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Effects of Coronavirus Disease on Trade for New Zealand

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Abstract. The coronavirus disease 2019 (COVID-19) is a humanitarian crisis that is spreading throughout the world. COVID-19 will be worse to countries that have weak healthcare and economic systems. Countries that are highly affected by coronavirus disease will have problems with international trade since the virus has a high infection rate. This will have effects on the trading economy which will cause export restrictions and trade barriers which make the country trade worse and can cause livelihood problems for the country. But there are countries that handle the pandemic excellently and manage to control the outbreak. Therefore, this research studies one country which is New Zealand on how the coronavirus disease affects their trading economy. This research consists of five phases of research methodology to be conducted before presenting the final findings. The five phases are dataset collection, data preprocessing, decision tree regressor, apriori algorithm under association rule mining and finally data visualizations. Using decision tree regressor, apriori algorithm and data visualizations for results, the outcomes of the findings show that the trade for New Zealand is not badly affected by the coronavirus pandemic and two association rules that support their economy have been discovered.

Keywords: Coronavirus disease, COVID-19, Trade, New Zealand, Decision tree regressor, Association rule mining, Apriori algorithm

1. Introduction

The emergence of the coronavirus disease in December 2019 (COVID-19) has led to global outbreak. This led to many economic sectors in most of the countries to be closed down due to the pandemic. This has also created a significant impact on global economy and policymakers are being forced to look for ways to respond since the pandemic is leading the world's economy into the unknown (Alabdullah, T. T. Y. et al., 2020). Furthermore, the pandemic caused almost all countries to close their borders. By closing their borders, trade barriers are automatically enforced. Whereas, business leaders are questioning whether the market drawdown clearly leads to a recession, how awful this COVID-19 recession would be, what the options are for growth and recovery and whether the unfolding crisis will leave any long-term structural consequences (Carlsson-Szlezak et al., 2020).

Going back to the purpose of this research which is to study the effect of coronavirus on trade for New Zealand, the models that will be used to the given data are predictive modelling and pattern discovery modelling. For this research, predictive modelling used is decision tree regressor and pattern discovery modelling used is apriori algorithm under association rule mining.

Three research problems have been identified. First is, in order to predict the data, predictive modelling will be used. Nonetheless, predictive modelling is used to predict the future, but it also can be used to predict anything not limited to predict into the future. Second, same goes to association rule mining, association rule mining used for pattern discovery, but which algorithm can provide the best pattern discovery for the given dataset. Third, one of the most crucial parts of reporting results is the data visualizations. Nonetheless, should not simply include lengthy summaries of raw data. Rather, organize and visualize the data in a way that emphasises and focuses on the results.

From the research problems, these are the research objectives. First, to implement predictive modelling to be used for effects of coronavirus on the trade outcomes for New Zealand. Second, to apply pattern discovery modelling to be used for effects of coronavirus among trade features for New Zealand. Third, to visualize the end results of this research.

2. Literature Review

A fundamental economic concept is the buying and selling commodities and services, with remuneration supplied between a buyer and a seller or the exchange of goods or services between parties. As a result, trade flows are vulnerable to demand shocks and supply shocks. In the context of COVID-19, supply shock comes in the forms of factory closure, travel bans, border closures and the like. These will bring down exports of the impacted sectors in affected nations (Baldwin, R. & Di Mauro, B. W., 2020). When a product is an input into the manufacturing of other products, its supply shocks in one country or in an industry within that country may cause supply shocks in different industries and countries.

According to Baldwin, R & Di Mauro, B. W. (2020), Hubei province in China is well known worldwide for the manufacturing of fibre optic components and its advanced microchip fabrication factories used to make flash memory chips in mobile phones. It is also stated that the outbreak in Hubei alone might reduce global smartphone shipments by 10%. In the case of COVID-19 which shocked demands, imports will fall the greatest, mostly in trade partners of the countries. Furthermore, the statistics data suggest from Baldwin, R & Di Mauro, B. W. (2020) that global trade has been notably impacted, reducing by 1.4% in the first half of 2020 and by 0.9% in the year overall.

