Association Rules and Lift

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Data Mining II

Introduction

This paper is about market basket analysis. This paper will be about the processes that are required to undergo market basket analysis on a dataset. There will be various concepts discussed. These concepts are items like the following the concepts of association rules, antecedents, and consequents. There will be a discussion on how the data needs to be prepared before it can be used for market basket analysis.

Background

The data that was used for this assessment was provided by the university. The dataset is composed of medical prescription transactions. The initial dataset was composed of 15001 entries. Half of the rows did not contain any information and this will be discussed in the Data Preparation and Analysis section of the paper. The number of columns in the dataset was twenty. Each of these columns corresponded to a prescription that was part of the transaction. This dataset will need to be formatted so that it can be used for market basket data analysis. The steps that will need to be performed will be discussed in the Data Preparation and Analysis.

Part I: Research Question

In this section of the paper, there will be a discussion of the proposed research question. This question will be relevant to the organization and will be answered using the data that has been provided. There will be a discussion of the goal of the analysis. What the analysis would like to accomplish using market basket analysis.

A1. The Research Question: The question that market basket would be able to answer is to see what other prescriptions are often prescribed with another drug. In a hospital setting drugs are often prescribed in lots. It may be beneficial to see which drugs are prescribed together. In this assessment, we will look at what drugs are often prescribed with lisinopril. This is important to know because these drugs are used to treat certain types of health disorders and would be interesting to see what other drugs this particular drug is prescribed with. This particular drug is used to treat high blood pressure (*Lisinopril: MedlinePlus Drug Information*, n.d.).

A2. Goal of the Analysis: The goal of the analysis is to see what drugs are prescribed in conjunction with lisinopril. We want to see what other drugs are prescribed to treat high blood pressure medication. If we can ascertain the drugs that are often prescribed we can ascertain if the drugs are possibly redundant and could be removed from the patient's medication list. The results of this market basket analysis can be passed on to the appropriate medical professionals for their input and a course of action.

Part II: Market Basket Justification

In this section, there will be a discussion on how market basket analysis is performed. This will discuss the algorithm's mechanics on how this type of analysis is performed. There will be an example of a transaction as given in the dataset. A discussion on one of the assumptions of market basket analysis will be also undertaken.

B1. How Market Basket Analyzes Data: In market basket analysis there is a defined goal. The goal of market basket analysis is to find patterns in the transactions that are performed by customers, but this is equally applicable to the patients who are the focus of this assessment. In the real world, there are often associations that are often exhibited when certain items are purchased. For example, if you were to buy hot dogs you would probably items that are often a compliment to the hot dogs. You would buy items like hot dog buns, and the condiments that go along with the hot dogs, e.g. ketchup, mustard, etc. This transaction can be seen as a pattern and the retailer can know what items to be grouped when setting up a display.

In this assessment, the customer is the patient, but the concept is still applicable here. Instead of looking for products that are purchased together, we are looking for the patterns of drugs that are prescribed for each of the transactions.

The algorithm uses a few ideas to analyze the data within the dataset. The first idea is that of the IF, THEN construct. This construct means that “If A then B.” Meaning that if A happens then it is logical that B will occur. Using the example from earlier if we buy hot dogs then we buy hot dog buns.

Some terms are associated with these concepts that should be understood. The first is the term known as the antecedent. In the example, the hot dogs were the antecedent it is the item that needs to occur first. The next term is known as the consequent this is what is logically expected to happen. In this example, the hot dog buns would be considered the consequent.

To derive the answers to the consequent there will be rules that will be created based on the likelihood that a particular pairing is to occur. These are used to determine the association between items found in a set. The rules are referred to as association rules. The association rules are between the items in the set.

When these rules are created some metrics can be used to see if the rules are useful. These metrics are support, confidence, and lift. Each of these metrics has a value that can be used to determine how well the rule works in predicting the result of the If-Then statement (Goriya, 2021). These metrics will be discussed in subsequent sections of this paper.

B2. An Example of a Transaction: In this section, you will find a sample transaction for the dataset provided. It is shown in the screenshot below. This is for the element at index 7401 of the dataframe. This data has not been augmented in any way. The data in the dataframe has not been prepared so "NaN" values will appear in the output. This will be handled in a later section of this paper.

```
Presc01        glyburide
Presc02       alprazolam
Presc03    acetaminophen
Presc04              NaN
Presc05              NaN
Presc06              NaN
Presc07              NaN
Presc08              NaN
Presc09              NaN
Presc10              NaN
Presc11              NaN
Presc12              NaN
Presc13              NaN
Presc14              NaN
Presc15              NaN
Presc16              NaN
Presc17              NaN
Presc18              NaN
Presc19              NaN
Presc20              NaN
Name: 7401, dtype: object
```

Image 1: A transaction sample.

