Assignment_2??xjgy

July 9, 2019

1 Assignment 2

The purpose of this assignment is to test your understanding of Classification. You will use the Titanic dataset and your goal is to predict whether a passenger Survives based on the passenger's features.

2 Instructions

2.1 General

1. Use the same train dataset as was used in the lecture. Instructions below for where to find them.
2. As usual: your grade depends on **both** the correct answer and properly presenting your process (as in the "Recipe" taught in class, and the Geron book Appendix B)
3. You will classify whether a passenger Survives or not using Logistic Regression.
4. You may use the code presented in class to **start** your assignment but I expect you to significantly enhance it. For example: you may use my code to get you started with plotting but it is up to you to decide whether this alone suffices.
5. Use 5-fold cross validation for all models. Report the average as your result.

2.2 Specific goals to address

1. Use a baseline model against which you will compare your models.
   - Discuss your choice. Is this the best baseline model to use ?
   - Create a variable SCORE_BASELINE that contains a Python scalar value: the accuracy for your baseline model.
2. You will conduct several experiments
   - present a Confusion Matrix for each experiment and discuss
   - you will create several variables per experiment that will be used for grading.
     - The variables for experiment 1 will have suffix "_1". For experiment 2, they will have suffix "_2", etc.
3. Experiment 1

- You will *extend* the results presented in the lecture
  - use the same features
  - use the same way of dealing with missing features
  - be sure to treat categorical features correctly
- Create a variable SCORE_1 that contains a Python scalar value: the accuracy for your experiment.
- Create a variable MISCLASSIFIED_SURVIVE_1 that contains a Python list of *at least 10* passengers
  - the list should contain the identity of passengers that were mis-classified as Surviving.
  - the "identity" of a passenger should be given as the *row number* within the unshuffled **train** data set,
  - The first row is considered row 0
- Create a variable MISCLASSIFIED_NOT_SURVIVE_1 that contains a Python list of *at least 10* passengers
  - the list should contain the "identity" of passengers that were mis-classified as Not Surviving.
  - The "identity" of a passenger should be given as the *row number* within the unshuffled **train** data set, as above

4. Experiment 2

- Turn Age from a continous variable to one that is assigned to buckets.
  - You will decide the range for each bucket. Discuss your choice
  - Treat the buckets as categorical features
- Compare your prediction to the previous experiment and discuss
- Create variables SCORE_2, MISCLASSIFIED_SURVIVE_2, MISCLASSIFIED_NOT_SURVIVE_2 analagous to the variables in Experiment 1

The correctness part of your grade will depend on the values you assign to these variables.

3 Extra credit

Create your own Logistic Regression model for the Titanic dataset given ! - Feel free to change **anything**, e.g., features or ways to treat missing values - We will create a hidden test dataset - Students whose model accuracy (evaluated on the hidden test dataset) are in the Top 33% of the class get extra credit !

4 Getting the data

You may obtain the train and test datasets from the repository using code from the following cell.

NOTE You may need to change the NOTEBOOK_ROOT variable to point to the directory into which you've cloned the repository. On my machine, it is `~/Notebooks/NYU`.

In [1]:
```
import pandas as pd
import os
import matplotlib.pyplot as plt
```

```
import numpy as np

TITANIC_PATH = "external/jack-dies/data"

train_data = pd.read_csv( os.path.join(TITANIC_PATH, "train.csv") )
test_data  = pd.read_csv( os.path.join(TITANIC_PATH, "test.csv")  )
```

5 Plotting data and getting a brief view of data

In [2]:
```
train_data.head()
```

Out[2]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

In [3]:
```
train_data.iloc[14,:]
```

Out[3]:
```
PassengerId                                  15
Survived                                      0
Pclass                                        3
Name           Vestrom, Miss. Hulda Amanda Adolfina
Sex                                      female
Age                                          14
SibSp                                         0
Parch                                         0
Ticket                                   350406
Fare                                     7.8542
Cabin                                       NaN
Embarked                                      S
Name: 14, dtype: object
```

In [4]:
```
train_data.columns
```

```
Out[4]: Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
               'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
              dtype='object')
```

```
In [5]: (num_obs, num_features) = train_data.shape
        print("There are {nr} observations and {nf} attributes (including the target)".format(r
```

```
There are 891 observations and 12 attributes (including the target)
```

As shown above, we have 10 raw features and 1 label (exlucidng Passenger ID)

Meaning of the attributes

The attributes have the following meaning: * **Survived**: that's the target, 0 means the passenger did not survive, while 1 means he/she survived.We use this as label * **Pclass**: passenger class. * **Name**, **Sex**, **Age**: self-explanatory * **SibSp**: how many siblings & spouses of the passenger aboard the Titanic. * **Parch**: how many children & parents of the passenger aboard the Titanic. * **Ticket**: ticket id * **Fare**: price paid (in pounds) * **Cabin**: passenger's cabin number * **Embarked**: where the passenger embarked the Titanic

Examining datatype and missing value is also important step to know better about the raw data

```
In [6]: train_data.info()
```

```
<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
```

Missing value and Nonnumerical data

Easily, we can find that **Age** , **Embarked** and **Cabin** have missing value. Also, **Cabin** have a large porpotion of missing, while **Embarked** only have 2 missing values

And **Name**, **sex**, **ticket**, **Cabin** and **Embarked** are objects. These need to be transformed.

```
In [7]: train_data.describe()
```

