GENERAL ASSEMBLY

COMMUNICATING RESULTS

Naumaan Nayyar

REVIEW QUESTIONS

- What's the link function used in logistic regression?

- What kind of machine learning problems does logistic regression address?

- What do the *coefficients* in a logistic regression represent? How does the interpretation differ from ordinary least squares? How is it similar?

REVIEW QUESTIONS

- How does True Positive Rate and False Positive Rate help explain accuracy?
- What would an AUC of 0.5 represent for a model? What about an AUC of 0.9?
- Why might one classification metric be more important to tune than another? Give an example of a business problem or project where this would be the case.

LEARNING OBJECTIVES

- Explain the trade-offs between the precision and recall of a model while articulating the cost of false positives vs. false negatives
- Describe the difference between visualization for presentations vs. exploratory data analysis
- Identify the components of a concise, convincing report and how they relate to specific audiences/stakeholders

COURSE

PRE-WORK

PRE-WORK REVIEW

- Understand results from a confusion matrix and measure true positive rate and false positive rate
- Create and interpret results from a binary classification problem
- Know what a decision line is in logistic regression

COMMUNICATING RESULT

WE BUILT A MODEL! NOW WHAT?

- We’ve built our model, but there is still a gap between your Notebook with plots/figures and a slideshow needed to present your results.

- Classes so far have focused on two core concepts:
    - developing consistent practices
    - interpreting metrics to evaluate and improve model performance

- But what does that mean to your audience?

WE BUILT A MODEL! NOW WHAT?

- Imagine how a non-technical audience might respond to the following statements:
  - The predictive model I built has an accuracy of 80%.
  - Logistic regression was optimized with L2 regularization.
  - Gender was more important than age in the predictive model because it has a larger coefficient.
  - Here's the AUC chart that shows how well the model did.

WE BUILT A MODEL! NOW WHAT?

- Who is your audience? Are they technical? What are their concerns?
- Remember: in a business setting, you may be *the only person* who can interpret what you've built.
- Some people may be familiar with basic visualization, but you will likely have to do a lot of "hand holding".
- You need to be able to efficiently explain your results in a way that makes sense to **all** stakeholders (technical or not).

WE BUILT A MODEL! NOW WHAT?

- Today, we'll focus on communicating results for "simpler" problems, but this applies to any type of model you may work with.

- First, let's review classification metrics, review our knowledge, and talk about how we might communicate what we know.

REVIEW

BACK TO THE CONFUSION MATRIX

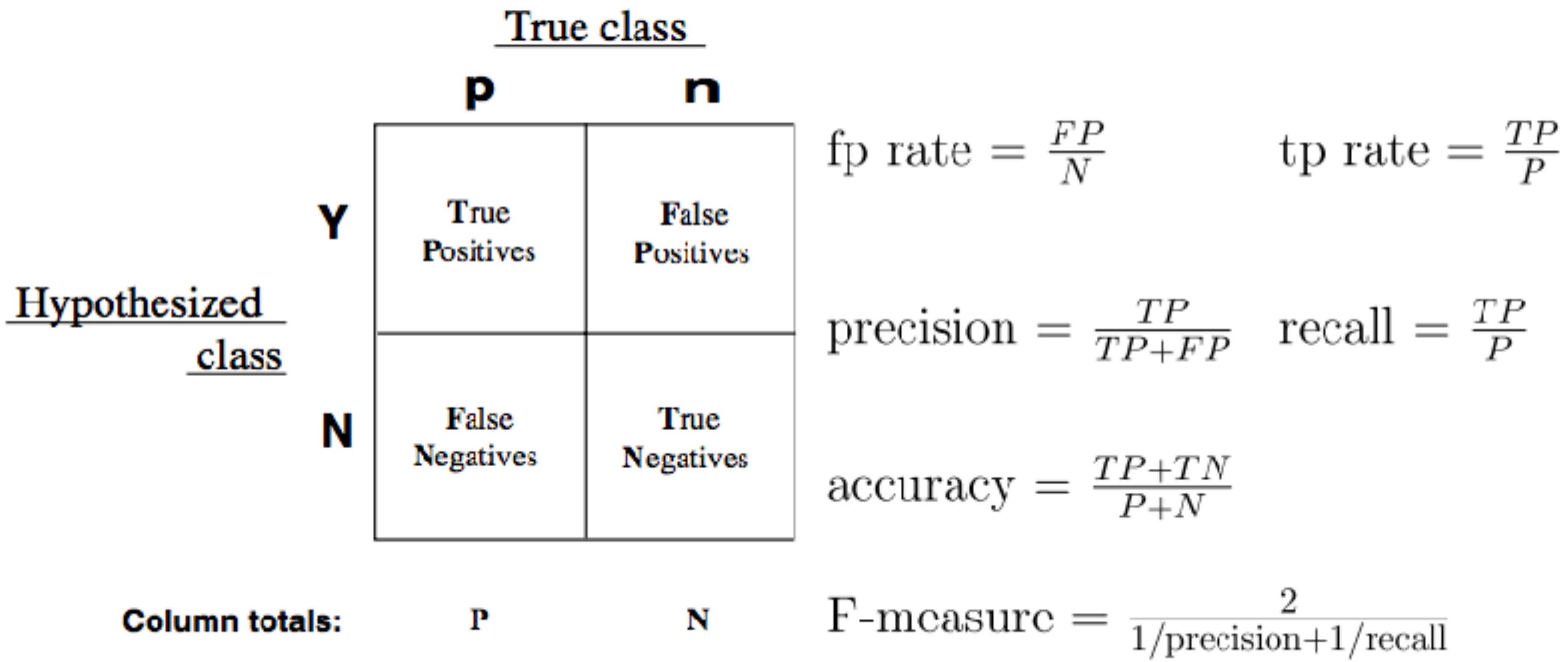
BACK TO THE CONFUSION MATRIX

- Confusion matrices allow for the interpretation of correct and incorrect predictions for *each class label*.

- It is the first step for the majority of classification metrics and goes deeper than just accuracy.

BACK TO THE CONFUSION MATRIX

‣ Let's recall our confusion matrix.



ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. Without looking at the previous slide, how do we calculate the following?
    a. Accuracy
    b. True positive rate
    c. False positive rate

DELIVERABLE

Answers to the above questions

PRECISION AND RECALL

PRECISION AND RECALL

- Our previous metrics were primarily designed for less biased data problems: we could be interested in both outcomes, so it was important to generalize our approach.

- For example, we may be interested if a person will vote for a Republican or Democrat. This is a binary problem, but we're interested in both outcomes.

PRECISION AND RECALL

- Precision and recall, metrics built from the confusion matrix, focus on *information retrieval*, particularly when one class is more interesting than the other.
- For example, we may want to predict if a person will be a customer. We care much more about people who will be a customer of ours than people who won't.

PRECISION AND RECALL

- *Precision* aims to product a high amount of relevancy instead of irrelevancy.
- Precision asks, "Out of all of our positive predictions (both true positive and false positive), how many were correct?"
- *Recall* aims to see how well a model returns specific data (literally, checking whether the model can *recall* what a class label looked like).
- Recall asks, "Out of all of our positive class labels, how many were correct?"

