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Artificial Intelligence Methods for Evaluating Global Trade Flows*

Feras A. Batarseh[†] Munisamy Gopinath[‡] Anderson Monken[§]

Abstract

International trade policies remain in the spotlight given the recent rethink on the benefits of globalization by major economies. Since trade critically affects employment, production, prices and wages, understanding and predicting future patterns of trade is a high-priority for decision making within and across countries. While traditional economic models aim to be reliable predictors, we consider the possibility that Artificial Intelligence (AI) techniques allow for better predictions and associations to inform policy decisions. Moreover, we outline contextual AI methods to decipher trade patterns affected by outlier events such as trade wars and pandemics. Open-government data are essential to providing the fuel to the algorithms that can forecast, recommend, and classify policies. Data collected for this study describe international trade transactions and commonly associated economic factors. Models deployed include Association Rules for grouping commodity pairs; and ARIMA, GBoosting, XGBoosting, and LightGBM for predicting future trade patterns. Models and their results are introduced and evaluated for prediction and association quality with example policy implications.

Keywords: AI, international trade, boosting, prediction, data mining, imports and exports, outlier events

JEL codes: F13, F17, C55, C8

* The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System. We thank Rob Vigfusson for his valuable comments.

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1. Background and Motivation

In recent years, many countries are concerned about rising trade deficits (value of exports less imports) and their implications for employment, production, and wages. For instance, the United States' goods and services trade deficit with China was $378.8 billion in 2018. Such numbers are forcing countries to either exit trade agreements or enforce tariffs, (e.g. Brexit, U.S. tariffs on Chinese goods). These shocks to global trade in commodities pose challenges to predict future trading patterns. International economics has a long history of improving our understanding of factors causing trade and the consequences of free flow of goods and services across countries. Nonetheless, the recent shocks to the free-trade regime raise questions on the quality of earlier predictions and their applicability in the context of large trade disputes. To address these challenges, this article, identifies AI techniques appropriate for the international trade setting and tests their validity in making high quality projections (Batarseh and Yang, 2018). Recent technological advancements in Artificial Intelligence (AI) as well as data democratization (Batarseh and Yang, 2020) have helped increase transparency, which is critical in the context of public decision-making. Given the Open Data and Big Data initiatives presented in 2008 and 2012 (White House, 2008), federal agencies are forced to share their data on public repositories such as www.data.gov, as well as many agency-specific repositories. The combination of data availability, AI advances and a contemporary context, i.e. trade wars, offer a unique opportunity to explore the applicability of AI techniques for nimble and improved trade projections to aid in decision-making.

The primary objective of the paper is to identify techniques most appropriate for economic forecasts, especially in the context of international trade, test their relevance using historical data on trade patterns and wherever appropriate, make quantitative and qualitative comparisons to current approaches.

2. AI for Economics and International Trade

Based on a recent study by the National Bureau of Economic Research (NBER), AI is *only recently* being applied to address economic issues. AI has been applied across multiple domains; it has been employed in addressing challenges in healthcare (Reddy and Aggarwal, 2015) (Batarseh and Latif, 2015), education (Niemi et al., 2018), and sports (Alamar, 2013). Athey and Imbens (2019) provide a detailed overview of AI techniques that economists should know about, but to date, AI applications to understand or predict patterns of international trade are limited (Gopinath, Batarseh and Beckman 2020).

The few economic applications include Gevel et al. (2013) on the nexus between Artificial Intelligence and Economics; Feng et al. (2014) on economic growth in the Chinese province of Zhejiang; Abadie et al. (2010) to the rising economics of tobacco in California; Milacic et al. (2016) and Kordanuli et al. (2016) for GDP growth; and Falat et al. (2015) for economic patterns.

Within AI, Machine learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) are 3 major pillars that have showed success in applications to various disciplines. ML for instance, is commonly understood as a number of computational algorithms that extract hidden insights from large sets of data.

DL is a set of bio-inspired methods that deploy neural networks to classify variable outputs, and allocate patterns that require extensive model training and hierarchical feature learning. RL however is a set of models that influence software agents to take action(s) in an environment in order to maximize the notion of cumulative reward and avoid punishment (using value functions).

In this study, multiple AI methods are applied to a big data set of international trade (imports/exports) with a focus on improved predictions. Experimental work presented in this paper utilizes AI methods in an optimized manner to provide predictions and associations regarding trade of specific commodities and countries (regressions, classifiers, clusters, associations and multiple other *actionable outcomes*). Given the dimensions of the data, and the high number of variables involved, several models are developed; few are compared to explain international trade patterns. Figure 1 illustrates top AI methods considered for this study.

Furthermore, the paper outlines approaches that are appropriate for the uncertain global trade environment in recent years. Trade wars between major economies, de-globalization trends, as well as the Covid-19 pandemic have seriously disrupted flows of goods and services within and across countries. Contextual AI, appropriate for this setting, is also discussed as a possible application to the trade setting.

