# Classification Metrics



#### **Data Science Process**

- 1. Define the problem
- 2. Gather data
- 3. Explore data
- 4. Model with data
- 5. Evaluate model
- 6. Answer problem



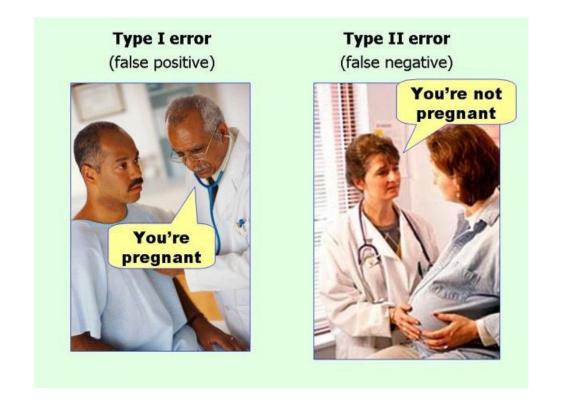
Suppose you build a logistic regression model predicting whether or not people will vote. You make predictions for 100 people, then check to see if they actually voted.

- There are 40 people you predicted to vote who did vote.
- There are 20 people you predicted to vote who didn't vote.
- There are 15 people you predicted to stay home who did vote.
- There are 25 people you predicted to stay home who didn't vote.

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- There are 40 people you predicted to vote who did vote.
  - These are called true positives.
- There are 20 people you predicted to vote who didn't vote.
  - These are called false positives.
- There are 15 people you predicted to stay home who did vote.
  - These are called **false negatives**.
- There are 25 people you predicted to stay home who didn't vote.
  - These are called **true negatives**.







How do I keep true positives/true negatives/false positives/false negatives straight?

- First word (true/false): Was I right?
- Second word (positive/negative): What did I predict?



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#### **Confusion Matrix**

It's helpful for us to list out the number of each category in a 2x2 grid called a **confusion matrix**.

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The axes or ordering of "Yes" vs. "No" may be rearranged!

Be clear what "Yes" / "Positive" means.



#### **Confusion Matrix**

A confusion matrix is a convenient way for us to visualize how our model performs.

However, there are metrics that can help us to summarize performance with one number.

- Accuracy
- Misclassification Rate
- Sensitivity
- Specificity
- Precision



## **Accuracy**

Interpretation: What percentage of observations did I correctly predict?

Accuracy = 
$$\frac{All\ Correct}{All\ Predictions}$$
 =  $\frac{TP + TN}{TP + FP + TN + FN}$ 

	Actual Positive	Actual Negative
Predicted Positive	40	20
Predicted Negative	15	25



#### **Misclassification Rate**

Interpretation: What percentage of observations did I incorrectly predict?

Misclassification Rate = 
$$\frac{All \ Incorrect}{All \ Predictions} = \frac{FP + FN}{TP + FP + TN + FN} = 1 - Acc$$

	Actual Positive	Actual Negative
Predicted Positive	40	20
Predicted Negative	15	25



# Sensitivity

Interpretation: Among those who will vote, how many did I get correct?

Sensitivity = 
$$\frac{True\ Positives}{All\ Positives} = \frac{TP}{TP + FN} = \frac{TP}{P}$$

a.k.a. True Positive Rate, Recall

	Actual Positive	Actual Negative
Predicted Positive	40	20
Predicted Negative	15	25



# **Specificity**

Interpretation: Among those who will not vote, how many did I get correct?

Specificity = 
$$\frac{True\ Negatives}{All\ Negatives} = \frac{TN}{TN + FP} = \frac{TN}{N}$$

#### a.k.a. True Negative Rate

	Actual Positive	Actual Negative
Predicted Positive	40	20
Predicted Negative	15	25





#### **Precision**

Interpretation: Among those I predicted to vote, how many did I get correct?

Precision = 
$$\frac{True\ Positives}{Predicted\ Positives} = \frac{TP}{TP + FP}$$

#### a.k.a. Positive Predictive Value

	Actual Positive	Actual Negative
Predicted Positive	40	20
Predicted Negative	15	25



# Example

Suppose I'm working on a fraud analytics team and our goal is to detect fraudulent credit card transactions. I take a random sample of 500 transactions. Of these transactions, 50 are fraudulent. I predict 100 total fraudulent transaction, 45 of which are correct.

- 1. Identify the TP, TN, FP, FN and construct a confusion matrix.
- Calculate the accuracy, misclassification rate, positive predictive value, recall, and true negative rate.





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Suppose I'm working on a fraud analytics team and our goal is to detect fraudulent credit card transactions. I take a random sample of 500 transactions. Of these transactions, 50 are fraudulent. I predict 100 total fraudulent transaction, 45 of which are correct.

When building my classification model, I want to optimize one of the above metrics. Given the use-case of identifying fraudulent transactions, which metric should I optimize as I build my model?



# Final Notes

We've explored binary classification these past two weeks.

We can construct confusion matrices for 3+ categories and calculate a lot of these metrics (accuracy, misclassification error, etc.), but they get a lot more complicated.

These get *especially* complicated when working with **ordinal data**.



