

Document Summarization (draft)

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March 26, 2017

Abstract

While humans are naturally able to produce high-level summaries upon reading paragraphs of text, computers still find such a task enormously difficult. Despite progress over the years, the general problem of document summarization remains intractable and

Inspired by recent work in deep learning, we apply the sequence-to-sequence (seq2seq) model with attention to the summarization problem. While seq2seq models are successful in a variety of natural language processing tasks, the computation does not scale well to tasks with long sequences such as documents. To that end, we propose a novel coarse-to-fine attention method to reduce the computational complexity of the standard attention model.

We evaluate our model on the CNN/Dailymail document summarization dataset. Results...

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Chapter 1

Introduction

1.1 Natural Language Processing

The field of natural language processing arises from a very simple question: how can we teach machines to read, speak, and understand the words that we use with such ease and fluency?

Such a question has been considered since the first computers were built. The classic Turing test, posed by Alan Turing in 1950, requires a machine to converse in a way that is indistinguishable from a human, and thus requires a fundamental grasp on how to properly use language. Although it was simple for Turing to conceptualize what a successful machine might look like, many have been stumped on how to actually construct such a system. Indeed, to this day, no machine has been able to fully pass the Turing test as it was originally posed.

While computers can now run computations at a rate that far exceeds human cognition, language tasks that we consider trivial still prove to be extraordinarily difficult for a machine to solve. Consider the problem of deciding words with multiple meanings such as “bass” (word sense disambiguation), or the problem of identifying to what or whom a certain pronoun refers (coreference). While humans reliably perform these functions on a daily basis, they are not at all easy for computers to handle.

However, the need for computers to understand language has never been greater. In today’s information age, NLP grows increasingly important as the accumulation of free-form text begins to outpace the ability of humans to read all of it. In fields such as medicine, this can mean missed diagnoses; in law, wasted effort on irrelevant documents; in international relations, misinterpretations of foreign articles. Successful text processing

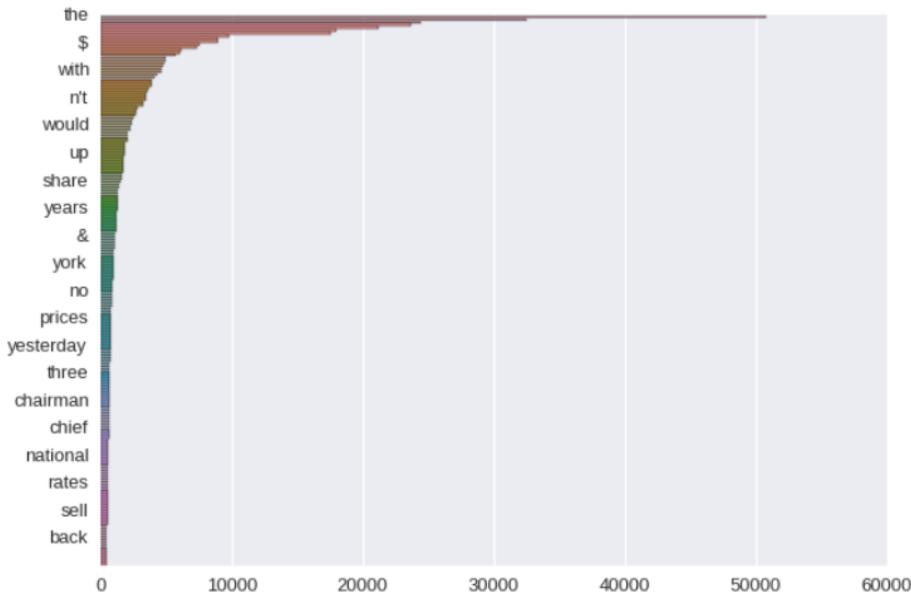


Figure 1.1: Zipf’s law, indicating the relationship between English words and their frequency. The distribution approximately follows an inverse power law. Image from CS287

systems can therefore have an immeasurably positive impact if deployed today.

1.2 Methods in NLP

We have established that NLP is a difficult yet worthwhile undertaking. In this section, we investigate the general philosophy of tackling these hard problems.

The key property of language that make it difficult for machines to handle is its discrete and combinatorial nature. When we form sentences, we can string together arbitrary words from our vocabulary, as long as we follow the rules of some highly structured grammar. In some sense, the essential difficulty in NLP lies in handling these complicated structured problems.

Linguistics attempts to answer this by building a formal theory of language. Indeed, many ideas from linguistics, including sentence parses, morphology, and semantics are invaluable in NLP for understanding the rules for how sentences and phrases can be put together. In order to solve a language problem, we might begin by enriching the surface form of text (the raw sentences and paragraphs) with the parse structure, parts of speech, coreferent entities, etc. We can then use this featurized form of language in whichever way we prefer.

Another mode of thought focuses on the role of statistics in language. A cursory examination of the distribution of English words reveals an interesting power law distribution known as Zipf’s law (figure 1.1). By drawing from ideas of information theory (Shannon, 1948), we can treat language as the result of some noisy probabilistic process, and we can reduce problems such as language modeling to learning parameters of some simple distributions.

Historically, there has been contention about the roles of linguistics and statistics in NLP. Certain practical problems seem to be better off without linguistic theory; as IBM researcher Frederick Jelinek famously said, “Every time I fire a linguist, the performance of the speech recognizer goes up.” Indeed, even naive models of language seem to perform well if given enough training data, as evidenced by the IBM models for machine translation (Brown et al., 1993).

Today, the linguistics-free approach has been taken to an extreme by deep learning systems. For the first time, neural networks are able to learn to perform language tasks in an end-to-end fashion (Collobert et al., 2011b), i.e. without the linguistic preprocessing that was once considered necessary. Neural methods have been adopted by user-facing systems like Google Translate with great success (Wu et al., 2016).

1.3 Automatic Summarization

In this thesis, we will consider the particular problem of *text summarization*. That is, given a document with several sentences of text, the goal is to produce a short summary that captures most or all of its salient points.

Nenkova and McKeown (2011) give a comprehensive overview of the problem of summarization. In particular, they provide a taxonomy of methods that researchers have developed to tackle the task:

Extractive vs. abstractive Extractive summaries extract certain sentences or phrases from the document, while abstractive summaries take a more holistic view and can in practice be anything (similar to how humans produce summaries).

Extractive methods are by far more popular due to the simplicity of building an extraction algorithm. Abstractive methods are much more difficult, as not only do we need to extract relevant content, but we also need to ensure grammaticality of the output (a difficult problem in itself).

Single- vs. multi-document Summarization was originally posed as the problem of producing a summary for a single document. However, with the onset of the Internet, there are often multiple documents on the same topic, and so a summarization system should be able to use all of them to produce a summary.

Interestingly, it has been noted that the multi-document problem is often easier due to redundant information across sources.

Keyword vs. headline Keyword summaries are allowed to simply be a bag-of-words of important keywords from the document, while headline summaries must form a coherent sentence.

Generic vs. query-focused Generic summaries make no assumptions about the reader and are meant to be generally informative, while query-focused summaries take into consideration a query and only return relevant information.

The contrast between these two methods highlights an important question in summarization: to what end are we summarizing documents? If we can answer this question, we can build systems to more accurately accomplish our desired tasks.

Most of this taxonomy is based upon insights from DUC (Document Understanding Conferences), a set of tasks released by NIST between 2001-2006 to promote research in summarization (Over et al., 2007).

The DUC tasks were fairly diverse and varied from year to year. DUC 2001 and 2002 asked for generic summaries of news articles, while DUC 2003 presented a multi-document problem. DUC 2004-2006 shifted to a more question-answering based approach, and many of the documents were accompanied by focused queries.

While DUC did not lead to any definitive answers on how best to summarize documents, some important empirical discoveries were noted. For the generic summarization tasks, it was found that the first sentence of news articles was a strong baseline that more sophisticated methods found hard to beat. Thus, the generic summary task was seen as ill-formed and not as interesting, leading to the more query-focused tasks in the later years.

DUC also inspired a lot of thinking on the best way to evaluate summaries. Evaluating a good summary is inherently ambiguous, and probably one of the hardest parts of the problem. While a single most effective metric for summarization may not exist, DUC

established several important criteria, including grammaticality, non-redundancy, and content coverage.

For extractive summaries, people have proposed simple metrics such as precision and recall on selected sentences. These naturally do not work too well since 1) not all sentences are equally informative, and 2) not all parts of a sentence are relevant.

When we don't have sentence labels as in the extractive case, the problem is harder. One proposed metric is recall on elementary discourse units (EDUs), labeled clauses within a summary that ought to be captured. ROUGE (Lin, 2004), inspired by the BLEU metric for machine translation (Papineni et al., 2002), is a cheap and fast method based on n-gram precision, recall, and length considerations.

None of these methods directly address the grammaticality of the output. Aside from using human evaluation, meaningful metrics for summaries is still very much an open question (Toutanova et al., 2016).

Going forward, we will limit our scope to the single-document, headline, and generic summarization case. We will explore a few different algorithms in extractive and abstractive summarization, and connect these approaches with recent trends in deep learning.

1.4 Summarization Methods

One of the first treatises on automatically producing summaries was Luhn (1958), which considered the problem of producing abstracts for scientific articles. At the time, computers were still monolithic machines that ran on punch cards, so automating the summarization process was quite ahead of its time.

Luhn (1958) proposed a simple sentence-ranking method to produce summaries. The algorithm gives each sentence a score based on the occurrence of frequently appearing words. This is one of the first examples of an extractive summarization method.

Since then, a variety of approaches have been used to solve summarization. We highlight some notable work in both the extractive and abstractive frameworks.

1.4.1 Extractive

The most popular methods for document summarization have generally been extractive due to their simplicity.

There are two natural procedures for extractive summarization: one is to produce a ranking of sentences based on some scoring function, and two is to classify sentences as either in the summary or not. Luhn (1958) is an example of the first approach.

Carbonell and Goldstein (1998) extend on the scoring-ranking method with an information metric, MMR (maximum marginal relevance), that penalizes pairwise similarity between sentences. Their work is one of the first that attempt to reduce redundancy in the summary.

Kupiec et al. (1995) pioneer the second method by treating sentence selection as a classification problem. They obtain a training corpus and apply a naive Bayes approach to classify sentences.

Ranking and classifying algorithms became more sophisticated over time, and most of these methods were soon applied to extractive summarization.

Shen et al. (2004) models sentence extraction as a sequential classification problem, training a linear-chain conditional random field to find the best subset of sentences.

Svore et al. (2007) use a basic neural network as a sentence classifier.

Deep learning models have also been used to extract sentences.

Cao et al. (2015) use convolutional neural networks to extract features for each sentence, combining these with document-level features to produce scores.

Cheng and Lapata (2016) apply the encoder-decoder model using recurrent neural networks to produce labels for each sentence.

finish

1.4.2 Abstractive

While extraction has proven to be successful, the method is inherently limited in its ability to summarize. The more challenging method, and also the closest to what humans do, is *abstractive* summarization. Instead of strictly requiring that all words of the summary come from the source document, any coherent text is allowed.

Two methods used to produce abstractive summaries are sentence compression and sentence fusion. Compression removes less useful information from sentences, while fusion is harder and combines information from sentences.

Compression: Knight and Marcu (2002) employs a noisy channel model, similar to machine translation, to deduce the “most probable” compression, while Clarke and Lapata (2008) uses an integer linear program. Cohn and Lapata (2008) extend the tree-based methods to allow for insertions and substitutions during compression, whereas

prior methods were purely deletion based. Zajic et al. (2004) successfully use a sentence compression algorithm along with an unsupervised topic model on the DUC 2004 task.

Fusion: align parse trees and combine phrases that are similar

finish

Durrett et al. (2016) apply an ILP approach, where they maximize a score based on textual and coreferent features with certain grammaticality and anaphora constraints.

Deep learning has also been successfully applied to abstractive summarization. Rush et al. (2015) propose a completely data-driven model for headline generation by training a sequence-to-sequence model with attention. More recently, Nallapati et al. (2016) apply the same approach on full documents, further demonstrating the feasibility of end-to-end models.

As with deep learning methods for extraction, these models require a large amount of supervised training data. One advantage of the abstractive model is that data in the document-abstract format is more easily obtainable than labeled extractive data.

1.4.3 In the Wild

Outside of the academic realm, summarization is an important problem in industry. One noteworthy summarization method is on Reddit¹: in order to summarize long forum discussions, Reddit uses technology from Smmry².

Smmry's algorithm is a simple extractive summarization method. It counts word occurrences, splits discussions by sentence, and ranks the sentences based on the sum of their word scores (perhaps tf-idf?). This algorithm bears extraordinary similarity to Luhn (1958) — although a variety of work has been done since then, the simplest approaches turn out to be the most practical.

1.5 Outline

Inspired by advances in deep learning for NLP, we set out to build a deep model to abstractively generate summaries. Along the way, we propose a new model architecture that extends the sequence-to-sequence model and attempts to reduce the computational complexity of the document summarization problem.

We provide an outline for the rest of this thesis. In Chapter 2, we give a survey of deep learning and motivate its use in solving our problem. In Chapter 3, we provide

¹reddit.com

²smmry.com

the necessary background material for understanding our models and algorithms. In Chapter 4, we describe our models formally. In Chapter 5, we describe the experimental setup, including our dataset, baselines, and practical details for training our models. In Chapter 6, we show results and analyze the outputs of our models. Finally, we conclude in Chapter 7.

Chapter 2

Related Work

2.1 Deep Learning

The history of neural networks dates back to the perceptron (Rosenblatt, 1958), a simple model that assumes data can be linearly separated. Due to this strict requirement, the machine learning community dismissed the idea as impractical, and research was sidelined for most of the 20th century.

Some other work continued: Rumelhart et al. (1986) showed that the backpropagation algorithm could be used to efficiently train general neural networks, but this was before the era of GPUs and modern computing, and so the algorithm could not be practically used.

Recently, neural networks have made a resurgence. In the ImageNet image classification competition in 2012, Krizhevsky et al. (2012) won using deep convolutional neural networks (LeCun and Bengio, 1995), beating the competition by a significant margin. This led to a renewed wave of research, especially due to the advancement of modern computing power and GPUs, which can train networks at 10 to 20 times the speed of standard CPUs. Today, deep models are successfully used in image recognition (Farabet et al., 2013), speech recognition (Hinton et al., 2012), and Go playing (Silver et al., 2016), just to name a few.

