

Lec 2

Word Representations, Text Classification

Recall

- Bag of word: one-hot every word & sum all one hot vecs in sentence

Subword Modelling

Handles conjugations!

companies expanding compan ies expand ing

Good: - share params
- save space { Zipf's law, handle out of vocab tokens

- Problems: - lack expressiveness if too few words
- if pieces too short, hard to compute
- need to balance subword length

Byte Pair Encoding ←

1. Start char level
2. Merge most frequent pairs
3. Iterate

seems like greedy Huffman info theory?

Unigram Models

Import SentencePiece
BPE / Unigram similar result
60k-80k good for English

Use unigram LM that can generate sentence
Pick a vocab size that maximises likelihood of corpus

$$P(X) = \prod_{i=1}^{|X|} P(x_i)$$

Segment sentence by maximising P(X)

- Limitations - Multilinguality is hard — since things depend on frequency, but data dist wrt lang not always balanced
→ Can workaroud by reweighting



- Arbitrary — "e st" or "es t"
- workaroud: subword regularisation

If adding new vocab, can do probability stuff and interpolate
 $\lambda P_{old}(x) + (1-\lambda) P_{new}(x)$

Embedding

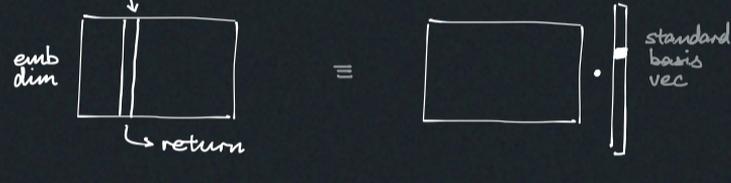
Handles word similarity!

Continuous BOW

I hate this movie

$$\vec{h} = [W] \left(\begin{matrix} \downarrow \text{lookup} \\ \downarrow \text{dense reprs} \end{matrix} \right)$$

Emb matrix



Training Embeddings — gradient descent

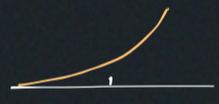
Hinge Loss

$$l = \max(y * s, 0)$$

Sigmoid + NLL

$$\sigma(y * s) = \frac{1}{1 + e^{-(y * s)}} \leftarrow \text{probability}$$

$$l = -\log \sigma(y * s)$$



no grad if $\hat{y} = y$

non-zero grad everywhere

→ then take derivative

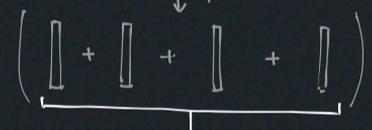
Neural Networks

Handles combined feature

→ Run NN over token embs to extract some feature

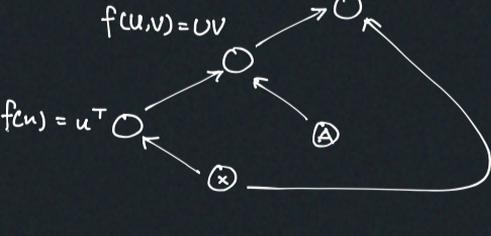
Deep Continuous BOW (CBOW)

I hate this movie



NNs — multilayer, tanh, ...
↓
feature

Computation Graph — DAG



Note: more node — slower

$$h = Wx + b$$

vs

$$h = \text{lin}(x)$$

$$h = \text{lin}(x)$$

← more optimised

Implementation:

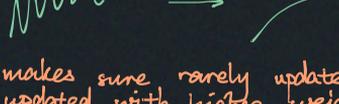
- Forward: like work scheduling
- Backward: take derivative in reverse topological order

Framework:

- PyTorch ← dynamic execution
- Tensorflow } ← define graph + compile
- JAX

Optimiser:

- Adam ← default
- Considers momentum & rolling average of gradient variance



makes sure rarely updated params are updated with higher weight!

- Scheduling



Visualisation:

- Dim reduction
- PCA
- t-SNE ← usually better than PCA but perplexity param sensitive

▷ Syntax