

A Large Scale, High Quality U.S. Occupational Database: Results from Merged ACS and IRS Write-Ins

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Purpose & motivation

- Worker occupation is a key driver in economic growth (Violante 2008), career progression (Yamaguchi 2011), and cross-sectional and intergenerational inequality (Card and DiNardo 2002, Long and Ferrie 2013).
- Universe-level occupation data available in some countries (e.g. Denmark), but administrative and data collection difficulties in the U.S.
- Census: American Community Survey
- IRS: Form 1040 “Occupation” field

Contribution

- Create near-universe dataset of coded worker occupations
 - Match e-filed Form 1040s and 1-Year ACS
- Evaluate quality of matched IRS/ACS write-ins
 - Token similarity
 - Semantic similarity
- Create a Large Language Model-based autocoder mapping text write-ins to Census 2018 occupation codes.
- (Preliminary) Evaluate cross-sectional and longitudinal accuracy of IRS occupational distribution

Data

- American Community Survey 2019 1-Year Microdata (ACS) write-ins
- IRS Tax Year 2018 Form 1040 write-ins

ACS and IRS Occupation Prompts

ACS

e. What was this person's main occupation?
(For example: 4th grade teacher, entry-level plumber)

Driver

f. Describe this person's most important activities or duties.
(For example: instruct and evaluate students and create lesson plans, assemble and install pipe sections and review building plans for work details)

*Pick people up in my car,
 drive them where they need to go, and drop them off*

F1040

Sign Here

Under penalties of perjury, I declare that I have examined this return and accompanying schedules and statements, and to the best of my belief and knowledge, they are true, correct, and complete. Declaration of preparer (other than taxpayer) is based on all information on which the preparer has relied.

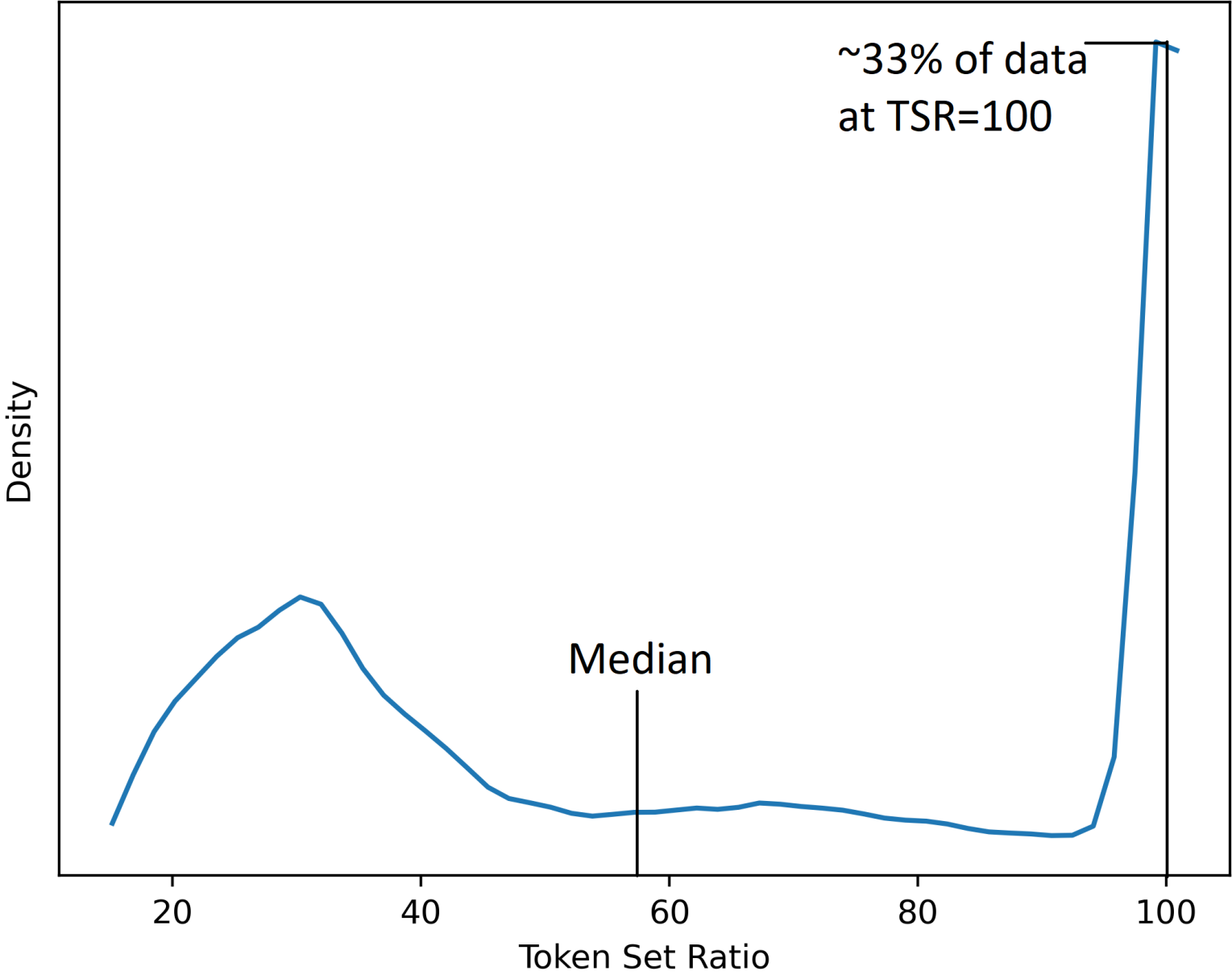
Your signature	Date	Your occupation
Spouse's signature. If a joint return, both must sign.	Date	Spouse's occupation

Joint return? See instructions. Keep a copy for your records.

Token Similarities

- Token Set Ratio: 0-100 score of similarity of two strings
- $\text{TSR}(\text{"Lawyer"}, \text{"Lawyer"}) = 100$
- $\text{TSR}(\text{"Clown"}, \text{"Teacher"}) = 17$
- $\text{TSR}(\text{"Lawyer"}, \text{"Attorney"}) = 29$
- $\text{TSR}(\text{"Paralegal"}, \text{"Paramedic"}) = 56$

Token Set Ratio Distribution



Transformer-based Autocoder

- BERT (Bidirectional Encoder Representations from Transformers) architecture for Large Language Modeling
 - Open Source LLM, pretrained on Wikipedia and the Toronto BookCorpus (3.3 billion words)
 - Maps a text string to a numerical vector representation (“encoding”).
- Occupational coding problem estimated as a Multinomial Logit with 565 choices
- Inputs: text written -> BERT encoding, industry category
- Target: assigned 2018 Census occupational code (565 categories).

Estimation Results

Model	Match Rate	Top 2	Top 10
ACS LLM Text + Industry	0.81	0.90	0.97
IRS LLM Text + Industry	0.42	0.54	0.77

Source: U.S. Census Bureau, 2019 American Community Survey 1-year and IRS Form 1040 Tax Year 2018

Semantic Similarity

- The ACS and IRS model each predict a probability distribution
- **Total Variation Distance (TVD)** between them measures prediction disagreement
- Results from TVD broadly agree with results from token-based analysis
- Approx. 50% paired entries semantically similar, approx. 33% high quality semantic matches

Agency Benefits

- IRS:
 - Fully coded occupational field
 - Response quality control via ACS comparisons
- Census:
 - Show feasibility of Open Source, Machine Learning-based occupation coding
 - Improved imputes for missing records

Conclusion

- Creating a near-universe file of coded occupations from Form 1040 write-ins is feasible when combined with ACS data.
- Economically significant information in IRS write-ins, but measurement challenges remain.
- Next steps: aggregation; years 2011-2018.

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Thank you!

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