Word2Vec with TensorFlow

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Deep Learning

Word embedding

- How to represent words in machine learning?

  My favorite pet is cat .

  - Treat words as discrete atomic symbols, and therefore 'cat' may be represented as '1' and 'pet' as '2.'

  - However, this embedding includes no semantics. Tasks learning from this representation causes models hard to train.

  - Better solutions?

Word embedding

- Intuition: Modeling relationships between words.
  - Semantics Similarity
    - CBOW (Continuous Bag-of-Words model),
    - Skip-Gram
  - Grammar / Syntax

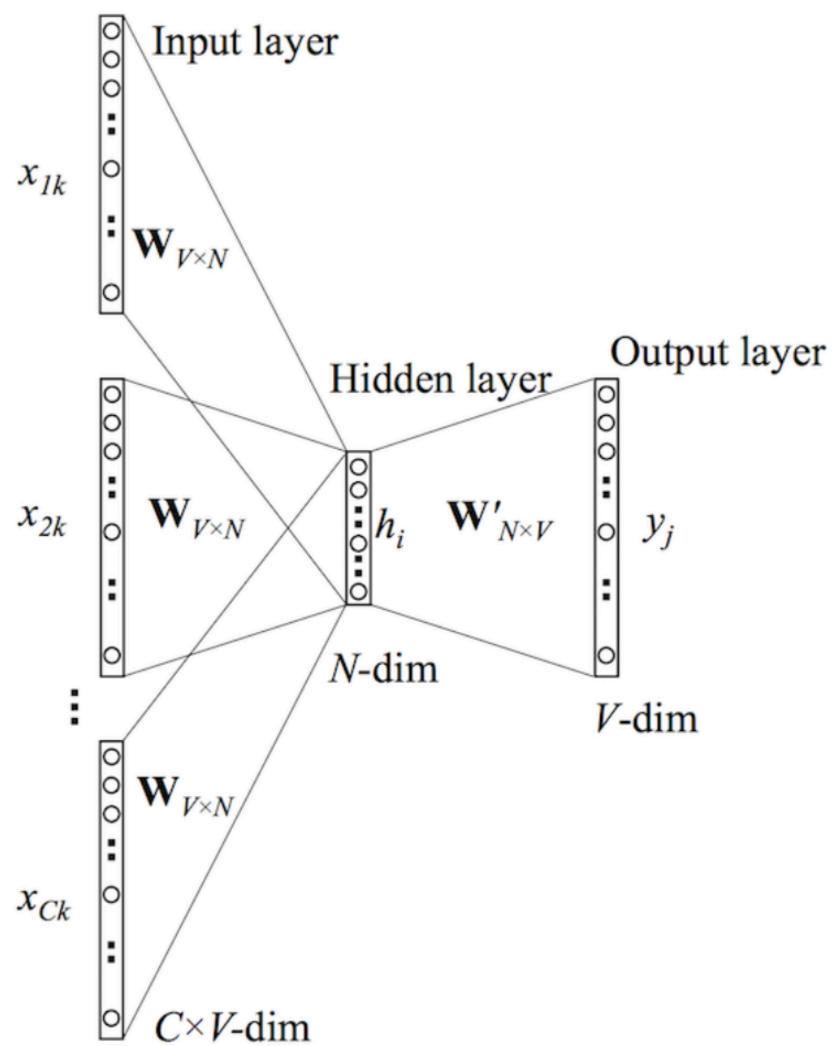
CBOW & Skip-Gram

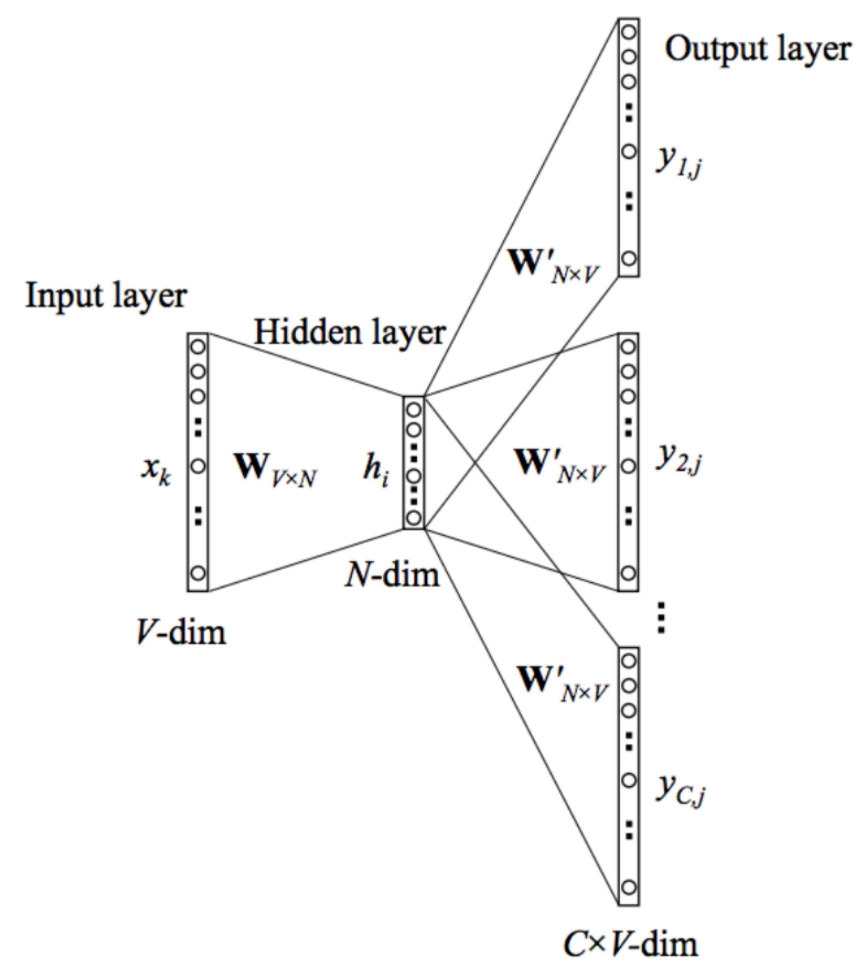
- Assumptions in CBOW & Skip-Gram:
  - Words with similar meaning / domain have the close contexts.

My favorite pet is ___. *cat, dog*

CBOW & Skip-Gram

- CBOW: Predicting the target words with context words.
- Skip-Gram: Predicting context words from the target words.





CBOW & Skip-Gram

- For example, given the sentence:

