A Markov Network Based Passage Retrieval Method for Multimodal Question Answering in the Cultural Heritage Domain

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Abstract. In this paper, we propose a Markov network based graphical framework to perform passage retrieval for multimodal question answering (MQA) with weak supervision in the cultural heritage domain. This framework encodes the dependencies between a question’s feature information and the passage containing its answer, with the assumption that there is a latent alignment between a question and its candidate answer. Experiments on a challenging multimodal dataset show that this framework achieves an improvement of 5% in terms of mean average precision (mAP) compared with a state-of-the-art method employing the same features namely (i) image match and (ii) word co-occurrence information of a passage and a question. We additionally construct two extended graphical frameworks integrating one more feature, namely (question type)-(named entity) match, into this framework in order to further boost the performance. The performance has been further improved by 2% in terms of mAP in one of the extended models.

Keywords: Multimodal Question Answering, Passage Retrieval, Markov Network, Graphical Framework

1 Introduction

Multimodal question answering (MQA) refers to answering a textual query on an image. In the cultural heritage domain, MQA enables asking questions on images of cultural artifacts for visitors in museums, landmarks and other sites. This allows a personalized, engaged and natural way for people to interact with cultural relics which, to our best knowledge, doesn’t exist yet.

A crucial component of an MQA system is the *passage retrieval* task that involves the identification of top-ranked passages that may contain the answer for a given question, thereby reducing the search space from a massive collection of documents to a fixed number of passages. Although passage retrieval in open-domain question answering (QA) is widely studied over the last decades, there

Fig. 1. An exemplary question-passage pair, the answer passage is retrieved by the model proposed in this paper

are few efforts on passage retrieval for MQA in the cultural heritage domain. In this paper, we address the task of retrieving passages (from a multimodal documentation) that contain the answers to a multimodal question. An exemplary question-passage pair is shown in Fig. 1. As in [13], we divide the multimodal questions into two categories: (i) the coarse *full-image* level questions on the entire image of an artwork, e.g., who is she?, and (ii) the finer *partial-image* level questions referring to the intricacies of an artwork, e.g., what happened to her left eye?

Compared with traditional passage retrieval in open-domain textual question answering, passage retrieval for MQA in the cultural heritage domain faces several key challenges. First, the multimodal setting injects some uncertainties into the passage retrieval problem, e.g., how to define the relevance of a passage and its associated images in the multimodal documents? How accurate is the definition of this relevance? Second, the text-based resources in the cultural heritage domain are often innately noisy, containing non-standard spelling, poor punctuation, obsolete grammar and word forms [7]. In addition, the information needs and tasks of cultural heritage users are often complex and diverse. For instance, the dataset we use in this paper covers 9 types of diverse questions with some of them being complex. Third, some questions inevitably have no answers due to historical reasons, in which case the questions should be classified as NIL questions, that is, having no answers. As we will see in section 4.1, this may lead to propagated errors for the passage retrieval task in case the questions are wrongly classified. Moreover, *partial-image* level questions require deep reasoning of both the textual and visual parts of a question.

With the increasing interest in deep learning, huge efforts have been put into both the textual QA task and the MQA task [11, 1] employing deep neural networks which need a large amount of question-answer pairs as training data and usually work on sentence-level answers (short answers). Due to the lack of large-scale training data and longer answers for MQA in the cultural heritage domain, current end-to-end deep neural networks cannot be directly applied in our task. In this paper, we propose a Markov network based graphical framework encoding

the dependencies between a question’s feature information and the passage containing its answer, with the assumption that there is a latent alignment between a question and its candidate answer. Experimental evaluation in terms of mAP shows that this framework achieves an improvement of 5% compared with the state-of-the-art proposed in [13] when using the same features namely (i) image match and (ii) word co-occurrence information of a passage and a question.

The main contributions of this paper are as follows: first, we propose and implement a weakly supervised Markov network based graphical framework to perform passage retrieval for MQA in the cultural heritage domain; second, we construct two extended forms of the framework integrating one more feature, namely (question type)-(named entity) match, to further boost the performance with 2% improvement in terms of mAP.

