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# Deep Neural Networks with Massive Learned Knowledge: Supplementary Material

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## A Sentiment Classification

### A.1 Transition matrices

$$M_{r=consistent,y=0} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad M_{r=contrastive,y=0} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \quad M_{r=concessive,y=0} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix},$$
$$M_{r=consistent,y=1} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad M_{r=contrastive,y=1} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \quad M_{r=concessive,y=1} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}.$$

In practice we add a small number  $\epsilon = 0.01$  to the matrices for smoothing.

### A.2 Architectures of the clause relation and sentiment networks

The clause sentiment network has the exact same architecture as the base network [Kim, 2014], and the discourse relation network first extracts representations of two input clauses individually using the same convolutional layer architecture, and concatenates the features before feeding into a fully-connected layer. For efficiency we tie the convolutional parameters across all the networks to share the representations, while leaving only the fully-connected layer parameters to be learned separately.

### A.3 Conjunction words

- *Consistent*: as well as; and; because; since; similarly; likewise; also; moreover; furthermore; so; therefore; consequently; hence; thus; meanwhile; in particular; in addition; namely; for example; for instance; then; as a result; besides; in other words; above all
- *Contrastive*: but; however; in contrast; whereas; on the contrary; instead; on the other hand
- *Concessive*: though; although; despite; in spite of; even though; even if; even as

### A.4 Negation and word polarity lexicons

We use Bing Lius Opinion Lexicon <sup>1</sup> for word polarity, which contains around 6,800 polarity-carrying words.

We use the LIWC <sup>2</sup> lexicon of “negate” category for negation words, which includes around 60 words.

## B Experiments

All experiments were performed on a Linux machine with 8 4.0GHz CPU cores, one Tesla K40c GPU, and 32GB RAM. We implemented neural networks on Theano <sup>3</sup>.

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<sup>1</sup><https://www.cs.uic.edu/liub/FBS/sentiment-analysis.html#lexicon>

<sup>2</sup><http://liwc.wpengine.com>

<sup>3</sup><http://deeplearning.net/software/theano>

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## References

[Kim, 2014] Kim, Y. (2014). Convolutional neural networks for sentence classification. *Proc. of EMNLP*.