

Tailoring Continuous Word Representations for Dependency Parsing



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Questions We Want to Answer

- ▶ What kind of embeddings will help dependency parsing (in-domain and out-of-domain)?
- ▶ How can we convert embeddings to parsing features?
- ▶ Are there good intrinsic measures of embedding quality?



Representation Models

▶ BROWN (Brown et al., 1992)

▶ SENNA (Collobert et al., 2011, 2008)

▶ TURIAN (Turian et al., 2010)

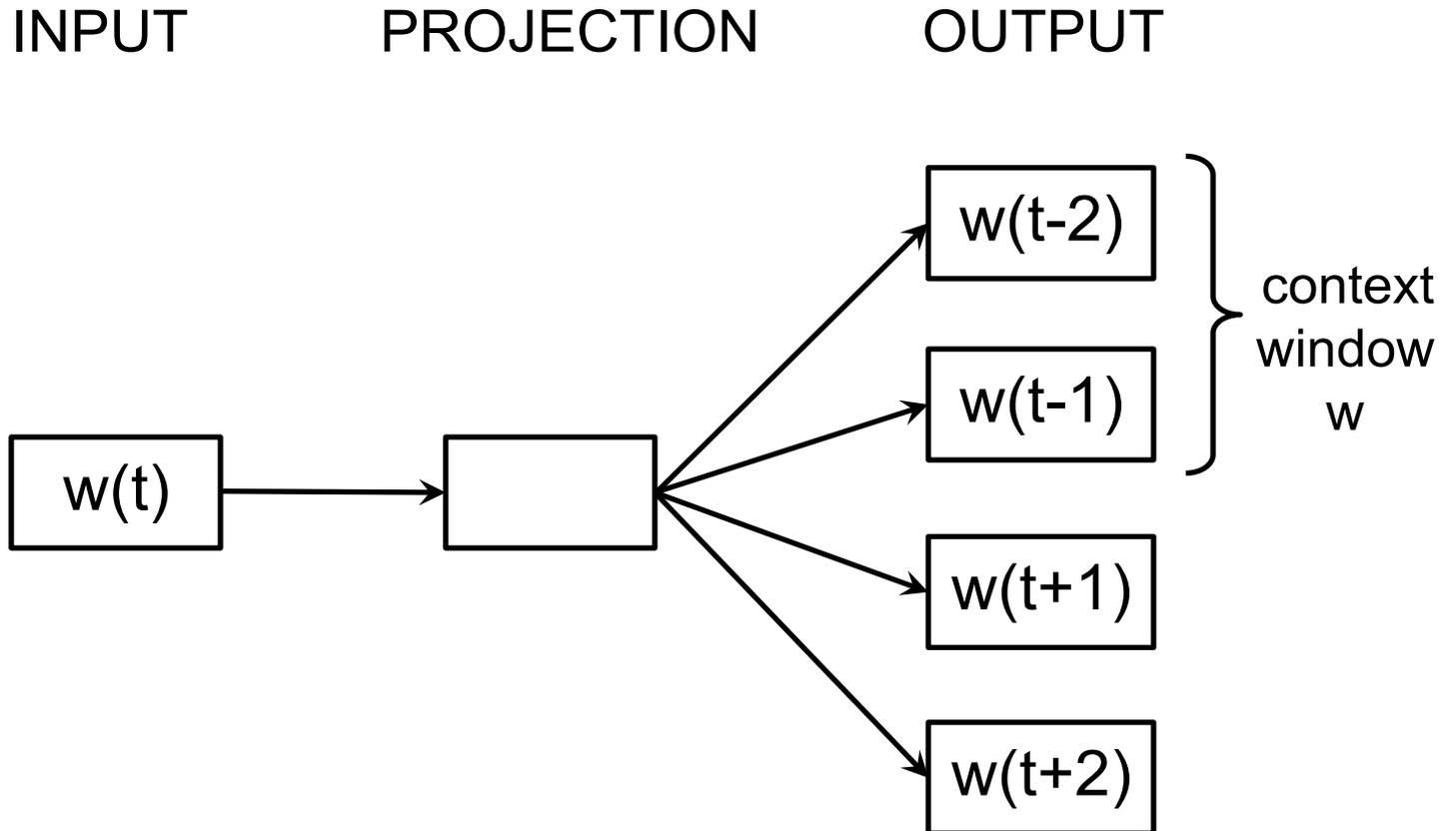
▶ HUANG (Huang et al., 2012)

▶ SKIP (Mikolov et al., 2013)

} discrete

} continuous

SKIP



Few mins. vs. days/weeks/months!!



