

# Multitask Learning for Twitter Sentiment Analysis

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## 1. MOTIVATION

- In machine learning, usually we focus on a single task. We optimize our model over a loss or a metric for the task at hand, either using a single model or an ensemble, whose hyperparameters we tune.
- As a result, we ignore information that may be useful, for instance training signals from related tasks.
- **Hypothesis:** We can enable our model to generalize better on the original task, by sharing representations between related tasks.

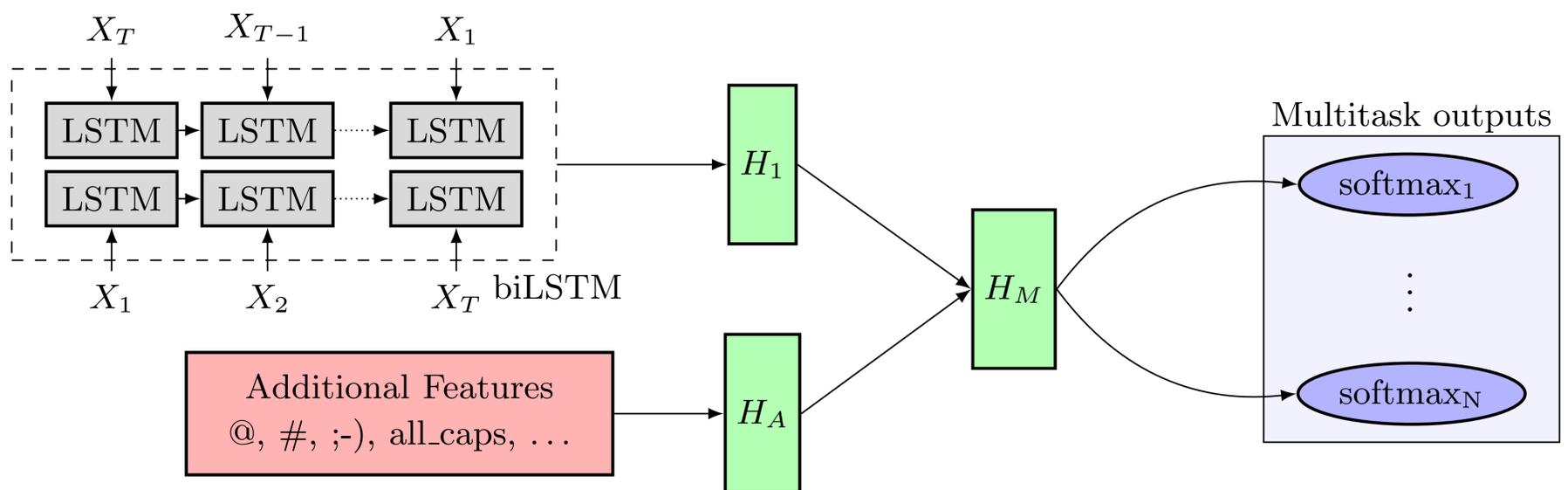


From wax on, wax off. . .



. . . to karate!

## 2. MULTI-TASK LEARNING WITH BiLSTM



The neural network architecture for multitask learning using hard weight sharing between the  $N$  tasks. A bidirectional LSTM is used for learning a tweet representation that can be combined with “Additional Features”. These can be domain-specific features or prior knowledge, are extracted in the preprocessing step and enable the network to integrate additional knowledge.

## 3. THE EXPERIMENTAL FRAMEWORK: TWITTER SENTIMENT CLASSIFICATION

We experiment with two sentiment classification tasks:

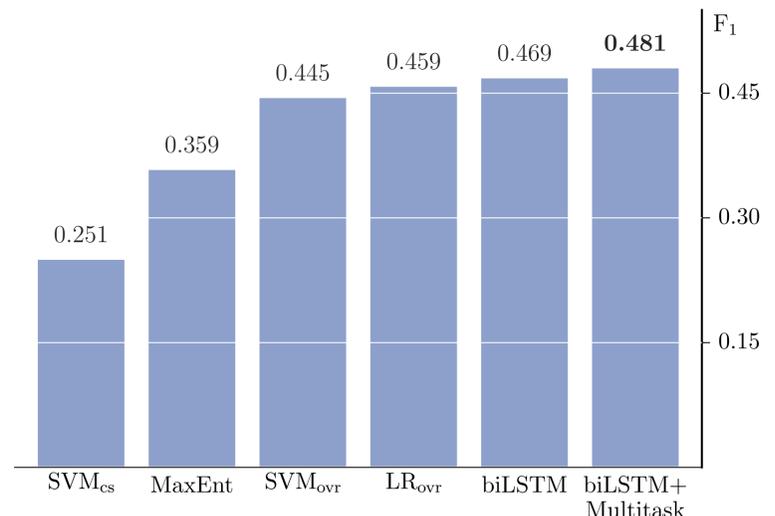
- Fine-grained: VeryPositive, . . . , VeryNegative. The primary task for this work.
- Ternary: Positive, Neutral, Negative

The performance improvements of may be due to:

1. Data Augmentation: Expands the set of training examples
2. Inductive bias: Prefer a hypothesis that performs well across tasks
3. Feature attention focusing: Decrease the weights on noisy features

	nbow	nbow+
SVM <sub>ovr</sub>	0.840	0.714
SVM <sub>cs</sub>	0.946	0.723
LR <sub>ovr</sub>	0.836	0.712
MaxEnt	0.842	0.715
Balikas et al. [1] (SOTA)	-	0.719
biLSTM (single task)	0.827±0.017	0.694±0.04
biLSTM+Multitask	0.786±0.025	<b>0.685±0.024</b>

The scores on macro-averaged mean absolute error. The best (lowest) score is shown in bold and is achieved in the multitask setting with the biLSTM architecture. nbow uses only text (GloVe embeddings), while nbow+ incorporates the “Additional Features”.



$F_1$  scores with nbow+: Multitask learning achieves the best score.

## REFERENCES

- [1] G. Balikas and MR Amini: “TwiSE at SemEval-2016 Task 4: Twitter Sentiment Classification”, SemEval, (2016)
- [2] R. Caruana: “Multitask Learning”, Machine Learning, (1997)
- [3] I. Goodfellow, Y. Bengio and A. Courville: “Deep Learning”, MIT Press, (2016)

Open Source Implementation: <https://github.com/balikasg/sigir2017>

## ACKNOWLEDGEMENTS

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