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

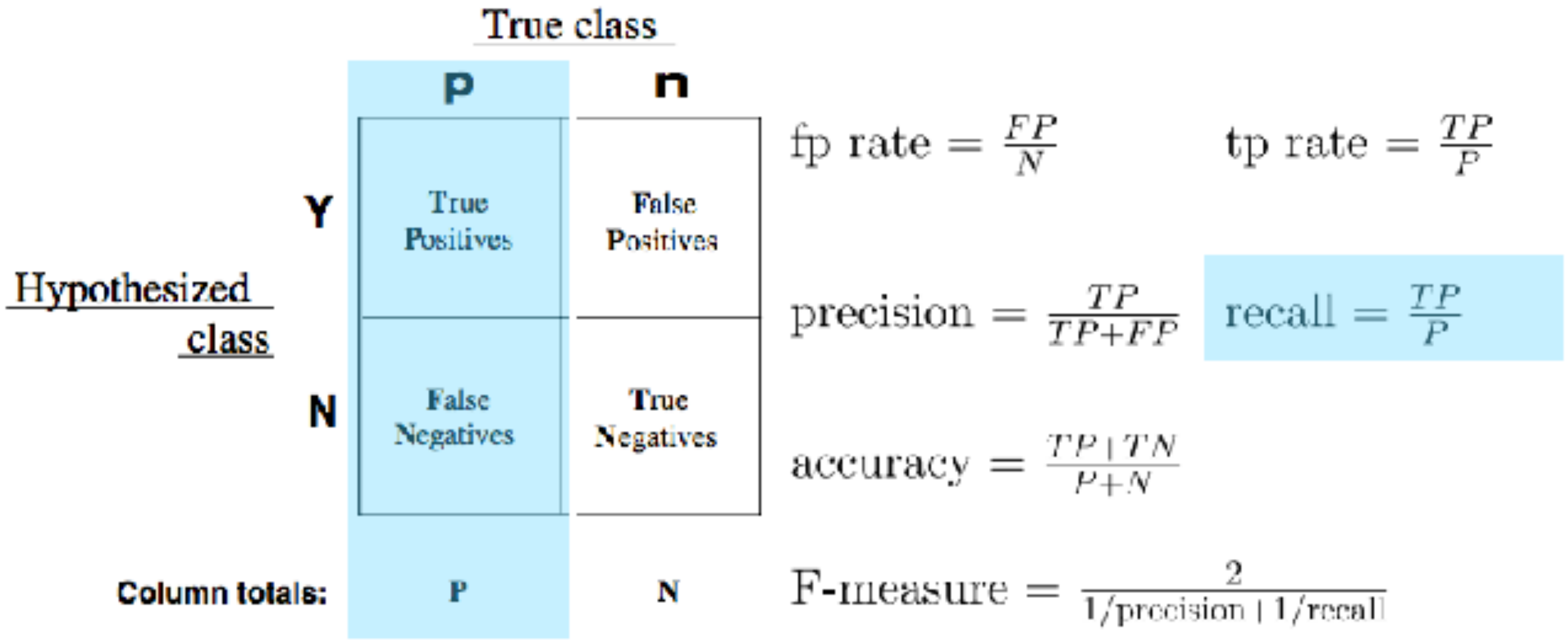
1. If the goal of the “recall” metric is to identify specific values of a class correctly, what other metric performs a similar calculation?

DELIVERABLE

Answers to the above question

THE MATH FOR RECALL

- Recall is the count of predicted *true positives* over the total count of that class label.
- This is the same as True Positive Rate or *sensitivity*.



THE MATH FOR RECALL

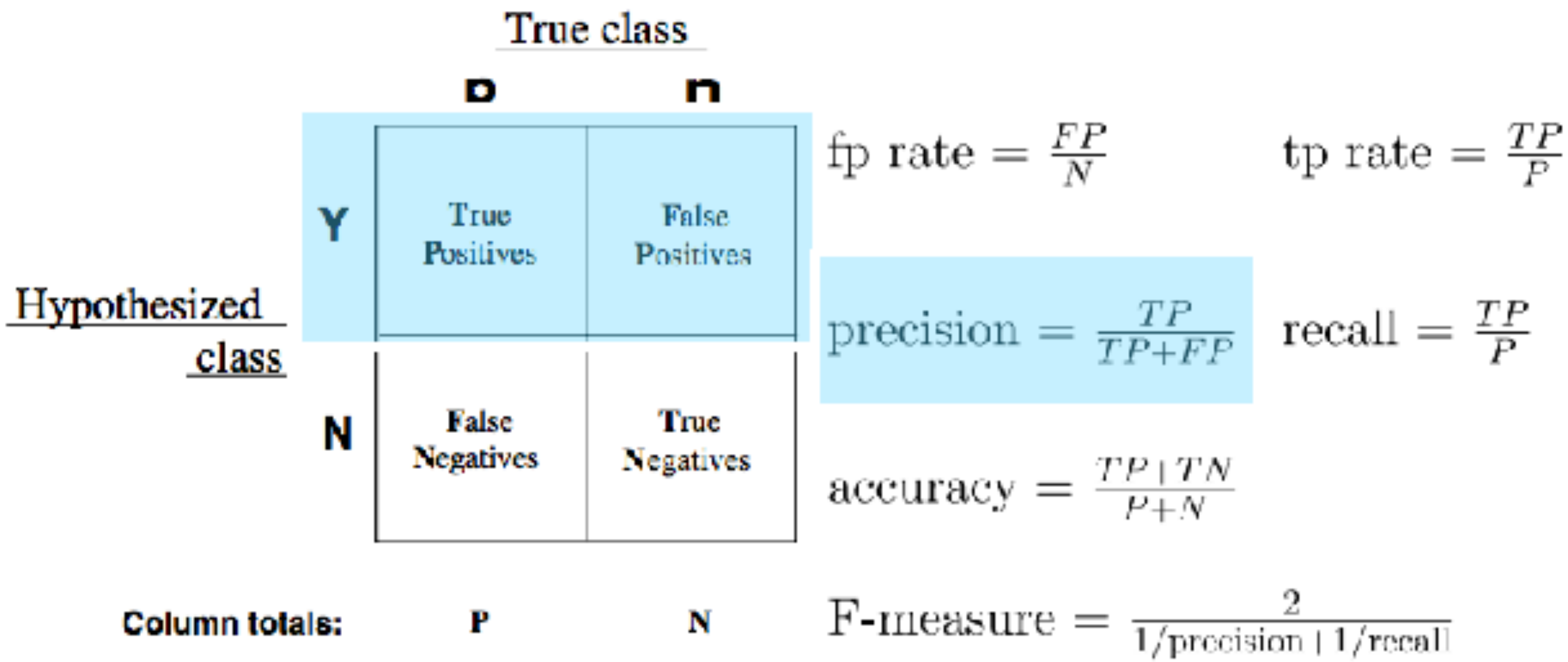
- Imagine predicting the color of a marble as either red or green. There are 10 of each.

- If the model identifies 8 identifies 8 of the green marbles as green, the recall is $8 / 10 = 0.80$.

- However, this says nothing of the number of *red* marbles that are also identified as green.

