COMP3420 Lesson 10

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Today's lesson

- Bag-of-words review and its problems.
- Wordnet
- Embeddings
- Example of using embeddings for colours
- Using embeddings without sequences
- Context drift

Reading

- Chollet: Section 11.3.3
- Jurafsky and Martin, Chapter 9 (optional)

Other administrative matters

Student survey for COMP3420 is now open.
We don't see it until after your exams, so be honest!

This is my first time teaching at Macquarie, so I'm very interested to hear feedback.

If you aren't happy with something in the course that you want fixed urgently, talk to Abid or email me (`greg.baker@mq.edu.au`)

Bag-of-words problems

Homographic Ambiguities Everywhere

Language features ambiguity at multiple levels.

Lexical Ambiguity

Example from Google's dictionary:

- bank (n): the land alongside or sloping down a river or lake.
- bank (n): financial establishment that uses money deposited by customers for investment, ...
- bank (v): form in to a mass or mound.
- bank (v): build (a road, railway, or sports track) higher at the outer edge of a bend to facilitate fast cornering.
- ...

Long-distance Dependencies

- Sentences are sequences of words.
- Words close in the sentence are often related.
- But, sometimes, there are relations between words far apart.

grammatical: "The man living upstairs $\boxed{\text{is}}$ very cheerful"
"The people living upstairs $\boxed{\text{are}}$ very cheerful"

knowledge: "I was born in France and I speak fluent $\boxed{\text{French}}$"

reference: "I bought a book from the shopkeeper and I liked $\boxed{\text{it}}$"

From the two examples above we can see that words that may be far from the gap determine what is the best word that fills the gap.

The third example shows that the reference of a pronoun can be fairly far from the pronoun itself.

Cross-culture concepts

A word might-or-might-not be translatable across different cultures or languages.

Dinner

Dinner

Review of bag-of-words model for embedding text

- Embedding method: each word of vocabulary is a dimension.
- Homographs are treated as if they were the same word
  - *I can kick the can*
- Synonyms are treated as different
  - *Begin*
  - *Start*
  - *Commence*
- Word order is ignored (unless using bigrams)
- No way of handling long-distance dependencies
- Context ignored

Wordnet

Introduction to WordNet

- Developed by Princeton University
- Large lexical database of English words
- Organizes words into sets of synonyms called synsets
- Word relationships captured through hypernyms and hyponyms
- Only contains "open-class words": nouns, verbs, adjectives, and adverbs.
- (Doesn't have determiners, prepositions, pronouns, conjunctions, and particles)
- WordNets exist for many languages (we'll just look at English) `http://globalwordnet.org/resources/wordnets-in-the-world/`

Grabbing dependencies

```
#!/usr/bin/env python3
import nltk
nltk.download('wordnet')
nltk.download('omw-1.4')
```

Wordnet synsets

```
#!/usr/bin/env python3

from nltk.corpus import wordnet as wn
synsets = wn.synsets('car')
print(synsets)
print(synsets[0].definition())
print(synsets[0].examples())
print(synsets[0].lemmas())
print(synsets[0].lemmas(lang='spa'))
```

```
[Synset('car.n.01'), Synset('car.n.02'), Synset('car.n.03'), Synset('car.n.04'), Synset('cable_car.n.01')]
a motor vehicle with four wheels; usually propelled by an internal combustion engine
['he needs a car to get to work']
[Lemma('car.n.01.car'), Lemma('car.n.01.auto'), Lemma('car.n.01.automobile'), Lemma('car.n.01.machine'), L
[Lemma('car.n.01.auto'), Lemma('car.n.01.automóvil'), Lemma('car.n.01.carro'), Lemma('car.n.01.coche'), Le
```

wordnet2.py (hypernyms)

```
#!/usr/bin/env python3

from nltk.corpus import
    wordnet as wn
synsets = wn.synsets('car')
print(synsets[0])
print(synsets[0].hypernyms())
x = synsets[0].hypernyms()[0]
while True:
    print(x.hypernyms())
    if len(x.hypernyms()) > 0:
        x = x.hypernyms()[0]
    else:
        break
```

```
Synset('car.n.01')
[Synset('motor_vehicle.n.01')]
[Synset('self-propelled_vehicle.n
[Synset('wheeled_vehicle.n.01')]
[Synset('container.n.01'), Synset
[Synset('instrumentality.n.03')]
[Synset('artifact.n.01')]
[Synset('whole.n.02')]
[Synset('object.n.01')]
[Synset('physical_entity.n.01')]
[Synset('entity.n.01')]
[]
```

How to find hyponyms — Hearst Patterns

Pattern	**Example**
X and other Ys	cats and other animals
Ys such as X	animals such as cats
Ys, including X	animals, including cats
Ys, especially X	animals, especially cats
X or other Ys	cats or other animals
Ys like X	animals like cats
...	...

