Use K-means clustering to segment a dataset into different groups

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Description

K-means clustering is an unsupervised machine learning algorithm that partitions data into **K** distinct groups based on feature similarities. In this lab, we will apply K-means clustering to a house prices dataset to uncover different price segments and analyze their characteristics.

Problem Statement

The goal of this lab is to segment the house prices dataset into different clusters to identify patterns and characteristics of properties in various price ranges. Understanding these segments can assist stakeholders in making informed decisions regarding pricing, marketing, and investment strategies.

Prerequisites

Completion of all previous lab guides (up to Lab Guide-05) is required before proceeding with Lab Guide-06.

Software Requirements

- **Python** : Python version 3.11.9
- **Visual Studio Code (VSCode)**: A lightweight code editor that provides powerful features for Python development, including extensions for linting, debugging, and version control.

Hardware Requirements

- A computer with at least **4 GB of RAM**.
- At least 1GB of free disk space.
- A GPU (optional, but recommended for faster training).

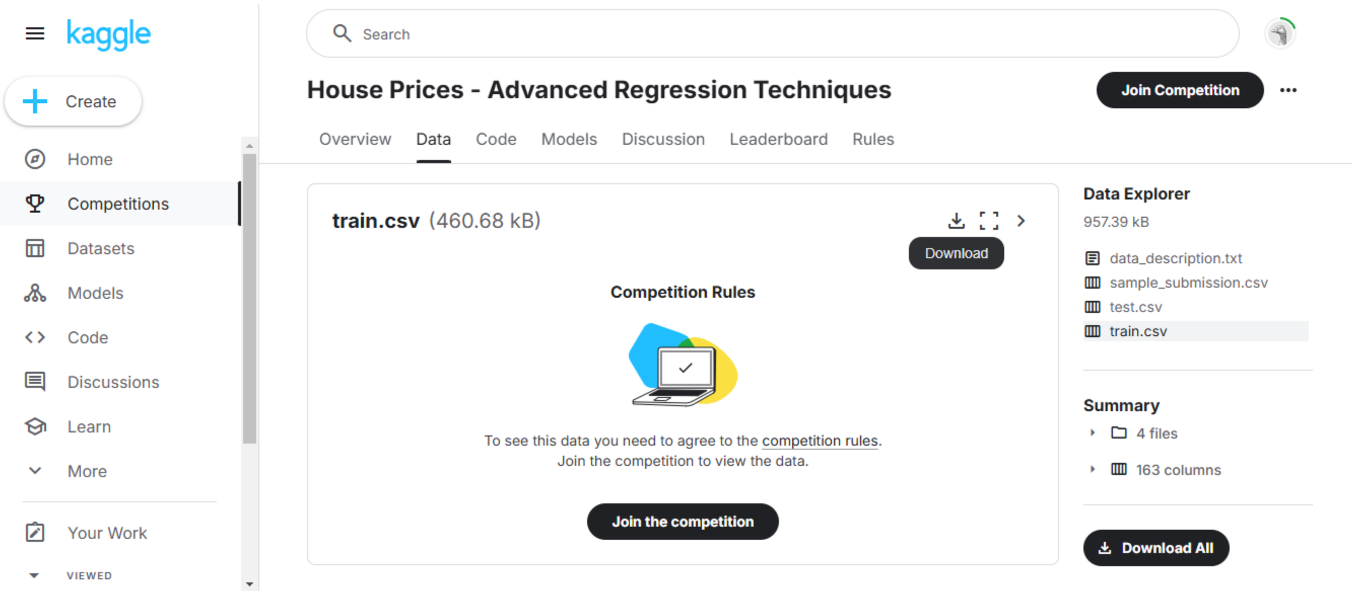
Setup Instructions

Downloading the Dataset

1. Sign in to Kaggle: Go to the **Kaggle website** and sign in to your account. If you don't have an account, create one.

2. Download the Dataset:

- Navigate to the **House Prices: Advanced Regression Techniques** competition page.



- Click on the "Data" tab and download the `train.csv` file (the dataset used for training).
- Move the downloaded `train.csv` file into your project directory.

Installing Required Libraries

You can install the required libraries using pip. Run the following command in your terminal or command prompt:

```
pip install pandas numpy matplotlib seaborn scikit-learn
```

```
PS C:\Users\Administrator\Desktop\AIML> pip install pandas numpy matplotlib seaborn scikit-learn
Collecting pandas
  Using cached pandas-2.2.3-cp311-cp311-win_amd64.whl.metadata (19 kB)
Collecting numpy
  Using cached numpy-2.1.2-cp311-cp311-win_amd64.whl.metadata (59 kB)
Collecting matplotlib
  Using cached matplotlib-3.9.2-cp311-cp311-win_amd64.whl.metadata (11 kB)
Collecting seaborn
  Using cached seaborn-0.13.2-py3-none-any.whl.metadata (5.4 kB)
Collecting scikit-learn
  Using cached scikit_learn-1.5.2-cp311-cp311-win_amd64.whl.metadata (13 kB)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\program files\python311\lib\site-packages (from pandas) (2.9.0.post0
)
Requirement already satisfied: pytz>=2020.1 in c:\program files\python311\lib\site-packages (from pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in c:\program files\python311\lib\site-packages (from pandas) (2024.2)
Requirement already satisfied: contourpy>=1.0.1 in c:\program files\python311\lib\site-packages (from matplotlib) (1.3.0)
Requirement already satisfied: cycler>=0.10 in c:\program files\python311\lib\site-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\program files\python311\lib\site-packages (from matplotlib) (4.54.1)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\program files\python311\lib\site-packages (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in c:\program files\python311\lib\site-packages (from matplotlib) (24.1)
Requirement already satisfied: pillow>=8 in c:\program files\python311\lib\site-packages (from matplotlib) (11.0.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\program files\python311\lib\site-packages (from matplotlib) (3.2.0)
Requirement already satisfied: scipy>=1.6.0 in c:\program files\python311\lib\site-packages (from scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in c:\program files\python311\lib\site-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\program files\python311\lib\site-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: six>=1.5 in c:\program files\python311\lib\site-packages (from python-dateutil>=2.8.2->pandas) (1
.16.0)
Using cached pandas-2.2.3-cp311-cp311-win_amd64.whl (11.6 MB)
Using cached numpy-2.1.2-cp311-cp311-win_amd64.whl (12.9 MB)
Using cached matplotlib-3.9.2-cp311-cp311-win_amd64.whl (7.8 MB)
Using cached seaborn-0.13.2-py3-none-any.whl (294 kB)
Using cached scikit_learn-1.5.2-cp311-cp311-win_amd64.whl (11.0 MB)                Activate Windows
Installing collected packages: numpy, pandas, scikit-learn, matplotlib, seaborn    Go to Settings to activate Windows.
Successfully installed matplotlib-3.9.2 numpy-2.1.2 pandas-2.2.3 scikit-learn-1.5.2 seaborn-0.13.2
```

Setting Up the Environment

1. Install Python:

You can download and install Python 3.11.9 from the official Python website:

- Visit the **official Python website**.
- Locate a reliable version of Python 3, **"Download Python 3.11.9"**.
- Choose the correct link for your device from the options provided: either Windows installer (64-bit) or Windows installer (32-bit) and proceed to download the executable file.

2. Install Visual Studio Code (VSCode):

Download and install VSCode from the official Visual Studio Code website:

Download Visual Studio Code

Using K-means Clustering

K-means Clustering K-means clustering is an unsupervised machine learning algorithm used to partition a dataset into K distinct groups (clusters) based on feature similarities. The algorithm works by randomly initializing K cluster centroids and iteratively refining them to minimize the distance between data points and their assigned centroids.

- **Create a new python file**
  - Create a Python file named `Kmeans_clustering.py` and write following code in it.

Data Preprocessing

- **Import Libraries**
- **Load the Dataset**
- **Explore the Dataset**
- **Check for Non-Numeric Entries**
- **Convert Columns to Numeric**
- **Fill Missing Values**

Import Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

Load the Dataset

```
df = pd.read_csv('./train.csv')
```

Explore the Dataset

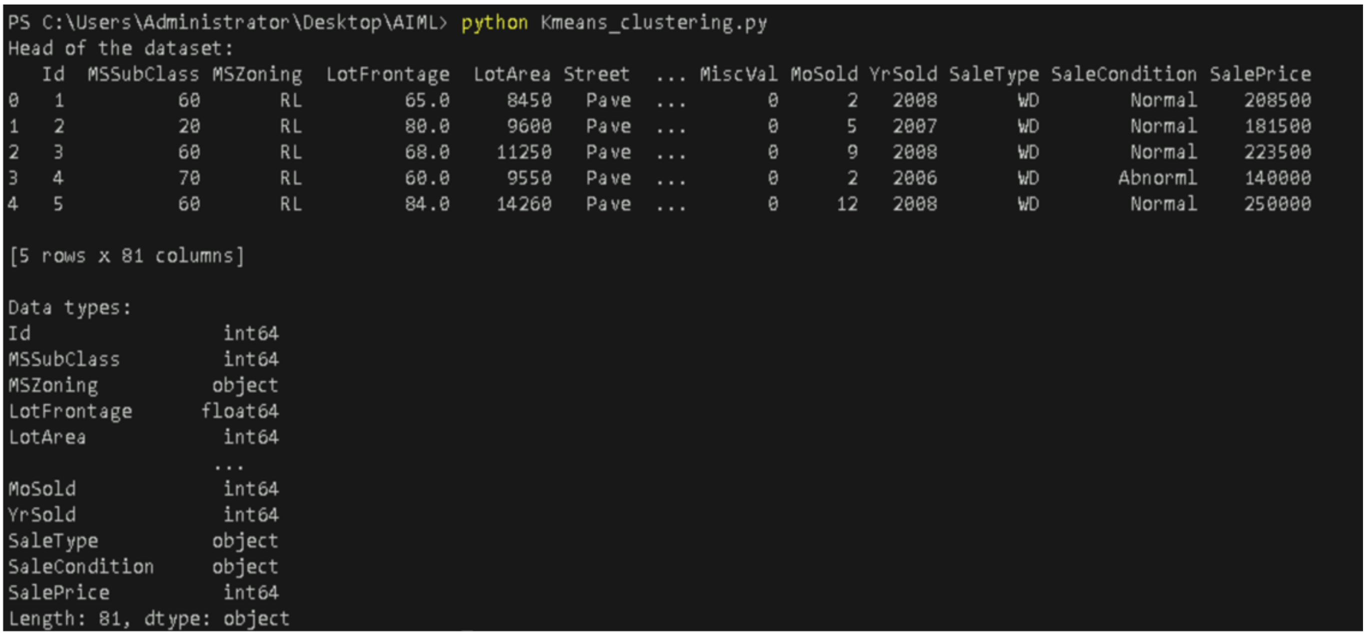
```
print("Head of the dataset:")
print(df.head())
print("\nData types:")
print(df.dtypes)
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python Kmeans_clustering.py
```

Output



```
PS C:\Users\Administrator\Desktop\AIML> python Kmeans_clustering.py
Head of the dataset:
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street  ... MiscVal MoSold YrSold SaleType SaleCondition SalePrice
0   1          60       RL         65.0     8450   Pave  ...       0      2   2008       WD        Normal    208500
1   2          20       RL         80.0     9600   Pave  ...       0      5   2007       WD        Normal    181500
2   3          60       RL         68.0    11250   Pave  ...       0      9   2008       WD        Normal    223500
3   4          70       RL         60.0     9550   Pave  ...       0      2   2006       WD       Abnorml    140000
4   5          60       RL         84.0    14260   Pave  ...       0     12   2008       WD        Normal    250000

[5 rows x 81 columns]

Data types:
Id                 int64
MSSubClass         int64
MSZoning          object
LotFrontage      float64
LotArea            int64
                  ...
MoSold             int64
YrSold             int64
SaleType          object
SaleCondition     object
SalePrice          int64
Length: 81, dtype: object
```

Check for Non-Numeric Entries

```
numeric_columns = ['LotArea', 'OverallQual', 'OverallCond', 'YearBuilt',
'SalePrice']
print("\nChecking for non-numeric entries:")
non_numeric_found = False  # Flag to check if any non-numeric entries were found

for column in numeric_columns:
    non_numeric_entries = df[~df[column].apply(lambda x: isinstance(x, (int,
float)))][column]
    if not non_numeric_entries.empty:
        print(f"Non-numeric entries found in {column}:")
        print(non_numeric_entries)
        non_numeric_found = True

if not non_numeric_found:
```

```
    print("No non-numeric entries found in the specified columns.")
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python Kmeans_clustering.py
```

Output

```
PS C:\Users\Administrator\Desktop\AIML> python Kmeans_clustering.py

Checking for non-numeric entries:
No non-numeric entries found in the specified columns.
```

Convert Columns to Numeric

```
for column in numeric_columns:
    df[column] = pd.to_numeric(df[column], errors='coerce')

print("\nChecking for NaN values after conversion:")
print(df[numeric_columns].isnull().sum())
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python Kmeans_clustering.py
```

Output

```
PS C:\Users\Administrator\Desktop\AIML> python Kmeans_clustering.py

Checking for non-numeric entries:

Checking for NaN values after conversion:
LotArea        0
OverallQual    0
OverallCond    0
YearBuilt      0
SalePrice      0
dtype: int64
```

Fill Missing Values

```
df[numeric_columns] = df[numeric_columns].fillna(df[numeric_columns].mean())
```

Applying K-means Clustering

- Feature Selection
- Standardize the Data
- Determine Optimal Number of Clusters (Elbow Method)
- Fit K-means Model with Optimal k

Feature Selection

```
features = df[numeric_columns]
print("\nFeatures DataFrame shape:")
print(features.shape)
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python Kmeans_clustering.py
```

Output

Standardize the Data

- **Standardization**: A preprocessing step to scale features to have a mean of zero and a standard deviation of one.

```
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)
```

Determine Optimal Number of Clusters (Elbow Method)

- **Elbow Method**: A technique to determine the optimal number of clusters by plotting the inertia against the number of clusters.

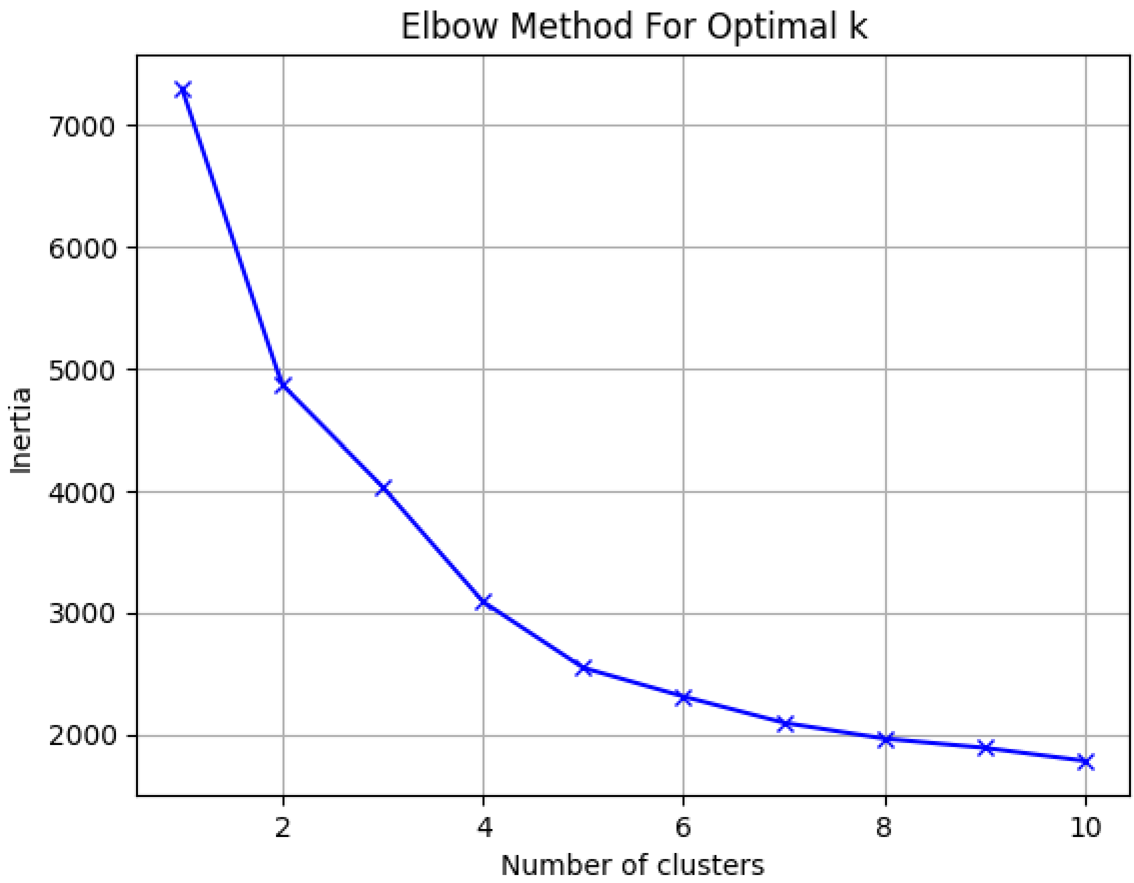
```
inertia = []
K = range(1, 11)  # Testing for k from 1 to 10

for k in K:
    kmeans = KMeans(n_clusters=k, random_state=0)
    kmeans.fit(features_scaled)
    inertia.append(kmeans.inertia_)

plt.plot(K, inertia, 'bx-')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method For Optimal k')
plt.grid()
plt.show()
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python Kmeans_clustering.py
```

Output



Fit K-means Model with Optimal k

```
optimal_k = 3  # Replace with the optimal k from the Elbow Method
kmeans = KMeans(n_clusters=optimal_k, random_state=0)
kmeans.fit(features_scaled)

df['Cluster'] = kmeans.labels_
```

Evaluating Clustering Performance

Analyze Cluster Characteristics

```
try:
    cluster_analysis = df.groupby('Cluster')[numeric_columns].mean()
    print("\nCluster Analysis:")
    print(cluster_analysis)
except Exception as e:
    print("Error in cluster analysis:", e)
```

Run the Python file

- Use the command below in your terminal to run the Python file:

```
python Kmeans_clustering.py
```

Output

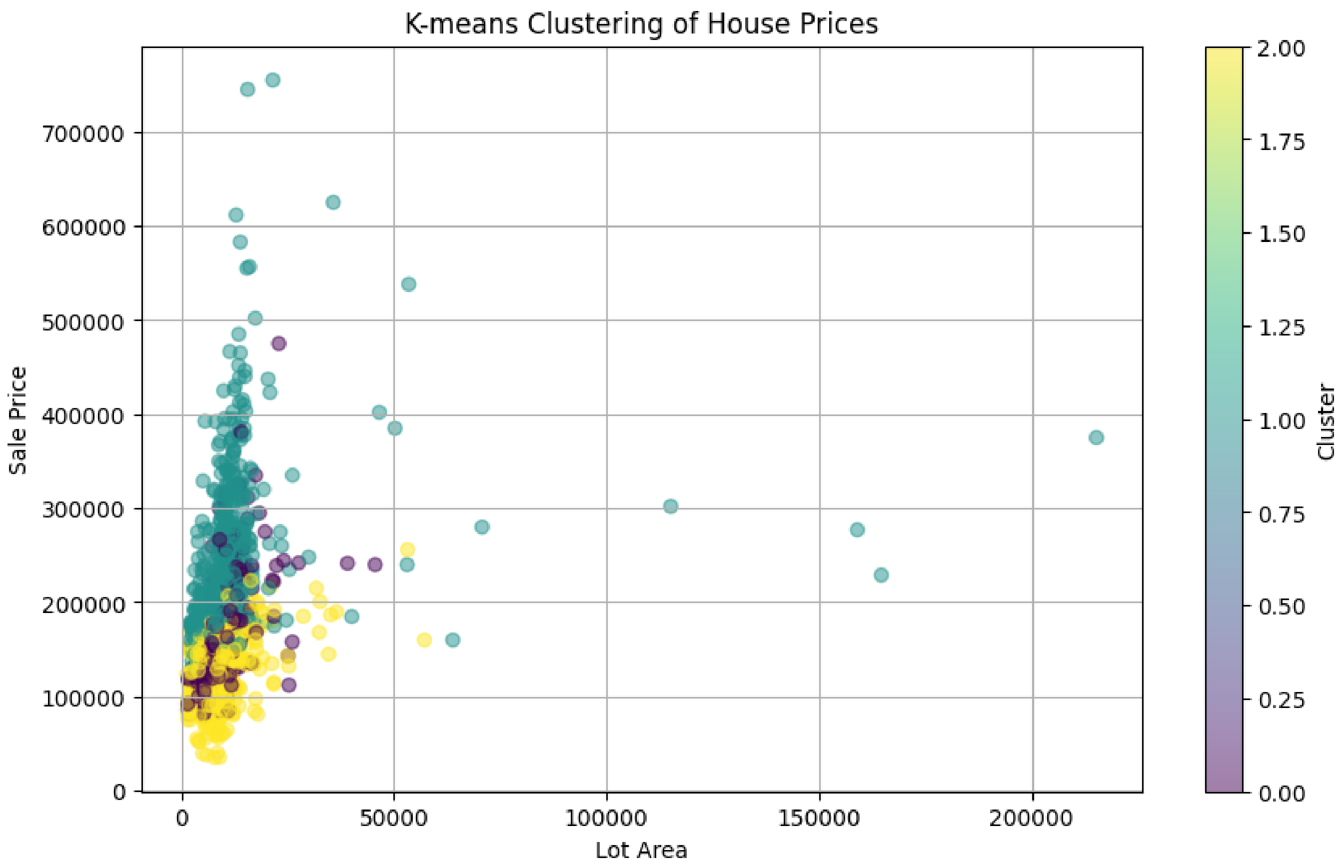
```
PS C:\Users\Administrator\Desktop\AIML> python Kmeans_clustering.py

Cluster Analysis:
              LotArea  OverallQual  OverallCond    YearBuilt      SalePrice
Cluster
0         9448.029851     5.582090     7.188060  1941.083582  153162.477612
1        11974.166667     7.408602     5.103943  1999.344086  246318.804659
2         9714.098765     5.116402     5.086420  1961.470899  132962.298060
```

Visualizing Results

Visualize Clusters

```
plt.figure(figsize=(10, 6))
plt.scatter(df['LotArea'], df['SalePrice'], c=df['Cluster'], cmap='viridis',
alpha=0.5)
plt.xlabel('Lot Area')
plt.ylabel('Sale Price')
plt.title('K-means Clustering of House Prices')
plt.colorbar(label='Cluster')
plt.grid()
plt.show()
```

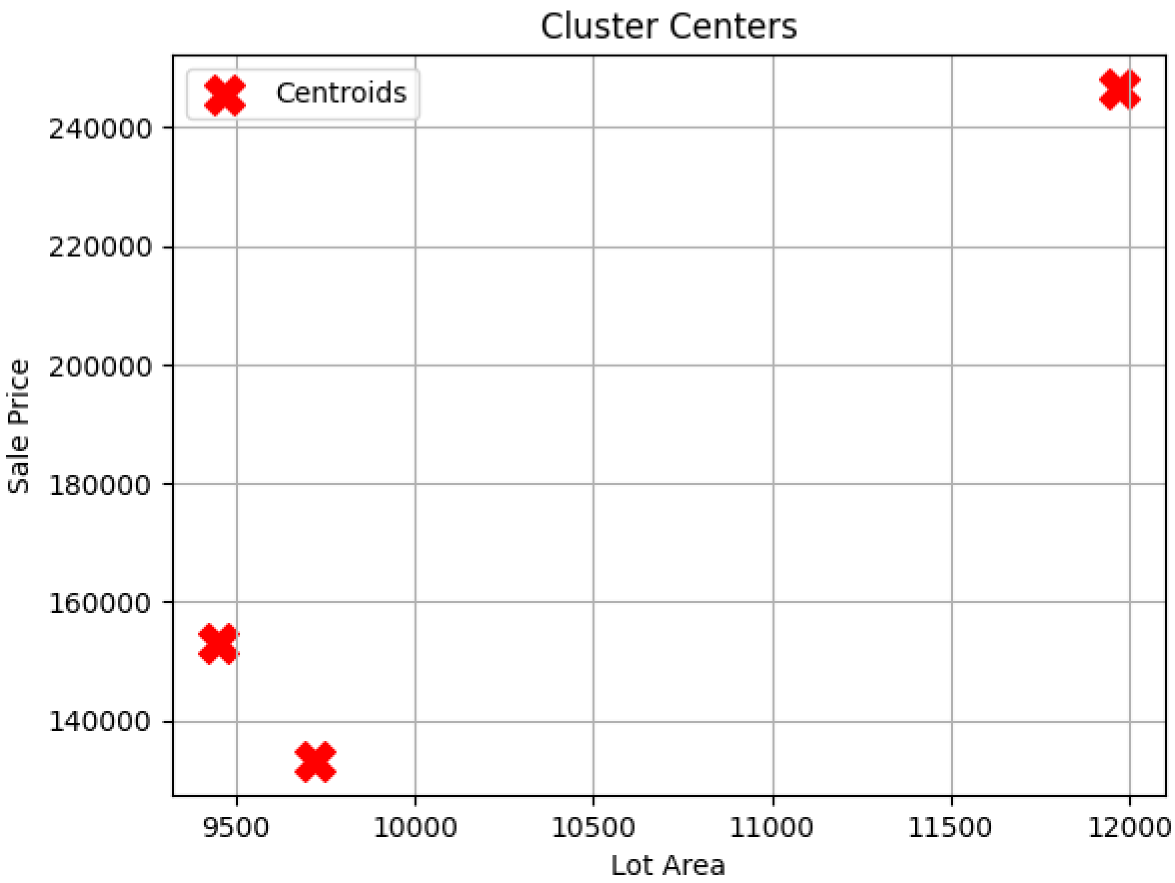
Output



Visualize Cluster Centers

```
centers = scaler.inverse_transform(kmeans.cluster_centers_)
plt.scatter(centers[:, 0], centers[:, 4], c='red', marker='X', s=200,
label='Centroids')
plt.xlabel('Lot Area')
plt.ylabel('Sale Price')
plt.title('Cluster Centers')
plt.legend()
plt.grid()
plt.show()
```

Output



References

- K-means Clustering Documentation - Scikit-learn
- StandardScaler Documentation - Scikit-learn
- Matplotlib Documentation