

PeopleSave: Recommending Effective Drugs Through Web Crowdsourcing

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Abstract—In this paper, we describe PeopleSave - a drug recommendation and feedback system for doctors on the basis of contextual patient reviews crowd-sourced from the Internet. Unlike other systems proposed in the past, we filter information sources to check for crowdsourcing feasibility and then assess the drug's effectiveness based on its reported detrimental effect on a patient. This helps in eliminating certain drugs that would almost certainly have an adverse effect on the patient's health and thereby obtain a set of recommendable drugs. These recommendations are further refined by analyzing the sentiment behind the opinions of patients who have been administered these drugs in the past. The resultant set of prescribable drugs agrees with those suggested by the consulted physicians for the considered sample set of diabetes patients. The critical assessment of the prototype system for Diabetes Type II drugs by both doctors and patients also reiterates the need for a feedback system that can possibly go a long way in improving patient experience of a drug. This leads us to conclude that PeopleSave, as a combination of the recommendation system prototype and the proposed feedback system, can be successful in improving the process of prescription of medicines for a varied range of medical conditions.

I. INTRODUCTION

The major roadblock in health-care till date has been insufficient diagnosis of the disease as well as unawareness of the patient's medical history. Even with paramedics prescribing medicines for the diagnosed problem, sometimes the medicines are ill-suited to the patient due to known or unknown allergies to certain drugs. It is common knowledge that drugs, especially commercially synthesized medicines for various medical conditions, bring along with them unavoidable side-effects. This makes it more challenging for physicians to prescribe drugs due to a dearth of comprehensive knowledge of patient response. There is a requirement to organize and structure information from as many patients and physicians possible, to build a case history for the kind of expected effect for various drugs on that person. We believe that crowdsourcing public opinion across different geographical and context domains available online can help understand the effects of drugs and help solve this problem.

To enable this interface between physicians and patients,

we propose PeopleSave - a drug recommendation system for doctors, specifically those treating diabetic patients, on the basis of drug reviews crowdsourced from the Internet. The reviews that we base our system on, as a test case, include information such as the type of diabetes the patient is suffering from, his/her age, gender, the drug they use and the dosage, the period of time they have been using this particular drug and their experience with the drug - its effectiveness in general, any side effects they have been observing, the average Drug Effectiveness Period (DEP) etc. This information is extracted through natural language processing algorithms, from crawled patient feedback on online drug review portals such as WebMD [1], Ask a Patient [2] etc.

As an initial case-study, we focus on drugs and corresponding reviews for treating Diabetes Type II, or *diabetes mellitus* only. Hence, based on the information provided by qualified endocrinologists, we proceed to quantify the degree of side-effects encountered by patients which serves to determine the level of severity associated with that particular side effect. This, coupled with the frequency of occurrence of the side effects among consumer reviews, yields a 'Threat Value' of drug. On the basis of these Threat Values, the drug recommender system shortlists the most suitable drugs for a particular patient by eliminating drugs that can prove to be harmful or specifically ineffective for that patient's medical conditions. The doctor then applies his own medical expertise and knowledge of the patient's history to prescribe the most suitable drug.

The recommender also proposes a feedback system wherein the patient can rate/review his experience of the prescribed drug. This helps build the knowledge base of the system and thereby improve it. Also, on the basis of the differences between the recommendations of the system and the actual prescription of the doctor and the consequent satisfaction of the patient, this feedback provides insight into the doctor's judgment and prowess. This in turn can act as a metric for rating or ranking doctors.

A major challenge in implementing such a recommender

is ensuring the reviews used to extract information are not false, self-motivated or unsuitable in any other manner. This problem is, to some extent, aggravated by the presence of anonymity. To counter this, we analyze the trend of sentiments towards a particular drug across portals to ensure that the reactions mentioned in patient reviews are sufficiently consistent. In the subsequent sections, the process flow behind PeopleSave is described in detail, and some preliminary filtration and drug elimination is demonstrated as an example.

II. RELATED WORK

Although there has been substantial work done in the area of web crowdsourcing and understanding the semantics of natural language text, we restrict ourselves to explore work relevant to the medical domain, more specifically for recommending and understanding the effect of prescribed drugs and therapies.

