# Hands-on Lab: Generative AI for Data Insights

One of the principal steps in understanding and interpreting data is drawing statistical and correlative insights from the data. In this lab, you will learn how to use efficient prompts on a Generative AI platform to create a Python script for generating insights on a data set available in a CSV file.

## Objectives

In this lab, you will learn how to create prompts to generate Python code that can:

- Generate a statistical description of all the features of the data set
- Generate regression and box plots for different attributes to compare their distribution against a target attribute
- Evaluate the correlation value, Pearson coefficient, and p-values for different parameters of the data set with the target parameter
- Create pivot tables for a group of parameters and visualize them using pcolor plots

## Data set

For this lab, you'll use a clean version of a publically available data set about laptop price prediction using specifications.

The CSV file for this clean version of the data set is available at the following URL:

```
URL = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DA0101EN-Coursera/laptop_pricing_dataset_mod2.csv
```

The dataset is a filtered and modified version of the Laptop Price Prediction using specifications dataset, available under the Database Contents License (DbCL) v1.0 on the Kaggle website.

## Testing environment

You can test the codes generated using this lab in a JupyterLite environment. Click the following link to launch a JupyterLite lab environment.

JupyterLite test environment

Follow the steps mentioned in this link to set up the testing environment.

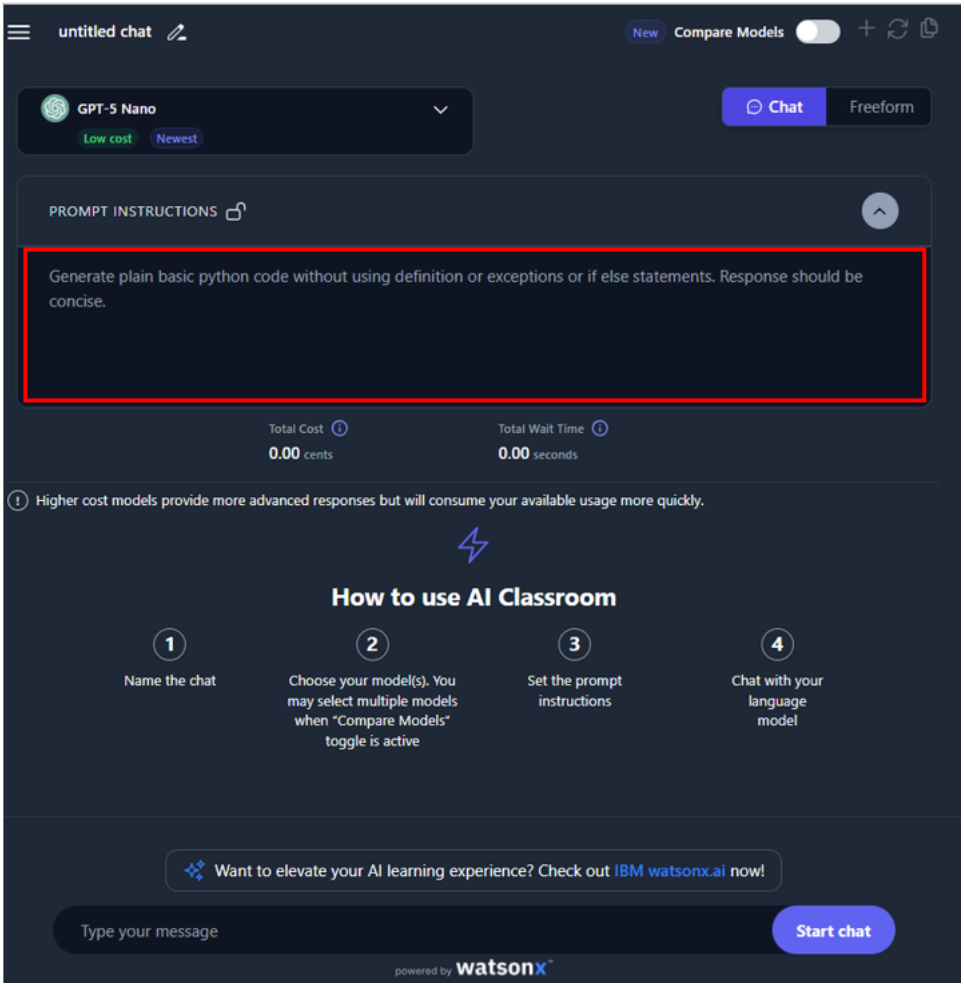
# Reading the data set and generating the statistical description

First, you must import the data set into the interface as a pandas data frame. To complete the first objective, you can further generate a statistical description of the data set.

The data set is now assumed to be completely prepared and ready for exploratory data analysis. The headers for the data set must be in the first row of the CSV file.

To read the CSV file to a data frame and a generate statistical description of the data set, provide the generative AI model with the following prompt.

You can set the prompt like below to get a defined output:




Now you can run the following in the type your message section and start the chat.

```
Write a python code to perform the following actions.
1. Import a data set from a CSV file, The headers for the data set must be in the first row of the CSV file.
2. Generate the statistical description of all the features used in the data set. Include "object" data types as well.
```

This prompt will display code that looks like what you see below:

```
This script reads a CSV file named data.csv with headers in the first row, creates a DataFrame, computes descriptive statistics for all columns (incl
import pandas as pd
# Path to the CSV file. The first row is treated as headers by default (header=0).
data_path = "data.csv"
# Read the CSV file into a DataFrame. Assumes the first row contains headers.
df = pd.read_csv(data_path)
# Generate descriptive statistics for all columns, including object (categorical) types.
description = df.describe(include="all")
# Output the description to stdout
print(description)
```

You can use the relevant code and run the code in the testing environment.

# Creating parameter visualizations

Next, you decided that you need to see the distribution of various attributes against the target attribute. The target attribute, in this case, is `Price`. Different forms of visualizations are for different types of attributes. Attributes with continuous values use regression plots, and the attributes with categorical values use box plots.
You can provide the generative AI model with a list of continuous values and another list of categorical values within a single prompt and ask the model to create a code that generates these plots.

The attributes with continuous values are `CPU_frequency`, `Screen_Size_inch` and `Weight_pounds`.
The attributes with categorical values are `Category`, `GPU`, `OS`, `CPU_core`, `RAM_GB` and `Storage_GB_SSD`.

Create the following prompt:

```
Write a Python code to perform the following actions.
1. Create regression plots for the attributes "CPU_frequency", "Screen_Size_inch" and "Weight_pounds" against "Price".
2. Create box plots for the attributes "Category", "GPU", "OS", "CPU_core", "RAM_GB" and "Storage_GB_SSD" against the attribute "Price".
```

The output should be as shown below.

```
This script generates regression plots of Price against CPU_frequency, Screen_Size_inch, and Weight_pounds, followed by box plots of Price by several
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
# Load dataset from CSV (expects columns: Price, CPU_frequency, Screen_Size_inch, Weight_pounds,
# Category, GPU, OS, CPU_core, RAM_GB, Storage_GB_SSD)
df = pd.read_csv('data.csv')
# Set Seaborn aesthetics
sns.set(style='whitegrid')
# Regression plots: Price vs numeric attributes
plt.figure(figsize=(6, 4))
sns.regplot(x='CPU_frequency', y='Price', data=df, scatter_kws={'alpha': 0.5})
plt.title('Price vs CPU_frequency')
plt.xlabel('CPU_frequency')
plt.ylabel('Price')
plt.tight_layout()
plt.show()
plt.figure(figsize=(6, 4))
sns.regplot(x='Screen_Size_inch', y='Price', data=df, scatter_kws={'alpha': 0.5})
plt.title('Price vs Screen_Size_inch')
plt.xlabel('Screen_Size_inch')
plt.ylabel('Price')
plt.tight_layout()
plt.show()
plt.figure(figsize=(6, 4))
sns.regplot(x='Weight_pounds', y='Price', data=df, scatter_kws={'alpha': 0.5})
plt.title('Price vs Weight_pounds')
plt.xlabel('Weight_pounds')
plt.ylabel('Price')
plt.tight_layout()
plt.show()
# Box plots: Price by categorical attributes
plt.figure(figsize=(8, 4))
sns.boxplot(x='Category', y='Price', data=df)
plt.xticks(rotation=45)
plt.title('Price by Category')
plt.tight_layout()
plt.show()
plt.figure(figsize=(8, 4))
sns.boxplot(x='GPU', y='Price', data=df)
plt.xticks(rotation=45)
plt.title('Price by GPU')
plt.tight_layout()
plt.show()
plt.figure(figsize=(8, 4))
sns.boxplot(x='OS', y='Price', data=df)
plt.xticks(rotation=45)
plt.title('Price by OS')
plt.tight_layout()
plt.show()
# For numeric attributes, create bins to enable box plots against Price
df['CPU_core_binned'] = pd.cut(df['CPU_core'], bins=6, include_lowest=True)
plt.figure(figsize=(8, 4))
sns.boxplot(x='CPU_core_binned', y='Price', data=df)
plt.xticks(rotation=45)
plt.title('Price by CPU_core (binned)')
plt.tight_layout()
plt.show()
df['RAM_GB_binned'] = pd.cut(df['RAM_GB'], bins=6, include_lowest=True)
plt.figure(figsize=(8, 4))
sns.boxplot(x='RAM_GB_binned', y='Price', data=df)
plt.xticks(rotation=45)
plt.title('Price by RAM_GB (binned)')
plt.tight_layout()
plt.show()
df['Storage_GB_SSD_binned'] = pd.cut(df['Storage_GB_SSD'], bins=6, include_lowest=True)
plt.figure(figsize=(8, 4))
sns.boxplot(x='Storage_GB_SSD_binned', y='Price', data=df)
plt.xticks(rotation=45)
```

```
plt.title('Price by Storage_GB_SSD (binned)')
plt.tight_layout()
plt.show()
```

You can use the relevant code generated by running this prompt.

