HLG-MOS ML Project Pilot Study

NAICS and NOC Models and Journey to Production



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Pilot Study Overview

- Objective: Develop machine learning models to code the North American Industry Classification System (NAICS) and National Occupational Classification (NOC).
- CCHS: Implementation of NAICS and NOC models in production
 - Models: FastText (approved for use)
 - Requirement: Error rate below 5 % (≥ human coders)
 - Quality Control: Confidence level, by class







System Terminology

G-Code: Generalized coding tool, includes word-matching and ML (FastText, XGBoost)

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oding Type Interactive Coding	Interactive Coding U	sing Delta 💿 Batch	Process	ing			
oding Databases							
Coding Database							Add
NAICS4_Q115_demo (SQL S	Server - SEDGCODEPROD - SED	GCode - METH)					
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oding Parameters							
Туре	Coding Method	Scoring Thresholds		Output Code(s)	Results	Stop Rule	
Full (Direct + Indirect)	Word	Winner:	9.5	Unique	Sort by code	Search all databases	
Direct Only	String (Levenshtein)	Possible:	8.5		Sort by score		
					Max items to Return:	Stop when wire	oner found
Indirect only	Use Keyword	Difference (Delta):	0.2		5		
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Text to Code	Fil	ter User Field	1	User Field 2 User Fie	eld 3 User Field 4 User	Field 5 User Field	e Im

Coding and Corrections Environment (CCE): Coding platform, which integrates automated and manual coding

I-Code v3.0.3.0		Production	
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No records ready for coding at	this moment		•
Province	Age	SAMPLEID	Possibles G-Code
Busname (self-employed)	Did you complete a high school diploma or its equivalent?		14403 2017
Industry (kind of business)	Were you an employee or self-employed?	NAICS 2017	NOC 2016
Occupation (kind of work)	Working in a family business without pay Refuse Don't know	NOC 2016	
Activity (main)	What is the highest certificate, diploma or degree that you have completed?	Occupation (kind of work)	
Machine-Learning: NOC 2016 Code	Less than high school opporta or its equivalent High school diploma or a high school equivalency certificate Trade certificate or diploma		
	College, CEGEP or other non-university certificate or diploma (dther than trades certificates or diplomas) University certificate or diploma below the bachelor's level		
	Bachelor's degree (e.g. B.A., B.Sc., LL.B.) University certificate, diploma, degree above the bachelor's level		



Transition of Coding Platforms





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Pipeline Flow of Records

 Records which did not obtain a high enough confidence score, to ensure to ensure an overall 95% accuracy for both classifications, were sent to be interactively coded

 After applying the threshold models were able to predict a NAICS code in 46.5% of records and a NOC code in 34.2% of records.

 Records with received both a NAICS and NOC code (23.5%) were sent for Methodology QC





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Methodology Quality Control (QC) Framework

- Models run on a testing datasets of 157,527 NOC records and 134,911 NAICS records from multiple surveys including: LFS, JVWS, CCHS, CHMS, CHSCY, SFS.
- QC by Class: Classes which had an error rate above 10% for NAICS and 15% for NOC, when run on the testing dataset, were flagged for interactive coding.
- QC Sample: Given a margin of error of 0.02, where p is 0.05, we calculated the quality control sample size as follows:

Margin of Error =
$$\sqrt{\frac{Z_{0.05}^2(P(1-\hat{p}))}{n}}$$

- Overall Error in production
 - Excluded by class: 10.5%
 - QC Sample: 4.2%







Journey to Implementation

Phase 1: Starting Point ~1.5 years ago

- Had management buy-in.
- Were using Word Matching for some auto-coding activities.
- Early CCE version could consume word-matching outputs, in Production as of Jan 2019.
- G-Code being used for auto-coding using Word Matching and integrated FastText as a prototype in Jan 2019.







Journey to Implementation

Phase 2: Evolution of the Pilot / Unit

- Developed technical capacity to develop quality models (learning / consultation)
 - Training Data, Pre-Processing, Feature Selection, Parameters, Analysis, etc.
- Collaborated with Methodology on development of a QC Sampling Strategy
- G-Code with FastText moved in to Production.
- Developed good working relationships with ML partners
 - Data Science Accelerator / Data Science Division
 - G-Code Methodology Team Statistical Integration Methods Division
 - ML Communities of Practice
 - Subject matter areas
- NAICS and NOC models used in Production for CCHS and CHMS.



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Journey to Implementation

Phase 3: Going Forward

- May be able to use models for other small surveys, such as the General Social Survey (GSS).
- Further improvement of models: boosting minority classes, additional data sources.
- Work towards development of models tailored to use for Job Vacancy and Wage Survey (JVWS) and Labor Force Survey (LFS).
- Revisit Methodology QC sampling plan to account for upcoming CCE development.
- Adapt upcoming Quality Validation Framework(s).





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Conclusions / Lessons Learned

Time Investment / Interdependencies

- Technical capacity
- IT systems development / Testing
- Methodology consultation
- Client approval
- Feasibility / Suitability ROI

Engagement / Buy-In

- Subject matter / Management
- Explainability / ML black box







Thank you!

Questions?





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Model Creation

- Algorithm: FastText (approved for use in G-Code)
- Training Data Sources
 - CCHS: 88,782 historical records
 - Labour Force Survey (LFS): 443,464 historical records
 - Standards Classification: 80,000 NOC and 40,000 NAICS index entries





Model Creation

Preprocessing Steps

- Exploratory: Multiple Bags of Words, Up-Sampling of Minority Class, Separation of English and French Models, Stemming and Lemmatization, and Pre-Trained FastText Embeddings.
- Production:
 - 1. Removal of Stop Words
 - 2. Lowercasing character conversion
 - 3. Merging of the variables 'Business Name' and 'Name of Employer'
 - 4. Application of a Caesar Cipher to differentiate text from "Company", "Industry", "Job Title" and "Job Description" when concatenated into a single field

Documented on UNECE, Working Documents: FastText_Techniques FastText Techniques



Temporary production pipeline with the CCE



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CCHS Autocoding

As the Coding and Corrections Environment (CCE) cannot currently consume results from G-Code ML models, we developed a temporary production pipeline to code CCHS

- Validation Pipeline
 - CCHS output files (2019 Q2) used as historical data.
 - Records = 7917.
- Production Pipeline
 - CCHS (2019 Q3, Q4) collection period.
 - Records = 7430, 7404



Comparison of pipelines







Production pipeline error rate

Table 1. Error rate of NAICS and NOC in CCHS production pipeline. Record flow follows the same path as described in Figure 1. Record number = 7430 (Q3), 7404 (Q4). (*) indicates the error rate of manual coders in production before verification is applied.

Collection Period

Q3

Q4

Classification	Interactive: Confidence Threshold	Interactive: QC by Class	Interactive: QC Sample	Machine- Learning: Non-QC
NAICS 2017	3.0*	5.5	2.2	N/A
NOC 2017	4.7*	6.3	2.5	N/A
Both	3.9*	10.6	4.2	N/A

Classification	Interactive: Confidence Threshold	Interactive: QC by Class	Interactive: QC Sample	Machine- Learning: Non-QC
NAICS 2017	1.1*	3.3	0.0	N/A
NOC 2017	1.6*	5.5	1.8	N/A
Both	1.3*	7.1	1.8	N/A





Figure 2. Per class analysis of NAICS and NOC. The 20 most frequently coded classes in each classification are displayed. Each class includes the stage (color coded in the legend) at which the record was coded in.

Table 1. NAICS and NOC model metrics tested on multiple surveys. Overall Accuracy, F1, Precision, and Recall were calculated on the entire training dataset. After a confidence threshold was applied, the error rate and coding rate were calculated on the remaining records. (*) A subset of the NOC training dataset, using only CCHS data, was evaluated using a different confidence threshold.

Measure	NAICS	NOC	NOC – CCHS*
Record #	64,249	157,527	7,088
Overall Accuracy (%)	80.5	64.4	70.8
Weighted Average F1-Score	80.4	51.5	70.6
Weighted Average Precision	81	53.3	71.9
Weighted Average Recall	80.5	51.8	71.0
Confidence Threshold (%)	96.0	99.9	99.0
Error Rate (%)	4.5	5.9	4.8
Coding Rate (%)	61.25	10.9	36.2



Table 4. NAICS and NOC model metrics for the CCHS production pipeline. Overall Accuracy, F1, Precision, and Recall were calculated on the 'Interactive: QC Sample'. Record number = 343.

Measure	NAICS 2017	NOC 2016	
Error Rate (%)	2.2	2.5	
Weighted Average F1-Score	97.5	96.9	
Weighted Average Precision	97.4	96.7	
Weighted Average Recall	97.8	97.5	