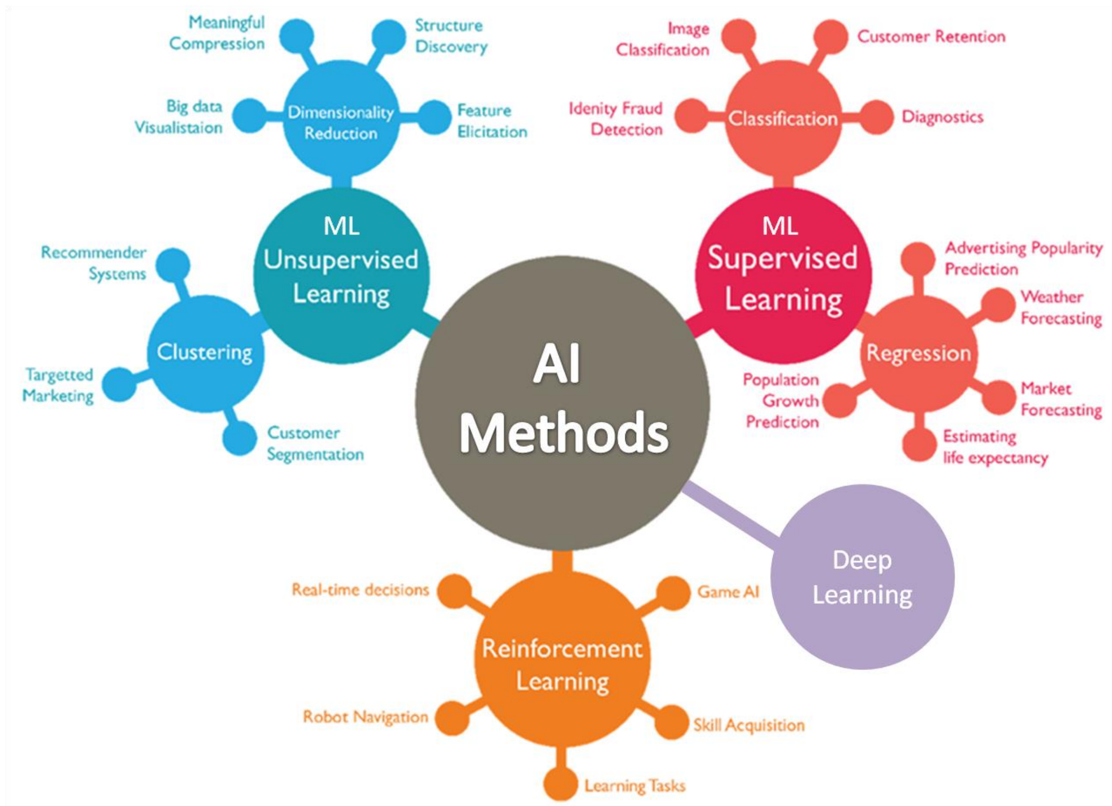

Figure 1: A Subset of the Most Commonplace AI Methods

3. Data Collection and Pre-Processing

For predictions using AI methods, data has been collected on several specific products – all the Harmonized System 4-digit level from USDA's Foreign Agricultural Services' Global Agricultural Trade System (FAS - GATS) (USDA 2019). GATS is a system published by the United States Department of Agriculture. To apply supervised methods, additional economic data is collected from the World Bank's *World Integrated Trade Solution* (WITS 2019) and U.S. ITC's Gravity Portal (2019). The trade data cover seven major commodities with a long history of trade data (starting in the 1960s): Wheat, Milk, Rice, Corn, Beef, Soy, and Sugar. They are merged with 30+ economic variables, such as: *Population*, *Currency*, *Island or Not*, *GDP of Origin*, *GDP of Destination*, *Distance*, *Landlocked or not*, *WTO Member*, *Hostility*, *EU Member,* and other ones (U.S. ITC Gravity Portal).

Afterwards, the economic and commodity data are merged into a SQL database. An R code is used to merge on *country-to-country* trade transactions, as well as year of economic variables. The data are merged using a SQL Inner Join. The 30+ economic variables' correlations are studied; results for the correlations (done in R) are plotted in Figure 2. Highest economic correlations, for example, are found between: *population* and *whether the country is an island*, also, between *currency* and *GDP*, and between *WTO membership* and *Free Trade Agreements*; amongst other existing factors.

For Association Rules (AR), data come from the World Trade Organization (WTO) Bilateral Imports dataset, which comprises annual country to country trade data from 1996 to 2018. Data come from countries reporting imports from trading partners around the world. Only countries that are part of the WTO report imports (the sample of countries is ~190). The AR application focused on the *chapter level* of the system: the 2-digit codes (HS-2). Data on the 96-chapter level trade products are downloaded from the WTO developer portal (https://apiportal.wto.org/). Using `Pandas` and `Numpy` libraries in Python, data are loaded into a *PostgreSQL* database for ease of analysis. The next two sections present the methods and the results of 1) Predictions and 2) Associations.

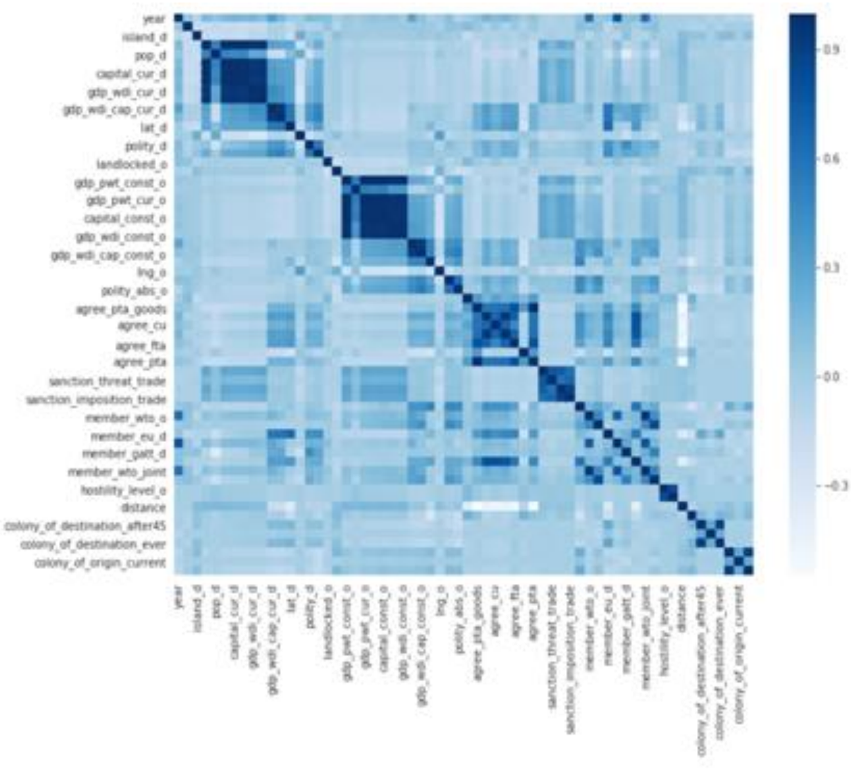

Figure 2: Correlations of 30+ Economic Variables

4. Predictions: Methods and Results

Supervised and unsupervised methods have been explored: Linear Regression, K-means clustering, Pearson correlations, Boosting, and Time Series such as Autoregressive Integrated Moving Average (ARIMA). Simple linear regression modeling is applied to the seven major commodities mentioned; the aim is to predict exports or imports of a specific commodity. For example, after importing required columns into a python environment, linear regression is deployed using the python libraries: *sklearn.linear_model* and *pandas* (Python 2019).

