**Introduction**

In this project, We have used various python libraries and jupyter notebook to work on predicting the house price by the following features:

- Year of sale of the house
- The age of the house at the time of sale
- Distance from city center
- Number of stores in the locality
- The latitude
- The longitude

https://www.kaggle.com/datasets/yasserh/housing-prices-dataset?resource=download

```
pip install utils
```

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

```
pip install pandas
```

```
pip install tensorflow
```

```
#Importing Libraries
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
import seaborn as sns

from utils import *
from sklearn.metrics import precision_score, recall_score, accuracy_score
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping, LambdaCallback

%matplotlib inline
tf.compat.v1.logging.set_verbosity(tf.compat.v1.logging.ERROR)

print('Libraries are imported.')
```

```
Libraries are imported.
```

**Importing Data:**

```
#Importing datasets
from google.colab import files
uploaded = files.upload()
```

Choose files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving data.csv to data.csv
```

```
#Fetching the data set
df = pd.read_csv('data.csv')
print(df)
```

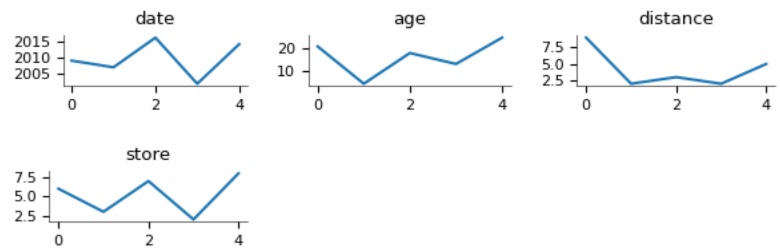
```
      date  age  distance  store  latitude  longtitude  price
0     2009   21         9      6        84         121  14264
1     2007    4         2      3        86         121  12032
2     2016   18         3      7        90         120  13560
3     2002   13         2      2        80         128  12029
4     2014   25         5      8        81         122  14157
...    ...  ...       ...    ...       ...         ...    ...
4995  2007   17         6      3        90         125  13539
4996  2016    7        10      0        85         129  14757
4997  2017    6        10      5        90         125  14102
4998  2010   37         3      5        81         128  14313
4999  2018    9         1      9        90         127  12770
```

