Annotation Order Matters:
Recurrent Image Annotator for Arbitrary Length
Image Tagging

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Abstract—Automatic image annotation has been an important
research topic in facilitating large scale image management and
retrieval. Existing methods focus on learning image-tag correla-
tion or correlation between tags to improve annotation accuracy.
However, most of these methods evaluate their performance using
top-k retrieval performance, where k is fixed. Although such
setting gives convenience for comparing different methods, it is
not the natural way that humans annotate images. The number
of annotated tags should depend on image contents. Inspired by
the recent progress in machine translation and image captioning,
we propose a novel Recurrent Image Annotator (RIA) model that
forms image annotation task as a sequence generation problem so
that RIA can natively predict the proper length of tags according
to image contents. We evaluate the proposed model on various
image annotation datasets. In addition to comparing our model
with existing methods using the conventional top-k evaluation
measures, we also provide our model as a high quality baseline
for the arbitrary length image tagging task. Moreover, the results
of our experiments show that the order of tags in training phase
has a great impact on the final annotation performance.

I. INTRODUCTION
Image annotation is a task to associate multiple semantic
tags regarding to the contents of images. With the rapid devel-
opment of Internet and social web applications, the amount of
online images created by users is continuously increasing. And
the large amount of images brings a heavy burden for image
management and retrieval. Since the major approaches for
people to search or to index images are through referring to the
associated tags, it is a necessary step to annotate these images
with proper tags. However, manually annotating images is an
expensive and labor intensive work for human beings. Hence
it is better if we can learn a model from available image-
tag samples and use the model to automatically label new
images with keywords (tags) from the annotation vocabulary.
In fact, this kind of technique is called automatic image
annotation (AIA) [1], and has been an important research topic
in computer vision for decades.

Previous researches focus on learning the image-to-tag
correlation as well as tag-to-tag correlation to improve the
annotation performance. Although much progress has been
made in the research community, most of the existing methods
overlooked a fundamental philosophy of recognition: recogniz-
ing the right things. A common conventional evaluation setting
has a fixed annotation length k, and a typical k value 5 has
been used in many previous methods [2]–[5] for the ease of
comparison. However, we argue that this convention can be
insufficiency in previous work, since it is not the normal way
that we humans annotate images, and the assumption of fixed
annotation length is not the fact of realistic images either,
as shown in Figure 1. Therefore arbitrary length annotation
is required for more reasonable annotation results. For top-k
predictions, traditional methods simply select the k tags with
highest prediction scores. For arbitrary length annotation, it is
possible to easily imagine a na""ve extension that is to threshold
the prediction scores. However, finding a good threshold is
more difficult than merely setting a hyper-parameter as we
might expect, because the optimal threshold can actually be
dependent on each different image.

Instead of struggling to find the appropriate threshold, we
want to import an explicit mechanism to model the annotation
length, for which we originally form the image annotation
task as a sequence generation problem. Therefore we propose
a novel model called Recurrent Image Annotator (RIA) that
jointly uses Convolutional Neural Networks and Recurrent Neural Networks (RNN) for predicting tag sequences. In the annotation phase, we just use an image as the initial input of RIA and then it will automatically generate annotation tags one by one, as shown in Figure 2. The idea is inspired by recent success of RNN in machine translation [6], and especially in image captioning [7], [8], where the task is to generate natural language sentences from images. The advantages of using RNN do not only include its nature to generate varied length outputs, but also its ability to refer to previous inputs when predicting the current time step output. Such ability allows RNN to exploit the correlations of both image-to-tag and tag-to-tag.

Now we have a CNN to extract image visual features, and an RNN to generate the tag sequence from the visual features, what do we need next? The answer is: an order. Both machine translation and image captioning aim to generate sentences, which have a natural order available for the RNN model to learn from. Unfortunately, in our image annotation task, there is no natural order available. Instead, we have to choose or learn an order to make our proposed model actually work.

