In [180]:

```
# Import library
import pandas as pd
import numpy as np

# Module for visualization
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

# To avoid unnecessary warning messages.
import warnings
warnings.filterwarnings('ignore')


# Built-in datasets
from sklearn.datasets import load_breast_cancer

# Create standardized data
from sklearn.preprocessing import StandardScaler

# Module for logistic regression model
from sklearn.linear_model import LogisticRegression
```

In [181]:

```
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier

sns.set(style='white', context='notebook', palette='deep')
```

Kaggle's Titanic Passenger Mortality Prediction Modeling

The Kaggle Titanic competition is a competition for machine learning beginners prepared by Kaggle. It is a competition to machine learn the passenger information and "Survived" answers in the train data to create a prediction of whether a passenger survived or died based on the passenger information provided in the test data.

In [182]:

```
test=pd.read_csv('test.csv')
train=pd.read_csv('train.csv')
answer=pd.read_csv('gender_submission.csv')
```

In [183]:

```
train
```

Out[183]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	
...	...	...	...	...	...	...	...	...	...	...	
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	

891 rows × 12 columns

In [184]:

```
test
```

Out[184]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	E
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	
...	...	...	...	...	...	...	...	...	...	...	
413	1305	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	
414	1306	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	
415	1307	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	
416	1308	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	
417	1309	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	

418 rows × 11 columns

The columns included in the data are as follows.

- PassengerId - Passenger identification unique ID
- Survived - Survival flag (0=dead, 1=alive)
- Pclass - Ticket class
- Name - Passenger's name
- Sex - Gender (male = male, female = female)
- Age
- SibSp - Number of siblings/spouses on Titanic
- parch - Number of parents/children traveling on Titanic
- ticket - Ticket number
- fare

- cabin - cabin number
- Embarked - port of embarkation

Pclass

- 1 = Upper class (rich)
- 2 = Intermediate class (general class)
- 3 = Lower class (working class)

Embarked

- C = Cherbourg
- Q = Queenstown
- S = Southampton

～GOAL～

Aim for the most accurate prediction model as much as possible!

Data Cleaning

Check for missing "train" data

In [185]:

```
train.isnull().sum(axis=0)
```

Out[185]:

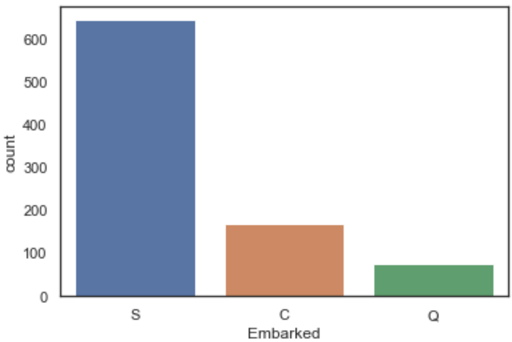
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [186]:

```
sns.countplot('Embarked',data=train)
```

Out[186]:

```
<AxesSubplot:xlabel='Embarked', ylabel='count'>
```



- The median value of the entire "Age" is inserted into the missing data of "Age" as a proxy data.
- Since "S" is the most common in the data, "S" is placed in the missing data of "Embarked" this time.
- Cabin" is not relevant to the forecast data, so we ignore it this time.

In [187]:

```
train["Age"] = train["Age"].fillna(train["Age"].median())
train["Embarked"] = train["Embarked"].fillna("S")
train
```

Out[187]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	I
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	I
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	I
...	...	...	...	...	...	...	...	...	...	...	
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	I
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	28.0	1	2	W./C. 6607	23.4500	I
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	I

891 rows × 12 columns

Converts categorical data strings to numbers.

In [188]:

```
train["Sex"][train["Sex"] == "male"] = 0
train["Sex"][train["Sex"] == "female"] = 1
train["Embarked"][train["Embarked"] == "S" ] = 0
train["Embarked"][train["Embarked"] == "C" ] = 1
train["Embarked"][train["Embarked"] == "Q"] = 2
train.head(10)
```

Out[188]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	NaN
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	NaN
5	6	0	3	Moran, Mr. James	0	28.0	0	0	330877	8.4583	NaN
6	7	0	1	McCarthy, Mr. Timothy J	0	54.0	0	0	17463	51.8625	E46
7	8	0	3	Palsson, Master. Gosta Leonard	0	2.0	3	1	349909	21.0750	NaN
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	1	27.0	0	2	347742	11.1333	NaN
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	1	14.0	1	0	237736	30.0708	NaN

The "test" data is similarly checked for missing data, proxy data is inserted, and categorical data strings are converted to numbers.

