Limpieza y validacion de los datos

January 7, 2019

1 Titanic

1.1 Apartado 1

El 15 de abril de 1912, el mayor transatlántico de pasajeros chocó con un iceberg durante su viaje inaugural. Cuando el Titanic se hundió, mató a 1502 de 2224 pasajeros y tripulantes. Esta tragedia sensacional conmocionó a la comunidad internacional y condujo a mejores regulaciones de seguridad para los buques. Una de las razones por las que el naufragio resultó en tal pérdida de vidas fue que no había suficientes botes salvavidas para los pasajeros y la tripulación. Aunque hubo algún elemento de suerte involucrado en sobrevivir al hundimiento, algunos grupos de personas tenían más probabilidades de sobrevivir que otros. El dataset titanic contiene datos de 887 de los pasajeros reales del Titanic. Las columnas describen diferentes atributos de la persona, incluso si sobrevivieron, su edad, su clase de pasajeros, su sexo y la tarifa que pagaron.

Queremos saber cual es la relación de los atributos de los pasajeron que tienen más probabilidad de sobrevivir.

1.2 Apartado 2

Integración y selección de datos a analizar. Importamos los paquetes que vamos a necesitar.

```
In [293]: # 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 [294]: # Visualization style
          %matplotlib inline
          sns.set()
```

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

```
In [295]: # Import test and train datasets
          dftrain = pd.read_csv('/Users/carinazavala/Documents/UOC/1er Semestre/Tipología y ci
          dftest = pd.read_csv('/Users/carinazavala/Documents/UOC/1er Semestre/Tipología y cicl
```

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

```
Out[295]:    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
```

1.3 Apartado 3

Analizamos los atributos del dataset. La variable de edad no contiene todos los valores por lo que necesita un tratamiento de datos. Para este caso haremos una imputación de datos nulos.

```
In [296]: dftrain = dftrain.replace('',np.NaN)
          dftrain
```

```
Out[296]:     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
          7              8         0       3
          8              9         1       3
          9             10         1       2
          10            11         1       3
          11            12         1       1
          12            13         0       3
          13            14         0       3
          14            15         0       3
          15            16         1       2
          16            17         0       3
          17            18         1       2
          18            19         0       3
```

```
19            20         1       3
20            21         0       2
21            22         1       2
22            23         1       3
23            24         1       1
24            25         0       3
25            26         1       3
26            27         0       3
27            28         0       1
28            29         1       3
29            30         0       3
..           ...       ...     ...
861          862         0       2
862          863         1       1
863          864         0       3
864          865         0       2
865          866         1       2
866          867         1       2
867          868         0       1
868          869         0       3
869          870         1       3
870          871         0       3
871          872         1       1
872          873         0       1
873          874         0       3
874          875         1       2
875          876         1       3
876          877         0       3
877          878         0       3
878          879         0       3
879          880         1       1
880          881         1       2
881          882         0       3
882          883         0       3
883          884         0       2
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
7	Palsson, Master. Gosta Leonard	male	2.0	3
8	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0
9	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1
10	Sandstrom, Miss. Marguerite Rut	female	4.0	1
11	Bonnell, Miss. Elizabeth	female	58.0	0
12	Saundercock, Mr. William Henry	male	20.0	0
13	Andersson, Mr. Anders Johan	male	39.0	1
14	Vestrom, Miss. Hulda Amanda Adolfina	female	14.0	0
15	Hewlett, Mrs. (Mary D Kingcome)	female	55.0	0
16	Rice, Master. Eugene	male	2.0	4
17	Williams, Mr. Charles Eugene	male	NaN	0
18	Vander Planke, Mrs. Julius (Emelia Maria Vande...	female	31.0	1
19	Masselmani, Mrs. Fatima	female	NaN	0
20	Fynney, Mr. Joseph J	male	35.0	0
21	Beesley, Mr. Lawrence	male	34.0	0
22	McGowan, Miss. Anna "Annie"	female	15.0	0
23	Sloper, Mr. William Thompson	male	28.0	0
24	Palsson, Miss. Torborg Danira	female	8.0	3
25	Asplund, Mrs. Carl Oscar (Selma Augusta Emilia...	female	38.0	1
26	Emir, Mr. Farred Chehab	male	NaN	0
27	Fortune, Mr. Charles Alexander	male	19.0	3
28	O'Dwyer, Miss. Ellen "Nellie"	female	NaN	0
29	Todoroff, Mr. Lalio	male	NaN	0
..	...	...	...	...
861	Giles, Mr. Frederick Edward	male	21.0	1
862	Swift, Mrs. Frederick Joel (Margaret Welles Ba...	female	48.0	0
863	Sage, Miss. Dorothy Edith "Dolly"	female	NaN	8
864	Gill, Mr. John William	male	24.0	0
865	Bystrom, Mrs. (Karolina)	female	42.0	0
866	Duran y More, Miss. Asuncion	female	27.0	1
867	Roebling, Mr. Washington Augustus II	male	31.0	0
868	van Melkebeke, Mr. Philemon	male	NaN	0
869	Johnson, Master. Harold Theodor	male	4.0	1
870	Balkic, Mr. Cerin	male	26.0	0
871	Beckwith, Mrs. Richard Leonard (Sallie Monypeny)	female	47.0	1
872	Carlsson, Mr. Frans Olof	male	33.0	0
873	Vander Cruyssen, Mr. Victor	male	47.0	0
874	Abelson, Mrs. Samuel (Hannah Wizosky)	female	28.0	1
875	Najib, Miss. Adele Kiamie "Jane"	female	15.0	0
876	Gustafsson, Mr. Alfred Ossian	male	20.0	0
877	Petroff, Mr. Nedelio	male	19.0	0
878	Laleff, Mr. Kristo	male	NaN	0
879	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)	female	56.0	0
880	Shelley, Mrs. William (Imanita Parrish Hall)	female	25.0	0
881	Markun, Mr. Johann	male	33.0	0

882	Dahlberg, Miss. Gerda Ulrika	female	22.0	0
883	Banfield, Mr. Frederick James	male	28.0	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
7	1	349909	21.0750	NaN	S
8	2	347742	11.1333	NaN	S
9	0	237736	30.0708	NaN	C
10	1	PP 9549	16.7000	G6	S
11	0	113783	26.5500	C103	S
12	0	A/5. 2151	8.0500	NaN	S
13	5	347082	31.2750	NaN	S
14	0	350406	7.8542	NaN	S
15	0	248706	16.0000	NaN	S
16	1	382652	29.1250	NaN	Q
17	0	244373	13.0000	NaN	S
18	0	345763	18.0000	NaN	S
19	0	2649	7.2250	NaN	C
20	0	239865	26.0000	NaN	S
21	0	248698	13.0000	D56	S
22	0	330923	8.0292	NaN	Q
23	0	113788	35.5000	A6	S
24	1	349909	21.0750	NaN	S
25	5	347077	31.3875	NaN	S
26	0	2631	7.2250	NaN	C
27	2	19950	263.0000	C23 C25 C27	S
28	0	330959	7.8792	NaN	Q
29	0	349216	7.8958	NaN	S
..	...	...	...	...	...
861	0	28134	11.5000	NaN	S
862	0	17466	25.9292	D17	S
863	2	CA. 2343	69.5500	NaN	S
864	0	233866	13.0000	NaN	S
865	0	236852	13.0000	NaN	S
866	0	SC/PARIS 2149	13.8583	NaN	C

```
867      0           PC 17590   50.4958           A24         S
868      0             345777    9.5000           NaN         S
869      1             347742   11.1333           NaN         S
870      0             349248    7.8958           NaN         S
871      1              11751   52.5542           D35         S
872      0                695    5.0000   B51 B53 B55         S
873      0             345765    9.0000           NaN         S
874      0          P/PP 3381   24.0000           NaN         C
875      0               2667    7.2250           NaN         C
876      0               7534    9.8458           NaN         S
877      0             349212    7.8958           NaN         S
878      0             349217    7.8958           NaN         S
879      1              11767   83.1583           C50         C
880      1             230433   26.0000           NaN         S
881      0             349257    7.8958           NaN         S
882      0               7552   10.5167           NaN         S
883      0   C.A./SOTON 34068   10.5000           NaN         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]
```

In [297]:
```
# Summary de datos train
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
```

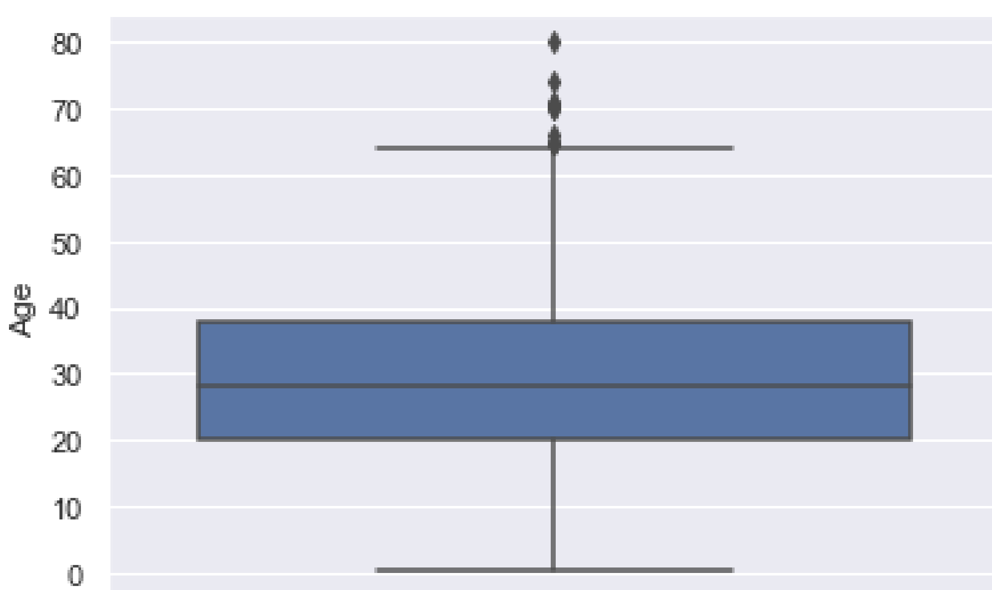
```
In [298]: # Hacemos lo mismo con los datos test
          dftest = dftest.replace('',np.NaN)
          dftest
          dftest.info()
```

```
<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
```

Para encontrar los posibles outliers haremos una gráfica boxplot. Utilizaremos la variable Age ya que es la variable donde pudieran existir los outliers.

```
In [299]: # Convertimos la variable Age a entero
          sns.boxplot(y = "Age", data=dftrain)
```

```
Out[299]: <matplotlib.axes._subplots.AxesSubplot at 0x1a215f9828>
```



Se observa que existen outliers pero son parte del análisis ya que una persona en promedio vive 80 años por lo que no afecta a nuestro modelo porque pertenece a él.

1.4 Apartado 4 y 5

Comenzaremos con el análisis de los datos. Hacemos una comparación de las distribuciones del data set train y test para conocer que tanto difieren uno del otro

```
In [300]: # Compare distribution of features in train and test data with describe
          dftrain.describe()
```

```
Out[300]:        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
```

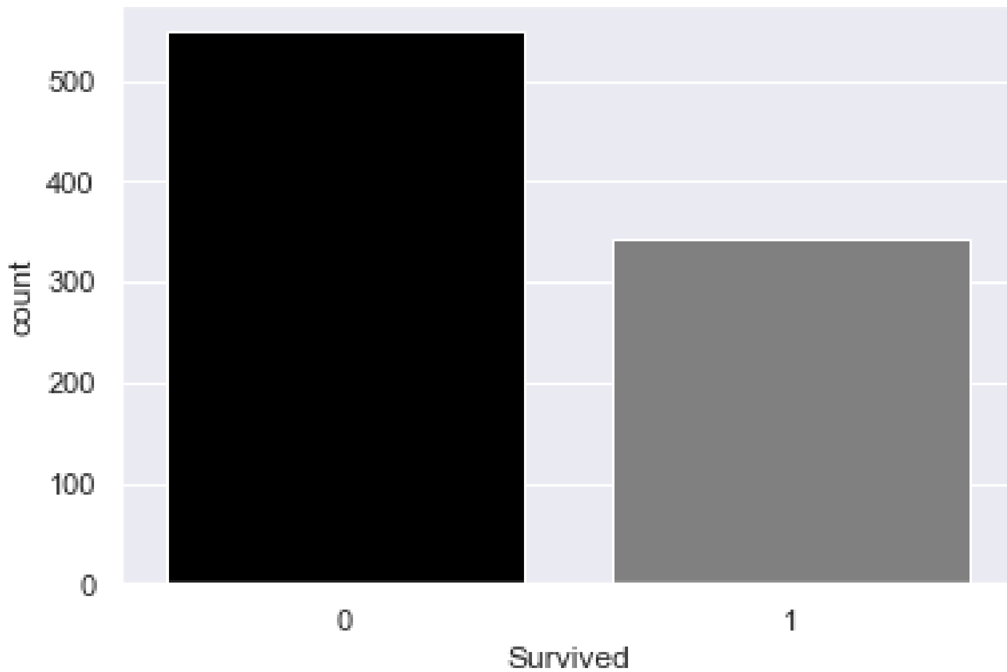
```
In [301]: dftest.describe()
```

```
Out[301]:        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 [302]:
```
# Review how many passengers survived and died in train data
sns.countplot(x='Survived', data=dftrain,
              palette=sns.color_palette(['black','grey']));
```



In [303]:
```
# 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 [304]:
```
dftest['Survived'] = 0
dftest[['PassengerId', 'Survived']].to_csv('no_survivors.csv', index=False)
```

Variable = Sex, Sobrevivieron más mujeres que hombres

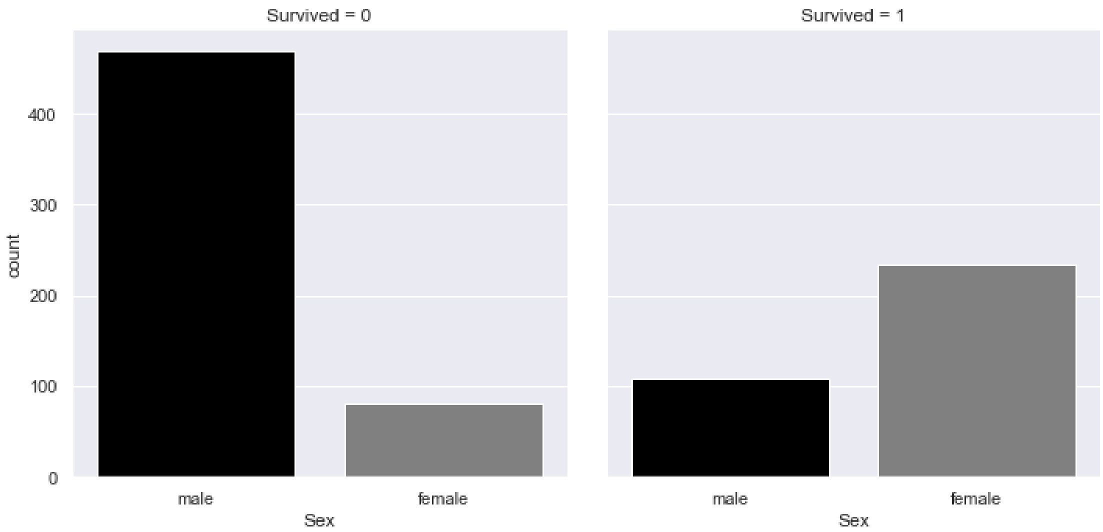
In [305]:
```
# Analizing survivors per sex in train data
dftrain.groupby(['Survived','Sex'])['Survived'].count()
# more female passengers survived
```

Out[305]:
```
Survived  Sex
0         female     81
```