> Remember to install the `seaborn` package on the testing environment.
> Also, remember to execute the statement `%matplotlib inline` for the plots to be visible directly in the console.

# Evaluate dependence

Usually, not all parameters in a data set have a direct or strong level of influence on the target variable. The level of influence is especially important for data scientists because the design of predictive models uses variables that affect the target variable the most.

To evaluate parametric interdependence, one can evaluate the correlation value, the Pearson coefficient, and p-values of different attributes with the target attribute.

Use the following prompt to write a prompt to evaluate dependence:

```
Write a Python code for the following.
1. Evaluate the correlation value, pearson coefficient and p-values for all numerical attributes against the target attribute "Price".
2. Don't include the values evaluated for target variable against itself.
3. Print these values as a part of a single dataframe against each individual attribute.
```

You can view the output for this prompt below.

```
Loads data from data.csv, finds numeric feature columns, excludes the target Price, and for each numeric attribute computes the Pearson correlation c
import pandas as pd
import numpy as np
from scipy.stats import pearsonr
# Load dataset (expects a column named 'Price' and numeric feature columns)
df = pd.read_csv('data.csv')
# Identify numeric attributes and exclude the target 'Price'
numeric_cols = df.select_dtypes(include=[np.number]).columns
attributes = [col for col in numeric_cols if col != 'Price']
# Compute Pearson r and p-value for each numeric attribute against Price
results = []
for attr in attributes:
    sub = df[[attr, 'Price']].dropna()
    r, p = pearsonr(sub[attr], sub['Price'])
    results.append({'Attribute': attr, 'Pearson_r': r, 'Correlation': r, 'p_value': p})
# Present as a single dataframe with one row per attribute
result_df = pd.DataFrame(results).set_index('Attribute')
print(result_df)
```

You can use the code generated here to test on the testing platform.

# Grouping and pivots

You can perform another form of exploratory data analysis by grouping different variables to create a pivot table, which serves as a matrix of different combinations of values as seen in the grouped variables. The respective value of the matrix is the average of all values of the target attribute that have the same combination. You can view this kind of matrix using a pcolor plot.

Say you need to create a group with parameters `GPU`, `CPU_core` and `Price`. You need a Pivot table, considering `Price` as the target variable and pcolor plot for that table.

You can follow the following prompt as an example:

```
Write a python code that performs the following actions.
```

```
1. Group the attributes "GPU", "CPU_core" and "Price", as available in a dataframe df
2. Create a pivot table for this group, assuming the target variable to be 'Price' and aggregation function as mean
3. Plot a pcolor plot for this pivot table.
```

You can see the output for this prompt below.

```
This script builds a pivot table of mean Price by GPU (rows) and CPU_core (columns), then visualizes the result with a pcolor heatmap. It assumes df
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
# Assumes df contains the columns: GPU, CPU_core, and Price
# Create a pivot table grouping by GPU (rows) and CPU_core (columns) with mean Price
pivot = df.pivot_table(values='Price', index='GPU', columns='CPU_core', aggfunc='mean')
# Plot a pcolor heatmap of the pivot table
plt.figure(figsize=(8, 6))
pc = plt.pcolor(pivot.values, cmap='viridis')
plt.colorbar(pc, label='Mean Price')
plt.xlabel('CPU_core')
plt.ylabel('GPU')
plt.title('Mean Price by GPU and CPU_core')
# Set axis tick labels
plt.xticks(np.arange(0.5, len(pivot.columns), 1), pivot.columns, rotation=45)
plt.yticks(np.arange(0.5, len(pivot.index), 1), pivot.index)
plt.tight_layout()
plt.show()
```

You can use the code from this output based on your requirements.

# Conclusion

Congratulations! You have completed this lab about generating data insights using generative AI tools.

Now you should be able to build efficient and helpful prompts that can create code to:

- Generate statistical descriptions of the data
- Create visualizations, such as regression plots and box plots, to understand the distribution of the data set against the target variable
- Evaluate the dependence of different attributes against the target attribute
- Group different variables to create a pivot table and visualize the data using a pcolor plot

## Author(s)

Abhishek Gagneja