Applied Deep Learning Final Report

As part of exercise 3 we have written a report containing an informative summary about our implemented *Keyword-Extractor*.
We have decided on taking on the problem of “Keyword Extraction” with the project type “Bring your own method”.
This subfield of Natural Language Processing has been chosen as it touches on various topics such as word embedding, text analysis/semantics, translation, summarization, etc. which are of big interest for future work.

General Information

- The goal of this project was to create a model which is able to predict keywords from a limited size input text.
  Keyword prediction in the traditional sense usually depends on bigger input sizes as semantic meaning can be more easily transcribed if more information is contained within the input.
- Considering the fact that most personal related data nowadays sent is through social media,
  these platforms contain lots of information waiting to be tapped into. As a Business Informatics student the dataset of Tweets [1] is of particular interest as it could lend insight into how one could use publicly available data for marketing/business strategy purposes. The twitter dataset was gathered by the linked study and contains around 41 million unprocessed tweets. Important to note is that tweets were removed that contained multiple hashtags, hashtags at the end or were part of a conversation and not a standalone tweet which reduced the amount of tweets to 110k.
  This way only tweets which included a single hashtag in a semantically natural sentences were picked for the study.
  Manual random evaluation has shown that in 90% of the cases the found hashtags fit well as keyphrases.
  This dataset has been preprocessed in some way or another (remove non-latin words, special characters, etc).
  Due to the sheer amount of data one needs to analyze to be able to find meaningful structures within, sophisticated algorithms are necessary which is why Deep Learning poses an interesting opportunity.
- Having heard that Decoder-Encoder RNNs can be used to translate sentences from one language to another in the course *Applied Deep Learning*, we have wanted to see if this could be used to do some sort of semantic keyword extraction. This project is based on the PyTorch Tutorial for sequence to sequence Networks and tries to *translate* tweets to their respective keywords.
  f
- We have created a Twitter Hashtag Extractor/Suggestor, which is able to suggest keywords based on a short text with limited size (like on Twitter, instagram, etc.).
  We compared different kinds of Neural networks by trying out different parameters and network architectures.
  Using an Encoder-Attention Decoder RNN reflecting the state-of-the-art proved the most successfull.
- After trying out a few different kinds of datasets, it became observable that keyword extraction was highly domain specific. Due to this we have focused on the Twitter Dataset found in the following chinese paper ([1]). Another thing that can be observed, is that, even though we reach a respectable prediction accuracy on the validation dataset (testTweet-keyword.txt) after training only on the training dataset (trnTweet-keyword.txt), it does not work ideally for own formulated tweets. It seems that the gathered data seems to have a specific lingo in common, which the Neural Network is able to detect within the training and validation dataset.
- Only looking at the Tweets [1] dataset we can say that Deep learning works pretty well for **this** kind of keyword extraction problem as it allows to make assumptions and find underlying structures not visible to the human eye. Looking at the bigger picture though, one must question the meaningfulness of the found model. Thus it can be said that Deep Learning proves useful for keyword extraction if one keeps the domain specific limitations in mind.
- The created embedding simply uses a self defined language dictionary which maps words to indices and vice versa.
  If we were to do the project again we would use a pre trained embedding which allows semantically similar words to be placed close to each other and thus carry more meaning.

Error Metric

To evaluate how well our model works we will see if our model classifies the correct keywords in a pool of a maximum 60 words. 60 was used as the maximum length of a Tweet is 280 characters (140 pre update) and the average characters per word are 4.79 (http://norvig.com/mayzner.html; 7.69 if only counting distinct words).

The achieved performance metrics used in the above mentioned chinese paper *Keyphrase Extraction Using Deep Recurrent Neural Networks on Twitter* (see Exercise 1 README) were:

	Precision	Recall	F1-score
Joint Layer RNN	80.74%	81.19%	80.97%

For their Joint Layer RNN they use more sophisticated deep recurrent neural networks, which jointly process keyword ranking, keyphrase generation, and keyphrase ranking and use word embeddings which contain semantic meaning.
This combined with the fact that the field of Deep Learning and especially Keyword Extraction was previously unbeknownst to me, made for an interesting challenge to see how well a more simple network would fare.

