

# ICEI-Tutorial

February 2, 2017

```
In [1]: import numpy as np
import pandas as pd
from patsy import dmatrices
import statsmodels.api as sm
from sklearn import svm
import warnings
import matplotlib.pyplot as plt

# To display plots inside notebook
%matplotlib inline

warnings.filterwarnings('ignore')

# notebook parameters
pd.set_option('display.max_rows', 15)
```

## 0.0.1 Data Handling

Let's read our data in using pandas:

```
In [2]: df = pd.read_csv(r"data/train.csv")
```

```
In [3]: df
```

```
Out[3]:
```

	PassengerId	Survived	Pclass	\
0	1	0	3	
1	2	1	1	
2	3	1	3	
3	4	1	1	
4	5	0	3	
5	6	0	3	
6	7	0	1	
..	...	...	...	
884	885	0	3	
885	886	0	3	
886	887	0	2	
887	888	1	1	
888	889	0	3	

```

889      890      1      1
890      891      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	
5	Moran, Mr. James	male	NaN	0	
6	McCarthy, Mr. Timothy J	male	54.0	0	
..	...	...	...	...	
884	Sutehall, Mr. Henry Jr	male	25.0	0	
885	Rice, Mrs. William (Margaret Norton)	female	39.0	0	
886	Montvila, Rev. Juozas	male	27.0	0	
887	Graham, Miss. Margaret Edith	female	19.0	0	
888	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	
889	Behr, Mr. Karl Howell	male	26.0	0	
890	Dooley, Mr. Patrick	male	32.0	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
5	0	330877	8.4583	NaN	Q
6	0	17463	51.8625	E46	S
..	...	...	...	...	...
884	0	SOTON/OQ 392076	7.0500	NaN	S
885	5	382652	29.1250	NaN	Q
886	0	211536	13.0000	NaN	S
887	0	112053	30.0000	B42	S
888	2	W./C. 6607	23.4500	NaN	S
889	0	111369	30.0000	C148	C
890	0	370376	7.7500	NaN	Q

[891 rows x 12 columns]

### To view the columns individually

```
In [4]: df['Name']
```

```

Out[4]: 0      Braund, Mr. Owen Harris
1      Cumings, Mrs. John Bradley (Florence Briggs Th...
2      Heikkinen, Miss. Laina
3      Futrelle, Mrs. Jacques Heath (Lily May Peel)
4      Allen, Mr. William Henry

```

```

5                                Moran, Mr. James
6                        McCarthy, Mr. Timothy J
...
884                    Sutehall, Mr. Henry Jr
885                Rice, Mrs. William (Margaret Norton)
886                    Montvila, Rev. Juozas
887                Graham, Miss. Margaret Edith
888                Johnston, Miss. Catherine Helen "Carrie"
889                    Behr, Mr. Karl Howell
890                    Dooley, Mr. Patrick
Name: Name, dtype: object

```

### To find the occurrence of each object

```
In [5]: df['Pclass'].value_counts()
```

```

Out[5]: 3      491
        1      216
        2      184
        Name: Pclass, dtype: int64

```

```
In [6]: df['Sex'].value_counts()
```

```

Out[6]: male      577
        female    314
        Name: Sex, dtype: int64

```

```
In [7]: help(pd.DataFrame.apply)
```

Help on method apply in module pandas.core.frame:

```

apply(self, func, axis=0, broadcast=False, raw=False, reduce=None, args=(), **kwargs) unbound pandas.core.frame.DataFrame
    Applies function along input axis of DataFrame.

```

Objects passed to functions are Series objects having index either the DataFrame's index (axis=0) or the columns (axis=1). Return type depends on whether passed function aggregates, or the reduce argument if the DataFrame is empty.

#### Parameters

-----

```

func : function
    Function to apply to each column/row
axis : {0 or 'index', 1 or 'columns'}, default 0
    * 0 or 'index': apply function to each column
    * 1 or 'columns': apply function to each row
broadcast : boolean, default False
    For aggregation functions, return object of same size with values
    propagated

```

`raw` : boolean, default False  
 If False, convert each row or column into a Series. If `raw=True` the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance

`reduce` : boolean or None, default None  
 Try to apply reduction procedures. If the DataFrame is empty, apply will use `reduce` to determine whether the result should be a Series or a DataFrame. If `reduce` is None (the default), apply's return value will be guessed by calling `func` an empty Series (note: while guessing, exceptions raised by `func` will be ignored). If `reduce` is True a Series will always be returned, and if False a DataFrame will always be returned.

`args` : tuple  
 Positional arguments to pass to function in addition to the array/series

Additional keyword arguments will be passed as keywords to the function

#### Notes

-----  
 In the current implementation `apply` calls `func` twice on the first column/row to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if `func` has side-effects, as they will take effect twice for the first column/row.

#### Examples

-----  

```
>>> df.apply(numpy.sqrt) # returns DataFrame
>>> df.apply(numpy.sum, axis=0) # equiv to df.sum(0)
>>> df.apply(numpy.sum, axis=1) # equiv to df.sum(1)
```

#### See also

-----  
`DataFrame.applymap`: For elementwise operations

#### Returns

-----  
`applied` : Series or DataFrame

```
In [8]: df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
Out[8]: PassengerId    0
        Survived      0
        Pclass        0
        Name          0
```

```
Sex          0
Age         177
SibSp        0
Parch        0
Ticket       0
Fare         0
Cabin       687
Embarked     2
dtype: int64
```

```
In [9]: df.apply(lambda x: sum(x.notnull()),axis=0)
```

```
Out[9]: PassengerId    891
Survived              891
Pclass                891
Name                  891
Sex                   891
Age                   714
SibSp                 891
Parch                 891
Ticket                891
Fare                  891
Cabin                 204
Embarked              889
dtype: int64
```

### To drop the column that is not required

