Normalizing tweets with edit scripts and recurrent neural embeddings

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Normalizing tweets

Convert tweets to canonical form easy to understand for downstream applications

Examples

`I will c wat i can do`
`I will see what I can do`
`imma jus start puttn it out there`
`I'm going to just start putting it out there`

Approaches

- Noisy-channel-style
- Finite-state transducers
- Dictionary-based
  - Hand-crafted
  - Automatically constructed

Labeled vs unlabeled data

- Noisy-channel:
  $$P(\text{target}|\text{source}) \propto \underbrace{P(\text{source}|\text{target})}_{\text{labeled}} \times \underbrace{P(\text{target})}_{\text{unlabeled}}$$
- Dictionary lookup:
  - Induce dictionary from unlabeled data
  - Labeled data for parameter tuning

Discriminative model

$$\underline{\text{target}}$$

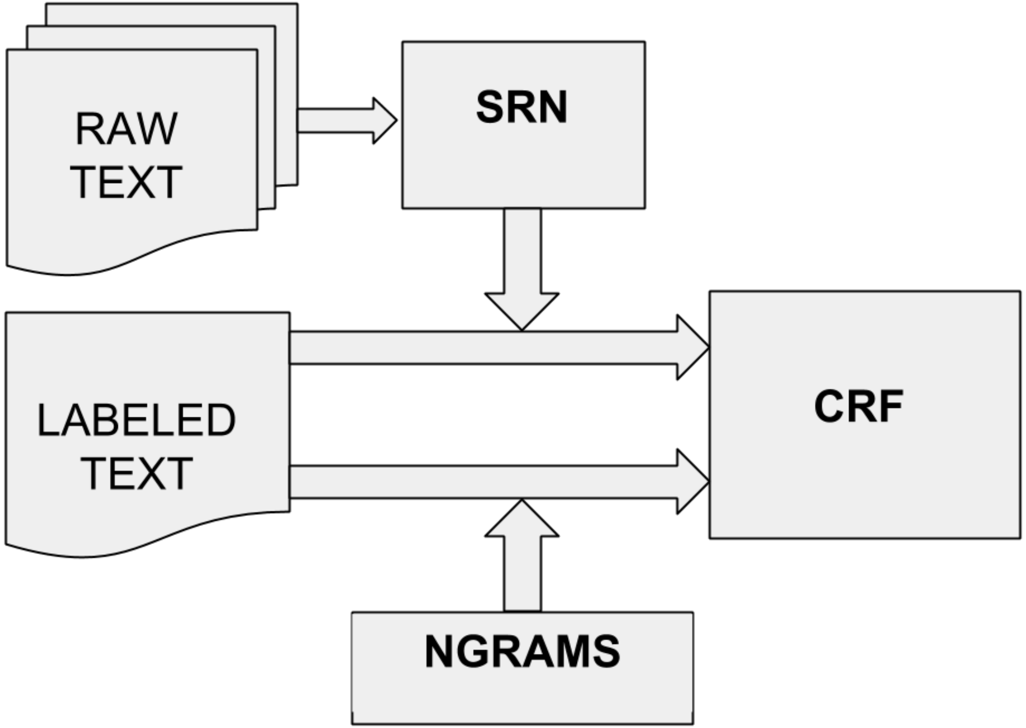
$$=$$

$$\text{argmax}_{\text{target}}\ \mathbf{P}(\mathbf{diff}(\text{source, target}) \mid \text{source})$$

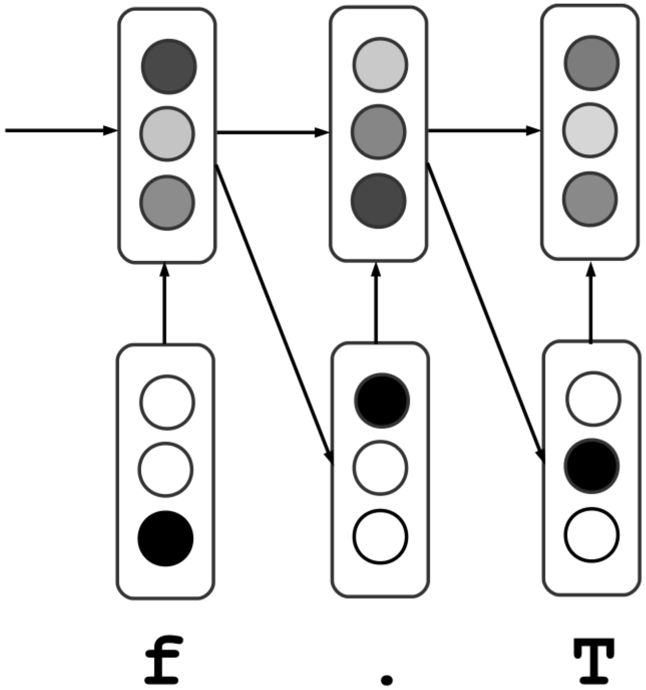
- $\mathbf{diff}(\cdot,\cdot)$ transforms source to target
- $\mathbf{P}(\cdot)$ is a Conditional Random Field

Signal from raw tweets included via **learned text representations.**

Architecture



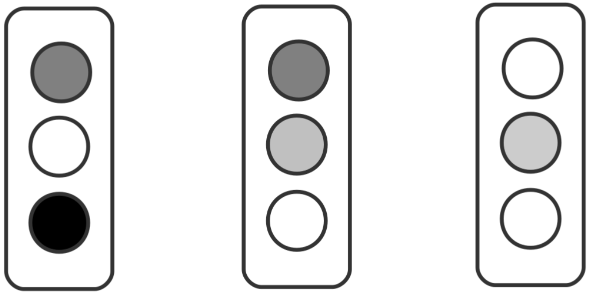
Simple Recurrent Networks



Elman, J. L. (1990). Finding structure in time. *Cognitive science*, *14*(2), 179-211.

Recurrent neural embeddings

- SRN trained to predict next character
- Representation:



- Embed string (at each position) in low-dimensional space

Visualizing embeddings

String	Nearest neighbors in embedding space			
should h	should d	will s	will m	should a
@justth	@neenu	@raven_	@lanae	@despic
maybe	u maybe y	cause i	wen i	when i

diff - Edit script

Input	c	_	w	a	t
diff	DEL	INS(see)	NIL	INS(h)	NIL
Output		see_	w	ha	t

Each position in string labeled with edit op

Features

- Baseline n-gram features

  `c _ w a t c_ _w wa at c_w _wa`

  `wat c_wa _wat c_wat`

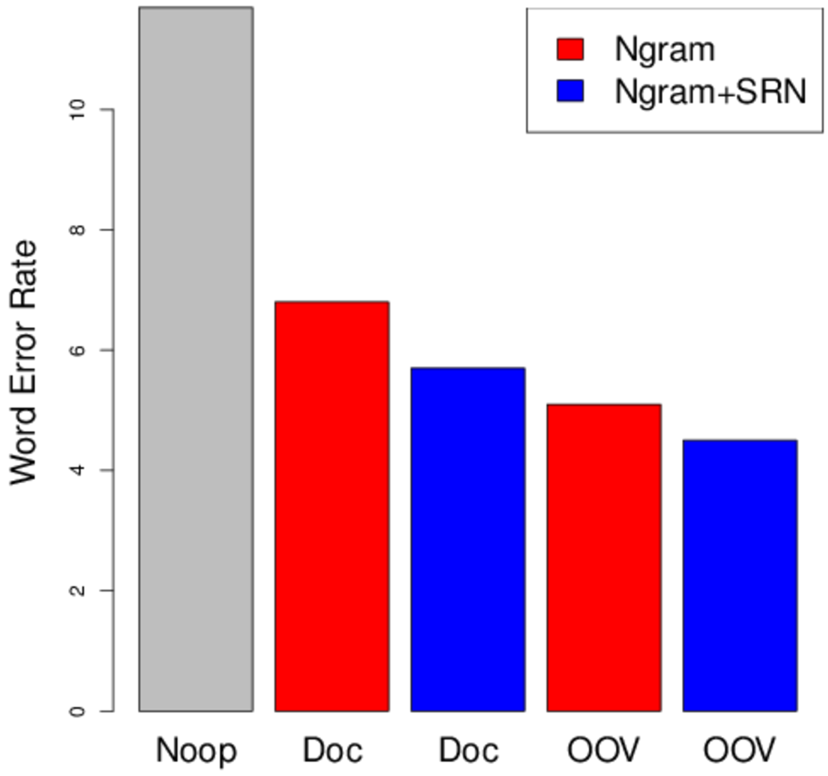
- SRN features
  - 400 MB raw Twitter feed
  - 400 hidden units
  - Activations discretized

Dataset

- Han, B., & Baldwin, T. (2011). Lexical normalisation of short text messages: Makn sens a# twitter. In *ACL*.

- 549 tweets, with normalized versions
- Only lexical normalizations

Results



- **No-op**
  make no changes
- **Doc**
  train on and label whole tweets
- **OOV**
  train on and label OOV-words

Compared to Han & Bo 2012

Method	WER (%)
No-op	11.2
S-dict	9.7
GHM-dict	7.6
HB-dict	6.6
Dict-combo	4.9
OOV NGRAM+SRN	**4.7**

Where SRN features helped

9	cont continued	5	gon gonna
4	bro brother	4	congrats congratulations
3	yall you	3	pic picture
2	wuz what’s	2	mins minutes
2	juss just	2	fb facebook

Conclusion

- **Supervised discriminative** model performs at state-of-the-art with little training data
- **Neural text embeddings** effectively incorporate signal from raw tweets