CS 839 Project Stage 4: Integrating and Performing Analysis

Aishwarya Ganesan
ag@cs.wisc.edu

David Liang
david.liang@wisc.edu

Viswesh Periyasamy
vperiyasamy@wisc.edu

1. Merging Schemas

We ran the entity matcher we developed in stage-3 on all the tuple pairs that survived the blocking step. Let M be the output of the entity matcher; it contains two columns namely, a_id and w_id, which identify products from Amazon and Walmart respectively. Let A and B be the tables that store Amazon and Walmart products respectively. A and B have identical schemas. Hence the schema E obtained by merging the two tables is identical except for the following difference: E has id and price columns for both Amazon and Walmart (as shown in the next section).

We merged the tuples as follows: we always select the value of the tuple as the one from Table A, unless this value is missing; in case the value from Table A is missing, we select the value from the tuple in Table B. We chose the above merging rule because we found the data in the Amazon products table to be cleaner and more complete. We append the code of the Python script (that merges the tables) to the end of this document as an Appendix.

However, once we performed the merging, we had to perform further steps to obtain clean data to perform analysis on.

Clean numeric values. For attributes with string values like *hard_disk_size*, *ram_size*, *cpu_speed*, etc., we had to clean the values so that the values are in the same unit. For example, the values of *hard_disk_size* were in GB, TB, KB, and MB in the data set. We cleaned the data so that all values are in GB uniformly. We also removed values that were extraneous or anamolies. For example, we removed those tuples that had processor_speeds lesser than 100 Mhz or values greater than 5 Ghz.

Clean string values. For attributes with string values like *brand*, *operating_system*, *cpu_manufacturer*, etc., we performed clustering to obtain a representative name. For example, for the attribute brand, we clustered similar values like Dell Commercial, Dell Computers, Dell Consumer, Dell USA, etc., and gave a representative name for the cluster (Dell in case of the above example).

2. Merged schema statistics

The merged table E has a schema with the following attributes:

```
a_id
w_id
amazon_price
walmart_price
brand
hard_disk_size
OS
cpu_manufacturer
processor_count
processor_speed
ram_size
screen_size
```

In total there are **4,173 tuples** in the merged table. Below are a few examples of tuples (product title excluded):

```
a_id  w_id amazon_price walmart_price brand hard disk size   OS \
a0    w2300   1099.0       1136.09    Acer         256.0   Windows 10
a102  w1746   199.99       244.0      Asus         16.0    Chrome
a1113 w3534   699.0        579.99     Apple        128.0   Mac OS X
a0    w2596   1099.0        997.49    Acer         256.    Windows 10
a1002 w2733   1297.5       1358.27     HP          256.0   Windows 7
 cpu   processor count processor speed  ram size  screen size
Intel         4               3.8         16.0        15.6
Intel         2               1.6         4.0         13.3
Intel         1               1.8         4.0         13.3
Intel         4               3.8         16.0        15.6
Intel         2               2.3         8.0         14.0
```

3. Frequent Item Sets

The first analysis we perform on the above data is to mine the frequent item sets and mine the association rules. association_rule_mining.py has the corresponding code.

Following are the frequent item sets that have a minimum support of 0.3 and with set sizes of one and two. More frequent item sets can be found in data/frequent_item_sets in stage-4 of our repository.

Table: Frequent Item Sets

Support	**Size**	**Frequent Item Set**
0.58	1	brand: Lenovo
0.35	1	hard_disk_size: 512.0 GB
0.88	1	operating_system: Windows 10
0.96	1	cpu_manufacturer: Intel
0.7	1	processor_count: 2
0.31	1	ram_size: 16.0 GB
0.56	1	screen_size: 14.0 in
0.31	1	screen_size: 15.6 in
0.32	2	brand: Lenovo, hard_disk_size: 512.0 GB
0.52	2	brand: Lenovo, operating_system: Windows 10
0.58	2	brand: Lenovo, cpu_manufacturer: Intel
0.53	2	brand: Lenovo, processor_count: 2
0.52	2	brand: Lenovo, screen_size: 14.0 in
0.31	2	hard_disk_size: 512.0 GB, operating_system: Windows 10
0.34	2	hard_disk_size: 512.0 GB, cpu_manufacturer: Intel
0.32	2	hard_disk_size: 512.0 GB, processor_count: 2
0.32	2	hard_disk_size: 512.0 GB, screen_size: 14.0 in
0.84	2	operating_system: Windows 10, cpu_manufacturer: Intel
0.62	2	operating_system: Windows 10, processor_count: 2
0.31	2	operating_system: Windows 10, ram_size: 16.0 GB
0.51	2	operating_system: Windows 10, screen_size: 14.0 in
0.69	2	cpu_manufacturer: Intel, processor_count: 2
0.56	2	cpu_manufacturer: Intel, screen_size: 14.0 in
0.54	2	processor_count: 2, screen_size: 14.0 in

Using the frequent item sets with a minimum support of 0.4, we performed some correlation analysis. We can make some of the following conclusions from the above analysis. Assuming a minimum support of 0.4, the brand Lenovo is associated with the Windows 10 operating_system with a confidence of 0.9. Assuming a minimum support of 0.4, laptops of Lenovo brand with the Windows 10 operating_system with screen_size of 14.0 inches are most likely to br associated with a processor_count of 2 with a confidence of 0.99. More such association rules we mined can be found in data/association_rules in our repository.

4. OLAP style analysis

We now perform some olap-style analysis on the merged table described previously. We have a fact table of laptops that gives the product prices in Amazon and Walmart. Some dimensions in this table are brand, operating system, processor (cpu) manufacturer etc. We perform different aggregate queries on the merged table where we group by based on different dimensions like brand, ram_size etc. The notebook olap.ipynb in our repository has the scripts used in this analysis.

4.1. Walmart vs. Amazon Pricing:

Observation 1: In general, prices are more expensive in Walmart than in Amazon.

	amazon_price	walmart_price
Mean	1385.5805966930266	1571.5141073568175

Observation 2: But if we drill down on the prices, using a particular brand, then we find that for a few brands like Apple, Alienware, Asus, Dell, etc., Amazon is pricier.

Drilling down by brand:

```
           amazon_price  walmart_price
brand
AORUS       2299.000000    2199.000000
Acer         487.122361     509.250694
Alienware   1785.146316    1714.692632
Aorus       2199.000000    2099.000000
Apple       1118.584123     729.805614
Asus         994.911304     864.117681
Bit          214.990000     179.000000
CTL          292.970000     264.810000
Dell         740.719229     692.582207
```

```
HP           928.033926    1066.269453
Huawei       689.280000     662.200000
LG          1247.030500     894.477000
Lenovo      1672.351025    2018.848058
MSI         1363.211951    1352.693659
Microsoft   2542.027500    2071.745000
OMEN        3599.000000    3563.950000
Panasonic   1224.791250     728.715000
Prostar     1318.549763    1217.438270
Razer       1604.247500    1790.990000
SLIDE        224.990000     224.990000
Samsung      972.627778     780.921111
Toshiba     1322.960000    1319.400000
VIZIO        979.990000     364.495000
```

4.2. Analysis by Brand:

We obtain average price by taking a mean of price of the product in Amazon and Walmart. **Observation 3: If we look at the average price range, Lenevo has a lot of products whose price > $1500**

```
brand    average_price_range     count
Acer     0-500                    87
         1000-1500                 8
         1500-2000                 2
         500-1000                 47
Apple    0-500                     1
         1000-1500                27
         1500-2000                 6
         2000-2500                 2
         500-1000                 78
Dell     0-500                    71
         1000-1500                52
         1500-2000                 8
         2000-2500                 2
         500-1000                243
HP       0-500                    89
         1000-1500               248
         1500-2000                46
         2000-2500                 4
         500-1000              125
Lenovo   0-500                  39
         1000-1500              66
         1500-2000            1592
         2000-2500             478
         2500-3000             133
         3000-3500               2
         500-1000              100
Prostar  1000-1500             259
         1500-2000              91
         500-1000               72
```

There a lot of Lenevo products in our database.