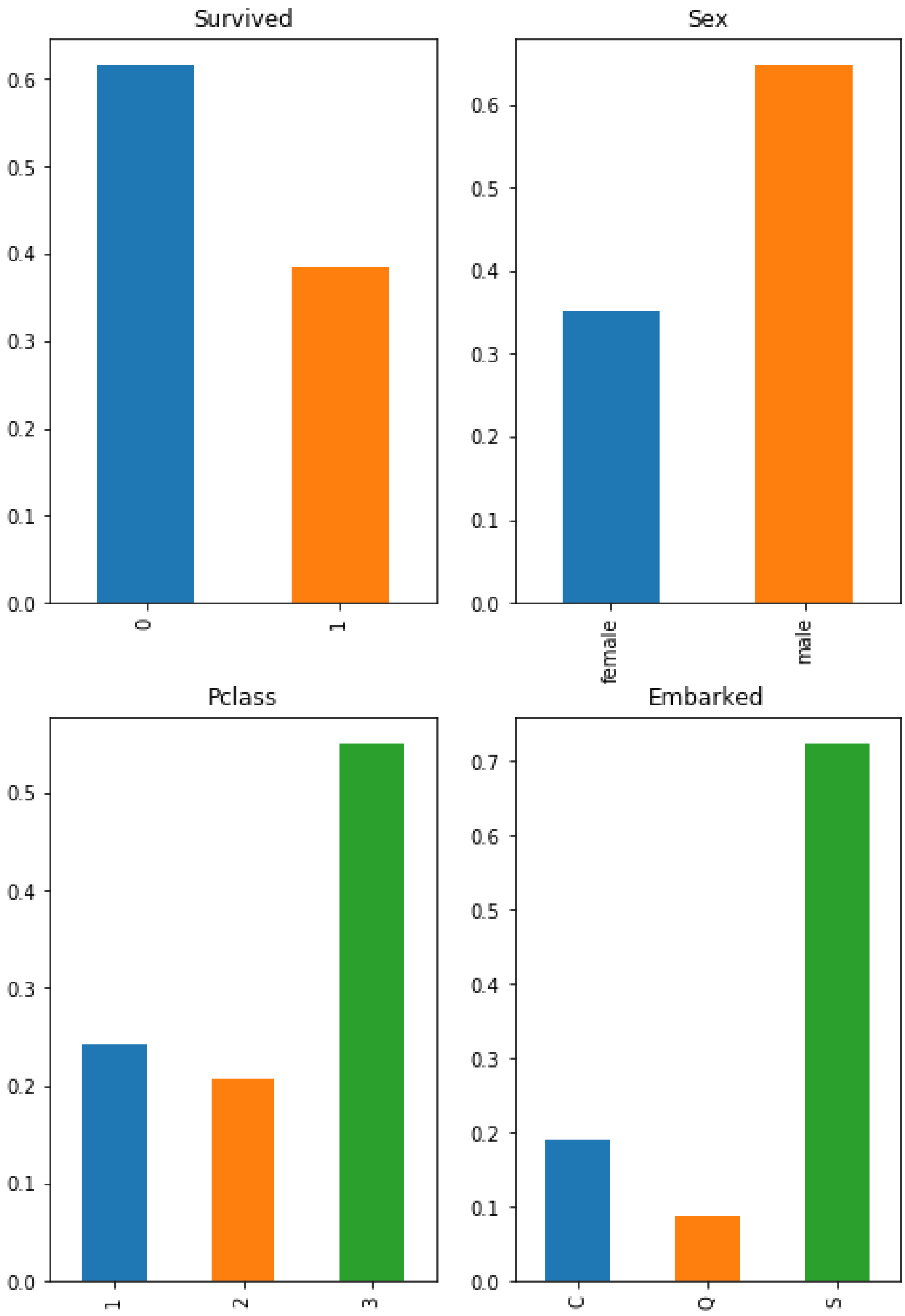
```
Out[7]:        PassengerId    Survived      Pclass         Age       SibSp  \
       count    891.000000  891.000000  891.000000  714.000000  891.000000
       mean     446.000000    0.383838    2.308642   29.699118    0.523008
       std      257.353842    0.486592    0.836071   14.526497    1.102743
       min        1.000000    0.000000    1.000000    0.420000    0.000000
       25%      223.500000    0.000000    2.000000   20.125000    0.000000
       50%      446.000000    0.000000    3.000000   28.000000    0.000000
       75%      668.500000    1.000000    3.000000   38.000000    1.000000
       max      891.000000    1.000000    3.000000   80.000000    8.000000

                   Parch        Fare
       count  891.000000  891.000000
       mean     0.381594   32.204208
       std      0.806057   49.693429
       min      0.000000    0.000000
       25%      0.000000    7.910400
       50%      0.000000   14.454200
       75%      0.000000   31.000000
       max      6.000000  512.329200
```

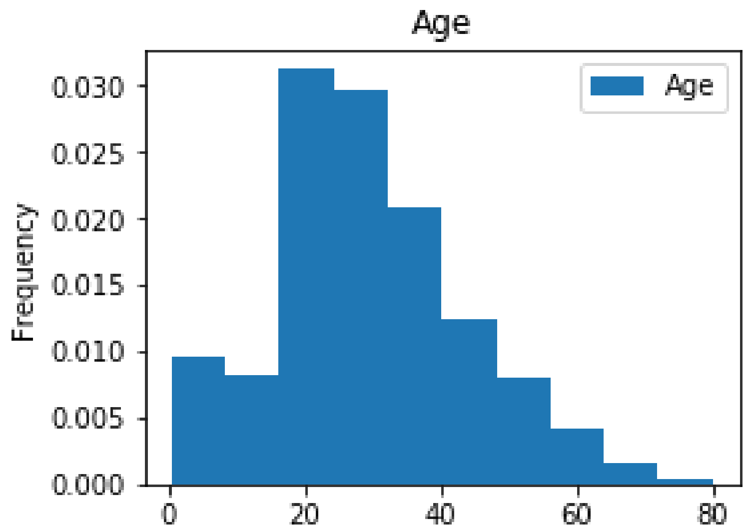
Using the plotting function seen in class

```
In [8]: def plot_attrs(df, attrs, attr_type="Cat", normalize=True, plot=True):
            """
            Plot/print the distribution of one or more attributes of DataFrame

            Parameters
            ----------
            df: DataFrame
            attrs: List of attributes (i.e., column names)

            Optional
            --------
            attr_type: String;
              "Cat" to indicate that the attributes in attrs are Categorical (so use value_cou
              Otherwise: the attributes must be numeric columns (so use histogram)
            """
            num_attrs = len(attrs)
            ncols=2
            nrows = max(1,round(num_attrs/ncols))
            if num_attrs==1:
                fig, axes = plt.subplots(nrows=nrows, ncols=1, figsize=(4, num_attrs*3))
            else:
                fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(ncols*4, num_attrs
            # Make sure axes is an array (special case when num_attrs==1)
            if num_attrs == 1:
                axes =np.array( [ axes ])
```

