WHICH GOODS GET **PRICIER?**

A Data-Driven Look at Tariff Effects on U.S. Consumer Prices

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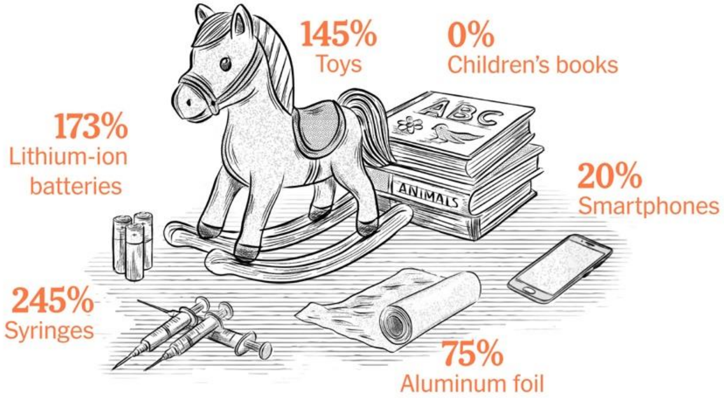
QUESTIONS:

Which goods are likely to be more expensive in near future due to tariff?

STRATEGY: Learn from historical data

Before 2018, Chinese goods entered the U.S. mostly under normal MFN (Most Favored Nation) rates (often 0–5% for many consumer products). In 2017, the U.S. Trade Representative (USTR) launched a Section 301 investigation into China's practices related to intellectual property, technology transfer, and innovation. Section 301 of the U.S. Trade Act of 1974 allows the USTR to investigate and respond to unfair trade practices by other countries. As a result of that investigation, the U.S. imposed additional tariffs on Chinese goods starting in mid-2018, covering Four escalating lists of products. These tariffs were on top of existing MFN tariff rates, which were typically low for Chinese consumer goods before this. Here's the breakdown of the 2018 Section 301 tariff lists:

List	Effective Date	Tariff Rate	Coverage
List 1	July 6, 2018	25%	~$34B worth of goods
List 2	August 23, 2018	25%	~$16B
List 3	September 24, 2018	Initially 10%, raised to 25% in May 2019	~$200B
List 4	List 4A imposed Sept 2019	15% (later reduced to 7.5%)	~$120B



MATERIAL AND METHODS

Raw Data:

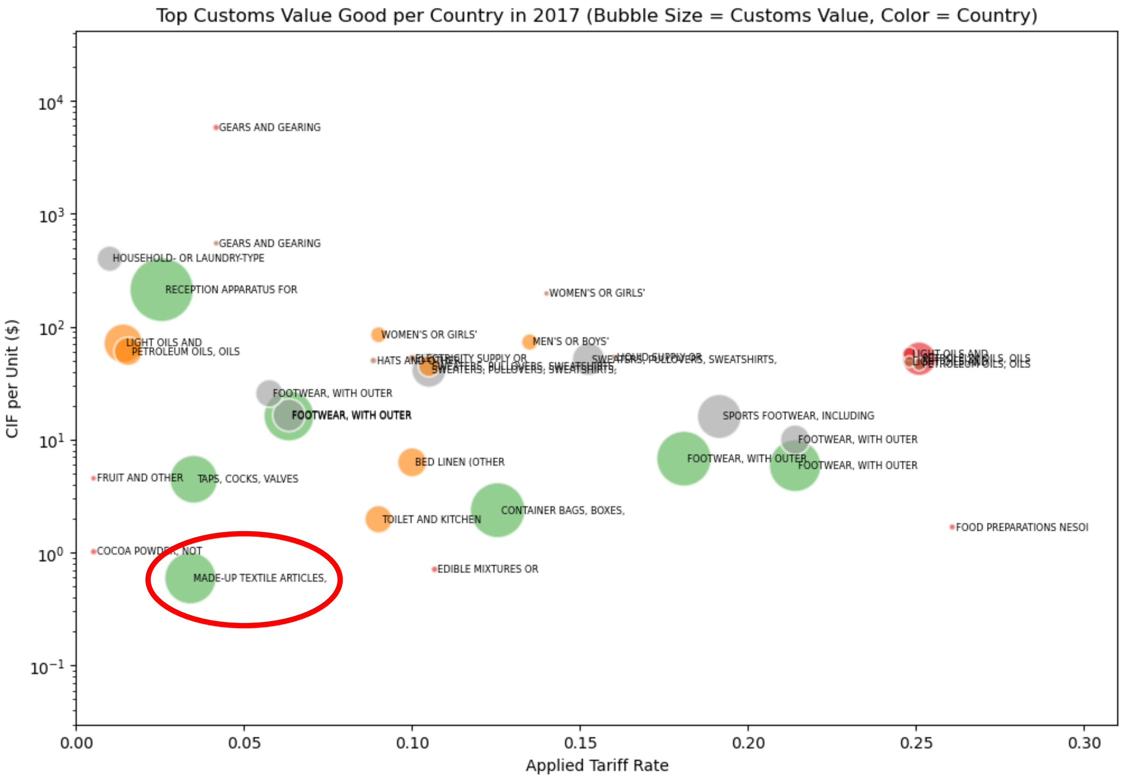
- Customer Price Index (CPI) data from the Bureau of Labor Statistics (BLS)
  2017 - 2024
- Imports data from U.S. International Trade Commission (USITC)
  Import Quantity, Customs Values, CIF import Value
  2017 (baseline), 2019 (tariff increase), 2024 (new baseline)
  China, Canada, Mexico, Vietnam, India, All countries
- Tariff data from USITC
  MFN rates of 2017, 2019 and 2024
  Additional tariff under Section 301 (2018-2019)

