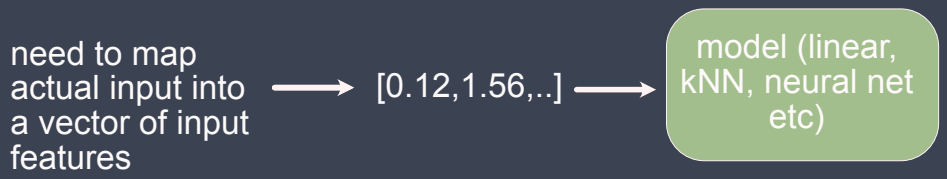
» Feature Engineering For Text

* Features: need to map actual input into a vector of input features *x* i.e. a vector of real-values



* A good choice of features can make a huge difference to a machine learning system, often the difference between success and failure.
* We'll focus first on choosing features for text input e.g. reviews, news articles. English language only.

» Feature Engineering For Text

Why is this hard?

- Words can have multiple meanings e.g. *bat*, *duck*, *flat*, *beam* (interpretation depends on context)
- Irony, sarcasm e.g. *This day just keeps getting better and better..!!*
- Run-together words like *hasn't* and *we're*.
- How to measure the "distance" between words with similar meanings ?
  - *great*, *wonderful*, *good* are easy ...
  - ... but what about *joe biden*, *president*, *parent* or *dublin*, *new york*, *ireland*
- How to encode rare/unique words, numbers etc e.g. names, emails addresses, phone numbers?

» Text Pre-processing

Text is a sequence of characters, words, sentences, paragraphs
→Focus on text as sequence of words here.

- Finding word boundaries is pretty easy in English - generally there are spaces or punctuation between words, just look at this slide
- First step is *tokenization*: split input character sequence into tokens.
  - E.g. *Here's example text, isn't it?*
  - Splitting on whitespace gives *Here's*, *example*, *text,*, *isn't*, *it?*
  - Should we split *Here's* into *Here* and *'s*? Should we treat *it?* and *it* as different tokens, or merge? Should we split *isn't* into *is* and *n't*?
    - Probably want to split *isn't* into *is* and *n't* if doing sentiment analysis as *n't* ("not") is important e.g to distinguish *is good* and *isn't good*. But probably ok to truncate *Here's* to *Here* since *'s* ("is") is a common, uninformative word
  - Not enough to just split on punctuation, need to use some language knowledge

» Text Pre-processing

Typically end up with different tokens for different forms of the same word e.g. *liked*, *liking*, *likes*. Can choose to merge these together into a single token e.g *like*. But again not so easy ...

* *Stemming*: merge by simply chopping off endings from tokens e.g. *liked*, *likes* $\rightarrow$ *like*. But then what about *liking*?
* *Lemmatisation* A bit smarter, use knowledge of language to merge properly.
* Need to be careful re capital letters e.g. *Us* and *US* could be pronoun and country. But if text is all caps then maybe *US*=*us* so need heuristics e.g. at start of sentence replace *Us* by *us*.
* Acronyms e.g. *eta*, *e.t.a.*, *E.T.A.* $\rightarrow$ *E.T.A.*
* Python
  * *sklearn*: tokenising splits on whitespace and chops *'s*, *'t* etc, no stemming. E.g. *likes liking liked* becomes *likes*, *liking*, *liked*
  * *ntlk* has more choices of tokeniser and stemmer.
    * E.g. applying word_tokenizer followed by PorterStemmer to *likes liking liked* gives *like*, *like*, *like*
    * E.g. *Here's example text, isn't it?* gives *here*, *'s*, *exampl*, *'* *text*, *,*, *is*, *n't*, *it*, *?*

» Python Code

```
import nltk
nltk.download('punkt')

from sklearn.feature_extraction.text import CountVectorizer
tokenizer = CountVectorizer().build_tokenizer()
print(tokenizer("Here's example text, isn't it?"))
from nltk.tokenize import WhitespaceTokenizer
from nltk.tokenize import word_tokenize
print(WhitespaceTokenizer().tokenize("Here's example text, isn't it?"))
print(word_tokenize("Here's example text, isn't it?"))

print(tokenizer("likes liking liked"))
print(WhitespaceTokenizer().tokenize("likes liking liked"))
print(word_tokenize("likes liking liked"))

from nltk.stem import PorterStemmer
stemmer = PorterStemmer()
tokens = word_tokenize("Here's example text, isn't it?")
stems = [stemmer.stem(token) for token in tokens]
print(stems)

tokens = word_tokenize("likes liking liked")
stems = [stemmer.stem(token) for token in tokens]
print(stems)
```