The remainder of this paper is organized as follows: section 2 introduces related research, section 3 describes the graphical frameworks, section 4 discusses feature extraction experiments and gives an analysis of the final results, section 5 concludes this paper and points out future research.

2 Related work

Our work is mainly inspired by [17] that learns entity linking across animal objects of a video and textual mentions from corresponding subtitles. It achieves good results on their cross-modal (vision and language) entity alignment task in a video documentary about wildlife. In contrast to our work, the entity alignment in [17] is more straightforward, e.g., zebra as an object label in the video should be mapped to (ambiguous) mentions of zebra in the text side. While in our task, the alignment for a question and a passage is latent due to their corresponding semantic meaning, requiring a deeper reasoning.

Graphical frameworks are quite popular in performing information retrieval (IR) and question answering [10, 15]. The difference between these frameworks is the way they encode dependencies in diverse graph structures. [10] focuses on dependencies between different terms while [15] emphasizes the evidence introduced by multiple passages by adding links between several passages sharing common words. In this paper, we encode the dependency of answer passages with feature-level evidence. Furthermore, we encode not only textual clues but also visual evidence i.e., the image match information of a question and a passage in a multimodal setting. [2] also performs passage retrieval in a feature based manner, while they represent features of a question-passage pair as a continuous feature vector, we perform this in a more compact and simple way by embedding them into a graphical framework as discrete variables.

3 Methodology

3.1 Task definition

Given a multimodal question, we assume that there is a latent alignment in this question and its candidate answers due to some matching features among

them. That is, the more closely a certain feature matches between a question and a passage, the more likely is the latent alignment between the question and the passage and vice versa. In this paper, we consider feature matches namely image match, word overlap and (question type)-(named entity) match. The first two features are the same as in [13] and the third feature is utilized to further improve the system performance.

This problem is formulated as follows: given a multimodal question q_i and a multimodal documentation D , a corresponding candidate passage set $P=\{pg_1, pg_2, \dots, pg_j, \dots, pg_n\}$ needs to be extracted from the documentation D , n is the number of candidate passages; the goal is to retrieve the passages containing the answers to question q_i ; that is, to predict the probability that a passage pg_j contains the answer to question q_i based on the corresponding feature match information.

For the feature match information, we rely on three sources:

1. *Image match* between a passage and a question ($pg_j.image \leftrightarrow q_i.image$) where a passage image $pg_j.image$ refers to the image surrounding pg_j .
2. *Word co-occurrence* ($word_overlap(q_i, pg_j)$) which refers to the word tokens occurring in both q_i and pg_j .

The extended graphical models have an additional feature:

3. *Question type - named entity match* ($q_i.question_type \leftrightarrow pg_j.entity$). As for certain types of questions in the dataset, i.e., ‘Who’ and ‘Where’ questions, e.g., who is this person? where are they from? the answers must contain named entities which are human names and location names respectively.

We address this task using a graphical model that encodes the dependencies between a question q_i ’s feature match and the candidate passage pg_j containing its answer, as described next.

3.2 Model

Pairwise Markov random fields (MRFs) forms a subclass of Markov networks which are associated with a set of node potentials and a set of edge potentials. The overall distribution is the normalized product of all the potentials (both node and edge) [4]. A pairwise MRF $G = \langle \{P^{answer}, PQ^{image}, PQ^{vec}\}, E \rangle$ is constructed in this paper to judge whether passage pg_j is relevant to question q_i . This MRF G is called basic framework (BF) further in this paper, and it includes the following components:

- A set P^{answer} of nodes $p_j \in \{0, 1\}$ in the first row of Fig. 2(a) with $p_j = 1$ when pg_j contains an answer and otherwise 0. We define a node potential φ_{p_j} for each p_j .
- A set PQ^{image} of nodes $pq_img_j \in \{0, 1\}$ in the left part of the second row in Fig. 2(a), denoting the match of passage image $pg_j.image$ and question image $q_i.image$. Here, $\varphi_{pq_img_j}$ represents the node potential for pq_img_j .
- A set PQ^{vec} of nodes $pq_vec_j \in \{0, 1\}$ in the right part of the second row in Fig. 2(a), denoting the word co-occurrence of passage pg_j and question q_i . $\varphi_{pq_vec_j}$ corresponds with the node potential for pq_vec_j .