In Africa trade volumes are predicted to drop by 8% for exports and by 16% for imports in 2020 (Banga, K. et al., 2020). Furthermore, referring to Mendez-Parra M. (2020), Africa's export revenue could fall between US$ 36 billion and US$ 54 billion.

Meanwhile in Jordan, the tourism industry received the first blow, with massive cancellations of visit and tourist services in many locations that generate jobs and incomes (Abu-Mater, W. et al., 2020). There is no doubt that Jordanian tourism business will suffer significantly as a result of the shutdown.

The COVID-19 pandemic has had a significant impact on the aviation sector due to travel restrictions and aircraft cancellations by the effects of the coronavirus (Roy, S., 2020). The aviation industry, as well as airports, are experiencing significant slowdowns due to a lack of air traffics and revenues. The global drop in airport revenues is estimated to be $39.2 billion in the second quarter of 2020 and roughly $97 billion for the full year.

As for the major markets of crude oil, Saudi Arabia announced selling discounts of up to 20% (Roy, S., 2020). This caused oil prices to plummet by nearly 30%. The COVID-19 pandemic had a negative impact on oil-dependent countries. The drop in oil prices, along with a decrease in demand for oil products in international markets, resulted in a revenue loss for oil-dependent countries.

Furthermore, for the tourism industry, the pandemic and global attempts to control the virus's transmission may force the international tourism sector to contract by 45% to 70% (Roy, S., 2020). While in Brazil, Brazil's tourism industry has suffered a huge setback, with nearly 80% of its hotels, national parks and tourist attractions closed. In the absence of public transportation, the tourism sector in Brazil might lose around $6.2 billion and visitor arrivals could drop by approximately 50% by 2020.

A global outbreak will cause moderate to severe demand contractions (Maital, S. & Barzani, E., 2020). Consumers will cut back on their spending due to close places of work, lower GDP and increase unemployment.

The other data mining techniques used in analyzing a similar dataset is

AdaBoostM1 and Simple logistic techniques (Roy, D. et al., 2021). Their data mining result shows accuracy and effectiveness in constructing model to predict upcoming economic crisis.

3. Research Methodology

3.1. Dataset collection

Dataset for this research is obtained from Data World. The data is about the effects of COVID-19 on trade on New Zealand that contains the country trade values from 1st February 2015 to 12th August 2020.

In this data, the number of samples is 46536 and the number of features is 11. The features are direction, year, date, weekday, current match date, country, commodity, transport mode, measure, value and cumulative. Three direction values which are reimports, imports and exports. All the current match dates are in the year 2020.

3.2. Data preprocessing

The reasons to do data preprocessing are generally due to the real-world data that could be incomplete, noisy or inconsistent. Null value removals will be done only if there is a null value in the dataset. In this dataset, no null value was found.

As for casting, the “current match date” and “date” data type is not the date type. In this case they are casted to a datetime type using the to_datetime() function.

3.3. Data Mining Algorithm: Decision Tree Regressor

The decision tree algorithm is versatile as it is highly effective at capturing interactions between features and is easy to visualize, making them effective at data classification and prediction (Desai, N. & Patel, V., 2021). A decision tree algorithm consists of nodes, which are a leaf node, decision node and a root node. The generated model traverses the tree, starting from the root node until it reaches a leaf node.

Starting with the root node, each node can be split into left and right child nodes using recursive partitioning. These nodes can then be split further, becoming the parent nodes of the subsequent children’s nodes. After the process of each node, and the tree is built on the given data, it is ready to use for prediction and regression tasks.

Decision tree regressor underwent hyperparameter tuning to find the optimal maximum tree depth during train test split cross validation. This is done for different values of maximum tree depth ranging from 1 to 30. The optimum value found for the maximum tree depth is 10.

