## Evaluating Machine Learning Performance on Large Scale Shipment Data for the 2022 CFS

Cecile Murray, Senior Data Engineer, U.S. Census Bureau Federal Committee on Statistical Methodology Conference October 24, 2023



## Disclaimers

- Any opinions and conclusions expressed herein are those of the author and do not reflect the views of the U.S. Census Bureau
- The Census Bureau has reviewed this data product to ensure the appropriate access, use, and disclosure avoidance protection of the confidential source data (Disclosure Review Board (DRB) approval number: Project No: P-7504831, DRB Approval Numbers: CBDRB-FY24-ESMD002-003)



#### Context

- 2022 Commodity Flow Survey (CFS) collected roughly 16x more data
- This was possible partially because we used machine learning (ML) to categorize shipments by commodity code instead of asking respondents to do so
- This change reduced respondent burden, but it also reduced the amount of human-validated data available for evaluating our ML process



#### Overview

- Describe ML problem and our architecture
- How we evaluated model performance
- Impact of ML on data quality



## ML goal: label shipments with SCTG code

			TO	r any line, con	tinue with o	column (J) o	n page 5 for the same line	8.		
Line No.		Shipment Date (C)		Shipment value (excluding freight charges and excise taxes) in whole dollars. Estimates	Net Shipment Weight in pounds. Estimates acceptable	For shipments consisting of more than one commodity, report the code and description of the commodity that contributed the greatest weight of the shipment in columns (F) through (I)				5
	Your Shipment ID Number					SCTG commodity code from accompanying	Commodity Description <sup>1</sup>	m in col. (G) nperature <sub>1,2</sub> lled? (Y/N)	Is item in col (G) a hazardous material? Enter "UN"	Continue with nn (J) on page
(A)	(B)	Month	Day	acceptable. (D)	(E)	booklet <sup>1</sup> (F)	(G)	) Is iter (E) Ter contro	or "NA" <sub>1</sub> number (I)	Outloo
Ex.1	123-5	4	26	224,235	4,840	34520	Mechanical machinery	Y		-
Ex.2	402H	4	26	1,375	50,125	20222	Sulfuric acid	N	1830	-
1		-								-
2										-
3	1									-
4										



## Brief overview of SCTG codes

- SCTG = Standard Classification of Transported Goods
- Product classification system for transportation analysis
- There are 42 2-digit SCTG major groupings
  - SCTG 24 is Plastics and Rubber
- Within those 42, there are 514 5-digit SCTG commodities
  - SCTG 24221 is "Plastics tubes, pipes, hoses, and fittings, including joints, elbows, and flanges"
  - SCTG 24225 is "Plastics household or toilet articles"







#### Internal model details

- Training data:
  - 2017 CFS shipment microdata
  - 2022 CFS shipment microdata where respondents validated description
- Models:
  - Two logistic regressions using industry NAICS code and shipment description as features
  - Models produce an SCTG label, as well as a probability score, which we use as a measure of model confidence
  - One model predicts at the 5-digit level, the other predicts at the 2-digit level



#### How we assign SCTG to shipments





## How do we know if the models are "good"?

- This type of model has worked well on similar problems in the past, but data and model drift commonly crop up over time
- Evaluate both model accuracy and overall system performance
- Quantitative approaches:
  - Have humans review model predictions for correctness
  - Cross-validation using training data



## Hand-coding shipments

- Have human SMEs validate SCTG codes for a sample of 882 shipments
  - 42 SCTG groupings \* 21 shipments = 882
- Human reviewers provided correct SCTG if the model prediction was incorrect



## Results of hand coding

- 5-digit model accuracy for SCTG assigned via ML only: **91%**
- 2-digit model accuracy for SCTG assigned via ML and imputation: 68%
  - Accuracy of first 2 digits of 5-digit prediction on SCTG assigned via ML and imputation: 78%
- When model confidence is low, so is measured model accuracy => we're not leaving good model predictions on the table
- Caveat: sample sizes are small



#### Cross-validation overview





### Cross-validation results

- 5-digit model accuracy on SCTG assigned via ML: 84%
- 2-digit model accuracy on SCTG assigned via ML and imputation: **72%** 
  - Accuracy of first 2 digits of 5-digit model on SCTG assigned via ML and imputation: 66%
- We see strong model performance across 2-digit SCTG major groupings
- Caveat: "real" data may look different than training data



## Takeaways from model evaluation

- Prediction quality overall is strong
- Strong performance across 2-digit SCTG groupings
- Importance of multiple ways to evaluate models and overall model pipeline



### Automated monitoring

- Automated ML training and prediction process runs roughly weekly
- We deployed the evaluation code along with that process so we always have a current snapshot of performance
- This can help us proactively and systematically identify quality problems with models



#### Impact on data quality

- We can use machine learning to code shipments with high quality and with minimal human validation
- Guaranteed consistency in coding shipments
- Ability to quantify relative accuracy of shipment labels and compare within and across survey cycle



#### Future work

- Develop process to generate more gold-standard data for training and evaluation
- Continue investigating ways to tune models
- Experiment with different model families, including neural networks



# Thank you!

Email: cecile.m.murray@census.gov



## Results of hand coding

Data segment	# observations	5-digit model accuracy	2-digit model accuracy	2-digit accuracy of 5-digit model
SCTG directly assigned by ML	511	91%	90%	93%
2-digit SCTG assigned by ML, last 3 imputed	210	80%	68%	78%
SCTG assigned by imputation only	80	61%	44%	48%
Invalid/out of scope/too vague	81			





Bureau

