Projektin tavoitteena on luoda mahdollisimman tarkka malli jolla ennustaa Titanicin onnettomuuden selviytyjät.

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Importoinnit

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn.metrics import accuracy_score
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import SGDClassifier
```

Datan tuonti

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

Datan katselua

In [3]:
```
data.describe(include = "all")
```

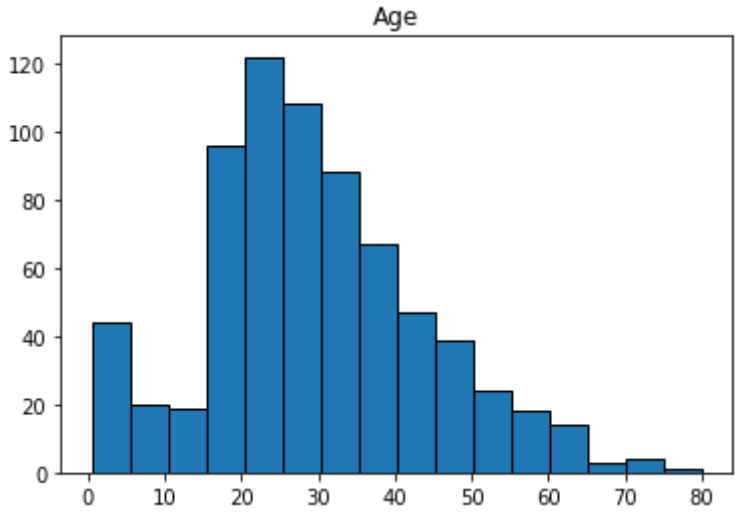
Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ti
count	891.000000	891.000000	891.000000	891	891	714.000000	891.000000	891.000000	
unique	NaN	NaN	NaN	891	2	NaN	NaN	NaN	
top	NaN	NaN	NaN	Mitchell, Mr. Henry Michael	male	NaN	NaN	NaN	34
freq	NaN	NaN	NaN	1	577	NaN	NaN	NaN	
mean	446.000000	0.383838	2.308642	NaN	NaN	29.699118	0.523008	0.381594	
std	257.353842	0.486592	0.836071	NaN	NaN	14.526497	1.102743	0.806057	