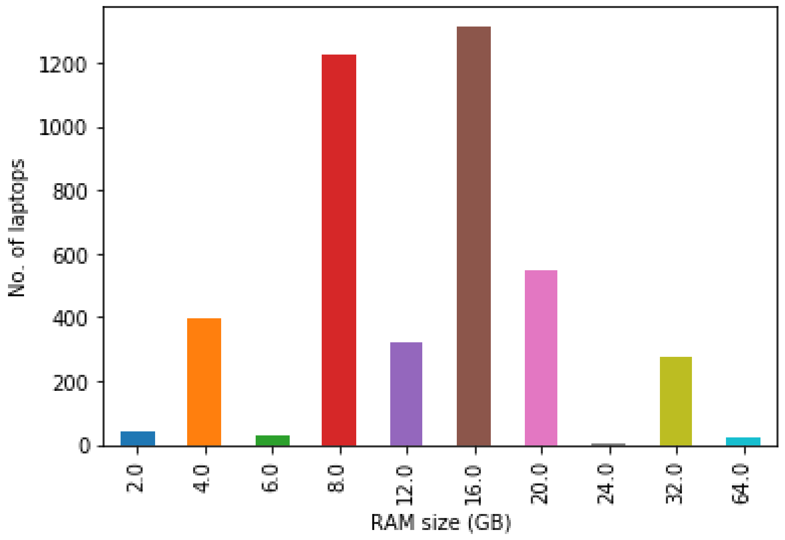
```
brand        count
Acer          144
Alienware      19
Apple         114
Asus           69
Dell          376
HP            512
LG             20
Lenovo       2410
MSI            41
Prostar       422
Samsung        18
```

Observation 4: Most of the Lenevo products in our database have Windows 10 as their operating systems

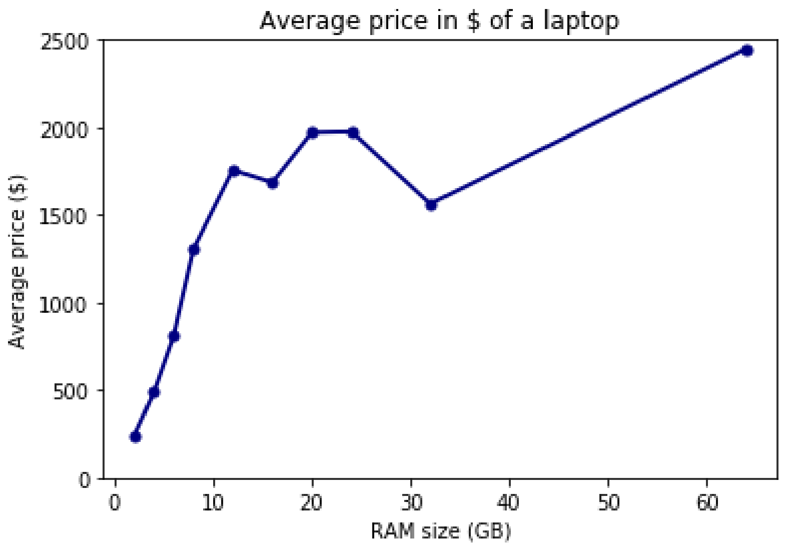
```
OS             count
Chrome           26
WINDOWS 10        1
Windows 10     2163
Windows 7       215
Windows 8         5
```

4.3. Analysis by RAM size:

Observation 5: RAM sizes of 8GB and 16GB are most popular.

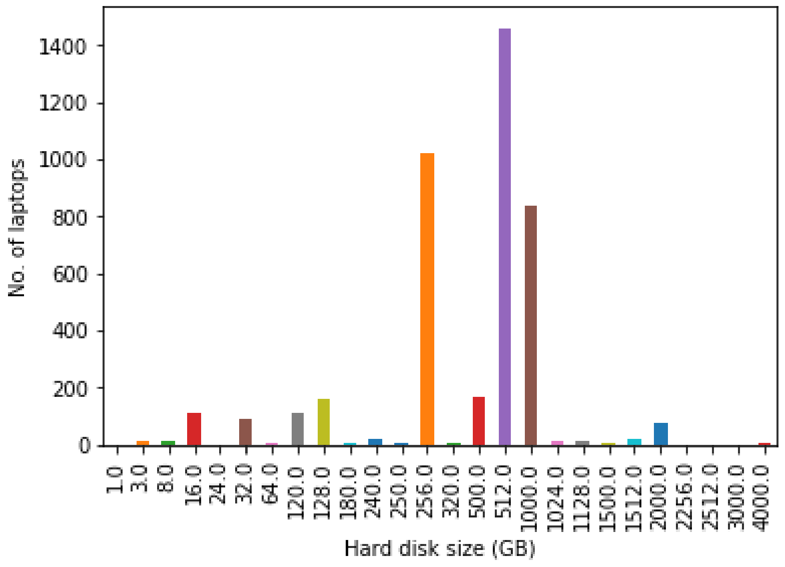


Observation 6: As the RAM size increases, the average price of a laptop increases.

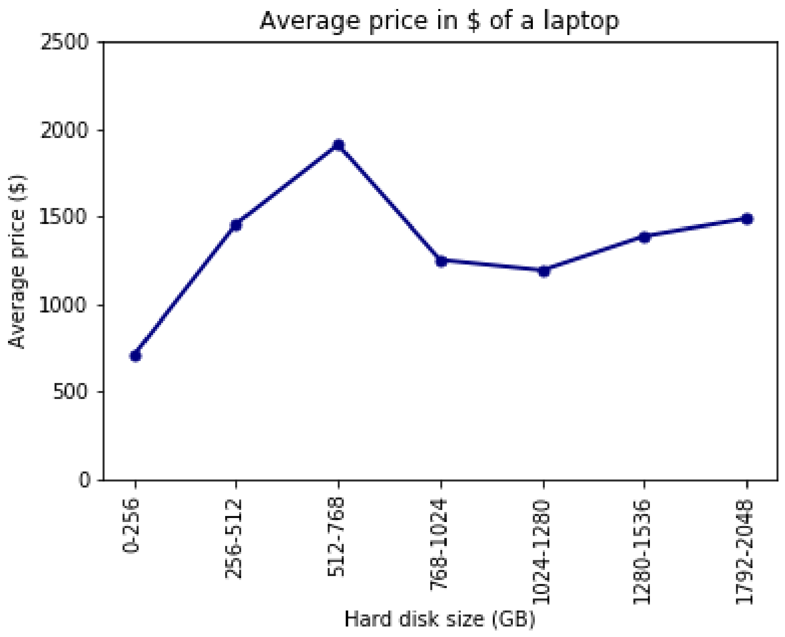


4.4. Analysis by Hard disk size:

Observation 7: Hard disk sizes of 256GB, 512GB, and 1TB are most popular.

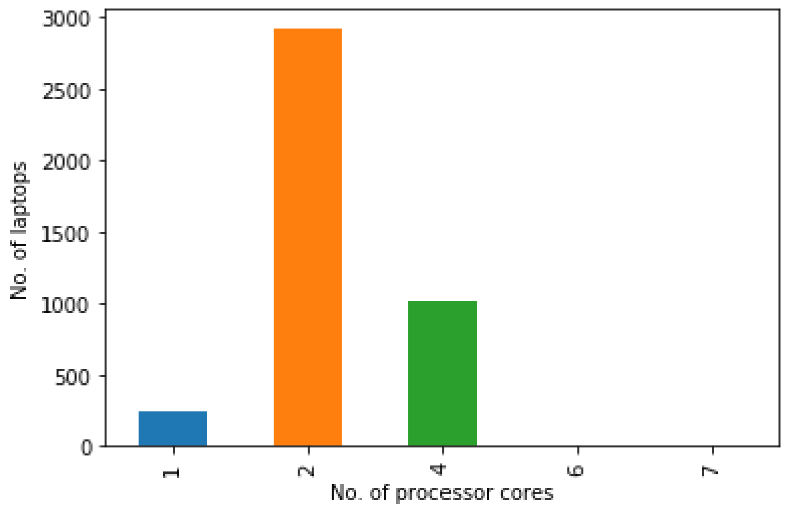


Observation 8: There is no obvious trend in the price of a laptop with the increase in hard disk size. A peak at 512GB could be due to the 512GB hard disks being SSDs instead of HDDs.

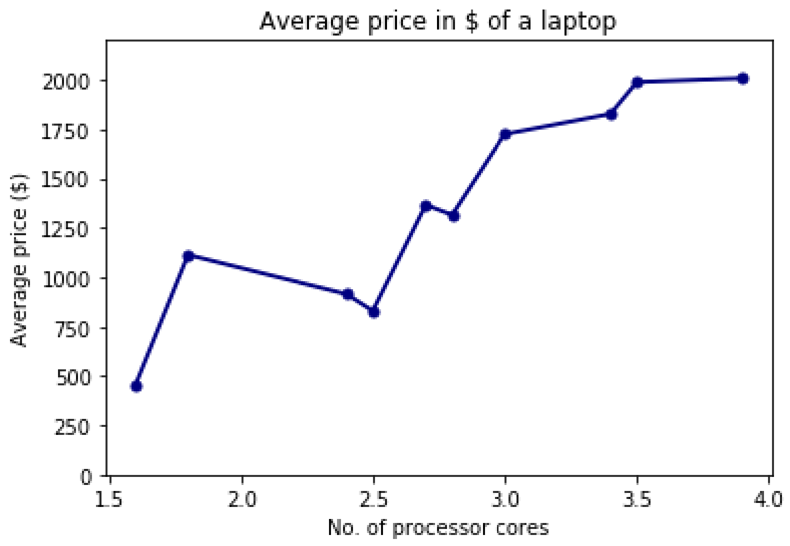


4.5. Analysis by Processor counts and speed:

Observation 9: Dual core processors are most popular.



Observation 10: There is an increase in the price of a laptop with the increase in the processor speed.



5. Price prediction analysis

Having matched entities between Walmart and Amazon, one task we wanted to investigate is whether we could predict the Amazon price and the Walmart price (multi-label classification) for the same entity given all of the other attributes. Originally we framed this as a regression task, however the data was too sparse and noisy to get price predictions that were remotely close to the actual prices. Specifically, the mean squared error was skyrocketing and upon inspection the predicted prices were several hundreds of dollars off, so we decided to reframe it for classification using price buckets. For example, whether or not the price is between \$0 and \$500, or between \$2500 and \$3000. We then used two classification algorithms well suited for multi-labeled, multi-class data sets: Decision Trees and Random Forests. Overall the process involved three steps: Data Cleaning, Vectorizing Features, and Classification. All code for this section can be found in `predict_prices.py`.

5.1. Data Cleaning

The data cleaning process has been described in 1. This data cleaning was especially important for String/categorical attributes which needed to be converted to one-hot encoding for feature vectors as every additional possible value added further and unnecessary dimensionality to our feature vectors.

5.2. Vectorizing Features

After cleaning the data thoroughly and manually inspecting it using table viewers such as Excel, we then converted each tuple into a feature vector. We ignored attributes like w_id (Walmart ID), a_id (Amazon ID), and product title (a large string representing the entire product title) as these were non-informative for the classification task. We then converted all String/categorical attributes to a one-hot binary encoding so that we could input them to the sci-kit learn models. This increased the dimensionality of each feature vector greatly but it was necessary in order to include these features for analysis.

Additionally, we converted the Amazon and Walmart price labels into buckets. We did this using an equal-width binning strategy where each price was digitized into a possible bucket or range of values that it fell into. This turned our regression task into a classification task as we now only had to predict which bucket a product fell into. This completed our conversion of each tuple into a feature vector with only numeric attributes.