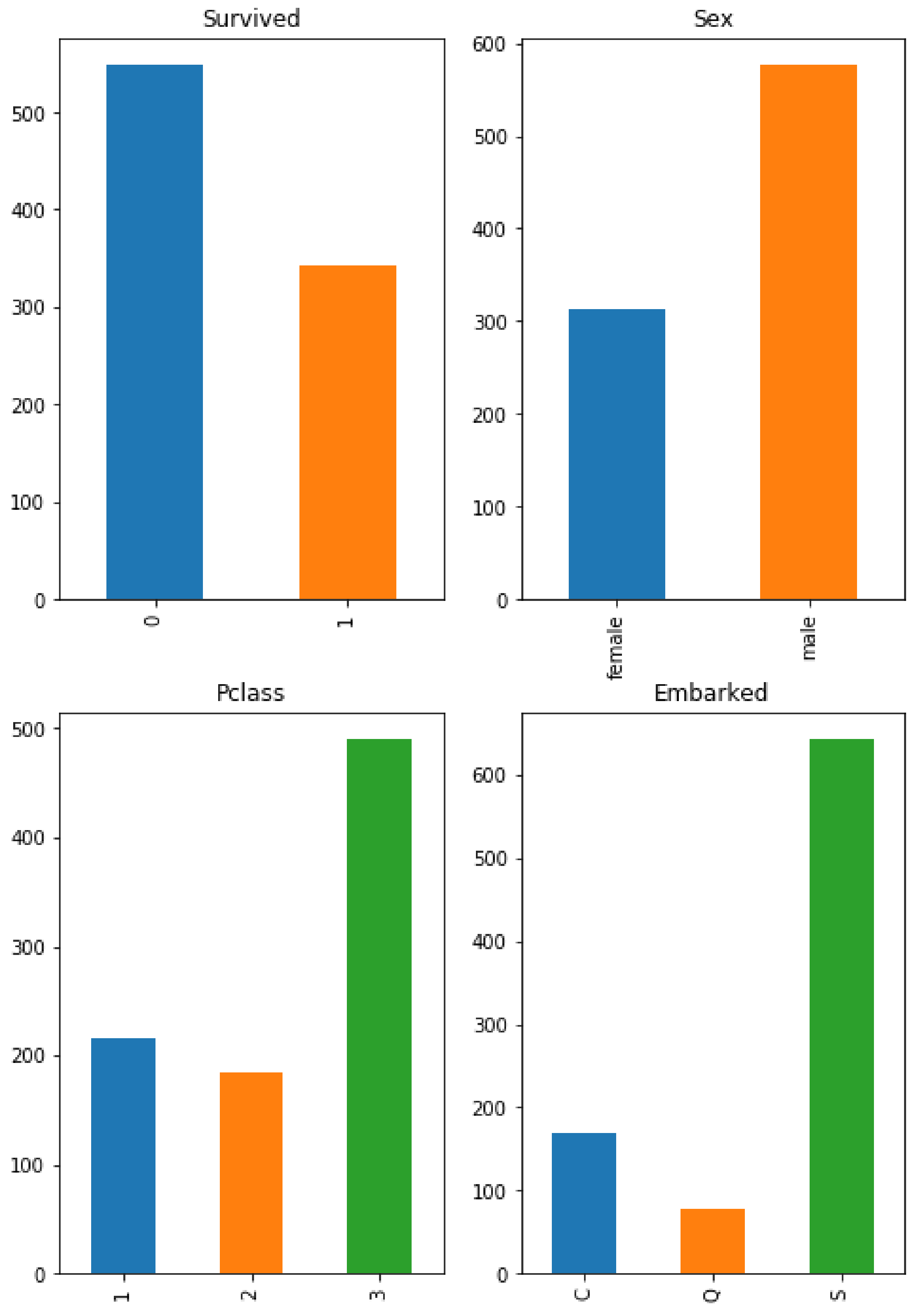
```
        for i, attr in enumerate(attrs):
            if attr_type == "Cat":
                alpha_bar_chart = 0.55
                plot_data = df.loc[:, attr ].value_counts(normalize=normalize).sort_index()

                args = { "kind":"bar" } #, "alpha":alpha_bar_chart}
                kind="bar"
            else:
                plot_data = df.loc[:, [attr] ]

                args = { "kind":"hist"}
                if normalize:
                    args["density"] = True
                kind="hist"

            if plot:
                _ = plot_data.plot(title=attr, ax=axes.flatten()[i], **args)
            else:
                print(attr + "\n")
                print(plot_data)
                print("\n")
```

```
In [9]: plot_attrs(train_data, [ "Survived", "Sex", "Pclass", "Embarked" ], attr_type="Cat", pl
        plot_attrs(train_data, [ "Age" ], attr_type="Num")
```


Survived
Sex
Pclass
Embarked
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
1
female
male
1
2
3
C
Q
S



