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A novel clinical decision support algorithm for constructing complete medication histories

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ABSTRACT

A patient's complete medication history is a crucial element for physicians to develop a full understanding of the patient's medical conditions and treatment options. However, due to the fragmented nature of medical data, this process can be very time-consuming and often impossible for physicians to construct a complete medication history for complex patients. In this paper, we describe an accurate, computationally efficient and scalable algorithm to construct a medication history timeline. The algorithm is developed and validated based on 1 million random prescription records from a large national prescription data aggregator. Our evaluation shows that the algorithm can be scaled horizontally on-demand, making it suitable for future delivery in a cloud-computing environment. We also propose that this cloud-based medication history computation algorithm could be integrated into Electronic Medical Records, enabling informed clinical decision-making at the point of care.

1. Background

It is estimated that 82% of American adults take at least one medication, and 29% take five or more medications [1]. Although prescription medication use undoubtedly improves the health and quality of life for millions of Americans, the increasing complexity of their use also comes with a number of disadvantages. Adverse drug events (ADEs) are responsible for nearly 700,000 emergency department visits and 120,000 hospitalizations annually [2] and contribute an estimated $21 billion in wasteful healthcare spending [3]. A meta-analysis revealed that 52% of outpatient and 45% of inpatient adverse drug reactions were preventable [4]. The major cause of many medication errors, including omissions, duplications, dosing errors, or unexpected drug interactions, were caused by a lack of thorough communication of medical information at transition points of care [5].

Continuity of care has been shown to be essential for high-quality patient care [6], with increased continuity resulting in improved outcomes such as better resource utilization, patient satisfaction, and treatment plan compliance, including medication adherence [7]. Continuity of care is not limited to provider continuity, but also includes information continuity, meaning that information on prior events (such as medication history) is used to give care that is appropriate to the patient's current circumstance [8]. Not only is informational continuity highly valued by patients, who identify lack of communication and conflicting information from professionals as a reason for treatment failure and for feelings of reduced confidence in their providers [9], it also has a profound impact on treatment outcomes. Gaps in continuity of medication management are associated with missed doses, recurrence of medical problems, and unplanned hospital readmissions [10].

Despite the clear advantages of maintaining a concise, complete, and accurate medication history, the process of gathering and organizing this medication history can be challenging for several reasons. First, if information is gathered directly from the patient interview, it can be inaccurate. Many patients lack knowledge about their medications or the reasons that they are prescribed certain medications, and others have difficulty remembering everything they take. Over-the-counter drugs and herbal medicines, which can cause drug interactions, are often forgotten [11], and many patients may be too ill, injured, young, or disabled to actively participate in the process [12]. Second, if the medication history is obtained from a hospital, pharmacy, insurer, or other provider, each data source will cover different subsets of medications for different periods of the patient's life. Those data sources also tend to overlap (e.g., prescription, pharmacy records, and insurance records often have the same medication). However, medication lists from multiple sources have different documentation formats, conventions, and coding standards, making it difficult to

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Table 1
Parsing example prescription items.

Prescription	Medication name	Strength	# Each dose	# Doses per day
AMOXICILLIN 500 MG CAPSULE; take 1 capsule by mouth three times a day	AMOXICILLIN	500 MG	1	3
ASPIRIN 325MG EC TABLETS; TK 1 T PO QD	ASPIRIN	325 MG	1	1
ADVAIR DISKUS 50050MCG RED 60S; INL 1 PUFF PO BID APPROXIMATELY 12 H APART	ADVAIR DISKUS	500/50 MG	1	2
PRISTIQ 100MG TABLETS; TK 1 T PO D	PRISTIQ	100 MG	1	1
ZOLPIDEM TARTRATE 5 MG TABLET; take 1 tablet by mouth at bedtime for sleep	ZOLPIDEM TARTRATE	5 MG	1	1

spot overlapping records. These factors make it very difficult to acquire an all-encompassing record of a patient's medication history, such as which medications are taken continuously, which medications have dose changes, which medications have interactions, etc.

Electronic or information technology interventions have demonstrated a significant reduction in medication discrepancies and have decreased the risk of potential adverse drug events [13]. Computer-based approaches facilitate a fast and accurate review of patient medications by automating the process using algorithms to search databases such as RxNorm to compare the names and therapeutic uses of multiple drugs and highlight those that overlap [14]. However, even current automated, electronic reconciliation systems are limited, with user interfaces that are confusing or difficult to read [15], as well as patient medication records that only represent a single-point in time rather than the full spectrum of the patient's medical history.

In this paper, we described our process to create and evaluate an automated, algorithmic solution for medication comparison and consolidation. We demonstrated that when the algorithm is used in conjunction with widely available charting libraries, a visual patient medication timelines could be quickly deployed on any computer with a web browser. We also evaluated the performance and scalability of the algorithm.

2. Development of the algorithm

In order to build a medication history timeline, we needed to take a collection of patient medication records from all sources, including doctor's prescriptions, pharmacy dispensing/refilling records, patient payment receipts, and insurance pay/or payment records. This collection often contained duplicated and overlapping records. For instance, the doctor prescription records and pharmacy sales records often overlapped, as the same medication is prescribed and then purchased. For a typical patient, there is no single data source to provide a complete history – e.g., the patient might see multiple doctors and some of them might not use electronic records; the patient might also buy some medications over the counter using his or her own funds.

Hence, we propose that the algorithm should create a superset of all records related to the patient, and then remove duplicates from the superset to create a set of unique medication records for the patient. It is a computationally intensive process that generally involves the following steps:

2.1. Parse prescription records

From a line of prescription records written in English, the algorithm needs to parse out and extract the following components:

- The name of the medication based on the active ingredient. If the medication has multiple active ingredients, it is called a combination medicine, and its name should be the generic name of each active ingredient separated by "/" symbols.
- The strength and formulation of the medicine. For instance, a medicine might come as "10 MG tablets".
- The prescribing physician's instructions on how many doses (i.e., tablets or injections) the user should take each time they use this medicine.
- The prescribing physician's instructions on how many times per day the user should take this medicine.

Table 1 shows a few examples of prescription items and how they should be parsed into components. These examples show a small sample of the large variety of notations and abbreviations physicians tend to use in their prescriptions. To correctly parse prescription records across multiple data sources, we needed to account for those variations and even potential typos.

The parsing algorithm borrows from established Natural Language Processing (NLP) algorithms. It parses individual words into tokens and then searches for important tokens to derive meaning. However, unlike natural language, prescription records are written in professional jargon and shorthands. Thus, they tend to have an internal structure for factual information devoid of adjectives or sentiments. For instance, each record contains components such as medication name, strength, dose, and frequency, as indicated in Table 1. This allowed us to build regular expression (RE)-based parsers that looked for specific patterns of phrases and combinations of words.

The RE parser needed to analyze highly fragmented text. As of October 2015, the Wikipedia page "list of abbreviations used in medical prescriptions" lists 181 common abbreviations and acronyms in English medical prescriptions [19]. However, there is no national standard on how to write prescriptions. Additionally, the Institute for Safe Medication Practices lists 62 abbreviations in a report named "List of Error-Prone Abbreviations, Symbols, and Dose Designations" [20]. To build an effective parser for such complex and varied text, we took an innovative approach, starting with a simple RE parser, and then evolving and enhancing it by "training" it with a real-world prescription data set. The training process works as follows:

1. We randomly choose 50 prescription records from a national prescription record data set containing one million real-world records.
2. A human coder parses the records and breaks them into components. The human coder has a Doctoral degree in Public Health, but she is not a physician.
3. The RE parser parses the records and generates a report that is compared side-by-side with the human results.
4. Teams of software developers and RE experts review the discrepancy between the human code and RE parser results. They enhance the RE algorithm with more refined rules until there are no errors. We paid special attention to not "overfit" the RE parser to the training records. An RE parser that matches the training set exactly will be able to get the training data 100% accurate, but will have little use for new data. So, we intended to keep the parser generic at the cost of a small percentage of parsing errors. The error is tolerated since the medication history generated from the tool should always be reviewed by a human clinician.