Methods:

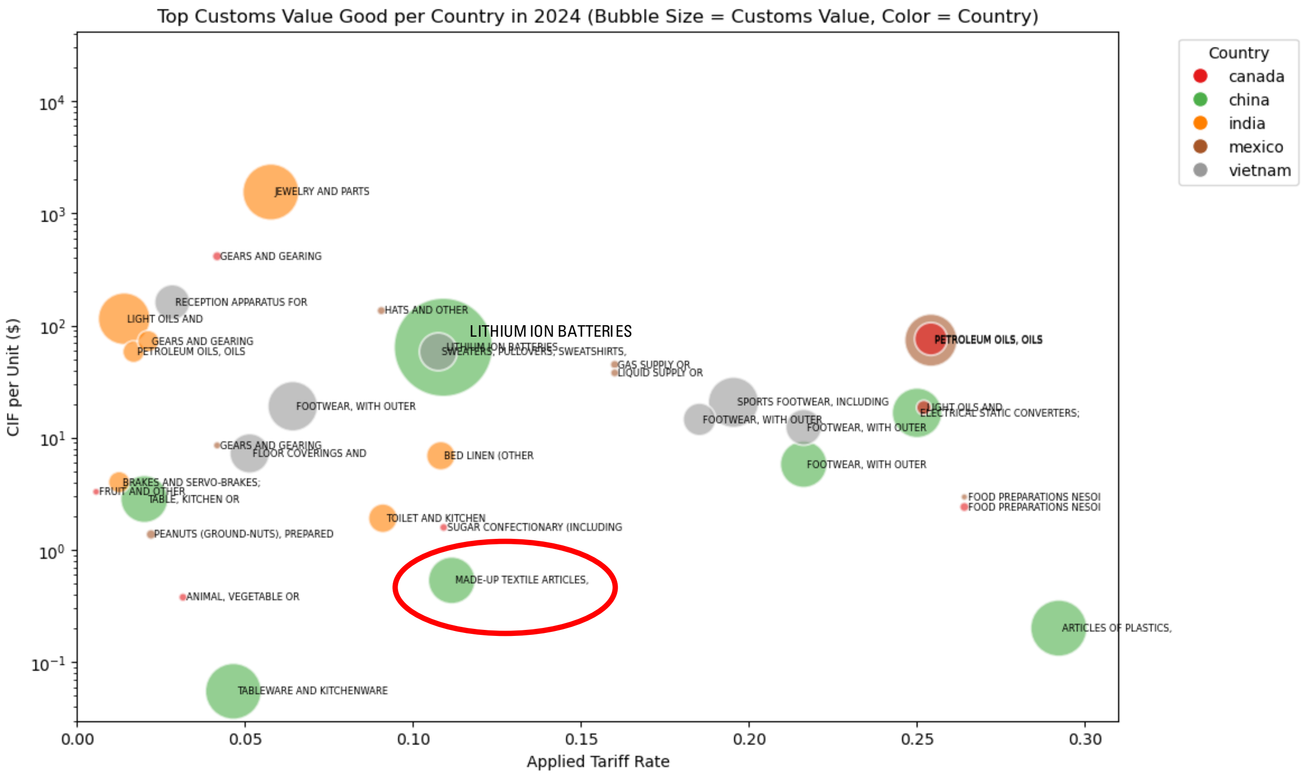
1. Define label – Price increase
   Label = 1 if CPI increase 5% from 2017 to 2020
   Label = 0 otherwise
2. Prepare feature from Imports and Tariff data
3. Building Classifiers
   ”Training Data”: 2017
   Cross validate various single basic models
   Grid search best parameters
   Optimize threshold
   Test Ensemble models
4. Select the final model based on F1 score
5. Apply model to 2024 Imports and Tariff data