min	1.000000	0.000000	1.000000	NaN	NaN	0.420000	0.000000	0.000000	

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ti
25%	223.500000	0.000000	2.000000	NaN	NaN	20.125000	0.000000	0.000000	
50%	446.000000	0.000000	3.000000	NaN	NaN	28.000000	0.000000	0.000000	
75%	668.500000	1.000000	3.000000	NaN	NaN	38.000000	1.000000	0.000000	
max	891.000000	1.000000	3.000000	NaN	NaN	80.000000	8.000000	6.000000	

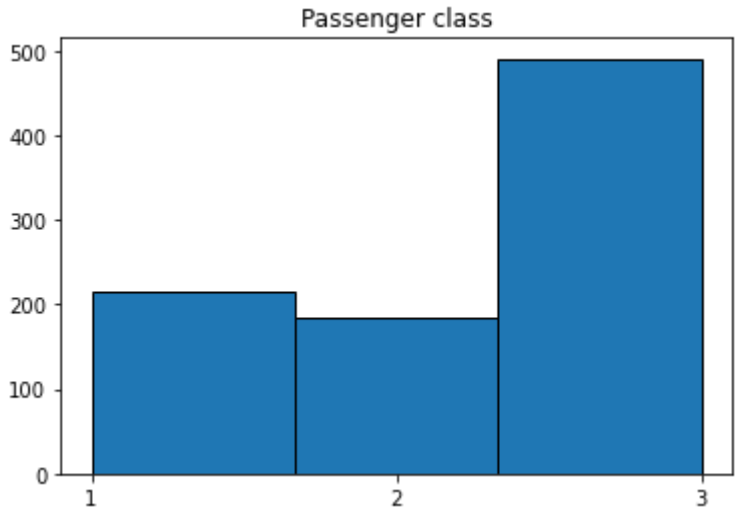
Histogrammi matkustajien iästä

In [4]:
```
plt.hist(data['Age'], 16, edgecolor='k')
plt.title('Age')
plt.show()
```



Histogrammi kunkin luokan matkustajamäärästä

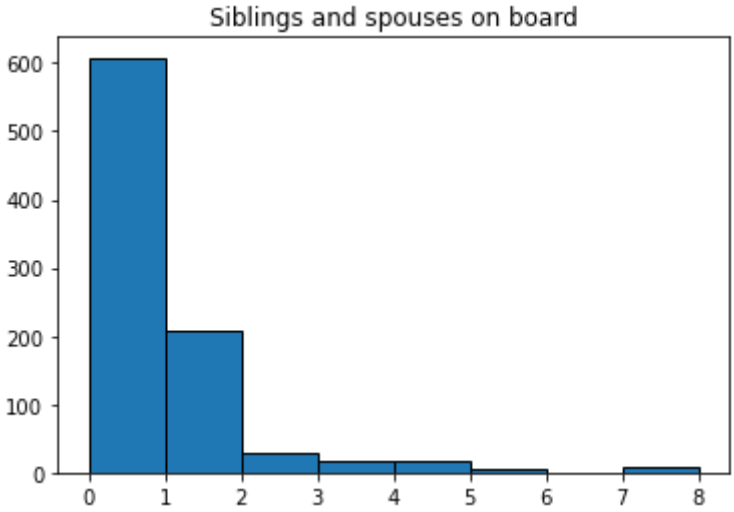
In [5]:
```
plt.hist(data['Pclass'], 3, edgecolor='k')
plt.xticks([1,2,3])
plt.title('Passenger class')
plt.show()
```



Histogrammi puolisojen ja sisarusten määrästä

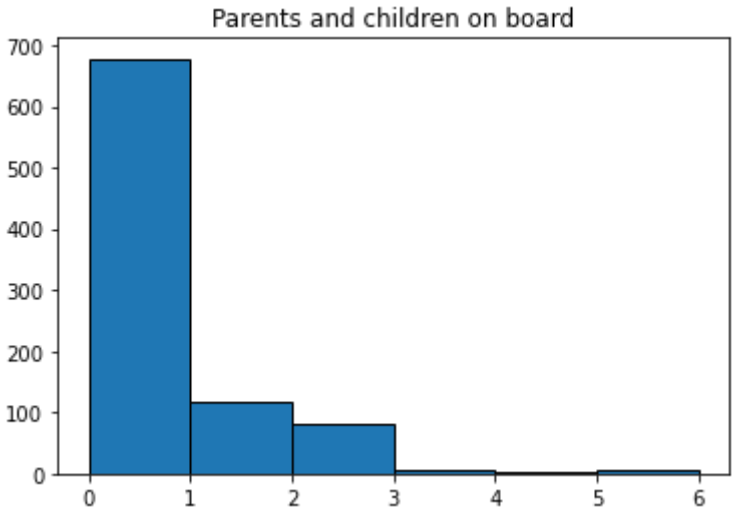
In [6]:
```
plt.hist(data['SibSp'], 8, edgecolor='k')
plt.title('Siblings and spouses on board')
```

