Name : Tazmeen Afroz

Roll no : 22P-9252

Section : BAI-5A

Assignment 01

Initial Data Loading and Exploration

In this section, we load the dataset and perform initial exploratory data analysis.

In [106…
```
import seaborn as sns

df = sns.load_dataset('mpg')

df.head()
```

Out[106…

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	origin
0	18.0	8	307.0	130.0	3504	12.0	70	usa
1	15.0	8	350.0	165.0	3693	11.5	70	usa
2	18.0	8	318.0	150.0	3436	11.0	70	usa
3	16.0	8	304.0	150.0	3433	12.0	70	usa
4	17.0	8	302.0	140.0	3449	10.5	70	usa

In [107…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64  
 2   displacement  398 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        398 non-null    int64  
 5   acceleration  398 non-null    float64
 6   model_year    398 non-null    int64  
 7   origin        398 non-null    object 
 8   name          398 non-null    object 
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
```

In [108…
```
df.isna().sum()
```

Out[108…
```
mpg             0
cylinders       0
displacement    0
horsepower      6
weight          0
acceleration    0
model_year      0
origin          0
name            0
dtype: int64
```

Data Cleaning and Preprocessing

Here, we handle missing values and identify numerical and categorical columns.

In [109…
```
import pandas as pd
df['horsepower'] = pd.to_numeric(df['horsepower'], errors='coerce')


df['horsepower']= df['horsepower'].fillna(df['horsepower'].median())
```

In [110…
```
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns
print(numerical_columns)

categorical_columns = df.select_dtypes(include=['object']).columns
print(categorical_columns)
```

