Exercise

This is a dataset related to how much money a person can get from a mortgage on his or her home. This dataset includes the following features:

- Gender: Gender of the borrower (including two values 'F' and 'M')
- Age: Age of the customer applying for a loan (including positive integer values)
- Income (USD): Customer's income in USD (value is a positive number)
- Income Stability: The level of customer's income stability (including three values of Low and High)
- Property Age: Life expectancy of the house in days (including positive integer values)
- Property Location: Location of the house (including 'Rural', 'Urban', and 'Semi-Urban')
- Property Price: The value of the house in USD (including positive real values)
- Loan Sanction Amount (USD): Amount that customers can borrow in USD (target value)

Based on practice sample #1, proceed:

1. Read data
2. Visualize some information of data
3. Normalize Data to train linear regression model
4. Train linear regression model and show the model's intercepts, coeficients
5. Learn on sklearn how to use Ridge, Lasso, and ElasticNet compare the error of all 3 algorithms with Linear Regression (https://scikit-learn.org/stable/index.html)
6. Let's try Polynomial of order 2 to compare the previous results. What will the result be if we choose the n order too high?

Submission Link: https://forms.gle/uKAq34QrbwTcbs5Z9 (Submit your .ipynb file)

```
# mount data from google drive to colab
```

TypeError

Please explain the error:

```
TypeError: 'NoneType' object
```

Hypothesis

The error `TypeError: 'NoneType' object is not subscriptable` indicates that you are trying to access an element of an object that is `None`. In this case, the traceback points to the line `df["age"].hist(bins=20)`.

Looking at the global variables, the variable `df` has a value of `None` and its type is `NoneType`.

The function `read_dataset(path)` is responsible for loading the data into the `df` variable. However, this function reads the CSV and then *displays* the head and description of the DataFrame, but it does not explicitly *return* the DataFrame. Because there is no `return` statement, the function implicitly returns `None`.

Therefore, when the line `df = read_dataset(PATH)` is executed, the `df` variable is assigned the value `None` instead of the loaded DataFrame. Subsequently, attempting to access `df["age"]` on a `None` object results in the `TypeError`.

Suggested Changes

```
from google.colab import drive
drive.mount('/content/drive')

#import library
import pandas as pd # pandas
import numpy as np # numpy
import time
```

```
Mounted at /content/drive
```

Prepare and Analyze Data

1. Load Dataset
2. Analyze Dataset
3. Preprocess data (type, null, missing, ...)
4. Feature Engineering

Load Dataset

```
def read_dataset(path):
    # Todo: read_csv from a path and return a DataFram
    df = pd.read_csv(path)
    display(df.head())
    display(df.describe())
    return df
```

```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

```
PATH = ("/content/drive/MyDrive/Dataset/Insurance.csv")

df = read_dataset(PATH)
```

To fix this, you need to modify the `read_dataset` function to return the DataFrame it creates.