TOP 7 CUSTOMS VALUE GOODS PER COUNTRY

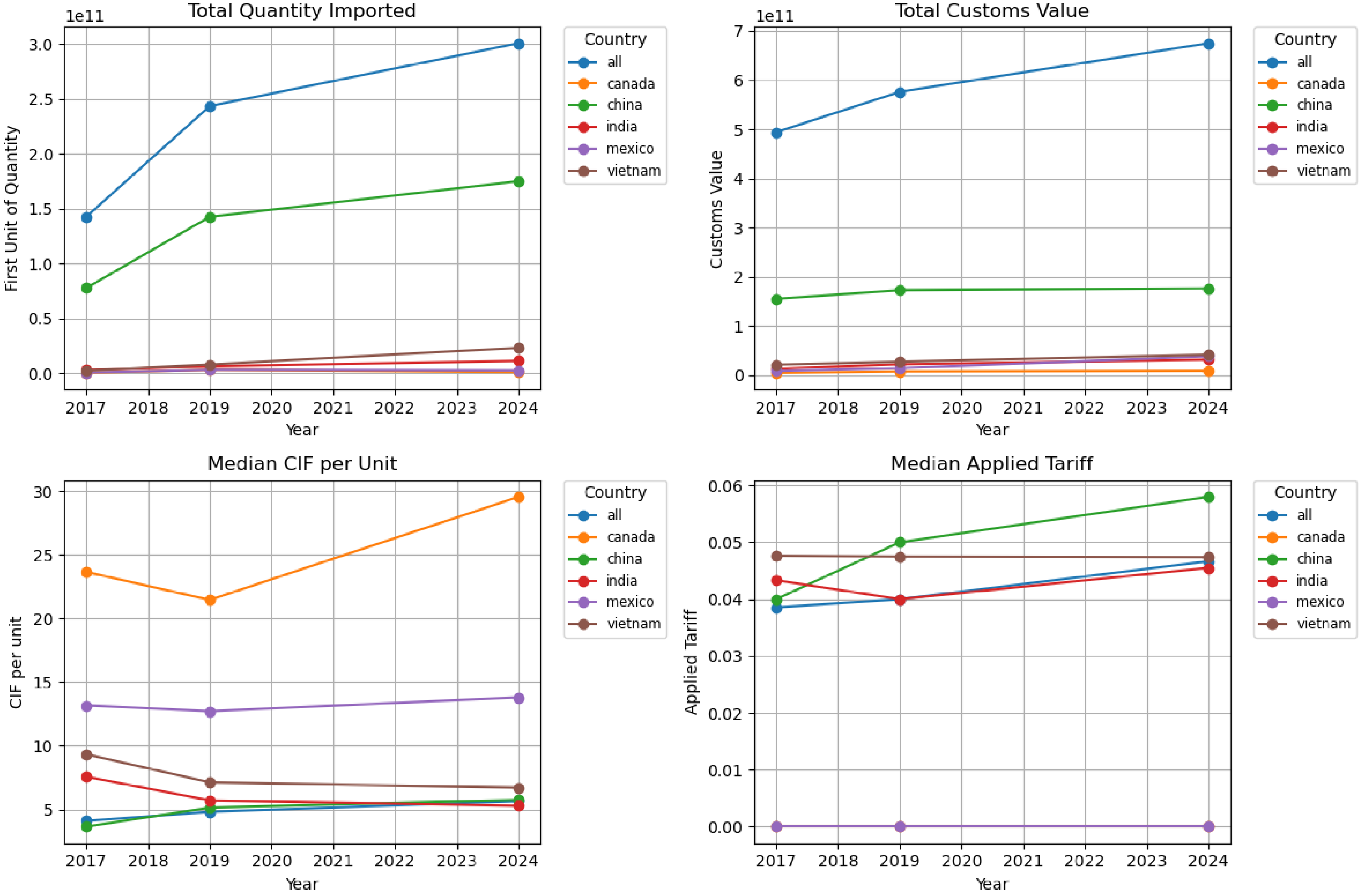
2017



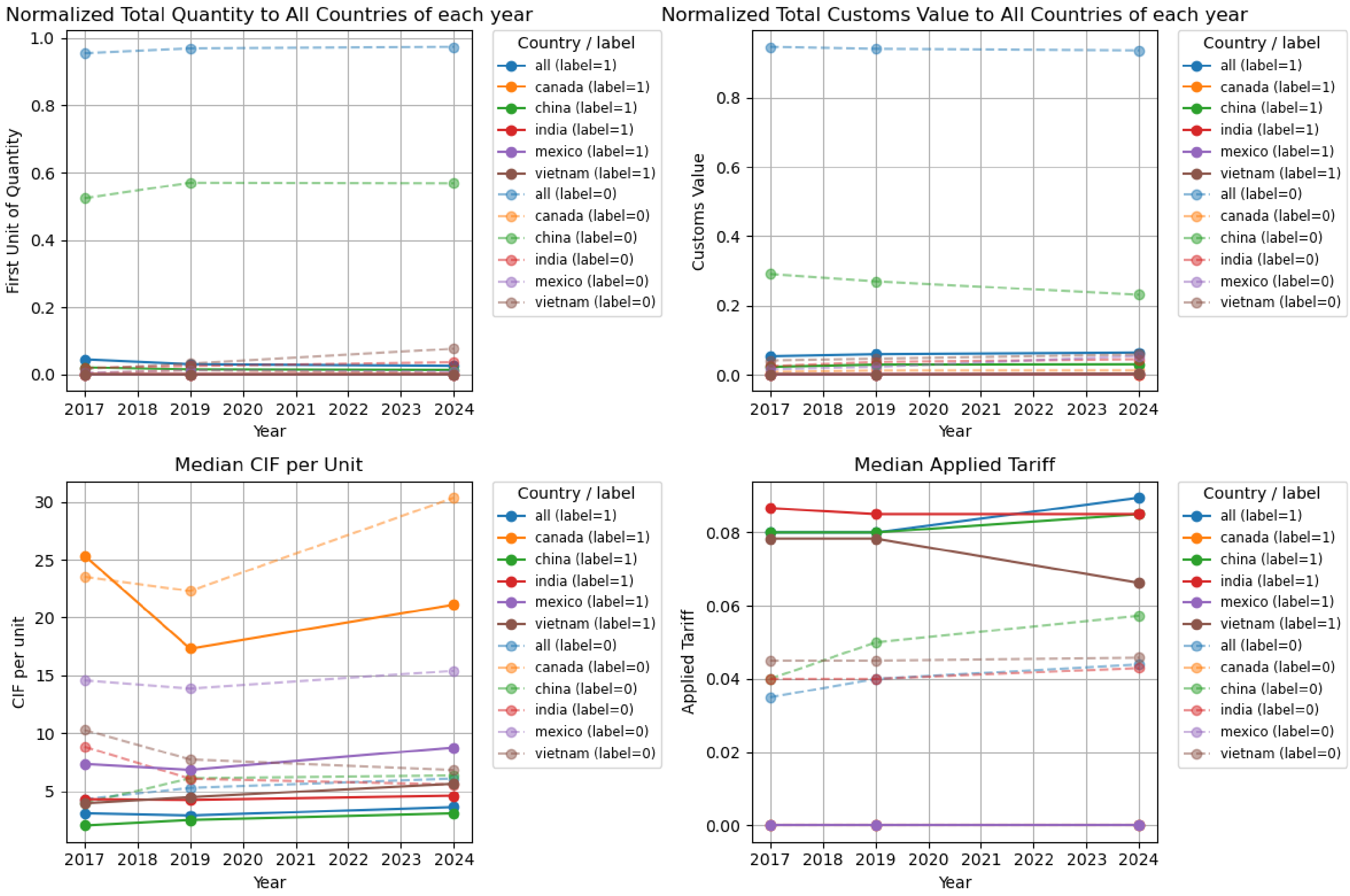
2024



FEATURES VS TIME



FEATURES VS TIME (Price Increase: label =1)



Normalized data seems less noisy.

-> Use normalized data for:

- Quantity
- Customs value
- CIF value

MODELS

Single Classifiers

We used RepeatedStratifiedKFold with GridSearchCV to tune hyperparameters for each classifier, incorporating SMOTE to handle class imbalance during training. To further improve model performance, we optimized the classification threshold by selecting the value that maximized the F1 score based on precision-recall curves from predicted probabilities.

Model	Mean F1 Score	Std F1 Score	Mean thresholds	Accuracy	Precision	ROC AUC
XGBoost	$\boxed{0.513}$	0.025	0.682	0.898	0.543	0.793
Random Forest	0.512	0.025	0.680	0.898	0.547	0.794
Decision Tree	0.482	0.024	0.869	0.879	0.457	0.757
MLP	0.444	0.027	0.638	0.860	0.395	0.757
KNN	0.414	0.026	0.858	0.878	0.444	0.733
