AUTOCODING OCCUPATION DATA

Occupational Employment Statistics (BLS-OES)

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SOC AUTOCODING (Standard Occupation Classification System)

CHALLENGE

- 850 imbalanced occupations, 10 million records, 600,000 term vocabulary
- Current model ~62% accurate

CONTRIBUTIONS

- Contextual Models (+ Open Source Module)
- Automatic discovery of 800,000+ unclassifiable records
- Addressing feedback loops

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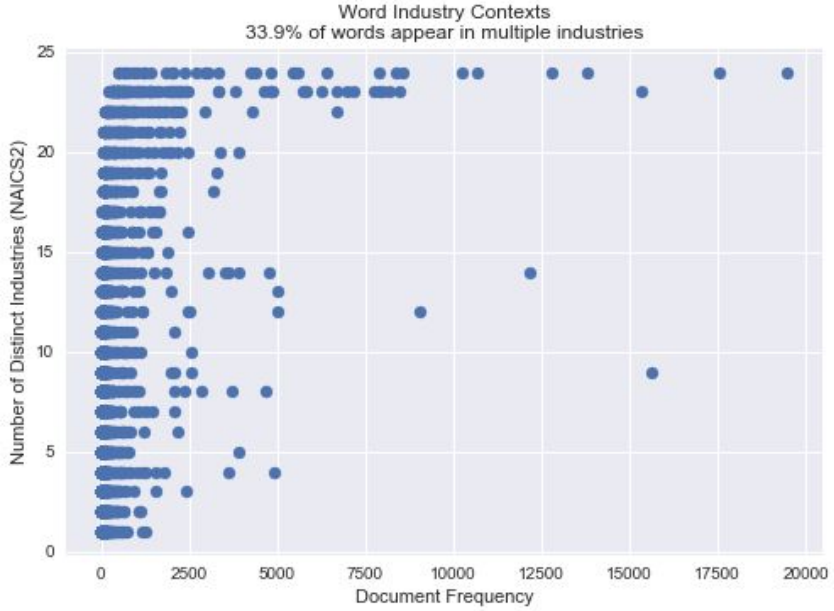
JOB TITLES LACK CONTEXT



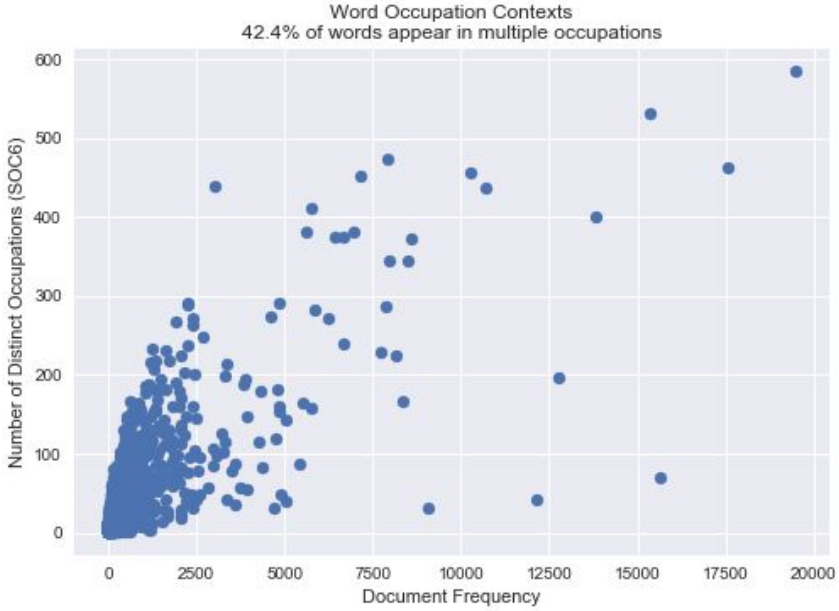


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Figure 1. Words that appear in multiple industries (left) and occupation groups (right).

CONTEXTUAL MODELING

- Autocoder is biased towards common jobs
- Classify rare jobs with word-industry interactions (`analyst_x_news`)
  - Computationally efficient: 23k actual interactions (10 mins) vs 600k possible (2 days)

	occupation	code	jobtitle	industry	count
0	Accountants and Auditors	13-2011	accountant	finance	7
1	Broadcast News Analysts	27-3021	news analyst	news	2
2	Computer Systems Analysts	15-1121	computer analyst	tech	2
3	Financial Analysts	13-2051	financial analyst	finance	2
4	Reporters and Correspondents	27-3022	reporter	news	7
5	Software Developers, Applications	15-1132	developer	tech	7

	correct	occupation	pred	proba	jobtitle	industry
0	False	Computer Systems Analysts	Software Developers, Applications	0.325774	analyst	tech
1	False	Broadcast News Analysts	Reporters and Correspondents	0.325774	analyst	news
2	False	Financial Analysts	Accountants and Auditors	0.325774	analyst	finance

	correct	occupation	pred	proba	jobtitle	industry
0	True	Computer Systems Analysts	Computer Systems Analysts	0.399234	analyst	tech
1	True	Broadcast News Analysts	Broadcast News Analysts	0.399234	analyst	news
2	True	Financial Analysts	Financial Analysts	0.399234	analyst	finance

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Table 1. Fictional example: interactions determine type of analyst based on industry.

MODEL RESULTS (73 candidate models)

	name	matrices	hyper	dedupe	partition	v_hacc	v_acc	v_f1_macro	v_prec_macro	v_rec_macro
14	M14	{'E', 'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}	H1	True	O4	0.71	0.629	0.441	0.569	0.407
33	M33	{'E', 'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}	H0	False	O4	0.71	0.629	0.423	0.553	0.39
15	M15	{'E', 'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}	H0	False		0.707	0.626	0.394	0.534	0.367
13	M13	{'E', 'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}	H0	True	O4	0.707	0.625	0.44	0.571	0.405
26	M26	{'E', 'WxN2', 'N2', 'M2E', 'N4', 'C', 'W', 'N6'}	H0	False		0.711	0.625	0.399	0.547	0.368
28	M28	{'E', 'M2', 'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}	H1	False		0.71	0.625	0.398	0.548	0.367
27	M27	{'E', 'M2', 'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}	H0	False		0.709	0.625	0.396	0.543	0.366
21	M21	{'E', 'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}	H1	False		0.707	0.625	0.394	0.534	0.366
46	M46	{'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}		False		0.703	0.622	0.389	0.526	0.362
8	M08	{'WxN2', 'N2', 'N4', 'C', 'W', 'N6'}	H0	False		0.703	0.62	0.387	0.522	0.361
60	PROD	{'E', 'W', 'N6', 'C'}		False		0.699	0.617	0.38	0.511	0.355

code	matrix
C	char grams
CxN2	char grams x NAICS-2
CxN4	char grams x NAICS-4
E	EIN
EN	narrative word grams
ENxN2	narrative word grams x NAICS-2
M2	major code
M2E	expanded major codes
M2L	leaked major code
M2LE	leaked expanded major codes
N2	NAICS-2
N4	NAICS-4
N6	NAICS-6
W	word grams
WxN2	single words x NAICS-2
WxN4	single words x NAICS-4

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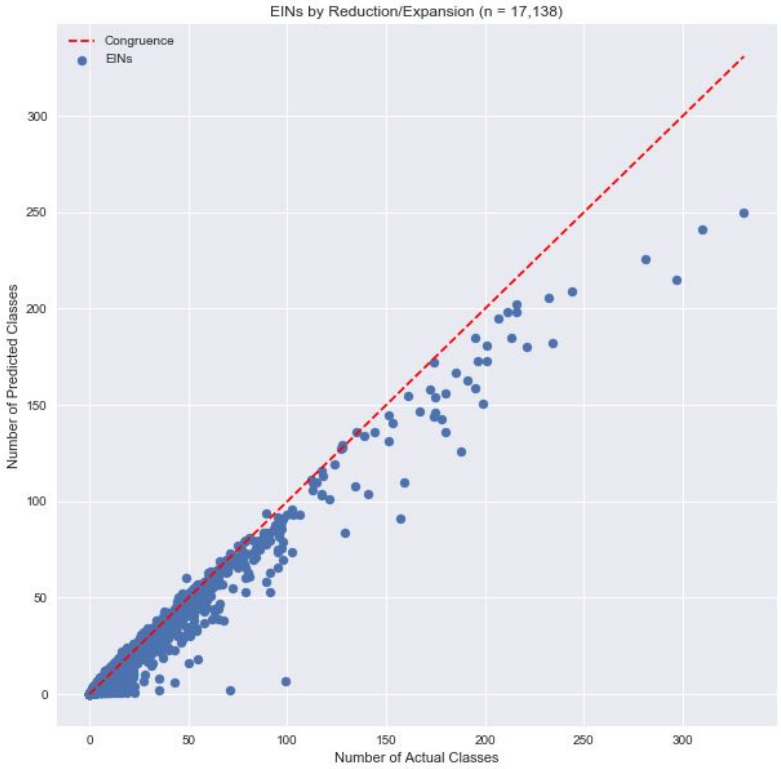
Table 2. Comparison of production model (PROD) with top ten models.

OCCUPATION REDUCTION

Figure 2. Cases where the autocoder misrepresents diversity of occupations employed at firms.

Helped automatically find 800,000+ cases (12% of training data) of unclassifiable data submitted by employers.



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