Is a Picture Worth Ten Thousand Words in a Review Dataset?

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ABSTRACT

While textual reviews have become prominent in many recommendation-based systems, automated frameworks to provide relevant visual cues against text reviews where pictures are not available is a new form of task confronted by data mining and machine learning researchers. Suggestions of pictures that are relevant to the content of a review could significantly benefit the users by increasing the effectiveness of a review. We propose a deep learning-based framework to automatically: (1) tag the images available in a review dataset, (2) generate a caption for each image that does not have one, and (3) enhance each review by recommending relevant images that might not be uploaded by the corresponding reviewer. We evaluate the proposed framework using the Yelp Challenge Dataset. While a subset of the images in this particular dataset are correctly captioned, the majority of the pictures do not have any associated text. Moreover, there is no mapping between reviews and images. Each image has a corresponding business-tag where the picture was taken, though. The overall data setting and unavailability of crucial pieces required for a mapping make the problem of recommending images for reviews a major challenge. Qualitative and quantitative evaluations indicate that our proposed framework provides high quality enhancements through automatic captioning, tagging, and recommendation for mapping reviews and images.

CCS Concepts

• Information systems → Data mining; Document topic models; • Computing methodologies → Neural networks;

1. INTRODUCTION

The usefulness of a review-based website (e.g., Yelp) largely depends on the quality of the materials produced by the recommendation system. To make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Figure 1: Suggested photos for a review describing a hamburger meal.
used to predict the label of each image, 2) a captioning algorithm that generates possible captions for images that were not captioned by the reviewer, and 3) a mechanism to map a review to a number of most relevant images. As an outcome of the proposed framework, we will be able to recommend images for each review as shown in Figure 1.

The paper contributes to the literature by describing a systematic approach to image recommendation for textual reviews, with minimal information available to create a mapping between both types. Section 2 outlines the problem and Section 3 describes the overall framework. Section 4 lists the evaluation techniques used. Section 5 provides descriptions of the experiments we performed. The related literature is described in Section 6 and we conclude the paper in Section 7. We deployed a Django-based website\(^1\) to visualize the outcomes.

2. PROBLEM DESCRIPTION

Let \( D = \{ (i_1, l_1, c_1, b_1), (i_2, l_2, c_2, b_2), \ldots, (i_N, l_N, c_N, b_N) \} \) be an image dataset containing \( N \) images \((i)\), along with their corresponding labels \((l)\), captions \((c)\), and business id \((b)\). A label can be a value from the following set of categories: \{food, inside, outside, drink, menu, none\}. A caption is expected to be a sentence but can be empty as well. Each image has exactly one business id.

Let \( R = \{ r_1, r_2, \ldots, r_{|R|} \} \) be a text dataset which contains all the reviews of a specific restaurant \( b \). We seek for a mapping \( M \), such that given a review \( r \in R \) we can select top \( k \) images \((i, l, c, b) \in D \) such that the image \( i \) is closely related to review \( r \). To establish such a mapping, we rely on relationships between a caption \( c \) of an image and review \( r \). Thus, a major task in the proposed framework is to generate a caption \( c \) for image \( i \), in case one does not exist, which can then be used to relate \( i \) to review \( r \). In turn, generating a caption \( c \) is performed using the probabilities of \( i \) belonging to the different possible categories of \( l \). In summary, we have three subtasks: (1) generate a label for images with none label, (2) generate caption-words based on the labels and the subset of images that has captions, and (3) for each review, find a set of relevant images by topically comparing the review and the image captions.

3. METHODOLOGY

Our framework solves the problem of recommending images for each review in three major steps. First, we use an image classifier to predict a label for images categorized as none. Second, we use a captioning algorithm, with the image features (obtained in the first step) and existing captions as inputs. This generates caption-words for images that do not have captions. Finally, we apply topic modeling on the reviews and captions separately to be able to create a probabilistic mapping. The following subsections describe these steps.

3.1 Image classification

The first step in our framework is to categorize each of the images labeled as none to one of the following categories: food, inside, outside, drink or menu. Our preliminary data analysis reveals that more than 25% of the restaurant images are labeled as none. We use a Convolutional Neural Network (CNN) image classifier to obtain class probabilities for all images in the test set (labeled as none).