```
[5000 rows x 7 columns]
```

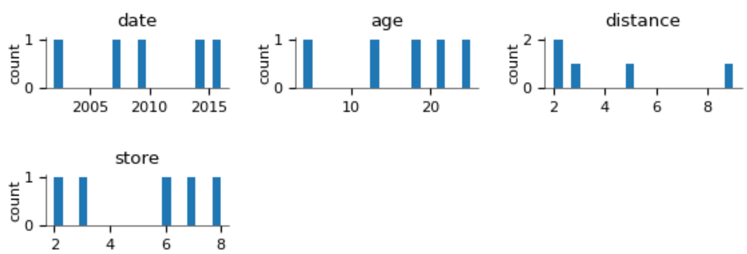
```
df.head()
```

| | date | age | distance | store | latitude | longtitude | price |
|---|---|---|---|---|---|---|---|
| **0** | 2009 | 21 | 9 | 6 | 84 | 121 | 14264 |
| **1** | 2007 | 4 | 2 | 3 | 86 | 121 | 12032 |
| **2** | 2016 | 18 | 3 | 7 | 90 | 120 | 13560 |
| **3** | 2002 | 13 | 2 | 2 | 80 | 128 | 12029 |
| **4** | 2014 | 25 | 5 | 8 | 81 | 122 | 14157 |

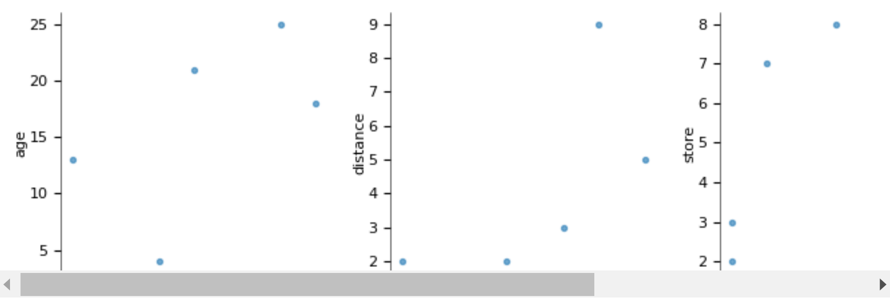
**Values**




**Distributions**

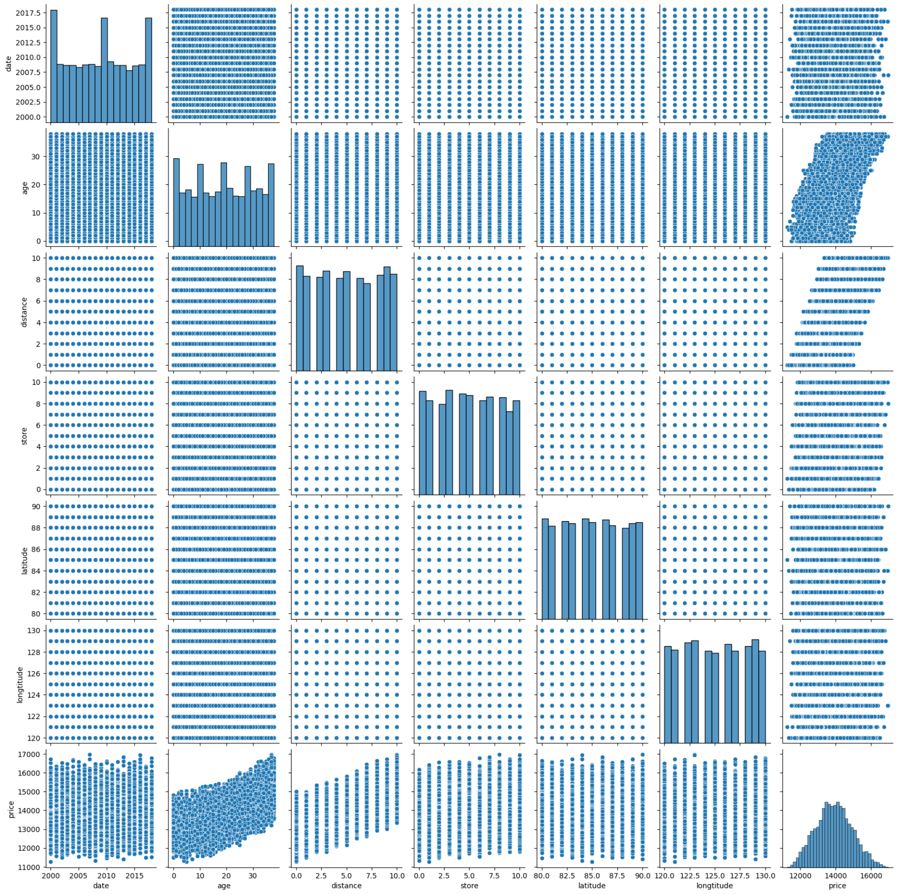



**2-d distributions**



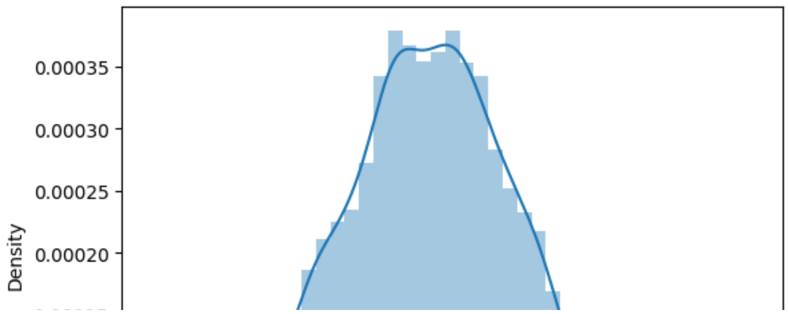