The decision tree regressor algorithm is as follows (Hastie, T. et al., 2009).

Input: N observations that are (x_{ij}, y_i) samples for $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, p$ with $x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ variables and y_i response.

Output: A decision tree T such that the cross-validated sum of squares is the minimum cost

- Greedily partition samples into M regions $R_1, R_2, \ldots, R_M$ to find the best binary partition in terms of minimum sum of squares:
    - Find the best split point to partition the samples into the two resulting regions.
    - Repeat the splitting process on each of the two regions.
- This process is repeated on all the resulting regions.

3.4. Data Mining Algorithm: Association Rule Mining

Association rules are if-then statements that help to discover patterns and relationships between unrelated data in a dataset (Kumbhare, T. A. & Chobe, S. V., 2014). There are two parts in association rule mining: the antecedent (if), which is anything found in the dataset, and the consequent (then), which is something found in combination with the antecedent. The association rules will be used to discover the connections between the objects which are commonly utilized together.

The apropri algorithm will be used because it is one of the most common algorithm for mining association rules. This algorithm is mainly used for frequent item set mining and association rules learning. The apriori algorithm has three relationships that it relies on which are support, confidence and lift as explained below:

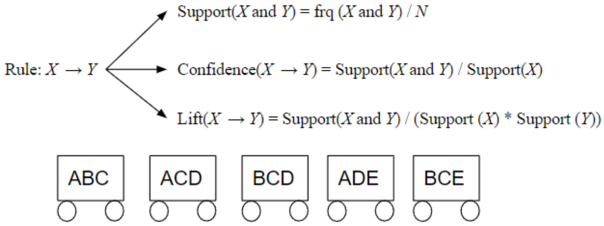
- Support: Show how frequently the if-then relationship appears in percentage.
- Confidence: The number of times the relationships are found to be correct in percentage.
- Lift: The scale of the observed support to be anticipated. If lift is more than 1, the rules are reasonably associated while if the lift is less than 1 are reasonably not.

3.4.1. Apriori Algorithm

The apriori algorithm relies on three relationships which are support, confidence, and lift. To explain the formula in Figure 1, it is given that the rule $X \rightarrow Y$ hence the Support *(X* and *Y) = Number of transactions in which X and Y appears / The total number of transactions*. While Confidence ($X \rightarrow Y$) = Support *(X* and *Y)* / Support *(X)*. Lastly for the Lift ($X \rightarrow Y$) = Support *(X* and *Y)* / ((Support (*X*) * Support (*Y*)). To find a single Support (X), the formula is similar to the Support (*X* and *Y*).

To give more clarity, take the example given in the figure below, the rule stated $A \rightarrow D$. To find the support, firstly see how many times *A* and *D* appear together and it is *two* times while the total transaction happens is *five* times. That gives the support value of *2 / 5*.

As for confidence, the value for support has already been known, only need to know how many times that *A* appears in the transactions. As can be seen, it appears three times out of five transactions. Then, the confidence equation which is Confidence = *(2 / 5) / (3 / 5) = 2 / 3*. Lastly for the lift, Lift = *(2 / 5) / ((3 / 5) * (3 / 5)) = 10 / 9*.



Rule	Support	Confidence	Lift
$A \rightarrow D$	2 / 5	2 / 3	10 / 9
$C \rightarrow A$	2 / 5	2 / 4	5 / 6
$A \rightarrow C$	2 / 5	2 / 3	5 / 6
$B \& C \rightarrow D$	1 / 5	1 / 3	5 / 9

Fig. 1: The apriori algorithm relies on support, confidence, and lift.

The apriori algorithm is as follows (Hastie, T. et al., 2009).

Input: Antecedents and consequents

Output: A set of association rules with high values of support, confidence, and lift.