The results below focus on one commodity: beef. Top countries exporting beef are: Australia, Germany, Netherlands, France, and United States. Although data for beef trade are available from 1960, data from 1989 to 2018 is used because of missing information on tariffs before 1988; years 2019-2021 are predicted (red line in Figure 3). As the figure illustrates, trade between nations is variant, and can change drastically over time; even for one commodity. Therefore, due to the high variance in the data, a simple regression model, although supervised, provides straight-line pointers to the future of beef trade (implying growth remains constant). Consequently, as an experimental model, an unsupervised K-means clustering model is developed to group countries into clusters (using *sklearn's cluster* and *K-Means* libraries in python).

Besides trade values, other economic variables are incrementally added to the modeling process. When all the economic variables are added, the aim is to identify which variables have the highest influence on trade predictions, and which ones could be controlled and tuned to change the forecasts. Different commodities had different rankings of economic variables, however, ***distance*** *(between the 2 countries undergoing trade),* ***population of the exporter***, and ***GDP of both countries*** had the highest impact on whether two countries would trade one of the seven major commodities or not. Feature importance (Gain of top economic variables) is illustrated in Figure 4. Consequently, ARIMA is applied to beef trade, the advantage of ARIMA is that it provides univariate predictions that improve the output. ARIMA results are presented in Table 1 and Figure 5; they illustrate the high and low confidence intervals of the model.

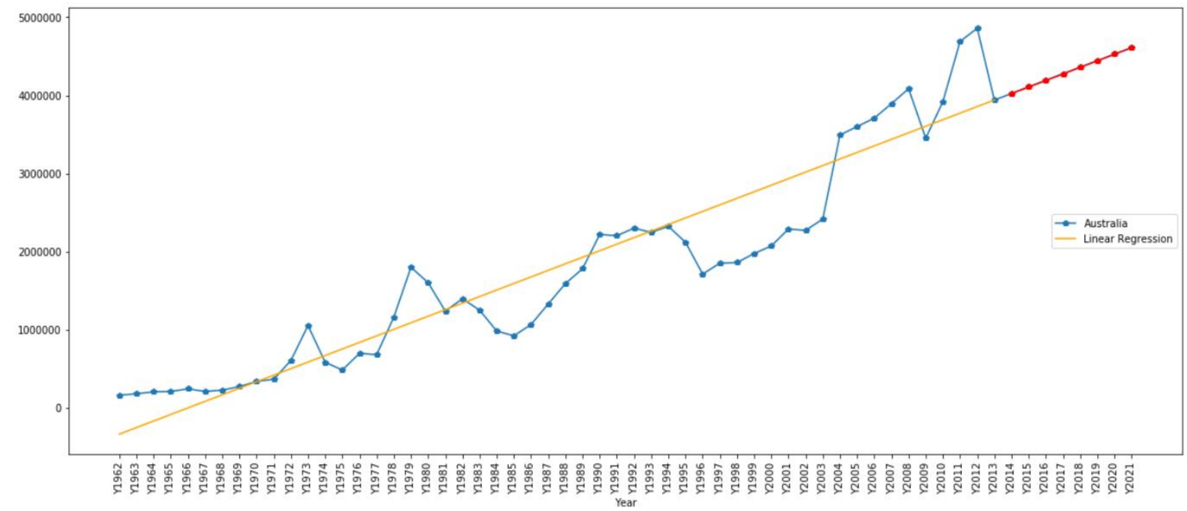

Figure 3: Australia's Beef Exports 1988-2021

Afterwards, boosting has been applied to elevate the quality of the models. Three different boosting models are deployed: Gradient Boost (GBoost), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Decision Tree (LightGBM). Python libraries are used to deploy the models (GBoost, XGBoost, and LightGBM) (Ke et al. 2017). After multiple iterations and hyper-parameters' tuning, LightGBM performed best for most commodities. A boosting algorithm is an algorithm that converts weak learners to strong learners. It is a method that improves predictions' quality of a model. Boosting trains weak learners sequentially, and in every cycle, each trying to correct its predecessor.

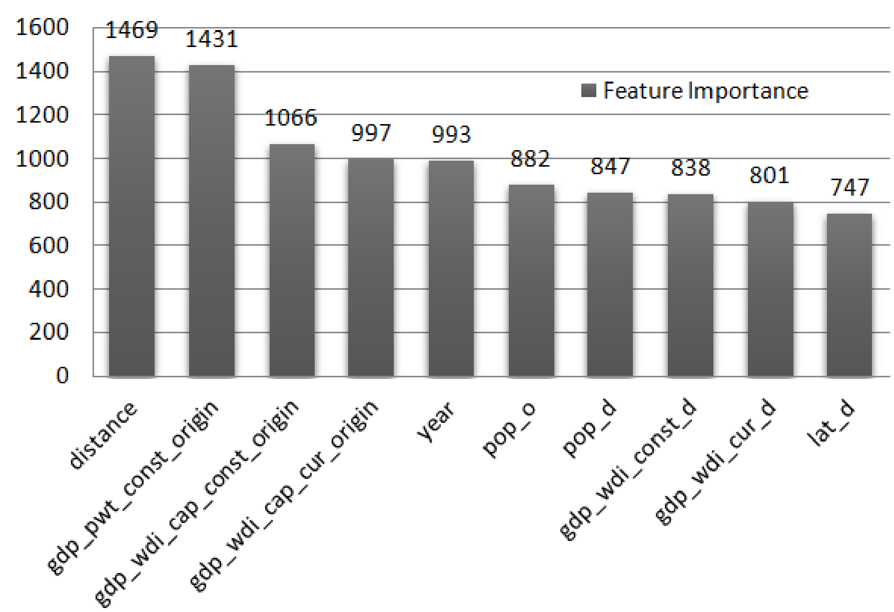

Figure 4: Strength of Variables in Predicting Trade Trends

Table 1: ARIMA Forecasting of Beef Trade Trends

Year	Actual	Forecast	Low 80	High 80	Low 95	High 95
2014	6939233	5594243	5208462	5980024	5004242	6184244
2015	7357932	5698666	5153090	6244242	4864279	6533053
2016	5921218	5803089	5134898	6471281	4781178	6825000
2017	5843209	5907513	5135951	6679074	4727511	7087514
2018	X	6011936	5149304	6874567	4692654	7331217
2019	X	6116359	5171393	7061325	4671159	7561559
2020	X	6220782	5200102	7241462	4659787	7781777
2021	X	6325205	5234053	7416358	4656432	7993979