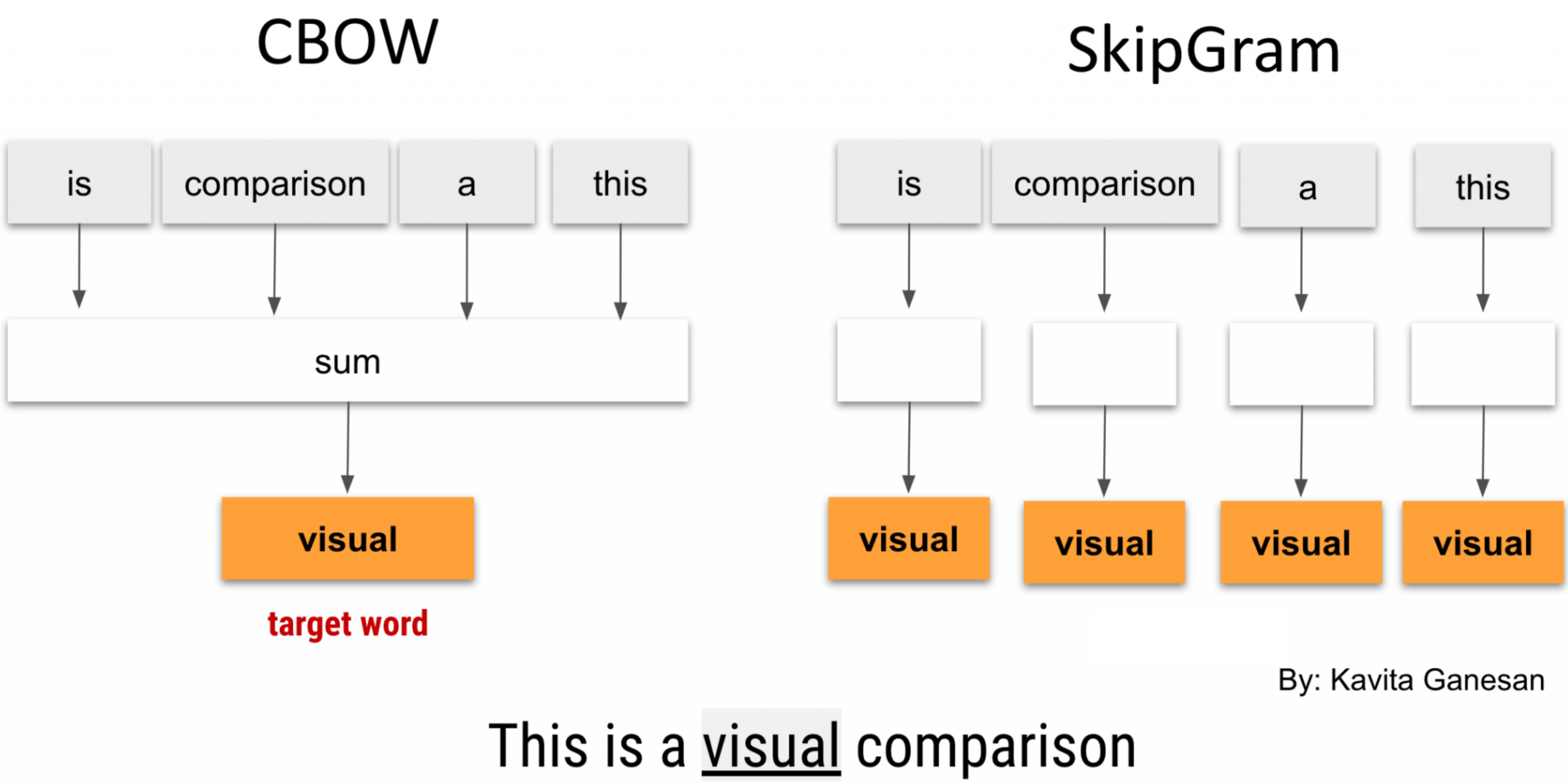
the quick brown fox jumped over the lazy dog.

- CBOW will be trained on the dataset:

```
([the, brown], quick), ([quick, fox], brown), …