Just like sentences obey the language rules to form the order, we believe that there exist intrinsic “language rules” for tags to form an order to describe an image. There are two points for an order to be good in our task. First, the order “rule” should be based on semantic image and tag information. Second, tag sequences in each training example should follow the same rule to be sorted, since only in this way can the model learn the “rule” from the training examples, and further generalize the prediction on the test images.

To facilitate the training of our model as well as testing the importance of tag orders, we propose several strategies to provide tag orders. And we compare the performance of our model with different tag orders in the experiments.

The main contributions of our work are as follows:

1) To our best knowledge, our work is one of the first\(^1\) to form image annotation task as a sequence generation problem, and we propose a novel RNN based model Recurrent Image Annotator to handle image annotation work.

2) We analyze the insufficiency in existing methods that they do not pay enough attention to generate image dependent number of tags, which should be a natural requirement in realistic tasks. We propose our RIA model as a high quality baseline for comparing the performance on arbitrary length image tagging. We hope that our work can help and encourage future work on this new task.

3) We propose and evaluate several orders for sorting the tag inputs of RIA model, and show the importance of tag order in the tag sequence generation problem.

\(^1\)We found a\(^2\) became publicly available on arXiv.org after we finished our work. Though there are several similar ideas existing in both papers, the focuses and motivations of ours are different. We pay more attention to the annotation length, and the tag sequence order used in training phase.

![Fig. 2. General architecture of RIA model. In test phase, once the RIA model receives the input image \(i\), and is triggered by the START signal, it predicts the first output tag. Then it starts a loop that uses previous output as input of the next time step, predicting the tag sequence \(Y\) recursively. The loop will continue until the STOP signal is predicted.]

II. RELATED WORK

In this section, we review previous work in AIA and introduce previous work related to our RIA model, i.e., CNN and RNN.

A. Automatic Image Annotation

Generally the existing methods of RIA can be grouped into three categories: generative models, discriminative models, and nearest neighbor type models. Generative models minimize the generative data likelihood based on topic models [10], where each topic is a distribution over image features and annotation tags, or mixture models [2], [11], [12], where the models define a joint distribution over image features and annotation tags. Different from generative models, discriminative models [13], [14] focus on directly learning a classifier for tag prediction, and recently CNN based multi-label classification models have been proposed [15], [16]. Another simple but powerful group of models are k-nearest-neighbor (KNN) based models [3]–[5], which also benefit from metric learning of multiple hand-crafted visual features.

B. Convolutional Neural Networks

The first step in AIA is to extract effective and efficient visual features from raw image pixels. Traditional methods usually use hand-crafted global or region based image features, or the combination of them [4], while recent researches indicate that features extracted from Convolutional Neural Networks (CNN) [17], [18] have significantly superior performance over these hand-crafted features on single-label image classification task [19], [20]. However, the recent work [21] show that deep CNN features do not outperform handcrafted features a lot in the traditional methods. We think one of the possible reasons is that the benefit from metric learning on multiple hand-crafted features is lost. Another problem is that currently there is no suitable loss function that can handle multi-label image classification perfectly for CNN models (for single-label classification task defining the optimal loss is trivial).
C. Recurrent Neural Networks

Recurrent Neural Networks (RNN) are networks with loops, which can be treated as multiple copies of the same network that are connected by passing messages (state) to the successor. However, the original architecture of RNN is difficult to train for long sequences due to gradient exploding and vanishing problem [23]. The gradient exploding problem can be easily coped with gradient clipping, i.e., limiting the absolute value of gradients. The vanishing problem is more difficult to handle, therefore several variants of RNN have been proposed for solving the problem of long term dependencies, for example, LSTM [23] and GRU [24]. These RNN variants use hidden cell states and gate functions to control how information from each previous time step is combined and propagated, and have been proved to work better than vanilla RNN [25].

We choose LSTM as our RNN sub-module just because it has been widely used and tested. Recent researches [25] compare LSTM and GRU, showing that they have similar performance. In our RIA model, RNN is used as a decoder to predict arbitrary length of annotation results.

