```python
# Problem Statement - Given 'Cement', 'Blast Furnace Slag', 'Fly Ash', 
'Water', 'Superplasticizer','Coarse Aggregate', 'Fine Aggregate', 
'Age'
# estimate the 'Strength' of cement

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

data=pd.read_csv("concrete_data.csv")

data
```

```
      Cement  Blast Furnace Slag  Fly Ash  Water  Superplasticizer  \
0      540.0                 0.0      0.0  162.0               2.5   
1      540.0                 0.0      0.0  162.0               2.5   
2      332.5               142.5      0.0  228.0               0.0   
3      332.5               142.5      0.0  228.0               0.0   
4      198.6               132.4      0.0  192.0               0.0   
...      ...                 ...      ...    ...               ...   
1025   276.4               116.0     90.3  179.6               8.9   
1026   322.2                 0.0    115.6  196.0              10.4   
1027   148.5               139.4    108.6  192.7               6.1   
1028   159.1               186.7      0.0  175.6              11.3   
1029   260.9               100.5     78.3  200.6               8.6   

      Coarse Aggregate  Fine Aggregate  Age  Strength  
0               1040.0           676.0   28     79.99  
1               1055.0           676.0   28     61.89  
2                932.0           594.0  270     40.27  
3                932.0           594.0  365     41.05  
4                978.4           825.5  360     44.30  
...                ...             ...  ...       ...  
1025             870.1           768.3   28     44.28  
1026             817.9           813.4   28     31.18  
1027             892.4           780.0   28     23.70  
1028             989.6           788.9   28     32.77  
1029             864.5           761.5   28     32.40  

[1030 rows x 9 columns]
```

```python
data.describe()
```

```
            Cement  Blast Furnace Slag      Fly Ash        Water  \
count  1030.000000         1030.000000  1030.000000  1030.000000   
mean    281.167864           73.895825    54.188350   181.567282   
std     104.506364           86.279342    63.997004    21.354219   
min     102.000000            0.000000     0.000000   121.800000   
25%     192.375000            0.000000     0.000000   164.900000   
50%     272.900000           22.000000     0.000000   185.000000   
75%     350.000000          142.950000   118.300000   192.000000   
```

```
max     540.000000          359.400000   200.100000   247.000000

       Superplasticizer  Coarse Aggregate  Fine Aggregate          Age
\
count        1030.000000       1030.000000     1030.000000  1030.000000

mean            6.204660        972.918932      773.580485    45.662136

std             5.973841         77.753954       80.175980    63.169912

min             0.000000        801.000000      594.000000     1.000000

25%             0.000000        932.000000      730.950000     7.000000

50%             6.400000        968.000000      779.500000    28.000000

75%            10.200000       1029.400000      824.000000    56.000000

max            32.200000       1145.000000      992.600000   365.000000


          Strength
count  1030.000000
mean     35.817961
std      16.705742
min       2.330000
25%      23.710000
50%      34.445000
75%      46.135000
max      82.600000
```

```
data.isnull().sum()
```

```
Cement                0
Blast Furnace Slag    0
Fly Ash               0
Water                 0
Superplasticizer      0
Coarse Aggregate      0
Fine Aggregate        0
Age                   0
Strength              0
dtype: int64
```

```
data.columns
```

```
Index(['Cement', 'Blast Furnace Slag', 'Fly Ash', 'Water',
'Superplasticizer',
       'Coarse Aggregate', 'Fine Aggregate', 'Age', 'Strength'],
      dtype='object')
```

```
# strength --> dependent variable
Y=data.iloc[:,8]
Y
```

```
0       79.99
1       61.89
2       40.27
3       41.05
4       44.30
        ...
1025    44.28
1026    31.18
1027    23.70
1028    32.77
1029    32.40
Name: Strength, Length: 1030, dtype: float64
```

```
y=data.Strength
y
```

```
0       79.99
1       61.89
2       40.27
3       41.05
4       44.30
        ...
1025    44.28
1026    31.18
1027    23.70
1028    32.77
1029    32.40
Name: Strength, Length: 1030, dtype: float64
```

```
y=data["Strength"]
y
```

```
0       79.99
1       61.89
2       40.27
3       41.05
4       44.30
        ...
1025    44.28
1026    31.18
1027    23.70
1028    32.77
1029    32.40
Name: Strength, Length: 1030, dtype: float64
```

```
# Independent variable
X=data.iloc[:,0:8]
X
```

```
      Cement  Blast Furnace Slag  Fly Ash  Water  Superplasticizer  \
0      540.0                 0.0      0.0  162.0               2.5
1      540.0                 0.0      0.0  162.0               2.5
2      332.5               142.5      0.0  228.0               0.0
3      332.5               142.5      0.0  228.0               0.0
4      198.6               132.4      0.0  192.0               0.0
...      ...                 ...      ...    ...               ...
1025   276.4               116.0     90.3  179.6               8.9
1026   322.2                 0.0    115.6  196.0              10.4
1027   148.5               139.4    108.6  192.7               6.1
1028   159.1               186.7      0.0  175.6              11.3
1029   260.9               100.5     78.3  200.6               8.6

      Coarse Aggregate  Fine Aggregate  Age
0               1040.0           676.0   28
1               1055.0           676.0   28
2                932.0           594.0  270
3                932.0           594.0  365
4                978.4           825.5  360
...                ...             ...  ...
1025             870.1           768.3   28
1026             817.9           813.4   28
1027             892.4           780.0   28
1028             989.6           788.9   28
1029             864.5           761.5   28

[1030 rows x 8 columns]
```

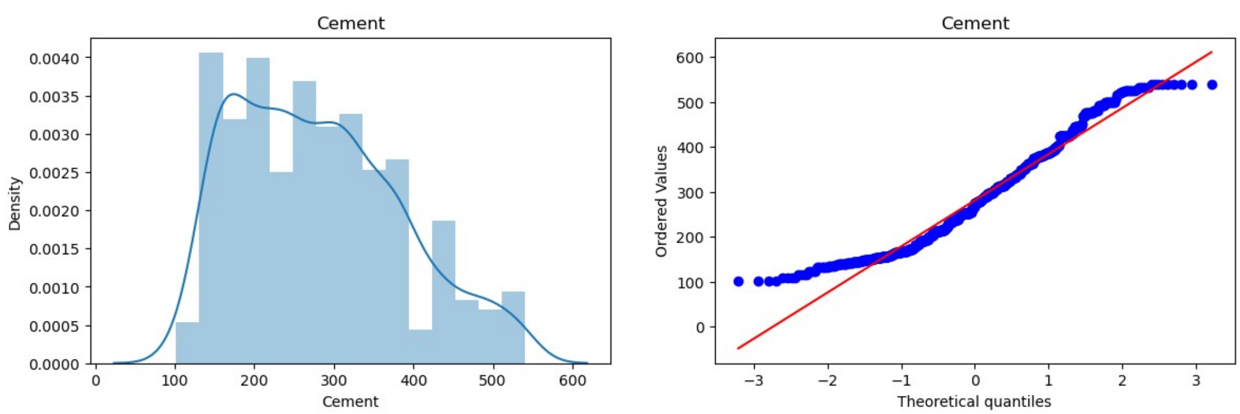
```
X=data.drop(columns=["Strength"])
X.columns
```

```
Index(['Cement', 'Blast Furnace Slag', 'Fly Ash', 'Water',
'Superplasticizer',
       'Coarse Aggregate', 'Fine Aggregate', 'Age'],
      dtype='object')
```

```
# split it into train and test -->

# Graph of columns

import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats

for col in X.columns:
    plt.figure(figsize=(14,4))
    plt.subplot(121)
```

