Multiple Set Prototype Image Reranking

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ABSTRACT

The existing methods for image search reranking suffer from the unreliability of the assumptions under which the initial text-based image search result is employed in the reranking process. In this paper, multiple set prototype-based reranking method is suggested address this problem in scalable fashion. The typical assumption that the top-images in the text-based search result are equally relevant is relaxed by linking the relevance of the images to their initial rank positions. Number of images is employed from the initial search result as the prototypes that serve to visually represent the query and that are subsequently used to construct Meta re-rankers. By applying different Meta re-rankers to an image from the initial result, re-ranking scores are generated, which are then aggregated using a linear model to produce the final relevance score and the new rank position for an image in the re-ranked search result. It improves the performance over the text-based image search engine.

Key concepts: Text based search, Prototype based meta reranker, Image Reranking.

1. Introduction

The existing web image search engines, including Bing, Google and Yahoo retrieve and rank images mostly based on the textual information associated with the image in the hosting web pages, such as the title and the surrounding text. While text-based image ranking is often effective to search for relevant images, the precision of the search result is largely limited by the mismatch between the true relevance of an image and its relevance inferred from the associated textual descriptions.

To improve the precision of the text-based image search ranking, visual reranking has been proposed to refine the search result from the text-based image search engine by incorporating the information conveyed by the visual modality. Based on the images in the initial result, visual prototypes are generated that visually represent the query. Each of the prototypes is used to construct a Meta reranker to produce a reranking score for any other image from the initial list. Finally, the scores from all Meta rerankers are aggregated together using a linear reranking model to produce the final relevance score for an image and to define its position in the reranked results list.

The linear reranking model is learned in a supervised fashion to assign appropriate weights to different meta rerankers. Since the learned model weights are related to the initial text-based rank position of the corresponding image and not to the image itself, the reranking model is query-independent and can be generalized across queries. Consequently, the proposed reranking method can scale up to handle any arbitrary query and image collection, just like the existing visual reranking approaches, even though supervision is introduced.

Multiple set prototype image reranking:

It is the searching of images and re-arranging of images which we get from text based search, by applying particular rule on images.

Text reranking:

It is the reranking of images which we get from database, when we apply text based search. It is about searching the images and reranking of them.

Visual reranking:

It is the re-arranging of images on the basis of visual similarities. Visual reranking has been proposed to purify the search result from the text-based image search engine by incorporating the information conveyed by the visual modality.

Visual prototype:
It is the creation of rules for image reranking by examining visual similarities on which further images has been reranked.

**Meta Reranker:**

Number of images from the initial search are take up result as the prototypes that serve to visually represent the query and that are subsequently used to construct meta reranker.

**Score vector:**

This is the score calculated from reranking model by checking relevance of images.

**Linear reranking model:**

The linear reranking model is learned in a supervised fashion to assign appropriate weights to different meta rerankers.

## 2. Proposed work:

To improve the performance of searching images visual search reranking is very good option. 4 steps are needed in our module text ranking, Prototype generation, Meta Re-Ranker and Re-Ranking Result

![Figure 1 Architecture of Image re-ranking.](image-url)

- **Text Ranking:**
  
  Initial search is text based search. We require image search engine to submit query from user. In the search engine query is in text format. It is text based Image search in which we get the image ranking on the bases of text query which we give.

- **Prototype generation:**
  
  In prototype generation phase we create a rules for image reranking on which further images has been reranked. In this we examine the visual similarities. From top L image set prototypes are generated using visual similarities. These prototypes are used as an input to the meta ranker.

- **Meta Ranking:**
  
  In meta reranking, multiple set prototype technique is used. This technique computes ranking score. Computed reranking score give as an input to reranking model to estimate ultimate reranking score. In re-ranking module use of SVM Classifier (Support Vector Machine) is beneficial. SVM handles the ranking problem. The basic idea is to decompose a ranking in to a set off pair-wise preferences and then to reduce the ranking-learning problem into a pair-wise classification problem.

- **Reranking Result:**
  
  In this step we get final reranked images in prototype based ranking. This paper proposed a prototype-based reranking framework, which constructs meta rerankers corresponding to visual prototypes representing the textual
query and learns the weights of a linear reranking model to combine the results of individual meta rerankers and produce the reranking score of a given image taken from the initial text-based search result.

3. Image Reranking Framework:
As illustrated in Fig.2, the proposed prototype-based reranking method consists of two steps.

