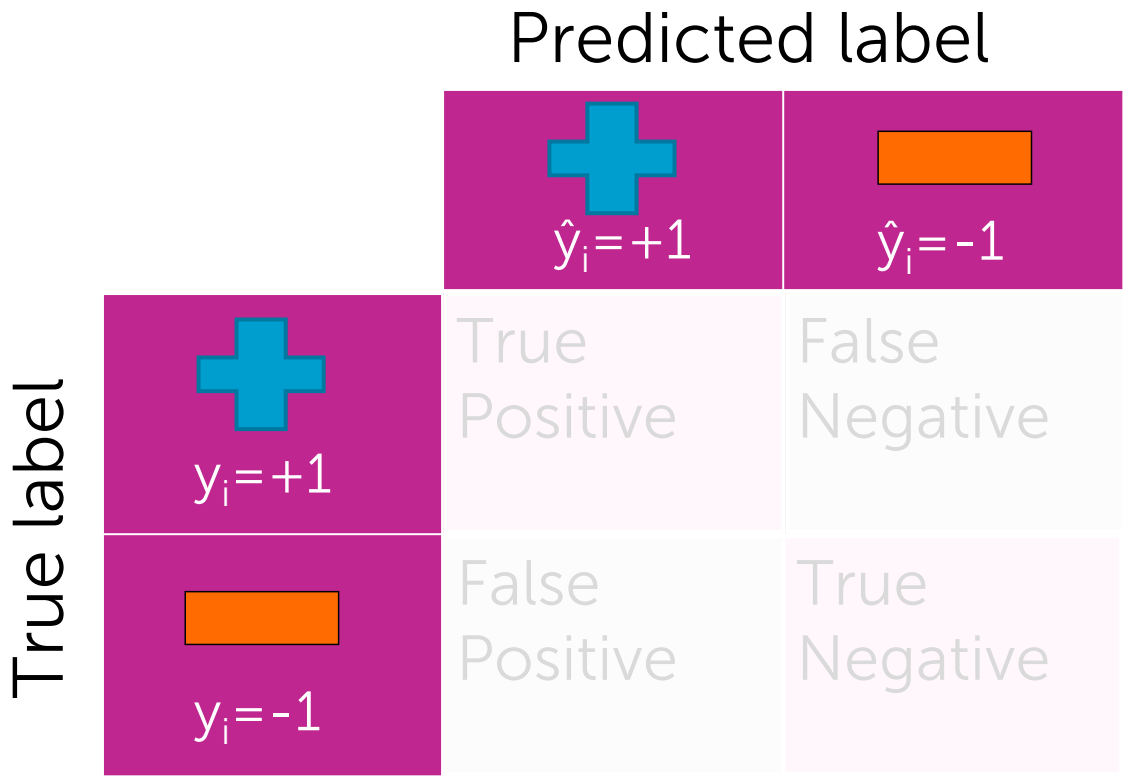
# Types of error: *Review*





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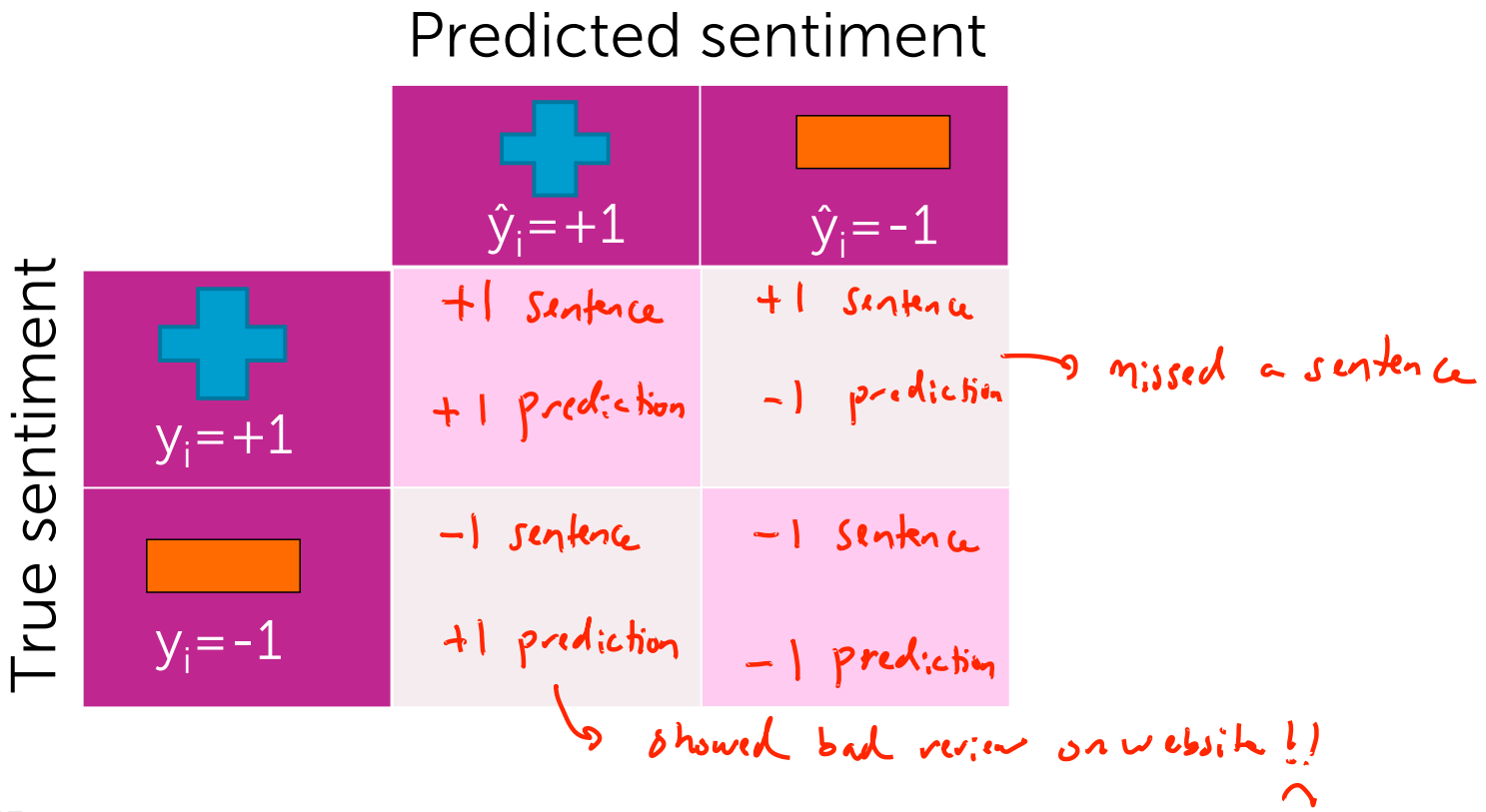
# Confusion matrix for sentiment analysis





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# Precision - Formula

- Fraction of positive predictions that are correct

$$\text{precision} = \frac{\text{\# true positives}}{\text{\# true positives + \# false positives}}$$

  - Best possible value : 1.0
  - Worst possible value : 0.0


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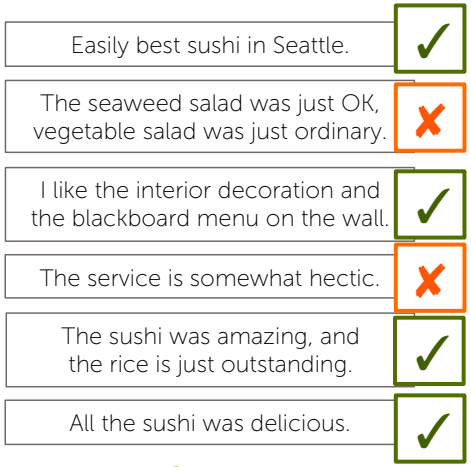
# Example: Calculating precision

Sentences predicted to be positive: $\hat{y}_i = +1$




4 correct

2 mistakes

$$\text{precision} = \frac{4}{4+2} = \frac{2}{3}$$



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# Why precision is important

Shown on website

Sentences predicted to be positive: $\hat{y}_i=+1$

2 negative sentences shown to potential customers… ☹

High precision means positive predictions actually likely to be positive!


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**Recall**:
Fraction of positive data predicted to be positive

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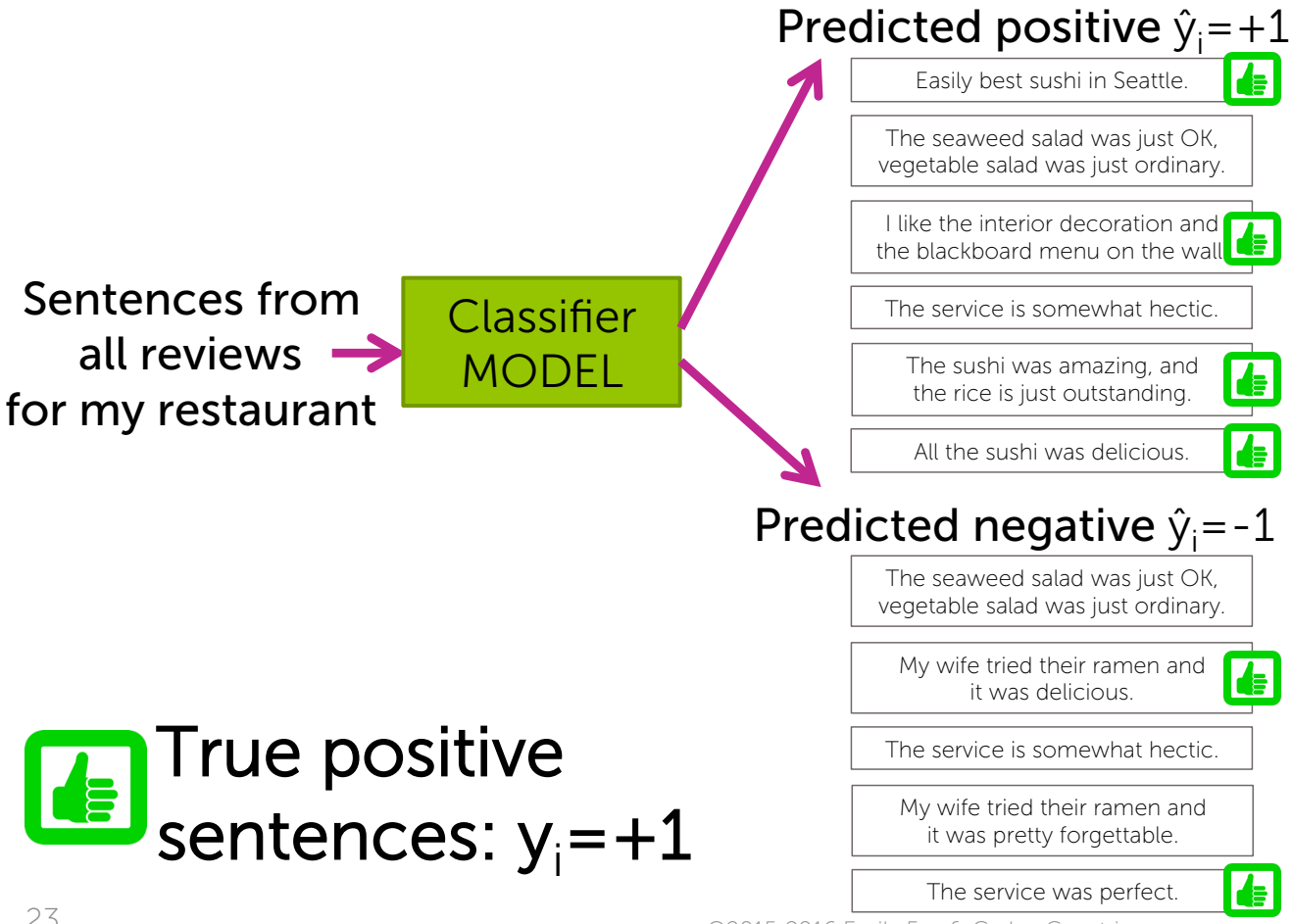
# Did I find all the positive sentences?




True positive sentences: $y_i=+1$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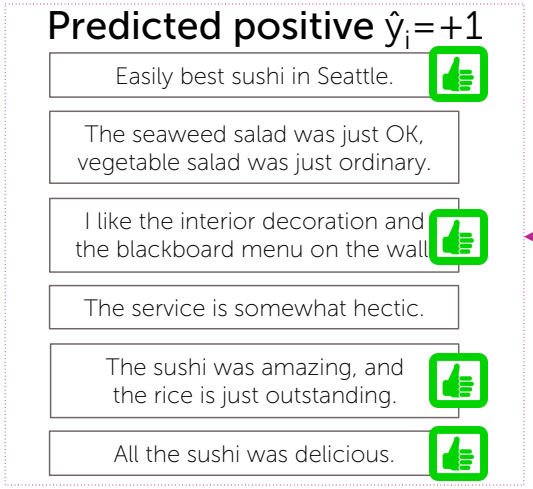
# What fraction of positive sentences were missed out?




Found 4 positive sentences

Model could not find 2 sentences that were actually positive

Missed 2 positive sentences



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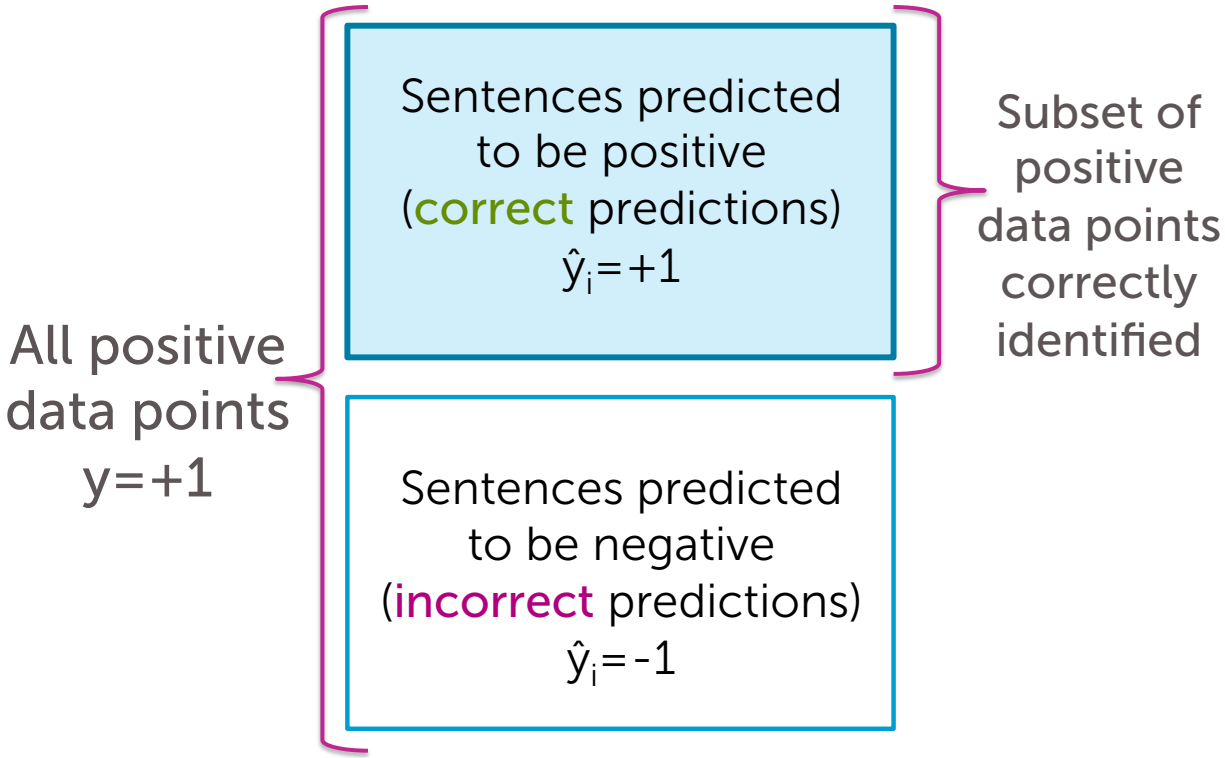
# Recall: Fraction of positive data predicted to be positive