- Firstly, pass over the data to compute the values of all single-item sets. Those whose value is less than the threshold is discarded.
- Repeat to generate all frequent itemsets.
    - Those size two item sets with value less than the threshold are discarded.
    - Each successive pass over the data considers only those item sets that can be formed by combining those that survived the previous pass with those retained from the previous pass.

Passes over the data continue until all candidate rules from the previous pass have value that is greater than the specified threshold and then return the most frequent itemsets.

3.5. Data visualizations for results

Data visualizations of the outcomes of this research will provide a clear understanding of what the data means. The visual representation of data generated enables one to identify and express real-time patterns, outliers, and new insights about the data's information.

4. Findings

From the decision tree regression algorithm result, it managed to get a high prediction accuracy of 89.47% among years from 2015 to 2020. The result shows accuracy and effectiveness in constructing model to predict the trade values.

From the apriori algorithm result, as we can see from Table 1 below, if the lift > 1, the antecedents support the consequents. It can conclude that the two association rules that affect the trade for New Zealand are direction of exports supporting all transportation modes and all transportation modes supporting direction of exports.

Table 1: Output for apriori function.

antecedents	consequents	support	confidence	lift
Direction_Exports	Transport_Mode_All	0.69	0.93	1.03
Transport_Mode_All	Direction_Exports	0.69	0.77	1.03

Figure 2 shows the data visualization for total trade values per year for reimports, we can see that in 2015 to 2017, the value for reimports was declining before it went back up in 2018. But in 2019, the value declined back. During the coronavirus pandemic in 2020 the value was increasing. When excise duties on a certain commodity are high, reimportation is common. Buyers who want particular domestic products but do not want to pay the high excise tax can purchase them from a country with a lower excise tax.

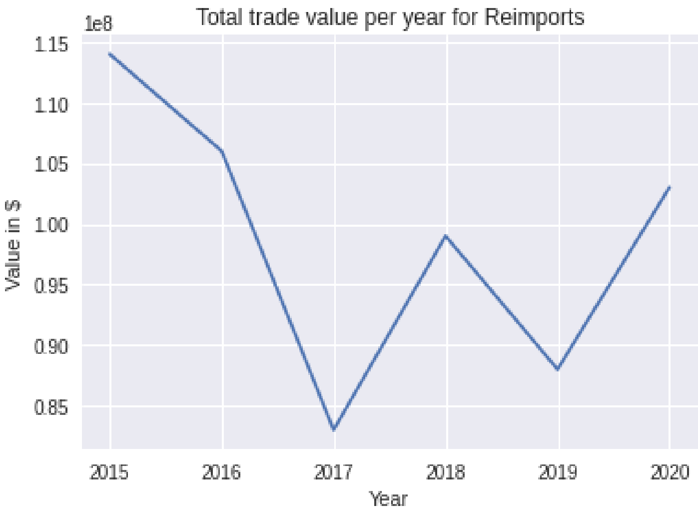


Fig. 2: Total trade value per year for reimports.

Figure 3 shows the data visualization for trade value per year for Imports and

Exports. New Zealand has higher export values per year than import values. For imports, in 2015 to 2016, the value dipped a little before it increased back from 2016 to 2019. In 2020, the value for imports decreased during the coronavirus pandemic. The same thing happened for exports, in 2015 to 2016 dipped a little before it increased back from 2016 to 2020. In 2020, the value for exports was actually increased during the coronavirus pandemic.

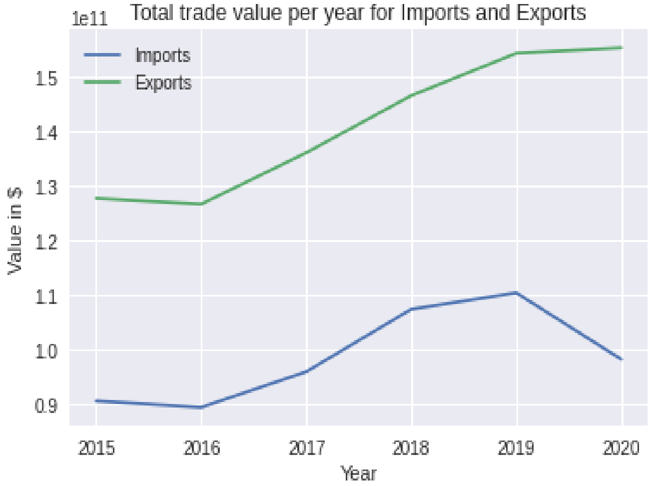


Fig. 3: Total trade value per year for imports and exports.

As for Figure 4, it shows the data visualization for total trade value for each commodity by year. From the figure below, it can be concluded that three commodity trade values for New Zealand in the year 2020 increased for fruit, meat and dairy compared to the previous year which was before the coronavirus pandemic.

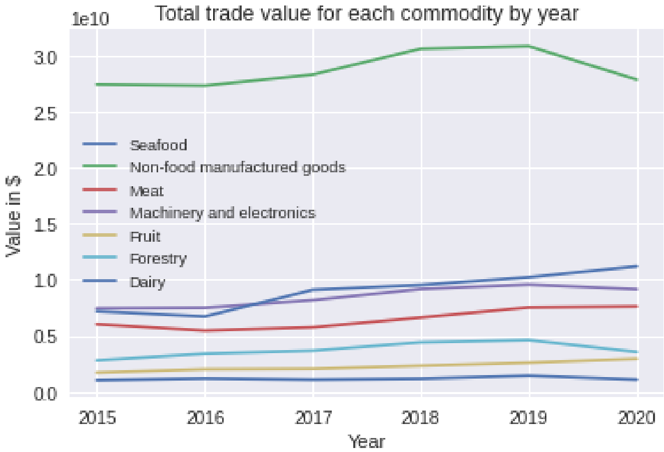


Fig. 4: Total trade value for each commodity by year.

Lastly, Figure 5 shows the data visualization for two biggest economic countries in the world which are USA and China for their trade value with New Zealand. As can be seen from the figure below, trade value with both USA and China in 2020 increased even though during the coronavirus pandemic.

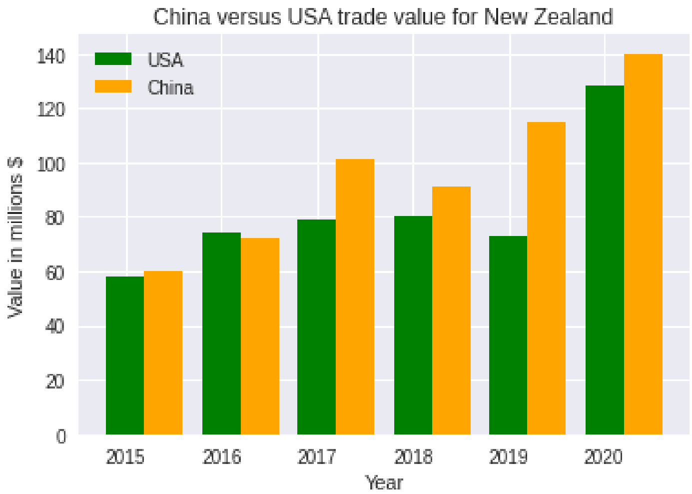


Fig. 5: China versus USA trade value with New Zealand.

5. Conclusion

In conclusion, three main accomplishments for this research have been achieved in effects of coronavirus on trade for New Zealand. First is modelling implementation using decision tree regressor achieved a high prediction accuracy on the trade outcomes for New Zealand before and after the coronavirus pandemic. Second, pattern discovery modelling using apriori algorithm has discovered two association rules among trade features on effects of coronavirus on trade for New Zealand. Third, data visualizations for the end results of the research.

Nonetheless, there is a limitation that can be made from this research. As of now, the dataset that was available was only up to year 2020. The possible future directions are combination with other dataset up to the end of the coronavirus pandemic and mitigation solution against coronavirus disease.

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