5.3. Classification

To perform the multi-label multi-classification task, we attempted two binning strategies: even increments of $200 and even increments of $500. We created bins from $0 all the way to the maximum price rounded off evenly ($6500), resulting in 33 bins for the first strategy and only 13 bins for the second strategy. We then performed 5-fold cross validation using our set of tuples (shuffled) and reported accuracy metrics for each classifier (Decision Tree and Random Forest). The results are displayed in the tables below.

Table 1: Using a binning strategy with bin-width of $200

Classifier	Retailer	Accuracy	Precision	Recall	F-1
Decision Tree	Amazon	0.872029	0.881569	0.872029	0.876770
Decision Tree	Walmart	0.329978	0.288899	0.329978	0.307264
Random Forest	Amazon	0.873708	0.884511	0.873708	0.879072
Random Forest	Walmart	0.336927	0.264181	0.336927	0.304575

Table 2: Using a binning strategy with bin-width of $500

Classifier	Retailer	Accuracy	Precision	Recall	F-1
Decision Tree	Amazon	0.942730	0.946339	0.942730	0.944529
Decision Tree	Walmart	0.537027	0.528575	0.537027	0.526495
Random Forest	Amazon	0.943449	0.946596	0.943449	0.945019
Random Forest	Walmart	0.542057	0.531078	0.542057	0.531475

Looking at Table 1, we can see that our classifiers' predictions of Amazon's prices are vastly closer to the actual than compared to Walmart's prices. One reason for this is that when we were consolidating attributes between merged tuples, we tended to prefer Amazon's attribute values as they were much cleaner than Walmart's values - it's possible that these are more indicative of Amazon's pricing as well. If we look at Table 2 where our binning strategy was much more broad, we see a sharp spike of improvement in all metrics for both Walmart and Amazon. However, we still see the lag in predicting Walmart's prices as compared to Amazon's prices.

6. Conclusions

With our analysis of Walmart and Amazon prices, we were able to see that Amazon prices were much easier to predict than Walmart prices. This could be a factor of us preferring Amazon attribute values when consolidating matched tuples, or it could be that the laptop prices were less varied on Amazon and therefore much easier to place into bins. As Walmart was much more difficult to predict, it is also possible that their laptop pricing is somewhat non-representative of the product (i.e. they do not price the laptop proportionately based on its attributes but rather to keep in line with their business goals).

If we performed further analysis, one thing we would have to refine is the data cleaning stage. Much of the data was extremely dirty and required several passes of manual rules and replacements, and due to our labor constraints we often had to consolidate a variety of values into one central value. This caused us to lose a lot of valuable details and information that some attributes had to offer. Furthermore, we encountered a lot of missing values which forced us to lose information about those tuples. With more time, we might have used tactics such as Information Extraction to fill in missing values (e.g. if the operating system is missing, go to the product title and extract it from there).

Coupled with these issues is the size of the dataset - it is much too small, and to draw more meaningful conclusions we would need a much larger set to train and test on. Given more time, we would crawl several more products (say tens of thousands) from each website so that we would have an ample supply to sample from.

Appendix: Code for Merging

The following is code of the Python script that merges the tables.

```
for match in matches:
  if match[0] in amazon_products and match[1] in  walmart_products:
    merged_tuple = match[0] + ',' + match[1]
    for i in range(1, len(metadata)):
       meta = metadata[i]
       if meta == 'price':
          merged_tuple += ',' + amazon_products[match[0]][meta]
          merged_tuple += ',' +  walmart_products[match[1]][meta]
       else:
```

```
    if amazon_products[match[0]][meta] != '':
       merged_tuple += ',' + amazon_products[match[0]][meta]
    else:
       merged_tuple += ',' + walmart_products[match[1]][meta]
```

However, we had to perform more steps after merging. The steps and the corresponding script files are as follows : i) clean numeric values (clean_numeric.py),ii) Clean string values (clean_strings.py)