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# Recall - Formula

- Fraction of positive data points correctly classified

$$\text{Recall} = \frac{\text{\# true positives}}{\text{\# true positives + \# false negatives}}$$

  - Best possible value : 1.0
  - Worst possible value : 0.0


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# Why is recall important?

**Predicted positive $\hat{y}_i = +1$**

- Easily best sushi in Seattle.
- The seaweed salad was just OK, vegetable salad was just ordinary.
- I like the interior decoration and the blackboard menu on the wall
- The service is somewhat hectic.
- The sushi was amazing, and the rice is just outstanding.
- All the sushi was delicious.

**Predicted negative $\hat{y}_i = -1$**

- The seaweed salad was just OK, vegetable salad was just ordinary.
- My wife tried their ramen and it was delicious.
- The service is somewhat hectic.
- My wife tried their ramen and it was pretty forgettable.
- The service was perfect.

Want to show positive sentences on website

2 positive sentences not shown to potential customers... ☹

High recall means positive data points are very likely to be discovered!



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# Precision-recall extremes

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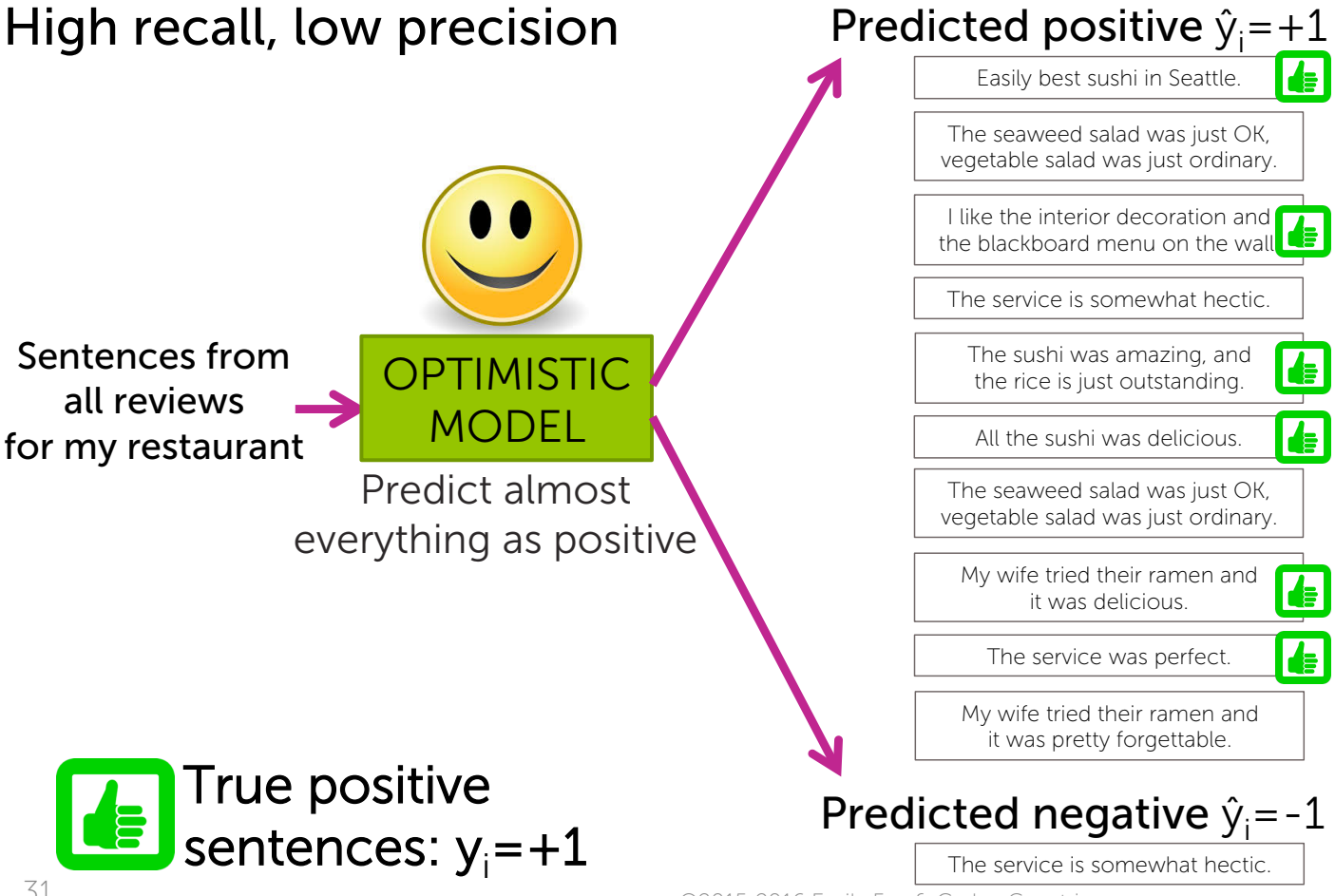
# Optimistic model:

## High recall, low precision




True positive sentences: $y_i=+1$



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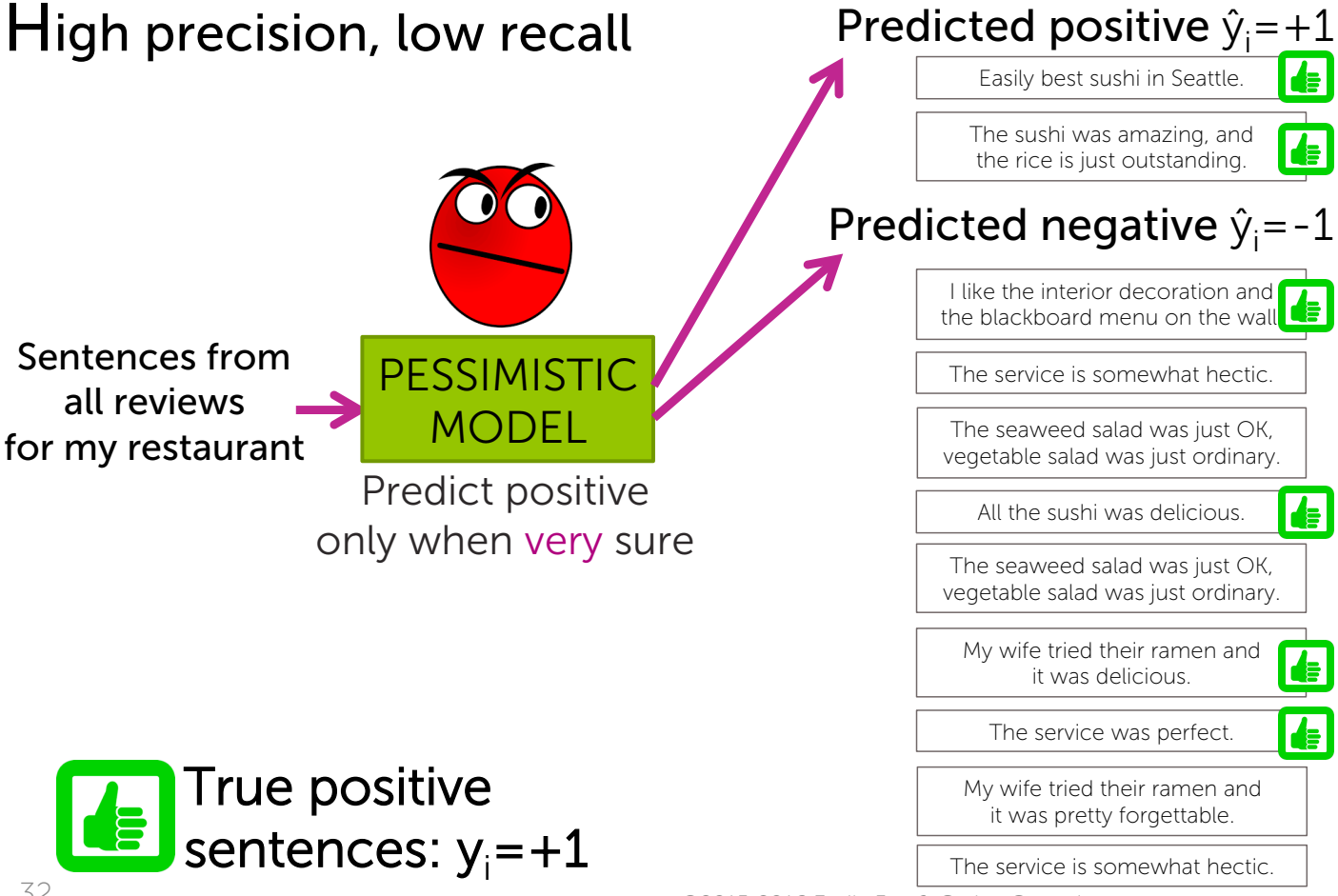
# Pessimistic model:

High precision, low recall




True positive sentences: $y_i=+1$



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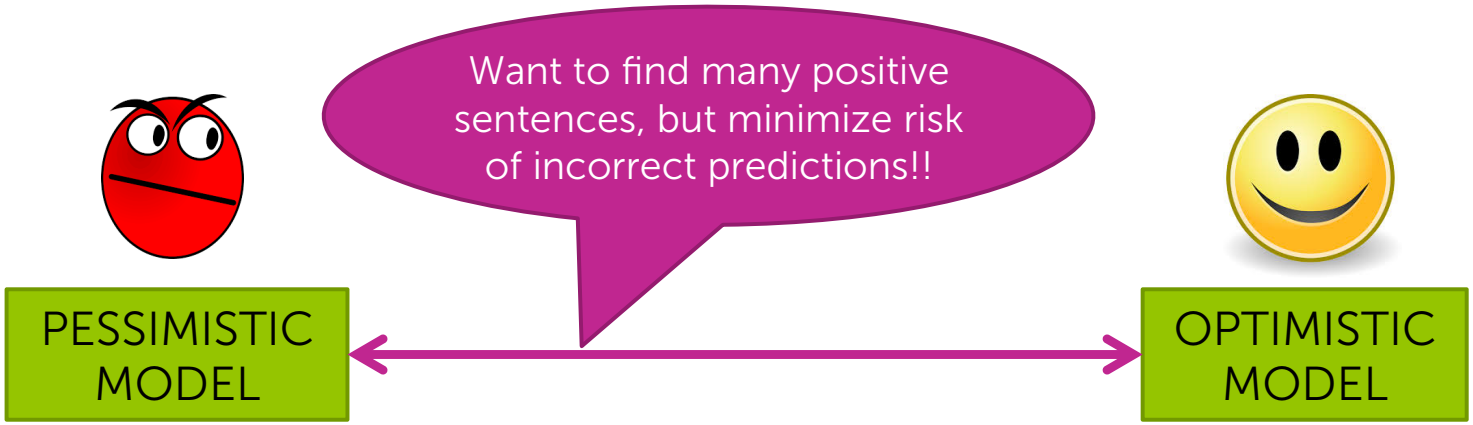
# Balancing precision & recall




**Finds all positive** sentences, but includes **many false positives**

**Finds few positive** sentences, but includes **no false positives**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# Tradeoff precision and recall

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# Can we tradeoff precision & recall?

Low precision, high recall

High precision, low recall

**Optimistic Model**
Predict almost everything as positive

**Pessimistic Model**
Predict positive only when very sure

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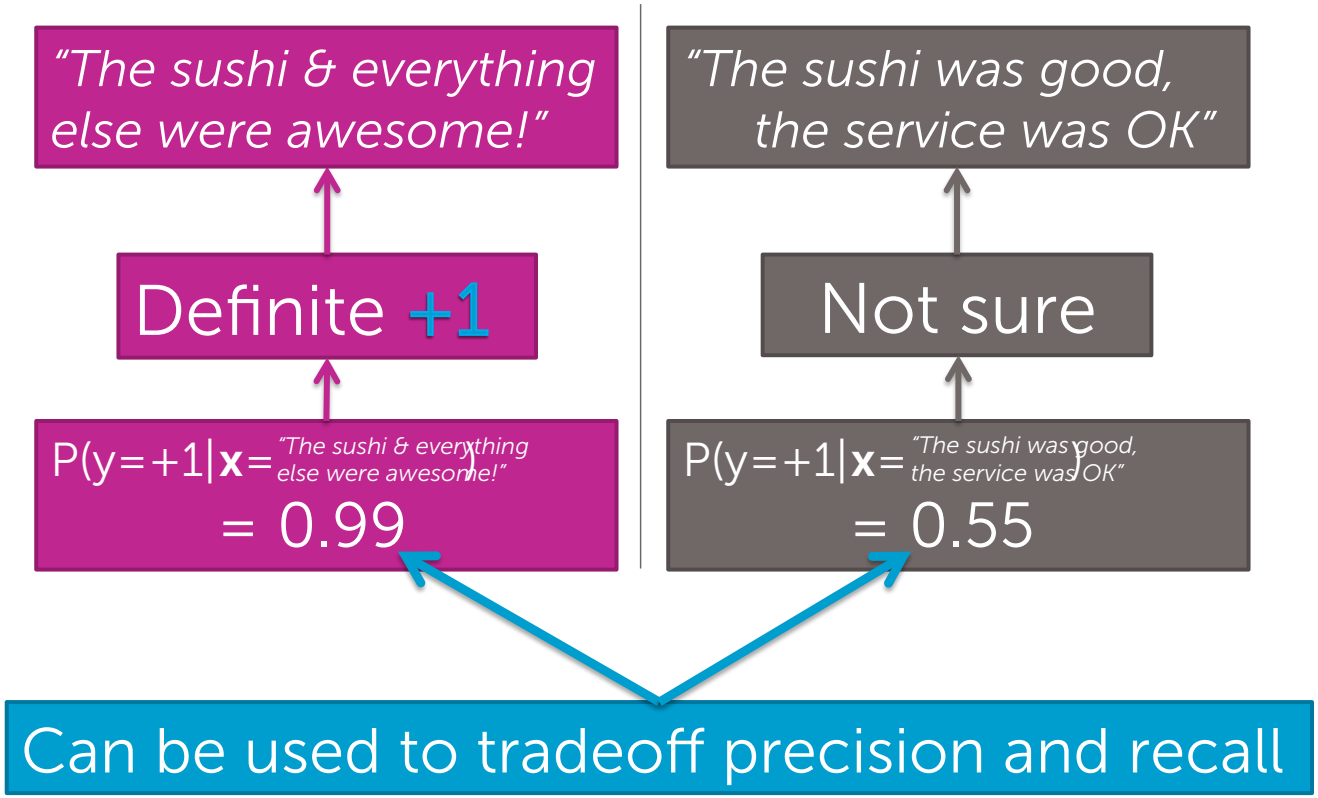
# How confident is your prediction?