The code for this can be found in section B2 of the accompanying Jupyter Notebook.

B3. One Assumption of Market Basket Analysis: If you are using the Apriori algorithm the assumption is any subset of an itemset must be frequent. For example, a transaction that contains {hot dogs, hot dog rolls, relish} will also contain {hot dogs, hot dog rolls}. If using the Apriori algorithm this would imply that if {hot dogs, hot dog rolls, relish} is a frequent transaction then {hot dogs, hot dog rolls} is also frequent (Chauhan, 2019).

This means that there are subsets of the rules, that are present and often occur along with the more complex rule. For example, {hot dogs, hot dog rolls, relish}, occurs frequently, but so will the subset of {hot dogs, hot dog rolls}. This subset will also occur with frequency.   This is one assumption that can be attributed to using market basket analysis using the Apriori algorithm.

Part III: Data Preparation and Analysis

In this section, there is a discussion on what was needed to get the dataset that was provided into a state that could be used for market basket analysis. Each step will be gone over that was used to yield a data set that is suitable for use in the analysis. This section will discuss some of the findings that were encountered during the data preparation.

C1. Data Transformation: The dataset that was provided was data about patient transactions. These transactions were the prescriptions that were prescribed. The number of prescriptions could range from one to no more than twenty being prescribed. All the steps that are described in this section can be found in section C1 of the Jupyter Notebook. In the notebook, you will also find the code that was used to accomplish the steps that are described below.

Reviewing the data in Excel, it was noted that there were rows that did not contain values. These rows contained NaN for all the columns. These were empty rows and these rows were not needed and will be dropped from the pandas dataframe. This was handled in Step 1: Drop the empty rows from the dataframe in section C1 of the Jupyter Notebook.

The next step will be to aggregate the prescriptions into a list of lists. Viewing the current of the transactions that were provided, we can see that some columns contain "NaN" values these values are not needed nor are they wanted when we go process the data in market basket analysis. The prescriptions will be stored in a list of lists. This was accomplished in Step 2: Create a list of lists for the prescription transactions of the notebook.

The data will then need to be encoded so that analysis can be performed. This encoding process will make use of the **TransactionEncoder()** method that is part of the **mlxtend.preprocessing** library. This was accomplished in Step 3: Encode the data to be ready for use.

The final task for this section was to output the cleaned dataset to a CSV file. This task was performed in Step 4: Output the cleaned data to a CSV file. The cleaned dataset can be found in the following CSV file:

- **Heino_D212_Task3_Market_Data.csv**

The code that was used to clean the data can be found in section C1 of the accompanying Jupyter Notebook. There will be a section header and relevant information included as Python comments where appropriate.

C2. Code to Generate Association Rules: The code to generate the association rules is accomplished using two methods. The first is the **apriori** method. This method was briefly discussed as an assumption in section B3. This method was utilized because the algorithm looks for frequent itemsets in a dataset and is used to generate the accompanying association rules (*Apriori Algorithm* | *Engati*, n.d.).

Then the resulting itemsets are used as arguments in the **association_rules** method of the **mlxtend.frequent_patterns** library. This method will generate the association rules along with the metrics that were discussed briefly in the previous section of this document.

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(amlodipine)	(abilify)	0.071457	0.238368	0.023597	0.330224	1.385352	0.006564	1.137144	0.299568
1	(abilify)	(amlodipine)	0.238368	0.071457	0.023597	0.098993	1.385352	0.006564	1.030562	0.365218
2	(amphetamine salt combo)	(abilify)	0.068391	0.238368	0.024397	0.356725	1.496530	0.008095	1.183991	0.356144
3	(abilify)	(amphetamine salt combo)	0.238368	0.068391	0.024397	0.102349	1.496530	0.008095	1.037830	0.435627
4	(amphetamine salt combo xr)	(abilify)	0.179709	0.238368	0.050927	0.283383	1.188845	0.008090	1.062815	0.193648
...	...	...	...	...	...	...	...	...	...	...
89	(diazepam)	(metoprolol)	0.163845	0.095321	0.022930	0.139951	1.468215	0.007312	1.051893	0.381390
90	(doxycycline hyclate)	(glyburide)	0.095054	0.170911	0.020131	0.211781	1.239135	0.003885	1.051852	0.213256
91	(glyburide)	(doxycycline hyclate)	0.170911	0.095054	0.020131	0.117785	1.239135	0.003885	1.025766	0.232768
92	(losartan)	(glyburide)	0.132116	0.170911	0.028530	0.215943	1.263488	0.005950	1.057436	0.240286
93	(glyburide)	(losartan)	0.170911	0.132116	0.028530	0.166927	1.263488	0.005950	1.041786	0.251529

94 rows × 10 columns

Image 2: Association rules.

The code to generate these rules can be found in section C2 in the section titled Generate the Association Rules. Please refer to this section if you would like to review the code that was used to generate the association rules.

C3. Values for Support, Lift, and Confidence: In this section, you will see a table that was the result of the code from section C2. It will display the following information:

- antecedent
- consequents
- antecedent support
- consequent support
- support
- confidence
- lift
- leverage
- convictions

The screenshot below shows all the metrics that were created using the code that was executed in the previous section (C2). Please note that there is the inclusion of a newer metric the Zhang metric.

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(amlodipine)	(abilify)	0.071457	0.238368	0.023597	0.330224	1.385352	0.006564	1.137144	0.299568
1	(abilify)	(amlodipine)	0.238368	0.071457	0.023597	0.098993	1.385352	0.006564	1.030562	0.365218
2	(amphetamine salt combo)	(abilify)	0.068391	0.238368	0.024397	0.356725	1.496530	0.008095	1.183991	0.356144
3	(abilify)	(amphetamine salt combo)	0.238368	0.068391	0.024397	0.102349	1.496530	0.008095	1.037830	0.435627
4	(amphetamine salt combo xr)	(abilify)	0.179709	0.238368	0.050927	0.283383	1.188845	0.008090	1.062815	0.193648
...	...	...	...	...	...	...	...	...	...	...
89	(diazepam)	(metoprolol)	0.163845	0.095321	0.022930	0.139951	1.468215	0.007312	1.051893	0.381390
90	(doxycycline hyclate)	(glyburide)	0.095054	0.170911	0.020131	0.211781	1.239135	0.003885	1.051852	0.213256
91	(glyburide)	(doxycycline hyclate)	0.170911	0.095054	0.020131	0.117785	1.239135	0.003885	1.025766	0.232768
92	(losartan)	(glyburide)	0.132116	0.170911	0.028530	0.215943	1.263488	0.005950	1.057436	0.240286
93	(glyburide)	(losartan)	0.170911	0.132116	0.028530	0.166927	1.263488	0.005950	1.041786	0.251529

94 rows × 10 columns

Image 3: Complete table listing all metrics.

The next table will display only the metrics that were required by the assessment and the rubric. The above table was only included for possible future reference later in this document.

	antecedents	consequents	support	lift	confidence
0	(amlodipine)	(abilify)	0.023597	1.385352	0.330224
1	(abilify)	(amlodipine)	0.023597	1.385352	0.098993
2	(amphetamine salt combo)	(abilify)	0.024397	1.496530	0.356725
3	(abilify)	(amphetamine salt combo)	0.024397	1.496530	0.102349
4	(amphetamine salt combo xr)	(abilify)	0.050927	1.188845	0.283383
...	...	...	...	...	...
89	(diazepam)	(metoprolol)	0.022930	1.468215	0.139951
90	(doxycycline hyclate)	(glyburide)	0.020131	1.239135	0.211781
91	(glyburide)	(doxycycline hyclate)	0.020131	1.239135	0.117785
92	(losartan)	(glyburide)	0.028530	1.263488	0.215943
93	(glyburide)	(losartan)	0.028530	1.263488	0.166927

94 rows × 5 columns

Image 4: Table listing all the required metrics.

The code that was used to accomplish the creation of the metrics can be found in section C3. Please note that this section made use of code found in C2 where the association rules were created.

C4. Explanation of the Top Three Rules: The top three rules for this dataset are shown in the screenshot below.

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
74	(lisinopril)	(carvedilol)	0.098254	0.174110	0.039195	0.398915	2.291162	0.022088	1.373997	0.624943
73	(glipizide)	(carvedilol)	0.065858	0.174110	0.022930	0.348178	1.999758	0.011464	1.267048	0.535186
30	(metformin)	(abilify)	0.050527	0.238368	0.023064	0.456464	1.914955	0.011020	1.401255	0.503221

Image 5: Top 3 rules generated by the Apriori algorithm.

The top three rules are evaluated by their lift score and confidence score. The lift score chosen for this was 1.9. Using this score as a metric we can see that the higher the lift score there is stronger the relationship that the consequent being related to the antecedent in the transaction. In the case of the first rule listed, the lift value is ~2.29 which indicates that there is a positive relationship between lisinopril and carvedilol and is 2.29 times more likely to occur than random.

The other metrics that were included with the top three rules are the confidence score, support, conviction, and leverage. The confidence score that was chosen as a threshold was .3. Which implies that when item A is prescribed there is at least 30% of prescriptions will also be prescribed item B will also be prescribed.

In the first listed rule, if lisinopril is prescribed then 39.9% of lisinopril prescriptions are prescribed along with carvedilol as indicated by the confidence score. The support score for the first rule means that this particular itemset, it appears in approximately 3.9% of the prescriptions that are ordered. The conviction score that is illustrated in the first rule means that the consequent is dependent on the antecedent. The value for the first was ~1.37. This would imply that there is a dependency of the consequent, carvedilol, on the antecedent lisinopril. While this may be considered a low score depending on the viewpoint since these values can go to infinity. The leverage score for the first rule indicates that there is a slight positive value. This means that this combination is more likely to occur than what is to be expected (Sharma, 2023).

The second rule, {glipizide, carvedilol}, if we look at the scores for the we see that if glipizide is prescribed then 34.8% of the prescription will contain carvedilol – the confidence level. The support score for this itemset is ~2.2% so this combination appears in this percentage of prescription transactions. The conviction value is ~1.26 which means that there is a dependence of carvedilol on glipizide. The lift value for the second rule was ~1.99 which indicates that there is a positive association between the two prescriptions in the transaction and this combination is 1.99 more likely to occur than random. This in turn implies that these two prescriptions are more often to occur than just by random.

The third rule, {metformin, Abilify}, the confidence level indicates that this ~45.5% of the prescriptions if metformin then Abilify will also be prescribed. The lift value for this rule is ~1.91 showing that there is a positive relationship between these two prescriptions. So this combination is 1.91 times more likely to occur than random.

The code for this can be found in section C4 of the Jupyter Notebook. Please refer to this section for the code as well as the output that was generated after executing the code.

Part IV: Data Summary and Implication

The results of the data analysis will be discussed in this section. In this section, there will be a recommended course of action based on the findings of the analysis.

D1. Summary of the Significance of Support, Lift, and Confidence:

These observations of the metrics that were discussed in the previous paragraphs can be applied to the other rules listed in this section. The basic concepts for support, lift, and confidence can be best summarized in the following manner (Sharma, 2023):

- Support – this metric looks at the percentage that contains a particular itemset. The higher this percentage the more likely this combination is likely to be prescribed and be found in the dataset.
- Lift – is the strength of the relationship between items A and B. In this assessment, the values that were generated for the top three rules all had values that were above 1.9. This means that these combinations will occur at least 1.9 more than random. These combinations are more likely to occur because there is a positive relationship between these particular combinations of prescriptions.
- Confidence – This metric is a measure of the transactions where the antecedent has occurred and the probability that both the antecedent and the consequent will occur. In the rules given above in section C4, we can see that if we prescribe lisinopril and carvedilol there 39.9 of transactions this combination will be found together.

D2. Discussion of Practical Significance of Findings:

In answering the question from section A, the following rules were the most relevant to answering the question based on the following metrics that were used to print the rules. The metrics used to prune the candidate rules were the following:

- lift - this value was set to 1.5 this was to give ample rules to sift through and prune using an additional parameter.
- confidence – this value was set to .2.

These values were chosen since other values yielded too many candidates for rules or too few. Using this parameter or metric it was possible to devise four rules at the initial run. The four rules are displayed in the following table. There will discussion about the metrics that are associated with these generated rules.

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
75	(carvedilol)	(lisinopril)	0.174110	0.098254	0.039195	0.225115	2.291162	0.022088	1.163716	0.682343
74	(lisinopril)	(carvedilol)	0.098254	0.174110	0.039195	0.398915	2.291162	0.022088	1.373997	0.624943
28	(lisinopril)	(abilify)	0.098254	0.238368	0.040928	0.416554	1.747522	0.017507	1.305401	0.474369
62	(lisinopril)	(atorvastatin)	0.098254	0.129583	0.021997	0.223881	1.727704	0.009265	1.121499	0.467090

Image 6: Data analysis results.

The next set of images shows heatmaps for some of the metrics that will be covered in the following paragraphs.

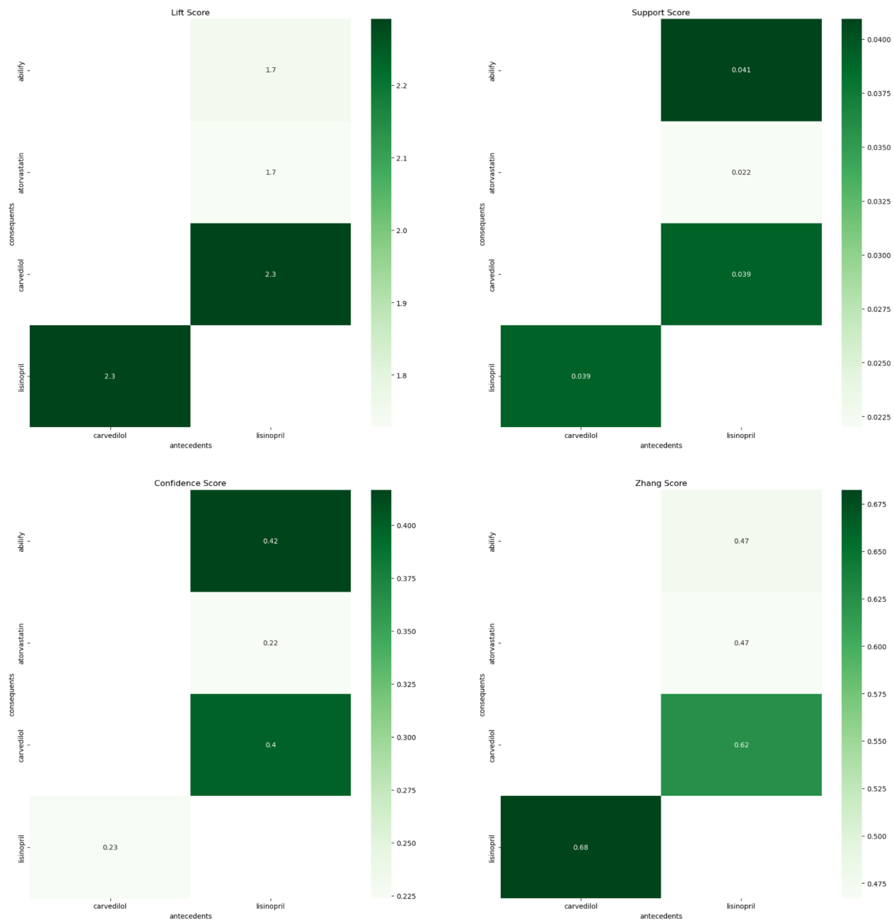

Image 7: Heatmaps for the Metrics.

For a better view of the graph please refer to the Jupyter Notebook. This part of the assessment can be found in section D2 – Create heatmaps for rules.

These four rules can be defined in the following manner:

- If carvedilol then lisinopril – While the question stated we want to look at the prescriptions that involved lisinopril we should also look at combinations that occur where lisinopril is the consequent. The reason for this will be elaborated on in section D3. Support for this is 3.9% which indicates that this particular combination only appears this often in the dataset. This result is true for the reverse of the conditional statement (If lisinopril then carvedilol). The confidence value is 22.5% means that when carvedilol is prescribed 22.5% of the time along with lisinopril. The lift of 2.29 indicates that this rule is useful for predicting the likelihood that prescribing the antecedent will be useful in predicting the consequent. This rule can be used to predict if carvedilol prescribed is lisinopril also prescribed. Looking at the Zhang metric there is a positive association between the combination of medications. The value for the Zhang metric was ~.68. Using this metric there is a positive association between the antecedent and the consequent. A value of 1 in this metric would indicate a strong positive association (IUYasik, 2023).

