Project Report

Natural Language Inference (RepEval 2017)

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Introduction: RepEval 2017 shared task [1] was focused on natural language inference. The prime goal was to build model which can transform sentences into fixed-length vector representations and reason using those representations. So, the task was to evaluate natural language understanding based on classified problem over sentence pairs. There are three classes of sentences in the dataset which are: Neutral, Contradiction and Entailment.

Dataset: The shared task features a new, dedicated dataset that spans several genres of text. The dataset is Stanford Natural Language Inference (SNLI) style corpus [2]. The shared task includes two evaluations, a standard in-domain (matched) evaluation in which the training and test data are drawn from the same sources, and a cross-domain (mismatched) evaluation in which the training and test data differ substantially.

Dataset has 393k sentence pairs in training set, 9815 sentence pairs in matched testing set and 9843 sentence pairs in mismatched testing set.

Baseline: Long Short-Term Memory (LSTM) is used as baseline model.

Description of the model is displayed in the following table.

| Properties | Value |
|------------------------|---------------------|
| LSTM | size = 128 |
| Dropout rate | 0.2 |
| Recurrent dropout rate | 0.2 |
| Activation function | sigmoid |
| Loss | binary_crossentropy |
| Optimizer | adam |
| Metrics | Accuracy |
| Batch size | 128 |

| Number of epochs | 10 |
|-------------------------|-----|
| Maximum sequence length | 120 |

Dataset used:

Training instances = 50000 sentence pairs (40000 for training and 10000 for validation)
Testing instances = 9815 sentence pairs from matched and 9843 sentence pairs from mismatched data set.

Dataset Processing: First, sentence pairs are concatenated to make one line. Then, all the sentence pairs are converted to sequence. After that, those sequences are converted into 2D array, padded with maximum sequence length.

Result:

Matched Accuracy = 68.8% Mismatched Accuracy = 68.9%

Multilayer Perceptron: In this model, one hidden layer is used in between input and output layer.

Description of the model is displayed in the following table.

| Input Layer | |
|---------------------|-------|
| Properties | Value |
| Input dimension | 1000 |
| Density | 512 |
| Activation function | relu |

| Hidden Layer | |
|---------------------|---------|
| Properties | Value |
| Input dimension | 784 |
| Density | 64 |
| Activation function | softmax |

| Output Layer | |
|---------------------|---------|
| Properties | Value |
| Dropout rate | 0.5 |
| Density | 4 |
| Activation function | softmax |

| Other Properties | |
|------------------|---------------------|
| Properties | Value |
| Loss | binary_crossentropy |
| Optimizer | adam |
| Metrics | accuracy |

Dataset used:

Training instances = 50000 sentence pairs (40000 for training and 10000 for validation)
Testing instances = 9815 sentence pairs from matched and 9843 sentence pairs from mismatched data set.

Dataset Processing: First, sentence pairs are concatenated to make one line. Then, all the sentence pairs are converted to sequence. After that, those sequences are encoded using one-hot encoding method.

Result:

Matched Accuracy = 71.8% Mismatched Accuracy = 72.0%

Character Level Encoding Decoding: This model implements a basic character-level mapping of sequence to sequence. For each sentence pair the premises are being translated character-by-character.

Model Description: Model starts with input sequences from one premise and corresponding target sequences from the other premise. An encoder LSTM converts input sequences to 2 state vectors. A decoder LSTM is trained to turn the target sequences into the same sequence but offset by one timestep in the future.

Dataset used: This model consumes a lot of time to run. So, different chunks of data used for training and testing. The variations of dataset are displayed in the following table.

| Training Set | | | |
|-----------------------------|-------------------------|-----------------------|----------------------------|
| Total Sentence Pairs | Neutral Sentence | Contradiction | Entailment Sentence |
| | Pairs | Sentence Pairs | Pairs |
| 2100 | 700 | 700 | 700 |
| 2700 | 900 | 900 | 900 |
| 3300 | 1100 | 1100 | 1100 |
| 3900 | 1300 | 1300 | 1300 |
| 4500 | 1500 | 1500 | 1500 |

| Testing Set | | | |
|-----------------------------|------------------|-----------------------|----------------------------|
| Total Sentence Pairs | Neutral Sentence | Contradiction | Entailment Sentence |
| | Pairs | Sentence Pairs | Pairs |
| 300 | 100 | 100 | 100 |
| 900 | 300 | 300 | 300 |
| 1500 | 500 | 500 | 500 |
| 2100 | 700 | 700 | 700 |
| 2700 | 900 | 900 | 900 |

Result:

| Training Sentence Pair | Matched Sentence Pair | Mismatched Sentence Pair | Number of Epochs | Matched Accuracy | Mismatched Accuracy |
|------------------------------|-----------------------------|-----------------------------|---------------------|---------------------|------------------------|
| 2100 | 300 | 300 | 5 | 0.0 | 0.0 |
| | | | 10 | 2.2 | 1.6 |
| | | | 15 | 2.6 | 2.1 |
| | | | 20 | 2.9 | 2.2 |
| 2700 | 900 | 900 | 5 | 2.1 | 2.5 |
| | | | 10 | 2.7 | 2.6 |
| | | | 15 | 3.1 | 2.9 |
| | | | 20 | 3.2 | 2.9 |
| 3300 | 1500 | 1500 | 5 | 2.0 | 2.1 |
| | | | 10 | 2.5 | 2.3 |
| | | | 15 | 2.8 | 2.7 |
| | | 20 | 3.0 | 3.1 | |
| 3900 | 2100 | 2100 | 5 | 0.0 | 1.0 |
| | | | 10 | 2.2 | 1.7 |
| | | | 15 | 2.9 | 2.1 |
| | | | 20 | 3.2 | 2.5 |
| 4500 | 2700 | 2700 | 5 | 1.2 | 1.5 |
| | | | 10 | 2.1 | 1.8 |
| | | | 15 | 2.8 | 2.5 |
| | | | 20 | 3.4 | 3.1 |

From the table above it is obvious that, accuracy increases for more data and more epochs. Even for this small portion of data the model takes much time. So, there is a possibility for better result, if more data are used for more number of epochs.

References:

- [1] <u>https://repeval2017.github.io/shared/</u>
- [2] http://www.nyu.edu/projects/bowman/multinli/