

Chapter 3 – Feature Engineering

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Introduction to feature Engineering

The datasets have been explored in the last two chapters through EDA. They were analyzed briefly in terms of the usage of different types of analysis techniques. Now, in this chapter, we are going to cover another aspect of data processing. Engineering and its domains will be explored in this chapter. Dataset will be analyzed. Then after doing some ore processing on that data, we will be looking into the extraction of the features from that dataset. The main aim of feature engineering is to provide more information for the analysis being performed on the dataset.

It is observed that some unnecessary features decrease the training speed, and may decrease the generalization performance on the dataset. Whereas, this might be the case when some additional features are required.

Feature Engineering is useful in the terms as depicted here:



In this chapter, we will be looking into the dataset of “Miami Housing Prices” having 17 columns and 13932 rows. We will be applying the strategies of feature selection to this dataset.

Feature engineering is the process of using the knowledge of feature selection to extract the features from raw data. It is a step to be performed after EDA on the dataset. Data scientists are concerned with the iteration process to reduce errors and improve the accuracy of their models. Once the definition of the feature set is ready for practical use, the next step in feature engineering is to manufacture features in production.

You can learn more about Feature Selection here:

https://www.youtube.com/watch?v=5bHpPQ6_OU4

Feature Selection

This technique deals with keeping some features and letting others go. But there is some logic to deciding which features should be cut off. In the upcoming sections, we will be looking into some strategies to perform it:

Removal of Unused Columns

In most cases, it is apparent that some columns are not used for further usage. They may not appear in data preprocessing or other relevant techniques. It is quite obvious to remove such columns so that a more simplified version of data can be obtained.

Dropping the columns with Missing values

Sometimes, it appears that a large number of null values create problems with data handling. People apply different strategies to clean up missing data. But the frequently occurring missing values, it is preferred to drop the entire column.

Low variance features

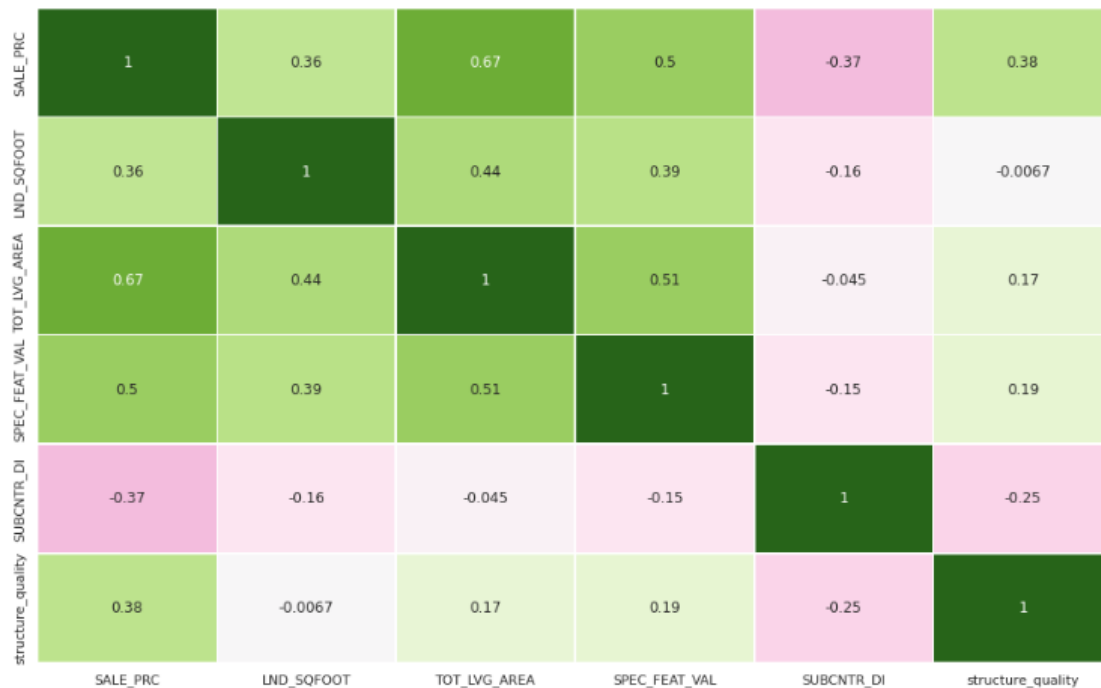
It is seen that a certain column may have values that are almost the same. And it would have 0 variances. Such a column can be dropped due to the low variance features. An ideal candidate can be the one having the lowest variance. The variances of each variable can be checked as:

```
# variance of numeric features
(df.select_dtypes(include=np.number).var().astype('str'))
```

Multi collinearity

When there is a correlation between any two features, multi-collinearity arises. Mostly it is expected that the two features are independent. Thus no collinearity exists between them. You will be seeing in the upcoming exercise about this scenario that “TOT_LVG_AREA” and “LND_SQFOOT” are more correlated with SALE_PRC. So you can eliminate one of them and let some other features predict the target variable.

It is shown as:



p-value

It is an indicator of the relationship between a predictor and a target. **Statsmodels** library gives us a summary of regression outputs which includes feature coefficients and the relevant p-values. The insignificant features can be removed one by one and the model is re-run each time until a set of features with significant p values and improved performance is achieved.

Note: You can practice the above-mentioned features through an upcoming exercise. Follow the steps mentioned in a guided exercise to practice these features

Exercise 3.01: Feature Engineering Strategies

In this exercise, we will be using the Miami House prices prediction-based dataset. We will be working on the features using the above-mentioned strategies to extract the features and work on them.

First, perform the steps mentioned below to cover the major aspects of feature selection techniques:

1. Firstly, open the collab notebook and load the dataset from GitHub. Print the shape of dataset as shown below:

```
import pandas as pd
data = 'https://raw.githubusercontent.com/fenago/datawrangling/main/miami-housing.csv'
df = pd.read_csv(data)
df.sample(5)
```

Output will be as follows:

	LATITUDE	LONGITUDE	PARCELNO	SALE_PRC	LND_SQFOOT	TOT_LVG_AREA	SPEC_FEAT_VAL	RAIL_DIST	OCEAN_DIST	WATER_DIST	CNTR_DIST	SUBCNTR_DI	Hwy_DIST	age	avno60plus	month_sold	s
11303	25.906808	-80.341709	3220210260270	365700.0	5504	2189	3911	11769.1	72200.2	6827.4	68060.5	63283.3	2411.0	17	0	8	
2198	25.821246	-80.226330	131220524450	150000.0	6600	894	1566	3112.3	27611.0	9974.5	19565.0	19565.0	3236.3	26	0	11	
7528	25.951972	-80.226996	3421020110850	175000.0	7725	1339	1738	9438.4	35495.7	3163.3	64659.1	64659.1	444.8	37	0	8	
544	25.898678	-80.188410	622300020060	340000.0	10275	1522	6927	6434.5	21800.8	2033.5	44298.3	43581.2	6927.2	29	0	11	
13092	25.677251	-80.415316	3059020050320	340000.0	8175	1967	23246	13638.7	42385.7	36370.1	81662.0	33766.0	8737.8	38	0	4	

2. Print the names of features/columns as shown below:

```
[2] df.shape
```

```
(13932, 17)
```

3. Print the total null values per column as shown below:

```
# total null values per column
df.isnull().sum()
```

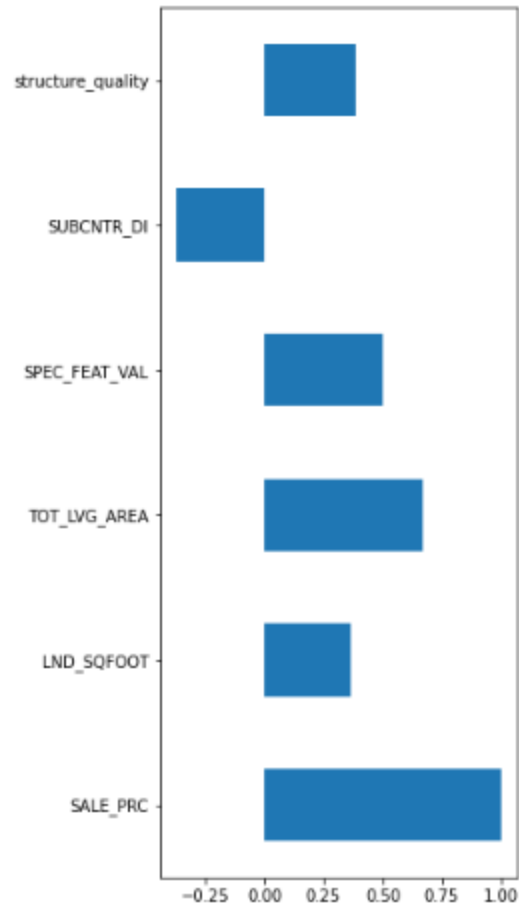
4. Features will be checked in such a way that if target variable and that feature is uncorrelated, just drop it. Drop uncorrelated numeric features with threshold <0.2. Show the correlation between target and features, as shown below:

```
# correlation between target and features
df_isnull = df.fillna(0)
```

```
[5] # drop uncorrelated numeric features (threshold <0.2)
corr = abs(df.corr().loc['SALE_PRC'])
corr = corr[corr<0.3]
cols_to_drop = corr.index.to_list()
df = df.drop(cols_to_drop, axis=1)
```

```
# correlation between target and features
(df.corr().loc['SALE_PRC']
.plot(kind='barh', figsize=(4,10)))
```

Output will be as follows:



- Check the feature with low variance in our dataset. Drop it after that as shown below:

```
import seaborn as sns
import numpy as np
# variance of numeric features
(df.select_dtypes(include=np.number).var().astype('str'))
```

SALE_PRC	100625155628.59306
LND_SQFOOT	36845977.33444123
TOT_LVG_AREA	661844.948052528
SPEC_FEAT_VAL	192958985.9153259
SUBCNTR_DI	491146528.77239436
structure_quality	1.2043837967004973
dtype:	object

