Pipelines in Machine Learning (Pipeline: chaining estimators)

- A pipeline is a process of sequentially applying a list of transformers and a final estimator i.e, a pipeline is a series of steps executed in an ordered to automate the machine learning workflow.
- Pipelines are majorly useful while deploying the model, where the steps are performed sequentially on the given data.
- We have to call 'fit' (on train data), 'predict' (on test data) on the data to fit the whole sequence of estimators created

- We can use pipelines (from built-in libraries) either from sklearn or imblearn

  - from sklearn.pipeline import Pipeline
  - from imblearn.pipeline import Pipeline
  - We use imblearn only when we want to use samplers in pipeline

--> **Reasons to use pipelines:**

```
1. Efficiency - Pipelines automate repetative tasks thus
reducing the manual intervention and saving time
2. Consistency - Pipelines are defined with a fixed workflow
and they are implemented sequentially (model training steps
remain constant throughout the project) making it easy in
transition from production to deployment
3. Scalability - Pipelines can be designed and scaled as the
project grows
4. Modularity - Pipelines enable the easy addition, removal, or
modification of components without disrupting the entire
workflow.
```

--> **ML model training pipeline:**

```
1. Data Ingestion - In this step data is collencted from the
source, such as database, files, APIs etc.,
2. Data Preprocessing - Raw data is often noise, contains
missing values, this preprocessing stage involves cleaning the
data, transforming and encoding making the data suitable for
the machine learning algorithms. Common steps in the data
preprocessing include treating missing values, incorrect
datatypes, transformation, encoding
3. Feature Engineering - In this stage, new features are
created using the existing data to improve model performance
(such as dimensionality reduction, feature selection, feature
```

```
extraction)
4. Model Training - The model (choosen ML algorithm) is then
trained on the preprocessed data. This process involves
adjesting the model's parameters to minimize the loss function.
5. Model Validation - The created model should be tested with
the validation dataset (the dataset model hasn't seen before),
this step is crucial to check the performance of the model
(generalization).
6. Hyperparameter Tuning - Here in this step, we have to search
for the optimal set of values that minimizes the validation
error and helps achieveing the best possible performance of the
model (Hyperparamets are the parameters of the ML algorithm
that are set before the training begins)
```

--> **Along with the advantages discussed pipelines are alos challenging in the following ways:**

```
1. Complexity: Designing a pipeline requires understanding the
dependencies between components and managing intricate
workflows.
2. Tool selection: Choosing the right tools and libraries can
be overwhelming due to the vast number of options available.
3. Integration: Combining different tools and technologies may
require custom solutions or adapters, which can be time-
consuming to develop.
4. Debugging: Identifying and fixing issues within a pipeline
can be difficult due to the interconnected nature of the
components
```

Let's initially start a pipeline that performs scaling and modelling

In [1]:
```
from sklearn.pipeline import Pipeline

#feature scaling
from sklearn.preprocessing import StandardScaler

#model
from sklearn.linear_model import LogisticRegression
```

In [2]:
```
#initialize the steps we want perform sequentially
#these steps should be a list with key-value inside a tuple

steps = [('standard_scaler', StandardScaler()),
        ('model', LogisticRegression())]
```

In [3]:
```
steps
```

Out[3]:
```
[('standard_scaler', StandardScaler()), ('model', LogisticRegression())]
```

In [4]:
```
pipe = Pipeline(steps)
```

```
pipe
```

Out[4]:

```
Pipeline
  StandardScaler
  LogisticRegression
```

In [5]:

```
#we can also visuzalize using set_config visualizing pipeline
from sklearn import set_config
```

In [6]:

```
set_config(display='diagram')
pipe
```

Out[6]:

```
Pipeline
  StandardScaler
  LogisticRegression
```

In [7]:

```
#create dataset
from sklearn.datasets import make_classification

X,y = make_classification(n_samples=200)
```

In [8]:

```
X.shape
```

Out[8]:

```
(200, 20)
```

In [9]:

```
y.shape
```

Out[9]:

```
(200,)
```

In [10]:

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randor
```

In [11]:

```
X_test.shape
```

Out[11]:

```
(40, 20)
```

In [12]:

```
X_train
```

Out[12]:
```
array([[ 2.10269722, -1.45290733, -0.79208765, ...,  0.7138159 ,
        -0.88455122,  0.74152932],
       [ 0.06467105, -0.96268001, -0.3719379 , ...,  1.27476612,
        -1.0455631 , -0.69619439],
       [ 0.77622353, -1.6724818 , -0.60888646, ..., -0.24024485,
         1.03612803,  0.61720647],
       ...,
       [-0.11637333, -2.25133249,  0.2784083 , ...,  0.9791436 ,
         1.78117968,  0.43350504],
       [-0.88685905, -0.0064142 , -0.63104365, ..., -0.76761549,
        -0.07025435, -0.22275399],
       [ 0.33191505, -0.17832865,  1.97099907, ..., -0.8813084 ,
         1.19409453, -1.1699808 ]])
```

In [13]:
```python
pipe.fit(X_train, y_train)
```

Out[13]:
```
Pipeline
  StandardScaler
  LogisticRegression
```

In [14]:
```python
#during prediction piplines perform only transform
y_pred = pipe.predict(X_test)
```

In [15]:
```python
y_pred
```

Out[15]:
```
array([0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0,
       1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0])
```

- Now lets try to include some more steps inside the pipeline

In [16]:
```python
from sklearn.decomposition import PCA
from sklearn.svm import SVC
```

In [17]:
```python
steps = [('standard_scaler', StandardScaler()),
        ('PCA', PCA(n_components=5)),
        ('SVC', SVC())]
steps
```

Out[17]:
```
[('standard_scaler', StandardScaler()),
 ('PCA', PCA(n_components=5)),
 ('SVC', SVC())]
```

In [18]:
```python
pipe_1 = Pipeline(steps)
pipe_1
```

Out[18]:

```
▸ Pipeline
▸ StandardScaler
▸ PCA
▸ SVC
```

In [19]:

```
#now perform every task included in the pipeline
pipe_1.fit(X_train, y_train)
```

Out[19]:

```
▸ Pipeline
▸ StandardScaler
▸ PCA
▸ SVC
```

In [20]:

```
pipe_1.predict(X_test)
```

Out[20]:

```
array([0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0,
       1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0])
```

Accessing Steps

we can also make the pipe perform only one task (of many tasks initiated) instead of doing everything thats included in the pipeline

In [21]:

```
pipe_1['standard_scaler'].fit_transform(X_train)
```

Out[21]:

```
array([[ 2.23771502, -1.40368064, -0.89159109, ...,  0.65159439,
        -0.66096327,  0.74527549],
       [ 0.03201156, -0.90944802, -0.47631076, ...,  1.18228926,
        -0.78938599, -0.79823949],
       [ 0.80210656, -1.62504911, -0.71051315, ..., -0.25100824,
         0.87096633,  0.61180466],
       ...,
       [-0.16392814, -2.20862919,  0.16649812, ...,  0.90261141,
         1.46521791,  0.41458602],
       [-0.99780507,  0.05463079, -0.73241354, ..., -0.74993466,
        -0.01148185, -0.28996217],
       [ 0.32124288, -0.11868826,  1.83947225, ..., -0.85749545,
         0.99696007, -1.30688826]])
```

In [22]:

```
pipe_1[0]
```

Out[22]:

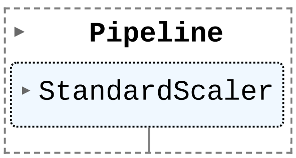
```
▾ StandardScaler
StandardScaler()
```

In [23]:
```
#the estimators are stored as a list elements
pipe_1[0].fit_transform(X_train)
```

Out[23]:
```
array([[ 2.23771502, -1.40368064, -0.89159109, ...,  0.65159439,
        -0.66096327,  0.74527549],
       [ 0.03201156, -0.90944802, -0.47631076, ...,  1.18228926,
        -0.78938599, -0.79823949],
       [ 0.80210656, -1.62504911, -0.71051315, ..., -0.25100824,
         0.87096633,  0.61180466],
       ...,
       [-0.16392814, -2.20862919,  0.16649812, ...,  0.90261141,
         1.46521791,  0.41458602],
       [-0.99780507,  0.05463079, -0.73241354, ..., -0.74993466,
        -0.01148185, -0.28996217],
       [ 0.32124288, -0.11868826,  1.83947225, ..., -0.85749545,
         0.99696007, -1.30688826]])
```

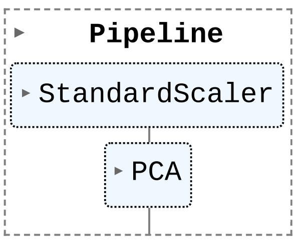
In [24]:
```
pipe_1[:1]
```

Out[24]:



In [25]:
```
pipe_1[:2]
```

Out[25]:



In [26]:
```
pipe_1.steps[0]
```

Out[26]:
```
('standard_scaler', StandardScaler())
```

make_pipeline

The utility function make_pipeline is a shorthand for constructing pipelines; it takes a variable number of estimators and returns a pipeline, filling in the names automatically (we dont have to assign names manually)

In [27]:
```
#now we have to make a custom pipeline
from sklearn.pipeline import make_pipeline
```

In [28]:
```
make_pipeline(StandardScaler(), LogisticRegression())
```

Out[28]:

```
Pipeline
StandardScaler
LogisticRegression
```

Nested Parameters

In [29]:
```
from sklearn.svm import SVC
```

In [30]:
```
pipe = Pipeline(steps = [
    ('sc', StandardScaler()),
    ('pca', PCA()),
    ('clf', SVC())
    ])

pipe
```

Out[30]:

```
Pipeline
StandardScaler
PCA
SVC
```

- In the above step we have intialized SVC as our model but with default parameter, now if we want to change the default parameters we can do it by the following syntax --

$$<\text{estimator}>\_\_<\text{parameter}>$$

eg: clf**degree = 2, clf**C=5

In [31]:
```
pipe.set_params(clf__C = 10) #the estimator C of SVC will be set to 10
```

Out[31]:

```
Pipeline
StandardScaler
PCA
SVC
```

In [32]:
```
pipe.set_params(clf__kernel = 'linear')
```

Out[32]:

```
Pipeline
StandardScaler
PCA
SVC
```

In [33]:

```
pipe22 = Pipeline(steps = [
    ('sc', StandardScaler()),
    ('pca', PCA()),
    ('clf', [SVC(), LogisticRegression()])
    ])

pipe22
```

Out[33]:

```
Pipeline
StandardScaler
PCA
list
```

GridSearchCV

In [34]:

```
from sklearn.model_selection import GridSearchCV
```

In [35]:

```
param_grid = dict(pca__ncomponents = [2,4,6],
                  clf__C = [2,5,8])

grid_search_pipe = GridSearchCV(pipe,param_grid)
grid_search_pipe
```

Out[35]:

```
GridSearchCV
estimator: Pipeline
StandardScaler
PCA
SVC
```

In [36]:

```
param_grid = dict(clf = [LogisticRegression(), SVC()],
                  pca = ['passthrough', PCA()],
                  clf__C = [2,4,6],
                  pca__n_components = [2,4,6])
GridSearchCV(pipe, param_grid)
```

Out[36]:

```
▸ GridSearchCV
▸ estimator: Pipeline
  ▸ StandardScaler
  ▸ PCA
  ▸ SVC
```

Column Transformer

- Each column transformer consists of three-element tuple
  - (Name, Object, Columns) i.e, Name of the transformer, The transformer to be applied, Columns (column indices) on which the transformer should be applied
  - Example: **[('scaling', StandardScaler(), [0,1])]** The scaling technique given the name 'scaling' which is the StandardScaler() will be applied on the columns 0,1. We can also pass the column names.
  - The purpose of the name of the transformer is to apply a particular transformer on the data, say we are performing scaling, pca,model, but we are only interested in performing scaling for some reasons then we can call only that particular transformer using the name assigned.
- We can also create multiple pipelines and combine them

In [37]:

```
import numpy as np
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LinearRegression
```

Simple column transformer

In [38]:

```
from sklearn.compose import ColumnTransformer
```

In [39]:

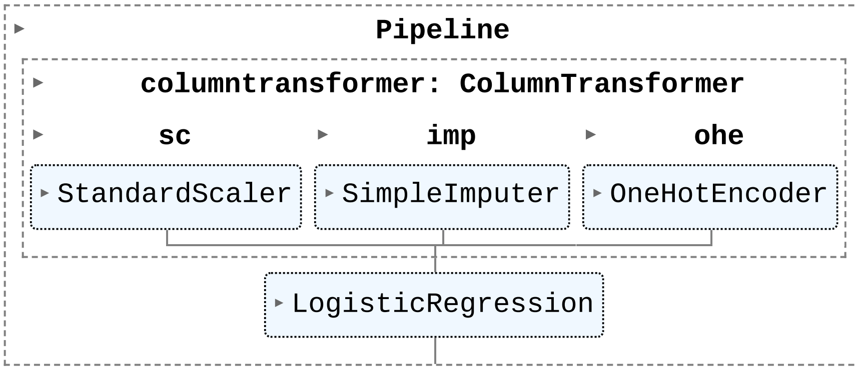
```
#supplying the scaling and encoding techniques directly
col_transformer = ColumnTransformer(
    [
        ('sc', StandardScaler(), [0,1]),
        ('imp', SimpleImputer(strategy='mean'), [0,1]),
        ('ohe', OneHotEncoder(), [2,3])
    ])

col_transformer
```

Out[39]:

```
▸ ColumnTransformer
▸ sc              ▸ imp            ▸ ohe
▸ StandardScaler  ▸ SimpleImputer  ▸ OneHotEncoder
```

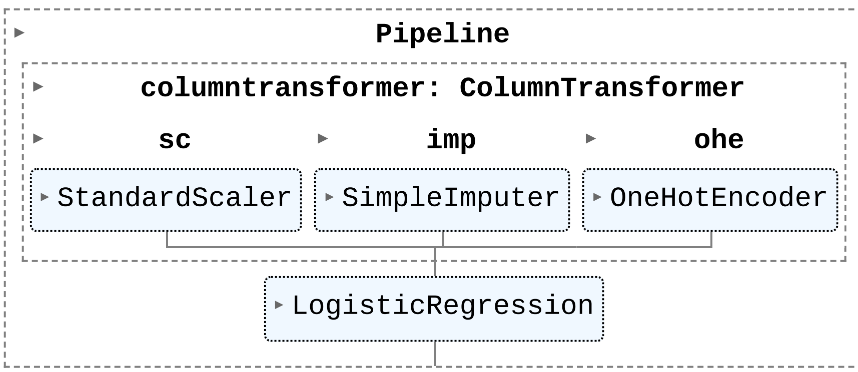
In [40]:
```
make_pipeline(col_transformer, LogisticRegression())
```

Out[40]:



In [41]:
```
#another way
t = [('sc', StandardScaler(), [0,1]),
   ('imp', SimpleImputer(strategy='mean'), [0,1]),
   ('ohe', OneHotEncoder(), [2,3])]

transformers = ColumnTransformer(transformers=t)

#make_pipeline
pip = make_pipeline(transformers, LogisticRegression())
pip
```

Out[41]:



> **Any columns that are not passed will be dropped by default and to change that, we need to pass an argument called 'reminder' which should be set to 'passthrough'**
>
> - When the reminder argument is passed then only the mentioned columns will be transformed and the rest will be passed as they are

In [42]:
```
t = [('ohe', OneHotEncoder(), [2,3])]

ColumnTransformer(transformers=t, remainder='passthrough') # by default remain
    # transformers argument should be a list of tuples
```

Out[42]:

```
ColumnTransformer
ohe                remainder
OneHotEncoder      passthrough
```

Creating multuiple pipelines and merging them

In [43]:

```python
#numerical processing
steps = [('imputation', SimpleImputer(strategy='mean'))]

num_pipe = Pipeline(steps)
num_pipe
```

Out[43]:

```
Pipeline
SimpleImputer
```

In [44]:

```python
#categorical processing
steps = [('imputation', SimpleImputer(strategy='most_frequent')),
        ('ohe', OneHotEncoder())]

#we can also fill with any other constant
#SimpleImputer(fill_value='missing', strategy='constant')
cat_pipe = Pipeline(steps)
cat_pipe
```

Out[44]:

```
Pipeline
SimpleImputer
OneHotEncoder
```

In [45]:

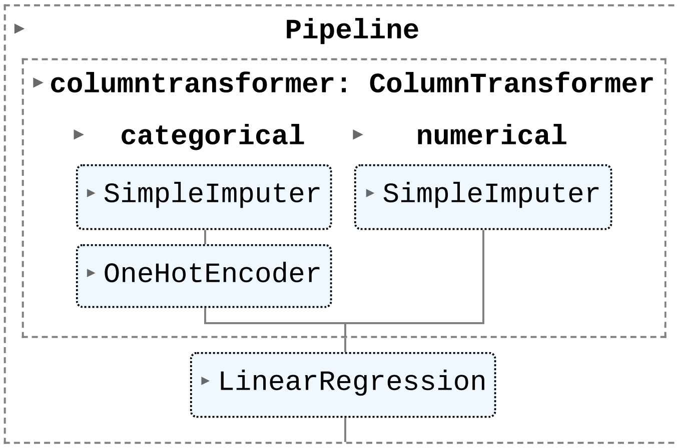
```python
preprocessor = ColumnTransformer(
    [
        ('categorical', cat_pipe, ['gender', 'qualification']),
        ('numerical', num_pipe, ['age'])
    ]
)

preprocessor
```

Out[45]:

```
ColumnTransformer
categorical        numerical
SimpleImputer      SimpleImputer
OneHotEncoder
```

In [46]:
```
final_pipeline = make_pipeline(preprocessor, LinearRegression())
final_pipeline
```

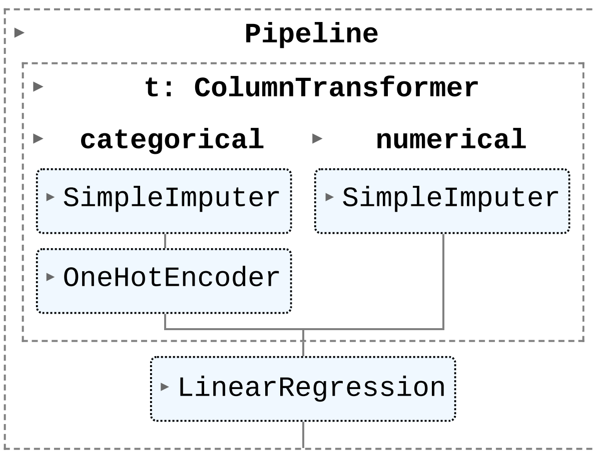
Out[46]:



OR we can also use

In [47]:
```
Pipeline(
    [
        ('t',preprocessor),
        ('m', LinearRegression())
    ])
```

Out[47]:



Difference between Pipeline and make_pipeline

- If we clearly observe the way we passed the steps inside the Pipeline and make_pipeline there are some differences between them and they can be listed as:

pipeline	make_pipeline
The pipeline requires naming the steps, manually.	make_pipeline names the steps, automatically.
Names are defined explicitly, without rules.	Names are generated automatically using a straightforward rule (lower case of the estimator).
Names cannot be changed based on the transformer or estimator used.	Names are readable, short, and easy to understand, and can be changed based on the estimator used.

In [48]:
```
import pandas as pd
```

In [49]:
```
data = {'gender':['M','F', 'M', 'M', 'F', 'M', 'F', 'F', 'M', 'M', np.nan, 'M']
       'age':[27,30,23,28,np.nan, 32, 35, 26, np.nan, 43, 36, 31],
       'qualification':['Bachelors', 'Bachelors', 'Bachelors', 'Masters', 'Bacl
                        'Masters','Masters', 'Phd', 'Bachelors', 'Masters'],
       'income':[25,30,22,28,41,32,42,38,30,35,33,28]}

df = pd.DataFrame(data)
df
```

Out[49]:

	gender	age	qualification	income
0	M	27.0	Bachelors	25
1	F	30.0	Bachelors	30
2	M	23.0	Bachelors	22
3	M	28.0	Masters	28
4	F	NaN	Bachelors	41
5	M	32.0	Masters	32
6	F	35.0	Phd	42
7	F	26.0	Masters	38
8	M	NaN	Masters	30
9	M	43.0	Phd	35
10	NaN	36.0	Bachelors	33
11	M	31.0	Masters	28

In [50]:
```
X = df[['gender', 'age', 'qualification']]
y = df.income
```

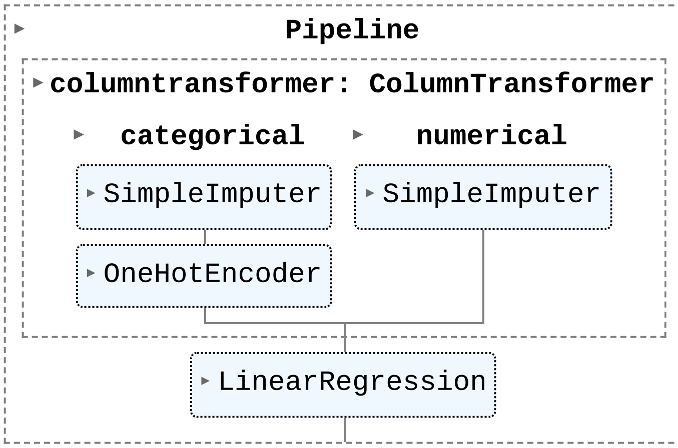
In [51]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3, random_
```

In [52]:
```
X_train.shape
```

Out[52]: (8, 3)

In [53]:
```
final_pipeline.fit(X_train, y_train)
```

Out[53]:



In [54]:
```
y_test
```

Out[54]:
```
6     42
11    28
4     41
10    33
Name: income, dtype: int64
```

In [55]:
```
y_pred = final_pipeline.predict(X_test)
y_pred
```

Out[55]:
```
array([40.56734052, 30.61563059, 31.16004553, 25.20448756])
```

Testing on an unknown data

In [56]:
```
test_data = pd.DataFrame(
    {'gender':[np.nan, 'M'],
    'age':[35, 26],
    'qualification':['Masters', 'Bachelors']})
test_data = pd.DataFrame(test_data)

final_pipeline.predict(test_data)
```

Out[56]:
```
array([31.45179123, 23.11408596])
```

Working on diabetic dataset

In [57]:
```
import pandas as pd
import numpy as np
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import FunctionTransformer
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LogisticRegression
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score

import warnings
warnings.filterwarnings('ignore')
```

In [58]:
```
#load dataset
def load_dataset(path):
    df = pd.read_csv(path)
    X = df.iloc[:,:-1]
    y = df.iloc[:,-1]
    display('X :',X, 'y :',y)
    print('*'*50)
    print(X.info())
    print('Null Values in y :',y.isnull().sum())
    return X,y
```

In [59]:
```
X,y = load_dataset('pima-indians-diabetes.csv')
```

'X :'

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction
0	6	148	72	35	0	33.6	0.627
1	1	85	66	29	0	26.6	0.351
2	8	183	64	0	0	23.3	0.672
3	1	89	66	23	94	28.1	0.167
4	0	137	40	35	168	43.1	2.288
...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171
764	2	122	70	27	0	36.8	0.340
765	5	121	72	23	112	26.2	0.245
766	1	126	60	0	0	30.1	0.349
767	1	93	70	31	0	30.4	0.315

768 rows × 8 columns

```
'y :'
0      1
1      0
2      1
3      0
4      1
      ..
763    0
764    0
765    0
766    1
767    0
Name: Class, Length: 768, dtype: int64
```

```
************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 8 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
dtypes: float64(2), int64(6)
memory usage: 48.1 KB
None
Null Values in y : 0
```

In [60]:
```
def check_skew(df):
    for i in df.columns:
        print('skewness for {} is {}'.format(i,df[i].skew()))

check_skew(X)
```

```
skewness for Pregnancies is 0.9016739791518588
skewness for Glucose is 0.17375350179188992
skewness for BloodPressure is -1.8436079833551302
skewness for SkinThickness is 0.10937249648187608
skewness for Insulin is 2.272250858431574
skewness for BMI is -0.42898158845356543
skewness for DiabetesPedigreeFunction is 1.919911066307204
skewness for Age is 1.1295967011444805
```

def transform(*args): for i in args: skew = df[i].skew() if skew>1 or skew<-1: if skew>1: check_root_skew = np.power(df[i], 1/35).skew() df[i] = np.power(df[i], 1/35) #print(i,':',check_root_skew) if skew<-1: check_power_skew = np.power(df[i], 2).skew() df[i] = np.power(df[i], 2) #print(i,':',check_power_skew) #else: #print(i,':',df[i].skew()) return df def root_trans(i): for i in args: return np.power(df[i], 1/35) def power_trans(i): for i in args: return np.power(df[i], 2) t = transform(*df.columns) t.skew()

In [61]:
```
#define a function that checks the skewness and converts if the data is skewed
def transform(df):
    for i in df.columns:
        skew = df[i].skew()
        skew_threshod = 1

        if skew>skew_threshod or skew<-skew_threshod:
            if skew>1:
                check_root_skew = np.power(df[i], 1/35).skew()
                df[i] = np.power(df[i], 1/35)
                #print(i,':',check_root_skew)

            if skew<-1:
                check_power_skew = np.power(df[i], 2).skew()
                df[i] = np.power(df[i], 2)
                #print(i,':',check_power_skew)
        #else:
            #print(i,':',df[i].skew())
    return df

def root_trans(i):
```

```
    for i in args:
        return np.power(df[i], 1/35)

def power_trans(i):
    for i in args:
        return np.power(df[i], 2)


transformed_X = transform(X)
transformed_X.skew()
```

Out[61]:

```
Pregnancies                 0.901674
Glucose                     0.173754
BloodPressure               0.122836
SkinThickness               0.109372
Insulin                    -0.049757
BMI                        -0.428982
DiabetesPedigreeFunction    0.156012
Age                         0.615204
dtype: float64
```

In [62]:

```
X_train, X_test, y_train, y_test =train_test_split(X,y,test_size=0.2, random_s
```

In [63]:

```
logistic_pipeline = make_pipeline(
    FunctionTransformer(transform),
    LogisticRegression()
)

decision_tree_pipeline = make_pipeline(
    FunctionTransformer(transform),
    DecisionTreeClassifier()
)

svc_pipeline = make_pipeline(
    FunctionTransformer(transform),
    SVC()
)

#transformed_data = pipeline.fit_transform(X)
```

In [64]:

```
pipelines = [logistic_pipeline, decision_tree_pipeline, svc_pipeline]
pipe_dict = {0:'Logistic Regression', 1:'Decision Tree', 2:'SVC'}
```

In [65]:

```
def model_train_predict(pipes, pipe_dict, X_train=None, X_test=None, y_train=No
    #X_train = transform(X_train)
    #X_test = transform(X_test)
    for i,pipe in enumerate(pipelines):
        pipe.fit(X_train, y_train)
        print('{} test accuracy {}'.format(pipe_dict[i],pipe.score(X_test, y_te

model_train_predict(pipes=pipelines,pipe_dict=pipe_dict,
                    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_
```

```
Logistic Regression test accuracy 0.7662337662337663
Decision Tree test accuracy 0.7597402597402597
SVC test accuracy 0.6948051948051948
```