» Feature Engineering For Text

We've now converted our text to tokens. How can we convert a single token to a feature vector? Two main approaches:

* *one-hot encoding*. Map a word to a large, sparse vector (sparse = many zeros)
* *vector embedding*. Map a word to a small-ish, dense vector (small-ish = 1000 elements or so, dense = no zero elements)

» One-hot Encoding

- Parse training data, extract all the tokens and use these to form a dictionary. Add special <UNK> token for unknown words (not in training data)
- A word is mapped to a vector which has length = number of words in dictionary, set all elements zero then place a 1 in element with same index as word in dictionary E.g. *movie* might map to feature vector $[0,\ 1,\ 0,\ 0,\ 0,\ 0]$

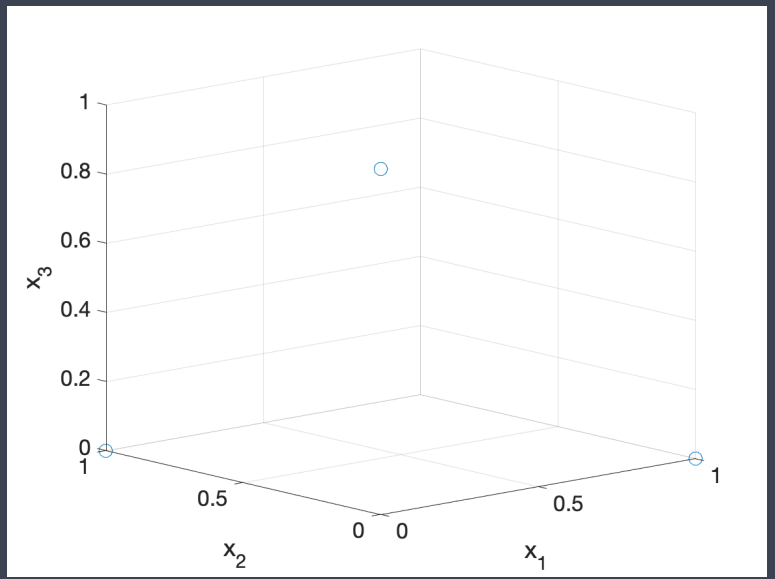
good	*movie*	*not*	*a*	*did*	*like*
0	1	0	0	0	0

- Length of feature vector = #distinct tokens (so can be pretty large e.g. 10-100K)
- *Note can use one-hot encoding with any discrete quantities, not just tokens/words*

» One-hot Encoding

Why not just map tokens to integers? E.g. map *i*'th token to integer *i*.

- Distances between feature vectors matter!
- Liable to mess up models unless distances reflect actual relationships
- Wth one-hot encoding all tokens are the *same* distance from one another e.g. Euclidean distance between any two tokens is $\sqrt{2}$
  - suppose have vectors $[0, 1, 0, 0, 0]$ and $[0, 0, 1, 0, 0]$
  - distance is $\sqrt{(0-0)^2 + (1-0)^2 + (0-1)^2 + (0-0)^2 + (0-0)^2} = \sqrt{2}$



» One-hot Encoding ⟶ Bag of Words

How can we map a *sequence* of tokens (sentence, paragraph, document) to a feature vector.

- Use *one-hot encoding* for each word in text, then add ...
- E.g. *a good good movie*

good	*movie*	*not*	*a*	*did*	*like*
0	0	0	1	0	0
1	0	0	0	0	0
1	0	0	0	0	0
0	1	0	0	0	0

add columns to get:

good	*movie*	*not*	*a*	*did*	*like*
2	1	0	1	0	0

» Bag of Words Model

How can we map *a sequence* of tokens (sentence, paragraph, document) to a feature vector.

- Count number of occurrences of each token in our text $\rightarrow$ later we'll then try to identify marker words like *excellent* or *disappointed*
- Length of feature vector = #distinct tokens
- Entry *i* of vector is set equal to number of times token *i* appears in text. E.g.

a good good movie
not a good movie
did not like

$\Rightarrow$

good	*movie*	*not*	*a*	*did*	*like*
2	1	0	1	0	0
1	1	1	1	0	0
0	0	1	0	1	1

- Note: we've thrown away information about the word order (and so any grammar) $\rightarrow$ that's why its called a "bag of words".

» Preserving Some Word Ordering

We can count pairs of tokens, triples etc

* *n-gram*: 1-gram = single token, 2-gram = pairs of tokens etc

a good good movie
not a good movie
did not like

$\Rightarrow$

good movie	*movie*	*did not*	*a*	. . .
1	1	0	1	. . .
1	1	0	1	. . .
0	0	1	0	. . .

* But can quickly end up with a huge feature vector as number of n-grams grows quickly e.g. if have q tokens then there there may be q^2 pairs of tokens.

» Python Bag of Words Example

```
docs = [
        'This is the first document.',
        'This is the second second document.',
        'And the third one.',
        'Is this the first document?']
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(docs)
print(vectorizer.get_feature_names())
print(X.toarray())
```

Output is:

```
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']
[[0 1 1 1 0 0 1 0 1]
 [0 1 0 1 0 2 1 0 1]
 [1 0 0 0 1 0 1 1 0]
 [0 1 1 1 0 0 1 0 1]]
```

```
vectorizer = CountVectorizer(ngram_range=(2, 2))
X = vectorizer.fit_transform(docs)
print(vectorizer.get_feature_names())
print(X.toarray())
```

Output is:

```
['and the', 'first document', 'is the', 'is this', 'second document', 'second second', 'the first', 'the second', 'the third', 'third one', 'this
is', 'this the']
[[0 1 1 0 0 0 1 0 0 0 1 0]
 [0 0 1 0 1 1 0 1 0 0 1 0]
 [1 0 0 0 0 0 0 0 1 1 0 0]
 [0 1 0 1 0 0 1 0 0 0 0 1]]
```

» Pruning: Remove Stop Words & Rare Words

Not all tokens or n-grams are interesting, so we can try to remove the boring ones so as to reduce the size of the feature vector.

* High-frequency tokens/n-grams
  * Words such as *the*, *a*, *is* are v common and don't help much with discriminating between text. Referred to as *stop words* → remove
  * sklearn:

```
import nltk
nltk.download('stopwords')
vectorizer = CountVectorizer(stop_words=nltk.corpus.stopwords.words('english'))
```

  * sklearn vectorizer also has df_max parameter to exclude words that occur in too many documents. Use cross-validation to choose a good value.
* Very low-frequency tokens/n-grams
  * Typos, tokens/n-grams that appear in only one document
  * Can encourage over-fitting e.g. classifier may learn to use a typo to identify a document → remove
  * sklearn vectorizer has df_min parameter to exclude words that occur in too few documents. Use cross-validation to choose a good value.
* How to distinguish between remaining medium-frequency tokens/n-grams?

» Word Importance: TF-IDF

Suppose have *a* set D of documents e.g. *a* set of movie reviews.

* *Term frequency (TF)* $tf(t, d)$ of token t in document d can be:
  * Raw count: number of times token t appears in *a* document $d \rightarrow$ usual choice
  * Boolean: 1 if t in document d, else 0
  * Normalised $\frac{\text{Number of times token } t \text{ appears in document } d}{\sum_{t' \in T} \text{Number of times token } t' \text{ appears in document } d}$, T the set of all tokens
  * $log(1 + \text{Number of times token } t \text{ appears in document } d)$
* E.g. $tf(t, d)$ of token *great* in *a great movie and a great day out* is 2 when using raw count while $tf(t, d)$ of token *terrible* is 0
* *Term frequency* $tf(t, d)$ *is larger when token t occurs a lot in document d*

» Word Importance: TF-IDF

* *Document frequency (DF)* $df(t)$ of token t is number of documents in D that contain token t
* *Inverse document frequency (IDF)* $idf(t)$ of token t in set of documents D is:
  * $idf(t) = log\frac{\text{Number of documents in } D}{1+df(t)}$ $\rightarrow$ add 1 to denominator to prevent divide-by-zero when $df(t) = 0$
    * sklearn a little different: $idf(t) = 1 + log\frac{1+\text{Number of documents in } D}{1+df(t)}$
  * *$idf(t)$ is large when $df(t)$ is small i.e. when token t occurs rarely in overall collection of documents D*
* *TF-IDF* $tfidf(t, d)$ of token t in document d is:
  * $tfidf(t, d) = tf(t, d) \times idf(t)$
  * $tfidf(t, d)$ increases with $tf(t, d)$ i.e. when token t occurs more often in document d
  * $tfidf(t, d)$ increases with $idf(t)$ i.e. when token t occurs more rarely in overall collection of documents D
  * *$tfidf(t, d)$ is large for a token that occurs a lot in document d but only rarely in overall collection of documents*
    $\rightarrow$ a reasonable heuristic for identifying informative tokens, and widely used