A cat is an animal

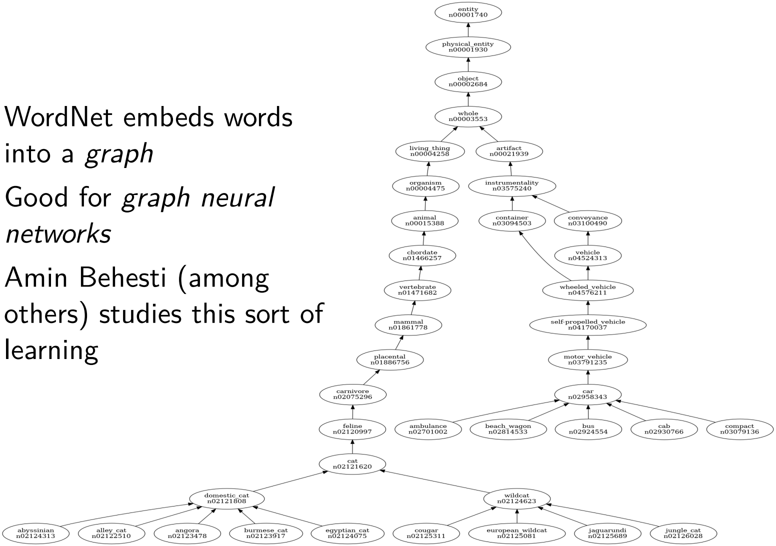
Hypernyms are the opposite of hyponyms

```python
#!/usr/bin/env python3

from nltk.corpus import
   wordnet as wn
synsets = wn.synsets('car')
for car_example in
   synsets[0].hyponyms()[:10]:
    print(car_example)
```

```
Synset('ambulance.n.01')
Synset('beach_wagon.n.01')
Synset('bus.n.04')
Synset('cab.n.03')
Synset('compact.n.03')
Synset('convertible.n.01')
Synset('coupe.n.01')
Synset('cruiser.n.01')
Synset('electric.n.01')
Synset('gas_guzzler.n.01')
```

WordNet as an embedding

- WordNet embeds words into a *graph*
- Good for *graph neural networks*
- Amin Behesti (among others) studies this sort of learning



Example: learn whether something is fluffy / furry

Thing	Fur
entellus	furry
king of beasts	furry
caracal	furry
Cervus elaphus	furry
Lepidochelys olivacea	not furry
monkey	furry
sea scooter	not furry
Macaca sylvana	furry
ichneumon	furry
wood pussy	furry

furfail.py

```
vectorizer = keras.layers.StringLookup()
vectorizer.adapt(train.Thing)
train_data = vectorizer(train.Thing)
validation_data = vectorizer(validation.Thing)

inputs = keras.Input(shape=(1,))
output = keras.layers.Dense(1,
          activation="sigmoid")(inputs)
model = keras.Model(inputs=[inputs],outputs=[output])
model.compile(
    loss='binary_crossentropy',
    metrics=['accuracy'])

history = model.fit(x=train_data, y=train.target,
    validation_data=(
        validation_data,
        validation.target),
    verbose=2,
```