In [189]:

```
test.isnull().sum(axis=0)
```

Out[189]:

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

In [190]:

```
test["Age"] = test["Age"].fillna(test["Age"].median())
test["Sex"][test["Sex"] == "male"] = 0
test["Sex"][test["Sex"] == "female"] = 1
test["Embarked"][test["Embarked"] == "S"] = 0
test["Embarked"][test["Embarked"] == "C"] = 1
test["Embarked"][test["Embarked"] == "Q"] = 2
test["Fare"] = test["Fare"].fillna(test["Fare"].median())
test.head(10)
```

Out[190]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	0	34.5	0	0	330911	7.8292	NaN	2
1	893	3	Wilkes, Mrs. James (Ellen Needs)	1	47.0	1	0	363272	7.0000	NaN	0
2	894	2	Myles, Mr. Thomas Francis	0	62.0	0	0	240276	9.6875	NaN	2
3	895	3	Wirz, Mr. Albert	0	27.0	0	0	315154	8.6625	NaN	0
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	1	22.0	1	1	3101298	12.2875	NaN	0
5	897	3	Svensson, Mr. Johan Cervin	0	14.0	0	0	7538	9.2250	NaN	0
6	898	3	Connolly, Miss. Kate	1	30.0	0	0	330972	7.6292	NaN	2
7	899	2	Caldwell, Mr. Albert Francis	0	26.0	1	1	248738	29.0000	NaN	0
8	900	3	Abrahim, Mrs. Joseph (Sophie Halaut Easu)	1	18.0	0	0	2657	7.2292	NaN	1
9	901	3	Davies, Mr. John Samuel	0	21.0	2	0	A/4 48871	24.1500	NaN	0

The model used in this study is a "decision tree model".

[https://qiita.com/3000manJPY/items/ef7495960f472ec14377 (https://qiita.com/3000manJPY/items/ef7495960f472ec14377)](https://qiita.com/3000manJPY/items/ef7495960f472ec14377)

First, let's create a predict model with independent variables other than "PassengerId," "Name," "Ticket," and "Cabin," which are not relevant to the prediction.

In [191]:

```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
```

In [192]:

```
# Obtain values for the dependent and independent variables for "train".
target = train["Survived"].values
features = train[["Pclass", "Sex", "Fare", "Age", "SibSp", "Parch", "Embarked"]].values
# Create decision tree model
my_tree_1 = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
#my_tree_1 =tree. DecisionTreeClassifier.score()
my_tree_1 = my_tree_1.fit(features, target)
# To get the value of the independent variable for "test"
test_features = test[["Pclass", "Sex", "Fare", "Age", "SibSp", "Parch", "Embarked"]].values
# Prediction with "my_tree_one" model using "test" independent variables
my_prediction = my_tree_1.predict(test_features)
```

In [193]:

```
print(my_prediction)
```

```
[0 0 1 1 1 0 0 0 0 0 0 1 0 1 1 0 1 1 0 1 1 1 1 1 0 1 1 1 0 0 0 1 0 1 1 1
 0 0 1 0 1 0 1 1 0 0 0 1 1 0 0 1 0 0 0 0 0 0 1 0 1 0 1 1 0 0 0 0 1 1 0 0 0
 1 0 0 1 0 1 1 0 0 0 1 0 1 0 1 1 0 1 0 0 0 0 1 0 1 0 1 0 0 0 1 0 0 0 1 0 0
 1 1 0 1 1 0 1 1 1 1 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0
 1 0 1 0 0 1 0 0 1 1 0 0 1 1 1 1 0 1 1 0 0 0 1 0 0 0 1 1 1 1 1 1 0 0 1 0 1
 0 1 1 0 0 0 0 1 1 1 0 1 0 0 1 1 1 0 1 0 0 0 0 1 0 0 1 0 1 0 0 1 0 1 0 1 0
 1 1 1 0 0 1 0 0 0 1 1 0 1 0 1 1 1 1 1 1 0 0 0 0 1 1 1 0 1 0 0 0 0 1 0 0 1
 0 0 0 1 1 0 0 1 1 1 0 1 0 1 1 0 1 0 0 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 1 1 0 1 0 0 0 1 1 0 1 1 1 0 0 0 0 0 0 1 1 0 1 0 0 0 1 0 0
 1 0 0 1 0 0 0 0 0 0 1 0 1 0 0 0 1 1 0 0 0 0 0 1 0 0 1 0 1 1 1 1 0 0 1 1 1
 0 1 0 0 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 1 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0
 0 1 0 1 1 0 0 1 0 0 1]
```