```

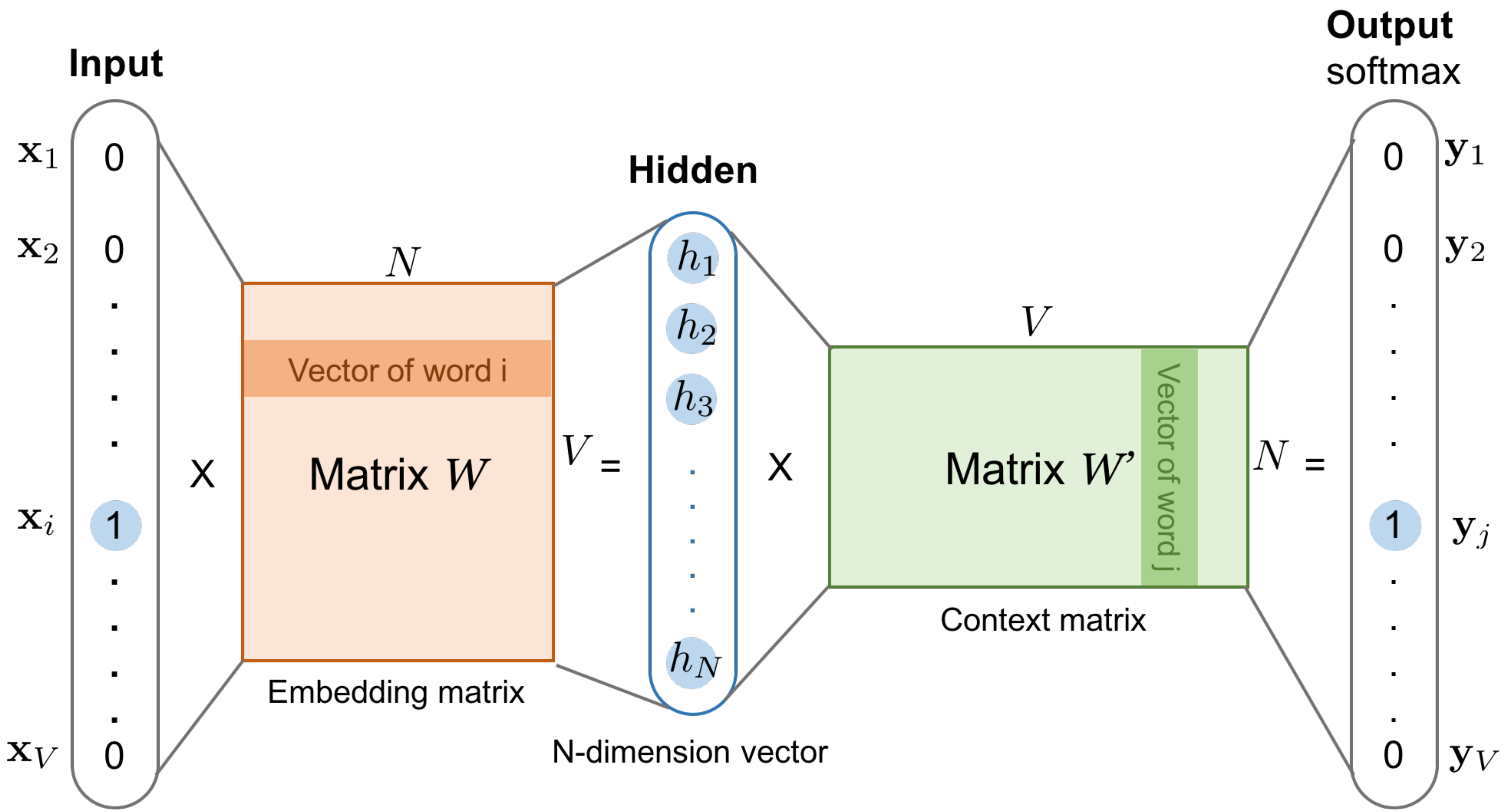
- Skip-Gram will be trained on the dataset:

```
(quick, the), (quick, brown), (brown, quick),
(brown, fox)…
```



Picture from https://kavita-ganesan.com/

Skip-Gram



Picture from https://lilianweng.github.io/

Softmax & Words classification

- Recap the softmax function:

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

- While training the embedding, we need to sum over the entire vocabulary in the denominator, which is costly.

$$p(w = i \,|\, \mathbf{x}) = \frac{\exp(h^\top v_{w_i'})}{\boxed{\sum_{j \in V} \exp(h^\top v_{w_j'})}}$$

$|V|$ **(vocabulary size) is thousands of millions**

Noise Contrastive Estimation

- Intuition: Estimate the parameters by learning to discriminate between the data w and some artificially generated noise $\tilde{w}$.

$$\textit{maximum likelihood estimation} \rightarrow \textit{noise contrastive estimation}$$

- Objective function:

$$\arg\max \ \log p(d=1 \mid w_t, x) + \sum_{\tilde{w}_i \sim Q}^{N} \log p(d=0 \mid \tilde{w}_i, x)$$

- Derive form:

$$\arg\max \ \log \frac{p(w_t \mid x)}{p(w_t \mid x) + Nq(\tilde{w})} + \sum_{\tilde{w}_i \sim Q}^{N} \log \frac{Nq(\tilde{w}_i)}{p(w_t \mid x) + Nq(\tilde{w}_i)}$$

Noise Contrastive Estimation

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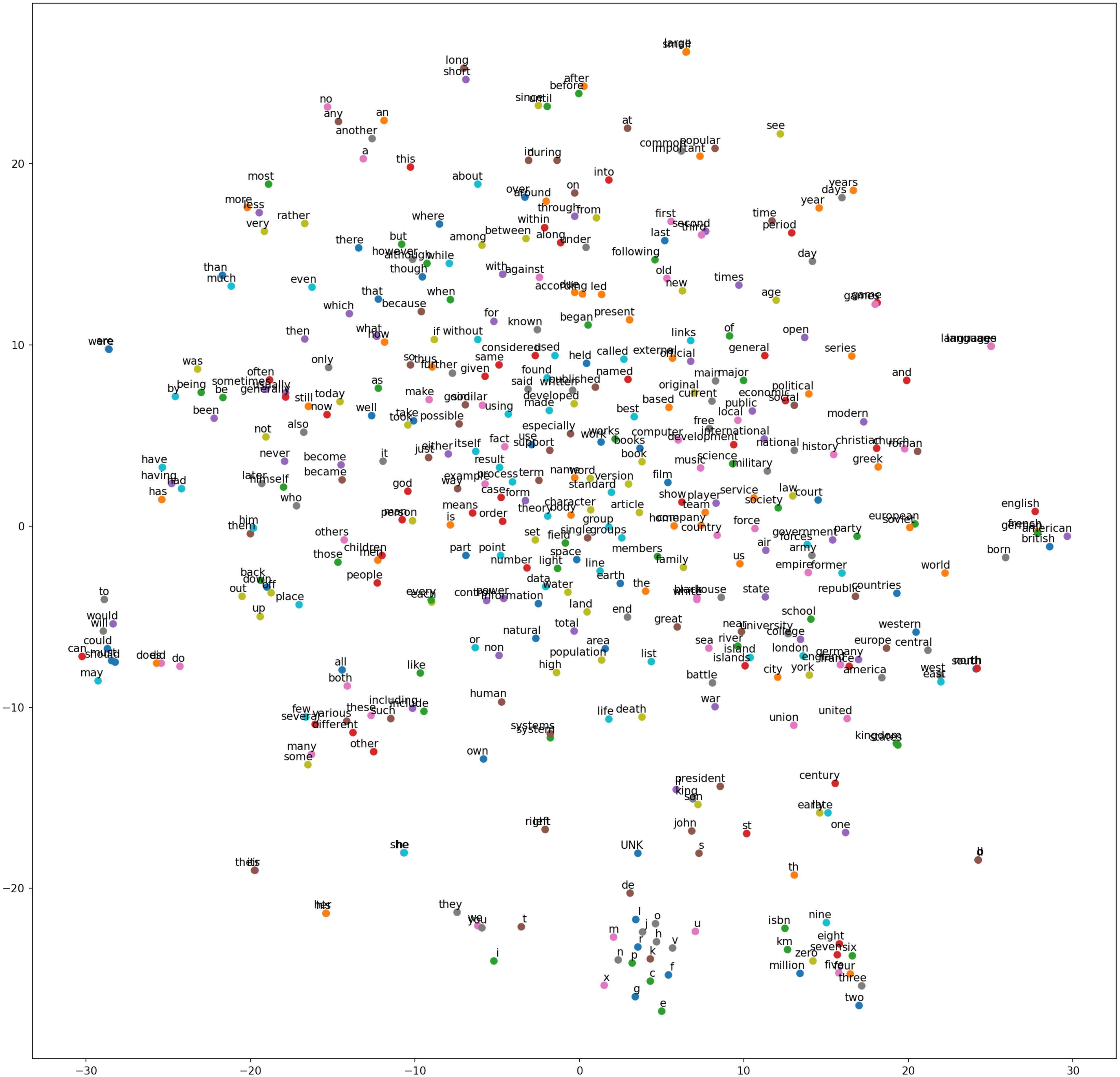
- After training: evaluate with softmax function.



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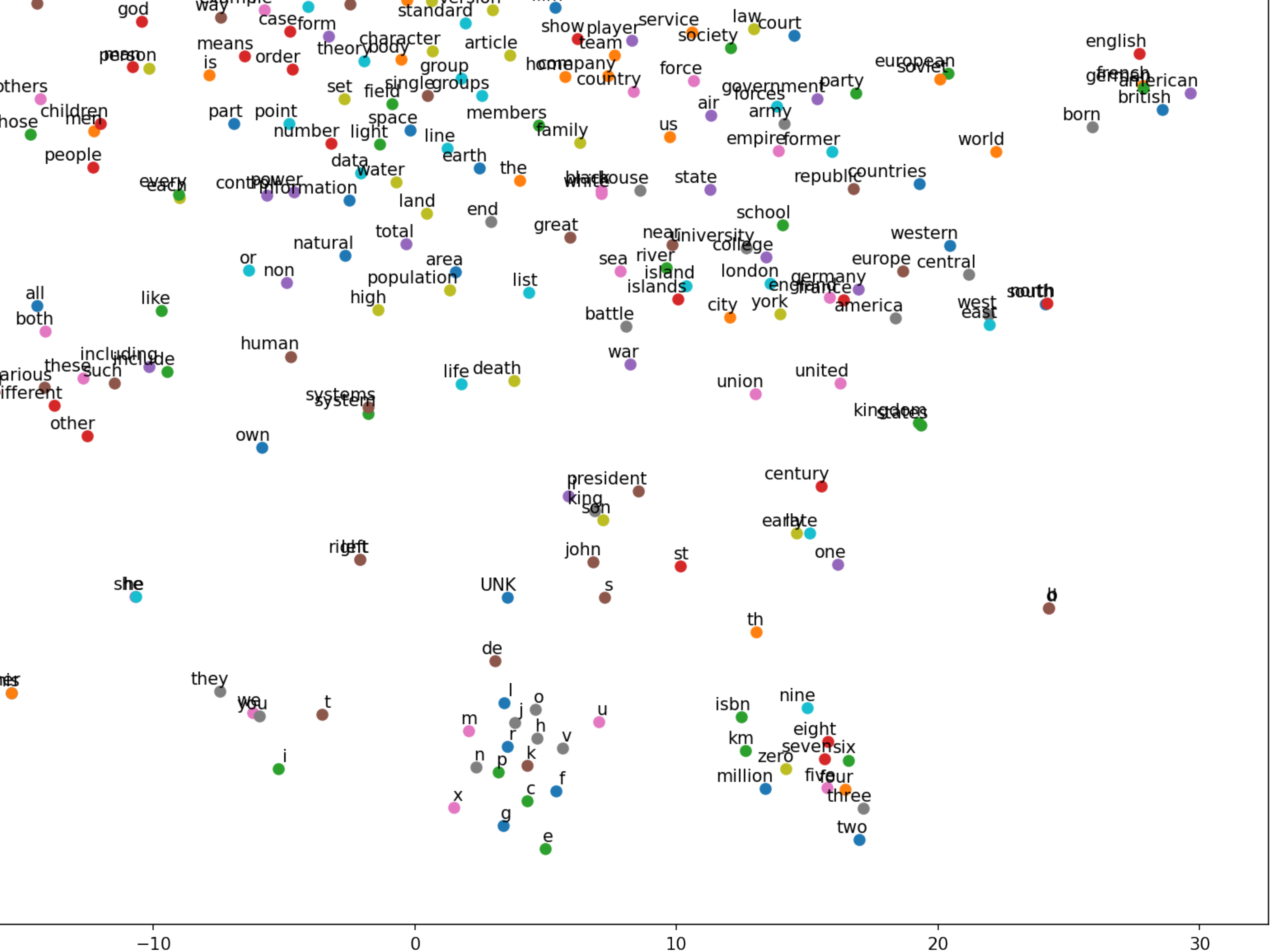

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Homework

- Functional API:

```
from tensorflow.keras import Model, Input

center_words = Input(shape=(), name='center_words', dtype='int32')
target_words = Input(shape=(1), name='target_words', dtype='int32')

embedding = embedding_lookup()(center_words)
loss = nce_loss()((embedding, target_words))

word2vec = Model(name='word2vec',
                 inputs=[center_words, target_words],
                 outputs=[loss])
```

Homework

- Model subclassing:

```
class ResNet(tf.keras.Model):

    def __init__(self):
        super(ResNet, self).__init__()
        self.block_1 = ResNetBlock()
        self.block_2 = ResNetBlock()
        self.global_pool = layers.GlobalAveragePooling2D()
        self.classifier = Dense(num_classes)

    def call(self, inputs):
        x = self.block_1(inputs)
        x = self.block_2(x)
        x = self.global_pool(x)
        return self.classifier(x)


resnet = ResNet()
```

Reference

- https://ruder.io/word-embeddings-softmax/index.html#noisecontrastiveestimation
- https://lilianweng.github.io/lil-log/2017/10/15/learning-word-embedding.html
- https://aegis4048.github.io/optimize_computational_efficiency_of_skip-gram_with_negative_sampling
- http://proceedings.mlr.press/v9/gutmann10a/gutmann10a.pdf
- https://papers.nips.cc/paper/5165-learning-word-embeddings-efficiently-with-noise-contrastive-estimation.pdf
- https://www.tensorflow.org/api_docs/python/tf/nn/nce_loss