THE MATH FOR PRECISION

- Precision, or positive predicted value, is calculated as the count of predicted true positives over the count of all values predicted to be positive.

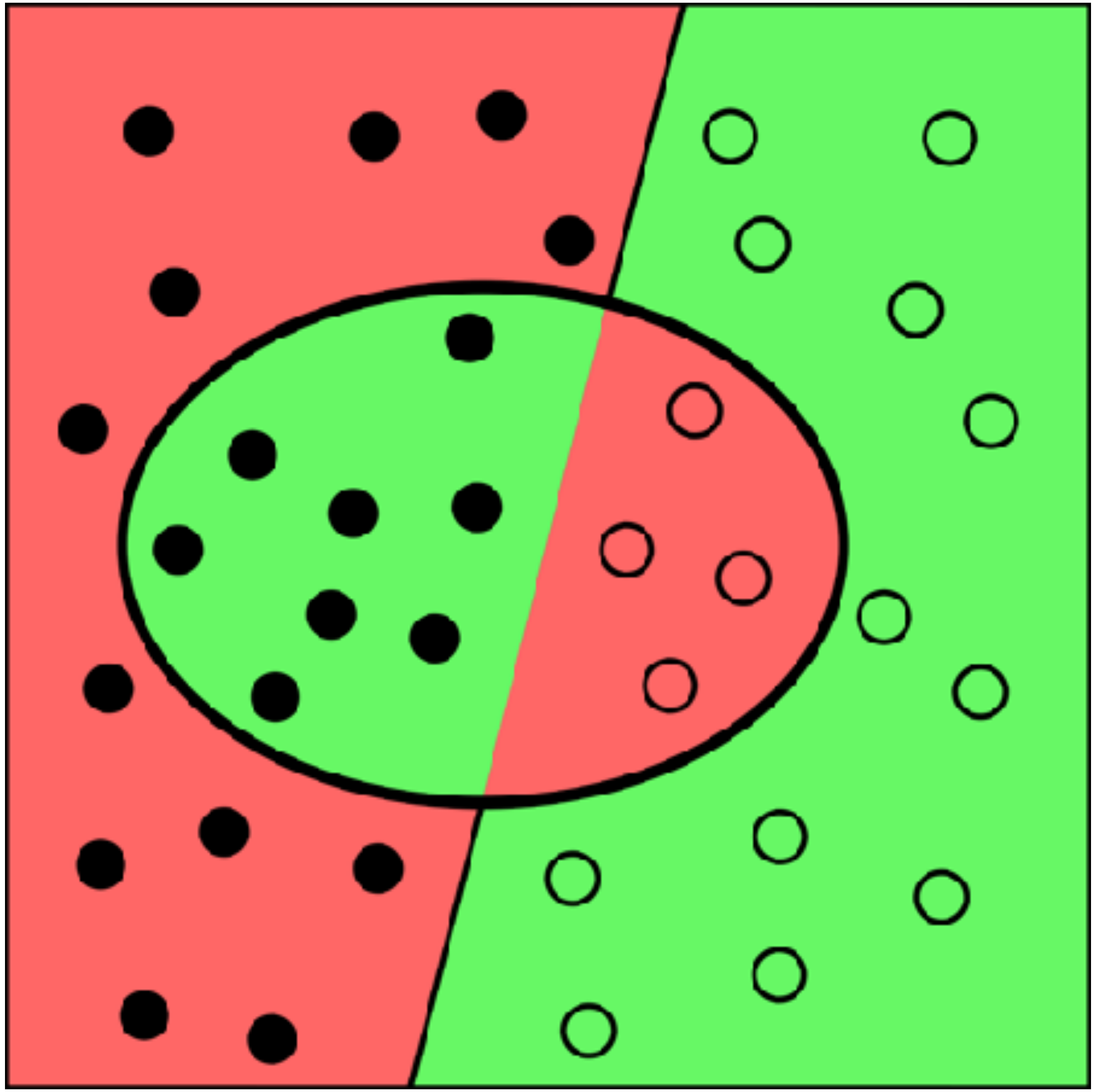


THE MATH FOR PRECISION

- Let’s use our marble example again.
- If a model predicts 8 of the green marbles as green, then precision would be 1.00, because all marbles predicted as green were in fact green.
- Let’s assume all red marbles were predicted correctly, and 2 green were predicted as red.
- The precision of red marbles would be 10 / (10 + 2) = 0.833.

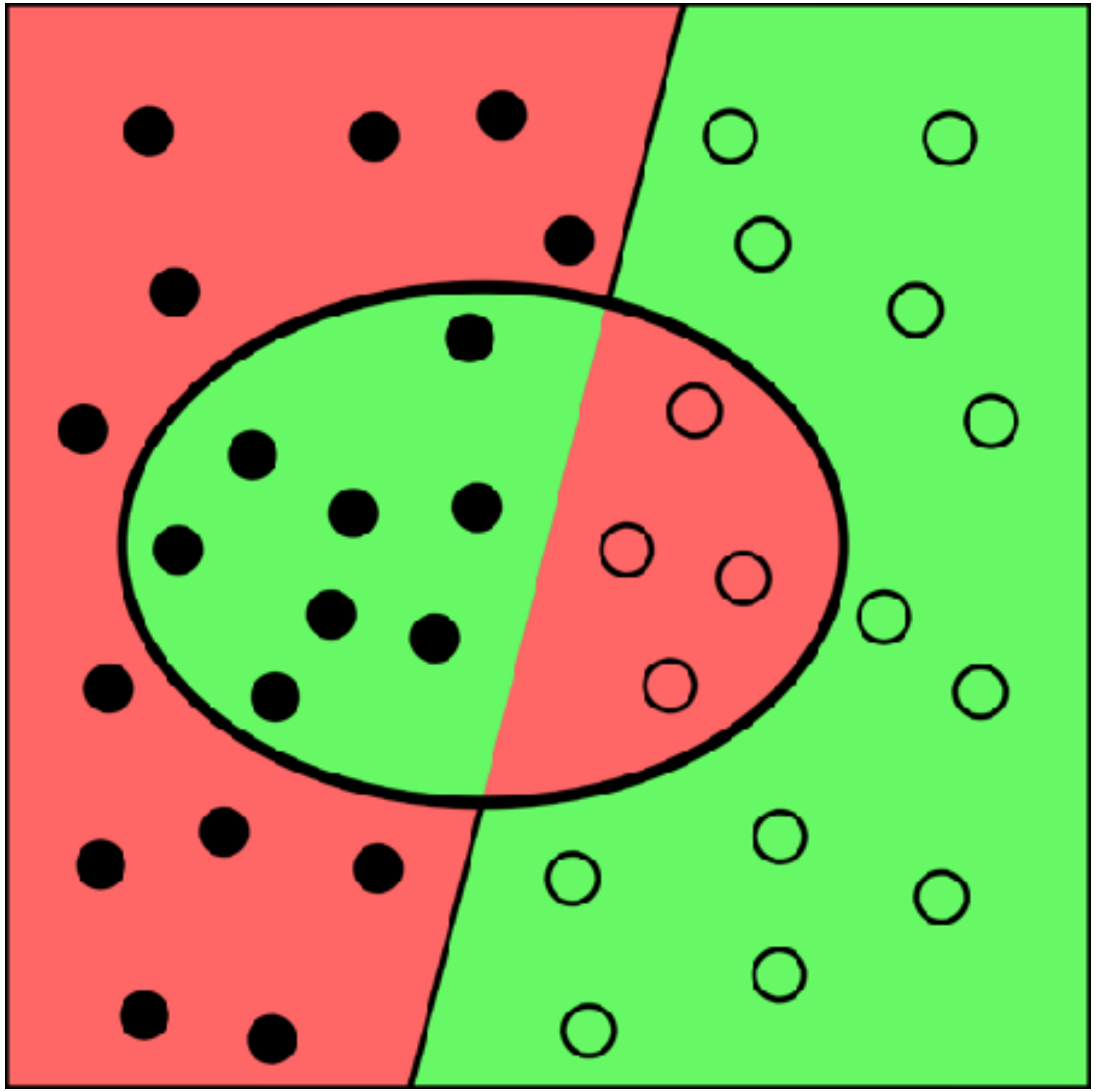
ANOTHER EXAMPLE

- Imagine we have another marble problem where we consider green to be our positive class. The diagram to the right shows our results.
- Shaded circles represent correct predictions (e.g. green was predicted as green).
- Unshaded circles represent incorrect predictions (e.g. green was predicted red).



ANOTHER EXAMPLE

- The background shows the true color.
- A shaded circle on a green background represents a green marble that was predicted as green.
- An unshaded circle on a red background represents a red marble that was predicted as green.



ANOTHER EXAMPLE

- For this example, we would have the following confusion matrix.

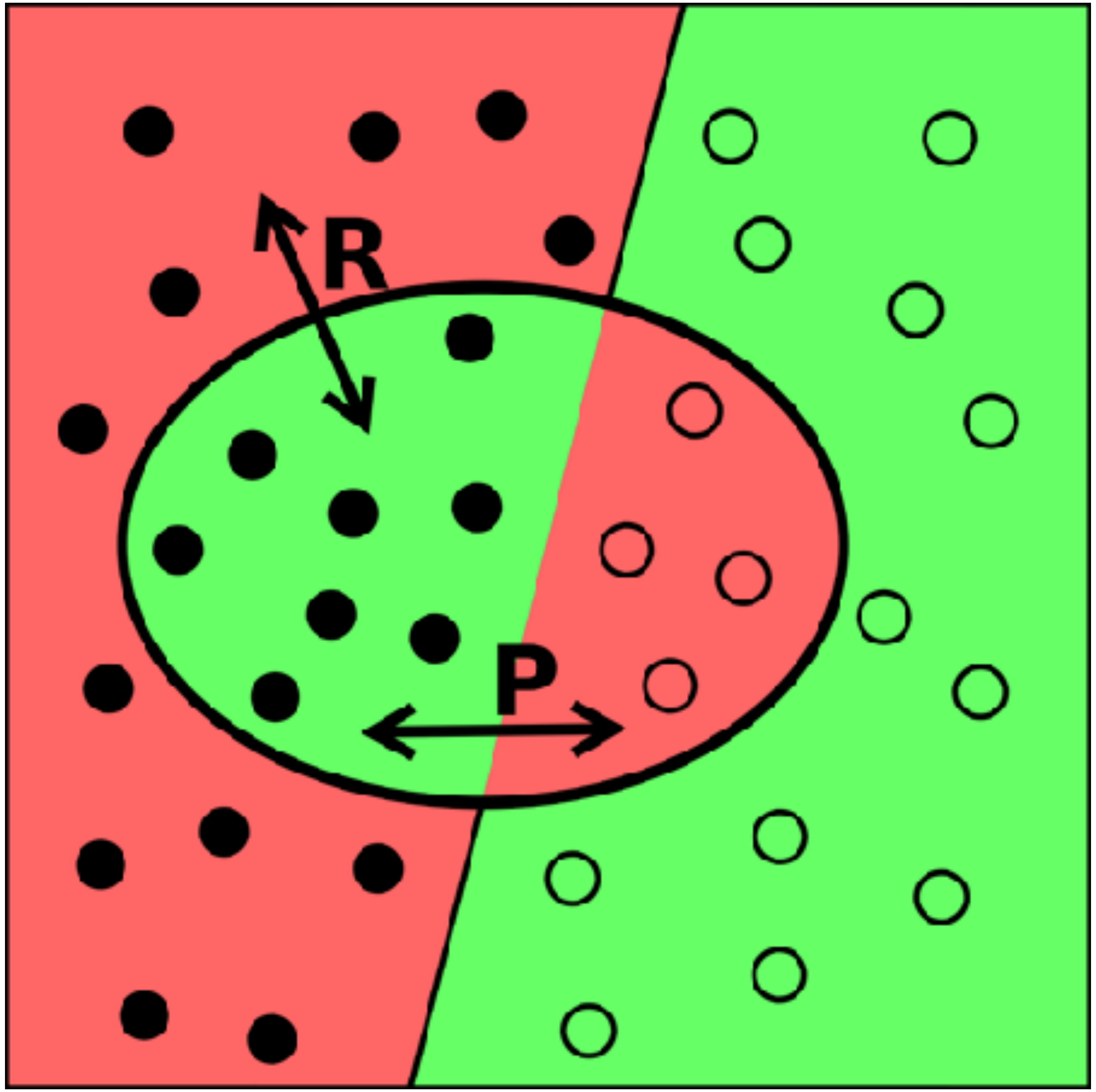
		True Class	
		Green	Red
Predicted Class	Green	8	4
	Red	12	12

- We could calculate precision for green marbles as 8 / (8 + 4) = 0.6666.

- We could calculate recall for green marbles as 8 / (8 + 12) = 0.4000.

ANOTHER EXAMPLE

- We could update our diagram to reflect these calculations.
- Notice we don't talk about the red marbles predicted as green.
- We've chosen to focus on our model's accuracy as it relates to predicting green marbles.



ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. What would the precision and recall be for the following confusion matrix (with “green” being “true”)?

	predicted_green	predicted_not_green
is_green	13	7
is_not_green	8	12

DELIVERABLE

Answers to the above question

THE DIFFERENCE BETWEEN PRECISION AND RECALL

- The key difference between the two is the attribution and value of error.
- Should our model be more picky in avoiding false positives (precision)?
- Or should it be more picky in avoiding false negatives (recall)?
- The answer should be determined by the problem you're trying to solve.

DEMO

UNDERSTANDING TRADEOFF

UNDERSTANDING TRADEOFF

- Let’s consider the following data problem: we are given a data set in order to predict or identify traits for typically late flights.
- Optimizing toward recall, we could assume that every flight will be delayed.
- The trade-off, a lower precision, is that this could create even further delays, missed flights, etc.

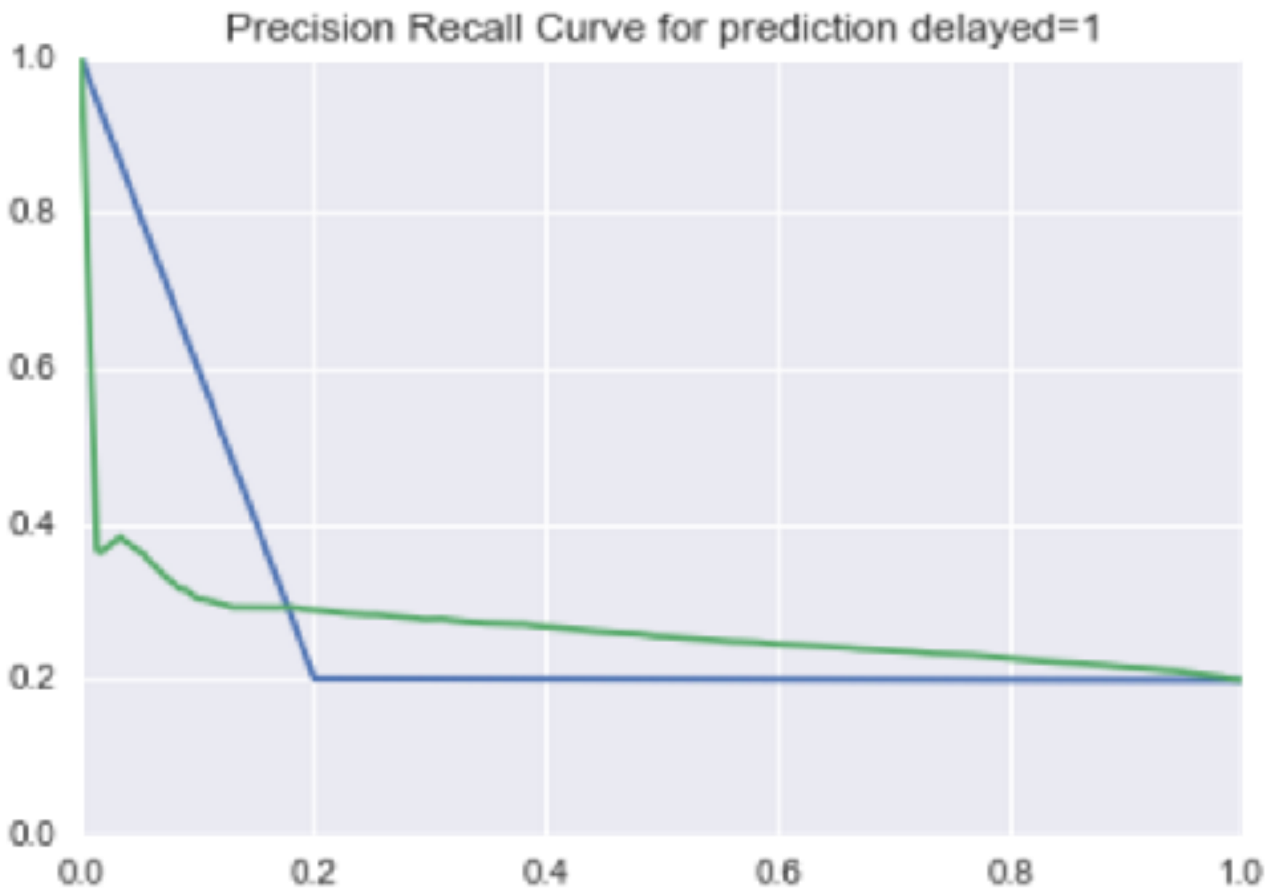
UNDERSTANDING TRADEOFF

- Optimizing toward precision, we would specifically look to identify flights that will be late.

- The trade-off here would be lower recall. We might miss flights that would be delayed, causing a strain on the system.

UNDERSTANDING TRADEOFF

- Below is a sample plot that shows how precision and recall are related for a model used to predict late flights.



UNDERSTANDING TRADEOFF

- This plot is based on choosing decision line thresholds, much like the AUC figure from the previous class.
- In terms of modeling delays, this would be like moving the decision line for lateness from a probability of 0.01 up to 0.99, and then calculating the precision and recall at each decision.

UNDERSTANDING TRADEOFF

- Interpreting our plot, there's a few interesting nuggets compared to the benchmark (blue line):
    - At a lower recall (below 0.2), there is a noticeable lower precision in the model.
    - Beyond 0.2 recall, the model outperforms the benchmark.
- Whether we're optimizing for recall or precision, this plot helps us decide based on the 0.2 threshold.

GUIDED PRACTICE

COST BENEFIT ANALYSIS

ACTIVITY: COST BENEFIT ANALYSIS

EXERCISE

DIRECTIONS (15 minutes)

One tool that complements the confusion matrix is cost-benefit analysis, where you attach a *value* to correctly and incorrectly predicted data.

Like the Precision-Recall trade off, there is a balancing point to the *probabilities* of a given position in the confusion matrix, and the *cost* or *benefit* to that position. This approach allows you to not only add a weighting system to your confusion matrix, but also to speak the language of your business stakeholders (i.e. communicate your values in dollars!).

ACTIVITY: COST BENEFIT ANALYSIS

EXERCISE

DIRECTIONS

Consider the following marketing problem:

As a data scientist working on marketing spend, you've built a model that reduces user churn--the number of users who decide to stop paying for a product--through a marketing campaign. Your model generates a confusion matrix with the following probabilities (these probabilities are calculated as the value in that position over the sum of the sample):

```
| TP: 0.2 | FP: 0.2 |
---------------------
| FN: 0.1 | TN: 0.5 |
```

ACTIVITY: COST BENEFIT ANALYSIS

EXERCISE

DIRECTIONS (15 minutes)

In this case:

- The *benefit* of a true positive is the retention of a user ($10 for the month)
- The *cost* of a false positive is the spend of the campaign per user ($0.05)
- The *cost* of a false negative (someone who could have retained if sent the campaign) is, effectively, 0 (we didn't send it... but we certainly didn't benefit!)
- The *benefit* of a true negative is 0: No spend on users who would have never retained.

To calculate Cost-Benefit, we'll use this following function:

```
(P(TP) * B(TP)) + (P(TN) * B(TN)) + (P(FP) * C(FP)) + (C(FN) * C(FN))
```

which for our marketing problem, comes out to this:

```
(.2 * 10) + (.5 * 0) - (.2 * .05) - (.1 * 0)
```

or $1.99 per user targeted.

ACTIVITY: COST BENEFIT ANALYSIS

EXERCISE

FOLLOW UP QUESTIONS

Think about precision, recall, and cost benefit analysis to answer the following questions:

1. How would you rephrase the business problem if your model was optimizing toward *precision*? i.e., How might the model behave differently, and what effect would if have?

2. How would you rephrase the business problem if your model was optimizing toward *recall*?

3. What would the most ideal model look like in this case?

DELIVERABLE

Answers to the above questions

SHOWING WORK

SHOWING WORK

- We’ve spent a lot of time exploring our data and building a reasonable model that performs well.

- However, if we look at our visuals, they are most likely:

    - Statistically heavy: Most people don’t understand histograms.

    - Overly complicated: Scatter matrices produce too much information.

    - Poorly labeled: Code doesn’t require adding labels, so you may not have added them.

SHOWING WORK

- In order to convey important information to our audience, make sure our charts are:
  - Simplified
  - Easily interpretable
  - Clearly labeled

SIMPLIFIED

- At most, you'll want to include figures that either explain a variable on its own or explain that variable's relationship with a target.
- If your model used a data transformation (like natural log), just visualize the original data.
- Try to remove any unnecessary complexity.

EASILY INTERPRETABLE

- Any stakeholder looking at a figure should be seeing the exact same thing you're seeing.
- A good test for this is to share the visual with others less familiar with the data and see if they come to the same conclusion.
- How long did it take them?

CLEARLY LABELED

- Take the time to clearly label your axis, title your plot, and double check your scales - especially if the figures should be comparable.

- If you're showing two graphs side by side, they should follow the same Y axis.

QUESTION TO ASK

- When building visuals for another audience, ask yourself these questions:
  - **Who**: Who is my target audience for the visual?
  - **What**: What do they already know about this project? What do they need to know?
  - **How**: How does my project affect this audience? How might they interpret (or misinterpret) the data?

DEMO

VISUALIZING MODELS OVER VARIABLES

VISUALIZING MODELS OVER VARIABLES

- One effective way to explain your model over particular variables is to plot the predicted values against the most explanatory variables.
- For example, in logistic regression, plotting the probability of a class against a variable can help explain the range of effect of the model.

VISUALIZING MODELS OVER VARIABLES

- We'll use the flight delay data for all following examples. Let's build our first model and plot.
- Open the starter code from the class repo and follow along.

VISUALIZING MODELS OVER VARIABLES

```
# read in the file and generate a quick model (assume we've done the data
exploration already)
import pandas as pd
import sklearn.linear_model as lm
import matplotlib.pyplot as plt

df = pd.read_csv('../../assets/dataset/flight_delays.csv')

df = df.join(pd.get_dummies(df['DAY_OF_WEEK'], prefix='dow'))
df = df[df.DEP_DEL15.notnull()].copy()
```

VISUALIZING MODELS OVER VARIABLES

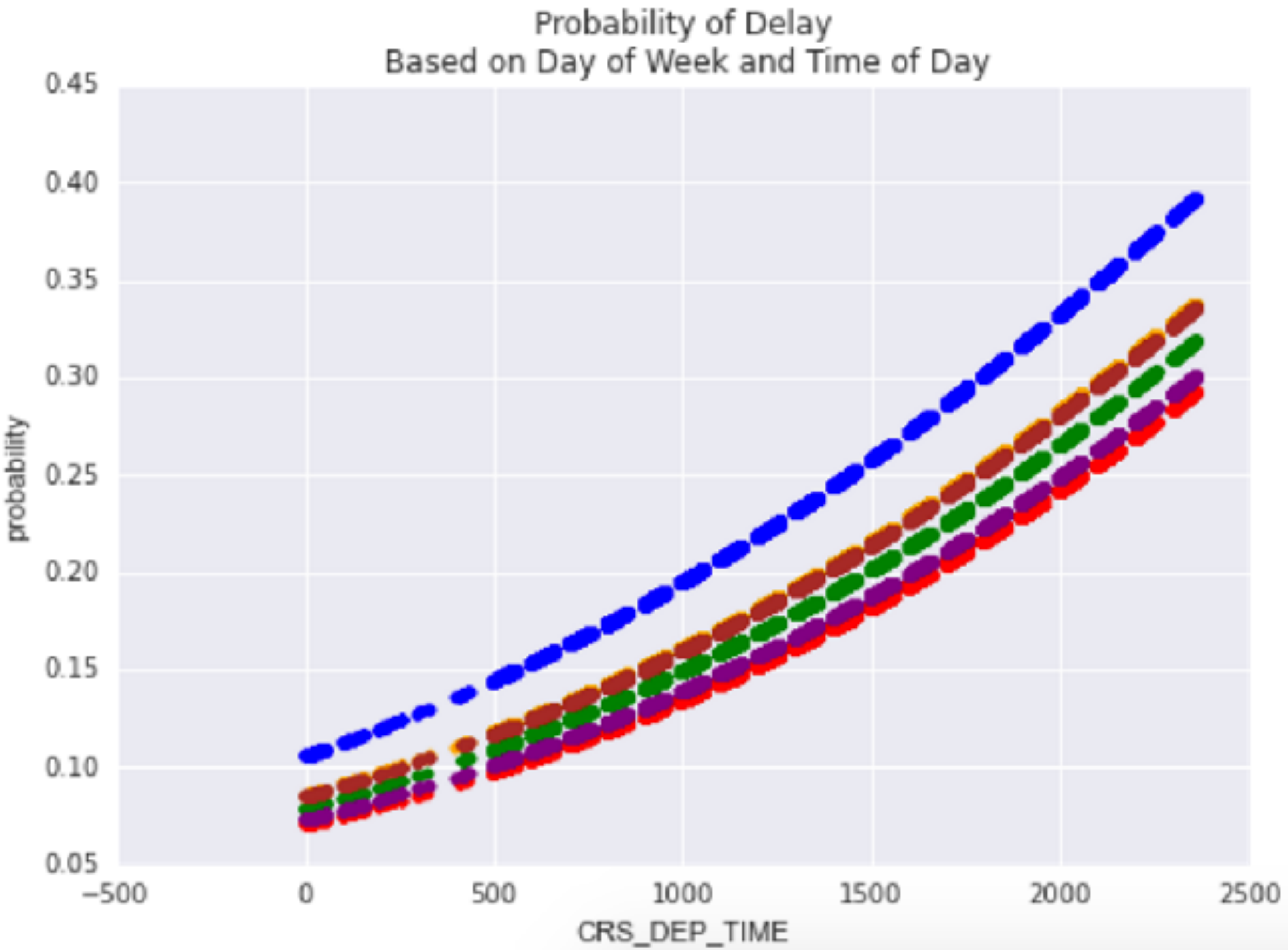
```
# Build a model
model = lm.LogisticRegression()
features = ['dow_1', 'dow_2', 'dow_3', 'dow_4', 'dow_5', 'dow_6']
model.fit(df[features + ['CRS_DEP_TIME']], df['DEP_DEL15'])

df['probability'] = model.predict_proba(df[features + ['CRS_DEP_TIME']]).T[1]
```

VISUALIZING MODELS OVER VARIABLES

```
# Create a plot
ax = plt.subplot(111)
colors = ['blue', 'green', 'red', 'purple', 'orange', 'brown']
for e, c in enumerate(colors):
    df[df[features[e]] == 1].plot(x='CRS_DEP_TIME', y='probability',
kind='scatter', color = c, ax=ax)

ax.set(title='Probability of Delay\n Based on Day of Week and Time of Day')
```

VISUALIZING MODELS OVER VARIABLES

- This visual can help showcase the range of effect on delays from both day of the week and time of day.
- Given this model, some days are more likely to have delays than others.
- The likelihood of delay increases as the day goes on.



ACTIVITY: TRY IT OUT

EXERCISE

DIRECTIONS

1. Adjust the model to make delay predictions using airlines instead of day of week, and time, then plot the effect on CRS_DEP_TIME=1.