Logistic Regression	0.392	0.023	0.553	0.816	0.309	0.701

MODELS

Ensembles

With relatively low F1 score obtained from single classifier, we decided to test out combination of different types of classifiers to see if it can increase the model performance.

Combo	Mean F1	Mean Accuracy	Mean Precision	Mean ROC AUC
Stacking (XGBoost+MLP)	0.488	0.887	0.486	0.785
Stacking (XGBoost+MLP+Logistic Regression)	0.485	0.889	0.506	0.786
Stacking (XGBoost+Logistic Regression)	0.484	0.887	0.491	0.784
Voting (XGBoost+MLP+Logistic Regression)	0.480	0.898	0.529	0.760
Voting (XGBoost+MLP)	0.479	0.894	0.515	0.773
Voting (XGBoost+MLP+KNN)	0.476	0.900	0.547	0.762
Voting (XGBoost+KNN+Logistic Regression)	0.476	0.902	0.559	0.751
Voting (XGBoost+Logistic Regression)	0.473	0.889	0.486	0.754
Voting (XGBoost+KNN)	0.463	0.900	0.549	0.757
Stacking (XGBoost+KNN)	0.457	0.898	0.540	0.754
Stacking (XGBoost+KNN+Logistic Regression)	0.447	0.897	0.532	0.756
Stacking (XGBoost+MLP+KNN)	0.444	0.895	0.531	0.752
Voting (MLP+KNN+Logistic Regression)	0.438	0.884	0.464	0.737
Voting (MLP+KNN)	0.431	0.886	0.475	0.741

FINAL MODEL

We selected **XGBoost** as the final model due to its consistently highest performance across key metrics -- including **F1 score (0.513)**, precision (0.543), and ROC AUC (0.793) -- after SMOTE rebalancing and threshold optimization, outperforming all other individual and ensemble models in both predictive accuracy and class discrimination.

CAVEAT

- Limited Feature Set

  Other factors beyond tariff: Supply chain dynamics; Market competition; Consumer behavior; Retail pricing strategies…

- Data granularity

  The CPI dataset does not have the same granularity as HTS6 (USITC data), which could lead to mislabeling goods within broader categories as having a price increase.

- Complex relationship

  Tariffs and price increases is not always linear and can be influenced by substitution effects and other complex economic dynamics.