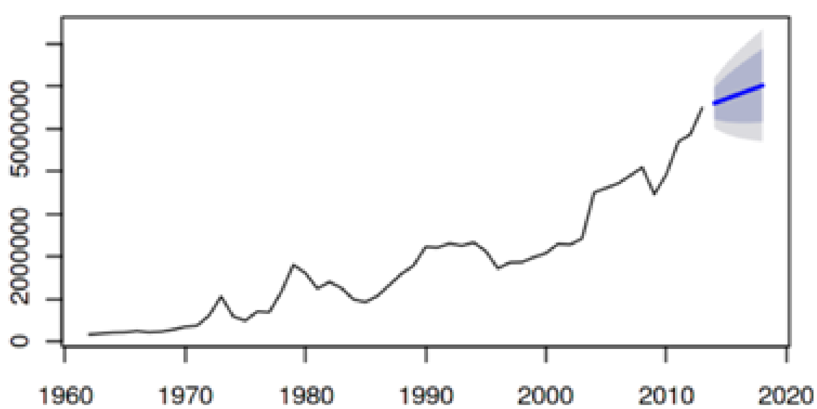

Figure 5: Australia's Beef Exports Predictions (ARIMA)

Results for trade predictions through the XGBoost Model scored predictions' quality = 69%, and through LightGBM scored a quality of **88%** (in contrast, GBoost scored the lowest of the three approaches). Parameter tuning for boosting models include: Number of leaves, Maximum Depth of the tree, Learning Rate, and Feature fraction. Small learning rates are optimal (0.01), with large tree depths. Additionally, to speed up training and avoid over-fitting, feature fraction is set to 0.6; that is, selecting 60% of the features before training each tree. Early stopping round is set to 500; that allowed the model to train until the *validation score* stops improving. Maximum tree depth is set to 8. Those tunings led to the best output through LightGBM. *Sugar* for instance had an R^2 score of 0.73, 0.88 for *Beef*, and 0.66 for *Corn*. Additionally, such tunings allowed for the extractions of the best economic variables that would affect trade of specific commodities. As mentioned for beef for example, *distance* had the highest effect (i.e. the US is better off trading beef to Canada and Mexico, its two closest neighbors). While Australia, being an island, has to focus its policies for beef exports on GDP measures, and the population of the importer. Feature Importance for all economic variables are *(name: split, gain.)*: *Distance: 1469, 6.38. GDP of Exporter: 1431, 6.22. Year: 993, 4.318. Population of Exporter: 882, 3.83. Population of Importer: 847, 3.68. Currency of Importer: 801, 3.48.* Figure 6 shows predictions for aggregate Australian exports of beef as well as its exports to the major trade partner: Japan.

The clustering model yielded very expected results: China and the US ended up in Cluster 1, as the biggest exporters and importers. Cluster 2 has other major exporters and importers: Japan, Germany, Canada, UK, India, and France. Cluster 3 has less important importer countries, such as most third-world countries.

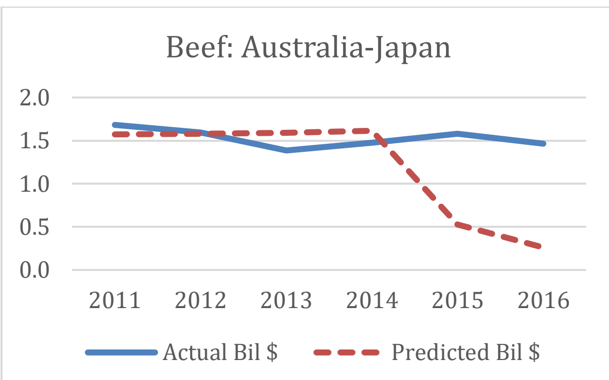

Figure 6(a): Supervised Model Projections

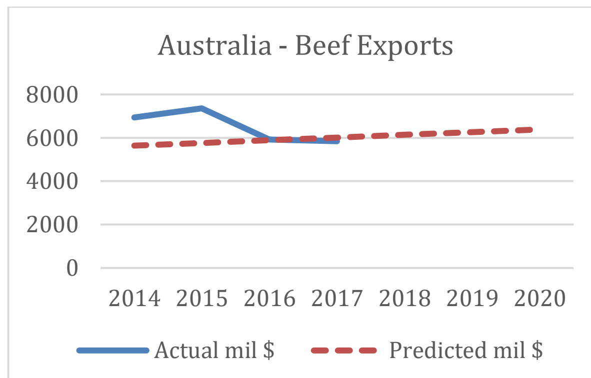

Figure 6(b): Unsupervised Model Projections

5. Associations: Methods and Results

Identifying commodities that are traded in association with each other point to substitutability and complementarities and has a direct implication on decision making when one commodity is targeted, e.g. U.S. soybeans or Chinese steel. AR is a popular method for discovering hidden relations between variables in big datasets. Piatetsky and Shapiro (1991) describe analyzing *strong* rules discovered in datasets. Based on the notion of strong rules, Agrawal et al. (1993) introduced the problem of mining association rules from transaction data.

The idea of AR is as follows: Let $X = \{x_1, x_2, ..., x_n\}$ be a set of n commodities. Let $T = \{t_1, t_2, ..., t_n\}$ be a set of transactions (where *Tt* is the total number of transactions). Each transaction in T has a unique

ID and contains a subset of the commodities (X) that are traded. A rule is defined as an implication of the form $X_a \Rightarrow X_b$ where $X_a, X_b \subseteq X$ and $X_a \cap X_b = \emptyset$.