Data irrelevancy — it is only as good as chance

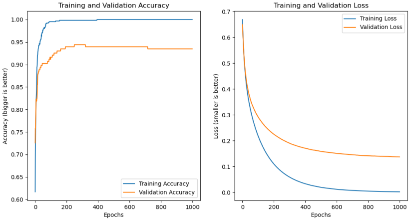
```
21/21 - 1s - loss: 14.4917 - accuracy: 0.5607 - val_loss: 0.6959 - val_accuracy: 0.4093 - 797ms/epoch - 38
21/21 - 0s - loss: 11.5815 - accuracy: 0.5607 - val_loss: 0.6979 - val_accuracy: 0.4093 - 108ms/epoch - 5m
21/21 - 0s - loss: 9.1865 - accuracy: 0.5607 - val_loss: 0.7000 - val_accuracy: 0.4093 - 114ms/epoch - 5ms
21/21 - 0s - loss: 6.6852 - accuracy: 0.5623 - val_loss: 0.7022 - val_accuracy: 0.4093 - 105ms/epoch - 5ms
21/21 - 0s - loss: 4.1274 - accuracy: 0.5623 - val_loss: 0.7047 - val_accuracy: 0.4093 - 108ms/epoch - 5ms
21/21 - 0s - loss: 1.6590 - accuracy: 0.5561 - val_loss: 0.7069 - val_accuracy: 0.4093 - 106ms/epoch - 5ms
21/21 - 0s - loss: 0.6782 - accuracy: 0.5717 - val_loss: 0.7074 - val_accuracy: 0.4093 - 113ms/epoch - 5ms
21/21 - 0s - loss: 0.6855 - accuracy: 0.5530 - val_loss: 0.7074 - val_accuracy: 0.4093 - 107ms/epoch - 5ms
21/21 - 0s - loss: 0.6878 - accuracy: 0.5452 - val_loss: 0.7076 - val_accuracy: 0.4093 - 99ms/epoch - 5ms/
21/21 - 0s - loss: 0.6843 - accuracy: 0.5623 - val_loss: 0.7076 - val_accuracy: 0.4093 - 99ms/epoch - 5ms/
```

fur-success.py 14–31 — Enrich with hypernym information

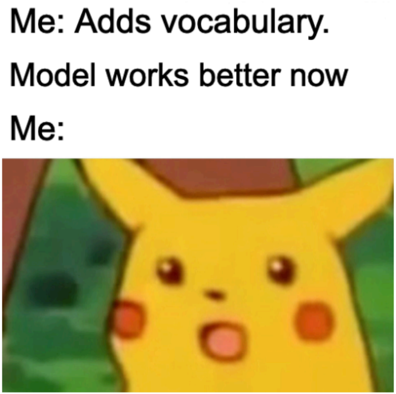
```python
def hypernym_line(synset):
    s = set()
    hypernyms = synset.hypernyms()
    for h in hypernyms:
        s.update([h])
        parents = hypernym_line(h)
        s.update(parents)
    return s
def enrich_with_hypernyms(x):
    synsets = wn.synsets(x)
    if len(synsets) == 0: return x
    first_synset = synsets[0]
    hypernyms = hypernym_line(first_synset)
    h = " ".join([x.lemma_names()[0] for x in
       hypernyms])
    return x + " " + h
df['enriched'] = df.Thing.map(enrich_with_hypernyms)
train, validation = train_test_split(df)
```

Concept similarity is now encoded

```
21/21 - 1s - loss: 0.6685 - accuracy: 0.6168 - val_loss: 0.6489 - val_accuracy: 0.7256 - 547ms/epoch - 26r
21/21 - 0s - loss: 0.6454 - accuracy: 0.6900 - val_loss: 0.6317 - val_accuracy: 0.7581 - 104ms/epoch - 5ms
21/21 - 0s - loss: 0.6263 - accuracy: 0.7305 - val_loss: 0.6164 - val_accuracy: 0.7581 - 105ms/epoch - 5ms
21/21 - 0s - loss: 0.6093 - accuracy: 0.7664 - val_loss: 0.6019 - val_accuracy: 0.7767 - 103ms/epoch - 5ms
21/21 - 0s - loss: 0.5936 - accuracy: 0.7850 - val_loss: 0.5890 - val_accuracy: 0.7860 - 105ms/epoch - 5ms
...
21/21 - 0s - loss: 0.0023 - accuracy: 1.0000 - val_loss: 0.1374 - val_accuracy: 0.9349 - 100ms/epoch - 5ms
21/21 - 0s - loss: 0.0023 - accuracy: 1.0000 - val_loss: 0.1374 - val_accuracy: 0.9349 - 100ms/epoch - 5ms
21/21 - 0s - loss: 0.0023 - accuracy: 1.0000 - val_loss: 0.1374 - val_accuracy: 0.9349 - 98ms/epoch - 5ms/
21/21 - 0s - loss: 0.0023 - accuracy: 1.0000 - val_loss: 0.1374 - val_accuracy: 0.9349 - 100ms/epoch - 5ms
21/21 - 0s - loss: 0.0023 - accuracy: 1.0000 - val_loss: 0.1374 - val_accuracy: 0.9349 - 103ms/epoch - 5ms
```



Wait? What?



- Don't we need to *reduce* the dimensionality to improve a model?

