An Attentive Survey of Attention Models

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Abstract

Attention Model has now become an important concept in neural networks that has been researched within diverse application domains. This survey provides a structured and comprehensive overview of the developments in modeling attention. In particular, we propose a taxonomy which groups existing techniques into coherent categories. We review the different neural architectures in which attention has been incorporated, and also show how attention improves interpretability of neural models. Finally, we discuss some applications in which modeling attention has a significant impact. We hope this survey will provide a succinct introduction to attention models and guide practitioners while developing approaches for their applications.

1 Introduction

Attention Model(AM), first introduced for Machine Translation [Bahdanau *et al.*, 2014] has now become a predominant concept in neural network literature. Attention has become enormously popular within the Artificial Intelligence(AI) community as an essential component of neural architectures for a remarkably large number of applications in Natural Language Processing, Statistical Learning, Speech and Computer Vision.

The intuition behind attention can be best explained using human biological systems. For example, our visual processing system tends to focus selectively on parts of the image, while ignoring other irrelevant information in a manner that can assist in perception [Xu *et al.*, 2015]. Similarly, in several problems involving language, speech or vision, some parts of the input can be more relevant compared to others. For instance, in translation and summarization tasks, only certain words in the input sequence may be relevant for predicting the next word. Likewise, in an image captioning problem, some regions of the input image may be more relevant for generating the next word in the caption. AM incorporates this notion of relevance by allowing the model to dynamically *pay attention to* only certain parts of the input that help in performing the task at hand effectively. An example of sentiment classification of Yelp reviews using AM is shown in Figure 1 [Yang *et al.*, 2016]. In this example, the AM learns that out of five sentences, the first and third sentences are more relevant. Furthermore, the words *delicious* and *amazing* within those sentences are more meaningful to determine the sentiment of the review.

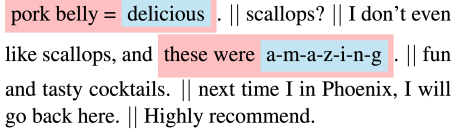

Figure 1: Example of attention modeling in sentiment classification of Yelp reviews. Figure from [Yang *et al.*, 2016]

The rapid advancement in modeling attention in neural networks is primarily due to three reasons. First, these models are now the state-of-the-art [Young *et al.*, 2018] for multiple tasks such as Machine Translation, Question Answering, Sentiment Analysis, Part-of-Speech tagging, Constituency Parsing and Dialogue Systems. Second, they offer several other advantages beyond improving performance on the main task. They have been extensively used for improving interpretability of neural networks, which are otherwise considered as black-box models. This is a notable benefit mainly because of growing interest in the fairness, accountability, and transparency of Machine Learning models in applications that influence human lives. Third, they help overcome some challenges with Recurrent Neural Networks(RNNs) such as performance degradation with increase in length of the input (Section 2) and the computational inefficiencies resulting from sequential processing of input (Section 4.3). Therefore, in this work we aim to provide a brief, yet comprehensive survey on attention modeling.

Organization: We briefly explain the AM proposed by Bahdanau *et al.* [2014] in Section 2 and describe our taxonomy in Section 3. We then discuss key neural architectures using AM and how attention is facilitating the interpretability of neural networks in Section 4 and 5 respectively. Finally, we present applications where attention has been widely applied in Section 6 and conclude the paper in Section 7.

Related surveys: There have been a few surveys on attention focusing on Computer Vision [Wang and Tax, 2016], and graphs [Lee *et al.*, 2018]. Another similar work is by Galassi *et al.* [2019], but we further incorporate an accessible taxonomy, key architectures and applications, and interpretability aspect of AM. We hope that our contributions will not only foster broader understanding of AM but also help AI developers & engineers to determine the right approach for their application domain.

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2 Attention Model

A sequence-to-sequence model consists of an encoder-decoder architecture [Cho *et al.*, 2014b] as shown in Figure 2(a). The encoder is an RNN that takes an input sequence of tokens $\{x_1, x_2, ..., x_T\}$, where T is the length of input sequence, and encodes it into fixed length vectors $\{h_1, h_2, ..., h_T\}$. The decoder is also an RNN which then takes a single fixed length vector h_T as its input and generates an output sequence $\{y_1, y_2, ..., y_{T'}\}$ token by token, where T' is the length of output sequence. At each position t, h_t and s_t denote the hidden states of the encoder and decoder respectively.

Challenges of traditional encoder-decoder: There are two well known challenges with this traditional encoder-decoder framework. First, the encoder has to compress all the input information into a single fixed length vector h_T that is passed to the decoder. Using a single fixed length vector to compress long and detailed input sequences may lead to loss of information [Cho *et al.*, 2014a]. Second, it is unable to model alignment between input and output sequences, which is an essential aspect of structured output tasks such as translation or summarization [Young *et al.*, 2018]. Intuitively, in sequence-to-sequence tasks, each output token is expected to be more influenced by some specific parts of the input sequence. However, decoder lacks any mechanism to selectively focus on relevant input tokens while generating each output token.

Key idea: AM aims at mitigating these challenges by allowing the decoder to access the entire encoded input sequence $\{h_1, h_2, ..., h_T\}$. The central idea is to induce attention weights α over the input sequence to prioritize the set of positions where relevant information is present for generating the next output token.

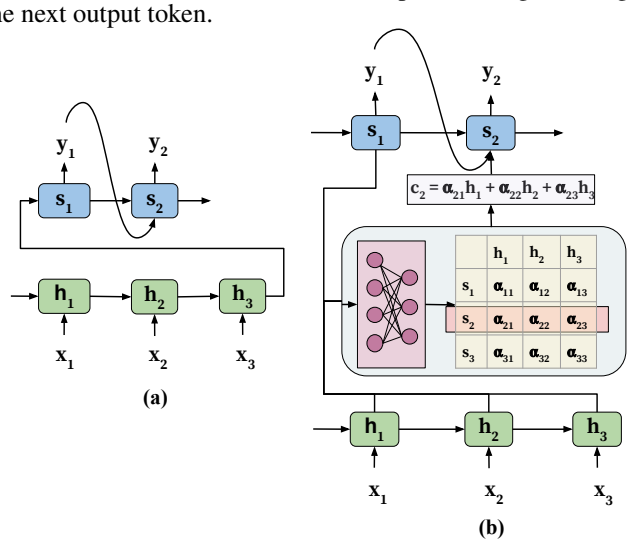


Figure 2: Encoder-decoder architecture: (a) traditional (b) with attention model

Usage of attention: The corresponding encoder-decoder architecture with attention is shown in Figure 2(b). The attention block in the architecture is responsible for automatically learning the attention weights α_{ij}, which capture the relevance between h_i (the encoder hidden state, which we refer to as candidate state) and s_j (the decoder hidden state, which we refer to as query state). These attention weights are then used for building a context vector c, which is passed as an input to the decoder. At each decoding position j, the context vector c_j is a weighted sum of all hidden states of the encoder and their corresponding attention weights, i.e. $c_j = \sum_{i=1}^{T} \alpha_{ij} h_i$. This additional context vector is the mechanism by which decoder can access the entire input sequence and also focus on the relevant positions in the input sequence.

Learning attention weights: The attention weights are learned by incorporating an additional feed forward neural network within the architecture. This feed forward network learns a particular attention weight α_{ij} as a function of two states, h_i (candidate state) and s_{j-1} (query state) which are taken as input by the neural network. Further, this feed forward network is jointly trained with encoder-decoder components of the architecture.

3 Taxonomy of Attention

We consider attention in four broad categories and elucidate the different types of attention within each category as shown in Table 1[1]. We would like to emphasize that these categories are not mutually exclusive. Attention can be applied as a combination of multiple categories eg. a multi-level, self and soft attention combination has been used by Yang *et al.* [2016]. Hence, one can think of these categories as dimensions along which attention can be considered while employing it for an application of interest. To make this concept comprehensible, we provide a list of key technical papers and specify the multiple types of attention used within the proposed approaches in Table 2.

Category	Type
Number of Sequences	distinctive, co-attention, self
Number of Abstraction Levels	single-level, multi-level
Number of Positions	soft/global, hard, local
Number of Representations	multi-representational, multi-dimensional

Table 1: Categories and types of attention within each category.

3.1 Number of sequences

Thus far we have only considered the case which involves a single input and corresponding output sequence. This type of attention, which we refer to as **distinctive**, is used when candidate and query states belong to two distinct input and output sequences respectively. Most attention models employed for translation [Bahdanau *et al.*, 2014], summarization [Rush *et al.*, 2015], image captioning [Xu *et al.*, 2015] and speech recognition [Chan *et al.*, 2016] fall within the distinctive type of attention.