» Python TF-IDF Example

```
docs = [
        'This is the first document.',
        'This is the second second document.',
        'And the third one.',
        'Is this the first document?']
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(docs)
print(vectorizer.get_feature_names())
print(X.toarray())
```

```
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']
[[0 1 1 1 0 0 1 0 1]
 [0 1 0 1 0 2 1 0 1]
 [1 0 0 0 1 0 1 1 0]
 [0 1 1 1 0 0 1 0 1]]
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(norm=None)
X = vectorizer.fit_transform(docs)
print(vectorizer.get_feature_names())
print(X.toarray())
```

```
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']
[[0.   1.22 1.51 1.22 0.   0.   1.   0.   1.22]
 [0.   1.22 0.   1.22 0.   3.83 1.   0.   1.22]
 [1.92 0.   0.   0.   1.92 0.   1.   1.92 0.  ]
 [0.   1.22 1.51 1.22 0.   0.   1.   0.   1.22]]
```

* Term frequency of *and* in document 3 is $tf(1,3) = 1$.
* Document frequency of *and* is $df(1) = 1$,
  $idf(1) = 1 + log((1+4)/(1+1) = 1.92$
* TF-IDF of *and* in document 3 is $tfidf(1,3) = 1 \times 1.92 = 1.92$
* TF-IDF of *document* in document 1= is
  $tfidf(2,1) = 1 \times (1 + log((1+4)/(1+3))) = 1.22$

» Using TF-IDF In Bag of Words Model

* Recall previously set entry i of vector equal to number of times token i appears in document d. E.g.

a good good movie
not a good movie
did not like

$\Rightarrow$

good	*movie*	*not*	*a*	*did*	*like*
2	1	0	1	0	0
1	1	1	1	0	0
0	0	1	0	1	1

* Alternative: set entry i of vector equal to TF-IDF $tfidf(i, d)$ of token i for document d
  * Entries are now real-valued, e.g.

a good good movie
not a good movie
did not like

$\Rightarrow$

good	*movie*	*not*	*a*	*did*	*like*
2.57	1.28	0	1.28	0	0
1.28	1.28	1.28	1.28	0	0
0	0	1.28	0	1.69	1.69

  * Often also normalise feature vector to improve numerics e.g. divide all entries in feature vector x by $\sqrt{\sum_{j=1}^{n} x_j^2}$ or $\sum_{j=1}^{n} |x_j|$ where n is length of vector x

» Using TF-IDF For Recommending News Articles

Example: Given a new news article find similar news articles

1. Have existing set of m articles[1]. Map each article to a feature vector using bag of words and TF-IDF, gives set of feature vectors $x^{(i)}$, $i = 1, 2, \ldots, m$
2. New article. Also map to feature vector x using BOW/TF-IDF
3. Find k nearest neighbours of x amongst the $x^{(i)}$, $i = 1, 2, \ldots, m$
   * What distance metric to use?
   * Could use Euclidean distance $\sqrt{\sum_{j=1}^{m} (x^{(i)} - x_j)^2}$
   * For text also common to use *cosine similarity* $\sum_{j=1}^{m} x_j^{(i)} \times x_j$
     * $x_j^{(i)} \times x_j$ is large when both $x_j^{(i)}$ and x_j are large, and small with one or both are small.
     * So cosine similarity is large when articles have many important (as ranked by TF-IDF) words in common

[1] We'll use data at https://www.kaggle.com/snapcrack/all-the-news

» Python Code For Recommending News Articles

```
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np

# first 1000 articles from news dataset at https://www.kaggle.com/snapcrack/all-the-news
text = pd.read_csv('articles1_1000.csv')
text.head()

x = text['content']
vectorizer = TfidfVectorizer(stop_words = 'english', max_df=0.2)
X = vectorizer.fit_transform(x)
indices = np.arange(x.size)

from sklearn.model_selection import train_test_split
train, test = train_test_split(indices, test_size=0.2)

from sklearn.metrics.pairwise import cosine_distances
from sklearn.neighbors import NearestNeighbors
nbrs = NearestNeighbors(n_neighbors=3,metric=cosine_distances).fit(X[train])

test=[test[0]]
found = nbrs.kneighbors(X[test], return_distance=False)

test_i=0
print('text:\n%.300s'%x[test[test_i]])
for i in found[0]:
        print('match %d:\n%.300s'%(i,x[train[i]]))
```