While neural networks are often treated as black box classifiers, Zeiler and Fergus (2014) show that the intermediate layers of deep convolutional networks contain abstracted qualities of the input, such as patterns, textures, and objects of the input. This suggests that neural networks are discovering features of the input and building generalized *representations* of their inputs.

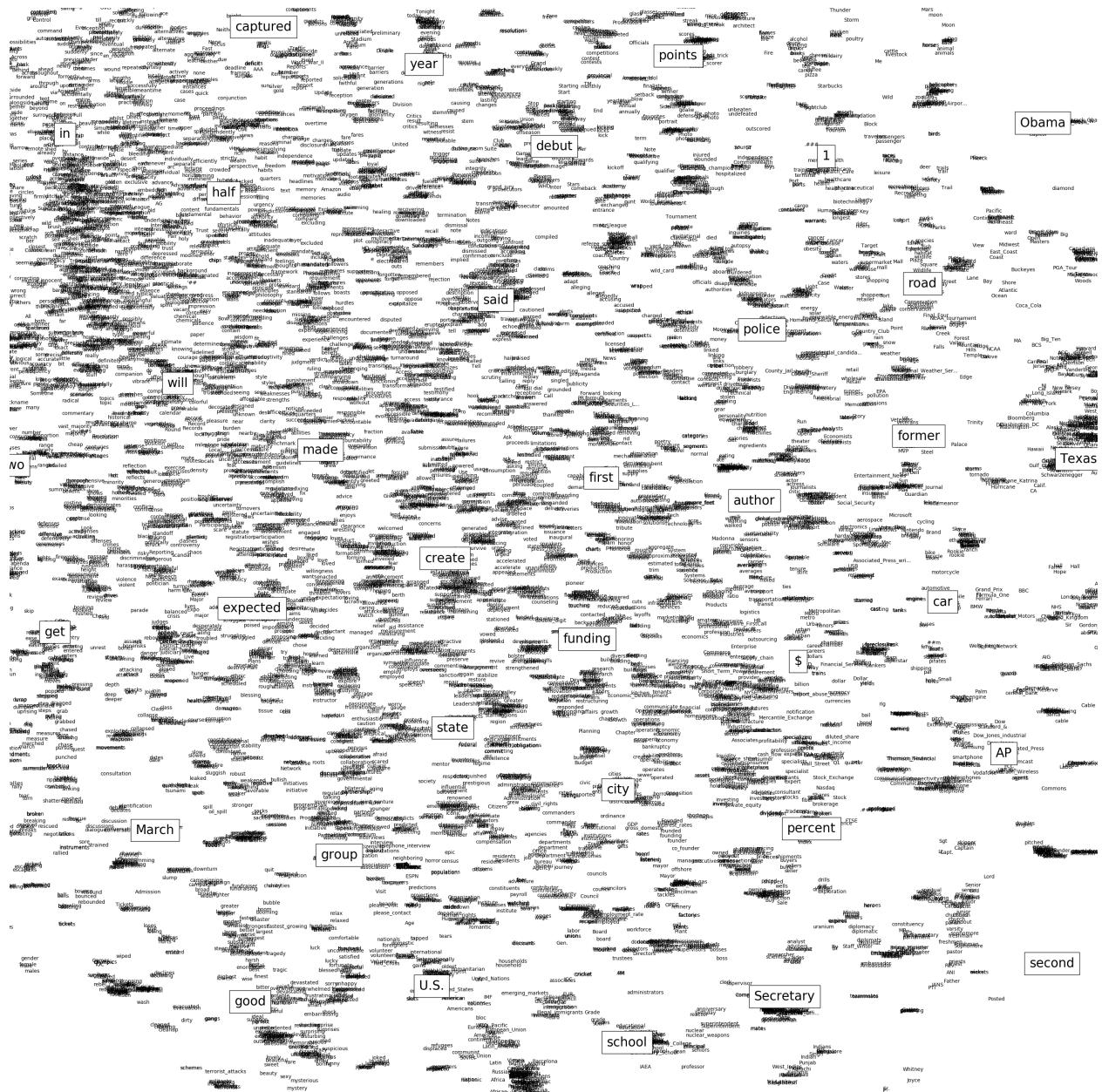


Figure 2.1: A visualization of word2vec word embeddings (Mikolov and Dean, 2013). Words with similar semantic meaning tend to be clustered together. Image from CS287.

The idea of learning representations of the input is highly general, and so it comes as no surprise that deep networks soon found applications in NLP. Mikolov and Dean (2013) show that by training a neural network on a Google News text corpus, the network learned to map words in the English language to a vector of real numbers known as *word embeddings*. These word embeddings are actually able to capture semantic properties of the words — for example, taking the vectors for *king*, *man*, and *woman*, we find that $v_{\text{king}} - v_{\text{man}} + v_{\text{woman}} \approx v_{\text{queen}}$, preserving the analogy that we usually make with text.

Since the onset of deep learning, deep models have found their way into nearly every corner of NLP. Much of their success relies on the ubiquity of the *long short-term memory* (LSTM) recurrent neural network (Hochreiter and Schmidhuber, 1997), a model used to both process and generate sequences of text. Several state-of-the-art algorithms are now based upon deep learning tools such as word vectors and LSTMs. While there is too much to cover here, Goldberg (2015) provides a concise summary of the models that have had the greatest impact on NLP.

2.2 Motivation

Why deep models? There are currently two general approaches to solving problems in NLP: one is to use as much linguistic theory as possible to reduce the problem, and another is to apply black box learners such as deep neural networks.

Deep models work fantastically well on many tasks, especially when it comes to lowering metrics. However, as big of a hammer as deep learning is, there must be nails available for the tool to hit. In order to further language understanding, datasets and tasks must be posed such that deep models can be applied; it is exactly in this domain that classical theory is still relevant. As ? argues, although neural models have come to dominate NLP papers, there will always be a need for domain experts to prepare the field so that deep learning can succeed.

With this caveat, there are many worthwhile reasons to study deep networks in NLP. First, they work! In fact, they work remarkably well without any feature engineering, which tends to be one of the fussiest parts of building machine learning algorithms.

Second, they are not mutually exclusive with standard feature extraction methods, and so can augment classical methods.

Third, we find that trained models can discover latent structure in language automat-

needs
work

ically, which may reveal insights about how language is used. As an example, sequence-to-sequence models with attention (Bahdanau et al., 2014) learn the concept of a word alignment in translation without any direct supervision.

It is this third point upon which we base this thesis. Although they began as black-box optimizers, end-to-end deep models are slowly being dissected into more understandable parts. Our goal is to test the hypothesis that such parts are in fact interpretable and are functioning as we expect them to.

With this goal in mind, we attempt to interpretably extend the existing sequence-to-sequence model with attention, and we analyze its resulting performance on the task of document summarization. In the next chapter, we provide the background for how we will do this.

Chapter 3

Background

In this chapter, we set up the relevant background ideas for our models.

3.1 Sequence-to-Sequence Attention Models

Many NLP problems can be posed as follows: given an input sequence of tokens $x_1, \dots, x_n \in \mathcal{V}$, we train a model to produce an output sequence $y_1, \dots, y_m \in \mathcal{Y}$. We normally pose this as a probabilistic problem and model the conditional probabilities, so that we wish to find

$$\begin{aligned} & \arg \max_{y_1, \dots, y_n \in \mathcal{Y}} p(y_1, \dots, y_m | x_1, \dots, x_n) \\ &= \arg \max_{y_1, \dots, y_n} p(y_1 | x_1, \dots, x_n) p(y_2 | y_1, x_1, \dots, x_n) \cdots p(y_m | y_1, \dots, y_{m-1}, x_1, \dots, x_n) \end{aligned} \tag{3.1}$$

this
looks
bad

The sequence-to-sequence architecture (Sutskever et al., 2014), also known as the encoder-decoder architecture, neatly provides a solution to this framework. By encoding the input x_1, \dots, x_n into a fixed size vector which we call the *context vector*, we proceed to generate the output y_1, \dots, y_m conditioned on this context vector.

The model has been used to great effect in a variety of NLP tasks, including machine translation (Sutskever et al., 2014; Bahdanau et al., 2014), question answering (Hermann et al., 2015), dialogue (Li et al., 2016a), caption generation (Xu et al., 2015), and in particular summarization (Rush et al., 2015).

A popular variant of sequence-to-sequence models are *attention* models (Bahdanau et al., 2014). The key idea is to keep an encoded representation of all parts of the input,

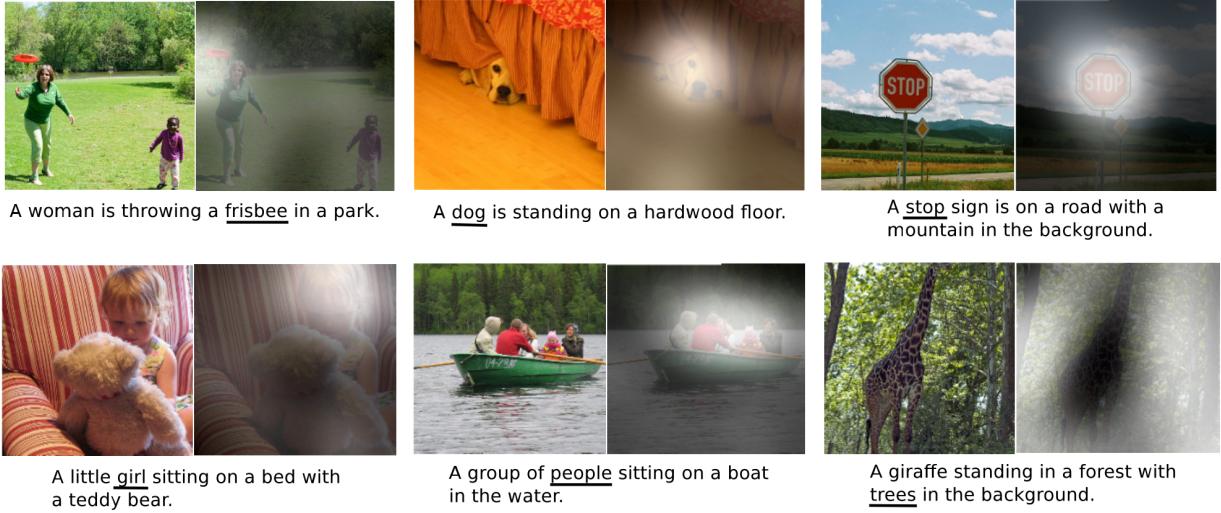


Figure 3.1: Attention of a caption generating neural model (Xu et al., 2015). Notice that the model learns to highlight the correct object when generating words.

attending to the relevant part each time we produce an output from the decoder.

Xu et al. (2015) show how attention models can be used to “summarize” an image and produce a caption. By analyzing where in the image their models attend to when generating each word of the caption, they qualitatively find that the model is essentially describing that region of the image. Figure 3.1 shows some examples.

Existing seq2seq methods are limited by the length of source and target sequences. For a problem such as document summarization, the source sequence of length N requires $O(N)$ seq2seq model computations. However, it makes sense intuitively that not every word of the document will be necessary for generating a summary, and so we would like to reduce the amount of necessary computations over the source document.

Therefore, in order to scale seq2seq methods for this problem, we aim to prune down the length of the source sequence in an intelligent way. In the problem of image captioning, Xu et al. (2015) show that when generating words of the caption, the model places attention on the relevant part of the image.

Xu et al. (2015) suggest “hard” attention as one possible solution to the discrete selection problem. While standard “soft” attention actually averages the representations of where the model attends to, for hard attention we make a hard decision and choose only one location. Such models can be trained using reinforcement learning. Before we elaborate on this method, we survey some other methods invented to overcome this discrete attention problem.

3.2 Conditional Computation

Many techniques have been proposed in the literature to handle the problem of large inputs to deep neural networks.

The term “conditional computation” was coined by Bengio et al. (2013), where the idea is to compute a subset of units for a given network per input. This would have the advantage of being much more efficient, especially for networks that handle extremely large inputs as is common in vision and NLP.

Several ideas have been proposed to conditionally compute on large inputs. Rae et al. (2016) use an approximate nearest neighbors approach for their “sparse access memory” model to train a large-scale neural Turing machine. Shazeer et al. (2017) introduces a mixture-of-experts model that selectively chooses a subset of “expert” networks at any given time during training. In the spirit of conditional computation, they only train K experts at a time using a sparse gating function.

3.2.1 Discrete units

One particular class of methods to perform conditional computation relies on the use of discrete units within our deep network. Discrete units can be produced using stochastic gates to select certain parts of the network for computation. Unfortunately, discrete variables cannot be backpropagated through as they are not differentiable. Several techniques have been proposed to get around this problem.

Bengio et al. (2013) propose the *straight-through* estimator for binary stochastic gates. We simply sample from the stochastic gates in the forward step, and backpropagate the gradient as if we had not sampled. While this works empirically for simple binary gates, it is theoretically unjustified.

In general, we usually want to sample from multinomial distributions given by the output of a softmax function. The function $\text{softmax} : \mathbb{R}^m \rightarrow [0, 1]^m$ produces a normalized probability distribution, where for $\mathbf{z} \in \mathbb{R}^m$,

$$\text{softmax}(\mathbf{z})_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \quad (3.2)$$

Martins and Astudillo (2016) propose an alternative to softmax called the *sparsemax* function. For a given \mathbf{z} , sparsemax projects the point to the probability simplex. It turns out that this function has a useful gradient while having a sparse output. The down-

side is that we are not guaranteed to have a one-hot vector as we get from sampling the multinomial distribution.

Reinforcement learning has also been proposed as an approach to handling discrete units in a network. In this thesis, we focus on the hard attention method of Xu et al. (2015). In the next section, we explain reinforcement learning and how it can be used to train the hard attention model.

3.3 Reinforcement Learning

Standard backpropagation training of neural networks assumes that the output is a deterministic and differentiable function of the input. Reinforcement learning, however, is a more general framework that makes no such assumptions.

The traditional setup of reinforcement learning (RL) assumes some agent is navigating an environment and earning rewards. We assume a state space \mathcal{S} , an action space \mathcal{A} , a reward function of state and action $R : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$, and a transition distribution $p(s_{t+1}|s_t, a_t)$ (so that our environment is Markovian).

We suppose that at time t , the agent is in state $s_t \in \mathcal{S}$, makes an action $a_t \in \mathcal{A}$, earns a reward $r_t = R(s_t, a_t)$, and transitions probabilistically to the next state s_{t+1} . Assuming the reward function is unknown, the agent wants to maximize total expected reward

$$\mathbb{E}_{s_t, r_t} \left[\sum_{t=0}^{\infty} \gamma^t r_t \right]$$

by finding an optimal action policy. Here, γ is a time discount factor.

3.3.1 Methods for training RL agents

A variety of methods have been invented for solving the RL problem, i.e. finding the optimal policy $\pi(s)$ for a given state s .

In general RL, we assume that we don't know the reward function $R(s, a)$ and we don't know the transition distribution $p(s_{t+1}|s_t, a_t)$. While the environment still gives us rewards for actions, finding the optimal policy requires knowing which states lead to those rewards. Since we don't know ahead of time which states are best, we are forced to extensively explore the state space to find what actions lead to the best rewards.

One method for deciding on an optimal policy is to use Q-learning (). In Q-learning,

we model a function $Q(s, a)$ that estimates the total expected reward of taking an action a in state s . Our optimal policy is then $\pi(s) = \arg \max_{a \in \mathcal{A}} Q(s, a)$.

An alternative to modeling the Q-function is to learn a policy $\pi : \mathcal{S} \rightarrow \mathcal{A}$ directly. We parametrize π with weights w , and assume that at training time, we have a probability distribution $p(a|s; w)$ over the actions that we sample from. Then assuming we get reward r , our update is

$$w \leftarrow w + \eta \mathbb{E}_a \left[r \cdot \frac{\partial \log p(a|s; w)}{\partial w} \right] \quad (3.3)$$

This is known as the policy gradient update or REINFORCE algorithm (Williams, 1992). We give the derivation in the next section.

If we have a full trajectory of states s_t and rewards r_t , then we can assume our action a_t at time t led to future discounted reward $R_t = \sum_{k=t}^{\infty} \gamma^{k-t} r_k$. We then have the update rule

$$w^{(t+1)} \leftarrow w^{(t)} + \eta \mathbb{E}_{a_t} \left[R_t \cdot \frac{\partial \log p(a_t|s_t; w)}{\partial w} \right] \quad (3.4)$$

3.4 Stochastic Computation Graphs

Aside from these classical applications of RL, the RL framework can be applied to train deep neural networks with stochastic units. We cast our learning problem with the neural network as an agent with a parametrized policy function $\pi : \mathcal{S} \rightarrow \mathcal{A}$, where the states \mathcal{S} are the inputs and the actions \mathcal{A} are the possible outputs of each stochastic unit. The rewards are then negative loss (e.g. from regression or classification).

More concretely, consider a sequential classification problem such as summarization, and consider the sequence-to-sequence model with attention. At each time step t of the decoder, our state s_t is given by the LSTM state and the encoded context, and our action a_t is where in the encoder context to attend to. The reward r_t is then the log-likelihood of predicting the gold word (according to some supervised dataset).

To obtain gradients for backpropagation, we can apply policy gradient methods for the nondifferentiable stochastic units. Because our network has both differentiable and nondifferentiable weights on the pathways to the output, we can consider it as a *stochastic computation graph* (Schulman et al., 2015).

Suppose that, given input x , our network has stochastic units drawn from some parametrized distribution $z \sim p(z|x; \phi)$. Then, a parametrized deterministic scalar function $f(z; \theta)$

diagram

gives us the output, and we want to maximize the expectation $\mathbb{E}_{z \sim p(z|x;\phi)}[f(z;\theta)]$.

To train the weights directly connected to the loss function (i.e. θ) we backpropagate the standard gradient:

$$\frac{\partial \mathcal{L}}{\partial \theta} = \frac{\partial}{\partial \theta} \mathbb{E}_{z \sim p(z|x;\phi)}[f(z;\theta)] = \mathbb{E}_{z \sim p(z|x;\phi)} \left[\frac{\partial f(z;\theta)}{\partial \theta} \right] \quad (3.5)$$

To train weights that are not directly connected, but precede an intermediate stochastic unit (i.e. ϕ), we backpropagate the weighted policy gradient:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \phi} &= \frac{\partial}{\partial \phi} \sum_z p(z|x;\phi) f(z;\theta) \\ &= \sum_z \frac{\partial p(z|x;\phi)}{\partial \phi} \cdot f(z;\theta) \\ &= \sum_z p(z|x;\phi) \frac{1}{p(z|x;\phi)} \frac{\partial p(z|x;\phi)}{\partial \phi} f(z;\theta) \\ &= \sum_z p(z|x;\phi) \frac{\partial \log p(z|x;\phi)}{\partial \phi} f(z;\theta) \\ \frac{\partial \mathcal{L}}{\partial \phi} &= \mathbb{E}_{z \sim p(z|x;\phi)} \left[\frac{\partial \log p(z|x;\phi)}{\partial \phi} f(z;\theta) \right] \end{aligned} \quad (3.6)$$

For a given x , we perform Monte Carlo sampling to obtain the gradients, e.g.

$$\frac{\partial \mathcal{L}}{\partial \phi} \approx \frac{1}{N} \sum_{i=1}^N \frac{\partial \log p(z_i|x;\phi)}{\partial \phi} f(z_i;\theta) \quad (3.7)$$

where $z_i \sim p(z|x;\phi)$ i.i.d. for $i = 1, \dots, N$. In practice, N is set to 1 for computational reasons.

Note that this generalizes the REINFORCE algorithm in equation ??, where $f(z;\theta)$ is the reward.

3.4.1 Baseline reward

In practice, the variance of the Monte Carlo gradient can be very high. One of the simplest ways to reduce the variance of the gradient estimator is to introduce a baseline reward b

which we subtract from our reward. This works because

$$\mathbb{E}_z \left[(f(z; \theta) - b) \frac{\partial \log p(z|x; \phi)}{\partial \phi} \right] = \mathbb{E}_z \left[f(z; \theta) \frac{\partial \log p(z|x; \phi)}{\partial \phi} \right] - b \mathbb{E}_z \left[\frac{\partial \log p(z|x; \phi)}{\partial \phi} \right] \quad (3.8)$$

The second term vanishes as

$$\begin{aligned} \mathbb{E}_z \left[\frac{\partial \log p(z|x; \phi)}{\partial \phi} \right] &= \sum_z p(z|x; \phi) \frac{\partial \log p(z|x; \phi)}{\partial \phi} = \sum_z p(z|x; \phi) \frac{1}{p(z|x; \phi)} \frac{\partial p(z|x; \phi)}{\partial \phi} \\ &= \frac{\partial}{\partial \phi} \sum_z p(z|x; \phi) = \frac{\partial}{\partial \phi}[1] = 0 \end{aligned}$$

Thus, the gradient with baseline is unbiased.

Including a baseline is proven to reduce the variance of the estimator (Weaver and Tao, 2001). Intuitively, we can think of it as an estimate of the value function $V(s)$ for a state s . There are a few ways to produce a baseline for a given reward, which we describe in section ????.

Our policy gradient update from equation 3.4 can therefore be summarized as

$$w^{(t+1)} \leftarrow w^{(t)} + \eta \mathbb{E}_{a_t} \left[(R_t - b) \frac{\partial \log p(a_t|s_t; w)}{\partial w} \right] \quad (3.9)$$

algorithm

3.4.2 Reinforcement Learning in NLP

In computer vision, these policy gradient methods have been fairly successful on several tasks (Mnih et al., 2014; Ba et al., 2015; Xu et al., 2015).

In NLP, reinforcement learning research is still preliminary, but has been attempted with varying degrees of success so far. Ranzato et al. (2015) apply RL to improve sequential estimation by e.g. training on BLEU rewards for machine translation. Narasimhan et al. (2015) uses RL play text-based games. Li et al. (2016b) uses RL to train an end-to-end dialogue system. Narasimhan et al. (2016) uses RL to improve information extraction on scarce data. Yogatama et al. (2017) uses RL along with an architecture called a tree LSTM that produces a tree-structured latent variable on a sentence using SHIFT and REDUCE actions. They show that the tree LSTM can produce reasonable parse structures by solely using RL methods.

Inspired by these ideas, we handle the document summarization problem by (1) im-

plementing conditional computation using coarse-to-fine attention at the sentence level, and (2) including reinforcement learning for a sparse coarse attention layer.

In the next chapter we describe our models in detail.

Chapter 4

Models

4.1 Sequence-to-sequence (seq2seq)

We first describe the neural network architecture of the seq2seq models, also known as encoder-decoder models (Bahdanau et al., 2014).

In the seq2seq model, an *encoder* recurrent neural network (RNN) reads the source sequence as input to produce the *context*, and a *decoder* RNN generates the output sequence using the context as input. One popular RNN choice is the long-short term memory (LSTM) network (Hochreiter and Schmidhuber, 1997).

More formally, suppose we have a vocabulary \mathcal{V} . A given input sentence $w_1, \dots, w_n \in \mathcal{V}$ is transformed into a sequence of vectors $x_1, \dots, x_n \in \mathbb{R}^{d_{in}}$ through a word embedding matrix $E \in \mathbb{R}^{|\mathcal{V}| \times d_{in}}$ as $x_t = Ew_t$.

An RNN is given by a parametrizable function f_{enc} and a hidden state $h_t \in \mathbb{R}^{d_{hid}}$ at each time step t with $h_t = f_{enc}(x_t, h_{t-1})$. For the LSTM, we keep an auxiliary state c_t along with h_t , and we compute f_{enc} as

$$f_t = \sigma(W^f x_t + U^f h_t + b_f) \quad (4.1)$$

$$i_t = \sigma(W^i x_t + U^i h_t + b_i) \quad (4.2)$$

$$o_t = \sigma(W^o x_t + U^o h_t + b_o) \quad (4.3)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W^c x_t + U^c h_{t-1} + b_c) \quad (4.4)$$

$$h_t = o_t \odot \tanh(c_t) \quad (4.5)$$

where W, U, b are learned parameters, and \odot is the elementwise product. Intuitively, c_t is the memory cell, f_t is the forget gate, i_t is the input gate, h_t is the output cell, and o_t is

the output gate.

LSTMs can be stacked on top of one another by treating the outputs \mathbf{h}_t of one LSTM as the inputs to another LSTM.

In stacked LSTMs, we will take the top sequence of hidden states $\mathbf{h}_1, \dots, \mathbf{h}_n$ to form a single context vector.

The decoder is another RNN f_{dec} that generates output words $y_t \in \mathcal{V}$. It keeps hidden state $\mathbf{h}_t^{dec} \in \mathbb{R}^{d_{hid}}$ as $\mathbf{h}_t^{dec} = f_{dec}(y_{t-1}, \mathbf{h}_{t-1}^{dec})$ similar to the encoder RNN. A context vector is produced at each time step using an attention function a that takes the encoded hidden states $[\mathbf{h}_1, \dots, \mathbf{h}_n]$ and the current decoder hidden state \mathbf{h}_t^{dec} and produces the context $\mathbf{c}_t \in \mathbb{R}^{d_{ctx}}$:

$$\mathbf{c}_t = a([\mathbf{h}_1, \dots, \mathbf{h}_n], \mathbf{h}_t^{dec}) \quad (4.6)$$

As in Luong et al. (2015), it is helpful to feed the context vector at time $t - 1$ back into the decoder RNN at time t , i.e. $\mathbf{h}_t^{dec} = f_{dec}([y_{t-1}, \mathbf{c}_t], \mathbf{h}_{t-1}^{dec})$.

Finally, a linear projection produces a distribution over output words $y_t \in \mathcal{V}$:

$$p(y_t | y_{t-1}, \dots, y_1, [\mathbf{h}_1, \dots, \mathbf{h}_n]) = \mathbf{W}^{out} \mathbf{c}_t + b^{out} \quad (4.7)$$

The models are trained to maximize the log probability of getting the sequences in the dataset correct. As the model is fully differentiable with respect to its parameters, we can train it end-to-end with stochastic gradient descent and the backpropagation algorithm.

We note that we have great flexibility in how our attention function a combines the encoder context and the current decoder hidden state. In the next few sections, we explain standard choices for a as well as our proposed coarse-to-fine attention model.

4.2 Model 0: Standard Attention

In Bahdanau et al. (2014), the function a is implemented with an *attention network*. We compute attention weights for each encoder hidden state \mathbf{h}_i as follows:

$$\beta_{t,i} = \mathbf{h}_i^\top \mathbf{W}^{attn} \mathbf{h}_t^{dec} \quad \forall i = 1, \dots, n \quad (4.8)$$

$$\alpha_t = \text{softmax}(\beta_t) \quad (4.9)$$

$$\tilde{\mathbf{c}}_t = \sum_{i=1}^n \alpha_{t,i} \mathbf{h}_i \quad (4.10)$$

The idea behind attention is to select the most relevant words of the source (by assigning higher attention weights) when generating output word y_t at time t .

The softmax function, defined as

$$\text{softmax}([\beta_1, \dots, \beta_n])_i = \frac{\exp(\beta_i)}{\sum_{j=1}^n \exp(\beta_j)}$$

normalizes the α_i to sum to 1 over the source sentence words. This gives us a notion of probability distribution over the encoder words — we can therefore write c_t as the expectation $\mathbb{E}_\alpha[h]$, where we pick h_i with probability α_i .

Our final context vector is then

$$c_t = \tanh(W^2[\tilde{c}_t, h_t^{dec}]) \quad (4.11)$$

for $W^2 \in \mathbb{R}^{2d_{hid} \times d_{ctx}}$ a learned matrix.

Going forward, we call this instantiation of the attention function MODEL 0.

4.3 Model 1 and 2: Coarse-to-Fine Soft Attention

We can leverage the same idea for text summarization, assuming we have a suitable representation of our input document. The simplest method for doing so would be to run an LSTM over the document.

