An Image-Enhanced Topic Modeling Method for Neuroimaging Literature

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Abstract. Topic modeling based on neuroimaging literature is an important approach to aggregate world-wide research findings for decoding brain cognitive mechanism, as well as diagnosis and treatment of brain and mental diseases, artificial intelligence researches, etc. However, existing neuroimaging literature mining only focused on texts and neglects brain images which contain a large amount of topic information. Following the writing and reading habits combining images with texts, we present in this paper an image-enhanced LDA (Latent Dirichlet Allocation), which extracts literature topics from both neuroimaging images and full texts. Combining topics from fMRI brain regions activation images with topics from full texts to model neuroimaging literatures more accurately. On the one hand, topics related brain cognitive mechanism can be pertinently extracted from activated brain images and their descriptions. On the other hand, topics from activated brain images can be integrated with topics from full text to model neuroimaging literature more accurately. The experiments based on actual data has preliminarily proved effectiveness of proposed method.

Keywords: Topic modeling · Literature mining · Image-enhanced LDA

1 Introduction

A series of important brain projects, such as Human Connectome Project [1], Adolescent Brain and Cognitive Development (ABCD) [2], and UK Biobank [3], have been launched to harness brain big data, especially neuroimaging data, for modeling cognitive functions of the brain. However, creating a detailed map of brain cognitive mechanism is involved with characterization of numerous entities, and it is difficult to be completed only depending on a data-driven approach in a or several laboratories. It is necessary to aggregate world-wide research findings.

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Neuroimaging literature mining provides a practical approach to realize such an aggregation. In recent year, neuroimaging articles are growing fast. Taking only fMRI (functional Magnetic Resonance Imaging) as an example, there are 482 relevant articles have been published in the journal PLoS One in 2018. Many researches [4–7] have focused on knowledge or information extraction from neuroimaging literature for systematically decoding brain cognition. Related researches have brought enormous influences in psychology, neuroscience and artificial intelligence. For example, the statistical data on the Neurosynth platform shows that 14371 Neurosynth-based articles had been published by July 2018.

However, existing researches of neuroimaging literature mining only focus on texts. A large number of neuroimaging images in literature are neglected. In fact, these images are closely related to literature topics. Extracting information from neuroimaging images and their description texts is very important for not only decoding brain cognition but also modeling literature topics. Based on the above observations, this paper proposes a new image-enhanced topic modeling method of neuroimaging literature, called Image-enhanced LDA, which combines neuroimaging images and full texts to extract literature topics. The rest of the paper is structured as follows: Previous work related to topic modeling is outlined in Sect. 2. The proposed the image-enhanced LDA method is detailed in Sect. 3. Experiments are performed to evaluate the effectiveness of proposed method in both systematically decoding brain cognition and modeling literature topics in Sect. 4. There is a briefly conclusion in Sect. 5.

2 Related Work

Topic modeling learns meaningful expressions of texts from document sets [8] and is basic work in text semantic analysis [9] and text mining [10]. The LDA model [11] is the most widely used probabilistic topic model. It detects the global semantic topic structure and gives topics of each document in the form of probability distribution. In order to effectively use the word order and textual structure for document modeling, various improved LDA models have been developed. SentenceLDA [12] introduced the information of textual structures and word dependence into topic modeling for achieving the higher topic granularity. LFTM (Latent Feature Topic Modeling) [13] integrated quantitative contextual information to extend the traditional LDA and DMM (Dirichlet Multinomial Mixture) models for improving the topic consistency evaluation. The generative topic embedding model [14] mined word collocation patterns from both the global document and the local context for generating coherent topics. In order to improve semantics and comprehensibility of topics, domain knowledge was integrated into topic modeling. Probase-LDA [15] combined LDA with the large-scale probabilistic knowledge base to improve semantic consistency and accuracy of topics. MicroASM (Micro Aspect Sentiment Model) [16] introduced the external seed dictionary into topic modeling for obtaining rich semantic topics.

In recent years, topic modeling based on deep neural network has become a research hot spot. Related researches used the deep neural network to model the context for overcoming various shortcomings of traditional probabilistic topic models, including poor model scalability, poor topic semantic coherence, insufficient feature expression ability [17]. TopicRNN (Recurrent Neural Network) used RNN to capture remote semantic dependency between potential topics for generating reasonable topics. TE-LSTM+SC (Topic-Enhanced LSTM neural network model with topic similarity constraint) [18] used LSTM (longCshort-term memory) to capture contextual features of textual sequences for obtaining potential semantic topics as diverse as possible.

Topic modeling is also a core research issue of neuroimaging literature mining. Neurosynth [19] recognized domain terms based on frequency. Poldrack et al. [4] identified literature topics by using LDA. Alhazmi et al. [6] extracted topic words based on frequency and constructed relations between semantic spaces of topics and brain activated regions by using correspondence analysis and hierarchical clustering.

Recognizing brain cognitive mechanism, including cognitive functions, activated brain regions and their relations, are the primary purpose of topic modeling on neuroimaging literature. Though information is mainly contained in neuroimaging images and related descriptions, existing researches on topic modeling of neuroimaging literature only focused on literature texts. Because abstracts and full texts of literature describe the whole research, topics obtained by performing probabilistic topic models on texts often contain information unrelated to brain cognitive mechanism. This led that further processing has to be added after topic modeling. For example, Poldrack et al. used the terms of Cognitive Atlas (http://www.cognitiveatlas.org) to filter the topics obtained by LDA. Furthermore, the topic information contained in neuroimaging images and their descriptions is also crucial to understand the whole literature. Hence, it should be combined with topics obtained from full texts for modeling neuroimaging literature.

3 Methodology

Based on the above observations, this paper proposes the image-enhanced LDA which extracts literature topics from both neuroimaging images and full texts. As shown in Fig. 1, the whole method includes two steps: topic learning from images is to extract topics related to activated brain areas from neuroimaging images, other steps is that topic learning from texts is to extract topics from texts in literature. The details will be introduced in the following subsections.

3.1 Topic Learning from Images

Topic learning from images is to extract topics related to activated brain areas from neuroimaging images in literature. This paper adopts the image caption generation technology [20] to complete this step. The overall architecture is shown in Fig. 2 and includes the following two phases.

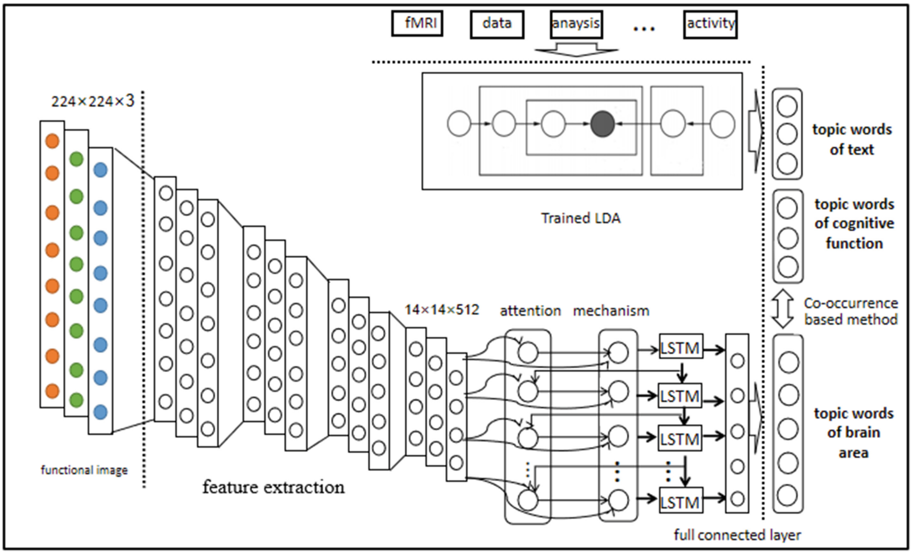

Fig. 1. The architecture of image-enhanced LDA.

The first phase is encoding which extracts a group of feature vectors from the input neuroimaging image I to represent different parts of image. CNN is used to realize this extraction. After encoding, I can be transformed into the following D-dimension feature vectors:

$$I = \{i_1, i_2, \cdots, i_L\},\ \ i_i \in R^D \tag{1}$$

where i denotes the ith feature vectors, L denotes total number of extracts feature vectors.

The second phase is decoding which generates a caption for each input fMRI brain image. A caption can be encoded as a sequence of $1 - of - K$ encoded words:

$$C = \{c_1, c_2, \cdots, c_L\},\ \ c_i \in R^K \tag{2}$$

where K is the size of the vocabulary and L is the length of the caption. As shown in Fig. 2, this paper adopts the architecture combining the attention and LSTM to generate the caption C based on I. The process can be described as follows:

$$\begin{pmatrix} i_t \\ f_t \\ o_t \\ g_t \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} T_{D+m+n,n} \begin{pmatrix} Ec_{t-1} \\ h_{t-1} \\ \hat{z}_t \end{pmatrix} \tag{3}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{4}$$

$$h_t = o_t \odot \tanh(c_t) \tag{5}$$

where i_t, f_t, o_t, g_t, h_t are the input, forget, memory, output, and hidden state of LSTM, m and n denote the dimensionality of embedding and LSTM, $E \in R^{m \times K}$ is an embedding matrix. $\hat{z} \in R^D$ is the context vector capturing the visual information associated with a particular input location. $\hat{z}_t$ is a dynamic representation of the relevant part of the image input at time t and can be calculated as follows:

$$\hat{Z}_t = \phi(\{i_i\}, \{\alpha_i\}) \tag{6}$$

where α_i is the weight of i_i and computed by an attention model, and ϕ is a function that returns a single vector given the set of feature vectors and corresponding weight value. They are calculated by using deterministic "Soft" attention [20].

Based on the generated captions of neuroimaging images in literature, the topic word related to activated brain region can be collected to construct a topic word set of activated brain regions as follows:

$$Bra = \{bra_1 \cdots bra_p\} \tag{7}$$

where each bra_1 is a topic word of activated brain region. Because there are standard terminology dictionaries about brain regions, recognizing entities about activated brain regions from image captions can directly adopt the dictionary-based method.

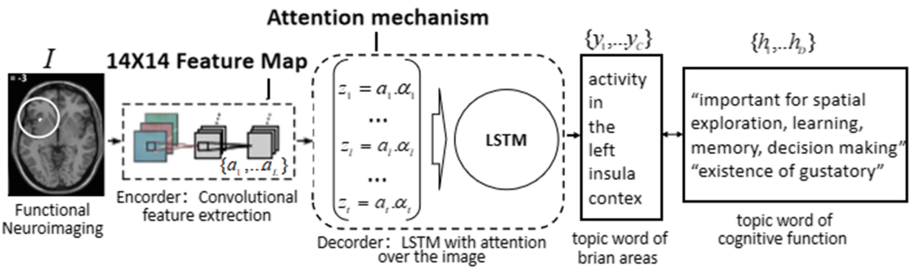

Fig. 2. The flow diagram of topic learning from images.

3.2 Topic Learning from Texts

Topic learning from texts is to extract topics from texts in literature. It includes two sub-steps: topic learning from image descriptions and topic learning from full texts.

Topic learning from image descriptions is to extract topics from the description texts corresponding to neuroimaging images. As stated above, recognizng brain cognitive mechanism are the primary purpose of topic modeling on neuroimaging literature. Topics obtained from fMRI brain image contain information about activated brain regions. The corresponding cognitive states are often contained in image descriptions. This paper adopts the co-occurrence-based method [5] to extract topics related to cognitive states from description texts. The co-occurrence window is set as a single sentence and the connected words include "reflect", "activate", "denote", etc. Different from brain regions, cognitive states lack a complete term dictionary. This paper uses the BiLSTM-CNN (Convolutional Neural Networks) model [21] to recognize entities of cognitive states. And then, a topic word set of cognitive states can be constructed as follows:

