DATA230 Project 1 Group 5: A Visual Analysis of Indian Trade Before and After COVID-19

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I. Introduction

India is one of the fastest developing countries, and for any developing country, trade with foreign countries is a key part of the economy and development. India's export progress is highly noticeable in the past few years. However, it still has more potential to reach to the next level, and for that, highly informative trade data analysis can play a key role. Data visualization pioneer, Tufte, emphasized the importance of exploring data [1]. The global COVID-19 pandemic has affected the whole world's economy. In this situation, India's economy has also suffered and so does India's trade with other countries. This data visualization report includes India's import and export data from 2010-2021 and some key insights on how the global pandemic has affected India's trade with foreign countries.

India's trade with foreign countries has always been a very big part of the country's economy. India was noted as the eighth largest commercial goods export country in 2016. An economical survey done by The Government of India suggested that 70% of India's total exports was done by the five major states–Maharashtra, Gujarat, Karnataka, Telangana and Tamil Nadu. There is a high correlation between these trades and the state's Gross State Domestic Product (GSDP) per capita.

However, the global pandemic has also affected the India's import exports with foreign countries. As the data released by the Department of Commerce at the end of April 2020 show, India's export for March 2020 decreased by 35% compared to last year's export data. These included commodities like meat, plastic and chemicals, cereals, textile and engineering goods, which were the major commodities in the previous years for export. Some of the main import commodities of India have been organic chemicals, oil, gems and stones and also some medical and technical equipment.

Data visualization is an effective method of data analysis to help researchers understand the data and decision makers form strategy and policy [2]. India's economy had significant growth during the last decade. In that situation, it is crucial to know if that growth had any impact from India's trade with foreign countries? If it had, then was the growth influenced by import or export of the country? How was India's economy bilateral trade affected by the pandemic?

These are a few questions that can be answered in this data visualization project. According to Dr. Khujan Singh from 'Empirical Analysis of India's Foreign Trade and Economic Growth' India's GDP and their export each year has a bidirectional relationship between them [3].

II. Related Works

Krishna (2017) found that scholarly collaboration on India's economics is fragmented and therefore has less scientific visibility [4]. Perhaps for this reason, there was a dearth of research materials on India's economics available in the San Jose State University research databases. There have been a few visualization studies done on Chinese bilateral trade relations [5] [6], global trade relations [7], or commodity specific trade [8] [5], but more research was available on the use of visualization in business intelligence and the study of business ecosystems [1] [9]. There has been no research specifically on the visualization of India's bilateral trade relation, but all of these aforementioned studies build a base for our research project.

One of the leading providers of business intelligence (BI) software is Tableau. Due to its growth, education researchers are studying how to effectively teach Tableau [2]. Faber (2020) describes how visualization is used in business ecosystems to analyze the competitive environment, supply chain, business health, and more [9]. Often, it is used internally for the benefit of the company; this is called a collaborative model [9]. The system Faber (2020) proposed introduces five network layouts: force-directed, chord diagram, tree mpa, matrix, and substrate-based layout [9]. Their system has drag and drop features and a filter similar to Tableau [9].

Bačić (2016) noted that business intelligence (BI) has proliferated industry, as evidenced by being ranked the top investment priority for decision making, but that there are disparate academic resources [1]. The author aimed to standardize some of the terminology and proposed a framework, based on the Stanford-binet non-verbal IQ measurement, for assessing BIV effectiveness [1]. The elements of the Stanford-binet non-verbal IQ are fluid intelligence, domain specific knowledge, quantitative reasoning, visual-spatial processing, and working and short memory [1]. The corresponding BIV elements are respectively exploration, interaction; business acumen, relevant data; analytical, statistics; representation, perception, cognition, cognitive effort; memory, storytelling [1].

Visualization was used to analyze the policy impact of China's plastic import ban also known as the National Sword Policy in 2017 [5]. Wang et. al (2020) mapped trade relations for plastic waste as a complex node network [5]. This same

technique has been used for many other commodities including fossil energy, electricity, rare earth minerals, scrap metal, waste electronics, secondhand clothing, and more [5]. The visualization showed that while there was a decrease in China's importation of plastic waste, this did not actually reduce global plastic waste; it was simply diverted to poorer neighboring countries [5]. The visualization also showed the impact of China's Belt and Road Initiative to develop other countries road infrastructure to improve trade relations [5].

Lovric et. al (2018) used social network analysis to visualize international trade of wood and non-wood forest products, like truffles [8]. Social network analysis (SNA) has been used since 1943 and often when analyzing international trade, countries are considered the primary unit, but another method is the relational approach using trade flows as the primary unit [8]. Network visualizations can show the flow of products across the world, characteristics of networks, grouping of countries, reciprocity, and commodity contribution to gross domestic product [8]. Lovric et al. (2018) noted that network visualization still needs contextual interpretation from subject matter experts to properly analyze the meaning of the visualization and the application to policy and should be used to guide and complement, not replace, classical statistical analysis [8].

Krempel (2002) was on the earlier side to public research about visualizing global trade [7]. They identified three trends that could be derived from world trade data: 1) globalization, 2) regionalization, and 3) macroeconomic imbalance theory [7]. They used gravity models, a type of network visualization, to look at bilateral trade flows between countries. Unlike geographical information systems (GIS) where each country is represented geographically, in a gravity model, the country is represented in product space according to its weight [7]. However, the use of GIS easily visualizes the impact of geography on bilateral trade flows, i.e. neighboring countries of geographic trade barriers [7]. They noted that network visualizations may be more appropriate when looking at multiple countries and that a single factor explanation is far too simplistic for global economic interpretations [7].

While other research focused on data analytics and decision making based on visualization of bilateral trade, Ye (2020) proposes a novel visualization for bilterateral trade called digital trade feature map (DTFM) where imports and exports are expressed as X and Y in the Cartesian coordinate system [6]. Ye (2020) notes that most visualizations are networks constructed by countries or regions as nodes and the weight and direction of the trade relationship expressed between these nodes. Some past research has expressed trade relations as an ecological network, gravity model [7], clustering model, and spatiotemporal representation using GIS [6]. These researchers also novelly applied the Hilbert Curve-Based Products Grid to commodities and their HS codes [6].

