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Optimize Searching Using Latent Dirichlet Allocation

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Abstract: This research focuses on topic modeling as a crucial method for exploring extensive document collections and uncovering latent topics within the data. Specifically, it highlights the Latent Dirichlet Allocation (LDA) algorithm from the perspective of natural language processing. The main objective is to gain an in-depth understanding of LDA algorithms and their implementation approaches. It covers dataset preparation, practical implementation of LDA, and exploring the potential benefits of integrating LDA into recommendation systems. A comprehensive analysis of LDA encompasses graphical representations, fundamental equations, optimization methodologies, and practical implementations, covering all procedural aspects. LDA analysis is performed on extracted verses from the King James version of the Bible as documents, revealing varying levels of topic associations across documents. Some documents show strong alignment with a single topic, while others have multiple topic assignments. The research findings reveal patterns and themes present in the data, providing valuable insights into the fundamental thematic composition of the analyzed documents. Additionally, the study contributes to existing knowledge by exploring the functionality, practical applications, and relevance of topic modeling and LDA in recommendation systems and natural language processing.

Keywords: *Bible verse, latent dirichlet allocation, recommendation system, topic modeling*

1. Introduction

Topic modeling has emerged as a key technique in data analysis for analyzing enormous amounts of untagged data. It enables us to compile topics from large document collections into summaries. In order to do this, topics are represented as word distributions, and statistical correlations between observable and unobservable factors are established. Thus, we are able to recognize the subjects or topics that are present in the data [1].

Latent Dirichlet Allocation (LDA) is a well-liked topic modeling method [2] that is built on a probabilistic framework [2]–[4]. Utilizing LDA, topics are created by examining the use of words in a number of documents. It is implied that each piece of data is made up of a variety of topics and that each word in the document is related to one of these topics [2].

The LDA model is widely recognized for its capacity to split and organize unstructured data, and recommender systems use it significantly. The LDA model can produce recommendations by using a topic distribution-based strategy and a suitable distance measure [3]. There are chances of exploring the selection of relevant context from the perspective of recommendation systems, especially when it comes to Bible verse recommendation. LDA, a topic modeling technique, efficiently captures the various underlying topics that are connected. However, comparing different fields in order to weigh context in relation to verse content necessitates comparison, which may limit unusual discoveries [5].

This research endeavor seeks to examine how topic modeling—more particularly, LDA—can be used to analyze untagged data and discover hidden topics in the Bible dataset. The paper is composed of the different approaches, methods, and LDA implementations.

2. Topic Modeling Approaches

Topic modeling (TM) is a widely used and valuable technique for identifying word usage patterns and establishing correlations among documents. It aims to associate concepts with documents across various topics [6]. One commonly employed statistical model for TM is LDA, which provides a probability distribution over words for each topic [7]. LDA is renowned for efficiently managing large sets of discrete data while capturing underlying statistical correlations [8]. Its applications encompass tasks such as categorization, information discovery, data summarization, and document similarity assessment.

Several studies have utilized LDA to extract significant topics from diverse datasets. For instance, a notable study compared LDA with Latent Semantic Analysis (LSA) within the context of TM, specifically using an English Bible dataset [9]. The results demonstrated that LDA outperformed LSA by a substantial margin (60–75%) in terms of document similarity assessment for both existing and unseen documents. Furthermore, LDA exhibited higher coherence scores and word association results that closely approximated human patterns compared to LSA. Building on this foundation, the same researchers [10] conducted an

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additional study focused on extractive summarization using LDA and English Bible data. It successfully developed an algorithm that utilized the LDA approach to identify crucial subjects and generate automatic summaries.

In another study [11], LDA was employed to identify topics in students' conclusions and recommendations, aiming to expedite the reading and evaluation process. The researchers utilized LDA techniques and incorporated a topic category for context. The study analyzed the quantity of documents, topics, and terms and employed TF-IDF and Cosine Similarity methods to measure similarity. Additionally, the NLPTools Library was applied to various tasks, including text categorization, modeling, and clustering.