- If lisinopril then carvedilol – This is the converse of the previous rule. It does have some interesting values for the metrics. While the values for the support, lift, and leverage are identical based on the table found in Image 6. There are a few values where the are differences. The first value is confidence. The value here is higher than the first rule's. The value here is 39.8% so there is a better percentage of being prescribed carvedilol if you are first prescribed lisinopril. It does raise the question of why does this happen. This question cannot be answered with the information that is currently available, and it cannot be answered by the author of this paper. The next value is the conviction this value is a little higher, but is it statistically significant? Without more information, it may be difficult to ascertain if this is a relevant difference.
- If lisinopril then Abilify - The support for this combination is ~4.1% so this combination will appear about 4% of the prescriptions that are ordered. The confidence value is 41.6% of the time when lisinopril is prescribed then Abilify seems to be prescribed. The lift value (1.74) indicates that there is a positive relationship between lisinopril and Abilify (Goel, 2018). Interpreting this based on the values given means that lisinopril and

Abilify occur approximately 1.74 times more than random. Zhang metric, as stated earlier, shows that there is a positive association between these drugs.

- If lisinopril then atorvastatin – The support for this combination is 2.1% it is the worst of the rules for this metric. This combination only appears in about 2% of the transactions in the data. The confidence value was 22.3% which means that this combination will only happen less than a quarter of the time will occur. It can be said that if lisinopril is prescribed then there is 22.3% that atorvastatin will be prescribed. The lift value (1.72) is greater than 1 and implies a positive relationship, and this pairing is likely to occur 1.74 times more than random. Zhang metric shows that there is a positive association between these drugs.

The rules that were stated above can be used in the future to help predict the occurrence of the prescribing of lisinopril with these other drugs. The lift values being greater than 1 indicate and the values of the metrics also indicate that there is a positive association between the pairs of drugs in this group of itemset and can be used to predict the antecedent and consequent (Zhang, 2019).

To help visualize the relationship between the antecedents and the consequents a parallel coordinates plot is shown below.