```
In [10]: df.drop(['Cabin'], axis=1)
```

```
Out[10]:
```

	PassengerId	Survived	Pclass	\
0	1	0	3	
1	2	1	1	
2	3	1	3	
3	4	1	1	
4	5	0	3	
5	6	0	3	
6	7	0	1	
..	...	...	...	
884	885	0	3	
885	886	0	3	
886	887	0	2	
887	888	1	1	
888	889	0	3	
889	890	1	1	
890	891	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
5		Moran, Mr. James	male	NaN	0
6		McCarthy, Mr. Timothy J	male	54.0	0
..		...	...	...	...
884		Sutehall, Mr. Henry Jr	male	25.0	0
885		Rice, Mrs. William (Margaret Norton)	female	39.0	0
886		Montvila, Rev. Juozas	male	27.0	0
887		Graham, Miss. Margaret Edith	female	19.0	0
888		Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1
889		Behr, Mr. Karl Howell	male	26.0	0
890		Dooley, Mr. Patrick	male	32.0	0

	Parch		Ticket	Fare	Embarked
0	0		A/5 21171	7.2500	S
1	0		PC 17599	71.2833	C
2	0	STON/O2.	3101282	7.9250	S
3	0		113803	53.1000	S
4	0		373450	8.0500	S
5	0		330877	8.4583	Q
6	0		17463	51.8625	S
..	...		...	...	...
884	0	SOTON/OQ	392076	7.0500	S
885	5		382652	29.1250	Q
886	0		211536	13.0000	S
887	0		112053	30.0000	S
888	2	W./C.	6607	23.4500	S
889	0		111369	30.0000	C
890	0		370376	7.7500	Q

[891 rows x 11 columns]

```
In [11]: df = df.drop(['Cabin'], axis=1)
         # df.drop(['Cabin'], axis=1, inplace=True)
```

```
In [12]: # Remove NaN values
         df = df.dropna()
         # df.dropna(inplace=True)
```

```
In [13]: df.head()
```

```
Out[13]:   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	Embarked
0	0	A/5 21171	7.2500	S
1	0	PC 17599	71.2833	C
2	0	STON/O2. 3101282	7.9250	S
3	0	113803	53.1000	S
4	0	373450	8.0500	S

Now let's check for the 'notnull' values

```
In [14]: df.apply(lambda x: sum(x.notnull()),axis=0)
```

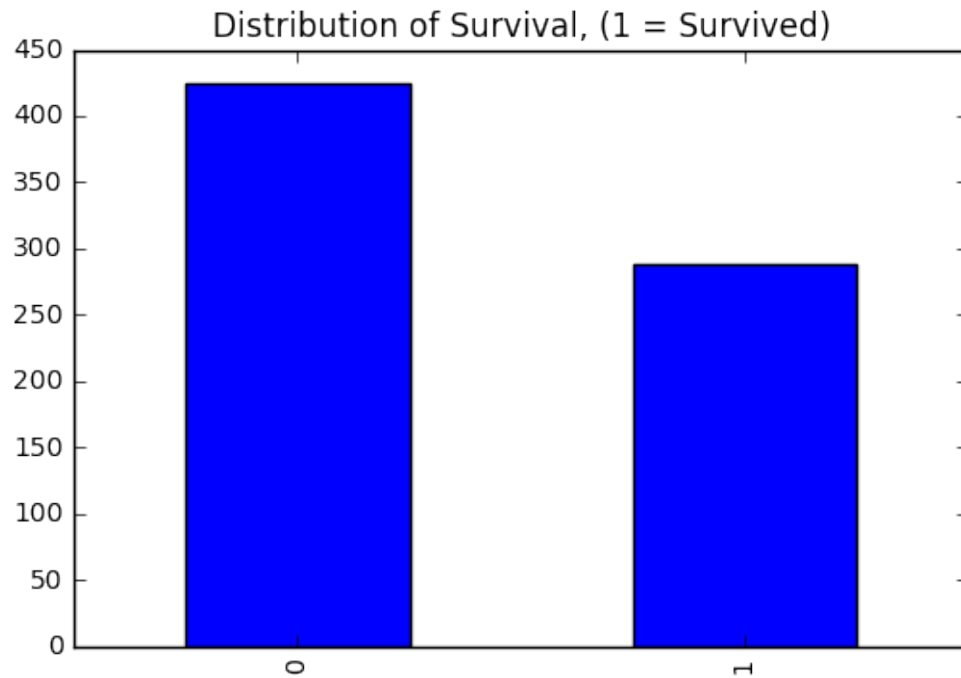
```
Out[14]: PassengerId    712
Survived              712
Pclass               712
Name                 712
Sex                  712
Age                  712
SibSp                712
Parch                712
Ticket               712
Fare                 712
Embarked             712
dtype: int64
```

## 0.0.2 Visualize our data graphically:

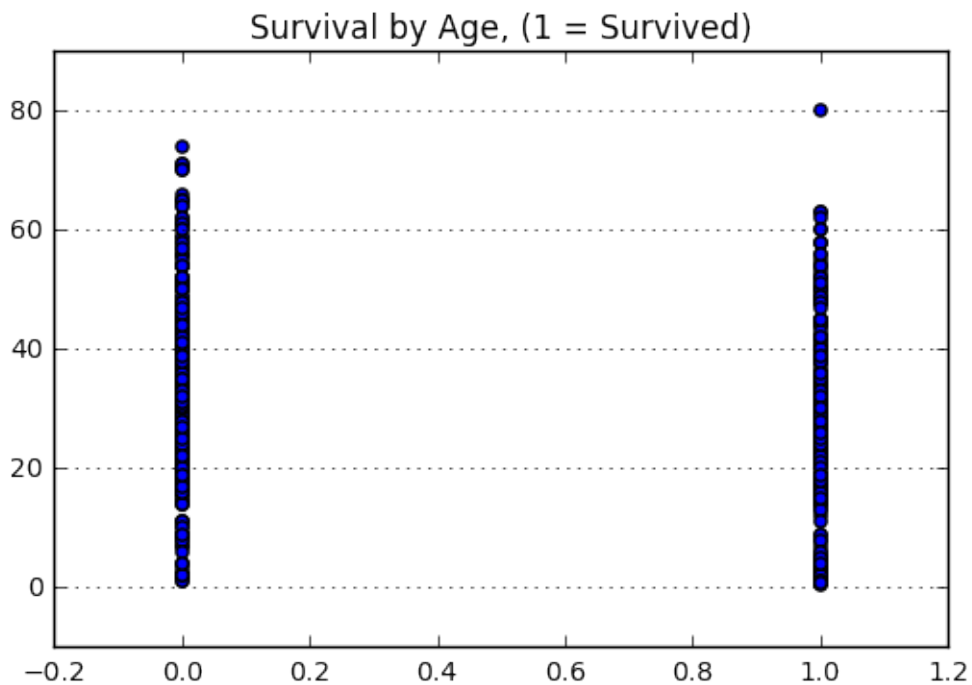
plot a bar graph of those who survived vs those who did not

```
In [15]: df['Survived'].value_counts().plot(kind='bar')
plt.title("Distribution of Survival, (1 = Survived)")
```

```
Out[15]: <matplotlib.text.Text at 0x20273b00>
```

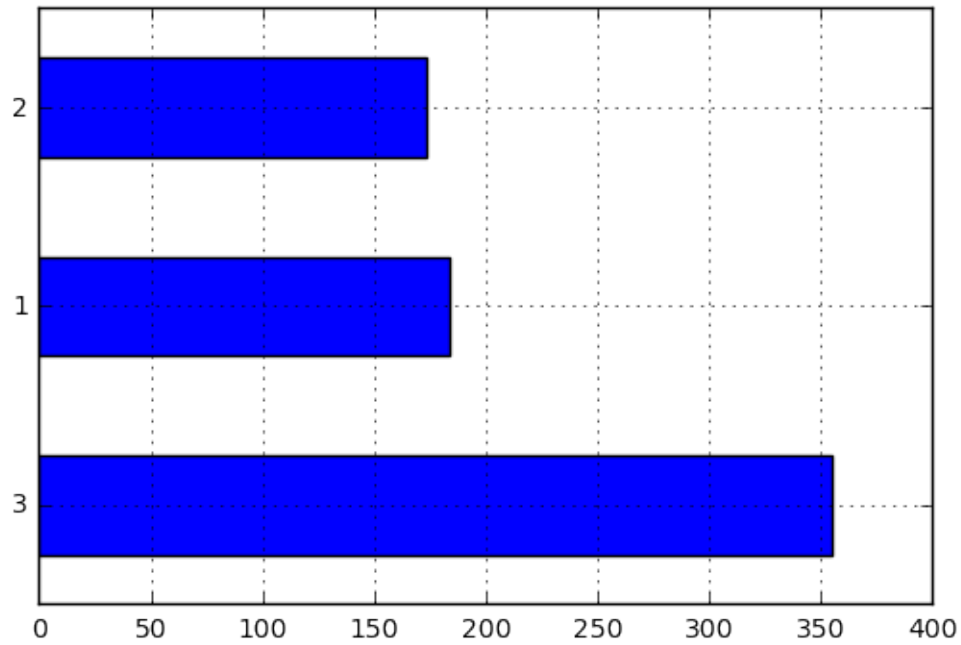


```
In [16]: plt.scatter(df.Survived, df.Age)
plt.title("Survival by Age, (1 = Survived)")
plt.grid(True, axis='y')
```





```
In [17]: df.Pclass.value_counts().plot(kind="barh")
plt.grid(True)
```



Checking for 'class 1' passengers

```
In [18]: df['Pclass'] == 1
```

```
Out[18]: 0      False
1       True
2      False
3       True
4      False
6       True
7      False
...
883    False
884    False
885    False
886    False
887     True
889     True
890    False
Name: Pclass, dtype: bool
```

Passing the 'class 1' passengers list to 'Age' --> To find out the age of 'class 1' passengers

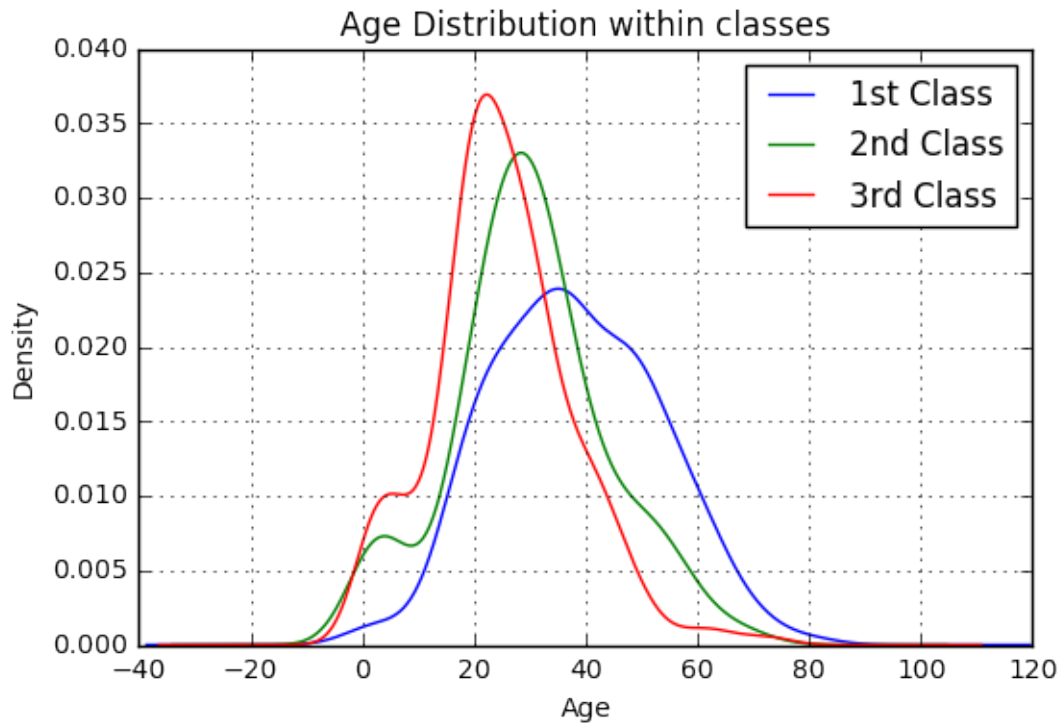
```
In [19]: df['Age'][df['Pclass'] == 1]
```

```
Out[19]: 1      38.0
         3      35.0
         6      54.0
        11      58.0
        23      28.0
        27      19.0
        30      40.0
         ...
       862      48.0
       867      31.0
       871      47.0
       872      33.0
       879      56.0
       887      19.0
       889      26.0
         Name: Age, dtype: float64
```

```
In [20]: len(df['Age'][df['Pclass'] == 1])
```

```
Out[20]: 184
```

```
In [21]: df['Age'][df['Pclass'] == 1].plot(kind='kde')
         df['Age'][df['Pclass'] == 2].plot(kind='kde')
         df['Age'][df['Pclass'] == 3].plot(kind='kde')
         plt.xlabel("Age")
         plt.title("Age Distribution within classes")
         # sets our legend for our graph.
         plt.legend(('1st Class', '2nd Class', '3rd Class'),loc='best')
         plt.grid(True)
```

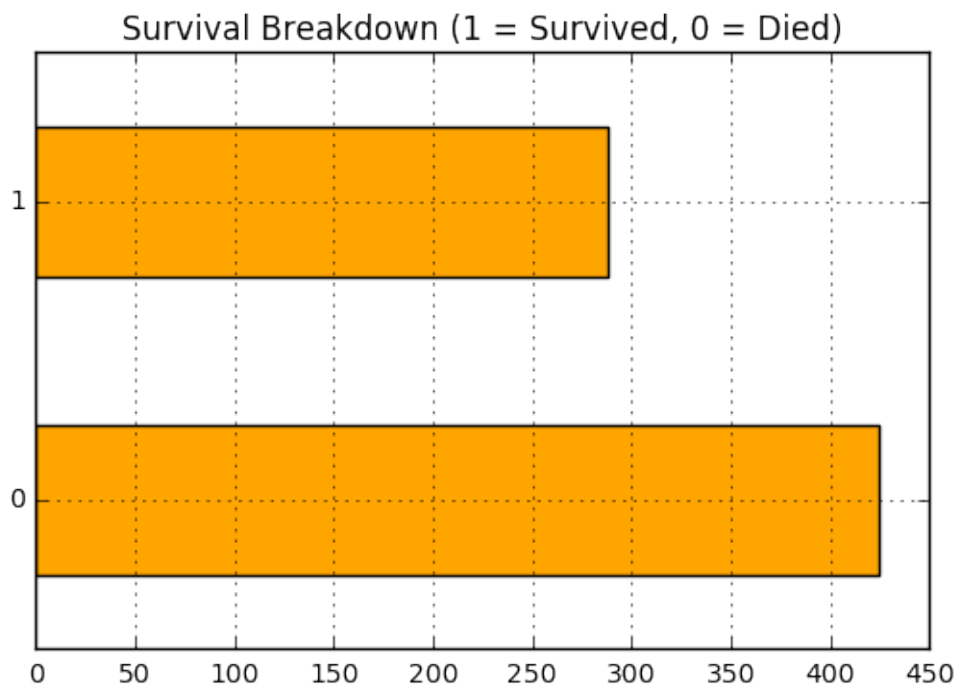


### 0.0.3 Exploratory Visualization:

The point of this competition is to predict if an individual will survive based on the features in the data like:

- Traveling Class (called pclass in the data)
- Sex
- Age
- Fare Price

```
In [22]: df['Survived'].value_counts().plot(kind='barh', color="orange")
plt.title("Survival Breakdown (1 = Survived, 0 = Died)")
plt.grid(True)
```



Find out the count of total male and female survived, in ascending order

```
In [23]: df['Survived'][df['Sex'] == 'male'].value_counts()
```

```
Out[23]: 0    360
         1     93
         Name: Survived, dtype: int64
```

```
In [24]: df['Survived'][df['Sex'] == 'female'].value_counts()
```

```
Out[24]: 1    195
         0     64
         Name: Survived, dtype: int64
```

```
In [25]: df_male = df['Survived'][df['Sex'] == 'male'].value_counts().sort_index()
         df_female = df['Survived'][df['Sex'] == 'female'].value_counts().sort_index()
```

```
In [26]: df_male
```

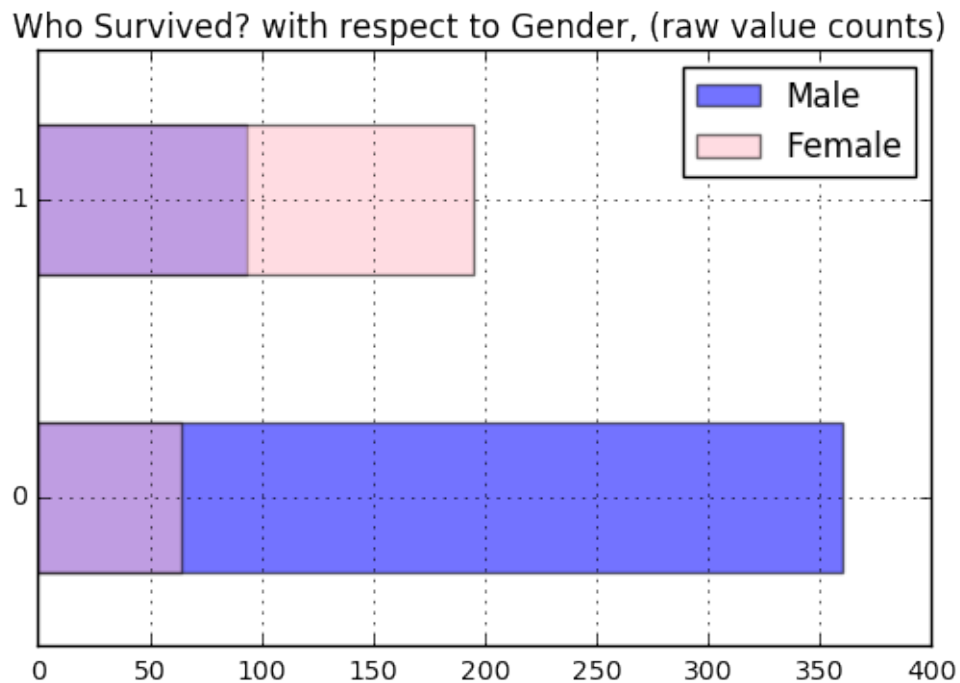
```
Out[26]: 0    360
         1     93
         Name: Survived, dtype: int64
```

```
In [27]: df_female
```

```
Out[27]: 0      64
         1     195
         Name: Survived, dtype: int64
```

```
In [28]: df_male.plot(kind='barh', color='blue', label='Male', alpha=0.55)
         df_female.plot(kind='barh', color='pink', label='Female', alpha=0.55)
         plt.grid(True)
         plt.legend(loc='best')
         plt.title("Who Survived? with respect to Gender, (raw value counts) ")
```

```
Out[28]: <matplotlib.text.Text at 0x212243c8>
```



Now let's find out the ratio of survived people

```
In [29]: df_male.sum()
```

```
Out[29]: 453L
```

```
In [30]: df_female.sum()
```

```
Out[30]: 259L
```

```
In [31]: df_male/float(df_male.sum())
```

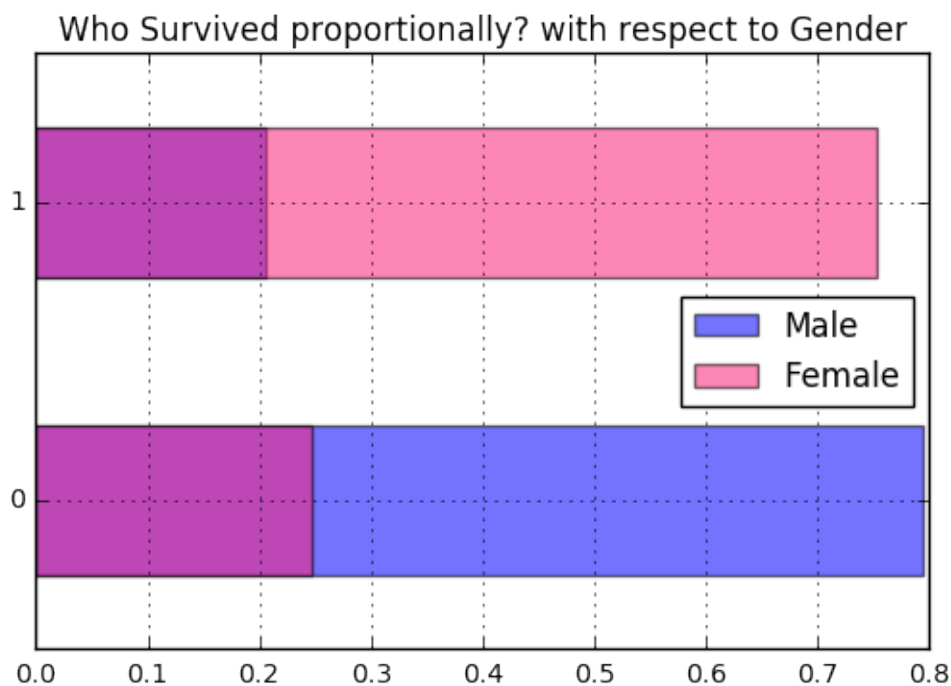
```
Out[31]: 0      0.794702
         1      0.205298
         Name: Survived, dtype: float64
```

```
In [32]: df_female/float(df_female.sum())
```

```
Out[32]: 0    0.247104  
         1    0.752896  
         Name: Survived, dtype: float64
```

```
In [33]: (df_male/float(df_male.sum())).plot(kind='barh', label='Male', alpha=0.55)  
(df_female/float(df_female.sum())).plot(kind='barh', color='#FA2379', label='Female', a  
plt.title("Who Survived proportionally? with respect to Gender")  
plt.grid(True)  
plt.legend(loc='best')
```

```
Out[33]: <matplotlib.legend.Legend at 0x213dc240>
```



Let's try going some more deeper, by finding out the the passenger class wise survival

```
In [34]: female_highclass = df['Survived'][(df['Pclass'] != 3) & (df['Sex'] == 'female')].value_c  
female_lowclass = df['Survived'][(df['Pclass'] == 3) & (df['Sex'] == 'female')].value_c  
male_highclass = df['Survived'][(df['Pclass'] != 3) & (df['Sex'] == 'male')].value_coun  
male_lowclass = df['Survived'][(df['Pclass'] == 3) & (df['Sex'] == 'male')].value_count
```

```
In [35]: female_highclass
```

```
Out[35]: 1    148  
         0     9  
         Name: Survived, dtype: int64
```

```
In [36]: female_lowclass
```

```
Out[36]: 0    55  
         1    47  
         Name: Survived, dtype: int64
```

```
In [37]: male_highclass
```

```
Out[37]: 0    145  
         1    55  
         Name: Survived, dtype: int64
```

```
In [38]: male_lowclass
```

```
Out[38]: 0    215  
         1    38  
         Name: Survived, dtype: int64
```

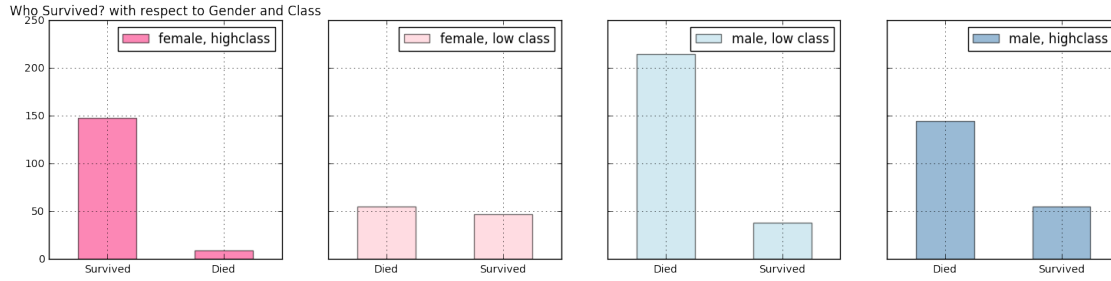
```
In [39]: fig = plt.figure(figsize=(18,4), dpi=1600)
```

```
ax1=fig.add_subplot(141)  
female_highclass.plot(kind='bar', label='female, highclass', color='#FA2479', alpha=0.5)  
ax1.set_xticklabels(["Survived", "Died"], rotation=0)  
plt.title("Who Survived? with respect to Gender and Class")  
plt.legend(loc='best')  
plt.grid(True)
```

```
ax2=fig.add_subplot(142, sharey=ax1)  
female_lowclass.plot(kind='bar', label='female, low class', color='pink', alpha=0.55)  
ax2.set_xticklabels(["Died", "Survived"], rotation=0)  
plt.legend(loc='best')  
plt.grid(True)
```

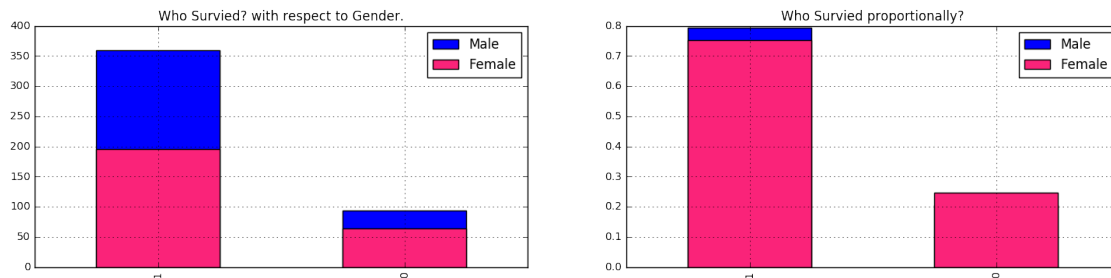
```
ax3=fig.add_subplot(143, sharey=ax1)  
male_lowclass.plot(kind='bar', label='male, low class', color='lightblue', alpha=0.55)  
ax3.set_xticklabels(["Died", "Survived"], rotation=0)  
plt.legend(loc='best')  
plt.grid(True)
```

```
ax4=fig.add_subplot(144, sharey=ax1)  
male_highclass.plot(kind='bar', label='male, highclass', alpha=0.55, color='steelblue')  
ax4.set_xticklabels(["Died", "Survived"], rotation=0)  
plt.legend(loc='best')  
plt.grid(True)
```



```
In [40]: fig = plt.figure(figsize=(18,4), dpi=1600)
ax1 = fig.add_subplot(121)
df.Survived[df.Sex == 'male'].value_counts().plot(kind='bar',label='Male')
df.Survived[df.Sex == 'female'].value_counts().plot(kind='bar', color='#FA2379',label='Female')
plt.title("Who Survied? with respect to Gender.")
plt.legend(loc='best')
plt.grid(True)

ax2 = fig.add_subplot(122)
(df['Survived'][df['Sex'] == 'male'].value_counts()/float(df['Sex'][df['Sex'] == 'male'].value_counts().sum()))
(df['Survived'][df['Sex'] == 'female'].value_counts()/float(df['Sex'][df['Sex'] == 'female'].value_counts().sum()))
plt.title("Who Survied proportionally?")
plt.legend(loc='best')
plt.grid(True)
```



Let's just create a formule for our model

```
In [41]: # Ref: http://patsy.readthedocs.org/en/latest/formulas.html
formula = 'Survived ~ C(Pclass) + C(Sex) + Age + SibSp + C(Embarked)'
```

'dmatrices' is used to used to create regression friendly dataframe

```
In [42]: y,X = dmatrices(formula, data=df, return_type='dataframe')
# instantiate our model
model = sm.Logit(y, X)
```



```

# fit our model to the training data
res = model.fit()

# save the result for outputing predictions later
result = [res, formula]
res.summary()

```

Optimization terminated successfully.  
Current function value: 0.444388  
Iterations 6

Out [42]: <class 'statsmodels.iolib.summary.Summary'>  
"""

```

                                Logit Regression Results
=====
Dep. Variable:                Survived    No. Observations:                712
Model:                        Logit       Df Residuals:                  704
Method:                       MLE        Df Model:                      7
Date:                         Thu, 02 Feb 2017    Pseudo R-squ.:                0.3414
Time:                         00:50:17    Log-Likelihood:               -316.40
converged:                     True        LL-Null:                      -480.45
                                      LLR p-value:                5.992e-67
=====

```

	coef	std err	z	P> z	[95.0% Conf. Int.]
Intercept	4.5423	0.474	9.583	0.000	3.613 5.471
C(Pclass) [T.2]	-1.2673	0.299	-4.245	0.000	-1.852 -0.682
C(Pclass) [T.3]	-2.4966	0.296	-8.422	0.000	-3.078 -1.916
C(Sex) [T.male]	-2.6239	0.218	-12.060	0.000	-3.050 -2.197
C(Embarked) [T.Q]	-0.8351	0.597	-1.398	0.162	-2.006 0.335
C(Embarked) [T.S]	-0.4254	0.271	-1.572	0.116	-0.956 0.105
Age	-0.0436	0.008	-5.264	0.000	-0.060 -0.027
SibSp	-0.3697	0.123	-3.004	0.003	-0.611 -0.129

```

=====
"""

```

## Let's try to do something with machine learning

```

In [43]: # Create our machine learning formula
formula_ml = 'Survived ~ C(Pclass) + C(Sex) + Age + SibSp + Parch + C(Embarked)'

In [44]: # set plotting parameters
plt.figure(figsize=(8,6))

# create a regression friendly data frame
y, x = dmatrices(formula_ml, data=df, return_type='matrix')

```

```

# select which features we would like to analyze
# try changing the selection here for different output.
# Choose : [2,3] - pretty sweet DBs [3,1] --standard DBs [7,3] -very cool DBs,
# [3,6] -- very long complex dbs, could take over an hour to calculate!
feature_1 = 2
feature_2 = 3

X = np.asarray(x)
X = X[:, [feature_1, feature_2]]

y = np.asarray(y)
# needs to be 1 dimensional so we flatten. it comes out of dmatirces with a shape.
y = y.flatten()

n_sample = len(X)

np.random.seed(0)
order = np.random.permutation(n_sample)

X = X[order]
y = y[order].astype(np.float)

# do a cross validation
nighty_precent_of_sample = int(.9 * n_sample)
X_train = X[:nighty_precent_of_sample]
y_train = y[:nighty_precent_of_sample]
X_test = X[nighty_precent_of_sample:]
y_test = y[nighty_precent_of_sample:]

# create a list of the types of kerneks we will use for your analysis
types_of_kernels = ['linear', 'rbf', 'poly']

# specify our color map for plotting the results
color_map = plt.cm.Paired
# color_map = plt.cm.coolwarm

# fit the model
for fig_num, kernel in enumerate(types_of_kernels):
    clf = svm.SVC(kernel=kernel, gamma=3)
    clf.fit(X_train, y_train)

    plt.figure(fig_num)
    plt.scatter(X[:, 0], X[:, 1], c=y, zorder=10, cmap=color_map)

    # circle out the test data
    plt.scatter(X_test[:, 0], X_test[:, 1], s=80, facecolors='none', zorder=10)

```

```

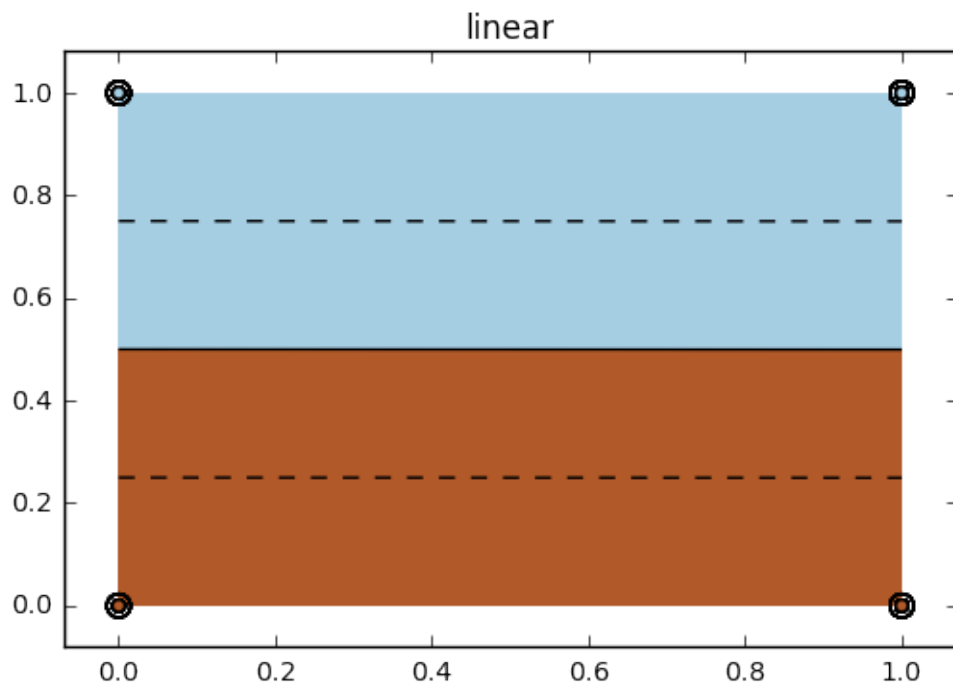
plt.axis('tight')
x_min = X[:, 0].min()
x_max = X[:, 0].max()
y_min = X[:, 1].min()
y_max = X[:, 1].max()

XX, YY = np.mgrid[x_min:x_max:200j, y_min:y_max:200j]
Z = clf.decision_function(np.c_[XX.ravel(), YY.ravel()])

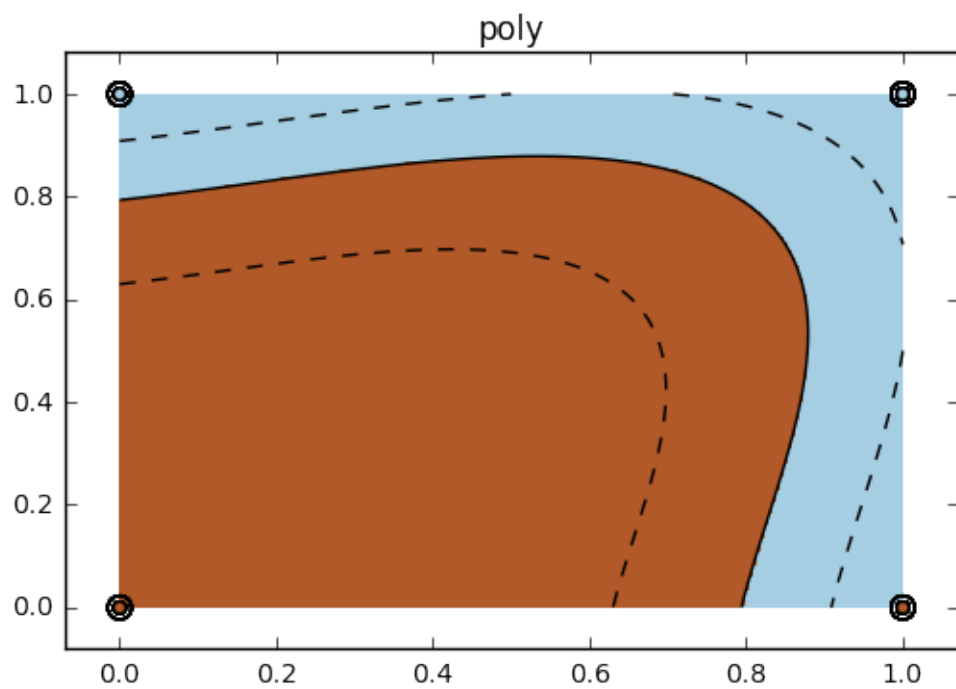
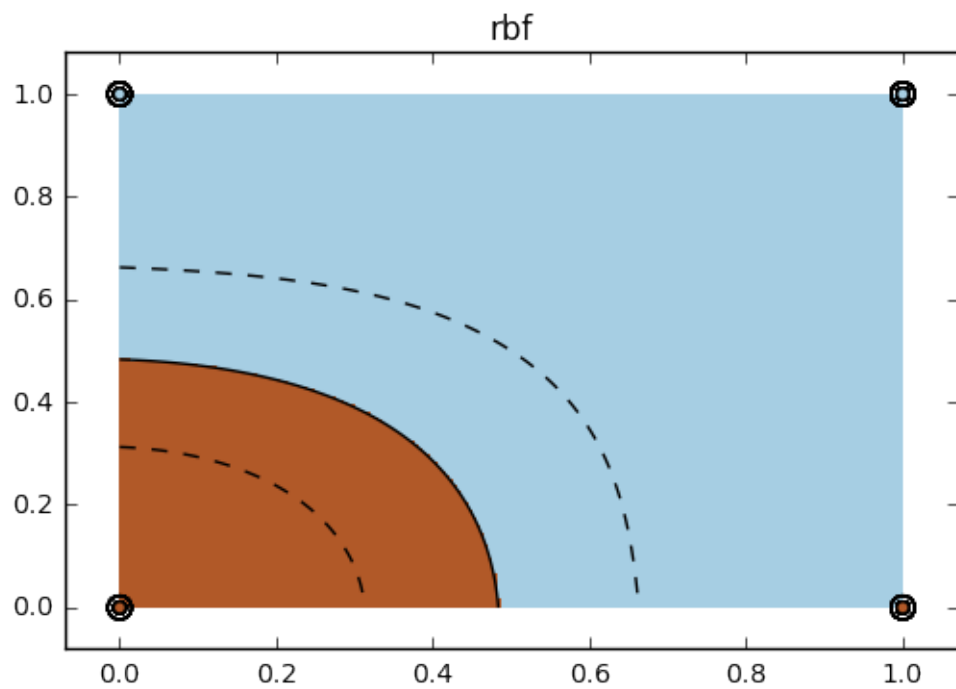
# put the result into a color plot
Z = Z.reshape(XX.shape)
plt.pcolormesh(XX, YY, Z > 0, cmap=color_map)
plt.contour(XX, YY, Z, colors=['k', 'k', 'k'], linestyles=['--', '-', '--'],
            levels=[-.5, 0, .5])

plt.title(kernel)
plt.show()

```



<matplotlib.figure.Figure at 0x21308da0>



```
In [45]: test_data = pd.read_csv(r"data/test.csv")
```



```

0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0., 0.]

```

### Convert the numpy array to dataframe

```
In [51]: res_svm = pd.DataFrame(res_svm, columns=['Survived'])
```

```
In [52]: res_svm
```

```

Out[52]:      Survived
0         0.0
1         0.0
2         0.0
3         0.0
4         0.0
5         0.0
6         0.0
..        ...
325        0.0
326        0.0
327        0.0
328        0.0
329        0.0
330        0.0
331        0.0

```

```
[332 rows x 1 columns]
```

```
In [53]: clf.predict(np.array([50, 1]))
```

```
Out[53]: array([ 0.])
```