

Machine Learning for Medical Coding in Health Care Surveys



Assessing Viability of Multi-label Classification of Verbatim Text for the NAMCS & NHAMCS-ED 2016-17 Surveys

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Automation Maturity Model

Human driver monitors environment System monitors environment 0 2 3 5 4 No Driver Partial Conditional High Full automation assistance automation automation automation automation The absence of any Systems that help The combination of Automated systems Automated systems The true electronic assistive features drivers maintain automatic speed that drive and that do everythingchauffeur: retains such as adaptive no human backup speed or stay in and steering monitor the full vehicle control. control-for example, required-but only needs no human cruise control. lane but leave the environment but cruise control and in limited rely on a human backup, and drives driver in control. in all conditions. lane keeping. driver for backup. circumstances. Humans and machine doctors Unlikely Now

Challenges of Manual Medical Coding

Patient 123456

Reason for Visit Text

Vertigo and dizziness



Reason for Visit Code

1225.0

Medical coding is...

- Essential
- Complex
- Labor-intensive

Research Question

Can machine learning help address the challenges of manual coding?

Data – Methods – Results – Discussion

Data

Sources of Verbatim Text

National Ambulatory Medical Care Survey (NAMCS)

Annual, nationally rep. survey of non-federally employed office-based physicians primarily engaged in direct patient care

National Hospital Ambulatory Medical Care Survey – Emergency Department (NHAMCS-ED)

Annual, nationally representative survey on utilization and provision of ambulatory care services in hospital emergency departments

2016 – 2017 survey data used for this project

Medical Coding Example

Patient 123456

| Reason for Visit Text | Reason for Visit Code |
|-----------------------|-----------------------|
| Vertigo and dizziness | 1225.0 |

Up to 5 reasons for visit

| Cause of Injury Text | Cause of Injury Code |
|--------------------------|----------------------|
| Struck by falling object | W20.8xxA |

Up to 3 causes of injury, truncated to first three characters

| Diagnosis Text | Diagnosis Code |
|--|----------------|
| Acute post traumatic headache, intractable | G44.311 |

Up to 5 diagnoses, truncated to first three characters

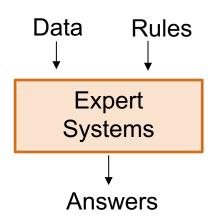
Methods

Expert Systems vs. Statistical Natural Language Processing

Two overarching schools of thought for Automated Computer Coding:

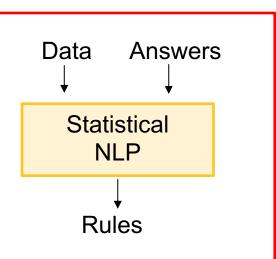
Expert Systems

- Designed to reason about a problem much as a human expert would
- Create rules to match response strings to an entry in a dictionary
- Requires expert knowledge and can be expensive to develop / maintain



Statistical Natural Language Processing (NLP)

- Designed to treat classification as an optimization problem
- Uses labeled examples to "learn" effective rules
- Often requires a large amount of high-quality labeled data



Classification Model Development

- 80% of data for training models, 20% for evaluation
- Multi-label text classification

| Multi-Class Text Classification | Multi-Label Text Classification |
|---|--|
| Assigns a single class to a set of input text | Assigns zero to many classes for a given set of input text |

- Models Considered:
 - Random Forests
 - Support Vector Machines
 - Multi-label k-Nearest Neighbors
 - Logistic Regression
- Best model based on precision and recall: Logistic Regression

Comparing Model Predictions to Humans

Jaccard Score

How many codes exist in both sets ÷ how many codes are in either set?

Code Set A

[31000, 19001, 11400, 11100]

Code Set B

[31000, 19001, 46050, 11100]

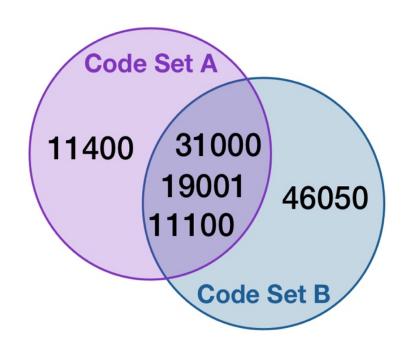
In Both

[31000, 19001, 11100] (size=3)

In Either

[31000, 19001, 11100, 11400, 46050] (size=5)

Jaccard Score: $3 \div 5 = 0.6$

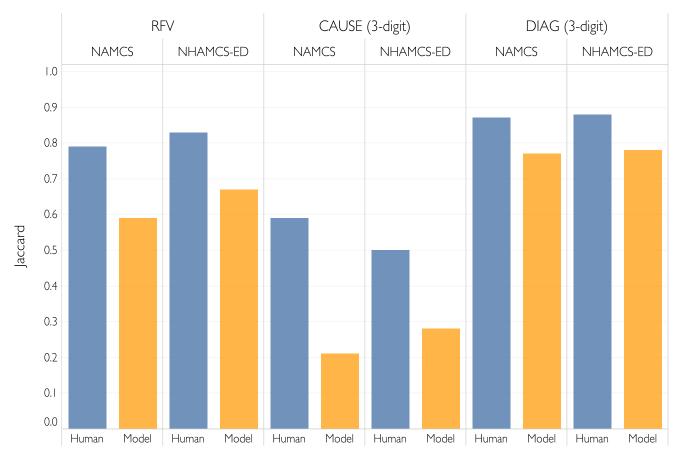


Can be applied when code sets come from two coders or from a coder and a predictive model.

Results

Performance Comparisons

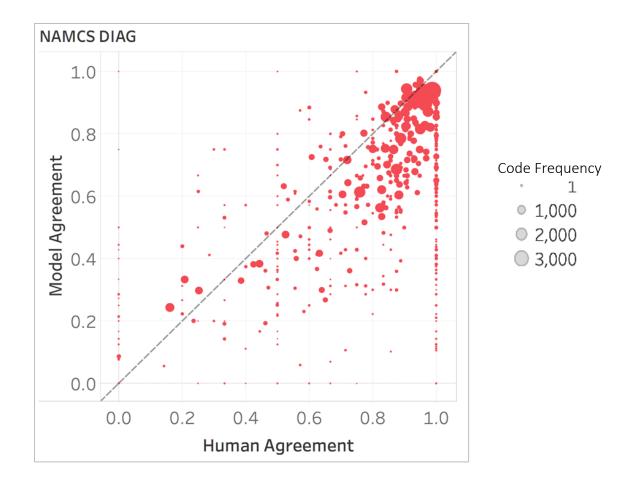
Jaccard Score for Human and Computer Coder Performance



- Humans consistently outperform the model
- Model performs well on both Reason for Visit and Diagnosis tasks
- Both humans and model perform worst on Cause of Injury

Performance by Medical Code

Performance on Individual Truncated ICD-10-CM Codes



- Points above the line are codes where model outperforms humans
- Humans and model both tend to perform well on the most frequent codes

Discussion

Potential Implementation Use Cases



Software double-codes every record as a support system for human coders

Recommendation System



Software displays recommended codes for each record, improving human coder efficiency

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for global good



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