III. Methods

A. Data Processing

Extracting the right features to analyze the pattern before and after the COVID-19 pandemic was a challenge because the necessary data was not available from one source. The first data set was from Kaggle–user Lakshya Agarwal scraped data from the Government of India, Department of Commerce website [10] [11]. The data was separated into two tables–imports and exports, ranged from 2010 to 2018, and contained the value of trade in US millions by country and commodity type (see Fig. III-A), Appendix A). It was a collection of nominal and ratio data.

Kaggle Data Description		
Column	**Data Type**	**Description**
HSCode	Integer	Harmonized System (HS2) Code - standardized commodity description and coding system
Commodity	String	Name of commodity as per HS2
Country	String	Country of import or export
Year	Integer	Year of import or export
Value	Float	Value of import or export (in US millions)

For the post COVID-19 pandemic dataset, we were not able to find the exact same data from the Government of India, Department of Commerce website, only aggregate data by country for 2018-2019, 2019-2020, and 2020-2021 [11]. The exact time frame was not clear, so 2018-2019 was assumed to be 2019 and so on. Six tables, for imports and exports over three years, were copied from the website to Microsoft Excel and contained the value of trade in US millions grouped by country. This differs from the Kaggle dataset in that it is not broken out by commodity type. Additionally, it compares the previous year's trade value (see Fig. III-A), Appendix B).

Department of Commerce Data Description		
Column	**Data Type**	**Description**
Country	String	Country of import or export
2018-2019	Float	Trade value in US millions of the previous year
%Share	Float	Percentage of total trade with India of the previous year
2019-2020	Float	Trade value in US millions of the current year
%Share	Float	Percentage of total trade with India of the current year
%Growth	Float	Percentage of growth from previous year

Since the post-COVID dataset was aggregated by country and did not break out the commodity types like the Kaggle pre-COVID dataset, to allow better comparison, the Kaggle data was grouped by country using pivot tables in Microsoft Excel and the import and export tables were merged into one table with a new column identifying if the data was import or export related data. Relevant data from the six tables from the Department of Commerce website were added to this master table of cleaned data–namely year, country, trade value, and import/export status. The analytics of percentage of total Indian trade and growth compared to the previous year were excluded from this analysis. The cleaned data results in five columns: country, value (US million), year (2010-2021), status (import or export), and COVID (pre-COVID or

post-COVID) (see Fig. III-A), Appendix C). The null values were imputed with zero. Additionally, the two datasets slightly differed in country names, for example "AFGHANISTAN" versus "AFGHANISTAN TIS". These types of differences were cleaned up for accurate comparison of countries across the years.

Cleaned Data Description		
Column	**Data Type**	**Description**
Country	String	Country of import or export
Value	Float	Value of import or export (in US millions)
Year	Integer	Year of import or export
Statues	String	Import or export status
COVID	String	Pre or post-COVID status

B. Tableau Visualizations

Tableau was used to create a visual dashboard to aid in analyzing this data. The cleaned data, a single Microsoft Excel document, was connected to Tableau. Several visualizations were created including tile dashlets, heat maps, bar chart, line graphs with predicted trends, heat table, interactive sliders to scroll through year and to compare import versus export, and finally navigation buttons to two additional dashboards. While several visualizations were created, only a few were carefully selected to convey important information on the main dashboard–namely the effect of COVID on India's economic trade. We determined that the additional visualization did not add to the redundancy gain rather created too much visual noise and violated several principles of visual design. According to the bottleneck theory of attention, individual have limited cognitive resources to attend to visual stimulus, so we selected only a few visualization to improve the expressiveness and effectiveness.

Once these visualizations were selected, they were carefully reviewed and analyzed for wording, color, and other elements of visual design. Sans serif fonts were used to avoid unnecessary visual noise. We aligned numbers to the right of columns and the accompanying column headers to the right as well (see Fig. 1). Considering that red-green colorblindness is the most common type of colorblindness, we avoid these colors opting for blues and oranges (see Fig. 4). The dashboards have a very high data-ink ratio.

While analytics on the imports and exports of India are the key insights, providing critical information of the pre and post covid can be analyzed based on the growth increased year by year, average annual trade, and the commodities overall involved. A deeper analysis on the same is also developed for more understanding of a specific year.

Map charts were being the primary charts in the dashboard as we all know the greater view of countries involved can be better understood by them. So the countries involved pre and post were illustrated by maps. While the countries involved were represented with their growth, the average annual trade comparison is also represented with the color-coding intensity. The more the average annual trade, the more the intensity of the color on the country.

The next important design feature is providing information on the selected year data using the filter and dashlet count update. The dashlets were used to provide the overall numerical results. While the bar charts on the annual trade provide the top 10 trade partners. We particularly could able to analyze the pre and post-trade of those countries. Individual charts are also being provided with labels representing the respective names.

The on-hover tooltips were also being embedded with the data like their average trade and respective year data when it comes to line charts. Few other interactive features were also being utilized to create more interactive charts.

C. Tableau Operation

The dashboard was published to Tableau Public available here: https://public.tableau.com/app/profile/sonia.meyer/viz/data230dashboardfinal/Data. The data files and Tableau workbooks are available on GitHub as well: https://github.com/soniawmeyer/Indian-Trade-Visualization.

Interactive charts development being the major part, dashboard development is the end product of our project and ideally being interactive. The initial step towards the dashboard development is developing individual charts which are embedded with required dimensions and measures. The next step would be using those individual charts embedded in the skeleton of the dashboard columns/rows. The challenge was also being grouping into one single page and per view. On a high level the dashboard would be having different based charts providing peculiar information on the data.

IV. Results

The results of our data analysis are displayed in the visualization of our two dashboards mainly include various dashlets, bar charts, heat maps, line graphs, and interactive filters for individual years. The third dashboard is a heat map of all the data presented as a pivot table as a reference point.

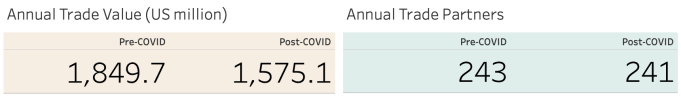


Figure 1. Annual Trade Analysis

A. Annual Trade Analysis

Figure 1 shows the overall trade analysis of all the countries and the number of trade partners involved pre and post COVID. Pre COVID years are 2010-2018 and post COVID years are 2019-2021. Since there were more years prior to COVID than after, we examined the average annual data to get the pre and post comparison. The trade value is report in US millions. This is the same for all visualization and data presented in this paper. For the count of countries traded with, null or zero value trade countries were filtered out. We used this dashlets concept as it is particularly static data that are being involved and would represent a quick idea on the various commodities and its value involved and the impact of a

pandemic. If we can see the analysis in the few of the countries were changed majorly and increased in few. The measures and dimensions are also very limited, but used to provide a quick view. The purpose of such a view would be very useful as major of the dashboards have such data to represent.

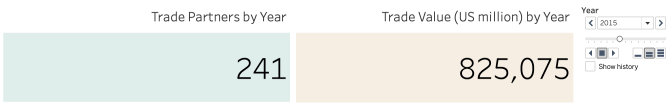


Figure 2. Annual Import v. Export by Year

In the deep dive dashboard, the other interactive actions on the dashlet were also used providing the same data, respective tool tips were modified for the same. In this dashlet, the data is divided by import or export status and the user can scroll through the years to once again see the dip after COVID (see Fig. 2. Color attributes were also being provided. Figure 2 shows a feature to ideally manage which year of the data to illustrate in the dashlets. On a whole, we are using dashlets to represent a few of the high level data like the number of countries and the total amount involved in the trade. The change of filter ideally refreshes the dashlet with that year selected. The data would ideally give the users a quick view of the exchange data involved at a high level. Any dashboard would need such a filter especially to analyze a particular event's impact. An interactive selection bar can help to quickly change the year without actually providing a value.

B. Trade Partners

Figure 3 shows the average trade value of the various countries that are involved in the imports and exports. The quick view of the various countries involved was represented with its average trade. The intensity of the color is being used to identify its trade value. The deeper the color, the higher the average value. This particular differentiation is ideally helpful to give a quick view of the country and its trade value and which has the more trade exchange. Especially to compare if its any major impact due to COVID. The idea of quick illustration can be identified here. The various interactive tool-tips help for a detailed view of the country's trade values. The average value of the countries is also being provided to decide on the factors.

Figure 4 shows the deeper detailed view of the trade value of the top ten countries which has been influenced by the COVID and has been a major trading country in the past. This data is similar to that of the heat map, but has been filtered for the top ten highest trade value across all years to identify the most important trading partners. This provides a closer look at how India's top trading partners have been affected by COVID. The interactive elements like tooltips and highlighters have been helpful for the same and have been utilized to concentrate on a few important details. The respective differentiation legends have also been provided.

Figure 5 shows a similar perspective to that of the bar chart using the same filter for the top ten countries by cumulative trade value of all the year (2010-2021), but it differs in that it offers an easy to visualize year-by-year trends and comparative analysis. Ideally, for any analytics, the key endpoint is to predict and analyze the future. So we have been using these charts to showcase the predictive trends using historical data. The major countries like the USA and China have been very much influencing the trade value. When we have been comparing for a decade, the predictions for such countries could give us a broader perspective on the upcoming trade values. Likewise, it can be used to maintain the same or increase with various measures. Individual countries can be analyzed with each year's data and can be compared with the other top 9 countries. The interactive elements are highly used to show accurate data and illustrate few other important data points.

C. Dashboard and Navigation

Figure 6 shows the main dashboard with several of the aforementioned visualization. There are two buttons that navigate to two additional dashboards. The 'Dive Deeper' button navigates to the dashboard shown in Figure 7 and the 'Explore Data' button navigates to the heat table shown in Figure 8. A lighter gray dashed line was added to the buttons to give a more three-dimensional eye-catching texture and improve the affordance of the object. The return navigation on the destination dashboards have a matching 'Back' button in the top right corner using Fitt's Law which tells us that the human eye is drawn towards corners.

Especially when it comes to deep-diving into an individual year and overall analytics of the average trade value. So we can use the dashboards for the same and each dashboard provides us specific data points that can be helpful to various possible analytics and predictions.

Figure 8 shows the view of the raw data as a pivot table with a heat map applied onto where the darker intensity color indicates a higher value. Ideally. one would like to explore the available entities to create a few of the data points on a whole. We have provided the raw data view for the future scaling of the dashboard. It helps to lay an objective as to what can be predicted using the available data, as one can only estimate using the available data.

V. Discussion

Our end goal on this dashboard development is to provide a high-level perspective of the imports and exports of India, also providing a few of the year-by-year analyses. Few charts have been also useful to get a quick level of the predictions on few country trade values. Various possible trends have been illustrated and dashlet data for a quick view has been helpful. Besides the fact, the reasons for the possible trends can be analyzed on a high level but the possible upcoming trends have been depicted.

