Teacher-student knowledge distillation from BERT for sentence classifiers

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Abstract

Acknowledgements

I thank Steve Renals of University of Edinburgh and Vova Vlasov of Rasa for supervising me throughout the academic year; patiently listening to my never-ending reports and providing helpful and optimistic comments.

Many thanks also to Ralph Tang whose work inspired this project, and to Slávka Heželyová who constantly supported me and motivated me to explain all of my work in non-technical stories and metaphors.

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Chapter 1

Introduction

1.1 Motivation

- After the deep learning hype started, NLP went through an era of LSTMs. Since 2017, the area has been becoming dominated by Transformer models pre-trained on large unlabelled corpora.

- As newer and bigger Transformer-based models were proposed in 2018 and 2019, improving on the SOTA, it was becoming clearer that their big size and low speed was rendering them difficult to use (both train and deploy) in practice outside of research labs.

- Recently, we've seen various early attempts at making Transformers – in particular BERT (Devlin et al., 2018) – smaller by removing attentional heads (Michel et al., 2019), quantisation and pruning (Cheong and Daniel, 2019; Sucik, 2019). In terms of actually down-sizing and accelerating the models, knowledge transfer using teacher-student knowledge distillation has led to the most attractive results (Mukherjee and Awadallah, 2019; Tang et al., 2019; Jiao et al., 2019; Sanh et al., 2019).

- However, these studies focus only on using knowledge distillation as a tool. Important questions about the nature of this technique and how it interacts with properties of the teacher and student models remain generally unexplored.

- In line with the increasing demand for explainable AI, it is desirable that, for the beginning, at least the researchers better understand the tools they use, in this case distillation of NLP knowledge from Transformer models. Indeed, such understanding is also useful for overcoming the limitations and designing new variants of this method for smaller and better classifiers.

1.2 Aims

I aim to better understand knowledge distillation by exploring its use for knowledge transfer from BERT into different student architectures on various NLP tasks.

This can be further broken down into three aims:

- Explore the effectiveness of knowledge distillation in very different NLP tasks. To cover a broad variety of tasks, I use sentence classification datasets ranging from binary sentiment classification to 57-way intent classification to linguistic acceptability.
- Explore how distilling knowledge from a Transformer varies with different student architectures. I limit myself to using the extremely popular BERT model (Devlin et al., 2018) as the teacher architecture. As students, I use two different architectures: a BiLSTM, building on the successful work of Ralph Tang (Tang et al., 2019; Tang and Lin, 2019), and a down-scaled BERT architecture.
- Explore how successfully can different types of NLP knowledge and capabilities be distilled. Since NLP tasks are often possible for humans to reason about, I analyse the models' behaviour (e.g. the mistakes they make) to learn more about knowledge distillation. I also probe the models for different linguistical capabilities, inspired by previous successful probing studies (Conneau et al., 2018; Tenney et al., 2019a).

1.3 Contributions

My actual findings. To be added later.

Chapter 2

Background

In this chapter, the Transformer models are introduced and set into the historical context; knowledge distillation is introduced, in particular its recent applications in NLP; and an overview of some relevant work in model understanding is given.

2.1 NLP before Transformers

By the very nature of the natural language, its processing has always meant processing sequences of variable length: be it written phrases or sentences, words (sequences of characters), spoken utterances, sentence pairs, or entire documents. Very often, NLP tasks boil down to making simple decisions about such sequences: classifying sentences based on their intent or language, assigning a score to a document based on its formality, deciding whether two given sentences form a meaningful question-answer pair, or predicting the next word of an unfinished sentence.

As early as 2008, artificial neural networks started playing a key role in NLP: Collobert and Weston (2008)[1] successfully trained a deep neural model to perform a variety of tasks from part-of-speech tagging to semantic role labelling. However, neural machine learning models are typically suited for tasks where the dimensionality of inputs is known and fixed. Thus, it comes as no surprise that NLP research has focused on developing better models that encode variable-length sequences into fixed-length representations. If any sequence (e.g. a sentence) can be embedded as a vector in a fixed-dimensionality space, a simple classification model can be learned on top of these vectors.

One key step in the development of neural sequence encoder models has been the idea of *word embeddings*: rich, dense, fixed-length numerical representations of words. When viewed as a lookup table – one vector per each supported word – such embeddings can be used to "translate" input words into vectors which are then processed further. Mikolov et al. (2013) introduced an efficient and improved

[1] See also Collobert et al. (2011).

way of learning high-quality word embeddings: *word2vec*. The embeddings are learnt as part of a larger neural network, which is trained to predict the next word given several previous words, and the previous words given the current word[2]. Such training can easily leverage large amounts of unlabelled text data and the embeddings learn to capture various properties from a word's morphology to its semantics. Released word2vec embeddings became very popular due to their easy use and performance improvements in many NLP tasks. **TO-DO: Add a simple illustration of learning word2vec.**

While word embeddings were a breakthrough, they themselves do not address the issue of encoding a sequence of words into a fixed-size representation. This is where Recurrent neural networks (RNNs) (Rumelhart et al., 1986) and later their improved variant – Long Short-Term Memory neural networks (LSTMs) (Hochreiter and Schmidhuber, 1997) – come into play. Although originally proposed long ago, they became popular in NLP, and in text processing in particular, only later (see e.g. Mikolov et al. (2010) and Graves (2013)). These recurrent encoders process one word at a time (see Fig. 2.1) while updating an internal ("hidden") fixed-size representation of the text seen so far. Once the entire sequence is processed, the hidden representation (also called "hidden state") is outputted and used make a simple prediction.

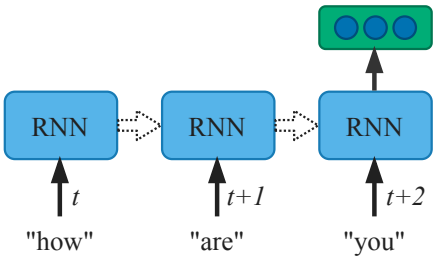

Figure 2.1. A recurrent neural network (RNN) consumes at each timestep one input word. Then, it produces a single vector representation of the inputs.

As various recurrent models started dominating NLP, one particularly influential architecture emerged, addressing tasks such as machine translation, where the output is a new sequence rather than a simple decision. This was the *encoder-decoder* architecture (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014), see Fig. 2.2. It uses a recurrent encoder to turn an input sentence into a single vector, and a recurrent decoder to generate an output sequence based on the vector.

Bahdanau et al. (2014) improved encoder-decoder models by introducing the concept of *attention*. The attention module helps the decoder produce better output by selectively focusing on the most relevant parts of the input at each decoder timestep. This is depicted in Fig. 2.3, showing the decoder just about to output the second word ("estás"). The steps (as numbered in the diagram) are:

[2]These are the so-called Continuous bag-of-words (CBOW) and Skip-gram (SG) tasks, respectively.

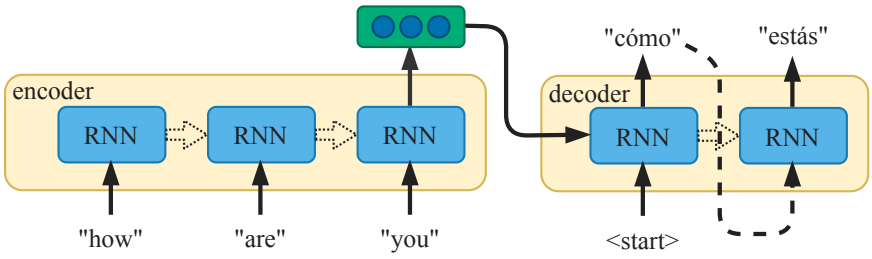

Figure 2.2. An encoder-decoder model for machine translation. Notice how the decoder initially takes as input the special <start> token and at later time consumes the previous output word.

1. the decoder's hidden state passed to the attention module,
2. the intermediate hidden states of the encoder also passed to the attention module,
3. the attention module, based on information from the decoder's state, selecting relevant information from the encoder's hidden states and combining it into the attentional *context vector*,
4. the decoder combining the last outputted word ("cómo") with the context vector and consuming this information to better decide which word to output next.

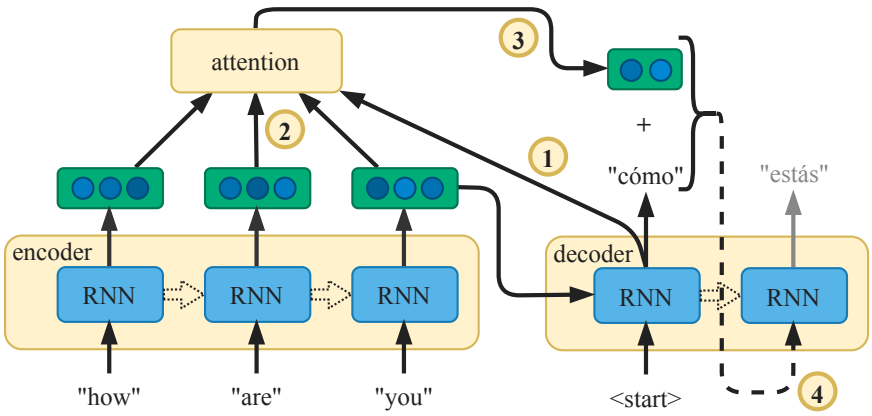

Figure 2.3. An encoder-decoder model for machine translation with added attention mechanism.

The attention can be described more formally[3]: First, the decoder state $\boldsymbol{h_D}$ is processed into a *query* $\boldsymbol{q}$ using

$$\boldsymbol{q} = \boldsymbol{h_D} W_Q$$

and each encoder state $\boldsymbol{h}_E^{(i)}$ is used to produce the *key* and *value* vectors, $\boldsymbol{k}^{(i)}$ and $\boldsymbol{v}^{(i)}$:

$$\boldsymbol{k}^{(i)} = \boldsymbol{h}_E^{(i)} \boldsymbol{W_K}, \quad \boldsymbol{v}^{(i)} = \boldsymbol{h}_E^{(i)} \boldsymbol{W_V} \ .$$

[3]My description does not exactly follow the original works of Bahdanau et al. (2014) and Luong et al. (2015). Instead, I introduce concepts that will be useful in later sections of this work.

Then, the selective focus of the attention is computed as an *attention weight* $w^{(i)}$ for each encoder state i, by combining the query with the i-th key:

$$w^{(i)} = \boldsymbol{q}^\top W_A \boldsymbol{k}^{(i)} \ .$$

The weights are normalised using softmax and used to create the context vector c as a weighted average of the values:

$$\boldsymbol{c} = \sum_i a^{(i)} \boldsymbol{v}^{(i)} \quad \text{where} \quad a^{(i)} = softmax(w^{(i)}) = \frac{e^{w^{(i)}}}{\sum_j e^{w^{(j)}}} \ .$$

Note that W_Q, W_K, W_V and W_A are matrices of learnable parameters, optimised in training the model. This way, the attention's "informed selectivity" improves over time.

For years, recurrent models with attention were the state of the art in many NLP tasks. However, as we will see, the potential of attention reached far beyond recurrent models.

2.2 Transformer-based NLP

2.2.1 Transformers

We saw how the attention mechanism can selectively focus on parts of a sequence to extract relevant information from it. This raises the question of whether processing the inputs in a sequential fashion with the recurrent encoder is still needed. In particular, RNN models are slow as a results of this sequentiality, with no room for parallelisation. In their influential work, Vaswani et al. (2017) proposed an encoder-decoder model based solely on attention and fully parallelised: the *Transformer*. The core element of the model is the *self-attention* mechanism, used to process all input words in parallel.

In particular, a Transformer model typically has multiple self-attention layers, each layer processing separate representations of all input words. Continuing with the three-word input example from Fig. 2.3, a high-level diagram of the workings of a self-attention layer is shown in Fig. 2.4. Importantly, the input word representations evolve from lower to higher layers such that they consider not just the one input word, but also all other words – the representation becomes *contextual* (also referred to as a *contextual embedding* of the word within the input sentence).

As for the internals of self-attention, the basic principle is very similar to standard attention. Self-attention too is used to focus on and gather relevant information from a sequence of elements, given a query. However, to produce a richer contextual embedding $\boldsymbol{h}_{l+1}^{(i)}$ in layer $l+1$ of the i-th input word, self-attention uses the incoming representation $\boldsymbol{h}_{\boldsymbol{l}}^{(i)}$ for the query, and considers focusing on all representations in layer l, including $\boldsymbol{h}_{\boldsymbol{l}}^{(i)}$ itself. Fig. 2.5 shows this in detail for input

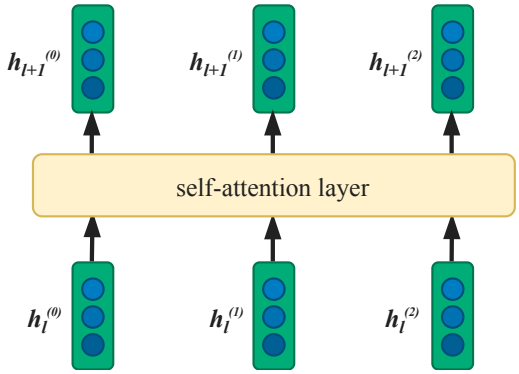

Figure 2.4. A high-level diagram of the application of self-attention in Transformer models. Three hidden states are shown for consistency with the length of the input shown in Fig. 2.3; in general, the input length can vary.

position $i = 0$. Query $\boldsymbol{q}^{(0)}$ is produced and matched with every key in layer l (i.e. $\boldsymbol{k}^{(0)}, \ldots, \boldsymbol{k}^{(2)}$) to produce the attention weights. These weights quantify how relevant each representation $\boldsymbol{h}_l^{(i)}$ is with respect to position $i = 0$. Then, the new contextual embedding $\boldsymbol{h}_{l+1}^{(i)}$ is constructed as a weighted sum of the values $\boldsymbol{v}^{(0)}, \ldots, \boldsymbol{v}^{(2)}$ (same as constructing the context vector in standard attention).

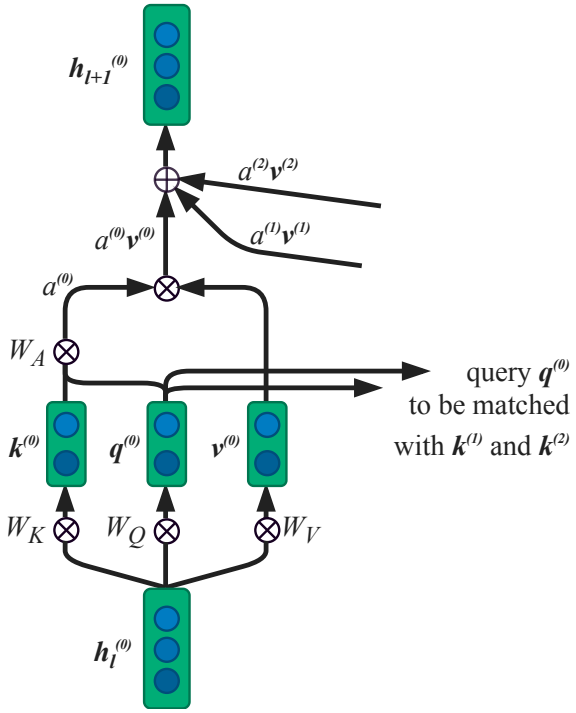

Figure 2.5. The internals of self-attention, illustrated on creating the next-layer hidden representation of the input position $i = 0$, given all representations in the current layer. Note that $\otimes$ stands for multiplication (matrix or scalar), and $\oplus$ denotes summation.

