reflection which is carried out by the tutors after each class. And it is the evidence of the PBL method efficiency, stimulates functioning of the Medical Education Centre, the Committee on implementation of new educational technologies, the «TEMPUS» working group and tutors for its improvement.

Thus, the implementation of PBL in educational process of «AMU» JSC, providing tutors and students with necessary conditions for the development of their creative potential, training in small groups and personal oriented environment contribute to the improvement of medical personnel training quality, competences perfection of undergraduates, increase of competitiveness of the Kazakhstan experts in the world market of medical services.

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MEDICAL DECISION SUPPORT SYSTEM BASED ON SEMANTIC PARSING AND TEMPORAL RELATION EXTRACTION

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Medical reports contain huge amounts of data about the patient’s health, medications, recommendations, procedures, etc. which are expressed mostly as narrative text. This information not only comprises the actual health condition of the patient, but also encompasses the past medical experience and events like symptoms, diseases, medications.

Our approach is based on the identification of medical semantic relations [1]. This technology that extracts important data from text is the cornerstone for many clinical applications. Structured information facilitates effective techniques to access and process data, which will result in construction of an intelligent a medical decision support system based on patient's records. This system will help doctors make decisions about the medication as well as plan proper treatment.

The vast majority of the events, including the patient's disease evolution, treatment results, or the effect of medication make sense only when given the corresponding temporal context [2]. Obtaining the chronological order of the patient’s medication can play a vital role in clinical research; e.g. the system can automatically analyze the impact of a vaccine, observing that the disease changes over time.

The process of identifying the chronological order of events is called temporal relation extraction. Our intermediate goal was the construction of a temporal information extraction system for patient’s records. It has been submitted to the ShARe/CLEF eHealth Evaluation Lab 2014 Task 2. [3]

The system performs deep semantic analysis based on dependency parsing. It analyzes the text from the perspective of grammatical relations between the words in the sentence. The structure of a sentence is determined by relation between a word and its dependents.

The system uses a lexicalized parser to annotate grammatical relations between diseases, disorders, and other constituents on a sentence level. Grammatical pattern matching rules are applied in order to annotate the specifics of individual disease/disorder cases.

In our system, a first preprocessing step identifies the sentence in which a mention of disease/disorder exists. The second step is Part Of Speech tagging. It tokenizes the text and labels words with special POS tags. In order to have temporal context we run a rule-based system for recognizing temporal expressions which outputs temporal tagging features. We use SUTime library to find out the time, date and duration occurrences within the records. We have added several patterns for recognizing medical time and date expressions. In the fourth step we perform syntactic parsing – with help of dependency parser we recognize the grammatical relations in the sentence. Given these relations, we precisely extract the modifiers of diseases/disorders mentioned in the sentence.

The parser produces the dependency trees that then are used for the extraction of information about the disorder by means of regular expression matching. For writing domain-specific extraction rules, we used Semgrex util. The proposed approach allows restricting the number of rules. Even simple relation patterns can already annotate a comprehensive number of uncertain disorder indications. Finally we run MetaMap as well as our personal vocabulary look-up to check whether the obtained lexical constituents can be identified and normalized (mapping of biomedical text to the UMLS – Unified Medical Language System – metathesaurus). If this lookup is successful, we output the concept CUI (Concept Unique Identifier).

Moreover, in order to improve the quality of temporal attribute prediction accuracy we apply Machine Learning algorithms on semantically analyzed sentences.

The proposed system can not only extract data and the relevant temporal information but also, as a consequence, construct the timeline of disease/medical events. Although, the timeline itself is not enough to build the decision support system, it can be used as a proxy to analyze and aggregate data.

First, the proper analysis of temporal data of the particular patient will help to build the formal patient clinical record. The decision support system then will leverage this information in order to encourage the doctor to monitor the course of a disease and propose a proper medication. Moreover, the signs of chronic diseases can be automatically identified using specified patterns.

Second, this timeline representation allows for elicitation the temporal relationships between the medical events, which will consequently advance the level of patient care not only for the specific patient, but also for patients with similar symptoms. By virtue of applying machine learning techniques and mining algorithms to a large corpus of temporal data we can extract hidden, yet unknown cause-effect relations between the events and identify implicit side effects of treatment. For instance, the fallout of a combination of several medications used in the therapy of a particular disease for the specific kind of patients can be determined. Based on statistical data the system can create a specific disease records, which takes into account many parameters.

Finally, the system will be able to provide a treatment plan, create preventive care records as well as identify high-risk groups.

Our experiments suggest that the combination of a deep parsing approach and machine learning methods results in an efficient way of extracting temporal information from patient's records. Although the research in temporal relation extraction is challenging, we believe that our approach yields the creation of the medical decision support system, which would have a great impact on patient care.

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