In Figure 1, from the dashlet data in the dashboard, one can identify the fact that COVID has been showing an impact in the countries that have been involved in the trade and resulting in the value of the annual trade. It has dropped from 1,849

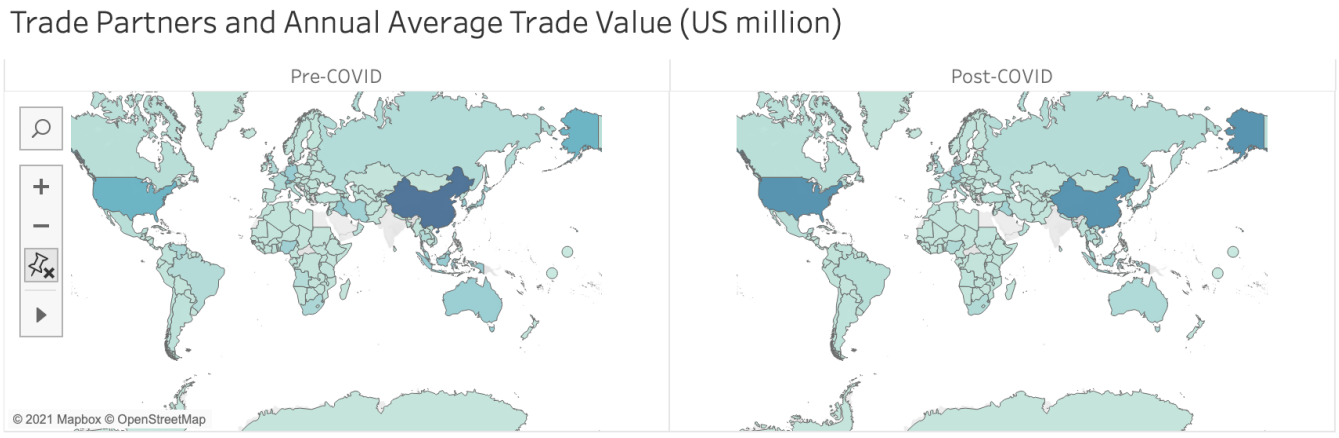


Figure 3. Countries Heat Map

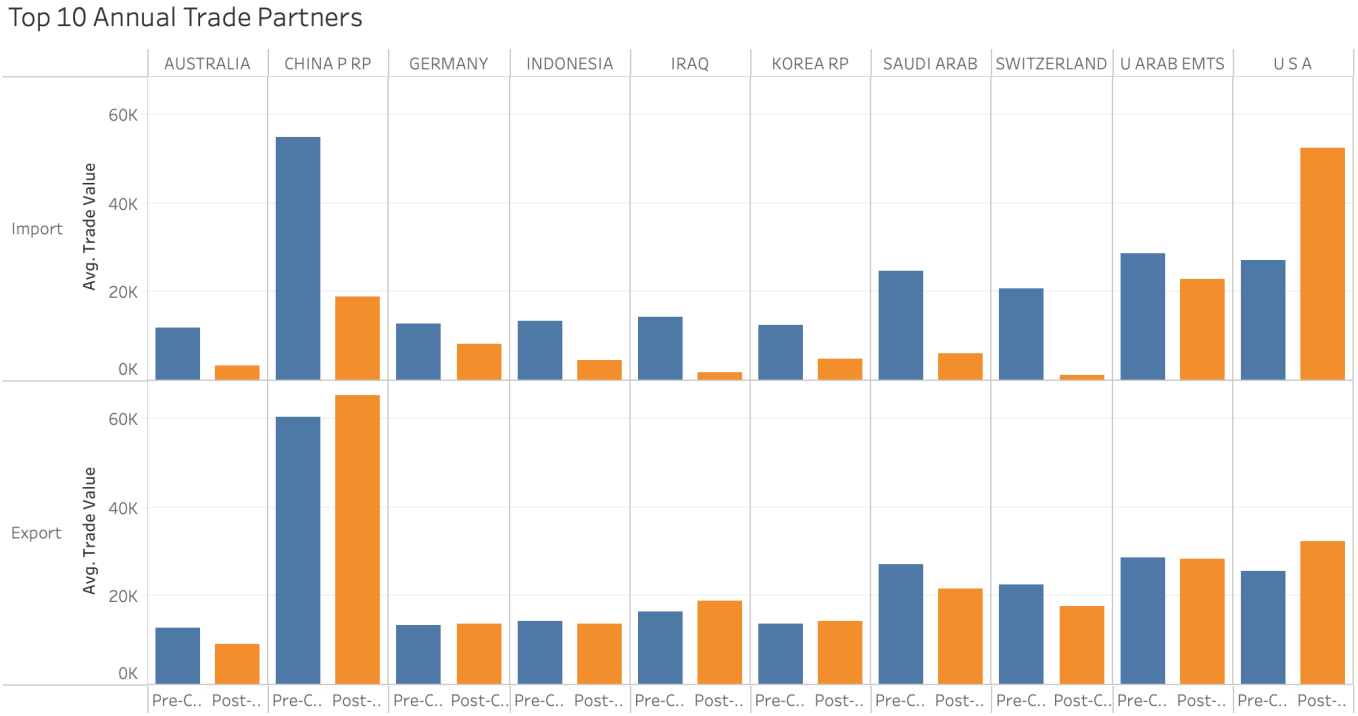


Figure 4. Top 10 trading countries

to 1,575 million dollars resulting in nearly a difference of 274 million dollars loss. It also illustrates that trading with a couple of countries has been halted completely (see Fig. 2. Both dashlets show there was a drop in trade both in the trade value and the number of countries traded with in 2019 indicating the COVID-19 pandemic was a major factor.

In figure 3, there are two heat maps side by side for comparison. Geography has a great impact on bilateral trade depending on geophysical barrier [7]. The countries that were influenced by the COVID have been identified easily. Especially USA and China, the individual trade values are also being illustrated accordingly with the interactive hover over feature. From these heat maps, it can easily be seen that the US increased in trade and China decreased in trade after COVID. For the other countries, the impact was not that high could be also identified. If anyone wants to ideal check with respect to the country can also be identified with ease.