Notice that, even though each contextual embedding considers all input positions, the next-layer contextual embeddings $\boldsymbol{h}_{l+1}^{(0)}, \ldots, \boldsymbol{h}_{l+1}^{(2)}$ can be computed all at the same time, in parallel: First, the keys, queries and values for all input positions are

computed; then, the attention weights with respect to each position are produced; finally, all the new representations are produced. It is this parallelism that allows Transformer models to run faster. As a result, they can be much bigger (and hence create richer input representations) than recurrent models while taking the same time to train.

Due to their parallel nature, self-attentional layers have no notion of an element's position within the input sequence. This means no sensitivity to word order. (Recurrent models sense this order quite naturally because they process input text word by word.) To alleviate this downside of self-attention, Transformers use *positional embeddings*. These are artificially created numerical vectors added to each input word, different across input positions, thus enabling the model's layers to learn to be position- and order-sensitive.

As an additional improvement of the self-attentional mechanism, Vaswani et al. introduce the concept of multiple self-attention heads. This is very similar to having multiple instances of the attention module in Fig. 2.3 (each instance being one head). The motivation behind multiple self-attention modules (heads) is to enable each head to learn different "focusing skills". **TO-DO: Check the following is correct!** The self-attention inputs are split into H parts (H being the number of heads) and each part is processed by one head. Afterwards, the heads' outputs are joined back together. **TO-DO: Add a diagram.**

Besides the self-attention-based architecture, there is one more important property that makes today's Transformer models perform so well on a wide variety of NLP tasks: the way these models are trained. First used for Transformers by Radford et al. (2018)[4], the general procedure is:

1. *Unsupervised pre-training*: The model is trained on one or more tasks, typically language modelling, using huge training corpora. For example, Radford et al. pre-train their model to do next word prediction (the standard language modelling task) on a huge corpus of over 7,000 books.

2. *Supervised fine-tuning*: The pre-trained model is trained on a concrete dataset to perform a desired downstream task, such as predicting the sentiment of a sentence, translating between languages, etc.

This two-step procedure is conceptually similar to using pre-trained word embeddings. In both cases, the aim is to learn general language knowledge and then use this as a starting point for focusing on a particular task. However, in this newer case, the word representations learned in pre-training are be better tailored to the specific architecture, and they are inherently contextual – compared to pre-trained word embeddings like word2vec which are typically context-insensitive.

Importantly, pre-trained knowledge makes models more suitable for downstream tasks with limited amounts of labelled data. The model no longer needs to acquire all the desired knowledge just from the small dataset; it contains pre-trained high-quality general language knowledge which can be reused in various

[4]The idea was previously used with recurrent models by Dai and Le (2015).

downstream tasks. This means that large, powerful Transformer models become more accessible: They are successfully applicable to a wider array of smaller tasks than large models that have to be trained from scratch.

2.2.2 BERT

Perhaps the most popular Transformer model today is BERT (**Bidirectional Encoder Representations from Transformers**), proposed by Devlin et al. (2018). Architecturally, it is a sequence encoder, which makes it suitable for classification tasks. While being heavily based on the original Transformer (Vaswani et al., 2017), BERT adds a few further tricks:

1. The model is bidirectional: It can be trained on language modelling that is not next-word prediction (prediction given left context), but word prediction given both the left and the right context.
2. It uses two very different pre-training classification tasks:
   (a) The *masked language modelling* (MLM) task encourages BERT to learn good contextual words embeddings. The task itself is to correctly predict the word at a given position in a sentence, given that the model can see the sentence, with the target word replaced with the special `MASK` token, with a different word, or left unchanged.
   (b) The *next-sentence prediction* (NSP) task encourages BERT to learn good sentence-level representations. Given two sentences, the task is to predict whether they formed a consecutive sentence pair in the text they came from.
3. The inputs are processed not word by word, but in *wordpieces*, which are sub-word units. This way, BERT can better deal with out-of-vocabulary words. (In word-level models, words that are not found in the model's vocabulary are replaced with a special `unknown` token, which means disregarding any information carried by the words.) The tokeniser module of BERT has a fixed vocabulary of wordpieces, which is used to tokenise (segment) the input text before it is further processed.

elaborate on pre-training add a detailed diagram. things beyond what was said about Transformers already: residual connections, classification using [CLS], the HL modules (tokeniser, embeddings, Transformer, hat), GeLU? mention how BERT has many extensions, tweaks, applications in other domains, languages. due to being published (in two variants) early.

2.2.3 Newer and larger Transformer models

Following the success of the early Transformers (Vaswani et al., 2017; Radford et al., 2018; Devlin et al., 2018), many further variants started emerging, includ-

ing:

- The OpenAI team released GPT-2 (Radford et al., 2019), a larger and improved version of their original, simple Transformer model GPT (Radford et al., 2018).
- (Lample and Conneau, 2019) introducd XLM, which uses cross-lingual pre-training and is thus better suited for downstream tasks in various languages. **TO-DO: check**
- Transformer XL (Dai et al., 2019), which features an improved self-attention for handling very long contexts. **TO-DO: check**

All these open-sourced, powerful pre-trained models were a significant step towards more accessible high-quality NLP (in the context of downstream tasks with limited data). However, the model size – often in 100s of million trainable parameters – meant these models could not be applied easily in practice (outside of research): They were memory-hungry and slow. Naturally, this inspired another stream of research: Compressing large, well-performing Transformer models (very often BERT) to make them faster and resource-efficient. **TO-DO: add some notable compression papers** I turn my focus to one compression method that worked particularly well so far: the teacher-student knowledge distillation.

2.3 Teacher-student knowledge distillation

2.3.1 A brief introduction to knowledge distillation

Knowledge distillation was introduced by (Bucila et al., 2006) as a way of knowledge transfer from large models into small ones. The aim is to end up with a smaller – and hence faster – yet well-performing model. The steps are 1) to train a big neural classifier model (also called the *teacher*), 2) let a smaller neural classifier model (the *student*) learn from it – by learning to mimic the teacher's behaviour. Hence also the name *teacher-student knowledge distillation*, often simply *knowledge distillation*.

There are different ways of defining the teacher's "behaviour" which the student learns to mimic. Originally, this was realised as learning to mimic the teacher's predictions: A dataset would be labelled by the teacher, and the student would be trained on these labels (which are in this context referred to as the *hard labels*). The dataset used for training the student (together with the teacher-generated labels) is referred to as the *transfer dataset*.

Later, Ba and Caruana (2014) introduced the idea of learning from the teacher-generated *soft labels*, which are the teacher's logits[5]. The idea is to provide the student with richer information about the teacher's decisions: While hard labels only express which class had the highest predicted probability, soft labels also

[5]For a classifier, the logits are the (unnormalised) predicted class probabilities.

describe how confident the prediction was and which other classes (and to what extent) the teacher was considering for a given example.

When soft labels were first used, the student's training loss function was the mean squared distance between the student's and the teacher's logits:

$$E_{MSE} = \sum_{c=1}^{C} (z_t^{(c)} - z_s^{(c)})^2 \tag{2.1}$$

where C is the number of classes and z_t, z_s are the the teacher's and student's logits. Hinton et al. (2015) proposed a more general approach, addressing the issue of overconfident teachers with very sharp logit distributions. The issue with such distributions is that they carry little additional information beyond the hard label (since the winning class has a huge probability and all others have negligibly small probabilities). To "soften" such sharp distributions, Hinton et al. proposed using the *cross-entropy loss* Eq. 2.2 in combination with softmax with temperature Eq. 2.3 (instead of the standard softmax) in training both the teacher and the student.

$$E_{CE} = \sum_{c=1}^{C} z_t^{(c)} \log z_s^{(c)} \tag{2.2}$$

$$p_c = \frac{\exp(z^{(c)}/T)}{\sum_{c=1}^{C} \exp(z^{(c')}/T)} \tag{2.3}$$

TO-DO: Change equation autoref. The temperature parameter T determines the extent to which the distribution will be "unsharpened" – two extremes being the completely flat, uniform distribution (for $T \to \infty$) and the maximally sharp distribution[6] (for $T \to 0$). When $T > 1$, the distribution gets softened and the student can extract richer information from it. Today, using soft labels with the cross-entropy loss with temperature is what many refer to simply as knowledge distillation.

Since 2015, further knowledge distillation variants have been proposed, enhancing the vanilla technique in various ways, for example:

- Papamakarios (2015, p. 13) points out that mimicking teacher outputs can be extended to mimicking mimicking the *derivatives* of the teacher's loss with respect to the inputs. This is realised by including in the student's loss function also the term: $\frac{\partial \boldsymbol{o}_s}{\partial \boldsymbol{x}} - \frac{\partial \boldsymbol{o}_t}{\partial \boldsymbol{x}}$ ($\boldsymbol{x}$ being an input, e.g. a sentence, and $\boldsymbol{o}$ being the output, e.g. the predicted class).
- Romero et al. (2015) proposed to additionally match the teacher's internal, intermediate representations of the input. Huang and Wang (2017) achieved this by learning to align the distributions of neuron selectivity patterns between the teacher's and the student's hidden layers. Unlike standard knowledge distillation, this approach is no longer limited only to classifier models with softmax outputs (see the approach of Hinton et al. (2015) discussed above).

[6] I.e. having the preferred class's probability 1.0 and the other classes' probabilities 0.

- Sau and Balasubramanian (2016) showed that learning can be more effective when noise is added to the teacher logits.
- Mirzadeh et al. (2019) showed that when the teacher is much larger than the student, knowledge distillation performs poorly, and improved on this by *multi-stage distillation*: First, knowledge is distilled from the teacher into an intermediate-size "teacher assistant" model, then from the assistant into the final student.

2.3.2 Knowledge distillation in NLP

Practically all the so far mentioned research in knowledge distillation was done in the domain of image processing. This comes as no surprise: It was image processing that was benefitting the most from the resurgence of deep learning. Ever since the AlexNet (Krizhevsky et al., 2012), bigger and bigger models were proposed, simultaneously driving the research in model compression so as to make the models usable in practice.

In natural language processing, research on knowledge distillation was rare for a long time. One notable work was the adaptation of distillation for sequence-to-sequence machine translation models – whose outputs are no longer simple classification scores – by Kim and Rush (2016). Another pioneering study compressed a recurrent neural language model for use on mobile devices (Yu et al., 2018).

However, the real need for model compression started very recently when huge Transformer models were introduced. This follows on from the main limitation of the otherwise very accessible pre-trained models: being huge and slow.

When distilling knowledge from big, pre-trained Transformer models, the main decision is whether to distil before or after fine-tuning on a concrete downstream task. Each option has its pros and cons. In the first scenario, the steps are: 1) distilling into a small student, 2) fine-tuning the student on any downstream task. One advantage is that the distillation is done only once and fine-tuning the student can be fast (due to the student's size). Since the distillation can be done on the same data that the teacher was pre-trained on – large corpora of unlabelled data, one does not have to worry about not having enough data. One possible downside is that the amount of general language knowledge contained in the pre-trained teacher will be too much to contain within a small student, hence requiring students that are themselves considerably large (and slow). Sanh et al. (2019) took this approach and while their student model is very successfully fine-tuned to a wide range of tasks, it smaller than the teacher (BERT base) only by 40%, still having 66M parameters.

In the second scenario, the steps are: 1) fine-tuning the pre-trained teacher on a downstream task, 2) distilling the teacher into a small student. In this case, the downstream task-specific language knowledge is likely to be much smaller than the teacher's overall pre-trained language knowledge, meaning that a much smaller

student can still contain all important knowledge from the fine-tuned teacher. However, with this approach, the teacher fine-tuning and distillation has to be done separately every downstream task, which can be resource-intensive. Even more importantly, the distillation procedure can suffer from lack of data, since the distillation is now being done only with the downstream task dataset, which will often be small and has to be augmented. Various ways of augmenting small datasets to increase the amount of transfer data have been proposed, with mixed success. Mukherjee and Awadallah (2019) use additional unlabelled in-domain sentences with labels generated by the teacher – an approach that only works if such in-domain sentences are available. Tang et al. (2019) propose augmentation based on simple, rule-based perturbation of existing sentences from the downstream task data. Finally, Jiao et al. (2019) and Tang and Lin (2019) use big Transformer models generatively to create new sentences. In the first case, BERT is repeatedly used to choose a suitable replacement for an existing word in a given sentence, eventually leading to a new sentence with many words changed for different ones. In the second case, a GPT-2 model is fine-tuned on the downstream task with a language model objective, and a new sentence is generated by repeatedly predicting the next token, conditioned on the sequence generated so far.

In this work, I adopt the approach of Tang and Lin (2019) as I view it as the most promising one so far. However, while they use only bidirectional LSTM students, I also experiment with a smaller version of BERT, similarly to Jiao et al. (2019). For detailed description of the system see Chapter 4.

2.4 Analysing and understanding NLP models

NNs are black boxes and (not) understanding the models is a serious issue. performance is typically more important than transparence, but recently the demand for explainable AI (XAI) has been increasing. additionally, understanding is opportunity for further improvements of the mdels and techniques.

in image processing, interpretability is easy thanks to visualising things. (somewhat similarly music.) notable works: maximising activation, visualising neurons' output for given input, maximum activation samples. in NLP, interpreting is more difficult, and also comes with a delay after image processing – same with the big model hype and compression hype. Belinkov and Glass (2018) give nice overview of work done up until 2018. they point out that many methods for analysing and interpreting models are adapted from image processing, especially visualising activations of single neurons on specific input examples. in attentional seq2seq models, the attention maps can be visualised to show soft alignments between input and output sequences. however, these methods taken from image processing are mostly qualitative, not suited for comparing models.

more quantitative and NLP-specific are the approaches that look at kinds of linguistic knowledge present in a model's internal representations of input. most

often, this means extracting activations for a set of inputs and trying to predict properties of the input from the activations by using a simple predictor model. if the prediction works well, then the activations must've contained linguistic knowledge relevant for the predicted property. since first proposed by Shi et al. (2016), this approach has been used repeatedly to explore various forms of representations. the first work was looking at how well NMT systems capture syntactic properties of input. later, Adi et al. (2017) used simpler artificial prediction tasks (sentence length, word content and word order) to better understand sentence embeddings produced by recurrent encoders. more recently, Conneau et al. (2018) curated a set of 10 probing tasks ranging from surface properties through syntactic to semantic ones, and compared different recurrent and convolutional sentence encoders (and many useful baseline models) in terms of the linguistic knowledge in their sentence representations. focusing specifically on Transformer models, Tenney et al. (2019b) propose a set of *edge probing* tasks which examine how much contextual knowledge about the entire sentence is captured within the representation of a single word. the tasks mimic the typical steps of a standard NLP pipeline – from POS tagging to identifying dependencies and entities to semantic role labelling. Tenney et al. (2019a) were able to localise the layers of BERT that are the most important for each of the tasks, showing that the different linguistic capabilities are ordered within the model in the typical NLP pipeline order: from simple POS tagging in the earlier layers to the most complex semantic tasks in the last layers.

while the abovementioned methods for analysing models provide valuable insights, they are incomplete. for one, they merely help us describe in intuitive terms the kinds of internal knowledge/specialisation observed in the models. in their overview of interpretability of machine learning, Gilpin et al. (2018) call this level of model understanding *interpretability* – comprehending what a model does. however, what we should strive to achieve, is *explainability*: the ability to "summarize the reasons for neural network behavior, gain the trust of users, or produce insights about the causes of their decisions". In this sense, today's methods for analysing neural NLP models achieve only interpretability because they enable us to describe but not explain (especially in terms of causality) the internals and decisions of the models.

In this work, I also attempt to mainly *interpret* the student and teacher models. I adopt two approaches:

1. analysing the mistakes the models make on the downstream task they were trained to do, including how confident the correct and incorrect predictions are

2. probing the models using the probing tasks curated by Conneau et al. (2018)

By comparing the findings between models trained on different downstream tasks or with different architectures, I try to characterise each task in terms of the linguistic capabilities it utilises. Further, I describe how different student model architectures influence how linguistic knowledge is distilled from a teacher and stored in the student, and what the effect on the student's confidence is. Finally,

I try to relate the observed effects to the method of knowledge distillation itself.

Chapter 3

Datasets

3.1 Downstream tasks

Since the BERT model I use as teacher is already pre-trained on large unlabelled corpora (for details see the original work by Devlin et al. (2018)), it can be fine-tuned well even on small downstream datasets.

Today, perhaps the most popular collection of challenging NLP tasks (challenging by the nature of the tasks and by the relatively small dataset size) is the GLUE benchmark (Wang et al., 2018). This collection comprises 11 tasks from semantic analysis to detecting textual similarity to natural language inference, framed as single sentence or sentence pair classification. Each task features a specific scoring metric (such as accuracy or F1), publicly available labelled training and development datasets, and a testing dataset whose labels have not been released. The test-set score accumulated over all tasks forms the basis for the popular GLUE leaderboard[1].

For simplicity, I use only the single-sentence classification tasks of the collection – the Corpus of Linguistic Acceptability (CoLA) and the Stanford Sentiment Treebank in its two-way classification format (SST-2).

- The CoLA task features 8.5k training sentences, 1k evaluation and 1k testing sentences. The (hand-crafted) sentences are collected from various linguistic literature and represent examples of acceptable and unacceptable English, making the task a binary classification. The scoring metric is Matthew's Correlation Coefficient (MCC, introduced by Matthews (1975)). This task is rather challenging since a given sentence can be perfectly grammatical and still not be acceptable English. As a non-native speaker, I myself struggle with some of the examples.
- The SST-2 task has considerably more data as it is easier to collect: 67k training, 9k evaluation and 18k testing sentences, extracted from movie reviews and labelled as positive or negative sentiment. The scoring metric

[1] https://gluebenchmark.com/leaderboard

is accuracy. The task is easier than CoLA and best models in the GLUE leaderboard achieve over 97% test-set score.

As the third task, I use an intent classification dataset collected by Rasa, a company building open-source tools for conversational AI[2]. The dataset is named Sara, after the company's own chatbot[3] which provides various information about Rasa and its products to the visitors of the company's website[4]. The dataset comprises 4.8k examples overall, split between 1k testing portion and 3.8k training portion. Each example is a human-generated utterance and has been manually labelled with one of 57 intents, helping the Sara chatbot learn to detect what a human is talking to it about. Originally, the dataset was initialised by Rasa employees talking to Sara. Later, many more examples were collected by deploying the chatbot and letting site visitors talk to it. The 57 intent types were designed by Rasa, starting with a smaller number of broader intents and refining the set after observing real questions humans were asking the chatbot. **TO-DO: verify this is true; my knowledge of the history of Sara is limited.** The main scoring metric is the multi-class micro-averaged F1 score.

I modified the Sara dataset by splitting the training portion into 2.8k training and 1k evaluation sentences (while keeping both sets class-balanced). I also anonymised the dataset by replacing all sensitive information with generic tokens. Namely, I replaced people's names and surnames with a single token `__PERSON_NAME__` and e-mail addresses with `__EMAIL_ADDRESS__`.

To stay consistent with the GLUE datasets for which test-set labels are not publicly available, I do not use the test portion of any of them when analysing the mistakes made by different models. Instead, I analyse the predictions on the evaluation set. This can be viewed as sheding light on the kind of model qualities that are actually optimised when choosing model parameters on this set.

3.2 Data augmentation for generating large transfer sets

As Tang et al. (2019) demonstrate, taking just the training sentences of a downstream task as the transfer set for knowledge distillation is not enough; especially for challenging tasks like CoLA where the training set comprises only several thousands of sentences (for results, see Table 1 in Tang and Lin (2019)). I adopt the approach that they found to work the best: Augmenting the training portion with additional sentences generated by a GPT-2 model (Radford et al., 2019). The concrete steps for this augmentation are:

1. Fine-tune the pre-trained GPT-2 model (the 345M-parameter version) on

[2]For transparency: I did a 3-month internship as Machine Learning researcher with Rasa in the summer of 2019.

[3]Demonstrated at https://github.com/RasaHQ/rasa-demo

[4]https://rasa.com/

the training sentences for 1 epoch with the language-modelling objective, i.e. learning to predict the next subword token of a sentence given the true sequence of tokens so far.

2. Sample a large number of prefixes (subword tokens) from the observed distribution of sentence-initial subword tokens in the training sentences.

3. For each sampled prefix, generate a sentence starting with it: by sampling from the predicted next-token distribution of the GPT-2 model, starting with just the prefix and stopping when the special end-of-sentence token is generated or the desired maximum sequence length is reached (in this case 128 tokens).

4. Add the generated sentences to the original training sentences and use as the transfer set, i.e. append with teacher-generated logits and use to train the students.

For consistency, I used the same number of augmentation sentences as Tang et al. (2019): 800k for each downstream task. Hence, the transfer set comprises 808.5k sentences for CoLA, 867k sentences for SST-2, and 802.8k sentences for Sara.

3.3 Probing tasks

For exploring the linguistic knowledge in the different teacher and student models, I use the probing task collection curated by Conneau et al. (2018). The datasets, along with tools for applying probing to neural models, are publicly available as part of the SentEval toolkit Conneau and Kiela (2018) for evaluating sentence representations. The collection contains 10 tasks, each having 100k training, 10k evaluation and 10k testing sentences. These are used for training the probing classifier, choosing its hyperparameters, and computing the task-specific score, respectively.

Each of the 10 probing tasks – grouped into three broad categories – focuses on a different linguistic capability (for more details, see the original paper of Conneau et al. (2018)):

Surface information:

- **Length** is about recovering the length of the sentence. The actual sentence lengths are grouped into 6 equal-width bins, making this task a 6-way classification.

- **WordContent** is about identifying which words are present in the sentence. A collection of 1000 mid-frequency words was created, and sentences were sampled such that each contains exactly one of these words. The task is therefore 1000-way classification.

Syntactic information:

- **Depth** is about classifying sentences by their syntactic parse tree depth, with depths ranging from 5 to 12 (hence 8-way classification).
- **BigramShift** is about recognising sentences in which the order of two randomly chosen adjacent words has been swapped (binary classification).
- **TopConstituents** is about recognising the top syntactic constituents – the nodes found in the syntactic parse tree just below the S (sentence) node. This is framed as 20-way classification, choosing from 19 most common top-constituent sequences and the "other" option.

Semantic information:

- **Tense** is binary classification, identifying the tense (present/past) of the main verb of the sentence (the verb in the main clause).
- **SubjNumber** is about determining the number (singular/plural) of the sentence's subject, framed as binary classification.
- **ObjNumber** is the same as SubjNumber, applied to the direct object of a sentence.
- **OddManOut** is binary classification, detecting whether a random word (verb or noun) in a sentence was replaced with a different one (verb or noun) or not. To make this task more difficult, the replacement word is chosen such that the frequency of the bigrams in the sentence stays roughly the same.
- **CoordinationInversion** works with sentences that contain two coordinate clauses whose order may have been artificially swapped. The binary classification is then about detecting which sentences are intact.

Considering the findings of Tenney et al. (2019a) about the NLP pipeline steps being implicitly captured inside BERT, choosing their approach to probing (together with the collection of tasks they curated) was an attractive option. However, the approach explores single-word representations, focuses primarily on more complex probing tasks (e.g. entity recognition, natural language inference, semantic roles) and the tasks are not open-sourced. In this sense, the SentEval toolkit is preferred as it was built for analysing sentence representations, the simpler surface and syntactic tasks have a better coverage, and the datasets are publicly available. In the future, however, the two collections of probing tasks could be used in combination.

Chapter 4

Implementation

4.1 Existing implementations used

For finetuning BERT, I used `transformers` (Wolf et al., 2019)[1] – a popular open-source PyTorch library curating and presenting many successful Transformer-based models in a unified way. My implementation of the distillation process is heavily based on the implementation accompanying DistilBERT (Sanh et al., 2019), which is today part of `transformers`[2].

The implementation of the BiLSTM student is based on the codebase accompanying the work of Tang and Lin (2019)[3] (which was originally built using an early version of the `transformers` library). The same codebase was used without many changes for fine-tuning the GPT-model and creating the augmentation sentences.

Finally, for probing, I adapted the SentEval toolkit (Conneau and Kiela, 2018) to suit my needs.

In terms of implementation, the most of my own work is in having integrated the different tools. In particular, I have combined the codebases of Sanh et al. (2019) and Tang and Lin (2019) and adapted the combination to offer richer options (e.g. initialising the student's embedding layers with trained word or wordpiece embeddings), to work with both BERT and BiLSTM students and to be more easily extendable to other architectures.

[1] https://github.com/huggingface/transformers, accessed January 30, 2019

[2] https://github.com/huggingface/transformers/tree/master/examples/distillation, accessed January 30, 2019

[3] https://github.com/castorini/d-bert, accessed January 30, 2019

4.2 System overview

Following Tang and Lin (2019), I used the large, case-insensitive (uncased) pre-trained BERT (340M params) as the teacher and finetuned it for 3 epochs using Adam optimizer with $\eta = 5e-5$ with linear warm-up over the first 10% of training steps, followed by linear decay, and with batch size $B = 36$. I will refer to this model as $BERT_T$. Somewhat surprisingly, while the teacher converged within 3 epochs for CoLA and SST-2 (in terms of the dev-set score), for Sara, it converged much more slowly. I empirically chose 10 epochs as the smallest number after which $BERT_T$ would sufficiently converge on the Sara dataset.

As students, I used:

- a bi-directional LSTM same as the one used by Tang and Lin (2019): with one LSTM layer with 300 units, followed by a linear layer with 400 units and ReLU activation function, with a softmax classifier on top, with 2.41M non-embedding trainable parameters. I will refer to this model as $LSTM_S$.
- a smaller version of the teacher BERT model, with all dimensions down-scaled 5x to roughly match the number of trainable non-embedding parameters: with 5 transformer layers, hidden dimension of 204, intermediate layers of size 750, and 3 attentional heads (amounting to 2.42M parameters). I will refer to this model as $BERT_S$.

$LSTM_S$ was trained to minimise the mean squared loss (MSE) between the teacher-generated logits and student's logits. While the cross-entropy loss with configurable temperature is more popular and in essence a generalisation of the MSE loss (see Hinton et al. (2015)), Tang and Lin (2019) report that the MSE loss led to slightly better performance in their experiments. For $BERT_S$, I use the traditional cross-entropy loss with temeperature set to $T = 3$ following the findings of Tsai et al. (2019) who experimented with different temperatures (note that $T = 3$ was used as the default also in the experiments of Tang and Lin (2019)).

Following preliminary experiments, I limited the number of training epochs to 30 for $LSTM_S$ (same budget was used by Tang and Lin (2019)) and to 60 for $BERT_S$ as it was converging much slower than the recurrent student. I stick to this training budget throughout my experiments.

some overall visualisation of all the components and how they interact

Chapter 5

Student tuning

Importantly, extensive tuning of the students' hyperparameters is certainly not the main objective of this work. However, my aim is to carry out an analysis of the teacher and student models and the distillation process. For such analysis to be of some value, it should be done using well-performing models which themselves are of practical value.

I tune a number of hyperparameters for the 2.4M-parameter students using the CoLA task. Afterwards, I tune a smaller number of parameters – which are the most likely to be task-dependent – separately for each downstream task, trying to obtain $LSTM_S$ and $BERT_S$ that would achieve 90% of the teacher's performance while being as small as possible. These student are then used for further analysis.

For both students, I first tune the following, in this order (for more details, see the next sections):

1. learning rate η
2. learning rate scheduling, more concretely the warm-up and decay of η
3. batch size B
4. embedding type (wordpiece vs word) and mode

Afterwards, I tune on each task separately the embedding type and the student size.

The starting configuration (which I change as I tune the different parameters) is:

- $BERT_S$: Adam with $\eta = 5e-5$, $B = 256$, learning rate warm-up over the first 10 epochs, followed by linear decay, and wordpiece embedding layer
- $LSTM_S$: Adadelta with $\eta = 1.0$, $B = 50$, no learning rate annealing, and word embedding layer in the multichannel mode, using word2vec

Initially, $LSTM_S$ had its embedding layer initialised with word2vec embeddings, but $BERT_S$ was initialised entirely from scratch. Naturally, this was posing a disadvantage for $BERT_S$ as it was starting with no knowledge. Hence, I added

the option to initialise the embedding layer with wordpiece embeddings from the corresponding finetuned $BERT_T$. I report results of parameter tuning for both of these variants of $BERT_S$.

5.1 Choosing η

Because Tang and Lin (2019) report not tuning their hyperparameters, I acknowledge their parameter choices but challenge many of them. In particular, they use Adadelta with $\eta = 1.0$ and $\rho = 0.95$ as the learning algorithm. I attempt to use the Adam algorithm as it is a generalised, improved version of Adadelta. Hence, for both students, I compare values of η from [5e-3, 1.5e-3, 5e-4, 1.5e-4, 5e-5, 1.5e-5, 5e-6] for the Adam optimizer, with betas fixed to 0.9 and 0.98.

TO-DO: add graphs

The best value was found to be $\eta = 5e-4$ for $LSTM_S$ and bth variants of $BERT_S$. For $BLSTM_S$, I abandoned the Adadelta optimizer as it performed worse than Adam.

5.2 Choosing learning rate annealing

I tried linear warm-up of η (starting from 0) over [0, 5, 10, 15, 20] epochs E_{WP} for $BERT_S$ and over [0, 5, 10, 15] epochs for $LSTM_S$.

TO-DO: add graphs

For $BERT_S$ initialised from scratch, $E_{WP} = 20$ and no decay worked the best. For the other students, decay was improving the performance slightly, with the best E_{WP} being 0 for $LSTM_S$ and 15 for $BERT_S$

5.3 Choosing batch size

Note that for $LSTM_S$ this was done prior to exploring the learnign rate annealing, as my aim was to merely verify that $B = 50$ reported by Tang and Lin (2019) was the best value. For $BERT_S$, I had much less intuition about suitable batch sizes. The explored values were [32, 64, 128, 256, 512] for $BERT_S$ and [32, 50, 128, 256, 512] for $LSTM_S$.

TO-DO: add graphs

Interestingly, while $LSTM_S$ preferred the smalles batch size $B = 32$, $BERT_S$ preferred much bigger batches: 256 when initialised from scratch and 128 with wordpiece embeddings initialised from $BERT_T$.

5.4 Choosing embedding type and mode

After observing that the best $LSTM_S$ consistently outperforms its counterpart $BERT_S$, I turned to exploring the effect of pre-trained knowledge present in the student before distillation. In $LSTM_S$, this lies in the word2vec embeddings. Additionally, the embedding layer is used in the *multichannel mode*: two parallel embedding layers are initialised from word2vec, with one being frozen during distillation and the other one allowed to be finetuned. In $BERT_S$, there is no pre-trained knowledge or there is the knowledge from the teacher's wordpiece embeddings (dimensionality reduced by a trainable linear layer to match the smaller hidden size of $BERT_S$.

I was interested to see whether the effect of different type of embeddings – word2vec pre-trained on general language modelling vs wordpiece pretrained on language modelling and finetuned on the particular downstream task – could explain some of the performance gap between $BERT_S$ and $LSTM_S$. Hence, I tried each of the 2 students with each of the 2 embedding types, combined with each of the following 2 modes: the multichannel mode described above, and the simple (*non-static*) mode where only one embedding instance is created, which is unfrozen and allowed to further train during distillation.

TO-DO: add graphs

Turns out $LSTM_S$ strongly prefers word embeddings in the multichannel mode, while $BERT_S$ is less decisive, with only slight preference for word embeddings and the multichannel mode. This also shows that the different embedding properties don't explain the worse performance of $BERT_S$.

5.5 Choosing task-specific parameters

For each dataset, I first tried different embedding types and modes, and then for the best-performing combination I tried up-scaling the students to get as close to 90% of $BERT_T$'s performance as possible, while keeping the size of each student reasonably smaller than the teacher.

5.5.1 CoLA

Here I had the optimal embedding type/mode already.

I tried expanding $LSTM_S$ by increasing the number of LSTM layers from 1 to [2, 3, 4, 5] and the width of the LSTM and fully-connected layers from the original 300 and 400 by 2x, 3x, 4x and 5x. In case of $BERT_S$, I tried increasing the number of layers from the original 5 to 10 and 15, and the other parameters (# of attentional heads, hidden and intermediate size) by 2x, 3x and 4x.

TO-DO: add graphs

For $LSTM_S$, the results are indecisive, without clear correlation between student size and performance. The best student was 2x deeper and 2x wider than the initial configuration.

For $BERT_S$, I soon observed that bigger models started dying after the first few epochs. TO-DO: add diagnostic graphs. This dying surfaced as the dev-set score flattening out and then decreasing towards 0, at which point the gradients in the model would explode. I identified the cause of this to be too big learning rate (thanks to the warm-up, the model was experiencing η starting from 0 and increasing towards the target value). Hence, by comparing the graphs for the linearly increasing η and the dev-set performance, I tried to manually identify η values as big as possible that were still enabling the model to improve fast (without making it plateau or die). These values were in the range from the originally chosen 5e-4 down to 8e-5 (generally lower η for bigger models). After this modification, all students trained normally, without dying. TO-DO: add graphs and conclusions once all of these have finished training.

5.5.2 SST-2

TO-DO: run experiments and report

5.5.3 Sara

TO-DO: run experiments and report

Chapter 6

Analysing the models

6.1 Analysing the models' predictions

This will involve for each downstream task:

1. gathering dev-set predictions made by the two best students and the teacher
2. looking at the mistakes made by each model (most confident mistakes and least confident mistakes first, maybe taking first 10-20 mistakes from each end), trying to describe then in intuitive terms if possible
3. comparing the mistakes made by different models, again trying to describe what I observe
4. looking at how confident the predictions were in general for each model (maybe the distribution of confidences?) and if possible, comparing this across models

My aim is to make at least some observations describable in human-understandable terms about how the models compare: how the 2 architecturally different students compare, and how their predicting behaviour compares to that of their teacher. Ideally, I will be also able to form some (even if weak) hypotheses that are further testable using probing tasks.

6.2 Probing the models for linguistic knowledge

Here, I will for each downstream task:

- probe each of the 3 models in different layers (e.g. the 24-layer $BERT_T$ in layers 1, 6, 12, 18, 24) to see how much linguistic knowledge and where is present in each model
- probe also the pretrained BERT (not finetund on any downstream task) and look at how knowledge is preserved/thrown away when the teacher gets

finetuned vs when students with little prior knowledge are trained during distillation

- compare how knowledge is present in the two architecturally different students, try to relate this to other differences noticed when analysing the students' predictions

For now, I have one graph summarising the results of probing just the teacher models, see Fig. 6.1.

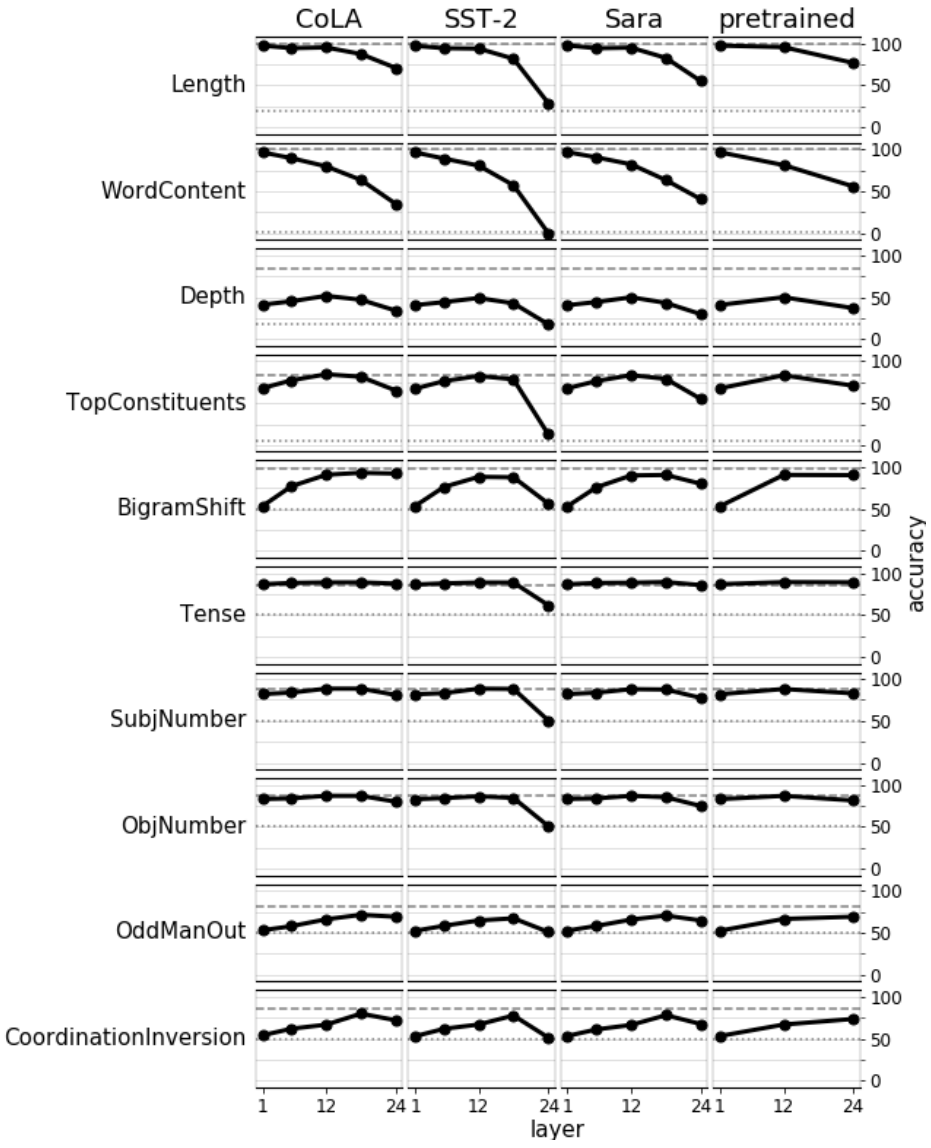

Figure 6.1. Probing the 3 finetuned teachers and the pretrained one. The dotted line shows baseline accuracy levels achieved by majority-class guessing, the dashed line shows human performance.

Chapter 7

Overall discussion and conclusions

Chapter 8

Future work

Chapter 9

Plan for the rest of the semester

Work finished:

- implementing everything related to distillation (incl. teacher finetuning and generating augmentation data with GPT-2)
- creating augmented transfer sets and finetuning the BERT teacher for each task
- exploring the model parameters shared across tasks (i.e. doesn't include embedding type and student size)
- implementing everything needed for probing
- implementing everything needed for gathering predictions for mistake/confidence analysis

Work to be done:

- now-Feb 10: finishing size exploration for SST-2 and Sara (ending up with best students for each downstream task)
- Feb 11-23: analysing the predictions of all models (includes Inovative Learning Week Feb 17-21 when I won't get terribly much done)
- Feb 11-16: probing the best students
- Feb 24-Mar 1: putting together overall analysis and conclusions
- Mar 2-Apr 2: buffer time and writing the report (a lot of coursework in this period as well)

Bibliography

Adi, Y., Kermany, E., Belinkov, Y., Lavi, O., and Goldberg, Y. (2017). Fine-grained analysis of sentence embeddings using auxiliary prediction tasks. *ICLR*, abs/1608.04207.

Ba, J. and Caruana, R. (2014). Do deep nets really need to be deep? In *NIPS*.

Bahdanau, D., Cho, K., and Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate.

Belinkov, Y. and Glass, J. R. (2018). Analysis methods in neural language processing: A survey. *Transactions of the Association for Computational Linguistics*, 7:49–72.

Bucila, C., Caruana, R., and Niculescu-Mizil, A. (2006). Model compression. In *KDD '06*.

Cheong, R. and Daniel, R. (2019). transformers.zip: Compressing transformers with pruning and quantization.

Collobert, R. and Weston, J. (2008). A unified architecture for natural language processing: Deep neural networks with multitask learning. In *Proceedings of the 25th International Conference on Machine Learning*, ICML 2008, page 160âĂŞ167, New York, NY, USA. Association for Computing Machinery.

Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., and Kuksa, P. (2011). Natural language processing (almost) from scratch. *J. Mach. Learn. Res.*, 12(null):2493âĂŞ2537.

Conneau, A. and Kiela, D. (2018). Senteval: An evaluation toolkit for universal sentence representations. *arXiv*, abs/1803.05449.

Conneau, A., Kruszewski, G., Lample, G., Barrault, L., and Baroni, M. (2018). What you can cram into a single $&!#* vector: Probing sentence embeddings for linguistic properties. In *ACL*.

Dai, A. M. and Le, Q. V. (2015). Semi-supervised sequence learning. In Cortes, C., Lawrence, N. D., Lee, D. D., Sugiyama, M., and Garnett, R., editors, *Advances in Neural Information Processing Systems 28*, pages 3079–3087. Curran Associates, Inc.

Dai, Z., Yang, Z., Yang, Y., Carbonell, J. G., Le, Q. V., and Salakhutdinov,

R. (2019). Transformer-XL: Attentive language models beyond a fixed-length context. In *ACL*.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding.

Gilpin, L. H., Bau, D., Yuan, B. Z., Bajwa, A., Specter, M., and Kagal, L. (2018). Explaining explanations: An overview of interpretability of machine learning.

Graves, A. (2013). Generating sequences with recurrent neural networks.

Hinton, G. E., Vinyals, O., and Dean, J. (2015). Distilling the knowledge in a neural network. *ArXiv*, abs/1503.02531.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural Comput.*, 9(8):1735âĂŞ1780.

Huang, Z. and Wang, N. (2017). Like what you like: Knowledge distill via neuron selectivity transfer. *arXiv*, abs/1707.01219.

Jiao, X., Yin, Y., Shang, L., Jiang, X., Chen, X., Li, L., Wang, F., and Liu, Q. (2019). TinyBERT: Distilling BERT for natural language understanding.

Kalchbrenner, N. and Blunsom, P. (2013). Recurrent continuous translation models. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1700–1709.

Kim, Y. and Rush, A. M. (2016). Sequence-level knowledge distillation. *arXiv*, abs/1606.07947.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *NIPS*.

Lample, G. and Conneau, A. (2019). Cross-lingual language model pretraining. *arXiv preprint arXiv:1901.07291*.

Luong, T., Pham, H., and Manning, C. D. (2015). Effective approaches to attention-based neural machine translation. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1412–1421, Lisbon, Portugal. Association for Computational Linguistics.

Matthews, B. W. (1975). Comparison of the predicted and observed secondary structure of t4 phage lysozyme. *Biochimica et Biophysica Acta (BBA)-Protein Structure*, 405(2):442–451.

Michel, P., Levy, O., and Neubig, G. (2019). Are sixteen heads really better than one?

Mikolov, T., Chen, K., Corrado, G., and Dean, J. (2013). Efficient estimation of word representations in vector space. In Bengio, Y. and LeCun, Y., editors, *1st International Conference on Learning Representations, ICLR 2013, Scottsdale, Arizona, USA, May 2-4, 2013, Workshop Track Proceedings*.

Mikolov, T., Karafiát, M., Burget, L., Černocký, J., and Khudanpur, S. (2010). Recurrent neural network based language model. In *INTERSPEECH*.

Mirzadeh, S., Farajtabar, M., Li, A., and Ghasemzadeh, H. (2019). Improved knowledge distillation via teacher assistant: Bridging the gap between student and teacher. *CoRR*, abs/1902.03393.

Mukherjee, S. and Awadallah, A. H. (2019). Distilling transformers into simple neural networks with unlabeled transfer data.

Papamakarios, G. (2015). Distilling model knowledge (MSc thesis). *arXiv*, abs/1510.02437v1.

Radford, A., Narasimhan, K., Salimans, T., and Sutskever, I. (2018). Improving language understanding by generative pre-training. *URL https://s3-us-west-2. amazonaws. com/openai-assets/researchcovers/languageunsupervised/language understanding paper. pdf*.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., and Sutskever, I. (2019). Language models are unsupervised multitask learners. *OpenAI Blog*, 1(8):9.

Romero, A., Ballas, N., Kahou, S. E., Chassang, A., Gatta, C., and Bengio, Y. (2015). Fitnets: Hints for thin deep nets. In *In Proceedings of ICLR*.

Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1986). *Learning Internal Representations by Error Propagation*, page 318âĂŞ362. MIT Press, Cambridge, MA, USA.

Sanh, V., Debut, L., Chaumond, J., and Wolf, T. (2019). DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter.

Sau, B. B. and Balasubramanian, V. N. (2016). Deep model compression: Distilling knowledge from noisy teachers. *arXiv*, abs/1610.09650.

Shi, X., Padhi, I., and Knight, K. (2016). Does string-based neural MT learn source syntax? In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1526–1534, Austin, Texas. Association for Computational Linguistics.

Sucik, S. (2019). Pruning BERT to accelerate inference. https://blog.rasa.com/pruning-bert-to-accelerate-inference/.

Sutskever, I., Vinyals, O., and Le, Q. V. (2014). Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pages 3104–3112.

Tang, R. and Lin, J. (2019). Natural language generation for effective knowledge distillation.

Tang, R., Lu, Y., Liu, L., Mou, L., Vechtomova, O., and Lin, J. (2019). Distilling task-specific knowledge from BERT into simple neural networks. *arXiv*, abs/1903.12136.

Tenney, I., Das, D., and Pavlick, E. (2019a). BERT rediscovers the classical NLP pipeline. In *ACL*.

Tenney, I., Xia, P., Chen, B., Wang, A., Poliak, A., McCoy, R. T., Kim, N., Van Durme, B., Bowman, S., Das, D., et al. (2019b). What do you learn from context? probing for sentence structure in contextualized word representations. In *7th International Conference on Learning Representations, ICLR 2019*.

Tsai, H., Riesa, J., Johnson, M., Arivazhagan, N., Li, X., and Archer, A. (2019). Small and practical BERT models for sequence labeling. In *EMNLP/IJCNLP*.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.

Wang, A., Singh, A., Michael, J., Hill, F., Levy, O., and Bowman, S. (2018). GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 353–355, Brussels, Belgium. Association for Computational Linguistics.

Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., and Brew, J. (2019). Huggingface's transformers: State-of-the-art natural language processing. *ArXiv*, abs/1910.03771.

Yu, S., Kulkarni, N., Lee, H., and Kim, J. (2018). On-device neural language model based word prediction. In *Proceedings of the 27th International Conference on Computational Linguistics: System Demonstrations*, pages 128–131, Santa Fe, New Mexico. Association for Computational Linguistics.