```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7b3142fac5e0>
```



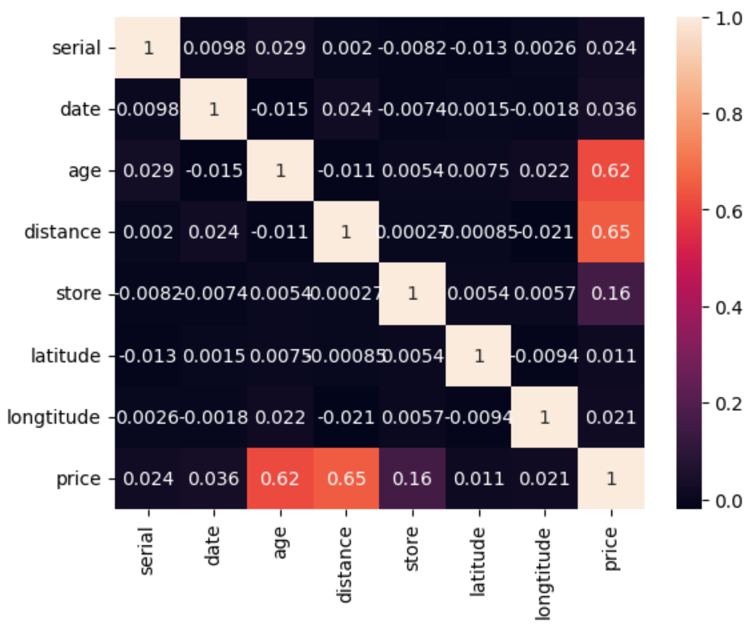
```
sns.distplot(df['price'])
```

```
<ipython-input-22-86c1ddc3c66a>:1: 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(df['price'])
<Axes: xlabel='price', ylabel='Density'>
```




```
sns.heatmap(df.corr(),annot = True) #Just to see the correlation between the features and the label
```

```
<Axes: >
```




### Checking For Missing Data:

```
#Checking For Missing Data
df.isna().sum()
```

```
serial        0
date          0
age           0
distance      0
store         0
latitude      0
longtitude    0
price         0
dtype: int64
```

### Data Normalization

Normalizing the data to bring all the different features to a similar range to make it easier for optimization algorithms to find minimas.

```
#Normalizing the data to bring all the different features to a similar range
#to make it easier for optimization algorithms to find minimas.
df = df.iloc[:,1:]
```

```
df_norm = (df - df.mean()) / df.std()
df_norm.head()
```

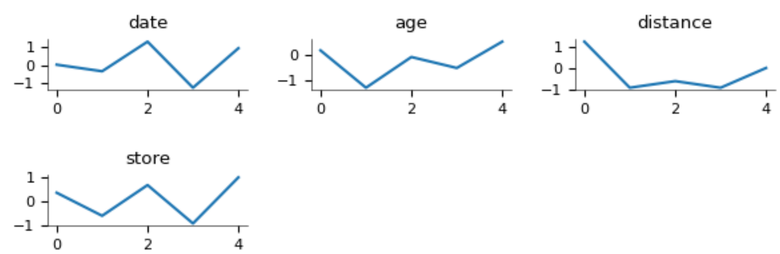
| | date | age | distance | store | latitude | longtitude | price |
|---|---|---|---|---|---|---|---|
| **0** | 0.015978 | 0.181384 | 1.257002 | 0.345224 | -0.307212 | -1.260799 | 0.350088 |
| **1** | -0.350485 | -1.319118 | -0.930610 | -0.609312 | 0.325301 | -1.260799 | -1.836486 |
| **2** | 1.298598 | -0.083410 | -0.618094 | 0.663402 | 1.590328 | -1.576456 | -0.339584 |
| **3** | -1.266643 | -0.524735 | -0.930610 | -0.927491 | -1.572238 | 0.948803 | -1.839425 |
| **4** | 0.932135 | 0.534444 | 0.006938 | 0.981581 | -1.255981 | -0.945141 | 0.245266 |

```
#Convert Label Value Back To Original:
y_mean = df['price'].mean()
y_std = df['price'].std()

def convert_label_value(pred):
    return int(pred * y_std + y_mean)
```

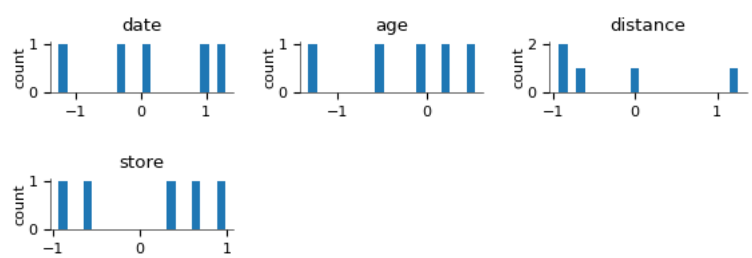
```
#Creating Training and Test Sets:

X = df_norm.iloc[:, :6] #Storing the features in 'X'
X.head()
```

| | date | age | distance | store | latitude | longtitude |
|---|---|---|---|---|---|---|
| **0** | 0.015978 | 0.181384 | 1.257002 | 0.345224 | -0.307212 | -1.260799 |
| **1** | -0.350485 | -1.319118 | -0.930610 | -0.609312 | 0.325301 | -1.260799 |
| **2** | 1.298598 | -0.083410 | -0.618094 | 0.663402 | 1.590328 | -1.576456 |
| **3** | -1.266643 | -0.524735 | -0.930610 | -0.927491 | -1.572238 | 0.948803 |
| **4** | 0.932135 | 0.534444 | 0.006938 | 0.981581 | -1.255981 | -0.945141 |

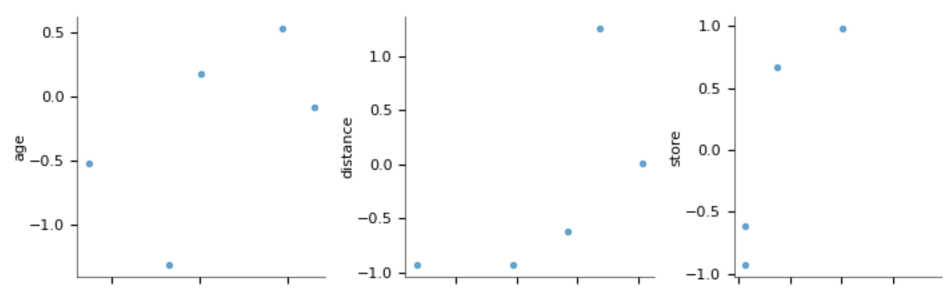
**Values**




**Distributions**




**2-d distributions**



```
Y = df_norm.iloc[:, -1] #Storing the labels in 'Y'
Y.head()
```

```
0    0.350088
1   -1.836486
2   -0.339584
3   -1.839425
4    0.245266
Name: price, dtype: float64
```

```
X_arr = X.values
Y_arr = Y.values

print('X_arr shape: ', X_arr.shape) #'shape' gives the dimension of the entity
print('Y_arr shape: ', Y_arr.shape)
```

```
X_arr shape:  (5000, 6)
Y_arr shape:  (5000,)
```

```
X_train, X_test, y_train, y_test = train_test_split(X_arr, Y_arr, test_size = 0.05, shuffle = True, random_state=0)
print('X_train shape: ', X_train.shape)
print('y_train shape: ', y_train.shape)
print('X_test shape: ', X_test.shape)
print('y_test shape: ', y_test.shape)
```

```
X_train shape:  (4750, 6)
y_train shape:  (4750,)
X_test shape:  (250, 6)
y_test shape:  (250,)
```

**Definig Model and Training data sets:**

```
#Creating the Neural Network Model

def get_model():

    model = Sequential([
        Dense(10, input_shape = (6,), activation = 'relu'), #10 neurons, Input Layer
        Dense(20, activation = 'relu'),                     #20 neurons, Hidden Layer
        Dense(5, activation = 'relu'),                      #5  neurons, Hidden Layer
        Dense(1)                                            #Output Layer
    ])                                                      #'relu' activation

    model.compile(
        loss='mse',                                         #Trained using Mean square error loss (Cost function)
        optimizer='adam'                                    #Optimizer used is 'adam' (One of the Fastest optimizers)
    )

    return model

model = get_model()
model.summary()
```

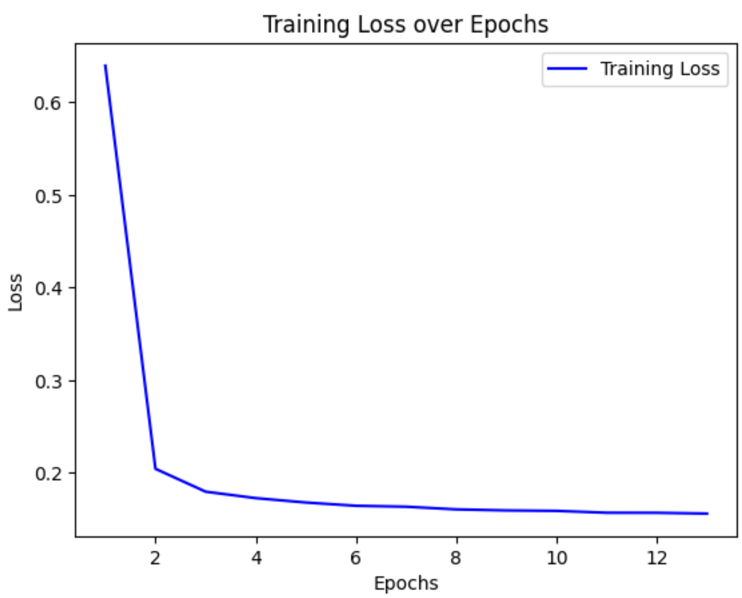
```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_8 (Dense)             (None, 10)                70