$$Cog = \{cog_1 \cdots cog_q\} \tag{8}$$

where cog_j is a topic word of cognitive state. Topic learning from full texts is to extract topics from the full texts of literature. LDA is adopted to obtain the following topics:

$$T = \{t_1 \cdots t_k\} \tag{9}$$

where each t_l is a topic words. Finally, the image-enhanced literature topics can be obtained by combining three types of topic words:

$$LiteratureTopics = \{Bra, Cog, T\} \tag{10}$$

4 Experiments and Evaluation

4.1 Experimental Data

Functional neuroimaging articles were crawled from the journal PLoS One by keywords "fMRI", "functional magnetic resonance imaging" or "functional MRI". All articles were published from 2018 to 2019. Select articles with more than three fMRI brain images. Finally, there are 130 articles were collected as experimental data. The training data set includes 100 articles. There are 314 brain regions activation images were collected from these articles. Image description related to activated brain regions, such as "Activity in the medial prefrontal cortex", were selected as the image captions. The test data set includes 30 articles with 108 brain regions activation images and their descriptions.

4.2 Baseline Methods

This paper chose four probabilistic topic models, including LDA, MicroASM, LF-LDA (Latent Feature-LDA) and LF-DMM, as baseline methods to verify the effectiveness of the proposed method on improving probabilistic topic modelling of neuroimaging literature. All baseline methods were performed on the full text of literature.

4.3 Experimental Result

Topic Learning from Images and Corresponding Descriptions. Different from existing probabilistic topic models, the proposed image-enhanced LDA extracts topic from images and corresponding descriptions. Topic learning from images can generate captions of fMRI brain regions activation images, which describe the topic information about activated brain regions. Topic words of brain regions can be extracted from these captions by using the dictionary-based method. Figure 3 gives the part of generated captions of activated brain regions [22,23]. Based on these captions, a groups of topic words about brain regions can be obtained. As shown in Fig. 3, not only a single activated brain region, such as "ventral striatum", "amygdala", but also multiple activated brain regions, such as "superior temporal gyrus, lingual gyrus" can be identified. Finally, captions of 64 images can be generated correctly. The precision rate is 59.3%.

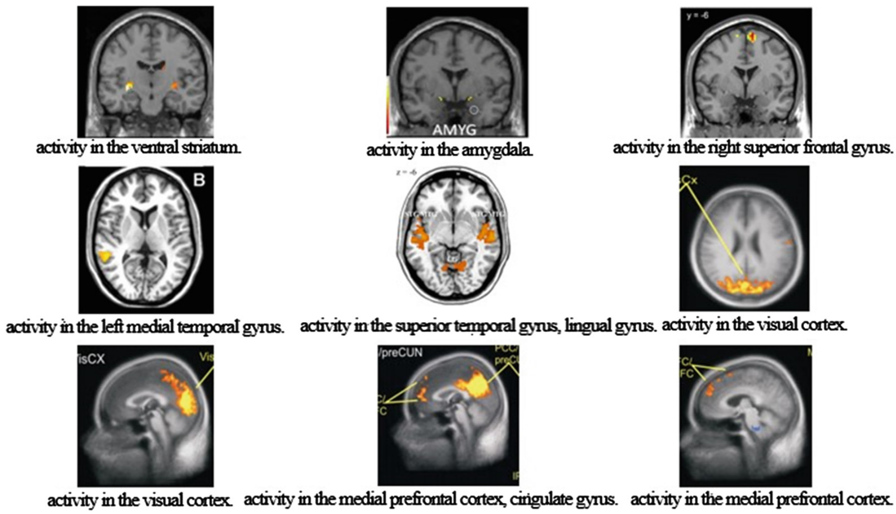

Fig. 3. The captions of brain activation regions generated by topic learning from images.

Topic learning from descriptions can extract topics about cognitive function states and identify relations between cognitive function and activated brain regions. The part of results is shown in Fig. 4. The information of brain cognitive mechanism is the primary purpose of topic modeling on neuroimaging literature. As shown in Fig. 4, a systematic view of brain cognition can be obtained by combining topic learning from images and corresponding descriptions. It shows the brain areas in the right, and some cognitive function or related elements (cognitive experiment elements)in the left. It suggests that the processed method can be effective to extract topics related brain cognitive mechanism by mining mixed neuroimaging literature.

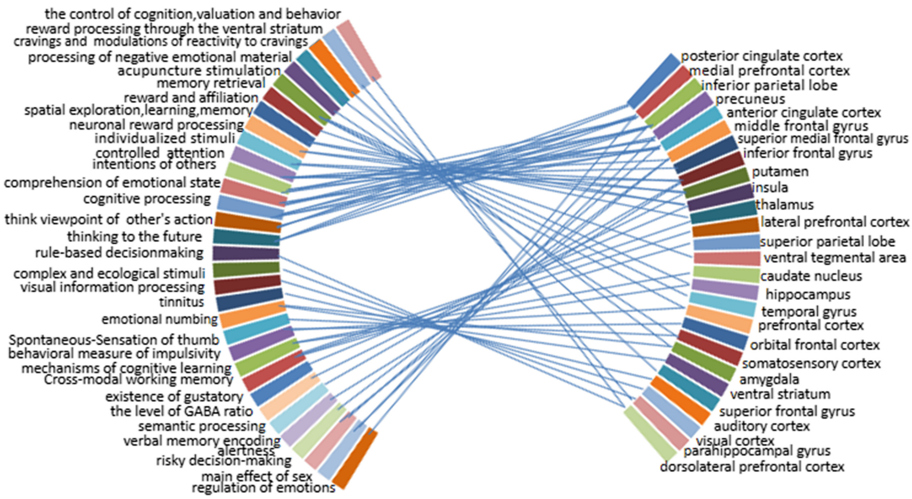

Fig. 4. The cognitive function and corresponding activated brain regions.

Topic Learning from Literature. Different from existing probabilistic topic models, the proposed image-enhanced LDA combines topics from images and corresponding descriptions with LDA topics from full texts. In order to verify the effectiveness of the combination, this paper chose four typical probabilistic topic models as baseline methods. However, how to evaluate the obtained topics became a difficulty. In this paper, all of the 30 test articles are related to brain cognitive researches based on fMRI. They have the similar topics. A good topic modeling method should be able to capture this similarity. Using this as the evaluation criterion, a variance analysis was performed on topic vectors, which were obtained by the proposed method and baseline methods. Topic vectors were constructed by using the average value of word2vec (word to vector) vectors of topic words. The experimental results are shown in Table 1. Based on the 30 test articles, the set of topic words obtained by the LFLDA has the largest variance value. The set of topic words obtained by the proposed image-enhanced LDA has the smallest variance value. Obviously, the proposed image-enhanced LDA can capture the similarity of test articles better than other baseline methods.

Table 1. Variance analysis of topic words.

Method	Image-enhanced LDA	LDA	MicroASM	LFLDA	LFDMM
Variance	2.79×10^{-6}	3.39×10^{-6}	1.091×10^{-5}	3.17×10^{-3}	4.0272×10^{-3}

5 Conclusion

Currently, neuroimaging literature has become a valuable source of knowledge. The method of neuroimaging literature mining is playing an important role on aggregate world-wide research findings for decoding brain cognitive mechanism, as well as diagnosis and treatment of brain and mental diseases, artificial intelligence researches, etc. This paper proposes the image-enhanced LDA to extract the topics of neuroimaging literature by fusing images and texts. There are two main contributions: Firstly, this paper proposes a feasible method to extract topics related brain cognitive mechanism. This effectively solves the problem that topics obtained by existing topic modeling methods of neuroimaging literature are mixed and need to be further processed. Second, this paper combines topics from fMRI brain regions activation images with topics from full texts to model neuroimaging literatures more accurately. The variance analysis shows the topic words obtained by the proposed method can better express neuroimaging than that obtained by other typical probabilistic topic models. There are also some limitations that it can add error about the influences of different brain map templates and image sharpness in extracting literature. In the future, it is interesting to use for the neural mechanisms of cognitive function. Moreover, it is also interesting to study the knowledge graph of the cognitive function by the method.

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