In line graph in Figure 5, the trends of the top ten average trade through the decade can be observed. For instance, a country like the USA can be compared with major traders like China, not only restricting the comparison to its own year-to-year analytics. Ideally, the few attributes like highest trade value, 152,761 million is being observed with country China in 2017, can be extracted easily with a quick view. Not

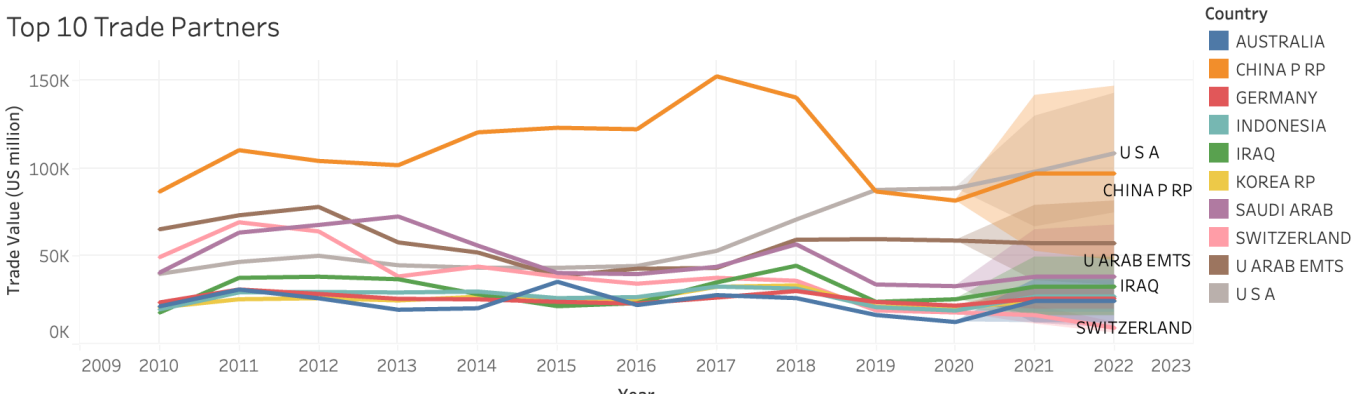


Figure 5. Top 10 Trading Countries - Analytics

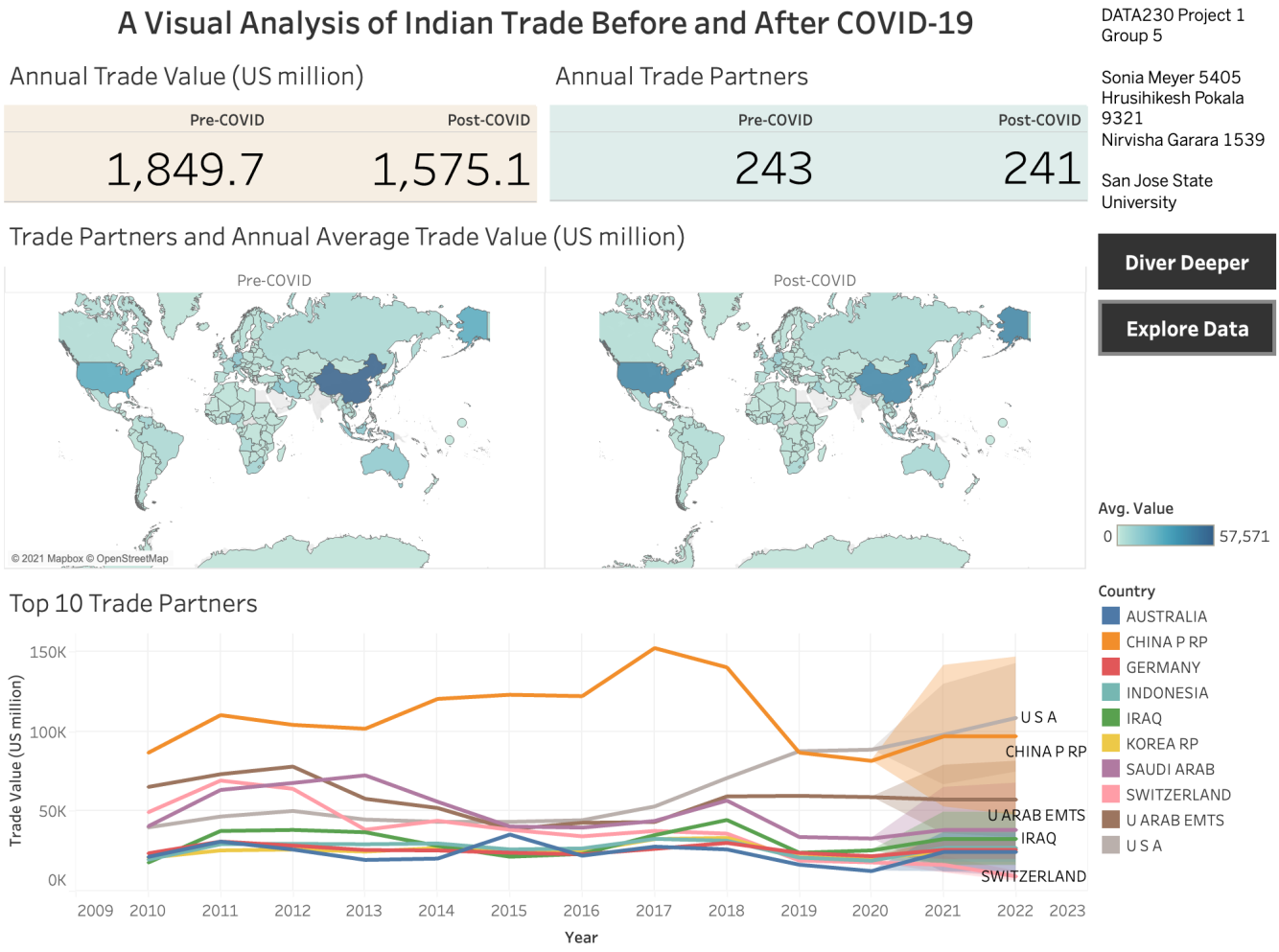


Figure 6. Main Dashboard

only is the historical data presented, but also users can see the predictive analysis for the upcoming year trade value. Through our literature review, we learned that China implemented the National Sword Policy in 2017 with the goal conserving the environment [5]. This policy banned the import of plastic waste. It would seem that this was the cause of the dip in trade value after 2017. Looking at the average values before and after COVID alone could not convey this nuanced event.