Natural Language Processing. Using algorithms to make systems understand human languages has been a much explored domain, including studies on implementing Natural Language Processing in the field of medicine, as shown by Spyns in [3]. The study sheds light on medicine-oriented NLP systems such as the Linguistics String Project - Medical Language Processor of New York University that enables physicians to intelligently retrieve information, RECIT - a multilingual system to analyze medical sentences and jargon, Aristote - a system to create databases for research purposes from pathology reports, Medi-cat which indexes symptoms and diagnoses from discharge summaries and various other partial NLP systems. However, most of these systems focus primarily on radiology reports only. Another drawback of these systems is the language independent but domain dependent nature of medical knowledge that hinders their scalability.

In this paper, we focus on diabetes as a domain but concurrently aim to keep the system flexible enough to be used for recommending drugs for other medical conditions. This is possible due to the availability of a wide range of online patient reviews across different medical disorders. We extract these reviews from drug review portals and analyze them using the Natural Language Toolkit [4], which is a free, open source, community-driven platform for building Python programs to work with human language data.

Sentiment Analysis. As pointed out by Pang and Lee in [5], sentiment analysis has great potential of providing access to opinion-oriented data. The analysis of medical text to glean its sentiment has been researched to some extent in [6] by Yun Niu et al. In their study, the authors have tried to learn the polarity of clinical outcomes and using the information so extracted to help answer the questions posed by clinicians. It shows that the combination of linguistic features and domain knowledge features leads to good classification performance. We take this work further and analyze patient review sentiments, keeping in mind the domain knowledge, in order to rank drugs based on their overall user-satisfaction sentiment.

Crowd-sourcing Medical Data. Although the idea of using online patient submitted reviews has been explored in the past in studies such as [7] by Liu et al., their research has mainly been focused on discovering side-effects of drugs from crowd-sourced data. We believe that data so obtained can be utilized to a much greater extent - to recommend suitable drugs for doctors to prescribe. Such assistive systems for medical experts have only been conceptualized using data sourced from biomedical literature, not patient reviews, in [8]. Another study, by Armstrong et al., [9] tries to validate the integrity of these patient reviews by comparing them to results of clinical trials. The inferences drawn from their comparison allow us to conclude that such reviews are credible enough to base our recommendation system on. In this work, we suggest further ways to independently validate such crowd-sourced data and also discuss the feasibility of, and suggest a model for, implementing it as a model for drug recommendation.

III. EXTRACTION AND FEASIBILITY OF USING CROWDSOURCED DATA

A. Processing Crowdsourced Data

1) *Sentiment Analysis:* The automatic sentiment analysis has been achieved by experimenting with SentiStrength [10] and the AlchemyAPI [11]. SentiStrength provides an estimate of the positive and negative sentiment in short texts by reporting two kinds of sentiment strengths: -1 (not negative) to -5 (extremely negative) and 1 (not positive) to 5 (extremely positive). We use the `computeSentimentScores()` functionality of the SentiStrength API where we pass the string as the input and it returns the positive and negative sentiment. The AlchemyAPI's Sentiment analysis feature provides easy mechanisms to detect positive or negative sentiments within documents by looking for words that carry positive or negative connotations and computes the overall positive or negative sentiment between -1 and 1.

Consider the patient review: 'Works very well, but weight loss is a problem'. SentiStrength will return a positive value of 2 and negative value of -2. We can see that the estimate appropriately matches with the general understanding of the sentence. While SentiStrength does work adequately for similar reviews, it falls short in judging reviews that are not quite straightforward. Consider the review: 'I feel great when taking Alavert. No exhaustion, nightmares, irritability, or weird dry/thick congestion feeling. Will never go back to other antihistimine again.'. SentiStrength assigns an overall negative sentiment of -3 and positive sentiment of +3, adding up to a neutral score of 0 (not positive). It is evident that the review in question is strongly positive, which is not the result secured from SentiStrength. Whereas in Alchemy API the same review produces a positive sentiment value of 0.7 (Considerably positive). It is obvious that this is a fitting estimate of the sentiment in the review. As inferred by Jongeling et al. in [12], the scores obtained from SentiStrength do not necessarily tally with those from other sentiment analysis APIs. We reassure the same empirically for drug review data, by drawing up a comparison of normalized sentiment scores

Website	Number of Drugs Reviewed	Number of Reviews Extracted	Features of each Review
webmd.com	7	3476	Ratings, Comment, Age, Gender, Duration
drugs.com	6	463	Ratings, Comment, Duration
askapatient.com	6	1326	Ratings, Side Effects, Comments, Gender, Age, Duration, Dosage

TABLE I
DETAILS OF REVIEWS COLLECTED FROM SOME OF THE PORTALS

Review Sentiment	AlchemyAPI Score	SentiStrength Score
Highly Positive	0.71	0.3
Slightly Positive	0.41	-0.003
Neutral	0.08	0.41
Slightly Negative	-0.48	0.17
Highly Negative	-0.711	0.1

TABLE II
COMPARISON BETWEEN ALCHEMYAPI AND SENTISTRENGTH

of both APIs (as provided in Table II) for review sample sizes ≥ 30 . This leads us to conclude that AlchemyAPI’s Sentiment Analysis feature fares better in accurately estimating the polarity of reviews than SentiStrength does. Hence the further analysis in our work has been carried out by utilizing AlchemyAPI.

2) *Side-Effect Classification*: The reviews gathered from the crowd-sourced data are processed using the Natural Language Toolkit (NLTK). Using it, we first tokenized the data, i.e., split it into one-word long tokens from actual sentences. This was followed by tagging the tokens - assigning a tag to each word that describes what kind of word it is (a noun, adjective, conjunction or preposition, for example). Grouping tokens into tags helps evaluate the different groups and select the relevant tokens for further analysis. In our case, we proceed with only the tokens that have been tagged as nouns or verbs.

The identified and tagged tokens are then examined and analyzed using the n-gram language model described in [13]. Herein, an n-gram is a sequence of n consecutive words from the review that might be identifiable as a possible side-effect. On identifying a k-gram as a side-effect, the (k-1)- to 1-gram occurrences of the same are ignored.

For example, if "pain in joints" is a sequence of words in a patient’s review, it is identified as a side-effect in the 3-gram analysis and is pinpointed as an equivalent to "joint pain". Thereafter, "pain in" and "pain" are ignored in the 2- and 1-gram iterations of the analysis. This ensures that each reported side-effect is taken into consideration and also no side-effect is counted more or less times than it has been reported.

B. Feasibility through Sentiment Analysis

The crowd-sourced patient reviews and comments need to be analyzed to obtain the contextual sentiment polarity behind the comments, in order to enhance the recommendation system by imparting a perspective on general customer satisfaction with the drug, hence the efficiency can be judged through analysis of patient reviews and comments. The data in Table III is a representation of the average values of

the sentiments of six distinct drugs accumulated from three different portals.

The feasibility test examines the similarity of responses to drugs across various domains, the consistency of which is an indicative factor of drug effect standards. The domains are chosen to be geographically diverse in order to acquire ample information to exhibit and examine whether the domain difference induces any characteristic disparity in the responses to various drugs. Assessment of the similarity of patient reviews across the different portals is achieved by calculating the Similarity Factor (SF), which is obtained by employing the values of number of observations(n) and the sum of squared difference of normalized sentiment values of reference(R) and test(T) portals [14]. The Similarity Factor for a particular drug j ,

$$SF_j = \sum_{i=1}^n (R_{ij} - T_{ij})^2$$

A low similarity factor is an indicator of consistency of patient reviews for a particular drug. This also has the potential to be a deciding factor in the validity of the crowdsourced information, as a vast number of people across diverse geographical domains having similar responses to the same drugs implies that the data is indeed genuine. The low SF also indicates the practicability of recommending that particular drug across disparate domains.

C. Feasibility through Hybrid Approach

A side-effect categorization and classification method is implemented by grouping together semantically similar side-effects that have been extracted from crowdsourced reviews and the summed-up frequency of occurrences of the aforementioned side-effects. This human-machine collaborative approach emulates a best-attempt bag-of-words model used in natural language processing, since it is difficult to directly implement it due to the non-standardized descriptions of the side-effects in reviews of general, untrained patients.

The data in Table 4 represents the normalized frequency values of sets of similar side-effects of a particular drug across the said portals. We then calculate the similarity scores in a manner analogous to that described in the previous subsection. A low similarity score suggests that the reported side-effects are common across portals and are indeed genuine. This validates the use of the recurrence factor of these side-effects in eliminating unsuitable drugs.

IV. DRUG ELIMINATION AND RECOMMENDATION

Once we have established the coherence of information crowdsourced from the review portals, we consult qualified

Review Portal	Actos	Byetta	Glucophage	Janumet	Januvia	Victoza
webmd.com	-0.455	-0.391	-0.386	-0.35	-0.396	-0.180
drugs.com	-0.366	-0.387	-0.527	-0.320	-0.314	-0.394
askapatient.com	-0.437	-0.303	-0.340	NA	-0.412	-0.338

TABLE III
COMPARISON BETWEEN AVERAGE SENTIMENT SCORES ACROSS PORTALS

Review Portal	Muscle Pain	Gastrointestinal Problems	Weakness or Dizziness
webmd.com	0.1202	0.80	0.796
drugs.com	0.1003	0.83	0.0697
askapatient.com	0.0911	0.854	0.0549

TABLE IV
COMPARISON OF NORMALIZED FREQUENCIES OF SIDE-EFFECTS OF GLUCOPHAGE ACROSS PORTALS

diabetes doctors and endocrinologists to understand the underlying ontology of drug therapy in diabetes explained in [15]. The processes are a key procedure in drug recommendation. Also, as against recommending a drug, which might be unsuitable or unavailable in the vicinity of the patient, we were advised to understand various hazards of the negative effects and negative sentiment of a drug and use drug elimination instead of recommendation. As per the endocrinologist panel, the advice against recommending a particular drug depends broadly on the patient's hazard factor and the effect's recurrence factor as per the reviews. The algorithm for quantifying the threshold of acceptance for recommending/eliminating a drug is based on the factors given below.

A. Dependence on Hazard Factor

The first layer of decision making is based on the Hazard Factor (HF) of each particular side-effect of the drug - the general level of adverse effect it may have on any patient, as determined by a qualified domain expert. For example, the general degree of seriousness of cardiac problems always exceeds that of cough or other flu-like symptoms. This would thus result in cardiac arrest being assigned a larger HF value.

As domain expertise is essential for the accurate assignment of HF values, we consulted a qualified endocrinologist to rank all the side-effects reported in the crowd-sourced data and assign them an HF value between 0 and 1. This ranking has been made keeping in mind a general notion of the degree of threat a certain side-effect poses to the life and health of a normal adult, without taking into account any other patient-specific medical conditions or medical history.

The HF value of the i^{th} side-effect is represented in the calculation of the Threat Value (described in section IV. D.) as HF_i .

B. Dependence on Recurrence Factor

The next layer is based on the Recurrence Factor (RF) of each specific side-effect of the drug. The RF value describes the frequency with which a particular side-effect has been reported in the data obtained from crowdsourced online reviews. The actual number of times a side-effect appears in the data is normalized to give the RF value. For example,

if out of the reviews of 100 patients of the type 2 diabetes control drug Actos, "headache" has been mentioned a total of 72 times and other recognizable side effects have been mentioned 127 times, the normalized RF score for headache is given by

$$RF_{headache} = 72 \div (72 + 127) = 72 \div 199 = 0.3618$$

The RF value gives the statistical likelihood of a patient, who is being considered for recommending a drug to, experiencing the same side-effect if he/she is administered that particular drug. The normalization of the occurrence is essential in order to gauge the influence of a particular side-effect in relation to others.

The RF value of the i^{th} side-effect is represented in the calculation of the Threat Value as RF_i .

C. Dependence on the Patient

The last layer is built upon the Personalized Hazard Factor (PHF) for a patient's definite reaction to the drug. This is characterized by the threat posed by the specific side-effect on the individual and is essentially dependent on a patient's individual case history which, among other useful case-dependent parameters, also contains records (if any) of overdoses or missed doses. For example, for a person with low BMI (< 18.5), any further weight loss is not advisable. Hence, the PHF of weight loss for this person would be substantially high.

Assuming that adequate patient medical history is available, PHF values can be assigned to each side effect by his/her physician as a score ranging from 0 to 1. This ensures that the drug recommendation process is more target specific and also considerably increases the effectiveness of the treatment.

The PHF value depends not only on the side-effect under consideration but also on the patient for whom the drug recommendation is sought. Therefore, in the calculation of the Threat Value, it is represented as PHF_{ij} for the i^{th} side-effect for the j^{th} patient.

D. Determination of Threat Value

The Threat Value is the quantification metric in the entire process of drug recommendation. The TV is represented as

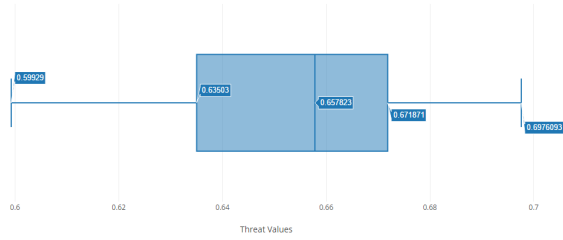


Fig. 1. Average Threat Values across portals for six different Drugs

a product of the HF, RF and PHF, and therefore provides an accurate method upon which the drugs can be ranked, and subsequently eliminated to provide an exclusive list of relatively more recommendable drugs.

Without access to a patient's medical history records and a physician's cognizance of his allergies or medical aversions, the TV of a distinct side-effect of a particular side-effect i , TV_i , is defined as the dot product of HF_i and RF_i .

$$TV_i = RF_i \times HF_i \quad (1)$$

Given that patient history is also available, we can further calculate TV specific to the patient. In this case, the TV of a distinct side-effect of a particular side-effect i for a patient j , TV_{ij} , is the dot product of the PHF_{ij} , HF_i and RF_i .

$$TV_{ij} = PHF_{ij} \times RF_i \times HF_i \quad (2)$$

The total TV of the drug is determined by the summation of the TVs of all of the side-effects of that particular drug. If the total number of side effects of a drug is n , the total threat value of the drug is given by

$$TV_{total} = \sum_{i=1}^n TV_i \quad (3)$$

V. IMPLEMENTATION AND PRELIMINARY RESULTS

Once it has been established that the reviews are sufficiently valid to be used as a firm basis for drug elimination, we proceed to calculate and record the average Threat Values of each drug across various portals. In our PeopleSave prototype, The scores of TV for drugs based on reviews crowd-sourced from multiple portals are calculated for six specific drugs, used for treating diabetes mellitus, using Equation (3). Here, we describe an illustrative elimination process where, due to the lack of personalized medical history of patients, the PHF value is not taken into consideration.

A. Drug Elimination

Step 1. At the first level, we eliminate drugs on the basis of the total threat value of the drug, as per the side-effects reported by the patients on all portals. Figure I shows the box-plots depicting TVs of six different drugs averaged across the set of portals under observation. We use the process of outlier elimination and based on the specificity

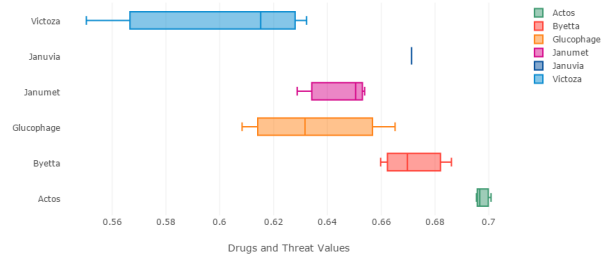


Fig. 2. Range of Threat Values of different drugs across portals

requirements of the physician, eliminate drugs that have a TV more than $n \times \sigma_s$ from the μ_s (where σ_s and μ_s are obtained from the average TV data series cumulative from all portals under observation) - $n \in \mathbb{Z}^+$, where n denotes the level of confidence in the system, simply based on threat values. As per this process, with $n = 3$, the drug Actos is most hazardous with its threat value being \geq the outlier threshold, which is 0.69.

Step 2. The subset of recommendable drugs are further filtered by the inferences that can be made from the data represented in Figure II. This figure represents the range of Threat Values of different drugs across various portals by means of box-plots. All drugs whose Total Threat Values fall below the decided threshold are included in the set of recommendable drugs. However, the high dispersion of Threat Values across the different domains in case of Victoza indicates the inconsistency of patient reviews and hence cannot be used as a credible indicator of the general effectiveness of the drug. Hence it is advised that Victoza either be not recommended or the physician be completely aware of the extensive effects of Victoza on the patient to be prescribing it.

B. Enhanced Recommendations

After elimination of drugs, the obtained set of recommendable drugs are ranked based on their overall sentiment scores calculated using the Alchemy API. This ranking demonstrates the comprehensive patient satisfaction including how effective the drug is and if he/she has been adversely affected by it in any way.

Figure III shows the cumulative distribution functions of the AlchemyAPI sentiment scores of the various drugs. This plot proves to be effective in enhancing the recommendations by helping us visualize the general patient sentiment towards each drug, e.g. Janumet is reported to have a relatively more positive sentiment than the other drugs in the recommendable set, like Januvia or Glucophage.

The list of prescribable drugs, along with the inferences made from the cumulative distribution function plots of sentiments, is then presented to the attending physician who would be able to make a more informed choice of drugs to prescribe if he is equipped with information about how a general patient has reported to be affected by the drug.

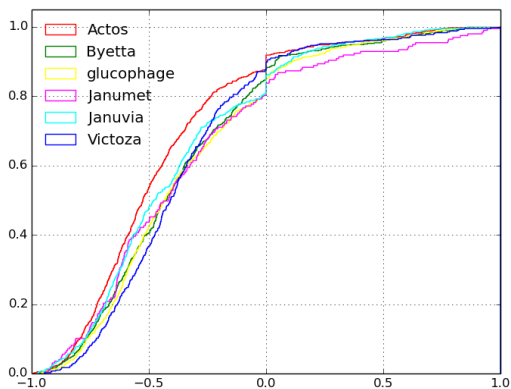


Fig. 3. Cumulative Distribution Functions of the AlchemyAPI Sentiment Scores of Various Drugs

This general notion, obtained through the process described in III.B, in conjunction with the recommended and ranked list of drugs, adds to the effectiveness of the prescription as it enables dynamic recommendations adjusted to these reviews.

VI. CONCLUSION AND FUTURE WORK

In this work, we presented PeopleSave - a crowdsourced medical review analysis system for drug elimination and recommendation. Preliminary results demonstrate that there is sufficient coherence amongst the crowdsourced data across different geographical and ontological domains, which is a desired metric for being able to confidently eliminate or recommend a subset of drugs from a given set of available medicines. Implementing this system can work as a great tool for doctors to make use of a large number of similar past cases on the basis of which to treat a particular patient. It will thereby ensure that each patient is treated in the most case-specific and efficient manner possible, even while making allowance for the fact that each case is unique with respect to the others.

Furthermore, we also draw attention to the lack of contextual patient reviews on the Internet. Though numerous drug review portals exist and provide useful information to doctors and patients, more detailed reviews with information about, say, the geographical region the patient is located in, the glucose levels of the patient, their height, weight and body mass index (BMI), insulin levels, plasma glucose concentration and other medical history including major illnesses or surgeries in the past and pregnancy history for women can help further narrow down the list of prescribable drugs and can go a long way in improving such recommendation systems. Information from non-invasive medical sensors can considerably further the systems effectiveness while prescribing drugs or long-term therapy by transmitting instantaneous reports to the doctor or physician, who can gauge these reactions to be either effective or detrimental in the long term to the patient.

In future work, we aim to use continuous sensor streams from clinical machines and smart sensors to gauge the effec-

tiveness rate and period of various similar class drugs across multiple patients. Numerous health sensor data can significantly enhance the drug recommendation system by providing accurate instantaneous information which makes judging patients' responses to drugs easier and more efficient. For example, periodic assessments of blood glucose levels from Smart Sensors like Gluco-wise [16] after being administered a particular insulin-based drug can reveal whether the glucose levels are actually diminishing or not and can also provide alerts if the glucose levels fall below the recommended threshold. Other sensor data such as heart rate and SP_{O_2} obtainable from [17] and [18] can be similarly effective in improving recommendations. Also, on completion of our ongoing process of association with Multi-speciality hospitals and the Central Drugs Standards Control Organization, we will be able to directly tap into the reservoir of patient data to examine change in glucose levels from HbA1c tests, and other attributes from the patient's pathological reports, which will help further remove the divide between prescription and effect of diabetic medication, and possibly more diseases in the near future.

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