What happened

We changed β from 1.0 down to almost 0.0 (and increased k). We made *some* vocabulary terms very effective.

$$V = kN^{\beta}$$

where:

- V is the size of the vocabulary
- N is the size of the corpus
- k and β are constants that depend on the language and the type of text
- Usually $.67 < \beta < .75$ (Jane Austen is verbose, so very low β; Shakespeare is concise, so very high β; 1.0 would be noise)

Explainer

	0
mammal	9.873138
dog	8.689872
genus	7.822046
whale	7.587407
american	7.585626

	0
snake	-9.926085
car	-9.148499
lizard	-8.403874
buggy	-8.201899
cart	-7.305783

What relu does

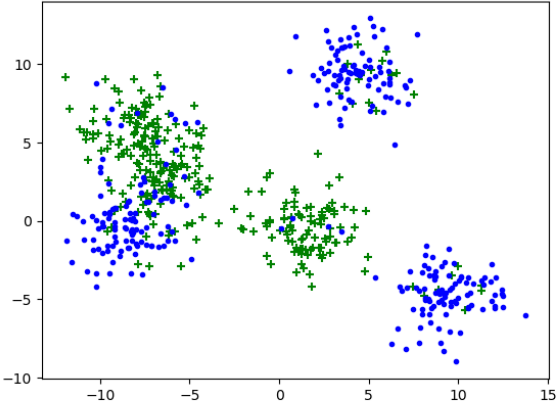
ReLU review

ReLU = **re**ctified **l**inear **u**nit

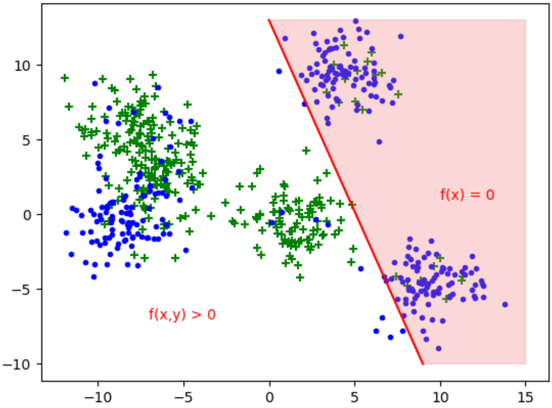
$$f(x) = \max(0, x) = \begin{cases} 0 & \text{if } x \leq 0, \\ x & \text{if } x > 0. \end{cases}$$

```
keras.layers.Dense(1, activation='relu')
```

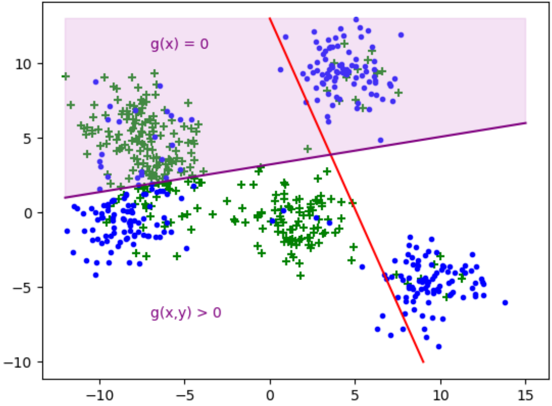
A 2D dataset (not necessarily language based)



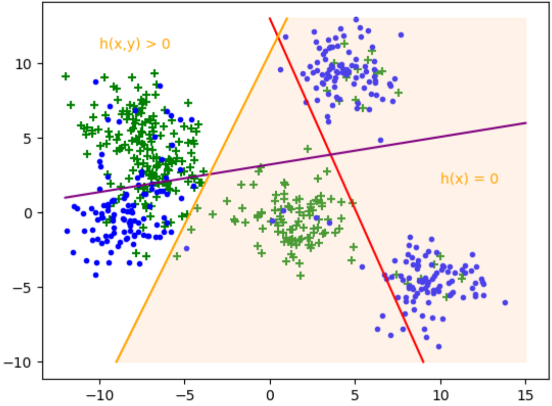
ReLU divides the data into a zero-region and a non-zero region



Adding another relu gives some more regions

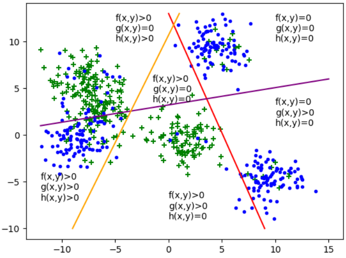


And so on with a third ReLU — not quite 8 regions



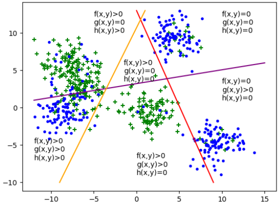
Observations about the null region

- All the `f(x)=g(x)=h(x)=0` points are indistinguishable
- Unless the optimizer allows a big enough "jump" to "capture" another point, the loss function from that region is constant.
- A line could only move if it alters the loss on the *other* sides of lines.
- The derivative of the loss function near the lines in the area is 0.
- If a word vector is in the null region, often no improvement is possible.



