"Linear Algebra Project Report"

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Introduction

This project involves using linear algebra concepts to analyze and predict product prices based on data extracted from e-commerce websites. By selecting a product category and employing web scraping tools to gather relevant features like price, rating, and reviews, and will transform this data for use in a linear regression model. The model will be trained and evaluated on this data to predict prices.

For the project we choose to build a system for **predicting laptops prices**. In this way we choose the Digikala as our dataset reference as mentioned a good dataset in the project documentation. We faced with lots of things including data scrambling, data cleaning, implementing <u>regression model</u>, creating an AI mode with training, gui for prediction and other processes which explained in detail below.

Let's Get Through

• Part 1 (Data Collection & Data Cleaning)

For our linear algebra project, we set out to collect data on laptops to perform a regression analysis on their prices. While ready-to-use datasets were available on various websites, the project guidelines required us to gather the data ourselves. We chose Digikala, a prominent e-commerce platform, as our data source.

Initial Attempts with Beautiful Soup:

Our first approach involved using Beautiful Soup, a popular Python library for web scraping. Initially, we were encouraged by the 200 HTTP status code responses, indicating successful connections. However, we soon realized that Digikala, being a sophisticated and secure website, implemented measures to deter automated scraping. Despite receiving 200 status codes, the HTML content returned was often a decoy, containing no useful data. This revelation meant that our initial code and efforts were futile.

```
chtml dir="rtl" lang="fa">chtml lang="fa">chtml dir="rtl" lang="fa">ch
```

As you see a fake HTML file is returned.

Switching to Selenium:

Given the limitations of Beautiful Soup, we shifted to Selenium, a tool designed for automating web browser interactions. Selenium provided more robust capabilities but introduced its own set of challenges. Each time we loaded a page, an intermediary screen appeared before the actual content was displayed. It took us considerable time to identify and bypass these preliminary screens to access the real HTML content.

Image Suggestion: A sequence of screenshots showing the intermediary screen and the final page content, illustrating the process of bypassing the initial screen.

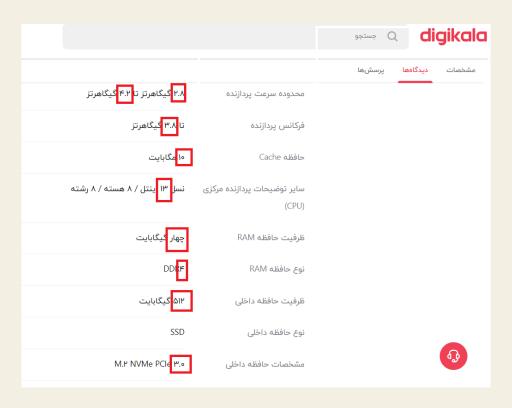
Handling Diverse Data Formats:

Once we accessed the correct HTML pages, we encountered another layer of complexity. The data was presented in various formats and styles. For instance, numerical values were sometimes embedded in strings, requiring us to parse and extract specific portions. Additionally, the data varied between integers, text, and mixed formats. In some cases, laptop specifications like storage size were written out in Persian, such as "بيك ترابايت" (one terabyte), necessitating conversion to numerical values like "1 TB."



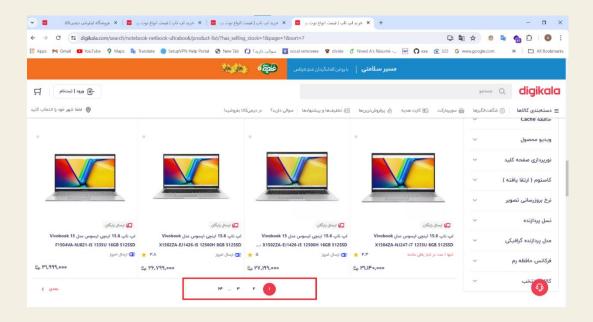
Language and Number Conversion:

Another significant hurdle was the language barrier. All the data, including numbers, was in Persian. We had to convert Persian numerals and words into English equivalents. This included translating Persian words for numbers and units into English, which was a meticulous and time-consuming process.



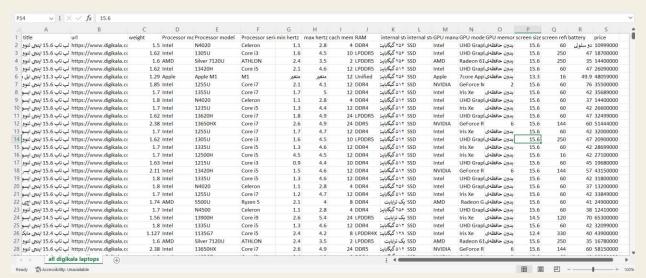
Automating the Process:

To efficiently manage these challenges, we developed a comprehensive script using Selenium. The script was designed to navigate through multiple pages, handle intermediary screens, and extract the relevant laptop information automatically. It also incorporated functions to parse, clean, and convert the data into a consistent format suitable for analysis.



Overcoming Challenges:

Despite the numerous obstacles, including misleading HTTP responses, intermediary page loads, varied data formats, and language translation issues, we successfully collected a robust dataset from Digikala. This dataset included detailed specifications and prices of laptops(1104), which we used for our subsequent regression analysis.



Still Dealing with data:

As it shown in the above picture there are still some problems with this dataset.

- o Column "*min hertz*" and "*max hertz*": In these two columns we have some fields with value "منغير", which is not a valid data (it should be a numerical value).
 - **Solution:** We surfed the web for this value and find out an acceptable value for both columns.
- o "internal storage" Column: This Column was a terrible column, because the values were in Persian. So, first of all I cast all of them to English, then another problem with that was that the values showed in the fields were combine of SSD and HDD values. So, we need to separate them. I defined a new column as "internal_storage_hdd", and with python script, divide them and put each part in the correct filed.

```
import pandas as pd
df = pd.read_csv('./all digikala laptops.csv')
df1 = pd.read_csv('./all digikala laptops.csv')
# converting persian data to english
df['internal storage'] = df['internal storage'].str.replace('1280' ,'نیک ترابلیت ر ۲۵۴ گیگلبیت', 'df['internal storage'] = df['internal storage'].str.replace('۱۲۸ 128' , 'گیگلبیت') 
df['internal storage'] = df['internal storage'].str.replace('۲۵۶ 256' , ' گیگلبیت') 
df['internal storage'] = df['internal storage'].str.replace('۵۱۲ 512' , ' گیگلبیت')
df['internal storage'] = df['internal storage'].str.replace('1024' ,' يک ترابايت')
df['internal storage'] = df['internal storage'].str.replace('2048'
df['internal storage'] = df['internal storage'].str.replace('گيگابايت',
# convert persian numbers to english
df['internal storage'] = df['internal storage'].str.replace('.', '0')
df['internal storage'] = df['internal storage'].str.replace(''',
df['internal storage'] = df['internal storage'].str.replace('Y',
df['internal storage'] = df['internal storage'].str.replace('r',
df['internal storage'] = df['internal storage'].str.replace('۴',
df['internal storage'] = df['internal storage'].str.replace('۵',
df['internal storage'] = df['internal storage'].str.replace('f',
df['internal storage'] = df['internal storage'].str.replace('v',
df['internal storage'] = df['internal storage'].str.replace('^', '8')
df['internal storage'] = df['internal storage'].str.replace('%', '9')
# df['internal storage'] = df['internal storage'].str.replace('j', 'and')
print(df['internal storage'])
# print(df)
df.to_csv('allDigikaLalaptops_CLEANED.csv', index=False, encoding='utf-8-sig')
```

- o "GPU memory" Column: We replace the value "بدون حافظهى مجزا" with zero.
- o "battery" Column: Replace the value "دو سلولى" with the mean of the all rows in the battery column.
- And lots of the columns were not numerical like: "processor manufacture", "processor mocel", "processor serie", "RAM", "internal storage type", "GPU manufacture", "GPU model". We need to somehow convert them into numerical values. As mentioned in the documentation, we used the <u>one-hot encoding</u> approach.

• One-hot decoding: One-hot encoding is a technique used to convert categorical data into a numerical format by representing each category as a binary vector with a single high (1) value indicating the presence of that category and all other positions being low (0).

• Part 2 (Linear Regression Model)

- o **Data Splitting:** Split the data into training and testing sets. We consider 20 percent of our dataset as test data and 80 percent of that for the model training.
- o Model Training: Fit a linear regression model using the training set.
- o Model Evaluation: Evaluate the model's performance on the testing set using metrics like
- o Mean Squared Error (MSE) and R-squared score. We achieve about *94 percent accuracy* in our model.

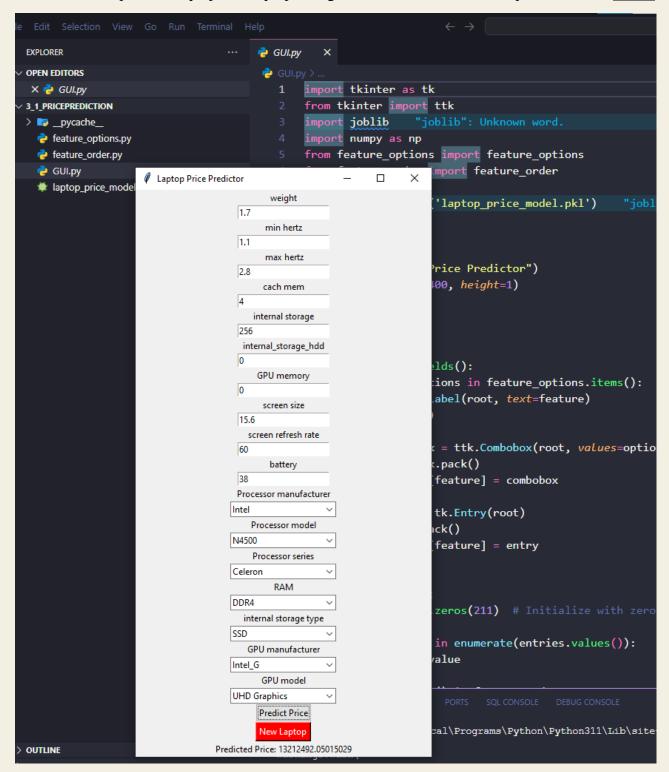
We also save the trained model for later price prediction.

```
# Slipt data (80% for train and 20% for test)
X = df_encoded.drop('price', axis=1)
y = df_encoded['price']
X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.2, random_state=42)
# Train a linear regression model
model = LinearRegression()
model.fit(X_train, y_train)
# Save the model to a file
joblib.dump(model, 'laptop_price_model.pkl')
### Model efficiency calculations ###
# Predict the prices on the test set
v pred = model.predict(X test)
# Calculate the Mean Absolute Error (MAE) and R-squared score
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

6

• Part 3 (Price Prediction)

As the last part of the project, we prepare a good GUI for a better user experience with "tkinter".



Challenges: In the process of using tkinter, we faced some bugs. When we want to design drop down menu (as we have now in the gui), we have to give the menu items as a list to them. Here we gave the list as a python file by name "feature_options". And, also when we want to predict the price of the laptop, we need a matrix feature. So, we defined another list in a python file by name "feature_order". And the challenge pops up here. When we want to get the index of the <u>GPU manufacture</u>, for example, intel, we get the index of the <u>cpu manufacture</u>, with the same name which was intel. In hence, the prediction wan not accurate. As **Solution**, we change the GPU manufacture names, by appending them "_G".

Conclusion

This project demonstrated the application of linear algebra concepts in real-world scenarios through the analysis and prediction of laptop prices based on data scraped from Digikala, an e-commerce platform. We overcame several challenges, including data scraping complexities, data cleaning, and translation of Persian numerical and textual data to English. By using Selenium for web scraping and one-hot encoding for handling categorical data, we successfully prepared a dataset suitable for linear regression analysis.

Our linear regression model, trained on this dataset, achieved a high accuracy of 94%, indicating strong predictive power. Additionally, we developed a user-friendly GUI using Tkinter, despite encountering and resolving several bugs related to menu item indexing.

Overall, this project highlights the importance of data preprocessing, the utility of linear regression in predictive modeling, and the integration of various tools and techniques to achieve a comprehensive solution. The full project files and documentation are available on GitHub for further exploration and validation.