A study [12] aimed to enhance LDA's topic classification capabilities in the context of online reviews of game apps from the Google Play store. The proposed hybrid LDA approach utilized a genetic algorithm (GA) to determine optimal weights for LDA topics, aiming to improve topic classification performance. The evaluation focused on measuring the accuracy of topic classification, specifically the fraction of correctly classified positives. However, the proposed enhancement fell short of adequately addressing the precision rate, which refers to the proportion of classified documents considered relevant.

Another study [13] explored the use of LDA for song title recommendation based on song lyrics searching. The researchers made minimal modifications to the LDA model, omitting stemming methods to extract words in their original form. LDA's capability to analyze the intrinsic meaning of text proved highly effective in generating satisfactory experimental results using English song datasets.

To address the issue of data sparseness, a study [14] proposed a smoothed LDA model based on Tolerance Rough Set Theory (TRST). The augmented LDA model had a TRST part that created term tolerance classes based on how often two terms appeared together and used information from these classes to change the probability of unknown words. The proposed algorithm underwent both theoretical and experimental verification.

Overall, these research papers highlight various applications and enhancements of LDA in topic modeling, demonstrating its versatility and effectiveness across different domains and datasets.

3. Research Method

The research explores the utilization of the LDA algorithm, a commonly used method in natural language processing and text analysis, to analyze the content of the Bible. By applying LDA to the Bible, hidden topics can be automatically revealed, capturing the underlying thematic framework of the text. The study focuses on understanding these algorithms and the methods to be applied.

The research involved three primary methods: dataset preparation, the process of implementation of the LDA model, and the development of the website application. The conceptual framework for system development is illustrated in Fig. 1.

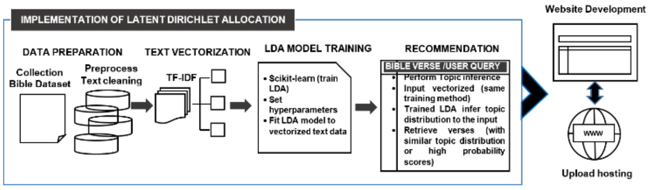

Fig 1: LDA-based Recommendation System

A. Dataset Preparation

a. *Dataset collection:* The King James Version dataset [15], available on www.kaggle.com, will be used for the purposes of this research study. Its dataset is composed of citations, books, chapters, verses, and words of the Bible, having 31,102 rows.

b. *Data Preparation:* Preprocessing steps involved text cleaning tasks, including the removal of stop words and punctuation marks.

c. *Text vectorization:* The dataset will convert the preprocessed text into a numerical representation suitable for LDA. The technique used is Term Frequency-Inverse Document Frequency (TF-IDF) vectorization.

B. LDA Implementation

To proceed with the LDA model training, the following procedural steps can be followed:

a. Utilize a suitable library, such as Gensim, to train the LDA model. Import the necessary modules from the chosen library.

b. Specify the desired number of topics and other hyperparameters for the LDA model. Set the values for parameters like the number of topics to be extracted from the text data.

c. Fit the LDA model to the vectorized text data. Transform the text data into a numerical representation, such as a document-term matrix or TF-IDF matrix. Then, use the fit method of the LDA model to train it on the vectorized data.

It also includes, in the process of LDA, topic identification, Content Organization, cross-referencing, and semantic search.

a. *Topic Identification:* Analyze the output of the LDA model to identify and label the topics present in the Bible. Assign meaningful names to each topic based on the most representative words or passages associated with them.

b. *Content Organization:* Group related passages or verses together based on their thematic similarities derived from the LDA model. Create a structure or index that organizes the Bible's content according to these topics, facilitating easier navigation and retrieval of specific topics or concepts.

c. *Cross-Referencing:* Utilize the LDA model to identify connections and common themes between different parts of the Bible. Explore related passages or verses across various topics to gain a broader understanding of the interconnectedness of biblical teachings.

d. *Semantic Search:* Implement a search functionality that leverages the LDA-based topic model. Users can search for specific topics or themes, and the system will retrieve relevant passages even if they don't explicitly contain the searched keywords. This allows for more comprehensive and intuitive searching within the Bible.

C. Recommendation

a. Perform Topic Inference on New Bible Verses or User Queries after training the LDA model.

b. Take a verse or query as input for topic inference. Vectorized the input using the same method employed during the model training phase.

c. Utilize the trained LDA model to infer the topic distribution of the input verse or query.

d. Retrieve verses with similar topic distributions or the highest probability scores based on the inferred topic distribution.

4. LDA Process

A. Graphical and Equation Representation of LDA

Fig. 2 illustrates the complete graphical model of LDA [16]. Within this representation, the box labeled D corresponds to the entirely of documents present in the corpus. Alternatively, Fig. 3 specifically depicts a corpus consisting of five documents. The box labeled N signifies the count of words within a document. Inside the N box, the variables w and z symbolize multiple words, signifying the diverse array of words found in the documents.

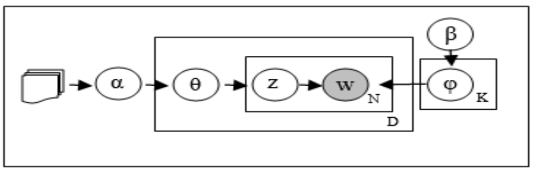

Fig 2: showcases the adapted graphical model of the LDA algorithm, sourced from "Latent Dirichlet Allocation" by GeeksforGeeks.

In the LDA framework, each word in a document is assumed to be associated with a latent or hidden topic, denoted as Z. By assigning topics to words within the documents, the topic-word distribution θ (theta) for the entire corpus can be derived. The distribution of topics within each document is controlled by the parameter Alpha (α), while the distribution of words within each topic is regulated by the parameter Beta (β).

The LDA graphical model can be summarized by the following equation (1):

$$P(W, Z, \theta, \varphi , \alpha, \beta) = \Pi_{j=1}^{M} P(\theta_j; \alpha) \, \Pi_{i=1}^{K} P(\varphi_i; \beta) \, \Pi_{t=1}^{N} P(Z_{j,t} \mid \theta_j) \, P(W_{j,t} \mid \varphi z_{j,t}) \quad (1)$$

To clarify the notation:

d. D=represents the count of documents.

e. N=represents the count of words

f. within a particular document

g. β=is the dirichlet prior used for modeling the

h. distribution of topics across documents

i. α=is the dirichlet prior used for modeling

j. the distribution of words across topics

k. θ_i=represents the distribution of topic

l. within document i

m. φ_k=represents the distribution of words

n. within topic k

o. z_{ij}=corresponds to the assigned topic

p. for the j-th word in document i

q. w_{ij}=refers to a specific word in the document

B. LDA optimizes the distributions

LDA aims to find the best way to represent the relationship between documents and topics, and topics and words [17]. It does this by starting with the documents and figuring out which topics could have generated them, and then which words could have generated those topics.

Initially, LDA assigns topics randomly to words in the documents. This means that each word in the document can be linked to different random topics. The output is a collection of documents composed of topics, with each topic containing words.

After the initial iteration, LDA generates initial matrices depicting the distribution of topics within the documents and the distribution of words within the topics. The goal is to improve these results through optimization. This involves going through all the documents and words, assuming that most of the topic assignments are correct except for the current word. LDA aims to refine and adjust the topic assignment of the current word using the existing accurate topic-word assignments.

The LDA algorithm goes through each document and word, calculating two probabilities. The first probability measures how many words in the document are currently assigned to the topic. The second probability calculates how many documents assign the word to the topic.

By combining these probabilities, LDA estimates the new probability for the topic assignment of the word. Multiple iterations are performed until a stable state is reached, which means the representation of the document-topic matrix and topic-word matrix is optimized.

In simple terms, LDA tries to find the best match between topics and words by looking at how topics can generate documents and how words can generate topics. It iteratively refines the topic assignments based on the words and documents, aiming for the most accurate representation of the relationships.

C. LDA implementation

The study employs the LDA approach to analyze the King James Version Bible dataset and demonstrates its implementation using the Gensim Library for topic extraction. The dataset focuses on five specific verses, serving as an initial representation of the corpus, as depicted in Fig. 3.

D1	'Peace I leave with you, my peace I give unto you: not as the world giveth, give I unto you. Let not your heart be troubled, neither let it be afraid.'
D2	'But the LORD said unto Samuel, Look not on his countenance, or on the height of his stature; because I have refused him: for the LORD seeth not as man seeth; for man looketh on the outward appearance, but the LORD looketh on the heart.'
D3	'Submit yourselves to every ordinance of man for the Lords sake: whether it be to the king, as supreme;'
D4	'All scripture is given by inspiration of God, and is profitable for doctrine, for reproof, for correction, for instruction in righteousness:'
D5	'Forasmuch then as the children are partakers of flesh and blood, he also himself likewise took part of the same; that through death he might destroy him that had the power of death, that is, the devil;'

Fig 3: Verse Corpus

To apply text processing to the corpus, the following steps are involved in preprocessing text data: converting the text into lowercase, splitting the text into words, removing stop words, eliminating punctuation, symbols, and special characters, and finally normalizing words using the lemmatization process (refer to Fig. 4).

D1	D2	D3	D4	D5
['peace', 'leave', 'you', 'peace', 'give', 'unto', 'you', 'world', 'giveth', 'give', 'unto', 'you', 'let', 'heart', 'troubled', 'neither', 'let', 'afraid'	['lord', 'said', 'unto', 'samuel', 'look', 'countenance', 'height', 'stature', 'refused', 'him', 'lord', 'seeth', 'man', 'seeth', 'man', 'looketh', 'outward', 'appearance', 'lord', 'looketh', 'heart']	['submit', 'every', 'ordinance', 'man', 'lord', 'sake', 'whether', 'king', 'supreme']	['scripture', 'given', 'inspiration', 'god', 'profitable', 'doctrine', 'reproof', 'correction', 'instruction', 'righteousness ']	['forasmuch', 'child', 'partaker', 'flesh', 'blood', 'also', 'likewise', 'took', 'part', 'same', 'death', 'might', 'destroy', 'power', 'death', 'is', 'devil']

Fig 4: Clean corpus

Fig. 5 depicts the outcome of the Document Term Matrix (DTM). The cleaned data, comprised of tokenized words, undergoes DTM processing, resulting in a dictionary comprising 59 unique tokens.

afraid	appearance	Stature	god	Destroy
give	countenance	every	inspiration	devil
giveth	height	king	instruction	flesh
heart	him	ordinance	profitable	forasmuch
leave let	look	sake	reproof	is
neither	looketh	submit	righteousness	likewise
peace	lord	supreme	scripture	might
troubled	man	whether	also	part
unto	outward	correction	blood	partaker
world	refused	doctrine	Child	power
you	said	given	Death	same
	Samuel			took
	seeth			

Fig 5: Term Dictionary

In Fig. 6, the process of converting a list of documents (corpus) into a Document Term Matrix (DTM) using the dictionary is illustrated. The DTM includes the index of each word along with its corresponding frequency.

D1	D2	D3	D4	D5
[(0, 1),	[(3, 1),	[(18, 1),	[(33, 1),	[(43, 1),
(1, 2),	(9, 1),	(19, 1),	(34, 1),	(44, 1),
(2, 1),	(12, 1),	(26, 1),	(35, 1),	(45, 1),
(3, 1),	(13, 1),	(27, 1),	(36, 1),	(46, 2),
(4, 1),	(14, 1),	(28, 1),	(37, 1),	(47, 1),
(5, 2),	(15, 1),	(29, 1),	(38, 1),	(48, 1),
(6, 1),	(16, 1),	(30, 1),	(39, 1),	(49, 1),
(7, 2),	(17, 2),	(31, 1),	(40, 1),	(50, 1),
(8, 1),	(18, 3),	(32, 1)]	(41, 1),	(51, 1),
(9, 2),	(19, 2),		(42, 1)]	(52, 1),
(10, 1),	(20, 1),			(53, 1),
(11, 3)]	(21, 1),			(54, 1),
	(22, 1),			(55, 1),
	(23, 1),			(56, 1),
	(24, 2),			(57, 1),
	(25, 1)]			(58, 1)]]

Fig 6: Corpus into Document Term Matrix

In Fig. 7, the output represents the assignment of weights to each of the 59 unique words based on the topics. This highlights the prominence of specific words within each topic. This process involves implementing LDA by creating an LDA model object using the Gensim library. The LDA model is then run and trained on the document term matrix to obtain the topics along with their respective indices.

Topic 0		Topic 1		Topic 2	
you	0.069	death	0.069	lord	0.105
unto	0.052	is	0.043	man	0.079
peace	0.052	likewise	0.043	looketh	0.054
let	0.051	devil	0.042	seeth	0.054
give	0.050	might	0.041	unto	0.029
troubled	0.034	same	0.041	heart	0.029
neither	0.033	power	0.040	samuel	0.029
world	0.033	also	0.040	said	0.029
giveth	0.032	partaker	0.039	him	0.029
afraid	0.031	blood	0.039	stature	0.029

Topic 3		Topic 4		Topic 5	
death	0.057	you	0.102	reproof	0.059
child	0.040	give	0.070	doctrine	0.059
took	0.037	let	0.070	inspiration	0.059
forasmuch	0.037	peace	0.069	god	0.059
destroy	0.036	unto	0.069	profitable	0.059
part flesh	0.035	heart	0.042	scripture	0.059
blood	0.034	leave	0.040	instruction	0.059
partaker	0.033	afraid	0.038	given	0.059
also	0.033	giveth	0.038	righteousnes	0.059
	0.032	world	0.037	s correction	0.059

Fig 7: Word Weights Based on the Topics

Fig. 8 illustrates the process of assigning topics to the documents. The DTM is processed using the LDA model, which assigns topics to the five documents along with their respective weights. The weight assigned to each document offers valuable insights into the primary topic being discussed.

DOC	TOPIC INDEX	TERM MATRIX
0	**4**	**0.9560794**
1	**2**	**0.9620972**
2	0	0.01666777
	1	0.016667515
	2	**0.916662**
	3	0.016667731
	4	0.01666745
	5	0.016667537
3	0	0.015152107
	1	0.015151965
	2	0.01515177
	3	0.015152086
	4	0.015151936
	5	**0.9242401**
4	**1**	**0.9536376)**

Fig 8: Topic Associations with the Documents

The analysis of the provided sample documents utilizing LDA has yielded interesting findings. The documents, specifically Doc 1, Doc 2, and Doc 5, have been exclusively allocated to specific topics. Document 1 is primarily linked to Topic 4, resulting in 95% of its content. In the same manner, Document 2 exhibits a significant focus on Topic 2, making up 96% of its overall content. Conversely, Document 5 is predominantly associated with Topic 1, comprising 95% of its content.

However, Document 3 and Document 4 demonstrate a broader distribution encompassing various topics. Document 3 exhibits an outstanding connection to Topic 2, as it contributes a significant portion of 91% of its content to that specific topic. In contrast, Document 4 predominantly corresponds to Topic 5, encompassing 92% of its overall content.

The LDA analysis reveals different levels of topic association among the sample documents. Certain documents demonstrate a significant correlation with a single topic, whereas others display multiple topic assignments. The aforementioned findings offer valuable insights into the fundamental thematic composition of the analyzed documents.

5. Conclusion and Future work

This paper introduces the Latent Dirichlet Allocation (LDA) method and its application for determining the probability of topics within a document. The utilization of a matrix as an initial representation is being discussed, as it facilitates the exploration of LDA for Bible Recommendation.

The future direction of this study involves incorporating similarity metrics to measure distances between documents, which holds promise for recommendation systems. The distribution of the LDA model across topics becomes a reference point for this process. By employing an appropriate distance metric within the relevant context, accurate recommendations can be generated. In summary, this study emphasizes the potential of LDA in the field of Bible recommendation and highlights how the initial concept of utilizing a term matrix can open avenues for further investigation in this area.

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