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# Basic classifier

Sentence from review

Input: $\mathbf{x}_i$

**Predict most likely class**

If $\hat{P}(y=+1|x_i) > 0.5$:

$\hat{y}_i = +1$

Else:

$\hat{y}_i = -1$



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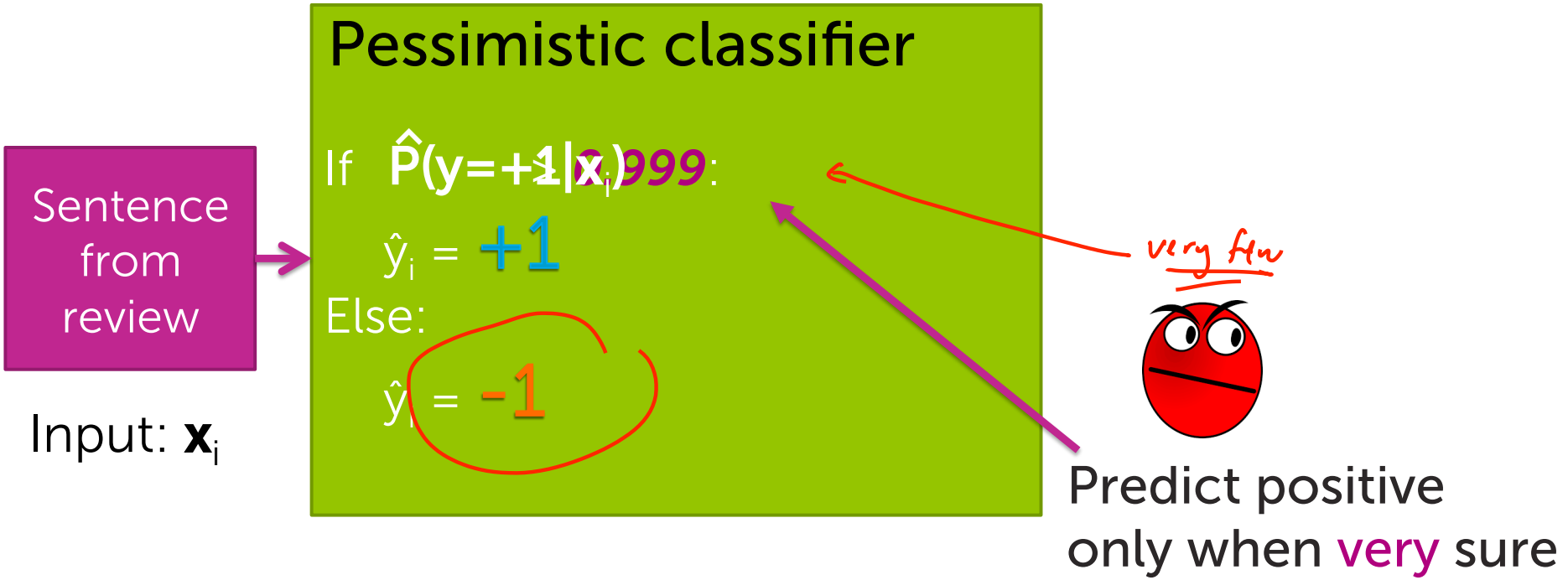
# Pessimistic: High precision, low recall





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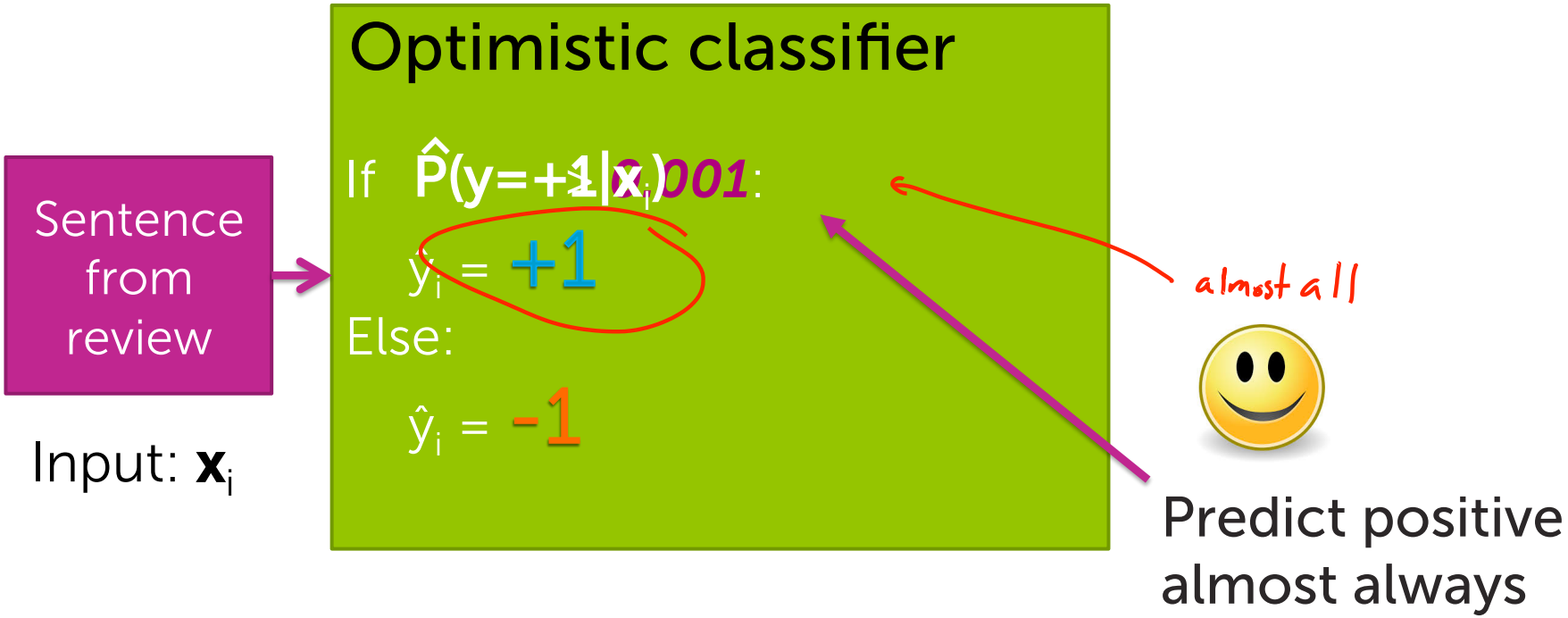
# Optimistic: Low precision, high recall





