EEC1509 - Machine Learning

Lesson #11 Kaggle Fundamentals

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Update repository

```
git clone https://github.com/ivanovitchm/EEC1509_MachineLearning.git
```

Ou ....

```
git pull
```

GitHub

Agenda

1. Getting Started with Kaggle
2. Feature Preparation, Selection and Engineering
3. Model Selection and Tuning
4. Creating a Kaggle Workflow

Introduction to Kaggle

- Approach a Kaggle competition.
- Explore the competition data and learn about the competition topic.
- Prepare data for machine learning.
- Train a model.
- Measure the accuracy of your model.
- Prepare and make your first Kaggle submission.

Getting Started Prediction Competition

Titanic: Machine Learning from Disaster

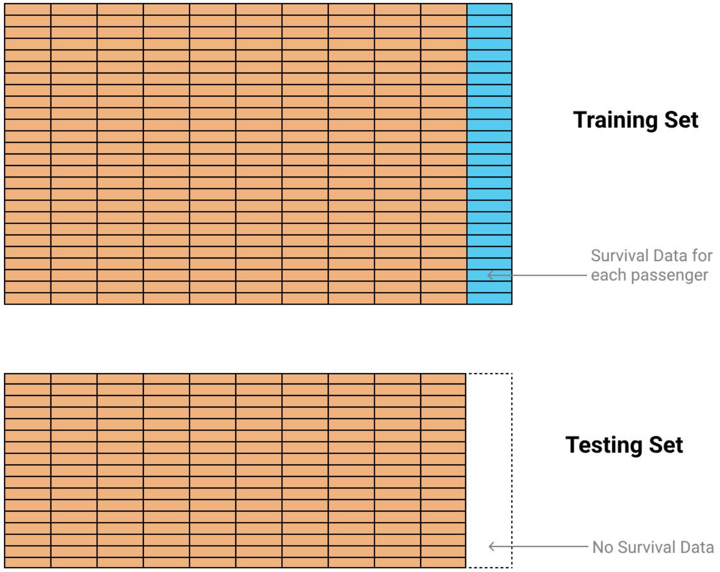
Start here! Predict survival on the Titanic and get familiar with ML basics

Kaggle · 10,331 teams · Ongoing

Overview Data Kernels Discussion Leaderboard Rules

Data Sources

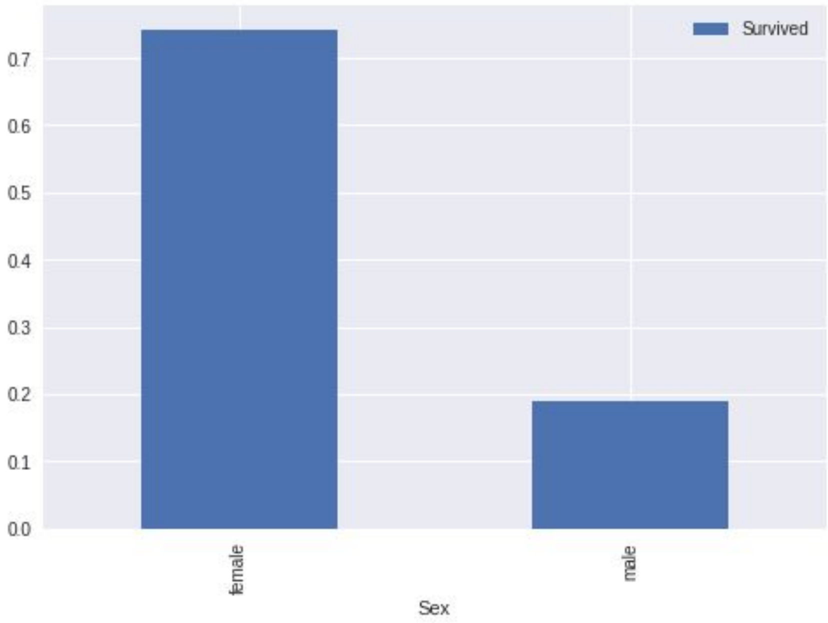
gender_submission.csv	418 x 2
test.csv	418 x 11
train.csv	891 x 12

