

Associating Medical Concept Relations with ICD-9-CM Coding Rules

Paweł Matykiewicz^{*‡}, Włodzisław Duch^{*†}, John Pestian[‡]

^{*}Department of Informatics,
Nicholaus Copernicus University,
ul. Grudziądzka 5, 87-100 Toruń, Poland
E-mail: pawelm@fizyka.umk.pl

[†]School of Computer Engineering,
Nanyang Technological University,
Blk N4 Nanyang Avenue, Singapore, 639798
Google: Duch

[‡]Department of Biomedical Informatics,
Cincinnati Children's Hospital Medical Center,
3333 Burnet Ave, Cincinnati, 45229, USA
E-mail: john.pestian@cchmc.org

Abstract—A simple method for mining interesting relations between concepts in a certain state is presented. Those relations should reveal same rules that a human coder uses while assigning ICD-9-CM billing codes. This study focuses only on three most occurring medical concepts in radiology dictations: *cough*, *fever* and *pneumonia*. An algorithm that tries to associate relation between two concepts in a certain states with information if one of them should be coded or not.

I. INTRODUCTION

Many hospitals and medical practices have to deal with wrong codes assign to a patient visit. Past and on-going studies do not agree about manual coding error [1]–[8] by reporting different error rates. One of the solutions to decrease these errors is incorporation of coding aid software [9]–[11]. An approach to the problem of aiding coding process by automatic assignment of most common codes is presented. The method uses three main components: Unified Medical Language System [24] as a background knowledge, states of medical concepts [12]–[15] as main *knowledge unit* and association rules [16]–[19] as a meaning binding technique. Binding meaning is a filtering process that captures meaningful *knowledge unit* and relations between them (see examples 4 and 5). Automatic code assigning might be also viewed as a text categorization problem [20]–[23]. In spite of known work in these area presented algorithm wants to make a way to collect proper *state + concept* knowledge units and relation between them. Automatic code assignment is a task that shows a practical use of those *knowledge units*. There are many potential applications for mining of meaningful conditions/modifiers of medical concepts [12]–[15].

II. DATA

As a data set we use one year of chest x-ray and renal ultrasound from Radiology Department in Cincinnati Children's Hospital Medical Center. As mentioned before in this study

we describe only a portion of that data outcome: *cough*, *fever* and *pneumonia*. The dictations have two main parts: *clinical history* - given by an ordering physician before a radiological procedure and *impression* - reported by a radiologist after the procedure. Example of a radiology report is given in the 1 figure. Two sub-sets of Unified Medical Language Systems

CLINICAL HISTORY: Cough, congestion, fever.

IMPRESSION: Increased markings with subtle patchy disease right upper lobe. Atelectasis versus pneumonia.

Fig. 1. An example of a radiology report. Fields that are irrelevant for coding purposes were discarded.

(UMLS) [24] are used: SNOMED CT Qualifiers Values and Linkage Concepts sub-trees as a state/modifiers terms, ICD-9-CM with SNOMED CT mapping as a medical concepts. SNOMED CT was chosen because of good clinical terminology coverage [25]–[26]. A natural way to map ICD-9-CM concepts is to use ICD-9-CM ontology [27]. Unfortunately it does not have too many synonyms so SNOMED CT mappings to ICD-9-CM are used for that reason. Hierarchical relations from UMLS were also extracted. Figures 2 and 3 show sub-trees of SNOMED CT and ICD-9-CM hierarchy respectively. States and concepts that occur in the data set less than 20 times were discarded that gives overall 3271 nodes (leafs and ancestors) and 796 hierarchical relations. A class of ICD-9-CM codes assign to a radiology dictation might be composed of up to three codes. These code are used by insurance companies to document reasons for ordering a radiology procedure. The used data set was prepared so classes that occur less than 100 times were discarded. That gives 15 classes with overall

All (2315)	786.2 (489)	786.2 780.6 (297)	786.2 780.6 486 (342)	786.2 486 (405)	486 (237)
786.2 (1552)	451	177	144	312	6
786.2 780.6 (146)	9	48	40	6	1
786.2 780.6 486 (0)	N/A	N/A	N/A	N/A	N/A
786.2 486 (0)	N/A	N/A	N/A	N/A	N/A
486 (617)	17	20	114	64	178

TABLE I

SUB-SET OF A CONFUSION MATRIX BEFORE RULES APPLICATION. THE BIGGEST ERROR IN EVERY CLASS IS BOLDED. *Cough* [CODE 786.2], *fever* [CODE 780.6] AND *pneumonia* [CODE 486] REPORTED.

