CSC 510 Software Engineering: Project 1

Group-P

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ABSTRACT

Choosing a textbook for a class is something that many professors do several times a year, but the vast number of available textbooks for any given subject makes choosing one that both meets the needs of the class and meets the budget constraints of today's students is a challenge. In this paper, we propose two methods for automatically learning topics from books, a set of evaluations for those methods, and a system that will use those methods in a web app that attempts to suggest textbooks to a professor that balance hitting all topics the course requires while still being economical for students.

1. INTRODUCTION

1.1 Background

One of the most basic tasks that a professor must do is identify what textbook to use for a given class. While some fields have textbooks that have become popular and are clearly the best in their subject matter, many fields (especially emerging ones) have no such exemplar and reading through all possible candidates would be too time consuming to be feasible. It would be a complex enough problem if there were not already a massive number of textbooks on sources such as Amazon, but self aware professors have attempted to use textbooks that are less expensive with hopes of allowing lower income students to attend more easily. This admirable intention serves to increase the already considerable time needed to find appropriate books, and there is no obvious heuristic to apply to searches to limit the field.

In the interests of making students lives less expensive, we propose exploring a system which can identify topics in books automatically, and which, given a set of requirements from a user (usually a professor), can suggest options of varying expense and completeness for a given set of topics. To do this, we propose exploring word clusters generated by Doc2Vec, a family of common natural language processing (NLP) algorithms that attempt to cluster similar words, and topics generated by latent dirichlet allocation (LDA), another common NLP algorithm that directly attempts to identify topics in text, to automatically infer the content of a set of textbooks.

We then intend to build a web app that will allow a user to specify a set of topics and which will use the mentioned algorithms to make suggestions while minimizing the cost of said textbooks. The actual web app will be a fairly simple single-page web app developed in Angular4 and using Bootstrap to hasten development of a modern UI.

Initially, the team expects LDA to find more appropriate topics than Doc2Vec simply because it is better purpose built. That said, Doc2Vec uses a sophisticated neural-network, which may behave better on shorter passages such as a table of contents or an index, allowing us to parse less of the book while still getting useful topics.

1.2 Deviations From Initial Plan

1.3 Planning

The Spiral Model.

Prototypes.

2. LITERATURE REVIEW

We propose two methods for analyzing and storing topics from books automatically: LDA and Doc2vec.

2.1 LDA

In this section, we describe the Latent Dirichlet allocation(LDA) method for storing topics against books.

LDA uses a Bayesian clustering approach to find topics relevant to the book. [**?**] The input to the method is a book

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(or later, a series of books) which consists of collection of words.

This method assumes that each book (or books) consists of topics and that each topic has several key words associated with it. The number of topics associated with a book can be variable, and can be changed for better optimization. In this association, the words comprising the text are thrown into a "bag-of-words" model such that grammer and word order are disregarded, but multiplicity is measurable. The calculated topics found from this bag-of-words are "latent" variables, that is they are not directly measurable but indirectly observed.

The performance of the method depends on the initial assumptions made. For example, some have assumed that books are random mixes of topics [**?**]. The number of topics can initally be chosen as constant for a given book, or as a function of a chosen Poisson distribution. [**?**] Topic distribution in the book is assumed to be a sparse Dirichlet function.

A sparse Dirichlet function implies that we assume that a topic will be discussed only in a small breadth of pages in the book, and also that words relating to this topic will predominantly figure in these pages.

The algorithm looks to identify unique words to identify as topic names. Words like "the" and "a" are common and will occur with equal probability throughout the text. However, in say one chapter of the book some words may occur much more frequently in that particular chapter than the rest of the book, which means that the probability of these words in that chapter is more, which then the algorithm can use to choose a topic name and also a list of words related to that topic.

2.2 Doc2Vec

Doc2Vec is a model that extends an existing model, Word2Vec. Doc2vec mirrors Word2Vec in most ways except that it adds context information. [**?**]

▬< HEAD ▬< HEAD Doc2Vec is an implementation of the Paragraph Vector (PV) introduced by Mikolov and Le in 2014 - an unsupervised algorithm that generates vector representations of text. [**?**] The basic difference between LDA and Doc2Vec is that LDA tries to form a structure of related words (a topic name with the list of associated words) out of books mainly on the basis of frequency of words in the document. While a simple yet powerful approach, it has a few drawbacks, such as semantics. For example, the words "powerful, strong and Paris" are equally distant when considered by a bag of words model, however "powerful" and "strong" are semantically close. [**?**]

Paragraph Vector involves predicting words in the paragraph. It is "unsupervised", which means that it predicts words in a paragraph and then uses these predictions to attempt to form structures of related words without any knowing of accuracy of the structure(s). The PV utilizes fixed length feature vectors learned from text sources of variable length. Mikolov offers two models of PV that are based on the implementation of Word2Vec: Distributed Memory Model (PV-DM) and Distributed Bag of Words (PV-DBOW). =======
subsubsectionIntroduction =======

2.2.1 Introduction

▬> doc Doc2Vec is an implementation of the Paragraph Vector (PV) introduced by Mikolov and Le in 2014 - an unsupervised algorithm that generates vector representations of text inspired from research of vector representations of words via neural networks. [**?**] By concatenationg or averaging vector represenations of words with other word vectors, the resulting vector can be used to predict future text. This technique offers one distinct advantage to bag-of-words models like LDA: the ability to record semantics due to the mapping of the word vectors into a vector space that allocates words of similar meaning together. For example, the words "powerful, strong and Paris" are equally distant when considered by a bag-of-words model, however "powerful" and "strong" are semantically close and should therefore be less distant from one another. [**?**]

PV is "unsupervised", which means that it predicts words in a paragraph and then uses these predictions to attempt to form structures of related words without any knowing of accuracy of the structure(s). The PV utilizes fixed length feature vectors learned from text sources of variable length.

2.2.2 Models

Mikolov offers two models of PV that are based on the implementation of Word2Vec: Distributed Memory Model (PV-DM) and Distributed Bag of Words (PV-DBOW). ▬> doc

PV-DM is similar to the Continuous Bag of Words (CBOW) model in Word2Vec such that is predicts the next word based on the given context. Paragraph vectors are concatenated with word vectors from that paragraph. Each word vector is representing a word from the given context and a new vector is generated by concatenating all of those word vectors together to predict other words. These word vectors are able to remember context and semantics. The paragraph vector allows the algorithm to remember the topic or 'label' of the paragraph, whether it is a sentence or a long document.

PV-DBOW follows the skip-gram model of Word2Vec. In this model, instead of concatenating the paragraph vector with the word vectors formed in close proximity in order to predict the next word, random text from the paragraph is selected and a random word is selected from that text. Because this model does not save the word vectors and therefore does not retain as much information about the context and semantics of the text, it requires less storage.

2.2.3 Application

-talk about different parameters and reults of gensim / Mikolov

-talk about using all three models : one of each and one that uses both

Mikolov and Le recommend using a combination of PV-DM and PV-DBOW for consistently accurate results. [**?**]

2.3 Related Work

Doc2Vec was recently tested as the algorithm behind a recommender system with the goal of recommending unseen Twitter messages (tweets) relative to a user's typical activity and interests. A graph based link prediction method was used to infer which unseen tweets the users would like by "predicting the presence or absence of edges between nodes" on the graph. [**?**] K values were tested in intervals divisible by 5 ranging from 5 to 35. The system preformed the best when K=30.

An LDA approach of a tagging system was implemented to

improve tag recommendations. [**?**] Tagging systems are often used for organizaing a user or organization's data. When this data is shared, tagging can be used to find or search for relative content.This system is similar to our proposed book recommendation system that uses subject topics to search for relative material. The initial tag data set was comprised of a large sample creating a diverse tag set. This set was used to elicit latent tags of sources that did not have that many tags to describe the document. Often, the tags recommended were more specifc. By increasing the number of tags and increasing specific tags, their approach contributed to the usefulness of searching for new content.

3. ARCHITECTURE

4. PROGRESS

5. VALIDATION

6. EVALUATION

Need to fix this section...

6.1 Evaluating LDA

6.2 Evaluating Doc2Vec

TO DO

6.2.1 Sentiment Prediction Accuracy

Need to figure out how to test the accuracy of doc2vec when it predicts future text

-gensim has a infer vector function that "infers a vector for given post-bulk trainng document"

-calling model.docvec[doc tag/id] should pull up the vectors that were trained already -I think gensm uses most similar function to find a good trained vector (good because it would predict the given document well) - so if the most similar trained vector is very different than the infered vector, the model is not good?

-I suppose we should be infering documents that were not used in training

-Error rate would be how far away best vectors are, lower the better?

6.2.2 Information Retrieval

One way to verify that our implementation of Doc2Vec is correctly mapping word vectors to other semantically similar word vectors is to test the trained model on an information retrieval task . [**?**] The data collected from stackoverflow is tagged with different topics that pertain to the content. The tags can then be used to organize the content via topic. The Doc2Vec model should report two documents that pertain to the same topic as less distant to each other than a third document that focuses on a different topic.

-Seperate content such that documents used for testing were not trained on

- 3 folders: two with the same topic, a third folder of different topics that don't include the picked special topic

▬< HEAD -Report resultsgit =======

-Report results (use DM, DBOW, and both together - follow gensim example at https://github.com/RaRe-Technologies/gensim/blob/develop/docs/notebooks/doc2vec-IMDB.ipynb

▬> doc

7. CONCLUSION

8. REFERENCES