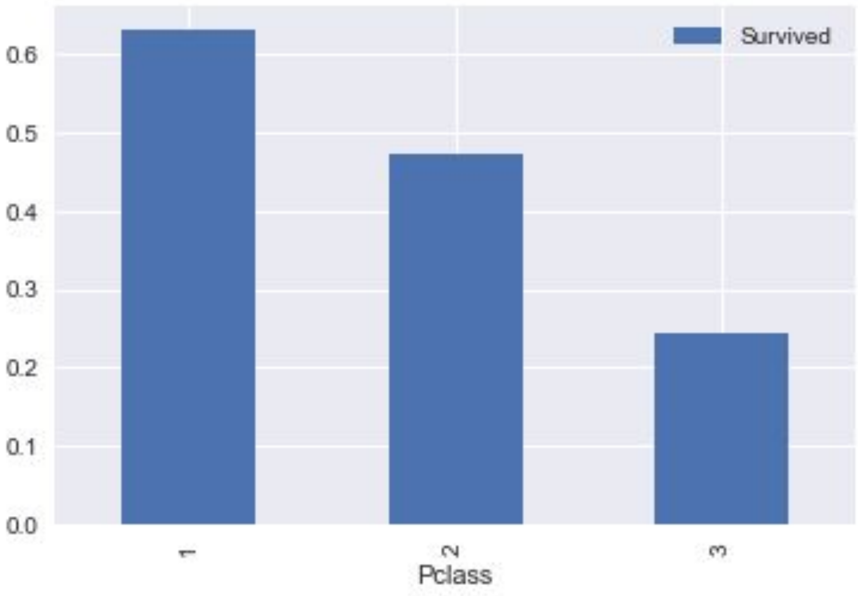


Exploring the Data

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

Exploring the Data





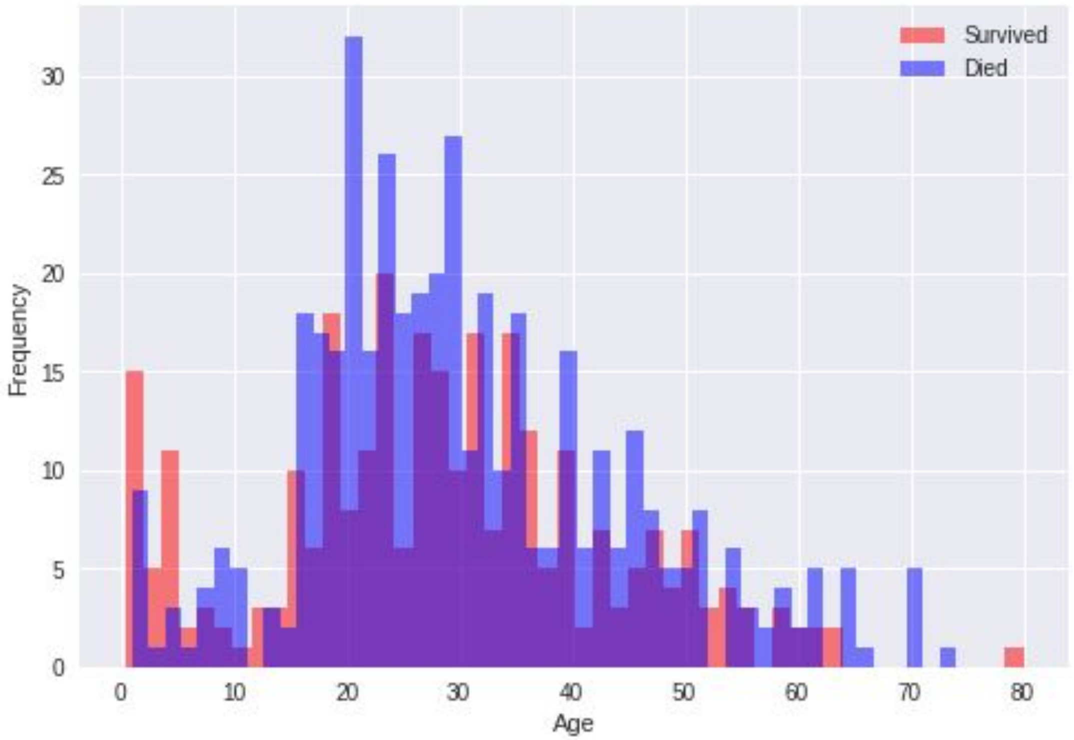
Exploring and Converting the Age Column

```
train["Age"].describe()
```

```
count    714.000000
mean      29.699118
std       14.526497
min        0.420000
25%       20.125000
50%       28.000000
75%       38.000000
max       80.000000
Name: Age, dtype: float64
```

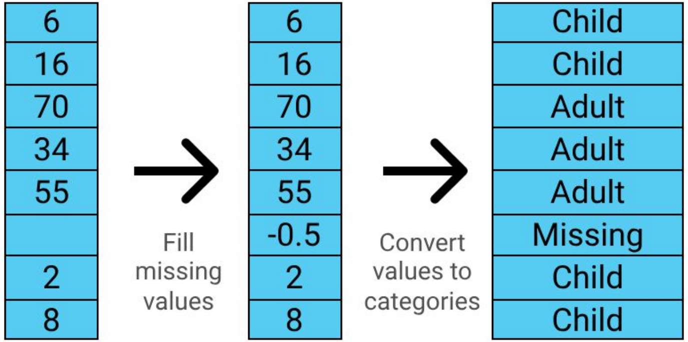
```
train.Age.isnull().sum()
```

```
177
```