```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'model_year'],
      dtype='object')
Index(['origin', 'name'], dtype='object')
```

Data Visualization

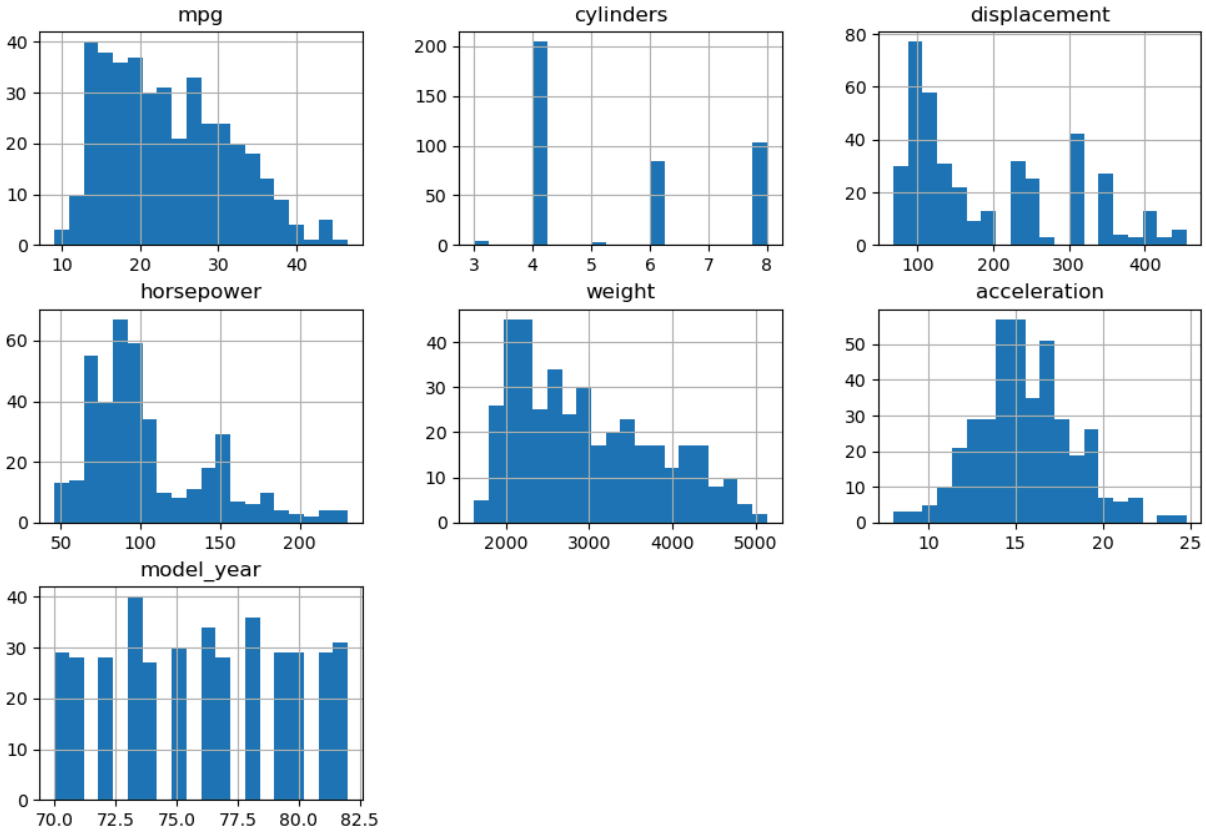
This section includes various visualizations to better understand the dataset.

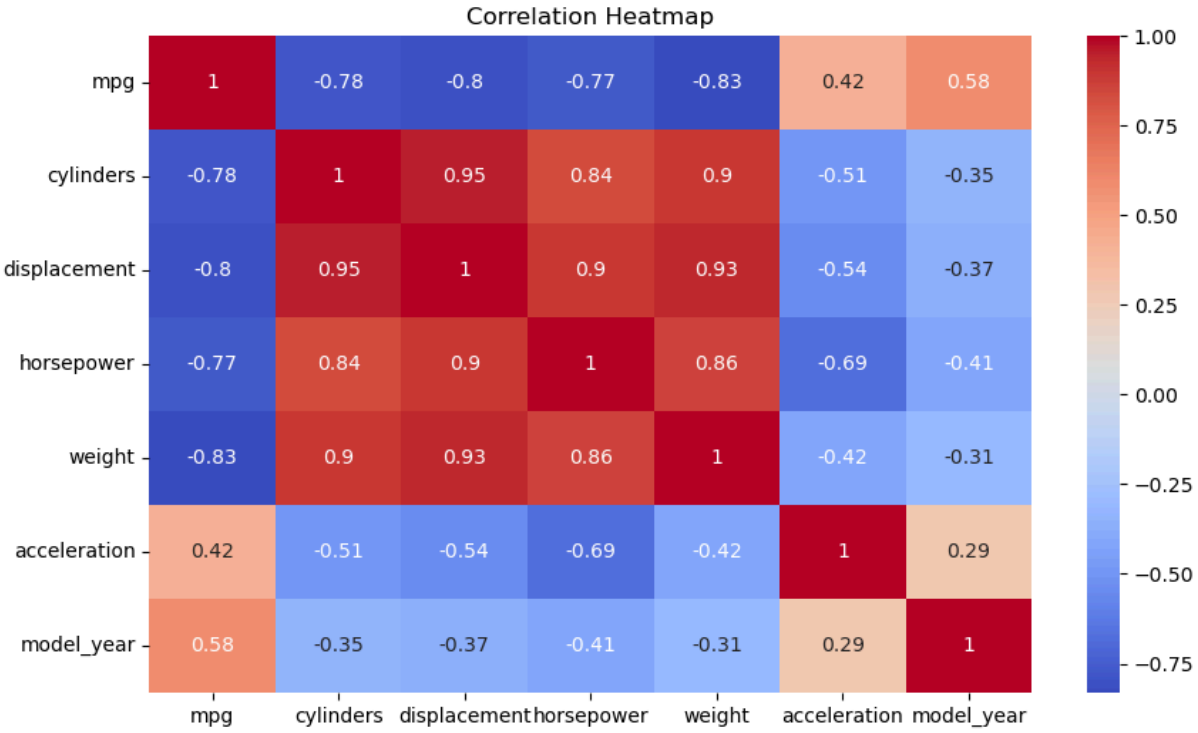
In [111…

```
import matplotlib.pyplot as plt

# Plot histograms
df.hist(bins=20, figsize=(12, 8))
plt.show()

# Correlation heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(df[numerical_columns].corr(), annot=True, cmap="coolwarm")
plt.title('Correlation Heatmap')
plt.show()
```





Task 1: Custom Transformation Using FunctionTransformer

In this task, we create and apply custom transformers using Scikit-Learn's FunctionTransformer.

as from the histogram we can see that the displacement and weight have a heavy tail so we can apply log transformation to them

In [112…

