Learning Convolutional Text Representations for Visual Question Answering

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ABSTRACT

Visual question answering is a recently proposed artificial intelligence task that requires a deep understanding of both images and texts. In deep learning, images are typically modeled through convolutional neural networks, and texts are typically modeled through recurrent neural networks. While the requirement for modeling images is similar to traditional computer vision tasks, such as object recognition and image classification, visual question answering raises a different need for textual representation as compared to other natural language processing tasks. In this work, we perform a detailed analysis on natural language questions in visual question answering. Based on the analysis, we propose to rely on convolutional neural networks for learning textual representations. By exploring the various properties of convolutional neural networks specialized for text data, such as width and depth, we present our "CNN Inception + Gate" model. We show that our model improves question representations and thus the overall accuracy of visual question answering models. We also show that the text representation requirement in visual question answering is more complicated and comprehensive than that in conventional natural language processing tasks, making it a better task to evaluate textual representation methods. Shallow models like fastText, which can obtain comparable results with deep learning models in tasks like text classification, are not suitable in visual question answering.

1 INTRODUCTION

Visual question answering (VQA) [1, 17] asks an agent to generate an accurate answer to a natural language question that queries an image (see Figure 1). This composite task involves a variety of artificial intelligence fields, such as computer vision, natural language answering, knowledge representation and reasoning. With the great success of deep learning in these fields, an effective VQA agent can be built with applications of deep learning models. A typical design is to use an answer generator based on a joint representation of visual and textual inputs [1]. A considerable body of research has been conducted on appropriately combining visual and textual representations [11, 19, 26, 39, 41], while the fundamental question of learning these representations specifically for visual question answering has not generated a lot of interests. In this work, we perform a detailed analysis on text data in VQA and design textual representation methods that are appropriate for this task.

In VQA, the subtask of extracting visual information can be well addressed by models commonly used in computer vision tasks like object detection [12, 25] and image classification [12, 22, 24, 33, 36], because they share similar demands for visual representations. Deep convolutional neural networks (CNNs) [24] have achieved significant breakthroughs in computer vision and can be directly used in VQA. In natural language processing, recurrent neural networks (RNNs) [32] are widely used to learn textual representations in tasks like text sentiment classification [7, 10, 18, 20, 23, 34, 42], language modeling [4, 6, 8, 28], and machine translation [2, 35, 38]. Parallel to image representations, most previous deep learning models on VQA [1, 11, 19, 26, 39, 41] directly rely on RNNs to extract textual information. However, our detailed analysis on text data reveals some special properties of text data in VQA. These results indicate that RNNs may not be the best fit for text representation in VQA.

With the above analysis and insights, we propose to apply CNNs for learning textual representations in VQA. CNNs for texts have been explored in simple text classification task [7, 10, 18, 20, 42] and shown comparable results with RNNs. Our experiments show that a very simple CNN-based model outperforms a RNN-based model that has much more parameters, a result that is consistent with our analysis. In further work, we incorporate techniques from CNNs for images and RNNs and make specialized improvements to build wider and deeper networks. Different methods for text vectorization are also explored and analyzed. Our best model yields a substantial improvement as compared to VQA models with RNN-based textual representations.

Recent study on text classification also shows that a shallow model like fastText [16] can achieve comparable accuracy with deep learning models in text classification. This result contradicts the common belief that deep learning models have higher representation power than shallow ones. It is speculated that simple text classification only needs shallow representation power. We conduct experiments on learning textual representations using fastText in VQA and observe a significant decrease in accuracy. This demonstrates the different requirements for textual representations in VQA, which makes the use of deep learning models necessary. We argue that VQA is an appropriate task to evaluate different textual representation models.