 dense_9 (Dense)             (None, 20)                220

 dense_10 (Dense)            (None, 5)                 105

 dense_11 (Dense)            (None, 1)                 6

=================================================================
Total params: 401
Trainable params: 401
Non-trainable params: 0
_________________________________________________________________
```

```
#Trainig the dataset into the model
early_stopping = EarlyStopping(monitor='val_loss', patience = 5) #Defining early stopping parameter (optional, to save time)

model = get_model()
```

```
preds_on_untrained = model.predict(X_test) #Make predictions on the test set before training the parameters

#Finally training the model-->
history = model.fit(
    X_train, y_train,
    validation_data = (X_test, y_test),
    epochs = 100,
    callbacks = [early_stopping]
)
```

```
8/8 [==============================] - 0s 2ms/step
Epoch 1/100
149/149 [==============================] - 2s 5ms/step - loss: 0.5439 - val_loss: 0.2443
Epoch 2/100
149/149 [==============================] - 0s 3ms/step - loss: 0.2028 - val_loss: 0.1632
Epoch 3/100
149/149 [==============================] - 0s 3ms/step - loss: 0.1755 - val_loss: 0.1520
Epoch 4/100
149/149 [==============================] - 0s 3ms/step - loss: 0.1695 - val_loss: 0.1476
Epoch 5/100
149/149 [==============================] - 0s 3ms/step - loss: 0.1653 - val_loss: 0.1514
Epoch 6/100
149/149 [==============================] - 0s 3ms/step - loss: 0.1627 - val_loss: 0.1491
Epoch 7/100
149/149 [==============================] - 0s 2ms/step - loss: 0.1610 - val_loss: 0.1538
Epoch 8/100
149/149 [==============================] - 0s 2ms/step - loss: 0.1603 - val_loss: 0.1457
Epoch 9/100
149/149 [==============================] - 0s 2ms/step - loss: 0.1584 - val_loss: 0.1499
Epoch 10/100
149/149 [==============================] - 0s 2ms/step - loss: 0.1572 - val_loss: 0.1502
Epoch 11/100
149/149 [==============================] - 0s 2ms/step - loss: 0.1566 - val_loss: 0.1484
Epoch 12/100
149/149 [==============================] - 0s 2ms/step - loss: 0.1560 - val_loss: 0.1553
Epoch 13/100
149/149 [==============================] - 0s 2ms/step - loss: 0.1560 - val_loss: 0.1493
```

```
# Finding The model accuracy:
def plot_loss(history):
    loss = history.history['loss']
    epochs = range(1, len(loss) + 1)
    plt.plot(epochs, loss, 'b-', label='Training Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title('Training Loss over Epochs')
    plt.legend()
    plt.show()


plot_loss(history)
```




```
from tensorflow.keras.models import Model
```

**Predicting the Price:**

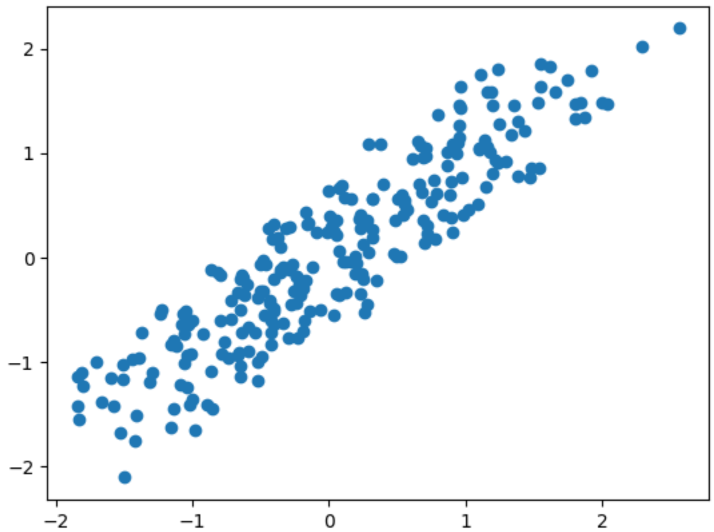
```
predictions = model.predict(X_test)
```