Fig. 2. (a): Basic framework structure. Each node in the first row refers to a binary variable denoting whether a certain passage contains an answer, and nodes in the second row denote image match and word co-occurrence features between a passage and question a question. The edges between the first and the second row encode corresponding dependencies. (b): Illustration of separated components in the basic framework

- $\forall j$, two edges are built for p_j namely, $\langle p_j, pq_img_j \rangle$ and $\langle p_j, pq_vec_j \rangle$. Respective edge potential denoting the dependency weights between p_j and its connected node variables are referred to by φ_{edge_pj} .

The objective is to maximize the joint probability of all variables for the BF:

$$P = \frac{1}{Z} \prod_{\substack{p_j \in P^{answer} \\ pq_img_j \in PQ^{image} \\ pq_vec_j \in PQ^{vec} \\ edge_pj \in E^{BF}}} \varphi_{p_j} * \varphi_{pq_img_j} * \varphi_{pq_vec_j} * \varphi_{edge_pj} \quad (1)$$

where Z is the normalization constant and E^{BF} is a set of the edges in the BF. The parameters in this equation are initialized as follows:

- As for φ_{p_j} , the potential value for p_j being 1 is a prior that allows to incorporate background knowledge (e.g., to indicate that certain passages are inherently related to certain questions). In our experiments, we use an uninformed prior, i.e., $\forall j$, we set $\varphi_{p_j} = 0.5$ with the assumption that all candidate passages have equal probability to be or not to be the answer to a question.
- $\forall j$, $\varphi_{pq_img_j}$ are assigned in the same way as in [13]: for all candidate passages, the passages in a document right before or after a relevant image of a query image have node potential values of 1 for pq_img_j being 1, and this score is then discounted by a fixed number (0.2 in our case) which is the same for all documents for further away passages. Details on relevant image extraction are explained in section 4.1.
- $\forall j$, $\varphi_{pq_vec_j}$ is assigned as the cosine score between a question vector and a passage vector when pq_vec_j is 1. Details on cosine score computation are provided in section 4.2. If a cosine score is 0, we assign the corresponding potential value to be a very small number near 0 to avoid side effects caused by 0 values.
- $\forall j$, φ_{edge_pj} is assigned empirically using a validation set.

Based on the assignments for $\varphi_{pq_img_j}$, the number of its distinct values is fixed to M (6 in our case, i.e., 1, 0.8, 0.6, 0.4, 0.2, 0). Accordingly, we utilize

M nodes to denote the image match information in the BF, i.e., the size of PQ^{image} is M . With this property, some passages share the same image match probability, i.e., different passages may be connected due to the shared image match feature. The size of P^{answer} and PQ^{vec} equals the number of candidate passages for q_i . Since each node p_j in the first row is only connected to its own feature match information regarding a question q_i , this framework is composed of several connected components as illustrated in Fig. 2(b).

3.3 Extended models

One additional feature (question type)-(named entity) information has been integrated into the two extended frameworks shown in Fig. 3. We call the extended model with two rows in Fig. 3(a) as EF-1 and the other extended model with three rows in Fig. 3(b) as EF-2 further in this paper.

Compared with the BF, EF-1 and EF-2 have an additional set PQ^{type} of nodes $pq_type_j \in \{0, 1\}$ as shown in Fig. 3. These nodes denote the (question type)-(named entity) match of a question and a passage. Here, $\varphi_{pq_type_j}$ represents the node potential of pq_type_j and is initialized empirically with pre-defined values according to corresponding match information extracted in section 4.3. There is another set P^{entity} of nodes $entity_k \in \{0, 1\}$ in EF-2 as shown in Fig. 3(b). Each $entity_k$ corresponds with an entity $entity_k$ in the candidate passages where $entity_k$ is 1 when $entity_k$ is the target entity to question q_i and 0 otherwise. Here, φ_{entity_k} refers to the node potential for $entity_k$. This potential is initialized as 0.5 when $entity_k$ is 1 with the hypothesis that an entity has equal probability to be or not to be the target answer for q_i . The size of P^{entity} equals the number of distinct named entities in the whole documentation. We construct an edge between the second and third row if and only if the question type and the named entities of the passage match. For example, if the given question q_i is a ‘Who’ question and passage pg_j has and $entity_k$ referring to ‘PERSON’, then there is an edge $\langle pq_type_j, entity_k \rangle$. φ_{edge_entity} refers to corresponding edge potential denoting the dependency weights between the node variables in the second and third row in EF-2. Also, since several passages may share some named entities, there may exist loops between the second and the third row.

Fig. 3. (a): Extended framework 1 integrating (question type)-(named entity) match (pq_type_j) in the second row (left part). (b): Extended framework 2 integrating also named entity information in the third row

The extended models have similar objective functions as the one used in the BF expressed in equation (1). As for EF-1, the additional $\varphi_{pq_type_j}$ should be added to the right side of equation (1) as an element for the product and both $\varphi_{pq_type_j}$ and φ_{entity_k} should be added to equation (1) in the same way as for EF-2.

3.4 Inference and NIL classification

If the graphical model has no cycles (e.g., basic framework and EF-1), belief propagation (BP) is employed as the inference method, otherwise when there are cycles (e.g., EF-2), loopy belief propagation (LBP) is applied. In either case, we use the implementation of [12]. Belief propagation works by passing real-valued messages along the edges between connected nodes and LBP starts from an initial set of node messages which are updated until convergence in an iterative manner. This way, the probability that passage pg_j contains an answer and the feature match information have mutual influence on each other. Using these inference algorithms, the aforementioned parameters for the three graphical frameworks (namely, edge potential φ_{edge_pj} in the BF, all edge potentials in the EF-1, all node and edge potentials in the EF-2) can be validated or updated respectively. The inference method yields a probability list $S_i = [s_1, s_2, \dots, s_j, \dots, s_n]$ in which s_j refers to the probability passage pg_j containing the answer to question q_i . As in [13], a threshold s is used to ascertain that a question has NIL as its answer. i.e, q_i has NIL as its answer if $\forall j, s_j < s$.

4 Experiments and results

There are two assumptions for the experiments introduced in this part: first, we benefit from the mature indoor positioning techniques for mobile devices e.g., Bluetooth, Wi-Fi positioning. Under these circumstances, the metadata (id, date, class, etc.) of the artwork regarding a multimodal question can be regarded as prior knowledge since the indoor position of visitors who ask these questions is known. Second, most digital archives of cultural heritage e.g., Europeana³, Google Arts & Culture⁴ support searching by the metadata of an artwork and return its related documents accordingly. Hence, for each artwork in a museum room, its related documents can be regarded as prior knowledge with known metadata.

The feature extraction and model construction are preceded by two pre-processing steps: (i) all tokens in the questions and the documentation are converted to lowercase format; (ii) passages in the *related documents* concerning the artwork metadata of question q_i are extracted, to be added to the graphical model (instead of adding passages from all the documents).

³ <http://www.europeana.eu/portal/en>

⁴ <https://www.google.com/culturalinstitute/beta/>

4.1 Relevant image extraction

Full-image retrieval: Full-image retrieval is the process of extracting relevant images from the documents, in response to the coarse *full-image* level questions concerning the entire artifact. We employ manual annotation in this task as in [13], since the related documents for a multimodal question are prior knowledge, the relevant images can then be manually annotated for our small-scale dataset concerning a museum room.

