# Classification

March 15, 2022

## 1 Supervised machine learning: Classification

Dataset Introduction The dataset used here is Titanic - Machine Learning from Disaster. This dataset is used for an example for classification problems. The datasets consists of the following columns

Features

survival - This feature tells us whether the passenger survived or not. This feature is gonna be used for predicting 0 = No; 1 = Yes

PassengerId - ID of the observation

pclass Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)

name - Name of the passenger

sex- Sex of the passenger

Age- Age of the passenger

sibsp - Number of siblings or spouse traveling with the passenger

parch - Number of parents, children traveling with the passenger

ticket- Ticket number of the passenger

fare - Fare amount paid by the passenger

cabin- Cabin allocated for the passenger

embarked - Place of embarkment of the passenger (C = Cherbourg; Q = Queenstown; S = Southampton)

Problem Statement - Predict survivability of a passenger based on the features The models will be focus on prediction rather than interpretability

[5]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LogisticRegression
```

```
from sklearn.model_selection import train_test_split,␣
↪GridSearchCV,StratifiedShuffleSplit
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import MinMaxScaler
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import precision_recall_fscore_support as score

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, accuracy_score,roc_auc_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from sklearn.model_selection import cross_val_score
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report

%matplotlib inline
```

[1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[2]:
```
import seaborn as sns
```

[6]:
```
data = pd.read_csv('/content/drive/MyDrive/ibm/Projects/EDA/train(EDA).csv')
```

Intial exploration of data

[7]:
```
print(data.shape)
print(data.columns.tolist())
print(data.dtypes)
```

```
(891, 12)
['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch',
'Ticket', 'Fare', 'Cabin', 'Embarked']
PassengerId      int64
Survived         int64
Pclass           int64
```

```
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

[8]:
```
data.head()
```

[8]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

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

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

We can see that the problem to solve here is to predict the survived column

[9]:
```
data.describe()
```

[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
```

## 2 Feature deletion

FInding columns which has unique values for each observation

[10]:
```
columnname = data.columns.to_list()
observation_length = data.shape[0]
dummies = []
for x in columnname:
  if len(data[x].unique()) == observation_length:
    dummies.append(x)
print(dummies)
```

```
['PassengerId', 'Name']
```

As they do not provide any useful info. We are gonna delete them

[11]:
```
data1 = data.copy()
data1.drop(dummies, axis = 1, inplace = True)
data1.shape
```

[11]:
```
(891, 10)
```

[12]:
```
data1.head()
```

[12]:
```
   Survived  Pclass     Sex   Age  SibSp  Parch            Ticket     Fare  \
0         0       3    male  22.0      1      0         A/5 21171   7.2500
1         1       1  female  38.0      1      0          PC 17599  71.2833
2         1       3  female  26.0      0      0  STON/O2. 3101282   7.9250
3         1       1  female  35.0      1      0            113803  53.1000
4         0       3    male  35.0      0      0            373450   8.0500

  Cabin Embarked
0   NaN        S
1   C85        C
2   NaN        S
3  C123        S
```

```
4   NaN        S
```

the ticket columns looks a little suspicious

[13]:
```
data1['Ticket'].describe()
```

[13]:
```
count        891
unique       681
top       347082
freq           7
Name: Ticket, dtype: object
```

it has a huge number of unique values lets check them to see any order or categories

[14]:
```
data['Ticket'].unique()
```

[14]:
```
array(['A/5 21171', 'PC 17599', 'STON/O2. 3101282', '113803', '373450',
       '330877', '17463', '349909', '347742', '237736', 'PP 9549',
       '113783', 'A/5. 2151', '347082', '350406', '248706', '382652',
       '244373', '345763', '2649', '239865', '248698', '330923', '113788',
       '347077', '2631', '19950', '330959', '349216', 'PC 17601',
       'PC 17569', '335677', 'C.A. 24579', 'PC 17604', '113789', '2677',
       'A./5. 2152', '345764', '2651', '7546', '11668', '349253',
       'SC/Paris 2123', '330958', 'S.C./A.4. 23567', '370371', '14311',
       '2662', '349237', '3101295', 'A/4. 39886', 'PC 17572', '2926',
       '113509', '19947', 'C.A. 31026', '2697', 'C.A. 34651', 'CA 2144',
       '2669', '113572', '36973', '347088', 'PC 17605', '2661',
       'C.A. 29395', 'S.P. 3464', '3101281', '315151', 'C.A. 33111',
       'S.O.C. 14879', '2680', '1601', '348123', '349208', '374746',
       '248738', '364516', '345767', '345779', '330932', '113059',
       'SO/C 14885', '3101278', 'W./C. 6608', 'SOTON/OQ 392086', '343275',
       '343276', '347466', 'W.E.P. 5734', 'C.A. 2315', '364500', '374910',
       'PC 17754', 'PC 17759', '231919', '244367', '349245', '349215',
       '35281', '7540', '3101276', '349207', '343120', '312991', '349249',
       '371110', '110465', '2665', '324669', '4136', '2627',
       'STON/O 2. 3101294', '370369', 'PC 17558', 'A4. 54510', '27267',
       '370372', 'C 17369', '2668', '347061', '349241',
       'SOTON/O.Q. 3101307', 'A/5. 3337', '228414', 'C.A. 29178',
       'SC/PARIS 2133', '11752', '7534', 'PC 17593', '2678', '347081',
       'STON/O2. 3101279', '365222', '231945', 'C.A. 33112', '350043',
       '230080', '244310', 'S.O.P. 1166', '113776', 'A.5. 11206',
       'A/5. 851', 'Fa 265302', 'PC 17597', '35851', 'SOTON/OQ 392090',
       '315037', 'CA. 2343', '371362', 'C.A. 33595', '347068', '315093',
       '363291', '113505', 'PC 17318', '111240', 'STON/O 2. 3101280',
       '17764', '350404', '4133', 'PC 17595', '250653', 'LINE',
       'SC/PARIS 2131', '230136', '315153', '113767', '370365', '111428',
       '364849', '349247', '234604', '28424', '350046', 'PC 17610',
       '368703', '4579', '370370', '248747', '345770', '3101264', '2628',
```

'A/5 3540', '347054', '2699', '367231', '112277',
'SOTON/O.Q. 3101311', 'F.C.C. 13528', 'A/5 21174', '250646',
'367229', '35273', 'STON/O2. 3101283', '243847', '11813',
'W/C 14208', 'SOTON/OQ 392089', '220367', '21440', '349234',
'19943', 'PP 4348', 'SW/PP 751', 'A/5 21173', '236171', '347067',
'237442', 'C.A. 29566', 'W./C. 6609', '26707', 'C.A. 31921',
'28665', 'SCO/W 1585', '367230', 'W./C. 14263',
'STON/O 2. 3101275', '2694', '19928', '347071', '250649', '11751',
'244252', '362316', '113514', 'A/5. 3336', '370129', '2650',
'PC 17585', '110152', 'PC 17755', '230433', '384461', '110413',
'112059', '382649', 'C.A. 17248', '347083', 'PC 17582', 'PC 17760',
'113798', '250644', 'PC 17596', '370375', '13502', '347073',
'239853', 'C.A. 2673', '336439', '347464', '345778', 'A/5. 10482',
'113056', '349239', '345774', '349206', '237798', '370373',
'19877', '11967', 'SC/Paris 2163', '349236', '349233', 'PC 17612',
'2693', '113781', '19988', '9234', '367226', '226593', 'A/5 2466',
'17421', 'PC 17758', 'P/PP 3381', 'PC 17485', '11767', 'PC 17608',
'250651', '349243', 'F.C.C. 13529', '347470', '29011', '36928',
'16966', 'A/5 21172', '349219', '234818', '345364', '28551',
'111361', '113043', 'PC 17611', '349225', '7598', '113784',
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'C.A. 37671', '315088', '7267', '113510', '2695', '2647', '345783',
'237671', '330931', '330980', 'SC/PARIS 2167', '2691',
'SOTON/O.Q. 3101310', 'C 7076', '110813', '2626', '14313',
'PC 17477', '11765', '3101267', '323951', 'C 7077', '113503',
'2648', '347069', 'PC 17757', '2653', 'STON/O 2. 3101293',
'349227', '27849', '367655', 'SC 1748', '113760', '350034',
'3101277', '350052', '350407', '28403', '244278', '240929',
'STON/O 2. 3101289', '341826', '4137', '315096', '28664', '347064',
'29106', '312992', '349222', '394140', 'STON/O 2. 3101269',
'343095', '28220', '250652', '28228', '345773', '349254',
'A/5. 13032', '315082', '347080', 'A/4. 34244', '2003', '250655',
'364851', 'SOTON/O.Q. 392078', '110564', '376564', 'SC/AH 3085',
'STON/O 2. 3101274', '13507', 'C.A. 18723', '345769', '347076',
'230434', '65306', '33638', '113794', '2666', '113786', '65303',
'113051', '17453', 'A/5 2817', '349240', '13509', '17464',
'F.C.C. 13531', '371060', '19952', '364506', '111320', '234360',
'A/S 2816', 'SOTON/O.Q. 3101306', '113792', '36209', '323592',
'315089', 'SC/AH Basle 541', '7553', '31027', '3460', '350060',
'3101298', '239854', 'A/5 3594', '4134', '11771', 'A.5. 18509',
'65304', 'SOTON/OQ 3101317', '113787', 'PC 17609', 'A/4 45380',
'36947', 'C.A. 6212', '350035', '315086', '364846', '330909',
'4135', '26360', '111427', 'C 4001', '382651', 'SOTON/OQ 3101316',
'PC 17473', 'PC 17603', '349209', '36967', 'C.A. 34260', '226875',
'349242', '12749', '349252', '2624', '2700', '367232',
'W./C. 14258', 'PC 17483', '3101296', '29104', '2641', '2690',
'315084', '113050', 'PC 17761', '364498', '13568', 'WE/P 5735',

```
'2908', '693', 'SC/PARIS 2146', '244358', '330979', '2620',
'347085', '113807', '11755', '345572', '372622', '349251',
'218629', 'SOTON/OQ 392082', 'SOTON/O.Q. 392087', 'A/4 48871',
'349205', '2686', '350417', 'S.W./PP 752', '11769', 'PC 17474',
'14312', 'A/4. 20589', '358585', '243880', '2689',
'STON/O 2. 3101286', '237789', '13049', '3411', '237565', '13567',
'14973', 'A./5. 3235', 'STON/O 2. 3101273', 'A/5 3902', '364848',
'SC/AH 29037', '248727', '2664', '349214', '113796', '364511',
'111426', '349910', '349246', '113804', 'SOTON/O.Q. 3101305',
'370377', '364512', '220845', '31028', '2659', '11753', '350029',
'54636', '36963', '219533', '349224', '334912', '27042', '347743',
'13214', '112052', '237668', 'STON/O 2. 3101292', '350050',
'349231', '13213', 'S.O./P.P. 751', 'CA. 2314', '349221', '8475',
'330919', '365226', '349223', '29751', '2623', '5727', '349210',
'STON/O 2. 3101285', '234686', '312993', 'A/5 3536', '19996',
'29750', 'F.C. 12750', 'C.A. 24580', '244270', '239856', '349912',
'342826', '4138', '330935', '6563', '349228', '350036', '24160',
'17474', '349256', '2672', '113800', '248731', '363592', '35852',
'348121', 'PC 17475', '36864', '350025', '223596', 'PC 17476',
'PC 17482', '113028', '7545', '250647', '348124', '34218', '36568',
'347062', '350048', '12233', '250643', '113806', '315094', '36866',
'236853', 'STON/O2. 3101271', '239855', '28425', '233639',
'349201', '349218', '16988', '376566', 'STON/O 2. 3101288',
'250648', '113773', '335097', '29103', '392096', '345780',
'349204', '350042', '29108', '363294', 'SOTON/O2 3101272', '2663',
'347074', '112379', '364850', '8471', '345781', '350047',
'S.O./P.P. 3', '2674', '29105', '347078', '383121', '36865',
'2687', '113501', 'W./C. 6607', 'SOTON/O.Q. 3101312', '374887',
'3101265', '12460', 'PC 17600', '349203', '28213', '17465',
'349244', '2685', '2625', '347089', '347063', '112050', '347087',
'248723', '3474', '28206', '364499', '112058', 'STON/O2. 3101290',
'S.C./PARIS 2079', 'C 7075', '315098', '19972', '368323', '367228',
'2671', '347468', '2223', 'PC 17756', '315097', '392092', '11774',
'SOTON/O2 3101287', '2683', '315090', 'C.A. 5547', '349213',
'347060', 'PC 17592', '392091', '113055', '2629', '350026',
'28134', '17466', '233866', '236852', 'SC/PARIS 2149', 'PC 17590',
'345777', '349248', '695', '345765', '2667', '349212', '349217',
'349257', '7552', 'C.A./SOTON 34068', 'SOTON/OQ 392076', '211536',
'112053', '111369', '370376'], dtype=object)
```

Ticket columns doesnt seem to have any ordering or category, As this also doesnt give any useful info. We shall delete it also

[15]:
```
data2 = data1.copy()
data2.drop(['Ticket'], axis = 1, inplace = True)
data2.shape
```

[15]: (891, 9)

# 3 Exploratory data analysis and cleaning

## 3.1 Numerical columns Analysis

[16]:
```
numerical_cols = data2.select_dtypes('number').columns.tolist()
print(numerical_cols)
```

```
['Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare']
```

[17]:
```
data2.describe()
```

[17]:

| | Survived | Pclass | Age | SibSp | Parch | Fare |
|---|---|---|---|---|---|---|
| count | 891.000000 | 891.000000 | 714.000000 | 891.000000 | 891.000000 | 891.000000 |
| mean | 0.383838 | 2.308642 | 29.699118 | 0.523008 | 0.381594 | 32.204208 |
| std | 0.486592 | 0.836071 | 14.526497 | 1.102743 | 0.806057 | 49.693429 |
| min | 0.000000 | 1.000000 | 0.420000 | 0.000000 | 0.000000 | 0.000000 |
| 25% | 0.000000 | 2.000000 | 20.125000 | 0.000000 | 0.000000 | 7.910400 |
| 50% | 0.000000 | 3.000000 | 28.000000 | 0.000000 | 0.000000 | 14.454200 |
| 75% | 1.000000 | 3.000000 | 38.000000 | 1.000000 | 0.000000 | 31.000000 |
| max | 1.000000 | 3.000000 | 80.000000 | 8.000000 | 6.000000 | 512.329200 |

### 3.1.1 Survived Column

[18]:
```
data2['Survived'].isnull().sum()
```

[18]: 0

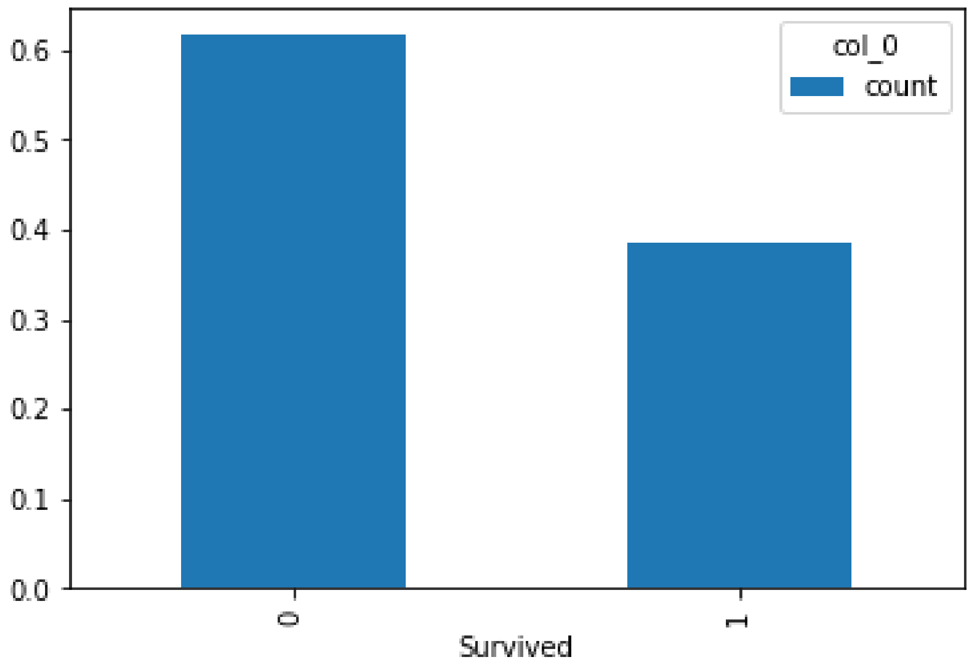
[19]:
```
data2['Survived'].unique()
```

[19]: array([0, 1])

[20]:
```
ct = pd.crosstab(index = data2['Survived'], columns = 'count')
ct = ct/data2.shape[0]
display(ct)
ct.plot(kind = 'bar')
```

| col_0 | count |
|---|---|
| Survived | |
| 0 | 0.616162 |
| 1 | 0.383838 |

[20]: <matplotlib.axes._subplots.AxesSubplot at 0x7f109681d190>




We can see that around 61 % people died and around 38% people survived

#### 3.1.2 Pclass column

[21]:
```
data2['Pclass'].isnull().sum()
```

[21]: 0

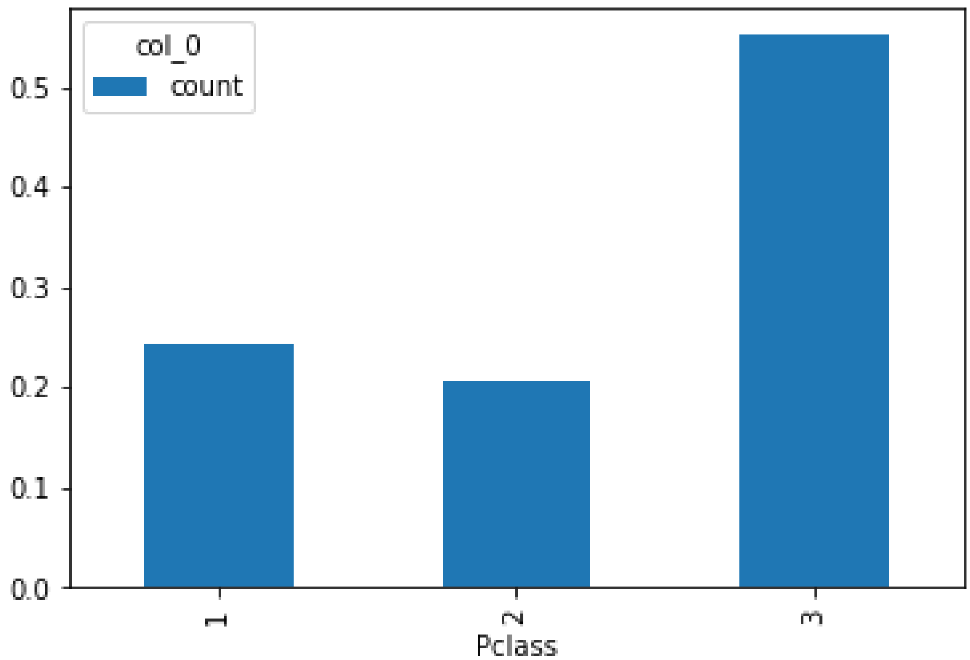
[22]:
```
data2['Pclass'].unique()
```

[22]: array([3, 1, 2])

[23]:
```
ct = pd.crosstab(index = data2['Pclass'], columns = 'count')
ct = ct/data2.shape[0]
print(ct)
ct.plot(kind = 'bar')
```

```
col_0      count
Pclass
1       0.242424
2       0.206510
3       0.551066
```

[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1096789910>




We can see that majority were of class 3

We can see there are 3 unique values for passenger class but these can be converted into categorical feature instead as they refer to a passenger class and also they also have an order to them

[24]:
```
Pclass = pd.Categorical(data2["Pclass"],
                        ordered=True)
Pclass.describe()
```

[24]:

| categories | counts | freqs |
|---|---|---|
| 1 | 216 | 0.242424 |
| 2 | 184 | 0.206510 |
| 3 | 491 | 0.551066 |

[25]:
```
data3 = data2.copy()
data3['Pclass'] = Pclass
data3.head()
```

[25]:

| | Survived | Pclass | Sex | Age | SibSp | Parch | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 3 | male | 22.0 | 1 | 0 | 7.2500 | NaN | S |
| 1 | 1 | 1 | female | 38.0 | 1 | 0 | 71.2833 | C85 | C |
| 2 | 1 | 3 | female | 26.0 | 0 | 0 | 7.9250 | NaN | S |
| 3 | 1 | 1 | female | 35.0 | 1 | 0 | 53.1000 | C123 | S |

```
4         0      3    male  35.0      0      0   8.0500   NaN        S
```

[26]:
```
# Do the one hot encoding
data3 = pd.get_dummies(data3, columns=['Pclass'])
data3.head()
```

[26]:
```
   Survived     Sex   Age  SibSp  Parch     Fare Cabin Embarked  Pclass_1  \
0         0    male  22.0      1      0   7.2500   NaN        S         0
1         1  female  38.0      1      0  71.2833   C85        C         1
2         1  female  26.0      0      0   7.9250   NaN        S         0
3         1  female  35.0      1      0  53.1000  C123        S         1
4         0    male  35.0      0      0   8.0500   NaN        S         0

   Pclass_2  Pclass_3
0         0         1
1         0         0
2         0         1
3         0         0
4         0         1
```

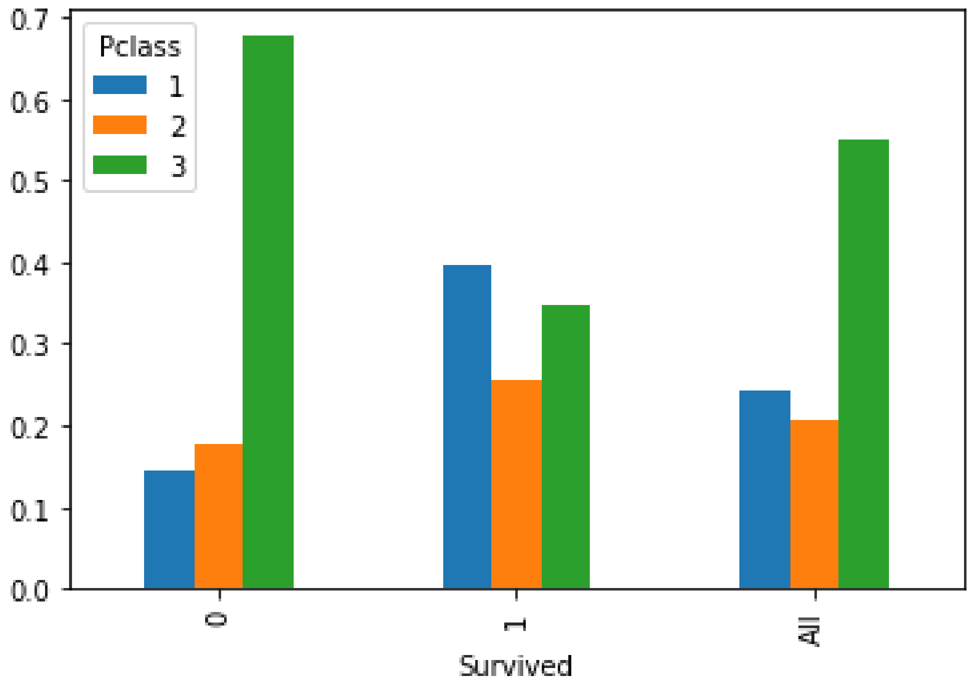
Lets see the survived ratio among the passenger classes

[27]:
```
survived_pclass = pd.crosstab(index=data2["Survived"],
                           columns=data2["Pclass"], margins = True)
display(survived_pclass/survived_pclass.loc["All","All"])
print(survived_pclass/survived_pclass.loc["All"])
survived_pclass = survived_pclass.div(survived_pclass["All"],
                   axis=0)
print(survived_pclass)

survived_pclass.pop('All')
survived_pclass.plot(kind = 'bar')
```

```
Pclass           1         2         3       All
Survived
0         0.089787  0.108866  0.417508  0.616162
1         0.152637  0.097643  0.133558  0.383838
All       0.242424  0.206510  0.551066  1.000000


Pclass          1         2         3       All
Survived
0         0.37037  0.527174  0.757637  0.616162
1         0.62963  0.472826  0.242363  0.383838
All       1.00000  1.000000  1.000000  1.000000
Pclass           1         2         3  All
Survived
0         0.145719  0.176685  0.677596  1.0
```

```
1          0.397661  0.254386  0.347953  1.0
All        0.242424  0.206510  0.551066  1.0
```

[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7f109677eb10>




[27]:

We can class 3 people have have died a lot when compared to other classes and class 1 people have survived the most when compared to other classes

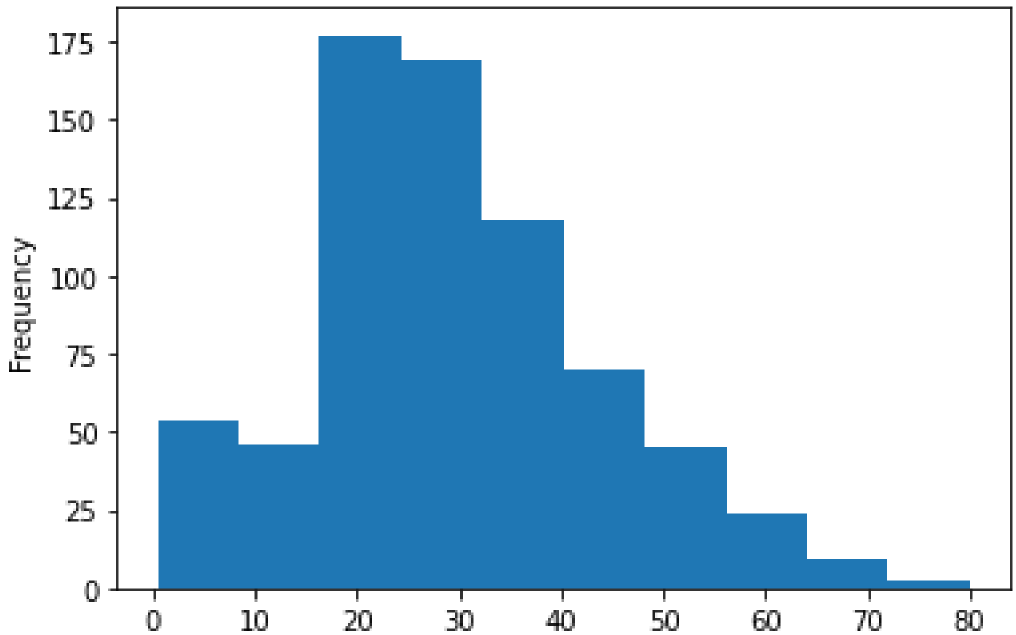
#### 3.1.3 Age column

[28]:
```
data3['Age'].isnull().sum()
```

[28]: 177

[29]:
```
data3['Age'].plot(kind = 'hist')
```

[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10961fbf90>




as age follows a normal distribution we can switch out the nan values with mean

[30]:
```
mean = np.nanmean(data3['Age'])
mean
```

[30]: 29.69911764705882

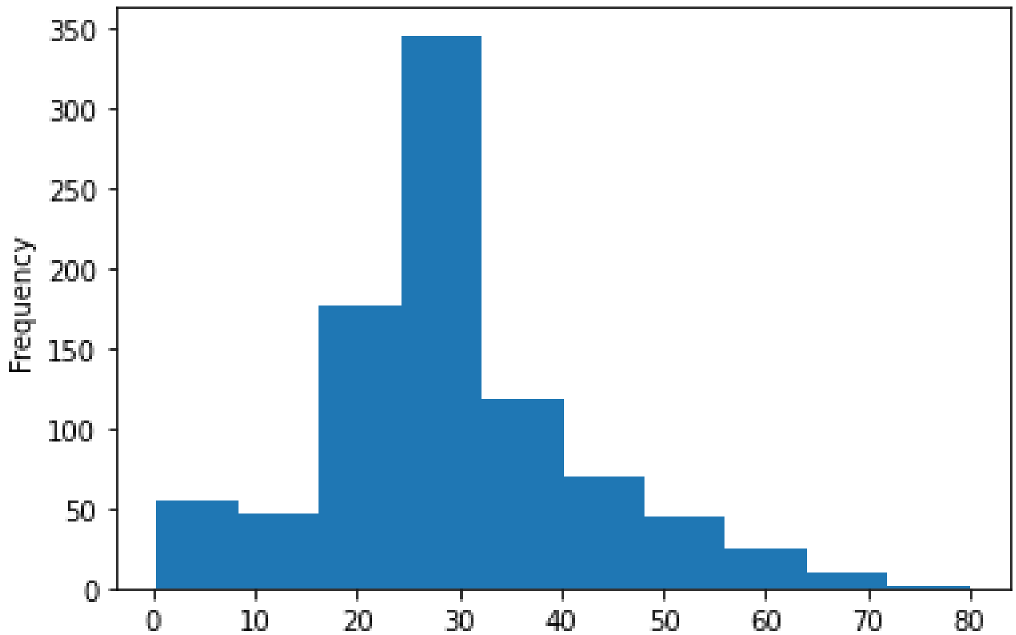
[31]:
```
data3['Age'].fillna(mean, inplace = True)
```

[32]:
```
data3['Age'].isnull().sum()
```

[32]: 0

[33]:
```
data3['Age'].plot(kind = 'hist')
```

[33]: <matplotlib.axes._subplots.AxesSubplot at 0x7f109611f6d0>




```
[34]: data3.head()
```

```
[34]:    Survived     Sex   Age  SibSp  Parch     Fare Cabin Embarked  Pclass_1  \
      0         0    male  22.0      1      0   7.2500   NaN        S         0
      1         1  female  38.0      1      0  71.2833   C85        C         1
      2         1  female  26.0      0      0   7.9250   NaN        S         0
      3         1  female  35.0      1      0  53.1000  C123        S         1
      4         0    male  35.0      0      0   8.0500   NaN        S         0

         Pclass_2  Pclass_3
      0         0         1
      1         0         0
      2         0         1
      3         0         0
      4         0         1
```

Using the original data lets what age range survived the most

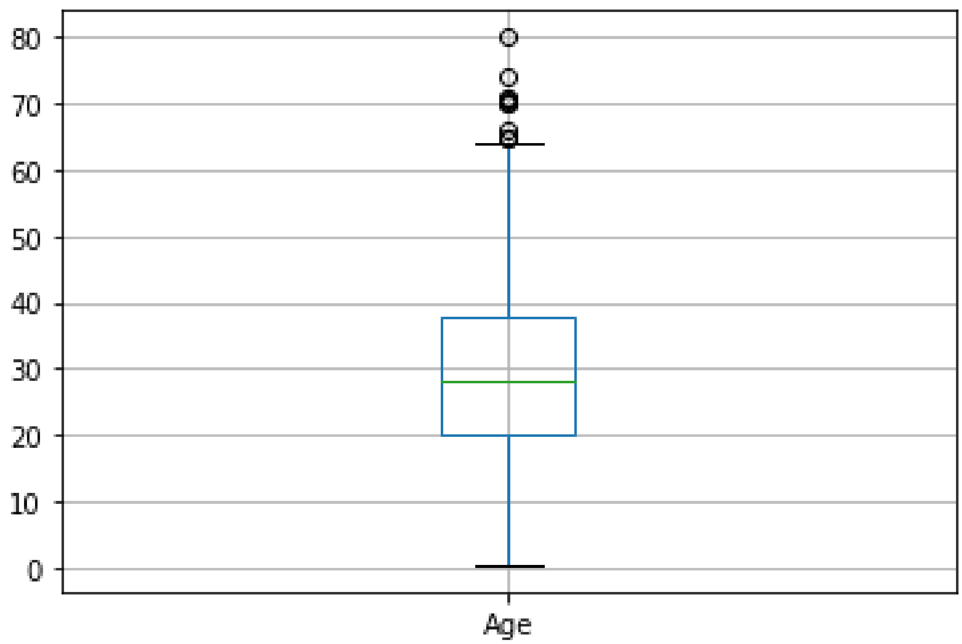
```
[35]: dummydata = data2.dropna(subset = ["Age"])
      dummydata
```

```
[35]:      Survived  Pclass     Sex   Age  SibSp  Parch     Fare Cabin Embarked
      0           0       3    male  22.0      1      0   7.2500   NaN        S
      1           1       1  female  38.0      1      0  71.2833   C85        C
      2           1       3  female  26.0      0      0   7.9250   NaN        S
      3           1       1  female  35.0      1      0  53.1000  C123        S
```

```
4            0       3     male  35.0      0      0   8.0500   NaN         S
..           …       …       …     …       …      …      …        …
885          0       3   female  39.0      0      5  29.1250   NaN         Q
886          0       2     male  27.0      0      0  13.0000   NaN         S
887          1       1   female  19.0      0      0  30.0000   B42         S
889          1       1     male  26.0      0      0  30.0000  C148         C
890          0       3     male  32.0      0      0   7.7500   NaN         Q

[714 rows x 9 columns]
```

[36]:
```
dummydata.boxplot(column = 'Age')
```

[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10960aba10>




[37]:
```
bins = [0,20,40,60,80,100,120]
labels = ['0-20','20-40','40-60','60-80','80-100','100+']

dummydata['Age_range'] = pd.cut(dummydata['Age'],bins = bins, labels = labels)
dummydata.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

[37]:
```
   Survived  Pclass     Sex   Age  SibSp  Parch     Fare Cabin Embarked  \
0         0       3    male  22.0      1      0   7.2500   NaN        S
1         1       1  female  38.0      1      0  71.2833   C85        C
2         1       3  female  26.0      0      0   7.9250   NaN        S
3         1       1  female  35.0      1      0  53.1000  C123        S
4         0       3    male  35.0      0      0   8.0500   NaN        S

  Age_range
0     20-40
1     20-40
2     20-40
3     20-40
4     20-40
```

[38]:
```python
dummydata['Age_range'].unique()
```

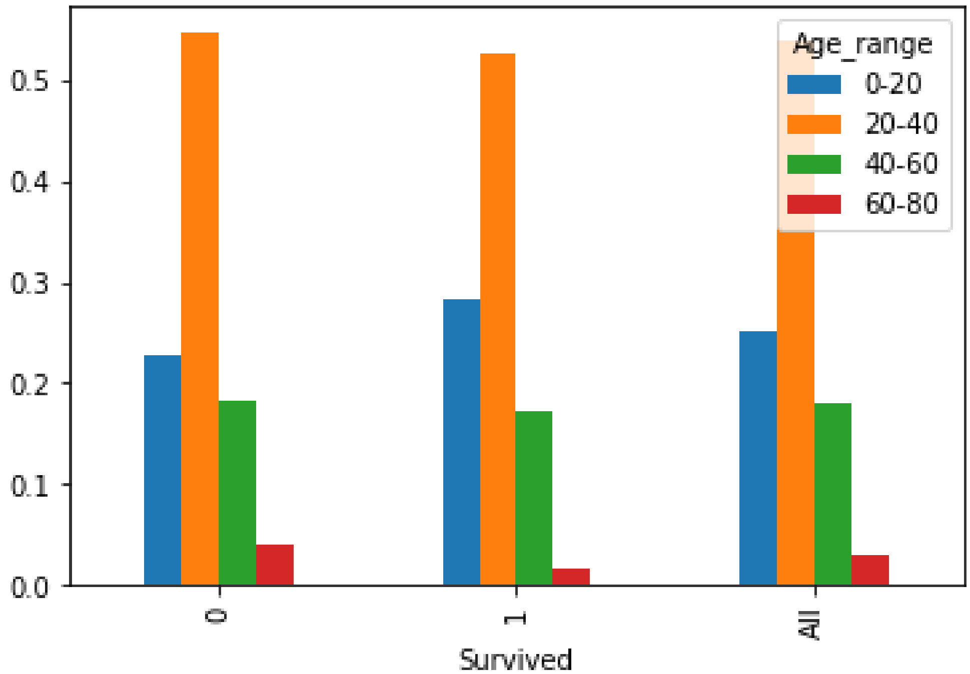
[38]:
```
['20-40', '40-60', '0-20', '60-80']
Categories (6, object): ['0-20' < '20-40' < '40-60' < '60-80' < '80-100' <
'100+']
```

[39]:
```python
survived_age = pd.crosstab(index=dummydata["Survived"],
                           columns=dummydata["Age_range"], margins = True)
display(survived_age/survived_age.loc["All","All"])
display(survived_age/survived_age.loc["All"])
survived_age = survived_age.div(survived_age["All"],
                   axis=0)
display(survived_age)

survived_age.pop('All')
survived_age.plot(kind = 'bar')
```

```
Age_range      0-20     20-40     40-60     60-80       All
Survived
0          0.135854  0.324930  0.109244  0.023810  0.593838
1          0.114846  0.214286  0.070028  0.007003  0.406162
All        0.250700  0.539216  0.179272  0.030812  1.000000


Age_range      0-20     20-40     40-60     60-80       All
Survived
0          0.541899  0.602597  0.609375  0.772727  0.593838
1          0.458101  0.397403  0.390625  0.227273  0.406162
All        1.000000  1.000000  1.000000  1.000000  1.000000


Age_range      0-20     20-40     40-60     60-80  All
```

```
Survived
0           0.228774  0.547170  0.183962  0.040094  1.0
1           0.282759  0.527586  0.172414  0.017241  1.0
All         0.250700  0.539216  0.179272  0.030812  1.0
```

[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095fd5f90>




### 3.1.4 Sibsp and parch column

[40]:
```
data3['SibSp'].isnull().sum()
```

[40]: 0

[41]:
```
data3['Parch'].isnull().sum()
```

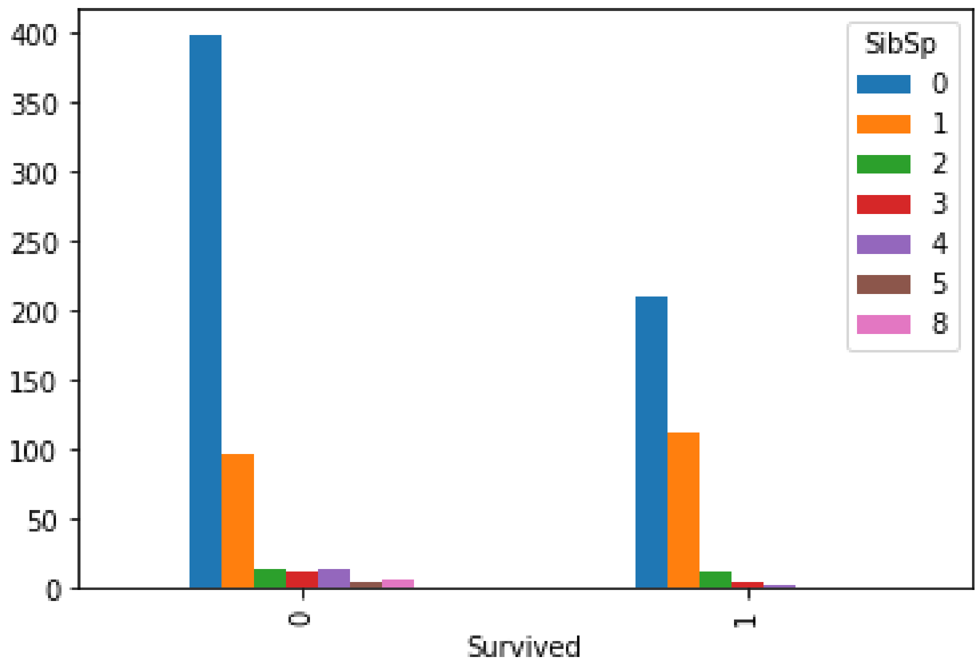
[41]: 0

[42]:
```
survived_SibSp = pd.crosstab(index=data3["Survived"],
                             columns=data3["SibSp"])
display(survived_SibSp)
survived_SibSp.plot(kind = 'bar')
```

```
SibSp       0    1    2    3    4  5  8
```

```
Survived
0           398   97  15  12  15  5  7
1           210  112  13   4   3  0  0
```

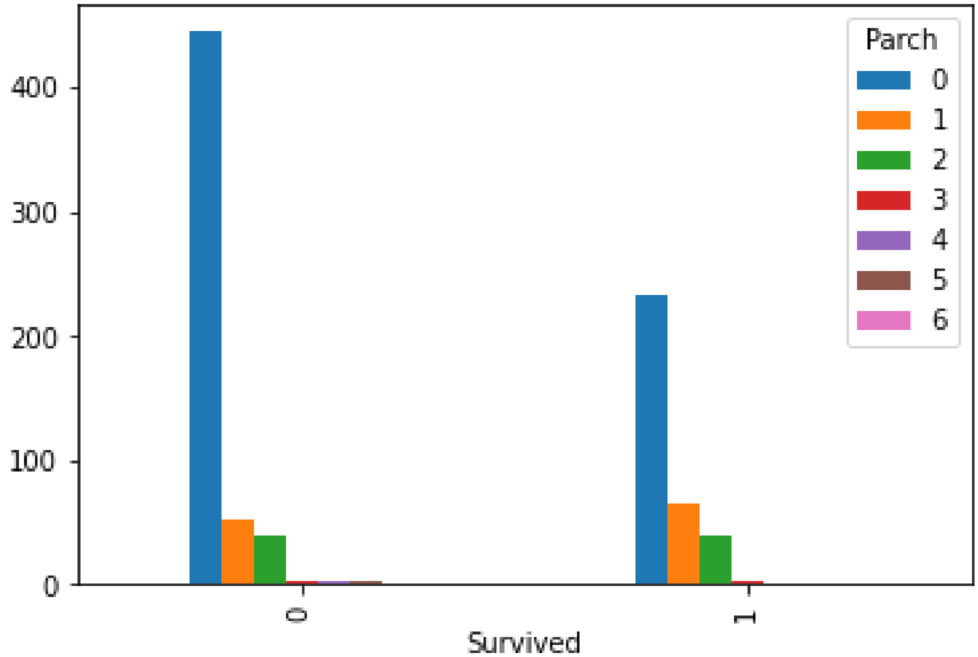
[42]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095f62e90>




[43]:
```
survived_parch = pd.crosstab(index=data3["Survived"],
                             columns=data3["Parch"])
display(survived_parch)
survived_parch.plot(kind = 'bar')
```

```
Parch       0   1   2  3  4  5  6
Survived
0         445  53  40  2  4  4  1
1         233  65  40  3  0  1  0
```

[43]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095ee88d0>




[44]:
```
def with_family(row):
  if (row['SibSp'] !=0) or (row['Parch'] != 0):
    return 1
  else:
    return 0
```

[45]:
```
data4 = data3.copy()
data4['with_family'] = data3.apply(lambda row : with_family(row), axis = 1)
data4.head()
```

[45]:
```
   Survived     Sex   Age  SibSp  Parch     Fare Cabin Embarked  Pclass_1  \
0         0    male  22.0      1      0   7.2500   NaN        S         0
1         1  female  38.0      1      0  71.2833   C85        C         1
2         1  female  26.0      0      0   7.9250   NaN        S         0
3         1  female  35.0      1      0  53.1000  C123        S         1
4         0    male  35.0      0      0   8.0500   NaN        S         0

   Pclass_2  Pclass_3  with_family
0         0         1            1
1         0         0            1
2         0         1            0
3         0         0            1
4         0         1            0
```

[46]:

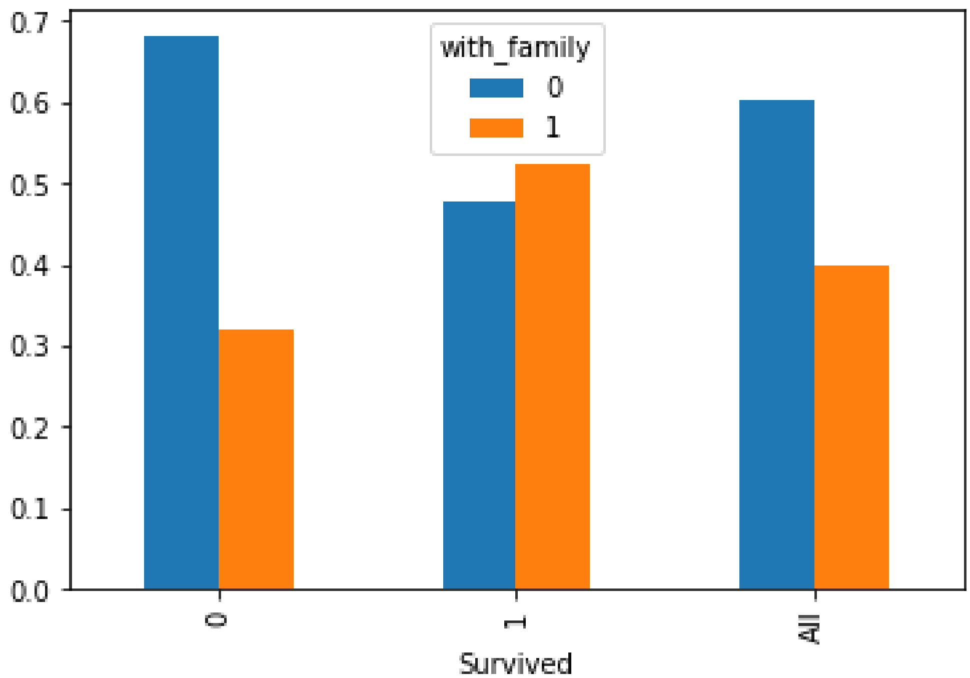
```
survived_fam = pd.crosstab(index=data4["Survived"],
                           columns=data4["with_family"], margins = True)
display(survived_fam/survived_fam.loc["All","All"])
display(survived_fam/survived_fam.loc["All"])
survived_fam = survived_fam.div(survived_fam["All"],
                   axis=0)
display(survived_fam)
survived_fam.pop('All')
survived_fam.plot(kind = 'bar')
```

```
with_family         0         1       All
Survived
0            0.419753  0.196409  0.616162
1            0.182941  0.200898  0.383838
All          0.602694  0.397306  1.000000
```

```
with_family         0        1       All
Survived
0            0.696462  0.49435  0.616162
1            0.303538  0.50565  0.383838
All          1.000000  1.00000  1.000000
```

```
with_family         0         1  All
Survived
0            0.681239  0.318761  1.0
1            0.476608  0.523392  1.0
All          0.602694  0.397306  1.0
```

[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10960333d0>



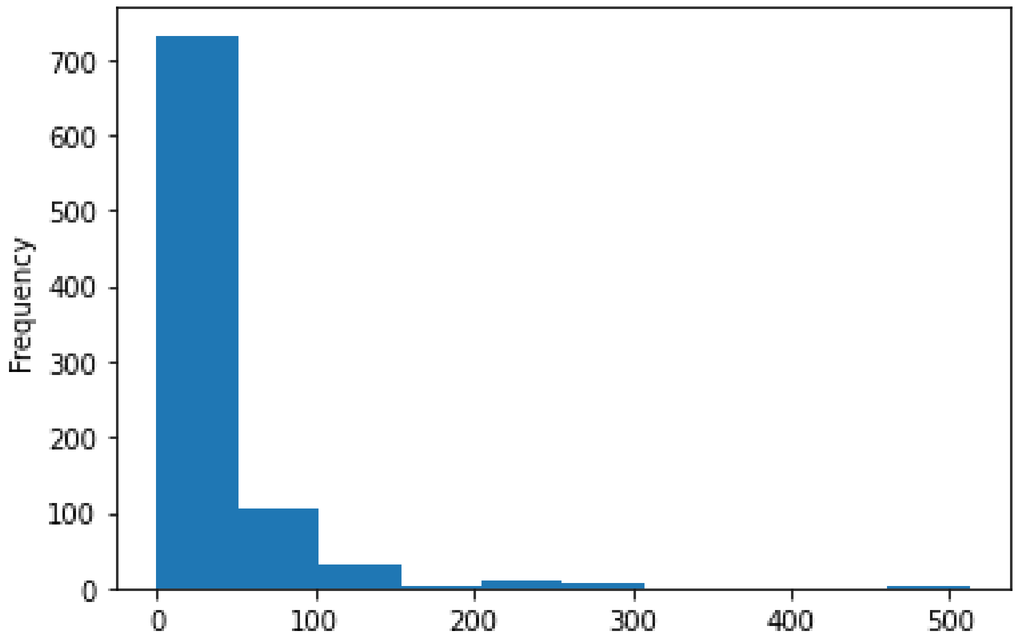

### 3.1.5 fare column

[47]:
```
data3['Fare'].isnull().sum()
```

[47]: 0

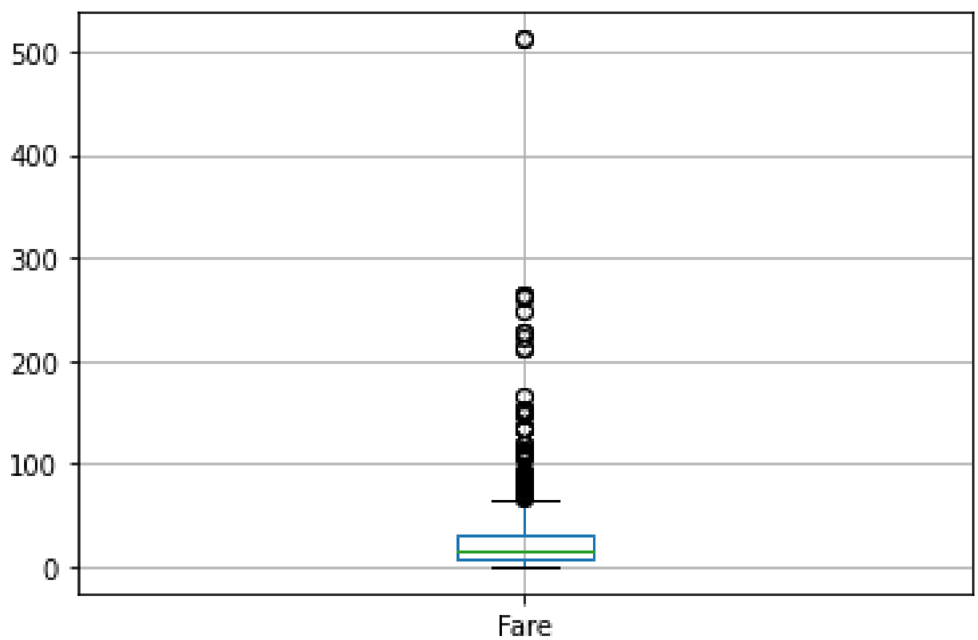
[48]:
```
data3['Fare'].plot(kind = 'hist')
```

[48]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095dbc0d0>




[49]:
```
data3.boxplot(column = ['Fare'])
```

[49]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095ccd790>



[50]:
```
index = np.where(data4["Fare"] >100)

data4.loc[index]
```

[50]:
```
     Survived     Sex        Age  SibSp  Parch      Fare            Cabin  \
27          0    male  19.000000      3      2  263.0000      C23 C25 C27
31          1  female  29.699118      1      0  146.5208              B78
88          1  female  23.000000      3      2  263.0000      C23 C25 C27
118         0    male  24.000000      0      1  247.5208          B58 B60
195         1  female  58.000000      0      0  146.5208              B80
215         1  female  31.000000      1      0  113.2750              D36
258         1  female  35.000000      0      0  512.3292              NaN
268         1  female  58.000000      0      1  153.4625             C125
269         1  female  35.000000      0      0  135.6333              C99
297         0  female   2.000000      1      2  151.5500          C22 C26
299         1  female  50.000000      0      1  247.5208          B58 B60
305         1    male   0.920000      1      2  151.5500          C22 C26
306         1  female  29.699118      0      0  110.8833              NaN
307         1  female  17.000000      1      0  108.9000              C65
311         1  female  18.000000      2      2  262.3750  B57 B59 B63 B66
318         1  female  31.000000      0      2  164.8667               C7
319         1  female  40.000000      1      1  134.5000              E34
325         1  female  36.000000      0      0  135.6333              C32
332         0    male  38.000000      0      1  153.4625              C91
334         1  female  29.699118      1      0  133.6500              NaN
337         1  female  41.000000      0      0  134.5000              E40
341         1  female  24.000000      3      2  263.0000      C23 C25 C27
373         0    male  22.000000      0      0  135.6333              NaN
377         0    male  27.000000      0      2  211.5000              C82
380         1  female  42.000000      0      0  227.5250              NaN
390         1    male  36.000000      1      2  120.0000          B96 B98
393         1  female  23.000000      1      0  113.2750              D36
435         1  female  14.000000      1      2  120.0000          B96 B98
438         0    male  64.000000      1      4  263.0000      C23 C25 C27
498         0  female  25.000000      1      2  151.5500          C22 C26
505         0    male  18.000000      1      0  108.9000              C65
527         0    male  29.699118      0      0  221.7792              C95
537         1  female  30.000000      0      0  106.4250              NaN
544         0    male  50.000000      1      0  106.4250              C86
550         1    male  17.000000      0      2  110.8833              C70
557         0    male  29.699118      0      0  227.5250              NaN
581         1  female  39.000000      1      1  110.8833              C68
609         1  female  40.000000      0      0  153.4625             C125
659         0    male  58.000000      0      2  113.2750              D48
660         1    male  50.000000      2      0  133.6500              NaN
679         1    male  36.000000      0      1  512.3292      B51 B53 B55
689         1  female  15.000000      0      1  211.3375               B5
```

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 698 | 0 | male | 49.000000 | 1 | 1 | 110.8833 | C68 |
| 700 | 1 | female | 18.000000 | 1 | 0 | 227.5250 | C62 C64 |
| 708 | 1 | female | 22.000000 | 0 | 0 | 151.5500 | NaN |
| 716 | 1 | female | 38.000000 | 0 | 0 | 227.5250 | C45 |
| 730 | 1 | female | 29.000000 | 0 | 0 | 211.3375 | B5 |
| 737 | 1 | male | 35.000000 | 0 | 0 | 512.3292 | B101 |
| 742 | 1 | female | 21.000000 | 2 | 2 | 262.3750 | B57 B59 B63 B66 |
| 763 | 1 | female | 36.000000 | 1 | 2 | 120.0000 | B96 B98 |
| 779 | 1 | female | 43.000000 | 0 | 1 | 211.3375 | B3 |
| 802 | 1 | male | 11.000000 | 1 | 2 | 120.0000 | B96 B98 |
| 856 | 1 | female | 45.000000 | 1 | 1 | 164.8667 | NaN |

| | Embarked | Pclass_1 | Pclass_2 | Pclass_3 | with_family |
|---|---|---|---|---|---|
| 27 | S | 1 | 0 | 0 | 1 |
| 31 | C | 1 | 0 | 0 | 1 |
| 88 | S | 1 | 0 | 0 | 1 |
| 118 | C | 1 | 0 | 0 | 1 |
| 195 | C | 1 | 0 | 0 | 0 |
| 215 | C | 1 | 0 | 0 | 1 |
| 258 | C | 1 | 0 | 0 | 0 |
| 268 | S | 1 | 0 | 0 | 1 |
| 269 | S | 1 | 0 | 0 | 0 |
| 297 | S | 1 | 0 | 0 | 1 |
| 299 | C | 1 | 0 | 0 | 1 |
| 305 | S | 1 | 0 | 0 | 1 |
| 306 | C | 1 | 0 | 0 | 0 |
| 307 | C | 1 | 0 | 0 | 1 |
| 311 | C | 1 | 0 | 0 | 1 |
| 318 | S | 1 | 0 | 0 | 1 |
| 319 | C | 1 | 0 | 0 | 1 |
| 325 | C | 1 | 0 | 0 | 0 |
| 332 | S | 1 | 0 | 0 | 1 |
| 334 | S | 1 | 0 | 0 | 1 |
| 337 | C | 1 | 0 | 0 | 0 |
| 341 | S | 1 | 0 | 0 | 1 |
| 373 | C | 1 | 0 | 0 | 0 |
| 377 | C | 1 | 0 | 0 | 1 |
| 380 | C | 1 | 0 | 0 | 0 |
| 390 | S | 1 | 0 | 0 | 1 |
| 393 | C | 1 | 0 | 0 | 1 |
| 435 | S | 1 | 0 | 0 | 1 |
| 438 | S | 1 | 0 | 0 | 1 |
| 498 | S | 1 | 0 | 0 | 1 |
| 505 | C | 1 | 0 | 0 | 1 |
| 527 | S | 1 | 0 | 0 | 0 |
| 537 | C | 1 | 0 | 0 | 0 |
| 544 | C | 1 | 0 | 0 | 1 |

```
550        C        1        0        0         1
557        C        1        0        0         0
581        C        1        0        0         1
609        S        1        0        0         0
659        C        1        0        0         1
660        S        1        0        0         1
679        C        1        0        0         1
689        S        1        0        0         1
698        C        1        0        0         1
700        C        1        0        0         1
708        S        1        0        0         0
716        C        1        0        0         0
730        S        1        0        0         0
737        C        1        0        0         0
742        C        1        0        0         1
763        S        1        0        0         1
779        S        1        0        0         1
802        S        1        0        0         1
856        S        1        0        0         1
```

we can see that extra money was payed for passenger class 1 .This outliers gives us this info so we donot the change the outlier

[51]:
```python
data4.describe()
```

[51]:
```
         Survived         Age       SibSp       Parch        Fare    Pclass_1  \
count  891.000000  891.000000  891.000000  891.000000  891.000000  891.000000
mean     0.383838   29.699118    0.523008    0.381594   32.204208    0.242424
std      0.486592   13.002015    1.102743    0.806057   49.693429    0.428790
min      0.000000    0.420000    0.000000    0.000000    0.000000    0.000000
25%      0.000000   22.000000    0.000000    0.000000    7.910400    0.000000
50%      0.000000   29.699118    0.000000    0.000000   14.454200    0.000000
75%      1.000000   35.000000    1.000000    0.000000   31.000000    0.000000
max      1.000000   80.000000    8.000000    6.000000  512.329200    1.000000

         Pclass_2    Pclass_3  with_family
count  891.000000  891.000000   891.000000
mean     0.206510    0.551066     0.397306
std      0.405028    0.497665     0.489615
min      0.000000    0.000000     0.000000
25%      0.000000    0.000000     0.000000
50%      0.000000    1.000000     0.000000
75%      0.000000    1.000000     1.000000
max      1.000000    1.000000     1.000000
```

[52]:
```python
bins = [0,20,40,60,80,100,520]
labels = ['0-20','20-40','40-60','60-80','80-100','100-520']
```

```
fare_range = pd.cut(data4['Fare'],bins = bins, labels = labels)
```

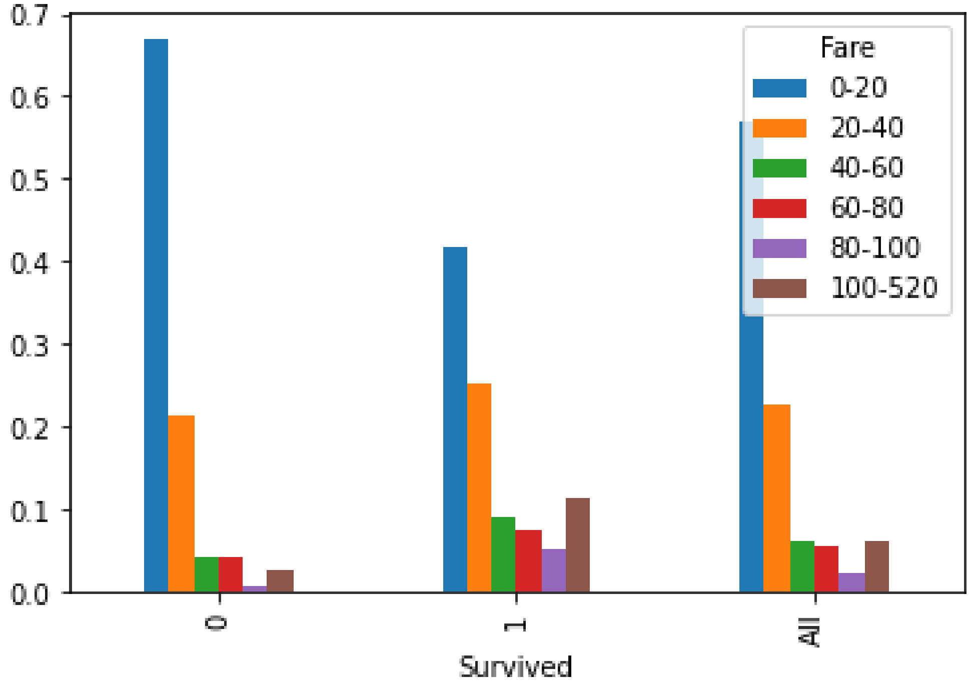
[53]:
```
survived_fare = pd.crosstab(index=data4["Survived"],
                            columns=fare_range, margins = True)
display(survived_fare/survived_fare.loc["All","All"])
display(survived_fare/survived_fare.loc["All"])
survived_fare = survived_fare.div(survived_fare["All"],
                    axis=0)
display(survived_fare)
survived_fare.pop('All')
survived_fare.plot(kind = 'bar')
```

| Fare | 0-20 | 20-40 | 40-60 | 60-80 | 80-100 | 100-520 | All |
|---|---|---|---|---|---|---|---|
| Survived | | | | | | | |
| 0 | 0.408676 | 0.130137 | 0.026256 | 0.026256 | 0.003425 | 0.015982 | 0.610731 |
| 1 | 0.162100 | 0.098174 | 0.035388 | 0.028539 | 0.020548 | 0.044521 | 0.389269 |
| All | 0.570776 | 0.228311 | 0.061644 | 0.054795 | 0.023973 | 0.060502 | 1.000000 |

| Fare | 0-20 | 20-40 | 40-60 | 60-80 | 80-100 | 100-520 | All |
|---|---|---|---|---|---|---|---|
| Survived | | | | | | | |
| 0 | 0.716 | 0.57 | 0.425926 | 0.479167 | 0.142857 | 0.264151 | 0.610731 |
| 1 | 0.284 | 0.43 | 0.574074 | 0.520833 | 0.857143 | 0.735849 | 0.389269 |
| All | 1.000 | 1.00 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 |

| Fare | 0-20 | 20-40 | 40-60 | 60-80 | 80-100 | 100-520 | All |
|---|---|---|---|---|---|---|---|
| Survived | | | | | | | |
| 0 | 0.669159 | 0.213084 | 0.042991 | 0.042991 | 0.005607 | 0.026168 | 1.0 |
| 1 | 0.416422 | 0.252199 | 0.090909 | 0.073314 | 0.052786 | 0.114370 | 1.0 |
| All | 0.570776 | 0.228311 | 0.061644 | 0.054795 | 0.023973 | 0.060502 | 1.0 |

[53]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095cc1e10>




### 3.2 categorical columns

[54]:
```
categorical_cols = data2.dtypes[data.dtypes == "object"].index
print(categorical_cols)
```

```
Index(['Sex', 'Cabin', 'Embarked'], dtype='object')
```

#### 3.2.1 Sex column

[55]:
```
data4['Sex'].unique()
```

[55]:
```
array(['male', 'female'], dtype=object)
```

[56]:
```
data4['Sex'].isnull().sum()
```

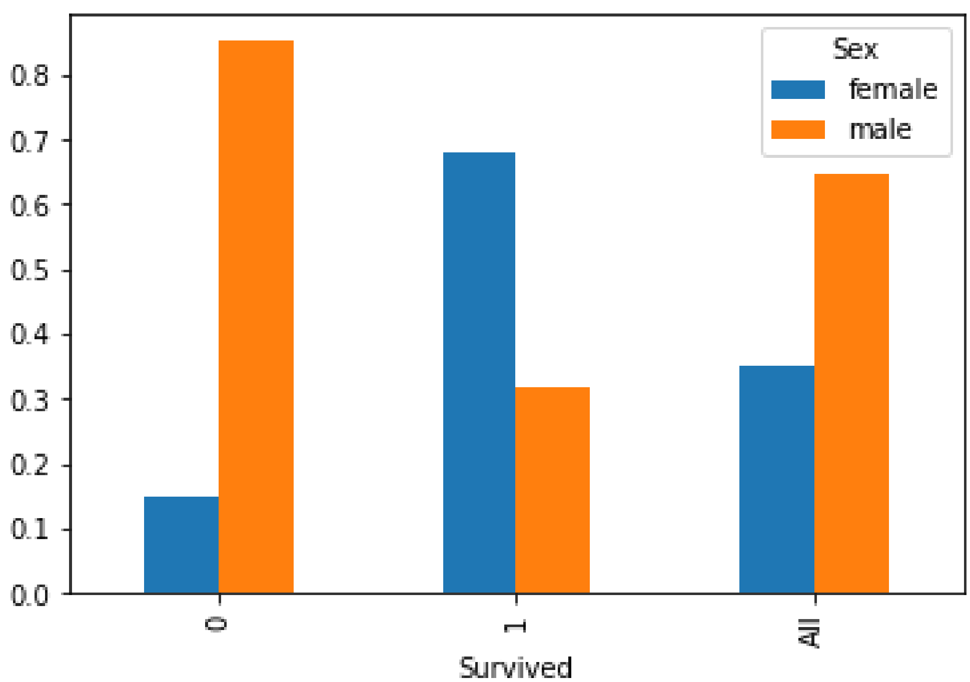
[56]:
```
0
```

[57]:
```
surviver_sex = pd.crosstab(index=data4["Survived"],
                           columns=data['Sex'], margins = True)
display(surviver_sex/surviver_sex.loc["All","All"])
display(surviver_sex/surviver_sex.loc["All"])
surviver_sex = surviver_sex.div(surviver_sex["All"],
```

```
                    axis=0)
display(surviver_sex)
surviver_sex.pop('All')
surviver_sex.plot(kind = 'bar')
```

```
Sex         female      male       All
Survived
0         0.090909  0.525253  0.616162
1         0.261504  0.122334  0.383838
All       0.352413  0.647587  1.000000


Sex         female      male       All
Survived
0         0.257962  0.811092  0.616162
1         0.742038  0.188908  0.383838
All       1.000000  1.000000  1.000000


Sex         female      male  All
Survived
0         0.147541  0.852459  1.0
1         0.681287  0.318713  1.0
All       0.352413  0.647587  1.0
```

[57]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095b89090>



[58]:
```python
# Do the one hot encoding
data4 = pd.get_dummies(data4, columns=['Sex'])
data4.head()
```

[58]:
```
   Survived   Age  SibSp  Parch     Fare Cabin Embarked  Pclass_1  Pclass_2  \
0         0  22.0      1      0   7.2500   NaN        S         0         0
1         1  38.0      1      0  71.2833   C85        C         1         0
2         1  26.0      0      0   7.9250   NaN        S         0         0
3         1  35.0      1      0  53.1000  C123        S         1         0
4         0  35.0      0      0   8.0500   NaN        S         0         0

   Pclass_3  with_family  Sex_female  Sex_male
0         1            1           0         1
1         0            1           1         0
2         1            0           1         0
3         0            1           1         0
4         1            0           0         1
```

### 3.2.2 Cabin

[59]:
```python
data4['Cabin'].isnull().sum()
```

[59]:
```
687
```

[60]:
```python
data4['Cabin'].unique()
```

[60]:
```
array([nan, 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
       'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
       'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
       'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
       'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
       'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
       'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
       'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
       'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
       'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
       'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
       'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
       'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
       'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
       'C148'], dtype=object)
```

even though this has a lot of nan values we cant delete this columns because dependind on which deck got flooded first the survival will on that so we assign a new cabin called a No cabin to this column for nan and also there seems to be repeating cabin letters which are unique so we can filter out the numbers

[61]:
```
cabin = data4["Cabin"].astype(str)

Cabin = np.array([obs[0] for obs in cabin])
ct = pd.crosstab(index = Cabin, columns = 'count')
display(ct)
Cabin = pd.Categorical(Cabin)

data5 = data4.copy()
data5['Cabin'] = Cabin
data5 = pd.get_dummies(data5, columns=['Cabin'])
data5.head()
```

```
col_0  count
row_0
A         15
B         47
C         59
D         33
E         32
F         13
G          4
T          1
n        687
```

[61]:
```
   Survived   Age  SibSp  Parch     Fare Embarked  Pclass_1  Pclass_2  \
0         0  22.0      1      0   7.2500        S         0         0
1         1  38.0      1      0  71.2833        C         1         0
2         1  26.0      0      0   7.9250        S         0         0
3         1  35.0      1      0  53.1000        S         1         0
4         0  35.0      0      0   8.0500        S         0         0

   Pclass_3  with_family  …  Sex_male  Cabin_A  Cabin_B  Cabin_C  Cabin_D  \
0         1            1  …         1        0        0        0        0
1         0            1  …         0        0        0        1        0
2         1            0  …         0        0        0        0        0
3         0            1  …         0        0        0        1        0
4         1            0  …         1        0        0        0        0

   Cabin_E  Cabin_F  Cabin_G  Cabin_T  Cabin_n
0        0        0        0        0        1
1        0        0        0        0        0
2        0        0        0        0        1
```

```
3         0         0         0         0         0
4         0         0         0         0         1

[5 rows x 21 columns]
```

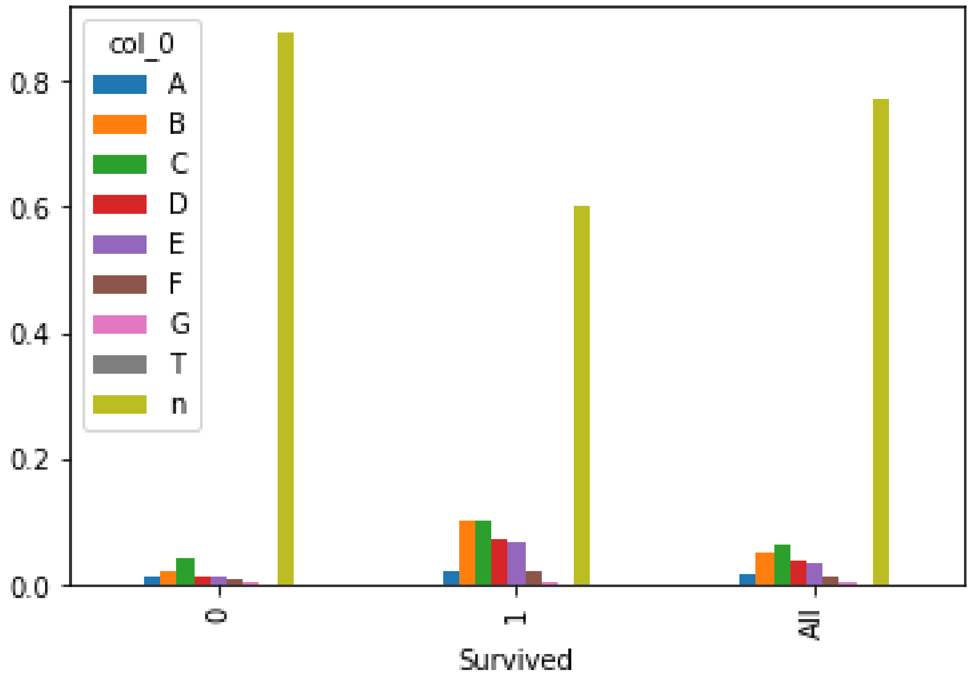
[62]:

```python
surviver_cabin = pd.crosstab(index=data4["Survived"],
                             columns=Cabin, margins = True)
display(surviver_cabin/surviver_cabin.loc["All","All"])
display(surviver_cabin/surviver_cabin.loc["All"])
surviver_cabin = surviver_cabin.div(surviver_cabin["All"],
                     axis=0)
display(surviver_cabin)
surviver_cabin.pop('All')
surviver_cabin.plot(kind = 'bar')
```

```
col_0            A         B         C         D         E         F  \
Survived
0         0.008979  0.013468  0.026936  0.008979  0.008979  0.005612
1         0.007856  0.039282  0.039282  0.028058  0.026936  0.008979
All       0.016835  0.052750  0.066218  0.037037  0.035915  0.014590

col_0            G         T         n       All
Survived
0         0.002245  0.001122  0.539843  0.616162
1         0.002245  0.000000  0.231201  0.383838
All       0.004489  0.001122  0.771044  1.000000


col_0            A         B        C         D     E         F    G    T  \
Survived
0         0.533333  0.255319  0.40678  0.242424  0.25  0.384615  0.5  1.0
1         0.466667  0.744681  0.59322  0.757576  0.75  0.615385  0.5  0.0
All       1.000000  1.000000  1.00000  1.000000  1.00  1.000000  1.0  1.0

col_0            n       All
Survived
0         0.700146  0.616162
1         0.299854  0.383838
All       1.000000  1.000000


col_0            A         B         C         D         E         F  \
Survived
0         0.014572  0.021858  0.043716  0.014572  0.014572  0.009107
1         0.020468  0.102339  0.102339  0.073099  0.070175  0.023392
All       0.016835  0.052750  0.066218  0.037037  0.035915  0.014590

col_0            G         T         n  All
```

```
Survived
0           0.003643  0.001821  0.876138  1.0
1           0.005848  0.000000  0.602339  1.0
All         0.004489  0.001122  0.771044  1.0
```

[62]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095be4a50>




### 3.2.3 embark column

[63]:
```
data5['Embarked'].unique()
```

[63]: array(['S', 'C', 'Q', nan], dtype=object)

[64]:
```
data5['Embarked'].isnull().sum()
```

[64]: 2

[65]:
```
surviver_embarked = pd.crosstab(index=data4["Survived"],
                                columns=data['Embarked'], margins = True)
display(surviver_embarked/surviver_embarked.loc["All","All"])
display(surviver_embarked/surviver_embarked.loc["All"])
surviver_embarked = surviver_embarked.div(surviver_embarked["All"],
                    axis=0)
```

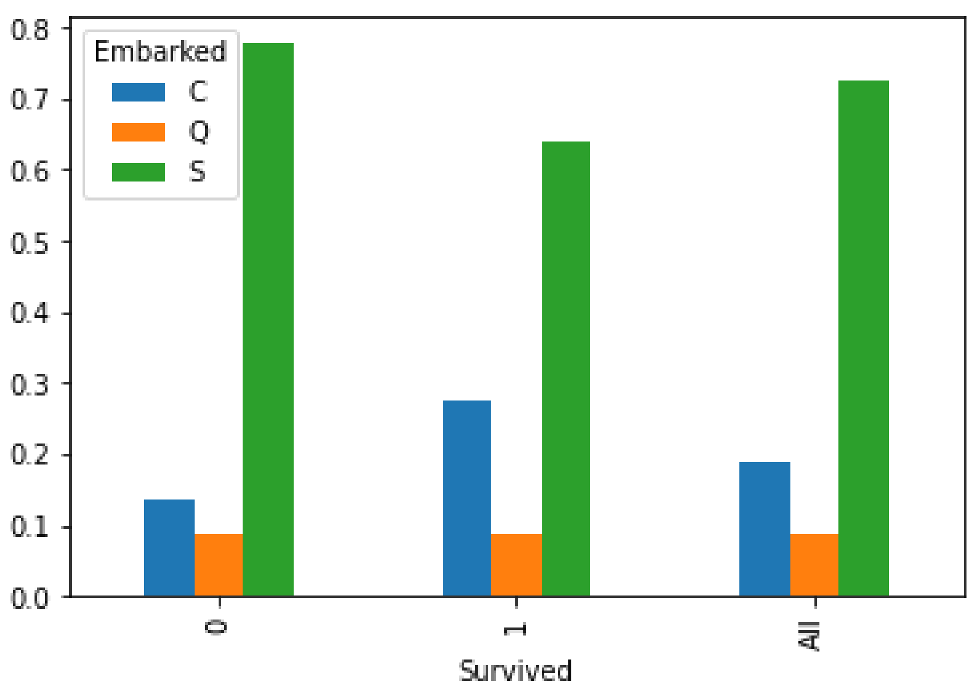
```python
display(surviver_embarked)
surviver_embarked.pop('All')
surviver_embarked.plot(kind = 'bar')
```

```
Embarked         C         Q         S       All
Survived
0         0.084364  0.052868  0.480315  0.617548
1         0.104612  0.033746  0.244094  0.382452
All       0.188976  0.086614  0.724409  1.000000
```

```
Embarked         C        Q         S       All
Survived
0         0.446429  0.61039  0.663043  0.617548
1         0.553571  0.38961  0.336957  0.382452
All       1.000000  1.00000  1.000000  1.000000
```

```
Embarked         C         Q         S  All
Survived
0         0.136612  0.085610  0.777778  1.0
1         0.273529  0.088235  0.638235  1.0
All       0.188976  0.086614  0.724409  1.0
```

[65]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095a0ae90>

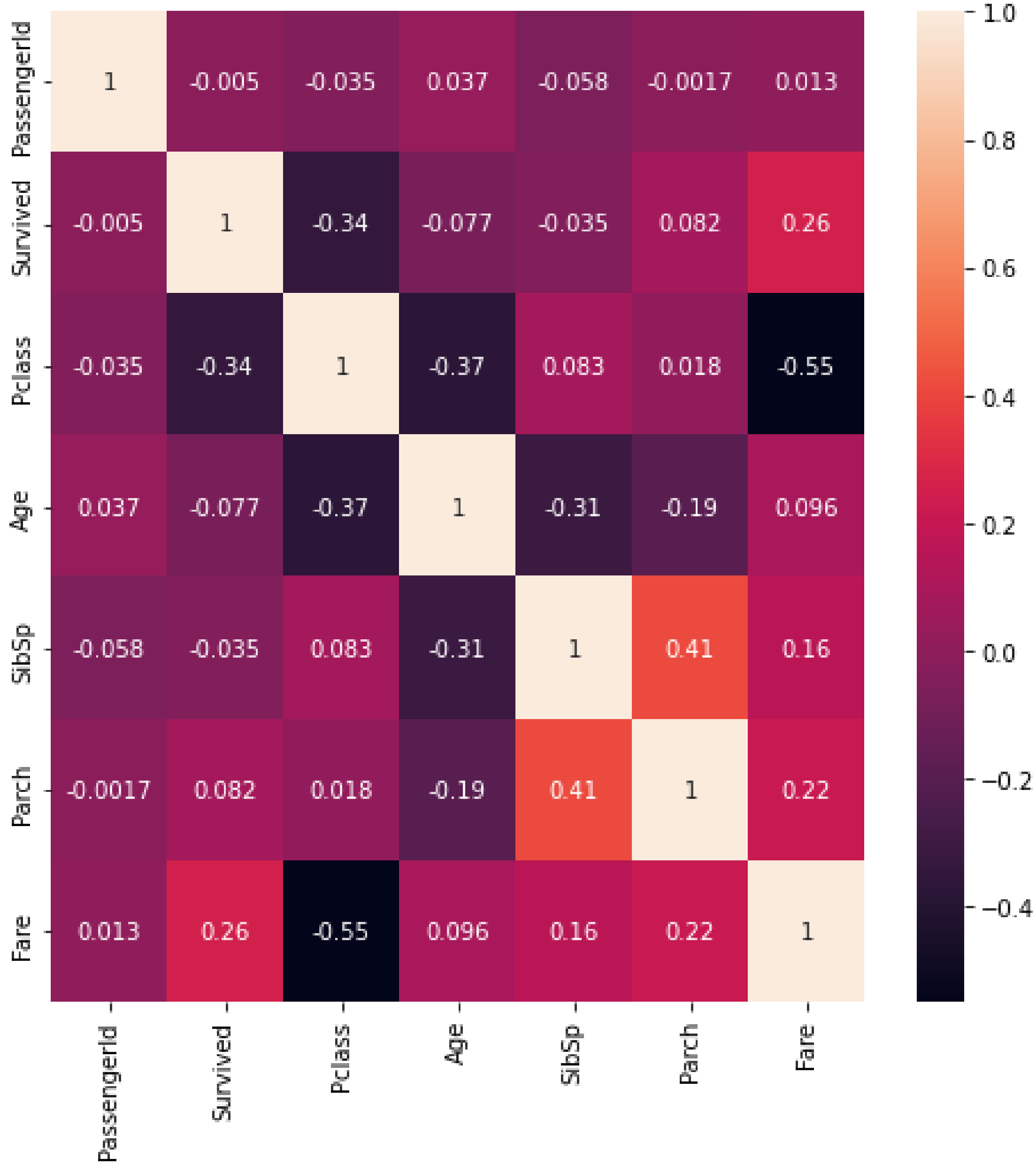


[66]:
```
# Do the one hot encoding
data6 = data5.copy()
data6 = pd.get_dummies(data6, columns=['Embarked'])
data6.head()
```

[66]:
```
   Survived   Age  SibSp  Parch     Fare  Pclass_1  Pclass_2  Pclass_3  \
0         0  22.0      1      0   7.2500         0         0         1
1         1  38.0      1      0  71.2833         1         0         0
2         1  26.0      0      0   7.9250         0         0         1
3         1  35.0      1      0  53.1000         1         0         0
4         0  35.0      0      0   8.0500         0         0         1

   with_family  Sex_female  …  Cabin_C  Cabin_D  Cabin_E  Cabin_F  Cabin_G  \
0            1           0  …        0        0        0        0        0
1            1           1  …        1        0        0        0        0
2            0           1  …        0        0        0        0        0
3            1           1  …        1        0        0        0        0
4            0           0  …        0        0        0        0        0

   Cabin_T  Cabin_n  Embarked_C  Embarked_Q  Embarked_S
0        0        1           0           0           1
1        0        0           1           0           0
2        0        1           0           0           1
3        0        0           0           0           1
4        0        1           0           0           1

[5 rows x 23 columns]
```

[67]:
```
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize=(8,8))
corr = data.corr()
sns.heatmap(corr, annot=True, ax = ax)
```

[67]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1095f1c7d0>




### 3.3 Hypothesis testing

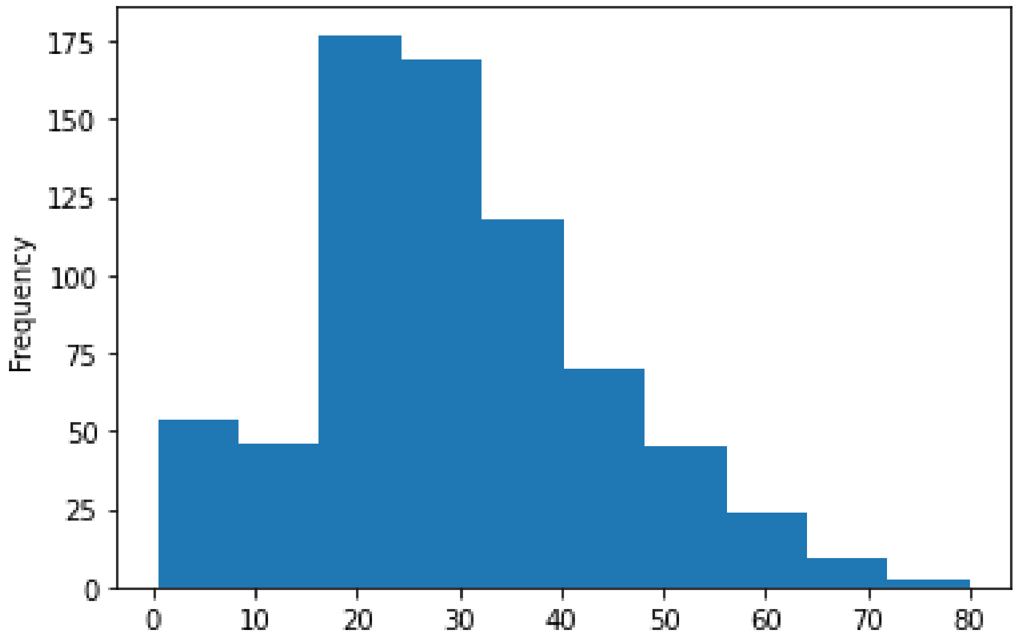
#### 3.3.1 H0: Data is normally distributed H1: Data is not normally distributed

[68]:
```
import scipy.stats as ss
```

[69]:
```
dummy = data[data['Age'].notna()].Age
```

[70]:
```
dummy.plot(kind = 'hist')
```

[70]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1093047a10>




[71]:
```
from scipy.stats import normaltest
stat, pvalue = normaltest(dummy)
print(stat, pvalue)
if pvalue<0.05:
  print("not a normal distribution")
else:
  print("Normal distribution")
```

```
18.105032952089758 0.00011709599657350757
not a normal distribution
```

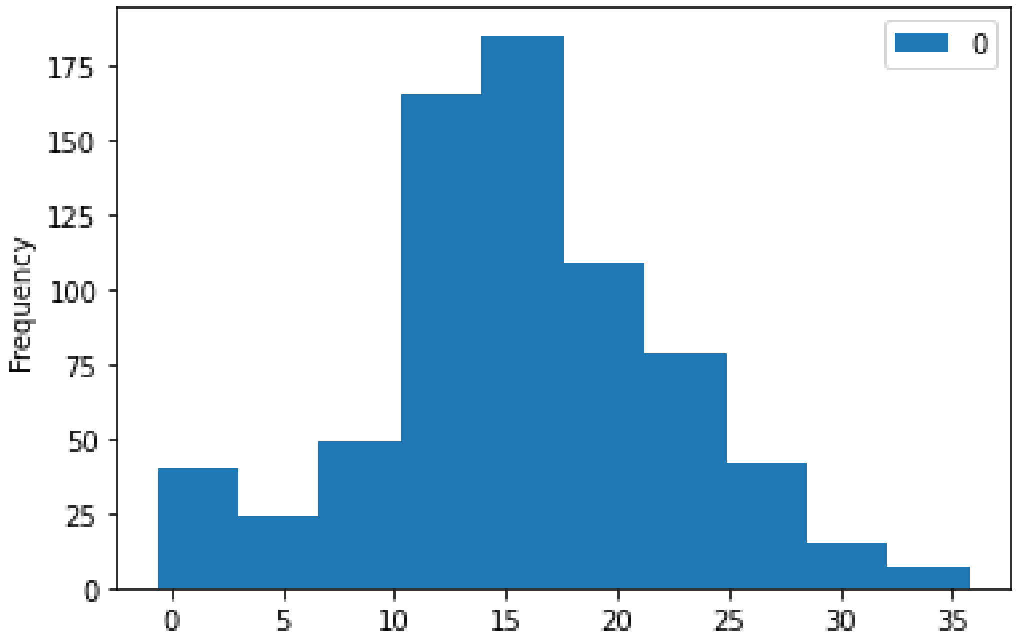
We apply boxcox to make the data normally distributed

[72]:
```
from scipy.stats import boxcox
```

[73]:
```
normal_Age = boxcox(dummy)
```

[74]:
```
pd.DataFrame(normal_Age[0]).plot(kind = 'hist')
```

[74]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1092ff2410>




[75]:
```
from scipy.stats import normaltest
stat, pvalue = normaltest(normal_Age[0])
print(stat, pvalue)
if pvalue<0.05:
  print("not a normal distribution")
else:
  print("Normal distribution")
```

```
1.2384147036970252 0.5383710072962454
Normal distribution
```

#### 3.3.2 H0: Sex doesnt matters for survival H1:Sex matters for survival

[76]:
```
surviver_sex = pd.crosstab(index=data4["Survived"],
                           columns=data['Sex'])
```

[77]:
```
surviver_sex
```

[77]:

| Sex<br>Survived | female | male |
|---|---|---|
| 0 | 81 | 468 |
| 1 | 233 | 109 |

[78]:
```
from scipy.stats import chi2_contingency
stat, p,dof, expected = chi2_contingency(surviver_sex)
```

```python
print(p)
if p <0.05:
  print('Sex matters in terms of survival')
else:
  print('Sex doesnt matter for survival')
```

```
1.1973570627755645e-58
Sex matters in terms of survival
```

### 3.3.3 H0:there is no relationship between age and fare H1: there is a relationship between age and fare

[79]:
```python
from scipy.stats import spearmanr
coef, p = spearmanr(data6[1:60]['Age'], data6[1:60]['Fare'])
print(p)
if p<0.05:
  print('there is a relationship between age and Fare')
else:
  print('there is no relationship between age and fare')
```

```
0.47931972164440195
there is no relationship between age and fare
```

# 4 Data splitting

[80]:
```python
feature_cols = list(data6.columns)
feature_cols.remove('Survived')
strat_shuf_split = StratifiedShuffleSplit(n_splits=1,
                                          test_size=0.3,
                                          random_state=42)

train_index, test_index = next(strat_shuf_split.split(data6[feature_cols],␣
 ↪data6.Survived))

# Create the dataframes
X_train = data6.loc[train_index, feature_cols]
y_train = data6.loc[train_index, 'Survived']

X_test  = data6.loc[test_index, feature_cols]
y_test  = data6.loc[test_index, 'Survived']
len(X_test), len(X_train)
```

[80]: (268, 623)

[81]:
```
X = data6[feature_cols]
y = data6['Survived']
```

## 5 Logistic Regression

Choosing best scaling method

[164]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler,␣
 ↪RobustScaler,PolynomialFeatures
scalers = {'standars': StandardScaler(),
           'minmax': MinMaxScaler(),
           'robust':RobustScaler()}
LR = LogisticRegression()
scores = {}
for scaler_label, scaler in scalers.items():
  trainingset = scaler.fit_transform(X_train)
  testset = scaler.transform(X_test)
  LR.fit(trainingset, y_train)
  predictions = LR.predict(testset)
  key = scaler_label + 'Scaling'
  scores[key] = roc_auc_score(y_test, predictions)

for key, val in scores.items():
  print(key, val)
```

```
standarsScaling 0.7901441600470727
minmaxScaling 0.7822594880847309
robustScaling 0.7931744630773758
```

robustScaling works best for logistic regression model

Hyperparameter tuning for polynomial features

[87]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold, cross_val_predict
from sklearn.pipeline import Pipeline
sf = StratifiedKFold(n_splits=3, shuffle = True, random_state=72018)
estimator = Pipeline([("Polynomial", PolynomialFeatures()),
                      ("RobustScaler",RobustScaler()),
                      ("LogisticRegression", LogisticRegression(max_iter =␣
 ↪10000000))])
params = {"Polynomial__degree":np.arange(1,5,1),
          "LogisticRegression__solver":["liblinear"]}
grid = GridSearchCV(estimator, params, cv =sf, scoring = 'accuracy' )
grid.fit(X, y)
print(grid.best_params_, grid.best_score_)
```

```
{'LogisticRegression__solver': 'liblinear', 'Polynomial__degree': 1}
0.8058361391694725
```

hyperparameter tuning of logistic regression

[88]:
```
params = {"LogisticRegression__C": np.logspace(-4, 4, 20),
          "LogisticRegression__penalty":['l1','l2'],
          "LogisticRegression__solver": ["liblinear"]}
estimator = Pipeline([("RobustScaler",RobustScaler()),
                      ("LogisticRegression", LogisticRegression())])
grid = GridSearchCV(estimator, params, cv=sf, scoring = 'accuracy')
grid.fit(X, y)
print(grid.best_params_, grid.best_score_)
C = grid.best_params_['LogisticRegression__C']
penalty = grid.best_params_['LogisticRegression__penalty']
solver = grid.best_params_['LogisticRegression__solver']
lr = LogisticRegression(C = C, penalty = penalty, solver = solver)
lr.fit(X_train, y_train)
```

```
{'LogisticRegression__C': 0.615848211066026, 'LogisticRegression__penalty':
'l2', 'LogisticRegression__solver': 'liblinear'} 0.809203142536476
```

[88]:
```
LogisticRegression(C=0.615848211066026, solver='liblinear')
```

Model evaluation

[156]:
```
pred_lr = lr.predict(X_test)
metrics = pd.DataFrame()
precision_lr, recall_lr, f1score, _ = score(y_test,pred_lr,average='weighted')
# adding lr stats to metrics DataFrame
lr_stats = pd.Series({'precision':precision_lr,
                      'recall':recall_lr,
                      'accuracy':accuracy_score(y_test, pred_lr),
                      'f1score':f1_score(y_test, pred_lr,average='weighted'),
                      'auc': roc_auc_score(y_test, pred_lr,average='weighted')},
                     name='Logistic Regression')
# Report outcomes
display(lr_stats)
print(classification_report(y_test, pred_lr))
```

```
precision    0.815939
recall       0.817164
accuracy     0.817164
f1score      0.816255
auc          0.802265
Name: Logistic Regression, dtype: float64


              precision    recall  f1-score   support
```

```
           0       0.84      0.87      0.85       165
           1       0.78      0.74      0.76       103

    accuracy                           0.82       268
   macro avg       0.81      0.80      0.80       268
weighted avg       0.82      0.82      0.82       268
```

[116]:
```python
score_lr_train=np.mean(cross_val_score(tree, X_train, y_train, cv=sf,␣
 ↪scoring='accuracy'))
print("Training Accuracy is : ",score_lr_train)
score_lr_test=np.mean(cross_val_score(tree, X_test, y_test, cv=sf,␣
 ↪scoring='accuracy'))
print("Testing Accuracy is : ",score_lr_test)
```

```
Training Accuracy is :  0.7881518642388207
Testing Accuracy is :  0.7984602580108199
```

# 6 KNN classifier

Scaling Selection

[90]:
```python
from sklearn.preprocessing import StandardScaler, MinMaxScaler,␣
 ↪RobustScaler,PolynomialFeatures
scalers = {'standars': StandardScaler(),
           'minmax': MinMaxScaler(),
           'robust':RobustScaler()}
LR = KNeighborsClassifier()
scores = {}
for scaler_label, scaler in scalers.items():
  trainingset = scaler.fit_transform(X_train)
  testset = scaler.transform(X_test)
  LR.fit(trainingset, y_train)
  predictions = LR.predict(testset)
  key = scaler_label + 'Scaling'
  scores[key] = roc_auc_score(y_test, predictions)

for key, val in scores.items():
  print(key, val)
```

```
standarsScaling 0.7616357752280083
minmaxScaling 0.7537216828478965
robustScaling 0.7337157987643426
```

hyperparameter tuning for polynomial features

[91]:
```python
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold, cross_val_predict
from sklearn.pipeline import Pipeline
sf = StratifiedKFold(n_splits=3, shuffle = True, random_state=72018)
estimator = Pipeline([("Polynomial", PolynomialFeatures()),
                      ("StandardScaler",StandardScaler()),
                      ("LogisticRegression", KNeighborsClassifier())])
params = {"Polynomial__degree":np.arange(1,5,1)}
grid = GridSearchCV(estimator, params, cv =sf, scoring = 'accuracy' )
grid.fit(X, y)
print(grid.best_params_, grid.best_score_)
```

```
{'Polynomial__degree': 1} 0.7845117845117845
```

hyperparamter tuning of KNN

[94]:
```python
params = {"KNN__n_neighbors":np.arange(1,30,1)}
estimator = Pipeline([("StandardScaler",StandardScaler()),
                      ("KNN", KNeighborsClassifier())])
grid = GridSearchCV(estimator, params, cv=sf, scoring = 'accuracy')
grid.fit(X, y)
print(grid.best_params_, grid.best_score_)
C = grid.best_params_['KNN__n_neighbors']

knn = KNeighborsClassifier(n_neighbors=C)
knn.fit(X_train, y_train)
```

```
{'KNN__n_neighbors': 12} 0.7968574635241302
```

[94]:
```
KNeighborsClassifier(n_neighbors=12)
```

Model evaluation

[196]:
```python
pred_knn = knn.predict(X_test)
precision_lr, recall_lr, f1score, _ = score(y_test,pred_knn,average='weighted')
# adding lr stats to metrics DataFrame
knn_stats = pd.Series({'precision':precision_lr,
                      'recall':recall_lr,
                      'accuracy':accuracy_score(y_test, pred_knn),
                      'f1score':f1_score(y_test, pred_knn,average='weighted'),
                      'auc': roc_auc_score(y_test,␣
 ↪pred_knn,average='weighted')},
                     name='KNN')
# Report outcomes
display(knn_stats)
print(classification_report(y_test, pred_knn))
```

```
precision    0.674231
recall       0.682836
```

```
accuracy     0.682836
f1score      0.673237
auc          0.643925
Name: KNN, dtype: float64

              precision    recall  f1-score   support

           0       0.71      0.81      0.76       165
           1       0.61      0.48      0.54       103

    accuracy                           0.68       268
   macro avg       0.66      0.64      0.65       268
weighted avg       0.67      0.68      0.67       268
```

[118]:
```
score_knn_train=np.mean(cross_val_score(knn, X_train, y_train, cv=sf,␣
 ↪scoring='accuracy'))
print("Training Accuracy is : ",score_knn_train)
score_knn_test=np.mean(cross_val_score(knn, X_test, y_test, cv=sf,␣
 ↪scoring='accuracy'))
print("Testing Accuracy is : ",score_knn_test)
```

```
Training Accuracy is :  0.6950250836120402
Testing Accuracy is :  0.5969621306699958
```

# 7 SVM

Scaling Selection

[96]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler,␣
 ↪RobustScaler,PolynomialFeatures
scalers = {'standars': StandardScaler(),
           'minmax': MinMaxScaler(),
           'robust':RobustScaler()}
LR = SVC()
scores = {}
for scaler_label, scaler in scalers.items():
  trainingset = scaler.fit_transform(X_train)
  testset = scaler.transform(X_test)
  LR.fit(trainingset, y_train)
  predictions = LR.predict(testset)
  key = scaler_label + 'Scaling'
  scores[key] = roc_auc_score(y_test, predictions)

for key, val in scores.items():
  print(key, val)
```

```
standarsScaling 0.7470726684318918
minmaxScaling 0.7719035010297147
robustScaling 0.794380700205943
```

Hyperparameter tuning for polynomial features

```
[97]: from sklearn.model_selection import GridSearchCV
      from sklearn.model_selection import KFold, cross_val_predict
      from sklearn.pipeline import Pipeline
      sf = StratifiedKFold(n_splits=3, shuffle = True, random_state=72018)
      estimator = Pipeline([("Polynomial", PolynomialFeatures()),
                            ("RobustScaler",RobustScaler()),
                            ("svn", SVC())])
      params = {"Polynomial__degree":np.arange(1,5,1)}
      grid = GridSearchCV(estimator, params, cv =sf, scoring = 'accuracy' )
      grid.fit(X, y)
      print(grid.best_params_, grid.best_score_)
```

```
{'Polynomial__degree': 1} 0.8103254769921436
```

hyperparameter tuning for svm

```
[98]: estimator = Pipeline([("RobustScaler",RobustScaler()),
                            ("svn", SVC())])
      params = {"svn__C":(0.1, 0.5, 1, 2, 5, 10, 20),
                "svn__gamma":(0.001, 0.01, 0.1, 0.25, 0.5, 0.75, 1),
                "svn__kernel":('linear', 'poly', 'rbf'),
               }
      grid = GridSearchCV(estimator, params, cv =sf, scoring = 'accuracy' )
      grid.fit(X, y)
      print(grid.best_params_, grid.best_score_)

      C = grid.best_params_['svn__C']
      gamma = grid.best_params_['svn__gamma']
      kernel = grid.best_params_['svn__kernel']

      svm = SVC(C = C,gamma = gamma, kernel = kernel)
      svm.fit(X_train, y_train)
```

```
{'svn__C': 1, 'svn__gamma': 0.25, 'svn__kernel': 'rbf'} 0.8181818181818182
```

```
[98]: SVC(C=1, gamma=0.25)
```

Model evaluation

```
[155]: pred_svm = svm.predict(X_test)
       precision_lr, recall_lr, f1score, _ = score(y_test,pred_svm,average='weighted')
       svm_stats = pd.Series({'precision':precision_lr,
                              'recall':recall_lr,
```

```
                        'accuracy':accuracy_score(y_test, pred_svm),
                        'f1score':f1_score(y_test, pred_svm,average='weighted'),
                        'auc': roc_auc_score(y_test,␣
 ↪pred_svm,average='weighted')},
                       name='Support vector machine')
# Report outcomes
display(svm_stats)
print(classification_report(y_test, pred_svm))
```

```
precision    0.652488
recall       0.664179
accuracy     0.664179
f1score      0.640135
auc          0.606884
Name: Support vector machine, dtype: float64
```

```
              precision    recall  f1-score   support

           0       0.68      0.85      0.76       165
           1       0.61      0.36      0.45       103

    accuracy                           0.66       268
   macro avg       0.64      0.61      0.60       268
weighted avg       0.65      0.66      0.64       268
```

[154]:

```
score_svm_train=np.mean(cross_val_score(svm, X_train, y_train, cv=sf,␣
 ↪scoring='accuracy'))
print("Training Accuracy is : ",score_svm_train)
score_svm_test=np.mean(cross_val_score(svm, X_test, y_test, cv=sf,␣
 ↪scoring='accuracy'))
print("Testing Accuracy is : ",score_svm_test)
```

```
Training Accuracy is :  0.6709479127957388
Testing Accuracy is :  0.6156471077819393
```

[109]:

```
```

```
Testing Accuracy is :  0.6156471077819393
```

# 8 Decision tree

Scaling selection

[86]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler,␣
↪RobustScaler,PolynomialFeatures
scalers = {'standars': StandardScaler(),
           'minmax': MinMaxScaler(),
           'robust':RobustScaler()}
LR = DecisionTreeClassifier()
scores = {}
for scaler_label, scaler in scalers.items():
  trainingset = scaler.fit_transform(X_train)
  testset = scaler.transform(X_test)
  LR.fit(trainingset, y_train)
  predictions = LR.predict(testset)
  key = scaler_label + 'Scaling'
  scores[key] = roc_auc_score(y_test, predictions)

for key, val in scores.items():
  print(key, val)
```

```
standarsScaling 0.7464548396587232
minmaxScaling 0.7318917328626066
robustScaling 0.7306854957340395
```

Hyperparameter tuning for polynomial features

[105]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold, cross_val_predict
from sklearn.pipeline import Pipeline
sf = StratifiedKFold(n_splits=3, shuffle = True, random_state=72018)
estimator = Pipeline([("Polynomial", PolynomialFeatures()),
                      ("Scaler",StandardScaler()),
                      ("DT", DecisionTreeClassifier())])
params = {"Polynomial__degree":np.arange(1,5,1)}
grid = GridSearchCV(estimator, params, cv =sf, scoring = 'accuracy' )
grid.fit(X, y)
print(grid.best_params_, grid.best_score_)
```

```
{'Polynomial__degree': 2} 0.7789001122334457
```

hyperparameter tuning for decision trees

[132]:
```
params = {"dt__criterion":("gini", "entropy"),
          "dt__splitter":("best", "random"),
          "dt__max_depth":(list(range(1, 25))),
          "dt__min_samples_split":[2, 3, 4],
          "dt__min_samples_leaf":list(range(1, 20))
          }
estimator =␣
↪Pipeline([("Polynomial",PolynomialFeatures(degree=2)),("Scaler",StandardScaler()),
```

```
                      ("dt",  DecisionTreeClassifier(random_state=42))])
grid = GridSearchCV(estimator, params, scoring="accuracy",cv=sf)
grid.fit(X, y)
print(grid.best_params_, grid.best_score_)
criterion = grid.best_params_['dt__criterion']
splitter = grid.best_params_['dt__splitter']
max_depth = grid.best_params_['dt__max_depth']
min_samples_split = grid.best_params_['dt__min_samples_split']
min_samples_leaf = grid.best_params_['dt__min_samples_leaf']
```

```
{'dt__criterion': 'entropy', 'dt__max_depth': 7, 'dt__min_samples_leaf': 5,
'dt__min_samples_split': 2, 'dt__splitter': 'random'} 0.8204264870931537
```

[133]:
```
tree = DecisionTreeClassifier(criterion = criterion, splitter = splitter,␣
 ↪max_depth = max_depth, min_samples_split = min_samples_split,␣
 ↪min_samples_leaf = min_samples_leaf )
tree.fit(X_train, y_train)
```

[133]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=7, min_samples_leaf=5,
                       splitter='random')
```

[150]:
```
pred_dt = tree.predict(X_test)
precision_lr, recall_lr, f1score, _ = score(y_test,pred_dt,average='weighted')
dt_stats = pd.Series({'precision':precision_lr,
                      'recall':recall_lr,
                      'accuracy':accuracy_score(y_test, pred_dt),
                      'f1score':f1_score(y_test, pred_dt,average='weighted'),
                      'auc': roc_auc_score(y_test, pred_dt,average='weighted')},
                     name='decision Tree')
# Report outcomes
display(dt_stats)
print(classification_report(y_test, pred_dt))
```

```
precision    0.795415
recall       0.794776
accuracy     0.794776
f1score      0.788565
auc          0.762195
Name: KNN, dtype: float64

              precision    recall  f1-score   support

           0       0.79      0.90      0.84       165
           1       0.80      0.62      0.70       103

    accuracy                           0.79       268
   macro avg       0.80      0.76      0.77       268
```

```
weighted avg       0.80      0.79      0.79       268
```

[153]:

```
score_tree_train=np.mean(cross_val_score(tree, X_train, y_train, cv=sf,␣
 ↪scoring='accuracy'))
print("Training Accuracy is : ",score_tree_train)
score_tree_test=np.mean(cross_val_score(tree, X_test, y_test, cv=sf,␣
 ↪scoring='accuracy'))
print("Testing Accuracy is : ",score_tree_test)
```

```
Training Accuracy is :  0.7817106404062927
Testing Accuracy is :  0.7908477773616314
```

# 9 RandomForest

[136]:

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler,␣
 ↪RobustScaler,PolynomialFeatures
scalers = {'standars': StandardScaler(),
           'minmax': MinMaxScaler(),
           'robust':RobustScaler()}
LR = RandomForestClassifier()
scores = {}
for scaler_label, scaler in scalers.items():
  trainingset = scaler.fit_transform(X_train)
  testset = scaler.transform(X_test)
  LR.fit(trainingset, y_train)
  predictions = LR.predict(testset)
  key = scaler_label + 'Scaling'
  scores[key] = roc_auc_score(y_test, predictions)

for key, val in scores.items():
  print(key, val)
```

```
standarsScaling 0.7622241835834069
minmaxScaling 0.7701088555457488
robustScaling 0.7670785525154457
```

[142]:

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier


estimator =␣
 ↪Pipeline([("Polynomial",PolynomialFeatures(degree=2)),("Scaler",MinMaxScaler()),
                      ("rf",  RandomForestClassifier(max_features='auto',␣
 ↪oob_score=True, random_state=1, n_jobs=-1))])
params = {"rf__criterion":("gini", "entropy"),
```

```
            "rf__max_depth":(list(range(1, 25))),
            "rf__min_samples_split":[2, 3, 4,10,12,16],
            "rf__min_samples_leaf":list(range(1, 20)),
            "rf__n_estimators": [50, 100, 400, 700, 1000]
            }


grid = GridSearchCV(estimator, params, scoring='accuracy', cv=sf, n_jobs=-1)

grid = grid.fit(X, y)

print( grid.best_score_, grid.best_params_,)
```

```
0.838383838384 {'min_samples_split': 10, 'n_estimators': 700, 'criterion':
'gini', 'min_samples_leaf': 1}
```

[144]:
```
rfc = RandomForestClassifier(min_samples_split = 10, n_estimators = 700,␣
 ↪criterion = 'gini',min_samples_leaf= 1)
rfc.fit(X_train, y_train)
```

[144]:
```
RandomForestClassifier(min_samples_split=10, n_estimators=700)
```

[151]:
```
pred_rfc = rfc.predict(X_test)
precision_lr, recall_lr, f1score, _ = score(y_test,pred_rfc,average='weighted')

rfc_stats = pd.Series({'precision':precision_lr,
                       'recall':recall_lr,
                       'accuracy':accuracy_score(y_test, pred_rfc),
                       'f1score':f1_score(y_test, pred_rfc,average='weighted'),
                       'auc': roc_auc_score(y_test,␣
 ↪pred_rfc,average='weighted')},
                      name='Random forest')
# Report outcomes
display(rfc_stats)
print(classification_report(y_test, pred_rfc))
```

```
precision    0.809013
recall       0.809701
accuracy     0.809701
f1score      0.805805
auc          0.783436
Name: Random forest, dtype: float64
```

```
              precision    recall  f1-score   support

           0       0.81      0.90      0.85       165
           1       0.80      0.67      0.73       103
```

```
    accuracy                           0.81       268
   macro avg       0.81      0.78      0.79       268
weighted avg       0.81      0.81      0.81       268
```

[152]:
```
score_rfc_train=np.mean(cross_val_score(rfc, X_train, y_train, cv=sf,␣
 ↪scoring='accuracy'))
print("Training Accuracy is : ",score_rfc_train)
score_rfc_test=np.mean(cross_val_score(rfc, X_test, y_test, cv=sf,␣
 ↪scoring='accuracy'))
print("Testing Accuracy is : ",score_rfc_test)
```

```
Training Accuracy is :  0.8009801189149015
Testing Accuracy is :  0.813358302122347
```

# 10 Model selection

[187]:
```
training = [score_lr_train, score_knn_train, score_svm_train, score_tree_train,␣
 ↪score_rfc_train]
testing = [score_lr_test, score_knn_test, score_svm_test, score_tree_test,␣
 ↪score_rfc_test]
```

[192]:
```
accuracy = pd.DataFrame([training, testing], columns = ['LogisticRegression','K␣
 ↪neighbours','Support vector machine','Decision tree', 'Random forest␣
 ↪classifier'], index =  ['Training','Testing'])
```

[163]:
```
metrics = pd.DataFrame()
metrics.append([lr_stats.T, knn_stats.T,svm_stats.T,dt_stats.T, rfc_stats.T])
```

[163]:

| | precision | recall | accuracy | f1score | auc |
|---|---|---|---|---|---|
| Logistic Regression | 0.815939 | 0.817164 | 0.817164 | 0.816255 | 0.802265 |
| KNN | 0.674231 | 0.682836 | 0.682836 | 0.673237 | 0.643925 |
| Support vector machine | 0.652488 | 0.664179 | 0.664179 | 0.640135 | 0.606884 |
| KNN | 0.795415 | 0.794776 | 0.794776 | 0.788565 | 0.762195 |
| Random forest | 0.809013 | 0.809701 | 0.809701 | 0.805805 | 0.783436 |

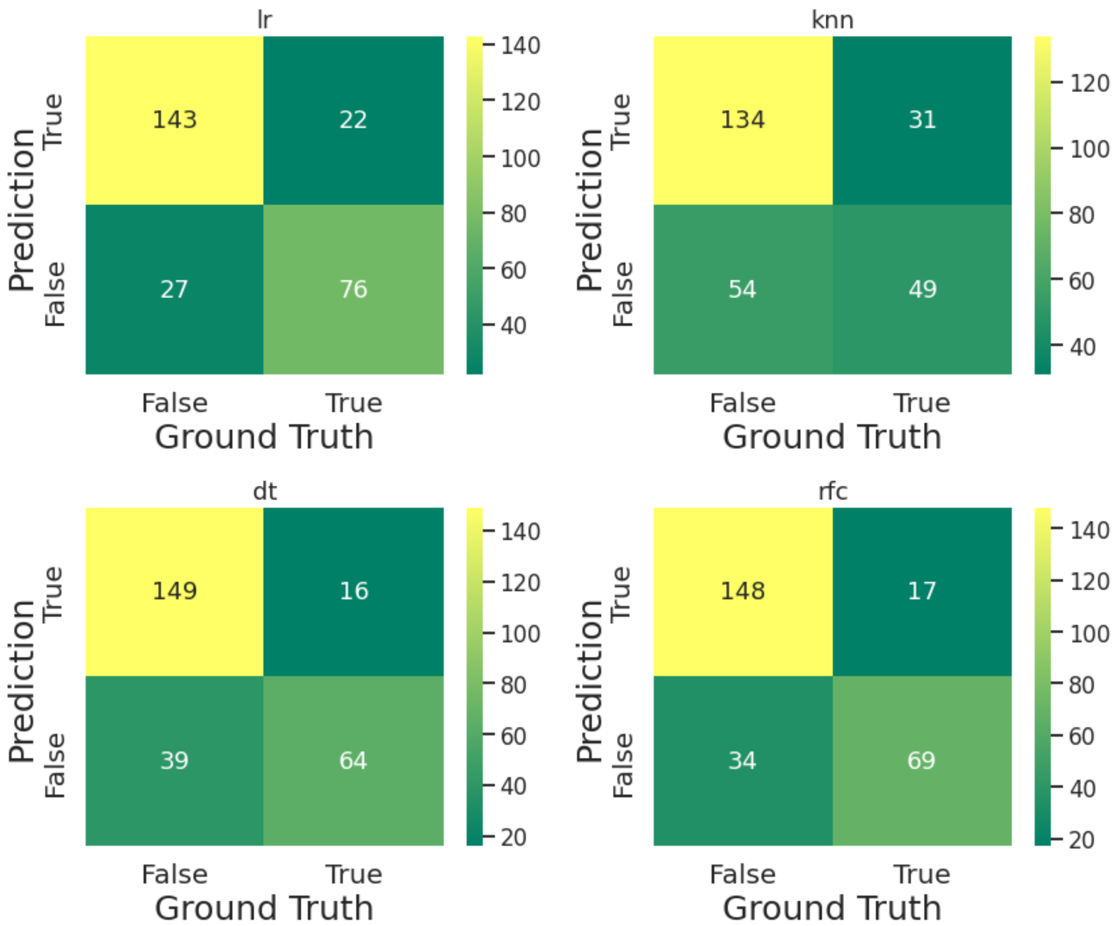
[194]:
```
accuracy.T
```

[194]:

| | Training | Testing |
|---|---|---|
| LogisticRegression | 0.788152 | 0.798460 |
| K neighbours | 0.695025 | 0.596962 |
| Support vector machine | 0.670948 | 0.615647 |
| Decision tree | 0.781711 | 0.790845 |
| Random forest classifier | 0.800980 | 0.813358 |

[198]:

```
fig, axList = plt.subplots(nrows=2, ncols=2)
axList = axList.flatten()
fig.set_size_inches(12, 10)


models = coeff_labels = ['lr', 'knn', 'dt', 'rfc']
cm = [confusion_matrix(y_test, pred_lr),
      confusion_matrix(y_test, pred_knn),
      confusion_matrix(y_test, pred_dt),
      confusion_matrix(y_test, pred_rfc)]
labels = ['False', 'True']

for ax,model, idx in zip(axList, models, range(0,4)):
    sns.heatmap(cm[idx], ax=ax, annot=True, fmt='d', cmap='summer');
    ax.set(title=model);
    ax.set_xticklabels(labels, fontsize=20);
    ax.set_yticklabels(labels[::-1], fontsize=20);
    ax.set_ylabel('Prediction', fontsize=25);
    ax.set_xlabel('Ground Truth', fontsize=25)

plt.tight_layout()
```




Thus gonna select Logistic regression as my final model

## 11 Conclusion

In these projects we were able to create 5 different models to classify if a person survived or not The final model had the following stats

[200]:
```
lr_stats
```

[200]:
```
precision    0.815939
recall       0.817164
accuracy     0.817164
f1score      0.816255
auc          0.802265
Name: Logistic Regression, dtype: float64
```

## 12 Next steps

We can look into feature importance and discard some of the feature to improve the prediction We can also apply boosting , bagging and Stackin to improve the performance