1. Try plotting the inverse: pick either model and plot the effect on CRS_DEP_TIME=0.

DELIVERABLE

The new plots

DEMO

VISUALIZING PERFORMANCE AGAINST BASELINE

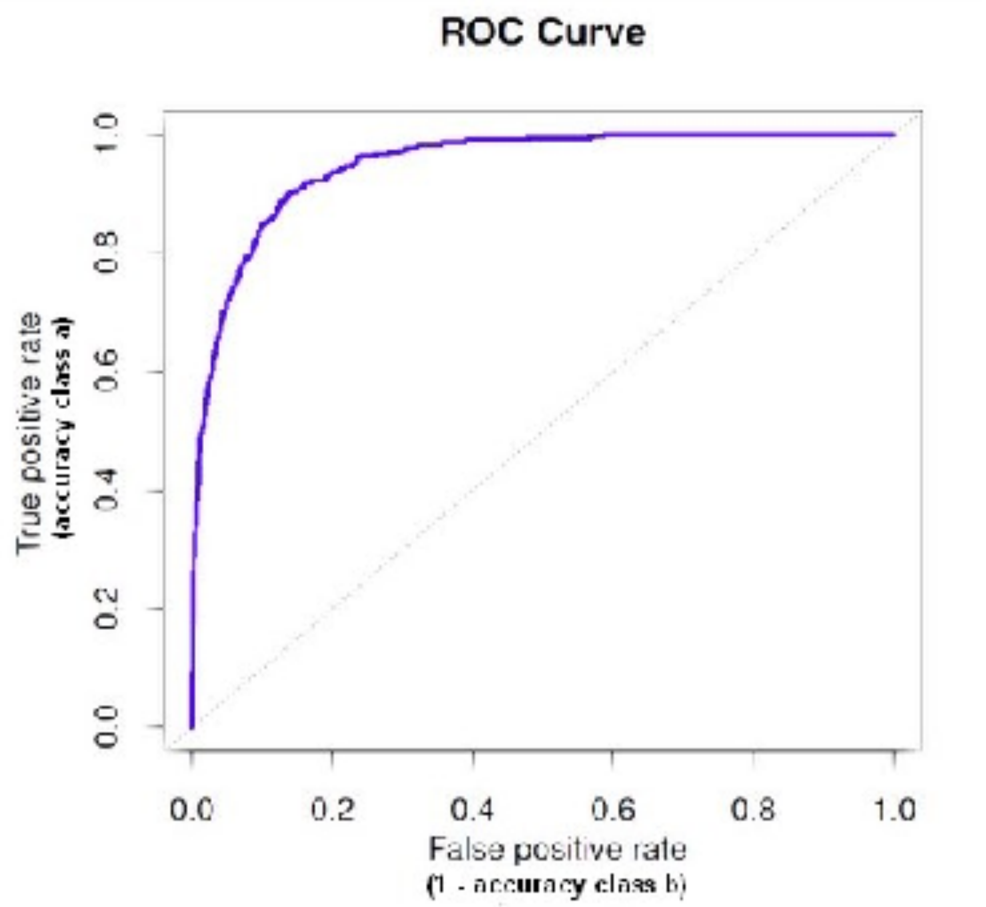
VISUALIZING PERFORMANCE AGAINST BASELINE

- Another approach of visualization is the effect of your model against a baseline, or - even better - against previous models.

- Plots like this will also be useful when talking to your peers - other data scientists or analysts who are familiar with your project and interested in the progress you’ve made.

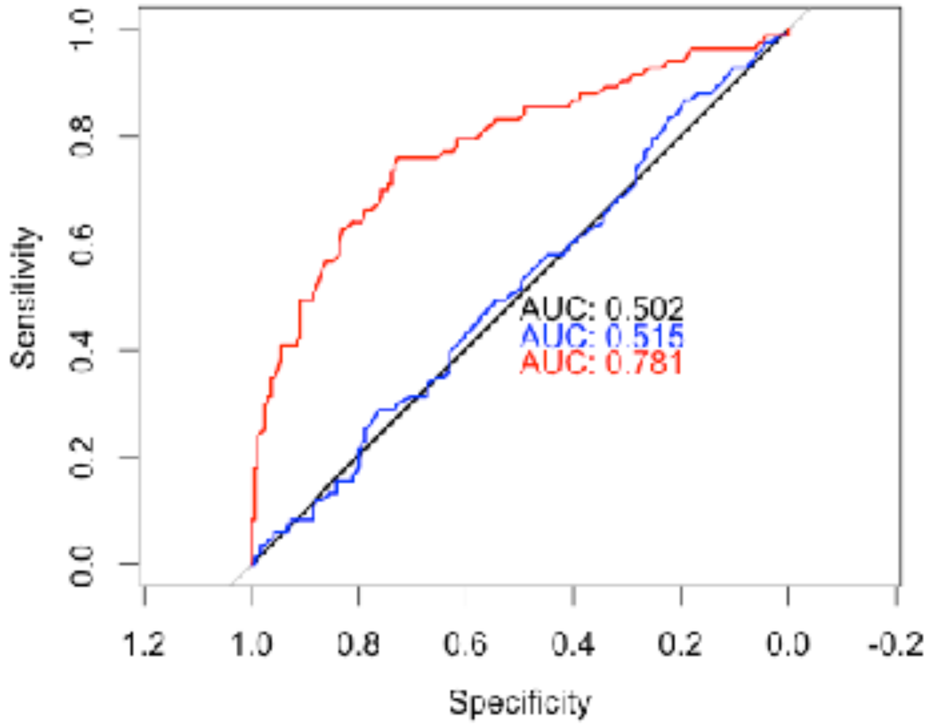
VISUALIZING PERFORMANCE AGAINST BASELINE

- For classification, we've practiced plotting AUC and precision-recall plots. Consider the premise of each:
  - AUC plots explain and represent "accuracy" as having the largest area under the curve. Good models will be high and to the left.
  - For precision-recall plots, it will depend on the *cost* requirements. Either a model will have good recall at the cost of precision or vice versa.



VISUALIZING PERFORMANCE AGAINST BASELINE

- When comparing multiple models:
  - For AUC plots, you'll be interested in which model has the *largest* area under the curve.
  - For precision-recall plots, based on the cost requirement, you are looking at which model has the best precision given the same recall, or the best recall given the same precision.



VISUALIZING PERFORMANCE AGAINST BASELINE

- Follow along with the starter code located in the class repo.
- We've plotted several models for AUC: a dummy model and additional features.

```
model0 = dummy.DummyClassifier()
model0.fit(df[features[1:-1]], df.DEP_DEL15)
df['probability_0'] = model0.predict_proba(df[features[1:-1]]).T[1]

model = lm.LogisticRegression()
model.fit(df[features[1:-1]], df.DEP_DEL15)
df['probability_1'] = model.predict_proba(df[features[1:-1]]).T[1]
```