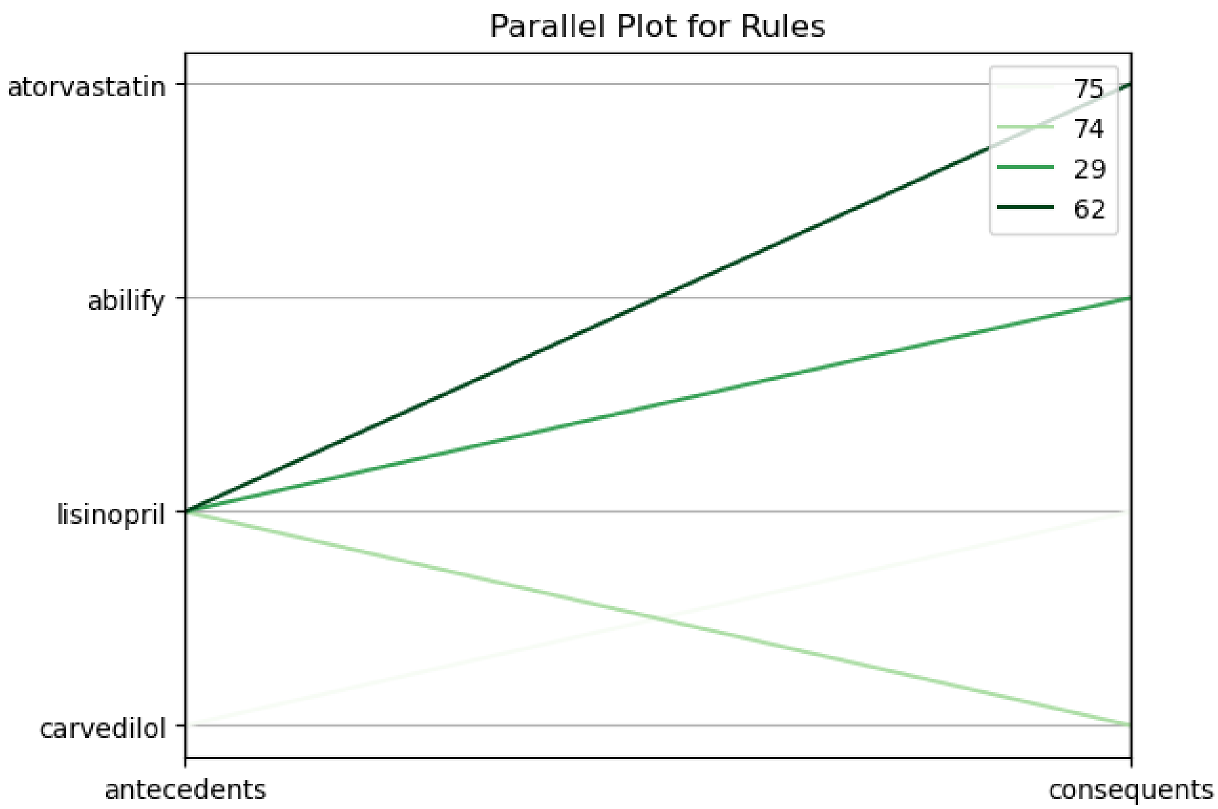

Image 8: Parallel plot of the relationships.

D3. Course of Action: The medications that came up during the generation of the rules developed the following associations:

- If carvedilol then lisinopril
- If lisinopril then carvedilol
- If lisinopril then Abilify
- If lisinopril then atorvastatin

Reviewing these medications it seems that there are drugs that are taken together to deal with complications from high blood pressure and heart disease[1] This combination is common and not unexpected. The recommended course of action is to look for medication that can be

[1] This information comes from the following website:
Drugs, herbs and supplements: MedlinePlus. (n.d.). MedlinePlus. Retrieved January 18, 2024, from https://medlineplus.gov/druginformation.html

administered as one pill as opposed to a series of medications. This will make it easier for the patient and will reduce the need to issue these medications to the patient while they are staying in the hospital. This observation may need to be reviewed by qualified medical staff. The analyst only raises this concern, because physicians do not always prescribe the easiest to dispense medication. This often happens by accident since multiple doctors may be reviewing the patient's case and may not want to interfere with the course of treatment that has been prescribed by another physician. This sometimes from a lack of communication among the attending physicians.

An additional course of action would be to review the cases for why these combinations of drugs were prescribed. Some questions need to be asked. These questions are:

- What are the reasons these combinations are prescribed?
- Was there a non-pharmacological alternative that could have been pursued before issuing the medication combination?

After doing some research there are a few reasons that may have occurred. The most notable observation is the medical establishment's "mechanistic and reductionist" view of administering medication (Miller, n.d.). The medical establishment looks to prescribing medication first as opposed to pursuing lifestyle changes. This approach should be further looked into before a medication is prescribed to the patient. Overprescribing medication makes it difficult to take or prescribe other medications when needed. The reason is that harmful interactions may occur. Using a more natural approach will make prescribing drugs for illnesses in the future and will lead to better outcomes since the patient will no longer be dependent on medication to lead a healthy life.

It is recommended that the organization looks at the policies that govern how these types of medication are prescribed and the reasoning behind them. Reducing a patient's dependence on medication makes sense. It makes it easier on the patient both financially and physically. The organization will benefit from fewer drug interaction problems that could lead to difficulties in treating a patient.

This is the recommended course of action and is open to review by the appropriate medical professionals. Reviewing these findings can shed some light on the practice of prescribing these medications and other medications that offer benefits instead of lifestyle changes or other more natural means of controlling these types of conditions.

Part V: Attachments

E1. Panopto Video

The link to the Panopto video can be found below. This will go over the code that was used to create this assessment and demonstrate that the code is functional.

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References

F. Web Resources

This section will contain citations that were used to generate code that will be found in the Jupyter Notebook. This section will not contain citations that were used in this document unless otherwise noted. The citations in this section are for code that was not presented in the material that was provided by the university or by DataCamp videos and other resources.

None, there were no other resources used to create the code for this assessment.

G. In-text Citations

In this section, you will find the citations for resources that were utilized to create the written document. You will find any resources related to code in the previous section unless otherwise noted in this document or the accompanying Jupyter Notebook.

Apriori algorithm | Engati. (n.d.). Engati. Retrieved January 15, 2024, from https://www.engati.com/glossary/apriori-algorithm

Chauhan, N. S. (2019, December 19). *Market basket analysis: A tutorial – KDnuggets*. KDnuggets. Retrieved January 15, 2024, from https://www.kdnuggets.com/2019/12/market-basket-analysis.html

Goel, N. (2018, July 23). Market basket analysis: Association Rules - Niharika Goel - Medium. *Medium*. Retrieved January 18, 2024, from https://medium.com/@niharika.goel/market-basket-analysis-association-rules-e7c27b377bd8

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