In [194]:

```
answer= answer['Survived']
```

In [195]:

```
print(answer.values)
```

```
[0 1 0 0 1 0 1 0 1 0 0 0 1 0 1 1 0 0 1 1 0 0 1 0 1 0 1 0 0 0 0 0 1 1 0 0 1
 1 0 0 0 0 0 1 1 0 0 0 1 1 0 0 1 1 0 0 0 0 0 1 0 0 0 1 0 1 1 0 0 1 1 0 1 0
 1 0 0 1 0 1 0 0 0 0 0 0 1 1 1 0 1 0 1 0 0 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0
 1 1 1 1 0 0 1 0 1 1 0 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 1 0 1 1 0 0 0 0 0 0
 0 0 1 0 0 1 0 0 1 1 0 1 1 0 1 0 0 1 0 0 1 1 0 0 0 0 0 1 1 0 1 1 0 0 1 0 1
 0 1 0 1 0 0 0 0 0 0 0 0 1 0 1 1 0 0 1 0 0 1 0 1 0 0 0 0 1 1 0 1 0 1 0 1 0
 1 0 1 1 0 1 0 0 0 1 0 0 0 0 0 0 1 1 1 1 0 0 0 0 1 0 1 1 1 0 0 0 0 0 0 0 1
 0 0 0 1 1 0 0 0 0 1 0 0 0 1 1 0 1 0 0 0 0 1 0 1 1 1 0 0 0 0 0 0 1 0 0 0 0
 1 0 0 0 0 0 0 0 1 1 0 0 0 1 0 0 0 1 1 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0
 1 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 1 1 0 0 0 1 0 1 0 0 1 0 1 1 0 1 1 0 1 1 0
 0 1 0 0 1 1 1 0 0 0 0 0 1 1 0 1 0 0 0 0 0 1 0 0 0 1 0 1 0 0 1 0 1 0 0 0 0
 0 1 1 1 1 1 0 1 0 0 0]
```

In [196]:

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(answer.values, my_prediction)
print(cm)
```

```
[[205  61]
 [ 40 112]]
```

In [197]:

```
print('Accuracy is' , accuracy_score(answer.values, my_prediction))
```

```
Accuracy is 0.7583732057416268
```

～Aiming for higher precision～

Find the each independent variable Feature Value and detect good variables with large effects.

Feature Value・・・In machine learning and pattern recognition, a feature is an individual measurable property or characteristic of a phenomenon.Choosing informative, discriminating and independent features is a crucial element of effective algorithms in pattern recognition, classification and regression. Features are usually numeric, but structural features such as strings and graphs are used in syntactic pattern recognition. The concept of "feature" is related to that of explanatory variable used in statistical techniques such as linear regression.

In [198]:

```
#Create a random forest model
RF = RandomForestClassifier(n_estimators=250,random_state=1)
RF.fit(features,target)
```

Out[198]:

```
RandomForestClassifier(n_estimators=250, random_state=1)
```

In [199]:

```
#Get feature value and importance value
features = train[["Pclass", "Sex", "Fare", "Age", "SibSp", "Parch", "Embarked"]].columns
importances = RF.feature_importances_

