Retrofitting Word Vectors to Semantic Lexicons

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Outline

- 论文方法概述
- 传统词向量生成工具
  - Glove, Skip-Gram, Global Context, Multilingual Vectors
- 语义词典（Semantic Lexicon）
  - PPDB, WordNet, FrameNet
- 实验
  - 数据集
    - Word Similarity: WS-353, RG-65, MEN
    - Syntactic Relations, Synonym Selection, Sentiment Analysis
  - 顺序模型：Retrofitting with Semantic Lexicons
  - 联合模型：Semantic Lexicons during Learning
    - lazy method, periodic method
  - 实验分析

Summary

论文方法概述

- 把语义信息加入词向量；语义相关的单词词向量有更大的相似性
- 两类方法
  - 顺序模型：先使用传统词向量生成工具，再使用语义信息修正词向量
  - 联合模型：修正传统词向量训练时的目标函数，在其中加入语义信息

传统词向量生成工具

传统词向量生成工具 tools

Glove

- stanford:Jeffrey Pennington, Richard Socher
- 收集单词对的共线情况

word2vec

Skip-Gram Vectors

Global Context Vector

tree-RNN + local and global (document) context features

Multilingual Vector

SVD + CCA

语义词典

Semantic Lexicon

PPDB

- 复述（paraphrase）预料集
- 220 million paraphrase pairs
- 6 个版本：S,M,L,XL,XXL,XXXL，容量依次增大，质量依次降低
- [VBN] ||| pruned ||| cropped ||| p(e|f)=4.33 p(f|e)=4.88 ... ||| 0-0

FrameNet

- tree-RNN + local and global (document) context features
- frame: $Cause\_change\_of\_position\_on\_a\_scale$ $\leftrightarrow$ $push, raise, \ldots, growth$

WordNet

WN_{syn}: 只对同义词连边

WN_{all}: 同义词、上位词、下位词都连边

实验时 $\alpha_i = 1, \beta_{ij} = degree(i)^{-1}$

实验数据集

Word Similarity

WS-353

- 353 个英语单词对（200 个 13 个人标，153 个 16 个人标）
- 相似度：0-10（可 0.5）

RG-65

- 65 对英语名词

MEN

- 3000 对单词（共现 700 次）

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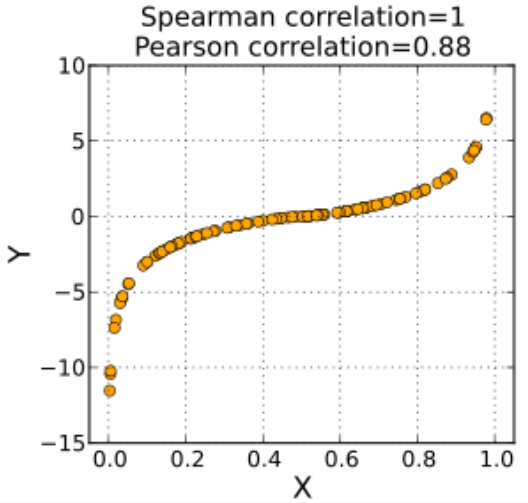
评价结果好坏采用斯皮尔曼等级相关系数



$$\rho = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \in [-1, 1]$$

Syntactic Relation(SYN-REL)

- Mikolov 给出（word2vec）
- 给定 a,b,c, 找到最合适的 d，满足：a is to b as c is to d
- 实验时找和 $(q_q - q_b + q_c)$ 余弦相似度最大的单词作为 q_d

Synonym Selection(TOEFL)

- 80 个问题，找出候选中与目标最相近的单词

  $rug \rightarrow \{sofa, ottoman, \mathbf{carpet}, hallway\}$

Sentiment Analysis (SA)

- Socher 给出（Glove）
- 6920(train)+872(dev)+1821(text) 个句子，正负情感极性

实验

顺序模型

Retrofitting with Semantic Lexicons

顺序模型：Retrofitting with Semantic Lexicons

Notation

$V = \{w_1, w_2, ..., w_n\}$: vocabulary

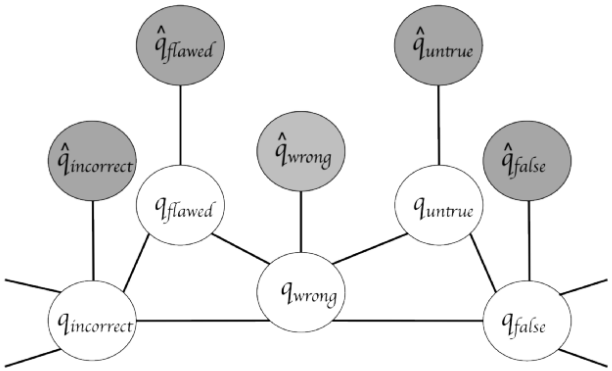
$E = \{(w_i, w_j), ...\} \subseteq V \times V$: edges

$\Omega = (V, E)$: ontology

$\hat{q}_i, q_i \in \mathbb{R}^d$: word vector

$\hat{Q} = (\hat{q}_1, ..., \hat{q}_n)$: original matrix

$Q = (q_1, ..., q_n)$: target matrix;



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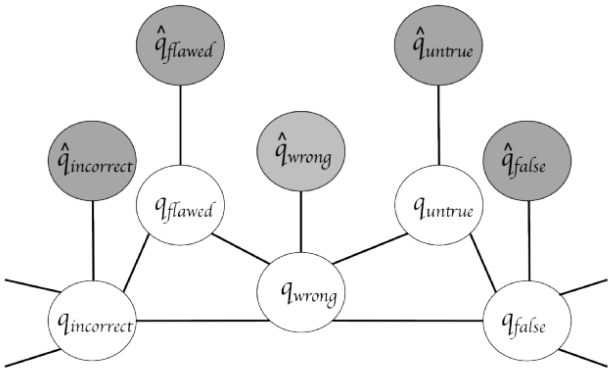
1. 传统工具 (word2vec) 生成初始向量空间 $\hat{Q}$
2. 根据语义字典生成 Ω
3. 最优化 $\Psi(Q) =$

$$\sum_{i=1}^{n} \left[\alpha_i \left\| q_i - \hat{q}_i \right\|^2 + \sum_{(i,j) \in E} \beta_{ij} \left\| q_i - q_j \right\|^2 \right]$$



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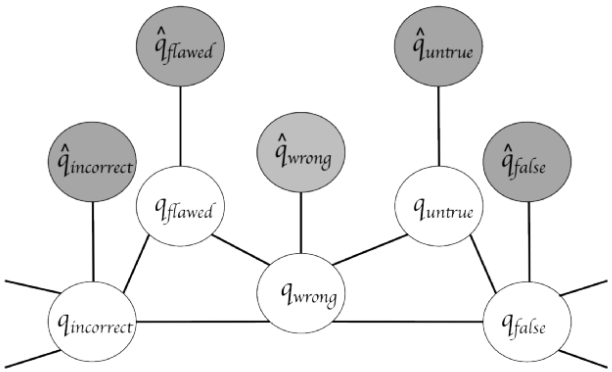

- (?)$\Psi(Q)$ 是凸函数 $\Rightarrow$ 沿切线更新 $\Rightarrow q_i = \frac{\sum_{j:(i,j) \in E} \beta_{ij} q_j + \alpha_i \hat{q}_i}{\sum_{j:(i,j) \in E} \beta_{ij} + \alpha_i}$

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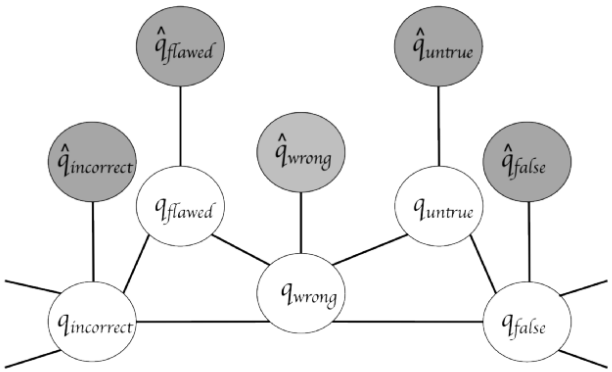

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- 10 次迭代收敛 ((?) 邻接矩阵距离小于 10^{-2})

Experiment

顺序模型 (Retrofitting with Semantic Lexicons)