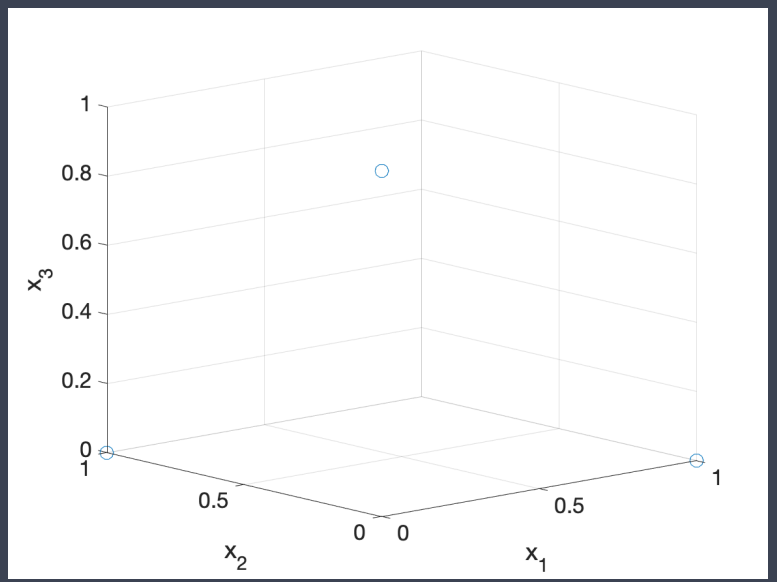
» Example Output

text:
PARIS – Former President Nicolas Sarkozy has been ordered by a judge to stand trial on charges of illegally financing his failed 2012 campaign, the Paris □prosecutors office said on Tuesday, the latest impediment for a politician who not long ago was hoping for a comeback. Mr. Sarkozy, 62, a me
match 151:
PARIS – New embezzlement allegations emerged on Wednesday against the French presidential candidate Fran□ois Fillon, adding uncertainty to an already tightly contested election. Mr. □Fillons campaign was thrown into turmoil last week after Le Canard Encha□n□, a weekly newspaper that mixes satir
match 562:
PARIS – France chose an idealistic, traditional candidate in □Sundays primary to represent the Socialist and parties in the presidential election this spring. The candidate, Beno□t Hamon, 49, who ran on the slogan that he would □make □Frances heart beat □, bested Manuel Valls, the former prime
match 534:
PARIS – Michel Onfray, a French pop philosopher, was sounding pretty upbeat on the phone, even though the title of his latest book is □Decadence: The Life and Death of the Tradition. □His book had just come out, with an impressive press run of 120, 000 copies, and was selling briskly in spit

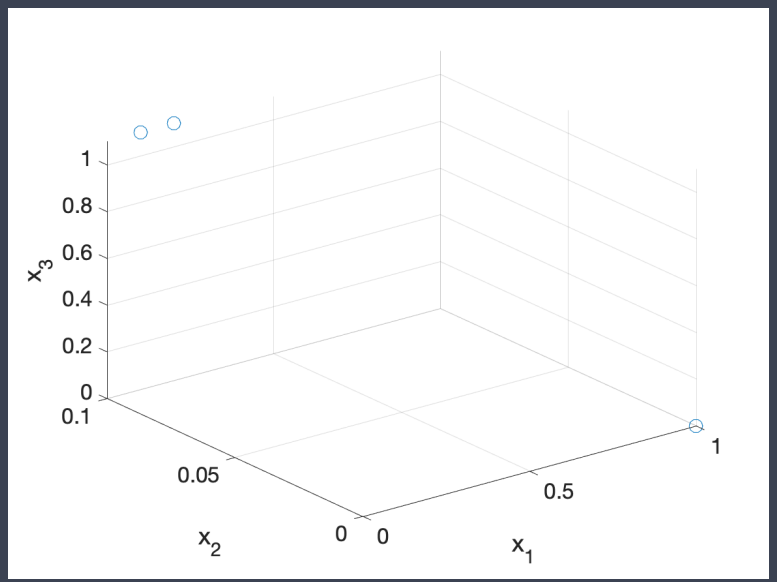
… not too bad! Extend to include the popularity of each news article and this would be a simple recommender system.

» Vector Embedding

- Map *a* word to *a* small-ish, dense vector (small-ish = 1000 elements or so, dense = no zero elements)
- Idea: words which have similar meaning are close together, words with different meaning are further apart
- E.g. *shocked* might have nearby words *horrified*, *amazed*, *astonished*, *dismayed*, *stunned*, *appalled*.



one hot encoding

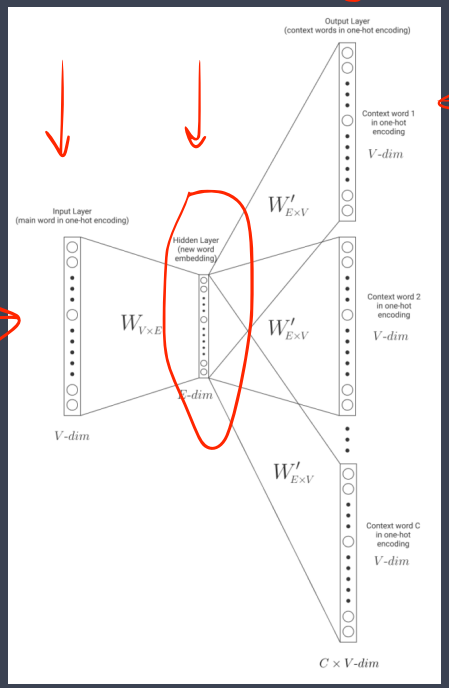


vector embedding

» Vector Embedding: Word2Vec and GloVe[2]

How to learn word embeddings? First idea (from 2013 or so):

- Train a neural net (with one hidden layer i.e. an MLP)
- Use a cost function that encourages assigning similar feature vectors to words that occur in similar contexts.
  - *skip-gram*. given target word, predict surrounding words



https://www.baeldung.com/cs/word-embeddings-cbow-vs-skip-gram

- Use weights from hidden layer of trained network as the vector embedding for a word.

[2] See https://en.wikipedia.org/wiki/Word2vec and https://en.wikipedia.org/wiki/GloVe_(machine_learning).

» Vector Embedding: Word2Vec and GloVe

- Can combine Word2Vec and GloVe with a bag of words model to map from a sequence of words to a feature vector.
  - Map each word to a feature vector
  - Then sum these vectors element-wise to get a single vector for the sequence of words
  - E.g. if two individual word vectors are $[0.1,\ 0.7,\ 0.3]$ and $[0.6,\ 0.2,\ 0.1] \rightarrow$ combined vector is $[0.7,\ 0.9,\ 0.4]$.

» Vector Embedding: BERT[3]

How to learn word embeddings? Second idea (from 2018 or so):

- Use a transformer neural net – afraid we haven't time to go into the details here.
- Uses word-piece tokenisation (see https://huggingface.co/learn/nlp-course/chapter6/6?fw=pt):
  - Add white space around punctuation (*there's* becomes *there ' s*
  - Split text on white space
  - Split words into individual letters, then increase vocabulary by merging common letter sequences e.g. ['example', 'of', 'word', 'piece', 'token', '##isation'], ['here', '', 's', 'example', 'text', ',', 'isn', '', 't', 'it', '?']
- Neural net takes sequence of one-hot encoded tokens as input, converts these to a sequence of embedding vectors
- Cost function: predict target word from surrounding words (delete target word from the text, then use the remaining text to try to predict the target word).
- So vector for a word changes depending on the context (the text surrounding the word) $\rightarrow$ probably a major reason for better performance.

[3] See https://en.wikipedia.org/wiki/BERT_(language_model) and https://www.sbert.net/

» Summary

- When working with text first port of call used to be TF-IDF plus bag of words.
- Word2Vec and GloVe were popular for a few years, but now overtaken by BERT and its relations
- BERT and related transformers are probably now the baseline against which to compare other methods.
  - But these are large-ish models and so computationally expensive (e.g. not suited to mobile handsets)
  - Need lots of training data (so usually use a pre-trained model and then fine-tune it)