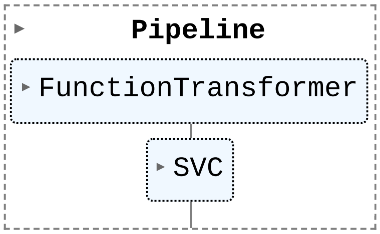
Changing the default parameters

In [66]:
```
svc_pipeline.steps
```

Out[66]:
```
[('functiontransformer',
  FunctionTransformer(func=<function transform at 0x7b884fb81750>)),
 ('svc', SVC())]
```

In [67]:
```
new_svc_pipe = svc_pipeline

new_svc_pipe.set_params(svc__kernel = 'linear')
```

Out[67]:



In [68]:
```
new_svc_pipe.fit(X_train, y_train)
new_svc_pipe.score(X_test, y_test)
```

Out[68]:
```
0.8051948051948052
```

GridSearchCV

In [69]:
```
param_grid = dict(svc__C = [2,4,6],
                  svc__kernel = ['linear', 'sigmoid', 'poly'])
            # C value should in general be low, to have high support vectors, 

grid_pipe = GridSearchCV(svc_pipeline, param_grid)
```

In [70]:
```
grid_pipe.fit(X_train, y_train)

print('Best params:',grid_pipe.best_params_)
print('Best Score:',grid_pipe.best_score_)
```

```
Best params: {'svc__C': 6, 'svc__kernel': 'linear'}
Best Score: 0.767119818739171
```

- The above modelling is just to illutrsate the concept of pipeline hence accuracy is not the main concern but the process we achieve it.

Titanic Dataset

In [71]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score, StratifiedKFold
```

In [72]:
```
df = pd.read_csv('train.csv')
df.head(3)
```

Out[72]:

	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
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

In [73]:
```
df.drop(['PassengerId', 'Name', 'Ticket', 'Cabin'], axis=1, inplace=True)
```

In [74]:
```
X = df.drop('Survived', axis=1)
y = df.Survived
```

In [75]:
```
X
```

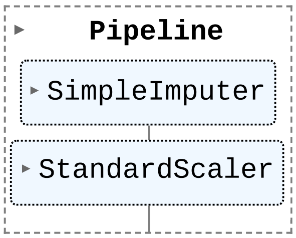
Out[75]:

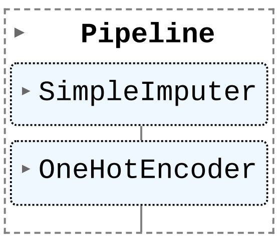
	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	3	male	22.0	1	0	7.2500	S
1	1	female	38.0	1	0	71.2833	C
2	3	female	26.0	0	0	7.9250	S
3	1	female	35.0	1	0	53.1000	S
4	3	male	35.0	0	0	8.0500	S
...	...	...	...	...	...	...	...
886	2	male	27.0	0	0	13.0000	S
887	1	female	19.0	0	0	30.0000	S
888	3	female	NaN	1	2	23.4500	S
889	1	male	26.0	0	0	30.0000	C
890	3	male	32.0	0	0	7.7500	Q

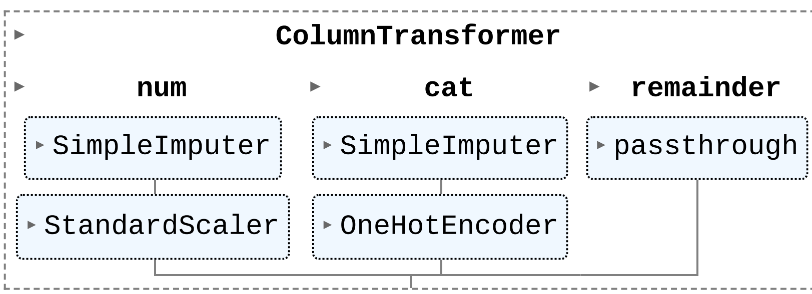
891 rows × 7 columns

In [76]:
```
#create a sep list of numerical and categorical features
num_features = ['Age', 'Fare']
cat_features = ['Sex', 'Embarked']

#creating a pipeline fro numerical features
num_pipeline = Pipeline(
    [
        ('si', SimpleImputer(strategy='mean')),
        ('sc', StandardScaler())
    ])

#creating a pipeline for categorical features
cat_pipeline = Pipeline(
```

```
    [
        ('si', SimpleImputer(strategy='most_frequent')),
        ('ohe', OneHotEncoder())
    ])

#merging both the pipelines using the column transformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', num_pipeline, num_features),
        ('cat', cat_pipeline, cat_features),
    ],
    remainder='passthrough'
)