VISUALIZING PERFORMANCE AGAINST BASELINE

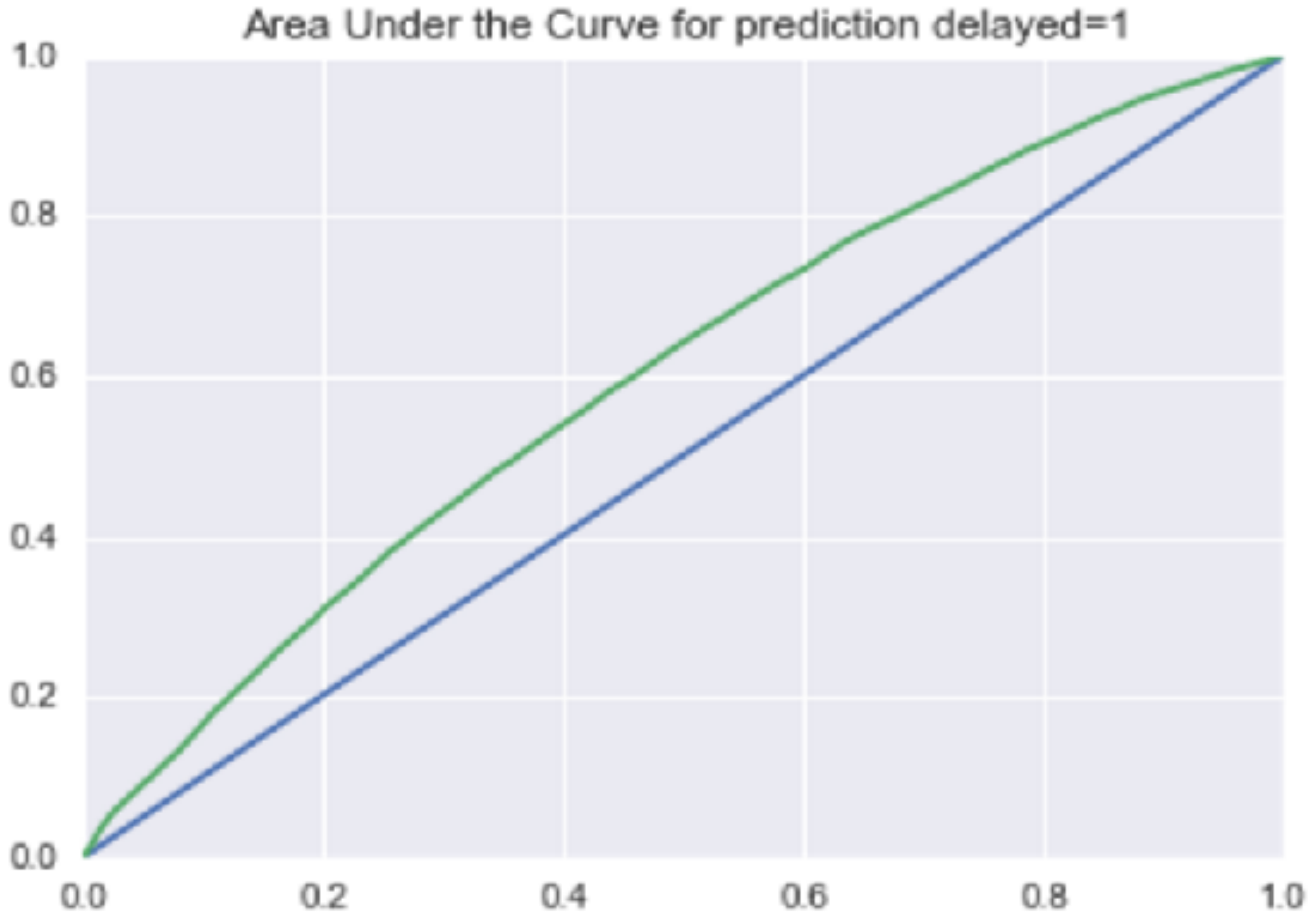
```
ax = plt.subplot(111)
vals = metrics.roc_curve(df.DEP_DEL15, df.probability_0)
ax.plot(vals[0], vals[1])
vals = metrics.roc_curve(df.DEP_DEL15, df.probability_1)
ax.plot(vals[0], vals[1])

ax.set(title='Area Under the Curve for prediction delayed=1', ylabel='TRP',
xlabel='FRP', xlim=(0, 1), ylim=(0, 1))
```

VISUALIZING PERFORMANCE AGAINST BASELINE

- This plot showcases:

1. The model using data outperforms a baseline dummy model.

1. By adding other features, there's some give and take with probability as the model gets more complicated.



ACTIVITY: TRY IT OUT

EXERCISE

DIRECTIONS

1. In a similar approach, use the sklearn precision_recall_curve function to enable you to plot the precision-recall curve of the two models from above. Keep in mind precision in the first array is returned from the function, but the plot shows it as the y-axis.
2. Explain what is occurring when the recall is below 0.2.
3. Based on this performance, is there a clear winner at different thresholds?

4. **Bonus**: Redo both the AUC and precision-recall curves using models that have been cross validated using kfold. How do these new figures change your expectations for performance?

DELIVERABLE

The new plots and associated answers

PROJECT PRACTICE

ACTIVITY: PROJECT PRACTICE

EXERCISE

DIRECTIONS (45 minutes)

Using models built from the flight data problem earlier in class, work through the same problems. Your data and models should already be accessible. Your goals:

1. There are *many* ways to manipulate this data set. Consider what is a proper "categorical" variable, and keep *only* what is significant. You will easily have 20+ variables. Aim to have at least three visuals that clearly explain the relationship of variables you've used against the predictive survival value.
2. Generate the AUC or precision-recall curve (based on which you think makes more sense), and have a statement that defines, compared to a baseline, how your model performs and any caveats. For example: "My model on average performs at x rate, but the features under-perform and explain less of the data at these thresholds." Consider this as practice for your own project, since the steps you'll take to present your work will be relatively similar.

DELIVERABLE

New models and performance statement

TOPIC REVIEW

REVIEW AND NEXT STEPS

- What do precision and recall mean? How are they similar and different to True Positive Rate and False Positive Rate?
- How does cost benefit analysis play a role in building models?
- What are at least two very important details to consider when creating visuals for a project's stakeholders?
- Why would an AUC plot work well for a data science audience but not for a business audience? What would be a more effective visualization for that group?

INDEPENDENT PRACTICE

EVALUATING LOGISTIC REGRESSION WITH ALTERNATIVE METRICS

ACTIVITY: EVALUATING LOGISTIC REGRESSION

EXERCISE

DIRECTIONS (35 minutes)

Kaggle's common online exercise is exploring survival data from the Titanic.

1. Spend a few minutes determining which data would be most important to use in the prediction problem. You may need to create new features based on the data available. Consider using a feature selection aide in sklearn. For a worst case scenario, identify one or two strong features that would be useful to include in this model.

DELIVERABLE

Answers to the above question and a Logistic model on the Titanic data

ACTIVITY: EVALUATING LOGISTIC REGRESSION

EXERCISE

DIRECTIONS (35 minutes)

1. Spend 1-2 minutes considering which *metric* makes the most sense to optimize. Accuracy? FPR or TPR? AUC? Given the business problem of understanding survival rate aboard the Titanic, why should you use this metric?

1. Build a tuned Logistic model. Be prepared to explain your design (including regularization), metric, and feature set in predicting survival using any tools necessary (such as a fit chart). Use the starter code to get you going.

DELIVERABLE

Answers to the above question and a Logistic model on the Titanic data

BEFORE NEXT CLASS

UPCOMING

- Project: Unit Project 3

LESSON

Q & A

EXIT TICKET

DON'T FORGET TO FILL OUT YOUR EXIT TICKET