Topic Modelling of Patient Opinion

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Masters of Computer Science

Bin Lu

School of Computer Science and Information Technology

Science, Engineering, and Technology Portfolio,

Royal Melbourne Institute of Technology

Melbourne, Victoria, Australia

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Declaration

This thesis contains work that has not been submitted previously, in whole or in part, for any other academic award and is solely my original research, except where acknowledged.

This work has been carried out since TODO:MONTH TODO:YEAR, under the supervision of Dr Jenny Zhang, Dr Daryl D'Souza, Dr Amanda Kimpton.

Bin Lu

School of Computer Science and Information Technology

Royal Melbourne Institute of Technology

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Abstract

Chapter 1

Introduction

Publicly available opinions and service feedback provide valuable informations for decision making for both service providers and consumers. With the help of websites, blogs, forums and social networks, it is never been so easy to express opinions and leave feedback. Analyzing the opinions becomes a challenge, not just because of the quantity of the data, most opinion from general users are free form text. The massive quantity of the data wont be effectively used until there is a systematically approach of analyzing and summarizing. Many techniques have been proposed to solve this problem. MDK-LDA model proposed by Chen(AAA [2013]) , the method extends the Latent Dirichlet Allocation(Blei et al. [2003]), the later one becoming the standard method in topic modelling and been extended in variety ways. The basic idea of LDA is treat each document in a collection as a vector of word count, each document is represented as a probability distribution over a number of topics, while each topic is represented as a probability distribution over a number of words. MDK-LDA introduces a new latent variable s in LDA to model s-sets. Each document is an admixture of latent topics while each topic is a probability distribution over s-sets. Another approach is Aspect-

based Summarization(Garcia-Moya.L and Berlanga-Llavori.R [2013]), it is usually composed of three main tasks: aspect identification, sentiment classification, and aspect rating. Generally this model is used to analyzing product review, it is designed to effectively retrieve features and sentiment for products.

Most previous studies focus on analyzing product reviews. We are interested to discover some model that suite service reviews. More specifically, reviews relate to healthcare. Study shows the effective governance is increasingly recognized as pivotal to improvements in healthcare quality(Bismark and Studdert [2013]), moreover current issue of effectiveness of the authority is affected by insufficient resource and inadequate information received(Bismark et al. [2013]). The object we are going to study is www.patientopinion.org.au, it is a publicly available healthcare forum. It allows user to post their own healthcare related story, the stories are not restricted from patient, it can also from hospital workers, nurses or doctors. The story can be positive or negative or a bit from both side. Although the story body is free form text, user still has to follow a certain template while submit the story.

Due to the unique characteristic of the data from Patient Opinion, the existing models of topic modelling may not give the best result, on other hand LDA has been approved a very effective model, and been used as a based model in many topic modelling studies. We choose LDA as our base model, and incorporate unique feature in Patient Opinion, specifically the section of Whats Good and What could be improved. These two sections are filled in by user while submitting the story, the template is provided by the website. Generally this will be the main topic or features user want to give feedback about in the story. And we assume user labeled story 100% accurate. The question we aim to answer in this thesis:

- How to use user specified features to improve the performance and accuracy in topic

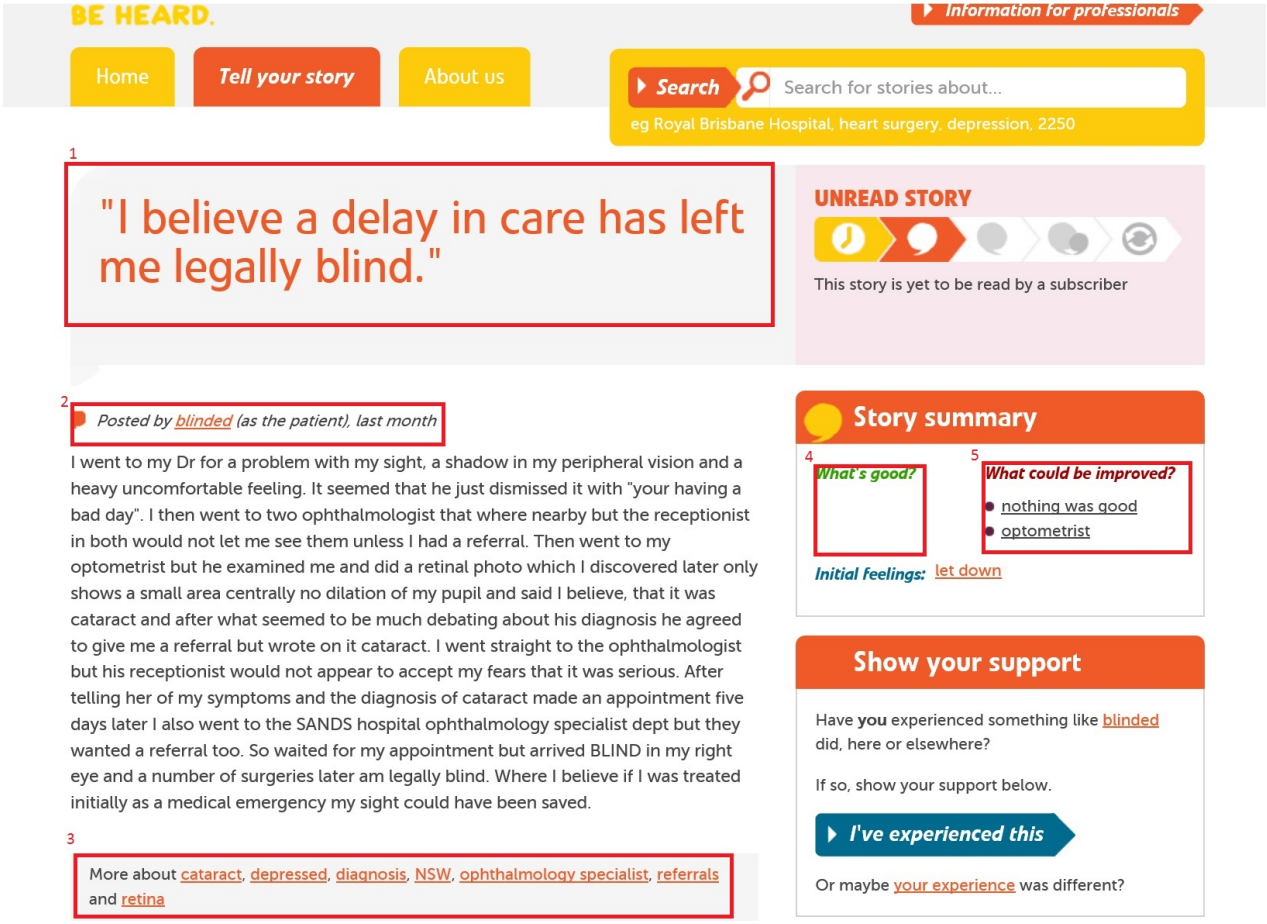

Figure 1.1: Patient Opinion Story Sample

```
    <article id="story" data-po-opinionid="59518" itemscope itemtype="http://data-vocabulary.org/Review">

<h1>
    <span class="top_dec"></span>
    <blockquote>
        &amp;quot;<span id="opinion_title" itemprop="summary" class="">I believe a delay in care has left me legally blind.</span>&amp;quot;
    </blockquote>
    <span class="btm_dec"></span>
</h1>

<p class="info">

         Posted by
                <span itemprop="reviewer"><a href="/opinions?author=blinded" title="Other opinions from blinded">blinded</a></span>

        (as <span id="opinion_author_role" class="">the patient</span>),
    <time itemprop="dtreviewed" datetime="2014-07-22T04:35:36Z" title="Submitted on 22/07/2014 at 04:35 and published by Patient Opinion on
04/08/2014 at 05:04">last month</time>
</p>

    <div class="story_copy">
        <blockquote id="opinion_body" itemprop="description" class="text ">
            <p>I went to my Dr for a problem with my sight, a shadow in my peripheral vision and a heavy uncomfortable feeling.  It seemed
that he just dismissed it with "your having a bad day".  I then went to two ophthalmologist that where nearby but the receptionist in both
would not let me see them unless I had a referral.  Then went to my optometrist but he examined me and did a retinal photo which I discovered
later only shows a small area centrally no dilation of my pupil and said I believe, that it was cataract and after what seemed to be much
debating about his diagnosis he agreed to give me a referral but wrote on it cataract.  I went straight to the ophthalmologist but his
receptionist would not appear to accept my fears that it was serious.  After telling her of my symptoms and the diagnosis of cataract made an
appointment five days later I also went to the SANDS hospital ophthalmology specialist dept but they wanted a referral too. So waited for my
appointment but arrived BLIND in my right eye and a number of surgeries later am legally blind.  Where I believe if I was treated initially as
a medical emergency my sight could have been saved.</p>
        </blockquote>

    </div>

    <div class="related clearfix">
        <p>
            More about <a href="/opinions/tags/cataract">cataract</a>, <a href="/opinions/tags/depressed">depressed</a>, <a
href="/opinions/tags/diagnosis">diagnosis</a>, <a href="/opinions/tags/nsw">NSW</a>, <a href="/opinions/tags/ophthalmology%20specialist">
ophthalmology specialist</a>, <a href="/opinions/tags/referrals">referrals</a> and <a href="/opinions/tags/retina">retina</a>
        </p>
    </div>
```

Figure 1.2: Patient Opinion Story Sample Source 1

modelling.

- What is the distribution of topics over locations (State level).

Figure 1.3: Patient Opinion Story Sample Source 2

Chapter 2

Related Works

2.1 LDA

2.2 MDK-LDA

Chapter 3

The Approach

3.1 A Section

3.2 Another Section

Chapter 4

Experiments

4.1 A Section

4.2 Another Section

Appendix A

Testbed Configuration

Bibliography

Leveraging multi-domain prior knowledge in topic models, 2013. AAAI Press.

M. M. Bismark and D. M. Studdert. Governance of quality of care: a qualitative study of health service boards in victoria, australia. *BMJ quality & safety*, pages bmjqs–2013, 2013.

M. M. Bismark, M. J. Spittal, L. C. Gurrin, M. Ward, and D. M. Studdert. Identification of doctors at risk of recurrent complaints: a national study of healthcare complaints in australia. *BMJ quality & safety*, 22(7):532–540, 2013.

D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent dirichlet allocation. *the Journal of machine Learning research*, 3:993–1022, 2003.

A.-S. Garcia-Moya.L and Berlanga-Llavori.R. Retrieving product features and opinions from customer reviews. *Intelligent Systems*, 28(3):19–27, 2013.