```
def read_dataset(path):
    # Todo: read_csv from a
    df = pd.read_csv(path)
    display(df.head())
    display(df.describe())
    return df # Add this lir
```

Use code with caution

▶ Sources

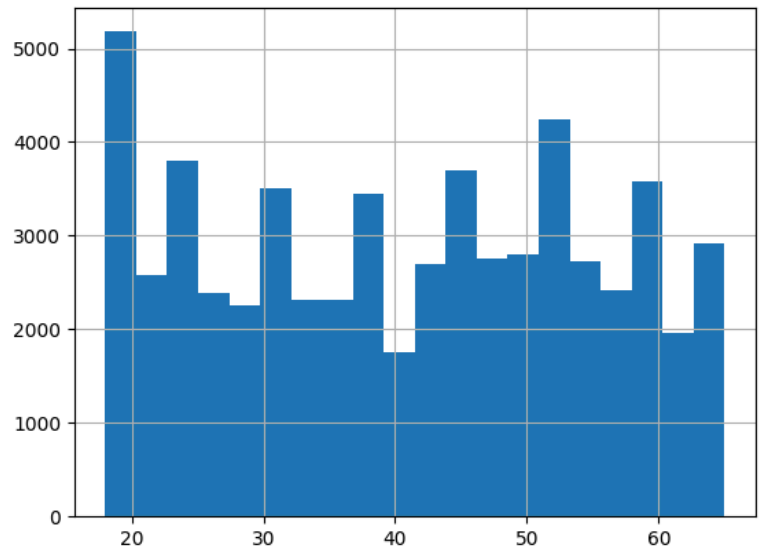
Rate this answer

	age	sex	bmi	children	smoker	region
0	43	female	25.800	0	yes	northwest
1	43	female	28.600	2	no	southwest
2	34	female	37.290	4	no	northeast
3	50	female	42.370	3	no	southeast
4	26	female	29.595	1	no	northeast

	age	bmi	children	
count	59333.000000	59333.000000	59333.000000	59
mean	40.791448	30.930536	1.107411	13
std	13.897712	6.121275	1.455713	10
min	18.000000	15.815000	-1.000000	
25%	28.000000	26.510000	0.000000	6
50%	42.000000	30.600000	1.000000	10
75%	52.000000	35.000000	2.000000	15
max	65.000000	54.130000	6.000000	63

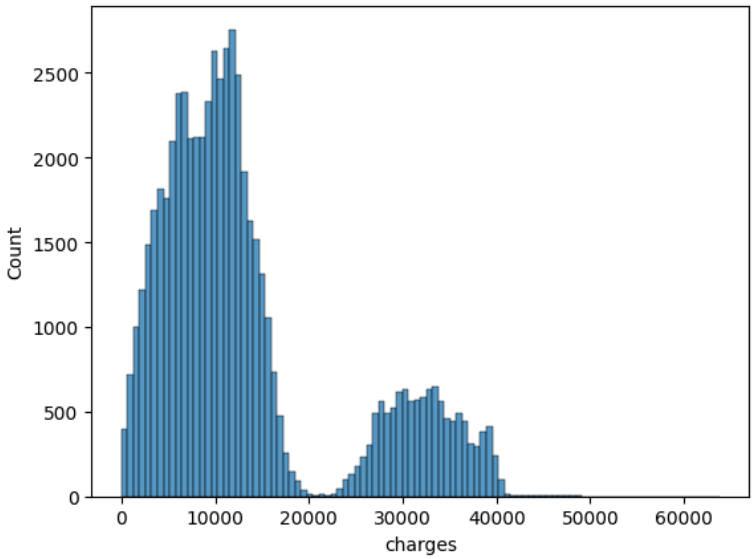
```
df["age"].hist(bins=20)
```

```
<Axes: >
```




```
import seaborn as sns
sns.histplot(x="charges", data=df, bins=100)
```

```
<Axes: xlabel='charges', ylabel='Count'>
```




```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attemp
```

Data Analysis

```
# Data analysis
# Todo: analyze your data here


# Null checking
df.isnull().sum()
```

	0
age	0
sex	0
bmi	0
children	0
smoker	0
region	0
charges	0

dtype: int64

Preprocessing

```
def preprocessing_data(df):
    # --- (Optional) Drop null datapoints or fill miss
    # Keep your data the same if you dont want to cust
    df = df
    return df


df = preprocessing_data(df.copy())
```

Feature Engineering

```
# ---- Method 1
start_time = time.time()
# data normalization
normalized_data = df.copy()
normalized_data["sex"] = normalized_data["sex"].apply(
normalized_data["smoker"] = normalized_data["smoker"].
normalized_data["region"] = normalized_data["region"].
#normalized_data

display(normalized_data.head())
display(normalized_data.corr())
print("Running time", time.time() - start_time)
```

	age	sex	bmi	children	smoker	region	
0	43	1	25.800	0	1	2	3112
1	43	1	28.600	2	0	0	873
2	34	1	37.290	4	0	3	1097
3	50	1	42.370	3	0	1	1527
4	26	1	29.595	1	0	3	515

	age	sex	bmi	children	
age	1.000000	0.004123	0.091252	0.008060	-(
sex	0.004123	1.000000	-0.049948	-0.017484	-(
bmi	0.091252	-0.049948	1.000000	0.030296	(
children	0.008060	-0.017484	0.030296	1.000000	(
smoker	-0.029931	-0.080734	0.002000	0.002852	1
region	-0.007996	0.015634	-0.149486	-0.021358	-(
charges	0.331857	-0.084363	0.202631	0.087100	(

Running time 0.1268773078918457