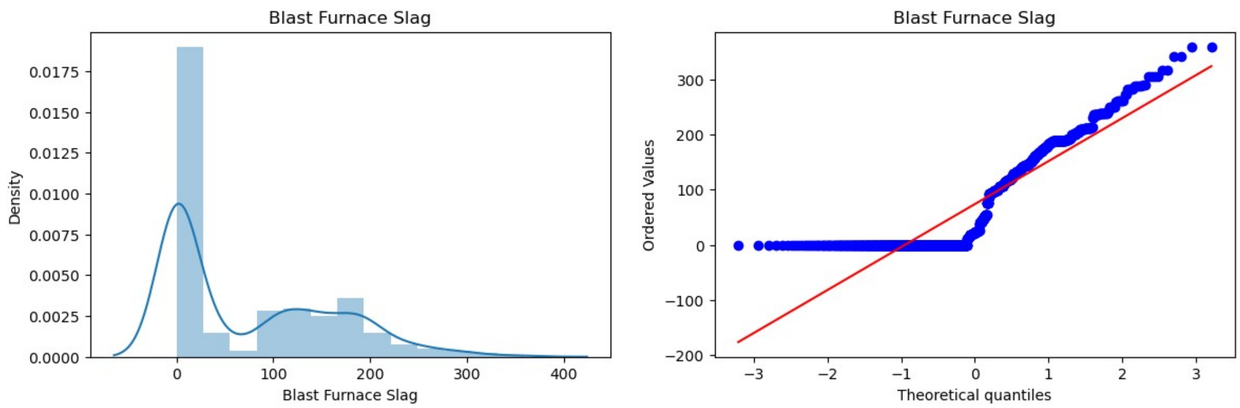
```
    sns.distplot(X[col])
    plt.title(col)

    plt.subplot(122)
    stats.probplot(X[col],dist="norm",plot=plt)
    plt.title(col)

    plt.show()
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4058884031.py:12: 
UserWarning: 

`distplot` is a deprecated function and will be removed in seaborn 
v0.14.0.

Please adapt your code to use either `displot` (a figure-level 
function with
similar flexibility) or `histplot` (an axes-level function for 
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X[col])
```

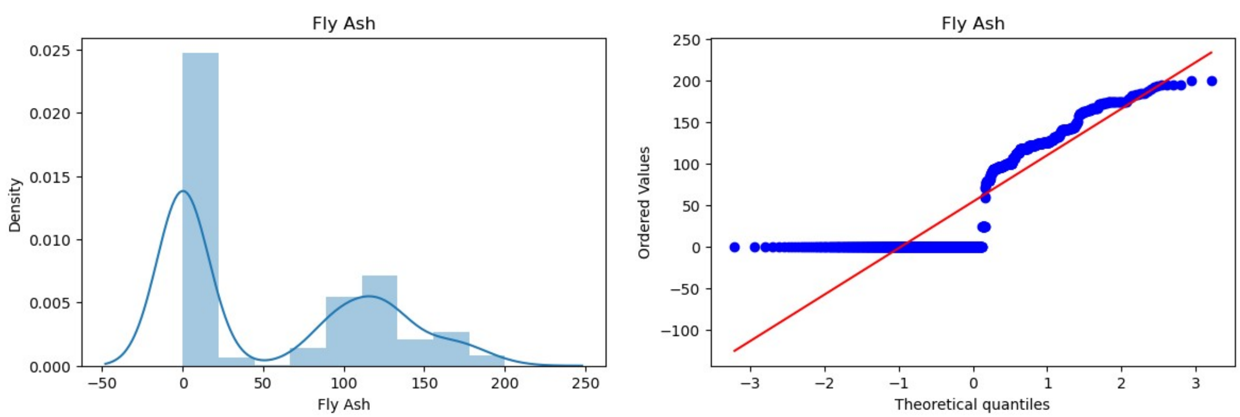



```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4058884031.py:12: 
UserWarning: 

`distplot` is a deprecated function and will be removed in seaborn 
v0.14.0.

Please adapt your code to use either `displot` (a figure-level 
function with
similar flexibility) or `histplot` (an axes-level function for 
histograms).

For a guide to updating your code to use the new functions, please see
```

```
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X[col])
```

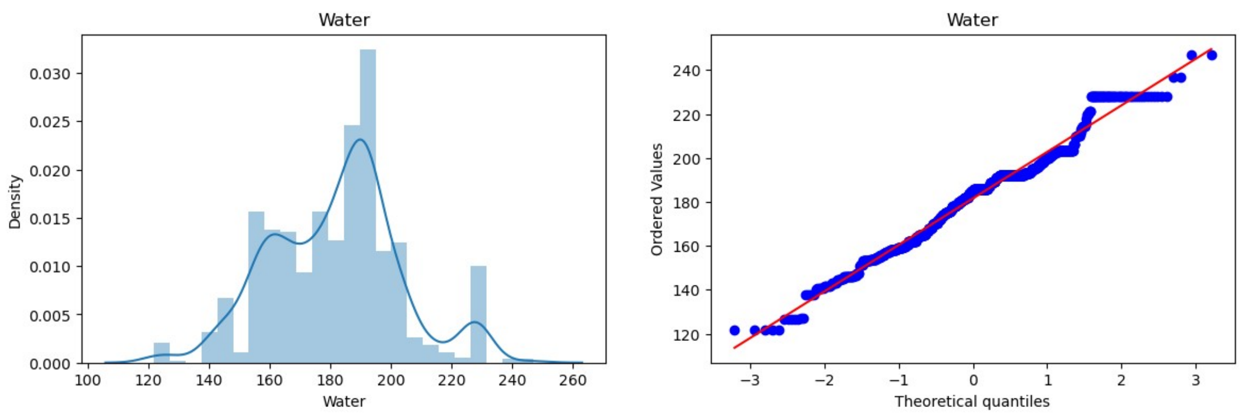



```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4058884031.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X[col])
```

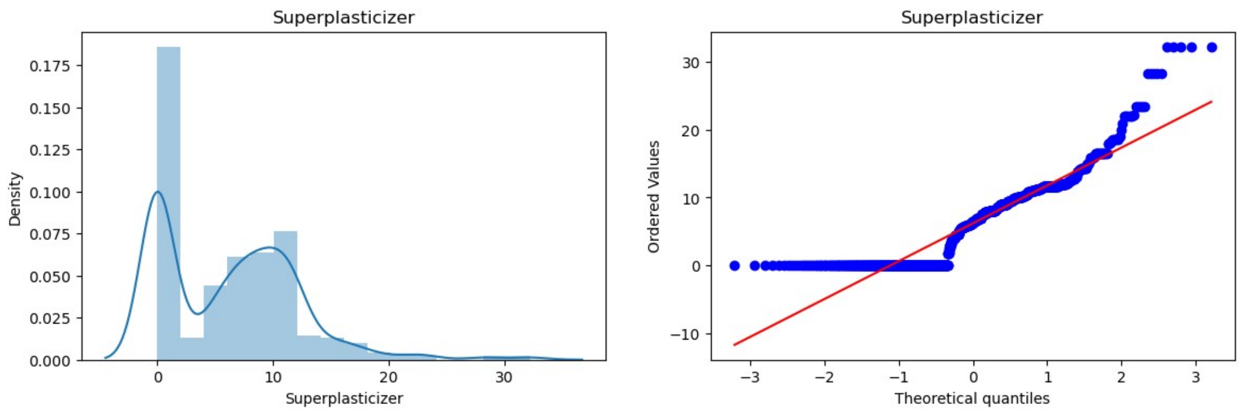



```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4058884031.py:12:
UserWarning:
```

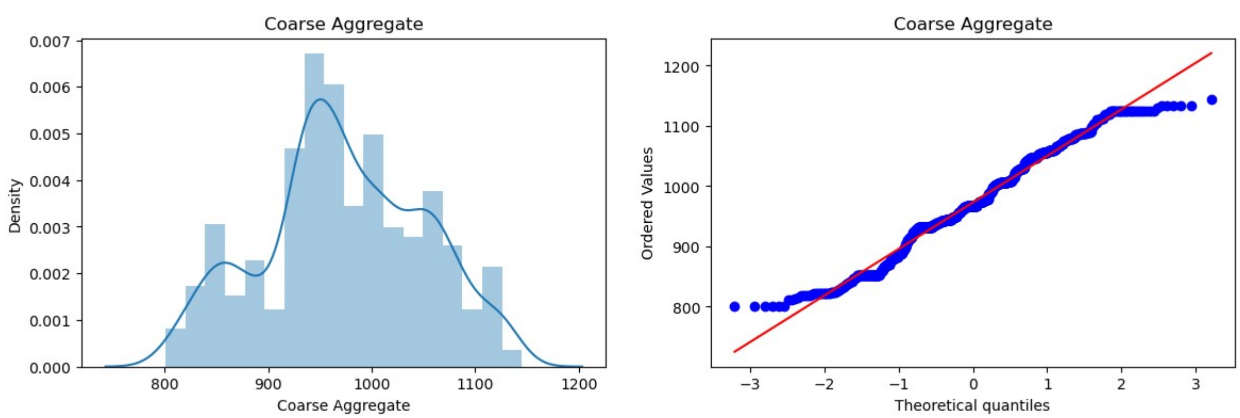
```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X[col])
```




```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4058884031.py:12: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X[col])
```