A **co-attention** model operates on multiple input sequences at the same time and jointly learns their attention weights, to capture interactions between these inputs. Lu *et al.* [2016] use a co-attention model for visual question answering. The authors argue that in addition to modeling visual attention on the input image, it is also important to model question attention because all words in the text of question

[1]Given the space constraints, we cannot cite all relevant papers, so we aim to cover a representative sample that outlines the scope of the field.

Reference	Application	Category			
		Number of Sequences	Number of Abstraction Levels	Number of Representations	Number of Positions
Bahdanau *et al.* [2014]	Machine Translation	distinctive	single-level	-	soft
Xu *et al.* [2015]	Image Captioning	distinctive	single-level	-	hard
Luong *et al.* [2015]	Machine Translation	distinctive	single-level	-	local
Yang *et al.* [2016]	Document Classification	self	multi-level	-	soft
Chan *et al.* [2016]	Speech Recognition	distinctive	single-level	-	soft
Lu *et al.* [2016]	Visual Question Answering	co-attention	multi-level	-	soft
Wang *et al.* [2017]	Sentiment Classification	co-attention	multi-level	-	soft
Ying *et al.* [2018]	Recommender Systems	self	multi-level	-	soft
Shen *et al.* [2018]	Language Understanding	self	single-level	multi-dimensional	soft
Kiela *et al.* [2018]	Sentence Representation	self	single-level	multi-representational	soft

Table 2: Summary of key papers for technical approaches in AMs. '-' means not applicable.

are not equally important to the answer of the question. Further, attention based image representation is used to guide the question attention and vice versa, which essentially helps to simultaneously detect key phrases in the question and corresponding regions of images relevant to the answer.

In contrast, for tasks such as text classification and recommendation, input is a sequence but the output is not a sequence. In this scenario, attention can be used for learning relevant tokens in the input sequence for every token in the *same* input sequence. In other words, the query and candidate states belong to the same sequence for this type of attention. For this purpose, **self** attention, also known as inner attention has been proposed by Yang *et al.* [2016].

3.2 Number of abstraction levels

In the most general case, attention weights are computed only for the original input sequence. This type of attention can be termed as **single-level**. On the other hand, attention can be applied on multiple levels of abstraction of the input sequence in a *sequential* manner. The output (context vector) of the lower abstraction level becomes the query state for the higher abstraction level. Additionally, models that use **multi-level** attention can be further classified based on whether the weights are learned top-down [Zhao and Zhang, 2018] (from higher level of abstraction to lower level) or bottom-up [Yang *et al.*, 2016].

We illustrate a key example in this category which uses the attention model at two different levels of abstraction, i.e. at word level and sentence level, for the document classification task [Yang *et al.*, 2016]. This model is called a "Hierarchical Attention Model"(HAM) because it captures the natural hierarchical structure of documents i.e. document is made up of sentences and sentences are made up of words. The multi-level attention allows the HAM to extract words that are important in a sentence and sentences that are important in a document as follows. It first builds an attention based representation of sentences with first level attention applied on sequence of word embedding vectors. Then it aggregates these sentence representations using a second level attention to form a representation of document. This final representation of the document is used as a feature vector for the classification task.

Note that the co-attention work [Lu *et al.*, 2016] described in Section 3.1 also belongs to multi-level category where it co-attends to the image and question at three levels: word level, phrase level and question level. This combination of co-attention and multi-level attention is depicted in Figure 3.

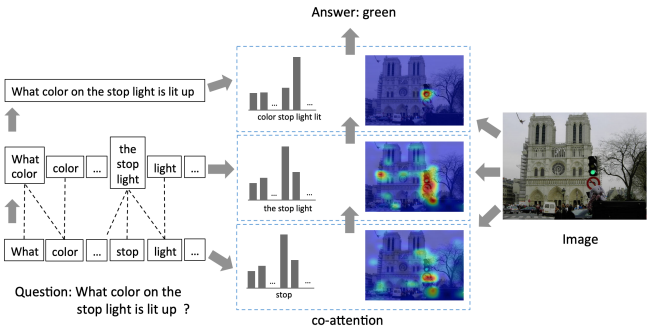


Figure 3: The AM proposed by Lu *et al.* [2016] for Visual Question Answering task which is a combination of co-attention (visual and text) and multi-level (word level, phrase level and question level) attention.

Zhao and Zhang [2018] propose to use "attention-via-attention", which also uses multi-level attention (with characters on the lower level and words on the higher level) but learns the attention weights in top-down fashion.

3.3 Number of positions

In the third category, the differences arise from positions of the input sequence where attention function is calculated. The attention introduced by Bahdanau *et al.* [2014] is also known as **soft** attention. As the name suggests, it uses a weighted average of all hidden states of the input sequence to build the context vector. The usage of the soft weighing method makes the neural network amenable to efficient learning through backpropagation, but also results in quadratic computational cost.

Xu *et al.* [2015] propose a **hard** attention model in which the context vector is computed from stochastically sampled hidden states in the input sequence. This is accomplished using a multinoulli distribution parameterized by the attention weights. The hard attention model is beneficial due to decreased computational cost, but making a hard decision at every position of the input renders the resulting framework non-differentiable and difficult to optimize. As a result, variational learning methods and policy gradient methods in reinforcement learning have been proposed in the literature to overcome this limitation.

Luong *et al.* [2015] propose two attention models, namely **local** and **global**, in context of machine translation task. The global attention model is similar to the soft attention model. The local attention model, on the other hand, is intermediate between soft and hard attention. The key idea is to first detect an attention point or position within the input sequence and pick a window around that position to create a local soft attention model. The position within input sequence can either be set (monotonic alignment) or learned by a predictive function (predictive alignment). Consequently, the advantage of local attention is to provide a parametric trade-off between soft and hard attention, computational efficiency and differentiability within the window.

3.4 Number of representations

Generally a single feature representation of the input sequence is used in most applications. However, in some scenarios, using one feature representation of input may not suffice for the downstream task. In this case, one approach is to capture different aspects of the input through multiple feature representations. Attention can be used to assign importance weights to these different representations which can determine the most relevant aspects, disregarding noise and redundancies in the input. We refer to this model as **multi-representational AM**, as it can determine the relevance of multiple representations of the input for downstream application. The final representation is a weighted combination of these multiple representations and their attention weights. One benefit of attention here is to directly evaluate which embeddings are preferred for which specific downstream tasks, by inspecting the weights.

Kiela *et al.* [2018] learns attention weights over different word embeddings of the same input sentence to improve sentence representations. Similarly, Maharjan *et al.* [2018] use attention to dynamically weigh different feature representations of books capturing lexical, syntactic, visual and genre information.

Based on similar intuition, in **multi-dimensional** attention, weights are induced for determining the relevance of each dimension of the input embedding vector. The intuition is that computing a score for each feature of the vector can select the features that can best describe the token's specific meaning in any given context. This is especially useful for natural language applications where word embeddings suffer from the polysemy problem. Examples of this approach are shown in Lin *et al.* [2017] for more effective sentence embedding representation and in Shen *et al.* [2018] for language understanding problem.

4 Network Architectures with Attention

In this section we describe three salient neural architectures used in conjunction with attention: (1) the encoder-decoder framework, (2) memory networks which extend attention beyond a single input sequence, and (3) architectures which circumvent the sequential processing component of recurrent models with the use of attention.

4.1 Encoder-Decoder

The earliest use of attention was as part of RNN based encoder-decoder framework to encode long input sentences [Bahdanau *et al.*, 2014]. Consequently, attention has been most widely used with this architecture.

An interesting fact is that AM can take any input representation and reduce it to a single fixed length context vector to be used in the decoding step. Thus, it allows one to decouple the input representation from the output. One could exploit this benefit to introduce hybrid encoder-decoders, the most popular being Convolutional Neural Network(CNN) as an encoder, and RNN or Long Short Term Memory (LSTM) as the decoder. This type of architecture is particularly useful for many multi-modal tasks such as image and video captioning, visual question answering and speech recognition.

However, not all problems where both input and output are sequential data can be solved with the aforementioned formulation (e.g. sorting or travelling salesman problem). *Pointer networks* [Vinyals *et al.*, 2015] are another class of neural models with the following two differences, (1) the output is discrete and points to positions in the input sequence (hence the name pointer network), and (2) the number of target classes at each step of the output depends on the length of the input (and hence variable). This cannot be achieved using the traditional encoder-decoder framework where the output dictionary is known apriori (eg. in case of natural language modeling). The authors achieve this using attention weights to model the probability of choosing the i^{th} input symbol as the selected symbol at each output position. This approach can be applied to discrete optimization problems such as travelling salesperson problem, and sorting.

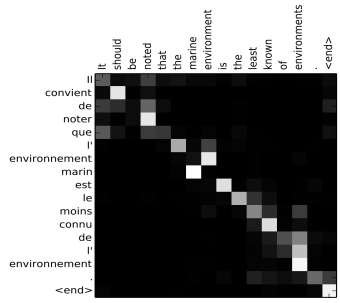
4.2 Memory Networks

Applications like question answering and chat bots require the ability to learn from information in a database of facts. The input to the network is a knowledge database and a query, where some facts are more relevant to the query than others.

End-to-End Memory Networks [Sukhbaatar *et al.*, 2015] achieve this by using an array of memory blocks to store the database of facts, and using attention to model relevance of each fact in the memory for answering the query. Using attention also provides computational advantage by making the objective continuous and enabling end-to-end training via backpropagation. End-to-End Memory Networks can be considered as a generalization of AM, wherein instead of modeling attention only over a single sequence they model it over a large database of sequences (facts).

4.3 Networks without RNNs

Recurrent architectures rely on sequential processing of input at the encoding step which results in computational inefficiency, as the processing cannot be parallelized [Vaswani *et al.*, 2017]. To address this, the authors propose *Transformer* architecture where the encoders and decoders are composed



(a) Alignment of French and English sentences in MT [Bahdanau *et al.*, 2014]

(b) Weights of items in user's history for recommendation [He *et al.*, 2018]

(c) Relevant image regions for image captioning [Xu *et al.*, 2015]

Figure 4: Examples of visualization of attention weights.

of a stack of identical layers with two sub-layers: position-wise Feed Forward Network(FFN) layer and multi-head self attention layer.

Position-wise FFN: The input is sequential which demands the model to make use of the temporal aspect of the input, yet components that capture this positional information (i.e. RNNs / CNNs) are not used. To account for this, the encoder phase in the Transformer generates content embedding as well as position encoding for each token of the input sequence using position-wise FFN.

Multi-Head Self-Attention: The self attention is used within each sub-layer to relate tokens and their positions within the same input sequence. Further, attention is known as multi-head, because several attention layers are stacked in parallel, with different linear transformations of the same input. This helps the model to capture various aspects of the input and improves its expressiveness.

Transformer architecture achieves significant parallel processing, shorter training time and higher accuracy for translation without any recurrent component, which is a notable benefit. However, the position encoding only weakly incorporates position information and might not work for problems that are more sensitive to positional variation. Shen *et al.* [2018] use temporal convolutions to encode positional information along with the self-attention mechanism of the transformer.

Additionally, there are more straightforward methods to break the sequential processing of input. Raffel and Ellis [2015] propose *Feed Forward Attention* models where they use AM to collapse the temporal dimension of data and use FFNs instead of RNNs to solve sequential data problems. In this scenario, AM is employed to produce a fixed length context vector from the variable length input sequence, which can be fed as an input to FFN.

5 Attention for Interpretability

There is a huge interest in the interpretability of AI models-driven by both performance as well as transparency and fairness of models[2]. However, neural networks, particularly deep learning architectures have been criticized for their lack of interpretability [Guidotti *et al.*, 2018].

Modeling attention is particularly interesting from the perspective of interpretability because it allows us to directly inspect the internal working of the deep learning architectures. The hypothesis is that the magnitude of attention weights highly correlates with how relevant a specific region of input is, for the prediction of output at each position in a sequence. This can be easily accomplished by visualizing the attention weights for a set of input and output pairs. Li *et al.* [2016] uphold attention as one of the important ways to explain inner workings of neural models.

As shown in Figure 4(a), Bahdanau *et al.* [2014] visualize attention weights which clearly show automatic alignment of sentences in French and English, despite the fact that subject-verb-noun locations differ from language to language. In particular, attention model shows non-monotonic alignment by correctly aligning *environnement marin* with *marine environment*. Figure 4(b) shows attention weights can help to recognize user's interests. User 1 seems to have a preference for "cartoon" videos , while user 2 prefers videos on "animals" [He *et al.*, 2018]. Finally, Xu *et al.* [2015] provide extensive list of visualizations of the relevant image regions (i.e. with high attention weights) which had a significant impact on the generated text in the image captioning task (example shown in Figure 4(c)).

We also summarize a few other interesting findings as follows. De-Arteaga *et al.* [2019] explore gender bias in occupation classification, and show how the words getting more attention during classification task are often gendered. Yang *et al.* [2016] note that the importance of words *good* and *bad* is context dependent for determining the sentiment of the review. The authors inspect the attention weight distribution of these words to find that they span from 0 to 1 which means the model captures diverse context and assign context-dependent weight to the words. Chan *et al.* [2016] note that in speech recognition, attention between character output and audio signal can correctly identify start position of the first character in audio signal and attention weights are similar for words with acoustic similarities. Finally, Kiela *et al.* [2018] find that the multi-representational attention assigns higher weights to GloVe, FastText word embeddings, particularly GloVe for low frequency words.

As another interesting application of attention, Lee *et al.* [2017] and Liu *et al.* [2018] provide a tool for visualizing attention weights of deep-neural networks. The goal is to interpret and perturb the attention weights so that one can simulate what-if scenarios and observe the changes in predictions interactively.

[2]https://fatconference.org

6 Applications

Attention models have become an active area of research because of their intuition, versatility and interpretability. Variants of attention models have been used to address unique characteristics of a diverse set of application domains eg. summarization, reading comprehension, language modeling, parsing etc. We discuss attention modeling in three application domains: (i) Natural Language Generation(NLG), (ii) Classification, and (iii) Recommender systems.

NLG tasks involve generating natural language text as the output. Some NLG applications that have benefited from incorporating an AM include Machine Translation (MT), Question Answering (QA) and Multimedia Description (MD).

MT uses algorithms to translate text or speech from one language to another. Modeling attention in neural techniques for MT allows for better alignment of sentences in different languages, which is a crucial problem in MT. The advantage of the attention model also becomes more apparent while translating longer sentences [Bahdanau *et al.*, 2014]. Several studies including [Britz *et al.*, 2017] and [Tang *et al.*, 2018] have shown performance improvements in MT using attention.

QA problems have made use of attention to (i) better understand questions by focusing on relevant parts of the question [Hermann *et al.*, 2015], (ii) store large amount of information using memory networks to help find answers [Sukhbaatar *et al.*, 2015], and (iii) improve performance in visual QA task by modeling multi-modality in input using co-attention [Lu *et al.*, 2016].

MD is the task of generating a natural language text description of a multimedia input sequence which can be speech, image and video [Cho *et al.*, 2015]. Similar to QA, here attention performs the function of finding relevant acoustic signals in speech input [Chorowski *et al.*, 2015] or relevant parts of the input image [Xu *et al.*, 2015] to predict the next word in caption. Further, Li *et al.* [2017] exploit the temporal and spatial structures of videos using multi-level attention for video captioning task. The lower abstraction level extracts specific regions within a frame and higher abstraction level focuses on small subset of frames selectively.

Document Classification: As mentioned earlier in Section 3, classification problems mainly make use of self attention to build more effective document representations. Yang *et al.* [2016] use a multi-level self attention, whereas Lin *et al.* [2017] propose a multi-dimensional and Kiela *et al.* [2018] propose a multi-representational self attention model.

Sentiment Analysis: Similarly, in the sentiment analysis task, self attention helps to focus on the words that are important for determining the sentiment of input. A couple of approaches for aspect based sentiment classification by Wang *et al.* [2016] and Ma *et al.* [2018] incorporate additional knowledge of aspect related concepts into the model and use attention to appropriately weigh the concepts apart from the content itself. Sentiment analysis application has also seen multiple architectures being used with attention such as memory networks [Tang *et al.*, 2016] and Transformer [Ambartsoumian and Popowich, 2018; Song *et al.*, 2019].

Recommender Systems: AMs have also been extensively used in recommender systems for user profiling, i.e., assigning attention weights to interacted items of a user to capture long and short term interests in a more effective manner. This is intuitive because all interactions of a user are not relevant for the recommendation of an item and user's interests are transient as well as varied in the long and short time span. Multiple papers use self attention mechanism for finding the most relevant items in user's history to improve item recommendations either with collaborative filtering framework [He *et al.*, 2018; Shuai Yu, 2019], or within an encoder-decoder architecture for sequential recommendations [Kang and McAuley, 2018; Zhou *et al.*, 2018].

Recently attention has been used in novel ways which has opened new avenues for research. Some interesting directions include smoother incorporation of external knowledge bases, pre-training embeddings and multi-task learning, unsupervised representational learning, sparsity learning and prototypical learning i.e. sample selection.

7 Conclusion

In this survey we have discussed different ways in which attention has been formulated in the literature, and have attempted to provide an overview of various techniques by discussing a taxonomy of attention, key neural network architectures using attention, and application domains that have seen significant impact. We discussed how the incorporation of attention in neural networks has led to significant gains in performance, provided greater insight into neural network's inner working by facilitating interpretability, and also improved computational efficiency by eliminating sequential processing of input. We hope that this survey will provide a better understanding of the different directions in which research has been done on this topic, and how techniques developed in one area can be applied to other domains.

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