In [62]:

```
# 数据分析和探索
import pandas as pd
import numpy as np
import random as rnd
import tensorflow as tf

# 可视化
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [63]:

```
# 获取数据，训练集train_df，测试集test_df，合并集合combine（便于对特征进行处理时统一处理：for df in
train_df = pd.read_csv("train.csv")
test_df = pd.read_csv('test.csv')
combine = [train_df, test_df]
```

In [64]:

```
train_df.head()
```

Out[64]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.25
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.92
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.05

In [65]:

```
# 查看各特征非空样本量及字段类型
train_df.info()
print("_"*40)
test_df.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
____________________________________________
<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
```

In [66]:

```
# 查看数值类（int，float）特征的数据分布情况
train_df.describe()
```

```
D:\Program Files\Anaconda3\lib\site-packages\numpy\lib\function_base.py:3652: Runtim
eWarning: Invalid value encountered in percentile
  interpolation=interpolation)
```

Out[66]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.0
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.20
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.69
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000
25%	223.500000	0.000000	2.000000	NaN	0.000000	0.000000	7.910
50%	446.000000	0.000000	3.000000	NaN	0.000000	0.000000	14.45
75%	668.500000	1.000000	3.000000	NaN	1.000000	0.000000	31.00
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.3

In [67]:

```
# 查看非数值类（object类型）特征的数据分布情况
train_df.describe(include=["O"])
```

Out[67]:

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889
unique	891	2	681	147	3
top	Davidson, Mr. Thornton	male	CA. 2343	G6	S
freq	1	577	7	4	644

In [68]:

```
train_df[["Pclass","Survived"]].groupby(["Pclass"],as_index=False).mean().sort_values(by="Survived",
# 富人和中等阶层有更高的生还率，底层生还率低
```

Out[68]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

In [69]:

```
train_df[["Sex","Survived"]].groupby(["Sex"],as_index=False).mean().sort_values(by="Survived",ascend
# 性别和是否生还强相关，女性用户的生还率明显高于男性
```

Out[69]:

	Sex	Survived
0	female	0.742038
1	male	0.188908

In [70]:

```
train_df[["SibSp","Survived"]].groupby(["SibSp"],as_index=False).mean().sort_values(by="Survived",as
# 有0到2个兄弟姐妹或配偶的生还几率会高于有更多的
```

Out[70]:

	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

In [71]:

```
train_df[["Parch","Survived"]].groupby(["Parch"],as_index = False).mean().sort_values(by="Survived",
# 相关
```

Out[71]:

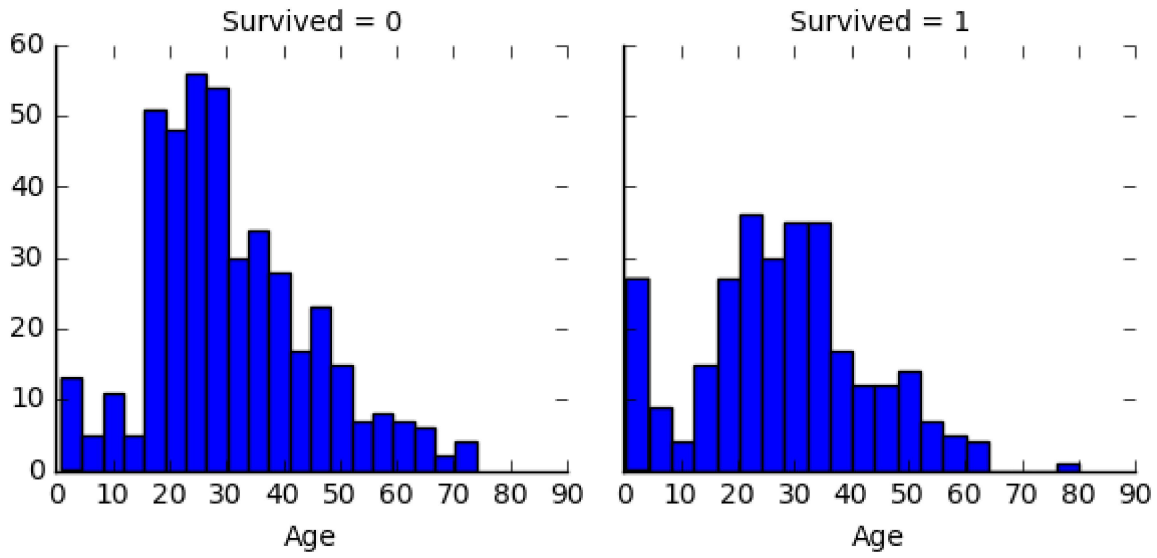
	Parch	Survived
3	3	0.600000
1	1	0.550847
2	2	0.500000
0	0	0.343658
5	5	0.200000
4	4	0.000000
6	6	0.000000

In [72]:

```
g = sns.FacetGrid(train_df,col="Survived")
g.map(plt.hist,"Age",bins=20)
# 婴幼儿的生存几率更大
```

Out[72]:

```
<seaborn.axisgrid.FacetGrid at 0x1a4a35b4240>
```

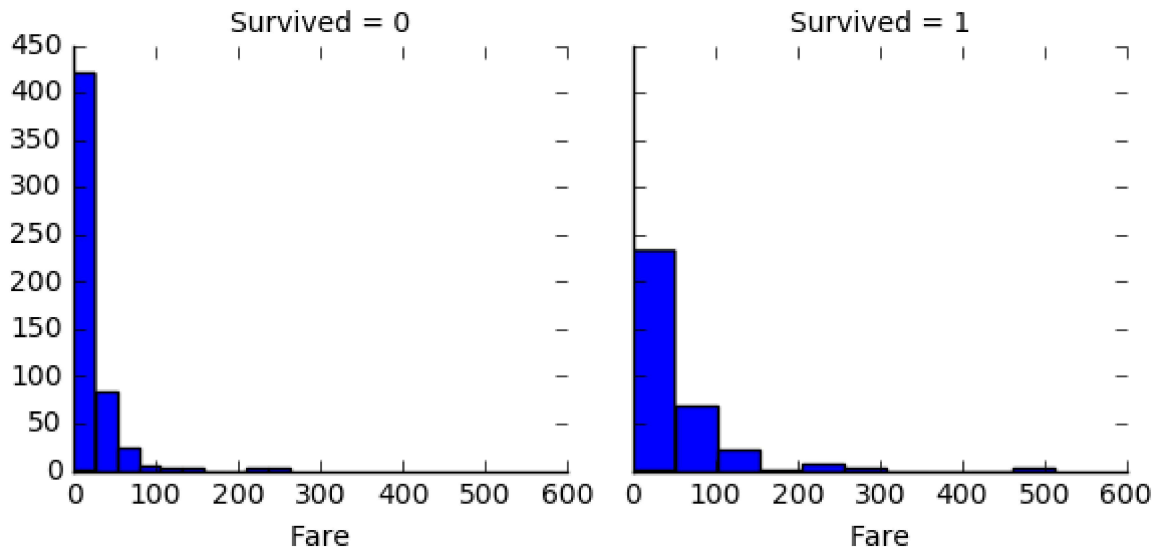


In [73]:

```
# Fare
g = sns.FacetGrid(train_df,col="Survived")
g.map(plt.hist,"Fare",bins=10)
# 票价最便宜的幸存几率低
```

Out[73]:

```
<seaborn.axisgrid.FacetGrid at 0x1a4a4dede10>
```

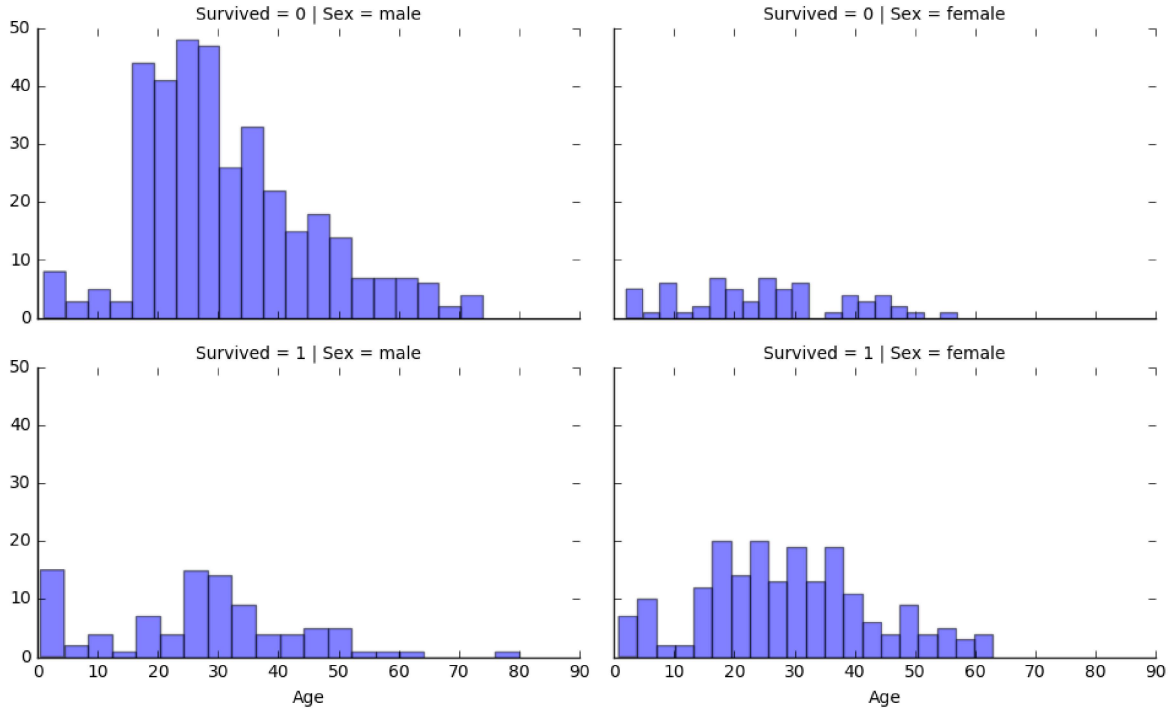


In [74]:

```
grid = sns.FacetGrid(train_df,row="Survived",col="Sex",aspect=1.6)
grid.map(plt.hist,"Age",alpha=.5,bins=20)
grid.add_legend()
# 女性的幸存率更高，各年龄段均高于50%
# 男性中只有婴幼儿幸存率高于50%，年龄最大的男性（近80岁）幸存
```

Out[74]:

<seaborn.axisgrid.FacetGrid at 0x1a4e0abdb70>



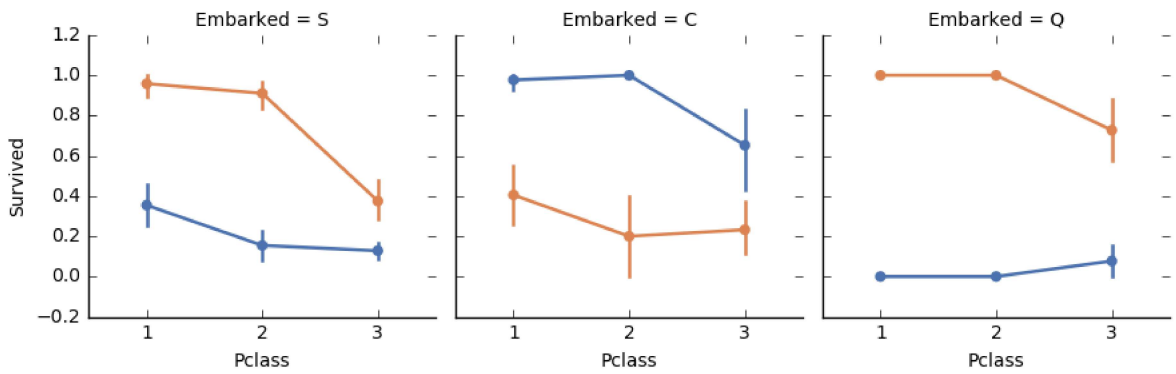
In [75]:

```
grid1 = sns.FacetGrid(train_df,col="Embarked")
grid1.map(sns.pointplot,"Pclass","Survived","Sex",palette = "deep")
#
```

```
D:\Program Files\Anaconda3\lib\site-packages\seaborn\axisgrid.py:715: UserWarning: U
sing the pointplot function without specifying `order` is likely to produce an incor
rect plot.
  warnings.warn(warning)
D:\Program Files\Anaconda3\lib\site-packages\seaborn\axisgrid.py:720: UserWarning: U
sing the pointplot function without specifying `hue_order` is likely to produce an i
ncorrect plot.
  warnings.warn(warning)
D:\Program Files\Anaconda3\lib\site-packages\scipy\stats\stats.py:1633: FutureWarnin
g: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr
[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an ar
ray index, `arr[np.array(seq)]`, which will result either in an error or a different
result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[75]:

```
<seaborn.axisgrid.FacetGrid at 0x1a4e0b539e8>
```



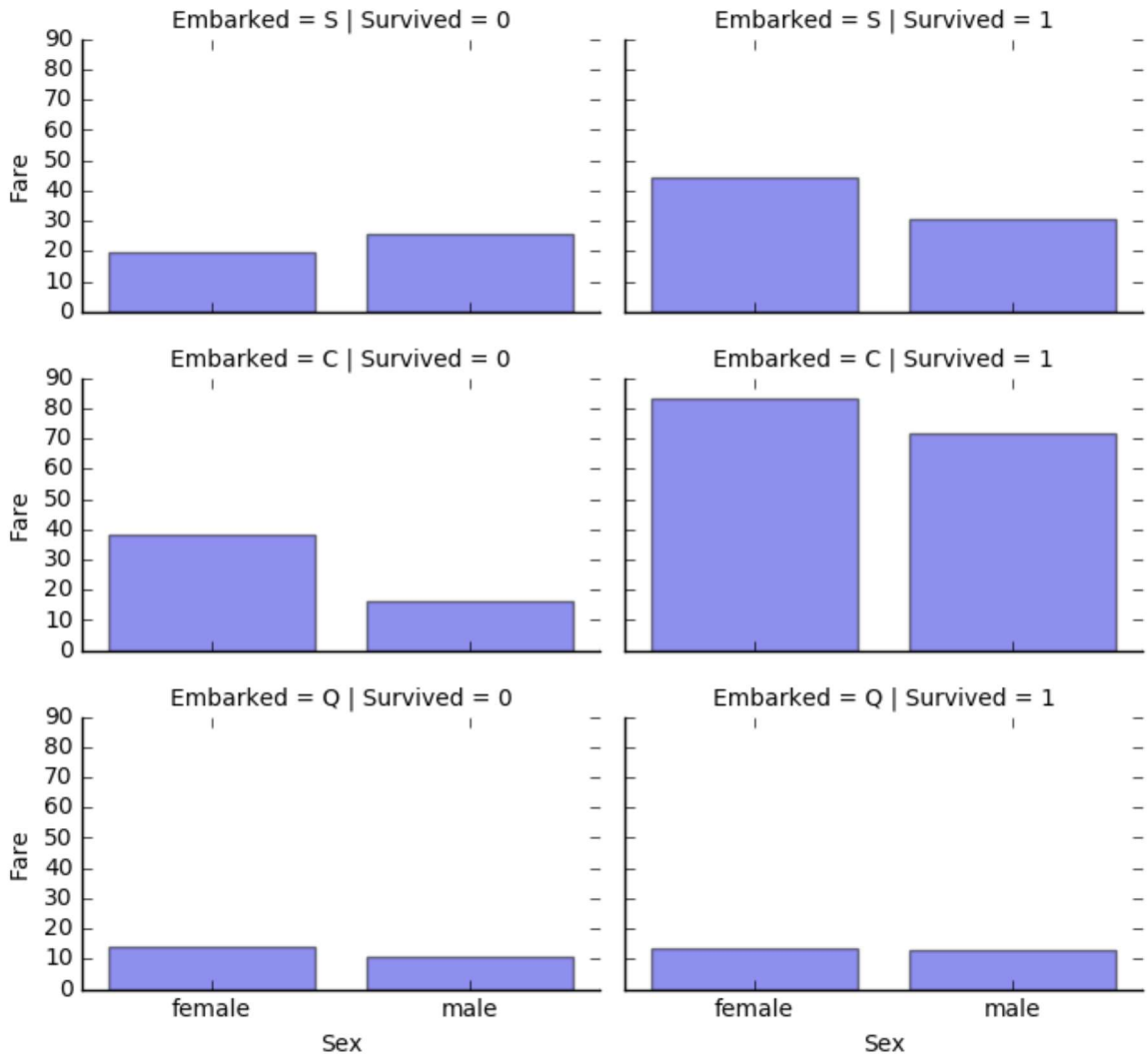
In [76]:

```
grid = sns.FacetGrid(train_df, row='Embarked', col='Survived', size=2.2, aspect=1.6)
grid.map(sns.barplot, 'Sex', 'Fare', alpha=.5, ci=None)
grid.add_legend()
```

```
D:\Program Files\Anaconda3\lib\site-packages\seaborn\axisgrid.py:230: UserWarning: T
he `size` paramter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
D:\Program Files\Anaconda3\lib\site-packages\seaborn\axisgrid.py:715: UserWarning: U
sing the barplot function without specifying `order` is likely to produce an incorre
ct plot.
  warnings.warn(warning)
```

Out[76]:

```
<seaborn.axisgrid.FacetGrid at 0x1a529b40160>
```



In [77]:

```
# Some features of my own that I have added in
# Gives the length of the name
train_df['NameLength'] = train_df['Name'].apply(len)
test_df['NameLength'] = test_df['Name'].apply(len)
```

In [78]:

```
# Feature that tells whether a passenger had a cabin on the Titanic
train_df['HasCabin'] = train_df["Cabin"].apply(lambda x: 0 if type(x) == float else 1)
test_df['HasCabin'] = test_df["Cabin"].apply(lambda x: 0 if type(x) == float else 1)
```

In [79]:

```
# 剔除Ticket（人为判断无关联）和Cabin（有效数据太少）两个特征
train_df = train_df.drop(["Ticket","Cabin"],axis=1)
test_df = test_df.drop(["Ticket","Cabin"],axis=1)
combine = [train_df,test_df]
print(train_df.shape,test_df.shape,combine[0].shape,combine[1].shape)
```

```
(891, 12) (418, 11) (891, 12) (418, 11)
```

In [80]:

```
# 根据姓名创建称号特征，会包含性别和阶层信息
# dataset.Name.str.extract(' ([A-Za-z]+)\.' -> 把空格开头.结尾的字符串抽取出来
# 和性别匹配，看各类称号分别属于男or女，方便后续归类

for dataset in combine:
    dataset['Title'] = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand=False)
pd.crosstab(train_df['Title'], train_df['Sex']).sort_values(by=["male","female"],ascending=False)
```

Out[80]:

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

In [81]:

```
# 把称号归类为Mr,Miss,Mrs,Master,Rare_Male,Rare_Female(按男性和女性区分了Rare)
for dataset in combine:
    dataset["Title"] = dataset["Title"].replace(['Lady', 'Countess', 'Dona'],"Rare_Female")
    dataset["Title"] = dataset["Title"].replace(['Capt', 'Col','Don','Dr','Major',
                                                 'Rev','Sir','Jonkheer',],"Rare_Male")
    dataset["Title"] = dataset["Title"].replace('Mlle', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Mme', 'Miss')
```

In [82]:

```
# 按Title汇总计算Survived均值，查看相关性
train_df[["Title","Survived"]].groupby(["Title"],as_index=False).mean()
```

Out[82]:

	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

In [83]:

```
# title特征映射为数值
title_mapping = {"Mr":1,"Miss":2,"Mrs":3,"Master":4,"Rare_Female":5,"Rare_Male":6}
for dataset in combine:
    dataset["Title"] = dataset["Title"].map(title_mapping)
    dataset["Title"] = dataset["Title"].fillna(0)
    # 为了避免有空数据的常规操作
train_df.head()
```

Out[83]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Fare	Emba
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	7.9250	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	8.0500	S

In [84]:

```
# Name字段可以剔除了
# 训练集的PassengerId字段仅为自增字段，与预测无关，可剔除
train_df = train_df.drop(["Name","PassengerId"],axis=1)
test_df = test_df.drop(["Name"],axis=1)
```

In [85]:

```
# 每次删除特征时都要重新combine
combine = [train_df,test_df]
combine[0].shape,combine[1].shape
```

Out[85]:

```
((891, 11), (418, 11))
```

In [86]:

```
# sex特征映射为数值
for dataset in combine:
    dataset["Sex"] = dataset["Sex"].map({"female":1,"male":0}).astype(int)
    # 后面加astype(int)是为了避免处理为布尔型?
train_df.head()
```

Out[86]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	NameLength	HasCabi
0	0	3	0	22.0	1	0	7.2500	S	23	0
1	1	1	1	38.0	1	0	71.2833	C	51	1
2	1	3	1	26.0	0	0	7.9250	S	22	0
3	1	1	1	35.0	1	0	53.1000	S	44	1
4	0	3	0	35.0	0	0	8.0500	S	24	0

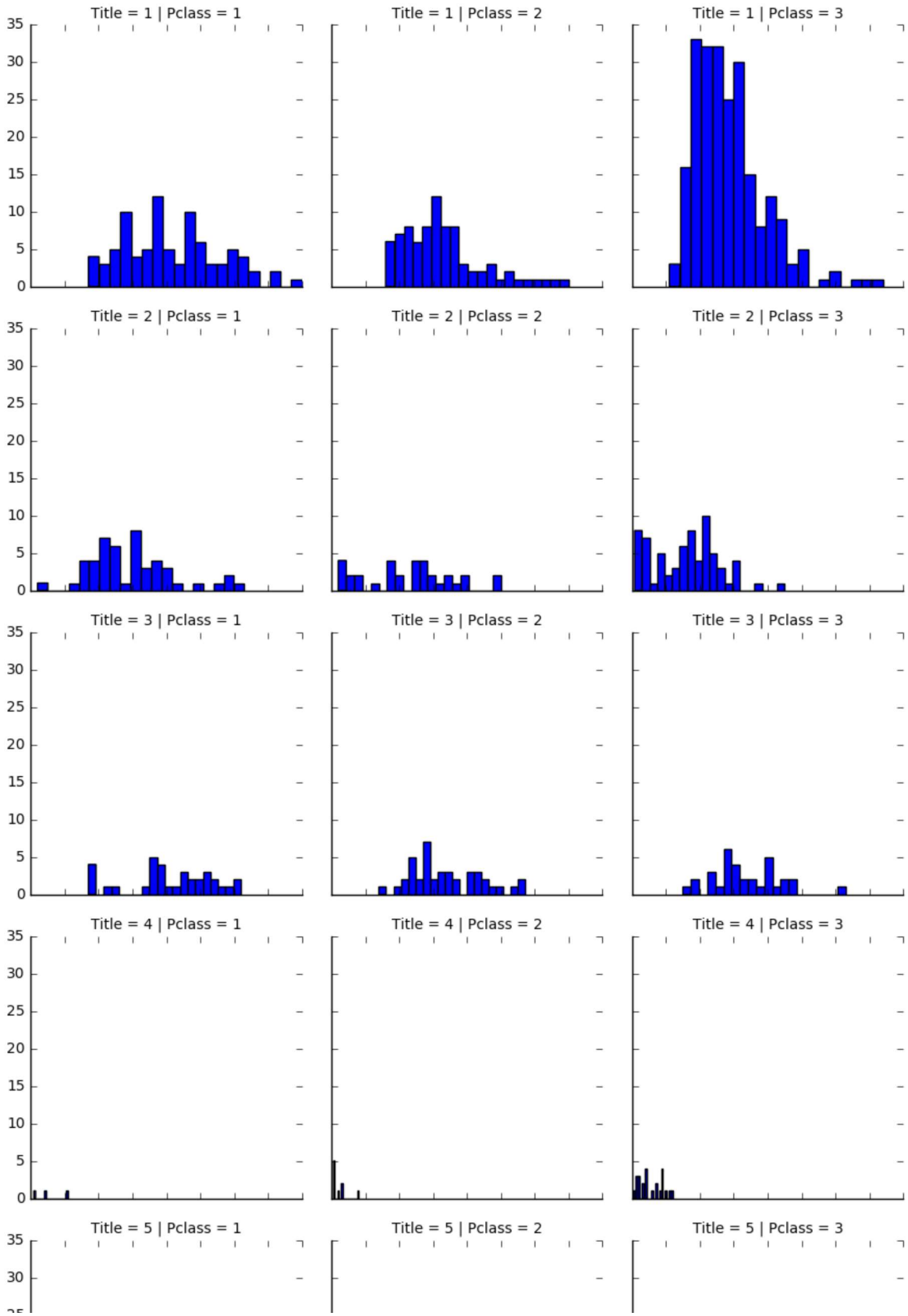
In [87]:

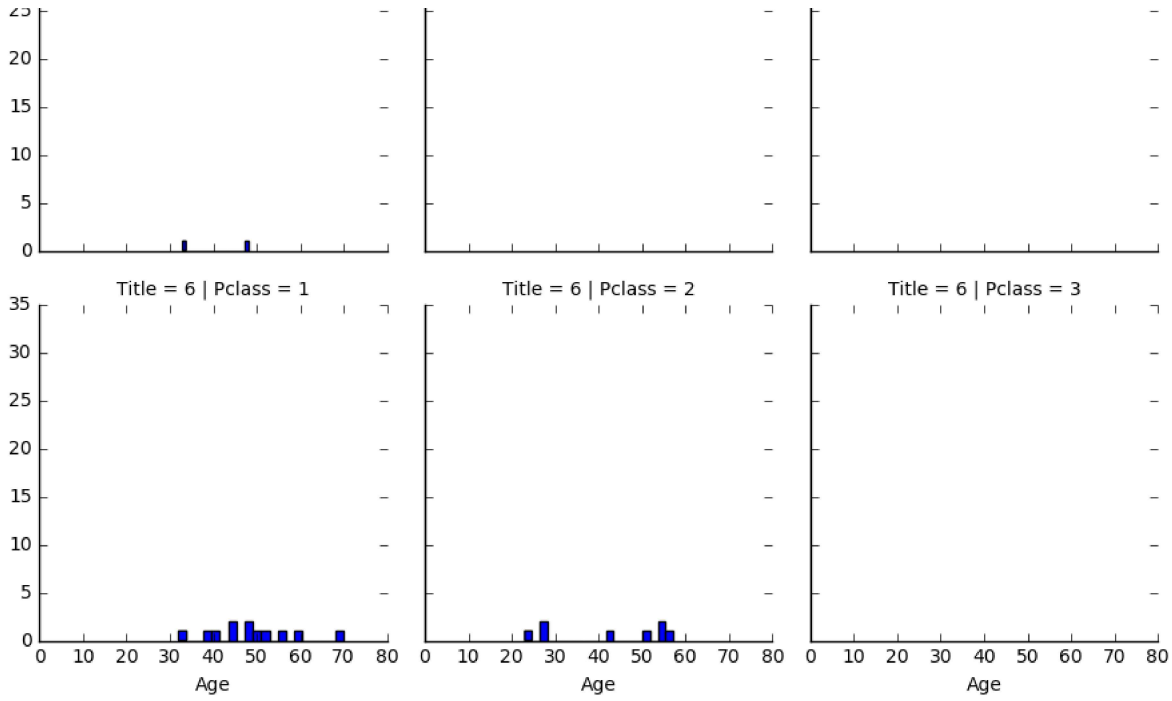
```
# 对Age字段的空值进行预测补充
# 取相同Pclass和Title的年龄中位数进行补充（Demo为Pclass和Sex）

grid = sns.FacetGrid(train_df,col="Pclass",row="Title")
grid.map(plt.hist,"Age",bins=20)
```

Out[87]:

<seaborn.axisgrid.FacetGrid at 0x1a529db1400>





In [88]:

```
guess_ages = np.zeros((6,3))
guess_ages
```

Out[88]:

```
array([[0., 0., 0.],
       [0., 0., 0.],
       [0., 0., 0.],
       [0., 0., 0.],
       [0., 0., 0.],
       [0., 0., 0.]])
```

In [89]:

```
# 给age年龄字段的空值填充估值
# 使用相同Pclass和Title的Age中位数来替代（对于中位数为空的组合，使用Title整体的中位数来替代）


for dataset in combine:
    # 取6种组合的中位数
    for i in range(0, 6):

        for j in range(0, 3):
            guess_title_df = dataset[dataset["Title"]==i+1]["Age"].dropna()

            guess_df = dataset[(dataset['Title'] == i+1) & (dataset['Pclass'] == j+1)]['Age'].dropna

            # age_mean = guess_df.mean()
            # age_std = guess_df.std()
            # age_guess = rnd.uniform(age_mean - age_std, age_mean + age_std)

            age_guess = guess_df.median() if ~np.isnan(guess_df.median()) else guess_title_df.median
            #print(i,j,guess_df.median(),guess_title_df.median(),age_guess)
            # Convert random age float to nearest .5 age
            guess_ages[i,j] = int( age_guess/0.5 + 0.5 ) * 0.5
    # 给满足6中情况的Age字段赋值
    for i in range(0, 6):
        for j in range(0, 3):
            dataset.loc[ (dataset.Age.isnull()) & (dataset.Title == i+1) & (dataset.Pclass == j+1),
                        'Age'] = guess_ages[i,j]

    dataset['Age'] = dataset['Age'].astype(int)

train_df.head()
```

Out[89]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	NameLength	HasCabi
0	0	3	0	22	1	0	7.2500	S	23	0
1	1	1	1	38	1	0	71.2833	C	51	1
2	1	3	1	26	0	0	7.9250	S	22	0
3	1	1	1	35	1	0	53.1000	S	44	1
4	0	3	0	35	0	0	8.0500	S	24	0

In [90]:

```
#创建是否儿童特征
for dataset in combine:
    dataset.loc[dataset["Age"] > 12,"IsChildren"] = 0
    dataset.loc[dataset["Age"] <= 12,"IsChildren"] = 1
train_df.head()
```

Out[90]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	NameLength	HasCabi
0	0	3	0	22	1	0	7.2500	S	23	0
1	1	1	1	38	1	0	71.2833	C	51	1
2	1	3	1	26	0	0	7.9250	S	22	0
3	1	1	1	35	1	0	53.1000	S	44	1
4	0	3	0	35	0	0	8.0500	S	24	0

In [91]:

```
# 创建年龄区间特征
# pd.cut是按值的大小均匀切分，每组值区间大小相同，但样本数可能不一致
# pd.qcut是按照样本在值上的分布频率切分，每组样本数相同
train_df["AgeBand"] = pd.qcut(train_df["Age"],8)
train_df[["AgeBand","Survived"]].groupby(["AgeBand"],as_index = False).mean().sort_values(by="AgeBar
```

Out[91]:

	AgeBand	Survived
0	[0, 17]	0.538462
1	(17, 21]	0.362903
2	(21, 25]	0.393939
3	(25, 26]	0.120370
4	(26, 31]	0.414062
5	(31, 36.5]	0.478261
6	(36.5, 45]	0.388430
7	(45, 80]	0.372549

In [92]:

```
# 把年龄按区间标准化为0到4
for dataset in combine:
    dataset.loc[ dataset['Age'] <= 17, 'Age'] = 0
    dataset.loc[(dataset['Age'] > 17) & (dataset['Age'] <= 21), 'Age'] = 1
    dataset.loc[(dataset['Age'] > 21) & (dataset['Age'] <= 25), 'Age'] = 2
    dataset.loc[(dataset['Age'] > 25) & (dataset['Age'] <= 26), 'Age'] = 3
    dataset.loc[(dataset['Age'] > 26) & (dataset['Age'] <= 31), 'Age'] = 4
    dataset.loc[(dataset['Age'] > 31) & (dataset['Age'] <= 36.5), 'Age'] = 5
    dataset.loc[(dataset['Age'] > 36.5) & (dataset['Age'] <= 45), 'Age'] = 6
    dataset.loc[ dataset['Age'] > 45, 'Age'] = 7
train_df.head()
```

Out[92]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	NameLength	HasCabi
0	0	3	0	2	1	0	7.2500	S	23	0
1	1	1	1	6	1	0	71.2833	C	51	1
2	1	3	1	3	0	0	7.9250	S	22	0
3	1	1	1	5	1	0	53.1000	S	44	1
4	0	3	0	5	0	0	8.0500	S	24	0

In [93]:

```
# 移除AgeBand特征
train_df = train_df.drop(["AgeBand"],axis=1)
combine = [train_df,test_df]
train_df.head()
```

Out[93]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	NameLength	HasCabi
0	0	3	0	2	1	0	7.2500	S	23	0
1	1	1	1	6	1	0	71.2833	C	51	1
2	1	3	1	3	0	0	7.9250	S	22	0
3	1	1	1	5	1	0	53.1000	S	44	1
4	0	3	0	5	0	0	8.0500	S	24	0

In [94]:

```
# 创建家庭规模FamilySize组合特征
for dataset in combine:
    dataset["FamilySize"] = dataset["Parch"] + dataset["SibSp"] + 1
train_df[["FamilySize","Survived"]].groupby(["FamilySize"],as_index = False).mean().sort_values(by='
```

Out[94]:

	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

In [95]:

```
# 创建是否独自一人IsAlone特征
for dataset in combine:
    dataset["IsAlone"] = 0
    dataset.loc[dataset["FamilySize"] == 1,"IsAlone"] = 1
train_df[["IsAlone","Survived"]].groupby(["IsAlone"],as_index=False).mean().sort_values(by="Survivec
```

Out[95]:

	IsAlone	Survived
0	0	0.505650
1	1	0.303538

In [96]:

```
# 移除Parch,Sibsp,FamilySize（暂且保留试试）
# 给字段赋值可以在combine中循环操作，删除字段不可以，需要对指定的df进行操作
train_df = train_df.drop(["Parch","SibSp"],axis=1)
test_df = test_df.drop(["Parch","SibSp"],axis=1)
combine = [train_df,test_df]
train_df.head()
```

Out[96]:

	Survived	Pclass	Sex	Age	Fare	Embarked	NameLength	HasCabin	Title	IsChil
0	0	3	0	2	7.2500	S	23	0	1	0.0
1	1	1	1	6	71.2833	C	51	1	3	0.0
2	1	3	1	3	7.9250	S	22	0	2	0.0
3	1	1	1	5	53.1000	S	44	1	3	0.0
4	0	3	0	5	8.0500	S	24	0	1	0.0

In [97]:

```
# 给Embarked补充空值
# 获取上船最多的港口
freq_port = train_df["Embarked"].dropna().mode()[0]
freq_port
```

Out[97]:

'S'

In [98]:

```
for dataset in combine:
    dataset["Embarked"] = dataset["Embarked"].fillna(freq_port)
train_df[["Embarked","Survived"]].groupby(["Embarked"],as_index=False).mean().sort_values(by="Surviv
```

Out[98]:

	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.339009

In [99]:

```
# 把Embarked数字化
for dataset in combine:
    dataset["Embarked"] = dataset["Embarked"].map({"S":0,"C":1,"Q":2}).astype(int)
train_df.head()
```

Out[99]:

	Survived	Pclass	Sex	Age	Fare	Embarked	NameLength	HasCabin	Title	IsChil
0	0	3	0	2	7.2500	0	23	0	1	0.0
1	1	1	1	6	71.2833	1	51	1	3	0.0
2	1	3	1	3	7.9250	0	22	0	2	0.0
3	1	1	1	5	53.1000	0	44	1	3	0.0
4	0	3	0	5	8.0500	0	24	0	1	0.0

In [100]:

```
# 去掉Embarked试试。。
#train_df = train_df.drop(["Embarked"],axis=1)
#test_df = test_df.drop(["Embarked"],axis=1)
#combine=[train_df,test_df]
#train_df.head()
```

In [101]:

```
# 给测试集中的Fare填充空值，使用中位数
test_df["Fare"].fillna(test_df["Fare"].dropna().median(),inplace=True)
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
PassengerId    418 non-null int64
Pclass         418 non-null int64
Sex            418 non-null int32
Age            418 non-null int32
Fare           418 non-null float64
Embarked       418 non-null int32
NameLength     418 non-null int64
HasCabin       418 non-null int64
Title          418 non-null int64
IsChildren     418 non-null float64
FamilySize     418 non-null int64
IsAlone        418 non-null int64
dtypes: float64(2), int32(3), int64(7)
memory usage: 34.4 KB
```

In [102]:

```
# 创建FareBand区间特征
train_df["FareBand"] = pd.qcut(train_df["Fare"],4)
train_df[["FareBand","Survived"]].groupby(["FareBand"],as_index=False).mean().sort_values(by="FareBa
```

Out[102]:

	FareBand	Survived
0	[0, 7.91]	0.197309
1	(7.91, 14.454]	0.303571
2	(14.454, 31]	0.454955
3	(31, 512.329]	0.581081

In [103]:

```
# 根据FareBand将Fare特征转换为序数值
for dataset in combine:
    dataset.loc[ dataset['Fare'] <= 7.91, 'Fare'] = 0
    dataset.loc[(dataset['Fare'] > 7.91) & (dataset['Fare'] <= 14.454), 'Fare'] = 1
    dataset.loc[(dataset['Fare'] > 14.454) & (dataset['Fare'] <= 31), 'Fare']   = 2
    dataset.loc[ dataset['Fare'] > 31, 'Fare'] = 3
    dataset['Fare'] = dataset['Fare'].astype(int)

train_df = train_df.drop(['FareBand'], axis=1)
combine = [train_df, test_df]

train_df.head(10)
```

Out[103]:

	Survived	Pclass	Sex	Age	Fare	Embarked	NameLength	HasCabin	Title	IsChildre
0	0	3	0	2	0	0	23	0	1	0.0
1	1	1	1	6	3	1	51	1	3	0.0
2	1	3	1	3	1	0	22	0	2	0.0
3	1	1	1	5	3	0	44	1	3	0.0
4	0	3	0	5	1	0	24	0	1	0.0
5	0	3	0	3	1	2	16	0	1	0.0
6	0	1	0	7	3	0	23	1	1	0.0
7	0	3	0	0	2	0	30	0	4	1.0
8	1	3	1	4	1	0	49	0	3	0.0
9	1	2	1	0	2	1	35	0	3	0.0

In [104]:

```
test_df.head(10)
```

Out[104]:

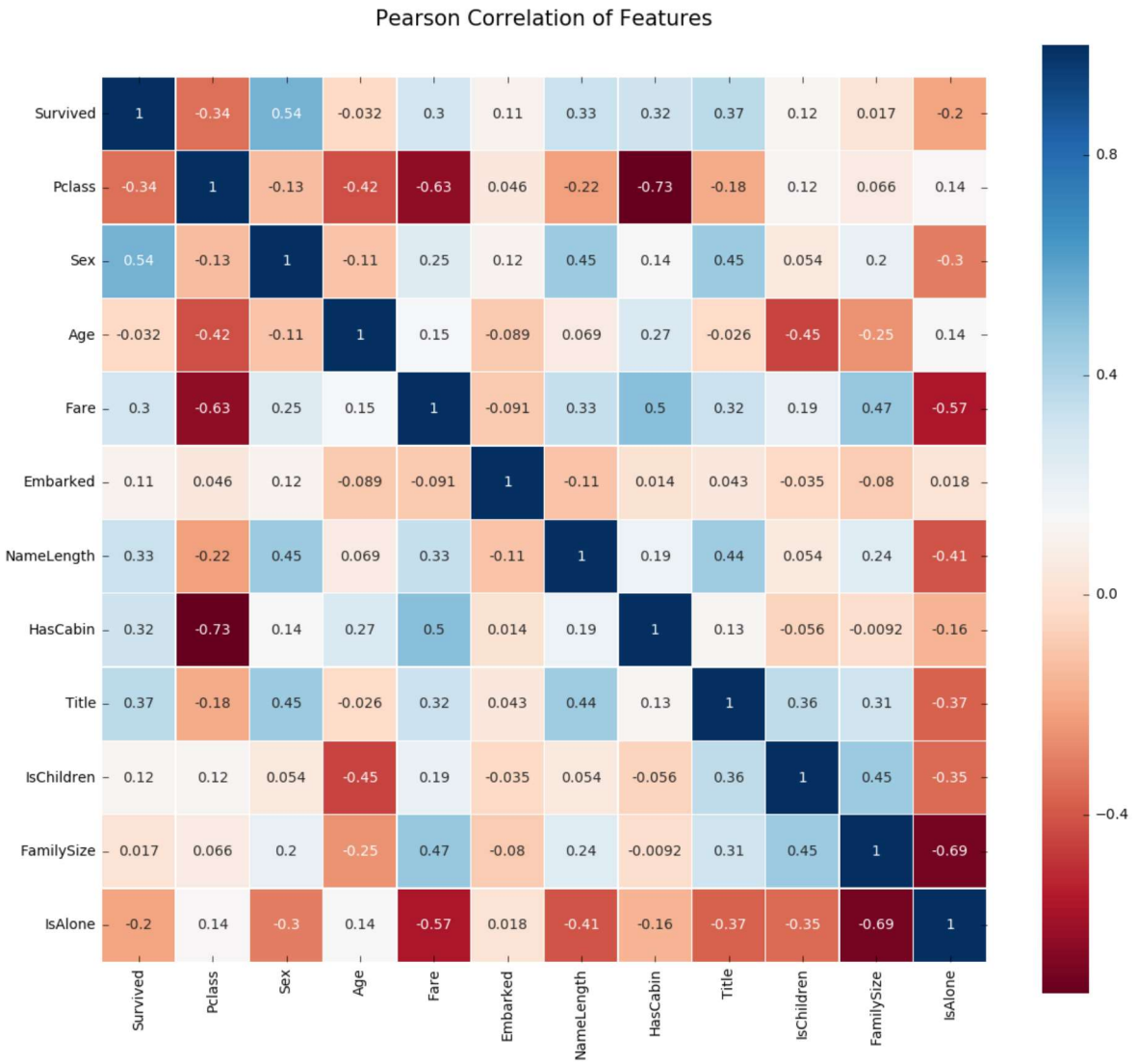
	PassengerId	Pclass	Sex	Age	Fare	Embarked	NameLength	HasCabin	Title	IsChil
0	892	3	0	5	0	2	16	0	1	0.0
1	893	3	1	7	0	0	32	0	3	0.0
2	894	2	0	7	1	2	25	0	1	0.0
3	895	3	0	4	1	0	16	0	1	0.0
4	896	3	1	2	1	0	44	0	3	0.0
5	897	3	0	0	1	0	26	0	1	0.0
6	898	3	1	4	0	2	20	0	2	0.0
7	899	2	0	3	2	0	28	0	1	0.0
8	900	3	1	1	0	1	41	0	3	0.0
9	901	3	0	1	2	0	23	0	1	0.0

In [105]:

```
# 用seaborn的heatmap对特征之间的相关性进行可视化
colormap = plt.cm.RdBu
plt.figure(figsize=(14,12))
plt.title('Pearson Correlation of Features', y=1.05, size=15)
sns.heatmap(train_df.astype(float).corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap=colormap, linecolor='white', annot=True)
```

Out[105]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a52a8d6518>
```



In [106]:

```
X_train = train_df.drop("Survived",axis=1)
Y_train = train_df["Survived"]
X_test_ = test_df.drop("PassengerId",axis=1).copy()
X_train.shape,Y_train.shape,X_test.shape
```

Out[106]:

```
((891, 11), (891,), (418, 11))
```

In [107]:

```
#训练集：dataset_X，dataset_Y
dataset_X = X_train[['Pclass', 'Sex', 'Age', 'Fare', 'Embarked','NameLength','HasCabin','Title','IsC
train_df['Deceased'] = train_df['Survived'].apply(lambda x: 1 - x)
dataset_Y=train_df[['Deceased', 'Survived']].values
#测试集：X_test
X_test=X_test_[['Pclass', 'Sex', 'Age', 'Fare', 'Embarked','NameLength','HasCabin','Title','IsChildr
PassengerId=test_df['PassengerId']
```

In [108]:

```
x = tf.placeholder(tf.float32, shape=[None, 11])
y = tf.placeholder(tf.float32, shape=[None,2])
# 使用逻辑回归模型
#y = σ(wx + b)
weights = tf.Variable(tf.random_normal([11, 2]), name='weights')
bias = tf.Variable(tf.zeros([2]), name='bias')
y_pred = tf.nn.softmax(tf.matmul(x, weights) + bias)
# 定义交叉熵
cross_entropy = - tf.reduce_sum(y * tf.log(y_pred + 1e-10), reduction_indices=1)
#定义损失函数
cost = tf.reduce_mean(cross_entropy)
# 使用梯度下降优化算法最小化损失函数
lr = 0.001
train_op = tf.train.GradientDescentOptimizer(lr).minimize(cost)
```

In [109]:

```
with tf.Session() as sess:
    print('start training')
    tf.global_variables_initializer().run()
    for epoch in range(70):
            total_loss = 0
            for i in range(len(dataset_X)):
            # prepare feed data and run
                feed_dict = {x: [dataset_X[i]], y: [dataset_Y[i]]}
                var, loss = sess.run([train_op, cost], feed_dict=feed_dict)
                total_loss += loss
            # display loss per epoch
            print('Epoch: %04d, total loss=%.9f' % (epoch + 1, total_loss))
    print("Train Complete")

    # 测试模型
    predictions = np.argmax(sess.run(y_pred, feed_dict={x: X_test}), 1)
    # 保存结果
    submission = pd.DataFrame({
        "PassengerId": PassengerId,
        "Survived": predictions
    })
    submission.to_csv("titanic-submission.csv", index=False)
    print('result saved')
```

```
start training
Epoch: 0001, total loss=6459.582044551
Epoch: 0002, total loss=980.471281188
Epoch: 0003, total loss=677.769217107
Epoch: 0004, total loss=580.194505227
Epoch: 0005, total loss=544.194216070
Epoch: 0006, total loss=526.636027896
Epoch: 0007, total loss=515.962032086
Epoch: 0008, total loss=508.350668270
Epoch: 0009, total loss=502.327286278
Epoch: 0010, total loss=497.250968245
Epoch: 0011, total loss=492.811649558
Epoch: 0012, total loss=488.843550477
Epoch: 0013, total loss=485.248924145
Epoch: 0014, total loss=481.964998726
Epoch: 0015, total loss=478.948390019
Epoch: 0016, total loss=476.167066120
Epoch: 0017, total loss=473.596368283
Epoch: 0018, total loss=471.216425245
Epoch: 0019, total loss=469.010815777
Epoch: 0020, total loss=466.965303232
Epoch: 0021, total loss=465.067767921
Epoch: 0022, total loss=463.307097400
Epoch: 0023, total loss=461.673533458
Epoch: 0024, total loss=460.157981752
Epoch: 0025, total loss=458.752053289
Epoch: 0026, total loss=457.448086967
Epoch: 0027, total loss=456.238776993
Epoch: 0028, total loss=455.117468656
Epoch: 0029, total loss=454.077860750
Epoch: 0030, total loss=453.113957214
Epoch: 0031, total loss=452.220405256
Epoch: 0032, total loss=451.391899164
Epoch: 0033, total loss=450.623748692
```

```
Epoch: 0034, total loss=449.911389946
Epoch: 0035, total loss=449.250650360
Epoch: 0036, total loss=448.637682131
Epoch: 0037, total loss=448.068852568
Epoch: 0038, total loss=447.540833578
Epoch: 0039, total loss=447.050454207
Epoch: 0040, total loss=446.594883294
Epoch: 0041, total loss=446.171498247
Epoch: 0042, total loss=445.777777445
Epoch: 0043, total loss=445.411418930
Epoch: 0044, total loss=445.070334234
Epoch: 0045, total loss=444.752655502
Epoch: 0046, total loss=444.456539161
Epoch: 0047, total loss=444.180268059
Epoch: 0048, total loss=443.922436242
Epoch: 0049, total loss=443.681559900
Epoch: 0050, total loss=443.456414425
Epoch: 0051, total loss=443.245674602
Epoch: 0052, total loss=443.048410049
Epoch: 0053, total loss=442.863497450
Epoch: 0054, total loss=442.690025429
Epoch: 0055, total loss=442.527136833
Epoch: 0056, total loss=442.374042870
Epoch: 0057, total loss=442.230097595
Epoch: 0058, total loss=442.094454616
Epoch: 0059, total loss=441.966686205
Epoch: 0060, total loss=441.846127971
Epoch: 0061, total loss=441.732222925
Epoch: 0062, total loss=441.624582943
Epoch: 0063, total loss=441.522673594
Epoch: 0064, total loss=441.426093297
Epoch: 0065, total loss=441.334546728
Epoch: 0066, total loss=441.247625535
Epoch: 0067, total loss=441.165045570
Epoch: 0068, total loss=441.086427445
Epoch: 0069, total loss=441.011617068
Epoch: 0070, total loss=440.940250359
Train Complete
result saved
```