#visualizing the pipelines created
display(num_pipeline, cat_pipeline, preprocessor)
```







In [77]:
```
pipeline = Pipeline(
    [
        ('preprocess', preprocessor),
        ('clf', RandomForestClassifier(random_state=0))
    ])
```

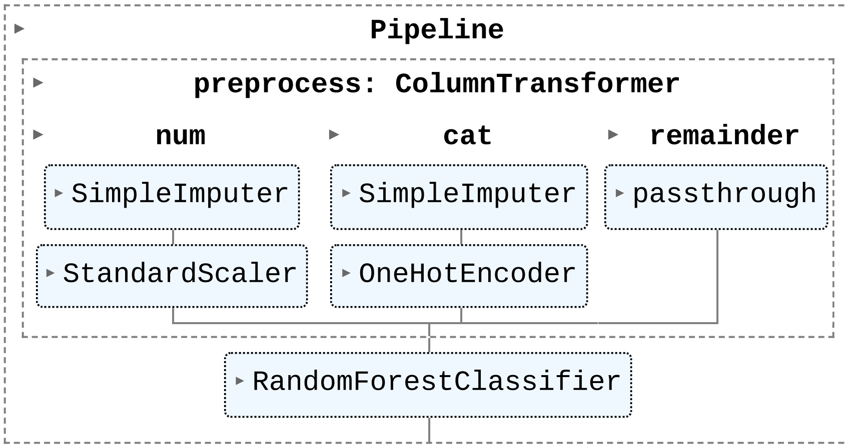
In [78]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_
```

In [79]:
```
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=0)
cross_val = cross_val_score(pipeline, X_train, y_train, cv=cv, scoring='accura

cross_val
```

Out[79]:
```
array([0.83216783, 0.8041958 , 0.85211268, 0.76760563, 0.8028169 ])
```

In [80]:
```
pipeline.fit(X_train, y_train)
```

Out[80]:



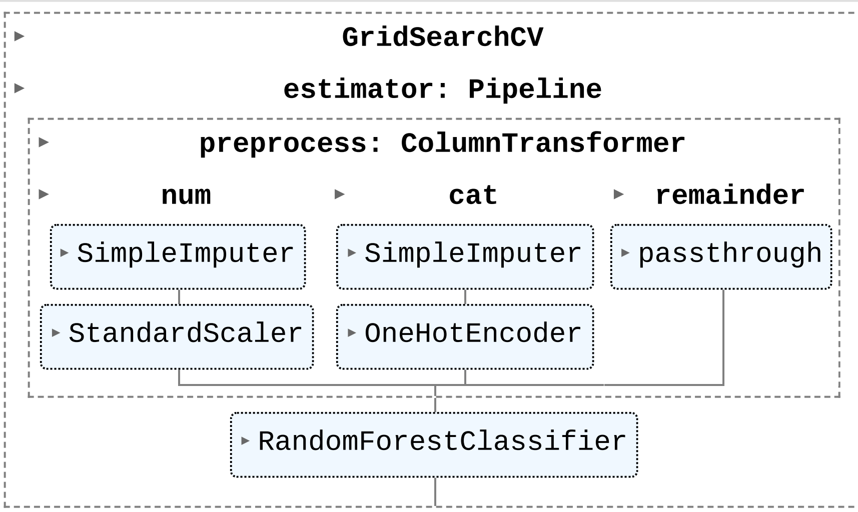
In [81]:
```
from sklearn.metrics import classification_report
```

In [82]:
```
y_pred = pipeline.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.93      0.88       110
           1       0.86      0.71      0.78        69

    accuracy                           0.84       179
   macro avg       0.85      0.82      0.83       179
weighted avg       0.85      0.84      0.84       179
```

In [83]:
```
param_grid = dict(
    clf__n_estimators = [60,80,120],
    clf__max_depth = [3,6,10],
    clf__criterion = ['gini', 'entropy']
)

grid_pipe = GridSearchCV(pipeline, param_grid)

grid_pipe.fit(X_train, y_train)
```

Out[83]:



In [84]:
```
print('Best params:',grid_pipe.best_params_)
print('Best Score:',grid_pipe.best_score_)
```

```
Best params: {'clf__criterion': 'entropy', 'clf__max_depth': 6, 'clf__n_estima
tors': 60}
Best Score: 0.8286417807544568
```

In [85]:
```
y_pred = grid_pipe.predict(X_test)
```

In [86]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.91      0.87       110
           1       0.83      0.70      0.76        69

    accuracy                           0.83       179
   macro avg       0.83      0.80      0.81       179
weighted avg       0.83      0.83      0.82       179
```

In [ ]: