mannheimer zentrum für europäische sozialforschung

Institute for Employment Research

The Research Institute of the Federal Employment Agency

A Comparison of Automatic Algorithms for Occupation Coding

BigSurv 2018

Barcelona

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Malte Schierholz

Occupations are analyzed within ...

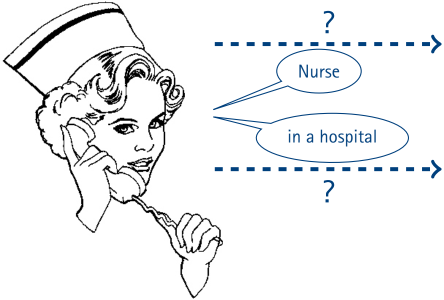
- Economics: individuals' tasks and duties, ...
- Sociology: social status, ...
- Medicine: health risks, ...

How to measure occupations in interviews?
With open-ended questions!

The Coding Problem

Assign verbatim answers to an official classification

Survey Answers



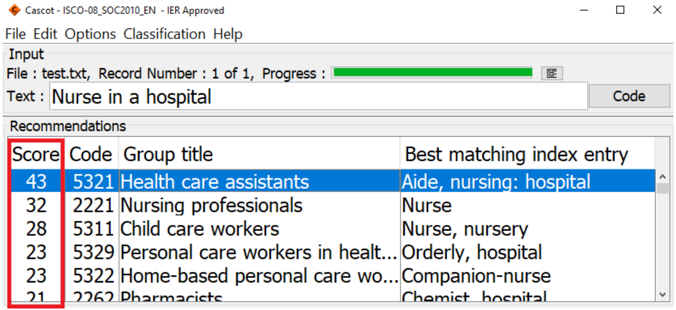
Classification

KldB 2010	Job Title (illustrative)
81302	Nurse
81313	Graduated Nurse
81323	Pediatric Nurse
⋮	⋮
81102	Doctor's Assistant
82102	Geriatric Nurse

→ Coding is mostly manual work and therefore expensive

→ How to automate it?

Modes of Automation



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Two modes of automation:

- Computer-assisted coding: Human choice, see picture
- Automated coding: Select top-ranked category

→ How to calculate scores / probabilities?

The Challenge

- Manual occupation coding is hard
  - Coders are trained on the classification and coding conventions
    (Geis and Hoffmeyer-Zlotnik (2000), Paulus and Matthes (2013))
  - Coders draw on information from multiple questions
  - Inter-coder reliabilities range between 61-83%
    (Prigge et al. (2014), Schierholz et al. (2018))

- High-dimensional classification problem
  - Our document-term matrix has 54.880 observations and 14.223 columns (words)
  - 1.291 outcome categories
  - $>$ 15 million parameters in a multinomial logistic regression

Ten Algorithms

Comprehensive comparison of ten algorithms:

1. Coding index (exact)
2. Coding index (\w similars) (Elias et al. (2014))
3. Memory-based Reasoning (Creecy et al. (1992))
4. Adapted Nearest Neighbor (Gweon et al. (2017))
5. Multinomial Logit (R-package `glmnet`, Friedman et al. (2010))
6. XGBoost (R-package `XGBoost`, Chen and Guestrin (2016))
7. Coding index + Bayes (fulltext similarity)
8. Coding index + Bayes (substring similarity)
9. Coding index + Bayes (wordwise similarity)
10. Highest probability

Items 1–4: Developed for occupation coding

Items 5–6: General purpose

Items 7–10: Own contribution

Ten Algorithms

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1.	Coding index (exact)	Coding Index	String identity
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10.	Highest probability	Among algorithms 6-9, select the algorithm with highest probability	

Algorithms for Automatic Coding (1)

First algorithm: **Consult a coding index**

2010 German Classification

(27.575 job titles)

Job title	Code
Säuglings- und Kinderkrankenschwester/-pfleger	81302
Säuglings- und Krankenschwester/-pfleger	81302
Säuglingskrankenschwester/-pfleger	81302
Säuglingsschwester/-pfleger	81302
Schwester/Pfleger (Kinderkrankenpflege)	81302
Schwester/Pfleger (Krankenpflege)	81302
Anästhesieschwester/-pfleger	81313
Dialysefachkraft	81313
Dialyseschwester/-pfleger	81313
Endoskopieassistent/in	81313
Endoskopieschwester/-pfleger	81313
Fachkrankenpfleger/in - Notfallpflege	81313

Source: KldB 2010

2018 US Classification

(6.539 job titles)

Job Title	Code	Category Title
Hospice Registered Nurse	29-1141	Registered Nurses
Obstetrical Nurse	29-1141	Registered Nurses
Oncology Registered Nurse	29-1141	Registered Nurses
PACU Nurse	29-1141	Registered Nurses
Pediatric Registered Nurse	29-1141	Registered Nurses
Post-Anesthesia Care Unit Nurse	29-1141	Registered Nurses
Psychiatric Nurse	29-1141	Registered Nurses
RN	29-1141	Registered Nurses
Triage Registered Nurse	29-1141	Registered Nurses
Certified Registered Nurse Anesthetist	29-1151	Nurse Anesthetists
Certified Registered Nurse Anesthetist (CRNA)	29-1151	Nurse Anesthetists
DNAP	29-1151	Nurse Anesthetists
Doctor of Nurse Anesthesia Practice	29-1151	Nurse Anesthetists
Certified Nurse Midwife	29-1161	Nurse Midwives
Certified Nurse Midwife (CNM)	29-1161	Nurse Midwives
Acute Care Nurse Practitioner	29-1171	Nurse Practitioners
Adult Nurse Practitioner	29-1171	Nurse Practitioners
Cardiology Nurse Practitioner	29-1171	Nurse Practitioners

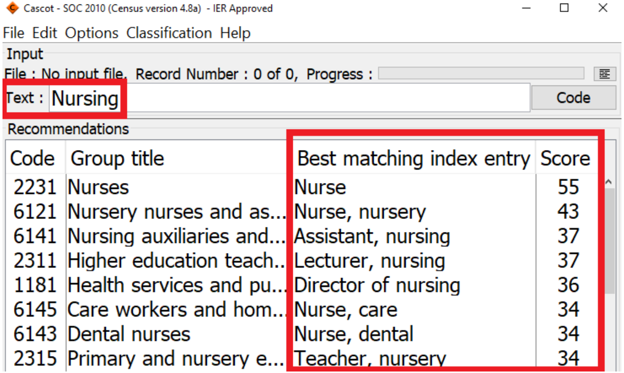
Source: 2018 SOC

Algorithms for Automatic Coding (2)

Second algorithm:

Consult a coding index (based on string similarity)

(Appel and Hellerman (1983), Wenzowski (1988), United Nations Statistical Commission and Economic Commission for Europe (1997), Elias et al. (2014))



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Algorithms for Automatic Coding (3–6)

Documents:

$d_1 =$ Nurse in a hospital $\rightarrow$

$d_2 =$ Hospital manager $\rightarrow$

$\vdots$

Document-term matrix:

...	a	hospital	in	manager	nurse	...
...	1	1	1	0	1	...
...	0	1	0	1	0	...
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

Prediction techniques:

Based on vector similarity (k-NN-like):

3. *Memory-based Reasoning*
   (Creecy et al. (1992))
4. *Adapted Nearest-Neighbor*
   (Gweon et al. (2017))

Based on loss minimization:

5. *Multinomial logistic regression*
   (R-package `glmnet`, Friedman et al. (2010))
6. *Gradient boosting with decision trees*
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New problem:

Algorithms 3-6 fail if important words (especially job titles) are not in the training data

- Infrequent jobs (e.g., ornithologist, horseshoer)
- Misspellings

Algorithm 2 already solved the issue. How to combine the different approaches?

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Algorithms for Automatic Coding (7–9)

A novel algorithm relies on the coding index, but uses past data as well.

Key idea:

- Training: Estimate for each entry in the coding index a posterior predictive distribution (Hierarchical Bayesian model)

$$\mathbb{P}(\text{code}_j | \text{index entry})$$

- Prediction: Search for a similar index entry and output its distribution as estimated

Three ways of calculating string similarity (Algorithms 7–9):

7. *Fulltext similarity*: Similar if the verbal answer differs by at most one character
8. *Substring similarity*: Similar if an entry from the coding index is a substring of the verbal answer
9. *Wordwise similarity*: Similar if one word in the verbal answer differs by at most one character

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Evaluation

Application in survey interviews envisioned:

- Only texts from the first open-ended question are available (unlike current coding situations)
- Let the computer decide what to ask next
  - Reduce respondent burden
  - Increase data quality

1\. What is the occupational activity you do in your main job?

Nursing

Next

2\.

Automated Coding

(=Computer selects the top-ranked category)

81302 (Nurse)

Computer-assisted Coding

(=Human chooses from a list of suggestions)

Welche Tätigkeit führen Sie in Ihrem Beruf hauptsächlich aus?

- ○ **eigenständige Pflege und Betreuung von Patienten und Assistenz bei ärztlichen Maßnahmen**
  Krankenschwester/-pfleger
- ◉ **Unterstützung von Pflegefachkräften bei der Versorgung und Pflege von Patienten in Krankenhäusern oder Pflegeheimen**
  Krankenpflegehelfer/in
- ○ **Betreuung und Pflege von kranken Säuglingen, Kindern und Jugendlichen in bestimmten medizinisch-pflegerischen Fachgebieten**
  Fachkinderkrankenschwester/ -pfleger
- ○ **Werksärzten bei allen regelmäßigen Untersuchungen und Maßnahmen der Mitarbeiter eines Betriebes assistieren**
  Werkpfleger/-schwester

Data

2 German surveys, coded into the latest German occupational classification

- Dataset 1: 55,944 texts from *BIBB/BAuA Employment Survey 2012*
  (Hartmann et al. (2012), Hall et al. (2015))
  - Split in training and test data
- Dataset 2: 1,064 texts from *Selectivity effects in address handling*
  (Schierholz et al. (2018))
  - Test data only

Coders had access to more occupational variables in the second study – higher coding quality?

1. Performance of Automated Coding
(=Computer selects the top-ranked category)

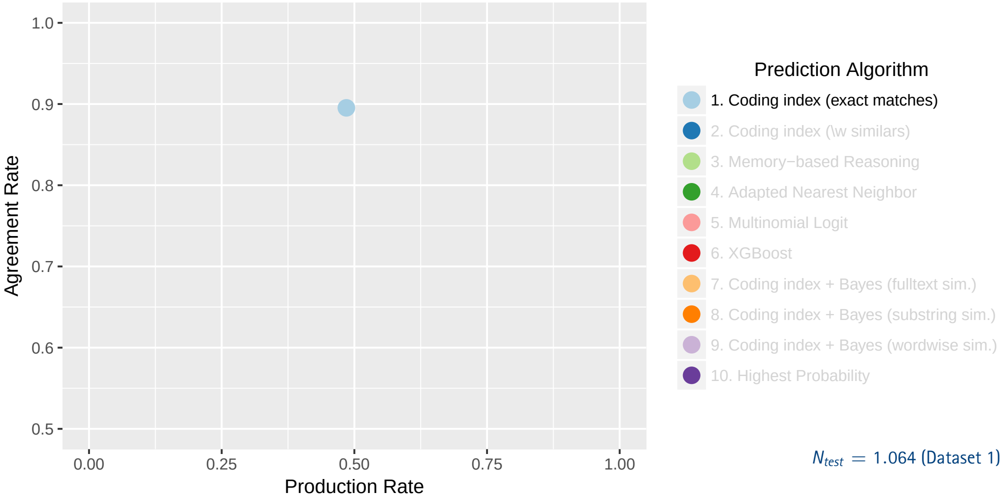
Metrics used:

- Production rate: Proportion of answers that are coded automatically
- Agreement rate: proportion of coded answers that are in agreement with human coder

Trade-Off: Production rate $\leftrightarrow$ Agreement rate

2. Performance of Computer-assisted Coding
(=Human coder chooses from a list of suggestions)

Automated Coding – Results



$N_{test} = 1.064$ (Dataset 1)

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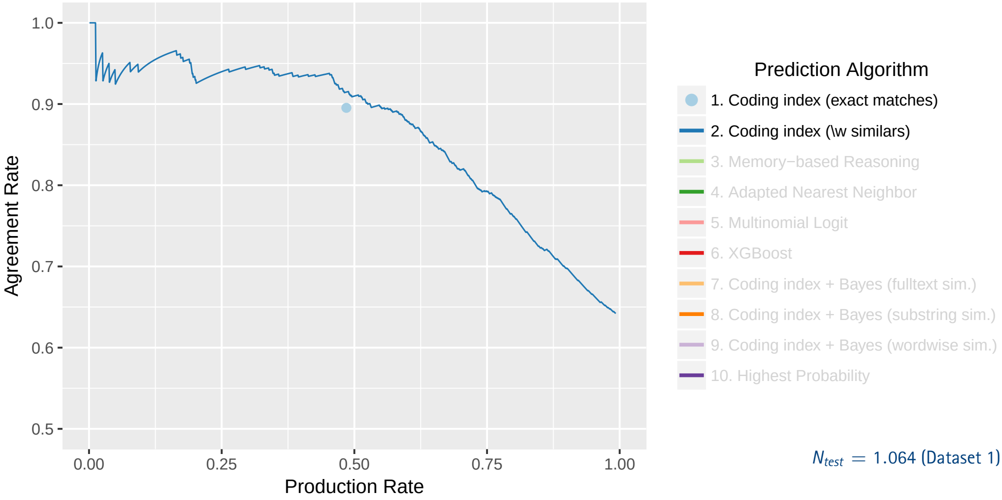

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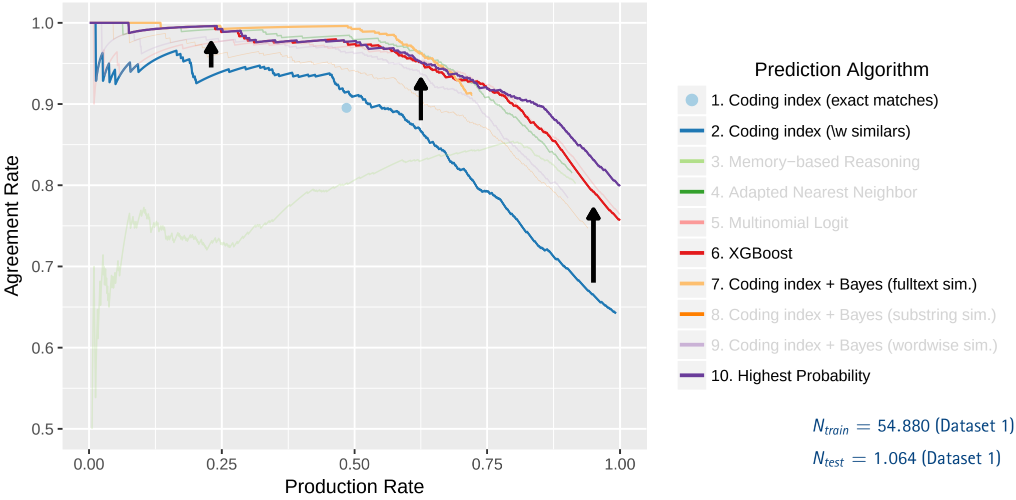
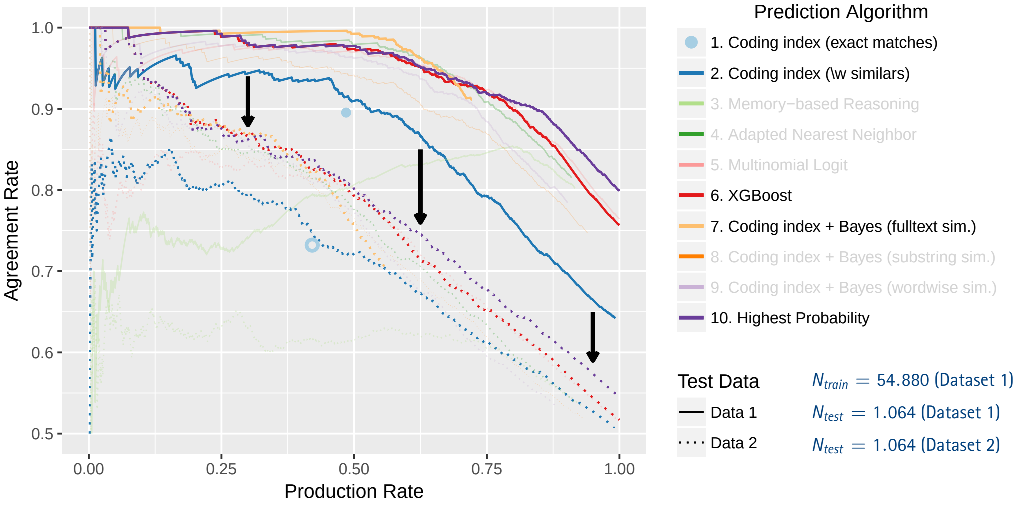


$N_{train} = 54.880$ (Dataset 1)

$N_{test} = 1.064$ (Dataset 1)

Automated Coding – Results



$N_{train} = 54.880$ (Dataset 1)

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$N_{test} = 1.064$ (Dataset 2)

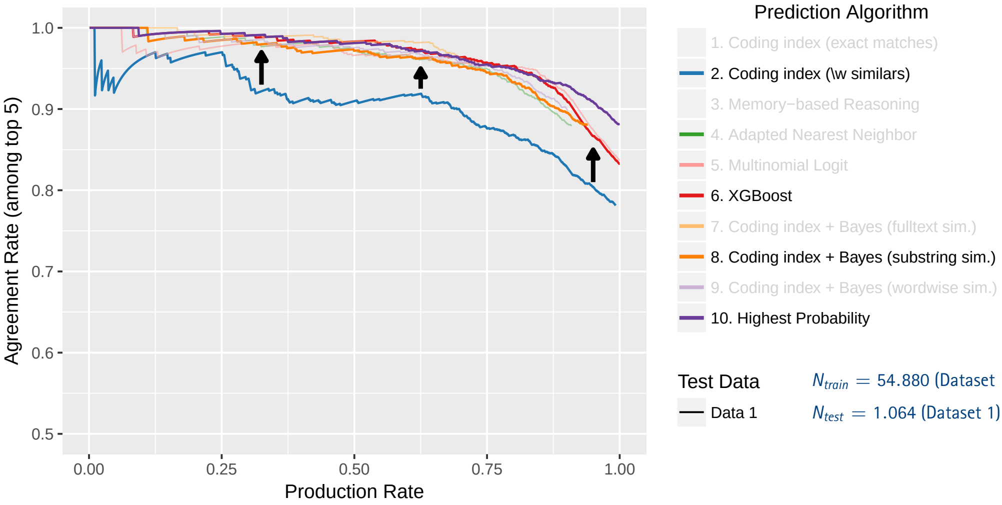
1. Performance of Automated Coding
(=Computer selects the top-ranked category)

2. Performance of Computer-assisted Coding
(=Human coder chooses from a list of suggestions)

Agreement rate is calculated in a different way:

- For automated coding: highest-ranked category in agreement with human coder? ($k = 1$ until now)
- For computer-assisted coding: human-coded category among top k suggestions? ($k = 5$ in the following)

Computer-Assisted Coding – Results



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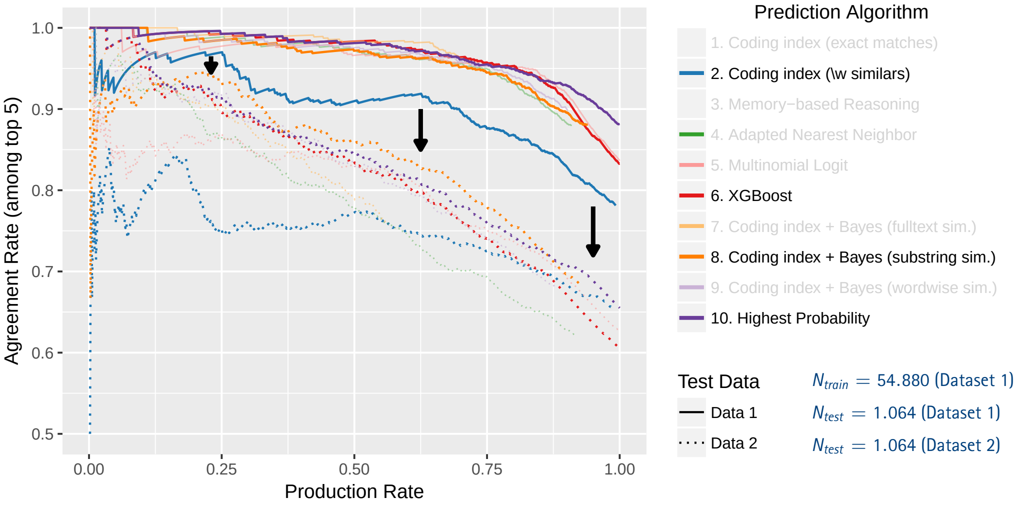

$N_{train} = 54.880$ (Dataset 1)

$N_{test} = 1.064$ (Dataset 1)

$N_{test} = 1.064$ (Dataset 2)

Summary

Performance

- Algorithm 2 (Coding index \w similars) is often used in practice but outperformed by other algorithms (e.g. 6. `XGBoost`)
- Combining the coding index and previously coded data is very promising (algorithms 7-10)
  - Best algorithm is problem-dependent

Generalization

- Poor generalization from one dataset to different test data

Application

- Agreement rates are often insufficient for fully automated coding
- Manual verification will usually be necessary, making computer-assisted coding most promising
  - Current plan: Suggest plausible answer options to respondents during the interview

Thank you!

Related publications:

The methods presented in this talk are also implemented in an R-Package:
`https://github.com/malsch/occupationCoding`

Background material:
Schierholz, M; Gensicke, M.; Tschersich, N. and Kreuter, F. (2018). Occupation Coding During the Interview, Journal of the Royal Statistical Society: Series A 181(2): 379–407.

Malte Schierholz
Malte.Schierholz@iab.de

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