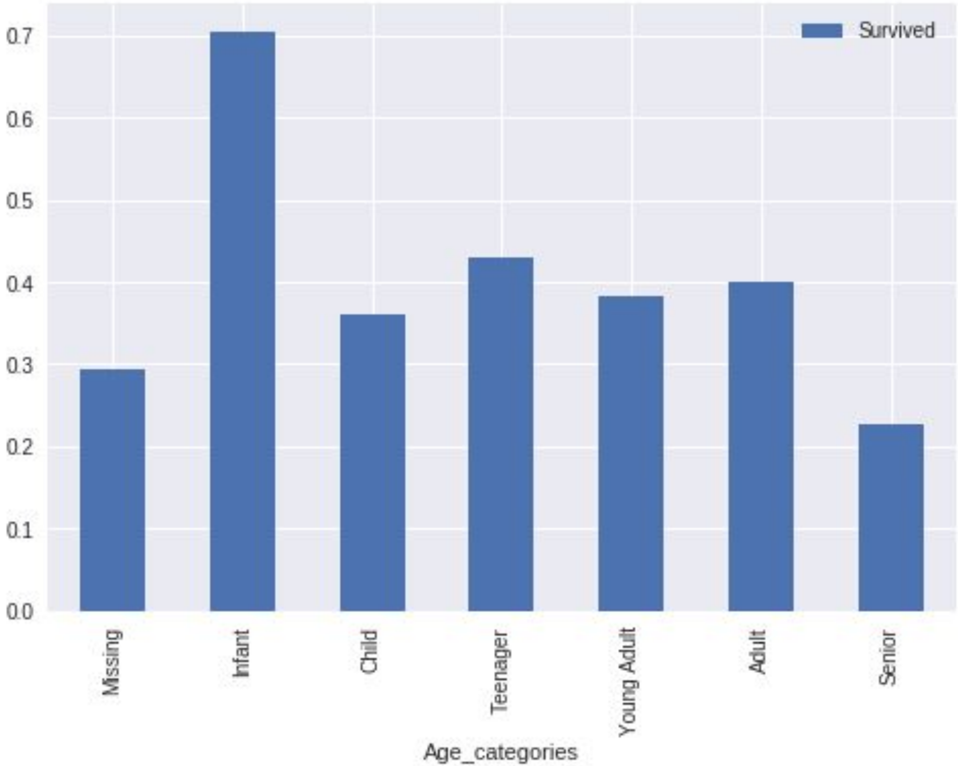


Exploring and Converting the Age Column

```
def process_age(df,cut_points,label_names):
    df["Age"] = df["Age"].fillna(-0.5)
    df["Age_categories"] = pd.cut(df["Age"],
                                  cut_points,
                                  labels=label_names)
    return df
cut_points = [-1,0,18,100]
label_names = ["Missing","Child","Adult"]
train = process_age(train,cut_points,label_names)
test = process_age(test,cut_points,label_names)
```



Exploring and Converting the Age Column



Preparing our Data for Machine Learning

- Sex
- Pclass
- Age
- Age_categories

- Before we build our model, we need to prepare these columns for machine learning.
- Most machine learning algorithms can't understand text labels, so we have to convert our values into numbers.

Preparing our Data for Machine Learning

Pclass
3
1
3
1
3
3
1
3
3
2

Pclass_1	Pclass_2	Pclass_3
0	0	1
1	0	0
0	0	1
1	0	0
0	0	1
0	0	1
1	0	0
0	0	1
0	0	1
0	1	0

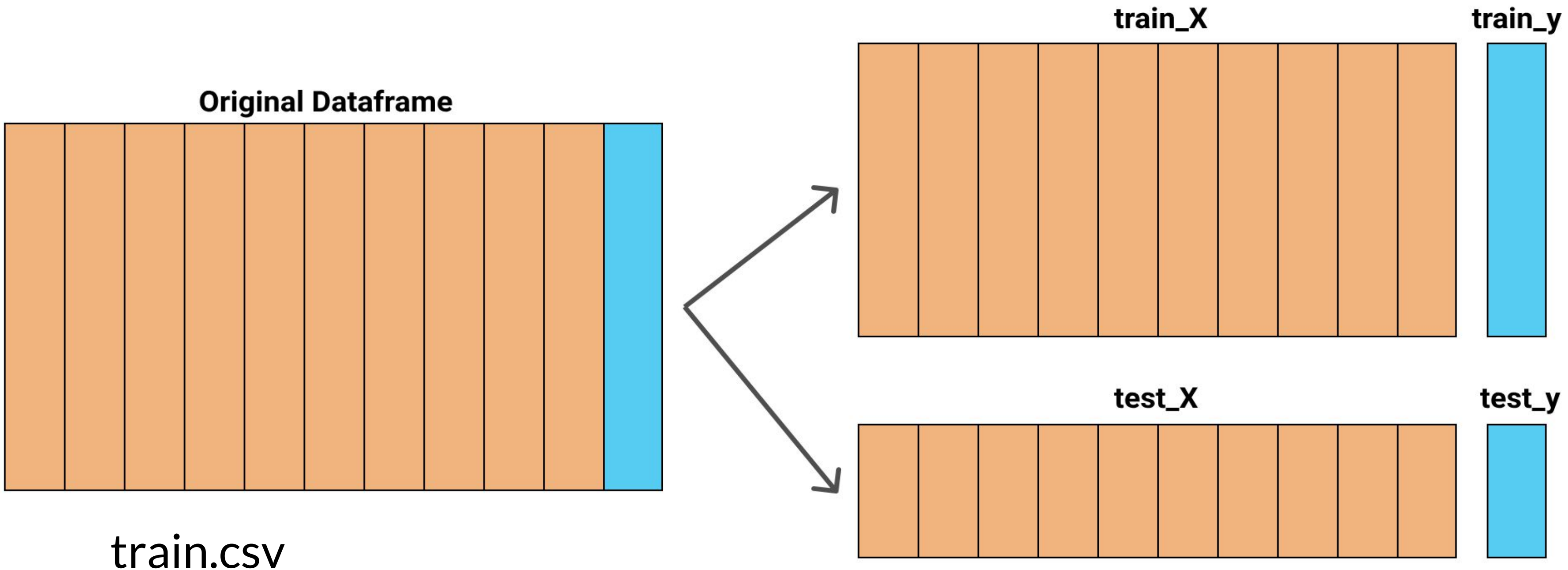
```
def create_dummies(df,column_name):
    dummies = pd.get_dummies(df[column_name],
                             prefix=column_name)
    df = pd.concat([df,dummies],axis=1)
    return df
train = create_dummies(train,"Pclass")
test = create_dummies(test,"Pclass")
```

Creating our First Machine Learning Model

The scikit-learn workflow consists of **four main steps**:

- **Instantiate** (or create) the specific machine learning model you want to use
- **Fit** the model to the training data
- Use the model to make **predictions**
- **Evaluate** the accuracy of the predictions

Creating our First Machine Learning Model



train.csv

Creating our First Machine Learning Model

```
holdout = test # from now on we will refer to this
               # dataframe as the holdout data

from sklearn.model_selection import train_test_split

columns = ['Pclass_1', 'Pclass_2', 'Pclass_3', 'Sex_female', 'Sex_male',
       'Age_categories_Missing','Age_categories_Infant',
       'Age_categories_Child', 'Age_categories_Teenager',
       'Age_categories_Young Adult', 'Age_categories_Adult',
       'Age_categories_Senior']

all_X = train[columns]
all_y = train['Survived']

train_X, test_X, train_y, test_y = train_test_split(
    all_X, all_y, test_size=0.20,random_state=0)
```

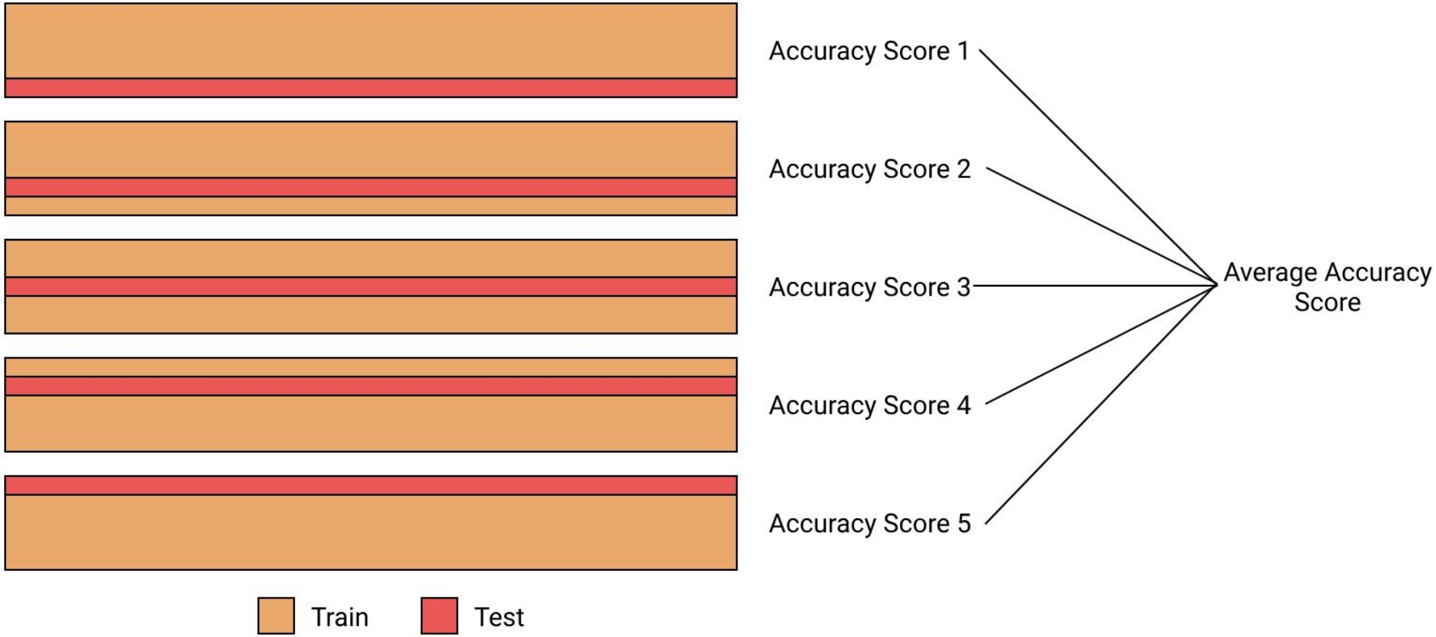
Making Predictions and Measuring their Accuray

```
from sklearn.metrics import accuracy_score

lr = LogisticRegression()
lr.fit(train_X, train_y)
predictions = lr.predict(test_X)

accuracy = accuracy_score(test_y, predictions)
print(accuracy)
```

```
0.8100558659217877
```

Our model's prediction	The actual value	Correct
0	0	Yes
1	0	No
0	1	No
1	1	Yes
1	1	Yes

Using cross validation for more accurate error measurement



Using cross validation for more accurate error measurement

```python
from sklearn.model_selection import cross_val_score
import numpy as np

lr = LogisticRegression()
scores = cross_val_score(lr, all_X, all_y, cv=10)
accuracy = np.mean(scores)
print(scores)
print(accuracy)
```

```
[0.8        0.81111111 0.7752809  0.87640449 0.80898876 0.78651685
 0.76404494 0.76404494 0.83146067 0.80681818]
0.8024670865963002
```

Making Predictions on Unseen Data

```
columns = ['Pclass_1', 'Pclass_2', 'Pclass_3', 'Sex_female', 'Sex_male',
           'Age_categories_Missing','Age_categories_Infant',
           'Age_categories_Child', 'Age_categories_Teenager',
           'Age_categories_Young Adult', 'Age_categories_Adult',
           'Age_categories_Senior']

lr = LogisticRegression()

lr.fit(all_X,all_y)

holdout_predictions = lr.predict(holdout[columns])
```

Creating a Submission File

PassengerId	Survived
892	0
893	1
894	0

```
holdout_ids = holdout["PassengerId"]

submission_df = {"PassengerId": holdout_ids,
                 "Survived": holdout_predictions}
submission = pd.DataFrame(submission_df)

submission.to_csv("submission.csv",index=False)
```

Making our first submission to kaggle

7999	new	kingsning	0.75598	2	13h
8000	new	hbruhn	0.75598	2	13h
8001	new	adam ardiansyah	0.75598	1	10h
8002	new	Penguin9	0.75598	10	6h
8003	new	Meghna Ayyar	0.75598	4	10h
8004	new	gauravgupta12	0.75598	3	3h
8005	new	Raph_Partouche	0.75598	1	3h
8006	new	IvanovitchSilva	0.75598	1	~10s

Your Best Entry ↑

Your submission scored 0.75598, which is not an improvement of your best score. Keep trying!

8007	▾ 878	Sudarshan Kannan	0.75119	7	2mo
8008	▾ 878	Raunak Kumar	0.75119	1	2mo
8009	▾ 878	cyrilb38	0.75119	1	2mo
8010	▾ 878	simon 27	0.75119	3	2mo

Next Steps

- **Improving the features:**
  - Feature Engineering: Create new features from the existing data.
  - Feature Selection: Select the most relevant features to reduce noise and overfitting.
- **Improving the model:**
  - Model Selection: Try a variety of models to improve performance.
  - Hyperparameter Optimization: Optimize the settings within each particular machine learning model.

1. Getting Started with Kaggle.ipynb

Preparing more features

	SibSp	Parch	Fare	Cabin	Embarked
count	891.000000	891.000000	891.000000	204	889
unique	NaN	NaN	NaN	147	3
top	NaN	NaN	NaN	C23 C25 C27	S
freq	NaN	NaN	NaN	4	644
mean	0.523008	0.381594	32.204208	NaN	NaN
std	1.102743	0.806057	49.693429	NaN	NaN
min	0.000000	0.000000	0.000000	NaN	NaN
25%	0.000000	0.000000	7.910400	NaN	NaN
50%	0.000000	0.000000	14.454200	NaN	NaN
75%	1.000000	0.000000	31.000000	NaN	NaN
max	8.000000	6.000000	512.329200	NaN	NaN

```
train[columns].isnull().sum()
```

```
SibSp         0
Parch         0
Fare          0
Cabin       687
Embarked      2
dtype: int64
```

```
holdout[columns].isnull().sum()
```

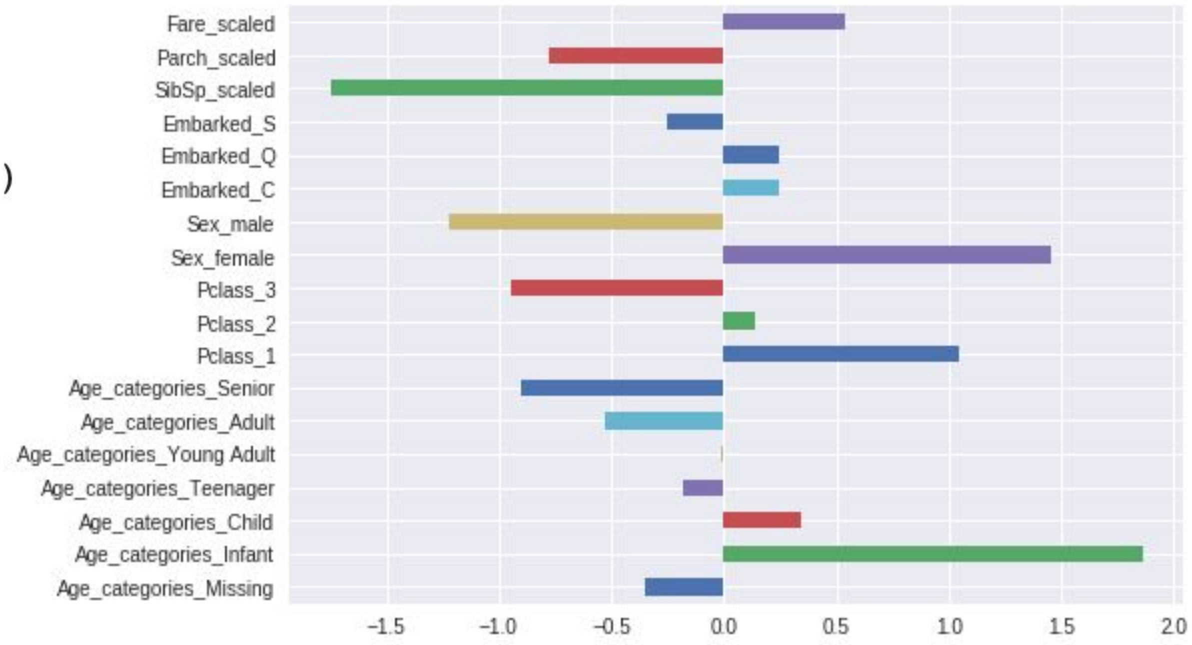
```
SibSp         0
Parch         0
Fare          1
Cabin       327
Embarked      0
dtype: int64
```

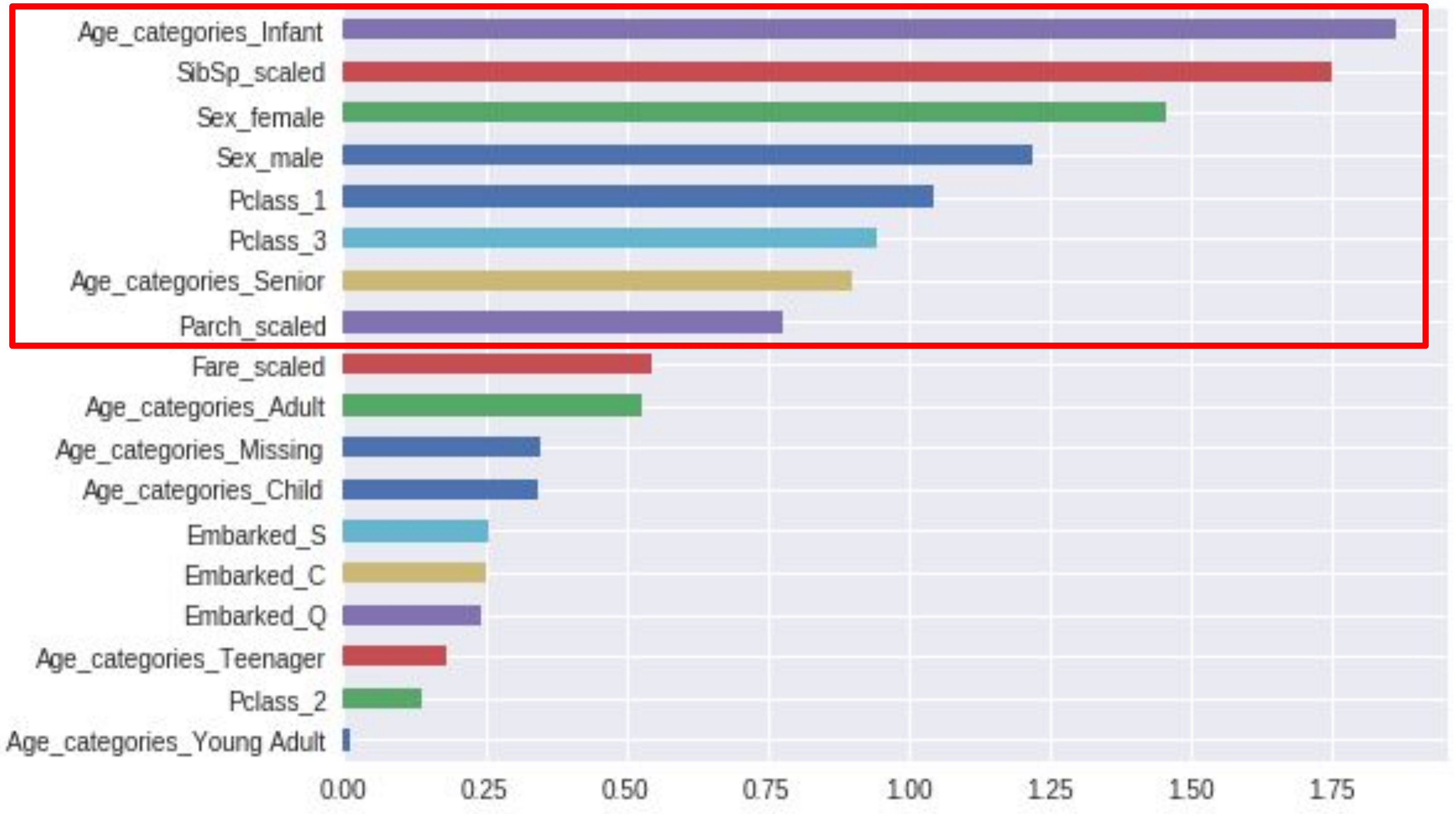
Preparing more features

```python
from sklearn.preprocessing import minmax_scale
# The holdout set has a missing value in the Fare column which
# we'll fill with the mean.
holdout["Fare"] = holdout["Fare"].fillna(train["Fare"].mean())
columns = ["SibSp","Parch","Fare"]

train["Embarked"] = train["Embarked"].fillna("S")
holdout["Embarked"] = holdout["Embarked"].fillna("S")

train = create_dummies(train,"Embarked")
holdout = create_dummies(holdout,"Embarked")

for col in columns:
    train[col + "_scaled"] = minmax_scale(train[col])
    holdout[col + "_scaled"] = minmax_scale(holdout[col])
```

Determining the most relevant features

```
lr = LogisticRegression()
lr.fit(train_X,train_y)
coefficients = lr.coef_
```




Age_categories_Infant
SibSp_scaled
Sex_female
Sex_male
Pclass_1
Pclass_3
Age_categories_Senior
Parch_scaled
Fare_scaled
Age_categories_Adult
Age_categories_Missing
Age_categories_Child
Embarked_S
Embarked_C
Embarked_Q
Age_categories_Teenager
Pclass_2
Age_categories_Young Adult
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75

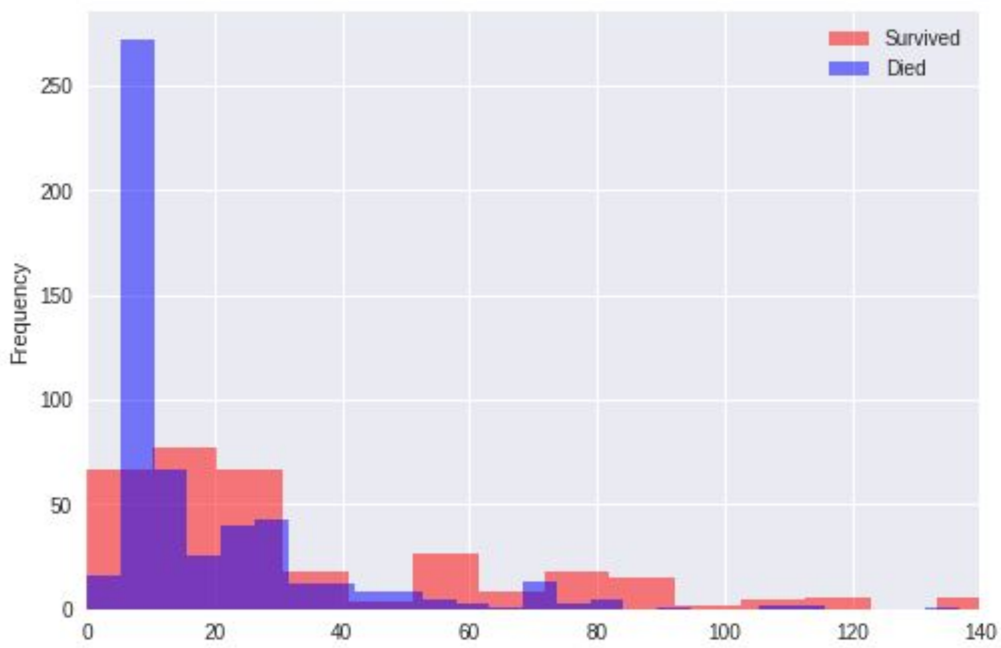
Training a model using relevant features

```python
from sklearn.model_selection import cross_val_score

columns = ['Age_categories_Infant', 'SibSp_scaled', 'Sex_female', 'Sex_male',
           'Pclass_1', 'Pclass_3', 'Age_categories_Senior', 'Parch_scaled']
all_X = train[columns]
all_y = train['Survived']

lr = LogisticRegression()
scores = cross_val_score(lr, all_X, all_y, cv=10)
accuracy = scores.mean()
print(accuracy)
```

```
0.8148019521053229
```

When you submit it to Kaggle, you'll see that the store is 77.33%

Engineering a new feature using binning



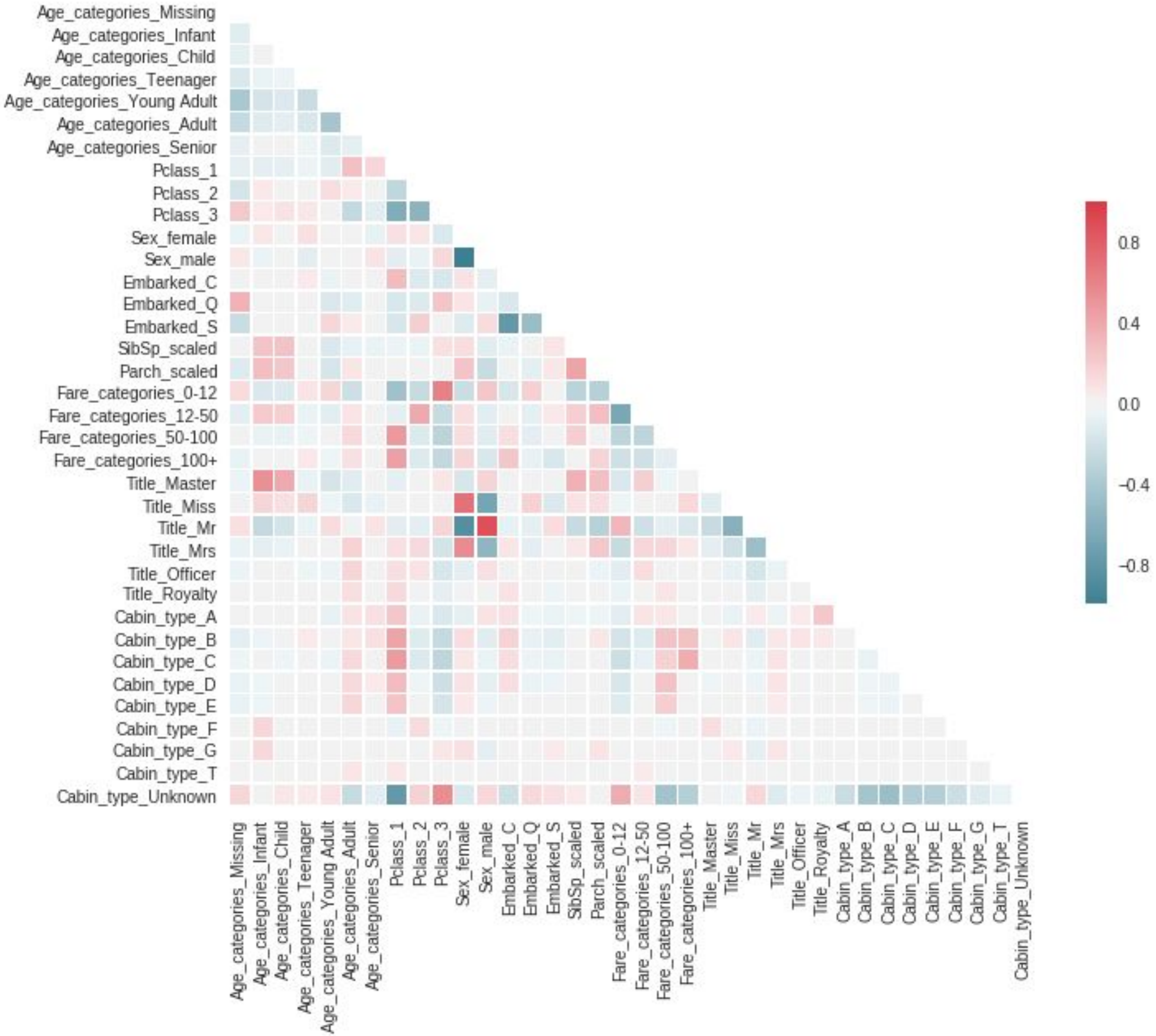
Looking at the values, it looks like we can separate the feature into four bins to capture some patterns from the data:

- 0-12
- 12-50
- 50-100
- 100+

Engineering features from text columns

	Name	Cabin
772	Mack, Mrs. (Mary)	E77
148	Navratil, Mr. Michel ("Louis M Hoffman")	F2
707	Calderhead, Mr. Edward Pennington	E24
879	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)	C50
21	Beesley, Mr. Lawrence	D56
456	Millet, Mr. Francis Davis	E38
97	Greenfield, Mr. William Bertram	D10 D12
263	Harrison, Mr. William	B94
393	Newell, Miss. Marjorie	D36
759	Rothes, the Countess. of (Lucy Noel Martha Dye...	B77

```
titles = {
    "Mme":          "Mrs",
    "Ms":           "Mrs",
    "Mrs" :         "Mrs",
    "Countess":     "Royalty",
    "Lady" :        "Royalty"
}
extracted_titles = train["Name"].str.extract('([A-Za-z]+)\.', expand=False)
train["Title"] = extracted_titles.map(titles)
```



Finding Correlated Features

Final Feature Selection using RFECV

```
from sklearn.feature_selection import RFECV

columns = ['Age_categories_Missing', 'Age_categories_Infant',
       'Age_categories_Child', 'Age_categories_Young Adult',
       'Age_categories_Adult', 'Age_categories_Senior', 'Pclass_1', 'Pclass_3',
       'Embarked_C', 'Embarked_Q', 'Embarked_S', 'SibSp_scaled',
       'Parch_scaled', 'Fare_categories_0-12', 'Fare_categories_50-100',
       'Fare_categories_100+', 'Title_Miss', 'Title_Mr', 'Title_Mrs',
       'Title_Officer', 'Title_Royalty', 'Cabin_type_B', 'Cabin_type_C',
       'Cabin_type_D', 'Cabin_type_E', 'Cabin_type_F', 'Cabin_type_G',
       'Cabin_type_T', 'Cabin_type_Unknown']

all_X = train[columns]
all_y = train["Survived"]
lr = LogisticRegression()
selector = RFECV(lr,cv=10)
selector.fit(all_X,all_y)

optimized_columns = all_X.columns[selector.support_]
```

Training a model using our optimized columns

4012	new	**Lech Brzozowski**	0.78468	5	12h
4013	new	**chen 10**	0.78468	6	10h
4014	new	**warrior2005**	0.78468	3	10h
4015	new	**Manoj reddy**	0.78468	1	10h
4016	new	**CharlieStElmo**	0.78468	17	8h
4017	▲ 752	**Topornin Dmitry**	0.78468	8	7h
4018	▲ 1072	**SuryaveerSingh**	0.78468	8	4h
4019	new	**Monster Zhong**	0.78468	2	1h
4020	new	**IvanovitchSilva**	0.78468	3	~10s

Your Best Entry ↑

You advanced 1,983 places on the leaderboard!

Your submission scored 0.78468, which is an improvement of your previous score of 0.77033. Great job!

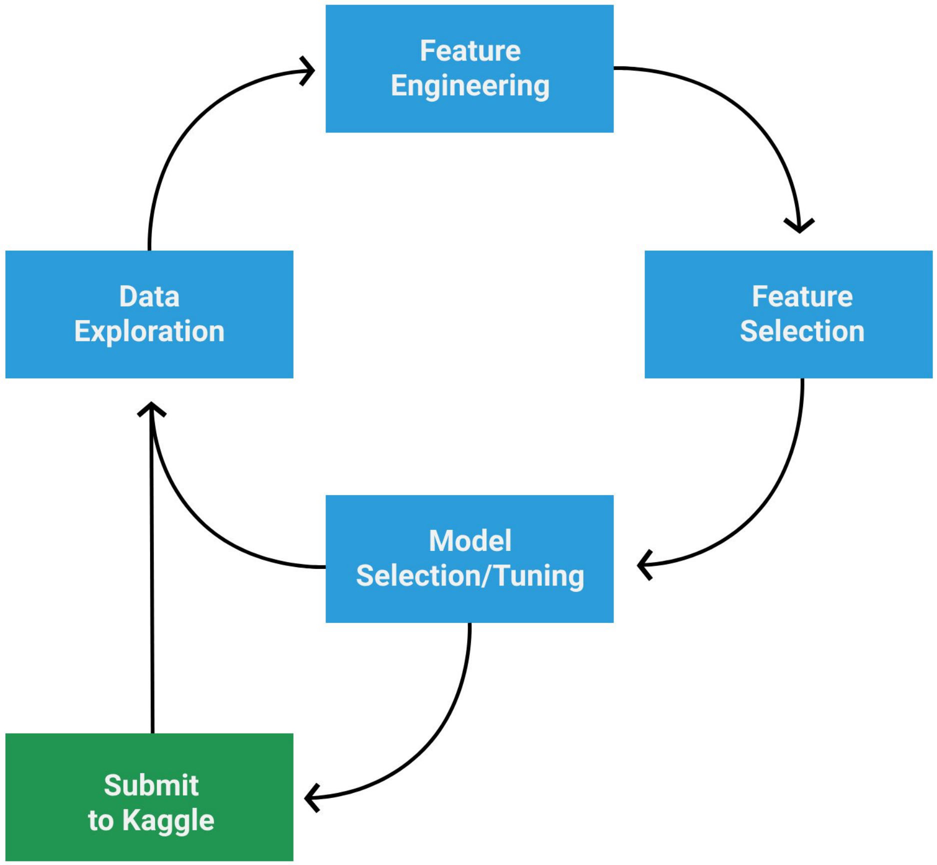
Tweet this!

Next Steps

Here are some ideas that you can use to work with features for this competition:

- Use **SibSp** and **Parch** to explore total relatives onboard.
- Create combinations of multiple columns, for instance **Pclass + Sex.**
- See if you can extract useful data out of the **Ticket** column.
- Try different combinations of features to see if you can identify features that overfit less than others.
- we'll look at selecting and **optimizing different models** to improve our score

2. Feature Preparation, Selection and Engineering.ipynb


Feature
Engineering
Data
Exploration
Feature
Selection
Model
Selection/Tuning
Submit
to Kaggle

Model	Cross-validation score	Kaggle score
Previous best Kaggle score	82.36%	78.48%
Logistic regression baseline	82.38%	
K-nearest neighbors, k == 1	78.57%	
K-nearest neighbors, k == 19	82.38%	
K-nearest neighbors, best model from grid search	82.82%	75.59%
Random forests, default hyperparameters	80.70%	
Random forests, best model from grid search	84.28%	77.55%

3. Model Selection and Tuning.ipynb
4. Guided Project - Creating a Kaggle Workflow.ipynb