```
# ---- Method 1
start_time = time.time()
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normalized_data = df.copy()
normalized_data["sex"] = normalized_data["sex"].apply(
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children	0.008060	-0.017484	0.030296	1.000000	(
smoker	-0.029931	-0.080734	0.002000	0.002852	1
region	-0.007996	0.015634	-0.149486	-0.021358	-(
charges	0.331857	-0.084363	0.202631	0.087100	(

Running time 0.4762847423553467

```
def normalize_data(df):
    # ---- Method 3
    start_time = time.time()
    # data normalization
    normalized_data = df.copy()
    normalized_data["sex"] = normalized_data["sex"].as
    normalized_data["smoker"] = normalized_data["smoke
    normalized_data["region"] = normalized_data["regio

    display(normalized_data.head())
    display(normalized_data.corr())
    print("Running time", time.time() - start_time)
    return normalized_data



# Heatmap
import seaborn as sns

normalized_data = normalize_data(df.copy())
sns.heatmap(normalized_data.corr())
```

	age	sex	bmi	children	smoker	region	
0	43	0	25.800	0	1	1	3112
1	43	0	28.600	2	0	3	873
2	34	0	37.290	4	0	0	1097
3	50	0	42.370	3	0	2	1527
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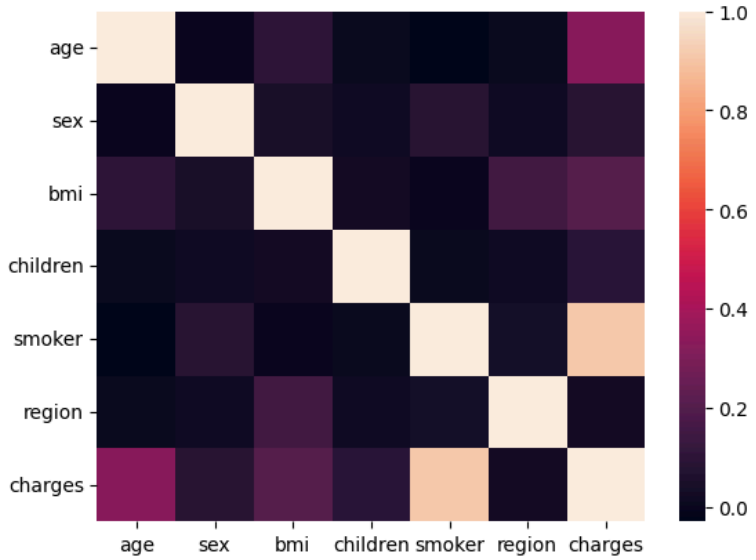
	age	sex	bmi	children	
age	1.000000	-0.004123	0.091252	0.008060	-0
sex	-0.004123	1.000000	0.049948	0.017484	0
bmi	0.091252	0.049948	1.000000	0.030296	0
children	0.008060	0.017484	0.030296	1.000000	0
smoker	-0.029931	0.080734	0.002000	0.002852	1
region	0.007996	0.015634	0.149486	0.021358	0
charges	0.331857	0.084363	0.202631	0.087100	0

```
Running time 0.27120494842529297
<Axes: >
```



Apply machine learning model

Train-test split

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error


def prepare_X_y(df):
    ## Split X, y from dataset
    columns = df.columns.tolist()     # Columns name
    columns.remove('charges')           # Remove y lab
    # columns = ["smoker_yes", "bmi", "age"]
    X = df[columns]        # X
    y = df.charges          # y
    return X, y


def split_train_test(X, y, train_size=0.7):
    trainX, testX ,trainY, testY = train_test_split(X,
    print('Training:' + str(trainX.shape))
    print('Test:' + str(testX.shape))

    return trainX, testX ,trainY, testY

trainX, testX ,trainY, testY = split_train_test(X, y)
```

```
Training:(41533, 6)
Test:(17800, 6)
```

```
TRAIN_SIZE = 0.7

trainX, testX ,trainY, testY = split_train_test(X, y,
```

```
Training:(41533, 6)
Test:(17800, 6)
```

Basic Linear Regression

```
from sklearn.linear_model import LinearRegression


def build_linear_model(X, y):
    model = LinearRegression(fit_intercept=True)
    model.fit(trainX, trainY)

    return model

model = build_linear_model(trainX, trainY)
# Compare on training dataset
pred = model.predict(trainX)
print("mean absolute error of linear model on train se
pred = model.predict(testX)
```

```
print("mean absolute error of linear model on test set

print(model.coef_) # print coefficient
print()
print(model.intercept_) # print intercept_
```

```
mean absolute error of linear model on train set
mean absolute error of linear model on test set  9
[  251.5138989     37.66451724   285.95725561   54
 23646.11182404  -317.42447355]

-10384.586630782997
```

Polynomial Transform

When the data feature does not conform to a linear function, a linear regression cannot be applied directly to the original data. Then, there are many possibilities that the data feature conforms to the polynomial function. Scikit-Learn supports converting data features to polynomials through `PolynomialFeatures`.

$$y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + \cdots$$

The formula above uses the transformation of the value x from one dimension to the other, with the aim of being able to use linear regression to find complex relationships between x and y.

```
#Linear Regression with Polynomial Transform
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline

def build_pipeline(X, y):
    poly_model = make_pipeline(PolynomialFeatures(2, i
    poly_model.fit(X, y)

    return poly_model

poly_model = build_pipeline(trainX, trainY)
# Compare on training dataset
poly_pred = poly_model.predict(trainX)
print("mean absolute error of linear model (with poly

poly_pred = poly_model.predict(testX)
print("mean absolute error of linear model (with poly
```

```
mean absolute error of linear model (with poly tra
mean absolute error of linear model (with poly tra
```

Linear Regression

```
def split_train_test(X, y, train_size=0.7):
    trainX, testX ,trainY, testY = train_test_split(X,
    print('Training:' + str(trainX.shape))
    print('Test:' + str(testX.shape))

    return trainX, testX ,trainY, testY

trainX, testX ,trainY, testY = split_train_test(X, y)
```

```
Training:(41533, 6)
Test:(17800, 6)
```

```
from sklearn.linear_model import Ridge, Lasso, Elastic
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler
```

Ridge Regression

```
from sklearn.linear_model import Ridge

# Huấn luyện mô hình Ridge Regression
ridge = Ridge(alpha=1.0)
ridge.fit(X_scaled, y)
ridge_predictions = ridge.predict(X_scaled)
```

Lasso Regression

```
# Lasso Regression
lasso = Lasso(alpha=0.1)
lasso.fit(X_scaled, y)
lasso_predictions = lasso.predict(X_scaled)
```

ElasticNet

```
elastic_net = ElasticNet(alpha=0.1, l1_ratio=0.5)
elastic_net.fit(X_scaled, y)
elastic_net_predictions = elastic_net.predict(X_scaled
```

```
linear_predictions = model.fit(X_scaled, y).predict(X_
mse_linear = mean_squared_error(y, linear_predictions)
mse_ridge = mean_squared_error(y, ridge_predictions)
mse_lasso = mean_squared_error(y, lasso_predictions)
mse_elastic_net = mean_squared_error(y, elastic_net_pr


print("MSE for Linear Regression:", mse_linear)
print("MSE for Ridge Regression:", mse_ridge)
print("MSE for Lasso Regression:", mse_lasso)
print("MSE for ElasticNet Regression:", mse_elastic_ne
```

```
MSE for Linear Regression: 826175.1490314518
MSE for Ridge Regression: 826175.4132536046
MSE for Lasso Regression: 826175.3191767012
MSE for ElasticNet Regression: 2548351.674109707
```

```
# N = 2
poly = PolynomialFeatures(degree=2)
X_poly = poly.fit_transform(X_scaled)

# Huấn luyện mô hình Linear Regression với các đặc trư
poly_model = LinearRegression()
poly_model.fit(X_poly, y)

# Dự đoán và tính MSE cho Polynomial Regression
poly_predictions = poly_model.predict(X_poly)
mse_poly = mean_squared_error(y, poly_predictions)

print("MSE for Polynomial Regression (degree=2):", mse
```