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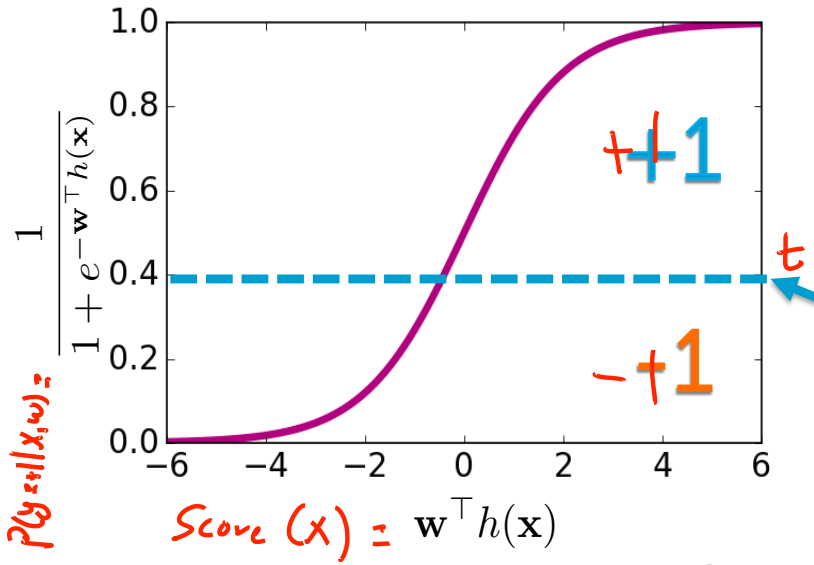
# Prediction probability threshold

Probability t above which model predicts true




Set $\hat{y} = +1$ if $\hat{P}(y|x) >= t$



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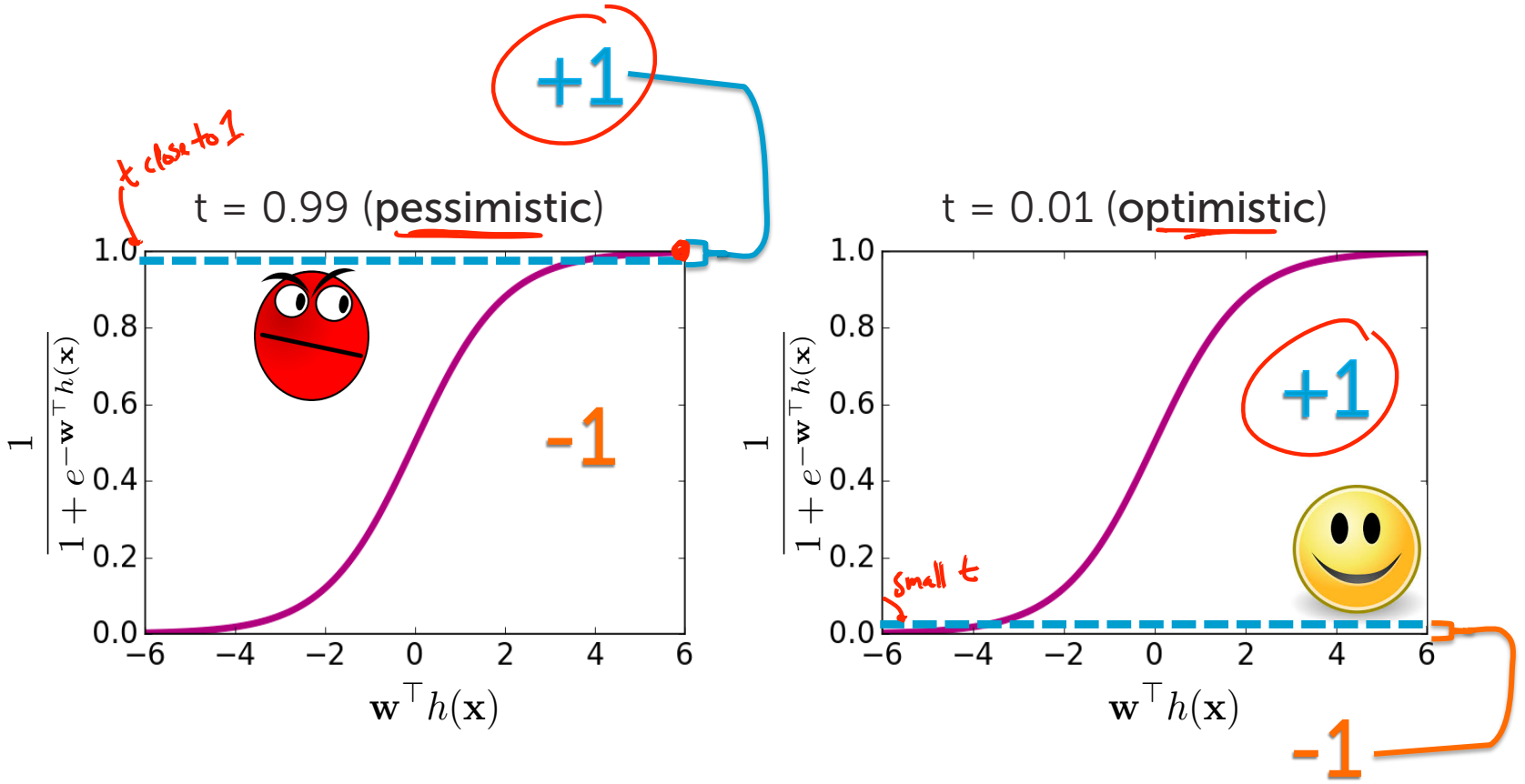
# Example threshold values





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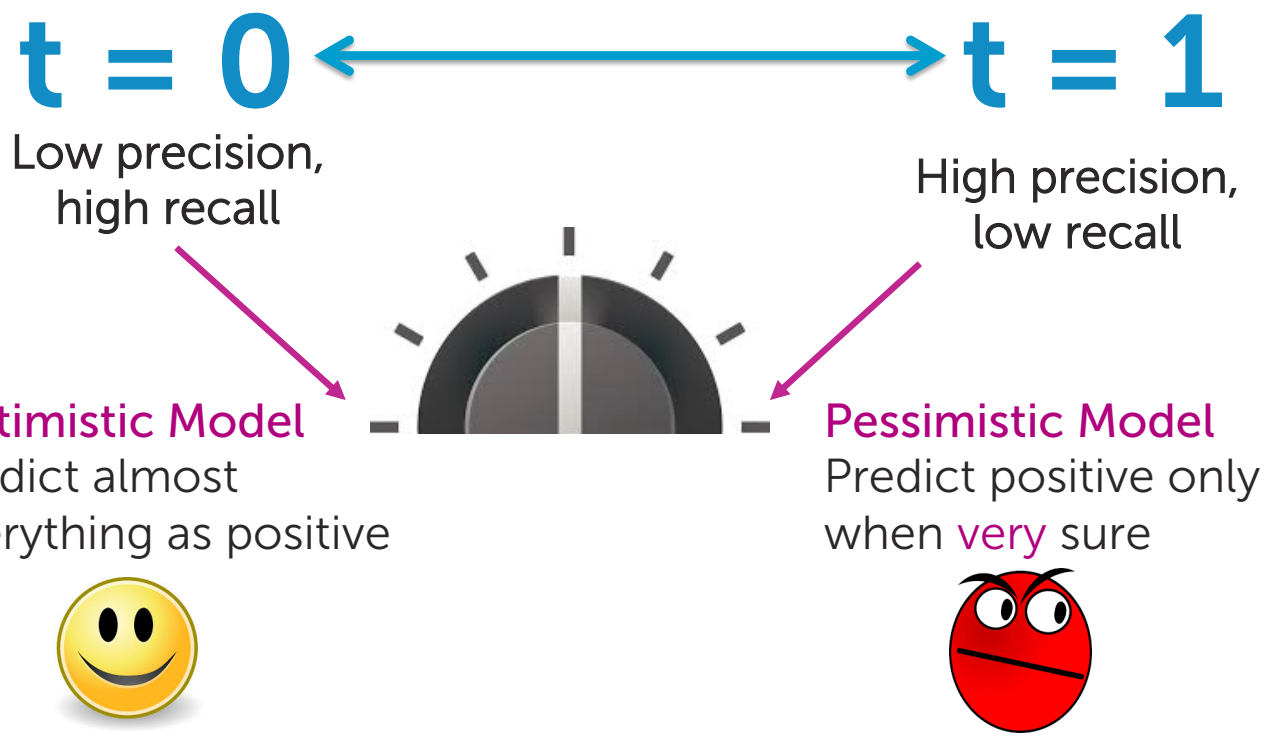
# Tradeoff precision & recall with threshold





