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Guideline-based Visualization of Medication in Chronic Disease

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Abstract

Chronic disease management at the General Practice level is a challenging task requiring synthesis of information across time and possibly several practitioners. Sparsity of data, lack of structure, lack of time are limiting factors of computer use in this domain. Authors are exploring the concept of visualization of individual patient's medication using a clinical guideline to provide some structure to the problem by creating a state-transition model. This approach was shown to be promising at the practice level in previous research [1,5] where an overall synthesis of practice decisions was created and alerts were generated on the basis of individual transactions or states - current focus is on individual patient and the sequence of states describing his/her medication history.

Keywords:

general practice, visualization, decision support, guideline

Introduction

In managing chronic diseases, the information on the past course of the disease can be important - but many practitioners see reviewing of past data as a (necessary) evil to be done as quickly as possible [2]. With more and more general practitioners (GPs) using a computer in their everyday practice [3] it is more than tempting to use the existing data to provide support for quality and continuity of care. Typically the data is rather unstructured, with highly variable quality in terms of completeness or adherence to some coding standards. In a comprehensive review it was shown, that prescription data is the one most complete and reliable [4]. Assuming, that medication reflects significant proportion of decision-making about a case a guideline-based state-transition model was created and used for analysis at the practice level, as well as for generation of patient-related alerts [1]. While this approach shows promising results, information on patients as drawn from the model does not take into account patient-specific sequences of states. In the current work we explore the visualization of these sequences as well as generating alerts based on sequential patterns for particular patients in line with the ideas of Aigner and Miksch [9].

Materials and methods

The backbone of the study was a state-transition model focusing on treatment of hypertension in diabetes mellitus based on an American Diabetes Association guideline [1]. The data used in the study were de-identified extracts from a general practice in rural Australia holding age, gender, visit dates, problem codes, blood pressure measurements and drug prescriptions. The extracts covered 6 years and contain more than 70000 prescriptions. Two sequences of events/states were generated for each patient: prescription path and treatment path.

Treatment path

According to methodology described in [1] medications were clustered into 6 groups (group B has 3 subgroups):

- Group A: Angiotensine converting enzyme inhibitors (ACEi) - ATC codes C09A and C09C
- Group B1: -blockers (BB) - ATC codes C07AA, C07AB
- Group B2: Diuretics - ATC codes C03AA, C03CA or C03D
- Group B3: Non-dihydropyridine Ca-channel blockers (NCCB) - ATC code C08D
- Group C: Dihydropyridine Ca-channel blockers (DCCB) - ATC code C08CA
- Group D: -blockers, hydralazines, clonidine - ATC codes C02CA, C02DB, C02AC

To simplify the model-building process we deviated slightly from standard ATC coding - combination drugs were coded as if a set of separate drugs was given.

Based on prescription data states were generated, using the amount and the daily dose of prescribed drug to calculate duration of treatment with a particular drug group. In this calculation we assumed, that patient starts the medication on the same day as it was prescribed, that the dosage is unchanged throughout the time covered by a particular prescription (and the patient adheres to the dosage).

All methods were implemented using Cache and Ensemble (Intersystems Inc.), graphs were generated using GraphViz software (www.graphviz.org).

Prescription path

A prescription is a sequence of prescription instances. A prescription instance is a drug, or combination of drugs as

prescribed on a particular day, disregarding dosage or quantities prescribed.

Results

A prescription path and a treatment path are shown simultaneously and provide different views on what was done. E.g. if a drug containing a BB and diuretic was prescribed and at the same time a potassium-sparing diuretic was prescribed the prescription instance is shown as B1+B2+B2; while the treatment path will show B1+B2 combination. (Figure 1).

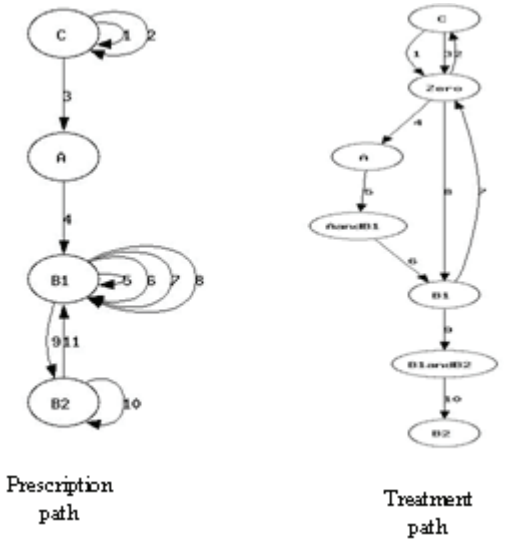

Figure 1 - Prescription path vs. Treatment path

Alerts

Visualisation of the paths should be in most cases enough for an experienced GP to see any unusual patterns. Analysing treatment paths allows to create an additional class of alerts, taking into account more than just one state or one transition Eventually the whole path can be taken into account in launching an alert - e.g. a cyclic repetition of transition tuple (A to B1 followed by B1 to A) for more than **n** (usually 2-4) times may be considered an unusual pattern and an alert should be launched.

Discussion

Guideline can be utilized at two levels in data analysis. First approach is to use the guideline to structure the problem space and then fit the data into the resulting of structure. Several authors applies such approach in hospital settings [6, 7, 8]. The guideline context make it easier for physicians to recognise and appreciate the rationale behind the graphs and alerts.

Alternate approach is to use data mining techniques to raw data and then compare the results to a guideline (e.g. [10]) This approach can be exploited either to improve the guideline or to detect exceptions in clinical workflow.

Conclusion

Authors extended the scope of previous research [1] by adding visualizations for individual patients as well as new types of alerts taking into account more than just one transition or just one therapeutic state. This approach is to be validated by a clinical study in next future.

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References

[1] Gadzhanova, S., Iankov, I.I., Warren, J.R., Stanek, J., Misan, G.M., Baig Z., Ponte, L.: Developing High-Specificity Anti-hypertensive Alerts by Therapeutic State Analysis of Electronic Prescribing Records. JAMIA, 2007; Vol 14, pp 100-109.

[2] Sullivan**,** F., Wyatt, J.C. How computers help make efficient use of consultations**.** BMJ, 2005;331:1010-1012.

[3] Western M, Dwan K, Makkai T, Del Mar C, Computerisation in Australian general practice. Aust Fam Phys 2003; 32(3): 1-6.

[4] Thiru K, Hassey A, Sullivan F, Systematic review of scope and quality of electronic patient record data in primary care. BMJ 2003; 326: 1070-80.

[5] Warren JR, Stanek J, Gadzhanova S, Iankov I, Misan G, Inferring 'therapeutic states' of patients from community electronic prescribing data. eJHI. 2006; 1(1): e5.

[6] Ríha A., Svátek V., Nmec P., Zvárová J.: Medical guideline as prior knowledge in electronic healthcare record mining. In: 3rd Int. Conf. on Data Mining Methods and Databases for Engineering, 25-27 September 2002, Bologna, Italy

[7] Svátek, V., íha, A., Peleška, A., Rauch, J.: Analysis of guideline compliance – a data mining approach. In: Kaiser, K, Miksch, S., Tu, S. W. (ed.). *Computer-Based Support for Clinical Guidelines and Protocols.* Amsterdam, IOS Press, 2004, s. 157–161. ISBN 1-58603-412-X.

[8] Advani, A.,Shahar, Y., Musen, M.A.: Medical Quality Assessment by Scoring Adherence to Guideline Intentions. 2001 Annual AMIA Conference, Washington, DC, Hanley and Belfus 2001.

[9] Aigner, W, Miksch, S.: Supporting Protocol-Based Care in Medicine via Multiple Coordinated Views. Proceedings of the Second International Conference on Coordinated & Multiple Views in Exploratory Visualization 2004.

[10] van der Aalst, W., Weijters, T., Maruster, L.: Workflow mining: discovering process models from event logs. IEEE Trans on Knowledge and Data Eng, 16 (9), 2004.