III. RECURRENT IMAGE ANNOTATOR

In this section, we describe the entire model architecture first, and then explain the details of each sub-module. For convenience and readability, we denote a single training example to predict arbitrary length of annotation results.

A. Image Embedding

We either use pre-trained CNN features or jointly train a CNN to extract image features. In both cases we add a linear projection layer to project the output of CNN into \( H \) dimensional space, where \( H \) is the number of nodes in RNN hidden layer. In this way the CNN can be directly joined with the RNN sub-module.

B. Tag Embedding

Instead of directly using one-hot vectors to represent tags, we map the tags to \( D \) dimensional embedding vectors by using a lookup table like the common way to learn distributed word embeddings [26]. The lookup table is trainable and can learn what kind of representation to generate through training. In this way, the learned \( D \) dimensional tag representation can be optimized for minimizing the annotation error.

D. Order of Tag Sequence

To use the original training annotations as the input of LSTM, we have to sort the tag set to a tag sequence. We

\[
\hat{y}_t = \arg \max_j s^t_j \quad \text{for} \quad j = 1, \ldots, V
\]

where \( s^t_j \) is the score for tag index \( j \) at time step \( t \) and \( V \) is the vocabulary size plus one (for \( STOP \) signal). On the other hand, \( h_t \) is based on the current input \( x_t \), the previous hidden state \( h_{t-1} \) and cell state \( c_{t-1} \). In this way, when predicting tags, the model can refer to both the current input tag and the previous predicted tags. The procedure that how hidden state and cell state propagate through time step is described as below:

\[
f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
 i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
 o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
 g_t = \tanh(W_g \cdot [h_{t-1}, x_t] + b_g) \\
 c_t = f_t \odot c_{t-1} + i_t \odot g_t \\
 h_t = o_t \odot \tanh(c_t)
\]

where \( f_t, i_t, o_t, g_t \) are the gate units of LSTM [23], and \( W_\cdot \) and \( b_\cdot \) represent the corresponding weights and bias. The \( \cdot \) and \( \odot \) stand for the operator of matrix multiplication and element-wise multiplication respectively. The loss function of RIA is defined as the cross-entropy of prediction score \( s^t \):

\[
L = \sum_{t=1}^{T} - \log \frac{\exp(s^t_o)}{\sum_{j=1}^{V} \exp(s^t_j)}
\]
TABLE II
EXPERIMENTAL RESULTS OF ARBITRARY LENGTH ANNOTATION

| Method            | Features | Corel 5K | ESP GAME | IAPR TC12 |
|-------------------|----------|----------|----------|-----------|
|                   |          | P        | R        | F        | N+       | P        | R        | F        | N+       | P        | R        | F        | N+       |
| RIA (dictionary)  | fc7      | 30       | 29       | 30       | 138      | 32       | 29       | 29       | 249      | 32       | 28       | 29       | 239      |
| RIA (random)      | fc7      | 34       | 34       | 32       | 139      | 36       | 24       | 27       | 230      | 33       | 25       | 28       | 241      |
| RIA (rare-first)  | fc7      | 32       | 35       | 32       | 139      | 33       | 31       | 31       | 249      | 35       | 34       | 34       | 267      |
| RIA (frequent-first) | fc7    | 30       | 30       | 29       | 126      | 34       | 23       | 24       | 216      | 31       | 20       | 22       | 207      |
| RIA (dictionary)  | conv5    | 27       | 28       | 26       | 119      | 30       | 26       | 26       | 234      | 30       | 25       | 26       | 240      |
| RIA (random)      | conv5    | 32       | 32       | 30       | 134      | 31       | 28       | 29       | 243      | 32       | 29       | 30       | 258      |
| RIA (rare-first)  | conv5    | 28       | 29       | 27       | 125      | 30       | 22       | 24       | 218      | 29       | 19       | 21       | 200      |
| RIA (frequent-first) | conv5   | 32       | 33       | 30       | 134      | 31       | 28       | 29       | 243      | 32       | 29       | 30       | 258      |
| RIA (dictionary)  | finetune | 26       | 29       | 26       | 128      | 31       | 30       | 29       | 251      | 32       | 34       | 31       | 261      |
| RIA (rare-first)  | finetune | 31       | 33       | 31       | 135      | 33       | 31       | 31       | 251      | 35       | 37       | 34       | 265      |