2 BACKGROUND

In this section, we describe two basic families of neural networks, namely convolutional neural networks [24] and recurrent neural networks [32], and their use in visual question answering [1, 17].
As CNNs are specialized for matrix data, recurrent neural networks (RNNs) are specialized for processing sequential data. Similar to long short-term memories (LSTMs) [13] and gated recurrent units (GRUs) [5]. In natural language processing, text data is naturally a type of sequential data so that RNNs are widely used in tasks like text sentiment classification [7, 10, 18, 20, 23, 34, 42], language modeling [4, 6, 8, 28], and machine translation [2, 35, 38]. Similar to CNNs for image data, RNNs work as feature extractors in these tasks by encoding sequential data into vector representations. In addition, as generative models, RNNs are also used as decoders in language modeling and machine translation.

As compared to using CNNs on sequential data, applying RNNs on image data is more natural. In terms of data size, CNNs for sequences must solve the problem of variable lengths while RNNs for images do not have this problem. With different ways to serialize matrix data, RNNs have been shown to be effective to some extent. Meanwhile, for video data, combination of RNNs and CNNs is an active research topic [3, 9].

2.3 Visual Question Answering

Visual question answering (VQA) requires an agent to answer a natural language question based on a corresponding image. It has drawn considerable attention from artificial intelligence, deep learning, computer vision, and natural language processing research communities. As compared to most traditional computer vision and natural language processing agents, an agent that solves the VQA problems is more likely to pass the Turing Test, since both visual and textual understanding and knowledge reasoning are needed in VQA. Deep learning has shown its power in a variety of AI tasks. However, training deep learning models demands a large amount of data. To this end, various datasets aimed at VQA are collected and made available [17]. In [1] a VQA dataset (COCO-VQA) with a well-defined quantitative evaluation metric was made available. This makes it feasible to develop computational methods based on recent achievements in deep learning. They also held a public VQA challenge based on this dataset in 2015. Most current deep learning models for COCO-VQA share a similar pattern. That is, they usually consist of four basic components: an image feature extractor, a text feature extractor, a feature combiner and a classifier.

Image Feature Extractor: Effective CNN-based visual representation models for computer vision, such as VGG [33], ResNet [12], and GooLeNet [36], have been used as the image feature extractor. The performance is consistent among tasks; that is, better image classification models yield better results when used in VQA models. This implies the image classification task shares similar requirements with the VQA task for feature extraction of image information. However, this is not the case on text side, as discussed in Section 3.

Text Feature Extractor: In VQA, RNNs like LSTMs and GRUs are commonly used as the text feature extractor. To the best of our knowledge, only a very simple CNN model has been used in [41] and achieved similar performance as RNNs. This work provides a detailed exploration of CNN-based text feature extractor and obtains considerably better results on VQA tasks.

Feature Combiner: Since VQA was initially proposed, most efforts have been devoted to improving the method for combining image and text feature vectors into a joint representation that contains the information needed to answer the question. In [1]
element-wise multiplication or concatenation was proposed. In [11] the multimodal compact bilinear (MCB) pooling, which approximately computes the out-product of two vectors, was proposed and won the VQA challenge on COCO-VQA [1]. MCB was improved in [19] by adding more parameters in the layer. In contrast, a RNN-based episodic memory architecture was proposed in [39] and used as the combiner. Moreover, attention mechanism, especially spatial visual attention, has been shown to be effective as part of the combiner with its ability to extract highly related information from images [26, 41].

**Classifier:** As proposed in [1], during training, the top K frequent answers in the training set are chosen to form an answer vocabulary. This casts the VQA problem into a K-class classification problem. The classifier used in VQA models is the *Softmax* function, which is typically used in other classification problems like image classification and text sentiment classification. For testing, the accuracy is computed by a specific evaluation metric as discussed in Section 4.1.

### 3 TEXT REPRESENTATIONS IN VQA

In this section, we discuss the special properties of text data in VQA. This motivates us to apply CNNs as the text feature extractor. We perform detailed analysis of text data in VQA and develop CNN models that achieve promising performance.

#### 3.1 Analysis of Texts in VQA

Natural language questions in VQA are different from other text data in several aspects. First, people tend to ask short questions, according to different VQA datasets [17]. For example, the longest question in the training set of COCO-VQA contains only 22 words, and the average length is 6.2. Most questions have 4 to 10 words. Second, the required level for textual understanding in VQA differs from that in conventional natural language processing tasks such as text sentiment classification. In sentiment analysis of movie reviews [18, 34], the learned text feature vector is given to a classifier to determine whether the author of a post likes or dislikes a movie. So the agent, or the feature extractor, will focus on emotional words but pay little attention to other contents. In VQA, in order to answer a question, a comprehensive understanding is required since a question can ask anything. As a result, the text feature extractor in VQA should be more powerful and computes comprehensive information from the raw texts. Third, questions are different from declarative sentences. Words in a question in VQA are highly related to the contents of its corresponding image.

Based on these properties, we argue that, as compared to RNNs, CNNs are the better choices for text feature extraction in VQA. By analyzing how human beings process questions, we observe that there are two keys in understanding questions: one is understanding the question type, which is usually determined by the first a few words, and the other is understanding the objects mentioned in the question and the relationships among them. In many cases, the question type directly describes what the answer looks like [1].

Answers to questions starting with “Is the”, “Is there”, “Do” are typically “yes” or “no”. “What number” and “How many” questions must have numbers as answers. Questions beginning with “What color”, “What animal”, “What sport” and so on all explicitly indicate their answers’ categories. Meanwhile, objects and their relationships are usually nouns and prepositional phrases, respectively, in the question sentence. They provide guidance on locating answer-related facts in the image, which is the fundamental module of the attention mechanism in VQA models.

Now the task of text feature extraction becomes clear; that is, to obtain a feature vector consisting of information about the question type and objects being queried. To be more specific, the textual representation is supposed to extract what the starting words, nouns as well as prepositional phrases represent. Considering words and phrases as features of text, a model specializing on feature detection should be an appropriate choice. While both CNNs and RNNs serve as feature extractors in their general usage, RNNs, including LSTMs and GRUs, do not have explicit feature extraction units. In contrast to convolutional connections in CNNs, the connections within and between units in RNNs are mostly fully-connected. To summarize, CNNs are conceptually more appropriate as the text feature extractor in VQA, which is also validated by our experiments. Additional advantages provided by CNNs are fewer parameters and easily parallelable, which accelerate training and testing while reducing the risk of over-fitting.

#### 3.2 Transforming Text Data

A challenge of applying CNNs for text data is how to convert raw texts in a format that CNNs can take, as they are originally designed for fixed-size matrix data like images. To apply CNNs on texts directly, we need to represent text data in the same way as how image data are represented. Each image is typically a 3-dimensional tensor, where the three dimensions correspond to height, width (in terms of number of pixels), and number of channels, respectively. Elements of the tensor are scalar pixel values. For example, a $256 \times 256$ RGB image may be stored as a $256 \times 256 \times 3$ tensor whose elements are RGB values of every location in each channel. Each pixel of the image is actually represented as a 3-component vector corresponding to 3 channels.

Intuitively, a text sentence can be considered as an image with height equal to 1. Inspired by the bag-of-words model in natural language processing, a vocabulary is first built to transform texts into pseudo images. The vocabulary can be either word-based that contains words appearing in the texts, or character-based, which is fixed for a particular language. It is also reasonable for the vocabulary to include punctuation as single words or characters. The width of text data is defined based on the vocabulary; that is, for word-level representations the width is number of words in a sentence; for character-level representation we count the number of characters. To make it concrete, we take the word-based vocabulary as an example, and the character-based case can be easily generalized in Section 3.3. Similar to pixels in an image, if we can convert each word as a vector, the length of the vector is the number of channels. The problem is then reduced to word vectorization, which is usually done by one-hot vectorization.