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# Precision-recall curve

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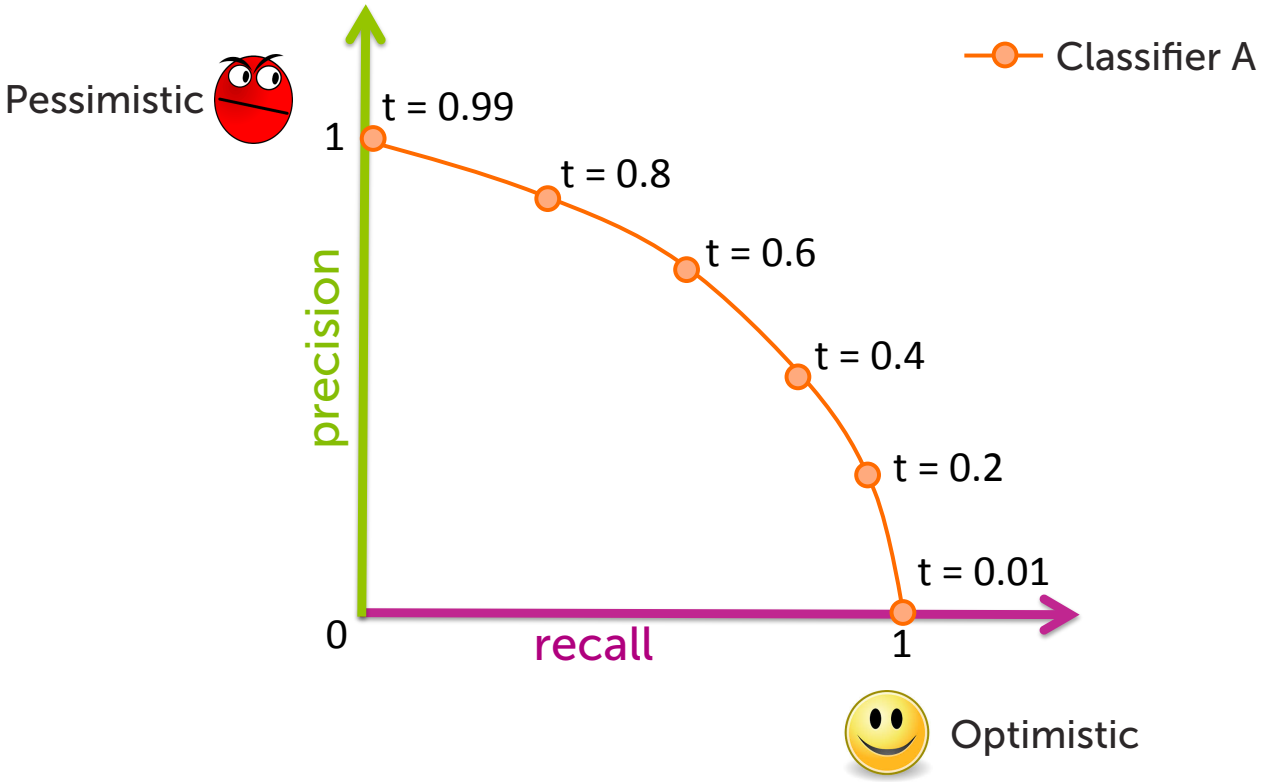
# The precision-recall curve





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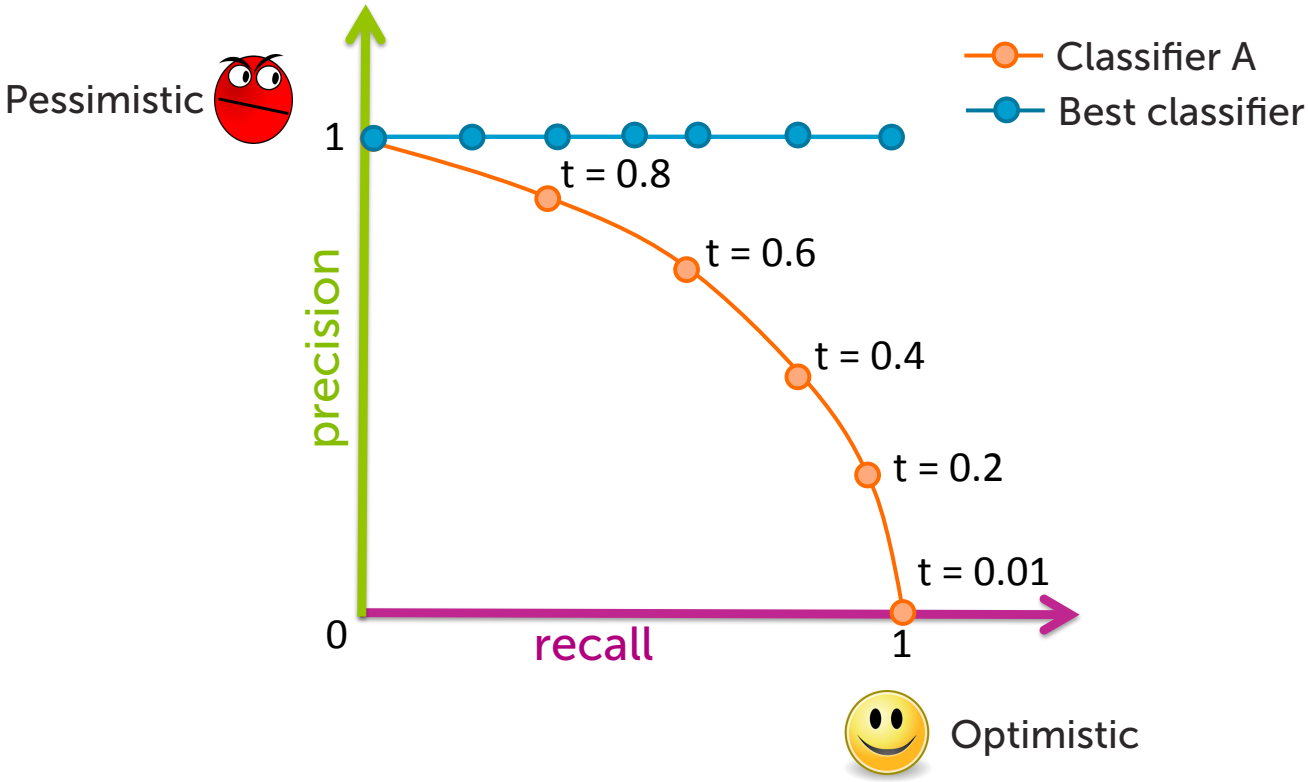
# What does the perfect algorithm look like?