```
            male      468
1           female    233
            male      109
Name: Survived, dtype: int64
```

In [306]:
```
# Plotting this in bar chart
sns.catplot(x='Sex', col='Survived', kind='count', data=dftrain,
           palette=sns.color_palette(['black','grey']))
```

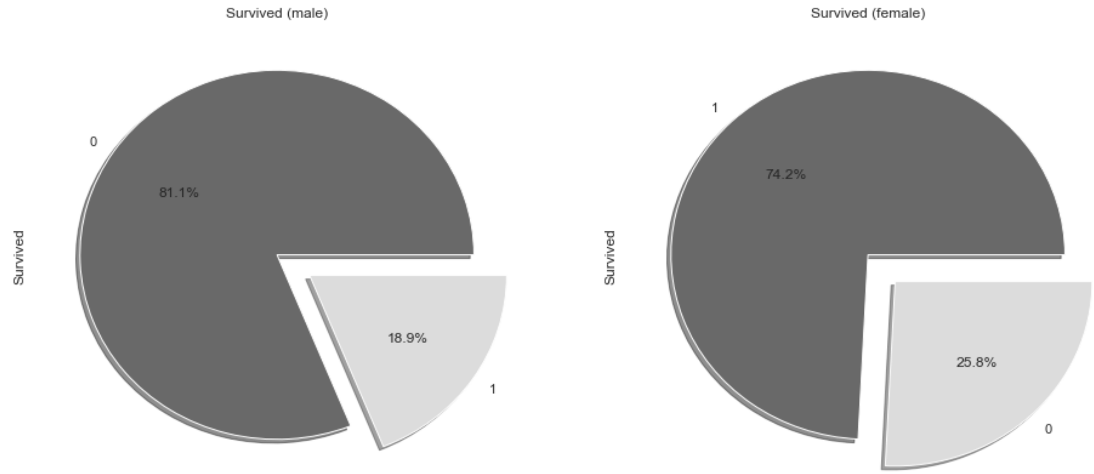
Out[306]: <seaborn.axisgrid.FacetGrid at 0x1a215f9dd8>



In [307]:
```
# Obtain the survived percentage per sex train data
print("% of women survived: " , dftrain[dftrain.Sex == 'female'].Survived.sum()/dftra
print("% of men survived:   " , dftrain[dftrain.Sex == 'male'].Survived.sum()/dftrain
```

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

In [308]:
```
# 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],a
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 [309]: dftest['Survived'] = dftest.Sex == 'female'
          dftest['Survived'] = dftest.Survived.apply(lambda x: int(x))
          dftest[['PassengerId', 'Survived']].to_csv('women_survive.csv', index=False)
```

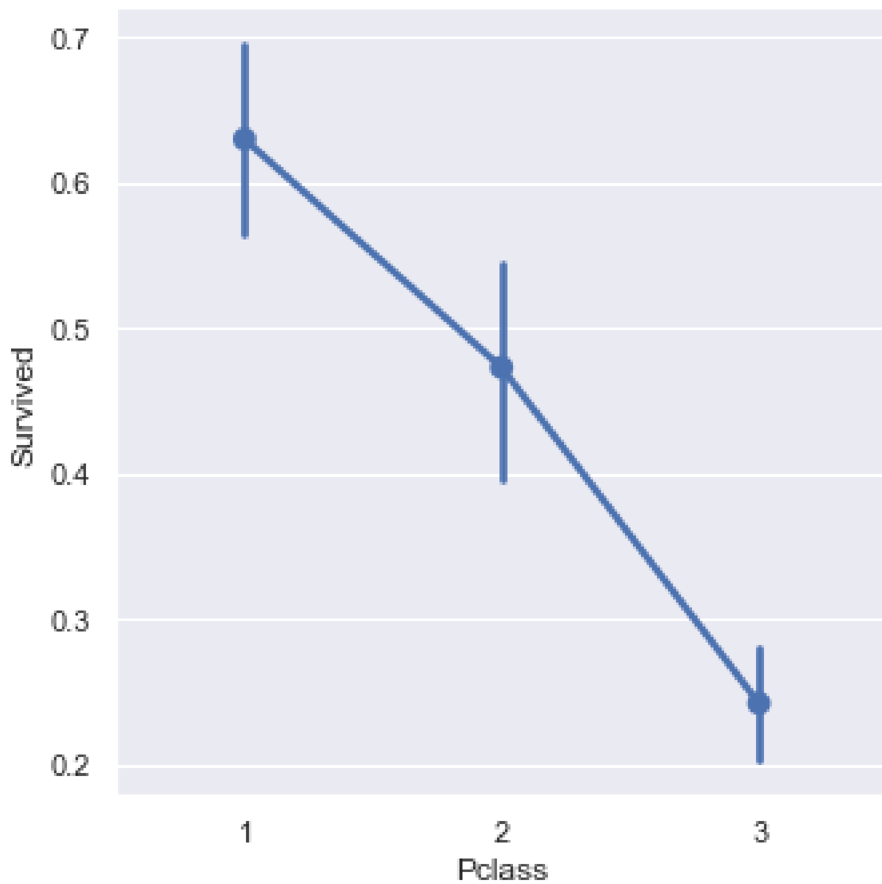
Passgenger Class, la tasa de supervivencia decrece con Pclass

```
In [310]: pd.crosstab(dftrain.Pclass, dftrain.Survived, margins=True).style.background_gradien

Out[310]: <pandas.io.formats.style.Styler at 0x1a1ebb84e0>
```

```
In [311]: print("% of survivals in")
          print("Pclass=1 : ", dftrain.Survived[dftrain.Pclass == 1].sum()/dftrain[dftrain.Pcla
          print("Pclass=2 : ", dftrain.Survived[dftrain.Pclass == 2].sum()/dftrain[dftrain.Pcla
          print("Pclass=3 : ", dftrain.Survived[dftrain.Pclass == 3].sum()/dftrain[dftrain.Pcla

% 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 [312]: 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
```



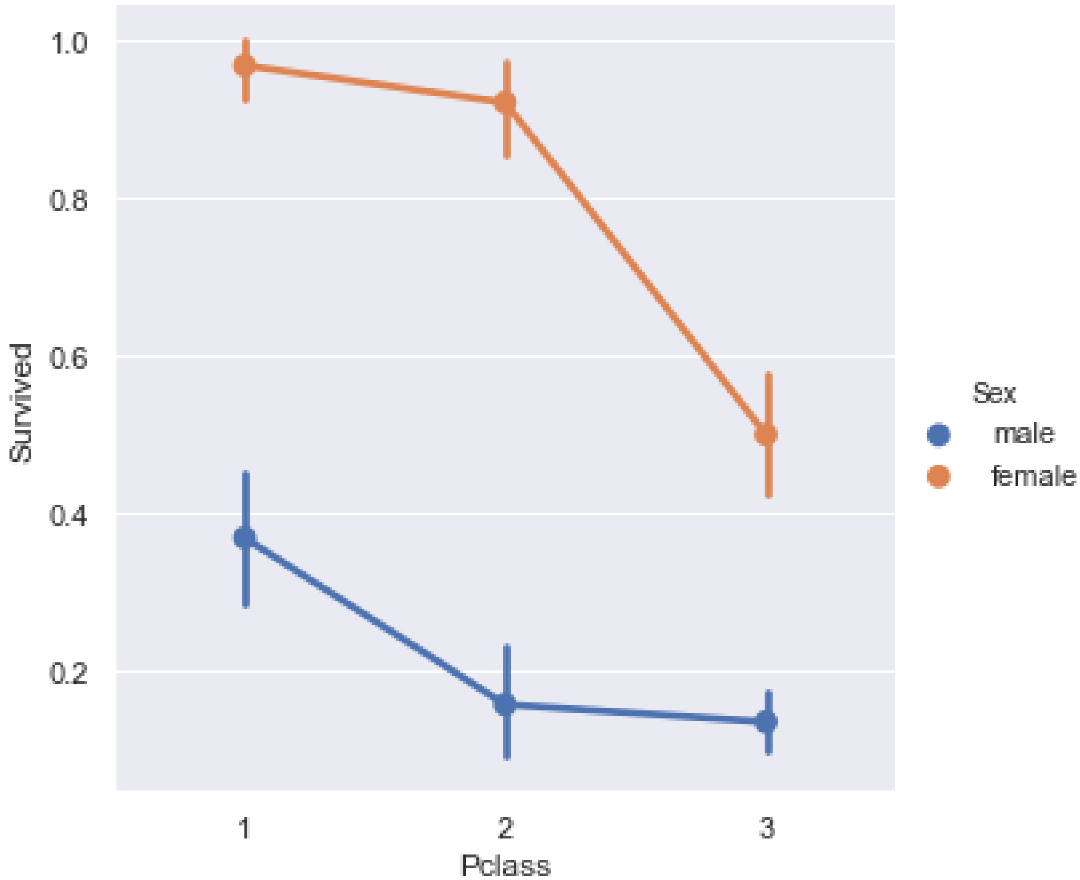
Class and Sex, casi todas las mujeres en Pclass 1 y 2 sobrevivieron y casi todos los hombres en Pclass 2 y 3 murieron

```
In [313]: pd.crosstab([dftrain.Sex, dftrain.Survived], dftrain.Pclass, margins=True).style.bacl
```

```
Out[313]: <pandas.io.formats.style.Styler at 0x1a208ffa90>
```

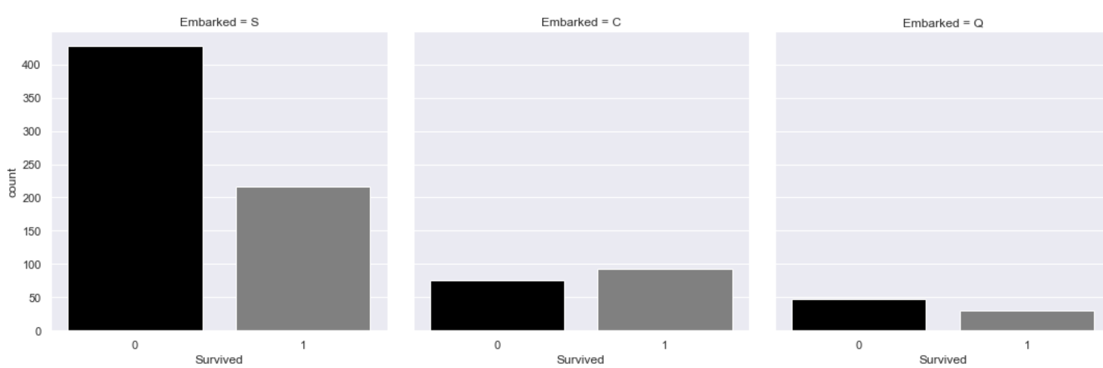
```
In [314]: sns.catplot('Pclass','Survived',hue='Sex', kind='point', data=dftrain);
```

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



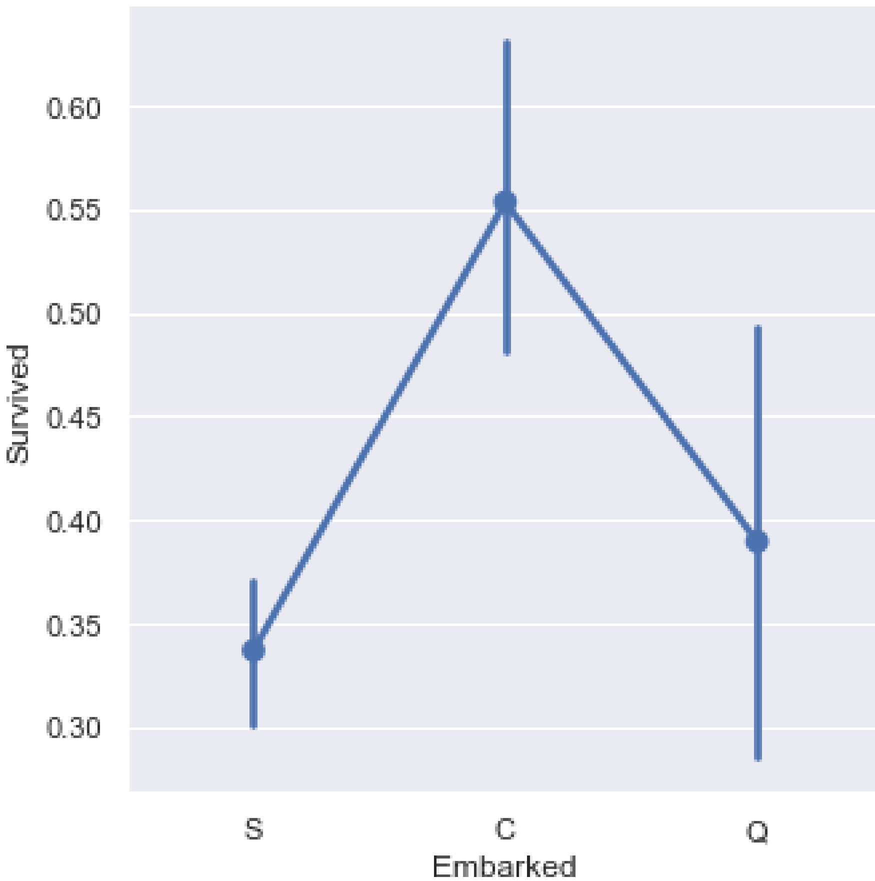
Embarked : Tasa de supervivencia menor para S y mayor para C

```
In [315]: sns.catplot(x='Survived', col='Embarked', kind='count', data=dftrain,
                      palette=sns.color_palette(['black','grey']));
```




```
In [316]: sns.catplot('Embarked','Survived', kind='point', data=dftrain)
          plt.show()
```

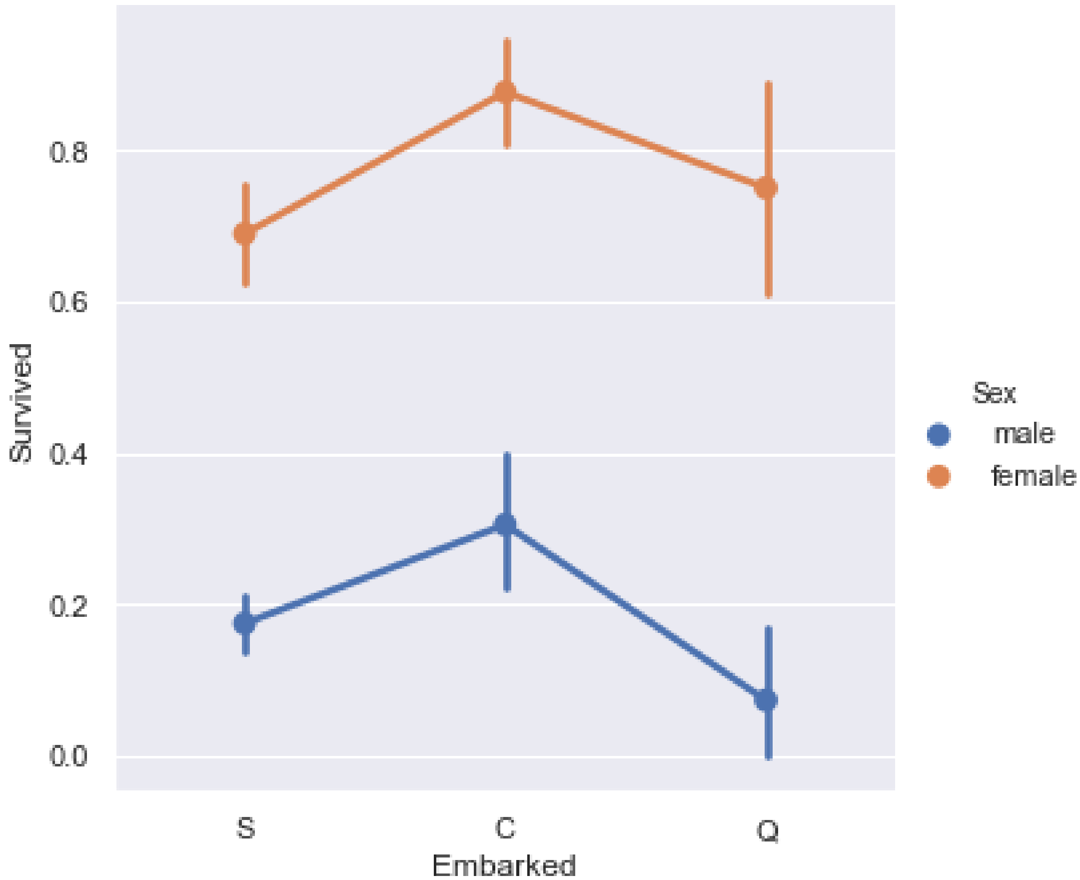
```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWar
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Embarked and Sex

```
In [317]: 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: FutureWar
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Embarked, Pclass y Sex :

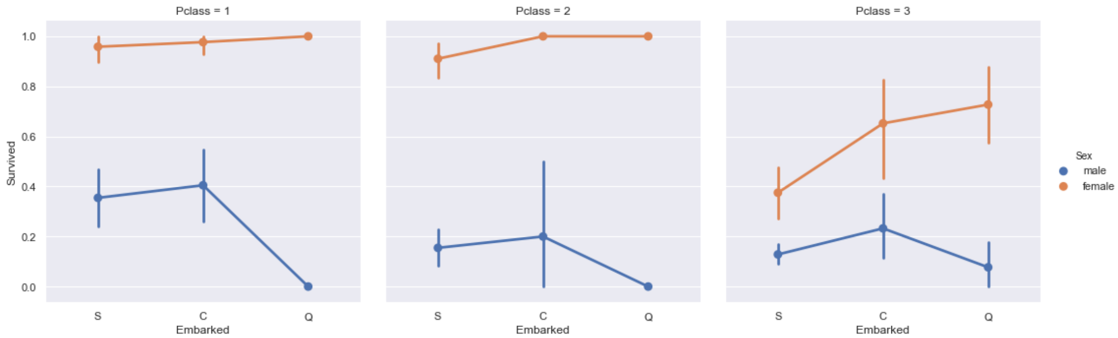
Practicamente todas las mujeres de Pclass 2 que embarcaron en C y Q sobrevivieron, también casi todas las mujeres de Pclass 1.

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 [318]: 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 [319]: pd.crosstab([dftrain.Survived], [dftrain.Sex, dftrain.Pclass, dftrain.Embarked], marg
```

```
Out[319]: 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 [320]: # 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

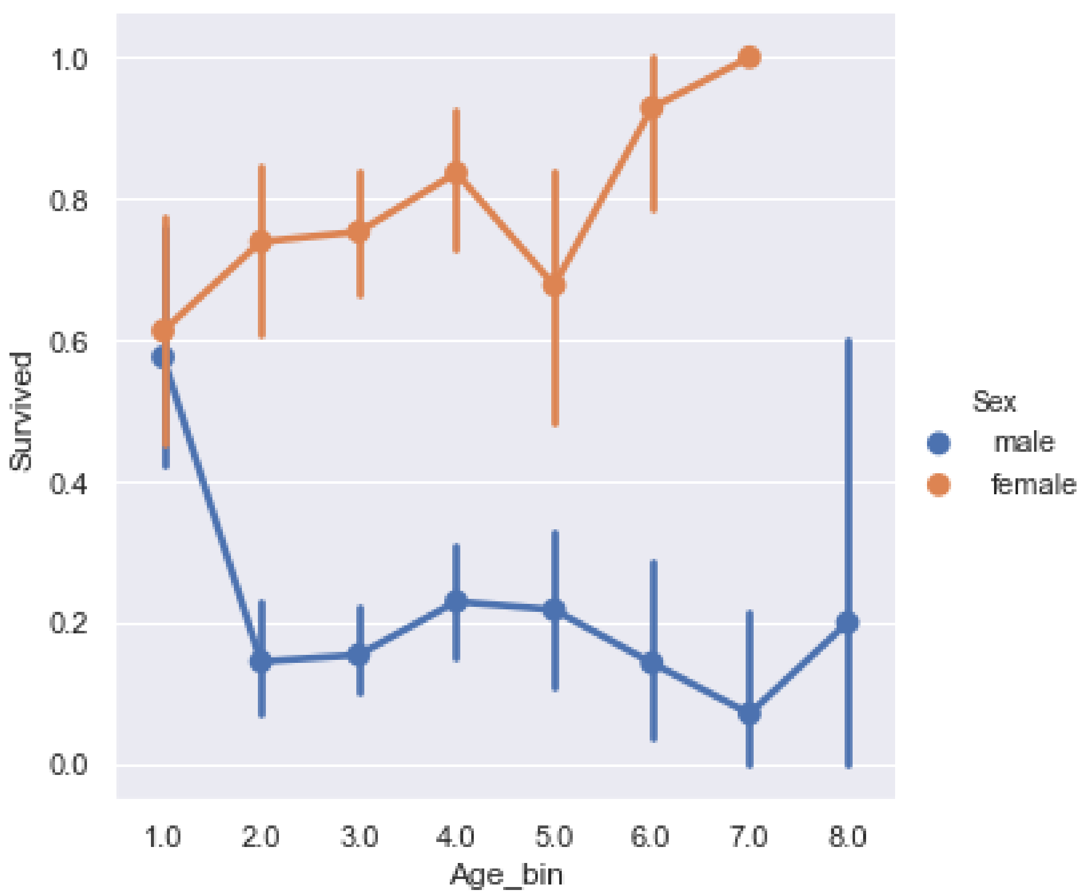
```
In [321]: for df in [dftrain, dftest]:
              df['Age_bin']=np.nan
              for i in range(8,0,-1):
                  df.loc[ df['Age'] <= i*10, 'Age_bin'] = i
```

```
In [322]: 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
```

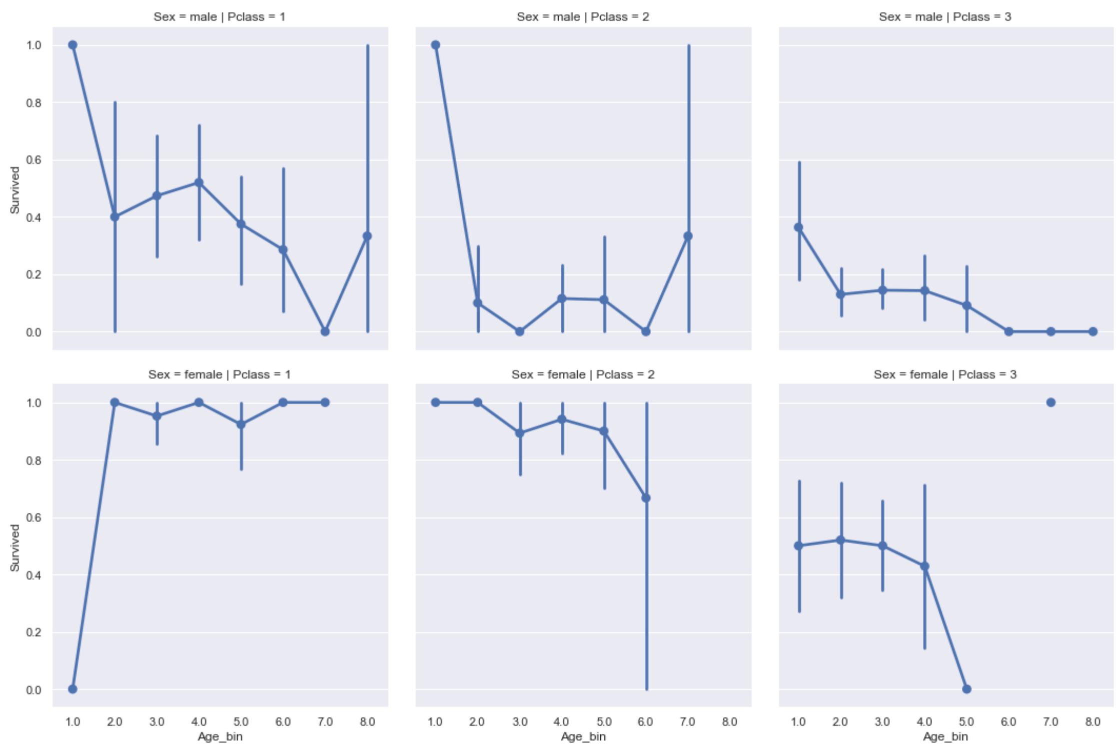
In [323]:
```
sns.catplot('Age_bin','Survived',hue='Sex',kind='point',data=dftrain)
plt.show()
```

```
/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 [324]: sns.catplot('Age_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: FutureWar
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```




```
In [325]: pd.crosstab([dftrain.Sex, dftrain.Survived], [dftrain.Age_bin, dftrain.Pclass], marg
```

```
Out[325]: <pandas.io.formats.style.Styler at 0x1a20aabfd0>
```

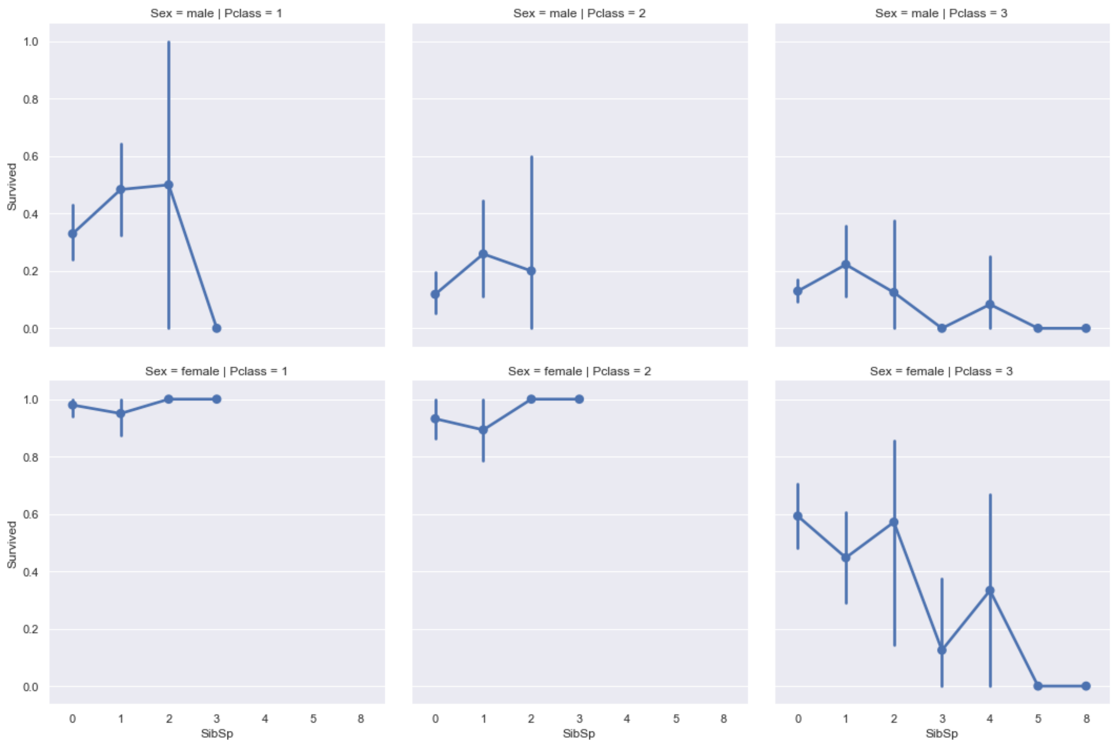
Para pasajeros en
*Age_bim=1(menores a 10): todos los hombres en Pclass=1 y 2 sobrevivieron.
*Mujeres en Pclass=3 y Age_bin= 5 murieron
*Menos del 50% de mujeres en Pclass=3 y Age_bin=4 sobrevivieron
*Más del 50% de hombres en Pclass=1 y Age_bin=4 sobrevivieron

```
In [326]: # in Pclass 1 and 2 all men in Age_bin = 1 survived
          dftest.loc[ (dftest.Sex == 'male') & (dftest.Pclass == 1) & (dftest.Age_bin == 1), '
          dftest.loc[ (dftest.Sex == 'male') & (dftest.Pclass == 2) & (dftest.Age_bin == 1), '
```

SibSp y Parch

```
In [327]: sns.catplot('SibSp','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 [328]: pd.crosstab([dftrain.Sex, dftrain.Survived], [dftrain.SibSp, dftrain.Pclass], margins
```

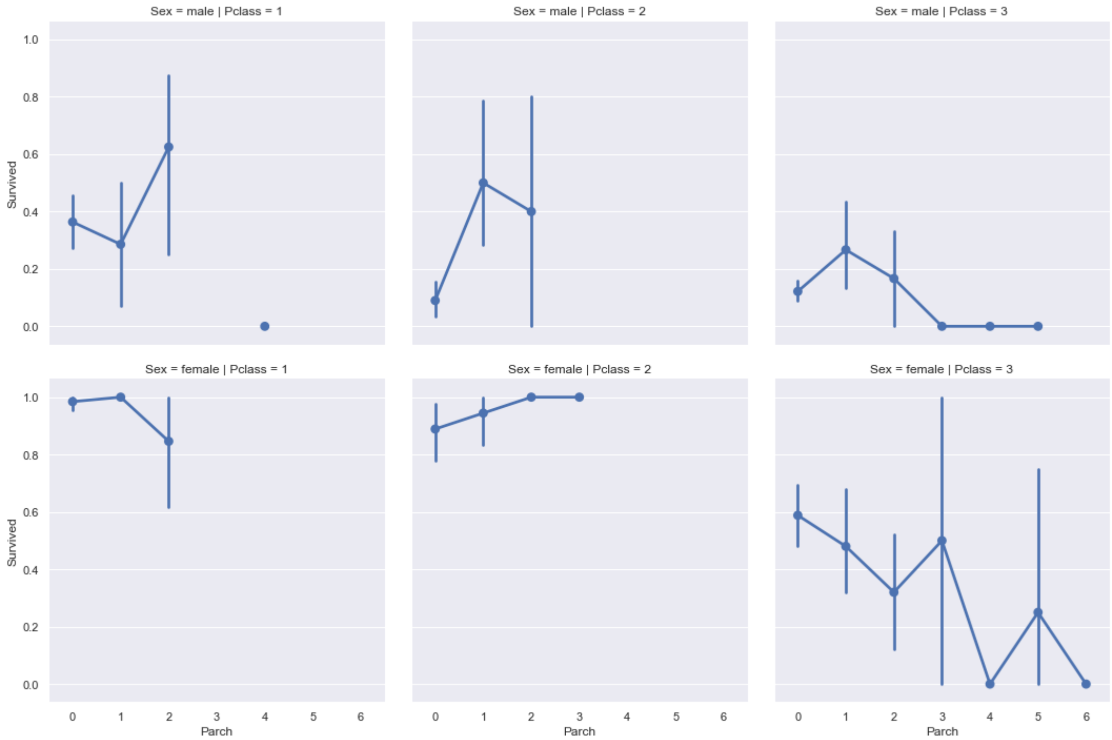
```
Out[328]: <pandas.io.formats.style.Styler at 0x1a20a50b38>
```

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

```
In [330]: sns.catplot('Parch','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 [331]: pd.crosstab([dftrain.Sex, dftrain.Survived], [dftrain.Parch, dftrain.Pclass], margins
```

```
Out[331]: <pandas.io.formats.style.Styler at 0x1a208fa9b0>
```

*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 [332]: # 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), 'S

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

          # 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[332]:

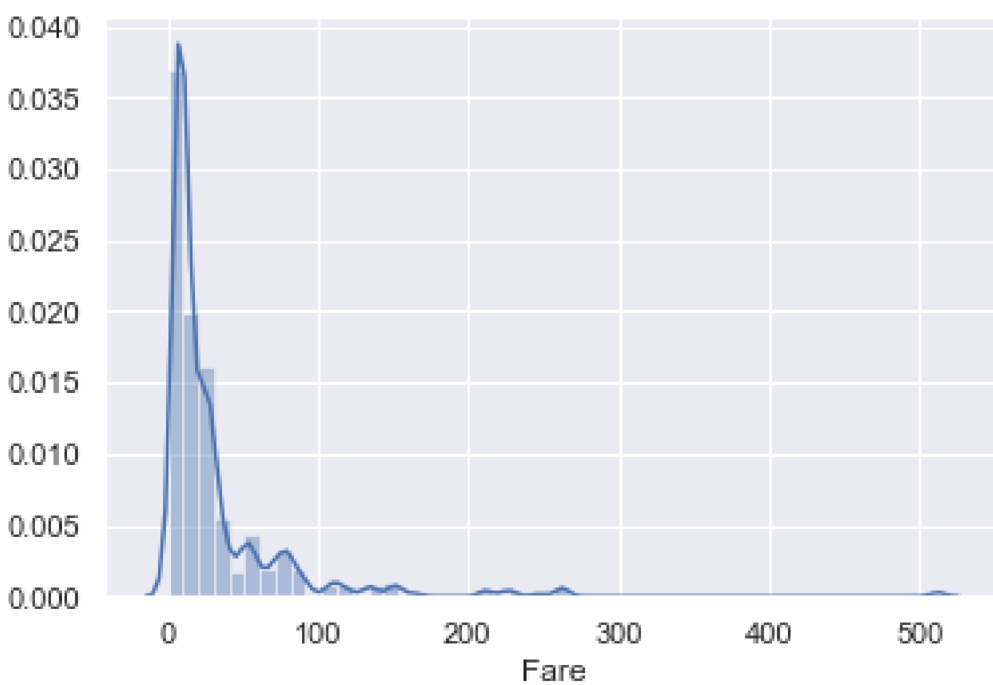
```
    PassengerId  Pclass                                           Name  \
0           892       3                               Kelly, Mr. James
1           893       3               Wilkes, Mrs. James (Ellen Needs)
2           894       2                      Myles, Mr. Thomas Francis
3           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 [333]: sns.distplot(dftrain['Fare'])
          plt.show()
```

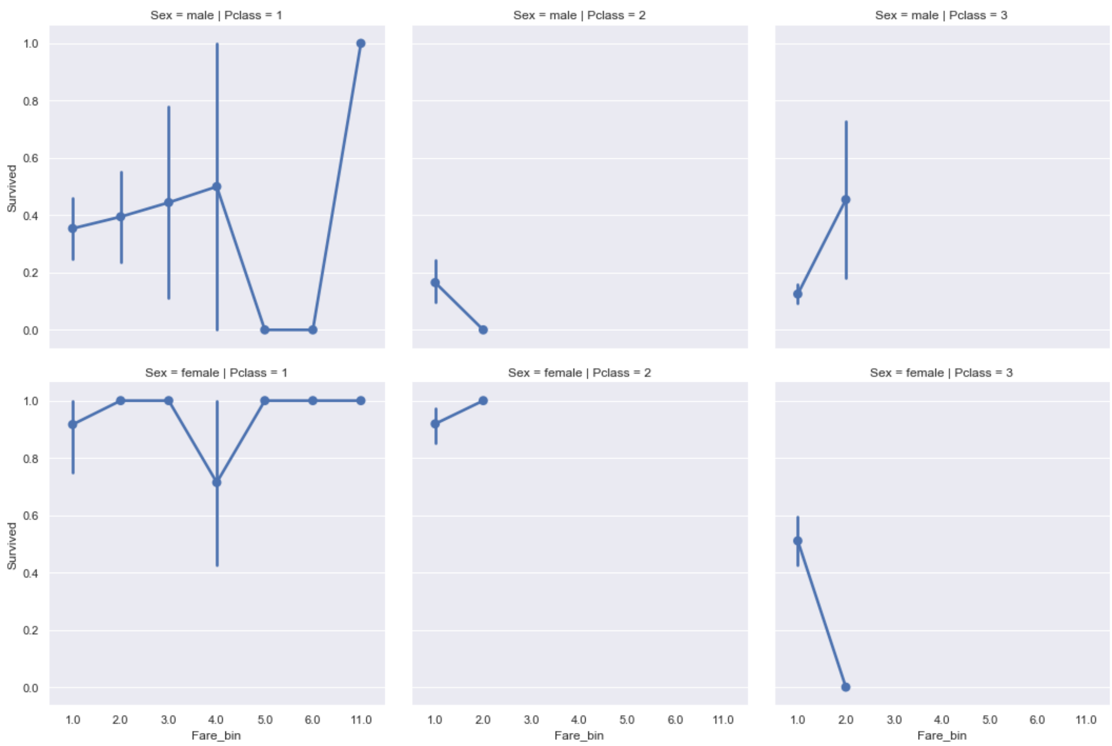
```
/Users/carinazavala/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarr
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [334]:
```
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 [335]:
```
sns.catplot('Fare_bin','Survived', col='Pclass' , row = 'Sex', kind='point', data=df
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 [336]:
```
pd.crosstab([dftrain.Sex, dftrain.Survived], [dftrain.Fare_bin, dftrain.Pclass], marg
```

Out[336]:
```
<pandas.io.formats.style.Styler at 0x1a215517b8>
```

In [337]:
```
# 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 [338]:
```
# modelo4
dftest[['PassengerId', 'Survived']].to_csv('model_4.csv', index=False)
```

In [339]:
```
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 [340]:
```
#1
dftrain_ml = dftrain.copy()
dftest_ml = dftest.copy()
```

In [341]:
```
#2
dftrain_ml = pd.get_dummies(dftrain_ml, columns=['Sex', 'Embarked', 'Pclass'], drop_f
dftrain_ml.drop(['PassengerId','Name','Ticket', 'Cabin', 'Age_bin', 'Fare_bin'],axis=
dftrain_ml.dropna(inplace=True)
```

In [342]:
```
#3
passenger_id = dftest_ml['PassengerId']
dftest_ml = pd.get_dummies(dftest_ml, columns=['Sex', 'Embarked', 'Pclass'], drop_fi
dftest_ml.drop(['PassengerId','Name','Ticket', 'Cabin', 'Age_bin', 'Fare_bin'],axis=1
```

Visualizamos los datos con .head y .info

In [343]:
```
dftrain_ml.head(10)
```

Out[343]:

	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 [344]: 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 [345]: dftest_ml.head(10)

Out[345]:

```
    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
```

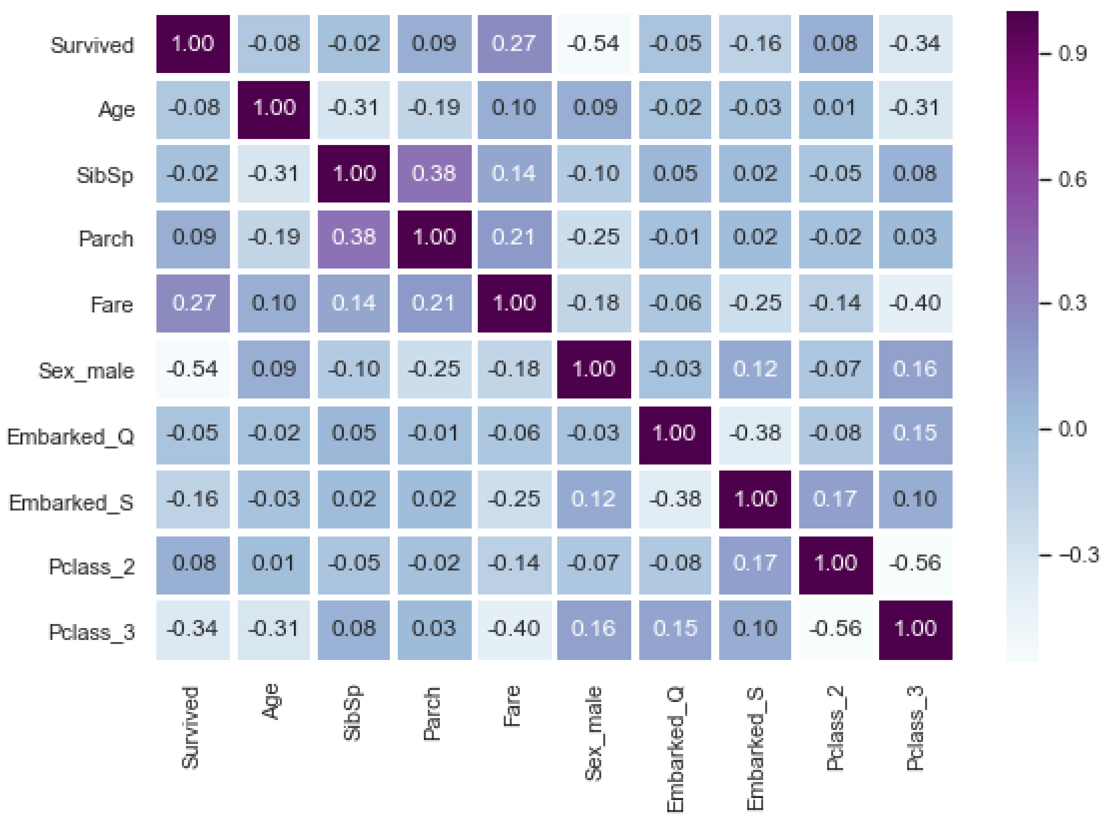
In [346]: dftest_ml.info()

```
<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 [347]: 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 [348]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

Transformación de dftrain_ml

In [349]:
```
# 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)
```

Out[349]:
```
   Survived       Age     SibSp     Parch      Fare  Sex_male  Embarked_Q  \
0 -0.530377  0.524570 -0.505895 -0.518978  0.759051 -0.202031    0.537409
1  0.571831  0.524570 -0.505895  0.691897 -1.317434 -0.202031   -1.860779
2 -0.254825 -0.551703 -0.505895 -0.506214 -1.317434 -0.202031    0.537409
3  0.365167  0.524570 -0.505895  0.348049 -1.317434 -0.202031    0.537409

   Embarked_S  Pclass_2
0   -0.565489  1.005618
1   -0.565489 -0.994413
2   -0.565489  1.005618
3   -0.565489 -0.994413
```

Transformación de dftest_ml

In [350]:
```
# 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[350]:
```
        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 [351]: 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 [352]: # 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 [353]: # 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

Para la comparación de los resultados se usan las siguientes métricas confusion matrix, accuracy score and classification report.

```
1.- Confusion matrix: Se utiliza para evaluar la calidad de la salida de un clasificador. For a
TN: Verdaderos negativos (predicción: no sobrevivió, verdad: no sobrevivió)
FP: Falsos positivos (predicción: sobrevivió, true: no sobrevivió)
FN: Falsos negativos (predicción: no sobrevivió, true: sobrevivió)
TP: Verdaderos positivos (predicción: sobrevivió, true: sobrevivió)

2.- Accuracy score: es un valor numérico resultado de la confusion matrix
accuracy_score=correct predictions/total predictions
              =(TP + TN) / (TP + TN + FP + FN)

3.- Classification report: La precisión es la relación tp / (tp + fp) donde tp es el número de
El retiro es la relación tp / (tp + fn) donde tp es el número de verdaderos positivos y fn el n
La puntuación F-beta se puede interpretar como una media armónica ponderada de la precisión y e
Los pesos de puntuación F-beta recuerdan más que la precisión por un factor de beta. beta == 1
```

In [354]:
```
from sklearn.metrics import accuracy_score,
classification_report, confusion_matrix
```

```
  File "<ipython-input-354-acc2a11b7d59>", line 1
    from sklearn.metrics import accuracy_score,
                                               ^
SyntaxError: trailing comma not allowed without surrounding parentheses
```

- Logistic Regression

In [ ]:
```
# Import logistic regression
from sklearn.linear_model import LogisticRegression

# Make an instance of the model
logreg = LogisticRegression()

# Fit the model with train and test data
logreg.fit(X_train,y_train)

# Make prediction for new observations
pred_logreg = logreg.predict(X_test)
```

In [ ]:
```
# Analyze result
print(confusion_matrix(y_test, pred_logreg))
print(classification_report(y_test, pred_logreg))
print(accuracy_score(y_test, pred_logreg))
```

In [ ]:
```
# Train again for all data
logreg.fit(X_train_all, y_train_all)
pred_all_logreg = logreg.predict(X_test_all)

# Submit into new dataframe
sub_logreg = pd.DataFrame()
sub_logreg['PassengerId'] = dftest['PassengerId']
sub_logreg['Survived'] = pred_all_logreg
#sub_logmodel.to_csv('logmodel.csv',index=False)
```

- Gaussian Naive Bayes

In [ ]:
```
# Import neighbors classifier
from sklearn.naive_bayes import GaussianNB

# Make an instance of the key neighbors classifier class
gnb=GaussianNB()

# Fit the model with train and test data
```

```
gnb.fit(X_train,y_train)

# Make prediction for new observations
pred_gnb = gnb.predict(X_test)
print(confusion_matrix(y_test, pred_gnb))
print(classification_report(y_test, pred_gnb))
print(accuracy_score(y_test, pred_gnb))
```

- KNN - KNeighborsClassifier

In [ ]:
```
# Import neighbors classifier
from sklearn.neighbors import KNeighborsClassifier

# Make an instance of the key neighbors classifier class
knn = KNeighborsClassifier(n_neighbors=20)

# Fit the model with train and test data
knn.fit(X_train_sc,y_train_sc)

# Make prediction for new observations
pred_knn = knn.predict(X_test)
print(confusion_matrix(y_test, pred_knn))
print(classification_report(y_test, pred_knn))
print(accuracy_score(y_test, pred_knn))
```

In [ ]:
```
# Analyze result
print(confusion_matrix(y_test, pred_knn))
print(classification_report(y_test, pred_knn))
print(accuracy_score(y_test, pred_knn))
```

In [ ]:
```
# Train again for all data
sub_knn = pd.DataFrame()
sub_knn['PassengerId'] = dftest['PassengerId']
sub_knn['Survived'] = pred_all_knn
#sub_knn.to_csv('knn.csv',index=False)
```

- Decision Tree Classifier

In [ ]:
```
# Import decision tree classifier
from sklearn.tree import DecisionTreeClassifier

# Make an instance of the decision tree classifier class
dtree = DecisionTreeClassifier()

# Fit the model with train and test data
dtree.fit(X_train,y_train)

# Make prediction for new observations
pred_dtree = dtree.predict(X_test)
```

```
print(classification_report(y_test,pred_dtree))
print(accuracy_score(y_test, pred_dtree))
```

Another decision tree with different parameters for max_features, max_depth and min_sample_split

```
In [ ]: dtree_2 = DecisionTreeClassifier(max_features=7 , max_depth=6,  min_samples_split=8)
        dtree_2.fit(X_train,y_train)
        pred_dtree_2 = dtree_2.predict(X_test)
        print(classification_report(y_test, pred_dtree_2))
        print(accuracy_score(y_test, pred_dtree_2))
```

```
In [ ]: # Train again for all data
        dtree_2.fit(X_train_all, y_train_all)
        pred_all_dtree2 = dtree_2.predict(X_test_all)
```

- Random Forest Classifier

```
In [ ]: # Import Random Forest classifier
        from sklearn.ensemble import RandomForestClassifier

        # Make an instance of the Random Forest classifier class
        rfc = RandomForestClassifier(max_depth=6, max_features=7)

        # Fit the model with train and test data
        rfc.fit(X_train, y_train)

        # Make prediction for new observations
        pred_rfc = rfc.predict(X_test)
        print(confusion_matrix(y_test, pred_rfc))
        print(classification_report(y_test, pred_rfc))
        print(accuracy_score(y_test, pred_rfc))
```

```
In [ ]: # Train again for all data
        rfc.fit(X_train_all, y_train_all)
        pred_all_rfc = rfc.predict(X_test_all)


        sub_rfc = pd.DataFrame()
        sub_rfc['PassengerId'] = dftest['PassengerId']
        sub_rfc['Survived'] = pred_all_rfc
        #sub_rfc.to_csv('randforest.csv',index=False)
```

- SVM Classifier

```
In [ ]: # Import
        from sklearn.svm import SVC

        # Make an instance  for SVC
```

```
        svc = SVC(gamma = 0.01, C = 100)#, probability=True)

        # Fit the model with train and test data
        svc.fit(X_train_sc, y_train_sc)

        # Make prediction for new observations
        pred_svc = svc.predict(X_test_sc)
        print(confusion_matrix(y_test_sc, pred_svc))
        print(classification_report(y_test_sc, pred_svc))
        print(accuracy_score(y_test_sc, pred_svc))
```

```
In [ ]: # Train again for all data
        svc.fit(X_train_all_sc, y_train_all_sc)
        pred_all_svc = svc.predict(X_test_all_sc)

        sub_svc = pd.DataFrame()
        sub_svc['PassengerId'] = dftest['PassengerId']
        sub_svc['Survived'] = pred_all_svc
        sub_svc.to_csv('svc.csv',index=False)
```

- k fold cross_validation

Este algoritmo divide los datos en conjuntos k y luego hace k ajustes utilizando cada conjunto k-1 veces como entrenamiento y una vez como datos de prueba

```
In [ ]: # Import
        from sklearn.model_selection import cross_val_score
```

para SVM Classififer

```
In [ ]: scores_svc = cross_val_score(svc, X_train_all_sc, y_train_all_sc, cv=10, scoring='accu
        print(scores_svc)
        print(scores_svc.mean())
```

para Random Forest Classifier

```
In [ ]: scores_rfc = cross_val_score(rfc, X_train_all_sc, y_train_all_sc, cv=10, scoring='accu
        print(scores_rfc)
        print(scores_rfc.mean())
```

```
In [ ]: para DecisionTreeClassifier
```

```
In [ ]: scores_dtree_2 = cross_val_score(dtree_2, X_train_all_sc, y_train_all_sc, cv=10, scori
        print(scores_dtree_2)
        print(scores_dtree_2.mean())
```

```
In [ ]: print("dtree_2 : " , scores_dtree_2.mean())
        print("rfc     : " , scores_rfc.mean())
        print("svc     : " , scores_svc.mean())
```

```
In [ ]: Los mejores resultados los obtenemos de Decision Tree, Random Forest y SVC Classifiers
```

4.1 Apartado 6

Por medio del análisis de datos encontramos realción entre las variables Sex, Age, Embarqued. Con estas variables se trabajó para hacer el modelo predictivo. Apartir de los resultados obtenidos podemos decir que la probabilidad de supervivencia de los pasajeros del titanic depende de las variables Sex, Age y Embarqued.