

Modeling Input Uncertainty in A Neural Network Dependency Parser.

Questions

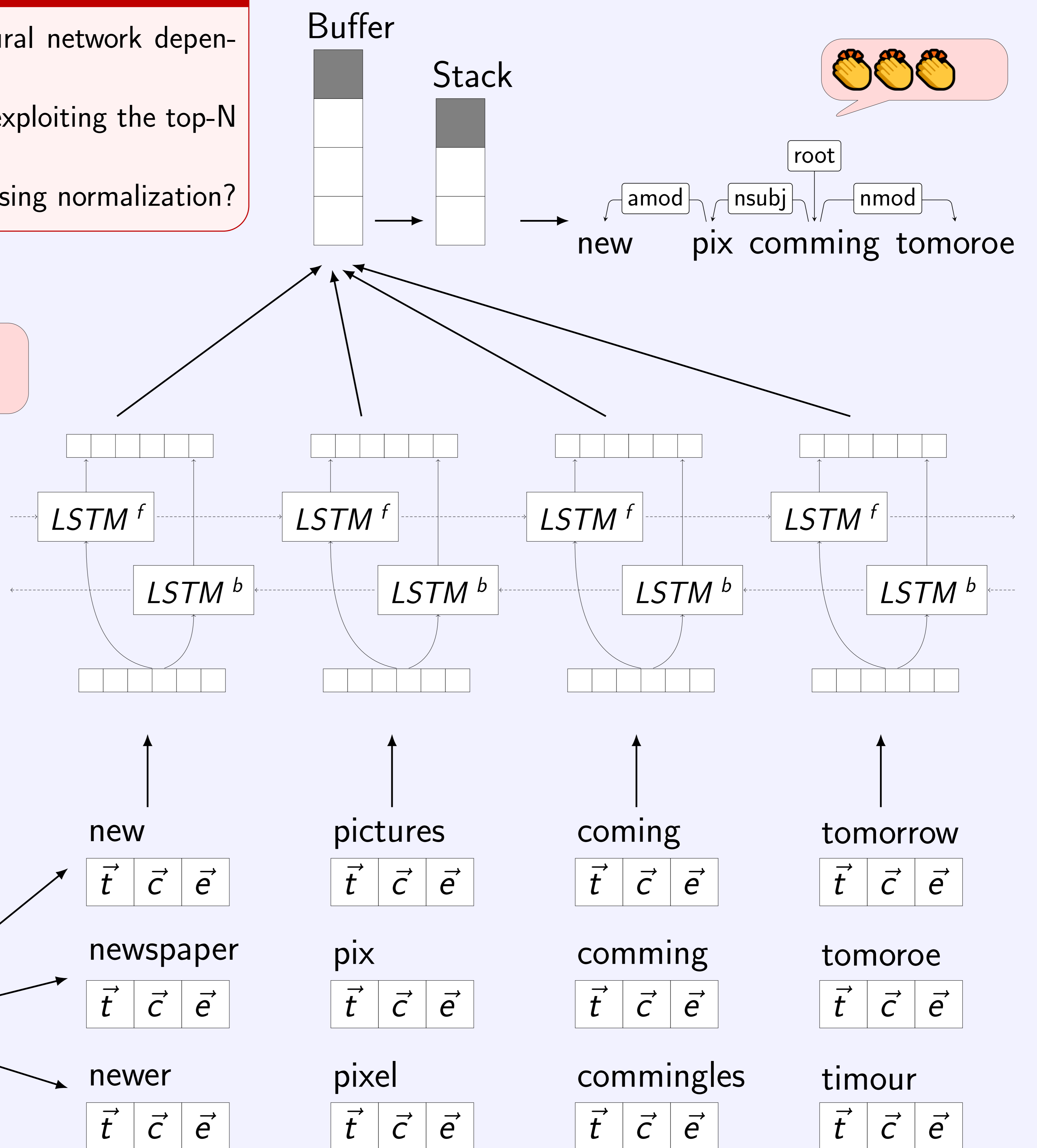
- Is using normalization beneficial for neural network dependency parsers?
- Can we improve parser performance by exploiting the top-N normalization candidates?
- What is the theoretical upperbound of using normalization?

We used the UUParser 2.0: (de Lhoneux et al., 2017)



Try our online demo:
 www.let.rug.nl/rob/monoise

MoNoise



Trebank

- All tweets from Owoputi and LexNorm which are still available
- Tokenization, Normalization, POS tags and dependency structure
- Also version available with predicted normalization
- Guidelines similar to PoSTWITA-UD (Sanguinetti et al., 2018), UD-TwitterAAE (Blodgett et al., 2018) and Twebank v2 (Liu et al., 2018)

Settings

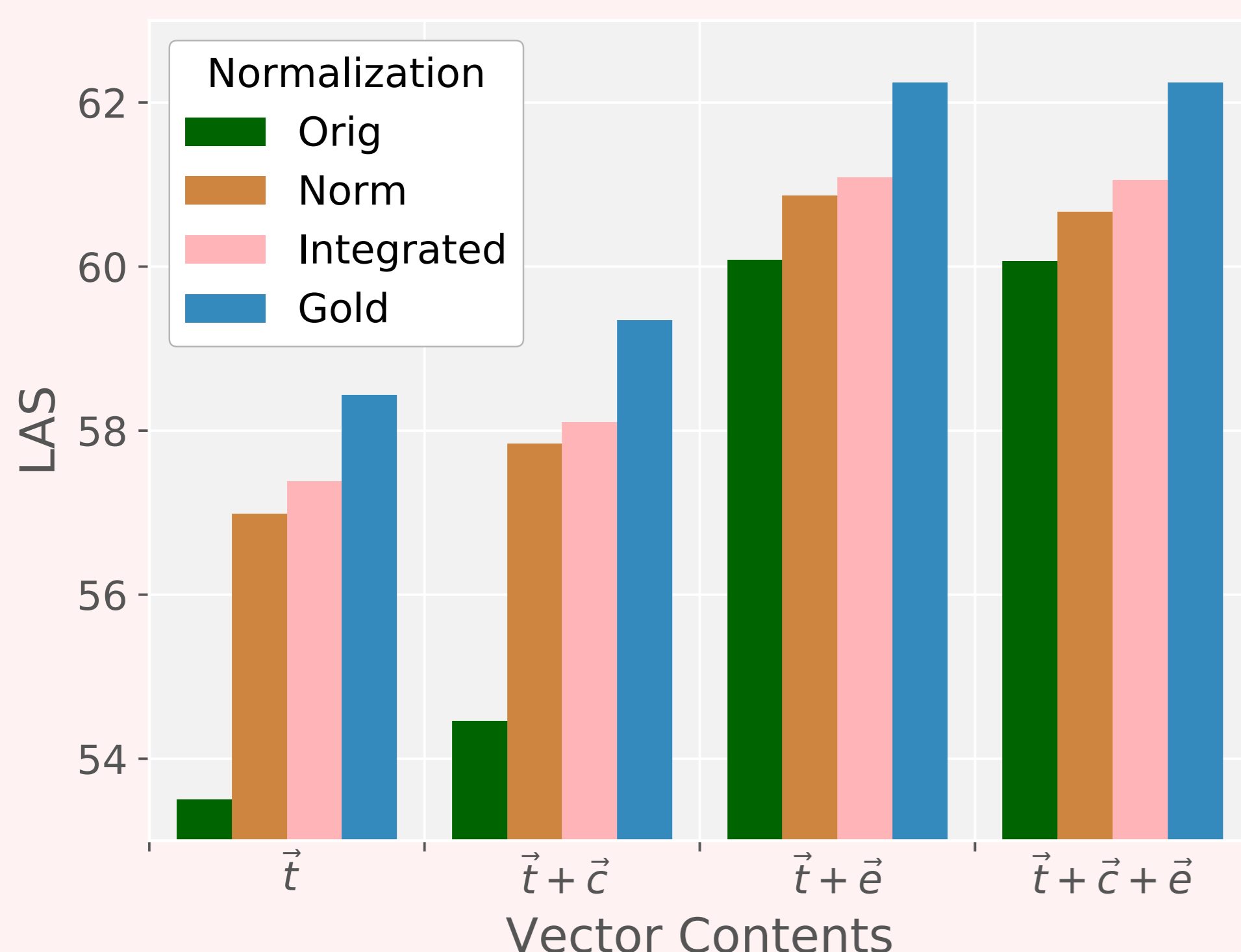
ORIG: $\vec{v}_i = \vec{w}_i$

NORM: $\vec{v}_i = \vec{n}_{i0}$

INTEGRATED: $\vec{v}_i = \sum_{j=0}^n p_{ij} * \vec{n}_{ij}$

GOLD: $\vec{v}_i = \vec{g}_i$

Results



Model	UAS	LAS
ORIG	69.63	59.64
NORM	70.51	61.76*
INTEGRATED	70.62	62.30*
GOLD	70.71	62.33

Conclusions

- * Using normalization directly is useful for dependency parsing, even when exploiting external and character embeddings
- * Integrating normalization results in even higher performance
- * New Twitter treebank
- * Source code:
 www.bitbucket.org/robvander/normpar