

# Other Word Embedding Types

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# Are there any other variations of Word2Vec?

- **fasttext**
  - An extension of Word2Vec that also incorporates **subword models**
  - Designed to better handle unknown words and sparsity in language

# fasttext

- Each word is represented as:

- Itself
- A bag of constituent n-grams



The diagram illustrates the fasttext representation of the word "super". It shows the word "super" in a blue box, followed by an equals sign, then the word in a red box with angle brackets "<super>", followed by a plus sign, and finally a red box containing the bag of constituent n-grams "<su, sup, upe, per, er>". A dashed red arrow points from the bullet point "A bag of constituent n-grams" to the red box containing the n-grams. Another dashed red arrow points from the bullet point "Itself" to the red box containing "<super>".

$$\boxed{\text{super}} = \boxed{\text{<super>}} + \boxed{\text{<su, sup, upe, per, er>}}$$



# fasttext

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- Skip-gram embedding is learned for each constituent n-gram
- Word is represented by the sum of all embeddings of its constituent n-grams
- Key advantage of this extension?
  - Allows embeddings to be predicted for unknown words based on subword constituents alone

Source code available online:  
<https://fasttext.cc/>

# Word2Vec and fasttext embeddings are nice ...but what's another alternative?

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- Word2Vec is an example of a **predictive** word embedding model
  - Learns to predict whether words belong in a target word's context
- Other models are **count-based**
  - Remember co-occurrence matrices?
- GloVe combines aspects of both predictive and count-based models





# Global Vectors for Word Representation (GloVe)

- Co-occurrence matrices quickly grow extremely large
- Intuitive solution to increase scalability?
  - Dimensionality reduction!
    - However, typical dimensionality reduction strategies may result in too much computational overhead
- GloVe learns to predict weights in a lower-dimensional space that correspond to the co-occurrence probabilities between words

# GloVe




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- Why is this useful?
  - Predictive models → black box
    - They work, but why?
  - GloVe models are easier to interpret
- GloVe models also encode the ratios of co-occurrence probabilities between different words ...this makes these vectors useful for word analogy tasks

# How does GloVe work?

	$c_1$	...	$c_n$
$t_1$	123	...	456
...	...	...	...
$t_n$	0	...	789



Build a huge word-context  
co-occurrence matrix



# How does GloVe work?

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$t_1$	123	...	456
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Build a huge word-context co-occurrence matrix

Define soft constraints for each word pair

Scaler biases for  $t_i$  and  $c_j$

$$w_i^T w_j + b_i + b_j = \log X_{ij}$$

Vector for  $t_i$

Vector for  $c_j$

Co-occurrence count for  $t_i c_j$

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...	...	...	...
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Build a huge word-context co-occurrence matrix

Define soft constraints for each word pair

$$w_i^T w_j + b_i + b_j = \log X_{ij}$$

Define a cost function

$$J = \sum_{i=1}^V \sum_{j=1}^V f(X_{ij}) (w_i^T w_j + b_i + b_j - \log X_{ij})^2$$

Weighting function:

$$f(X_{ij}) = \begin{cases} \left(\frac{X_{ij}}{x_{max}}\right)^\alpha, & X_{ij} < XMAX \\ 1, & \text{otherwise} \end{cases}$$

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0.4 0.7 1.2 4.3 0.9 6.7 1.3 0.5 0.7 5.3



# In sum, GloVe is a log-bilinear model with a weighted least-squares objective.

- Why does it work?
  - Ratios of co-occurrence probabilities have the potential to encode word similarities and differences
  - These similarities and differences are useful components of meaning
- GloVe embeddings perform particularly well on analogy tasks



# Which is best ... Word2Vec or GloVe?

- It depends on your data!
- In general, Word2Vec and GloVe produce similar embeddings
- Word2Vec → slower to train but less memory intensive
- GloVe → faster to train but more memory intensive
- Word2Vec and GloVe both produce context-independent embeddings
- Contextual embeddings:
  - ELMo (Peters et al., 2018; <https://www.aclweb.org/anthology/N18-1202/>)
  - BERT (Devlin et al., 2019; <https://www.aclweb.org/anthology/N19-1423/>)