Lexicon	MEN-3k	RG-65	WS-353	TOEFL	SYN-REL	SA
Glove	73.7	76.7	60.5	89.7	67.0	79.6
+PPDB	1.4	2.9	–1.2	**5.1**	–0.4	**1.6**
+WN_{syn}	0.0	2.7	0.5	**5.1**	–12.4	0.7
+WN_{all}	**2.2**	**7.5**	**0.7**	2.6	–8.4	0.5
+FN	–3.6	–1.0	–5.3	2.6	–7.0	0.0
SG	67.8	72.8	65.6	85.3	73.9	81.2
+PPDB	**5.4**	3.5	**4.4**	**10.7**	–2.3	**0.9**
+WN_{syn}	0.7	3.9	0.0	9.3	–13.6	0.7
+WN_{all}	2.5	**5.0**	1.9	9.3	–10.7	–0.3
+FN	–3.2	2.6	–4.9	1.3	–7.3	0.5
GC	31.3	62.8	62.3	60.8	10.9	67.8
+PPDB	**7.0**	6.1	2.0	**13.1**	**5.3**	**1.1**
+WN_{syn}	3.6	6.4	0.6	7.3	–1.7	0.0
+WN_{all}	6.7	**10.2**	**2.3**	4.4	–0.6	0.2
+FN	1.8	4.0	0.0	4.4	–0.6	0.2
Multi	75.8	75.5	68.1	84.0	45.5	81.0
+PPDB	**3.8**	4.0	**6.0**	**12.0**	**4.3**	0.6
+WN_{syn}	1.2	0.2	2.2	6.6	–12.3	**1.4**
+WN_{all}	2.9	**8.5**	4.3	6.6	–10.6	**1.4**
+FN	1.8	4.0	0.0	4.4	–0.6	0.2

- frameNet 数据少，效果差
- $[Append{:}A]$ 语义：Glove 好，句法：word2vec 好
- $PPDB$, WN_{all} 好
- retrofitting 对于句法信息没有提升效果

联合模型：Semantic Lexicons during Learning

修改传统模型的训练过程，加入语义信息

lazy mode

核心思想：在传统模型的目标函数中加入体现语义信息的正则项

Q 的先验：$p(Q) \propto \exp\left(-\gamma \sum_{i=1}^{n} \sum_{j:(i,j)\in E} \beta_{ij} \left\| q_i - q_j \right\|^2\right)$

1. $p(Q)$ 加入目标函数中
2. 每次更新 k 个单词的向量（lazy update）

periodic mode

核心思想：递归的过程中每更新 k 个词后使用下式更新所有的单词向量

$$q_i = \frac{\sum_{j:(i,j)\in E} \beta_{ij} q_j + \alpha_i \hat{q}_i}{\sum_{j:(i,j)\in E} \beta_{ij} + \alpha_i}$$

Experiment

联合模型效果测试

- log-bilinear (LBL) vectors 为基准 (Mnih and Teh, 2012)
- lazy Mode: k=100,000

Method	k, γ	MEN-3k	RG-65	WS-353	TOEFL	SYN-REL	SA
LBL (Baseline)	$k = \infty, \gamma = 0$	58.0	42.7	53.6	66.7	31.5	72.5
LBL + Lazy	$\gamma = 1$	–0.4	4.2	0.6	–0.1	0.6	1.2
	$\gamma = 0.1$	0.7	8.1	0.4	–1.4	0.7	0.8
	$\gamma = 0.01$	0.7	9.5	1.7	2.6	1.9	0.4
LBL + Periodic	$k = 100\text{M}$	3.8	18.4	3.6	12.0	4.8	1.3
	$k = 50\text{M}$	3.4	**19.5**	4.4	18.6	0.6	**1.9**
	$k = 25\text{M}$	0.5	18.1	2.7	**21.3**	–3.7	0.8
LBL + Retrofitting	–	**5.7**	15.6	**5.5**	18.6	**14.7**	0.9

Experiment

对比实验

Yu and Dredze (2014)

- word2vec(CBOW)+retrofitting(PPDB)

Corpus	Vector Training	MEN-3k	RG-65	WS-353	TOEFL	SYN-REL	SA
WMT-11	CBOW	55.2	44.8	54.7	73.3	40.8	74.1
	Yu and Dredze (2014)	50.1	47.1	53.7	61.3	29.9	71.5
	CBOW + Retrofitting	**60.5**	**57.7**	**58.4**	**81.3**	**52.5**	**75.7**

Xu et al. (2014)

- word2vec(CBOW)+retrofitting(PPDB)

Wikipedia	SG	**76.1**	66.7	**68.6**	72.0	40.3	73.1
	Xu et al. (2014)	–	–	68.3	–	44.4	–
	SG + Retrofitting	65.7	**73.9**	67.5	**86.0**	**49.9**	**74.6**

Experiment

多语言效果实验（每种语言独立测试）

- retrofitting(WN_{all})

Language	Task	SG	Retrofitted SG
German	RG-65	53.4	**60.3**
French	RG-65	46.7	**60.6**
Spanish	MC-30	54.0	**59.1**

Experiment

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Language	Task	SG	Retrofitted SG
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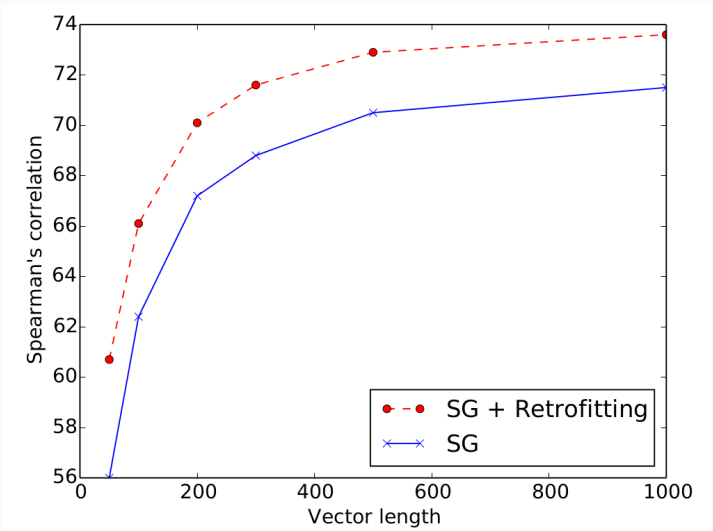
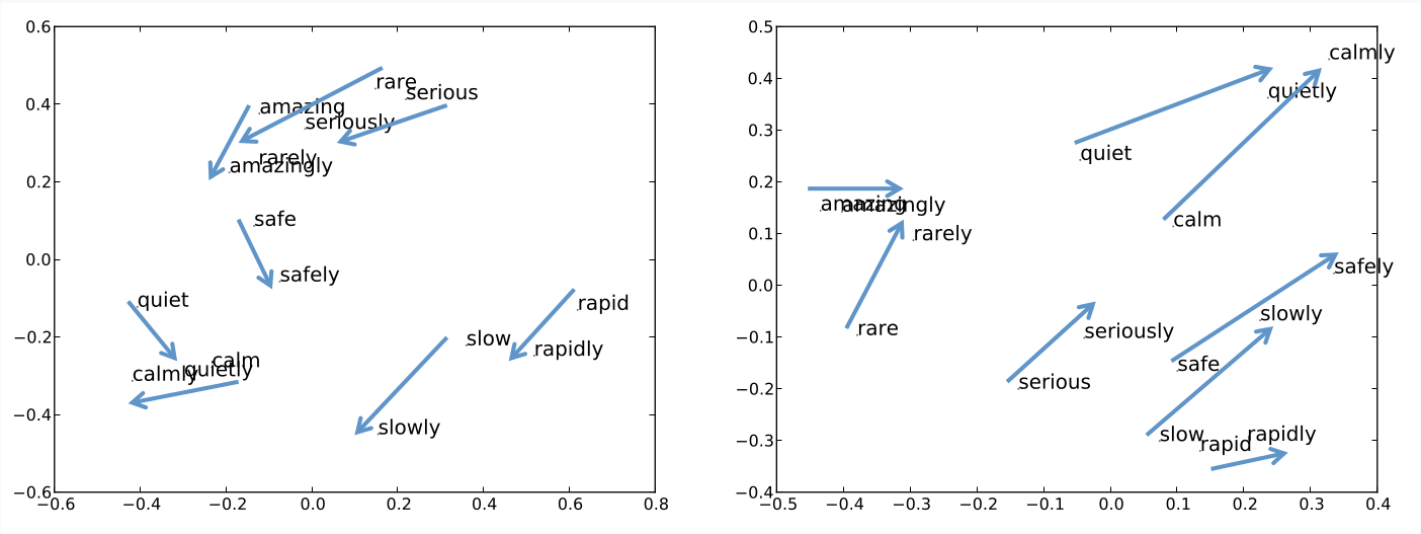
retrofitting 和向量长度效用实验



Experiment

可视化

利用 PCA 从 SG 训练得到的 100 维向量压缩为 2 维。左右图分别为使用 retrofitting 前后的向量位置



谢谢

大多数数据集可以在上面找到：http://www.cs.cmu.edu/ mfaruqui/suite.html

Append:A

GloVe vs word2vec

Model	Semantic	Syntactic	Total
GloVe (W+C)	79.6	61.0	69.4
word2vec (W)	72.7	65.8	68.9

https://docs.google.com/document/d/1ydIujJ7ETSZ688RGfU5IMJJsbxAi-kRl8czSwpti15s/mobilebasic