- Drop correlated features as shown below:

```
[ ] # drop correlated features
df = df.drop(['SPEC_FEAT_VAL', 'SUBCNTR_DI', 'structure_quality'], axis=1)
```

7. Specify the numerical features as shown below

```
df_num = df[['LND_SQFOOT', 'TOT_LVG_AREA']]
df_num.sample(5)
```

8. Create a crosstab/contingency table of numerical features in each column as shown below:

```
crosstab = pd.crosstab(df_num['LND_SQFOOT'], df_num['TOT_LVG_AREA'])
crosstab
```

9. Run Chi-squared test on the contingency table that will tell us whether the two features are independent as shown below:

```
from scipy.stats import chi2_contingency
chi2_contingency(crosstab)
```

It will produce the following output:

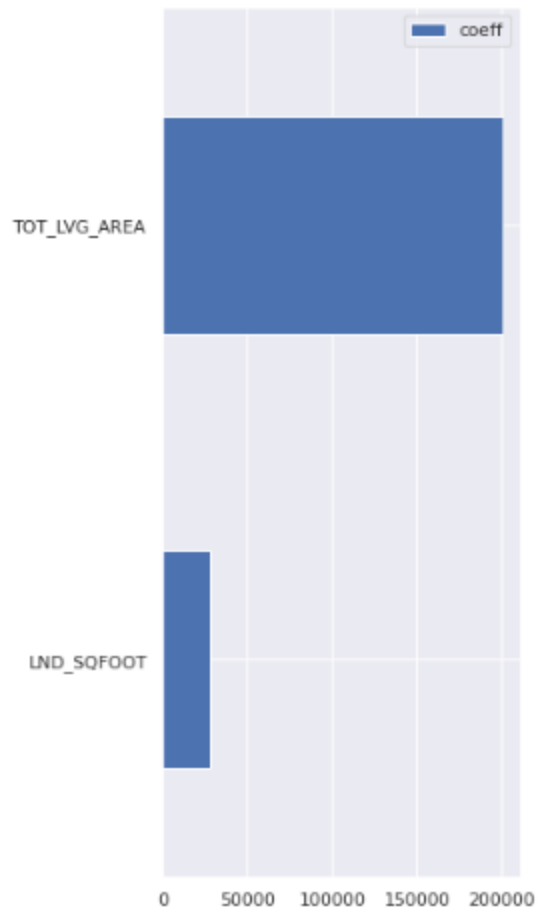
```
(16452824.212234832,
 0.0,
 13977015,
 array([[2.15331611e-04, 7.17772036e-05, 1.43554407e-04, ...,
        7.17772036e-05, 7.17772036e-05, 7.17772036e-05],
        [2.15331611e-04, 7.17772036e-05, 1.43554407e-04, ...,
        7.17772036e-05, 7.17772036e-05, 7.17772036e-05],
        [2.15331611e-04, 7.17772036e-05, 1.43554407e-04, ...,
        7.17772036e-05, 7.17772036e-05, 7.17772036e-05],
        ...,
        [6.45994832e-04, 2.15331611e-04, 4.30663221e-04, ...,
        2.15331611e-04, 2.15331611e-04, 2.15331611e-04],
        [4.30663221e-04, 1.43554407e-04, 2.87108814e-04, ...,
        1.43554407e-04, 1.43554407e-04, 1.43554407e-04],
        [2.15331611e-04, 7.17772036e-05, 1.43554407e-04, ...,
        7.17772036e-05, 7.17772036e-05, 7.17772036e-05]]))
```

10. Visualize the feature coefficients as shown below:

```
# feature coefficients
coeffs = model.coef_
# visualizing coefficients
index = X_train.columns.tolist()
(pd.DataFrame(coeffs, index = index, columns = ['coeff']).sort_values(by = 'coeff')
 .plot(kind='barh', figsize=(4,10)))
```

Following output will be produced:

<matplotlib.axes._subplots.AxesSubplot at 0x7f5599ef0710>



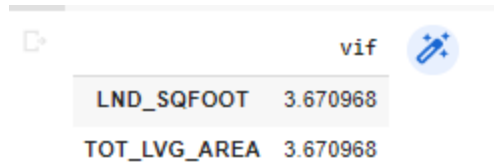
11. Then filter variables near zero coefficient value as shown below:

```
# filter variables near zero coefficient value
temp = pd.DataFrame(coeffs, index = index, columns = ['coeff']).sort_values(by = 'coeff')
temp = temp[(temp['coeff']>1) | (temp['coeff']< -1)]
# drop those features
cols_coeff = temp.index.tolist()
X_train = X_train[cols_coeff]
X_test = X_test[cols_coeff]
```