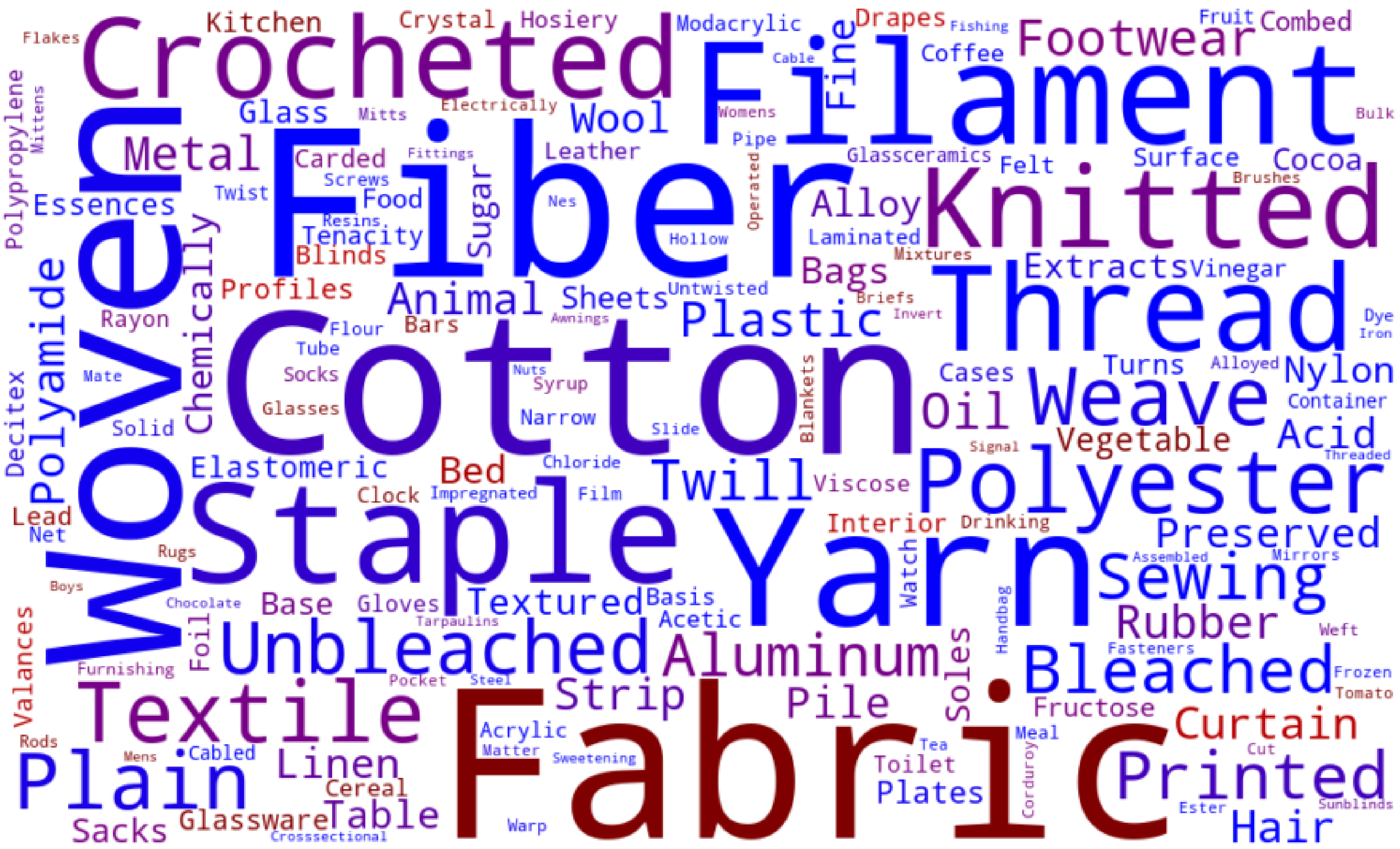
- New products emergence

  New high-value products—such as lithium-ion batteries, which were absent in 2017 and 2019 but prominent in 2024—cannot be captured by models trained solely on historical data, limiting their ability to reflect shifting trade dynamics.

RESULT

The output of the data analysis is based on HTS codes and description. To better reflect the affected goods, we applied a WordCloud to highlight the major items likely to experience an increase in customs prices in near future.

Imported Goods Likely to Become More Expensive (Chinese -- more in Red)



Thank you!