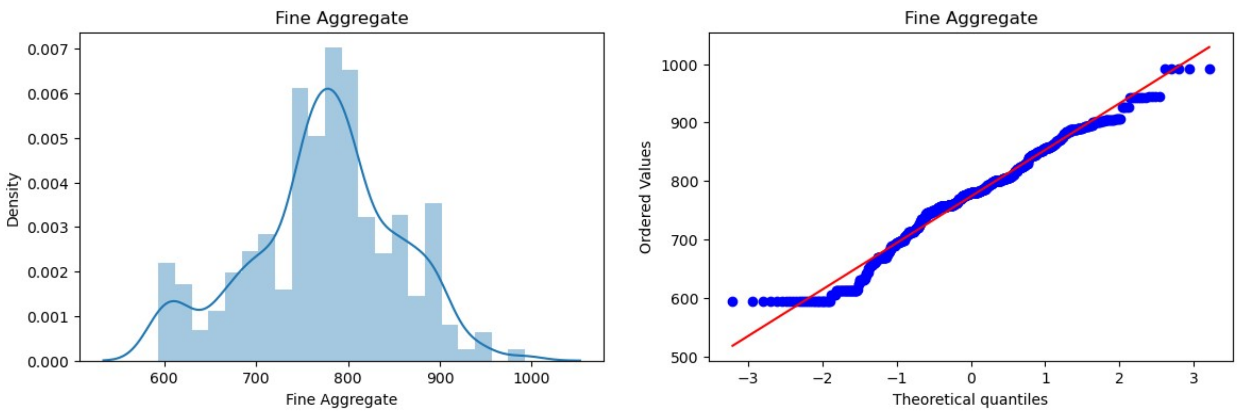



```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4058884031.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X[col])
```

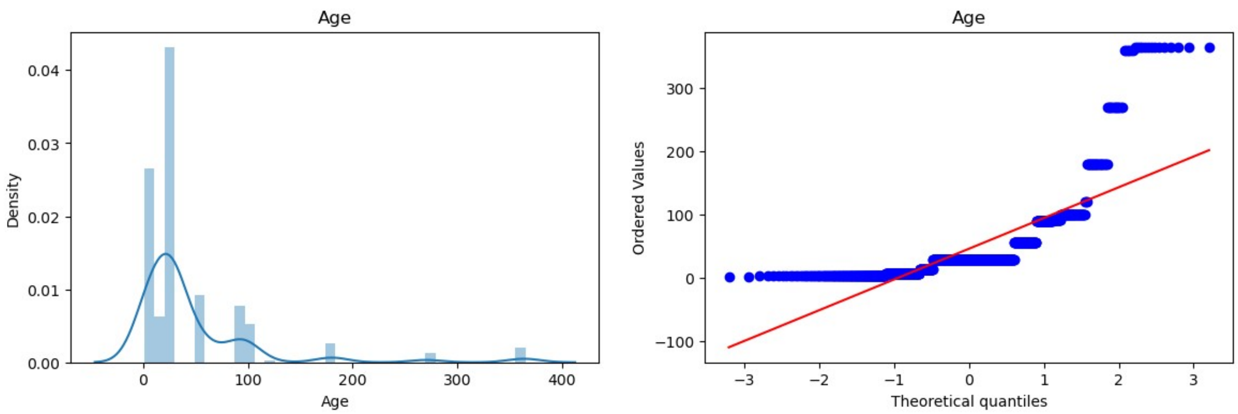



```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4058884031.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
```

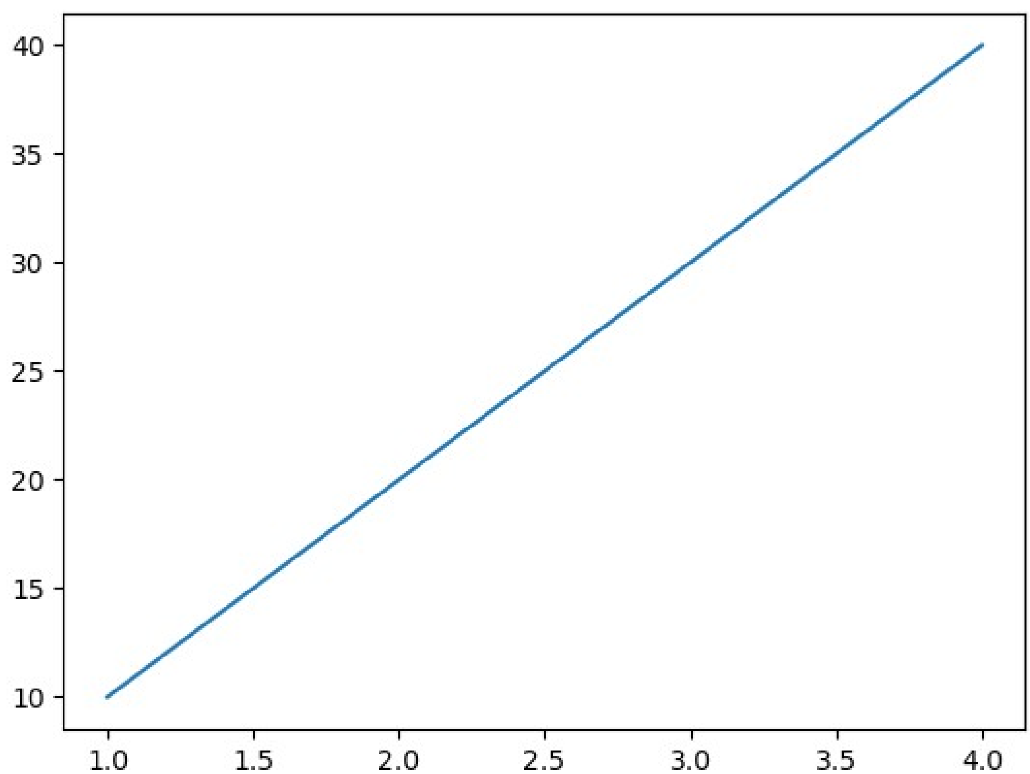
```
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X[col])
```




```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4058884031.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(X[col])
```




```
x=[1,2,3,4]
y=[10,20,30,40]

plt.plot(x,y)
plt.show()
```