More observations

- We took a 2D space (x, y) and turned it into a 3D space $(f(x, y), g(x, y), h(x, y))$
- Points where $f(x, y) = 0$ are orthogonal to points where $g(x, y) = h(x, y) = 0$
  - Many other sets of orthogonal vectors too
- With enough relu lines, we could give almost every point its own region



Word Embeddings

Key ideas behind word embeddings

- **The Curse of Dimensionality** means that the dot product of two vectors with random values is going to be close to zero
- We can assign a random vector to each word
- Adjust the vectors to make similar words have a dot product bigger than zero
- Any way of adjusting those vectors is reasonable

One-hot vs. word embeddings

One-hot

- Sparse
- Binary values (typically)
- High-dimensional
- Hard-coded

Word embeddings

- Dense
- Continous values
- Lower-dimensional
- Learned from data

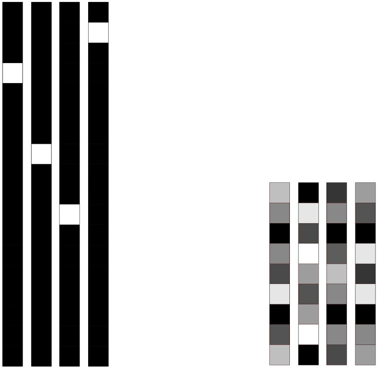
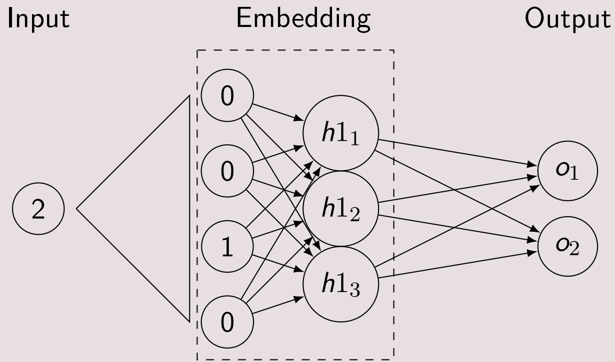


Image from Chollet (2018) "Deep Learning with Python:", Manning. Figure 6.2, page 184.

Embedding Layer in Keras

The input of a Keras embedding layer is a sequence of word indices which will be internally converted into their one-hot representations.

A Keras Embedding Layer (for one word)



Processing Sequences of Words in Keras

- The input of a Keras embedding layers is a sequence of words. It might be one or it might be a million words.
- The output is a sequence of word embeddings, perhaps 300 dimensions each.
- So the next layer up may have to deal with input that is shaped 1×300 or 100000×300. This causes a problem. Here are potential solutions:
  - Choose a problem where you always have the same number of words in each document, like the example we'll do in a moment
  - Add a pooling layer (e.g. take the average) of all the words' embeddings.
  - Trim and pad sequences so that they are the same length. `keras.utils.pad_sequences` can help with this
  - Use a layer that works on sequences (we'll do this next week)

A fun example with colours

- `https://cosmiccoding.com.au/tutorials/encoding_colours/`
- Start with a data set of similar and dissimilar colours
- Assign a random 2D vector to each colour name. This is an **embedding** of colours into R^2. We do this using an Embedding layer.
  - Each 2D vector value is an *updateable* parameter.
  - Gradient descent will improve those vector values.
- Train a classifier to predict whether two colours are similar or not

The data set

Colour_x	Colour_y	colours_are_similar
Chocolate	GoldOchre	1.0
SlateBlueMedium	Gray92	0.0
SpringGreen	YellowLight	0.0
Pink2	Tomato2	0.0
GeraniumLake	GeraniumLake	1.0

colour_number	Colour	hex
313	Aquamarine4	#458b74
119	BrownOchre	#87421f
477	MediumPurple1	#ab82ff
46	PaleGreen	#98ff98
478	MediumPurple2	#9f79ee

colour-embedding.py 19–34

```
def euclidean_distance(tensor):
    x1, y1, x2, y2 = tensor[:, 0], tensor[:, 1],
        tensor[:, 2], tensor[:, 3]
    distance = (x1 - x2)**2 + (y1 - y2)**2
    return tf.expand_dims(distance, axis=-1)

inputs = keras.Input(shape=(2,))
embedding_layer = Embedding(
    input_dim=len(colour_lookup),
    output_dim=2,
    input_length=2
)(inputs)
flattening_layer = Flatten()(embedding_layer)
distance_layer =
   Lambda(euclidean_distance)(flattening_layer)
output = Dense(1, activation="sigmoid")(distance_layer)
model = keras.Model(inputs=[inputs], outputs=[output])
model.compile(loss='binary_crossentropy')
```

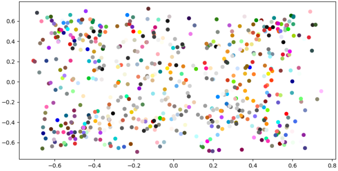
Notes on colour-embedding.py

A *sigmoid* activation can't say whether two points are close to each other, so we need a layer that provides a distance measure. That's the *Lambda* layer.

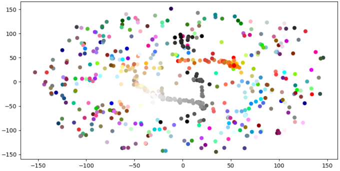
We didn't care about validation loss, or a training set: we just wanted the values of the embedding layer.

Evolution of the embedding parameters over time

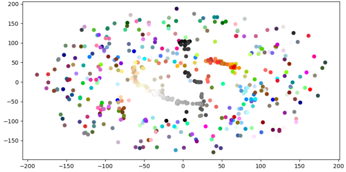
Initial (random) weights



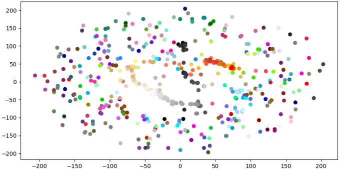
Epoch 1000



Epoch 2000



Epoch 3000



I made a video `colour-animation.mp4`

Four Ways to Obtain Word Embeddings

Manually e.g. WordNet

Naively e.g. bag-of-words

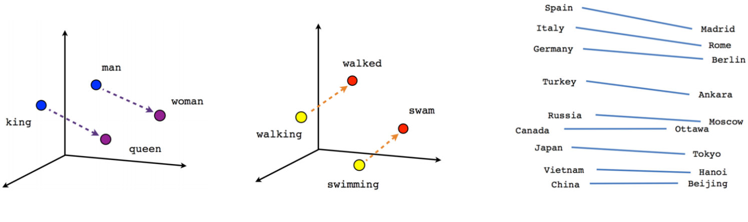
Jointly Learn the word embeddings jointly with the task you care about (e.g. document classification) — what we just did with colours

Pre-trained Use pre-trained word embeddings — we'll do this with Enron

Word2vec was the first pre-trained word embedding

If you don't count manual approaches as being pre-training

- First introduced in 2013 by a team of researchers led by Tomas Mikolov at Google. Word2vec was trained on a large-scale dataset, the Google News corpus.
- Comprised of about 100 billion words from news articles.
- Resulted in a vocabulary size of around 3 million unique words.
- The pretrained word vectors provided by the authors used a 300-dimensional vector space.



Male-Female   Verb tense   Country-Capital

Methods

If the training set contains "Mary sat at the bank" …

CBOW: Continuous Bag-of-Words
: CBOW attempts to predict "sat" given "Mary", "at", `[blank]` "the", "bank".

Continuous skip-gram
: Skip-gram attemps to predict "Mary", "at", "the", "bank" given "sat"

FastText: An Extension of Word2vec

- **Overview:** FastText is a word embedding technique and an extension of Word2vec, developed by Facebook's AI Research (FAIR) lab in 2016.
- **Key Improvement:** Considers subword information (character-by-character sequences) to create embeddings.
- Helps solve out-of-vocabulary (OOV) problems
- Works well in morphologically-rich languages like Turkish, Arabic, Russian, Finnish (where words change form a lot)

ELMo / BERT — Contextual Embeddings

Not a simple lookup; needs context to create embeddings. Google search uses BERT.

http://jalammar.github.io/illustrated-bert/

Using embeddings

enron-with-embeddings.py 25–32

```
sequence_length = 200
vectorizer = TextVectorization(
    output_sequence_length=sequence_length,
    output_mode='int')
vectorizer.adapt(train_data.email_text)
train_vectors = vectorizer(train_data.email_text)
# Display a few training vectors
print(train_vectors[:2])
```

```
  tf.Tensor(
[[    9    48   124     6   439   215    21    89    99   165  1040  4635
    117  1040  4635   117     0     0     0     0     0     0 ...
    ...
    0     0     0     0     0     0     0     0]
[     9    76  4651   321   123    15     2   162   834     7     2  7987
     87    29   443    19    29    38    11     2   407   942     6    76
    100    29    14  6195  1665   781     7   195    29    82   443     5
    ...
   1233 36061 16228   446  7131  6389    62 36100]
```

enron-with-embeddings.py 37–41

```
vocab_size = vectorizer.vocabulary_size()
inputs = keras.Input(shape=(sequence_length,))
embedding_layer = keras.layers.Embedding(
    input_dim=sequence_length,
    output_dim=16)(inputs)
```

Embed the first `sequence_length` (200) words of each Enron email as a vector with 16 dimensions

enron-with-embeddings.py 42–47

```
averaging_layer =
    keras.layers.GlobalAveragePooling1D()(embedding_layer)
thinking_layer = keras.layers.Dense(8,
    activation="relu")(averaging_layer)
output = Dense(1, activation="sigmoid")(thinking_layer)
model = keras.Model(
     inputs=[inputs],
     outputs=[output])
```

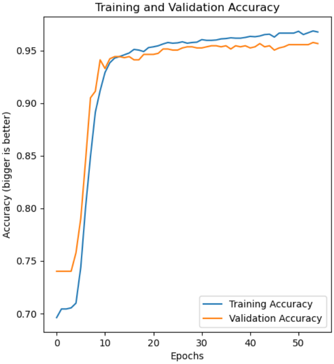
`AveragePooling`: If there's a significant word, it will have a strong signal in some direction (in 16 dimensional space), and even averaged over 200 words we can still slice it apart from the rest of the data

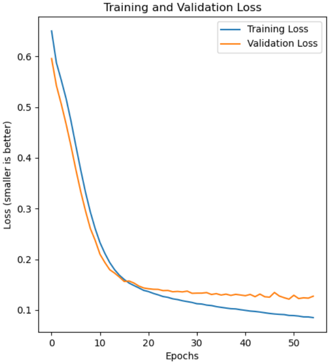
8 `thinking_layer` neurons can slice the space into hundreds of regions.

Model summary

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 200)]             0
 embedding (Embedding)       (None, 200, 16)           3200
 global_average_pooling1d (G  (None, 16)               0
 lobalAveragePooling1D)
 dense (Dense)               (None, 8)                 136
 dense_1 (Dense)             (None, 1)                 9
=================================================================
Total params: 3,345
Trainable params: 3,345
Non-trainable params: 0
```

Slightly disappointing results





GloVe embeddings

- GloVe takes into account both local and global context in its training process
- Sometimes leads to more accurate word representations
- GloVe's matrix factorization-based approach can handle sparse data better than Word2Vec
- Sometimes works better on smaller corpora.

In reality:

- On small problems, with small documents bag-of-words wins
- On larger documents word2vec and GloVe are about equivalent
- On large documents BERT does better than either, but embedding takes much longer

enron-pretrained.py 35–40 Read in the GloVe vectors

```
embeddings_index = {}
with open('glove.6B.50d.txt') as f:
    for line in f:
        word, coefs = line.split(maxsplit=1)
        coefs = np.fromstring(coefs, "f", sep=" ")
        embeddings_index[word] = coefs
```

the	0.418000	0.24968	-0.41242	...	-0.78581
,	0.013441	0.23682	-0.16899	...	0.30392
.	0.151640	0.30177	-0.16763	...	0.10216
of	0.708530	0.57088	-0.4716	...	-0.80375
to	0.680470	-0.039263	0.30186	...	-0.26044

enron-pretrained.py 42–48 Match GloVe up with our vocabulary

```
voc = vectorizer.get_vocabulary()
word_index = dict(zip(voc, range(len(voc))))
embedding_matrix = np.zeros((len(voc)+2, 50))
for word, i in word_index.items():
    embedding_vector =
        embeddings_index.get(word)
    if embedding_vector is not None:
         embedding_matrix[i] = embedding_vector
```

- There are two extra words of vocabulary: “padding” and “OOV”, hence `len(voc)+2`
- Words not found in embedding index will be all-zeros.
- This includes the representation for “padding” and “OOV”

enron-pretrained.py 51–61 Use that data in our embedding layer

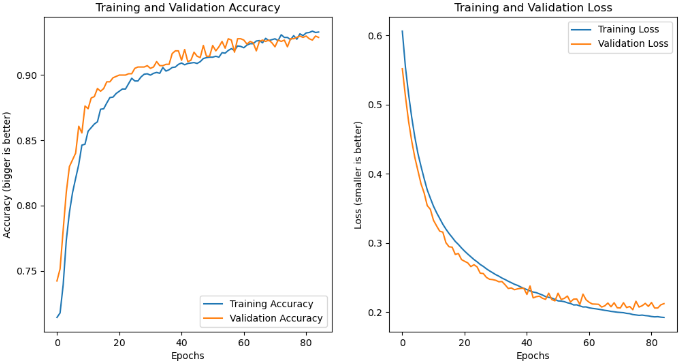
```
from keras.initializers import Constant
embedding_layer = keras.layers.Embedding(
 input_dim=len(voc)+2,
 output_dim=50,
 embeddings_initializer=Constant(embedding_matrix),
 trainable=False)

vocab_size = vectorizer.vocabulary_size()
inputs = keras.Input(shape=(sequence_length,))
embedding = embedding_layer(inputs)
averaging_layer =
    keras.layers.GlobalAveragePooling1D()(embedding)
```

- Everything afterwards is the same as the for `enron-with-embeddings.py`
- But far fewer modifiable parameters, so trains faster.

Model summary

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 200)]             0
 embedding (Embedding)       (None, 200, 50)           1888600
 global_average_pooling1d (G  (None, 50)               0
 lobalAveragePooling1D)
 dense (Dense)               (None, 8)                 408
 dense_1 (Dense)             (None, 1)                 9
=================================================================
Total params: 1,889,017
Trainable params: 417
Non-trainable params: 1,888,600
```

Even more disappointing results



Drift

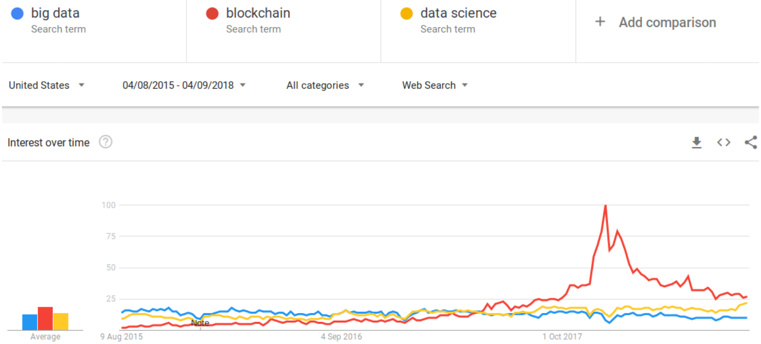
We use "Context" in different ways

The words surrounding a target word give meaning to a word
: ELMo, BERT are contextual embeddings.

The universe around your language model
: Context drift makes your model worse over time

So many words!

- Any language features a large number of distinct words.
- New words are coined.
- Words change their use in time.
- There are also names, numbers, dates ...an infinite number.



https://trends.google.com

Context drift

- You train a language model today
- In the future there will be more and more new words
- Existing vocabulary will be used less, and get used differently
- The task may change: should a very relevant GPT-generated email be labelled as “spam”?
- **Your model will perform worse over time**

Wrap-up

Take-home Messages 1

We have gone in-depth into three different word embedding approaches:

Bag-of-words Non-contextual: Homographs and synonyms handled poorly, loss of word order information

WordNet Pseudo-contextual: you have to work out which synset is right for the context; homographs and synonyms handled well; hard to use in deep learning

Vector embeddings A word is turned into a vector

Take-home Messages 2

There are many ways of generating vector embeddings. We have worked with two of them, and mentioned a third

Jointly with the task Let gradient descent find the correct answer

Word2vec / Glove Non-contextual, homographs and synonyms handled poorly

ELMo / BERT Contextual, generating an embedding based on surrounding words

Any method that puts synonyms close to each other and keeps non-synonyms apart is good.

Take-home Messages 3

- Looked at a geometric interpretation of ReLU activation
- Context drift is a major challenge for text classification problems

Not-in-the-exam research idea: James-Stein estimator

- Let's say that there is a "best" vector for some word (contextual, non-contextual, whatever)
- Gradient descent methods for finding that vector is like an experiment with some noise.
- We assume that the result we get from the experiment is the best estimator for the real value.
- Unless we are embedding in one or two dimensions, that last dot point isn't true. The James-Stein estimator gives a better result.

What's Next

Week 11

- Processing text sequences.
- Reading: Chollet, Section 11.4
- Reading: Jurafsky & Martin, Chapters 9 and 10.