For this project we define the error metric as the amount of correctly predicted keywords divided by the amount of actual keywords.
Training data Example:

- Sentence = *I've been having a big bang theory marathon today courtesy of my DVR. I would love to find a real-life Leonard. I'm in Crushville.*
- Keywords = *big bang theory* (3 keywords)
- Prediction = *the big bang* (2 correct keywords)
  -> correctly predicted percentage = 0,66

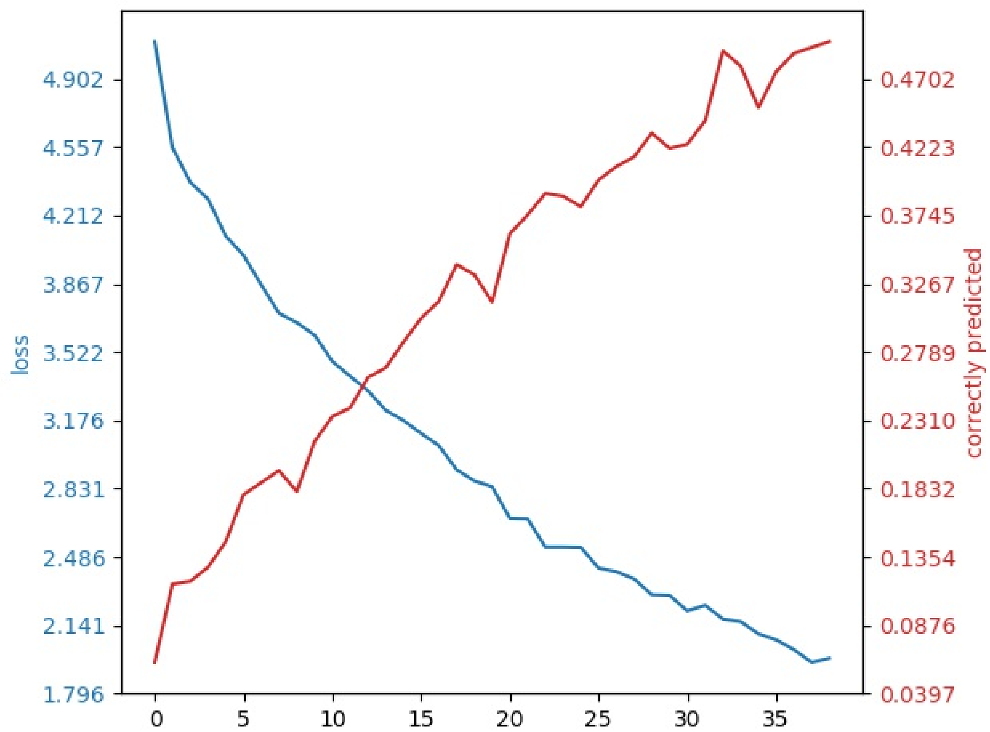
Error metric target

Considering the fact that we not only try to find one of the actual keywords, but all of them, we have set our correctly predicted percentage target to **0,3.** Thus we are happy if we are able to correctly predict 30 percent of the actual keywords (i.e. 100 sentences with 3 keywords each: try to correctly predict around 100 keywords).

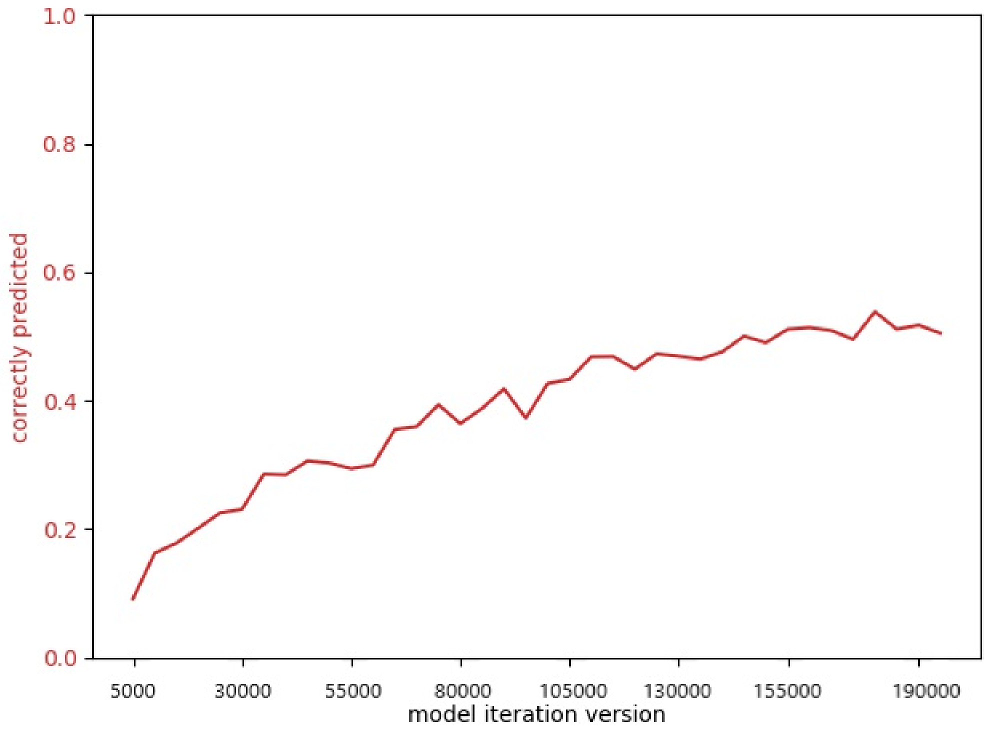
Error metric achieved

Much to our surprise we were able to achieve correctly predicted percentage values of over 50 percent on the validation dataset. This is after running it on the training set for close to 200.000 iterations which is approximately twice the size of the training dataset. One iteration in this case means that one line of the training dataset was randomly chosen.

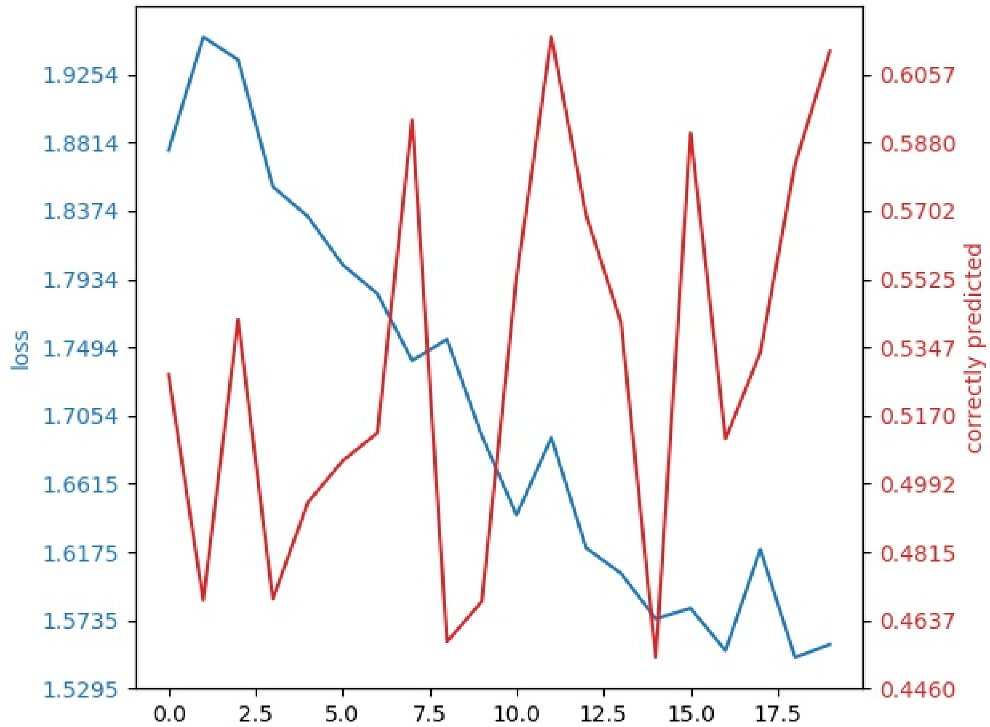
During training we have evaluated and plotted the loss as well as the error metric on the training dataset. We have decided to call it quits after 200.000 iterations (save model every 5000 iterations -> 40 models) to ensure that it would not overfit to our training data.



Now looking at the error metric on the validation set we can see that this seems to similarly progress and converge after a certain point at which self defined early stopping kicked in.



Training the model for another 100.000 iterations (save model every 5000 iterations -> 20 models) seems to have decreased the loss even further on the training dataset. Looking at the correctly predicted percentage on the validation dataset below, we see that it seems to oscillate around 0,53 (min: 45%, max 60%). Thus we say that we have achieved an error metric of above 50 percent on our validation dataset.



Trying out a few examples ourself we see that this unfortunately does not seem to work too well with self formulated sentences which do not fit within Twitter culture. This could be explained by the fact that even though the training and validation datasets are different, they resemble each other in styling and lingo.

This could be ameliorated by gathering more data, finetuning the neural network or letting it train even longer. Another way to improve this, would be to use some other form of embedding which places semantically close words next to each other in a vector space. GoogleNews-vectors-negative300.txt contains 3 million words with 300 features each which has already been trained with Google News data (100 billion words; https://code.google.com/archive/p/word2vec/). Simply converting the file from binary to txt using gensim (see preprocessing in original repository) took 30 mins and resulted in a 11GB file text; this huge dimensionality is why it was skipped for this project.

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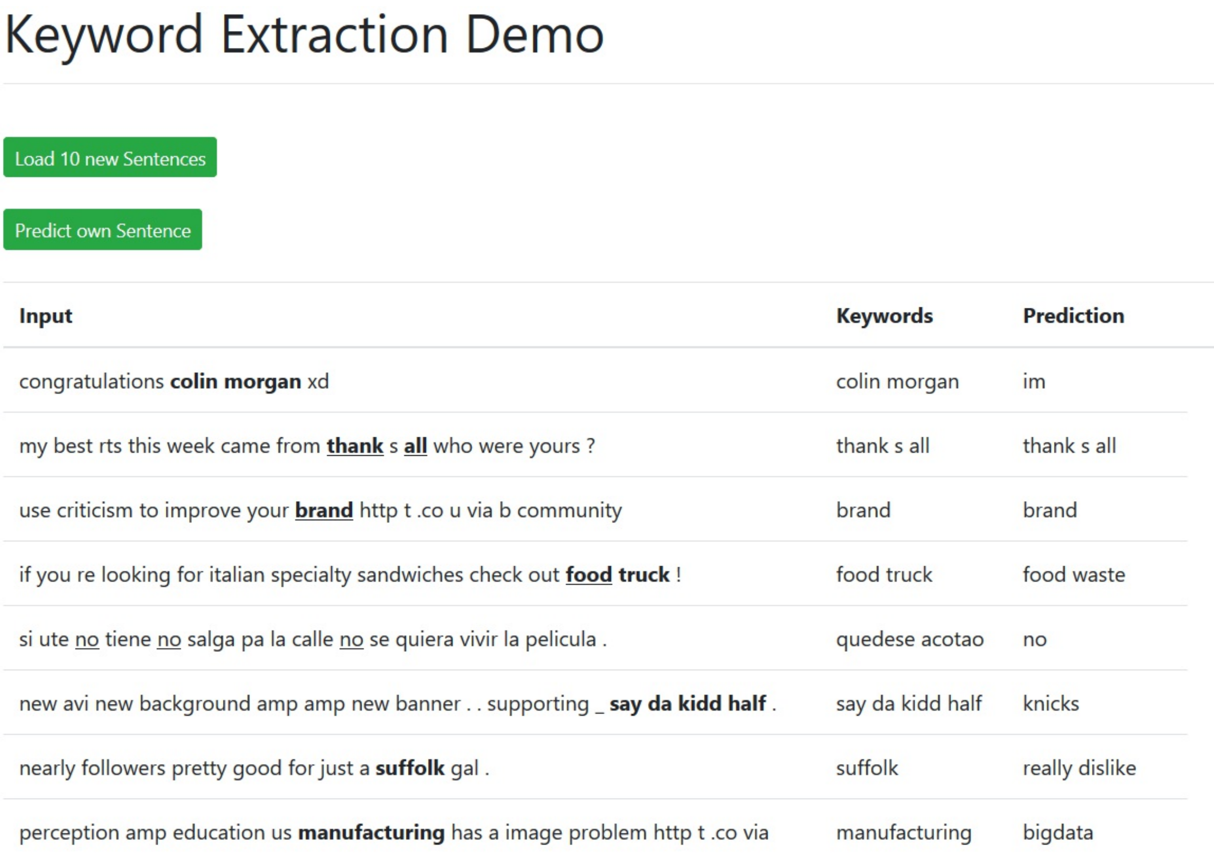
Project structure & How to

- src/settings_configuration.py

Contains all the necessary parameters which were changed/finetuned and information to try out and test this project.
To run a short **demo** showing a short visualization and analysis on the test dataset (testTweet-keyword.txt) simply **run the main method after setting the directory** in line 4 of settings_configuration.py. A **prerequisite** for this is, that there exists a pre-trained model to load (see parameters MODEL_ITERATIONS_VERSION, date_folder). To try it out with my pretrained model, **copy the content of this folder** (OneDrive Link (https://1drv.ms/u/s!ApPEwo6udEbQhe0K-FGEXV49RM4z8w?e=o0Lpdo); >150MB which is why it cannot be pushed onto Git) into the /models/2019-12-18-0349 directory.

Some of the parameters which can be tried out are as follows.

- SERVER_MODE: allows us to run a frontend demo by calling *npm run serve* within the client folder and *python src/main.py*.
  This will create the following interface on *http://localhost:8080/* :



Keyword Extraction Demo

Load 10 new Sentences

Predict own Sentence

Input	Keywords	Prediction
congratulations **colin morgan** xd	colin morgan	im
my best rts this week came from **thank** s **all** who were yours ?	thank s all	thank s all
use criticism to improve your **brand** http t .co u via b community	brand	brand
if you re looking for italian specialty sandwiches check out **food truck** !	food truck	food waste
si ute no tiene no salga pa la calle no se quiera vivir la pelicula .	quedese acotao	no
new avi new background amp amp new banner . . supporting _ **say da kidd half** .	say da kidd half	knicks
nearly followers pretty good for just a **suffolk** gal .	suffolk	really dislike
perception amp education us **manufacturing** has a image problem http t .co via	manufacturing	bigdata

- TRAIN: defines if we start training or start testing our model

Training specific:

- NEW_MODEL: lets us keep training a model instead of starting from new
- EVALUATE_ON_TRAINING_WHILE_TRAINING: prints out evaluation analysis on training dataset during training

```
Started Training_______________________________________
11m  9s (- 1105m  8s) ( 5000 1%) Loss: 5.0906 Train eval score = 0.0615 (254/4131)
22m 19s (- 1094m 12s) (10000 2%) Loss: 4.5539 Train eval score = 0.1164 (509/4373)
33m 27s (- 1081m 54s) (15000 3%) Loss: 4.3795 Train eval score = 0.1183 (505/4268)
44m 35s (- 1070m 13s) (20000 4%) Loss: 4.2944 Train eval score = 0.1282 (531/4142)
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.
.
415m 36s (- 707m 38s) (185000 37%) Loss: 2.0175 Train eval score = 0.4880 (1565/3207)
426m 54s (- 696m 32s) (190000 38%) Loss: 1.9526 Train eval score = 0.4921 (1527/3103)
438m 18s (- 685m 32s) (195000 39%) Loss: 1.9734 Train eval score = 0.4962 (1519/3061)
```

Testing/Evaluation specific:

- EVALUATE_ON_TESTING: lets us define if we want to evaluate on training (trnTweet-keyword.txt) or validation (testTweet-keyword.txt) dataset during our testing (see TRAIN = FALSE)
- TEST_EVALUATION_MODE: Try out different modes (values 1 to 4) to see the project in action. Except for Mode 4 all can be run from the default settings without any extra steps necessary (pre-trained model required).

```
 1.   Randomly evaluates some sentences (RANDOM_EVALUATION_AMOUNT) (see pictures/EvalModeRandom.png)
        0 ___________________
        Input              =  i nominate thegrandehipsta ariana rilakkuma contest
        Predicted Keywords =  ariana rilakkuma contest <EOS>
        Actual Keywords    =  ariana rilakkuma contest
        1 ___________________
        Input              =  how to create a social media marketing strategy in easy steps
        Predicted Keywords =  social media marketing <EOS>
        Actual Keywords    =  social media
        2 ___________________
        Input              =  for presidents day we ll be posting a series of videos with great presidential speeches in film
and tv !
        Predicted Keywords =  day <EOS>
        Actual Keywords    =  presidents day

 2.   Compare the loaded model on test dataset                     (see pictures/EvalModeValidationSet.png)
      STARTING EVALUATION ITERATION___________________________________________________________________________
      Sentence:    retweet the tity follow train in my last tweet ! !
      Keywords:    tity follow train
      Prediction:  follow train

      Sentence:    visiting stjohnsshopping this friday ? look out for the smart swaps roadshow ! see where we ll be next
      Keywords:    smart swaps
      Prediction:  smart swaps
      0m 4s (- 0m 40s) (10 10%) Test eval score = 0.5500 (11/20)

 3.   Evaluate User Input                                          (see pictures/EvalModeInput.png)
      STARTING CONSOLE INPUT EVALUATION___________________________________________________________________________
      Please enter input: Trying out a few examples ourself we see that this unfortunately does not seem to work too well
with self formulated sentences which do not fit within Twitter culture.
      Input              =  trying out a few examples we see that this unfortunately does not seem to work too well with self
sentences which do not fit within twitter culture .
      Predicted Keywords =  twitter <EOS>
      Please enter input: After trying out a few different kinds of datasets, it became observable that keyword extraction
was highly domain specific
      Input              =  after trying out a few different kinds of it became that keyword extraction was highly domain
specific
      Predicted Keywords =  gold <EOS>

 4.   Compare different models on test dataset (needs to let the model train for multiple epochs / iterations; was used to
create the plots)
```

Interesting Findings

Even though we did not use any form of true semantic embedding (like word2vec, GloVe),
the neural network seems to have picked up on underlying information which sometimes
allows it to predict words close in meaning to the actual keywords.
These sometimes fit even better than the actual keywords.

Some examples of this are:

- ```
  1m 25s (- 0m 21s) (4000 80%) Test eval score = 0.5123 (1000/1952)
      Sentence:    my comments about oprah s no phone zone campaign
      Keywords:    no
      Prediction:  android
  ```
- ```
  0m 10s (- 0m 24s) (300 30%) Test eval score = 0.5654 (108/191)
      Sentence:    the rumours of samsung s potential acquisition of blackberry won t abate
      Keywords:    blackberry
      Prediction:  samsung
  ```
- ```
  Sentence:    pakistan army deployed in islamabad on request of district administration
  Keywords:    islamabad
  Prediction:  pakistan
  ```

This even seems to hold true for insider knowledge within a certain topic.
In the following case the neural networks seems to have learned that geminis and lions seem to be similar within the astrology world.
(Or at least come up in similar contexts.)

Input	Keywords	Prediction
when a gemini likes you they can't wait for ou to make the first move. They'll make their move first	gemini	lions
  ```

Work Breakdown Structure

As can be seen in the following table, a lot of time went into preparation and trying to understand the problem at hand. This is to be expected when researching a new topic for the first time. More time than necessary was spent on this, but this was due to own interest. For future work it would be interesting to see, how well a project progresses if one starts the implementation without much background knowledge. Implementing the Network and finetuning it took less time than estimated, but this is due to the fact that this was cut short as the scope of the project has already become too large. All in all the project was a lot of fun and proved very successful as an introduction to Deep Learning.

Task	Time estimate	Actual time
Find topic and create plan	10h	25h
Understand Papers		10h
Dataset collection + preparation	5h	2h
Network design + implementation	20h	18h
Training + finetuning	15h	13h
Building application	5h	6h
Report + presentation	*14h	10h
Lecture	*16h	14h
	3 ECTS + **10h**	3 ECTS + **23h**

* taken from the lecture TISS website

References

[1] Wang, Yang et al. (2016). Keyphrase Extraction Using Deep Recurrent Neural Networks on Twitter. 836-845. 10.18653/v1/D16-1080.

[2] Basaldella, Marco et al. (2018). Bidirectional LSTM Recurrent Neural Network for Keyphrase Extraction. *IRCDL*.

[3] Meng, Rui et al. (2017). Deep Keyphrase Generation. 582-592. 10.18653/v1/P17-1054.

[4] Dabiri, Sina (2018). Tweet-Classification-Deep-Learning-Traffic. Github repository: https://github.com/sinadabiri/Tweet-Classification-Deep-Learning-Traffic

[5] Johnson, Rie & Zhang, Tong. (2015). Semi-supervised Convolutional Neural Networks for Text Categorization via Region Embedding. Advances in neural information processing systems. 28. 919-927.

[6] Yang, Zichao et al. (2016). Hierarchical Attention Networks for Document Classification. *HLT-NAACL*.