The sets of commodities X_a is called antecedents (left-hand-side or LHS) and the set of commodities X_b is called consequents (right-hand-side or RHS) of the rule.

Besides antecedent-consequent rules, the quality of the associations is measured through the following three metrics:

1. $Support = \frac{X_a + X_b}{Tt}$
2. $Confidence = \frac{X_a + X_b}{X_a}$
3. $Lift = \frac{(X_a + X_b)/\,X_a}{(X_b/Tt)}$

Support indicates that for example 67% of customers purchased beer and diapers together. Confidence is that 90% of the customers who bought beer also bought diapers (confidence is the best indicator of AR). While lift represents the 28% increase in expectation that someone will buy diapers, when we know that they bought beer (i.e. lift is the conditional probability).

In our study, AR mining is performed using the `arules` library in R. Data are pulled and processed from *PostgreSQL*. Transactions in the data represent each country-country pair's trade for a given year. The goods in the data are the 96 commodity code trade dummies, which are boolean values depending on whether trade occurred for a specific country-country pair for a given year. Apriori association rules are collected with a minimum support of 0.35 and a maximum number of antecedents set to 3. Results are visualized in `plotly` and exported using R. The top ***4 million+*** rules are pulled out of the models, and migrated into a structured relational SQL database (called: `AR-Trade`). The rules are pulled for U.S. trade for top trade countries in Asia (China, Korea, and Japan); as well as the top trade countries in Europe (UK, Spain, France, and Germany). Relational SQL tables include the following columns:

Lhs (antecedent), Rhs (consequent), Lhs name, Rhs name, Support, Confidence, Lift, Count, Country_O, Country_D. AR results are plotted using an `R-Shiny` dashboard, as well as R plots using the `arulesViz` library such as through this script:

```
isS4(AR-Trade)
AR-Trade@lhs
plot(AR-Trade)
```

Results are recorded and analyzed.

AR is applied to HS2 commodity codes, and so for instance, if *beer leads to diapers* at the grocery store, then *oil seeds lead to cotton* in international trade. In future work, we aim to deploy HS6 AR analysis to directly influence production decisions in the U.S., provide tariff insights, and other potential trade policies. Table 2 presents example top commodity pairs as antecedents and consequents.

Table 2: A Sample of Top AR Associations

ID	Antecedent	Consequent	Sum of Confidence
1	Products of the milling industry; malt; starches; inulin; wheat gluten	Knitted or crocheted fabrics	935
2	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Cereals	902
3	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Clocks and watches and parts thereof	891
4	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Cocoa and cocoa preparations	883.71
5	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Copper and articles thereof	891
6	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Cork and articles of cork	879.71
7	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Cotton	891
8	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles	891
9	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Essential oils and resinoids; perfumery, cosmetic or toilet preparations	891
10	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	Explosives; pyrotechnic products; matches; pyrophoric alloys; certain combustible preparations	891

The next section digs deeper into AR, and presents examples on bilateral trade between China and Australia, USA and top world traders, as well as China's top food and agriculture commodities' associations.

6. Bilateral Association Results

As discussed prior, ARs provide means to determine goods that are often traded together. This cause and effect analysis is especially important when countries choose to enact trade restrictions and tariffs against other nations. The effect of losing the trade of one commodity between two countries depends on that commodity's relative impact on other commodities' trade - how many other commodities get traded alongside it. Table 3 is an example that describes how AR can be used to analyze the effects of recent Chinese trade restrictions.

Tariffs imposed between countries can both have international effects while also resulting in domestic economic consequences. In May of 2020, China placed tariffs against Australian Barley and restricted import of Australian Beef in apparent retaliation for Australia's government echoing the calls of the international community to investigate Beijing's response to Covid-19. Using AR confirms the choice of commodities to target were statistically sound for China's economy, because beef and barley are not in the top commodities that most impact the Australian-Sino commodity trade flows, AR analysis is performed for imports of Chinese goods to Australia and vice-versa for 1996 to 2019 across all available HS-6 level commodities (count = 4615). Rule building confidence threshold is set to 0.8, support threshold at 0.35 and up to three antecedents are allowed per rule. A total of 5,676,885 rules resulted, and antecedents across these rules were summed to determine commodities that have the most impact on the Sino-Australian trade relationship. Table 3 shows the top 25 commodities and the appearance count of AR. More results are available in a Github public repository: https://github.com/fbatarse-gmu/TradeAI.

Table 3: China-Australia Top Trade Associations (HS-6)

Rule #	Antecedent commodity	HS-6 Code	Count of Rules
1	Cereals; rice, semi-milled or wholly milled, whether or not polished or glazed	100630	46990
2	Peel; of citrus fruit or melons (including watermelons), fresh, frozen, dried or provisionally preserved in brine, in sulphur water and other preservative solutions	081400	46927
3	Vegetables, leguminous; beans (vigna spp., phaseolus spp.), shelled or unshelled, uncooked or cooked by steaming or boiling in water, frozen	071022	46920