```
plt.show()
```



Histogrammi lapsien ja aikuisten määrästä

In [7]:
```
plt.hist(data['Parch'], 6, edgecolor='k')
plt.title('Parents and children on board')
plt.show()
```



In [8]:
```
pd.pivot_table(data, index = 'Survived', values = ['Age','Parch','Fare','Pclass'])
```

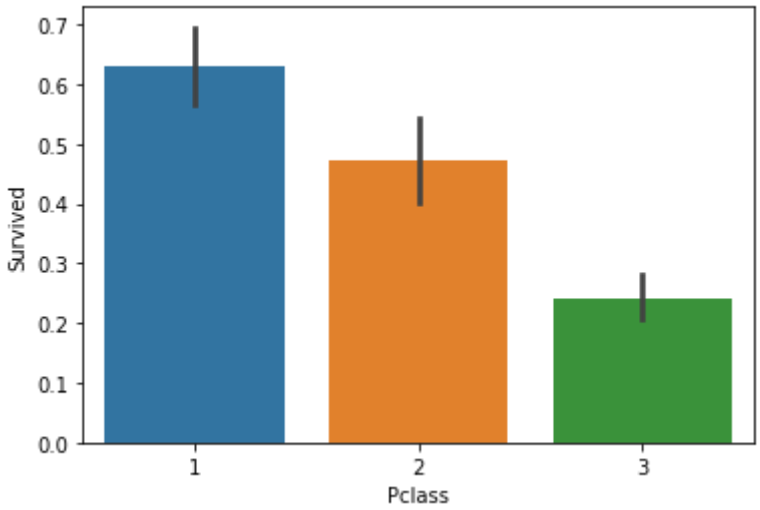
Out[8]:

Survived	Age	Fare	Parch	Pclass
0	30.626179	22.117887	0.329690	2.531876
1	28.343690	48.395408	0.464912	1.950292

Verrataan selviytymistä luokkien välillä

In [9]:
```
sns.barplot(x='Pclass', y='Survived', data=data)
```

Out[9]:
```
<AxesSubplot:xlabel='Pclass', ylabel='Survived'>
```

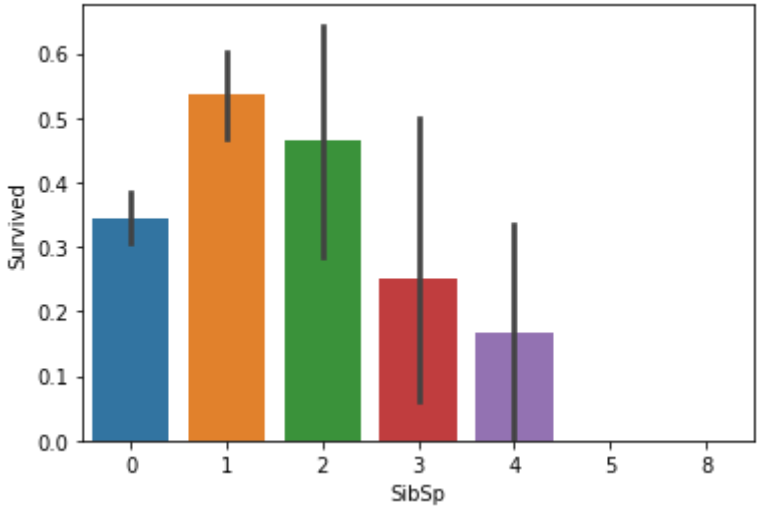


- Kuvasta selviää että paremmalla luokalla oli huomattava etu selviytymisessä

Verrataan selviytymistä sisarusten/puolisoiden määrässä

In [10]:
```
sns.barplot(x='SibSp', y='Survived', data=data)
```

Out[10]:
```
<AxesSubplot:xlabel='SibSp', ylabel='Survived'>
```

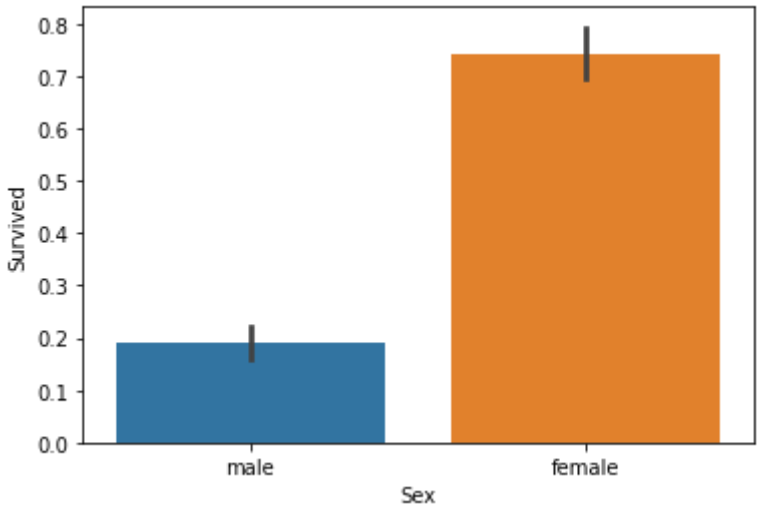


- Mitä enemmän matkustajalla oli mukana sisaruksia, sitä huonommaksi selviytymisprosentti meni. Kuitenkin jos ei ollut yhtään sisarusta mukana, selviytyminen oli epätodennäköisempää kuin niillä kenellä oli 1-2.

Verrataan sukupuolen vaikutusta selviytymiseen

In [11]:
```
sns.barplot(x='Sex', y='Survived', data=data)
```

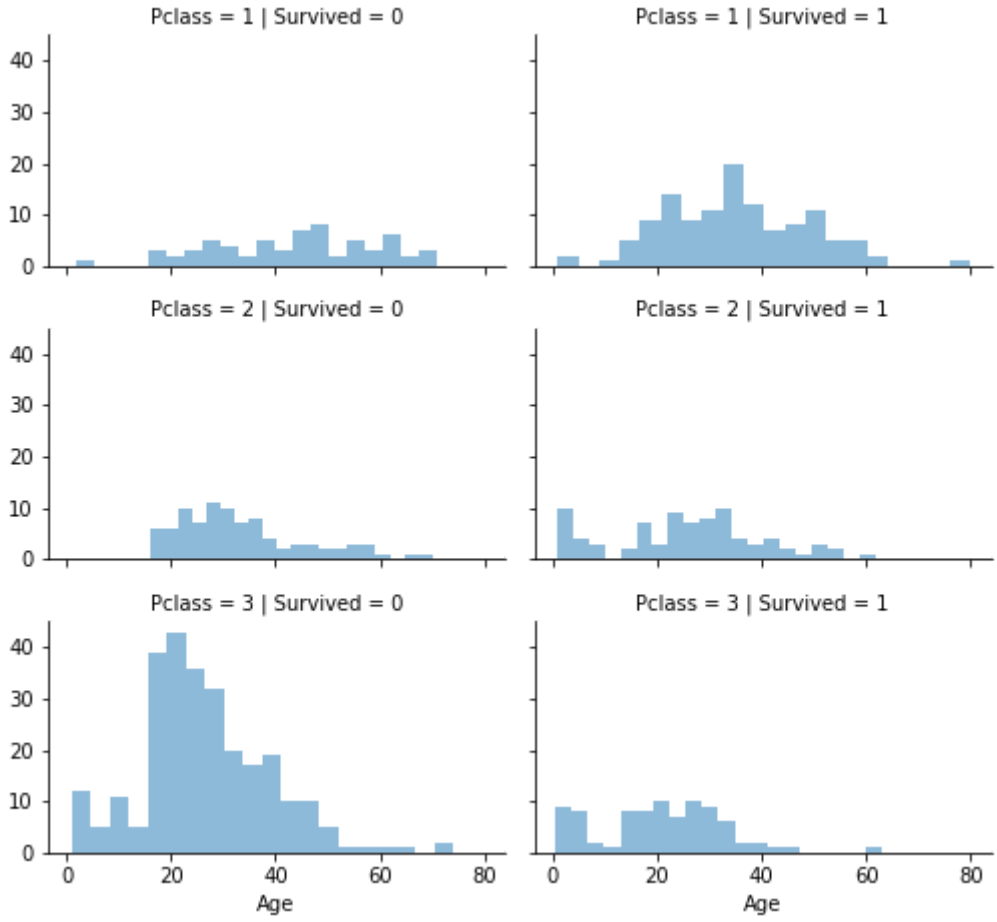
Out[11]:
```
<AxesSubplot:xlabel='Sex', ylabel='Survived'>
```



- Kuvasta selviää, että naisilla oli paljon korkeampi selviytymistodennäköisyys kuin miehillä.

Alhaalla vertailussa hyttiluokat, ikä ja selviytyminen.

In [12]:
```
grid = sns.FacetGrid(data, col='Survived', row='Pclass', height=2.2, aspect=1.6)
grid.map(plt.hist, 'Age', alpha=.5, bins=20)
grid.add_legend();
```



In [13]:
```
data.head(5)
```

Out[13]:

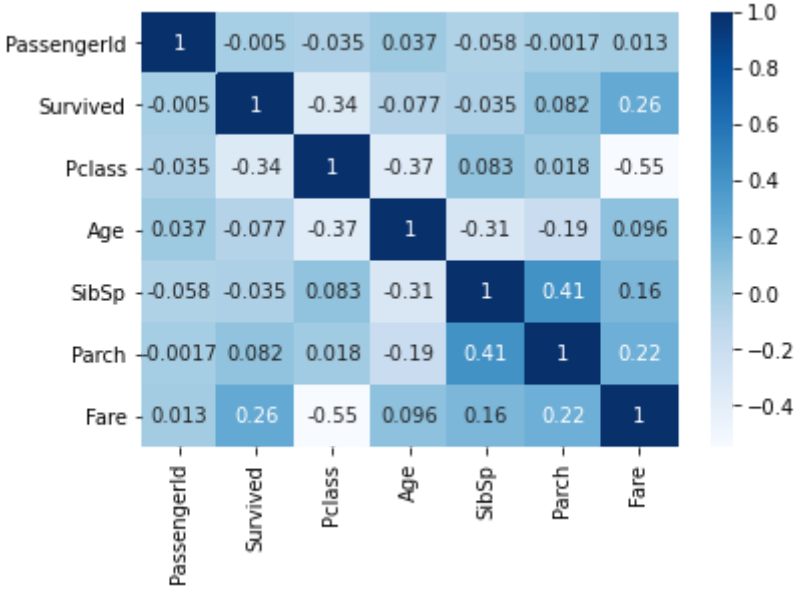
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN

Korrelaatio selviytymisen ja muiden kolumnien välillä

In [14]:
```
def titanic_corr(data):
    correlation = data.corr()
    sns.heatmap(correlation, annot=True, cbar=True, cmap="Blues")

titanic_corr(data)
```



Data siivousta

Testi datan katselua

In [15]:
```
test.describe(include="all")
```

Out[15]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
count	418.000000	418.000000	418	418	332.000000	418.000000	418.000000	418	417.0
unique	NaN	NaN	418	2	NaN	NaN	NaN	363	
top	NaN	NaN	Cassebeer, Mrs. Henry Arthur Jr (Eleanor Genev...	male	NaN	NaN	NaN	PC 17608	
freq	NaN	NaN	1	266	NaN	NaN	NaN	5	
mean	1100.500000	2.265550	NaN	NaN	30.272590	0.447368	0.392344	NaN	35.6
std	120.810458	0.841838	NaN	NaN	14.181209	0.896760	0.981429	NaN	55.9
min	892.000000	1.000000	NaN	NaN	0.170000	0.000000	0.000000	NaN	0.0
25%	996.250000	1.000000	NaN	NaN	21.000000	0.000000	0.000000	NaN	7.8
50%	1100.500000	3.000000	NaN	NaN	27.000000	0.000000	0.000000	NaN	14.4
75%	1204.750000	3.000000	NaN	NaN	39.000000	1.000000	0.000000	NaN	31.5
max	1309.000000	3.000000	NaN	NaN	76.000000	8.000000	9.000000	NaN	512.3

Embarked rivi, täytetään tyhjät rivit yleisimmällä arvolla

In [16]:
```
data['Embarked'].value_counts()
```

Out[16]:
```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [17]:
```
data = data.fillna({"Embarked": "S"})
```