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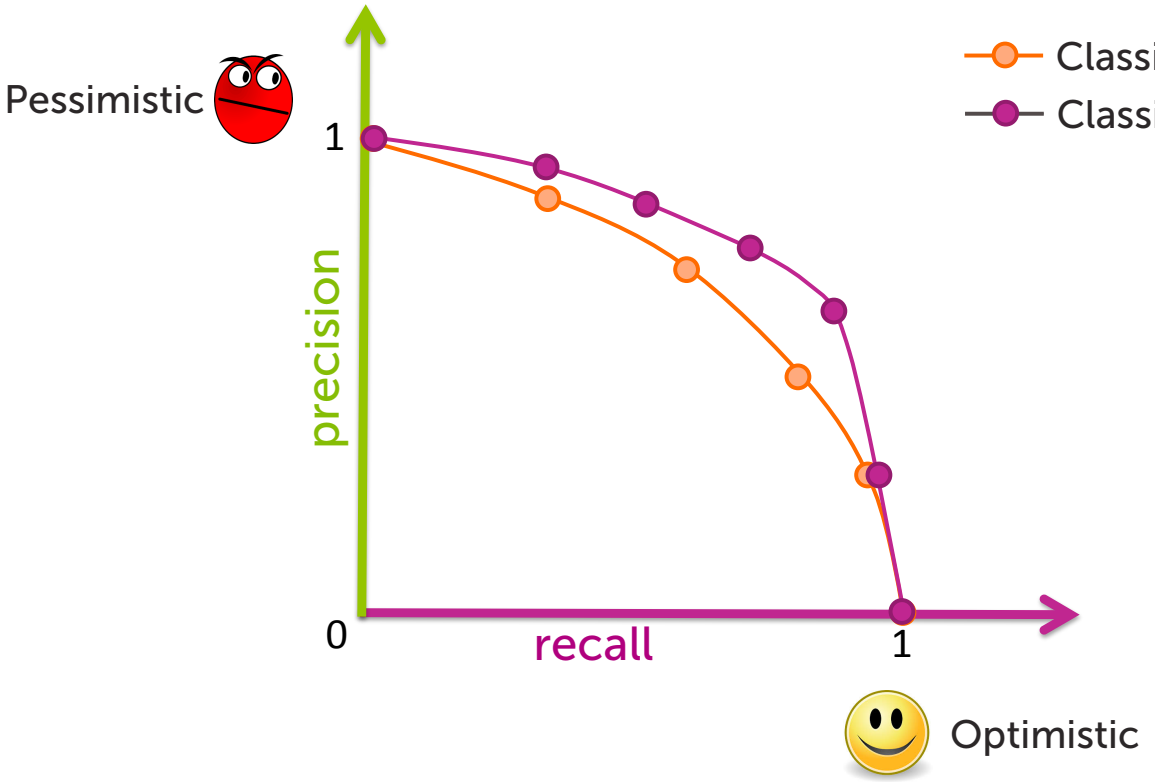
# Which classifier is better? A or B?





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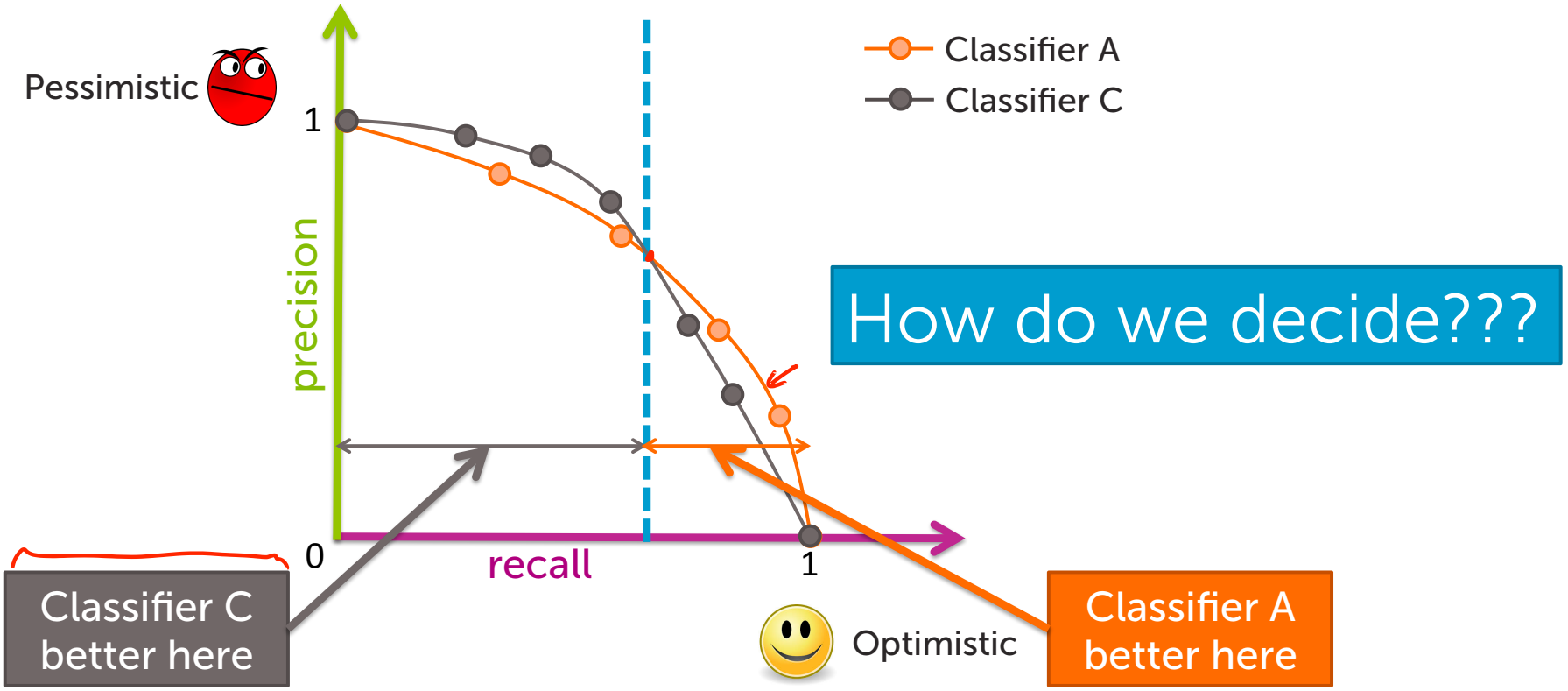
# Which classifier is better? A or C?





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# Compare algorithms

- Often, reduce precision-recall to single number to compare algorithms
  - F1 measure, area-under-the-curve (AUC),…

# Precision at k

Showing k=5 sentences on website

**Sentences model most sure are positive**

precision at k = 0.8



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# Summary of precision-recall

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# What you can do now...

- Classification accuracy/error are not always right metrics
- Precision captures fraction of positive predictions that are correct
- Recall captures fraction of positive data correctly identified by the model
- Trade-off precision & recall by setting probability thresholds
- Plot precision-recall curves.
- Compare models by computing precision at k


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# Thank you to Dr. Krishna Sridhar

Dr. Krishna Sridhar

Staff Data Scientist, Dato, Inc.



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