Given a vocabulary $V$, each word can be represented as a one-hot vector; namely a $|V|$-component vector with one 1 at the position corresponding to the index of the word in $V$ and 0s for other entries, where $|V|$ is the size of $V$. With one-hot vectorization, the number of channels becomes $|V|$. As a result, a sentence with $L$ words is
treated as a $1 \times L$ pseudo image with $|V|$ channels, and it can be given into CNNs directly by modifying the height of convolutional kernels into 1 consistently. Although one-hot embedding works well as inputs to CNNs in some cases [14, 15], it is sometimes preferable to have a lower dimensional embedding. There are two primary reasons. First, if $|V|$ is large, which is usually the case for word-based vocabulary, computation efficiency is low due to the sparsity and high dimensionality of inputs. Second, one-hot embedding is semantically meaningless. Thus, an extra embedding layer is usually inserted before CNNs. This layer maps the $|V|$-component vectors into $d$-component vectors, where $d$ is much smaller than $|V|$ [6, 10, 18, 20]. The embedding layer is basically a multiplication of one-hot vectors with a $|V| \times d$ matrix to perform a look-up operation. These distributed representations can capture a variety of syntactic and semantic relationships between words. The embedding matrix can be trained as part of the networks, which are task-specialized, or can be pre-trained using word embedding like Word2Vec [27, 29, 30] or GloVe [31]. After the embedding layer, the pseudo images will have $d$ channels. Figure 2 provides a complete view of the transformations.

### 3.3 Word-Based versus Character-Based Representations

Note that once a vocabulary is built, the remaining process to transform text data follows the same path for different vocabularies. It is clear that the vocabulary $V$ defines the pixels in the pseudo image obtained from text data. In the above example, each word becomes a pixel. If the vocabulary is character-based, each character, including space character and single punctuation, will be a pixel. In this case, suppose a sentence has $C$ characters in total, the resulting pseudo image has a size of $1 \times C$ with $|V|$ channels. The embedding layer then converts $|V|$ channels into $d$ channels.

The main advantage of character-based vocabulary is that it produces much longer inputs since $C$ is usually larger than $L$. This makes it possible for using deeper models. For long texts, transforming text data using character-based vocabulary and applying very deep CNNs leads to impressive performance [7, 42]. Another advantage is that characters may include knowledge about how to form words. However, for short texts, the size of the transformed data is still small even with character-based vocabulary. Our experiments show that models that work well for long texts with character-based vocabulary fail to obtain high performance in VQA (Section 3.5). It is believed that the inputs are too short for the models to learn that space is the delimiter for words, which is naturally given in word-based vocabulary case. The combination of character-based and word-based vocabularies for short texts has been explored in [10] and achieved comparable results. In this method, characters corresponding to each word are grouped together. Instead of computing the sentence representation directly from characters, word representation is generated intermediately. Each group of characters is transformed by character-based vocabulary and then fed into a smaller textual representation model to generate a word vector. The word vector is then concatenated with the corresponding word embedding from word-based vocabulary to form a larger word representation. More details are given in Figure 2. These two methods that involve character-based vocabulary are explored in our experiments. Nevertheless, due to the special properties of texts in VQA, character-based vocabulary seems to have little effect on the overall performance.

### 3.4 Handling Variable-Length Inputs

Another problem for text data is that each sentence is composed of different numbers of words, and this leads to variable sizes of inputs and outputs of convolution layers. However, the outputs of the whole CNN module are expected to be fixed-sized, in order to serve as inputs to next module. Moreover, the sizes of inputs to CNNs should also be consistent in consideration of training.

Inspired by the pooling layers applied for down-sampling after convolution layers in CNNs for images [24], several pooling layers specialized for text data of variable lengths have been proposed [14, 18, 20]. One basic idea is to apply pooling for the whole sentence and select the $k$ largest values instead of performing pooling repeatedly for each local area of images. This is called $k$-max pooling. By fixing $k$ for the last pooling layer of the CNN-based module, the requirement for fixed-sized outputs is satisfied. If $k = 1$, it results in max-pooling over the whole length. More details are given in Figure 2.

While pooling layers can provide fixed-sized outputs regardless of the size of inputs, the same size for all inputs is also required due to particular optimization techniques such as batch training. The solution to this requirement is to perform padding and cropping. Cropping is usually used in the case of long texts, especially with character-based vocabulary, which simply cuts the part longer than a fixed length. For short texts like questions in VQA, zero padding is typically used to pad each input to the same length of the longest sentence. This involves a minor problem that we are only aware of the longest length in the training set while there can be longer data during testing. Thus in practice, a combination of padding and cropping is used. Note that with fixed-sized inputs, pooling over each local area as in images is also feasible [7]. In this work, we perform zero-padding and max-pooling over the whole sentence for most experiments based on the properties of texts in VQA. Cropping is only used in validation and testing.

### 3.5 Deeper Networks for Short Texts

Note that in the training set of COCO-VQA, the average length of questions is only 6.2 words, while the longest one consists of 22 words. Character-based vocabulary results in longer inputs where the average is 30.9 and the longest training sample in COCO-VQA becomes 100 characters. Thus, in batch training of texts in VQA, zero-padding is heavily used in both cases. After padding, the lengths of inputs seem to be appropriate for a model with multiple convolution layers. However, our analysis and experiments show that adding layers actually leads to worse results. First, if a local max-pooling is added after convolution layers, it usually hurts the performance since a local area may be all zero-padded, which makes the outputs meaningless. Second, when a global max-pooling is applied, more layers also do not work well. In this case, zero-padding does not affect the outputs, but the module will actually obtain the same results as applied directly on the original short texts. Deeper networks are known to suffer from over-fitting when the input size is small. In fact, comparing to long texts, where most
Observations imply that the CNNs for texts in VQA should not be promising outcomes from multi-layer CNNs (Section 3.6). These same for other words. Note that the CNN module is shared among different words.

Embedding obtained from word-based vocabulary, generating the final pseudo image with module followed by a max-pooling over the whole word generates a word embedding, which is then concatenated to the word same one-hot vectorization process. Then the embedding layer changes the number of channels to $d_c = 15$. A CNN-based module followed by a max-pooling over the whole word generates a word embedding, which is then concatenated to the word embedding obtained from word-based vocabulary, generating the final pseudo image with $d + d_c$ channels. The process is the same for other words. Note that the CNN module is shared among different words.

Samples have more than 1000 characters [7] and multi-layer CNNs work well, the length of texts in VQA is not enough for obtaining promising outcomes from multi-layer CNNs (Section 3.6). These observations imply that the CNNs for texts in VQA should not be deep. Our experiments show that one-layer models achieved better performance.
3.6 Residual Networks

For long texts and images, deeper networks are important and beneficial. Obstacles on going deeper are that very deep networks become hard to train and suffer from the degradation problem [12]. Residual networks (ResNet) [12] overcome these obstacles by adding skip connections from inputs to outputs of one layer or several layers. These skip connections are named residual connections. They enable CNNs with hundreds of layers to be trained efficiently and avoid the accuracy saturation problem. Modified ResNet with 49 layers for long texts has been explored in text classification with character-based vocabulary [7]. Note that each sample in text data used in [7] has more than 1000 characters.

We experiment with a ResNet with 8 layers on texts in VQA with character-based vocabulary. The results indicate that the inputs are too short, and deeper networks suffer from over-fitting instead of training and degradation problems. Also, residual connections are used when we add one more layer to the one-layer models but it also hurts the performances. It turns out that, unlike mappings learned by intermediate layers in very deep models, the mappings learned by the text feature extractor in VQA is not similar to identity function, making the application of skip connections inappropriate.

3.7 Inception Modules

Inception modules, proposed by [20, 36], involve combining convolutional kernels of different sizes in one convolution layer. This technique enables wider convolution layers. For using inception modules for texts is straight-forward; that is, different-sized kernels extract features from phrases of different lengths. Based on this interpretation, the choice of the number of kernels and their corresponding sizes should be data-dependent, because different-sized phrases may have diverse importance in various text data. We explore the settings and several improvements in our experiments.

3.8 Gated Convolutional Units

LSTMs and GRUs improve RNNs by adding gates to control information flow. In particular, the output gate controls information flow along the sequential dimension. With this functionality, the output gate can be used on any deep learning models. In [37] an output gate is also applied on CNNs. Unlike LSTMs and GRUs that use fully-connected connections, convolutional connections are used when generating output gates in CNNs. Given an input to CNNs, which in our case is the transformed data $I \in \mathbb{R}^{1 \times L \times d}$ from text data, two independent 1-D convolutional kernels $K$ and $K_g$ are used to form the output $O$ of the convolution layer as follows:

$$g = \sigma(K_g * I + b_g), \quad O = g \odot \tanh(K * I + b),$$

where $g$ is the output gate, $\sigma$ is the sigmoid function, $*$ represents convolution, $\odot$ denotes element-wise multiplication, $b$ and $b_g$ are bias terms. Gated convolutional networks for language modeling was proposed in [8], and the activation function for the original outputs was removed. That is, Eq. (2) is replaced with

$$O = g \odot (K * I + b).$$

In our experiments, we explore both methods and combined gates with inception modules, where different-sized kernels also generate different gates. We achieve our best results with the method in Eq. (3).

3.9 fastText

It is commonly believed that deep models like CNNs and RNNs are more powerful in general. In [16] a shallow model termed fastText was proposed, and it achieved comparable results with deep learning models on several text classification tasks. In fastText, the embedding vectors of text data are used as inputs, and the CNN module is replaced by a simple average operation. Formally, on a word-based vocabulary, since the $1 \times L$ pseudo image with $d$ channels is actually a concatenation of $L$ $d$-component word vectors, the average over $L$ word vectors results in a $d$-component sentence vector. This sentence representation is given directly into the classifier. As compared to deep learning models that use CNNs and RNNs, fastText obtains improvements in terms of accuracy while achieving a 15,000-fold speed-up due to the small number of parameters.

The performance of fastText casts doubts on using deep models, but it is argued that simple text classification tasks may not take full advantage of the higher representation power of deep learning [16]. As stated in Section 3.1, the task of text understanding in VQA is much more complicated and comprehensive, which makes it a better way to evaluate the capability of different models. According to our experiments, deep learning methods are superior to fastText in VQA, a result that is consistent with our analysis.

4 EXPERIMENTAL STUDIES

4.1 General Settings

We report experimental results on COCO-VQA dataset [1]1, which consists of 204,721 MSCOCO real images with 614,163 questions. The data are divided into 3 subsets: training (82,783 images with 248,349 questions), validation (40,504 images with 121,512 questions) and testing (81,434 images with 244,302 questions). In COCO-VQA, answers from ten different individuals are collected for each question as ground truths. For training, the top $K = 3000$ frequent answers among all answers of the training set were chosen to build the answer vocabulary. In each iteration, an in-vocabulary answer is sampled as the label from ten ground truths of each question. If all of the ten answers are out of the answer vocabulary, the question is skipped. To evaluate the accuracy of a generated answer, following evaluation metric was proposed [1]:

$$\text{Accuracy} = \min \left( \frac{\# \text{of humans that provided that answer}}{3}, 1 \right),$$

where the generated answer is compared with each of the ten ground truth answers, and the corresponding accuracy is computed.

Since evaluation on the testing set can only be processed on remote servers during the VQA challenge [1], and the testing labels are not published, we choose to train and validate our models on the training sets only instead of the training+validation set like [1, 11], and test on the validation set.

1http://visualqa.org/download.html
Our baseline model is the challenge winner [11], which uses a 2-layer LSTM as the text feature extractor. This model is retrained on the training set only. Meanwhile, unlike in [11], we do not use additional data sources like the pre-trained word embedding (Word2Vec, GloVe) and other dataset (Visual Genome [21]) to augment training. In order to explore the power of models, we argue that additional data will narrow the performance gap of different models. For comparison, we only improve the text feature extractors using CNN-based models in all experiments. All the results are reported in Table 1. The retrained baseline model is shown as “LSTM (baseline)” in Part 1 of the table. Our code is publicly available³.

### 4.2 Word-Based Models

Several CNN-based text feature extractors on word-based vocabulary are implemented. The word-based vocabulary, which includes all words that appear in the training set, has size $|V| = 13321$. For word embedding, we fix the dimension $d = 300$. Dropout is applied on textual representations before they are given into next module. Part 2 in Table 1 shows the results of these models.

“CNN Non-Inception” model is a one-layer model with one $1 \times 3$ convolutional kernel. With max-pooling over the whole sentence, it produces a $2048$-component contextual vector representation. This simple CNN-based model already outperforms the baseline model, demonstrating that CNN-based model is better than RNN-based one in VQA.

“CNN Inception (word)” model explores wider CNNs by replacing the single $1 \times 3$ kernel in “CNN Non-Inception” model with several different-sized kernels in the same layer, as stated in Section 3.7. Different kernel settings are explored and their results are given in Table 2. Settings are named in the format “width of kernel (number of feature maps output by this kernel)”. Note that the height of kernel is always 1. The resulting textual vector representation has 2048 components. All these models outperform “CNN Non-Inception” model, showing that features extracted from phrases of different lengths complement each other. Table 1 includes the best results. For all models using inception modules, different kernel settings are explored. We only report the best result for other models.

“CNN Inception + Residual” model tries going deeper. It adds an identical layer with a residual connection from inputs to outputs to “CNN Inception (word)” model (Section 3.6). The best kernel setting is $1(512)+3(512)+5(512)+7(512)$. The extra layer is supposed to further extract text features but hurt performance in experiments. We conjecture that there is no need to go deeper for the short inputs in VQA. Character-based vocabulary will result in longer inputs and deeper models on it are discussed in Section 4.3.

“CNN Inception + Bottleneck” model is inspired by the bottleneck architecture proposed by [12]. We apply bottleneck on the convolution layer of “CNN Inception (word)” model with kernel setting $3(1024)+5(1024)$. For deep models on image tasks, this architecture improves the accuracies while reducing the number of parameters. However, it causes a significant decrease in accuracy to our one-layer model for VQA, which indicates that the bottleneck design is only suitable to very deep models.

“CNN Inception + Gate (tanh)” model and “Inception + Gate” model are CNN-based models with output gates introduced in Section 3.8, with Eqs. (2) and (3), respectively. Note that we combine the gate architecture with the inception module: for each kernel $K$ in the same convolution layer, there is a corresponding $K_g$. Both methods improve “CNN Inception (word)” model by adding output gates. With Eq. (3), we achieve our best text feature extractor with 61.33% accuracy. See Figure 3 for a comparison in accuracy per question type between “Inception + Gate” model and “LSTM (baseline)” model. We can see for most question types, “Inception + Gate” model outperforms “LSTM (baseline)” model.

### 4.3 Character-Based Models

Results for models that involve character-based vocabulary are reported in parts 3 and 4 in Table 1. The two models in part 3 use character-based vocabulary only, while the model in part 4 uses a combination of both vocabularies (Section 3.3). The character-based vocabulary collects $|V_{\text{c}}| = 45$ characters: all lowercase characters in English, punctuation as well as the space character. The kernel settings for both inception-like models below are $2(512)+3(512)+4(512)+5(512)$. Dropout is also applied.

“CNN Inception (char)” model applies the same inception module as “CNN Inception (word)” model but replaces the word-based inputs with character-based inputs. The accuracy drops drastically. As explained in Section 3.3, it is due to the short length of the inputs, which is not enough for the model to learn how to separate characters into words.

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³https://github.com/divelab/vqa-text

### Table 1: Comparison of different text feature extractors. Accuracies per answer type are shown. Models are trained on the COCO-VQA training set and tested on the validation set.

| Models                | Y/N | No. Other | All   |
|-----------------------|-----|-----------|-------|
| LSTM (baseline)       | 81.47 | 34.07    | 51.14 | 60.35 |
| CNN Non-Inception     | 81.75 | 35.55    | 51.34 | 60.73 |
| CNN Inception (word)  | 81.91 | **35.99** | 51.67 | 61.03 |
| CNN Inception + Residual | 81.01 | 34.45    | 51.69 | 60.51 |
| CNN Inception + Bottleneck | 80.12 | 35.51    | 50.58 | 59.74 |
| CNN Inception + Gate (tanh) | 82.09 | 35.47    | 51.84 | 61.10 |
| CNN Inception + Gate | **82.46** | 35.38    | 52.02 | **61.33** |
| CNN Inception (char)  | 78.15 | 33.79    | 46.67 | 56.83 |
| CNN Deep Residual     | 77.19 | 33.39    | 46.09 | 56.14 |
| CNN Inception (char+word) | 82.05 | 35.39    | 51.43 | 60.88 |

### Table 2: Overall accuracies for “CNN Inception (word)” models with different kernel settings. See Section 4.2 for details.

| Settings | Accuracy |
|----------|----------|
| 2(512)+3(512)+4(512)+5(512) | 61.03 |
| 1(512)+3(512)+5(512)+7(512) | 60.96 |
| 3(1024)+5(512)+7(512) | 60.97 |
| 1(512)+3(1024)+5(512) | 60.95 |
| 3(1024)+5(1024) | 60.80 |
“CNN Deep Residual” model attempts to take advantage of the longer inputs provided by character-based vocabulary. We stack 5 convolution layers with residual connections and 3 local pooling layers to build a deep model. Contrast to the results of [7, 42], the model fails to work well. Again, comparison indicates the input length as the cause of failure.

“CNN Inception (char+word)” model makes use of both word-based and character-based vocabularies as shown in Figure 2. In our model, the characters of each word generate a 150-component word embedding vector, which is concatenated with the 150-component word embedding from word-based vocabulary to form a 300-component vector representing the word. As compared to “CNN Inception (word)” model, it leads to a slight accuracy decrease. This demonstrates that using character-based vocabulary is not able to provide useful information from constituent characters of the word. Based on these experiments, we conclude that character-based vocabulary is not helpful in short input cases like texts in VQA.

We compare the numbers of parameters of CNN-based text feature extractor with LSTM-based ones in Table 3. While CNNs improve the accuracy, much fewer parameters are needed to train them. This reduces the risk of over-fitting.

4.4 Deep Learning Models versus fastText

As introduced in Section 3.9, fastText is a shallow model that achieves comparable results with deep learning models like CNNs and RNNs in text classification tasks [16]. This result contradicts the common belief that deep models can learn better representations. It has been conjectured [16] that the simple text classification task may not be the right one to evaluate textual representation methods. Given the higher requirement for textual understanding in VQA, we compare these models in VQA. In addition to the original fastText model (“fastText (word)”), which averages word embedding to obtain sentence representation, we also explore fastText (“fastText (char+word)”) with character-based vocabulary. Similar to the idea in Section 3.3, character embedding of each word is averaged to generate part of the word embedding. The results are given in Table 4. We can see the performance gap between deep learning models and fastText. Clearly, VQA is an appropriate task to evaluate textual representation methods and demonstrates the power of deep models.

5 CONCLUSIONS

We propose to apply CNNs on textual representations as the text feature extractor in VQA. By incorporating recent research achievements in CNNs for images, our best model improves textual representations and the overall accuracy of VQA. By comparing deep models with the fastText, we show that while better textual representations lead to better results in VQA, VQA is in turn an appropriate task to evaluate textual representation methods due to its comprehensive requirement for texts. Based on our research, we believe that our CNN-based textual representation methods can be extensively used for learning textual representations in other tasks with texts of similar properties.

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Learning Convolutional Text Representations for Visual Question Answering

Z. Wang et al.

Table 4: Comparison of results between deep learning models and fastText.

| Models                   | Accuracy |
|--------------------------|----------|
| LSTM (baseline)          | 60.35    |
| CNN Inception + Gate     | 61.33    |
| fastText (word)          | 59.30    |
| fastText (char+word)     | 59.24    |

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