Project Report on OSDA

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Project Based on Titanic Survivor Predictions

Overview

The data has been split into two groups:
training set (train.csv)
test set (test.csv)
The training set should be used to build your machine learning models. For the training set, we provide the outcome (also known as the "ground truth") for each passenger. Your model will be based on "features" like passengers' gender and class. You can also use feature engineering to create new features.
The test set should be used to see how well your model performs on unseen data. For the test set, we do not provide the ground truth for each passenger. It is your job to predict these outcomes. For each passenger in the test set, use the model you trained to predict whether or not they survived the sinking of the Titanic.

Variable	Definition	Key	Variable
survival	Survival	0 = No, 1 = Yes	survival
pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd	pclass
sex	Sex		sex
Age	Age in years		Age
sibsp	# of siblings / spouses aboard the Titanic		sibsp
parch	# of parents / children aboard the Titanic		parch
ticket	Ticket number		ticket
fare	Passenger fare		fare
cabin	Cabin number		cabin
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton	embarked

1. Basic fields
PassengerId passenger id
Training set 891 (1- 891), test set 418 (892 - 1309)
Survived Whether rescued or not

1=yes, 2=no
Rescued: 38%
Stricken: 62% (actual % in distress: 67.5%)
Pclass Ticket class
Represents socio-economic status. 1=advanced, 2=intermediate, 3=low
1 : 2 : 3 = 0.24 : 0.21 : 0.55
Name Name
Example: Futrelle, Mrs. Jacques Heath (Lily May Peel)
Example: Heikkinen, Miss. Laina
Sex Gender
male male 577, female female 314
Male : Female = 0.65 : 0.35
Age Age (missing 20% of data)
Training set: 714/891 = 80%
Test set: 332/418 = 79%
SibSp Total number of siblings or spouses of peers
68% none, 23% have 1 ... max 8
Parch Total number of parents or children in the same row
76% none, 13% with 1, 9% with 2 ... max 6
Some children travelled only with a nanny, therefore parch=0 for them.
Ticket Ticket number (format not standardised)
Example: A/5 21171
Example: STON/O2. 3101282
Fare
The test set is missing one data
Cabin number
The training set has only 204 data, the test set has 91 data
Example: C85
Embarked Port of embarkation
C = Cherbourg 19%, Q = Queenstown 9%, S = Southampton 72%
Training set with two less data

7 Steps to Workflow
Problem definition
Acquisition of training and test data
Data preparation and cleaning
Analyze, identify patterns, and explore the data
Modelling, predicting, and solving the problem
Visualise, report, and show steps to solve and final solution
Present results, provide or present results.

2. Exploring the data
2.1 Basic information on features (head, info, describe)
Explore the data

View field structures, types and head examples
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId 891 non-null int64
Survived 891 non-null int64
Pclass 891 non-null int64
Name 891 non-null object
Sex 891 non-null object
Age 714 non-null float64
SibSp 891 non-null int64
Parch 891 non-null int64
Ticket 891 non-null object
Fare 891 non-null float64
Cabin 204 non-null object
Embarked 889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.6+ KB

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
PassengerId 418 non-null int64
Pclass 418 non-null int64
Name 418 non-null object
Sex 418 non-null object
Age 332 non-null float64
SibSp 418 non-null int64
Parch 418 non-null int64
Ticket 418 non-null object
Fare 417 non-null float64
Cabin 91 non-null object
Embarked 418 non-null object
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB

2.2 Correlation of several enumerated features with Survived (direct group aggregation for mean value)
Higher survival rates for the rich and middle classes, lower survival rates for the bottom

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

Gender and survival are strongly correlated, with female users having a significantly higher survival rate than males

