New Embedded Representations and Evaluation Protocols for Inferring Transitive Relations

Point embeddings for words and entit

- Each word w has focus embedding u_w and embedding v_{w}
- Word c (not) in context of word $f \Rightarrow$ want la (small) $u_f v_c \dots$ GloVe, word2vec
- Entities treated like words over multi-toker
 - Young <u>Albert</u> took violin lessons from ...
 - Albert linked to entity ID m. 0jcx
 - Embeddings of m.Ojcx (but not other Alberts) *relativity* become similar

Order embedding (OE) loss

- "x less preferred than y": $x \prec y$
- OE defines $\ell(x, y) = \| \max\{\mathbf{0}, \mathbf{u}_y \mathbf{u}_x\} \|_2^2$
- If $x \prec y$ ($x \not\prec y$) then we want small (large) loss
- Overall loss is sum of

$$\mathcal{L}_{+} = \sum_{x \prec y} \ell_{+}(x, y) = \sum_{x \prec y} \ell(x, y)$$
$$\mathcal{L}_{-} = \sum_{x \not\prec y} \ell_{-}(x, y) = \sum_{x \not\prec y} \max\{0, \alpha - \ell(x \mid y)\}$$
Does not

recognize that violation in one dimension enough

Rectangle losses



Sanitized evaluation protocol

- Give no credit for computing transitive closure
- Sample $L_+ \subset \operatorname{clo}(T)$
- Perturb each $(x, y) \in L_+$ to negative sample (x', y')
- Discard if $(x', y') \in \operatorname{clo}(T)$
- Sample pos dev $D_+ \subset (\operatorname{clo}(T) \setminus \operatorname{clo}(L_+))$
- Discard (x, y) from D_+ if x or y is o.o.v. from $L_+ \cup L_-$
- Sample pos eval $E_+ \subset \operatorname{clo}(T) \setminus (\operatorname{clo}(L_+) \cup \operatorname{clo}(D_+))$
- Perturb and discard as before

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ties	How to represent ty
d context	Points, like entities
	 Entity instance-of type and type s
arge	 Antisymmetry? Transitivity?
	Subspace of \mathbb{R}^{D} [Jameel+2016]
n spans	 Type t represented by D+1 points
	 Minimize nuclear norm of $[t^1 - t^0]$
s) and	• Also $\min_{\{\boldsymbol{e}, \boldsymbol{\tilde{t}}\}} \sum_{t} \sum_{e \in t} \min_{(\lambda_0, \dots, \lambda_D) \in \Delta^{D+t}}$
	 Degeneracies; also does not han

Improved OE loss

$$\ell_{+}(x,y) = \max_{\substack{d \in [1,D] \\ d \in [1,D]}} [u_{y,d} - u_{x,d}]_{+},$$

$$\ell_{-}(x,y) = \min_{\substack{d \in [1,D] \\ d \in [1,D]}} [u_{x,d} - u_{y,d}]_{+},$$
If $x \prec y$, then, for some dimension

Normalize per-instance loss using sigmoid:

$$\ell_+(x,y) = \sigma \left(\begin{array}{c} \psi \max_{\substack{l \in [1,D]}} [u_{y,d} + \Delta_{\max} - \alpha] \\ & \uparrow d \in [1,D] \end{array} \right)$$

Far from convex, but

"Leaky" evaluation protocol

- T = available partial order, clo(T) transitive closure• WordNet has |*T*]=82115, |clo(*T*)|=838073
- Sample positive eval fold $E_+ \subset \operatorname{clo}(T)$
- Sample positive dev fold $D_+ \subset \operatorname{clo}(T) \setminus E_+ \dots 4000$
- Rest learn fold $L_+ = \operatorname{clo}(T) \setminus (E_+ \cup D_+) \dots 830k(!)$
- Plus negative samples L_, D_, E_, typically 1:1 Local closed world assumption
- With 830k of 838k known, what's left to discover?

Results with leaky and sanitized protocols

	Leaky protocol			Sanitized protocol				
	OE	σΟΕ	Rect	OE	σΟΕ	Rect		
Acc	0.922	0.921	0.926	0.574	0.742	0.767		
AP	1	1	1	0.977	0.969	0.986		
Ρ	0.994	0.915	0.973	0.987	0.925	0.983		
R	0.850	0.929	0.877	0.151	0.527	0.544		
F1	0.916	0.922	0.923	0.262	0.671	0.722		

- Sanitized protocol destroys recall and F1 of OE
- Rectangle is better than σOE is (much) better than OE
- σOE and rectangle better even with leaky protocol

 $z,y)\},$

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ypes?

subtype-of type

$$\left\| oldsymbol{t}^{0}, \dots, oldsymbol{t}^{D}, \dots, oldsymbol{t}^{D} - oldsymbol{t}_{0} \right\|_{2}^{2}$$

 $\left\| oldsymbol{e} - \sum_{d} \lambda_{d} oldsymbol{t}^{d} \right\|_{2}^{2}$
 $\left\| oldsymbol{e} - \sum_{d} \lambda_{d} oldsymbol{t}^{d} \right\|_{2}^{2}$
 $\left\| oldsymbol{e} - \sum_{d} \lambda_{d} oldsymbol{t}^{d} \right\|_{2}^{2}$

ons, we want $u_{x,d} \ge u_{v,d}$

nsion, we want $u_{x,d} \leq u_{v,d}$

 $u_{x,d}$]_|

...4000

- Dominance [Vendrov+2015]
 - $x \subseteq y$ represented by

- - contained



- TC = transitive closure on
- L_{+} gave 0/1 acc = 88.6%
- Gaussian embedding worse, 86.6%; OE at 90.6%
- OE was actually undersold, gains more when training fold shrunk
- Still rewarded for computing transitive closure

- $x \prec y =$ "relevant"
- $x \prec y$ irrelevant
- AUC, MAP, NDCG etc.
- Rectangle has higher precision at lower recall than OE
- gitlab.com/soumen.chakrabarti/ rectangle



Recall