Partial-image retrieval: Partial-image retrieval is the process of extracting relevant image parts from corresponding full images⁵, in response to the finer *partial-image* level questions concerning only a part of an artwork. In this task, we need to further filter the relevant images for a partial multimodal question by excluding the parts of images that do not concern the partial question image. For example, full relevant images containing the upper body of Akhenaten are relevant for *full-image* level questions such as ‘who is this man?’ but not for *partial-image* question ‘why is he barefoot?’ whose question image is a photo of Akhenaten’s feet. A convolutional neural network (CNN) based method is applied to perform this task wherein the question image is compared with the sub-images detected from the full relevant images using selective search [16]. CNN-based retrieval methods have constantly been proposed in recent years and are gradually replacing the hand-crafted local detectors and descriptors [19]. In this task, we extract the 4096-dimensional descriptor for an input image from the fully-connected (FC7) layer of AlexNet [6] pre-trained on ImageNet [3]. Cosine distance is then utilized to retrieve the relevant partial images for a certain query image. A threshold ($k = 0.3$) is set to filter out irrelevant sub-images. It yields a reasonable retrieval performance with an average accuracy of 0.60.

4.2 Word co-occurrence extraction

In this task, the questions and passages are represented as vectors in a common vector space, where each word represents an axis. A passage is represented as a bag-of-words (bow) as its vector is given by the number of word occurrences (or term frequency, tf), $pg_j = [tf_{1,j}, tf_{2,j}, \dots, tf_{V,j}]$, where V is the vocabulary size, i.e., the number of distinct word types in the target collection. A textual query q_i is also represented as a V -dimensional vector in the same space. We compute the cosine similarity of a query vector and a passage vector to measure the word co-occurrence between them. Stop words are removed and stemming is applied in this procedure.

4.3 Question classification and named entity extraction

Question classification: We follow [14] for defining the question types. Question classification refers to classifying all questions into the pre-defined types.

⁵ These full images are obtained by full-image retrieval described in the beginning of section 4.

		Precision	Recall	F1 score
Rule-based method	Who	0.97	0.95	0.96
	Where	1	0.9	0.94
Logistic regression	Who	0.425	0.9375	0.607
	Where	0.66	0.88	0.75

Table 1. Evaluation results for question classification on ‘Who’ and ‘Where’ questions

	Precision	Recall	F1 score
PERSON	0.87	0.87	0.87
LOCATION	1	0.9	0.94

Table 2. Evaluation results for PERSON and LOCATION type named entities

There are basically two different approaches for question classification: rule-based and machine learning based [5]. We implemented two simple cases of both methods. In the rule-based method, surface words ‘who’, ‘identity’, ‘name’ and ‘whose’ are applied to detect ‘Who’ type questions, while the word ‘where’ is used to detect ‘Where’ type questions. As for the machine learning based approach, we predict the category of the questions with logistic regression trained on the UIUC dataset⁶. The questions in the training and test set are represented as bag-of-words vectors which serve as the input for the logistic regression method. The question type classification in this study is a multi-class classification task. We employed a cross-entropy loss function for logistic regression, using the Scikit-learn library⁷. Since most of the recent learning-based and hybrid approaches use the taxonomy proposed by [8], and the category of the questions in the training set is different from this paper, we need to classify the predicted category to our pre-defined category according to their semantic meaning after the prediction phase.

Table 1 shows the results of these two approaches. Notably, the rule-based method achieves better results in our task. The logistic regression has a relatively lower performance mainly due to the category difference between the training and the test set. Therefore, the rule-based method is utilized to obtain question types.

Named entity recognition: Stanford named entity recognizer (NER) [9] is employed to detect three types of named entities in the passages namely ‘PERSON’, ‘LOCATION’ and ‘ORGANIZATION’. This NER may classify the same entity to different categories in different documents (based on the context). We employ a majority voting scheme to determine the category label. E.g., if ‘Nefertiti’ occurs as ‘PERSON’ 100 times and as ‘ORGANIZATION’ 50 times, we label it as ‘PERSON’ in the database. In this task, we assume that the named entity in the cultural heritage domain is not ambiguous, i.e., each named entity belongs to only one category.

The performance of the modified NER introduced in the previous paragraph is evaluated with 100 randomly sampled passages from the documentation as shown in Table 2. Evaluation for ‘ORGANIZATION’ entities was out of the scope of this paper.

⁶ <http://cogcomp.cs.illinois.edu/Data/QA/QC/>

⁷ http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

		mAP	MRR	NIL Precision	NIL Recall
Full	BF	0.13	0.17	0.31	0.77
	EF-1 (BF + additional feature)	0.14	0.18	0.34	0.77
	EF-2 (BF + additional feature)	0.15	0.19	0.35	0.76
Partial	BF	0.091	0.091	0.67	0.77
	BF + partial-image retrieval	0.092	0.092	0.67	0.77

Table 3. Evaluation results for full-image and partial-image level questions

		What	When	Who	Why	Where	Which	How	Yes or no	Selective
Full	BF	0.13	0.06	0.13	0.09	0.04	0.02	0.5	0.19	0.06
	EF-1	0.13	0.06	0.13	0.09	0.07	0.02	0.5	0.19	0.06
	EF-2	0.13	0.06	0.12	0.09	0.19	0.01	0.5	0.18	0.10
Partial	BF	0.06	-	-	0.05	-	-	-	0.15	0.33
	BF +	0.06	-	-	0.05	-	-	-	0.16	0.33

Table 4. mAP scores for each type of questions. ‘BF+’ refers to ‘BF + partial-image retrieval’ as in Table 3 and ‘-’ means there is no such type of questions

4.4 Final results of the MQA

A small validation dataset⁸ is used to estimate the optimal values for parameters in the graphical frameworks and the threshold s for NIL classification introduced in section 3. As for the dataset, there are 807 multimodal questions, 204 multimodal documents and 19587 corresponding paragraphs. Since some passages are filtered out by their constituted entity types in the extended models, the average number of potentially relevant passages per question in the extended models is less than that of the basic framework. This average number of potentially relevant passages per question is 1292 for the BF and 1109 for the extended models. Corresponding standard deviations of the potentially relevant passage numbers for the two model types are 1364 and 1301 respectively. Other details about the dataset can be found in [14].

There may be several answers to a question, we therefore apply the mean average precision method [13] to evaluate each model’s performance. Mean reciprocal rank (MRR) [18] is also employed to evaluate the system’s performance to find the top-ranked answer. NIL precision and recall [13] are computed to evaluate the system’s ability to detect questions without ground-truth answers.

The evaluation results for the test set⁹ are shown in Table 3. Notably, the BF achieves a mAP score of 0.13 for the *full-image* level questions. This is 5% higher than the best result (0.08) obtained in [13] which employs the same features namely image match and the word co-occurrence as in the BF but uses them sequentially rather than complementarily. After integrating the additional feature namely (question type)-(named entity) match into the BF, the system performance is improved due to the excellent performance in detecting ‘Where’ questions as shown in Table 3. Here, EF-2 achieves better performance with a mAP score of 0.15 and a MRR score of 0.19. For *partial-image* level questions, the system works 1% better in mAP score when performing partial-image retrieval.

⁸ 20% of the data with 86 question-passage pairs.

⁹ 344 *full-image* level questions and 385 *partial-image* level questions.

The mAP scores shown in Table 4 indicate the system’s qualification in answering ‘How’ type questions in the *full-image* level question set. With the additional feature, better performance is achieved for ‘Where’ questions but not in the case of ‘Who’ questions mainly due to the propagated error of the NIL classification. On one hand some questions having ground-truth answers are wrongly classified as NIL questions with no answers, thus do not contribute to the final mAP score. On the other hand, some NIL questions are classified as questions with ground-truth answers, resulting in an average precision of 0¹⁰.

5 Conclusion and future work

In this paper, we have proposed an MRF to perform passage retrieval for MQA in the cultural heritage domain. This framework encodes the dependencies between a question’s feature match and the passage containing its answer. We built a basic framework incorporating two features: one textual (word co-occurrence) and one visual (image match) feature. We have also explored extended forms of this framework, by integrating one more feature, i.e., (question type)-(named entity) match. Experiments show that the basic framework improves over the state-of-the-art by 5% in terms of mAP computed over 344 multimodal questions, and the extended models obtain further improvement with an additional feature.

The graphical models are applied on a challenging small-scale dataset on which it is difficult to train a supervised model. In future work, we will investigate domain adaption methods which can leverage large-scale/external datasets and overcome the limits of the scale of our dataset.

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¹⁰ This reason is figured out by manually checking the mAP score for each ‘Who’ question in different models.

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