4	Vegetables, leguminous; peas (pisum sativum), shelled or unshelled, fresh or chilled	070810	46920
5	Fish; dried (whether or not salted but not smoked), n.e.s. in item no. 0305.51	030559	46875
6	Bamboo used primarily for plaiting	140110	46832
7	Vegetables, leguminous; n.e.s. in heading no. 0713, shelled, whether or not skinned or split, dried	071390	46781
8	Fish preparations; fish prepared or preserved, whole or in pieces (but not minced), n.e.s. in heading no. 1604	160419	46764
9	Vegetable preparations; mushrooms, prepared or preserved otherwise than by vinegar or acetic acid	200310	46710
10	Food preparations; tapioca and substitutes thereof, prepared from starch in the form of flakes, grains, pearls, siftings or similar	190300	46677
11	Flours and meals of oil seeds or oleaginous fruits; excluding soya beans and mustard seeds	120890	46590
12	Vegetables and mixed vegetables; n.e.s. in heading no. 0711, provisionally preserved but unsuitable in that state for immediate consumption	071190	46545
13	Fruit, edible; dates, fresh or dried	080410	46512
14	Vegetables, leguminous; (other than peas or beans), shelled or unshelled, uncooked or cooked by steaming or boiling in water, frozen	071029	46482
15	Vegetable roots and tubers; sweet potatoes, with high starch or inulin content, whether or not sliced or in the form of pellets, fresh or dried	071420	46467
16	Fruit, edible; figs, fresh or dried	080420	46443
17	Meat preparations; of swine, meat or meat offal (including mixtures), prepared or preserved, n.e.s. in heading no. 1602	160249	46410
18	Vegetable preparations; vegetables and mixtures of vegetables (excluding potatoes), prepared or preserved otherwise than by vinegar or acetic acid, frozen	200490	46405
19	Vegetables, leguminous; n.e.s. in item no. 0713.30, dried, shelled, whether or not skinned or split	071339	46324
20	Vegetables; uncooked or cooked by steaming or boiling in water, frozen, n.e.s. in chapter 7	071080	46279
21	Vegetables, leguminous; peas (pisum sativum), shelled or unshelled, uncooked or cooked by steaming or boiling in water, frozen	071021	46251
22	Fish; salted or in brine, but not dried or smoked, n.e.s. in item no. 0305.6	030569	46113
23	Vegetables, alliaceous; garlic, fresh or chilled	070320	46113
24	Vegetable oils; ground-nut oil and its fractions, other than crude, whether or not refined, but not chemically modified	150890	46069

25	Vegetable preparations; beans, (not shelled), prepared or preserved otherwise than by vinegar or acetic acid, not frozen	200559	46025

Additionally, top HS-2 ARs from USA's bilateral trade with China, Japan, France, and Germany are presented in Table 4. Table 5 presents the top five results for China's food and agricultural commodities trade.

Table 4: USA Trade Associations with other Countries (HS-2)

Antecedent 1	**Antecedent 2**	**Consequent**	**Country_O**	**Country_D**
Ores, slag and ash	Works of art, collectors' pieces and antiques	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	USA	China
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Works of art, collectors' pieces and antiques	Ores, slag and ash	USA	China
Ores, slag and ash	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Works of art, collectors' pieces and antiques	USA	China
Ores, slag and ash	Works of art, collectors' pieces and antiques	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	USA	China
Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Works of art, collectors' pieces and antiques	Ores, slag and ash	USA	China
Ores, slag and ash	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals,	Works of art, collectors' pieces and antiques	USA	China

	of radioactive elements or of isotopes			
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Works of art, collectors' pieces and antiques	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	USA	China
Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Works of art, collectors' pieces and antiques	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	USA	China
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Works of art, collectors' pieces and antiques	USA	China
Ores, slag and ash	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	USA	China
Ores, slag and ash	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	USA	China
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Ores, slag and ash	USA	China
Ores, slag and ash	Works of art, collectors' pieces and antiques	Organic chemicals	USA	China
Organic chemicals	Works of art, collectors' pieces and antiques	Ores, slag and ash	USA	China
Inorganic chemicals; organic or inorganic	Works of art, collectors' pieces and antiques	Mineral fuels, mineral oils and products of	USA	France

compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes		their distillation; bituminous substances; mineral waxes		
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Works of art, collectors' pieces and antiques	USA	France
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Works of art, collectors' pieces and antiques	Organic chemicals	USA	France
Organic chemicals	Works of art, collectors' pieces and antiques	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	USA	France
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Organic chemicals	Works of art, collectors' pieces and antiques	USA	France
Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Works of art, collectors' pieces and antiques	Organic chemicals	USA	France
Organic chemicals	Works of art, collectors' pieces and antiques	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	USA	France
Inorganic chemicals; organic or inorganic compounds of precious metals, of rare	Organic chemicals	Works of art, collectors' pieces and antiques	USA	France

earth metals, of radioactive elements or of isotopes				
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Organic chemicals	USA	France
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Organic chemicals	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	USA	France
Inorganic chemicals; organic or inorganic compounds of precious metals, of rare earth metals, of radioactive elements or of isotopes	Organic chemicals	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	USA	France
Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	Works of art, collectors' pieces and antiques	Pharmaceutical products	USA	France
Pharmaceutical products	Works of art, collectors' pieces and antiques	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	USA	France
Glass and glassware	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Ceramic products	USA	Germany
Ceramic products	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with	Glass and glassware	USA	Germany

	precious metal, and articles thereof; imitation jewellery; coin			
Ceramic products	Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	USA	Germany
Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Articles of stone, plaster, cement, asbestos, mica or similar materials	USA	Germany
Articles of stone, plaster, cement, asbestos, mica or similar materials	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Glass and glassware	USA	Germany
Articles of stone, plaster, cement, asbestos, mica or similar materials	Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	USA	Germany
Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Prepared feathers and down and articles made of feathers or of down; artificial flowers; articles of human hair	USA	Germany
Prepared feathers and down and articles made of feathers or of down; artificial flowers; articles of human hair	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with	Glass and glassware	USA	Germany

	precious metal, and articles thereof; imitation jewellery; coin			
Prepared feathers and down and articles made of feathers or of down; artificial flowers; articles of human hair	Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	USA	Germany
Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Umbrellas, sun umbrellas, walking sticks, seat sticks, whips, riding cropsand parts thereof	USA	Germany
Umbrellas, sun umbrellas, walking sticks, seat sticks, whips, riding crops and parts thereof	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Glass and glassware	USA	Germany
Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Ceramic products	USA	Japan
Ceramic products	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Glass and glassware	USA	Japan
Ceramic products	Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles	USA	Japan

		thereof; imitation jewellery; coin		
Glass and glassware	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Articles of stone, plaster, cement, asbestos, mica or similar materials	USA	Japan
Articles of stone, plaster, cement, asbestos, mica or similar materials	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Glass and glassware	USA	Japan
Articles of stone, plaster, cement, asbestos, mica or similar materials	Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	USA	Japan
Glass and glassware	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Prepared feathers and down and articles made of feathers or of down; artificial flowers; articles of human hair	USA	Japan
Prepared feathers and down and articles made of feathers or of down; artificial flowers; articles of human hair	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Glass and glassware	USA	Japan
Prepared feathers and down and articles made of feathers or of down; artificial flowers; articles of human hair	Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	USA	Japan

