Ensemble Modeling Techniques for NAICS Classification in the Economic Census

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Machine Learning Applications
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Disclaimer

Any opinions and conclusions expressed herein are those of the authors and do not reflect the views of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product [Data Management System (DMS) number: P-7504847, subproject P-7514952; Disclosure Review Board (DRB) approval number: CBDRB-FY23-ESMD002-034].



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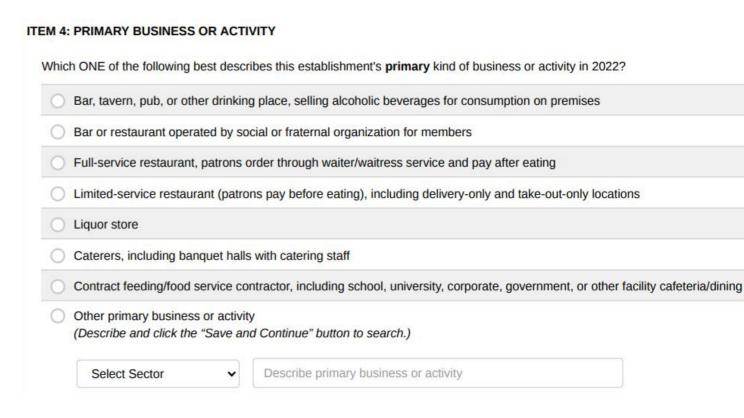
Background: North American Industry Classification System (NAICS)

- U.S. Census Bureau classifies business establishments by NAICS code based on primary business activity
- NAICS is utilized throughout the survey life cycle
 - Sample selection
 - Data collection
 - Analytical review
 - Publication
- Hierarchical 6-digit coding structure
 - First two digits of NAICS code represent economic sector (22 Utilities)
 - Additional non-zero digits add industry detail (221210 Natural Gas Distribution)



Background: Primary Business or Activity Question from the Economic Census

- Question asks respondents to describe their business
- There are prelisted descriptions, but the respondent also has the option of writing in a business description
- Manual coding of write-in text is resource-intensive

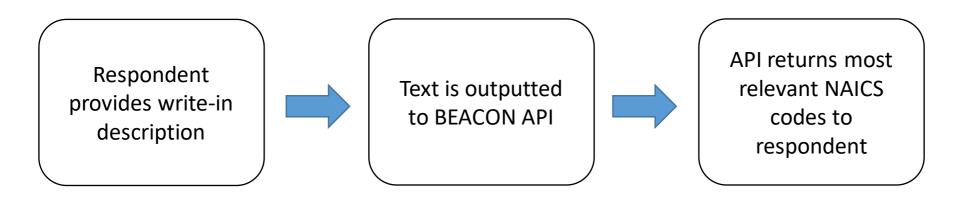




Source: 2022 Economic Census

Background: What is BEACON?

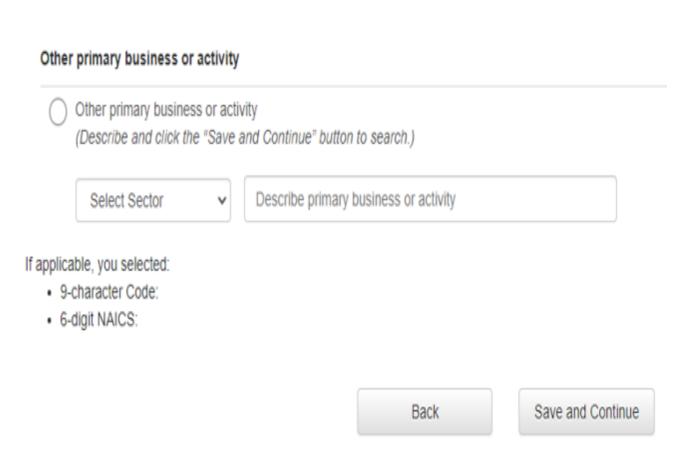
- <u>Business Establishment Automated Classification of NAICS</u>
- A machine learning tool developed by the Economic Statistical Methods Division (U.S. Census Bureau) to classify NAICS for establishments based on a write-in business description





Background: Goals of BEACON

- Assist respondents in selfdesignating their NAICS codes
- Improve accuracy of selfdesignated NAICS codes
- Reduce manual coding of write-ins





Background: Training Data

- Historic write-in responses to the Economic Census (EC)
- Frequent write-in text that was autocoded during 2017 EC
- Business descriptions from IRS SS-4 forms*
- Classification Analytical Processing System (CAPS) items
- Harmonized System commodity descriptions
- Variables
 - Business description text
 - Corresponding NAICS code

| Business Description Text | NAICS |
|----------------------------------|--------|
| This is a car dealership. | 441110 |
| R&D lab – medical/health | 541715 |
| we mainly repair furniture, | 811420 |
| some sales | |



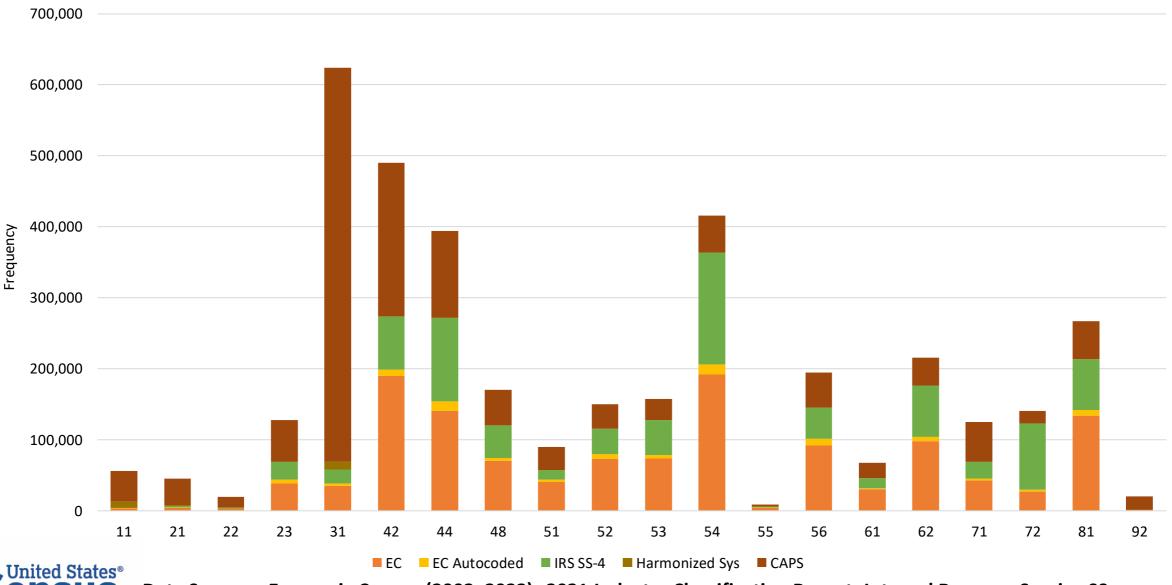
Background: Training Data

| Data Source | Number of Observations | Advantages | Disadvantages |
|----------------------|------------------------------|---|--|
| EC | ~ 1,611,000 (single-unit) | | Descriptions not perfectly classifiedDescriptions contain misspellings |
| EC Autocoded | ~ 98,000 * | Improves consistency with autocoding during 2017 EC | Relatively small data source |
| IRS SS-4 | ~ 865,000 (single-unit) | • | Descriptions not perfectly classifiedDescriptions contain misspellings |
| CAPS | ~ 1,508,000 * | Provides a rich vocabularyDescriptions are classified correctly | Does not always reflect natural language |
| Harmonized System | ~21,000 | Provides examples of industry- specific abbreviations/terminology | Relatively small data source Does not always reflect natural language |



^{*}Includes duplicates and variations of original observations.

BEACON Training Data Breakdown by Sector and Source



Data Sources: Economic Census (2002–2022), 2021 Industry Classification Report, Internal Revenue Service SS-4 (2002–2016), Classification Analytical Processing System, Harmonized System

Methodology: Text Cleaning

- Removal of extraneous words/symbols
 - Remove extra white space and common "stop" words ("the", "and", "or", etc.)
 - Account for numbers and punctuation
- Correct common misspellings
 - Map stems of misspelled words to stems of correctly spelled words
 - For example, "manifactur" → "manufactur"
- Stem
 - Apply prefix/suffix stripping rules to reduce number of word variations
 - For example, "manufacturing" → "manufactur", "cars" → "car"
- Lemmatize
 - Map synonyms and abbreviations to a common concept
 - For example, "mfg" → "manufactur", "auto" → "car"



Methodology: Dictionary

Words and word combinations that BEACON recognizes

All model features are based on the data dictionary

- Associations between words and NAICS codes in the training data influence predictions
 - "tutor" is highly associated with NAICS 611691 Exam Preparation and Tutoring
 - "store" occurs in many NAICS codes and is therefore less predictive



Methodology: Model Ensemble

- Model ensemble
 - Information retrieval models look at how words, combinations, and entire descriptions are distributed across NAICS codes
 - Individual predictions are averaged, yielding relevance scores
- Relevance scores
 - Range in value between 0 and 100
 - Reflect how confident BEACON is that the NAICS code is correct



Model Stacking: Overview

- Separate prediction problem into two parts
 - Create multiple models to generate initial predictions
 - Use these predictions as inputs to meta-model

Proposal:

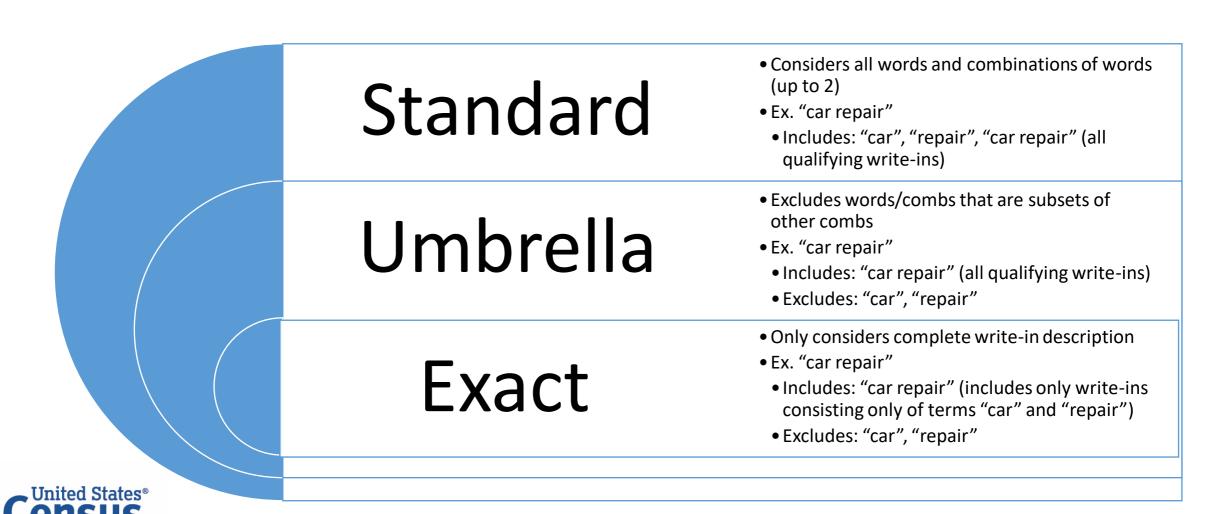
- Generate predictions from component models within BEACON
- Refine initial predictions with predictions from meta-models

Sources:

- Todorovski, L. and Džeroski, S. (2003). Combining Classifiers with Meta Decision Trees. *Machine Learning*, *50*, 223–249. Netherlands: Kluwer Academic Publishers.
- Merz, C. (1999). Using Correspondence Analysis to Combine Classifiers. *Machine Learning*, 36, 33–58.



Model Stacking: Within BEACON



Model Stacking: Within BEACON

- "Standard" and "Umbrella" models
 - The NAICS distributions of the words/stems and word/stem combinations are averaged using "purity weights" that give more weight to the NAICS distributions of words that are more predictive.
 - The purity weight is a function of the maximum proportion.
- Final scores
 - The scores from the "Standard", "Umbrella", and "Exact" models are averaged
 - Three model weight parameters $w_{standard}$, w_{umb} , and w_{exact} (= 1 w_{all} w_{umb})



Model Stacking: Proposal

- Generate predictions from component models within BEACON
 - "Standard"
 - "Umbrella"
 - "Exact"
- Refine initial predictions with predictions from meta-models
 - Logistic Regression
 - Decision Tree
 - Random Forest



Model Stacking: Evaluation Metrics

- Top-*k*
 - Measures success rate where success is % of times that true NAICS code is found in top-k predictions within sector
 - Evaluated for k = 1, 2, 3, 4, 5
- F₁ score
 - Harmonic mean of precision and recall



of individual component models.

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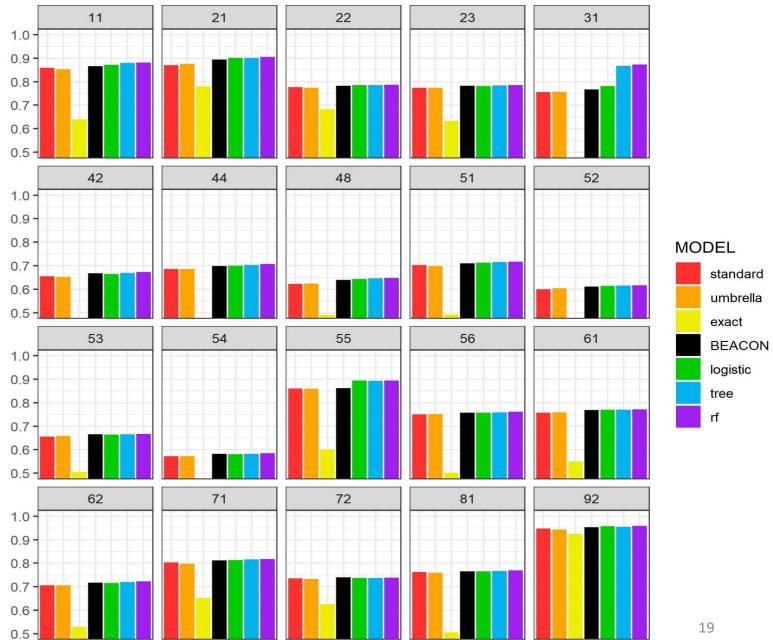
BEACON model tends to produce more accurate predictions than any of its component models.

Data Sources: Economic Census (2002–2022), 2021 Industry Classification Report, Internal Revenue Service SS-4 (2002–2016), Classification Analytical Processing System, Harmonized System



Top-K by model

NAICS: 6-digit, k=1



Meta-models offer similar potential for incremental improvement.

Random forest and decision trees methods appear most promising.

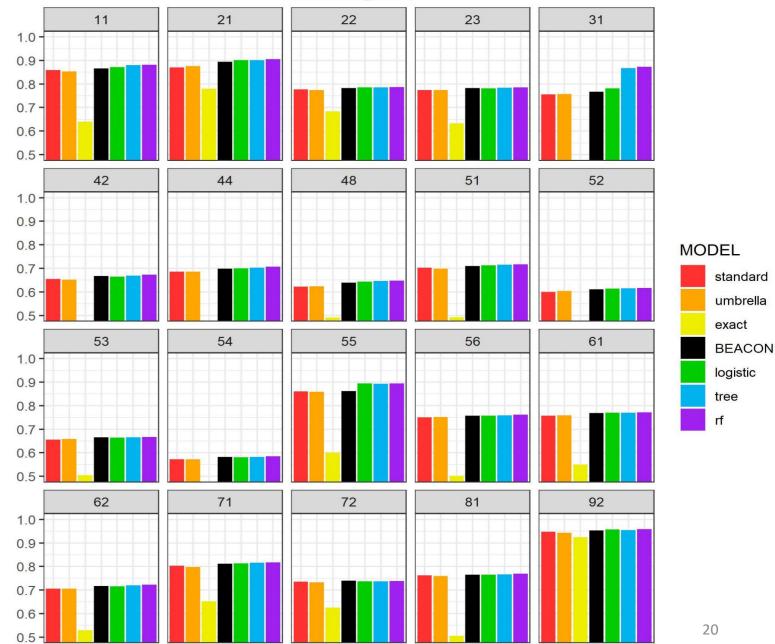
Potential improvement in manufacturing sector (31) is encouraging.

Data Sources: Economic Census (2002–2022), 2021 Industry Classification Report, Internal Revenue Service SS-4 (2002–2016), Classification Analytical Processing System, Harmonized System



Top-K by model

NAICS: 6-digit, k=1



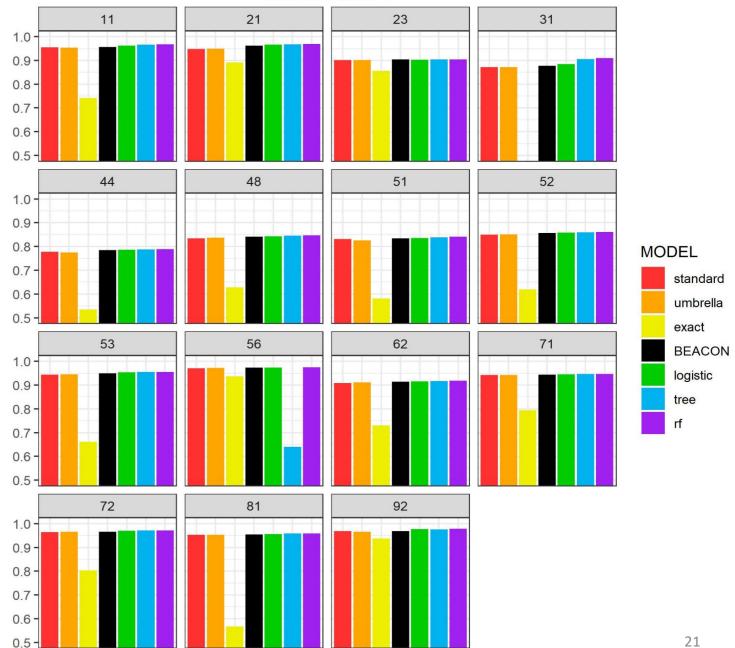
Similar results were found at other NAICS levels.

Data Sources: Economic Census (2002–2022), **2021** Industry Classification Report, Internal Revenue Service SS-4 (2002–2016), **Classification Analytical Processing System, Harmonized System**



Top-K by model

NAICS: 3-digit, k=1



Meta-models improved performance in sectors where **BEACON** was already doing well.

F₁ score of BEACON in NAICS codes where meta-model outperformed BEACON is higher than that of NAICS codes where BEACON outperformed meta-model.

Median BEACON F₁ score: 3-digit NAICS codes

| | RF | Tree | LR |
|---|------|------|------|
| NAICS codes where F_1 score of meta-model $> F_1$ score of BEACON | 0.93 | 0.93 | 0.95 |
| NAICS codes where F_1 score of BEACON > F_1 score of meta-model | 0.85 | 0.85 | 0.89 |



Data Sources: Economic Census (2002–2022), 2021 **Industry Classification Report, Internal Revenue** Service SS-4 (2002–2016), Classification Analytical **Processing System, Harmonized System** 22

Meta-models improved performance in sectors where BEACON was already doing well.

F₁ score of BEACON in NAICS codes where meta-model outperformed BEACON is higher than that of NAICS codes where BEACON outperformed meta-model.

Median BEACON F₁ score: 6-digit NAICS codes

| | RF | Tree | LR |
|---|------|------|------|
| NAICS codes where F ₁ score of meta-model > F ₁ score of BEACON | 0.89 | 0.89 | 0.89 |
| NAICS codes where F_1 score of BEACON > F_1 score of meta-model | 0.85 | 0.86 | 0.85 |



Data Sources: Economic Census (2002–2022), 2021 Industry Classification Report, Internal Revenue Service SS-4 (2002–2016), Classification Analytical Processing System, Harmonized System

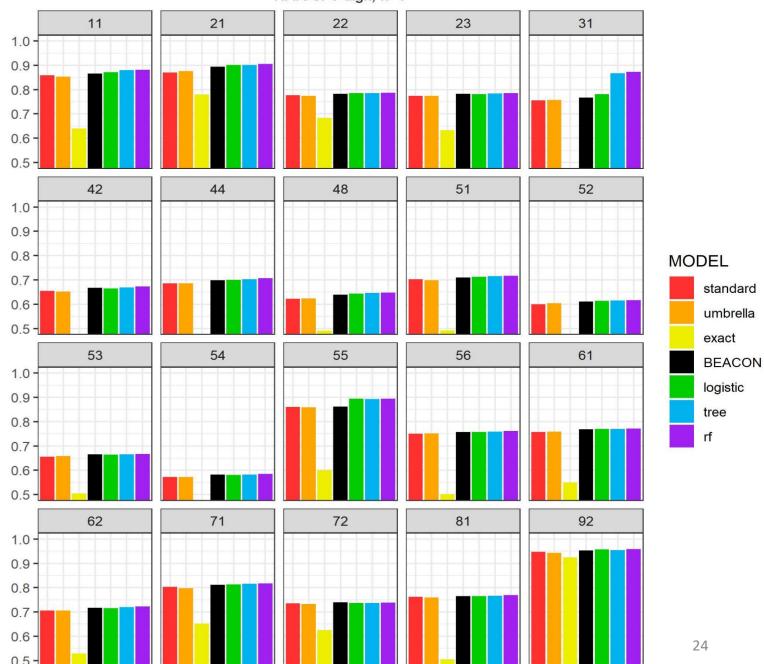
Meta-models may offer more potential for providing a single predicted NAICS than for providing multiple NAICS codes to a respondent.

Data Sources: Economic Census (2002–2022), 2021 Industry Classification Report, Internal Revenue Service SS-4 (2002–2016), Classification Analytical Processing System, Harmonized System



Top-K by model

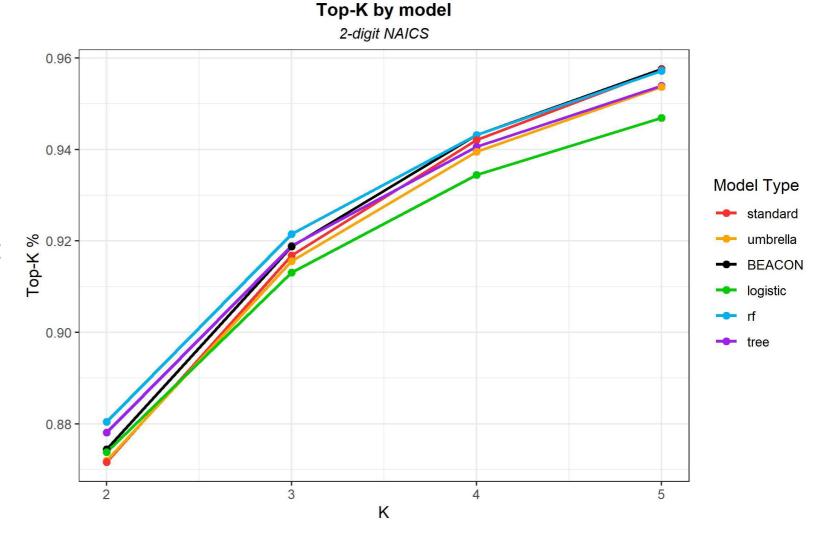
NAICS: 6-digit, k=1



BEACON performed as well or better than meta-models as top-k goal was relaxed.

BEACON is well-equipped at providing multiple NAICS codes to respondent.

Data Sources: Economic Census (2002–2022), 2021 Industry Classification Report, Internal Revenue Service SS-4 (2002–2016), Classification Analytical Processing System, Harmonized System





Conclusions

• Meta-models performed best, compared to BEACON, at predicting single best NAICS code.

 BEACON performed as well or better than meta-models when goal was to include best NAICS code as one of several potential NAICS codes.

 Meta-models may be helpful in manufacturing sector, which has more NAICS codes than any other sector.



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