TABLE III
EXPERIMENTAL RESULTS OF TOP-5 ANNOTATION

| Method         | Features | Corel 5K | ESP GAME | IAPR TC12 |
|----------------|----------|----------|----------|-----------|
| MBRM [2]       | HC1      | 24       | 25       | 25       | 122      | 18       | 19       | 19       | 209      | 24       | 23       | 24       | 223      |
| JEC [3]        | HC2      | 28       | 27       | 29       | 139      | 22       | 25       | 23       | 224      | 28       | 29       | 29       | 250      |
| TagProp [4]    | HC3      | 33       | 42       | 37       | 160      | 39       | 27       | 32       | 239      | 46       | 35       | 40       | 266      |
| 2PKNN [5]      | HC4      | 39       | 40       | 40       | 177      | 51       | 23       | 32       | 245      | 49       | 32       | 39       | 274      |
| JEC fc7        | 31       | 32       | 31       | 141      | 26       | 22       | 24       | 234      | 28       | 21       | 24       | 237      |
| 2PKNN fc7      | 33       | 30       | 32       | 160      | 40       | 23       | 29       | 250      | 38       | 23       | 29       | 261      |
| RIA (dictionary) | fc7    | 30       | 29       | 30       | 138      | 32       | 27       | 27       | 241      | 31       | 26       | 27       | 233      |
| RIA (rare-first) | fc7    | 32       | 35       | 32       | 139      | 32       | 31       | 31       | 249      | 35       | 34       | 33       | 267      |

1 HC: hand-crafted features.
2 For a fair comparison, we only use bold fonts for the highest value among the methods using the same fc7 features.

provide four orders: dictionary order, random order, rare-first order and frequent-first order. The dictionary order sorts the tags for each image alphabetically; the random order generates random tag sequence for each image as its name suggests; the rare-first order put the rarer tag before the more frequent ones; the frequent-first order put the more frequent tag before the less frequent ones.

IV. DATASETS AND EXPERIMENTAL SETUP

In this section we first present the dataset used in our experiments, then we describe the different experimental settings and the evaluation measures for the experiments. Finally we explain the training details in our experiments.

A. Datasets

We adopt three image annotation datasets that have been used in previous work: Corel 5K [10], ESP Game [27], and IAPR TC12 [28]. This allows us to also compare our RIA model with existing methods in the conventional top-5 evaluation setting. Table I shows statistics of the training sets of three datasets, some of which are described in a mean / maximum manner.

B. Experimental Setting

First, we compare RIA model with different tag sequence orders in the task of arbitrary length annotation. To further explore the image embedding submodule, we also compare the RIA models trained with different kinds of CNN features.

Second, we compare RIA model with existing methods on the three datasets in top-5 evaluation measures. For a fair comparison, especially we want to compare with the state-of-the-art methods that use the same CNN features as we adopt in our model.

C. Evaluation Measures

For both top-5 annotation and arbitrary length annotation, we use precision \( P \), recall \( R \) and F-measure \( F \) averaged over classes to be the main evaluation measures. Another widely used measure for these three datasets, \( N^+ \), which represents the number of classes with non-zero recall value, is also reported.

D. Training Details

We use three different ways to obtain the visual features: the last fully-connected layer of a pre-trained CNN denoted as \( fc7 \), the last convolutional layer of a pre-trained CNN denoted as \( conv5 \), and the output of a jointly trained (fine-tuned) CNN. The specific CNN model used here is the VGG-16 net [19]. For the tag sequence prediction module (LSTM), we set the dimension of hidden states \( H \) and input \( D \) both to be 1024, and we finally choose the number of hidden layers to be 1 after exhaustive validations.
The learning rate policy used in our experiment is Adam \cite{Kingma2014Adam}, which has been widely used recently. We set the initial learning rate, $\beta_1$, $\beta_2$ and $\epsilon$ as 0.0001, 0.9, 0.999, 0.1, respectively. Dropout with a ratio of 0.5 is used in the tag classification layers of RNN. All the hyper-parameters are selected by cross-validation.

V. EXPERIMENTAL RESULTS

A. Arbitr ary Length Annotation

Table II shows that $fc7$ features achieve better performance than $conv5$ features in our model. The fined-tuned CNN features have a similar performance to $fc7$ features, but need much more training time. Thus in the following experiments we only compare our models using $fc7$ features with other methods. Also, the rare-first order outperforms other orders in almost all evaluation measures. From Figure 3, we observe that models using rare-first order converge faster than others, and the difference is even more significant in the larger datasets ESP Game and IAPR TC12. The random order has a slight advantage over other orders in precision, while in terms of recall it has very poor performance. For F-measure, dictionary and random order have similar performance. The frequent-first order has the worst performance in recall and F-measure.

We compare the experimental results with our expectation: First, though dictionary order actually assigns all the tags of training examples in the same rule, it is almost meaningless since it does not provide any semantic information about the images or tags, and thus it leads to a poor performance. Second, though random order provides some possible proper orders for each training example, it does not follow the same...
rule and makes the model confused about the noisy orders, which may also result in a low recall rate. Third, rare-first order considers the frequency of tags and to some extent can help handle the rare tags problem, which is very important for improving the per-class measures. Besides, it uses the same rule to sort tags of all training examples, hence makes it easy for the model to learn. Finally, the frequent-first order has worse performance than we expected. We analyze the reasons why frequent-first order performs poorly especially in large datasets: the frequent tags are usually easier to predict than rare tags, and the frequent-first order puts the frequent tags first, so easy work becomes easier, but hard work becomes more difficult, which causes the extremely low per-class mean recall rate. The lowest N+ score also indicates that frequent-first order harms the ability of the model to correctly predict rare tags.

Our experiments show that the order of tag sequence is crucial for tag sequence generation. However, note that we are only using several naive approaches to decide the order, and we believe that there should be better ways to choose or learn an optimal order for this task.

### B. Top-5 annotation

As shown in Table [III] in the conventional top-5 annotation task, our model outperforms several state-of-the-art methods that use the same CNN features. Although the same methods with multiple hand-crafted features and metric learning have better performance, the advantage of using deep features is that we can avoid the complexity of hand-crafted features and the expensiveness of metric learning. Besides the comparable performance to several state-of-the-art methods, our model also runs in an extremely fast testing speed: 5 ms per image on an NVIDIA Titan X GPU. This is very difficult for KNN based methods to achieve, especially in large scale practical problems. That is because the testing time of KNN based methods is increasing linearly with the size of training examples, while the testing time of our model is constant, i.e., not affected by the dataset size.

### VI. Conclusion

We transformed the image annotation task to a sequence generation problem, and proposed a novel Recurrent Image Annotator model that receives an image as input and predicts a sequence of tags recursively. We evaluated our model in the traditional top-5 evaluation setting on three different image annotation datasets. The experimental results show that our model can achieve comparable performance to some state-of-the-art methods. On the condition of only using deep features without expensive metric learning, our model outperforms several state-of-the-art methods. We also evaluated our model on the arbitrary length annotation task, where the model has to decide appropriate annotation length automatically. To explore the influence of the tag sequence order used in the training phase, we evaluated several order candidates and our experiments confirmed the importance of a proper order in the tag sequence generation problem. From the empirical experimental results, we conclude that RNN model is capable of doing image annotation task, and since this is only a start for adopting RNN or other sequence generation techniques in this field, we believe that there is much more to explore in the future work.

### References

[1] D. Zhang et al., “A review on automatic image annotation techniques,” Pattern Recognition, vol. 45, no. 1, pp. 346–362, 2012.

[2] S. Feng et al., “Multiple bernoulli relevance models for image and video annotation,” in Proc. of IEEE CVPR, vol. 2, 2004, pp. 1002–1009.

[3] A. Makadia et al., “A new baseline for image annotation,” in Computer Vision–ECCV 2008. Springer, 2008, pp. 316–329.

[4] M. Guillaumin et al., “Tagprop: Discriminative metric learning in nearest neighbor models for image auto-annotation,” in Proc. of IEEE CVPR, 2009, pp. 309–316.

[5] Y. Verma and C. Jawahar, “Image annotation using metric learning in semantic neighbourhoods,” in Computer Vision–ECCV 2012. Springer, 2012, pp. 836–849.

[6] D. Bahdanau et al., “Neural machine translation by jointly learning to align and translate,” arXiv preprint arXiv:1409.0473, 2014.

[7] J. Mao et al., “Explain images with multimodal recurrent neural networks,” arXiv preprint arXiv:1510.01900, 2014.

[8] O. Vinyals et al., “Show and tell: A neural image caption generator,” in Proc. of IEEE CVPR, 2015, pp. 3156–3164.

[9] J. Wang et al., “Cnn-rnn: A unified framework for multi-label image classification,” arXiv preprint arXiv:1604.04573, 2016.

[10] P. Duygulu et al., “Object recognition as machine translation: Learning a lexicon for a fixed image vocabulary,” in Computer Vision–ECCV 2002. Springer, 2002, pp. 97–112.

[11] G. Carneiro et al., “Supervised learning of semantic classes for image annotation and retrieval,” IEEE TPAMI, vol. 29, no. 3, pp. 394–410, 2007.

[12] V. Lavrenko et al., “A model for learning the semantics of pictures,” in Proc. of NIPS, 2003, pp. 553–560.

[13] C. Cusano et al., “Image annotation using svm,” in Electronic Imaging 2006. International Society for Optics and Photonics, 2003, pp. 330–338.

[14] D. Grangier and S. Bengio, “A discriminative kernel-based approach to rank images from text queries,” IEEE TPAMI, vol. 30, no. 8, pp. 1371–1384, 2008.

[15] Y. Gong et al., “Deep convolutional ranking for multilabel image annotation,” arXiv preprint arXiv:1312.4984, 2013.

[16] Y. Wei et al., “Cnn: Single-label to multi-label,” arXiv preprint arXiv:1406.5726, 2014.

[17] Y. LeCun et al., “Gradient-based learning applied to document recognition,” Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.

[18] A. Krizhevsky et al., “Imagenet classification with deep convolutional neural networks,” in Proc. of NIPS, 2012, pp. 1097–1105.

[19] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in Proc. of IEEE CVPR, 2015, pp. 605–600.

[20] K. He et al., “Deep residual learning for image recognition,” arXiv preprint arXiv:1512.03385, 2015.

[21] V. N. Murthy et al., “Automatic image annotation using deep learning representations,” in Proc. of ACM ICMR, 2015, pp. 603–606.

[22] R. Pascanu et al., “On the difficulty of training recurrent neural networks,” arXiv preprint arXiv:1211.5063, 2012.

[23] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[24] K. Cho et al., “Learning phrase representations using rnn encoder-decoder for statistical machine translation,” arXiv preprint arXiv:1406.1078, 2014.

[25] J. Chung et al., “Empirical evaluation of gated recurrent neural networks on sequence modeling,” arXiv preprint arXiv:1412.3555, 2014.

[26] T. Mikolov et al., “Efficient estimation of word representations in vector space,” arXiv preprint arXiv:1301.3781, 2013.

[27] L. Von Ahn and L. Dabbish, “Labeling images with a computer game,” in Proc. of ACM SIGCHI, 2004, pp. 319–326.

[28] M. Grubinger, “Analysis and evaluation of visual information systems performance,” Ph.D. dissertation, Victoria University, 2007.

[29] D. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.