Normalization

Normalization is a method of scaling data so that all of the features have a range of 0 to 1. This can be done by subtracting the minimum value of each feature from each value and then dividing by the difference between the minimum and maximum values of that feature. Normalization makes it easier for machine learning algorithms to learn the relationships between the different features in a dataset. This can lead to improved accuracy of the machine learning model.

```
import sklearn
from sklearn.preprocessing import MinMaxScaler# normalization

norm=MinMaxScaler()
scaled_data=norm.fit_transform(data)
scaled_data
```

```
array([[1.        , 0.        , 0.        , ..., 0.20572002,
0.07417582,
        0.96748474],
       [1.        , 0.        , 0.        , ..., 0.20572002,
0.07417582,
        0.74199576],
       [0.52625571, 0.39649416, 0.        , ..., 0.        ,
0.73901099,
        0.47265479],
       ...,
       [0.10616438, 0.38786867, 0.54272864, ..., 0.46663322,
0.07417582,
        0.26622649],
       [0.1303653 , 0.51947691, 0.        , ..., 0.48896136,
0.07417582,
        0.37922013],
       [0.36278539, 0.27963272, 0.39130435, ..., 0.42022077,
0.07417582,
        0.37461069]])
```

```
print(len(scaled_data))
```

```
1030
```

```
print(scaled_data[0])
```

```
[1.         0.         0.         0.32108626 0.07763975 0.69476744
 0.20572002 0.07417582 0.96748474]
```

```
data.iloc[0,:]
```

```
Cement                  540.00
Blast Furnace Slag        0.00
Fly Ash                   0.00
Water                   162.00
Superplasticizer          2.50
Coarse Aggregate       1040.00
Fine Aggregate          676.00
Age                      28.00
```

```
Strength                      79.99
Name: 0, dtype: float64
```

```
data.head()
```

```
   Cement  Blast Furnace Slag  Fly Ash  Water  Superplasticizer  \
0   540.0                 0.0      0.0  162.0               2.5
1   540.0                 0.0      0.0  162.0               2.5
2   332.5               142.5      0.0  228.0               0.0
3   332.5               142.5      0.0  228.0               0.0
4   198.6               132.4      0.0  192.0               0.0

   Coarse Aggregate  Fine Aggregate  Age  Strength
0            1040.0           676.0   28     79.99
1            1055.0           676.0   28     61.89
2             932.0           594.0  270     40.27
3             932.0           594.0  365     41.05
4             978.4           825.5  360     44.30
```

```
data.describe()
```

```
            Cement  Blast Furnace Slag      Fly Ash        Water  \
count  1030.000000         1030.000000  1030.000000  1030.000000
mean    281.167864           73.895825    54.188350   181.567282
std     104.506364           86.279342    63.997004    21.354219
min     102.000000            0.000000     0.000000   121.800000
25%     192.375000            0.000000     0.000000   164.900000
50%     272.900000           22.000000     0.000000   185.000000
75%     350.000000          142.950000   118.300000   192.000000
max     540.000000          359.400000   200.100000   247.000000

       Superplasticizer  Coarse Aggregate  Fine Aggregate          Age
\
count       1030.000000       1030.000000     1030.000000  1030.000000

mean           6.204660        972.918932      773.580485    45.662136

std            5.973841         77.753954       80.175980    63.169912

min            0.000000        801.000000      594.000000     1.000000

25%            0.000000        932.000000      730.950000     7.000000

50%            6.400000        968.000000      779.500000    28.000000

75%           10.200000       1029.400000      824.000000    56.000000

max           32.200000       1145.000000      992.600000   365.000000


          Strength
```

```
count  1030.000000
mean     35.817961
std      16.705742
min       2.330000
25%      23.710000
50%      34.445000
75%      46.135000
max      82.600000
```

```
scaled_data.shape
```

```
(1030, 9)
```

```
data.shape
```

```
(1030, 9)
```

```
help(MinMaxScaler)
```

```
Help on class MinMaxScaler in module sklearn.preprocessing._data:

class MinMaxScaler(sklearn.base.OneToOneFeatureMixin,
sklearn.base.TransformerMixin, sklearn.base.BaseEstimator)
 |  MinMaxScaler(feature_range=(0, 1), *, copy=True, clip=False)
 |
 |  Transform features by scaling each feature to a given range.
 |
 |  This estimator scales and translates each feature individually
such
 |  that it is in the given range on the training set, e.g. between
 |  zero and one.
 |
 |  The transformation is given by::
 |
 |      X_std = (X - X.min(axis=0)) / (X.max(axis=0) - X.min(axis=0))
 |      X_scaled = X_std * (max - min) + min
 |
 |  where min, max = feature_range.
 |
 |  This transformation is often used as an alternative to zero mean,
 |  unit variance scaling.
 |
 |  Read more in the :ref:`User Guide <preprocessing_scaler>`.
 |
 |  Parameters
 |  ----------
 |  feature_range : tuple (min, max), default=(0, 1)
 |      Desired range of transformed data.
 |
 |  copy : bool, default=True
 |      Set to False to perform inplace row normalization and avoid a
```

```
 |      copy (if the input is already a numpy array).
 |
 |  clip : bool, default=False
 |      Set to True to clip transformed values of held-out data to
 |      provided `feature range`.
 |
 |      .. versionadded:: 0.24
 |
 |  Attributes
 |  ----------
 |  min_ : ndarray of shape (n_features,)
 |      Per feature adjustment for minimum. Equivalent to
 |      ``min - X.min(axis=0) * self.scale_``
 |
 |  scale_ : ndarray of shape (n_features,)
 |      Per feature relative scaling of the data. Equivalent to
 |      ``(max - min) / (X.max(axis=0) - X.min(axis=0))``
 |
 |      .. versionadded:: 0.17
 |         *scale_* attribute.
 |
 |  data_min_ : ndarray of shape (n_features,)
 |      Per feature minimum seen in the data
 |
 |      .. versionadded:: 0.17
 |         *data_min_*
 |
 |  data_max_ : ndarray of shape (n_features,)
 |      Per feature maximum seen in the data
 |
 |      .. versionadded:: 0.17
 |         *data_max_*
 |
 |  data_range_ : ndarray of shape (n_features,)
 |      Per feature range ``(data_max_ - data_min_)`` seen in the data
 |
 |      .. versionadded:: 0.17
 |         *data_range_*
 |
 |  n_features_in_ : int
 |      Number of features seen during :term:`fit`.
 |
 |      .. versionadded:: 0.24
 |
 |  n_samples_seen_ : int
 |      The number of samples processed by the estimator.
 |      It will be reset on new calls to fit, but increments across
 |      ``partial_fit`` calls.
 |
```

```
 |  feature_names_in_ : ndarray of shape (`n_features_in_`,)
 |      Names of features seen during :term:`fit`. Defined only when
`X`
 |      has feature names that are all strings.
 |
 |      .. versionadded:: 1.0
 |
 |  See Also
 |  --------
 |  minmax_scale : Equivalent function without the estimator API.
 |
 |  Notes
 |  -----
 |  NaNs are treated as missing values: disregarded in fit, and
maintained in
 |  transform.
 |
 |  For a comparison of the different scalers, transformers, and
normalizers,
 |  see :ref:`examples/preprocessing/plot_all_scaling.py
 |  <sphx_glr_auto_examples_preprocessing_plot_all_scaling.py>`.
 |
 |  Examples
 |  --------
 |  >>> from sklearn.preprocessing import MinMaxScaler
 |  >>> data = [[-1, 2], [-0.5, 6], [0, 10], [1, 18]]
 |  >>> scaler = MinMaxScaler()
 |  >>> print(scaler.fit(data))
 |  MinMaxScaler()
 |  >>> print(scaler.data_max_)
 |  [ 1. 18.]
 |  >>> print(scaler.transform(data))
 |  [[0.   0.  ]
 |   [0.25 0.25]
 |   [0.5  0.5 ]
 |   [1.   1.  ]]
 |  >>> print(scaler.transform([[2, 2]]))
 |  [[1.5 0. ]]
 |
 |  Method resolution order:
 |      MinMaxScaler
 |      sklearn.base.OneToOneFeatureMixin
 |      sklearn.base.TransformerMixin
 |      sklearn.utils._set_output._SetOutputMixin
 |      sklearn.base.BaseEstimator
 |      sklearn.utils._metadata_requests._MetadataRequester
 |      builtins.object
 |
 |  Methods defined here:
```

```
 |
 |  __init__(self, feature_range=(0, 1), *, copy=True, clip=False)
 |      Initialize self.  See help(type(self)) for accurate signature.
 |
 |  fit(self, X, y=None)
 |      Compute the minimum and maximum to be used for later scaling.
 |
 |      Parameters
 |      ----------
 |      X : array-like of shape (n_samples, n_features)
 |          The data used to compute the per-feature minimum and
maximum
 |          used for later scaling along the features axis.
 |
 |      y : None
 |          Ignored.
 |
 |      Returns
 |      -------
 |      self : object
 |          Fitted scaler.
 |
 |  inverse_transform(self, X)
 |      Undo the scaling of X according to feature_range.
 |
 |      Parameters
 |      ----------
 |      X : array-like of shape (n_samples, n_features)
 |          Input data that will be transformed. It cannot be sparse.
 |
 |      Returns
 |      -------
 |      Xt : ndarray of shape (n_samples, n_features)
 |          Transformed data.
 |
 |  partial_fit(self, X, y=None)
 |      Online computation of min and max on X for later scaling.
 |
 |      All of X is processed as a single batch. This is intended for
cases
 |      when :meth:`fit` is not feasible due to very large number of
 |      `n_samples` or because X is read from a continuous stream.
 |
 |      Parameters
 |      ----------
 |      X : array-like of shape (n_samples, n_features)
 |          The data used to compute the mean and standard deviation
 |          used for later scaling along the features axis.
 |
```

```
 |      y : None
 |          Ignored.
 |
 |      Returns
 |      -------
 |      self : object
 |          Fitted scaler.
 |
 |  transform(self, X)
 |      Scale features of X according to feature_range.
 |
 |      Parameters
 |      ----------
 |      X : array-like of shape (n_samples, n_features)
 |          Input data that will be transformed.
 |
 |      Returns
 |      -------
 |      Xt : ndarray of shape (n_samples, n_features)
 |          Transformed data.
 |
 |
----------------------------------------------------------------------
 |  Data and other attributes defined here:
 |
 |  __annotations__ = {'_parameter_constraints': <class 'dict'>}
 |
 |
----------------------------------------------------------------------
 |  Methods inherited from sklearn.base.OneToOneFeatureMixin:
 |
 |  get_feature_names_out(self, input_features=None)
 |      Get output feature names for transformation.
 |
 |      Parameters
 |      ----------
 |      input_features : array-like of str or None, default=None
 |          Input features.
 |
 |          - If `input_features` is `None`, then `feature_names_in_`
is
 |            used as feature names in. If `feature_names_in_` is not
defined,
 |            then the following input feature names are generated:
 |            `["x0", "x1", ..., "x(n_features_in_ - 1)"]`.
 |          - If `input_features` is an array-like, then
`input_features` must
 |            match `feature_names_in_` if `feature_names_in_` is
defined.
```

```
 |
 |      Returns
 |      -------
 |      feature_names_out : ndarray of str objects
 |          Same as input features.
 |
 |
----------------------------------------------------------------------
 |  Data descriptors inherited from sklearn.base.OneToOneFeatureMixin:
 |
 |  __dict__
 |      dictionary for instance variables (if defined)
 |
 |  __weakref__
 |      list of weak references to the object (if defined)
 |
 |
----------------------------------------------------------------------
 |  Methods inherited from sklearn.base.TransformerMixin:
 |
 |  fit_transform(self, X, y=None, **fit_params)
 |      Fit to data, then transform it.
 |
 |      Fits transformer to `X` and `y` with optional parameters
`fit_params`
 |      and returns a transformed version of `X`.
 |
 |      Parameters
 |      ----------
 |      X : array-like of shape (n_samples, n_features)
 |          Input samples.
 |
 |      y :  array-like of shape (n_samples,) or (n_samples,
n_outputs),                default=None
 |          Target values (None for unsupervised transformations).
 |
 |      **fit_params : dict
 |          Additional fit parameters.
 |
 |      Returns
 |      -------
 |      X_new : ndarray array of shape (n_samples, n_features_new)
 |          Transformed array.
 |
 |
----------------------------------------------------------------------
 |  Methods inherited from sklearn.utils._set_output._SetOutputMixin:
 |
 |  set_output(self, *, transform=None)
```

```
 |      Set output container.
 |
 |
See :ref:`sphx_glr_auto_examples_miscellaneous_plot_set_output.py`
 |      for an example on how to use the API.
 |
 |      Parameters
 |      ----------
 |      transform : {"default", "pandas"}, default=None
 |          Configure output of `transform` and `fit_transform`.
 |
 |          - `"default"`: Default output format of a transformer
 |          - `"pandas"`: DataFrame output
 |          - `None`: Transform configuration is unchanged
 |
 |      Returns
 |      -------
 |      self : estimator instance
 |          Estimator instance.
 |
 |
----------------------------------------------------------------------
 |  Class methods inherited from
sklearn.utils._set_output._SetOutputMixin:
 |
 |  __init_subclass__(auto_wrap_output_keys=('transform',), **kwargs)
from builtins.type
 |      This method is called when a class is subclassed.
 |
 |      The default implementation does nothing. It may be
 |      overridden to extend subclasses.
 |
 |
----------------------------------------------------------------------
 |  Methods inherited from sklearn.base.BaseEstimator:
 |
 |  __getstate__(self)
 |      Helper for pickle.
 |
 |  __repr__(self, N_CHAR_MAX=700)
 |      Return repr(self).
 |
 |  __setstate__(self, state)
 |
 |  __sklearn_clone__(self)
 |
 |  get_params(self, deep=True)
 |      Get parameters for this estimator.
 |
```

```
 |      Parameters
 |      ----------
 |      deep : bool, default=True
 |          If True, will return the parameters for this estimator and
 |          contained subobjects that are estimators.
 |
 |      Returns
 |      -------
 |      params : dict
 |          Parameter names mapped to their values.
 |
 |  set_params(self, **params)
 |      Set the parameters of this estimator.
 |
 |      The method works on simple estimators as well as on nested
objects
 |      (such as :class:`~sklearn.pipeline.Pipeline`). The latter have
 |      parameters of the form ``<component>__<parameter>`` so that
it's
 |      possible to update each component of a nested object.
 |
 |      Parameters
 |      ----------
 |      **params : dict
 |          Estimator parameters.
 |
 |      Returns
 |      -------
 |      self : estimator instance
 |          Estimator instance.
 |
 |
----------------------------------------------------------------------
 |  Methods inherited from
sklearn.utils._metadata_requests._MetadataRequester:
 |
 |  get_metadata_routing(self)
 |      Get metadata routing of this object.
 |
 |      Please check :ref:`User Guide <metadata_routing>` on how the
routing
 |      mechanism works.
 |
 |      Returns
 |      -------
 |      routing : MetadataRequest
 |          A :class:`~utils.metadata_routing.MetadataRequest`
encapsulating
```

```
 |          routing information.
```

