EVALUATING ANTI-HYPERTENSION MEDICATIONS USAGE ON PATIENT CARE ONLINE BLOGS

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Abstract— Throughout history, the area of drug discovery and development has been a financial strain due to the associated high costs. In order to offset this financial burden, drug companies are continually increasing the price of medications to consumers. Some consumers remain unaware of the types of medications available on the market and the gap in cost between these types. The two main types of medications available on the market are: 1) Generic drugs and 2) Brand name drugs. The purpose of this paper is to examine the similarities and difference of generic and brand name drugs from patient's reviews at major medications blogs like dugs.com. A subjectivity sentimental analysis framework has been developed that can effectively score these reviews without going into the complexities of using natural language or machine learning approaches. The developed framework use a well-known rule based subjectivity API known as VADER besides an effective web crawler. Results of this analysis shows more sentiments are with the generic antihypertension drugs compared to the brand drugs. The validation of these results was based on Google Trends. More concrete analysis of the results on wider list of medications as well as more blogs is left to our future work.

Keywords— Sentimental analysis, Antihypertension drugs, Branded drugs, Generic drugs, Web crawling, Text analytics

1. INTRODUCTION

Recent trends regarding causes of death and age-adjusted incidence of major cardiovascular events in the United States have shown an impressive decline in the risk of myocardial infarction and stroke [1] which have been attributed to better preventive therapies, including the use of drugs to lower blood pressure (aka hypertension) [2]. However, many antihypertensive drugs are now available in generic formulations at fractions of the cost of their branded counterparts. According to the FDA regulations, a generic drug product is one that is comparable to an innovator drug product in dosage form, strength, route, quality, performance characteristics and intended use. The FDA rules are tagged as “abbreviated” because they do not require going through clinical trial data in order to establish safety and efficacy. The only requirement is to show that the generic drug is bioequivalent to the brand drug. The test for such equivalence may include simple laboratory tests like maintaining the same plasma concentration as the brand drug in healthy volunteers. This FDA requirement caused many clinical and pharmaceutical researches to attempt comparing Brand vs Generic drugs. However, this

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comparison has been done without involving the drug consumer's opinions on their usage (branded vs generic). Compared to other industries, pharmaceutical companies are arriving late to the Big Data and Social Media analytics. Historically, pharmaceutical companies have seen tremendous profit margins and thus there were in a position not to take on expansive and technical informatics initiatives to drive their commercial focus. Now, with the healthcare reform and new regulations, the whole picture has been changed. These companies are currently implementing Big Data Analytics strategies for a number of initiatives, including customer targeting, assessing performance, characterizing disease states and patient populations. Actually the ability to access, analyze, and manage vast volumes of data while rapidly evolving the Information Architecture may help to improve the efficiency of the drug discovery, marking and development process. In this direction we need to note that Big Data is only helpful when it's the right data, and that can be a struggle for a whole host of reasons when it comes to the issue of comparing the consumer's opinions on hypertension drugs. Analyzing generic data streams on hypertension drugs will be meaningless without distinguishing between single agent hypertension drug class (*e.g.*, diuretics, beta-blockers, calcium antagonists, ACE inhibitors and ARBs) and multi-agent hypertension drug class (*e.g.*, includes two- or more drug antihypertensive drug combination products). Harnessing pharmaceutical big data (aka Big Pharma), and distilling it into relevant insights requires correlating it to the right products to make the information valuable and actionable. This research paper is an attempt to explore using the Big Data analytics in providing insights on the difference between generic and branded antihypertension drugs from patients and consumers point of view through analyzing big data collected from specialized social media blogs like drugs.com¹, webmd² and patientslikeme³ where detailed drug usage reviews are provided.

2. SENTIMENT ANALYSIS FOR MEDICATIONS COMPARISON

Researchers have used various approaches for sentiment analysis. Most of the early studies were focused on document-level analysis for assigning the sentiment orientation of a document or a review [3]. However, these document-level sentiment analysis approaches are less effective when review texts are rather short or complex to be analyzed by simple natural language processing (NLP) and scoring techniques. Even the use of machine learning techniques that overcome the barriers of NLP techniques fails to correctly reflect the context of reviews sentiments as it treats reviews based on bag-of-words model. In this paper we have adopted an approach that computes sentiments of drugs reviews based on the subjectivity of the review text along with the average rating of the drug under review. Our developed approach avoids the difficulties associated with both the NLP approach as well as the machine learning approach. Figure 1 illustrates how reviewers comment and score a drug like Amlodipine. For the purpose of this study we have used twenty two drugs for treating hypertension with the help of a local pharmacist. Table I illustrates the selected drugs and their classification as generic and brand drugs.

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¹ <https://www.drugs.com/>

² <https://www.webmd.com/>

³ <https://www.patientslikeme.com/>

Table I. Antihypertension drug sample.

Brand name	Generic name	Generic available in Canada
Tenormin	atenolol	Y
Norvasc	amlodipine	Y
Adalat XL	nifedipine	Y
Altace	ramipril	Y
Mavik	trandolapril	N
Vasotec	enalapril	Y
Coversyl	perindopril	N
Diovan	valsartan	Y
Atacand	candesartan	Y
Mircardis	telmisartan	Y
Cozaar	losartan	Y

Fig. 1 A Sample of Reviews for Amlodipine

Our approach employs two major components: A drug targeting crawler and VADER API⁴ for scoring the subjectivity of the drugs reviews. VADER [4] is a simple rule-based model for general sentiment analysis, and it is a powerful approach that outperforms in eleven approaches notably other approaches used for sentiment scoring including LIWC, ANEW, the General Inquirer, SentiWordNet, and machine learning oriented techniques relying on Naive Bayes, Maximum Entropy, and Support Vector Machine (SVM). Figure 2 illustrate the workflow sequence of the processes used in our approach.

⁴ <https://github.com/cjhutto/vaderSentiment>

Fig. 2 The Subjectivity Scoring Workflow Sequence.

2.1. CRAWLING DRUG REVIEWS USING SCRAPY

Scrapy is a python application framework for crawling web sites and extracting structured data which can be used for a wide range of useful applications, like data mining, information processing or historical archival. Scrapy defines important methods like `name()`, `start_requests()` and `parse()`. The `parse()` method usually parses the response, extracting the scraped data as dicts and also finding new URLs to follow and creating new requests ([Request](#)) from them. Figure 3 illustrates how we can use scrapy to extract reviews from drugs.com.

```
class MySpider(BaseSpider):
    name = "MyScrapperDrugsCom"
    allowed_domains = ["https://drugs.com/"]

    myfile = open("link2.csv")
    start_urls = []

    for row in myfile:
        for i in range(1,20):
            start_urls.append("https://drugs.com/" + str(row).replace("'", '').strip() + "?page=" + str(i))

    # start_urls.append("https://www.drugs.com/comments/doxycycline/for-acne.html")

    def parse(self, response):
        hxs = Selector(response)
        varDrugName = (hxs.xpath('//div[@class="contentBox"]/h1/text()')).extract()
        varDrugReview = (hxs.xpath('//div[@class="user-comment"]/p[1]/span/text()')).extract()

        # varDrugName = str(varDrugName).replace("User Reviews for", "").replace("[", "").replace("]", "").replace("'", "").strip()
        DrugName = [x.encode('ascii', 'ignore') for x in varDrugName]
        # print DrugName[0].replace("User Reviews for", "").replace("[", "").replace("]", "").replace("'", "").strip()
        name = list()
        time.sleep(5)
        for j in range(len(varDrugReview)):
            name.append(DrugName[0].replace("User Reviews for", "").replace("[", "").replace("]", "").replace("'", "").strip())
            result = zip(name, [x.encode('ascii', 'ignore') for x in varDrugReview])
            myfile = open("FinalReviews3.csv", 'a')
            wr = csv.writer(myfile, quoting=csv.QUOTE_ALL)

        for i in result:
            print str(i)
            wr.writerow(i)
```

Fig. 3 Crawling Drugs Reviews using Scrapy for Drugs.Com

At the end, we can store the data in any format we want. Figure 4 illustrate the resulted data.

```
C:\c2-2\MyScrapperDrugsCom\H115 scrapy crawl MyScrapperDrugsCom
/Users/H115/Desktop/Project/Other/Scrapy/MyScrapperDrugsCom/MyScrapperDrugsCom/spiders/mySpiderDrugsCom.py:71: ScrapyDeprecationWarning: MyScrapperDrugsCom.spiders.mySpiderDrugsCom
MySpider inherits from deprecated class scrapy.spiders.BaseSpider, please inherit from scrapy.spiders.Spider. (warning only on first subclass, there may be others)
class MySpider(BaseSpider):
2017-07-28 17:00:23 [scrapy] INFO: Scrapy 3.3.3 started (bot: MyScrapperDrugsCom)
2017-07-28 17:00:23 [scrapy] INFO: Overridden settings: {'DOWNSPIDER_MODULES': ['MyScrapperDrugsCom.spiders'], 'SPIDER_MODULES': ['MyScrapperDrugsCom.spiders'], 'BOT_NAME': 'MyScrapperD
rugsCom'}
2017-07-28 17:00:26 [scrapy] INFO: Enabled extensions:
['scrapy.extensions.logstats.LogStats',
'scrapy.extensions.telnet.TelnetConsole',
'scrapy.extensions.corestats.CoreStats']
2017-07-28 17:00:28 [scrapy] INFO: Enabled downloader middlewares:
['scrapy.downloadermiddlewares.httpauth.HttpAuthMiddleware',
'scrapy.downloadermiddlewares.downloadtimeout.DownloadTimeoutMiddleware',
'scrapy.downloadermiddlewares.useragent.UserAgentMiddleware',
'scrapy.downloadermiddlewares.retry.RetryMiddleware',
'scrapy.downloadermiddlewares.defaultheaders.DefaultHeadersMiddleware',
'scrapy.downloadermiddlewares.redirect.MetaRefreshMiddleware',
'scrapy.downloadermiddlewares.httpcompression.HttpCompressionMiddleware',
'scrapy.downloadermiddlewares.redirect.RedirectMiddleware',
'scrapy.downloadermiddlewares.cookies.CookiesMiddleware',
'scrapy.downloadermiddlewares.chunked.ChunkedTransferMiddleware',
'scrapy.downloadermiddlewares.stats.DownloaderStats']
2017-07-28 17:00:28 [scrapy] INFO: Enabled spider middlewares:
['scrapy.spidermiddlewares.httperror.HttpErrorMiddleware',
'scrapy.spidermiddlewares.offsite.OffsiteMiddleware',
'scrapy.spidermiddlewares.referer.RefererMiddleware',
'scrapy.spidermiddlewares.urllength.UrlLengthMiddleware',
'scrapy.spidermiddlewares.depth.DepthMiddleware']
2017-07-28 17:00:26 [scrapy] INFO: Enabled tree pipelines:
[]
2017-07-28 17:00:28 [scrapy] INFO: Spider opened
2017-07-28 17:00:28 [scrapy] INFO: Crawled 0 pages (at 0 pages/min), scraped 0 items (at 0 items/min)
2017-07-28 17:00:28 [scrapy] DEBUG: Telnet console listening on 127.0.0.1:6025
2017-07-28 17:00:29 [scrapy] DEBUG: Crawled (200) GET https://www.drugs.com/comments/doxycycline/for-acne.html (referer: None)
['Doxycycline', '"I\'ve been taking this for around a week and a half now, I\'m supposed to take this for 2 months, Haven\'t really seen any change other than my cheeks are clearing
up a little but my forehead is getting worse :("']
['Doxycycline', '"It started to clear up my acne after a few months of taking it, but the side effects were awful. I felt nauseous instantly afterwards and then was also sometimes a
bit, I couldn\'t eat or lie down for at least an hour afterwards and if I did I was guaranteed to be sick. I also had to make sure that I ate beforehand and didn\'t take the medicat
ion on an empty stomach because that would also cause sickness. The reason was the worst part because I had to sit for half an hour feeling sick before I actually was able to
even sleep. I eventually stopped taking it after about a year because my acne had completely cleared up, but then 6 months later it came back... only a temporary fix for me and the s
ide effects of it almost made it pointless."']
['Doxycycline', '"Best effective drug I\'ve taken for acne. DON\'T TAKE WITHOUT A REAL!!! I but really thought everyone said to avoid upset stomach but it came into the side of your
stomach lining if you do this and you can get alcoholics really bad burping/breath around the chin this cleared up immediately. Was able to get off and still have clear skin fo
r 4 year after."']
['Doxycycline', '"I\'m on doxycycline currently I\'ve been on it for 3 months now I was prescribed for 6 months, Acne hasn\'t been waxing... the moment I feel like my skin is cle
aring it takes a few days for the worst, it\'s crazy... if it was my choice I\'d jump on doxycycline the first time I see and not have to worry about this acne any more."']
['Doxycycline', '"This cleared up my skin wonderfully! I occasionally get a couple every now and then but they are small and go away fast. It takes a few months to begin working however."']
['Doxycycline', '"I\'ve been taking doxycycline for about a year now and it is amazing!!!! I had terrible acne during my 7th grade year and had very low self-esteem, so I made my
parents take me to a doctor and he prescribed me doxycycline. He told me it would get worse before it got better! After a month of taking it I could notice the difference and today I
only get an acne spot every 3 months to 4 let\'s be honest and I totally RECOMMEND it!! BUT there are some side effects, do not take it with MILK trust me I was either on the bottom
of a class crying or throwing up!! Also take it with a big meal like dinner. Unless if you want something with MILK for dinner, wait a few hours after drinking the MILK and take it with
some crackers. Hopefully this helped!!"]
['Doxycycline', '"I have been taking this medication for a month at 100mg twice a day. I have had to limit my sun exposure and wear SPF 50+ sunscreen as I have been getting horrend
ous sunburns since I have started taking them. My hands were so burned that they swelled up and blistered, making it very painful to even wash my hands. Every time I go outside, my
anxiety of how much sunburn I am wearing, I am guaranteed to get a sunburn. I was prescribed Bactrim to help with my acne but it is not worth it to me and I will no longer be taking
```

Fig. 4 Snapshot of the Resulted Data from Drugs.com.

We used for visualizing the drugs sentiment data the Django framework⁵. The approach can be better described into two levels. Level 1 illustrates a bird view to the subjectivity sentiment approach that we have used. In level 2 the data flows between the major components of the analysis are described (See Figure 5).

⁵ <https://www.djangoproject.com/>

Fig. 5 Two levels description of the used sentiment approach.

Using our subjectivity sentiment framework we have collected 7976 reviews from the three mentioned drug reviews blogs. With our framework we are able to search for antihypertension drugs from these blogs and score the sentiments on them. Figure 6 illustrates our search for user's reviews on a drug like Norvasc between the periods of 2007-2016.

Fig. 6. Our Drug Subjectivity Dashboard

Based on the results obtained from these blogs we can compare different hypertension drugs. Figure 7 illustrates a comparison between Diovan and Mavac.

Fig. 7 One comparison between two antihypertension drugs

However, in most of the comparisons we have performed we found that the generic drugs have better sentiments compared to the brand drugs. This result may be somehow surprising and for this we decided to go and use the google trends⁶ for validation. In Figure 8 we provide our search for the twenty two antihypertension drugs that we have listed in our table 1. In this figure we are grouping each five drugs in one comparison and providing a final comparison for the winning drugs at the end. We also provide the map for the regions of the world where the drug have more sentiment.

⁶ <https://trends.google.com/trends/>

Fig. 8 Using Google Trends for Validating Our Findings

3. CONCLUSIONS

In this article we have described our initial phase of developing a framework for evaluating the sentiments on antihypertension drugs. The framework described avoids the complexities of using NLP and ML approaches. The sentiment approach uses a rule based approach as defined by the VADER API along with the average rating of the users for each drug as given by the notable drugs blogs like drugs.com. The framework employs an effective crawler based on the python scrapy API as well as using the python Django API for visualization. The crawled results shows more positive sentiments are with the Generic Antihypertension drugs compared with the Branded drugs. We are intending to expand our search and use other methods besides the Google trends to determine with greater confidence the difference between the sentiments when it comes to generic vs branded drugs.

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