```
import numpy as np
from sklearn.preprocessing import FunctionTransformer

log_transformer = FunctionTransformer(np.log,inverse_func=np.exp)

# as from the  histogram we can see that the displacement and weight have a
df['log_displacement'] = log_transformer.transform(df[['displacement']])
df['log_weight'] = log_transformer.transform(df[['weight']])
# Step 2: Create a ratio transformer (horsepower to weight)
ratio_transformer = FunctionTransformer(lambda X: X[:, 0] / X[:, 1])

# Apply the ratio transformer to horsepower and weight
df['horsepower_to_weight'] = ratio_transformer.transform(df[['horsepower', '


df[['displacement', 'log_displacement', 'weight', 'log_weight', 'horsepower_
```

Out[112…

	displacement	log_displacement	weight	log_weight	horsepower_to_weight
0	307.0	5.726848	3504	8.161660	0.037100
1	350.0	5.857933	3693	8.214194	0.044679
2	318.0	5.762051	3436	8.142063	0.043655
3	304.0	5.717028	3433	8.141190	0.043694
4	302.0	5.710427	3449	8.145840	0.040591

Task 2: Building Custom Transformer Class

Here, we create a custom StandardScalerClone transformer by subclassing BaseEstimator and TransformerMixin.

In [113…

```
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.utils.validation import check_array, check_is_fitted

# Here    => StandardScalerClone is defined as a subclass of both BaseEstima

class StandardScalerClone(BaseEstimator, TransformerMixin):
    def __init__(self, with_mean=True):
        self.with_mean = with_mean

    def fit(self, X, y=None):
        X = check_array(X)              # input validation to ensure that X
        self.mean_ = X.mean(axis=0)     # axis=0 to calculate the mean of ea
        self.scale_ = X.std(axis=0)     # standard deviation of each feature
        self.n_features_in_ = X.shape[1] # number of features
        return self

    def transform(self, X):
        check_is_fitted(self)        # check if the estimator is fitted by v
        X = check_array(X)
        assert self.n_features_in_ == X.shape[1]         # check if the numb
        if self.with_mean:
            X = X - self.mean_              # calculate the mean of each feat
        return X / self.scale_              # divide the result by the standa

    def get_feature_names_out(self, input_features=None):
        check_is_fitted(self)
        if input_features is None:
            input_features = [f"x{i}" for i in range(self.n_features_in_)]
        return np.asarray(input_features, dtype=object)


scaler = StandardScalerClone()
df['horsepower_scaled'] = scaler.fit_transform(df[['horsepower']])

df[['horsepower', 'horsepower_scaled']].head()
```

Out[113…

	horsepower	horsepower_scaled
0	130.0	0.673118
1	165.0	1.589958
2	150.0	1.197027
3	150.0	1.197027
4	140.0	0.935072

Task 3: Clustering-Based Custom Transformer

In this task, we implement a clustering-based transformer using K-Means and RBF kernel.

In [114…

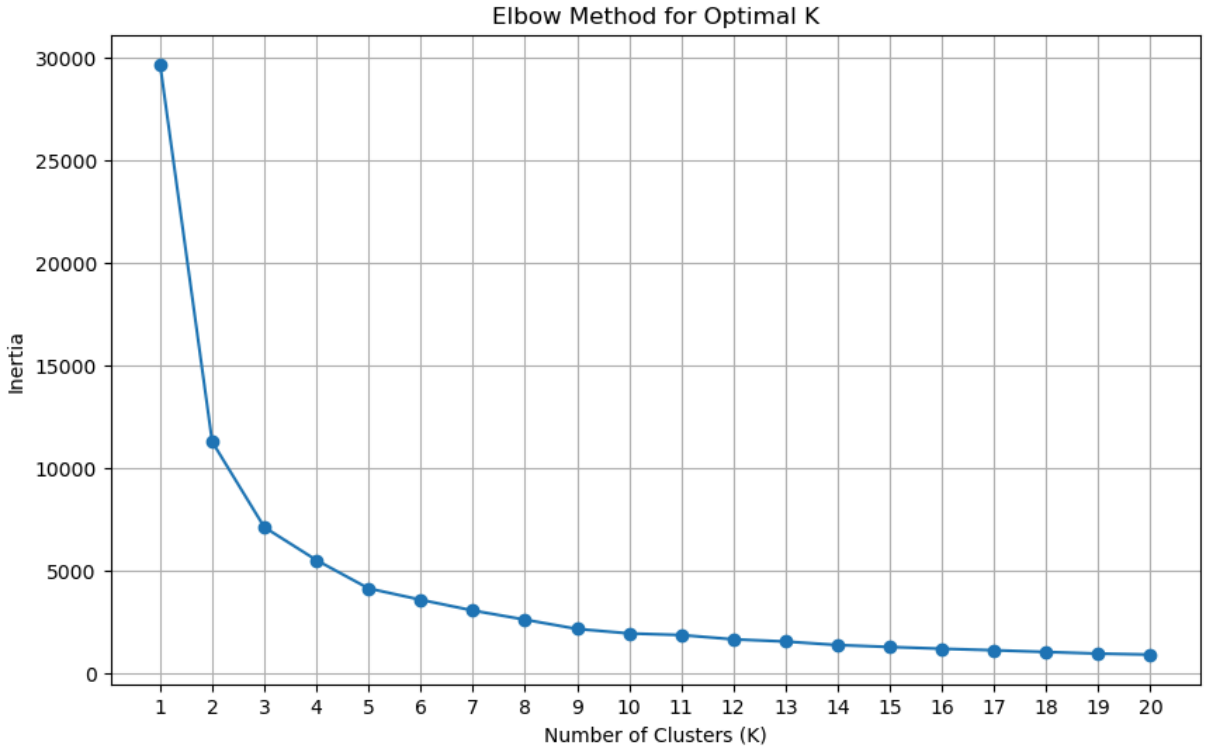
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

X = df[['mpg', 'model_year']]


inertia = []
k_values = range(1, 21)

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X)
    inertia.append(kmeans.inertia_)

# Plotting the Elbow Curve
plt.figure(figsize=(10, 6))
plt.plot(k_values, inertia, marker='o')
plt.title('Elbow Method for Optimal K')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.xticks(k_values)
plt.grid(True)
plt.show()
```



In [115…

```python
from sklearn.cluster import KMeans
from sklearn.metrics.pairwise import rbf_kernel

class ClusterSimilarity(BaseEstimator, TransformerMixin):

 def __init__(self, n_clusters=4, gamma=1.0, random_state=None):
    self.n_clusters = n_clusters
    self.gamma = gamma
    self.random_state = random_state

 def fit(self, X, y=None, sample_weight=None):
    self.kmeans_ = KMeans(self.n_clusters,
    random_state=self.random_state)
    self.kmeans_.fit(X, sample_weight=sample_weight)
    return self
 def transform(self, X):
    return rbf_kernel(X, self.kmeans_.cluster_centers_,
    gamma=self.gamma)

 def get_feature_names_out(self, names=None):
    return [f"Cluster {i} similarity" for i in
    range(self.n_clusters)]

cluster_simil = ClusterSimilarity(n_clusters=4, gamma=0.1, random_state=42)

similarities =cluster_simil.fit_transform(df[['model_year', 'mpg']])

# Convert similarities to DataFrame for inspection
similarities[:3].round(2)
```

Out[115…
```
array([[0.  , 0.  , 0.19, 0.01],
       [0.  , 0.  , 0.57, 0.  ],
       [0.  , 0.  , 0.19, 0.01]])
```

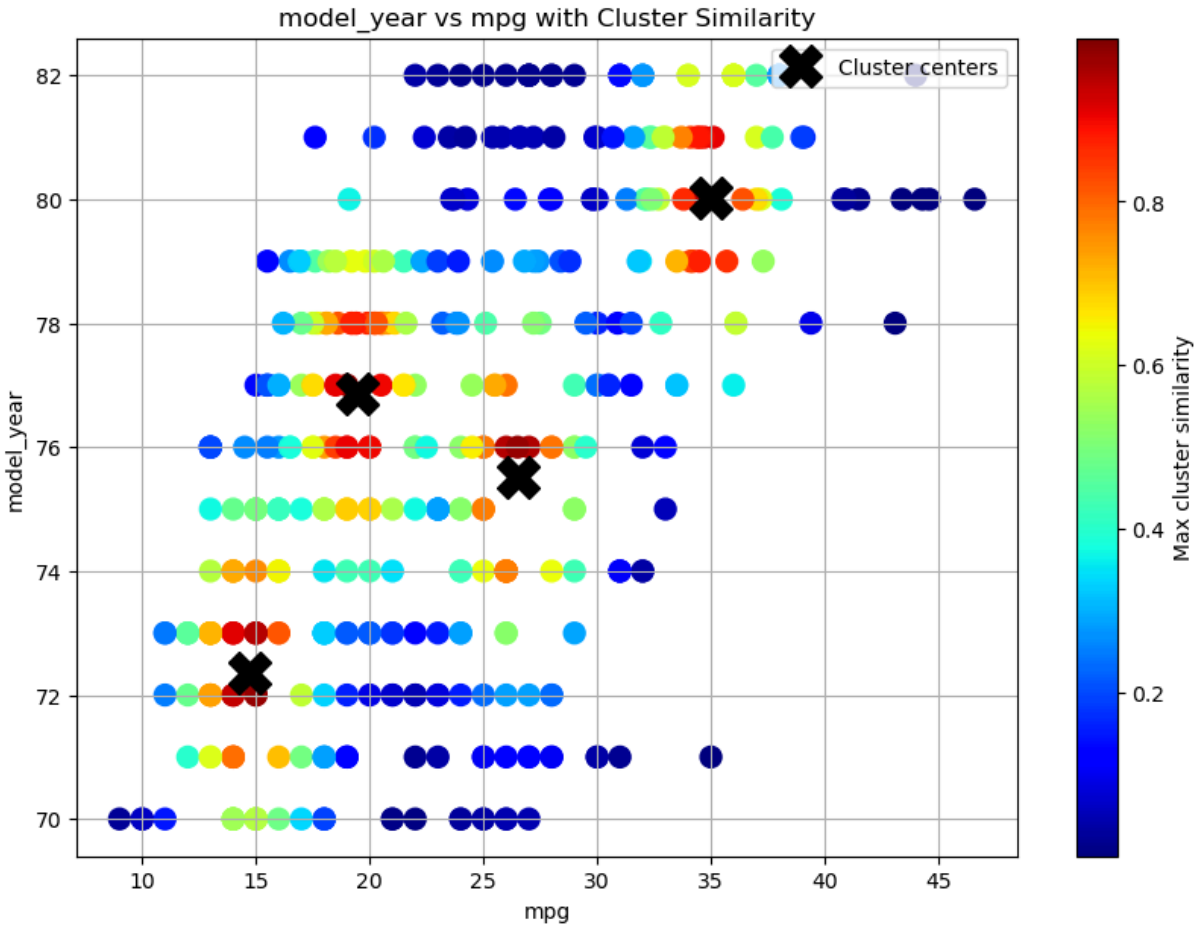
In [116…
```
df_renamed = df.rename(columns={
    "model_year": "model_year",
    "mpg": "mpg"
})


df_renamed["Max cluster similarity"] = similarities.max(axis=1)


df_renamed.plot(kind="scatter", x="mpg", y="model_year", grid=True,
                s=100,
                c="Max cluster similarity", cmap="jet", colorbar=True,
                legend=True, sharex=False, figsize=(10, 7))

plt.plot(cluster_simil.kmeans_.cluster_centers_[:, 1],  # mpg
         cluster_simil.kmeans_.cluster_centers_[:, 0],  # model_year
         linestyle="", color="black", marker="X", markersize=20,
         label="Cluster centers")

# Add legend and display the plot
plt.legend(loc="upper right")
plt.title('model_year vs mpg with Cluster Similarity')
plt.show()
```



Task 4: Pipelines and ColumnTransformers

In this final task, we combine all transformers into a pipeline and apply them to both numerical and categorical features.

In [117…
```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder

# Numerical pipeline
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScalerClone())
])

# Categorical pipeline
cat_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(sparse_output=False))
])

# Combine into a ColumnTransformer
full_pipeline = ColumnTransformer([
    ('num', num_pipeline, numerical_columns),
    ('cat', cat_pipeline, categorical_columns)
], verbose_feature_names_out=False)

df_prepared = full_pipeline.fit_transform(df)
```

In [118…
```
print(df_prepared)
```

```
[[-0.7064387   1.49819126  1.0906037  ...  0.          0.
   0.        ]
 [-1.09075062  1.49819126  1.5035143  ...  0.          0.
   0.        ]
 [-0.7064387   1.49819126  1.19623199 ...  0.          0.
   0.        ]
 ...
 [ 1.08701694 -0.85632057 -0.56103873 ...  0.          0.
   0.        ]
 [ 0.57460104 -0.85632057 -0.70507731 ...  0.          0.
   0.        ]
 [ 0.95891297 -0.85632057 -0.71467988 ...  0.          0.
   0.        ]]
```

In [119…
```
feature_names = full_pipeline.get_feature_names_out()
df_prepared_with_names = pd.DataFrame(df_prepared, columns=feature_names, ir

print("Shape of prepared data:", df_prepared_with_names.shape)
print("\nFirst few rows of prepared data with column names:")
print(df_prepared_with_names.head())
```

```
Shape of prepared data: (398, 315)

First few rows of prepared data with column names:
        mpg  cylinders  displacement  horsepower    weight  acceleration  \
0 -0.706439   1.498191      1.090604    0.673118  0.630870     -1.295498
1 -1.090751   1.498191      1.503514    1.589958  0.854333     -1.477038
2 -0.706439   1.498191      1.196232    1.197027  0.550470     -1.658577
3 -0.962647   1.498191      1.061796    1.197027  0.546923     -1.295498
4 -0.834543   1.498191      1.042591    0.935072  0.565841     -1.840117

   model_year  origin_europe  origin_japan  origin_usa  ...  \
0   -1.627426            0.0           0.0         1.0  ...
1   -1.627426            0.0           0.0         1.0  ...
2   -1.627426            0.0           0.0         1.0  ...
3   -1.627426            0.0           0.0         1.0  ...
4   -1.627426            0.0           0.0         1.0  ...

   name_volvo 145e (sw)  name_volvo 244dl  name_volvo 245  name_volvo 264gl
\
0                   0.0               0.0             0.0               0.0
1                   0.0               0.0             0.0               0.0
2                   0.0               0.0             0.0               0.0
3                   0.0               0.0             0.0               0.0
4                   0.0               0.0             0.0               0.0

   name_volvo diesel  name_vw dasher (diesel)  name_vw pickup  name_vw rabbi
t  \
0                0.0                      0.0             0.0             0.
0
1                0.0                      0.0             0.0             0.
0
2                0.0                      0.0             0.0             0.
0
3                0.0                      0.0             0.0             0.
0
4                0.0                      0.0             0.0             0.
0

   name_vw rabbit c (diesel)  name_vw rabbit custom
0                        0.0                    0.0
1                        0.0                    0.0
2                        0.0                    0.0
3                        0.0                    0.0
4                        0.0                    0.0

[5 rows x 315 columns]
```

In [120…

```
feature_names = full_pipeline.get_feature_names_out()
df_prepared_with_names = pd.DataFrame(df_prepared, columns=feature_names, ir

df_prepared_with_names.head()
```

Out[120…

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	c
0	-0.706439	1.498191	1.090604	0.673118	0.630870	-1.295498	-1.627426	
1	-1.090751	1.498191	1.503514	1.589958	0.854333	-1.477038	-1.627426	
2	-0.706439	1.498191	1.196232	1.197027	0.550470	-1.658577	-1.627426	
3	-0.962647	1.498191	1.061796	1.197027	0.546923	-1.295498	-1.627426	
4	-0.834543	1.498191	1.042591	0.935072	0.565841	-1.840117	-1.627426	

5 rows × 315 columns

In [ ]: