Image Recommendation for Wikipedia Articles

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Abstract. Multimodal learning, which is simultaneous learning from different data sources such as audio, text, images; is a rapidly emerging field of Machine Learning. It is also considered to be learning on the next level of abstraction, which will allow us to tackle more complicated problems such as creating cartoons from a plot or speech recognition based on lips movement.
In this paper, we propose to identify the best-performing state-of-the-art techniques for recommending the most relevant images for a Wikipedia article. In other words, we need to create a shared text-image representation of an abstract notion paper describes, so that having only a text description machine would "understand" which images would visualize the same notion accurately.

Keywords: Multimodal Learning · Text-Image Similarity · Image Recommendation.

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1 Introduction

Every day we perceive the world around us through multiple cognitive feelings such as sight, smell, hearing, touch, taste. Moreover, our ability to consolidate all the information from different sources into one complete picture helps us comprehensively understand the world.

With a trend to digitizing in the last few decades, more and more information is recorded in different kids of medial such as audio, image, video, text, and 3D modeling. That also created new challenges of efficiently processing a significant amount of recorded information, where we already have significant achievements. However, every type of digital storage only captures some subset of available information. For example, image only captures visual appearance, while audio - the sound, just as our sight and ears do. Thus all scientific progress in processing some data carrier is bounded by limitation of what that medium can capture. In other words, to digitally create a notion of dog, we cannot only have a visual representation. Just as humans, we need to combine all the information streams, which describes the same entity from different perspectives, and combine them into one comprehensive representation.

That is the motivation for multimodal representation learning, which aims to combine different types of data into a complete representation of a real-world entity. In that context, the word "modality" refers to a particular way of encoding information. Thus a problem in the domain of e.g., image processing is called unimodal, while a problem in the domain of multiple information encodings e.g., image to caption generation, is called multimodal since it works with both: image and text modalities [1]

By having a complete representation of an entity, which was created via multimodal data that captures complementary/supplementary information subsets of an object, we have more comprehensive computational "understanding" of that entity. That will help us to increase the precision of existing data science applications and also extend its limits to more abstract problems such as not only identifying the objects on an image but understanding its value. For example[1], early researches on speech recognition showed that by involving visual modality of lips movement on top of sound modality, we get extra information which allows us to increase the quality of voice recognition task, just as it does for humans[2]

In this project, we are going to research possible approaches for the "Image Recommendation for Wikipedia Articles" problem, which is also part of multimodal representation learning domain. That is, based on the article's text information, we need to recommend images describing the same notion. In other words, we need to create a high-level representation of some entity, described by both text and images. So that later one we can "understand" which image representation of the notion is the best suited for a given text description.

In scope of this project, we are going to explore state-of-the-art techniques of multimodal representation learning and whether they can be applied to solve this problem. We believe this project will be valuable from both a research and an application perspective.

This report is an official Project Proposal of Master's Thesis, which will define a problem, provide rigor overview of state-of-the-art approaches in problem's domain, specify goals of the project, suggest a solution approach and provide a time plan of the thesis. To fully comprehend material, the reader should be familiar with basic Machine Learning notions[?], Convolutional Neural Network(CNN)[?], basics of Computer Vision and Natural Language Processing[?].

2 Problem Formulation

Wikipedia is the biggest collection of human knowledge containing more than 35 million pages and having nearly 9 billion views per month[?] And it continually growing, having more than 500 new pages per day[?], and all of that only in its English version.

As a part of 2030 strategy, one of the key goals is to break down any barriers for accessing free information. By researching possibilities to automatically recommend images for Wikipedia editors, it will help to get better media enrichment of articles, which in turn will make information easier and faster to comprehend[10]. Also, it would be helpful as automation of time-consuming task to search for and add a proper article visualization.

Thus in order to facilitate the qualitative growth of Wikipedia, we are going to research how to approach the problem of Image Recommendation System for Wikipedia articles. In other words, having a text with wiki formatting, we need to identify the most relevant images from Wikimedia Commons database.

3 Data

All data is publicly available on Wikipedia. Specifically, we have more than 35 million Wikipedia pages with a fair amount of them enriched with images. We also have Commons image dataset[?], containing more than 55 million images. That is the real-world data, where ultimately the solution should be applied.

But for initial problem research we would only use a reliable subset of above specified data for training. In particular, Wikipedia has a notion of featured articles[?], which are the best articles with qualitative text and a lot of supporting visualization. In other words, it's a high quality manually created dataset of more than 5000 articles[?], each of which has multiple associated images. Although, it still requires proper preprocessing and cleaning before using.

4 Related Work

While during the last decades there was much progress in a field of unimodal representation, research in multimodal learning was limited by simple concatenation of unimodal features[4]. However, during recent years, the scientific landscape in this domain has been rapidly evolving[3]. One of the triggers for it was the success of deep learning models, which have a powerful representation ability with

multiple levels of abstractions. Thus they were also incorporated in multimodal learning. As Guo et al. suggested[1], we can divide all the multimodal learning approaches into three categories 1) joint representation, which aims to integrate modality-specific features into some common space 2) coordinated representation, which aims to preserve modality-specific features, while introducing a space to measure multimodal similarities 3) intermediate representation, which aims to encode features of one modal to some intermediate space, from where we later generate features of another modal.

In this chapter, we will cover available techniques to extract features from text and image modalities, overview available solutions in each type of multimodal learning, and then summarise their applicability for our problem.

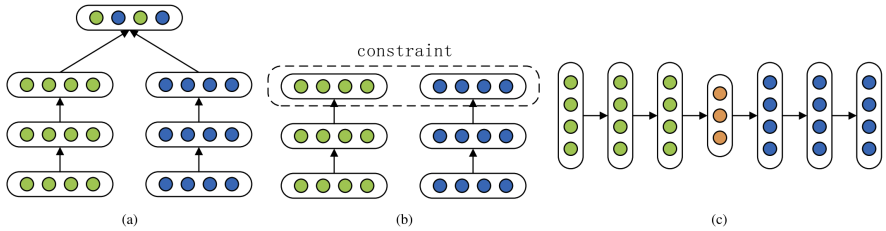

Fig. 1. Three types of frameworks about deep multimodal representation. (a) Joint representation aims to learn a shared semantic subspace.(b) Coordinated representation framework learns separated but coordinated representations for each modality under some constraints. (c) intermediate representation framework translates one modality into another and keep their semantics consistent.[1]

4.1 Unimodal Representation

Image The most popular model used in feature extraction from images are different types of Convolutional Neural Network(CNN), such as LeNet[5], AlexNet[6], GoogleNet[7], VGGNet[8] and ResNet[9]. When working with big datasets, it is preferable to use pre-trained version of chosen CNN. This field has tremendous development in recent years, and thus currently we already have well-defined solution for most problems.

Text A popular way to extract features from the text is to encode it to vector, as is done in word2vec[?] or Glove[?] algorithms. They map words into one-hot encoded vector space of language vocabulary. Although, the common problem with those approaches is when some words are not present in vocabulary or out-of-vocabulary error. However, there are also a variety of solutions to this problem, such as character embeddings[?] or character n-grams[?].

An alternative and more powerful tool for dealing with text is recurrent neural network(RNN)[?], which is more context-aware and can make better encoding of the n-th word, knowing what was already in a sentence. One of the most successful realizations of RNN is long short-term memory(LSTM)[?].

4.2 Joint Representation

The main idea of joint representation is to integrate multimodal features into a single input, which we then process as some artificial unimodal input with well-known machine learning techniques. More formally, it aims to project unimodal representations into a shared semantic subspace, where the multimodal features can be fused[3], as shown in Figure 1(a). Up until recently, that was the primary technique in multimodal learning, where shared features were fused by concatenating them together. However, now, the most popular choice is to use a distinct hidden layer, where modality-specific features will be combined into a single output vector.

This approach was historically the first one and is still commonly applicable in video classification[?][?], event detection[?][?], sentiment analysis[?][?], and visual question answering[?]. However, its main disadvantage is neglecting the fact that different modalities have not only supplementary information, that is which show the same notion from different perspectives, but also complementary information, where one modality captures the information which another cannot.{hard-to-read?} For example, lips movement and audio of a speech are mostly supplementary sources, while images of some bird and audio of it singing are mostly supplementary sources. Because of that, much information gets lost in that shared space.

Although it has advantages of being a simple method and producing modality-invariant common space of features, it cannot be used to infer the separated representations for each modality[1]. Thus methods from this category are not applicable to our problem

4.3 Intermediate Representation

Intermediate Representation models aim to encode features of one modality to some intermediate space, from which later features of another modality can be generated(or decoded), as shown on Figure 1(c). To prevent the intermediate space from being related only to a source modality, during encoder-decoder training we maximize, e.g., the likelihood of target sentence given source image, so that error function employs the error of decoding. Subsequently, the generated intermediate representation tends to capture the shared semantics from both modalities[1].

Some interesting application of that model was proposed by Mor et al. [?], where algorithm encodes a musical track into intermediate space, which then will be decoded by multiple decoders into a space of some specific instrument. In other words, encoder extracts instrument-invariant generic musical features, which then each decoder transforms into features of its target instrument.

The general advantage of such approach is that it is one of the best ways to generate new features in a target domain. Thus this technique is used in Image Caption[?], Video Description[?], and Text to Image[?] generations. The disadvantages of that model are that 1) it can only encode one modality, 2) complexity of designing a feature generator should be taken into account[1] and 3) intermediate space also extracts only shared subspace from two modalities. Moreover, because we need to query existing information rather than generate one, those methods are also not suitable for our problem solution.

4.4 Coordinated Representation

The last type of multimodal learning is a coordinated representation. Instead of learning from a joint representation, it learns from modal-specific representations separately but with a shared constraint, which is some loss function identifying cross-modal similarity/correlation. Since different modalities hold unique information about an object, that approach operates with all available knowledge. A visual explanation can be seen in Figure 1(b). Regarding constraint function, a commonly used option is cross-modal similarity functions, where learning objective is to preserve both inter-modality and intra-modality similarity structure. In other words, it would force cross-modal distance for elements with the same semantics be as small as possible, while with dissimilar - as big as possible.

The cross-modal ranking is a widely used constrain, where the loss function is defined in the following way

$$\sum_{i}\sum_{t^-} max(0, \alpha - S(i,t) + S(i,t^-)) + \sum_{t}\sum_{i^-} max(0, \alpha - S(t,i) + S(t,i^-)),$$

where (i,t) is a matching image-text pair, α is margin, S is a similarity function, i^- is mismatching pair to t and vise versa. Frome et al. [?] used a combination of dot-product similarity and margin rank loss to learn a visual-semantic embedding model(DeViSE) for visual recognition[1]. DeViSE trains deep networks for both image and text features, and then adjust features based on above mentioned ranked loss, though in more simplified form.

After the success of DeViSE, Kiros et al. [?] extended this model in order to create image captions. Specifically, they used the full version of cross-modal ranking as a loss function and also employed LSTM to learn text features. Socher et al. [?] also used DeViSE model to perform cross-modal retrieval of text and images. They introduced dependency trees based recursive neural network (DTRNN) to encode language modality and argued that the proposed DTRNN is robust to surface changes such as word order[1].

In addition to cross-modal ranking, another widely used constraint is Euclid distance, which is also used for ensuring that similarity structure for both intra-modality and inter-modality is preserved. That is, for inter-modality, we map text and image features into low-dimensional space, where we can calculate the distance between feature vectors. The idea here is to ensure that inter-modality features of the same semantics are as close as possible[Pan et al. ??]. While for

intra-modality, we want to preserve the similarity between neighborhood items, that is:

$$d(m_i, m_j) + m < d(m_i, m_k), \forall m_j \in N(m_i), \forall m_k \notin N(m_i),$$

where m is data point of any modality, m_i point of interest, N(m) - denotes neighborhood of m[Wang et al.?]

So, Coordinated Representation preserves all modality-specific information. It also explicitly compares features from different modalities, thus having data from one, we can identify the closest data point from another modality. Because of those properties, it is used for cross-modal retrieval[?][?], retrieval-based visual description[?], and transfer knowledge across modalities[??]. Thus it can be applied for our problem of Image Recommendation for articles, and we will proceed with those methods.

5 Solution Approach

After rigor overview of related work, Coordinated Representation techniques were identified as the most prominent direction for our problem. Coordinated Representation approach aims to exploit modality-specific features fully, thus we train each feature modality separately.

To make the system learn right features in each modality, we map all of them into space where inter-modality similarity can be evaluated but also preserving the intra-modality similarity structure[11][?][other options from prev chapter?]. Then we identify loss function, by enforcing some similarity/correlation/distance function in that space return high values for mismatches modality pairs and small otherwise. That would be a loss function, which each modality-specific model will be minimizing, thus empowering modality-specific feature learning. Please refer to Figure [?] for a visual representation of the algorithm.

As a possible example of the above-specified approach, we could have the following learning pipeline:

1. Separately learn features of each modality:
   - text: we can vectorize text via word2vec algorithm and then learn its features with some CNN model.
   - image: its features can be learned via the conventional way of using some popular CNN model as well.
2. Minimize loss function, which is calculated based on both text and image features, and used for training both separate networks. Loss function maps text and image into one space, where we minimize the distance between matching image-text pair AND maximizing mismatching image-text distances. That is:

   $$\sum_i \sum_{t^-} max(0, \alpha - S(i,t) + S(i,t^-)) + \sum_t \sum_{i^-} max(0, \alpha - S(t,i) + S(t,i^-)),$$

   where (i,t) is a matching image-text pair, α is margin, i^- is mismatching pair to t and vise versa, S is a similarity function e.g. $S(i,t) = ||M_i i - M_t t||^2$, where M_i and M_t are some transform matrices.

6 Methodology

6.1 Methodological Approach

The research question is defined as "Research whether it is possible to implement a system, which would recommend relevant Commons[?] images for a specific Wikipedia article" and implies Quantitative research. It is aiming to discover whether state-of-the-art techniques of multimodal representation learning can solve this specific problem for Wikipedia. Since we would have a supervised dataset, classic supervised learning result evaluation techniques would be applied.

6.2 Methods of Data Collection

Existing Wikipedia data will be used to conduct the research. More specifically, we will use a collection of featured articles[?], where each page went through thorough manual review procedure by the Wikipedia community and represent the best Wikipedia can offer. Thus it is theoretically the best possible quality for machine learning algorithms.

6.3 Methods of Analysis

We will select candidate algorithms by analyzing recent literature surveys of a corresponding domain, and choosing the most prominent state-of-the-art approaches described there. We will also check the most cited approaches to solve a similar problem. In that way, we can ensure that all state-of-the-art methods existing in that field would be reviewed and then the most applicable would be adequately tested.

7 Goals

The goal of the project is to research whether it is possible to implement a system, which would recommend relevant Commons[?] images for a specific Wikipedia article. Thus we are planning to investigate the scientific landscape in that area and provide report whether it can solve our specific problem of image recommendation with Wikipedia dataset. We do not expect to create a complete end-to-end solution but rather investigate a path towards it.

8 Time Plan

Date	Milestone
10 Sep 2019	Kick Start
16 Sep 2019	Project Proposal's Abstract Submission
30 Sep 2019	Project Proposal Submission
1 Nov 2019	Start of Implementation
15 Nov 2019	Finalise Approach and Solution
1 Dec 2019	Start of Evaluation
10 Dec 2019	Finalise Evaluation Planning
23 Dec 2019	Finalise Implementation
27 Dec 2019	Finalise Evaluation
31 Dec 2019	Finalise Review of Related Work
8 Jan 2020	Thesis Final Submission

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