```
8/8 [==============================] - 0s 3ms/step
```

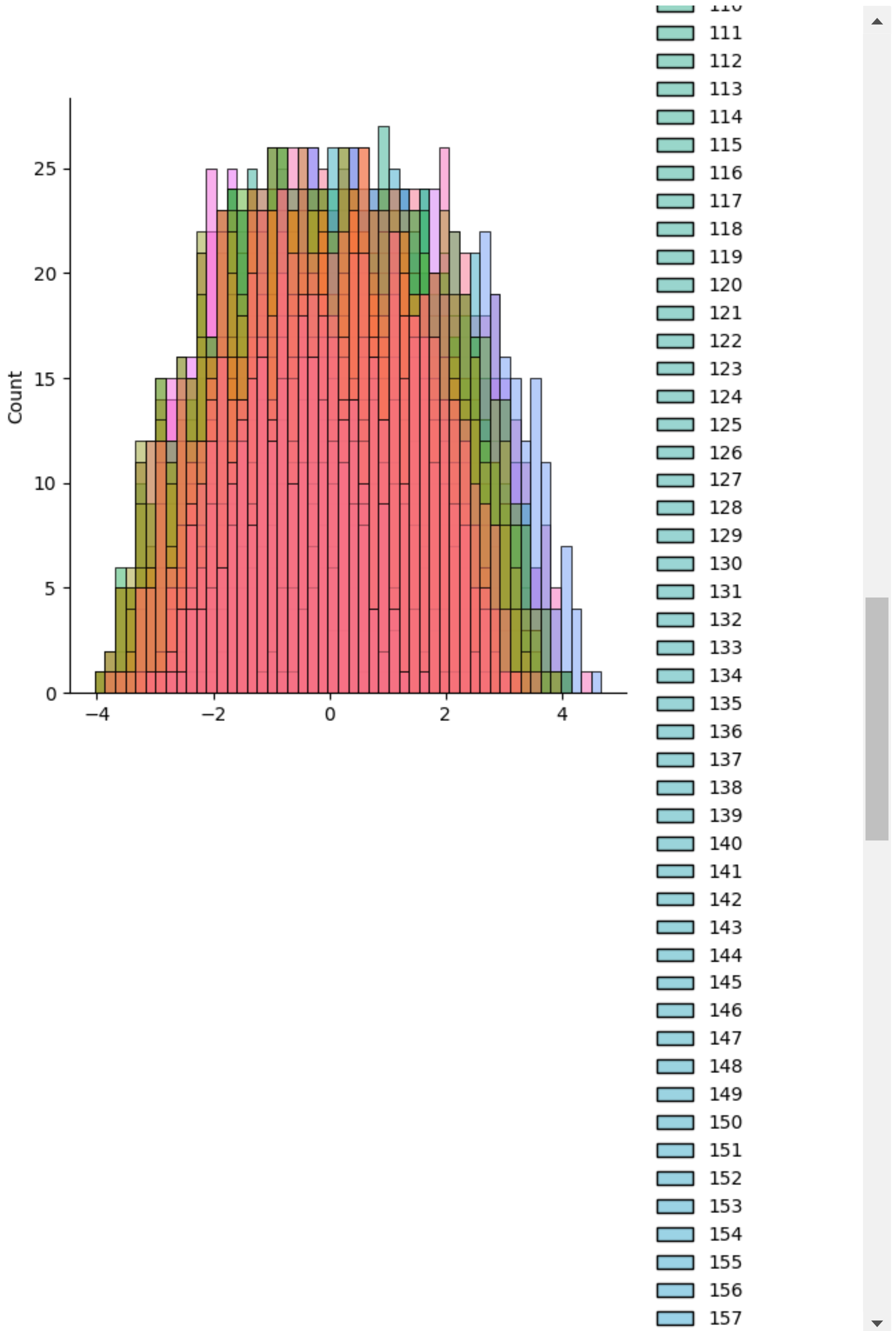
```
sns.displot(predictions)
```

```
plt.scatter(y_test, predictions)
```

```
<matplotlib.collections.PathCollection at 0x7b313b490130>
```




```
sns.displot((y_test-predictions), bins=50);
```


Count
0
5
10
15
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25
−4
−2
0
2
4
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112
113
114
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