Word embeddings

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Interpretable word embeddings

- $x \in \mathbb{R}^K$, where x^i is some i-th interpretable feature, e.g.
  - x^1: part of speech
  - x^2: gender (for nouns)
  - x^3: tense (for verbs)
  - x^4: starts from capital letter
  - x^5: #[letters]
  - x^6: category: machine learning, physics, biology, ...
  - x^7: subcategory: supervised, unsupervised, semi-supervised learning
  - ...
- Need to invent features for each task and extract them.
- Want this to be done automatically!

Uninterpretable word embeddings

- Clustering words with similar meaning to similar representations.
- **Distributional hypothesis:**
  words have similar meaning <=> they co-occur together frequently.
- "accuracy of SVM", "SVM gave accuracy", "lower accuracy, compared to SVM"
  - SVM and accuracy are connected!
- Typical dimensionality of embedding $\in [300, 500]$.

Phrase embeddings

We can treat collocations as separate units.

- e.g. fast food, post office, happily married, proud smile.
- may can extract collocations with

$$(w_i, w_j)\text{-collocation} \Longleftrightarrow \frac{p(w_i w_j) - \delta}{p(w_i)p(w_j)} > \textit{threshold}$$

δ - parameter, discouraging rarely co-occurring words as collocations.

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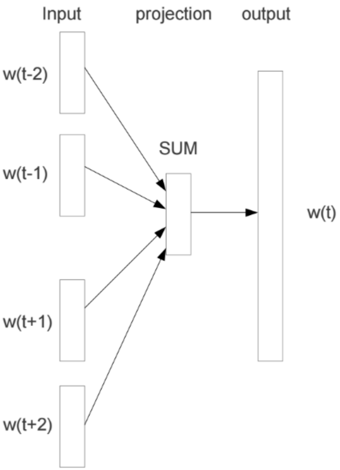
Word2vec

- For each w models evaluate:
  - target word embedding v_w
  - context word embedding $\tilde{v}_w$
- Target&context embeddings may be averaged or concatenated later.

Continious bag of words (CBOW)



Continuous bag of words (CBOW)

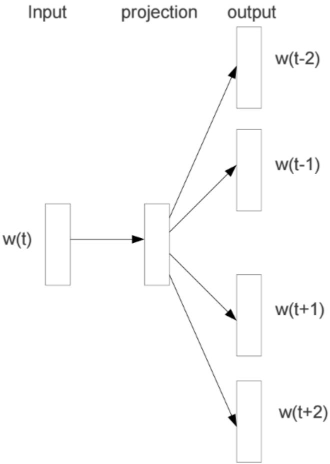
CBOW: predict current word given context.

$$\frac{1}{T}\sum_{t=1}^{T}\ln p(w_t|w_{t-c},..w_{t-1},w_{t+1},...w_{t+c})\to\max_{\theta}$$

where $v_{context}=\sum_{-c\le i\le c,\,i\ne 0}v_{w_{t+i}}$ and

$$p(w_t|w_{t-c},..w_{t-1},w_{t+1},...w_{t+c})=\frac{\exp\left(v_{context}^T\tilde{v}_{w_t}\right)}{\sum_{w=1}^{V}\exp\left(v_{context}^T\tilde{v}_w\right)}$$

Skip-gram model



Skip-gram model

Skip-gram: predict context, given current word:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\le i\le c,\, i\ne 0}\ln p(w_{t+i}|w_t)\to\max_{\theta}$$

$$p(w_{t+i}|w_t)=\frac{\exp\left(v_{w_t}^T\tilde{v}_{w_{t+i}}\right)}{\sum_{w=1}^{V}\exp\left(v_{w_t}^T\tilde{v}_w\right)}$$

Comments

- May extract embeddings for other objects, appearing in a sequence.
  - symbols, trigrams of symbols (see *FastText*), sentences
  - genes in DNA sequence
  - services ordered by a customer
- May use ensemble of embeddings from different methods.

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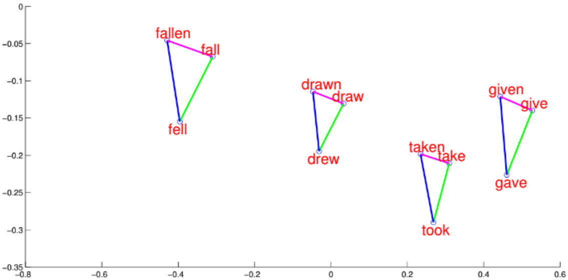
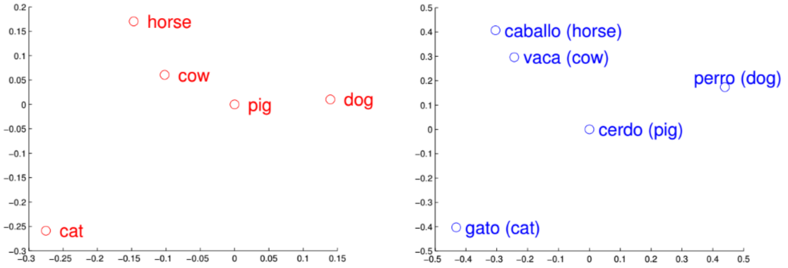
Word forms

Similar in meaning and in spelling words cluster together.



So word embeddings may help in obtaining forms of rare words.

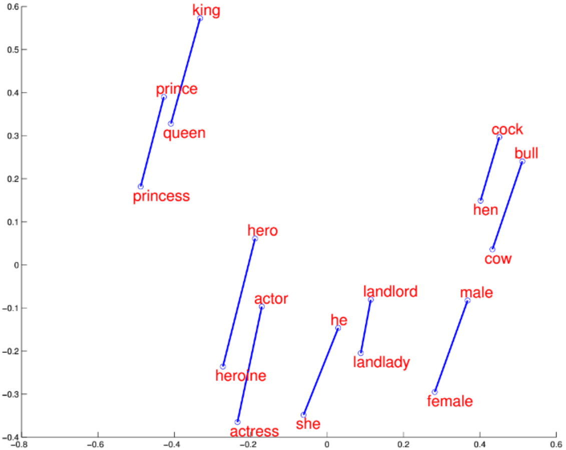
Word embeddings for different languages are similar[1]



So word embeddings may help in language translation.

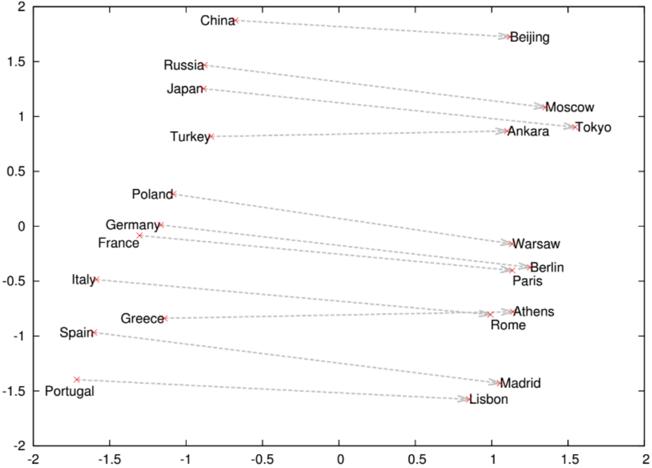
[1] Images were manually rotated and scaled.

Regularities in vector space



So (prince-princess)+queen≈king! Helps in question answering.

Regularities in vector space



So (Beijing-China)+Russia≈Moscow! Helps in question answering.

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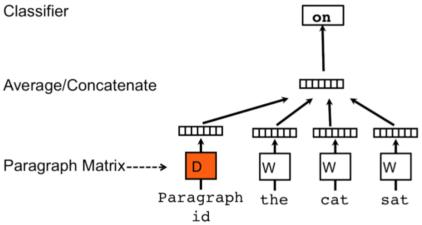
Paragraph to vector - motivation

- Now need to encode the paragraph (document) into fixed size vector.
- Simple approach: paragraph vector - average of word vectors it contains.
    - or weighted average, considering side information about a word (e.g. stop word/specific term, etc.)
- Alternative: learn paragraph representation.

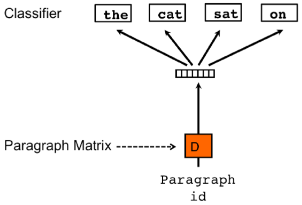
Paragraph vector - PV-DM model



Distributed Memory Model of Paragraph Vectors (PV-DM)

- On training documents are divided into paragraphs. Each paragraph is associated its column in paragraph2vec matrix D.
- The same task is solved as in CBOW, using vectors and general paragraph information (context).
- Called *Distributed Memory Model of Paragraph Vectors (PV-DM)*.

Model



model

- Similar to skip-gram: predicts random sequence of words from the paragraph, using paragraph embedding only.
- Compared to previous, model is simpler: need to estimate only D & softmax parameters; word embedding are not used.
- Called *Distributed Bag of Words version of Paragraph Vector (PV-DBOW)*

StarSpace[2]

- Facebook library to convert general objects into vector representations.
- Available at github.
- Learns representations of 2 kinds of objects (x and y, may coincide) into the same space embedding$\in \mathbb{R}^D$.
    - $x \to a \in \mathbb{R}^D$; $y \to b \in \mathbb{R}^D$ - can compare different objects!
- Representations are found by sampling randomly matching pair (a, b) and K mismatched pairs

$$\sum_{(a,b)\in E+;\ b^-\in E^-} L^{batch}\left(sim(a,b), sim(a,b_1^-), ...sim(a,b_K^-)\right) \to \min_{\{a\},\{b\}}$$

where $sim\left(a,b\right) = a^T b$ or $sim\left(a,b\right) = \frac{a^T b}{\|a\|\|b\|}$; L - hinge (worked better) or log-loss.

[2]Wu et al. StarSpace: Embed All The Things!

StarSpace: Applications

- Multiclass classification: *a*-feature vector, *b*-class.
- Multiclass classification: *a*-feature vector, *b*-one of matching classes.
- Collaborative filtering: *a*-user, *b*-item, he likes.
  - does not extend to new users and items
- Collaborative filtering: *a*-"user"=avg. of items user likes, with excluded item *b*.
  - extends to new users, by averaging their item embeddings
  - does not extend to new items
- Collaborative filtering: *a*-"user"=avg. of items user likes, with excluded item *b*. Inside *a*=avg(liked items), *b*=avg(contained features) - e.g. document consists of words.
  - extends both to new users and new items, as all are featurized.

StarSpace: Applications

- Link prediction in graphs. Consider graph of relations (h, r, t) where h-head concept, r-relationship, t-tail concept, e.g. (Beyonce, born in, Houston). Then 2 options possible for sampled (h, r, t):
- $a = (h + r)/2$, $b = t$ or $a = h$, $b = (r + t)/2$
  - thus, can do question answering (Beyonce, born in, ?)
- Information retrieval:
  - supervised data given: a-query, b-relevant document
  - no supervision: a-random sentence from document b
    - both methods produce document embeddings!
- Word embeddings: a-surrounding words, b-central word.
- Sentence embeddings: a, b-random sentences from the same document (or close enough to each other)

May find embeddings for 2 tasks simultaneously (sum losses). E.g. jointly learn sentence embeddings and sentence classification according to sentiment (semi-supervised learning).

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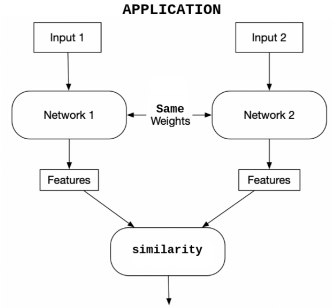
Siamese network

- Siamese network uses 2 or more duplicate networks, producing embeddings.
- Then these embeddings are compared.

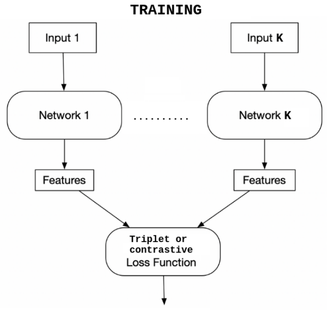


Application: finding similarity or a relationship between two comparable things.

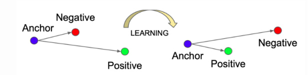
Application examples

- Classification:
  - input: two objects
  - output: how semantically similar they are (a proxy for class similarity)
- Information retrieval. inputs: are a document and a query,
  - input: a document and a query (may be an image and a visual query-find by image)
  - application: ranking by relevance to a query
- Paraphrase detection:
  - inputs: two sentences
  - output: a score of how similar they are.
- Signature verification
  - inputs: scans of two signatures
  - output: a score that they belong to the same person

Training



- Loss function:
  - similar objects should have similar embeddings
  - different objects should have distant embeddings



Losses[4]

Contrastive loss[3]:

$$\mathbb{I}[y_i = y_j] \left\| f_\theta(x_i) - f_\theta(x_j)) \right\|^2 + \mathbb{I}[y_i \neq y_j] \max \left\{0, \alpha - \| f_\theta(x_i) - f_\theta(x_j)) \| \right\}^2$$

Triplet loss:

- x - random object,
- x, x^+ are similar (belong to the same class)
- x, x^- are dissimilar (belong to different classes)
- $\alpha > 0$ - hyperparameter (desired margin between positive and negative pairs)

$$\mathcal{L}(x, x^+, x^-) = \max \left\{ \left\| f_\theta(x) - f_\theta(x^+)) \right\|^2 - \left\| f_\theta(x) - f_\theta(x^-)) \right\|^2 - \alpha; 0 \right\}$$

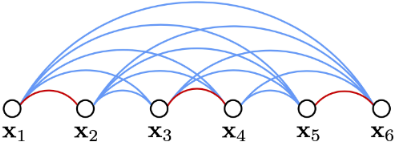
[3] Chopra et al. Learning a Similarity Metric Discriminatively, with Application to Face Verification.

[4] Good overview of losses.

Lifted structural loss

(a) Contrastive embedding

(b) Triplet embedding



(c) Lifted structured embedding

Lifted structural loss[5] utilizes all pairwise similarities.

[5] Deep Metric Learning via Lifted Structured Feature Embedding.

Lifted structural loss

- Define $D_{ij} = \|f(x_i) - f(x_j)\|_2$, P, N-the sets of positive and negative pairs.

$$\mathcal{L} = \frac{1}{2|P|} \sum_{(i,j)\in P} \max\left\{0; \mathcal{L}_{struct}^{ij}\right\}^2$$

$$\mathcal{L}_{struct}^{ij} = D_{ij} + \max\left\{ \max_{(i,k)\in N} \varepsilon - D_{ik}, \max_{(j,k)\in N} \varepsilon - D_{jk} \right\}$$

- Red parts represent *hard negative mining*.
    - concentrated on hardest negative object, slow training
- Solution: smoothed version:

$$\mathcal{L}_{struct}^{ij} = D_{ij} + \log\left(\sum_{(i,k)\in N} e^{\varepsilon - D_{ik}} + \sum_{(j,k)\in N} e^{\varepsilon - D_{jk}} \right)$$

Soft-Nearest Neighbors Loss[7]

- Soft-Nearest Neighbors Loss uses many positive objects from the minibatch.

$$\mathcal{L} = -\frac{1}{B}\sum_{i=1}^{B}\log\left(\frac{\sum_{j=1\dots B; i\neq j; y_i=y_j} e^{-\left\|f(x_i), f(x_j)\right\|^2/\tau}}{\sum_{k=1,\dots B; i\neq k} e^{-\|f(x_i), f(x_k)\|^2/\tau}}\right)$$

- τ - large => distance dominated by very similar embeddings, distant embeddings do not contribute.
- See also self-supervised contrastive loss[6].

Triplet and contrasive losses may be used for metric learning:

$\rho_\theta(x, x')$ small for x, x' belonging to the same class

[6]Khosla et al. Supervised Contrastive Learning

[7]Frosst et al. Analyzing and Improving Representations with the Soft Nearest Neighbor Loss.

Siamese architecture vs. classification

- Classification learns "what represents each class".
- Siamese network learns "what distinguishes each class from other classes".
- Classification outputs class scores.
- Siamese network outputs distances to each class in embedding space.
- Siamese network
    - is more robust to class imbalance
        - since during training consider instance of each class in turn evenly
        - model learns what makes classes the same/different from other pairs, so few examples of rare class may be enough (*one shot learning*).
    - works well in ensemble with classifier
        - use completely different logic, so much diversity in ensemble
    - requires more training
        - instance based learning=>pairwise learning.

Embeddings for classifier and Siamese network

Embeddings for classifier (last layer of MLP) and Siamese network for MNIST: