Who Were Most Likely to Survive the Titanic Catastrophe?

Using logistic Regression

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Data Cleaning

Dropped Features

The first features to be dropped were:

- Passenger ID: Not relevant towards survival
- Ticket: Also not relevant, mostly random string/number
- Cabin: 77% of data in this column was missing

	# of Missing	Percent
Cabin	1014	0.774637
Age	263	0.200917
Embarked	2	0.001528
Fare	1	0.000764
Ticket	0	0.000000

Kept Features

- Survived: What we want to predict
- Pclass: Class of passenger
- Name: The title in names can be used
- Sex: Male or female
- Age: Age in years, can include values less than a year to zero
- SibSp: Number siblings / spouses
- Parch: Number of parents / children
- Fare: Fare paid to board
- Embarked: Location embarked from

Data Types I

- Survived:
  - Nominal datatype
  - 1 meaning survival
- Pclass:
  - Ordinal datatype
  - 1,2,3 that represents the status of the passenger, with 1 being high-class and 3 being low-class
- Name:
  - Nominal data type.
  - Information such as Titles can be pulled from this

Data Types II

- Age and Fare:
  - Continuous and quantitative data types
- SibSp and Parch:
  - Discrete quantitative data types
  - Can be used to create another feature to describe Family Size
- Sex and Embarked:
  - Nominal data types
  - Can be turned into and used as dummy variables

Missing Data

- Age, Embarked, and Fare
  - These 3 columns had some missing data but not a significant amount
  - The mode, most frequent value, of each column was used to fill in missing data for that column

	# of Missing	Percent
Cabin	1014	0.774637
Age	263	0.200917
Embarked	2	0.001528
Fare	1	0.000764
Ticket	0	0.000000

Unique Title Counts

Mr	757
Miss	260
Mrs	197
Master	61
Rev	8
Dr	8
Col	4
Major	2
Mlle	2
Ms	2
Sir	1
Capt	1
Jonkheer	1
Don	1
Mme	1
Lady	1
the Countess	1
Dona	1

- From the Name we could identify meaningful socioeconomic Title and do One Hot Encoding on them
- We see that there are not many repeats for other Titles than Mr, Miss, Mrs and Master
- Using them, would result in a over fitting
- We found that using the first 4 gives us better results

Feature Engineering II

Created a new feature named Family size

- Combined Sibsp (number of siblings) and Parch (parents) to form the new feature Family Size
- Family Size was shown to be highly correlated to Sibsp and Parch, so these two variables were later dropped
- This new combined feature, as well as having less features to work with, improves modeling


Pearson Correlation of Features
Age 1 -0.046 0.19 -0.11 0.026 -0.4 0.045 -0.19 -0.053 -0.18 0.15 -0.25 0.21 -0.35
Embarked -0.046 1 -0.24 0.045 -0.052 0.19 0.098 0.066 -0.17 0.068 0.094 -0.05 -0.058 0.017
Fare 0.19 -0.24 1 0.22 0.031 -0.56 -0.19 0.16 0.26 0.23 -0.19 0.091 0.14 0.012
Parch -0.11 0.045 0.22 1 0.0089 0.018 -0.21 0.37 0.082 0.79 -0.3 0.068 0.22 0.25
PassengerId 0.026 -0.052 0.031 0.0089 1 -0.038 0.013 -0.055 -0.005 -0.031 0.014 -0.05 0.034 0.0023
Pclass -0.4 0.19 -0.56 0.018 -0.038 1 0.12 0.061 -0.34 0.05 0.12 0.03 -0.18 0.095
Sex_code 0.045 0.098 -0.19 -0.21 0.013 0.12 1 -0.11 -0.54 -0.19 0.87 -0.67 -0.57 0.16
SibSp -0.19 0.066 0.16 0.37 -0.055 0.061 -0.11 1 -0.035 0.86 -0.24 0.08 0.065 0.33
Survived -0.053 -0.17 0.26 0.082 -0.005 -0.34 -0.54 -0.035 1 0.017 -0.55 0.33 0.34 0.085
FamilySize -0.18 0.068 0.23 0.79 -0.031 0.05 -0.19 0.86 0.017 1 -0.33 0.09 0.16 0.36
Mr 0.15 0.094 -0.19 -0.3 0.014 0.12 0.87 -0.24 -0.55 -0.33 1 -0.58 -0.49 -0.26
Miss -0.25 -0.05 0.091 0.068 -0.05 0.03 -0.67 0.08 0.33 0.09 -0.58 1 -0.21 -0.11
Mrs 0.21 -0.058 0.14 0.22 0.034 -0.18 -0.57 0.065 0.34 0.16 -0.49 -0.21 1 -0.093
Master -0.35 0.017 0.012 0.25 0.0023 0.095 0.16 0.33 0.085 0.36 -0.26 -0.11 -0.093 1
Age
Embarked
Fare
Parch
PassengerId
Pclass
Sex_code
SibSp
Survived
FamilySize
Mr
Miss
Mrs
Master
0.9
0.6
0.3
0.0
−0.3
−0.6