![Image Reranking Framework](image)

**Online:**
In the online part, when a textual query is submitted to the image search engine by a user, initial search is performed using any contemporary text-based search technique. Then, visual prototypes are generated and for each prototype a meta reranker is constructed. Then, for each of the top N images in the initial search result, an L-dimensional score vector is obtained comprising the scores from all meta rerankers when applied to that image. Finally, the score vector is used as input to a reranking model, which has already turned to offline to estimate the ranking scores in the reranked image search list.

**Offline:**
The offline component is devoted to learning the reranking model from user-labeled training data. Since the learned model will be used for reranking the text-based search results, the training set is constructed from these results through the following steps. First, several representative queries sampled from the query log are selected. Then, using these queries the top images are retrieved from the text-based image search engine and downloaded for processing. Finally, for each query-image pair, people are invited to label the relevance between them to form the ground-truth. After the training data is collected, score vector can be computed from the meta rerankers, as mentioned in the online part, for each image and the corresponding query. Then the reranking model is learned and stored in the memory to be used in the online part for responding to user’s submitted queries.

**Learning the reranking model:**
The linear reranking model is learned by estimating the weights of the combined scores coming from different meta rerankers. This problem can be addressed using a learning-to-rank method, by regarding the score vector as the ranking feature of an image. Ranking SVM is among the most popular learning to rank algorithms. This algorithm adapts the widely used SVM classifier to handle a ranking problem. The basic idea is to decompose a ranking into a set of pair-wise preferences and then to reduce the ranking-learning problem into a pair-wise classification problem. The basic idea is to decompose a ranking into a set of pair-wise preferences and then to reduce the ranking-learning problem into a pair-wise classification problem.

Standard efficient approaches to learning an SVM classifier, such as sequential minimal optimization, can be directly employed for learning the Ranking SVM. Moreover, a fast algorithm, e.g., the cutting-plane algorithm, can be adopted to speed up the training of a linear Ranking SVM.
The reason why the learned reranking model described above can be generalized across queries beyond those used for the training is that the model weights are not related to specific images but to their rank positions in the text-based search result. The separation of the model weights from specific images is the key to ensure that there ranking model only needs to be learned once and can then be applied to any arbitrary query. The existing learning-to-rerank methods, including the supervised-reranking and query-relative classifier, design the reranking model based on the hand-designed ranking features defined at a higher abstraction level or on the ordered visual words, respectively. Compared to them, the prototype-based learning to rerank method learns how likely the images at each of the ranked position in the text-based result are to be relevant to the query. In other words, the method directly learns the characteristics of the underlying text-based image search engine and requires less expert input in terms of the reranking feature. Consequently, the prototype-based reranking method can be expected to generalize even better over a broad set of queries and perform well for any underlying text-based search engine.

4. Constructing Meta Rerankers:

One of the key steps in the Multiple Set Prototype image reranking method is the construction of meta rerankers. The computed scores are used as input for the reranking model to estimate the ultimate ranking scores to determine the rank position of the images in the reranked result. There are three types to construct meta rerankers, depending on how the prototypes are generated from the initial text-based search result. Single image prototype, Multiple average prototype and multiple set prototype are the three algorithms for constructing meta rerankers.

Single-Image Prototype:

A straightforward way to generate a set of prototypes is to select top images from the text-based result, as illustrated in Fig.3.

![Figure 3 Single-Image prototype](image)

If we denote this set as \(E_{i}^{L}\), then the meta reranker can be built simply based on the visual similarity \(S(.)\) between the prototype \(P_{i}\) and the image \(I_{j}\) to be reranked:

\[
M_{i}(I_{j} | P_{i}) = S(I_{j}, P_{i})
\]  

(1)

The score vector aggregating the values (1) from all meta rerankers is then used as input to the linear reranking model in order to compute the definitive ranking score for image \(I_{j}\):

\[
R_{i}(I_{j}) = \sum_{E_{i}^{M} \in E_{i}^{M}} W_{i} S(I_{j}, P_{i})
\]  

(2)

Where \(W_{i}\) are the individual weights from the model weight vector \(W\).

Multiple average prototype:

Prototype \(P_{i}^{MA}\) can be constructed by first selecting the top \(L\) images in the initial search result list and then by cumulatively averaging the features of all images ranked starting from the topmost position to the position \(i\), as illustrated in Fig. 4. In other words, the prototype \(P_{i}^{MA}\) can be defined as:

\[
P_{i}^{MA} = \frac{1}{i} \sum_{j=1}^{i} I_{j}
\]  

(3)
Then, this prototype can be employed to compute the scores of individual meta rerankers by again computing the visual similarity between a prototype and the image to be reranked:

$$M^{\text{MA}}(f|\mathcal{P}^{\text{MA}}) = S(f, \mathcal{P}^{\text{MA}})$$ (4)

![Multiple Average prototype](image)

**Figure 4** Multiple Average prototype

**Multiple set prototype:**

The multiple-set prototype $\mathcal{P}^{\text{MZ}}$ at rank $i$ is defined as a bag of images ranked from the topmost position to the rank $i$, as illustrated in Fig.5.

![Multiple set prototype](image)

**Figure 5** Multiple set prototype

$$\mathcal{P}^{\text{MZ}} = \{I_j\}_{j=1}^i$$ (5)
The multiple-average prototype is the average of features for the images in the multiple-set prototype and can be seen as a special case of this prototype. The multiple-set prototype is a more flexible representation, which can support the development of more types of Meta rerankers. Given a multiple-set prototype $P_{M}$, can learn a visual classifier by regarding all the images in $P_{M}$ as positive samples, which is then employed as meta reranker and the prediction score is used as the meta reranking score. Since a discriminative learning method is usually more effective for learning a visual model, there is SVM in this paper. However, it needs not only positive samples but also negative samples.

The Meta reranker with a multiple-set prototype can be defined as follows:

$$R_{M}(I_j | P_{M}) = p(I_j | \theta)$$  \hspace{1cm} (6)

$$\hat{\theta} = \arg\max_{\theta} P(I_j | \theta)$$  \hspace{1cm} (7)

Here is the analysis of the properties of the reranking method based on the multiple-average prototype. By using the dot product as the similarity measure, a corresponding meta reranker, leads to the following expression:

$$R_{M}(I_j) = \sum_{i=1}^{m} \left( w_i \times \sum_{k=1}^{K} a_k S(I_k, I_j) \right)$$  \hspace{1cm} (8)

$$= \sum_{i=1}^{m} a_i \times S(I_i, I_j)$$  \hspace{1cm} (9)

$$a_i = \frac{\sum_{k=1}^{K} w_k}{K}$$  \hspace{1cm} (10)

The above expressions transform the model based on a multiple average prototype on to the model based on a single-image prototype, however, with different weights. It states that the ranking in the text-based search result represents the ordering of the importance for each individual image to be used as a prototype for reranking. In other words, there ranking based on a multiple-average prototype will rely more on the initial text-based result than that based on a single-image prototype.

Here, model weights written as,

$$w_i = \alpha \sum_{k=1}^{K} (-1)^{m_{ik}} a_k$$  \hspace{1cm} (11)

weights for individual images by the reranking based on a multiple-average prototype will decline gradually with the decreasing ranks. This may make this reranking model less aggressive and more robust than the one based on a single-image prototype. Meanwhile, it makes the reranking model learned by the multiple-average prototype-based reranking method hardly over-fitting to the training queries.

5. Conclusion

This paper proposed multiple set prototype image reranking framework, which constructs meta rerankers corresponding to visual prototypes representing the textual query and learns the weights of a linear reranking model to combine the results of individual meta reraners and produce the reranking score of a given image taken from the initial text-based search result. It improves the performance by 25.48% over the text-based search result by combining prototypes and textual ranking features. A natural extension of the approach described in this paper would be to apply the proposed methods to learn concept models from image search engines in a semiautomatic fashion. Compared to the fully automatic methods, the semi-automatic approach could learn the concept models for any arbitrary concept much better and with only little human supervision. While our proposed methods have proved effective for reranking image search results, there is envision of two directions for future work to further improve the reranking performance. First, It could be could further speed up the Prototype-Set method variant while decreasing the precision degradation. Since top images are incrementally added into the multiple-set prototypes to train the meta rerankers, one of the possible approaches in this direction is to utilize the online learning algorithms. Second, although it assume that the rank position is generally correlated with the relevance value of the image found there, and while our results show that this assumption can be regarded valid in a general case, still deviations from this expectation can occur for individual queried. One possible approach here would be to automatically estimate the query-relative reliability and accuracy of each meta-reranker and then incorporate it into the reranking model. Another approach may be to learn the reranking models for different query classes.

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