However, the attention step becomes computationally difficult — for each word we generate, we need to compare it to every word of the document in order to determine which part to attend to. Therefore, we propose a hierarchical method of attending to the document by first attending to sentences, then to the words within sentences. We call this method *coarse-to-fine attention*¹.

To be able to attend to both sentences and words in a hierarchical manner, we need to construct encodings of the document at both levels. Thus, we run a low-level LSTM encoder on the words of each sentence for a fine-grained representation of the text, and a simpler encoder model (e.g. bag of words) for coarse-grained sentence representations. Sukhbaatar et al. (2015) demonstrate how coarse representations can be useful by using memory networks to access information for simple question-answering tasks. Li et al.

¹The term coarse-to-fine attention has previously been introduced in the literature (Mei et al., 2016). However, their idea is different: they use coarse attention to reweight the fine attention computed over the entire input. Similar ideas have also been called hierarchical attention (Nallapati et al., 2016).

(2015) use the idea of coarse and fine encodings to develop a hierarchical autoencoder for representing paragraphs of text.

Therefore, if we can make our model first use coarse attention to choose sentences, then use fine attention to choose words only from that sentence, then we avoid the computational cost of searching over the entire document. This idea runs into a very serious problem, however: by posing the attention as a discrete selection process, the neural network loses the key property of being differentiable, and so standard backpropagation no longer applies.

For a large source input like a document, it may be computationally inefficient to run an RNN over the entire source. Instead, we can consider organizing the document into distinct sentences and select one sentence to attend to at a time.

Specifically, suppose we have sentences s_1, \dots, s_m with words $w_{i,1}, \dots, w_{i,n_i}$ for sentence s_i , so that we can apply an RNN to each separately to get corresponding hidden states $h_{i,j}$ for $i = 1, \dots, m$ and $j = 1, \dots, n_i$. For attention, we then consider two options.

Model 1 We can follow MODEL 0 and compute attention weights $\alpha_{i,j}$ for each hidden state $h_{i,j}$ by normalizing over all states. We call this MODEL 1.

Model 2 Alternatively, rather than taking attention over the entire document, we can instead have a two-layered hierarchical attention mechanism: first, we have weights $\alpha_1^s, \dots, \alpha_m^s$ for each sentence, and then for sentence s_i , we have another set of weights $\alpha_{i,1}^w, \dots, \alpha_{i,n_i}^w$. Our final attention weight on word $w_{i,j}$ is then $\alpha_{i,j} = \alpha_i^s \cdot \alpha_{i,j}^w$.

In order to compute the sentence attention weights α_i^s , we need to produce representations of each sentence; i.e., given the words $w_{i,1}, \dots, w_{i,n_i}$ of the sentence, we produce a vector representation $h_i^s \in \mathbb{R}^{d_{sent}}$.

Our first option is bag of words: we simply take the representation as

$$h_i^s = \sum_{j=1}^{n_i} E w_{i,j} \quad (4.12)$$

i.e. the sum of the word embeddings, where E is another embedding matrix.

Alternatively, we can use a convolutional method: as in Kim (2014), we perform a convolution over each window of words in the sentence using a fixed kernel width. We use max-over-time pooling to obtain a fixed-dimensional sentence representation in \mathbb{R}^{d_f} where d_f is the number of filters.

Explicitly, fix a sentence and suppose we have word vectors $\mathbf{x}_1, \dots, \mathbf{x}_n$ with $\mathbf{x}_j = \mathbf{E}w_j \in \mathbb{R}^{d_{in}}$, and suppose we have kernel width k and convolution weights $\mathbf{W}^{conv} \in \mathbb{R}^{d_f \times d_{in}k}$ where d_f is the number of filters. Then applying the convolution $\mathbf{W}^{conv} * [\mathbf{x}_1, \dots, \mathbf{x}_n]$ gives result $\mathbf{u} = [\mathbf{u}_1, \dots, \mathbf{u}_{n-k+1}]$ with j th element

$$\mathbf{u}_j = \mathbf{W}^{conv} \cdot [\mathbf{x}_j, \mathbf{x}_{j+1}, \dots, \mathbf{x}_{j+k-1}] \in \mathbb{R}^{d_f}$$

Our final output is given by

$$\mathbf{h}^s = \text{max-over-time}(\tanh(\mathbf{u} + \mathbf{b}^{conv})) \quad (4.13)$$

where max – over – time takes the maximum along the j -indexing dimension.

Thus, using the sentence representations, we can compute attention over the sentences. For the words in each sentence, we run an LSTM over each sentence separately, and create attention weights over each sentence in the same way as MODEL 0. Using attention on word $w_{i,j}$ as $\alpha_{i,j} = \alpha_i^s \cdot \alpha_{i,j}^w$, we can proceed exactly as in MODEL 0 by computing the weighted average over hidden states $\mathbf{h}_{i,j}$.

We call this method of attention MODEL 2.

4.4 Model 3: Coarse-to-Fine Sparse Attention

With the previous models, we are required to compute hidden states over all words and sentences in the document, so that if we have M sentences and N words per sentence, the computational complexity is $O(MN)$ for each attention step.

However, if we are able to perform conditional computation and only compute on M^+ of the sentences, we can reduce the complexity to $O(M^+N)$. If we are able to make M^+ constant or even 1, this would give significant benefits to our overall complexity.

In our experiments, we will apply stochastic sampling to the attention distribution α in the spirit of Xu et al. (2015) and “hard attention”. Specifically, rather than computing the context $\tilde{\mathbf{c}}$ as an expectation over α (i.e. $\mathbf{c} = \sum_{i=1}^n \alpha_i \mathbf{h}_i$), we can sample from the probability distribution α to obtain a single state \mathbf{h}_i , and we set $\tilde{\mathbf{c}} = \mathbf{h}_i$ as the sampled hidden state.

In our case, we take MODEL 2 and apply hard attention at the sentence level, but keep the word level attention per sentence as is. That is, we sample from the attention weights $\alpha_1^s, \dots, \alpha_m^s$ to obtain a one-hot encoding for the sentence attention, and apply the same multiplication with this one-hot vector on the word-level attention weights $\alpha_{i,1}^w, \dots, \alpha_{i,n_i}^w$

for all $i = 1, \dots, m$. We call this *Model 3*.

Because the hard attention model loses the property of being end-to-end differentiable, we use reinforcement learning to train our network.

4.4.1 Practical considerations

Recall the policy gradient update from section ??? at time t of the decoder:

$$w \leftarrow w + R_t \frac{\partial \log p(\alpha_t | y_1, \dots, y_{t-1})}{\partial w} \quad (4.14)$$

Since samples from α_t at time t of the RNN decoder can also affect future rewards, we use a discount factor of $\gamma = 0.5$, so that the reward is $R_t = \sum_{s=t}^n \gamma^{n-s} r_s$ at time t , where $r_t = \log p(y_t | y_1, \dots, y_{t-1})$ is the single step reward.

While this gradient is theoretically unbiased, because the gradient is sampled through a stochastic process, it tends to have high variance in practice. Thus, we implement a few variance reduction techniques to stabilize training.

Baseline reward As described in section ???, we subtract a baseline from the reward to reduce variance while keeping the gradient unbiased.

In practice, we keep a separate baseline b_t for each decoder time step t . Then our total discounted reward at time t becomes

$$R_t = \sum_{s=t}^n \gamma^{n-s} (r_s - b_s) \quad (4.15)$$

Our policy gradient update then becomes

$$w \leftarrow w + R_t \frac{\partial \log p(\alpha_t | y_1, \dots, y_{t-1})}{\partial w} \quad (4.16)$$

There are a few methods for producing the baseline. We follow Xu et al. (2015) and keep an exponentially moving average of the reward for each time step t :

$$b_t \leftarrow b_t + \beta(r_t - b_t) \quad (4.17)$$

where r_t is the average minibatch reward and β is a learning rate (set to 0.1).

While several papers suggest using a learned baseline from the RNN state in RL tasks

(e.g. Mnih et al., 2014; Ranzato et al., 2015), we have not found this to be effective. In our experiments, we found that attempting to learn the baseline failed to converge, most likely because there is not enough correlation between the RNN state and the reward.

In addition to including a baseline, we also scale the rewards by a tuned hyperparameter — we found that scaling helped to stabilize training. We empirically set this scale to 0.3.

Randomly training using soft attention Xu et al. (2015) explain that training hard attention with REINFORCE has very high variance, even when including a baseline. Thus, for every minibatch of training, they randomly use soft attention instead of hard attention with some probability (they use 0.5). The backpropagated gradient is then the standard soft attention gradient instead of the REINFORCE gradient.

While this method helps stabilize training, it's aesthetically not very pleasing. Our goal in coarse-to-fine attention is to reduce computation over the encoded hidden states, while this method requires that we perform the full amount of computation as soft attention for a random subset of minibatches. However, we include this training method in our experiments to test how feasible hard attention is.

4.5 Test Time

At test time, we use beam search.

asdf

Chapter 5

Experiments

5.1 Data

5.1.1 CNN/Dailymail

Experiments were performed on the CNN/Dailymail dataset from Hermann et al. (2015). While the dataset was created for a question-answering task, the dataset format is suited for summary. Each data point is a news document accompanied by up to 4 “highlights”, and we take the first of these as our target summary.

Train, validation, and test splits are provided along with document tokenization and sentence splitting. We do additional preprocessing by replacing all numbers with # and appending end of sentence tokens to each sentence. We limit our vocabulary size to 50000 most frequent words, replacing the rest with <unk> tokens. We dropped the documents which had an empty source (which came from photo articles).

Table 5.1 lists statistics for the CNN/Dailymail dataset. Figure 5.1 shows examples source and target pairs from the dataset.

In the context of these new datasets, the summarization task has not yet been fully standardized. Research in the area is still largely preliminary, with only a few papers reporting results (Nallapati et al., 2016). While CNN/Dailymail may not be the most suitable dataset for the task due to its noisiness (Chen et al., 2016), a better alternative is yet to exist.

Figure 5.1: Examples of source and target for the CNN/Dailymail dataset. The source is a news article, and the target is one of the given highlights.

Dataset	CNN	Dailymail
Train size	90266	196961
Valid size	1220	12148
Avg. # words per doc.	794	832
Avg. # sent. per doc.	21	29
Avg. # words per sent.	36	27
Avg. # words per summary	13	15

Table 5.1: Statistics for CNN/Dailymail data.

5.2 Implementation details

A few implementation details were necessary to make minibatch training possible. First, instead of taking attention over each individual sentence, we arrange the first 400 words of the document into a 10 by 40 image, and take each row to be a sentence. Second, we pad short documents to the maximum length with a special padding word, and allow the model to attend to it. However, we zero out word embeddings for the padding states and also zero out their corresponding LSTM states. We found in practice that very little of the attention ended up on the padding words.

Ideally, we would prefer to not truncate documents, especially since later context can be important for summarizing the document. Due to memory issues, this is a problem we still have to resolve.

5.3 Models

5.3.1 Baselines

For a baseline, we take the first 15 words of the document (chosen as the average length of a sentence in the training dataset). We call this FIRST.

Others...

5.3.2 Our models

We ran experiments with Models 0 to 3 as described above. Model 0 serves as the baseline.

- Model 0: Soft attention.

- Model 1: Organized by sentence, soft attention over all.
- Model 2: Hierarchical LSTM, coarse-to-fine with soft attention.
- Model 3: Hierarchical LSTM, coarse-to-fine with hard attention over sentences.

5.4 Training

We train with minibatch stochastic gradient descent (SGD) with batch size 20 for 20 epochs, renormalizing gradients below norm 5. We initialize the learning rate to 0.1 for the sentence encoder and 1 for the rest of the model, and begin decaying it by a factor of 0.5 each epoch after the validation perplexity stops decreasing.¹

We use 2 layer LSTMs with 500 hidden units, and we initialize word embeddings with 300-dimensional word2vec embeddings (Mikolov and Dean, 2013). For convolutional layers, we use a kernel width of 6 and 600 filters.

Our models are implemented using Torch (Collobert et al., 2011a) based on a past version of Harvard’s OpenNMT system². We ran our experiments on a GPU (specs?).

In the next chapter we show results.

¹We tried more complicated SGD optimization methods such as Adagrad (Duchi et al., 2011) and Adam (Kingma and Ba, 2015), but found that they did not perform as well. This could be due to gradient norms that are too large.

²<https://github.com/harvardnlp/seq2seq-attn>

Chapter 6

Results

6.1 Evaluation

We report metrics for best validation perplexity and ROUGE scores (Lin, 2004). We use the ROUGE balanced F-scores with ROUGE-1 (unigrams), ROUGE-2 (bigrams), and ROUGE-L (longest common substring). We choose F-score since recall is biased towards longer predicted sentences.

To generate summaries for evaluation, we run beam search with a beam size of 5.

Model	PPL	ROUGE-1	ROUGE-2	ROUGE-L
FIRST	-	23.1	9.8	20.5
BERKELEY	-			
MODEL 0	13.6			
MODEL 1				
MODEL 2 CONV	15.8			
MODEL 2 SPARSEMAX	16.1			
MODEL 3 HARD ONLY	32.3			
MODEL 3 SEMI SAMPLING	23.3			
MODEL 2 BOW	16.4			
MODEL 2 LSTM				
MODEL 2 5x80 CONV	14.8			
MODEL 2 2x200 CONV				
MODEL 2 CONV +POS	15.8			

Table 6.1: Summarization results for CNN/Dailymail.

Model	Entropy
MODEL 0	
MODEL 1	
MODEL 2 CONV	
MODEL 2 BOW	
MODEL 2 CONV +ENTROPY	
MODEL 2 SPARSEMAX	

Table 6.2: Entropy over sentence attention. All numbers are for We computed MODEL 0 and MODEL 1 entropy by summing over each row.

6.2 Analysis

See Table 6.1 for summary results.

We investigate the entropy of the sentence attention on the validation set in Table 6.2.

We see hard attention takes longer to converge.

We see that the attention is very spread out over sentences. In particular, we notice that the word-level attention focuses on specific stop words for all decoder time steps. We posit this may be due to ??? See Appendix A for more visualizations.

We show some predicted summaries from the model.

Chapter 7

Conclusion

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Appendix A

Attention Visualizations

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