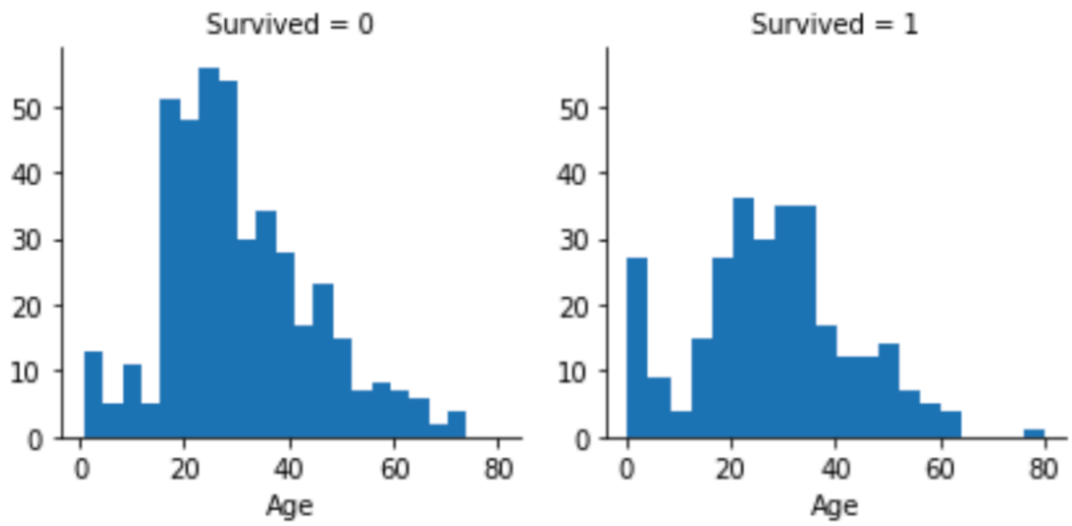
	Sex	Survived
0	female	0.742038
1	male	0.188908

The chances of surviving with 0 to 2 siblings or spouses are higher than with more

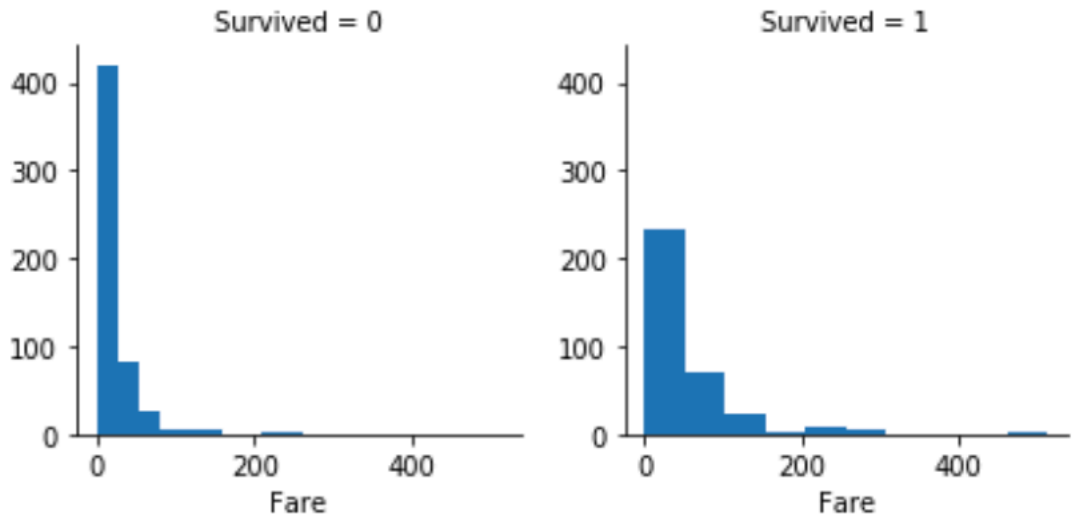
	SibSp	Survived
1	1	0.535885
2	2	0.464286
0	0	0.345395
3	3	0.250000
4	4	0.166667
5	5	0.000000
6	8	0.000000

2.3 Separate histograms were used to look at the distribution of survivorship and non-survivorship for characteristics with a long span such as age

Greater chance of survival for babies and young children



Low chance of survival for the cheapest ticket



3. Feature cleaning

3.1 HasCabin

#Removal of the features Ticket (no human judgement correlation) and Cabin (too little valid data)

3.2 Title

Create a designation feature based on the name, which will contain gender and class information

dataset.Name.str.extract(' ([A-Za-z]+)\.' -> Extract strings starting with space . Ending strings are extracted

Match with gender to see if each type of title belongs to male or female for subsequent categorization

Categorise titles as Mr,Miss,Mrs,Master,Rare_Male,Rare_Female (with Rare differentiated by male and female)

Summarize Survived Means by Title to see correlation

Sex	female	male
Title		
Mr	0	517
Master	0	40
Dr	1	6
Rev	0	6
Col	0	2
Major	0	2
Capt	0	1
Don	0	1
Jonkheer	0	1
Sir	0	1
Miss	182	0
Mrs	125	0
Mlle	2	0
Countess	1	0
Lady	1	0
Mme	1	0
Ms	1	0

	Title	Survived
0	Master	0.575000
1	Miss	0.704301
2	Mr	0.156673
3	Mrs	0.792000
4	Rare_Female	1.000000
5	Rare_Male	0.285714

3.3 Sex

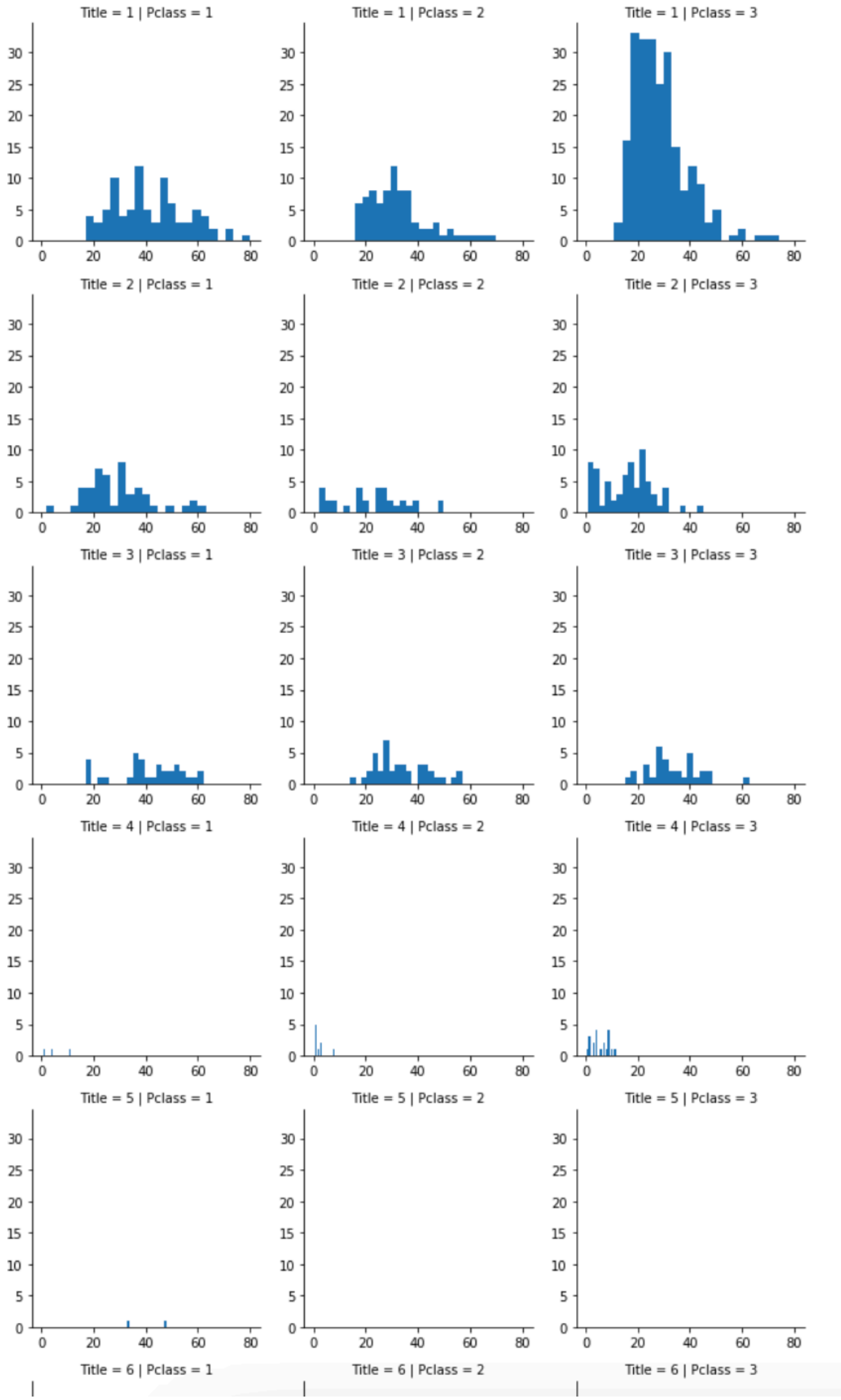
 # Sex features mapped to values

	Survived	Pclass	Sex
0	0	3	0
1	1	1	1
2	1	3	1
3	1	1	1
4	0	3	0

3.4 Age

Predictive supplementation for null values in the Age field

Take the median age of the same Pclass and Title for supplementation (Demo for Pclass and Sex)


Title = 1 | Pclass = 1
Title = 1 | Pclass = 2
Title = 1 | Pclass = 3
Title = 2 | Pclass = 1
Title = 2 | Pclass = 2
Title = 2 | Pclass = 3
Title = 3 | Pclass = 1
Title = 3 | Pclass = 2
Title = 3 | Pclass = 3
Title = 4 | Pclass = 1
Title = 4 | Pclass = 2
Title = 4 | Pclass = 3
Title = 5 | Pclass = 1
Title = 5 | Pclass = 2
Title = 5 | Pclass = 3
Title = 6 | Pclass = 1
Title = 6 | Pclass = 2
Title = 6 | Pclass = 3

Populate valuation with empty values for the age field
Use the median Age of the same Pclass and Title instead (for combinations where the median is empty, use the median of the Title as a whole instead)
3.4 IsChildren
Create whether **c**hild features based on age

Fare	Embarked	NameLength	HasCabin	Title	IsChildren
'.2500	S	23	0	1	0.0
'1.2833	C	51	1	3	0.0
'.9250	S	22	0	2	0.0
;3.1000	S	44	1	3	0.0
;.0500	S	24	0	1	0.0

Create age interval features
pd.cut is a uniform cut by the size of the value, each set of value intervals is the same size, but the number of samples may not be the same
pd.qcut is cut by frequency of distribution of samples over values, same number of samples per group

	Survived	Pclass	Sex	Age	SibSp	Parch
0	0	3	0	2	1	0
1	1	1	1	6	1	0
2	1	3	1	3	0	0
3	1	1	1	5	1	0
4	0	3	0	5	0	0

3.5 Family Size
Create family size FamilySize portfolio features

	FamilySize	Survived
0	1	0.303538
1	2	0.552795
2	3	0.578431
3	4	0.724138
4	5	0.200000
5	6	0.136364
6	7	0.333333
7	8	0.000000
8	11	0.000000

3.6 IsAlone

Create whether the IsAlone feature is alone

	IsAlone	Survived
0	0	0.505650
1	1	0.303538

3.7 Embarked

Get the most ports of embarkation

	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.339009

3.8 Fare

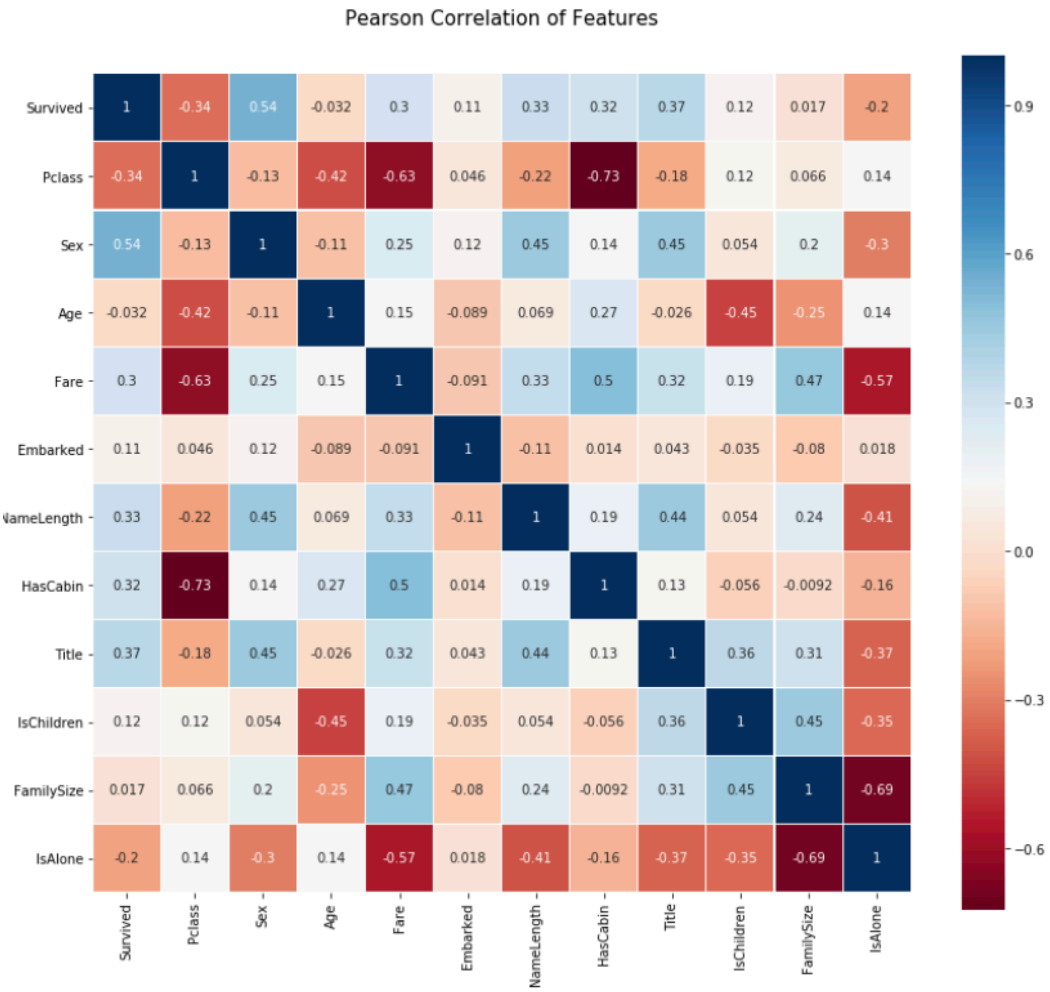
Fill the test set with null values for Fare, using the median

Convert Fare features to ordinal values based on FareBand

	FareBand	Survived
0	(-0.001, 7.91]	0.197309
1	(7.91, 14.454]	0.303571
2	(14.454, 31.0]	0.454955
3	(31.0, 512.329]	0.581081

3.9 Feature correlation visualization¶

Visualization of correlation between features using seaborn's heatmap



4. Modelling and optimisation

4.1 Model comparison

4.1.1 LazyFCA

Acc = 79.05

Precision = 0.35

Recall = 0.20

4.1.2 Logistic Regression
Acc = 82.15
Precision = 0.76
Recall = 0.70

4.1.3 Support Vector Machines
Acc = 83.28
Precision = 0.81
Recall = 0.72

4.1.4 KNN
Acc = 85.3
Precision = 0.81
Recall = 0.67

4.1.5 Decision Tree
Acc = 88.78
Precision = 0.79
Recall = 0.69

4.1.6 Random Forest
Acc = 83.15
Precision = 0.80
Recall = 0.71

Model	Accuracy	Precision	Recall
LazyFCA	79.05	0.35	0.20
Logistic Regression	82.15	0.76	0.70
Support Vector Machines	83.28	0.81	0.72
KNN	85.30	0.81	0.67
Decision Tree	88.78	0.79	0.69
Random Forest	83.15	0.80	0.71

Conclusion

It is clear that lazy learning methods do not compare favourably with existing machine learning methods on a variety of metrics, with decision trees being the most prominent in the current task followed by KNN algorithms. However, the overall prediction level is not very high, and there is probably still room for improvement in feature selection and modelling.