

UNIVERSITY OF CALIFORNIA, SAN DIEGO

Deep Learning for Image Understanding

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requirements for the degree
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by

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DEDICATION

To my family.

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PREVIEW

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ABSTRACT OF THE DISSERTATION

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by

Yufei Wang

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Professor Garrison W. Cottrell, Chair
Professor Nuno Vasconcelos, Co-Chair

Computer vision and image understanding is the problem of interpreting images by locating, recognizing objects, attributes and other higher level features in an image. In this thesis, I seek to tackle this broad problem using deep learning techniques. More specifically, I build deep neural network based models to solve two specific problems to understand images in a high level: album wise image understanding with event-specific image importance score, and description generation for an image.

I first focus on the understanding of a collection of images in an event album. In an event album, some images are more important or interesting to save or present than others, and I show

that with an event-specific image importance property, we can learn the interestingness of an image given an album, and the performance of the model generated importance score is very close to human preference. I build a siamese network that can predict image importance score given the event type of that image, using novel objective function and learning scheme. Next, to make the process fully automated, I propose an iterative updating procedure for event type and image importance score prediction, that can simultaneously decide the event type of the album and the importance score of every image. It consists of a Convolutional Neural Network that recognizes the event type, a Long-Short Term Memory (LSTM) that uses sequential information for event type recognition, and a siamese network that predicts image importance score.

Furthermore, not just limited to describing an image with a score or by a classified type, I seek the possibility to describe it with a phrase or sentence. I propose a coarse-to-fine LSTM based method that decomposes the original image description into a skeleton sentence and its notable attributes, and demonstrate that in this way the language model can generate better descriptions, with the capability to generate image descriptions that better accommodates user preference.

Chapter 1

Introduction

PREVIEW

Computer vision and image understanding is one of the main problem of artificial intelligence. It involves many attempts to help computer “see” images better. Early study for image understanding mostly focused on extracting the low level features, such as feature extraction for edges, corners, and optical flow [47, 14, 52]. The understanding of middle level features such as image segmentation, object detection and recognition then became major focus for many research studies [21, 36, 78, 119, 8]. More recently, with the access to large scale images with high quality annotations through the internet, and the speed up of computing with hardware innovation (GPUs), deep neural networks [43, 69] have brought great innovation into many research areas. Convolutional Neural Networks (CNN) has especially inspired great advance for many problems in image understanding [70, 98, 108, 38, 41]. Recurrent Neural Networks (RNN) and Long-Short Term Memory (LSTM) are widely used in sequence learning, such as machine translation [105] and image captioning [126].

In this thesis, I seek to use deep learning techniques to solve two problems in image understanding. First, I use a siamese network based model and LSTM based model to simultaneously predict album-wise event type and image importance for personal album organization. Second, I propose a coarse-to-fine LSTM based model for image caption generation. In this chapter, I provide relevant background knowledge for the topics relevant to this thesis.

1.1 Deep Learning

Most recently, thanks to the easy access to large scale image set via internet and great efforts researchers take to collect high quality annotations [94], the advance in network architecture [65, 100, 107, 48, 54], and development of faster computing hardware (GPUs), deep learning has been a great success, and has brought large performance boost to many areas in computer vision and image understanding, including object recognition [65, 48], object detection [41, 40, 93, 91], semantic segmentation [98, 64, 17, 130, 22], image captioning [117, 126, 81], and so on.

Deep convolutional neural networks (DCNN) are a type of feed forward network especially designed for image related task. They are advantageous over traditional multilayer perceptron networks in that they are much deeper, with tens or even hundreds of layers, and can learn the image from low level features to very high level features. The basic structure of unit in a DCNN consists of three layers: 1) a two dimensional convolutional layers that learns directly from the input image or from the activation of the previous layers. It preserves the spatial information of the input image and learns translation invariant features; 2) a spatial pooling layer which shrinks the size of features and at the same time enlarges the receptive field of the network; 3) a non-linear activation layer which improves the complexity and expressiveness of the network. With the stack of such units, the network is able to learn different level of features, from the low level features like corner and edges in the early layers, to the high level features like object parts and attributes in the late layers. The output of the stack of units is a high level feature vector representing the input image. In addition to the basic units, there are many variations of the network architecture to enhance the network's ability to interpret images [54, 48, 106, 49, 53].

On top of the feature extraction layers, the features are used for different tasks. For example, for object recognition, the final layer is an aggregated layer over different locations followed by a Softmax layer with cross-entropy loss function, and the output of the layer is the probability distribution of each object category given the input; for semantic segmentation, the output will be probability of each image pixel being in each object/stuff category.

With the use of back-propagation [71], DCNN's can learn the features from the image data directly, and greatly exceeds the performance of human designed features.

Recurrent neural networks (RNN), on the other hand, is different from feed forward networks in that the network not only takes its current input example as input, but also what it has perceived previously. It is designed for understanding a sequence of data, such as texts, handwriting, and spoken words. For each time step of an RNN, it has two sources of input: the present input data, and the output hidden state of the network in the previous time-step. The

learning of RNN relies on back-propagation through time [84], the extension of back-propagation.

In this thesis, I seek to use deep learning techniques for image understanding problems.

1.2 Album-wise Image Understanding

The first problem I aim to tackle is to understand personal photo albums. A personal photo album is a collection of photos that we take in an event, for example a wedding event, or a trip event. The high level understanding of such photo collection involves two stages: recognizing the event type of the photo album, and suggesting the most important/interesting images in the collection to represent the album or to save for future use.

For event recognition, there are three types of approaches. The most popular approach takes videos as input and uses spatiotemporal features for event recognition [122]. The second approach uses single image as cue to recognize event type. This approach does not use temporal information or relevant frame importance, and only uses object level and scene level features from a single image [73]. In between the two approaches, album-wise event recognition has useful album-wise temporal information, but the images in an album are very sparse in time and is not temporally continuous. Bossard *et al.*[3] found the sequential information of the albums is helpful for learning the event type of the albums, despite their sparsity.

On the other hand, image importance is a complex image property that correlates with various factor, such as aesthetics [23], image interestingness [45, 28], and image memorability [55]. In this thesis, I propose a novel image property named event-specific image importance. To study this property, we collected the CUration of Flickr Events Dataset (CUFED), and let the human annotator to decide the image importance score given an event album. We intentionally gave vague instructions on how annotators decide the importance of an image, to encourage them to rate based on their intuition. We found out that the image importance is indeed highly related to the event type of the album it is in, and although the image importance is a highly subjective

property, there is significant consistency across different annotators on the importance score they give in an album.

In this thesis, in Chapter 2, I propose a deep siamese architecture that learns the relative importance score of an image given the album event type it is from, assuming the event type of an album is given in advance. Further, in Chapter 3, I propose an iterative procedure that jointly learns the event type of an album and the importance score for each image. Thus, the two tasks for personal album understanding can be solved simultaneously with our framework.

1.3 Image Captioning

With the advance of image understanding with the development of deep learning, the research on image understanding is not constrained to the interpretation of an image with classification scores or detected tags, and the task of automatically describing the images with a sentence has drawn great attention. The problem is more challenging than conventional computer vision task in that the description generation requires high level understanding of the image beyond simple object recognition. It also requires the organization of a sentence that correctly conveys the notable information in the image.

The dominant approach for image captioning is inspired by the machine translation task [105]. For machine translation, an Encoder-Decoder network is used to map the input sequence to a vector of a fixed dimensionality, and then to decode the target sequence from the vector. The popular network used for encoding/decoding is Recurrent Neural Network (RNN), in which each element of the text sequence share the same unit parameters, and is sequentially fed into the network. RNN can deal with sequences with arbitrary length. Specifically, Long-Short Term Memory (LSTM), a variation of RNN, is commonly used [50]. It is capable to learn long-term dependencies with a cell state.

Similar to machine translation, an image can be viewed as a sentence in the source

language, and an Encoder-Decoder network is used to translate it from the source language to the target sentence. Since the source “sentence” is in fact an image in the image captioning task, a CNN is used as Encoder, and LSTM is used as a Decoder.

Despite the great success in image captioning, most of the existing LSTM based methods suffer from two problems: 1) they tend to parrot back the sentences from the training corpus; and 2) the nature of predicting sentence words one by one means the attributes of a sentence is predicted before the object they are referring to, which is counter-intuitive.

To solve these two problems, in Chapter 4, I propose a coarse-to-fine model which decomposes the original caption into two parts: skeleton sentence which contains the main objects and structure in the sentence, and notable attributes for each object in the skeleton sentence.

1.4 Organization of the Thesis

In this thesis, I aim to tackle the two problems in high level image understanding. The rest of the thesis is organized as follows:

In Chapter 2, I introduce the problem of event-specific image importance. I collected a dataset for the study of this image property, and collect annotations of album-wise event type and image-wise importance score for the dataset, using Amazon Mechanical Turk (AMT). With the dataset, we show that the event-specific image importance property is subjective yet learnable. Furthermore, we propose a siamese network based architecture that can learn the image importance score with performance close to human perception, and the model assumes the event type information is known in advance.

In Chapter 3, I further extend our model to learn image importance score with no prior knowledge, by proposing an iterative procedure to learn the two album properties at the same time: album-wise event type recognition and image-wise importance score prediction. We show