In [18]:
```
combine = [data, test]

for dataset in combine:
    dataset['Title'] = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand=False)

pd.crosstab(data['Title'], data['Sex'])
```

Out[18]:

Sex	female	male
Title		
Capt	0	1
Col	0	2
Countess	1	0
Don	0	1
Dr	1	6
Jonkheer	0	1
Lady	1	0
Major	0	2

Sex	female	male
Title		
Master	0	40
Miss	182	0
Mlle	2	0
Mme	1	0
Mr	0	517
Mrs	125	0
Ms	1	0
Rev	0	6
Sir	0	1

Groupataan tittelit paremmin, jotta ne on helpompi muuttaa numeerisiksi

In [19]:
```
for dataset in combine:
    dataset['Title'] = dataset['Title'].replace(['Lady', 'Capt', 'Col',
    'Don', 'Dr', 'Major', 'Rev', 'Jonkheer', 'Dona'], 'Rare')

    dataset['Title'] = dataset['Title'].replace(['Countess', 'Lady', 'Sir'], 'Royal'
    dataset['Title'] = dataset['Title'].replace('Mlle', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Mme', 'Mrs')

data[['Title', 'Survived']].groupby(['Title'], as_index=False).mean()
```

Out[19]:

	Title	Survived
0	Master	0.575000
1	Miss	0.702703
2	Mr	0.156673
3	Mrs	0.793651
4	Rare	0.285714
5	Royal	1.000000

Muutetaan tittelit numeerisiksi

In [20]:
```
title = {"Mr": 1, "Miss": 2, "Mrs": 3, "Master": 4, "Royal": 5, "Rare": 6}
for dataset in combine:
    dataset['Title'] = dataset['Title'].map(title)
    dataset['Title'] = dataset['Title'].fillna(0)

data.head()
```

Out[20]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN

Age rivi, täytetään tyhjät arvot mean arvolla

In [21]:
```
data["Age"] = data["Age"].replace(np.NaN, data["Age"].mean())
```

Dropataan turhat columnit / rivit

In [22]:
```
# dropataan Name
data = data.drop(['Name'], axis = 1)
test = test.drop(['Name'], axis = 1)

# dropataan Fare
data = data.drop(['Fare'], axis = 1)
test = test.drop(['Fare'], axis = 1)

# dropataan Ticket
data = data.drop(['Ticket'], axis = 1)
test = test.drop(['Ticket'], axis = 1)

# dropataan Cabin
data = data.drop(['Cabin'], axis = 1)
test = test.drop(['Cabin'], axis = 1)
```

Sex columni, muutetaan arvot numeerisiksi

In [23]:
```
sex_mapping = {"male": 0, "female": 1}
data['Sex'] = data['Sex'].map(sex_mapping)
test['Sex'] = test['Sex'].map(sex_mapping)

data.head()
```

Out[23]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Embarked	Title
0	1	0	3	0	22.0	1	0	S	1
1	2	1	1	1	38.0	1	0	C	3
2	3	1	3	1	26.0	0	0	S	2

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Embarked	Title
3	4	1	1	1	35.0	1	0	S	3
4	5	0	3	0	35.0	0	0	S	1

Embarked columni, muutetaan arvot numeerisiksi

In [24]:
```
embarked_mapping = {"S": 1, "C": 2, "Q": 3}
data['Embarked'] = data['Embarked'].map(embarked_mapping)
test['Embarked'] = test['Embarked'].map(embarked_mapping)
```

Testataan miltä data näyttää

In [25]:
```
data.head()
```

Out[25]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Embarked	Title
0	1	0	3	0	22.0	1	0	1	1
1	2	1	1	1	38.0	1	0	2	3
2	3	1	3	1	26.0	0	0	1	2
3	4	1	1	1	35.0	1	0	1	3
4	5	0	3	0	35.0	0	0	1	1

In [26]:
```
test.head()
```

Out[26]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Embarked	Title
0	892	3	0	34.5	0	0	3	1
1	893	3	1	47.0	1	0	1	3
2	894	2	0	62.0	0	0	3	1
3	895	3	0	27.0	0	0	1	1
4	896	3	1	22.0	1	1	1	3

Modelin testausta

In [27]:
```
from sklearn.model_selection import train_test_split

predictors = data.drop(['Survived', 'PassengerId'], axis=1)
target = data["Survived"]
x_train, x_val, y_train, y_val = train_test_split(predictors, target, test_size = 0.
                                                  random_state = 0)
```

Gaussian Naive Bayes

In [28]:
```
gaussian = GaussianNB()
cv = cross_val_score(gaussian,x_train,y_train,cv=7)
gaussian.fit(x_train, y_train)
y_pred = gaussian.predict(x_val)
acc_gaussian = round(accuracy_score(y_pred, y_val) * 100, 2)
```

```
print(cv)
print(acc_gaussian)
```

```
[0.8        0.7979798  0.83838384 0.81818182 0.77777778 0.84848485
 0.86868687]
78.17
```

Logistic Regression

In [29]:
```
logreg = LogisticRegression(max_iter=2000)
cv = cross_val_score(logreg,x_train,y_train,cv=7)
logreg.fit(x_train, y_train)
y_pred = logreg.predict(x_val)
acc_logreg = round(accuracy_score(y_pred, y_val) * 100, 2)
print(cv)
print(acc_logreg)
```

```
[0.77       0.81818182 0.7979798  0.80808081 0.7979798  0.84848485
 0.85858586]
79.7
```

Support Vector Machines

In [30]:
```
svc = SVC()
cv = cross_val_score(svc,x_train,y_train,cv=7)
svc.fit(x_train, y_train)
y_pred = svc.predict(x_val)
acc_svc = round(accuracy_score(y_pred, y_val) * 100, 2)
print(cv)
print(acc_svc)
```

```
[0.65       0.5959596  0.63636364 0.65656566 0.5959596  0.66666667
 0.64646465]
66.5
```

Decision Tree

In [31]:
```
decisiontree = DecisionTreeClassifier()
cv = cross_val_score(decisiontree,x_train,y_train,cv=7)
decisiontree.fit(x_train, y_train)
y_pred = decisiontree.predict(x_val)
acc_decisiontree = round(accuracy_score(y_pred, y_val) * 100, 2)
print(cv)
print(acc_decisiontree)
```

```
[0.68       0.80808081 0.86868687 0.80808081 0.78787879 0.7979798
 0.83838384]
77.66
```

Random Forest

In [32]:
```
randomforest = RandomForestClassifier()
cv = cross_val_score(randomforest,x_train,y_train,cv=7)
randomforest.fit(x_train, y_train)
y_pred = randomforest.predict(x_val)
acc_randomforest = round(accuracy_score(y_pred, y_val) * 100, 2)
print(cv)
print(acc_randomforest)
```

```
[0.75       0.77777778 0.83838384 0.77777778 0.80808081 0.81818182
 0.78787879]
79.19
```

KNN

In [33]:
```
knn = KNeighborsClassifier()
cv = cross_val_score(knn,x_train,y_train,cv=7)
knn.fit(x_train, y_train)
y_pred = knn.predict(x_val)
acc_knn = round(accuracy_score(y_pred, y_val) * 100, 2)
print(cv)
print(acc_knn)
```

```
[0.73       0.76767677 0.83838384 0.80808081 0.78787879 0.80808081
 0.81818182]
78.17
```

Stochastic Gradient Descent

In [34]:
```
sgd = SGDClassifier()
cv = cross_val_score(sgd,x_train,y_train,cv=7)
sgd.fit(x_train, y_train)
y_pred = sgd.predict(x_val)
acc_sgd = round(accuracy_score(y_pred, y_val) * 100, 2)
print(cv)
print(acc_sgd)
```

```
[0.65       0.4040404  0.73737374 0.76767677 0.7979798  0.74747475
 0.78787879]
76.14
```

Gradient Boosting Classifier

In [35]:
```
gbk = GradientBoostingClassifier()
cv = cross_val_score(gbk,x_train,y_train,cv=7)
gbk.fit(x_train, y_train)
y_pred = gbk.predict(x_val)
acc_gbk = round(accuracy_score(y_pred, y_val) * 100, 2)
print(cv)
print(acc_gbk)
```

```
[0.79       0.80808081 0.87878788 0.81818182 0.77777778 0.84848485
 0.84848485]
82.23
```

Verrataan modeleita taulukossa

In [36]:
```
models = pd.DataFrame({
    'Model': ['Support Vector Machines', 'KNN', 'Logistic Regression',
              'Random Forest', 'Naive Bayes',
              'Decision Tree', 'Stochastic Gradient Descent', 'Gradient Boosting Cla
    'Score': [acc_svc, acc_knn, acc_logreg,
              acc_randomforest, acc_gaussian, acc_decisiontree,
              acc_sgd, acc_gbk]})
models.sort_values(by='Score', ascending=False)
```

Out[36]:

	Model	Score
7	Gradient Boosting Classifier	82.23
2	Logistic Regression	79.70
3	Random Forest	79.19
1	KNN	78.17
4	Naive Bayes	78.17
5	Decision Tree	77.66

	Model	Score
6	Stochastic Gradient Descent	76.14
0	Support Vector Machines	66.50

Accuracy / Confusion matrix jne.

s_train = data[["Pclass", "Sex", "Age", "SibSp", "Parch", "Fare"]] d_train = data[['Survived']]

sgd_clf = SGDClassifier(max_iter=50, random_state=42) sgd_clf.fit(s_train, d_train.values.ravel()) cross_clf_score = cross_val_score(sgd_clf, x_train, y_train, cv = 3, scoring = 'accuracy') cross_clf_score.mean()

y_train_clf_pred = cross_val_predict(sgd_clf, s_train, d_train.values.ravel(), cv=3) confusion_matrix(y_train, y_train_clf_pred)

print(precision_score(y_train, y_train_clf_pred))

print(recall_score(y_train, y_train_clf_pred))

print(f1_score(y_train, y_train_clf_pred))

Tehdään ennustus

Valitaan Gradient Boosting Classifier, koska se antoi parhaimmen tuloksen modelien testauksessa

In [37]:
```
test_ids = test["PassengerId"]
y = data["Survived"]
X = data.drop("Survived", axis=1)

X_train, X_val, y_train, y_val = train_test_split(X, y)
```

In [38]:
```
clf = GradientBoostingClassifier(random_state=0, n_estimators=100).fit(X_train, y_tr
```

In [39]:
```
predictions = clf.predict(X_val)
from sklearn.metrics import accuracy_score
accuracy_score(y_val, predictions)
```

Out[39]:
```
0.7937219730941704
```

Täytetään test data Age tyhjät arvot mediaanilla

In [40]:
```
test.Age = test.Age.fillna(test.Age.median())
```

Tarkistetaan, ettei ole enää nolla-arvoja

In [41]:
```
test.isnull().sum()
```

Out[41]:
```
PassengerId    0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Embarked       0
```

```
Title          0
dtype: int64
```

In [42]:
```
submission_preds = clf.predict(test)
```

Tehdään datasta csv tiedosta, joka submitataan Kaggleen

In [43]:
```
df = pd.DataFrame({"PassengerId": test_ids.values,
                   "Survived": submission_preds,
                  })
```

In [44]:
```
df.to_csv("submission.csv", index=False)
```

Arviointi

- Pääsimme tavoitteeseemme, joka oli saada mahdollisimman tarkka malli, jolla ennustaa Titanicin selviytyjiä. Sovimme projektin aikana, ettemme fine-tunaa malleja, koska emme ymmärtäneet, miten tämä tulisi tehdä. Tästä huolimatta pääsimme projektin aikana testaamaan eri malleja sekä kokeilemaan millaisia tuloksia niillä sai. Tulosten perusteella valitsimme parhaiten suoriutuneen mallin, joka oli Gradient Boosting Classifier.
- Lähetettyämme submissionin Kagglelle tulokseksi tuli 0.77033. Olemme tyytyväisiä tähän tulokseen, joka on hyvä, mutta parantamisen varaa kuitenkin on huomattavasti.