Standarization

Standardization is a method of scaling data so that all of the features have a mean of 0 and a standard deviation of 1. This can be done by subtracting the mean of each feature from each value and then dividing by the standard deviation of that feature. Standardization makes it easier for machine learning algorithms to learn the relationships between the different features in a dataset.

```
# mean = 0 , std = 1

data

      Cement  Blast Furnace Slag  Fly Ash  Water  Superplasticizer  \
0      540.0                 0.0      0.0  162.0               2.5
1      540.0                 0.0      0.0  162.0               2.5
2      332.5               142.5      0.0  228.0               0.0
3      332.5               142.5      0.0  228.0               0.0
4      198.6               132.4      0.0  192.0               0.0
...      ...                 ...      ...    ...               ...
1025   276.4               116.0     90.3  179.6               8.9
1026   322.2                 0.0    115.6  196.0              10.4
1027   148.5               139.4    108.6  192.7               6.1
1028   159.1               186.7      0.0  175.6              11.3
1029   260.9               100.5     78.3  200.6               8.6

      Coarse Aggregate  Fine Aggregate  Age  Strength
0               1040.0           676.0   28     79.99
1               1055.0           676.0   28     61.89
2                932.0           594.0  270     40.27
3                932.0           594.0  365     41.05
4                978.4           825.5  360     44.30
...                ...             ...  ...       ...
1025             870.1           768.3   28     44.28
1026             817.9           813.4   28     31.18
1027             892.4           780.0   28     23.70
1028             989.6           788.9   28     32.77
1029             864.5           761.5   28     32.40

[1030 rows x 9 columns]

import sklearn
from sklearn.preprocessing import StandardScaler
```

```
scaler=StandardScaler()
standarize_data=scaler.fit_transform(data)
standarize_data
```

```
array([[ 2.47791487, -0.85688789, -0.84714393, ..., -1.21767004,
        -0.27973311,  2.64540763],
       [ 2.47791487, -0.85688789, -0.84714393, ..., -1.21767004,
        -0.27973311,  1.56142148],
       [ 0.49142531,  0.79552649, -0.84714393, ..., -2.24091709,
         3.55306569,  0.26662698],
       ...,
       [-1.27008832,  0.75957923,  0.85063487, ...,  0.0801067 ,
        -0.27973311, -0.72572939],
       [-1.16860982,  1.30806485, -0.84714393, ...,  0.19116644,
        -0.27973311, -0.18253855],
       [-0.19403325,  0.30849909,  0.3769452 , ..., -0.15074782,
        -0.27973311, -0.20469738]])
```

```
col = ['Cement', 'Blast Furnace Slag', 'Fly Ash', 'Water',
'Superplasticizer','Coarse Aggregate', 'Fine Aggregate', 'Age',
'Strength']
```

```
new_data=pd.DataFrame(standarize_data,columns=col)
```

```
new_data
```

```
        Cement  Blast Furnace Slag   Fly Ash     Water
Superplasticizer  \
0     2.477915           -0.856888 -0.847144 -0.916764         -
0.620448
1     2.477915           -0.856888 -0.847144 -0.916764         -
0.620448
2     0.491425            0.795526 -0.847144  2.175461         -
1.039143
3     0.491425            0.795526 -0.847144  2.175461         -
1.039143
4    -0.790459            0.678408 -0.847144  0.488793         -
1.039143
...        ...                 ...       ...       ...               .
..
1025 -0.045645            0.488235  0.564545 -0.092171
0.451410
1026  0.392819           -0.856888  0.960068  0.676200
0.702626
1027 -1.270088            0.759579  0.850635  0.521589         -
0.017528
1028 -1.168610            1.308065 -0.847144 -0.279579
0.853356
1029 -0.194033            0.308499  0.376945  0.891719
0.401166
```

```
      Coarse Aggregate  Fine Aggregate       Age  Strength
0             0.863154       -1.217670 -0.279733  2.645408
1             1.056164       -1.217670 -0.279733  1.561421
2            -0.526517       -2.240917  3.553066  0.266627
3            -0.526517       -2.240917  5.057677  0.313340
4             0.070527        0.647884  4.978487  0.507979
...                ...             ...       ...       ...
1025         -1.323005       -0.065893 -0.279733  0.506781
1026         -1.994680        0.496893 -0.279733 -0.277762
1027         -1.036064        0.080107 -0.279733 -0.725729
1028          0.214641        0.191166 -0.279733 -0.182539
1029         -1.395062       -0.150748 -0.279733 -0.204697

[1030 rows x 9 columns]
```

```
new_data.describe()
```

```
             Cement  Blast Furnace Slag       Fly Ash         Water  \
count  1.030000e+03        1.030000e+03  1.030000e+03  1.030000e+03
mean  -4.552992e-16       -1.241725e-16 -5.518779e-17 -1.655634e-16
std    1.000486e+00        1.000486e+00  1.000486e+00  1.000486e+00
min   -1.715253e+00       -8.568879e-01 -8.471439e-01 -2.800211e+00
25%   -8.500535e-01       -8.568879e-01 -8.471439e-01 -7.808939e-01
50%   -7.915193e-02       -6.017783e-01 -8.471439e-01  1.608294e-01
75%    6.589606e-01        8.007446e-01  1.002278e+00  4.887927e-01
max    2.477915e+00        3.310675e+00  2.281084e+00  3.065647e+00

       Superplasticizer  Coarse Aggregate  Fine Aggregate
Age  \
count      1.030000e+03      1.030000e+03    1.030000e+03
1.030000e+03
mean      -8.278168e-17      6.760504e-16   -4.759946e-16  2.069542e-
17
std        1.000486e+00      1.000486e+00    1.000486e+00
1.000486e+00
min       -1.039143e+00     -2.212138e+00   -2.240917e+00 -7.073594e-
01
25%       -1.039143e+00     -5.265174e-01   -5.319697e-01 -6.123314e-
01
50%        3.271508e-02     -6.329352e-02    7.386739e-02 -2.797331e-
01
75%        6.691307e-01      7.267605e-01    6.291661e-01  1.637312e-
01
max        4.353642e+00      2.214224e+00    2.733062e+00
5.057677e+00

           Strength
count  1.030000e+03
mean  -2.759389e-17
```

```
std     1.000486e+00
min    -2.005552e+00
25%    -7.251305e-01
50%    -8.222491e-02
75%     6.178744e-01
max     2.801717e+00

# split it into train and test -->

# Graph of columns

import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats

for col in new_data.columns:
    plt.figure(figsize=(14,4))
    plt.subplot(121)
    sns.distplot(new_data[col])
    plt.title(col)

    plt.subplot(122)
    stats.probplot(new_data[col],dist='norm',plot=plt)
    plt.title(col)
    plt.show()
```

Power Transformation

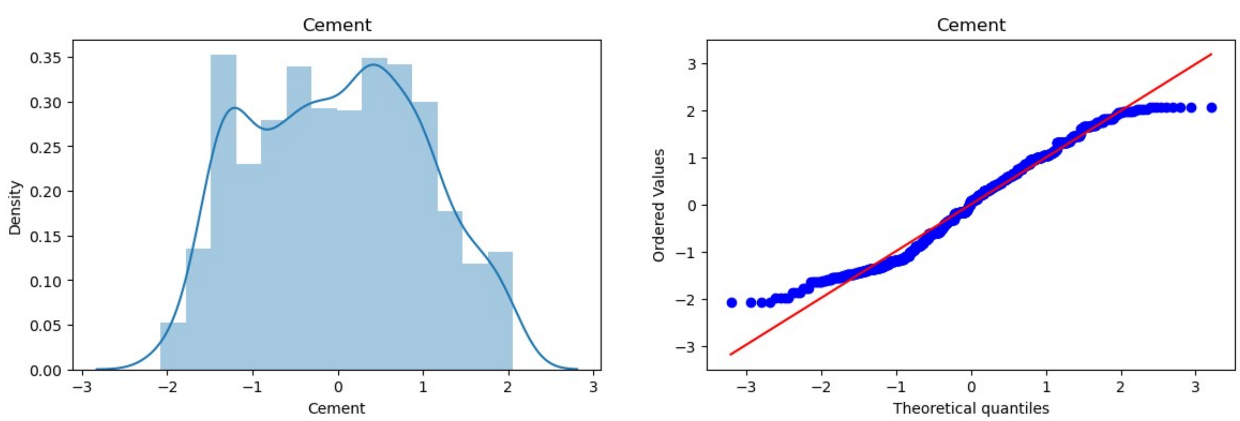
One way to deal with non-normally distributed data is to use a transformation, such as the Box-Cox transformation and .shift method. The Box-Cox transformation can transform the data so that it is more normally distributed. This can help the machine learning model to learn the relationships between the features more accurately.

```
# Convert non-gaussian dist --> gaussian/normal dist --> model will
work best

from sklearn.preprocessing import PowerTransformer

pt=PowerTransformer()
transformed_data=pt.fit_transform(new_data)
transformed_data

array([[ 2.05650838, -0.95205192, -0.87967207, ..., -1.19614697,
         0.00950547,  2.27730841],
       [ 2.05650838, -0.95205192, -0.87967207, ..., -1.19614697,
         0.00950547,  1.46684657],
       [ 0.6039513 ,  0.99819281, -0.87967207, ..., -2.07733536,
         2.03309437,  0.35789695],
```

```
       ...,
       [-1.42533686,  0.97522582,  1.00074512, ...,  0.02678941,
         0.00950547, -0.70199526],
       [-1.28368984,  1.28616188, -0.87967207, ...,  0.14061271,
         0.00950547, -0.09315573],
       [-0.06624139,  0.64264306,  0.66275592, ..., -0.20402303,
         0.00950547, -0.11672768]])

transformed_df=pd.DataFrame(transformed_data,columns=data.columns)
transformed_df

        Cement  Blast Furnace Slag   Fly Ash     Water
Superplasticizer  \
0     2.056508           -0.952052 -0.879672 -0.916616          -
0.566981
1     2.056508           -0.952052 -0.879672 -0.916616          -
0.566981
2     0.603951            0.998193 -0.879672  2.155435          -
1.154810
3     0.603951            0.998193 -0.879672  2.155435          -
1.154810
4    -0.778911            0.921720 -0.879672  0.493335          -
1.154810
...        ...                 ...       ...       ...               .
..
1025  0.092621            0.786298  0.806677 -0.085948
0.604129
1026  0.516259           -0.952052  1.068425  0.679235
0.815850
1027 -1.425337            0.975226  1.000745  0.525897
0.154557
1028 -1.283690            1.286162 -0.879672 -0.273966
0.935670
1029 -0.066241            0.642643  0.662756  0.892557
0.559712

      Coarse Aggregate  Fine Aggregate       Age  Strength
0             0.862194       -1.196147  0.009505  2.277308
1             1.057562       -1.196147  0.009505  1.466847
2            -0.530827       -2.077335  2.033094  0.357897
3            -0.530827       -2.077335  2.141250  0.402112
4             0.064198        0.624899  2.136860  0.581981
...                ...             ...       ...       ...
1025         -1.318224       -0.120092  0.009505  0.580894
1026         -1.978349        0.462154  0.009505 -0.195276
1027         -1.035222        0.026789  0.009505 -0.701995
1028          0.208671        0.140613  0.009505 -0.093156
1029         -1.389191       -0.204023  0.009505 -0.116728

[1030 rows x 9 columns]
```

