Applying Language Technologies on Healthcare Patient Records for Better Treatment of Bulgarian Diabetic Patients

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The problem

Building the Bulgarian Diabetic Register

- *(i)* keep the established practice of patient registration without burdening the medical experts with additional paper work;
- *(ii)* reuse the existing standard records in compliance with all legal requirements for safety and data protection;
- *(iii)* save time and resources by avoiding multiple patient registrations and disturbance of the diagnostic and treatment process.

Outline

- NLP in the biomedical domain
- Integration platform
- NLP modules
  - Medication extraction
  - Diabetic positive statements extraction
- Experiments and results

Background

Example: “The anamnesis is taken from the patient and medical documentation. He enters the clinic again on the occasion of decompensated diabetes mellitus. Complains from burning pain in the lower limbs…”

- The most important findings about the patients are kept as free texts in various documents and languages.
- These text descriptions are usually oriented to human readers.
- Thus Information Extraction (IE) becomes the dominating natural language processing (NLP) approach to biomedical texts.

BITool

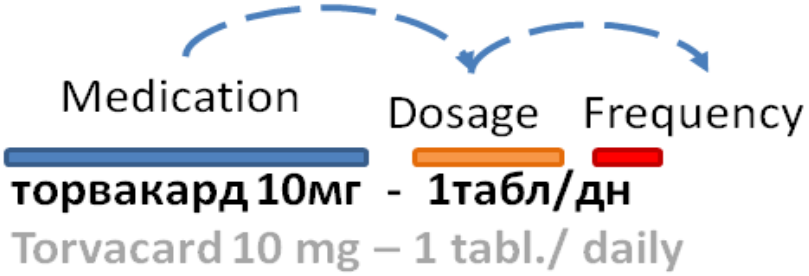
- Integration platform of the analyses performed on the medical data.
- Business Intelligence tool can deliver various types of findings to decision makers in order to improve the public health policy and the management of Bulgarian healthcare system.
- The data of the Health Insurance Fund contains a lot of information that is structured using codes of medical classifications and nomenclatures.
- In this study we are interested in the analysis of free texts and capturing some essential entities described there.
- By means of NLP techniques integrated with the *BITool* we discover the potential diabetic patients which were not formally diagnosed with diabetes.

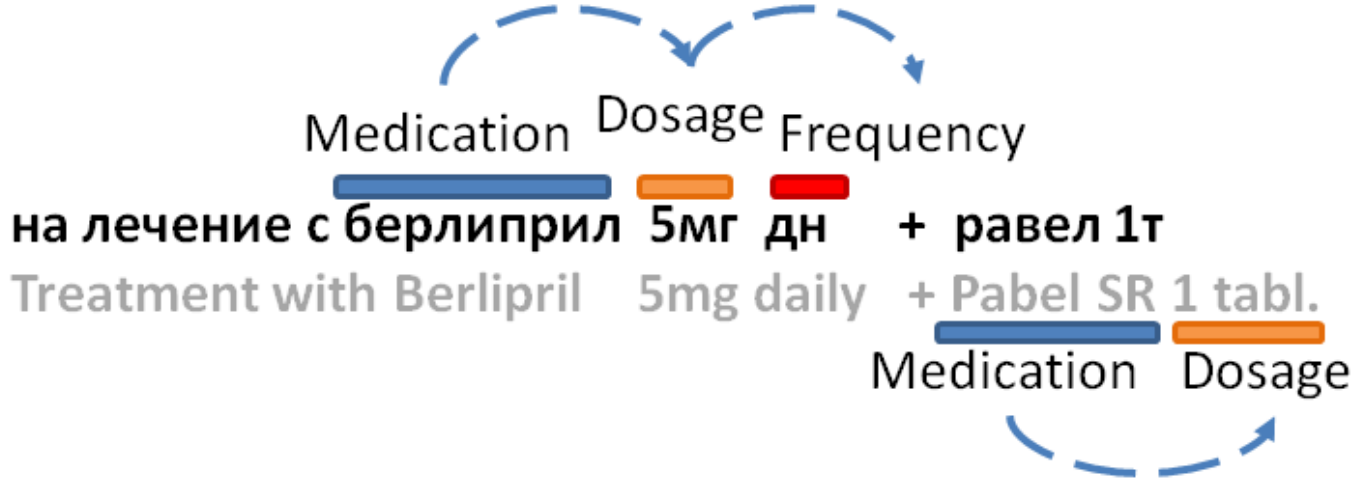
Knowledge Discovery

(*i*) the **medical treatment** – if the patient has diabetes he/she would also take appropriate drugs

(*ii*) **statements in the anamnesis** about the patient having diabetes or its complications.

Regular expressions of linguistic patterns for analysis of Dosage





Structuring drug treatment information

- Automatic procedure analyses the free texts in the *Prescribed treatment* section:
  - drug names;
  - dosages;
  - modes of admission;
  - frequency and treatment duration
- Assigns the corresponding ATC and NHIF codes to each medication event.
- Using regular expressions to describe linguistic patterns.
- More than 80 different patterns for matching text units deal with the ATC and NHIF code, medication name, dosage and frequency.

Drug extractor performance

- The extractor handles 2,239 drugs names included in the NHIF nomenclatures
- Manual evaluation on 33,641 diabetic patients for 2013
  - precision - 95.2%
  - sensitivity - 93.7%
  - The labelled data is split to 20 equal subsets and randomly selected records are evaluated by an expert (about 40% of each subset). The average of the subset evaluation is the final score of the module.

Drug extraction - error analysis

The major reasons for incorrect recognition of drug events are:

- misspelling of drug names;
- drug names occurring in the contexts of other descriptions;
- undetected descriptions of drug allergies, sensibility, intolerance and side effects;
- drug treatment described by (exclusive) *OR*;
- negations and temporally interconnected events of various kinds:

  - undetected descriptions of cancelled medication events;

  - of changes or replacements in therapy;

  - of insufficient treatment effect and change of therapy.

Drug extraction - error analysis

- About 30% of the medication events in the test corpus are described without any dosage.
- Lack of explicit descriptions occurs mostly for treatment of accompanying diseases.
- After applying the recognition algorithm and default daily dosage, the number of records lacking dosage reduces to 15.7% in the final result.

Discovering potential diabetic patients

- Medical experts propose criteria for happening of the event "*having diabetes*": e.g. high blood sugar or high glycated hemoglobin in the text of the section *Lab test results* or
- Admission of drugs used for diabetes treatment mentioned in the *Anamnesis, or*
- Statements in the *Anamnesis* describing diabetes or its symptoms.

Input data

- Chunks extracted from a concordancer built for the string *диабет* (*diabetes*).
- 67,904 distinct chunks extracted from the records of 156,310 patients who are not formally diagnosed with diabetes.
- Chunks contain the word *diabetes* and a 6-token window of its left and right context.

Our goal is: classify the chunks according to the hipotesis “has diabetes”.

Example chunks

Sample chunks which demonstrate the variety of positive and negative examples:

(i) NEG Фамилност- обременен/а-**диабет**ици по майчина линия/.
*Family - heredity - **diabet**ic on maternal line.*

(ii) NEG Необходимо е изключване на стероиден **диабет**; насочва се към ТЕЛК...
*It is necessary to exclude steroid **diabet**es; re-directing to TEMC...*

(iii) POS Покачва кръвно налягане. Има **диабет**. Оплаква се от сърцебиене...
*Raises the blood pressure. Has **diabet**es. Complains of palpitation...*

Rule-based rough filtering

- Most of the input chunks are negative examples.
- About 10% of the input records match several patterns of negative examples

  “*no evidence about diabetes*”,

  “*no diabetes in the family*” etc.
- With a set of 41 expressions in the filter, the number of chunks was reduced to 26,000 (about 1/3 of the initial corpus size).

Supervised classification of positive/negative examples

- Two random subsets were annotated:
  - one of 282 documents – development set used for feature selection
    - 74 positive and ;
    - 208 negative examples;
  - one of 1,000 documents – used for testing
    - 187 positive and;
    - 813 negative examples.

Classification overview

- Several algorithms on the same dataset: NaiveBayes, J48, SVM and JRip, all with boolean features - JRip and J48 performed best.

- Classification with nominal features with MaxEnt algorithm - outperformed all the rest in means of precision.

Experiment 1

- 93 features which correspond to stems of terms occurring in the text of **positive examples** (excluding numbers).
- J48 recognised only 63.1 % of the positive examples
- JRip recognised 91.2%.
- The rules inferred by JRip are only 2 but obviously they fit well the data.

Rule 1*:* (*family*) = *false*) and (*sugar* = *true*) and (*noninsulindependent*= *true*)

=> class=pos (30.0/2.0)

Rule 2*:* (*family* = false) and (*sugar* = true) and (*treat* = true)

=> class=pos (6.0/0.0)

Experiment 2

- 112 textual features which correspond to the stems of terms occurring in **positive and negative examples**.
- The terms are pre-filtered manually by an expert.
- JRip and J48 performed worse than in the first experiment and scored precision under 70%.

Results from Experiments 1 and 2

	Exp. 1: 93 pos features; stems only; 10-fold cross-validation						Exp. 2: 112 pos/neg features; stems only; 10-fold cross-validation					
	JRip			J48			JRip			J48		
Class	P	R	F	P	R	F	P	R	F	P	R	F
positive	91.2	16.6	28.1	66.7	21.4	32.4	61.1	29.4	39.7	65.8	52.4	58.3
negative	83.9	99.6	91.1	84.4	97.5	90.5	85.5	95.7	90.3	89.5	93.7	91.6
w eighted avg	85.2	84.1	84.1	81.1	83.3	79.6	80.9	83.3	80.8	85.1	86	85.4

Experiment 3

- Automatic feature-selection
- The initial feature set contained 10,576 attributes
- Applied on it the chi-squared attribute evaluator implemented in Weka
- 151 features were selected
- JRip - **65.3%** precision when adding bigrams and **73.1%** when adding trigrams
- J48 - **86.1%** precision and **87.2** when adding trigrams
- In the tree built by J48 one could clearly see the importance of bigrams and trigrams features
- Out of 17 tree leaves, only 4 are unigrams; the rest are bigrams and trigrams.

Results from Experiment 3

	Exp. 3a: 151 automatically selected stem features + bigrams; 10-fold cross-validation						Exp. 3b: 151 automatically selected stem features + bigrams + trigrams; 10-fold cross-validation					
	JRip			J48			JRip			J48		
Class	P	R	F	P	R	F	P	R	F	P	R	F
positive	65.3	41.2	50.5	**86.1**	36.4	51.1	73.1	40.6	52.2	**87.2**	36.4	51.3
negative	87.5	95	91.1	87.1	98.6	92.5	87.6	96.6	91.9	87.1	98.8	92.6
weighted avg	83.4	84.9	83.5	86.9	87	84.8	84.9	86.1	84.5	87.1	87.1	84.9

Experiment 4

- Trained a model with **MaxEnt** using
  - all textual features plus bigrams and
  - all textual features plus bigrams and trigrams as nominal values
- Similar results in both experiments.
- Outperformed J48 and JRip in means of precision.
- The best precision on positive examples was reached when including bigrams and trigrams 91.5%
- MaxEnt with nominal features has the advantage that the features are not pre-set

Results from Experiment 4

	MaxEnt					
	Exp. 4a: all stems + bigrams; 10-fold cross validation			Exp. 4b: all stems+bigrams + trigrams; 10-fold cross validation		
Class	**P**	**R**	**F**	**P**	**R**	**F**
positive	91.3	22.6	36.2	**91.5**	20	32.8
negative	85.6	84.2	85	85.6	84.2	84.9
weighted avg	88.45	53.4	60.6	88.55	52.1	58.9

Results from Experiments 1 and 2

	Exp. 1: 93 pos features; stems only; 10-fold cross-validation						Exp. 2: 112 pos/neg features; stems only; 10-fold cross-validation					
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Results from Experiment 3

	Exp. 3a: 151 automatically selected stem features + bigrams; 10-fold cross-validation						Exp. 3b: 151 automatically selected stem features + bigrams + trigrams; 10-fold cross-validation					
	JRip			J48			JRip			J48		
Class	P	R	F	P	R	F	P	R	F	P	R	F
positive	65.3	41.2	50.5	**86.1**	36.4	51.1	73.1	40.6	52.2	**87.2**	36.4	51.3
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weighted avg	83.4	84.9	83.5	86.9	87	84.8	84.9	86.1	84.5	87.1	87.1	84.9

Results from Experiment 4

	MaxEnt					
	Exp. 4a: all stems + bigrams; 10-fold cross validation			Exp. 4b: all stems+bigrams + trigrams; 10-fold cross validation		
Class	**P**	**R**	**F**	**P**	**R**	**F**
positive	91.3	22.6	36.2	**91.5**	20	32.8
negative	85.6	84.2	85	85.6	84.2	84.9
weighted avg	88.45	53.4	60.6	88.55	52.1	58.9

Error analysis

- The positive examples in our database are so rare that the data quality has major impact on the training – misspellings, mixed Cyrillic and Latin names, numbers.

- Having a larger corpus and having more golden data will help for learning better the patterns of positive examples.

- Nevertheless the current results show that such a hybrid method combining rule-based and machine learning approach can be used to prove the hypothesis *having diabetes* with high precision.

Summary

- The IE modules are exploited quite carefully, for extraction of a limited number of entities and events only.
- They are tested in various scenarios and gradually improve their performance using hybrid rule-based and machine learning approaches.
- Automatic extraction from the records' free text essential entities related to the drug treatment such as **drug names**, **dosages**, **modes of admission**, **frequency** and **treatment duration** with precision **95.2%**;
- Classification the records according to the hypothesis "*having diabetes*" with precision **91.5%**
- Deliver these findings to decision makers in order to improve the public health policy and the management of Bulgarian healthcare system.
- Large-scale analysis of medical texts can be viewed as a reliable technology if the input is well-structured into zones and the extraction task has clear and well-defined target entities.

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