12. Finally, check Variance Inflation Factor for multicollinearity as shown below:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
# calculate VIF
vif = pd.Series([variance_inflation_factor(X.values, i) for i in range(X.shape[1])], index=X.columns)
# display VIFs in a table
index = X_train.columns.tolist()
vif_df = pd.DataFrame(vif, index = index, columns = ['vif']).sort_values(by = 'vif', ascending=False)
vif_df[vif_df['vif']<10]
```

Following output will be produced:



LND_SQFOOT	3.670968
TOT_LVG_AREA	3.670968

Feature Importance

As we have already worked on some feature selection techniques. Feature importance is an essential domain of the feature selection technique that helps in understanding it better through the following ways:

- SelectKBest
- Linear regression
- Random Forest
- XGBoost
- Recursive Feature Elimination

Linear regression, SelectKBest, and Decision Tree classification will be practiced through the upcoming exercises.

A **decision tree** splits the data using a particular feature that contributes toward decreasing the impurity. Thus finding the best feature is an important part of how the algorithm works in a classification task. Moreover, an attribute, ***feature_importances_***, can be used to access the best features.

We have covered it in the following way:

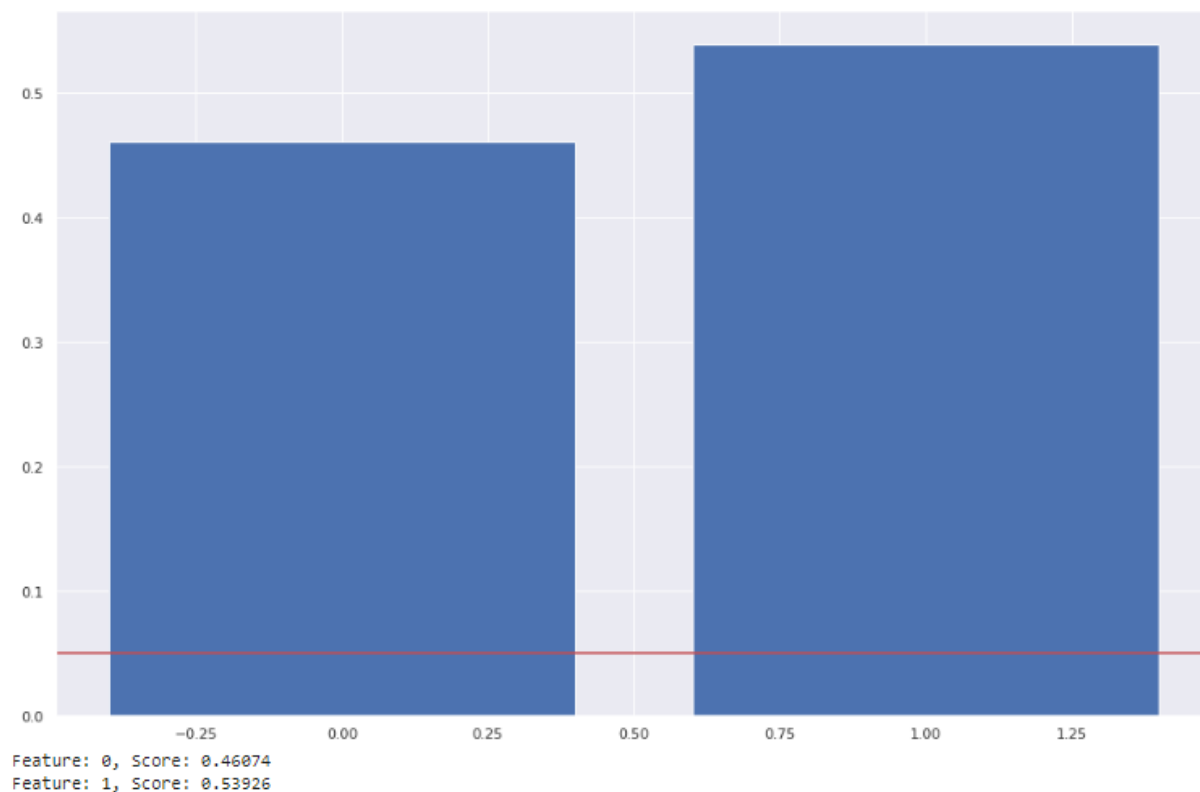
```
from sklearn.tree import DecisionTreeClassifier #Decision Tree
model = DecisionTreeClassifier()
model.fit(X_train, y_train)
# get importance
importance = model.feature_importances_
# summarize feature importance
for i,v in enumerate(importance):
    print('Feature: %0d, Score: %.5f' % (i,v))
```

Plots were also built using the following snippet:

```
# plot feature importance
```

```
plt.bar([x for x in range(len(importance))], importance)
plt.axhline(y=0.05, color='r', linestyle='-')
plt.show()
#use only high important features to feed into a model
for i,v in enumerate(importance):
    if v >= 0.05:
        print('Feature: %0d, Score: %.5f' % (i,v))
```

The following output was obtained from the above code snippet:



Note: You can practice the above-mentioned methodologies through an upcoming exercise. Follow the steps mentioned in a guided exercise to practice these features

Exercise 3.02: Feature Importance

In this exercise, we will be using the Miami House prices prediction-based dataset. We will be working with the features using the `feature_importances_` attribute in this exercise:

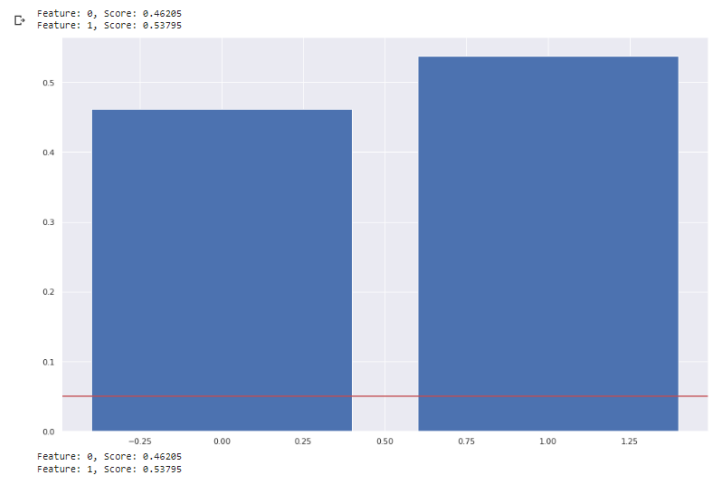
First, perform all the steps mentioned in Exercise 3.01 to cover the major aspects of feature selection techniques: Then follow the steps mentioned below to explore feature importance:

1. After performing the previous steps, implement a model through decision trees. Then plot the features importance as shown below:

```
import matplotlib.pyplot as plt
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, random
from sklearn.tree import DecisionTreeClassifier #Decision Tree
model = DecisionTreeClassifier()
model.fit(X_train, y_train)
# get importance
importance = model.feature_importances_
# summarize feature importance
for i,v in enumerate(importance):
    print('Feature: %0d, Score: %.5f' % (i,v))

# plot feature importance
plt.bar([x for x in range(len(importance))], importance)
plt.axhline(y=0.05, color='r', linestyle='-')
plt.show()
#use only high important features to feed into a model
for i,v in enumerate(importance):
    if v >= 0.05:
        print('Feature: %0d, Score: %.5f' % (i,v))
```

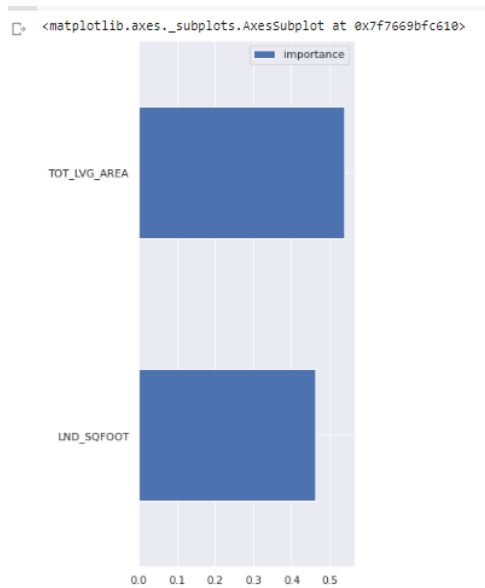
Output will look like the following figure:



2. Finally check out the feature importance as shown below:

```
[25] # feature importance
importances = model.feature_importances_
# visualization
cols = X.columns
(pd.DataFrame(importances, cols, columns = ['importance'])
.sort_values(by='importance', ascending=True)
.plot(kind='barh', figsize=(4,10)))
```

Output will be as follows:



Principal Component Analysis

Principal Component Analysis (PCA) is a frequently used technique by data scientists to make a more efficient model training. It helps in visualizing the data in lower dimensions. Its main purpose is to reduce the dimensionality of high-dimensional feature space.

The original features are projected into new dimensions here. The main aim is to find the number of components that can better illustrate the variance of the data.

It is done through the following snippet:

```
# import PCA module
from sklearn.decomposition import PCA
# scaling data
X_scaled = scaler.fit_transform(X)
# fit PCA to data
pca = PCA()
pca.fit(X_scaled)
evr = pca.explained_variance_ratio_
# visualizing the variance explained by each principal component
s
plt.figure(figsize=(12, 5))
plt.plot(range(0, len(evr)), evr.cumsum(), marker="o", linestyle="--")
plt.xlabel("Number of components")
plt.ylabel("Cumulative explained variance")
```

Note: You can practice the above-mentioned strategy through an upcoming exercise. Follow the steps mentioned in a guided exercise to practice these features

Exercise 3.03: Principal Component Analysis

In this exercise, we will be using the Miami House prices prediction-based dataset. We will be working with the features using the above-mentioned strategies to extract the features and work on them.

First, perform all the steps mentioned in Exercise 3.01 and 3.02 to cover the major aspects of feature selection and feature importance techniques.

Then follow the steps mentioned below to perform Principal component Analysis:

1. Firstly, import modules as shown below:

```
[ ] # import modules
from sklearn.feature_selection import (SelectKBest, chi2, SelectPercentile, SelectFromModel, SequentialFeatureSelector, SequentialFeatureSelector)
```

2. Then select K best features as shown below:

```
# select K best features
X_best = SelectKBest(chi2, k='all').fit_transform(X,y)
# number of best features
X_best.shape[1]
```

Output will be as follows:

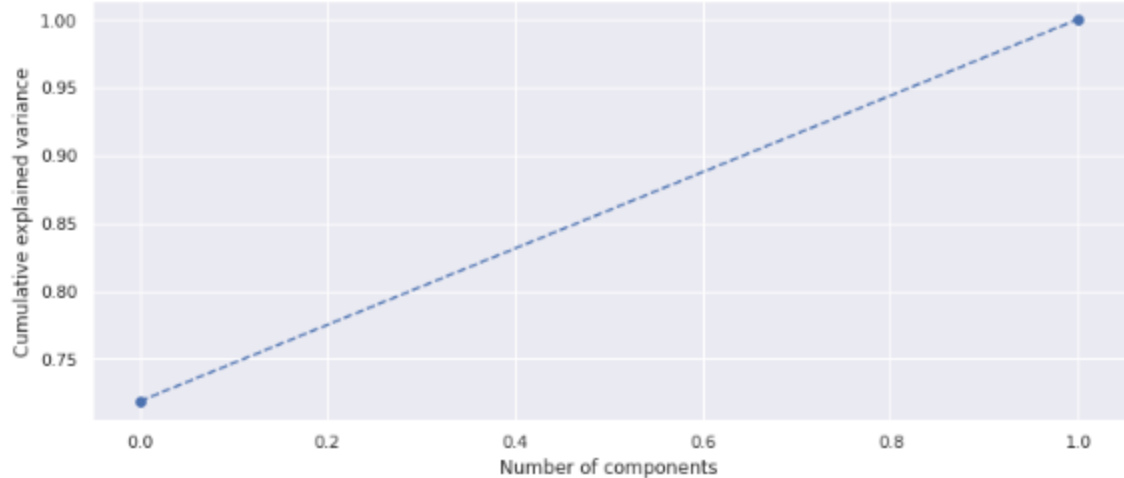
2

3. Import PCA module, scale data and fit PCA to data as shown below:

```
# import PCA module
from sklearn.decomposition import PCA
# scaling data
X_scaled = scaler.fit_transform(X)
# fit PCA to data
pca = PCA()
pca.fit(X_scaled)
evr = pca.explained_variance_ratio_
# visualizing the variance explained by each principal components
plt.figure(figsize=(12, 5))
plt.plot(range(0, len(evr)), evr.cumsum(), marker="o", linestyle="--")
plt.xlabel("Number of components")
plt.ylabel("Cumulative explained variance")
```

Output will be as follows:

Text(0, 0.5, 'Cumulative explained variance')



Automated Feature Selection Techniques

Sklearn library of python has built-in methodologies to cover feature selection. It provides an entire module to deal with the feature selection. Some such automated processes within **sklearn** are:

Chi-square based technique

The chi-squared-based technique selects a certain number of user-defined features based on the total number of records and their absolute values. These scores are determined by computing chi-squared statistics between X (independent) and y (dependent) variables.

You can use **sklearn** to determine the number of features you want to keep. If you want to keep all features, implementation will look like this:

```
# select K best features
X_best = SelectKBest(chi2, k='all').fit_transform(X,y)
# number of best features
X_best.shape[1]
```

Regularization

It is used to reduce overfitting. If you are having a lot of features, regularization controls their effect either by setting feature coefficients to zero – **L1 Regularization** or by shrinking feature coefficients – **L2 Regularization**.

We have implemented a **LinearSVC** algorithm with **penalty = 'L1'**. Implementation is as follows:

```
# implement algorithm
from sklearn.svm import LinearSVC
```

```
model = LinearSVC(penalty= 'l1', C = 0.002, dual=False)
model.fit(X,y)
# select features using the meta transformer
selector = SelectFromModel(estimator = model, prefit=True)
X_new = selector.transform(X)
X_new.shape[1]

# names of selected features
feature_names = np.array(X.columns)
feature_names[selector.get_support()]
```

Sequential Selection

This is one of the classical statistical techniques. One feature can be added or removed at a time and model performance is checked until it is optimized enough to meet your needs. This technique has two variants. The forward selection technique starts with a 0 feature. One feature is then added which minimizes the error, then another feature is added, and so on.

On the other hand, the backward selection is the opposite. The model starts with all features and calculates the error. Then one feature is eliminated and the process continues until the desired number of features remains.

Note: You can practice the above-mentioned features through an upcoming exercise. Follow the steps mentioned in a guided exercise to practice these features

Exercise 3.04: Automated Feature selection

In this exercise, we will be using the Miami House prices prediction-based dataset. We will be working with the features using the above-mentioned strategies to practice the automated feature selection techniques.

First, perform all the steps mentioned in Exercise 3.01, 3.02, and 3.03 to cover the major aspects of feature selection, feature importance techniques.

Then follow the steps mentioned below to explore automated feature selection techniques:

1. Firstly, import modules as shown below:

```
# import modules
from sklearn.feature_selection import (SelectKBest, chi2, SelectPercentile, SelectFromModel, SequentialFeatureSelector, SequentialFeatureSelector)
```

2. Then select K best features with chi2 as shown below:

```
# select K best features
X_best = SelectKBest(chi2, k='all').fit_transform(X,y)
# number of best features
X_best.shape[1]
```

It will produce the following output:

2

3. Keep 75% top features as shown below:

```
# keep 75% top features
X_top = SelectPercentile(chi2, percentile = 75).fit_transform(X,y)
# number of best features
X_top.shape[1]
```

It will produce the following output:

1

4. Finally implement Regularization through algorithm as shown below:

```
# implement algorithm
from sklearn.svm import LinearSVC
model = LinearSVC(penalty='l1', C = 0.002, dual=False)
model.fit(X,y)
# select features using the meta transformer
selector = SelectFromModel(estimator = model, prefit=True)
X_new = selector.transform(X)
X_new.shape[1]

# names of selected features
feature_names = np.array(X.columns)
feature_names[selector.get_support()]
```

Binning

Binning is a method that takes a column with continuous numbers and places the numbers in “bins” based on pre-defined ranges. In this way, a new categorical variable feature is achieved. Let us say, we are using the column, **SALE_PRC** from our dataset. It is indicating the prices of houses, and we will be adding some random values of our own to adjust them into the bins. And we will make 3 bins for it as: “[200000, 400000, 390000]”.

Bins Ranges

Firstly, the ranges for these bins need to be determined. There are many ways to do so. One way is to divide the bins up evenly on the basis of the distribution of values. It can be visualized in terms of histograms by passing one parameter of bins to **plt.hist()** method.

Note: You can practice the above-mentioned features through an upcoming exercise. Follow the steps mentioned in a guided exercise to practice these features

Exercise 3.05: Binning Features

In this exercise, we will be using the Miami House prices prediction-based dataset. We will be working on the features using the above-mentioned strategies to put certain values of a feature into a bin with ranges.

First, perform the steps mentioned below to cover the major aspects of feature selection techniques including binning.

1. Open collab notebook and load the dataset from GitHub.
2. Check the shape of dataset as shown below:

▼ Shape of data

```
[7] df.shape  
df.head()
```

It will produce the following output:

	SALE_PRC	TOT_LVG_AREA	SPEC_FEAT_VAL
0	440000.0	1753	0
1	349000.0	1715	0
2	800000.0	2276	49206
3	988000.0	2058	10033
4	755000.0	1684	16681

3. Use `nunique()` to find out the number of unique values over the column axis and use `value_counts()` function to find out the number of all values over the column axis as shown below:

```
df['SALE_PRC'].unique()  
df['SALE_PRC'].nunique()  
df['SALE_PRC'].value_counts()
```

It will produce the following output:

```

250000.0    196
300000.0    193
260000.0    163
270000.0    163
280000.0    152
...
543000.0     1
1137000.0     1
1228000.0     1
586500.0     1
233500.0     1
Name: SALE_PRC, Length: 2111, dtype: int64

```

4. Use countplots as shown below:

```
sns.countplot(df['SALE_PRC'])
```

5. Finally make another column for binning as shown below:

```
[10] df['Price_Bin'] = df['SALE_PRC']
```

6. Add values to add in that bin as follows:

```
[11] other_prices = [200000, 400000, 390000]
```

```
[12] df.loc[df['SALE_PRC'].isin(other_prices), 'Price_Bin'] = "Others"
```

```
[13] df['Price_Bin'].unique()
```

```
array([440000.0, 349000.0, 800000.0, ..., 148600.0, 167900.0, 233500.0],
      dtype=object)
```

```
[14] df['Price_Bin'].nunique()
```

It will give final output:

```
2109
```

Activity 3.01: Perform the Steps Mentioned Below:

For this activity, you have to use a Real estate Pricing dataset, and work on its features. Binning will be done here for the Prices. Follow the Steps mentioned below to perform the task:

1. Open the Collab notebook and import the necessary libraries
2. Load the given dataset.
3. Then look for the shape of the dataset and print values using the head function. Output will look like the output given below:

	No	X1 transaction date	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude	Y house price of unit area
0	1	2012.917	32.0	84.87882	10	24.98298	121.54024	37.9
1	2	2012.917	19.5	306.59470	9	24.98034	121.53951	42.2
2	3	2013.583	13.3	561.98450	5	24.98746	121.54391	47.3
3	4	2013.500	13.3	561.98450	5	24.98746	121.54391	54.8
4	5	2012.833	5.0	390.56840	5	24.97937	121.54245	43.1

4. Use nunique() to find out the number of unique values over the column axis of “Y house price of unit area”.

```
42.5    4
40.3    4
29.3    4
40.6    4
37.4    4
..
55.9    1
22.9    1
21.5    1
55.1    1
63.9    1
Name: Y house price of unit area, Length: 270, dtype: int64
```

5. Use value_counts() function to count the total values of the same feature.
6. Then plot the count plots.
7. Then perform binning, by making another column for the same feature.
8. Create a copy of the feature in that new column
9. Then add some new values. Perform in the way similar to the one given below:

```
[7] other_prices = [58.99, 45.8, 20.89]

[8] df.loc[df['Y house price of unit area'].isin(other_prices), 'Price_Bin'] = "Others"

[9] df['Price_Bin'].unique()
```

Output will be as follows:

```
array([37.9, 42.2, 47.3, 54.8, 43.1, 32.1, 40.3, 46.7, 18.8, 22.1, 41.4,
      58.1, 39.3, 23.8, 34.3, 50.5, 70.1, 37.4, 42.3, 47.7, 29.3, 51.6,
      24.6, 47.9, 38.8, 27.0, 56.2, 33.6, 47.0, 57.1, 25.0, 34.2, 49.3,
      55.1, 27.3, 22.9, 25.3, 46.2, 15.9, 18.2, 34.7, 34.1, 53.9, 38.3,
      42.0, 61.5, 13.4, 13.2, 44.2, 20.7, 38.9, 51.7, 13.7, 41.9, 53.5,
      22.6, 42.4, 21.3, 63.2, 27.7, 55.0, 44.3, 50.7, 56.8, 36.2, 59.0,
      40.8, 36.3, 20.0, 54.4, 29.5, 36.8, 25.6, 29.8, 26.5, 48.1, 17.7,
      43.7, 50.8, 18.3, 48.0, 45.4, 43.2, 21.8, 16.1, 41.0, 51.8, 59.5,
      34.6, 51.0, 62.2, 38.2, 32.9, 45.7, 30.5, 71.0, 47.1, 26.6, 28.4,
      39.4, 23.1, 7.6, 53.3, 46.4, 12.2, 13.0, 30.6, 59.6, 31.3, 32.5,
      45.5, 57.4, 48.6, 62.9, 60.7, 37.5, 30.7, 39.5, 20.8, 46.8, 47.4,
      43.5, 42.5, 51.4, 28.9, 40.1, 52.2, 45.1, 39.7, 48.5, 44.7, 40.9,
      15.6, 35.6, 57.8, 39.6, 11.6, 55.5, 55.2, 73.6, 43.4, 23.5, 14.4,
      58.8, 35.1, 45.2, 36.5, 19.2, 36.7, 42.6, 15.5, 55.9, 23.6, 21.5,
      25.7, 22.0, 20.5, 37.8, 42.7, 36.6, 48.2, 39.1, 31.6, 25.5, 45.9,
      31.5, 46.1, 21.4, 44.0, 26.2, 31.1, 58.0, 20.9, 43.8, 40.2, 78.3,
      38.5, 46.0, 49.0, 12.8, 46.6, 19.0, 33.4, 14.7, 17.4, 32.4, 23.9,
      61.9, 39.0, 40.6, 29.7, 28.8, 21.7, 22.3, 15.0, 30.0, 13.8, 52.7,
      25.9, 43.9, 63.3, 24.4, 53.0, 31.7, 38.1, 23.7, 41.1, 23.0, 117.5,
      40.5, 49.7, 34.0, 44.8, 34.4, 55.3, 56.3, 44.5, 37.0, 24.5, 28.5,
      16.7, 36.9, 35.7, 23.2, 38.4, 29.4, 50.2, 24.7, 19.1, 78.0, 42.8,
      41.6, 49.8, 26.9, 18.6, 37.7, 33.1, 62.1, 22.8, 30.9, 50.4, 42.9,
      41.2, 30.8, 11.2, 53.7, 28.6, 30.1, 45.3, 44.9, 40.0, 24.8, 42.1,
      41.5, 49.5, 69.7, 12.9, 67.7, 38.6, 35.3, 31.9, 32.2, 37.3, 35.5,
      37.2, 28.1, 15.4, 50.0, 52.5, 63.9], dtype=object)
```

Note: Firstly perform the above-mentioned Steps, then open up the solution to consult your way of performance.

In order to check the solution, you can access it from here:

https://github.com/fenago/datawrangling/blob/main/Chapter%203/Activity_3_01_Solution.ipynb

Conclusion

In this chapter, we have covered all the main techniques and strategies used for feature engineering. Core concepts with exercises have been covered. It was seen that feature engineering techniques require features to be used in an efficient manner. Moreover, they must be analyzed briefly before their extraction.

Binning variables were also seen in detail. These techniques can help data scientists to organize their datasets on the basis of certain features so that the results of post-processing techniques must be optimized. Such techniques are applied prior to fitting the model such as dropping columns with missing values, columns with multi-collinearity, and dimensionality reduction with PCA. While some other techniques must be pursued after base model implementation such as feature coefficients, p-value, and VIF.

In the upcoming chapters, we will be looking into the Encoding and normalizing techniques. We will learn how different features can be encoded.