In bar chart in Figure 4 chart from the dashboard, the users can easily get a few of the information on the top ten trade

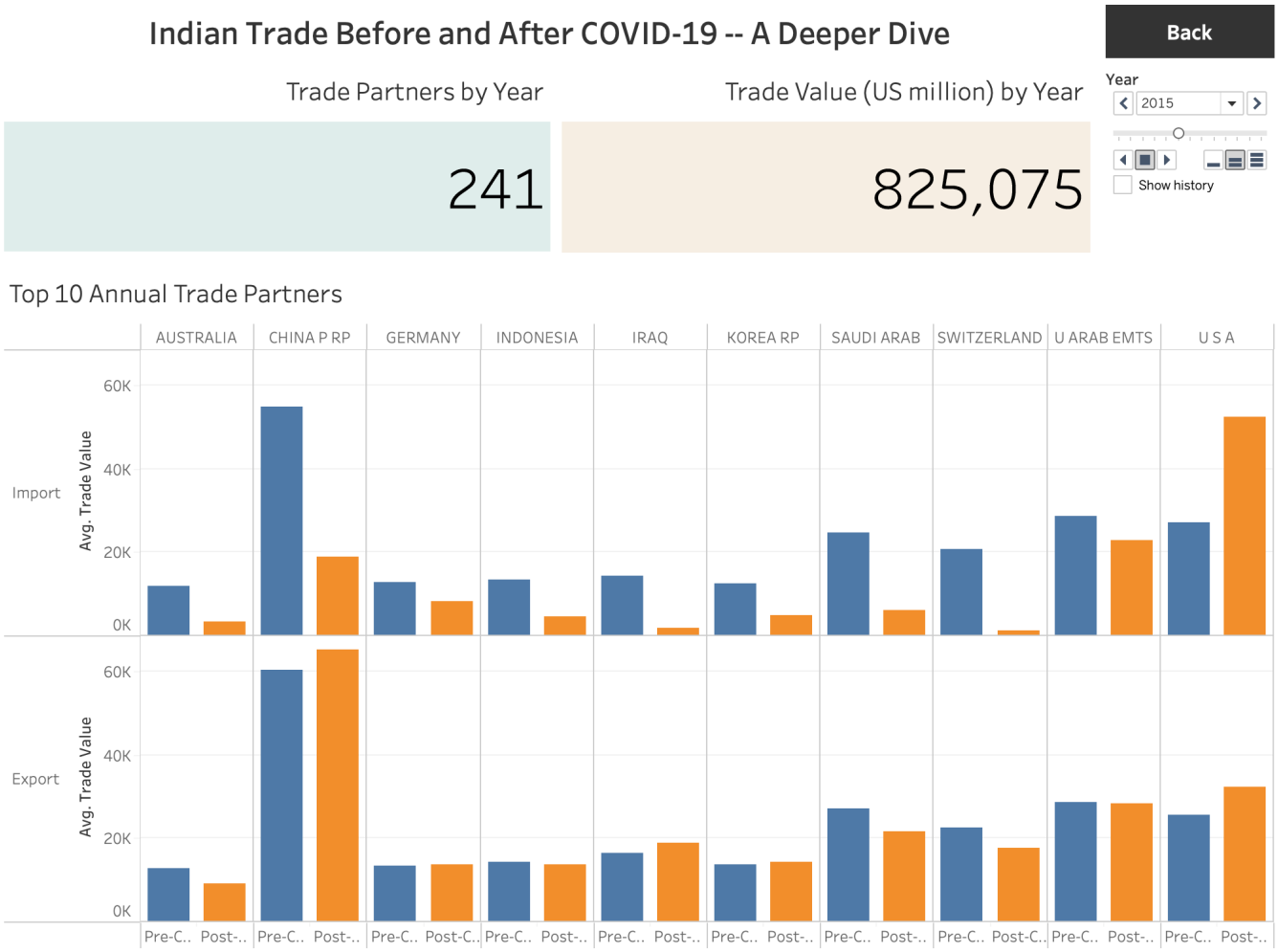


Figure 7. Deepdive Dashboard

partners and their pre and post COVID analysis. This shows the same data as the heat map, but with a filter on the top ten countries. Ideally, with a quick view of a country like the USA, the value of trade has been increased considerably due to various needs. While the other countries have been found with trends of decent dip and adverse dip. The import and export analysis are being easily analyzed by the users. Interestingly, the US is the only country to show an increase in imports to India, while both China and the US have a slight increase in exports from India. All other countries show a decrease in imports and export after COVID.