# make a table
df = pd.DataFrame({"features":features,"importances":importances}).sort_values("importances", ascend
df.reset_index(drop=True)
```

Out[199]:

	features	importances
0	Fare	0.270900
1	Sex	0.263822
2	Age	0.256137
3	Pclass	0.087143
4	SibSp	0.051692
5	Parch	0.038120
6	Embarked	0.032187

The above table suggests that "Fare," "Sex," and "Age" contribute significantly to the forecast. If we only use them as independent variables, the predictive value would increase...?

In [200]:

```
# Get the values of the dependent and independent variables for "train"
target_2 = train["Survived"].values
features_2 = train[["Sex", "Fare", "Age"]].values
# Create decision tree model
my_tree_2 = tree.DecisionTreeClassifier()
my_tree_2 = my_tree_2.fit(features_2, target_2)
# Get the value of the independent variable for "test"
test_features_2 = test[["Sex", "Fare", "Age"]].values
# Prediction with "my_tree_one" model using "test" independent variables
my_prediction_2 = my_tree_2.predict(test_features_2)
```

In [201]:

```
print(my_prediction_2)
```

```
[0 0 1 1 0 0 0 1 1 0 0 0 1 0 1 1 0 1 1 0 0 1 1 0 1 0 1 1 1 0 0 0 1 0 1 0 0
 0 0 1 0 1 0 1 1 0 0 0 1 1 0 0 1 0 1 0 0 0 1 1 0 1 0 1 0 0 1 0 0 1 1 0 0 0
 1 0 0 1 0 1 1 0 0 0 1 0 1 1 1 0 1 1 1 0 0 0 1 1 1 0 1 0 0 0 1 0 0 0 1 0 0
 0 1 1 1 0 1 1 0 1 1 0 1 0 0 1 0 1 0 0 1 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 1 0
 1 0 1 0 0 1 0 0 1 1 0 1 1 1 1 1 0 1 1 0 1 0 0 1 0 1 0 1 0 0 1 1 0 0 1 0 0
 0 0 0 0 0 0 0 1 1 0 0 1 0 0 0 0 1 0 1 0 0 0 0 1 0 1 1 0 1 0 0 1 0 1 0 1 0
 0 1 1 0 0 1 0 0 0 1 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 0 1
 0 0 0 1 1 0 0 1 0 0 0 0 0 1 0 1 1 0 0 0 0 0 1 1 0 0 0 0 0 1 0 1 0 1 0 0 0
 1 0 0 0 0 0 0 0 1 1 0 1 1 1 0 1 0 0 1 1 0 0 0 0 0 0 0 1 1 0 1 0 0 0 1 0 1
 1 0 0 1 0 0 1 0 0 1 1 0 1 0 0 0 1 1 0 0 1 0 0 1 0 0 1 0 1 1 1 1 0 0 1 1 0
 0 1 0 0 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 1 1 0 0 1 0 1 0 0 1 0 1 0 0 0 0
 1 1 1 1 1 0 0 1 0 0 0]
```

In [202]:

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(answer.values, my_prediction_2)
print(cm)
```

```
[[209  57]
 [ 42 110]]
```

In [203]:

```
print('Accuracy is' , accuracy_score(answer.values, my_prediction_2))
```

```
Accuracy is 0.7631578947368421
```

Accuracy remained at approximately 0.76.

In [204]:

```
#Create a random forest model
RF = RandomForestClassifier(n_estimators=250,random_state=1)
RF.fit(features_2,target_2)
```

Out[204]:

```
RandomForestClassifier(n_estimators=250, random_state=1)
```

In [205]:

```
#Get feature value and importance value
features = train[["Sex", "Fare", "Age"]].columns
importances = RF.feature_importances_

#make a table
df = pd.DataFrame({"features":features,"importances":importances}).sort_values("importances",ascendi
df.reset_index(drop=True)
```

Out[205]:

	features	importances
0	Fare	0.441837
1	Age	0.292880
2	Sex	0.265282

Possible Causes

- The number of data is not enough for just 891.
- Although the feature values are somewhat concentrated in "Fare", they are somewhat distributed among the three, making it difficult to determine which one to rely on.

Then created a decision tree model with two explanatory variables as the top two feature values, "Fare" and "Age".

In [206]:

```
# Get the values of the dependent and independent variables for "train"
target_3 = train["Survived"].values
features_3 = train[["Sex", "Fare"]].values
# Create decision tree model
my_tree_3 = tree.DecisionTreeClassifier()
my_tree_3 = my_tree_3.fit(features_3, target_3)
# Get the value of the independent variable for "test"
test_features_3 = test[["Sex", "Fare"]].values
# Prediction with "my_tree_one" model using "test" independent variables
my_prediction_3 = my_tree_3.predict(test_features_3)
```

In [207]:

```
print(my_prediction_3)
```

```
[0 1 0 0 1 0 0 1 1 0 0 0 1 0 1 1 0 0 1 1 0 0 1 0 1 0 1 0 1 0 0 0 1 0 1 0 0
 0 0 1 0 0 0 1 1 0 0 0 1 1 0 0 1 1 0 0 0 0 0 1 0 0 0 1 0 1 1 0 0 1 1 0 1 0
 1 0 0 1 0 1 1 0 0 0 0 0 1 0 1 1 1 0 1 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0
 0 1 1 1 0 0 1 1 1 1 0 1 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 1 0 0 1 0 0 1 0 0 1 1 1 1 0 0 1 0 0 1 0 0 0 1 0 0 1 1 1 1 1 0 0 1 0 1
 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 1 0 1 0 0 0 0 1 0 0 1 0 1 0 1 0
 1 0 1 0 0 1 0 0 0 1 0 0 0 0 1 0 1 1 1 1 1 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 1
 0 0 0 1 1 0 0 0 0 0 0 1 0 1 1 0 1 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 1 0 0
 1 0 0 0 0 0 0 0 1 1 1 0 1 1 0 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0
 1 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 1 1 0 0 0 1 0 1 0 0 1 0 1 1 0 1 0 0 0 1 1
 0 1 0 0 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 1 0 0 0 1 0 1 0 0 1 0 1 0 0 1 0
 0 1 1 1 1 0 0 1 0 0 0]
```

In [208]:

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(answer.values, my_prediction_3)
print(cm)
```

```
[[243  23]
 [ 30 122]]
```

In [209]:

```
print('Accuracy is' , accuracy_score(answer.values, my_prediction_3))
```

```
Accuracy is 0.8732057416267942
```

Accuracy improved from about 0.76 to about 0.87.

In [210]:

```
#Create a random forest model
RF = RandomForestClassifier(n_estimators=250,random_state=1)
RF.fit(features_3,target_3)
```

Out[210]:

RandomForestClassifier(n_estimators=250, random_state=1)

In [211]:

```
#Get feature value and importance value
features = train[["Sex", "Fare"]].columns
importances = RF.feature_importances_

#make a table
df = pd.DataFrame({"features":features,"importances":importances}).sort_values("importances",ascendi
df.reset_index(drop=True)
```

Out[211]:

	features	importances
0	Fare	0.65932
1	Sex	0.34068

It is considerd that reducing the number of independent variables and concentrating the feature value toward "Fare" to some extent led to the improvement in accuracy.

Conversely, when we created a prediction model using only "Fare," which has the largest feature value as the independent variable, we obtained a Score of 0.67224. It is not good to rely on only "Fare".

〜Aiming for higher precision〜

I noticed that children of passengers have a higher survival rate regardless of sex. Wouldn't it be better to classify the independent variable "Sex" into the three categories of "male", "female", and "child", and create a model to improve the accuracy?

In [212]:

```
# A person under 16 years of age is considered a child.

def male_female_child(passenger):
    # Get age and gender data.
    age,sex = passenger
    # Check age and if under 16, child. Otherwise, return gender as is.
    if age < 16:
        return '2'
    else:
        return sex

# Add a new column named person.
train['person'] = train[['Age','Sex']].apply(male_female_child,axis=1)
test['person'] = test[['Age','Sex']].apply(male_female_child,axis=1)
```

In [213]:

```
train.head(10)
```

Out[213]:

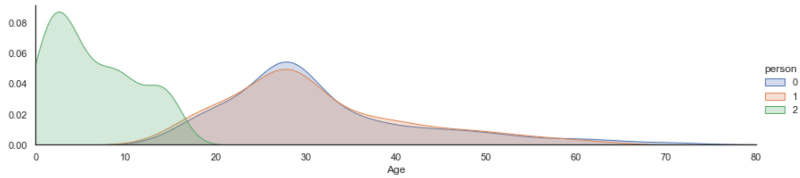
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	NaN
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	NaN
5	6	0	3	Moran, Mr. James	0	28.0	0	0	330877	8.4583	NaN
6	7	0	1	McCarthy, Mr. Timothy J	0	54.0	0	0	17463	51.8625	E46
7	8	0	3	Palsson, Master. Gosta Leonard	0	2.0	3	1	349909	21.0750	NaN
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	1	27.0	0	2	347742	11.1333	NaN
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	1	14.0	1	0	237736	30.0708	NaN

In [214]:

```
# FacetGrid allows you to draw multiple kernel density estimation graphs in a single plot.
fig = sns.FacetGrid(train, hue="person",aspect=4)
fig.map(sns.kdeplot,'Age',shade= True)
oldest = train['Age'].max()
fig.set(xlim=(0,oldest))
fig.add_legend()
```

Out[214]:

<seaborn.axisgrid.FacetGrid at 0x7f8ec6160eb0>

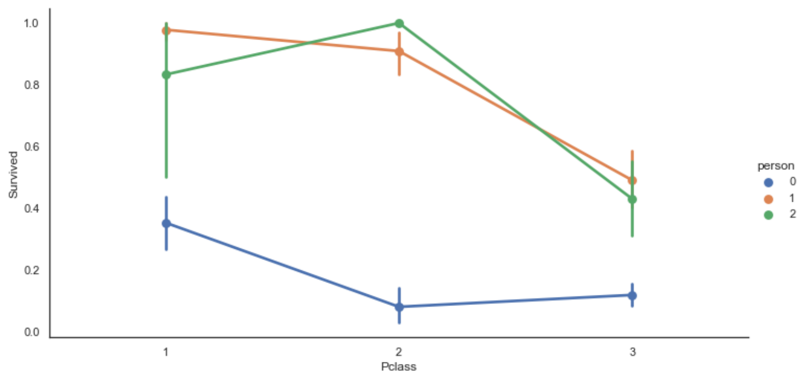


In [215]:

```
sns.catplot('Pclass', 'Survived', hue='person', data=train, order=[1,2,3], kind='point', aspect=2)
```

Out[215]:

<seaborn.axisgrid.FacetGrid at 0x7f8ec6147dc0>



I created a predictive model using "person" and "Fare" as indeoendent variables for the three categories of "male," "female," and "child."

In [216]:

```
# Get the values of the dependent and independent variables for "train"
target_4 = train["Survived"].values
features_4 = train[["person", "Fare"]].values
# Create decision tree model
my_tree_4 = tree.DecisionTreeClassifier()
my_tree_4 = my_tree_4.fit(features_4, target_4)
# Get the value of the independent variable for "test"
test_features_4 = test[["person", "Fare"]].values
# Prediction with "my_tree_one" model using "test" independent variables
my_prediction_4 = my_tree_4.predict(test_features_4)
```

In [217]:

```
print(my_prediction_4)
```

```
[0 1 0 0 1 1 0 0 1 0 0 0 1 0 1 1 0 0 1 1 0 0 1 0 1 0 1 0 1 0 0 0 1 0 1 0 0
 0 0 1 0 0 0 1 1 0 0 0 1 1 0 0 1 1 0 0 0 0 0 1 0 0 0 1 1 1 1 0 0 1 1 0 1 0
 1 0 0 1 0 1 0 0 0 0 0 0 1 0 1 1 1 0 1 0 0 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0
 0 1 1 1 0 0 1 1 1 1 0 1 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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 0 1 0 0 0 0 0 1 0 1 0 1 0 0 0 1 0 0 1 0 0 1 0 1 0 0 0 0 1 0 0 1 0 1 0 1 0
 1 0 1 0 0 1 0 0 1 1 0 0 0 0 1 0 1 1 1 1 1 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 1
 0 0 0 1 1 0 0 0 0 0 0 1 0 1 1 0 1 0 0 0 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0 0 0
 1 0 0 0 0 0 0 0 1 1 0 1 1 1 0 0 0 1 1 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0
 1 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 1 1 0 0 0 1 0 1 0 0 1 0 1 1 0 1 0 0 0 1 1
 0 1 0 0 1 1 0 0 0 1 0 0 0 1 0 1 0 0 0 0 1 1 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0
 0 1 1 1 1 0 0 1 0 0 0]
```

In [218]:

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(answer.values, my_prediction_4)
print(cm)
```

```
[[241  25]
 [ 26 126]]
```