Glass and glassware	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Umbrellas, sun umbrellas, walking sticks, seat sticks, whips, riding crops and parts thereof	USA	Japan
Umbrellas, sun umbrellas, walking sticks, seat sticks, whips, riding crops and parts thereof	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	Glass and glassware	USA	Japan
Umbrellas, sun umbrellas, walking sticks, seat sticks, whips, riding crops and parts thereof	Glass and glassware	Natural or cultured pearls, precious or semiprecious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	USA	Japan

Table 5: Top Five Food and Ag Commodities for China (HS-6)

Antecedents	Consequent	Antecedent 1 name	Antecedent 2 name	Consequent name	Support	Confidence	Lift	Count
{120220, 170490}	{120210}	Ground-nuts; shelled, not roasted or otherwise cooked, whether or not broken	Sugar confectionery; (excluding chewing gum, including white chocolate), not containing cocoa	Ground-nuts; in shell, not roasted or otherwise cooked	0.3	0.81	2.33	593
{120210, 170490}	{120220}	Ground-nuts; in shell, not roasted or otherwise cooked	Sugar confectionery; (excluding chewing gum, including white chocolate), not containing cocoa	Ground-nuts; shelled, not roasted or otherwise cooked, whether or not broken	0.3	0.9	2.31	593
{120210, 200310}	{120220}	Ground-nuts; in shell, not roasted or otherwise cooked	Vegetable preparations; mushrooms, prepared or preserved otherwise than by	Ground-nuts; shelled, not roasted or otherwise cooked, whether or not broken	0.3	0.92	2.36	589

			vinegar or acetic acid					
{120220, 200310}	{120210}	Ground-nuts; shelled, not roasted or otherwise cooked, whether or not broken	Vegetable preparations; mushrooms, prepared or preserved otherwise than by vinegar or acetic acid	Ground-nuts; in shell, not roasted or otherwise cooked	0.3	0.82	2.34	589
{070320, 120210}	{120220}	Vegetables, alliaceous; garlic, fresh or chilled	Ground-nuts; in shell, not roasted or otherwise cooked	Ground-nuts; shelled, not roasted or otherwise cooked, whether or not broken	0.3	0.91	2.34	586

The next section presents contextual methods, and discussions on how contextual analysis and AI can aid in detecting outlier events and understanding their effects.

7. Outlier Events and Contextual AI

Outlier events or uncertainty affects economic outcomes. Uncertainty can arise from natural disasters, health pandemics or market disruptions as in the recent trade war between U.S. and China. Such uncertainty sets in motion a cascade of events: price changes, behavioral changes by producers and consumers, shipping and transportation issues, worker welfare and others. Moreover, the strength of cascading events varies by product or region of analysis. The three most critical adverse world incidents since the 1870s were World War II, the Great Depression in America, and World War I. Results from multiple studies suggest that the Great Influenza Pandemic of 1918-1920 is the next most important negative economic shock for the world (Barro et al., 2020). Not all outliers are created equal; the historical record suggests that the 1918 influenza was an outlier among outliers, with unusual circumstances including the co-occurrence of World War I. No other influenza pandemic on record had such devastatingly high mortality rates, with estimates ranging from 20 to 50 million excess deaths over the period 1918-20 (Fan et al., 2020). The ongoing Covid-19 pandemic is likely to be the next big outlier. Prior to Covid-19, researchers at the U.S. Centers for Disease Control and Prevention (CDC) calculate (using traditional models) that deaths in the United States could reach 207,000 and the initial cost to the economy could approach $166 billion, or roughly 1.5 percent of GDP in case of an international pandemic similar to the 1918 outbreak (Garrett, 2008).

Modeling and predicting the implications of such outlier events is an important endeavor. During these outlier events, analysis is performed in uncharted waters. Issues arise such as the need to use daily if not hourly data (but not monthly data) for pattern recognition and predictions. Additionally, decisions become timelier and need to be executed in a quick manner using real time analysis and on-demand analytics.

AI methods are ideal in this context to not only help understand the impact of uncertainty or outliers but also provide on-time information to economic agents including policy makers.

Deploying *context* (a prominent field within AI) to represent outlier events is complex but appropriate for the current coronavirus pandemic. The context within a dataset can be represented as *features* (Turney, 2002). Features in general fall into three categories: primary features, irrelevant features, and contextual features. Primary features are the traditional ones which are pertinent to a particular domain. Irrelevant features are features which occur randomly and can be safely removed, while contextual features are the ones to pay close attention to. The above categorization helps in eliminating irrelevant data but additional work is needed to clearly define context: Recognition and Exploitation of Contextual Clues via Incremental Meta-Learning, IML (Widmer, 1996), which is a two-level learning model in which a Bayesian classifier is used for context classification, and meta algorithms are used to detect contextual changes. An alternative to IML is context-sensitive feature selection (Domingos, 1997), which out performs traditional feature selection such as forward and backward sequential selection. Dominogos's (1997) method uses a clustering approach to select locally-relevant features.

Bergadano et al. (1992) introduced a two-tier contextual classification adjustment method called POSIEDON. The first tier captures the basic properties of context, and the second tier captures property modifications and context dependencies. Context injections however, have been more successful when they are applied to specific domains. For example, adding context to data has significantly improved the accuracy of algorithms for solving Natural Language Processing (NLP) problems. Dinh et al. (2012) combined the output from the classifier with a set of words manually labeled with context. A transformation-based learning algorithm was then used to generate new rules for the classifier. Their approach increased the contextual accuracy of their application by 4.8% as well as in software testing, i.e. significant improvements in time and quality of testing results due to context (Batarseh, 2014).

The issue of deriving context from data for outlier detection however, is challenging since Williams (2018) pointed out that data science algorithms could have an opacity problem when ignoring the context. This can cause models to be racist or sexist (for example). It is often observed that Google translator refers to women as 'he said' or 'he wrote' when translating from Spanish to English. This finding was also verified by Google Inc. Another opacity example is a word embedding algorithm which classifies European names as pleasant and African American names as unpleasant (Zou et al., 2018). If a reductionist approach is considered, adding or removing data can surely redefine context, especially in the case of outlier events. It is observed however, that most real-world data science projects use incomplete data (Sesa and Syed, 2016) (Kang, 2013). Data incompleteness occurs within one of the following categorizations: 1) Missing Completely at Random (MCAR), 2) Missing at Random (MAR), and 3) Missing not at Random (MNAR). MAR depends on the observed data, but not on unobserved data while MCAR depends neither on observed data nor unobserved data (Schafer and Graham, 2002) (Graham, 2009). There are various methods to handle missing data issues which includes list wise or pair wise detections, multiple imputation, mean/median/mode imputation, regression imputation, as well as learning without handling missing data.

All the aforementioned methods require high quality data, since several types of bias can occur in any phase of the data science lifecycle or while extracting context. Bias can begin during data collection, data cleaning, modeling, or any other phase. Biases which arise in the data are independent of the sample size or statistical significance, and they can directly affect the context of the results or the model. They also affect the association between variables, and in extreme cases, they can even reflect the opposite of a true association or correlation (Pannucci, 2010). Based on reviewing multiple works in data science, the most commonly observed bias is class imbalance due to covariate shifts. Class imbalance is represented by the un-equal ratio of categories which can occur due to changes in the distribution of data (covariate shifts). Class imbalance depends on four factors: 1) degree of class imbalance 2) the complexity of the concept represented by the data 3) the overall size of the training size and 4) the type of classifier (Japkowicz, 2002). Datasets with imbalance create difficulties in information retrieval, filtering tasks, and knowledge representation (Lewis and Ringuette, 1994) (Lewis and Catlett, 1994) – which (if not accounted for) may lead to misinformation in the agricultural or economic domain. We aim to explore with the mentioned methods and test them along with the presented AI methods during conventional and outlier times. For instance, variations of RL methods can lead to pointers in causality and endogeneity. Injecting contextual data from outlier events (i.e. relevant to a black swan situation such as the Covid-19 pandemic) would lead to retraining of the models in a manner that would influence the patterns found. DL and RL models have the ability to seamlessly include outlier data and use it for predictions and classifications; a notion that we intend to explore and experiment with in our future work.

8. Traditional Economics and Other Conclusions

This study proposed a novel approach to understanding international trade patterns using AI methods. While traditional trade studies for over a century have provided important insights, the emerging big data environment and ongoing outlier events necessitate a nimbler and data-driven approach. First, we laid out AI methods appropriate for predicting trade patterns: Linear Regression, K-means clustering, Pearson correlations, Time Series such as Autoregressive Integrated Moving Average (ARIMA), and supervised and unsupervised AI methods. Applying these methods to agricultural products and using beef as example, we demonstrated that AI methods provide improved predictions relative to traditional models. Within this application, clustering major economies provided even better predictions. Next, we outlined association rules that can identify paired purchases in international trade. Using aggregated trade data, we demonstrated that such rules can identify complementarities and substitutability in international trade transactions. Finally, we showed how contextual AI's classification of features into regular, irregular and contextual along with bias elimination can aid in modeling the recent outlier events like the trade war and Covid-19 pandemic. Results from the big data framework are aimed to be presented in data dashboards to the farmer to update them on daily events during outliers, and to policy makers at agricultural agencies. A sample example of what we envision a farm dashboard would be is illustrated in Figure 7. Such dashboards allow farmers to take decisions on irrigation, seeding, weather modeling, among many other timely frequent decisions.

A key objective of quantitative economic analyses is to uncover relationships – e.g. demand, supply, prices or trade – for use in making predictions or forecasts of future outcomes. However, when the current systems generates forecasts for decision making, they require a range of ad hoc, expert-driven or a combination of simple forecasting models supplemented by subject matter expertise to econometrics-based methods and mega-models, i.e. applied general equilibrium. Employing such approaches, many international institutions and government agencies project economic variables including trade flows to inform decisions in national and multilateral contexts (such as the World Economic Outlook – International Monetary Fund).

These predictions are highly valued by producer and consumer groups as well as policymakers in making decisions. However, some of these predictions based on a combination of simple linear models and expert judgment, have limitations (Isengildina-Massa et al. 2011). Little guidance exists on theoretical modeling of trade policy uncertainty and its implications for producer and consumer behavior. As a result, ad hoc approaches to incorporating uncertainty can create specification bias in quantifying economic relationships and consequently, less precise outcomes on future agricultural trade patterns. The later, i.e. less precise forecasts, impacts producer and consumer decisions as well as government expenditures. These mega-models draw information from a variety of sources, e.g. elasticities, which can introduce additional specification errors or mismatch data distributions.

Figure 7: Precision Agriculture Tools for Farmers during Outlier Events (Sfiligo, 2016)

In sum, traditional models – ad hoc, econometrics or mega-models – have been challenged both on modeling uncertainties, and providing accurate and on-time information for policy and decision making. AI methods have the ability to provide solutions to these drawbacks. While better predictions are a key ingredient in decision-making of economic agents and public officials, the AI approaches can address additional dimensions not necessarily dealt with in traditional studies. For instance, there has been a challenge to achieve consensus at international bodies such as the United Nations, World Trade Organization and others since 2000. For instance, the Doha round of multilateral trade negotiations initiated in 2001 has not been concluded as of today. Some have argued that G20, a group of 20 nations that account for much of world's GDP and population, has become increasingly assertive on multilateral policies. For instance, In Annex II of G20's Strategy for Global Trade Growth (SGTG, 2020), the G20 declares developing a world trade outlook *indicator*, and promoting further e-commerce development. That includes an initiative on an electronic World Trade Platform (e-WTP). The AI models illustrated in this paper can allow for contrasting between decisions made by G20 versus engaging all countries like at the United Nations. In sum, the experimental work in this article indicates the high relevance of AI for predicting trade patterns with a greater accuracy than traditional approaches. Future work will expand the scope of commodities as well as AI methods, e.g. causality and reinforcement learning, to simulate trade outcomes under alternative policy scenarios including outlier events in recent times.

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