Convolutional Neural Network algorithms require that all of the images have the same dimension and are shaped as a square. We resized the images so that the smallest dimension of the image is 64 or 224 pixels, and then cropped the image in the other dimension to obtain a 64-by-64 pixel or 224-by-224 pixel image. We tested and implemented CNN models using two Python 2.7 libraries based on the Theano deep-learning library: Keras and Lasagne. The CIFAR10 and GoogleNet provide high-level functions for deep learning algorithms, including convolution, pooling and fully-connected layers, as well as backpropagation and optimization routines, whereas Theano provides the back-end of the computation and includes GPU support.

We used a number of different CNN models to evaluate their accuracy. One of these models was based on the CIFAR10 data while the others were designed to work with the ImageNet data: VGG-16, VGG-19 and GoogleNet. The CIFAR10 model is relatively simple, with only 14 layers. The VGG-16 model adds four convolutional layers and one fully-connected layer, which significantly increases the complexity of the model. The VGG-19 and GoogleNet models add even a larger number of layers, consisting of 19 and 22, respectively. We also used MATLAB’s Bag-of-Features with SVM classification algorithm as a baseline. We used six-fold cross validation for evaluation of all these approaches.

3.2 Image captioning

We leverage a Lasagne-based implementation of the Neural Image Caption (NIC) generator to predict captions for images with no caption. The NIC generator uses a special form of a recurrent neural network (RNN) called Long-Short Term Memory (LSTM) network to sequentially create a fixed-dimensional vector, required due to the variable length of the input and output sentences. LSTM nets are a special type of RNN capable of learning long-term dependencies. LSTM nets apply weighted layered gates between the input, output and previous hidden states. By assigning different magnitudes to every gate (between 0 and 1), the information flow is modified so that the previous information is useful for the model, and if not, the model forgets the information. LSTM nets are able to train the gates automatically through backpropagation, obtaining a more robust

\[^1\]Available at: https://auto-captioning.herokuapp.com\]
The LSTM net uses information about an image as input. We obtain a lower-dimensional representation for each image using a Convolutional Neural Network (CNN). Out of the several CNN models described in Section 3.1, we chose the GoogLeNet model trained on 224-by-224 images to feed the image features to the LSTM net because of GoogLeNet’s flexible compatibility with LSTM. The captioning results presented in this paper are resultant from image features generated by GoogLeNet. The complete model is outlined in Figure 2. In the figure, $S_i$ represents a word of a sentence, $W_e$ represents the trained parameters, $p_i$ is a probability distribution over all the words in the vocabulary and the log $p_i(s_i)$ is the log-likelihood of the correct word at each step.

Captions are generated by maximizing the log-likelihood of obtaining the correct caption given an image. The LSTM net is trained sequentially and takes into account the image as well as all of the previously seen words to infer the next word of the output sentence. At each position of the output sentence only the word with the highest probability is selected, which has the disadvantage of not providing the globally optimal solution. The detailed sampling method required for this inference model is described in [35].

While prediction of caption-words by learning relationships using existing captions seems a logical direction, we did not target the problem of correcting captions in case they are not appropriate. Based on our study, not reported in this paper, many of the captions do not describe the relevant image well. For example, a caption “Hurrah it’s my birthday” for a picture of a pasta dish only increases the noise-level rather than providing informative features. A possible solution is crowdsourcing a subset of data to obtain an accurate training set. However, this aspect is out of the scope of the current paper.

Figure 3 shows a screenshot of our website for a picture of a glass of margarita. The suggested caption-words include margarita as well as another cocktail, Bloody Mary. This sample indicates that our proposed system was able to closely predict content of the image and map them with textual snippets.

### 3.3 Topic modeling and review enhancement

We leverage Latent Dirichlet Allocation (LDA) [4] to model the topics of the reviews. For each review, we select the best topic and select the top $t$ representative terms of that topic, regardless if they appear on the review or not. For each review, we recommend the top $\phi$ images based on the presence of the $t$ representative terms in the review and in the captions of the images available for the business for which the review was written. An image is ranked higher for a particular review if a representative term is present both in the image caption and in the review, compared to an image which contains the representative term only in its caption.

We start by selecting images using representative terms that are present in both the review and the image caption. If $\phi$ images cannot be found, we select images for which captions contain representative terms but the review does not. This process ensures that the image selection is not solely driven by overlaps between a review and a caption, rather reviews and image captions without any overlap may become candidates for potential mapping due to the use of topical terms during the ranking. Figure 1 shows a sample of recommended images for a text review written for a burger.

### 4. Evaluation

We use different metrics to evaluate the quality of the results for each of the main components of the framework: image classification, image captioning, and topic modeling. For image classification, we use the top-1 accuracy, which is the percentage of test images that were classified correctly,
as defined by Equation (1). We only use the top-1 accuracy because of the small number of possible labels.

\[
\text{accuracy} = \frac{\text{images labeled correctly}}{\text{total images}} \times 100\% \quad (1)
\]

The evaluation of the quality of the image captioning results was performed using a combination of two different metrics: Bilingual Evaluation Understudy (BLEU) and a confidence score. The BLEU method, proposed by Pаницa, et al. [28], computes the geometric mean of n-gram precisions. Since the training set consists mostly of short sentences (captions), we removed the brevity penalty typically used, which prevents that very short sentences have very high scores with just a few words match. We obtained a range of BLEU-1 to BLEU-4 scores using the corpus_bleu function of NLTK, a Python library focused on Natural Language Processing. The BLEU metric has some shortcomings, particularly because it does not take into account the probability with which a caption is generated.

Because of this limitation, we designed a metric that measures a confidence score for each generated caption. When a caption is being generated, we take the top k candidate words at each position in a sentence. For each position, we use Equation (2) to measure the non-uniformity of probabilities for the k candidates:

\[
\nu(X) = \frac{|U(\nu) - X|}{2 - 2/k} \quad (2)
\]

where X is the normalized probability distribution of the top k candidates where k > 1, and U is a uniform probability distribution over size k. Ideally, we would like a very high non-uniformity value (\(\nu(X) = 1\)) which means that we are very confident that the top word should be next. A uniform distribution (\(\nu(X) = 0\)) would indicate a random selection of top words. We compute the confidence for a generated caption with the following equation:

\[
\text{Confidence}(W) = \frac{\sum_{i=1}^{m} (e^{\nu(w_i)})^{p(w_i)}}{[m \times e^1] - m} - m \quad (3)
\]

where W is an array of m words, W = \(\{w_1, w_2, ..., w_m\}\) representing the generated sentence, \(\nu(w)\) is the normalized truncated probability distribution of top k words for each position in the sentence in which w has the highest probability, and \(p(w)\) is the probability of the word w from the original distribution. This metric has a range of \([0.0, 1.0]\), where higher confidence is better.

The evaluation of the LDA topics was performed using perplexity, which measures the model fit of an unseen set of documents, where the value decreases as a function of the log-likelihood of the holdout documents. An LDA model with lower perplexity is better. We use the following bounded definition of perplexity, presented by Hoffman, et al. [17]:

\[
\text{perplexity}(n^{\text{test}}, \lambda, \alpha) \leq \exp\left(\sum_{i} E_q[\log p(n^{\text{test}}, \theta_i, z_i | \alpha, \beta)] - E_q[\log q(\theta_i, z_i)]\right) \left(\sum_{i, w} n^{\text{test}}_{i, w}\right) \quad (4)
\]

where \(n^{\text{test}}\) is the total word count of the holdout documents, \(\lambda\) is the posterior parameterization over \(\beta\), \(\alpha\) is the Dirichlet parameter, \(n^{\text{test}}_{i, w}\) is the word count of holdout document \(i\), \(\theta_i\) is a vector of topic weights for document \(i\), \(z_i\) is a vector of per-word topic assignments for the words in document \(i\), \(\beta\) is a dictionary of topics, \(q\) is a variational distribution which is indexed by a set of free parameters, and \(n^{\text{test}}_{i, w}\) is the number of times the word \(w\) appears in the holdout document \(i\).

### Table 1: Characteristics of the Griffin cluster.

| Component | Technology |
|-----------|------------|
| Nodes     | (7x) Compute Nodes |
| Processor | 8 cores/processor |
| Memory (RAM) | 4GB/core |
| Hard Drive | 1TB SATA 7.2K RPM 16MB cache |
| Video Card | (2x) NVIDIA Tesla M2090, 1.3GHz |

### 5. EXPERIMENTS

In this section, we seek to answer the following questions about the proposed framework.

1. How do different CNN architectures compare in terms of the accuracy of image classification? How do these results compare with a simpler method, e.g. SVM using bag-of-features? (Section 5.1)
2. How does changing model hyperparameters for the NIC generator affect the results in terms of confidence and BLEU-4 score? What is the relationship between the confidence score and the BLEU score for the generated captions? (Section 5.2)
3. How well does our framework generate captions for the images of the Yelp dataset? (Section 5.3)
4. How does varying different hyperparameters affect the perplexity of the resulting LDA model? (Section 5.4)
5. Can we relate reviews with images based on the top words obtained through topic modeling? (Section 5.5)

We focused on the 25,071 (out of 77,445) restaurants detected in the Yelp dataset. The restaurant image dataset contains 98,786 images with an average of 4 images per restaurant; 62% of the images do not contain any caption and 25% are labeled as none. The total number of reviews for restaurants is 1,363,242.

Deep Neural Networks, such as CNNs and LSTM nets, require large memory and computing-power. We used two different devices for our experiments: an ASUS K501UX laptop, and the Griffin computing cluster, at the University of Texas at El Paso. The ASUS laptop has a 2.5 GHz Intel Core i7 6500U processor, 8GB memory, and NVIDIA GTX950M 914 MHz 2GB video card. Due to the low memory capacity of the NVIDIA GTX950M, the laptop was limited to training images of 64 by 64 pixels. Table 1 provides the configuration of the Griffin computing cluster.

### 5.1 Image classification

We tested different CNN architectures to compare the accuracy obtained with each of them for the image classification problem. The architectures include: a simple CIFAR10 model (11-layer deep), VGG-16 [31] (16-layer deep), VGG-19 [31] (19-layer deep) and GoogleNet [33] (22-layer deep). We also used the MATLAB® Bag-of-Features-based SVM classifier as a baseline, to verify the gain in accuracy obtained by using a neural network versus a simpler method.
Table 2: Results for image classification based on labels.

| Model              | Image size | Learn. rate | Epochs | Accy.  |
|--------------------|------------|-------------|--------|--------|
| Simple model       | 64 x 64   | 0.0001      | 160    | 94.12% |
| VGG-16             | 64 x 64   | 0.0001      | 160    | 94.78% |
| VGG-19             | 224 x 224 | 0.001       | 10     | 83.79% |
| GoogleNet          | 224 x 224 | 0.001       | 10     | 78.93% |
| BoF SVM            | 64 x 64   | N/A         | N/A    | 69.00% |

Table 3: Detailed results for image classification using images of 64 by 64 pixels.

|                     | CIFAR10 model | VGG-16 model |
|---------------------|---------------|--------------|
| Epochs              | 160 epochs    |              |
| Average time        | 188           | 1,220        |
| (sec per epoch)     |               |              |
| Total time          | ~8 hours      | ~54 hours    |
| Best training       | 95.70%        | 99.78%       |
| accuracy            |               |              |
| Best test accuracy  | 94.12%        | 94.78%       |

All of the models were used to classify the images into five different classes. The weight initialization for all the CNN models was a uniform random distribution between −0.5 and 0.5. Table 2 presents the configurations used and the accuracy obtained for each model. The results indicate that using neural networks improves significantly the accuracy of the image classification models. The models using 64-by-64-pixel images were trained from scratch using Keras, while the models using 224-by-224-pixel images were trained with Lasagne after initializing the model weights to the ones obtained using the ImageNet dataset. This, along with the smaller learning rate and the higher number of epochs trained, might explain the higher accuracy of the models trained with 64-by-64-pixel images.

Table 3 presents more details about the results for the models that use images of 64 by 64 pixels. Each of these models was trained for 160 epochs. The VGG-16 model obtained 94.78% accuracy on the test data, while the CIFAR10 model obtained a 94.12% accuracy. Our observation is that the difference in the accuracy for the training data is significantly larger, and that the error on this dataset for the VGG-16 model is very small (0.22%). Thus, the VGG-16 model might be overfitting the training data.

The VGG-16 model took significantly longer to train compared to the simple model, with 54 hours against the 8 hours that the CIFAR10 model required. This is a result of the difference in the number of layers, and in particular the number of convolution operations required by each model. While the CIFAR10 model only has one convolutional layer, the VGG-16 has five.

Figure 4 shows how the accuracy for both of the models changes as the number of epochs increases. As can be seen, the CIFAR10 model outperforms the VGG-16 for the first five epochs. After the sixth iteration, the VGG-16 model appears to be consistently better than CIFAR10, albeit by a small margin. The graph also shows that the accuracy of each classifier seems to reach a steady state, but the accuracy still varies from epoch to epoch, which indicates that the training may be reduced to around 60 epochs.

To further evaluate the CNN model used for the image captioning component of our framework, GoogLeNet, we performed a participant-based evaluation of the predicted labels of 240 randomly selected images originally labeled as None. All these images and the predicted labels were given to one participant for evaluation. The participant was asked to mark the predicted labels as correct or incorrect and comment on anything observed. Based on the participant’s comments, there were 38 images that did not belong to any of the five classes because of lack of relevance of the image contents with the labels. These 38 images include phone numbers, face images, group photos, and other irrelevant images. Out of the 202 remaining images, according to the participant, 149 images were labeled correctly (73.76%). Our observation from this study was that the CNN model did not perform as good when attempting to distinguish between inside and outside labels, particularly in dark settings. We proceed with the results obtained from GoogLeNet because this model provides a decent level of accuracy on average and is compatible with the neural image caption generator.

5.2 Image captioning

The NIC generator has several hyperparameters that can affect the quality of the resulting captions: maximum sequence length (max_seq_len), batch size (batch_sz), embedding size (embedding_sz), learning rate (lr), and num-

Figure 4: Accuracy per epoch on testing data.

Figure 5: Effect of embedding size and learning rate settings on quality of NIC generator.
Table 4: Results of evaluation of generated image captions.

| Evaluator | Min | Max | Avg | Median |
|------------|-----|-----|-----|--------|
| Participant 1 | 1 | 10 | 6.29 | 6     |
| Participant 2 | 1 | 10 | 5.01 | 4     |
| Participant 3 | 1 | 10 | 4.92 | 3     |
| Participant 4 | 1 | 10 | 5.61 | 6     |
| Participant 5 | 1 | 10 | 6.40 | 8     |

the BLEU score because this score is highly dependent on the sequence of selected words. We use a confidence score, as described in Section [3] to measure the strength of each BLEU value. This allows us to isolate high quality BLEU scores. Figure 7 shows how the BLEU-n scores change with increasing confidence score of the captions. For each point in the figure, we compute the BLEU-n score using only the samples that have a confidence score greater than the value on the X-axis. The generated captions exhibit a confidence level higher than 95% to obtain a corpus-level BLEU-1 score of 70% and a BLEU-4 score of 45%. Evaluation using BLEU-1 score is more appropriate for this study given that captions are generally small and frequent larger-grams are scarce.

5.3 Caption evaluation

To qualitatively evaluate the generated captions, we asked five participants to manually assign a score to each generated caption for one hundred images. For each image, we presented the participant with five captions generated by the NIC generator (or less, if there were repetitions). Each set of captions was evaluated using a score on a scale of 1 to 10, with 10 meaning that all five captions have terms related to the image and 1 meaning that no caption has any term related to the image. As a baseline, the participants were asked to rate an image captioning with a score of 2 if only one caption out of five contained exactly one term related to the image.

The one hundred images used for this evaluation are the first hundred images that appear in our website. This subset of images contains 40 images labeled by our CNN predictor as food, 17 images as drink, 16 images as outside, 14 images as menu, and 13 images labeled as inside.

Table 4 presents a summary of the scores provided by each of the participants. In general, the average of these scores is 5.646, and the median is 6 which indicates that, on average, at least half of the captions generated for an image have some terms related to the image content. Based on an overall calculation of all the scores provided by all participants, 73.2% of the images have a score of 3 or higher. This indicates that 73.2% of the images have at least one predicted caption containing terms related to the image. This result demonstrates high quality prediction given that there can be a tremendous amount of possible word combinations for captioning.

5.4 Topic modeling

The Gensim implementation of Latent Dirichlet Allocation used in our framework has the following parameters: number of topics (n_topics), words per topic, iterations (iters), α, η, κ and θ_0. For all of the experiments, we used the ten top words for each topic. As mentioned in Section [3], lower perplexity is expected in a better model. In Figure 8, we show the effect of setting κ to {0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4}.

Available at: https://auto-captioning.herokuapp.com
0.8, 0.9, 1.0} and \( \tau_0 \) to \{1, 64, 256, 1024\} on the perplexity of the LDA model, while both \( \alpha \) and \( \eta \) are set to symmetric, \texttt{n\_topics} is 20, and \texttt{iters} is 50. The results show that the locally optimal values for \( \kappa \) and \( \tau_0 \) are 0.5 and 1, respectively.

Using these values for \( \kappa \) and \( \tau_0 \), we test changing \( \alpha \) between \{'symmetric', 'asymmetric', 'auto'\} and \( \eta \) between \{'symmetric', 'auto'\}, while the other hyperparameters remain the same. Figure 9 presents the effect of changing these variables, where the optimal values for \( \alpha \) and \( \eta \) are 'auto' and 'symmetric', respectively.

Finally, we test setting \texttt{n\_topics} to \{20, 50, 100\} and \texttt{iters} to \{50, 100, 150\}, while the other hyperparameters remain the same. Figure 10 presents the effect of changing these variables, where the optimal values for \texttt{n\_topics} and \texttt{iters} are 20 and 150, respectively.

In this section we have shown that certain hyperparameters, such as \( \kappa \) and \( \tau_0 \), can have a significant impact on the perplexity of the model. Our observation is that choosing the wrong values for \( \kappa \) and \( \tau_0 \) may result in a 1.45 times increase in perplexity, while a modification of \( \alpha \) and \( \eta \) can result in a 1.2 times increase in perplexity. Changes in the number of topics and iterations demonstrate a 1.1 times increase in perplexity. Thus, a careful optimization of these parameters is required to obtain the optimal LDA model in terms of perplexity.

### 5.5 Recommending images for reviews

In this subsection, we describe a few review-to-image recommendations obtained by our framework. We provided a sample in Figure 1 of Section 1 that illustrates that our framework was able to recommend relevant images for a review on a burger-meal. Another review, its top topical words, and recommended images are shown in Figure 11. The review was taken from Yelp’s entry for the Mon Ami Gabi restaurant in Las Vegas. This example shows that the recommended set contains the images of the fountains of the Bellagio hotel across the street as described in the review.

Summaries of five more reviews with the top three recommended images for each are provided in Table 5. The table shows that our framework is able to recommend images of main dishes, as well as outside features such as the Bellagio.
6. RELATED WORK

Yelp introduced images in the Yelp Challenge recently. To the best of our knowledge, no previous publications have focused on enhancing Yelp reviews by recommending related images. The literature associated with the tasks involved in this paper is described below.

The problem of image classification has been studied for at least half a century, with initial approaches focusing on manual extraction of textural features [15]. Due to the difficulty of manual feature extraction, several automatic algorithms have been developed including histogram-based SVM classification [1], as well as pyramid matching with sparse coding [37] and locality-constrained linear coding [36]. Other methods use a bag-of-features approach, followed by a classifier such as SVM [2].

Recently, there has been a lot of interest in deep neural networks. In the area of image classification, a surge has been observed in convolutional neural networks (CNNs). CNNs are neural networks formed by three different types of layers: convolutional layers, pooling layers and fully-connected layers. These layers can be stacked in many different ways, and research is advancing in the direction of deeper networks. Some of the most relevant CNN models include AlexNet [20], VGG [31], GoogLeNet [33] and ResNet [16].

The image captioning algorithm used in this paper, based on the work by Vinyls, et al. [35], combines a Convolutional Neural Network (CNN) with a special form of a Recurrent Neural Network (RNN) called Long Short-Term Memory (LSTM). Alternatives to using LSTM include primitive rule-based systems [13, 38] or object detection combined with templates [12, 25, 21] or Language Models [27, 1, 22, 23, 11] for caption generation. These are heavily hand-designed alternatives and would be too laborious to implement. Another alternative method for captioning and ranking of these captions is co-embedding images and text in the same vector space [32].

Topic modeling has also been widely used in text mining in the past decade. Of particular interest are latent semantic indexing (LSI) [8] and probabilistic LSI (pLSI) [18], which map documents to a latent semantic space. Latent Dirichlet Allocation (LDA) [4], which is used in this work, is a probabilistic approach that generalizes pLSI. Variations of this algorithm include dynamic topic modeling [3] and online LDA [2]. Neural networks have also been used for topic modeling [24, 30].

7. CONCLUSIONS

The framework we designed to enhance Yelp reviews by recommending images requires no supervision. The training samples are gathered from the existing information pieces available with the data. A part of the proposed methodology focuses on enhancing and improving the existing data by providing additional information, i.e., categorizing images and predicting caption-words for them. One of the future directions of this work is to provide further enhancements through the use of multi-label classification where existing caption-words will be used as labels. Another future goal is to develop models to track the performance of a business and the sentiment detected in review and caption texts.

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