In [219]:

```
print('Accuracy is' , accuracy_score(answer.values, my_prediction_4))
```

```
Accuracy is 0.8779904306220095
```

The scores were almost the same, although slightly improved from the model accuracy for the independent variables "Sex" and "Fare".

Check correlation coefficients

In [220]:

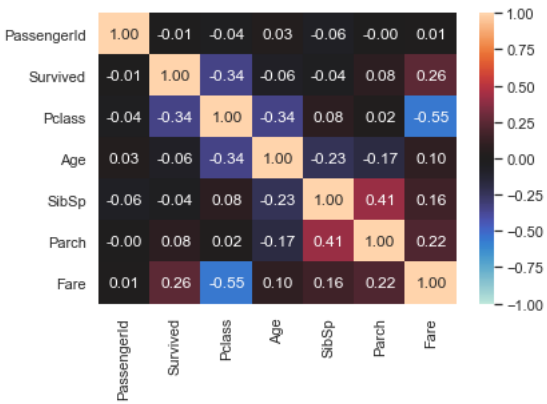
```
corr_mat = train.corr(method='pearson')
corr_mat
```

Out[220]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	1.000000	-0.005007	-0.035144	0.034212	-0.057527	-0.001652	0.012658
Survived	-0.005007	1.000000	-0.338481	-0.064910	-0.035322	0.081629	0.257307
Pclass	-0.035144	-0.338481	1.000000	-0.339898	0.083081	0.018443	-0.549500
Age	0.034212	-0.064910	-0.339898	1.000000	-0.233296	-0.172482	0.096688
SibSp	-0.057527	-0.035322	0.083081	-0.233296	1.000000	0.414838	0.159651
Parch	-0.001652	0.081629	0.018443	-0.172482	0.414838	1.000000	0.216225
Fare	0.012658	0.257307	-0.549500	0.096688	0.159651	0.216225	1.000000

In [221]:

```
sns.heatmap(corr_mat,
         vmin=-1.0, #Minimum value
         vmax=1.0, #Maximum value
         center=0, #Median
         annot=True, # True:Display values in a grid
         fmt='.2f', #formatting
          xticklabels=corr_mat.columns.values,#X-axis label
         yticklabels=corr_mat.columns.values #Y-axis label
        )
plt.show()
```



I created a predictive model using "Survived" and "Pclass" and "Fare" as explanatory variables, which had a slightly higher correlation with "Survived".

In [222]:

```
# Get the values of the dependent and independent variables for "train"
target_5 = train["Survived"].values
features_5 = train[["Pclass", "Fare"]].values
# Create decision tree model
my_tree_5 = tree.DecisionTreeClassifier()
my_tree_5 = my_tree_5.fit(features_5, target_5)
# Get the value of the independent variable for "test"
test_features_5 = test[["Pclass", "Fare"]].values
# Prediction with "my_tree_one" model using "test" independent variables
my_prediction_5 = my_tree_5.predict(test_features_5)
```

In [223]:

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(answer.values, my_prediction_5)
print(cm)
```

```
[[203  63]
 [ 94  58]]
```

In [224]:

```
print('Accuracy is' , accuracy_score(answer.values, my_prediction_5))
```

```
Accuracy is 0.6244019138755981
```

The accuracy has dropped considerably.

I tried a Kaggle titanic competition by using a decision tree model. As a result, I created a prediction model with approximately 88% accuracy. Looking ahead, we may be able to create even more accurate models by using not only decision tree models but also other machine learning methods such as logistic regression models and random forests.

Fin.