Syntactically Tailored Embeddings

- ▶ Context window size (SKIP)
 - ▶ Smaller window → syntactic/functional similarity
 - ▶ Larger window → topical similarity

The morning flight at the JFK airport was delayed

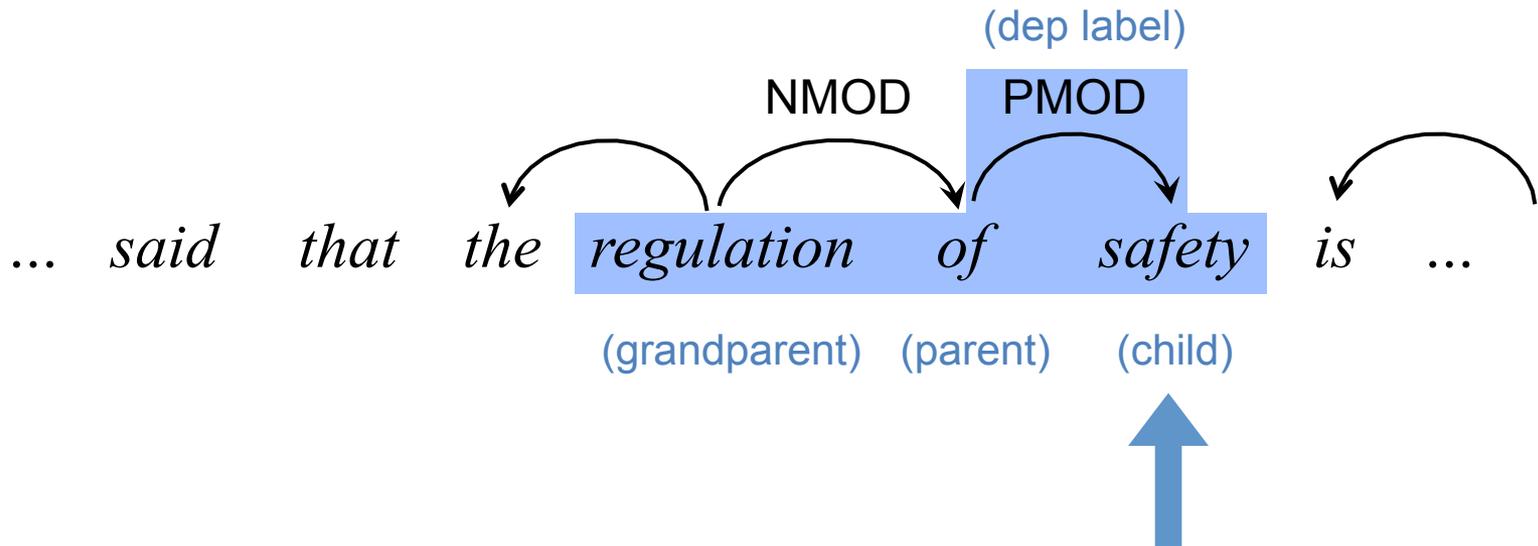
context window

- ▶ Similar effect in distributional representations (Lin and Wu, 2009)



Syntactically Tailored Embeddings

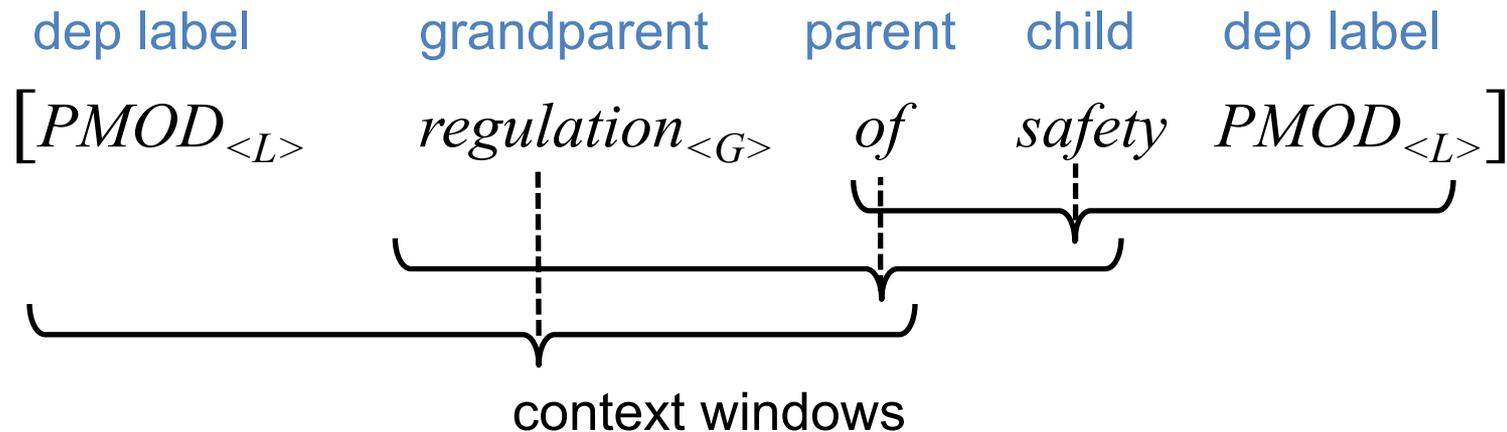
- ▶ Syntactic context (SKIP_{DEP})
 - ▶ Condition on dependency context instead of linear
 - ▶ First parse a large corpus with baseline parser:





Syntactically Tailored Embeddings

- ▶ Syntactic context (SKIP_{DEP})
 - ▶ Condition on dependency context instead of linear
 - ▶ Then convert each dependency to a tuple:



- ▶ Syntactic information in clustering, topic, semantic space models
(Sagae and Gordon, 2009; Haffari et al., 2011; Grave et al., 2013; Boyd-Graber and Blei, 2008; Pado and Lapata, 2007)



Cluster Examples

▶ SKIP, $w = 10$:

[attendant, takeoff, airport, carry-on, airplane, flown, landings, flew, fly, cabins, ...]

[maternity, childbirth, clinic, physician, doctor, medical, health-care, day-care, ...]

[transactions, equity, investors, capital, financing, stock, fund, purchases, ...]



Cluster Examples

▶ SKIP, $w = 1$

[Mr., Mrs., Ms., Prof., III, Jr., Dr.]

[Jeffrey, William, Dan, Robert, Stephen, Peter, John, Richard, ...]

[Portugal, Iran, Cuba, Ecuador, Greece, Thailand, Indonesia, ...]

[his, your, her, its, their, my, our]

[Your, Our, Its, My, His, Their, Her]

[truly, wildly, politically, financially, completely, potentially, ...]



Intrinsic Evaluation

(Finkelstein et al., 2002)

Representation	SIM	TAG
BROWN	–	89.3
SENNA	49.8	85.2
HUANG	62.6	78.1
SKIP, $w = 10$	44.6 	71.5 
SKIP, $w = 5$	44.4	81.1
SKIP, $w = 1$	37.8	86.6
SKIP _{DEP}	34.6	88.3



Topical

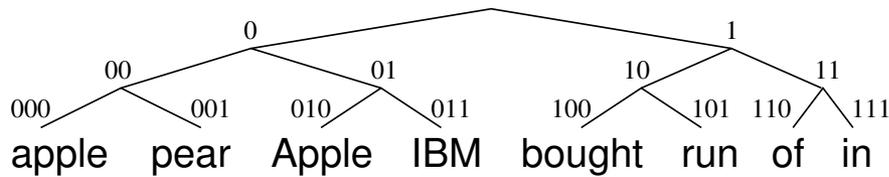


Syntactic/
Functional



Dependency Parsing Features

▶ Brown Cluster Features (Koo et al., 2008):



apple → 00010100010
 {
 prefix4
 {
 prefix6

prefix6	→	110010	000101
prefix4	→	1100	0001
tag	→	VBD	NN

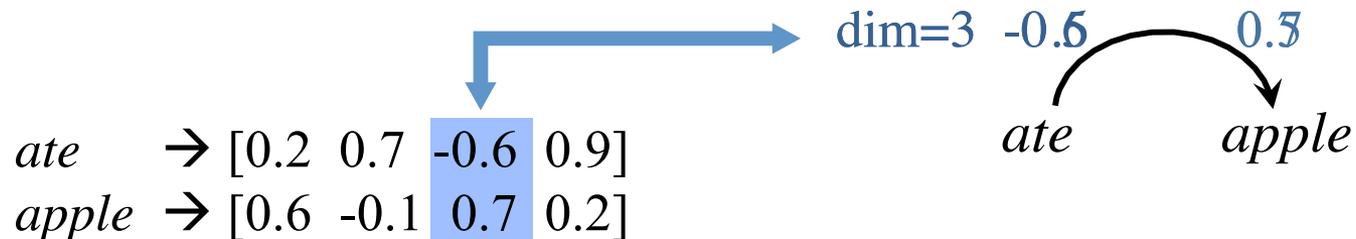
ate *apple*
 (parent) (child)



Dependency Parsing Features

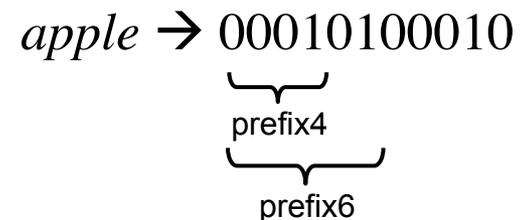
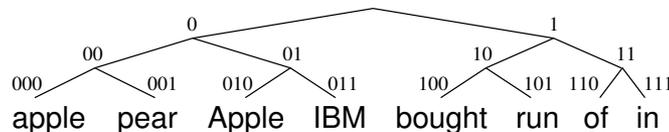
- ▶ Continuous Representation Features:

- ▶ Per-dimension bucket features:



- ▶ Hierarchical clustering (bit string) features:

$linkage(E, \text{'ward'}, \text{'euclidean'})$





Parsing Experiments

- ▶ Setup: MSTParser (2nd order) w/ standard processing
- ▶ Per-dim bucket << Hierarchical clustering features:

System	Test
Baseline	92.0
SENNA (Buckets)	92.0
SENNA (Hier. Clustering)	92.3
HUANG (Buckets)	91.9
HUANG (Hier. Clustering)	92.4



Parsing Experiments

► Main WSJ results:

System	Test
Baseline	91.9
BROWN	92.7
SENNA	92.3
TURIAN	92.3
HUANG	92.4
SKIP	92.3
SKIP _{DEP}	92.7
Ensemble Results	
ALL – BROWN	92.9
ALL	93.0

(faster)

(complementary)



Parsing Experiments

▶ Main Web results:

System	Test Avg (5 domains)
Baseline	83.5
BROWN	84.2
SENNA	84.3
TURIAN	83.9
HUANG	84.1
SKIP	83.7
SKIP _{DEP}	84.1
Ensemble Results	
ALL-BROWN	84.7
ALL	84.9

(faster)

(complementary)



Correlation w/ Intrinsic Metrics

- ▶ Correlation only for variations of a single model

Representation	SIM	TAG	Parsing F1
SKIP, $w = 10$	44.6 	71.5 	92.70 
SKIP, $w = 5$	44.4 	81.1 	92.86 
SKIP, $w = 1$	37.8 	86.6 	92.94 
SKIP _{DEP}	34.6 	88.3 	93.33 



Topical



Syntactic/
Functional



Conclusion

- ▶ Improvements ~ Brown but with faster training
- ▶ Hierarchical clustering >> bucket (per-dim) features
- ▶ Syntactic context helps
- ▶ Intrinsic metrics ~correlate with parsing accuracy

Thank you!



Data (dependency embeddings and features) at:

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