8263 documents. This paper reports 3 out of 15 classes plus 2 false positive classes related to *cough* [code 786.2], *fever* [code 780.6] and *pneumonia* [code 486]. Simple mapping

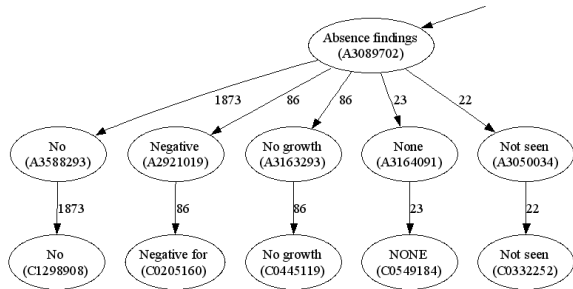


Fig. 2. A small part of SNOMED CT hierarchical structure. Edges labels denote occurrence of a child node.

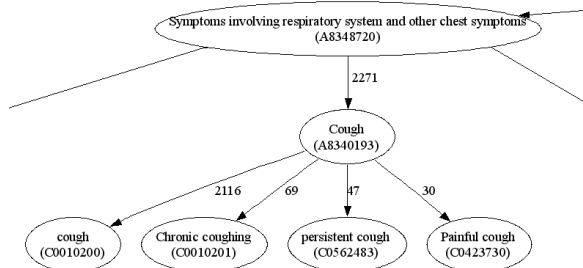


Fig. 3. A small part of ICD-9-CM hierarchical structure. Edges labels denote occurrence of a child node. Leafs are either original ICD-9-CM nodes or SNOMED CT mappings.

of ICD-9-CM concepts (concept modifiers are not included) from UMLS gives $\approx 29.2\%$ accuracy (the trace of a confusion matrix) in case of the reported sub-set of all classes in the original data set. The mapping algorithm was same as in [28].

III. ALGORITHM

This study focuses on two meaning of modifiers/states: code or not to code. ICD-9-CM guidelines ?? say that only sure diseases should be coded. Second requirement is to code

sign and symptoms only if other findings are not present. Our approach wants to learn those guidelines from the data. Examples of guidelines in use are shown in figures 4 and 5. These two requirements are enough to make standard

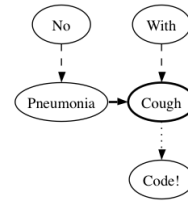


Fig. 4. A relation example. A symptom can be coded because of no definitive diagnosis.

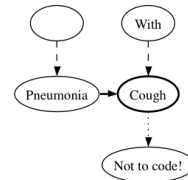


Fig. 5. A relation example. A symptom is not coded because of definitive diagnosis.

categorization techniques to fail. A method that extracts rules for a state of a concept might show improvement over standard Natural Language Processing techniques since they do not capture difficult medical relations. Information if a code assign by simple mapping algorithm is a false positive or true positive serves as a information if a disease is codeable or not. This way a filter is applied to search only for meaningful realtions and states of concepts. Schema for gathering conditional probabilities is shown in figure 6. This algorithm is a very simple

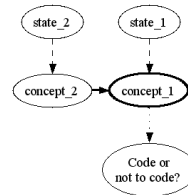


Fig. 6. A mining schema. Which states and concepts determine $concept_1$ true positive or false positive meaning?

exhaustive search approach that looks for all combinations of the nearest state of a concept with other concepts in the same radiology dictation. Once this kind of relation is acquired all possible combinations of ancestors are gathered for the conditional probabilities. The conditional probability is if a $concept_1$ in a context of a state and relation to other concept should be coded or not.

IV. MINING

The cut-off for rules is 0.8 confidence and 20 for support. That gives 149 rules. Table VI shows some rules that mention

All (2315)	786.2 (413)	786.2 780.6 (266)	786.2 780.6 486 (352)	786.2 486 (361)	486 (209)
786.2 (1552)	733	265	47	106	11
786.2 780.6 (146)	15	72	17	4	2
786.2 780.6 486 (0)	N/A	N/A	N/A	N/A	N/A
786.2 486 (0)	N/A	N/A	N/A	N/A	N/A
486 (617)	27	31	60	85	218

TABLE II

SUB-SET OF A CONFUSION MATRIX AFTER RULE APPLICATION. THE BIGGEST ERROR IN EVERY CLASS IS BOLDED. *Cough* [CODE 786.2], *fever* [CODE 780.6] AND *pneumonia* [CODE 486] REPORTED.

cough, *fever* or *pneumonia* and interactions between them. The data is very noisy because of human coding errors so for some association rules there is not too big confidence.

V. RESULTS

Applying 149 rules to the whole data set gives improvement of $\approx 15\%$ for the *cough* [code 786.2], *fever* [code 780.6] and *pneumonia* [code 486] mixture classes.

VI. CONCLUSION

Presented algorithm shows an approach for learning ICD-9-CM guidelines from the data. This establishes a method for filtering meaningful relations and states/modifiers of concepts. A novel way for assessing interesting relations and modifiers was presented. This method might be extended to other applications that make use of background knowledge.

REFERENCES

- [1] Silfen E., Documentation and coding of ED patient encounters: an evaluation of the accuracy of an electronic medical record, *The American Journal of Emergency Medicine* **24** (2006) 664–687.
- [2] O'Malley K. J., Cook K. F., Price M. D., Raiford Wildes K., Hurdle J. F., and Ashton M. C., Measuring diagnoses: ICD code accuracy, *Health Research and Educational Trust*, **40** (2005) 1620–1639.
- [3] Singh J. A., Holmgren A. R., and Noorbaloochi S., Accuracy of veterans administration databases for a diagnosis of rheumatoid arthritis, *Arthritis & Rheumatism*, **3** (2004) 952–957.
- [4] Jordan K., Porcheret M., and Croft P., Quality of morbidity coding in general practice computerized medical records: a systematic review, *Family Practice*, **21** (2004) 396–412.
- [5] Campbell S. E., Campbell M. K., Grimshaw J. M., and Walker A. E., A systematic review of discharge coding accuracy, *Journal of Public Health Medicine*, **23** (2001) 205–211.
- [6] Surján G., Questions on validity of International Classification of Diseases-coded diagnoses, *International Journal of Medical Informatics*, **54** (1999) 77–95.
- [7] Iezzoni L. I., Assessing quality using administrative data, *Annals of Internal Medicine*, **127** (1997) 666–674.
- [8] Hohnloser J. H., Kadlec P., and Puerner F., Experiments in coding clinical information: an analysis of clinicians using a computerized coding tools, *Computers and Biomedical Research*, **28** (1995) 393–401.
- [9] Orueta J. F., Urraca J., Berraondo I., and Darpon J., Can primary care physicians use the ICD-9-MC? An evaluation of the quality of diagnosis coding in computerized medical records, *Gaceta Sanitaria*, **20** (2006) 194–201.
- [10] Sistrom C., Drane W., Networked ICD-9 Coding System for a Radiology Department, *American Journal of Roentgenology*, **176** (2001) 335–339.

- [11] Rossi C. R., Alberti V., Mancino G., Flor L., Martello T., Poeta L., Lise M., Diana L., Puppini G., Comparison between manual and automatic coding of medical record statistical cards at a university hospital, *Medical informatics*, **18** (1993) 53–59.
- [12] Chapman W. W., Dowling J. N., Inductive creation of an annotation schema for manually indexing clinical conditions from emergency department reports, *Journal of Biomedical Informatics* **39** (2006) 196–208.
- [13] Mendonça E. A., Haas J., Shagina L., Larson E., Friedman C., Extracting information on pneumonia in infants using natural language processing of radiology reports, *Journal of Biomedical Informatics* **32** (2005) 314–321.
- [14] Friedman C., Shagina L., Lussier Y., Hripcsak G., Automated encoding of clinical documents based on natural language processing, *Journal of the American Medical Informatics Association* **11** (2004) 392–402.
- [15] Chapman W. W., Dowling J. N., and Wagner M. M., Fever detection from free-text clinical records for biosurveillance, *Journal of Biomedical Informatics*, **37** (2004) 120–127.
- [16] Doddi S., Marathe A., Ravioe S. S., Torney D. C., Discovery of association rules in medical data, *Medical Informatics and the Internet in Medicine*, **26** (2001), 25–33.
- [17] Delgado M., Sánchez, Martín-Bautista M. J., Vila M.-A., Mining association rules with improved semantics in medical databases, *Artificial Intelligence in Medicine*, **21** (2001) 241–245.
- [18] Agrawal R., Srikant R., Fast algorithms for mining association rules in large databases, *Proceedings of the 20th International Conference on Very Large Data Bases*, **Morgan Kaufmann** (1994) 487–499.
- [19] Agrawal R., Imielinski T., and Swami A. N., Mining association rules between sets of items in large databases, *Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data*, **ACM Press** (1993) 207–216.
- [20] Pakhomov S. V. S., Buntrock J. D., Chute C. G., Automating the assignment of diagnosis codes to patient encounters using example-based and machine learning techniques, *Journal of the American Medical Informatics Association* **13** (2006) 516–525.
- [21] Hazlehurst B., Frost H. R., Sittig D. F., Stevens V. J., MediClass: a system for detecting and classifying encounter-based clinical events in any electronic medical record, *Journal of the American Medical Informatics Association*, **12** (2005) 517–529.
- [22] Ribeiro-Neto B., Laender A. H. F., and de Lima L. R. S., An experimental study in automatically categorizing medical documents, *Journal of the American Society for Information Science* **52** (2001) 391–401.
- [23] Aronow D., Fangfang F, Croft B. Ad hoc classification of radiology reports, *Journal of the American Medical Informatics Association*, **6** (1999) 393–411.
- [24] Lindberg D. A. B., Humphreys B. L., McCray A. T., The unified medical language system, *Methods of Information in Medicine*, **32** (1993) 281–291.
- [25] Melton G. B., Parsons S., Morrison F. P., Rothschild A. S., Markatou M., Hripcsak G., Inter-patient distance metrics using SNOMED CT defining relationships, *Journal of Biomedical Informatics*, in print (2006).
- [26] Penz J. F., Brown S. H., Carter J. S., Elkin P. L., Nguyen V. N., Sims S. A., Lincoln M.J., Evaluation of SNOMED coverage of Veterans Health Administration terms, *Medinfo IOS Press* **11** (2004) 540–544.
- [27] U.S. Department of Health and Human Services, Classification of Diseases, Functioning, and Disability, <http://www.cdc.gov/nchs/icd9.htm>, October 18, 2006
- [28] Matykiewicz P., Duch W., Pestian J., Unambiguous concept mapping in a medical domain, *Lecture Notes in Artificial Intelligence*, **4029** (2006) 941–950.

Rule no.	confidence	support	<i>state</i> ₂	<i>concept</i> ₂	<i>state</i> ₁	<i>concept</i> ₁	Meaning
1	1.00	61	Unapproved attribute	Cough	Absence findings	Focal pneumonia	do not code
2	1.00	38	Unapproved attribute	General symptoms	No	Focal pneumonia	do not code
3	1.00	24	General information qualifier	Symptoms involving respiratory system ...	No	Focal pneumonia	do not code
4	0.99	99	0	Cough	Absence findings	Focal pneumonia	do not code
5	0.98	50	0	0	General adjectival modifier	cough	code
6	0.97	34	Absence findings	Pneumonia, organism unspecified	Exclude	Pneumonia NOS	do not code
7	0.96	22	With	Symptoms involving respiratory system ...	No	Fever NOS	do not code
8	0.94	134	0	0	0	cough	code
9	0.93	148	0	0	Unapproved attribute	cough	code
10	0.91	20	No	Fever NOS	Unapproved attribute	cough	code
11	0.80	32	0	Pneumonia, organism unspecified	With	cough	do not code

TABLE III

EXAMPLE OF FEW RULES/ASSOCIATIONS BETWEEN MEDICAL RELATIONS AND TWO CODING MEANINGS (TO CODE OR NOT TO CODE) WITH HIGHEST CONFIDANCE AND SUPPORT.