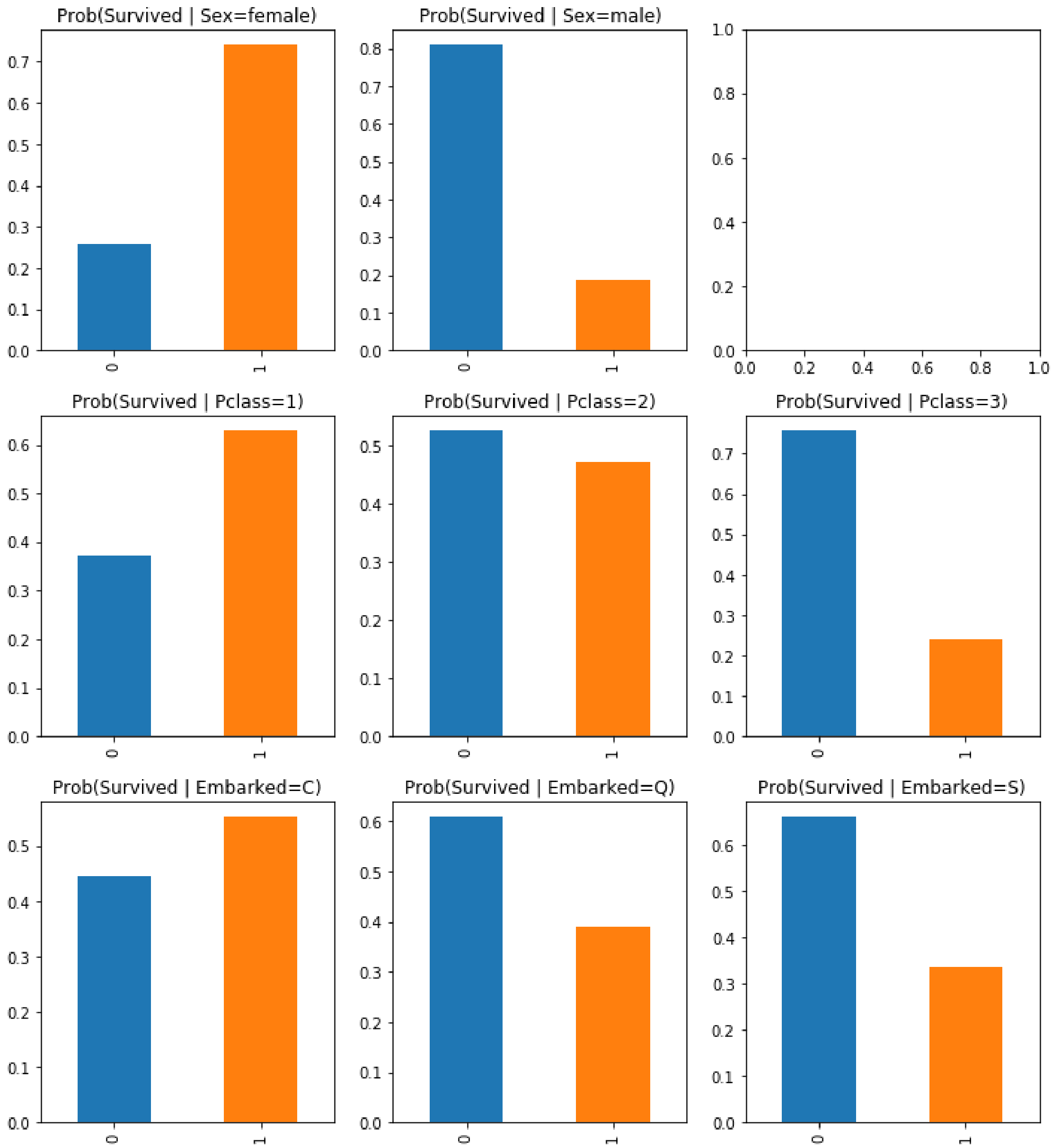

```
In [10]: plot_attrs(train_data, [ "Survived", "Sex", "Pclass", "Embarked" ], attr_type="Cat", p
```


Survived
0
100
200
300
400
500
0
1
Sex
0
100
200
300
400
500
600
female
male
Pclass
0
100
200
300
400
500
1
2
3
Embarked
0
100
200
300
400
500
600
C
Q
S

```
In [11]: def plot_cond( df, var, conds, ax, normalize=True):
             """
             Plot probability of a value in column var of DataFrame df, conditional on conditi

             Parameters
             ----------
             df: DataFrame
             var: String.  Name of column in df whose density we will plot
             conds: Dictionary
             - keys are Strings, which are names of columns in df
             - values are values that could be compared with column at the key


             """
             plot_data = df.copy()
             title_array = []

             for cond, val in conds.items():
                 title_array.append( "{c}={v}".format(c=cond, v=val))
                 plot_data = plot_data.loc[ plot_data.loc[:, cond] == val, : ]

                 args = { "kind": "bar"}


             plot_data = plot_data.loc[:, var ]

             title = ", ".join(title_array)
             title = "Prob({v} | {t})".format(v=var, t=title)
             plot_data.value_counts(normalize=normalize).sort_index().plot(title=title, ax=ax,

         def plot_conds(df, specs):
             """
             Print multiple conditional plots using plot_cond

             Parameters
             -----------
             df: DataFrame
             specs: List. Each element of the list is a tuple (var, conds)
             -  each element of the list generates a call to plot_cond(df, var, conds)
             """
             num_specs = len(specs)
             ncols=3
             nrows = max(1,round(.4999 + num_specs/ncols))

             fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(ncols*4, num_specs*1.

             # Make sure axes is an array (special case when num_attrs==1)
             if num_specs == 1:
```

```
            axes =np.array( [ axes ])

        for i, spec in enumerate(specs):
            if spec is None:
                continue
            (var, conds) = spec
            plot_cond(df, var, conds, ax=axes.flatten()[i])
```

```
In [12]: plot_conds(train_data, [ ("Survived", { "Sex": "female"}),
                                  ("Survived", { "Sex": "male"}),
                                  None,
                                  ("Survived", { "Pclass": 1}),
                                  ("Survived", { "Pclass": 2}),
                                  ("Survived", { "Pclass": 3}),

                                  ("Survived", { "Embarked":"C"}),
                                  ("Survived", { "Embarked":"Q"}),
                                  ("Survived", { "Embarked":"S"}),
                                ]
                   )
```



6 Making pipeline for numerical data

In [13]:
```
from sklearn.base import BaseEstimator, TransformerMixin

# A class to select numerical or categorical columns
# since Scikit-Learn doesn't handle DataFrames yet
#fit: doesn't do anything and just return to the original DataFrame
# transform: transfer DataFrame into Series
class DataFrameSelector(BaseEstimator, TransformerMixin):
```

```
    def __init__(self, attribute_names):
        self.attribute_names = attribute_names
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        return X[self.attribute_names]



from sklearn.pipeline import Pipeline
try:
    from sklearn.impute import SimpleImputer # Scikit-Learn 0.20+
except ImportError:
    from sklearn.preprocessing import Imputer as SimpleImputer

num_features = ["Age", "SibSp", "Parch", "Fare"] #numerical features

num_pipeline = Pipeline([
        ("select_numeric", DataFrameSelector( num_features )), #set the parameter for
        ("imputer", SimpleImputer(strategy="median")),          #set the parameter for
    ])
```

7 Making pipeline for non-numerical data

To correctly deal with the catogorical data: - transfer categorical data into dummy variables - delete one of dummy variables for each category

The second step is to reduce colinearity of the dummy variables: eliminating one of the dummy variable is a way to cut down colinearity/

```
In [14]: class MostFrequentImputer(BaseEstimator, TransformerMixin):
             def fit(self, X, y=None):
                 self.most_frequent_ = pd.Series([X[c].value_counts().index[0] for c in X],
                                                 index=X.columns)
                 return self
             def transform(self, X, y=None):
                 return X.fillna(self.most_frequent_)

         class droplastcolumn(BaseEstimator, TransformerMixin):

                 self.whichcolumn = whichcolumn
             def fit(self, X, y=None):
                 return self
             def transform(self, X, y=None):
                 return np.delete(X, self.whichcolumn, 1)

         class SexToInt(BaseEstimator, TransformerMixin):
             def fit(self, X, y=None):
```

```
            return self

        def transform(self, X, y=None):


            sex = X["Sex"]
            X["Sex"] = 0
            X[ sex == "female" ] = 1

            return(X)

from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import FeatureUnion

cat_features = [ "Pclass" ]
sex_features = [ "Sex" ]

cat_pipeline = Pipeline([
        ("select_cat", DataFrameSelector( cat_features )),
        ("imputer", MostFrequentImputer()),
        ("cat_encoder", OneHotEncoder(sparse=False)),
       ("drop_one_of_dummy",droplastcolumn(-1)),
    ])

sex_pipeline = Pipeline([
        ("select_cat", DataFrameSelector( sex_features )),
        ("imputer", MostFrequentImputer()),
        ("SexToInt", SexToInt()),
    ])

preprocess_pipeline = FeatureUnion(transformer_list=[
        ("num_pipeline", num_pipeline),
        ("sex_pipeline", sex_pipeline),
        ("cat_pipeline", cat_pipeline),
    ])
```

```
In [15]: X_train=preprocess_pipeline.fit_transform(train_data) #it is a ndarray
         X_train.shape #each column refers to  ["Age", "SibSp", "Parch", "Fare"] ["Sex"]["Dum_
```

```
Out[15]: (891, 7)
```

```
In [16]: X_train[0]
```

```
Out[16]: array([22.  ,  1.  ,  0.  ,  7.25,  0.  ,  0.  ,  0.  ])
```

```
In [17]: X_train_index = ["Age", "SibSp", "Parch", "Fare","Sex","Dum_Pclass_1","Dum_ Pclass_2"]
```

```
In [18]: y_train = train_data["Survived"]
```

8 Baseline Model

There are two reasons why I choose most_frequent model as baseline model here: - First is that the model has highest accuracy among all the baseline models - Another is that most frequent model tells us how the data is biased. Comparing this accuracy with later models, we can know how much we improve by using better models

```
In [19]: from sklearn.model_selection import cross_val_score
         from sklearn.dummy import DummyClassifier
         dmy_clf = DummyClassifier(strategy="most_frequent")
         acc_scores_dmy = cross_val_score(dmy_clf, X_train, y_train, cv=5, scoring="accuracy")
         SCORE_BASELINE =  acc_scores_dmy
         print("{s}: Accuracy = {a:.4f}".format(s="Baseline Model most_frequent", a=acc_scores_
```

```
Baseline Model most_frequent: Accuracy = 0.6162
```

9 Experiment 1

I will use Logistic Model and 5-fold cross validation.

```
In [20]: from sklearn import linear_model, preprocessing, model_selection
         from sklearn.ensemble import RandomForestClassifier

         logistic_clf = linear_model.LogisticRegression(solver='liblinear')
```

To evaluate the model, accuracy is used

```
In [21]: SCORE_1 = cross_val_score(logistic_clf, X_train, y_train, cv=5, scoring = "accuracy")
         SCORE_1 = SCORE_1.mean()
         SCORE_1
```

```
Out[21]: 0.7868160254657532
```

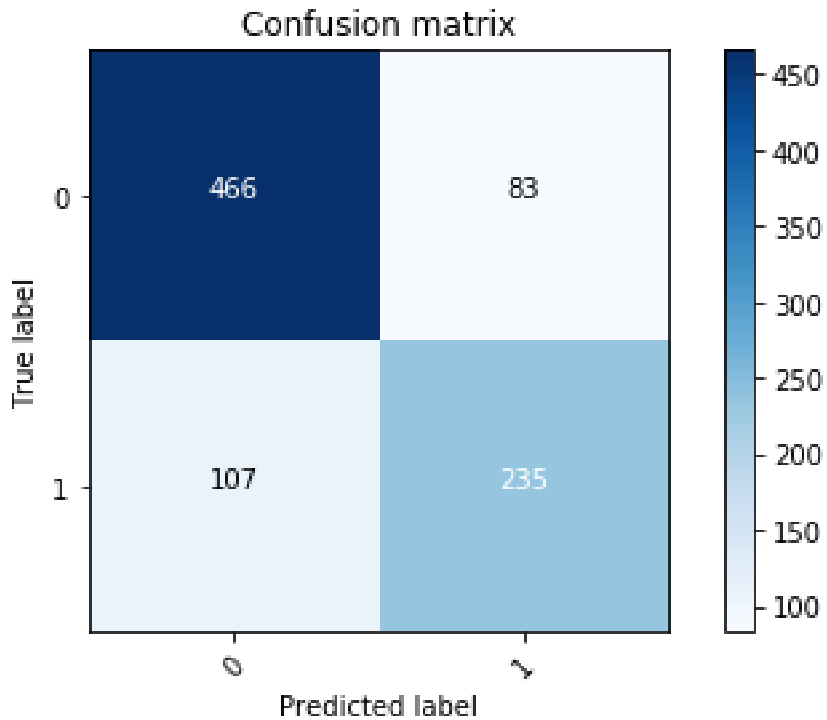
```
In [22]: print("{s}: Accuracy = {a:.4f}".format(s="Experiment_1 Model  ", a=SCORE_1.mean()))
```

```
Experiment_1 Model  : Accuracy = 0.7868
```

```
In [23]: from sklearn.model_selection import cross_val_predict
         from sklearn import datasets, svm, metrics
         from sklearn.metrics import precision_recall_curve
         expected_1 = y_train
         predicted_1 = cross_val_predict(logistic_clf, X_train, y_train, cv=5)

         confusion_mat_1 = metrics.confusion_matrix(expected_1, predicted_1)
```

```
In [24]: # %load mnist_plot_confusion.py
         import itertools

         def plot_confusion_matrix(cm, classes,
                                   normalize=False,
                                   title='Confusion matrix',
                                   cmap=plt.cm.Blues):
             """
             This function prints and plots the confusion matrix.
             Normalization can be applied by setting `normalize=True`.
             """
             if normalize:
                 # Normalize by row sums
                 cm_pct = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                 cm = np.around( 100 * cm_pct, decimals=0).astype(int)

                 print("Normalized confusion matrix")
             else:
                 print('Confusion matrix, without normalization')

             plt.imshow(cm, interpolation='nearest', cmap=cmap)
             plt.title(title)
             plt.colorbar()
             tick_marks = np.arange(len(classes))
             plt.xticks(tick_marks, classes, rotation=45)
             plt.yticks(tick_marks, classes)

             fmt = '.2f' if normalize else 'd'
             fmt = 'd'
             thresh = cm.max() / 2.
             for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                 # Plot coordinate system has origin in upper left corner
                 # -  coordinates are (horizontal offset, vertical offset)
                 # -  so cm[i,j] should appear in plot coordinate (j,i)
                 plt.text(j, i, format(cm[i, j], fmt),
                          horizontalalignment="center",
                          color="white" if cm[i, j] > thresh else "black")

             plt.ylabel('True label')
             plt.xlabel('Predicted label')
             plt.tight_layout()

In [25]: plot_confusion_matrix(confusion_mat_1, range(2))
```

```
Confusion matrix, without normalization
```



9.1 Displaying the missclassified label

Create a function to find missclassified pessengers and display first 10 of them for MISCLASSIFIED_SURVIVE, MISCLASSIFIED_NOT_SURVIVE

```
In [26]: def Find_miss(expected, predicted):
             MISCLASSIFIED_SURVIVE=[] #Create empty list to append missclassified index number
             MISCLASSIFIED_NOT_SURVIVE=[] #Create empty list to append missclassified index nu
             sum_ =  np.array(expected)+np.array(predicted) # Take a sum of predicted group an
             all_mis = np.argwhere(sum_==1)              #misclassified ones are stored in 
             all_mis = all_mis.flatten()
             for i,item in enumerate(all_mis):
                 if predicted[item]==1:
                     MISCLASSIFIED_SURVIVE.append(item)
                 else:
                     MISCLASSIFIED_NOT_SURVIVE.append(item)
             return (MISCLASSIFIED_SURVIVE, MISCLASSIFIED_NOT_SURVIVE) #return to two lists
```

```
In [27]: MISCLASSIFIED_SURVIVE_1, MISCLASSIFIED_NOT_SURVIVE_1 = Find_miss(expected_1, predicte
         len(MISCLASSIFIED_SURVIVE_1)
```

```
Out[27]: 83
```

In [28]: `len( MISCLASSIFIED_NOT_SURVIVE_1)`

Out[28]: 107

In [29]:
```
print('\033[1m' + "This chart below presents the firts 10 missclassfied pessengers' da
train_data.iloc[MISCLASSIFIED_SURVIVE_1[0:10],:]
```

This chart below presents the firts 10 missclassfied pessengers' data(Missclassified as surviv

Out[29]:

	PassengerId	Survived	Pclass
14	15	0	3
18	19	0	3
24	25	0	3
27	28	0	1
34	35	0	1
38	39	0	3
41	42	0	2
49	50	0	3
64	65	0	1
83	84	0	1

	Name	Sex	Age	SibSp
14	Vestrom, Miss. Hulda Amanda Adolfina	female	14.0	0
18	Vander Planke, Mrs. Julius (Emelia Maria Vande...	female	31.0	1
24	Palsson, Miss. Torborg Danira	female	8.0	3
27	Fortune, Mr. Charles Alexander	male	19.0	3
34	Meyer, Mr. Edgar Joseph	male	28.0	1
38	Vander Planke, Miss. Augusta Maria	female	18.0	2
41	Turpin, Mrs. William John Robert (Dorothy Ann ...	female	27.0	1
49	Arnold-Franchi, Mrs. Josef (Josefine Franchi)	female	18.0	1
64	Stewart, Mr. Albert A	male	NaN	0
83	Carrau, Mr. Francisco M	male	28.0	0

	Parch	Ticket	Fare	Cabin	Embarked
14	0	350406	7.8542	NaN	S
18	0	345763	18.0000	NaN	S
24	1	349909	21.0750	NaN	S
27	2	19950	263.0000	C23 C25 C27	S
34	0	PC 17604	82.1708	NaN	C
38	0	345764	18.0000	NaN	S
41	0	11668	21.0000	NaN	S
49	0	349237	17.8000	NaN	S
64	0	PC 17605	27.7208	NaN	C
83	0	113059	47.1000	NaN	S

In [30]:
```
print('\033[1m' + "This chart below presents the firts 10 missclassfied pessengers' da
train_data.iloc[MISCLASSIFIED_NOT_SURVIVE_1[0:10],:]
```

This chart below presents the firts 10 missclassfied pessengers' data(Missclassified as not su

```
Out[30]:     PassengerId  Survived  Pclass  \
        17           18         1       2
        21           22         1       2
        25           26         1       3
        36           37         1       3
        65           66         1       3
        68           69         1       3
        74           75         1       3
        78           79         1       2
        81           82         1       3
        85           86         1       3

                                                  Name     Sex    Age  SibSp  \
        17                      Williams, Mr. Charles Eugene    male    NaN      0
        21                             Beesley, Mr. Lawrence    male  34.00      0
        25  Asplund, Mrs. Carl Oscar (Selma Augusta Emilia...  female  38.00      1
        36                                  Mamee, Mr. Hanna    male    NaN      0
        65                          Moubarek, Master. Gerios    male    NaN      1
        68                     Andersson, Miss. Erna Alexandra  female  17.00      4
        74                                     Bing, Mr. Lee    male  32.00      0
        78                       Caldwell, Master. Alden Gates    male   0.83      0
        81                          Sheerlinck, Mr. Jan Baptist    male  29.00      0
        85  Backstrom, Mrs. Karl Alfred (Maria Mathilda Gu...  female  33.00      3

            Parch   Ticket     Fare Cabin Embarked
        17      0   244373  13.0000   NaN        S
        21      0   248698  13.0000   D56        S
        25      5   347077  31.3875   NaN        S
        36      0     2677   7.2292   NaN        C
        65      1     2661  15.2458   NaN        C
        68      2  3101281   7.9250   NaN        S
        74      0     1601  56.4958   NaN        S
        78      2   248738  29.0000   NaN        S
        81      0   345779   9.5000   NaN        S
        85      0  3101278  15.8500   NaN        S
```

10 Experiment 2

10.0.1 Putting age into buckets

In this model, I will still use logistic model. But a different pipeline for data preprocessing.

We can't use age as numerical data for regression model. In experiment 2, we will assign age into several backets and then treat them as categorical data(turn them into dummy varaiable and then drop a column)

Create a class to transform numerical age into Categorical data

```
In [31]: # Class to turn numerical continuous Age into categorical data
         # Parameter n refers to the length of interval of each bucket
```

```
# the bucket starts from 0 and is designed to include the max of age in the largesy b
class Age_bucket(BaseEstimator, TransformerMixin):
    def __init__(self, n):
        self.n = n
    def fit(self, X, y=None):
        return self
    def transform(self, X):       #
        age = X.flatten()

        out = []                      #define a list to store transformed data for age
        num = int(np.ceil(age.max()/self.n))     # find out how many buckets we need

        for i,item in enumerate(age):
            for j in np.arange(num):
                if item<((j+1)*self.n):
                    out.append(j)
                    break
        out = pd.Series(out)
        return np.array(out).reshape(-1,1)
```

10.0.2 Make a pipeline for Age (Age Buckets)

Create a pipeline for age transformation by using the class defined just now

Disccussion: I choose 15 as the length of each interval, because I will think under 15 years old children are similar. 15-30 similar. We can't divide age into too many small buckets, since it might cause overfitting problem.

```
In [32]: num_features_age = ["Age"]
         age_pipeline = Pipeline([
                 ("select_numeric", DataFrameSelector( num_features_age )), #set the parameter
                 ("imputer", SimpleImputer(strategy="median")),         #set the parameter for
                 ("Agebucket",  Age_bucket(n =15)),
                 ("cat_encoder", OneHotEncoder(sparse=False)),
                 ("drop_one_of_dummy",droplastcolumn(-2)),              #drop the second last 
                                                                        #Because last column m
                                                                        # droping it,we might 
             ])
```

10.0.3 Make a pipeline for other numerical data

```
In [33]: num_features_2 = [ "SibSp", "Parch", "Fare"] #numerical features

         num_pipeline_2 = Pipeline([
                 ("select_numeric", DataFrameSelector( num_features_2 )), #set the parameter f
                 ("imputer", SimpleImputer(strategy="median")),         #set the parameter for
             ])
```

10.0.4 FeatureUnion using numerical_2, Age pipeline and previous two categorical pipline

```
In [34]: preprocess_pipeline_2 = FeatureUnion(transformer_list=[
                 ("num_pipeline_2", num_pipeline_2),
                 ("age_pipeline", age_pipeline),
                 ("sex_pipeline", sex_pipeline),
                 ("cat_pipeline", cat_pipeline),
             ])
```

10.0.5 Processing data and making predictions

```
In [35]: X_train_2 = preprocess_pipeline_2.fit_transform(train_data)
         y_train_2  = train_data["Survived"]
         X_train_2.shape
```

```
Out[35]: (891, 11)
```

```
In [36]: SCORE_2 = cross_val_score(logistic_clf, X_train_2, y_train_2, cv=5, scoring = "accura
         SCORE_2 = SCORE_2.mean()
         SCORE_2
```

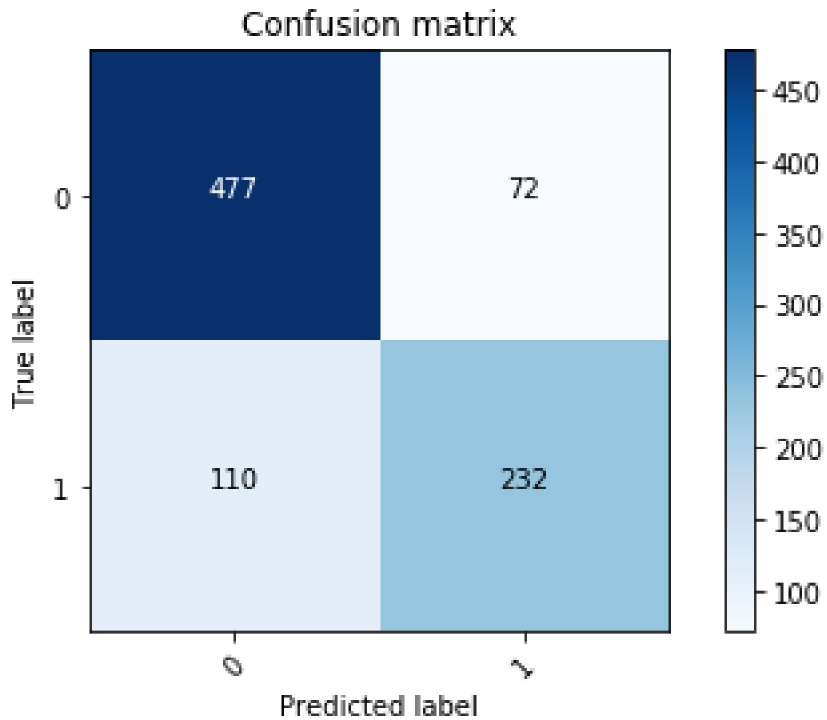
```
Out[36]: 0.7957166977505749
```

Discussion: Assigning age into buckets helps improve the score. There is an intuitive way to understand this: old people and children will be in priority and they will have more possiblities to live. However, if age treated as one numerical variable, this large age effect might offset young age effect in linear model.

```
In [37]: expected_2 = y_train_2
         predicted_2 = cross_val_predict(logistic_clf, X_train_2, y_train_2, cv=5)

         confusion_mat_2 = metrics.confusion_matrix(expected_2, predicted_2)
```

```
In [38]: plot_confusion_matrix(confusion_mat_2, range(2))
```

```
Confusion matrix, without normalization
```



In [39]:
```
MISCLASSIFIED_SURVIVE_2, MISCLASSIFIED_NOT_SURVIVE_2 = Find_miss(expected_2, predicte
train_data.iloc[MISCLASSIFIED_SURVIVE_2[0:10],:]
```

Out[39]:

	PassengerId	Survived	Pclass	\
14	15	0	3	
18	19	0	3	
24	25	0	3	
40	41	0	3	
41	42	0	2	
49	50	0	3	
100	101	0	3	
111	112	0	3	
113	114	0	3	
114	115	0	3	

	Name	Sex	Age	SibSp	\
14	Vestrom, Miss. Hulda Amanda Adolfina	female	14.0	0	
18	Vander Planke, Mrs. Julius (Emelia Maria Vande...	female	31.0	1	
24	Palsson, Miss. Torborg Danira	female	8.0	3	
40	Ahlin, Mrs. Johan (Johanna Persdotter Larsson)	female	40.0	1	
41	Turpin, Mrs. William John Robert (Dorothy Ann ...	female	27.0	1	
49	Arnold-Franchi, Mrs. Josef (Josefine Franchi)	female	18.0	1	
100	Petranec, Miss. Matilda	female	28.0	0	
111	Zabour, Miss. Hileni	female	14.5	1	

```
113                              Jussila, Miss. Katriina  female  20.0      1
114                                Attalah, Miss. Malake  female  17.0      0

     Parch  Ticket     Fare Cabin Embarked
14       0  350406   7.8542   NaN        S
18       0  345763  18.0000   NaN        S
24       1  349909  21.0750   NaN        S
40       0    7546   9.4750   NaN        S
41       0   11668  21.0000   NaN        S
49       0  349237  17.8000   NaN        S
100      0  349245   7.8958   NaN        S
111      0    2665  14.4542   NaN        C
113      0    4136   9.8250   NaN        S
114      0    2627  14.4583   NaN        C
```

In [40]:
```
train_data.iloc[MISCLASSIFIED_NOT_SURVIVE_2[0:10],:]
```

Out[40]:
```
    PassengerId  Survived  Pclass  \
8             9         1       3
17           18         1       2
21           22         1       2
23           24         1       1
25           26         1       3
36           37         1       3
55           56         1       1
65           66         1       3
68           69         1       3
74           75         1       3

                                                 Name     Sex   Age  SibSp  \
8   Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)  female  27.0      0
17                       Williams, Mr. Charles Eugene    male   NaN      0
21                              Beesley, Mr. Lawrence    male  34.0      0
23                       Sloper, Mr. William Thompson    male  28.0      0
25  Asplund, Mrs. Carl Oscar (Selma Augusta Emilia...  female  38.0      1
36                                   Mamee, Mr. Hanna    male   NaN      0
55                                  Woolner, Mr. Hugh    male   NaN      0
65                           Moubarek, Master. Gerios    male   NaN      1
68                    Andersson, Miss. Erna Alexandra  female  17.0      4
74                                      Bing, Mr. Lee    male  32.0      0

    Parch  Ticket     Fare Cabin Embarked
8       2  347742  11.1333   NaN        S
17      0  244373  13.0000   NaN        S
21      0  248698  13.0000   D56        S
23      0  113788  35.5000    A6        S
25      5  347077  31.3875   NaN        S
36      0    2677   7.2292   NaN        C
```

```
55      0     19947  35.5000    C52         S
65      1      2661  15.2458    NaN         C
68      2   3101281   7.9250    NaN         S
74      0      1601  56.4958    NaN         S
```

11 Extra credit problem

Featuren Engineering - Using numerical_pipeline_3, inlude "Fare" - Using age_pipeline, include Age - Using sex_pipeline, include Sex - Using catgorical_pipeline, include Pclass - Using famliy_size_pipeline, include family size

In [41]:
```
num_features = [ "Fare"] #numerical features

num_pipeline_3 = Pipeline([
        ("select_numeric", DataFrameSelector( num_features )), #set the parameter for
        ("imputer", SimpleImputer(strategy="median")),         #set the parameter for
    ])
```

In [42]:
```
# Famliy size pipeline
features = ["SibSp", "Parch"]

class family_size(BaseEstimator, TransformerMixin):
    def __init__(self, features):
        self.features = features
    def fit(self, X, y=None):
        return self
    def transform(self, X, y=None):
        out = X[features[0]]+X[features[1]]
        return np.array(out).reshape(-1,1)
family_size_pipeline =  Pipeline([
        ("family_size", family_size(features)),
        ("cat_encoder", OneHotEncoder(sparse=False)),
        ("drop_one_of_dummy",droplastcolumn(-3)),

    ])
```

In [43]:
```
preprocess_pipeline_3 = FeatureUnion(transformer_list=[
        ("num_pipeline_3", num_pipeline_2),
        ("age_pipeline", age_pipeline),
        ("sex_pipeline", sex_pipeline),
        ("cat_pipeline", cat_pipeline),
        ("family_size_pipeline ",family_size_pipeline ),
    ])
```

In [44]:
```
X_train_3 = preprocess_pipeline_3.fit_transform(train_data)
y_train_3 = train_data["Survived"]
```

In [45]:
```
SCORE_3 = cross_val_score(logistic_clf, X_train_3, y_train_3, cv=5, scoring = "accura
SCORE_3 = SCORE_3.mean()
SCORE_3
```

```
Out[45]: 0.8069968760051734
```

Comparing with experiment 1 and 2, combining "SibSp", "Parch" can make more contribution to the final accuracy

Family size is a helpful feature to logistic model