```
In [1]: import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
   from patsy import dmatrices
   from sklearn.linear_model import LogisticRegression
   from sklearn.cross_validation import train_test_split, cross_val_score
   from sklearn import metrics

%matplotlib inline
```

## Pre-Task: Describe the goals of your study

## Part 1: Aquire the Data

```
In [ ]: psql -h dsi.c20gkj5cvu3l.us-east-1.rds.amazonaws.com -p 5432 -U dsi_stud
    ent titanic
    password: gastudents
```

1. Connect to the remote database

In [	]:	
In [	]:	

2. Query the database and aggregate the data

```
In [ ]:
```

5. What are the risks and assumptions of our data?

## **Part 2: Exploratory Data Analysis**

1. Describe the	e Data
In [ ]:	
2. Visualize the	Data
In [ ]:	
In [ ]:	
In [ ]:	
Part 3: Da	nta Wrangling
1. Create Dumi	my Variables for Sex
In [ ]:	
In [ ]:	
In [ ]:	
Part 4: Lo	gistic Regression and Model Validation
1. Define the va	ariables that we will use in our classification analysis
In [ ]:	
2. Transform "\	/" into a 1-Dimensional Array for SciKit-Learn
In [ ]:	
3. Conduct the	logistic regression
In [ ]:	

4. Examine the coefficients to see our correlations  In []:  6. Test the Model by introducing a Test or Validaton set  In []:  7. Predict the class labels for the Test set  In []:  8. Predict the class probabilities for the Test set  In []:  9. Evaluate the Test set  In []:  10. Cross validate the test set  In []:  11. Check the Classification Report  In []:	In [ ]:	
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7. Predict the class labels for the <i>Test</i> set  In [ ]:  8. Predict the class probabilities for the <i>Test</i> set  In [ ]:  9. Evaluate the <i>Test</i> set  In [ ]:  10. Cross validate the test set  In [ ]:	6. Test the Model	by introducing a <i>Test</i> or <i>Validaton</i> set
7. Predict the class labels for the <i>Test</i> set  In [ ]:  8. Predict the class probabilities for the <i>Test</i> set  In [ ]:  9. Evaluate the <i>Test</i> set  In [ ]:  10. Cross validate the test set  In [ ]:	In [ ]:	
In []:  8. Predict the class probabilities for the Test set  In []:  9. Evaluate the Test set  In []:  10. Cross validate the test set  In []:  11. Check the Classification Report  In []:		
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In [ ]:  9. Evaluate the Test set  In [ ]:  10. Cross validate the test set  In [ ]:  11. Check the Classification Report  In [ ]:	In [ ]:	
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9. Evaluate the <i>Test</i> set  In [ ]:  10. Cross validate the test set  In [ ]:  11. Check the Classification Report  In [ ]:	8. Predict the clas	ss probabilities for the <i>Test</i> set
In [ ]:  10. Cross validate the test set  In [ ]:  11. Check the Classification Report  In [ ]:	In [ ]:	
In [ ]:  10. Cross validate the test set  In [ ]:  11. Check the Classification Report  In [ ]:		
In [ ]:  11. Check the Classification Report  In [ ]:	9. Evaluate the <i>T</i> e	st set
In [ ]:  11. Check the Classification Report  In [ ]:	In [ ]:	
In [ ]:  11. Check the Classification Report  In [ ]:	40. 0	
11. Check the Classification Report  In [ ]:	10. Cross validate	the test set
In [ ]:	In [ ]:	
In [ ]:		
	11. Check the Cla	ssification Report
12. What do the classification metrics tell us?	In [ ]:	
12. What do the classification metrics tell us?		
	12. What do the c	lassification metrics tell us?

13. Check the Confusion Matrix

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14. What does the Confusion Matrix tell us?

15. Plot the ROC curve

```
In [ ]:
```

16. What does the ROC curve tell us?

## Part 5: Gridsearch

- 1. Use GridSearchCV with logistic regression to search for optimal parameters
  - Use the provided parameter grid. Feel free to add if you like (such as n\_jobs).
  - Use 5-fold cross-validation.

2. Print out the best parameters and best score. Are they better than the vanilla logistic regression?

```
In [ ]:
```

3. Explain the difference between the difference between the L1 (Lasso) and L2 (Ridge) penalties on the model coefficients.

4. What hypothetical situations are the Ridge and Lasso penalties useful?

5. [BONUS] Explain how the regularization strength (C) modifies the regression loss function. Why do the Ridge and Lasso penalties have their respective effects on the coefficients?
In [ ]:
6.a. [BONUS] You decide that you want to minimize false positives. Use the predicted probabilities from the model to set your threshold for labeling the positive class to need at least 90% confidence. How and why does this affect your confusion matrix?
In [ ]:
Part 6: Gridsearch and kNN
1. Perform Gridsearch for the same classification problem as above, but use KNeighborsClassifier as your estimator
At least have number of neighbors and weights in your parameters dictionary.
In [ ]:
2. Print the best parameters and score for the gridsearched kNN model. How does it compare to the logistic regression model?
In [ ]:
3. How does the number of neighbors affect the bias-variance tradeoff of your model?
[BONUS] Why?
In [ ]:
4. In what hypothetical scenario(s) might you prefer logistic regression over kNN, aside from model performance metrics?
In [ ]:

5. Fit a new k	NN model with the optimal parameters found in gridsearch.
In [ ]:	
6. Construct model? If so,	the confusion matrix for the optimal kNN model. Is it different from the logistic regression how?
In [ ]:	
7. [BONUS] P model on the	Plot the ROC curves for the optimized logistic regression model and the optimized kNN same plot.
In [ ]:	
1. Gridsearch 'average_pre	BONUS] Precision-recall  the same parameters for logistic regression but change the scoring function to cision'  recision' will optimize parameters for area under the precision-recall curve instead of for
In [ ]:	
part 5?	ne best parameters and score. Are they different than the logistic regression gridsearch in
In [ ]:	
3. Create the this be?	confusion matrix. Is it different than when you optimized for the accuracy? If so, why would
In [ ]:	

4. Plot the precision-recall curve. What does this tell us as opposed to the ROC curve?

See the sklearn plotting example here. (http://scikit-learn.org/stable/auto examples/model selection/plot precision recall.html)

In [ ]:
Part 8: [VERY BONUS] Decision trees, ensembles, bagging
1. Gridsearch a decision tree classifier model on the data, searching for optimal depth. Create a new decision tree model with the optimal parameters.
In [ ]:
2. Compare the performace of the decision tree model to the logistic regression and kNN models.
In [ ]:
3. Plot all three optimized models' ROC curves on the same plot.
In [ ]:
4. Use sklearn's BaggingClassifier with the base estimator your optimized decision tree model. How does the performance compare to the single decision tree classifier?
In [ ]:
5. Gridsearch the optimal n_estimators, max_samples, and max_features for the bagging classifier.
In [ ]:
6. Create a bagging classifier model with the optimal parameters and compare it's performance to the other two models.
In [ ]: