Limpieza y validacion de los datos

January 7, 2019

Importamos los paquetes que vamos a necesitar.

```
In [75]: # Import modules
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn import tree
         from sklearn.metrics import accuracy_score
         import numpy as np
```

```
In [3]: # Visualization style
        %matplotlib inline
        sns.set()
```

1 Importamos ahora el set de datos train y test para su exploración y análisis

```
In [6]: # Import test and train datasets
        dftrain = pd.read_csv('/Users/carinazavala/Documents/UOC/1er Semestre/Tipología y ciclo
        dftest = pd.read_csv('/Users/carinazavala/Documents/UOC/1er Semestre/Tipología y ciclo

        # View first lines of training data
        dftrain.head(n=4)
```

```
Out[6]:    PassengerId  Survived  Pclass  \
        0            1         0       3
        1            2         1       1
        2            3         1       3
        3            4         1       1

                                                        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

           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
```

In [8]:
```
# Summary visualization of train data
dftrain.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
```

In [ ]:
```
# Do same visualization of test data
dftest.head(n=4)
```

In [ ]:
```
dftest.info()
```

Comparamos las distribuciones de los datos train y test para conocer qué tanto difieren uno del otro

In [9]:
```
# Compare distribution of features in train and test data with describe
dftrain.describe()
```

Out[9]:
```
        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

In [10]:
```
dftest.describe()
```

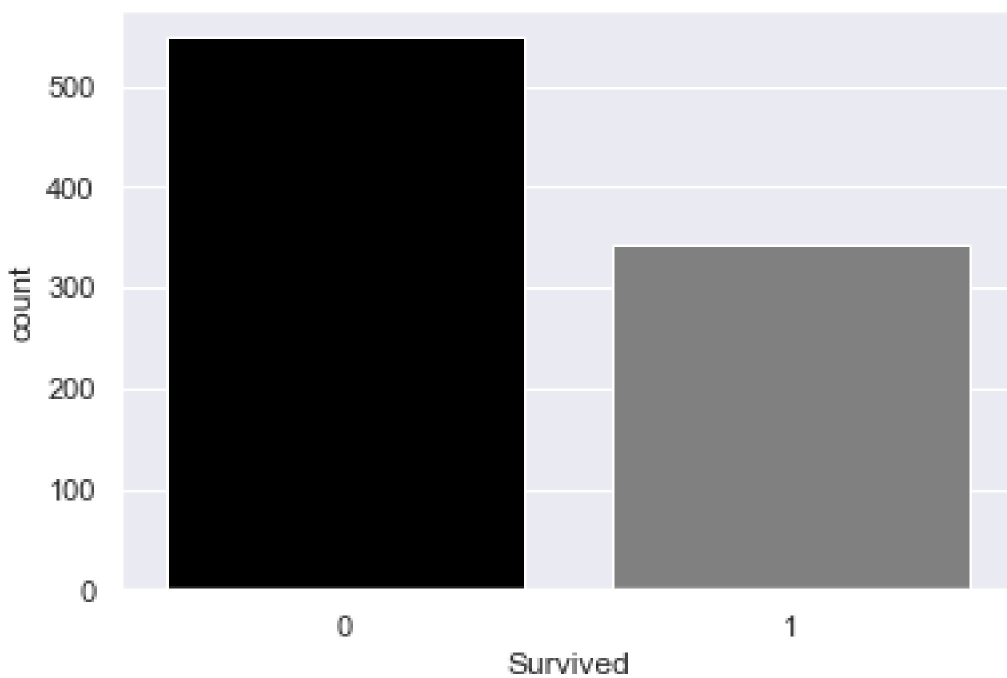
Out[10]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
mean	1100.500000	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.841838	14.181209	0.896760	0.981429	55.907576
min	892.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	1.000000	21.000000	0.000000	0.000000	7.895800
50%	1100.500000	3.000000	27.000000	0.000000	0.000000	14.454200
75%	1204.750000	3.000000	39.000000	1.000000	0.000000	31.500000
max	1309.000000	3.000000	76.000000	8.000000	9.000000	512.329200

La desviación estándar son similares comparando Pclass y Age en los datos train y test, pero para Parch y Fare son ligeramente mayores en test, mientras que, SibSp es mayor en train.

Visualización gráfica de pasajeros que sobrevivieron o murieron en train.

In [16]:
```
# Review how many passengers survived and died in train data
sns.countplot(x='Survived', data=dftrain,
              palette=sns.color_palette(['black','grey']));
```



In [12]:
```python
# Obtain the survived percentage in train data
print(dftrain.Survived.sum()/dftrain.Survived.count())

# the result shows that 38 % survived
```

```
0.3838383838383838
```

38% de los pasajeros sobrevivieron ->modelo1:sin sobrevivientes submission:0.627 accuracy

In [25]:
```python
dftest['Survived'] = 0
dftest[['PassengerId', 'Survived']].to_csv('no_survivors.csv', index=False)
```

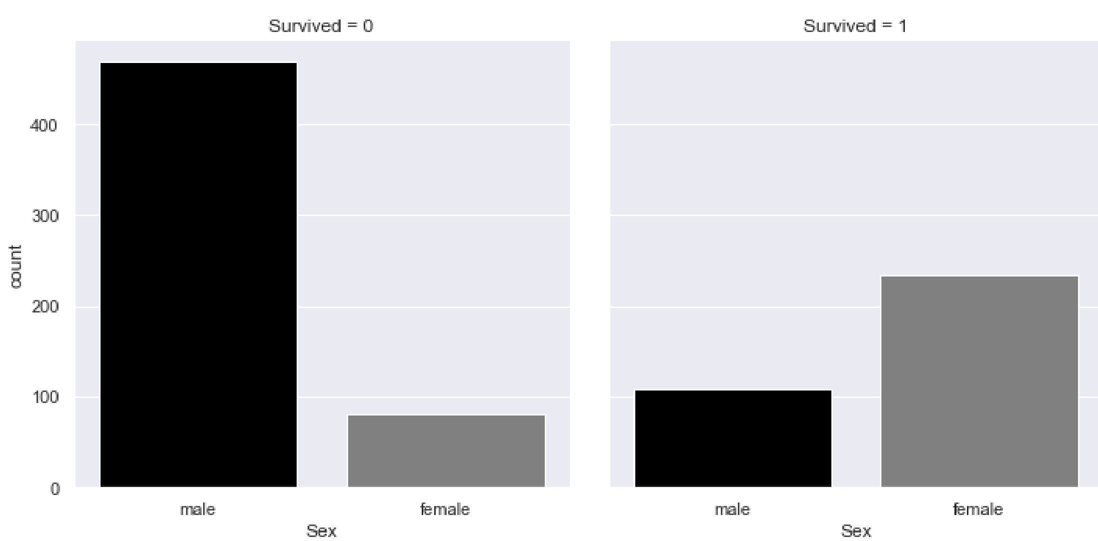
Variable = Sex, Sobrevivieron más mujeres que hombres

In [13]:
```python
# Analizing survivors per sex in train data
dftrain.groupby(['Survived','Sex'])['Survived'].count()
# more female passengers survived
```

Out[13]:
```
Survived  Sex
0         female     81
          male      468
1         female    233
          male      109
Name: Survived, dtype: int64
```

In [15]:
```python
# Plotting this in bar chart
sns.catplot(x='Sex', col='Survived', kind='count', data=dftrain,
            palette=sns.color_palette(['black','grey']))
```

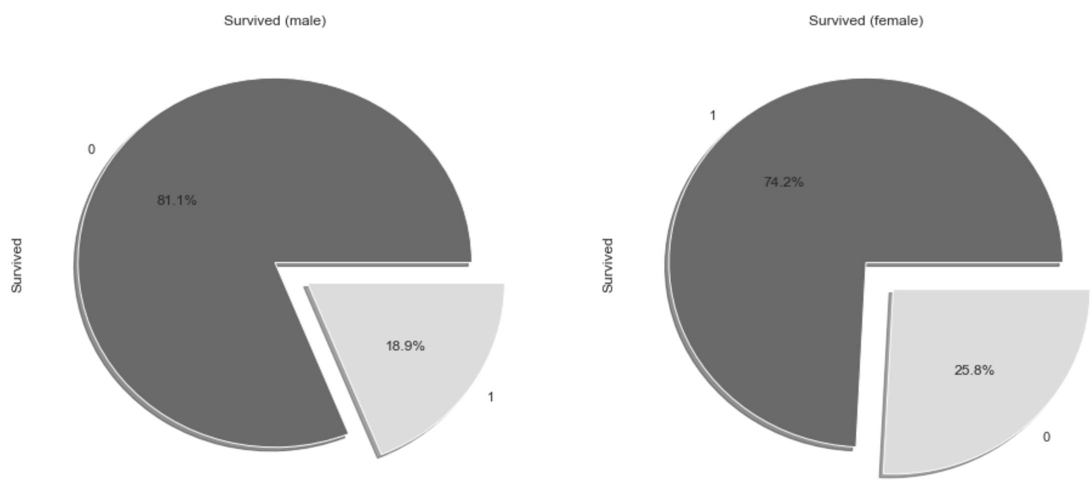
Out[15]:
```
<seaborn.axisgrid.FacetGrid at 0x1a1cb89320>
```



```
In [17]: # Obtain the survived percentage per sex train data
         print("% of women survived: " , dftrain[dftrain.Sex == 'female'].Survived.sum()/dftrai
         print("% of men survived:   " , dftrain[dftrain.Sex == 'male'].Survived.sum()/dftrain
```

```
% of women survived:  0.7420382165605095
% of men survived:    0.18890814558058924
```

```
In [28]: # Visualization of percentage per sex survivors in pie plott
         colors=['dimgrey','gainsboro']
         f,ax=plt.subplots(1,2,figsize=(16,7))
         dftrain['Survived'][dftrain['Sex']=='male'].value_counts().plot.pie(explode=[0,0.2],au
         dftrain['Survived'][dftrain['Sex']=='female'].value_counts().plot.pie(explode=[0,0.2]
         ax[0].set_title('Survived (male)')
         ax[1].set_title('Survived (female)')

         plt.show()
```



En los datos de entrenamiento el 74% de las mujeres sobrevivieron
->modelo2: todas las mujeres sobrevivieron y todos los hombres murieron submission:0.766 accueracy

```
In [26]: dftest['Survived'] = dftest.Sex == 'female'
         dftest['Survived'] = dftest.Survived.apply(lambda x: int(x))
         dftest[['PassengerId', 'Survived']].to_csv('women_survive.csv', index=False)
```

Passgenger Class, la tasa de supervivencia decrece con Pclass

```
In [27]: pd.crosstab(dftrain.Pclass, dftrain.Survived, margins=True).style.background_gradient
```

Out[27]: <pandas.io.formats.style.Styler at 0x1a1cbd7b70>

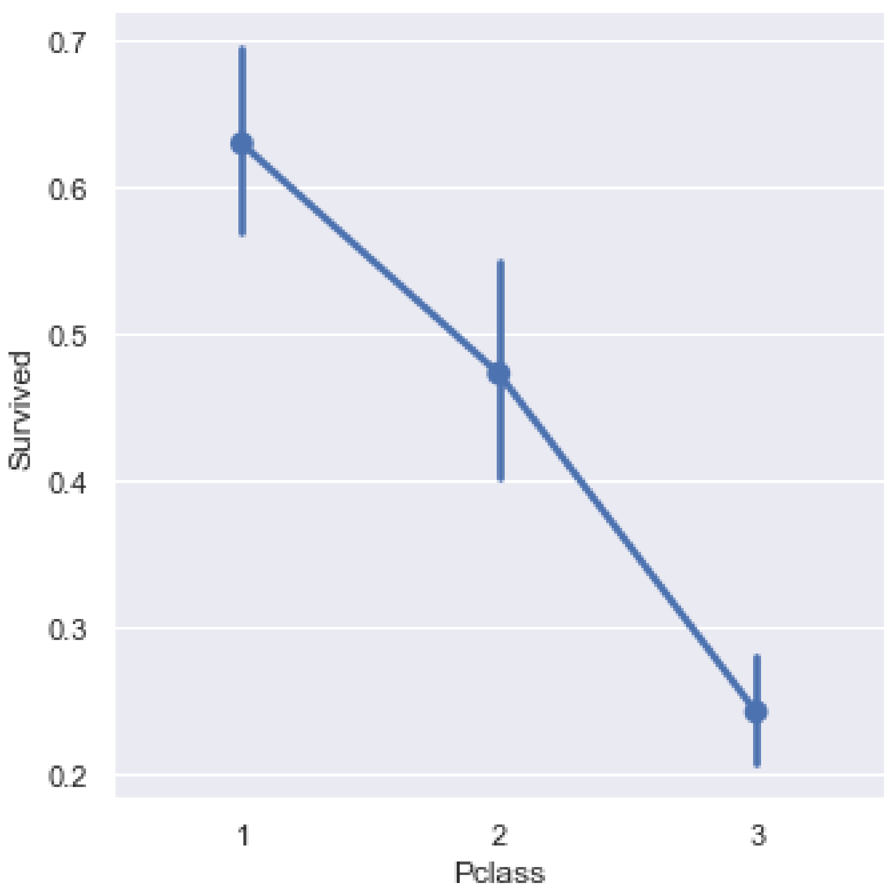
In [29]:
```
print("% of survivals in")
print("Pclass=1 : ", dftrain.Survived[dftrain.Pclass == 1].sum()/dftrain[dftrain.Pclas
print("Pclass=2 : ", dftrain.Survived[dftrain.Pclass == 2].sum()/dftrain[dftrain.Pclas
print("Pclass=3 : ", dftrain.Survived[dftrain.Pclass == 3].sum()/dftrain[dftrain.Pclas
```

```
% of survivals in
Pclass=1 :  0.6296296296296297
Pclass=2 :  0.47282608695652173
Pclass=3 :  0.24236252545824846
```

Hubieron más sobrevivientes con Pclass=1 el 62.9%, visualización gráfica de este comportamiento.

In [30]:
```
sns.catplot('Pclass','Survived', kind='point', data=dftrain);
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarn
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



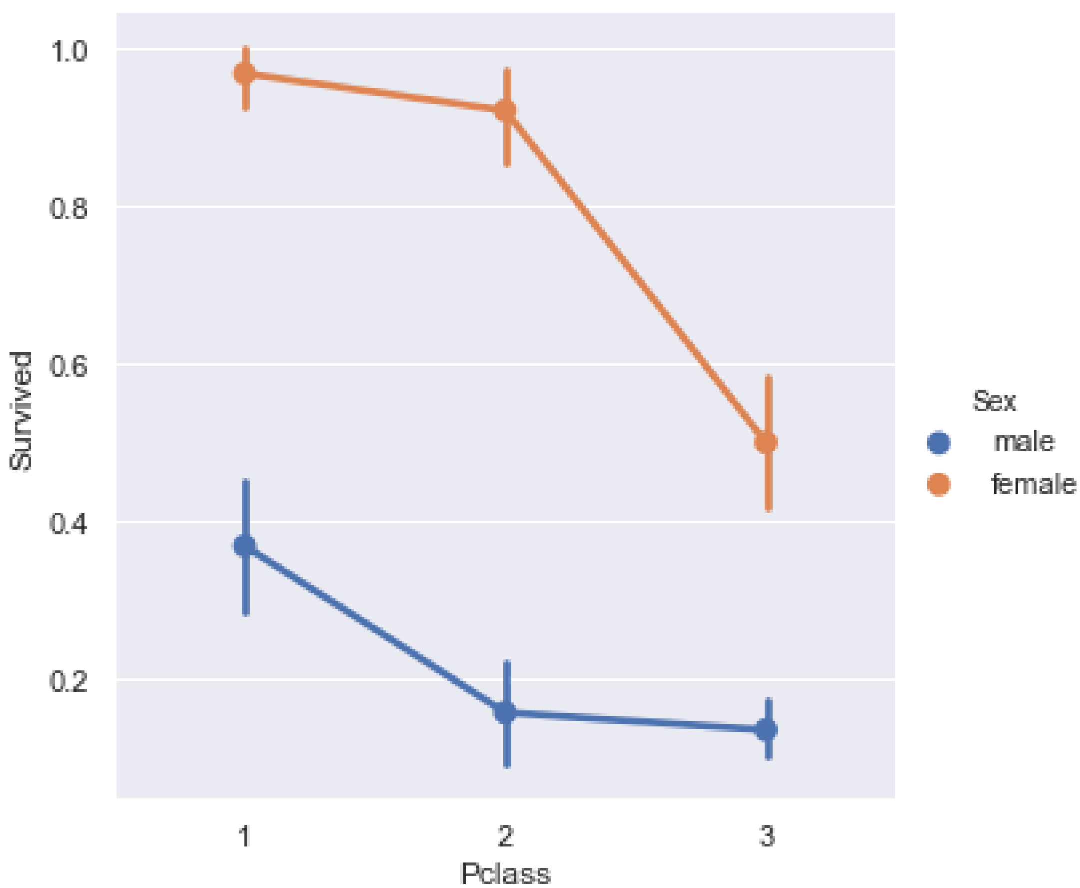
Class and Sex, casi todas las mujeres en Pclass 1 y 2 sobrevivieron y casi todos los hombres en Pclass 2 y 3 murieron

```
In [32]: pd.crosstab([dftrain.Sex, dftrain.Survived], dftrain.Pclass, margins=True).style.backg
```

```
Out[32]: <pandas.io.formats.style.Styler at 0x1a1e5217b8>
```

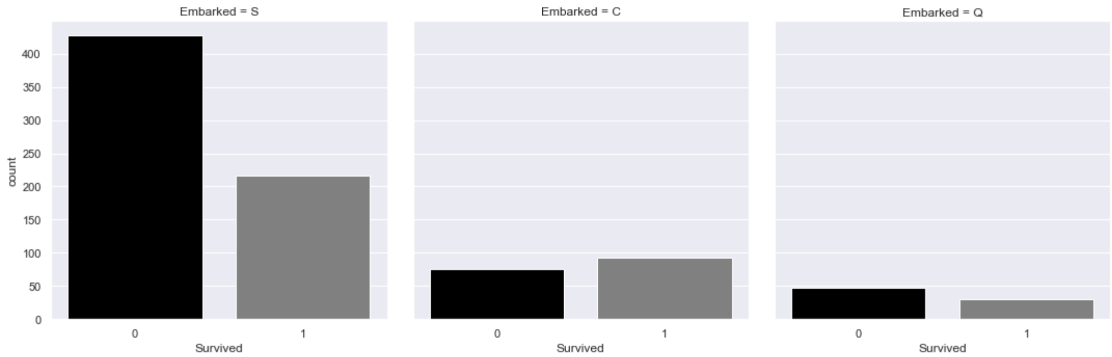
```
In [33]: sns.catplot('Pclass','Survived',hue='Sex', kind='point', data=dftrain);
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarn
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



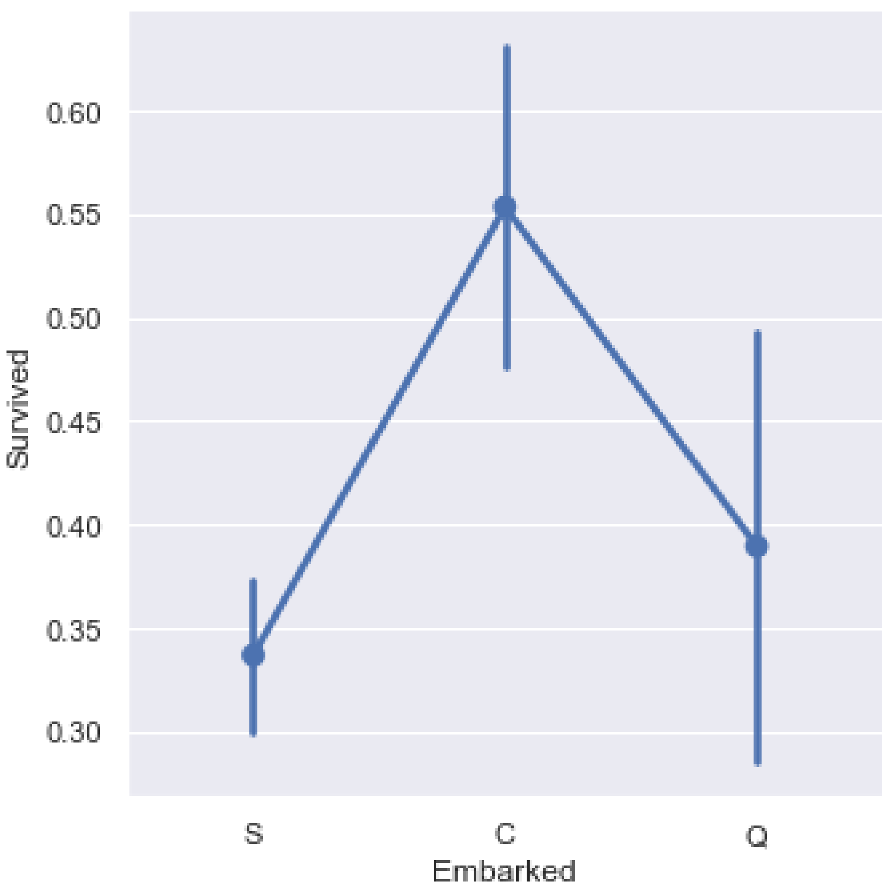
Embarked : Tasa de supervivencia menor para S y mayor para C

```
In [34]: sns.catplot(x='Survived', col='Embarked', kind='count', data=dftrain,
                    palette=sns.color_palette(['black','grey']));
```




```
In [35]: sns.catplot('Embarked','Survived', kind='point', data=dftrain)
         plt.show()
```

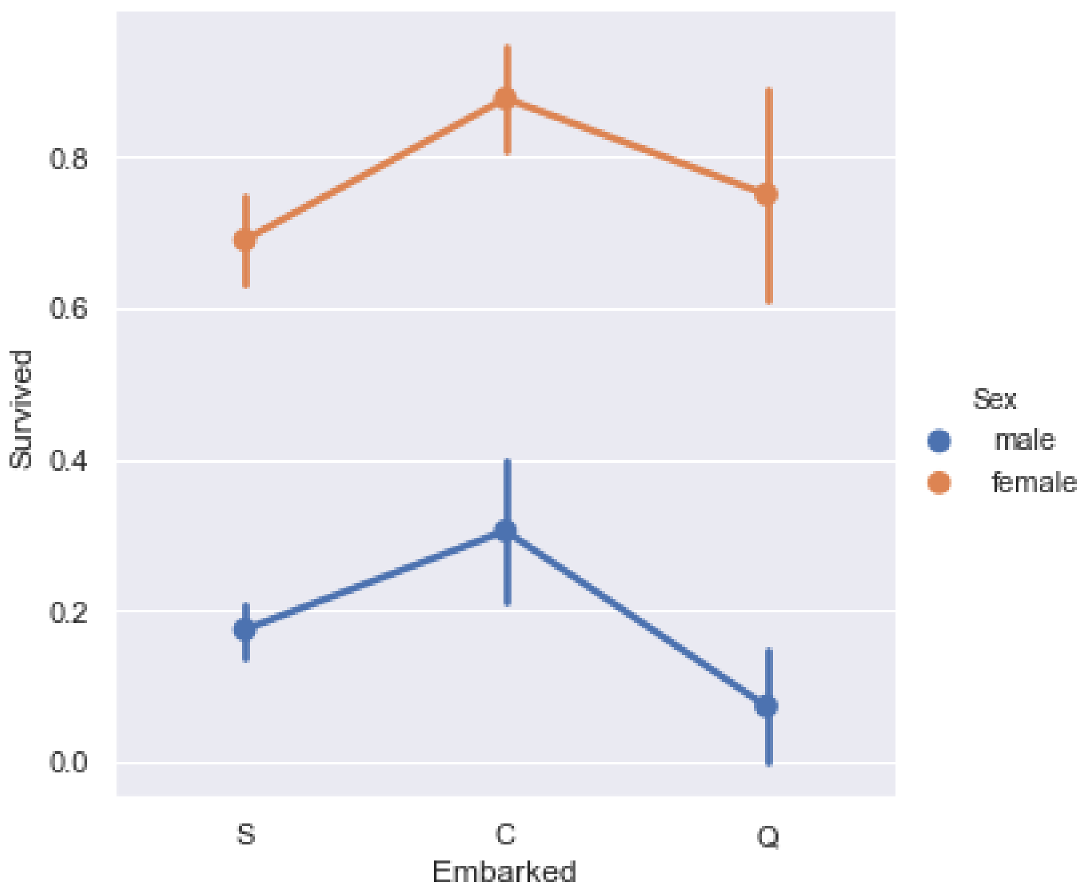
```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarn
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Embarked and Sex

```
In [37]: sns.catplot('Embarked','Survived', hue= 'Sex', kind='point', data=dftrain)
         plt.show()
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarn
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Embarked, Pclass y Sex :

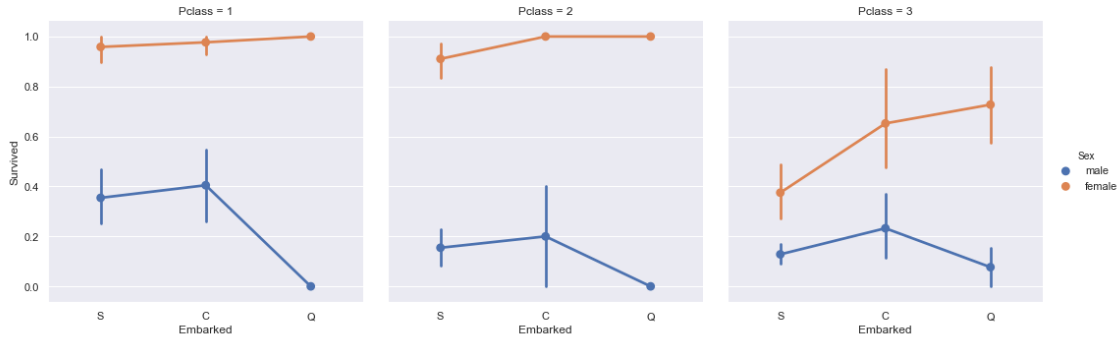
Practicamente todas las mujeres de Pclass 2 que embarcaron en C y Q sobrevivieron, también casi todas las mujeres de Pclass 1.

Todos los hombres de Pclass 1 y 2 embarcados en Q murieron, la tasa de supervivencia de los hombres en Pclass 2 y 3 fue menor a 0.2

Los hombres restantes en Pclass 1 embarcados en S y Q, tuvieron una tasa de supervivencia cercana a 0.4

```
In [38]: sns.catplot('Embarked','Survived', col='Pclass', hue= 'Sex', kind='point', data=dftra
         plt.show()
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarn
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [39]:
```python
pd.crosstab([dftrain.Survived], [dftrain.Sex, dftrain.Pclass, dftrain.Embarked], margi
```

Out[39]:
```
Sex      female                                   male                                  \
Pclass        1          2           3                1          2          3
Embarked      C  Q   S   C  Q    S    C    Q    S     C  Q    S    C  Q    S    C    Q
Survived
0             1  0   2   0  0    6    8    9   55    25  1   51    8  1   82   33   36
1            42  1  46   7  2   61   15   24   33    17  0   28    2  0   15   10    3
All          43  1  48   7  2   67   23   33   88    42  1   79   10  1   97   43   39

Sex            All
Pclass
Embarked    S
Survived
0         231  549
1          34  340
All       265  889
```

modelo3 : basado en PClass, Sex y Embarked , submission : 0.779 accuracy

In [40]:
```python
# model 3
dftest['Survived'] = 0
# all women survived
dftest.loc[ (dftest.Sex == 'female'), 'Survived'] = 1
# except for those in Pclass 3 and embarked in S
dftest.loc[ (dftest.Sex == 'female') & (dftest.Pclass == 3) & (dftest.Embarked == 'S')
dftest[['PassengerId', 'Survived']].to_csv('embarked_pclass_sex.csv', index=False)
```

Edad, continuo numérico a 8 contenedores

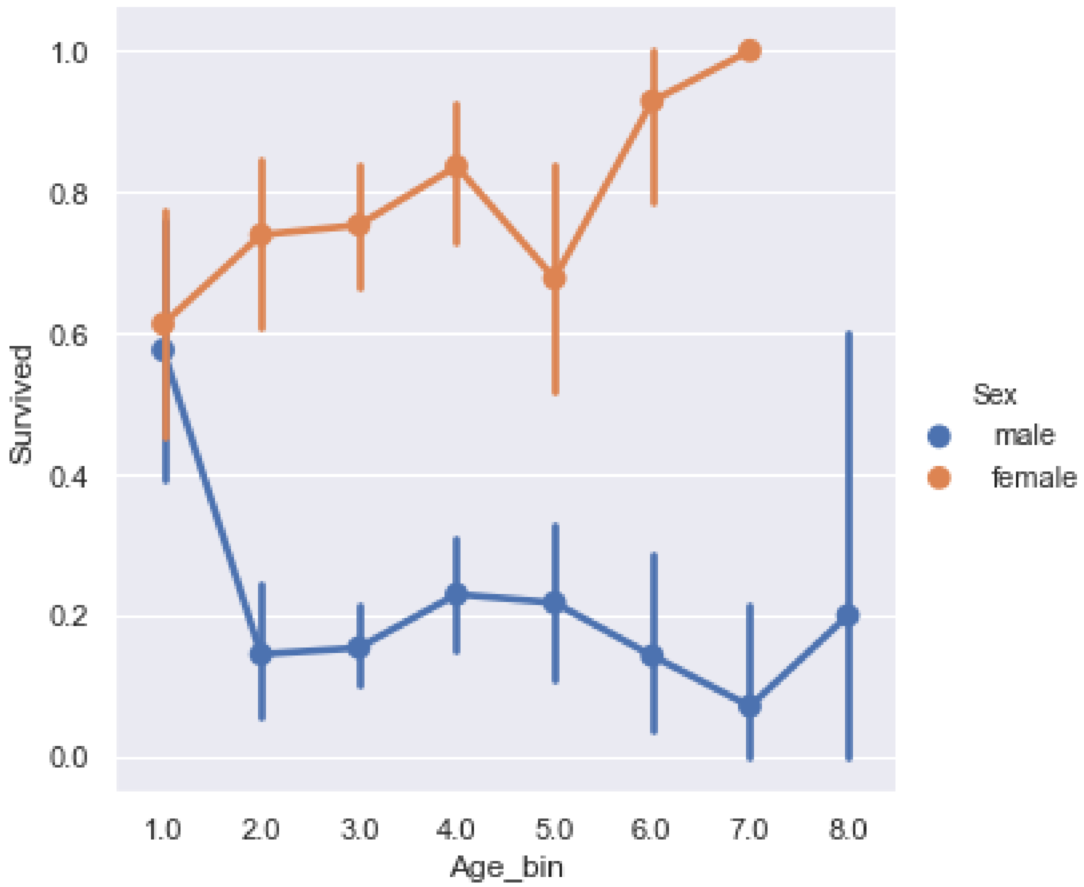
In [45]:
```python
for df in [dftrain, dftest]:
    df['Age_bin']=np.nan
    for i in range(8,0,-1):
        df.loc[ df['Age'] <= i*10, 'Age_bin'] = i
```

```
In [46]: print(dftrain[['Age' , 'Age_bin']].head(10))
```

```
    Age  Age_bin
0  22.0      3.0
1  38.0      4.0
2  26.0      3.0
3  35.0      4.0
4  35.0      4.0
5   NaN      NaN
6  54.0      6.0
7   2.0      1.0
8  27.0      3.0
9  14.0      2.0
```

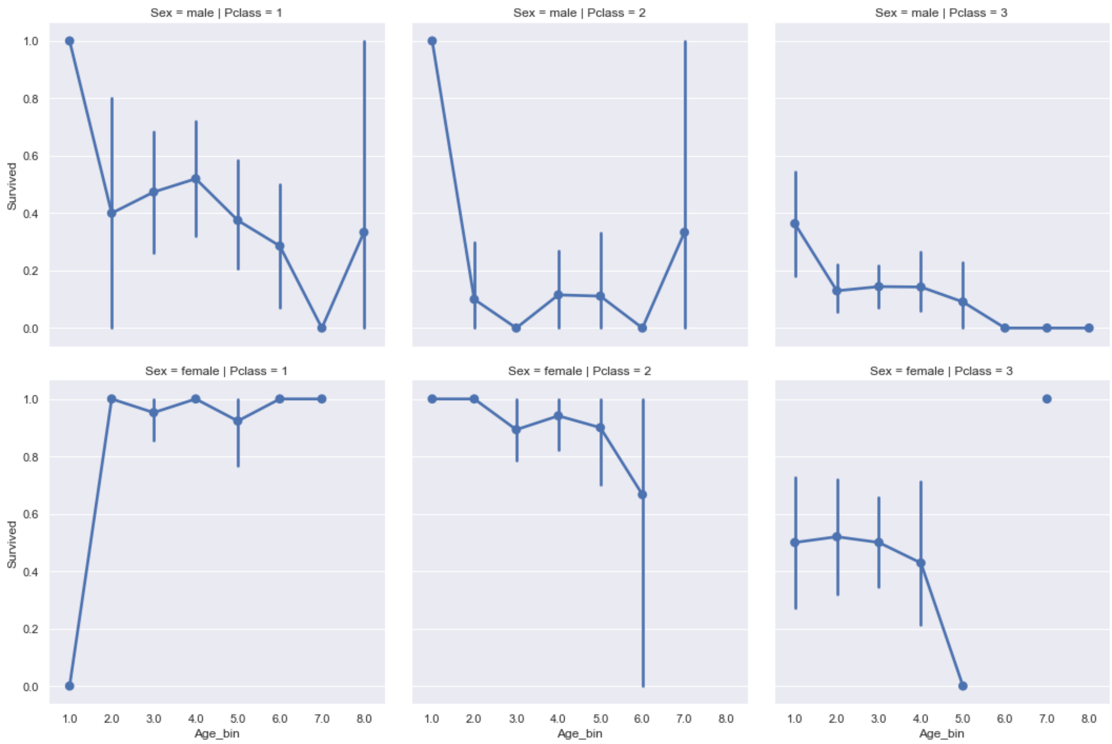
```
In [47]: sns.catplot('Age_bin','Survived',hue='Sex',kind='point',data=dftrain)
         plt.show()
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarn
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



```
In [48]: sns.catplot('Age_bin','Survived', col='Pclass' , row = 'Sex', kind='point', data=dftra
         plt.show()
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWar
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```




```
In [49]: pd.crosstab([dftrain.Sex, dftrain.Survived], [dftrain.Age_bin, dftrain.Pclass], margi
```

```
Out[49]: <pandas.io.formats.style.Styler at 0x1a1f10cc18>
```

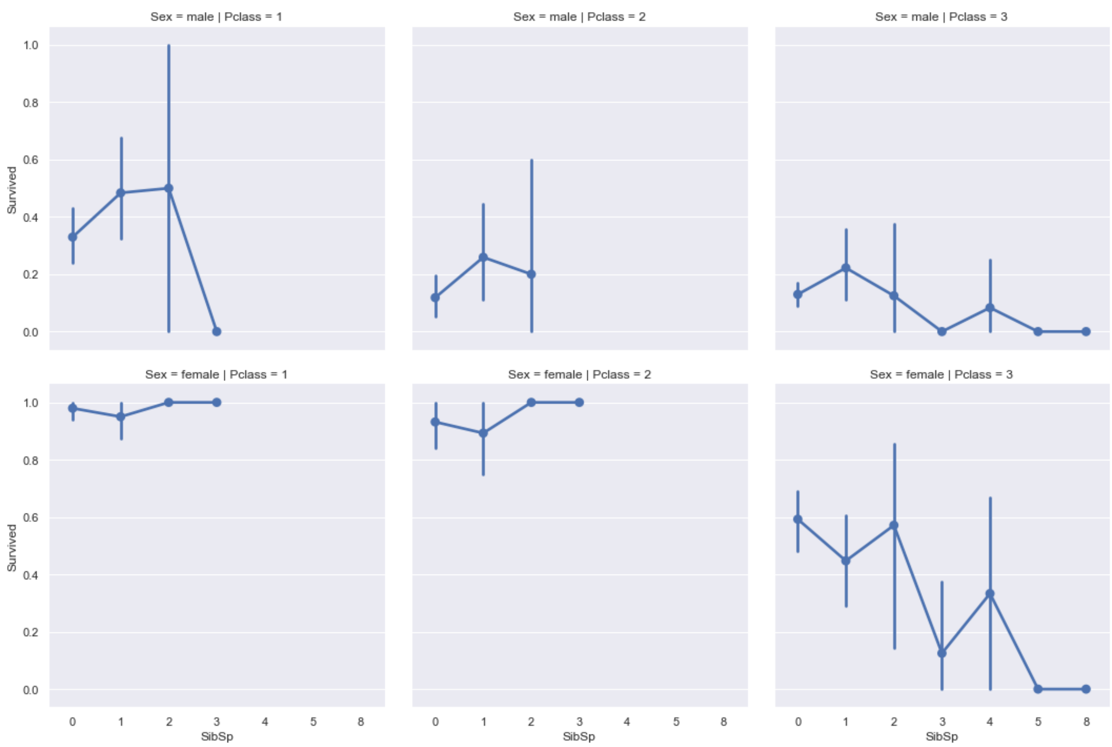
Para pasajeros en
*Age_bim=1(menores a 10): todos los hombres en Pclass=1 y 2 sobrevivieron.
*Mujeres en Pclass=3 y Age_bin= 5 murieron
*Menos del 50% de mujeres en Pclass=3 y Age_bin=4 sobrevivieron
*Más del 50% de hombres en Pclass=1 y Age_bin=4 sobrevivieron

```
In [50]: # in Pclass 1 and 2 all men in Age_bin = 1 survived
         dftest.loc[ (dftest.Sex == 'male') & (dftest.Pclass == 1) & (dftest.Age_bin == 1), 'S
         dftest.loc[ (dftest.Sex == 'male') & (dftest.Pclass == 2) & (dftest.Age_bin == 1), 'S
```

SibSp y Parch

```
In [51]: sns.catplot('SibSp','Survived', col='Pclass' , row = 'Sex', kind='point', data=dftrai
         plt.show()
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWar
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```




```
In [52]: pd.crosstab([dftrain.Sex, dftrain.Survived], [dftrain.SibSp, dftrain.Pclass], margins
```

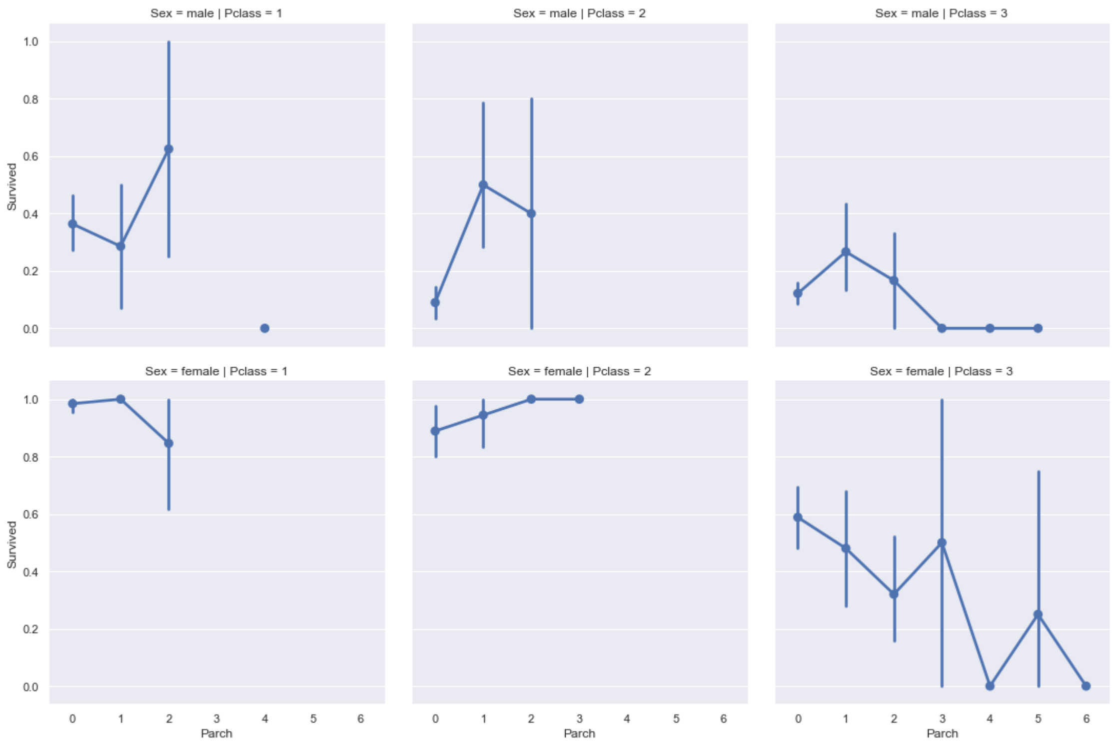
```
Out[52]: <pandas.io.formats.style.Styler at 0x1a1f969b70>
```

*Para hombres, no hubo porcentaje de sobrevivencia para ningún valor arriba de 0.5 en SibSp.
*Para mujeres, pasajeras con SibSp=3 y Pclass=3 murieron con SibSp>4
*Para mujeres, pasajeras con SibSp=1 y Pclass=3 el porcentaje de sobrevivencia está por denajo de 50%

```
In [55]: # all females with SibSp > 7 died
         dftest.loc[ (dftest.Sex == 'female') & (dftest.SibSp > 7) , 'Survived'] = 0
```

```
In [56]: sns.catplot('Parch','Survived', col='Pclass' , row = 'Sex', kind='point', data=dftrai
         plt.show()
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWar
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```




```
In [57]: pd.crosstab([dftrain.Sex, dftrain.Survived], [dftrain.Parch, dftrain.Pclass], margins=
```

```
Out[57]: <pandas.io.formats.style.Styler at 0x1a1f124c88>
```

*Mujeres con Parch = 2 y Pclass = 3 la tasa de supervivencia está. por debajo de 0.5.
*Todas las mujeres con Parch = 4 y Pclass = 3 murieron.
*Todas las mujeres con Parch > 4 murieron.
*Las mujeres con Parch = 1 y Pclass = 3 tasa de supervivencia está por debajo de 0.5
*Para hombres todas las tasas de supervivencia es menor a 0.5 para cualquier valor de Parch, excepto para Parch = 2 y Pclass = 1.

```
In [60]: # survival rate is below 0.5 for females with Parch = 2 and Pclass = 3
         dftest.loc[ (dftest.Sex == 'female') & (dftest.Pclass == 3) & (dftest.Parch == 2), 'Su

         # All females with Parch = 4 and Pclass = 3 died
         dftest.loc[ (dftest.Sex == 'female') & (dftest.Pclass == 3) & (dftest.Parch == 4), 'Su

         # all females with Parch > 4 died
         dftest.loc[ (dftest.Sex == 'female') & (dftest.Parch > 4) , 'Survived'] = 0

         # For males with Parch = 2 and Pclass = 1 survival rate is above 0.5
         dftest.loc[ (dftest.Sex == 'male') & (dftest.Pclass == 1) & (dftest.Parch == 1) , 'Su

         dftest.head(20)
```

Out[60]:

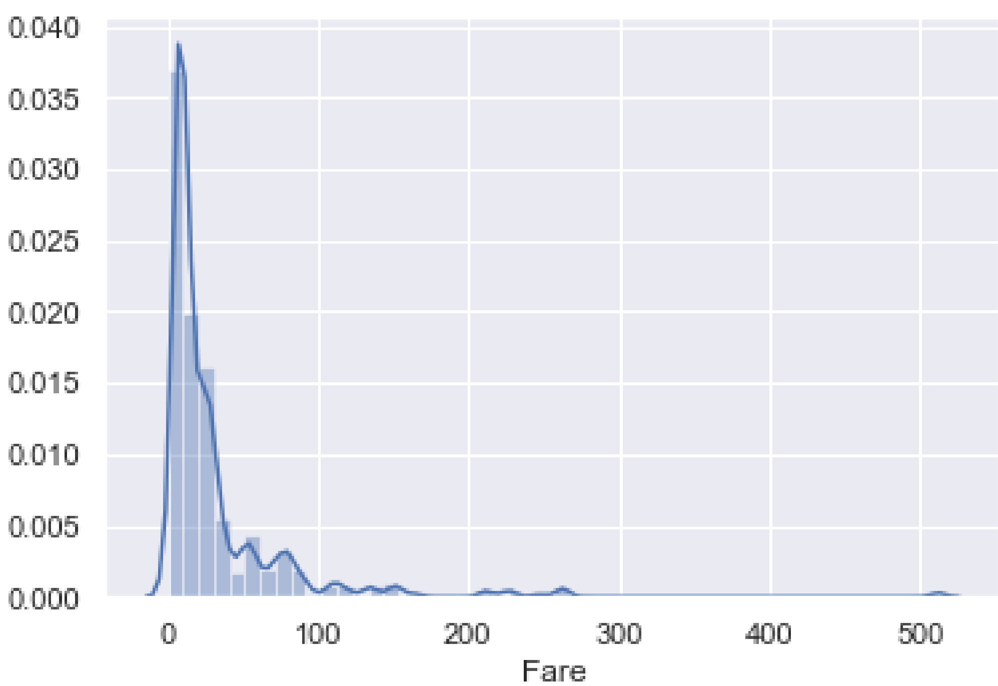
```
    PassengerId  Pclass                                          Name  \
0           892       3                              Kelly, Mr. James
1           893       3              Wilkes, Mrs. James (Ellen Needs)
2           894       2                     Myles, Mr. Thomas Francis
3           895       3                              Wirz, Mr. Albert
4           896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)
5           897       3                    Svensson, Mr. Johan Cervin
6           898       3                          Connolly, Miss. Kate
7           899       2                  Caldwell, Mr. Albert Francis
8           900       3     Abrahim, Mrs. Joseph (Sophie Halaut Easu)
9           901       3                       Davies, Mr. John Samuel
10          902       3                              Ilieff, Mr. Ylio
11          903       1                    Jones, Mr. Charles Cresson
12          904       1  Snyder, Mrs. John Pillsbury (Nelle Stevenson)
13          905       2                          Howard, Mr. Benjamin
14          906       1  Chaffee, Mrs. Herbert Fuller (Carrie Constance...
15          907       2  del Carlo, Mrs. Sebastiano (Argenia Genovesi)
16          908       2                             Keane, Mr. Daniel
17          909       3                             Assaf, Mr. Gerios
18          910       3                  Ilmakangas, Miss. Ida Livija
19          911       3         Assaf Khalil, Mrs. Mariana (Miriam")"

       Sex   Age  SibSp  Parch              Ticket     Fare Cabin Embarked  \
0     male  34.5      0      0              330911   7.8292   NaN        Q
1   female  47.0      1      0              363272   7.0000   NaN        S
2     male  62.0      0      0              240276   9.6875   NaN        Q
3     male  27.0      0      0              315154   8.6625   NaN        S
4   female  22.0      1      1             3101298  12.2875   NaN        S
5     male  14.0      0      0                7538   9.2250   NaN        S
6   female  30.0      0      0              330972   7.6292   NaN        Q
7     male  26.0      1      1              248738  29.0000   NaN        S
8   female  18.0      0      0                2657   7.2292   NaN        C
9     male  21.0      2      0          A/4 48871  24.1500   NaN        S
10    male   NaN      0      0              349220   7.8958   NaN        S
11    male  46.0      0      0                 694  26.0000   NaN        S
12  female  23.0      1      0               21228  82.2667   B45        S
13    male  63.0      1      0               24065  26.0000   NaN        S
14  female  47.0      1      0         W.E.P. 5734  61.1750   E31        S
15  female  24.0      1      0      SC/PARIS 2167  27.7208   NaN        C
16    male  35.0      0      0              233734  12.3500   NaN        Q
17    male  21.0      0      0                2692   7.2250   NaN        C
18  female  27.0      1      0  STON/O2. 3101270   7.9250   NaN        S
19  female  45.0      0      0                2696   7.2250   NaN        C

    Survived  Age_bin
0          0      4.0
1          0      5.0
2          0      7.0
```

```
3          0      3.0
4          0      3.0
5          0      2.0
6          1      3.0
7          0      3.0
8          1      2.0
9          0      3.0
10         0      NaN
11         0      5.0
12         1      3.0
13         0      7.0
14         1      5.0
15         1      3.0
16         0      4.0
17         0      3.0
18         0      3.0
19         1      5.0
```

Fare : numérica continua a 12 contenedores

```
In [61]: sns.distplot(dftrain['Fare'])
         plt.show()
```

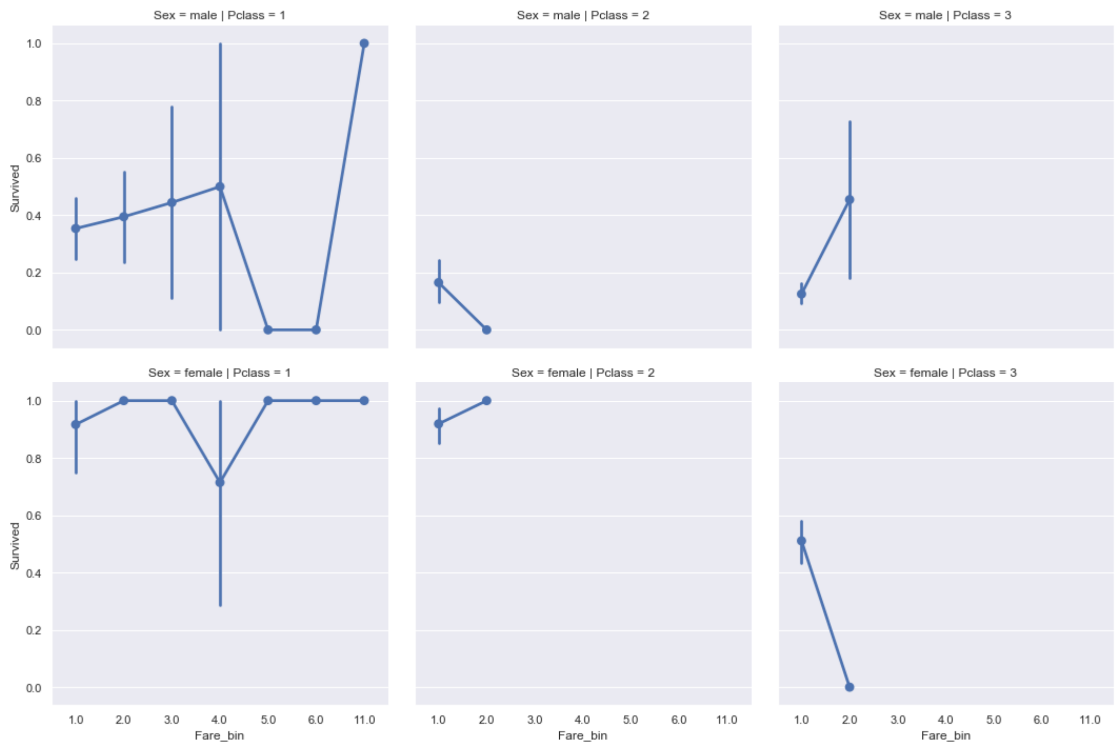
```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarn
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [62]:
```
for df in [dftrain, dftest]:
    df['Fare_bin']=np.nan
    for i in range(12,0,-1):
        df.loc[ df['Fare'] <= i*50, 'Fare_bin'] = i
```

In [63]:
```
sns.catplot('Fare_bin','Survived', col='Pclass' , row = 'Sex', kind='point', data=dft
plt.show()
```

```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarn
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [76]:
```
pd.crosstab([dftrain.Sex, dftrain.Survived], [dftrain.Fare_bin, dftrain.Pclass], marg
```

Out[76]:
```
<pandas.io.formats.style.Styler at 0x1a1e644cf8>
```

In [77]:
```
# males in Fare_bin = 11 survived
dftest.loc[ (dftest.Sex == 'male') & (dftest.Fare_bin == 11), 'Survived'] = 1
```

modelo4: modelo3 + Age_bin, SibSp,Parch and Fare_bin submission:0.789 accuracy

In [78]:
```
# modelo4
dftest[['PassengerId', 'Survived']].to_csv('model_4.csv', index=False)
```

In [79]:
```
dftest.drop(['Survived'],axis=1,inplace=True)
```

2 Data wrangling

Construir dos nuevos dataframes dftrain_ml y dftest_ml, los cuales sólo contendrán ordinales y no nulos para ser usados en algoritmos de machine learning

1.Copiar los datos para los nuevos dataframes 2.Convertir de categóricas a numéricas las variables con pd.get_dummies 3.Dejar de lado las variables que no sean útiles en la predicción 4.Usar Standard scaler y aplicar la división train/test

In [80]:
```
#1
dftrain_ml = dftrain.copy()
dftest_ml = dftest.copy()
```

In [81]:
```
#2
dftrain_ml = pd.get_dummies(dftrain_ml, columns=['Sex', 'Embarked', 'Pclass'], drop_fi
dftrain_ml.drop(['PassengerId','Name','Ticket', 'Cabin', 'Age_bin', 'Fare_bin'],axis=
dftrain_ml.dropna(inplace=True)
```

In [82]:
```
#3
passenger_id = dftest_ml['PassengerId']
dftest_ml = pd.get_dummies(dftest_ml, columns=['Sex', 'Embarked', 'Pclass'], drop_firs
dftest_ml.drop(['PassengerId','Name','Ticket', 'Cabin', 'Age_bin', 'Fare_bin'],axis=1
```

Visualizamos los datos con .head y .info

In [83]:
```
dftrain_ml.head(10)
```

Out[83]:

	Survived	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S	\
0	0	22.0	1	0	7.2500	1	0	1	
1	1	38.0	1	0	71.2833	0	0	0	
2	1	26.0	0	0	7.9250	0	0	1	
3	1	35.0	1	0	53.1000	0	0	1	
4	0	35.0	0	0	8.0500	1	0	1	
6	0	54.0	0	0	51.8625	1	0	1	
7	0	2.0	3	1	21.0750	1	0	1	
8	1	27.0	0	2	11.1333	0	0	1	
9	1	14.0	1	0	30.0708	0	0	0	
10	1	4.0	1	1	16.7000	0	0	1	

	Pclass_2	Pclass_3
0	0	1
1	0	0
2	0	1
3	0	0
4	0	1
6	0	0
7	0	1
8	0	1
9	1	0
10	0	1

```
In [84]: dftrain_ml.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 714 entries, 0 to 890
Data columns (total 10 columns):
Survived      714 non-null int64
Age           714 non-null float64
SibSp         714 non-null int64
Parch         714 non-null int64
Fare          714 non-null float64
Sex_male      714 non-null uint8
Embarked_Q    714 non-null uint8
Embarked_S    714 non-null uint8
Pclass_2      714 non-null uint8
Pclass_3      714 non-null uint8
dtypes: float64(2), int64(3), uint8(5)
memory usage: 37.0 KB
```

```
In [85]: dftest_ml.head(10)
```

Out[85]:

	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S	Pclass_2	\
0	34.5	0	0	7.8292	1	1	0	0	
1	47.0	1	0	7.0000	0	0	1	0	
2	62.0	0	0	9.6875	1	1	0	1	
3	27.0	0	0	8.6625	1	0	1	0	
4	22.0	1	1	12.2875	0	0	1	0	
5	14.0	0	0	9.2250	1	0	1	0	
6	30.0	0	0	7.6292	0	1	0	0	
7	26.0	1	1	29.0000	1	0	1	1	
8	18.0	0	0	7.2292	0	0	0	0	
9	21.0	2	0	24.1500	1	0	1	0	

	Pclass_3
0	1
1	1
2	0
3	1
4	1
5	1
6	1
7	0
8	1
9	1

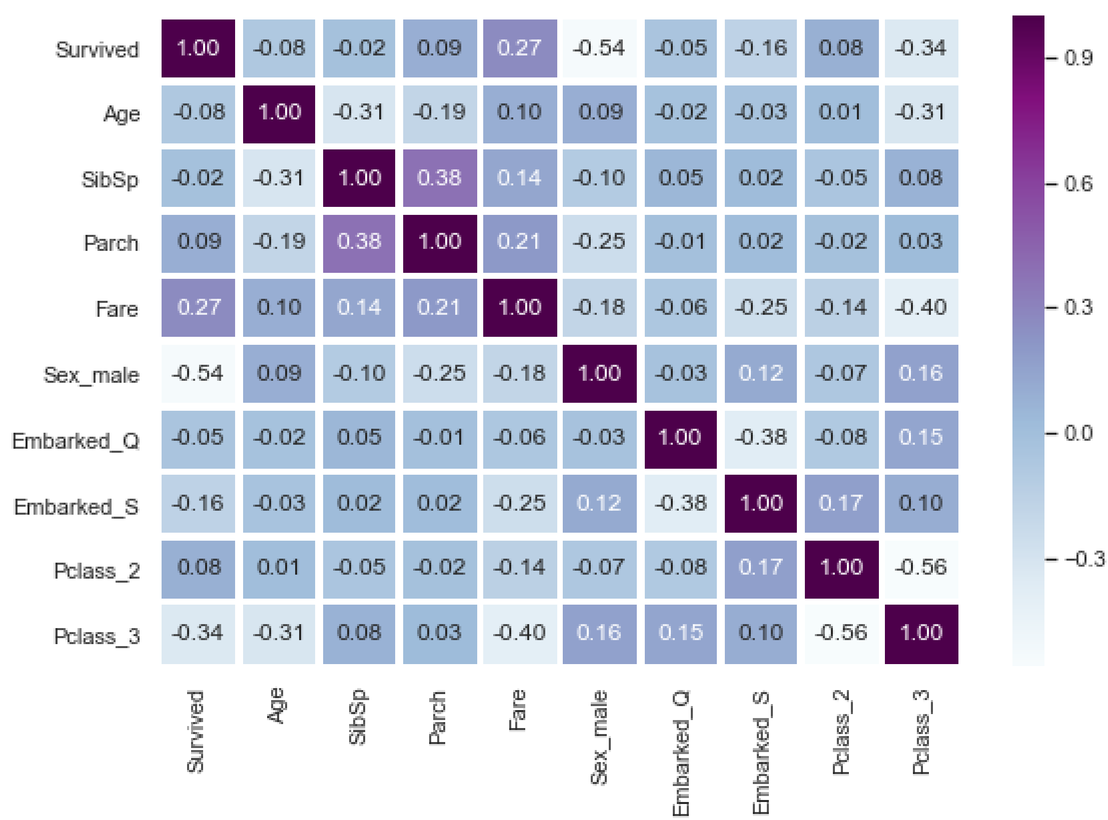
```
In [86]: dftest_ml.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
```

```
Data columns (total 9 columns):
Age           332 non-null float64
SibSp         418 non-null int64
Parch         418 non-null int64
Fare          417 non-null float64
Sex_male      418 non-null uint8
Embarked_Q    418 non-null uint8
Embarked_S    418 non-null uint8
Pclass_2      418 non-null uint8
Pclass_3      418 non-null uint8
dtypes: float64(2), int64(2), uint8(5)
memory usage: 15.2 KB
```

Matriz de correlación

In [99]:
```python
corr = dftrain_ml.corr()
f,ax = plt.subplots(figsize=(9,6))
sns.heatmap(corr, cmap='BuPu', annot = True, linewidths=2.5 , fmt = '.2f',ax=ax)
plt.show()
```



Correlaciones

Survived vs Fare están correlacionadas positivamente Survived vs Sex_male están correlacionadas negativamente Survived vs Pclass_3 están correlacionadas negativamente SibSp vs Parch están correlacionadas positivamente

3 Preprocesamiento de datos con Standard Scaler

Es necesario estandarizar transformar los datos para calcular la media y desviación estándar en un conjunto de entrenamiento (dftrain_ml) para que luego se vuelva a aplicar la misma transformación en el conjunto de prueba (dftest_ml).

```
In [92]: from sklearn.preprocessing import StandardScaler
         scaler = StandardScaler()
```

Transformación de dftrain_ml

```
In [ ]: # for dftrain_ml
        scaler.fit(dftrain_ml.drop('Survived',axis=1))
        scaled_features = scaler.transform(dftrain_ml.drop('Survived',axis=1))
        dftrain_ml_sc = pd.DataFrame(scaled_features, columns=dftrain_ml.columns[:-1])
        dftrain_ml_sc.head(4)
```

Transformación de dftest_ml

```
In [101]: # for dftest_ml
          dftest_ml.fillna(dftest_ml.mean(), inplace=True)
          # scaler.fit(dftest_ml)
          scaled_features = scaler.transform(dftest_ml)
          dftest_ml_sc = pd.DataFrame(scaled_features, columns=dftest_ml.columns)
          dftest_ml_sc.head(4)
```

```
Out[101]:         Age     SibSp     Parch      Fare  Sex_male  Embarked_Q  Embarked_S  \
          0  0.330723 -0.551703 -0.505895 -0.508025  0.759051    4.949747   -1.860779
          1  1.191823  0.524570 -0.505895 -0.523705 -1.317434   -0.202031    0.537409
          2  2.225142 -0.551703 -0.505895 -0.472885  0.759051    4.949747   -1.860779
          3 -0.185937 -0.551703 -0.505895 -0.492267  0.759051   -0.202031    0.537409

             Pclass_2  Pclass_3
          0 -0.565489  1.005618
          1 -0.565489  1.005618
          2  1.768380 -0.994413
          3 -0.565489  1.005618
```

Dividir train/test utilizaremos el 70% de los datos para el entrenamiento y el 30% para pruebas

```
In [102]: from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(dftrain_ml.drop('Survived',axis=
          X_train_sc, X_test_sc, y_train_sc, y_test_sc = train_test_split(dftrain_ml_sc, dftra
```

```
In [103]: # all data
          # unscaled
          X_train_all = dftrain_ml.drop('Survived',axis=1)
          y_train_all = dftrain_ml['Survived']
          X_test_all = dftest_ml

          # scaled
          X_train_all_sc = dftrain_ml_sc
          y_train_all_sc = dftrain_ml['Survived']
          X_test_all_sc = dftest_ml_sc
```

```
In [104]: # fillna: fill nan with mean values for that column
          X_test_all.fillna(X_test_all.mean(), inplace=True)
          print("*")
```

```
*
```

4 Algoritmos de machine learning y comparación del resultado de los modelos

```
In [ ]:
```