Explicit Retrofitting of Distributional Word Vectors

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You shall know the meaning of the word by the company it keeps

Words that occur in similar contexts tend to have similar meanings

Harris, 1954
Words co-occur in text due to
- Paradigmatic relations (e.g., synonymy, hypernymy), but also due to
- Syntagmatic relations (e.g., selectional preferences)

Distributional vectors conflate all types of association
- *driver* and *car* are not paradigmatically related
  - Not synonyms, not antonyms, not hypernyms, not co-hyponyms, etc.
- But both words will co-occur frequently with
  - *driving, accident, wheel, vehicle, road, trip, race*, etc.
Vector specialization using external resources

- **Key idea**: refine vectors using external resources
- Specializing vectors for **semantic similarity**

1. **Joint specialization models**
   - Integrate external constraints into the learning objective
   - E.g., Yu & Dredze, ’14; Kiela et al., ’15; Osborne et al., ’16; Nguyen et al., ’17

2. **Retrofitting models**
   - Modify the pre-trained word embeddings using lexical constraints
   - E.g., Faruqui et al., ’15; Wieting et al., ’15; Mrkšić et al., ’16; Mrkšić et al., ’17
Vector specialization using external resources

- **Joint specialization models**
  - (+) Specialize the *entire* vocabulary (of the corpus)
  - (−) Tailored for a *specific* embedding model

- **Retrofitting models**
  - (−) Specialize *only* the vectors of words found in external constraints
  - (+) Applicable to *any* pre-trained embedding space
  - (+) Much *better performance* than joint models (Mrkšić et al., 2016)
This work

- **Best of both worlds**
  - Performance and flexibility of retrofitting models, while
  - Specializing entire embedding spaces (vectors of all words)

- **Simple idea**
  - Learn an explicit retrofitting/specialization function
  - Using external lexical constraints as training examples
Explicit Retrofitting Model
Explicit retrofitting

- Constraints (synonyms and antonyms) used as training examples for learning the explicit specialization function
- Non-linear: Deep Feed-Forward Network (DFFN)
Constraints to training instances

- Specialization function: \( x' = f(x) \)
- Distance function: \( g(x_1, x_2) \)
- Assumptions
  1. \((w_i, w_j, \text{syn})\) – embeddings as close as possible after specialization
     \[ g(x_i', x_j') = g_{\text{min}} \]
  2. \((w_i, w_j, \text{ant})\) – embeddings as far as possible after specialization
     \[ g(x_i', x_j') = g_{\text{max}} \]
  3. \((w_i, w_j)\) – the non-costraint words stay at the same distance
     \[ g(x_i', x_j') = g(x_i, x_j) \]
Constraints to training instances

- **Micro-batches** – each constraint \((w_i, w_j, r)\) paired with
  - K pairs \(\{(w_i, w_m^k)\}_k - w_m^k\) most similar to \(w_i\) in distributional space
  - K pairs \(\{(w_j, w_n^k)\}_k - w_n^k\) most similar to \(w_j\) in distributional space
  - Total: \(2K+1\) word pairs

\[
M(w_i, w_j, r) = \{(x_i, x_j, g_r)\} \cup \left\{\left(\begin{array}{l} x_i \\ x_m^k \\ g(x_i, x_m^k) \end{array}\right)\right\}_{k=1}^K \cup \left\{\left(\begin{array}{l} x_j \\ x_n^k \\ g(x_j, x_n^k) \end{array}\right)\right\}_{k=1}^K
\]
Loss function

- **Contrastive Objective (CNT)**

\[ J_{CNT} = \sum_{M_s \in S} \sum_{i=2}^{2K+1} \left( \left( g_i - g_{\text{min}} \right) - \left( g'_i - g'_1 \right) \right)^2 \]

- **Regularization**

\[ J_{REG} = \sum_{i=1}^{N} g(x_1^i, f(x_1^i)) + g(x_2^i, f(x_2^i)) \]
Evaluation
Model Configuration

- Distance function $g$: cosine distance
- DFFN activation function: hyperbolic tangent

- Constraints from previous work (Zhang et al, ’14; Ono et al., ‘15)
  - 1M synonymy constraints
  - 380K antonymy constraints
  - But only 57K unique words in these constraints!

- 10% of micro-batches used for model validation
  - H (hidden layers) = 5, $d_h$ (layer size) = 1000, $\lambda = 0.3$
  - $K = 4$ (micro-batch size = 9), batches of 100 micro-batches
  - ADAM optimization (Kingma & Ba, 2015)
Intrinsic Evaluation

- **SimLex-999** *(Hill et al., 2014)*, **SimVerb-3500** *(Gerz et al., 2016)*
- **Important aspect**: percentage of test words covered by constraints
- **Comparison with Attract-Repel** *(Mrkšić et al., 2017)*
Intrinsic Evaluation

- Intrinsic evaluation depicts two extreme settings
  - **Lexical overlap** setting
    - Synonymy and antonymy constraints contain 99% of SL and SV words
    - Performance is an *optimistic* estimate or true performance
  - **Lexically disjoint** setting
    - Constraints contain 0% of SL and SV words
    - Performance is a *pessimistic* estimate of true performance

- Realistic setting: **downstream tasks**
  - Coverage of test set words by constraints between 0% and 100%
Donwstream tasks: DST & LS

- **Dialog state tracking (DST)** – first component of a dialog system
  - Neural Belief Tracker (NBT) (Mrkšić et al., ’17)
  - Makes inferences *purely* based on an embedding space
  - 57% of words in NBT test set (Wen et al., ‘17) covered by specialization constraints

- **Lexical simplification (LS)** – complex words to simpler synonyms
  - Light-LS (Glavaš & Štajner, ‘15) – decisions *purely* based on an embedding space
  - 59% of LS dataset words (Horn et al., 14) found in specialization constraints

- **Crucial to distinguish similarity from relatedness**
  - DST: „cheap pub in the east” vs. „expensive restaurant in the west”
  - LS: „Ferrari’s **pilot** Sebastian Vettel won the race.”, ”**driver**” vs. ”**airplane**”
Downstream tasks – Evaluation

- Lexical simplification (LS) and Dialog state tracking (DST)
Cross-lingual specialization transfer
Language transfer

- Lexico-semantic resources such as WordNet needed to collect synonymy and antonymy constraints
- **Idea:** use shared bilingual embedding spaces to transfer the specialization to another language

- Most models learn a (simple) linear mapping
  - Using word alignments ([Mikolov et al., 2013]; **Smith et al., 2017**)
  - Without word alignments ([Lample et al., 2018]; **Artetxe et al., 2018**)

*Image taken from Lample et al., ICLR 2018*
Cross-lingual transfer – results

- Transfer to three languages: DE, IT, and HR
  - Different levels of proximity to English
  - Variants of SimLex-999 exist for each of these three languages

Cross-lingual specialization transfer
Conclusion

- **Retrofitting models** specialize (i.e., fine-tune) distributional vectors for semantic similarity
  - **Shortcoming:** specialize only vectors of words seen in external constraints

- **Explicit retrofitting**
  - Learning the specialization function using constrains as training examples
  - Able to specialize distributional vectors of all words
  - Good intrinsic (SL, SV) and downstream (DST, LS) performance

- **Cross-lingual specialization transfer** possible for languages without lexico-semantic resources
Thank you for attention!

- **Code & data**
  - https://github.com/codogogo/explirefit

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