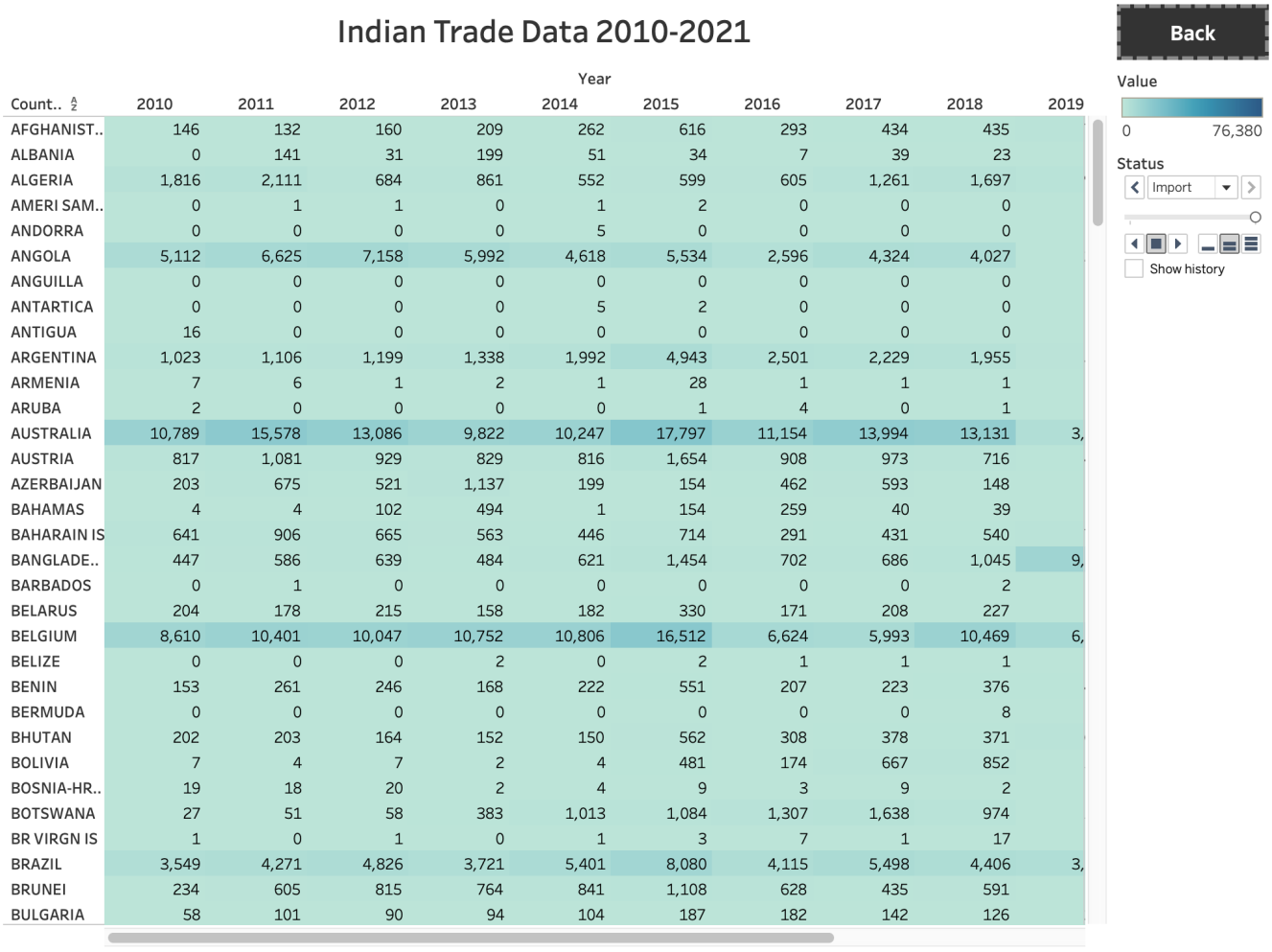
Ideally trading information is a crucial piece of information for various commodities buyers and sellers. Its been playing a crucial role in a few of the domains like medical. Upon the various pandemic crisis, a various irregular pattern has been observed especially since the last couple of years.

Identifying such abnormal data would always help the end users to take some good measures in the balance of trade. The more historical data in detail, the more is the accuracy of the prediction charts.

Applying Bačić's framework based on the Stanford-binet non-verbal IQ to our dashboard, our dashboard excels in the domains of fluid intelligence, visual-spatial processing, and working and short term memory. It lacks in domain specific knowledge and could have more robust quantitative reasoning. Access to the raw data as a heat table and the interactivity of the filters allows deeper exploration and interaction. The dashboard is simple and requires little cognitive effort given what we know about human attention and capacity. It tells a clear story of the effect of COVID on India's trade. There are some analytic included like the forecasting of trends for top ten countries and the aggregation of data for comparison. The area most lacking in domain specific knowledge, but we did have relevant data.

VI. Future Work

We used a Tableau forecasting function to predict trade values by country in 2022. It will be interesting to compare the data at that time to determine the accuracy of the predictions. Additionally, it could be quite lucrative if we are able to accurately predict commodity trade and the accompanying stock



Count..	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
AFGHANIST..	146	132	160	209	262	616	293	434	435	
ALBANIA	0	141	31	199	51	34	7	39	23	
ALGERIA	1,816	2,111	684	861	552	599	605	1,261	1,697	
AMERI SAM..	0	1	1	0	1	2	0	0	0	
ANDORRA	0	0	0	0	5	0	0	0	0	
ANGOLA	5,112	6,625	7,158	5,992	4,618	5,534	2,596	4,324	4,027	
ANGUILLA	0	0	0	0	0	0	0	0	0	
ANTARTICA	0	0	0	0	5	2	0	0	0	
ANTIGUA	16	0	0	0	0	0	0	0	0	
ARGENTINA	1,023	1,106	1,199	1,338	1,992	4,943	2,501	2,229	1,955	
ARMENIA	7	6	1	2	1	28	1	1	1	
ARUBA	2	0	0	0	0	1	4	0	1	
AUSTRALIA	10,789	15,578	13,086	9,822	10,247	17,797	11,154	13,994	13,131	3,
AUSTRIA	817	1,081	929	829	816	1,654	908	973	716	
AZERBAIJAN	203	675	521	1,137	199	154	462	593	148	
BAHAMAS	4	4	102	494	1	154	259	40	39	
BAHARAIN IS	641	906	665	563	446	714	291	431	540	
BANGLADE..	447	586	639	484	621	1,454	702	686	1,045	9,
BARBADOS	0	1	0	0	0	0	0	0	2	
BELARUS	204	178	215	158	182	330	171	208	227	
BELGIUM	8,610	10,401	10,047	10,752	10,806	16,512	6,624	5,993	10,469	6,
BELIZE	0	0	0	2	0	2	1	1	1	
BENIN	153	261	246	168	222	551	207	223	376	
BERMUDA	0	0	0	0	0	0	0	0	8	
BHUTAN	202	203	164	152	150	562	308	378	371	
BOLIVIA	7	4	7	2	4	481	174	667	852	
BOSNIA-HR..	19	18	20	2	4	9	3	9	2	
BOTSWANA	27	51	58	383	1,013	1,084	1,307	1,638	974	
BR VIRGN IS	1	0	1	0	1	3	7	1	17	
BRAZIL	3,549	4,271	4,826	3,721	5,401	8,080	4,115	5,498	4,406	3,
BRUNEI	234	605	815	764	841	1,108	628	435	591	
BULGARIA	58	101	90	94	104	187	182	142	126	

Figure 8. Exploring the data

prices trends. Machine learning algorithms or deep learning techniques could be used to predict trends using real-time data to address real-world problems. Additionally, historical analysis using data prior to 2010 would provide interesting insight into long-term economic trends. Interactive features in the dashboard are more likely to improve with respect to adding up more filters based on the various dimension and measures. Looking forward to few other major digital providers to extract such related information.

If the Indian Bureau of Commerce released the commodity specific data and we were able to extract that data for the period 2019 to 2021, future data analysis on commodities before and after COVID would be interesting. We mostly analyzed and visualized gross trade value in US millions by country, but it would be interesting to look at growth by country or percentage of total Indian trade value as another metric. Finally, consultation with a subject matter expert in economics and world events could provide further insight and context to the trends seen in the visualizations. Additionally, a subject matter expert could provide policy analysis and suggestions based on the data visualizations.

VII. What did we learn?

Visualization is an excellent way to illustrate what has been learned from the data. Apart from various raw data analysis and classical statistical analysis, the graphical representation of the same data can illustrate more information quickly. Visualization can be effectively used with a small or large data set and learning is very intuitive. It is important to clean data and filter out irrelevant information for more streamlined analysis. On using Tableau, we found we were able to build the whole dashboard with ease in each and every step. The chart building was also very simple using the various measures and dimensions available in the filtered data. The data source management is as simple as loading the data. Out of all the features, dashboard management and layout preparation are the most flexible.

Primarily, we learned how to use Tableau, and how easy it is to design and customize charts with various measures and dimensions derived from our imported data. Mostly what we

learned though is that there is more to learn. Other Tableau features we would like to learn more about are how to more effectively collaborate in Tableau, how to use multiple data sources effectively, how to use custom formulas to create new columns in Tableau for better data analytics, and a deeper understanding of the Tableau forecasting functions. Overall, this was a great learning experience for all of us.

APPENDIX A
KAGGLE DATA PREVIEW

Id	HSCode	Commodity	value	country	year
0	5	PRODUCTS C	0	AFGHANISTA	2018
1	7	EDIBLE VEGE	12.38	AFGHANISTA	2018
2	8	EDIBLE FRUI	268.6	AFGHANISTA	2018
3	9	COFFEE, TEA	35.48	AFGHANISTA	2018
4	11	PRODUCTS C	0	AFGHANISTA	2018
5	12	OIL SEEDS AI	8.32	AFGHANISTA	2018
6	13	LAC; GUMS,	108.78	AFGHANISTA	2018
7	20	PREPARATIO	0.65	AFGHANISTA	2018
8	25	SALT; SULPH	0.05	AFGHANISTA	2018
9	27	MINERAL FU	0	AFGHANISTA	2018
10	39	PLASTIC AND	0	AFGHANISTA	2018
11	41	RAW HIDES A	0	AFGHANISTA	2018
12	49	PRINTED BO	0	AFGHANISTA	2018
13	51	WOOL, FINE	0.17	AFGHANISTA	2018
14	52	COTTON.	0.01	AFGHANISTA	2018
15	57	CARPETS AN	0.02	AFGHANISTA	2018
16	68	ARTICLES OF	0.01	AFGHANISTA	2018
17	71	NATURAL OF	0.01	AFGHANISTA	2018
18	72	IRON AND S	0.02	AFGHANISTA	2018
19	74	COPPER AND	0.36	AFGHANISTA	2018

APPENDIX B
SCRAPED DATA PREVIEW

S.No.	Country	2018-2019	%Share	2019-2020	%Share	%Growth
1	AFGHANISTAN	435.44	0.08	529.84	0.11	21.68
2	ALBANIA	22.62	0.00	47.51	0.01	110.07
3	ALGERIA	1696.96	0.33	1996.76	0.42	17.67
4	AMERI SAMOA	0.00	0.00	3.08	0.00	770050.00
5	ANDORRA	0.04	0.00	0.03	0.00	-13.07
6	ANGOLA	4027.49	0.78	3649.02	0.77	-9.40
7	ANGUILLA	0.19	0.00	0.10	0.00	-49.51
8	ANTARTICA	0.03	0.00	0.08	0.00	138.32
9	ANTIGUA	0.15	0.00	0.20	0.00	30.01
10	ARGENTINA	1954.99	0.38	2327.26	0.49	19.04
11	ARMENIA	0.91	0.00	1.56	0.00	71.56
12	ARUBA	0.55	0.00	0.30	0.00	-44.39
13	AUSTRALIA	13131.21	2.55	9782.22	2.06	-25.50
14	AUSTRIA	716.43	0.14	629.74	0.13	-12.10
15	AZERBAIJAN	147.87	0.03	273.91	0.06	85.23

APPENDIX C
CLEANED DATA PREVIEW

Country	Value	Year	Status	COVID
AFGHANISTA	146.01	2010	Import	Pre-COVID
AFGHANISTA	146.01	2010	Export	Pre-COVID
AFGHANISTA	132.49	2011	Import	Pre-COVID
AFGHANISTA	132.49	2011	Export	Pre-COVID
AFGHANISTA	159.53	2012	Import	Pre-COVID
AFGHANISTA	159.53	2012	Export	Pre-COVID
AFGHANISTA	208.76	2013	Import	Pre-COVID
AFGHANISTA	208.76	2013	Export	Pre-COVID
AFGHANISTA	261.92	2014	Import	Pre-COVID
AFGHANISTA	261.92	2014	Export	Pre-COVID
AFGHANISTA	615.8	2015	Import	Pre-COVID
AFGHANISTA	615.8	2015	Export	Pre-COVID
AFGHANISTA	292.9	2016	Import	Pre-COVID
AFGHANISTA	292.9	2016	Export	Pre-COVID
AFGHANISTA	433.77	2017	Import	Pre-COVID
AFGHANISTA	433.77	2017	Export	Pre-COVID

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