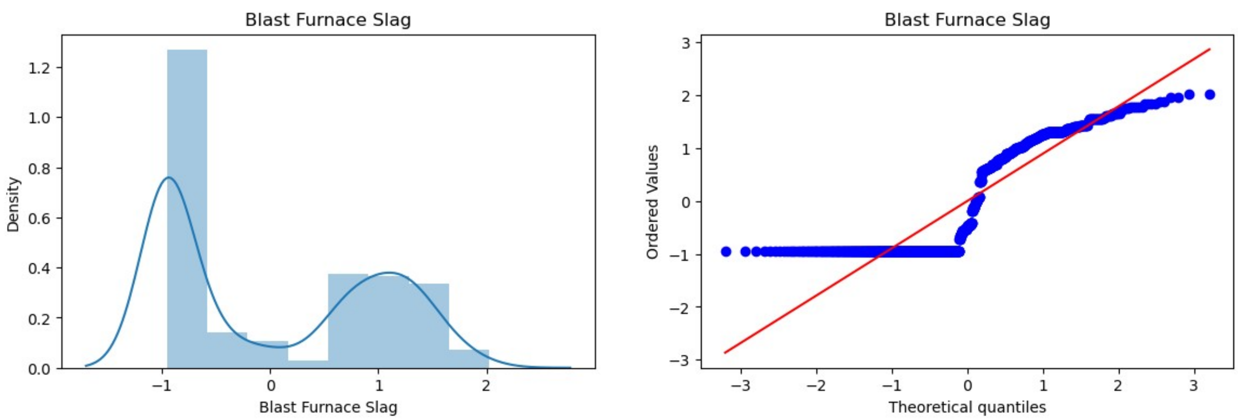
```
# split it into train and test -->

# Graph of columns

import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats

for col in transformed_df.columns:
    plt.figure(figsize=(14,4))
    plt.subplot(121)
    sns.distplot(transformed_df[col])
    plt.title(col)

    plt.subplot(122)
    stats.probplot(transformed_df[col],dist="norm",plot=plt)
    plt.title(col)
    plt.show()
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```

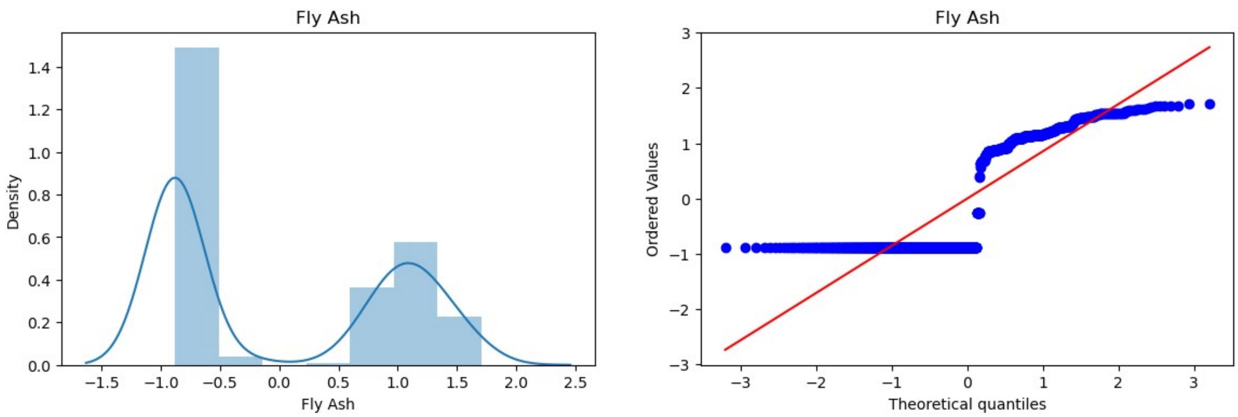



```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:
```

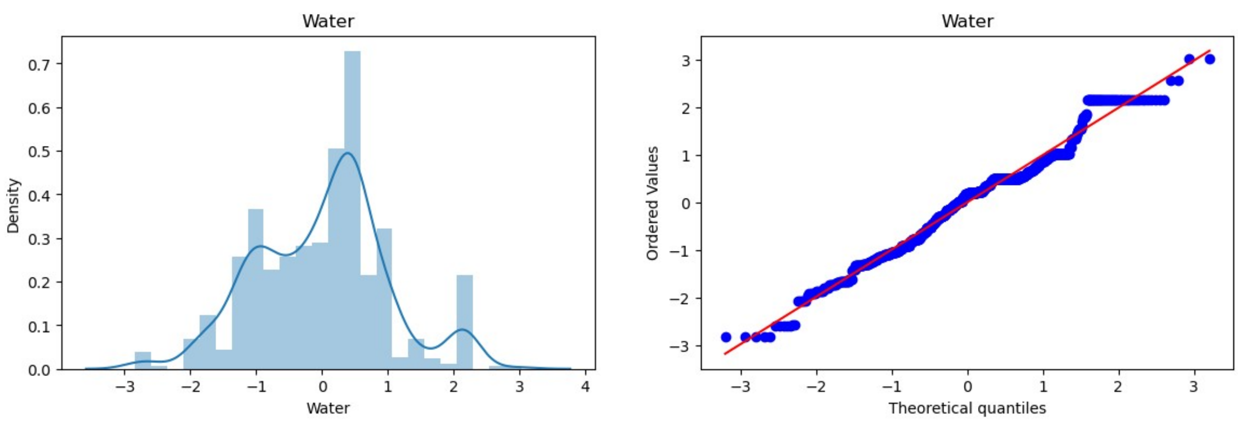
```
`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```




```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```

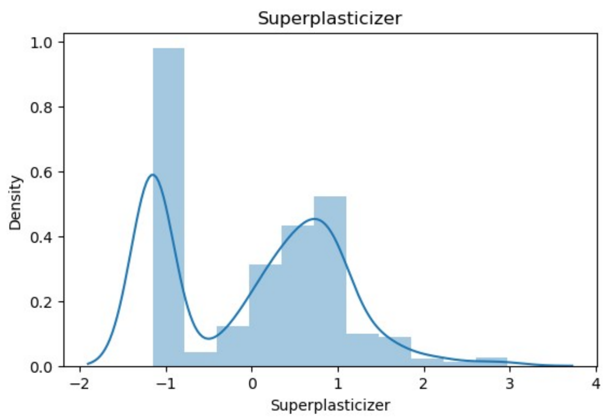


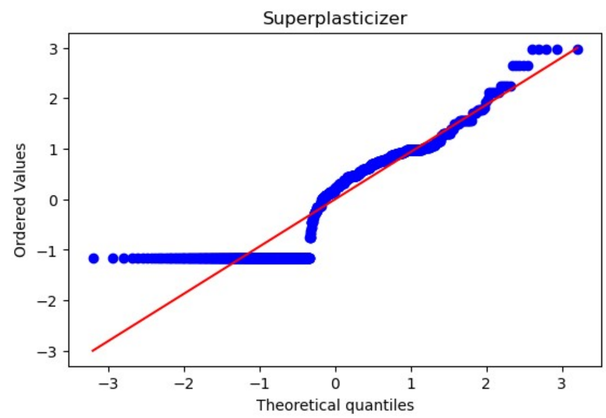

```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```



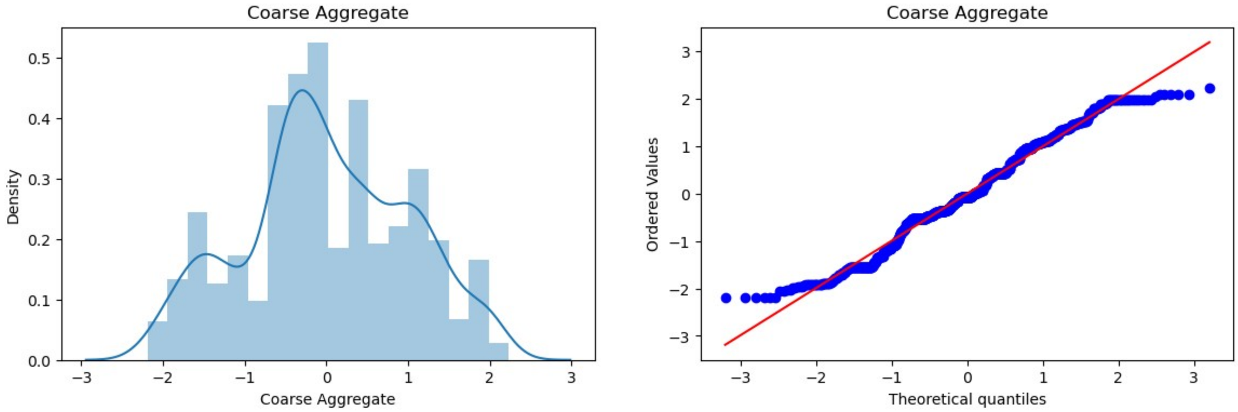

```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
```

```
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```

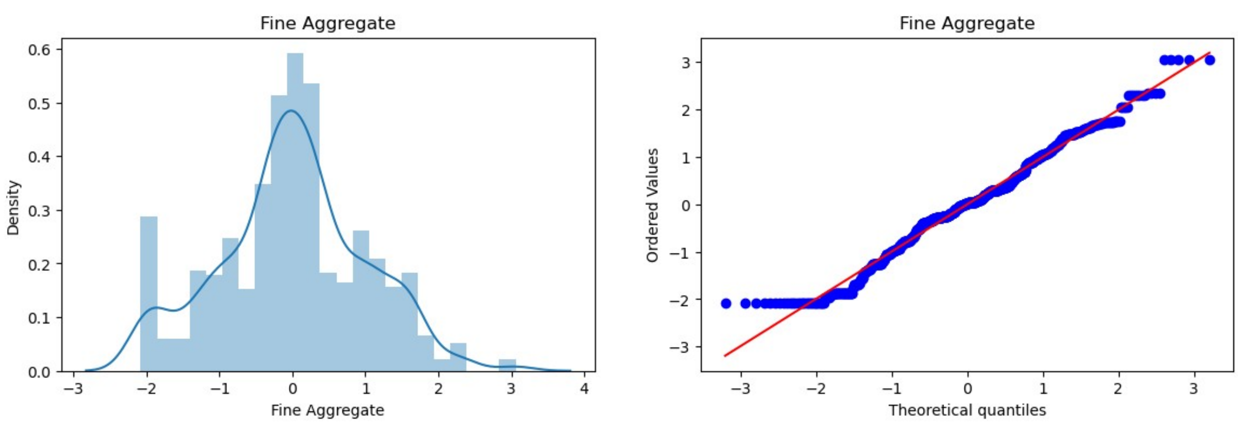





```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```

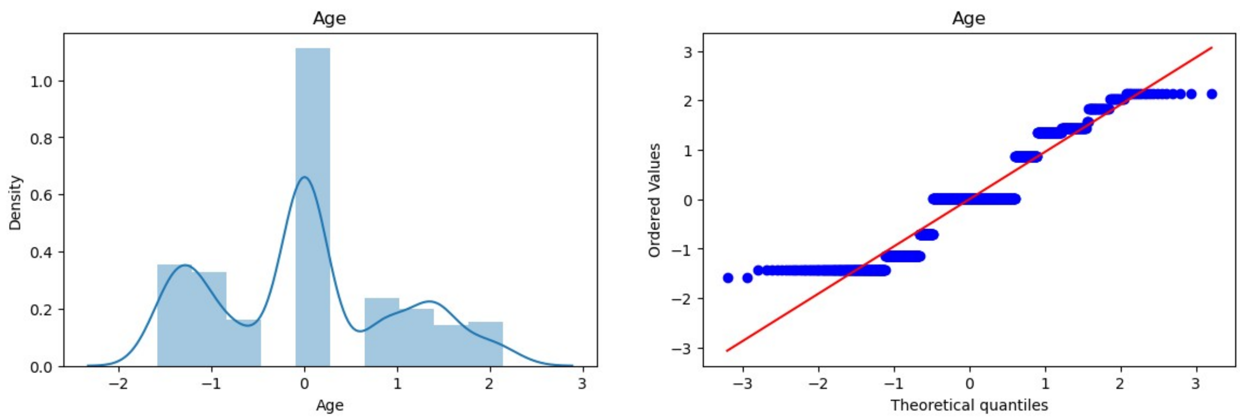



```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```

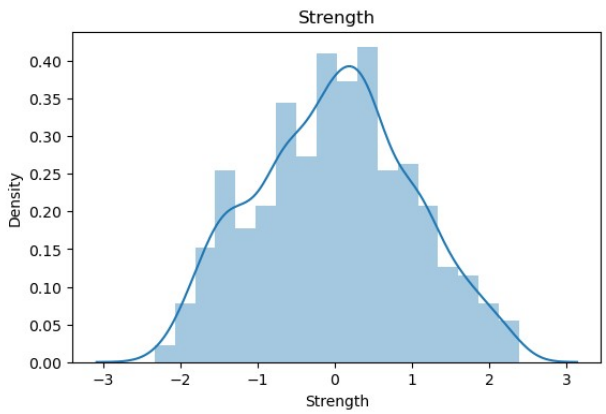


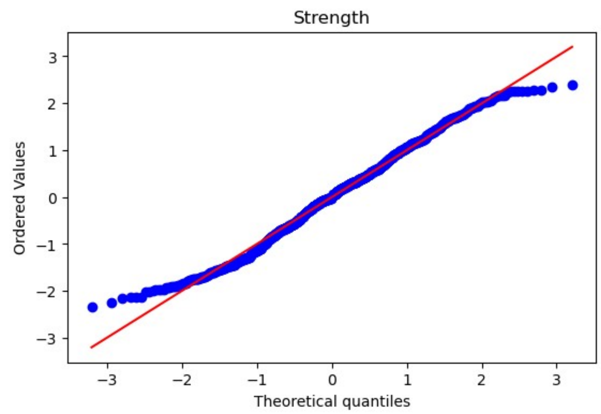

```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
```

```
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```




```
C:\Users\hp\AppData\Local\Temp\ipykernel_1228\4146890477.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(transformed_df[col])
```





Pre-processing task --> numerical data --> scaling -> normalization // standarization

Pre processing task -> categorical data --> label encoding // onhot encoding

Label Encoding:-Label encoding is a process of converting categorical data into numerical data.

This is done by assigning a unique integer value to each category. For example, if you have a column of data with the categories "f" and "m", you will be label encoded according to the alphabetical order: "f" = 0 "m" = 1

```
data = {"Color" :
["Red","Blue","Green","Red","Blue","Green","Red","Blue","Green"],
       "Age" : [25,35,45,55,56,67,65,75,85]}

print(data)

{'Color': ['Red', 'Blue', 'Green', 'Red', 'Blue', 'Green', 'Red',
'Blue', 'Green'], 'Age': [25, 35, 45, 55, 56, 67, 65, 75, 85]}

import pandas as pd

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

	Color	Age
0	Red	25
1	Blue	35
2	Green	45
3	Red	55
4	Blue	56
5	Green	67
6	Red	65
7	Blue	75
8	Green	85

```
copy_df=df.copy()
```

```
from sklearn.preprocessing import LabelEncoder
```

```
label = LabelEncoder()
df["Color"] = label.fit_transform(df["Color"])
df
```

	Color	Age
0	2	25
1	0	35
2	1	45
3	2	55
4	0	56
5	1	67
6	2	65
7	0	75
8	1	85

```
copy_df
```

	Color	Age
0	Red	25
1	Blue	35
2	Green	45
3	Red	55
4	Blue	56
5	Green	67
6	Red	65
7	Blue	75
8	Green	85

OneHotEncoder:-One-hot encoding is a process of converting categorical data into a one-hot encoded representation.

This is done by creating a new column for each possible category in the original column. The value of each new column is either 0 or 1, depending on whether the original column had that value.

```
from sklearn.preprocessing import OneHotEncoder

ohe = OneHotEncoder()
df["Color"] = ohe.fit_transform(color)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[107], line 4
      1 from sklearn.preprocessing import OneHotEncoder
      3 ohe = OneHotEncoder()
----> 4 df["Color"] = ohe.fit_transform(color)

NameError: name 'color' is not defined
```

```
df
```

	Color	Age
0	2	25
1	0	35
2	1	45
3	2	55
4	0	56
5	1	67
6	2	65
7	0	75
8	1	85

```
df[["Color"]]
```

	Color
0	2
1	0
2	1
3	2
4	0
5	1
6	2

```
7      0
8      1
```

```
df[["Color"]].ndim
```

```
2
```

```
print(type(df[["Color"]]))
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
import numpy as np
color = np.array(df["Color"]).reshape(-1,1)
```

```
print(color.ndim)
```

```
2
```

```
enc=OneHotEncoder()
X = [['male', 'from US', 'uses Safari'], ['female', 'from Europe',
'uses Firefox']]
enc.fit_transform(X).toarray()
```

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

```
print(len(X))
```

```
2
```

```
data = {"Name" : ["abc","xyz"],
       "Color" : ["red","blue"]}
df=pd.DataFrame(data)
```

```
df
```

```
  Name Color
0  abc   red
1  xyz  blue
```

```
enc=OneHotEncoder()
new=enc.fit_transform(df).toarray()
```

```
print(new)
```

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