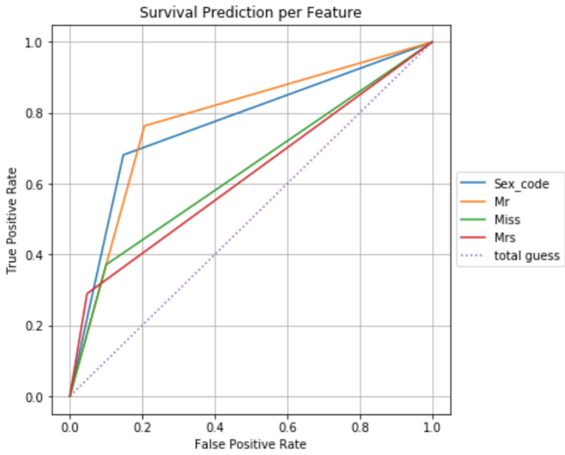
Model Testing

Cleaning is done.
We are left with a total of 10 Features:

- Mr, Mrs, Miss, and Master
- Sex_code
- FamilySize
- Fare
- Age
- Embarked
- Pclass

Feature Prediction Testing

Taking each feature individually, we test to look if they are a good predictor of Survival



Feature	Accuracy
Sex_code	0.786756
Title_Mr	0.782267
Title_Mrs	0.698092
Title_Miss	0.696970
Pclass	0.679012
Fare	0.666667
Embarked	0.636364
Title_Master	0.622896
Age	0.616162
FamilySize	0.616162

- Logistic regression requires the features to be scaled. We used the sklearn.preprocessing.StandardScaler
- Evaluate different combination of parameters by doing a Grid Search with Cross-Validation over the following processed datasets
  - Standardized Features (9 features)
  - PCA with 7 components
  - PCA with 8 components

```
Cumulative sum:  0.9601661693062497     with 7 components
Cumulative sum:  0.9933474854884274     with 8 components
```

Logistic Regression Parameters

- Logistic Regression has 5 different solvers, where each is able to perform different norm penalizations
- Below is our parameters grid

```
param_grid = [
    { 'solver':['liblinear'] },
    { 'solver':['newton-cg'], 'penalty':['l2', 'none'], 'multi_class':['ovr', 'multinomial', 'auto'] },
    { 'solver':['lbfgs'], 'penalty':['l2', 'none'], 'multi_class':['ovr', 'multinomial', 'auto'] },
    { 'solver':['saga'], 'l1_ratio':[0.5, 0.6, 0.75, 0.9], 'max_iter':[800], 'penalty':['elasticnet'] },
    { 'solver':['sag'], 'penalty':['l2'] }
]
```

Standardized Features Accuracy

```
Best parameters:
 {'l1_ratio': 0.75, 'max_iter': 800, 'penalty': 'elasticnet', 'solver': 'saga'}
 0.8305274971941639

0.8271604938271605 {'solver': 'liblinear'}
0.8271604938271605 {'multi_class': 'ovr', 'penalty': 'l2', 'solver': 'newton-cg'}
0.8282828282828283 {'multi_class': 'ovr', 'penalty': 'none', 'solver': 'newton-cg'}
0.8271604938271605 {'multi_class': 'multinomial', 'penalty': 'l2', 'solver': 'newton-cg'}
0.8282828282828283 {'multi_class': 'multinomial', 'penalty': 'none', 'solver': 'newton-cg'}
0.8271604938271605 {'multi_class': 'auto', 'penalty': 'l2', 'solver': 'newton-cg'}
0.8282828282828283 {'multi_class': 'auto', 'penalty': 'none', 'solver': 'newton-cg'}
0.8271604938271605 {'multi_class': 'ovr', 'penalty': 'l2', 'solver': 'lbfgs'}
0.8282828282828283 {'multi_class': 'ovr', 'penalty': 'none', 'solver': 'lbfgs'}
0.8271604938271605 {'multi_class': 'multinomial', 'penalty': 'l2', 'solver': 'lbfgs'}
0.8282828282828283 {'multi_class': 'multinomial', 'penalty': 'none', 'solver': 'lbfgs'}
0.8271604938271605 {'multi_class': 'auto', 'penalty': 'l2', 'solver': 'lbfgs'}
0.8282828282828283 {'multi_class': 'auto', 'penalty': 'none', 'solver': 'lbfgs'}
0.8282828282828283 {'l1_ratio': 0.5, 'max_iter': 800, 'penalty': 'elasticnet', 'solver': 'saga'}
0.8282828282828283 {'l1_ratio': 0.6, 'max_iter': 800, 'penalty': 'elasticnet', 'solver': 'saga'}
0.8305274971941639 {'l1_ratio': 0.75, 'max_iter': 800, 'penalty': 'elasticnet', 'solver': 'saga'}
0.8305274971941639 {'l1_ratio': 0.9, 'max_iter': 800, 'penalty': 'elasticnet', 'solver': 'saga'}
0.8271604938271605 {'penalty': 'l2', 'solver': 'sag'}
```

PCA Accuracy

- Using 7 components

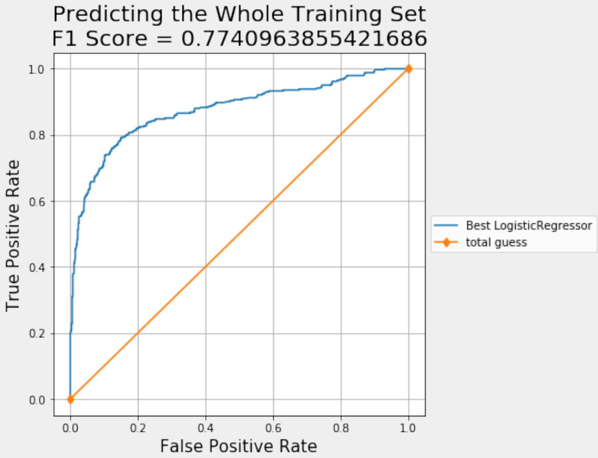
```
Best parameters:
 {'solver': 'liblinear'}
 0.8237934904601572
```

- Using 8 components

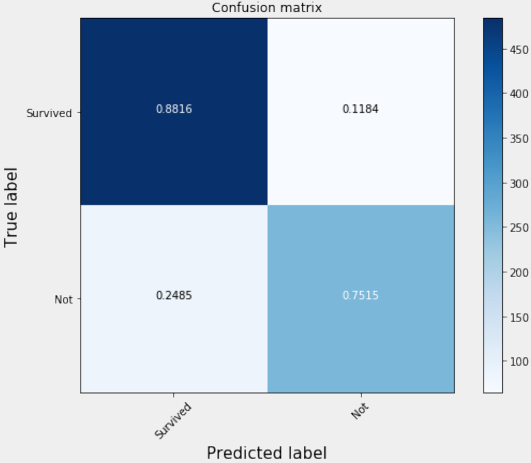
```
Best parameters:
 {'multi_class': 'ovr', 'penalty': 'none', 'solver': 'newton-cg'}
 0.8260381593714927
```

- Standarized Features results in better accuracy!

ROC Curve


Predicting the Whole Training Set
F1 Score = 0.7740963855421686
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Best LogisticRegressor
total guess

	Survived	Not
Survived	484	65
Not	85	257



Accuracy=0.8316 | Misclass=0.1684
Recall=0.8506 | Precision=0.8816

Kaggle Scores I

Kaggle Score: 0.58851

- Submitted a file with only passengers of Pclass 1 or 2 surviving

Kaggle Score: 0.76555

- Kaggle sample submission where all females on-board survived

Kaggle Scores II

Kaggle Score: 0.79425

- Used the "liblinear" logistic regression solver with all variables after cleaning

Kaggle Score: 0.79904

- Used the "saga" solver
- Elasticnet penalty and l1_ratio of 0.75
- "saga" looks to be the best solver to use

Kaggle Score: 0.80382

- "saga" solver used again, but this time the SibSp and Parch features were dropped
- Elasticnet penalty and l1_ratio of 0.75
- This resulted to be the best model

References

- https://www.kaggle.com/ldfreeman3/a-data-science-framework-to-achieve-99-accuracy
- https://www.kaggle.com/startupsci/titanic-data-science-solutions

Thanks!

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