21) Working with Text Data: Word Embedding

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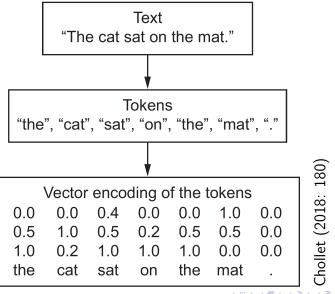
Reference

Chollet (2018): Ch 6.1

https://www.manning.com/books/deep-learningwith-python

https://github.com/fchollet/deep-learning-withpython-notebooks/blob/master/6.1-one-hotencoding-of-words-or-characters.ipynb

From Text to Tokens to Vectors



Bag-of-Words

2-grams:

```
{"The", "The cat", "cat", "cat sat", "sat", "sat on", "on", "on the", "the", "the mat", "mat"}
```

3-grams:

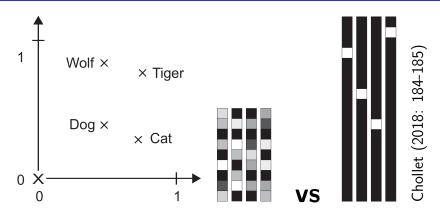
```
{"The", "The cat", "cat", "cat sat", "The cat sat", "sat", "sat on", "on", "cat sat on", "on the", "the", "sat on the", "the mat", "mat", "on the mat"}
```

Word-Level One-Hot Encoding

```
from keras.preprocessing.text import Tokenizer
samples = ['The cat sat on the mat.', 'The dog ate my homework.']
# We create a tokenizer, configured to only take
# into account the top-1000 most common words
tokenizer = Tokenizer(num words=1000)
# This builds the word index
tokenizer.fit on texts(samples)
# This turns strings into lists of integer indices.
sequences = tokenizer.texts to sequences(samples)
# You could also directly get the one-hot binary representations.
# Note that other vectorization modes than one-hot encoding are sup
one hot results = tokenizer.texts to matrix(samples, mode='binary')
# This is how you can recover the word index that was computed
word index = tokenizer.word index
print('Found %s unique tokens.' % len(word index))
```

Found 9 unique tokens.

Word Embedding vs One-Hot



Dense vs Sparse

Lower-Dimensional vs High-Dimensional

Learned from Data vs Hardcoded

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```
from keras.datasets import imdb
from keras import preprocessing
```

```
# Number of words to consider as features
max features = 10000
# Cut texts after this number of words
# (among top max features most common words)
maxlen = 20
# Load the data as lists of integers.
(x train, y train), (x test, y test) = imdb.load data(num words=max features)
# This turns our lists of integers
# into a 2D integer tensor of shape `(samples, maxlen)`
x train = preprocessing.sequence.pad sequences(x train, maxlen=maxlen)
x test = preprocessing.sequence.pad sequences(x test, maxlen=maxlen)
/usr/local/lib/python3.6/dist-packages/numpy/lib/format.py in read array(fp, allow pic
    694
               # The array contained Python objects. We need to unpickle the data.
```

695 if not allow_pickle:
--> 696 raise ValueError("Object arrays cannot be loaded when "
697 "allow_pickle=False")
698 if pickle_kwargs is None:

ValueError: Object arrays cannot be loaded when allow pickle=False

New Code to Load IMDB

```
import numpy as np
# save np.load
np load old = np.load
# modify the default parameters of np.load
np.load = lambda *a,**k: np load old(*a,
                                 allow pickle=True, **k)
# call load data with allow pickle implicitly set to true
(train data, train labels), (test data,
          test labels) = imdb.load data(num words=10000)
# restore np.load for future normal usage
np.load = np load old
```

Reviews	Total	Positive	Negative
Training	25,000	50%	50%
Testing	25,000	50%	50%

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from keras.models import Sequential from keras.layers import Flatten, Dense

```
model = Sequential()
# We specify the maximum input length to our Embedding layer
# so we can later flatten the embedded inputs
model.add(Embedding(10000, 8, input_length=maxlen))
# After the Embedding layer,
# our activations have shape `(samples, maxlen, 8)`.
# We flatten the 3D tensor of embeddings
# into a 2D tensor of shape `(samples, maxlen * 8)`
model.add(Flatten())
# We add the classifier on top
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop', loss='binary crossentropy',
              metrics=['acc'])
model.summarv()
```

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 20, 8)	80000
flatten_1 (Flatten)	(None, 160)	0
dense_1 (Dense)	(None, 1)	161
Total narams: 80.161		:======

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Validation Accuracy of 75%

```
Epoch 1/10
20000/20000 loss: 0.6560 - acc: 0.6482 - val_loss: 0.5906 - val acc: 0.7146
Epoch 2/10
20000/20000 loss: 0.5189 - acc: 0.7595 - val_loss: 0.5117 - val acc: 0.7364
Epoch 3/10
20000/20000 loss: 0.4512 - acc: 0.7933 - val_loss: 0.4949 - val acc: 0.7470
Epoch 4/10
20000/20000 loss: 0.4190 - acc: 0.8069 - val_loss: 0.4905 - val acc: 0.7538
Epoch 5/10
20000/20000 loss: 0.3965 - acc: 0.8198 - val_loss: 0.4914 - val acc: 0.7572
Epoch 6/10
20000/20000 loss: 0.3784 - acc: 0.8311 - val_loss: 0.4953 - val acc: 0.7594
Epoch 7/10
20000/20000 loss: 0.3624 - acc: 0.8419 - val_loss: 0.5004 - val acc: 0.7574
Epoch 8/10
20000/20000 loss: 0.3474 - acc: 0.8484 - val_loss: 0.5058 - val acc: 0.7572
Epoch 9/10
20000/20000 loss: 0.3330 - acc: 0.8582 - val_loss: 0.5122 - val acc: 0.7528
Epoch 10/10
20000/20000 loss: 0.3194 - acc: 0.8669 - val_loss: 0.5183 - val acc: 0.7554
```

Pretrained Word Embeddings

GloVe Word-Embeddings

https://nlp.stanford.edu/projects/glove (822 MB zip)

Precomputed Embeddings from 2014 English Wikipedia

100-dimensional embedding vectors for 400,000 words

from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import numpy as np

```
maxlen = 100 # We will cut reviews after 100 words
training samples = 200 # We will be training on 20
validation samples = 10000 # We will be validating
max words = 10000 # We will only consider the top
tokenizer = Tokenizer(num words=max words)
tokenizer.fit on texts(texts)
sequences = tokenizer.texts to sequences(texts)
word index = tokenizer.word index
print('Found %s unique tokens.' % len(word index))
data = pad sequences(sequences, maxlen=maxlen)
labels = np.asarray(labels)
print('Shape of data tensor:', data.shape)
print('Shape of label tensor:', labels.shape)
```

Found 88582 unique tokens.

Shape of data tensor: (25000, 100)

Shape of label tensor: (25000,)

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Parsing and Preparing the GloVe

```
glove dir = '/home/ubuntu/data/'
embeddings index = \{\}
f = open(os.path.join(glove dir, 'glove.6B.100d.txt'))
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings index[word] = coefs
f.close()
print('Found %s word vectors.' % len(embeddings_index))
```

Found 400000 word vectors.

```
embedding dim = 100
embedding matrix = np.zeros((max words, embedding dim))
for word, i in word index.items():
   embedding vector = embeddings index.get(word)
   if i < max words:
        if embedding vector is not None:
            # Words not found in embedding index will be
            embedding matrix[i] = embedding vector
```

Layer (type)	Output Shape	Param #
embedding_4 (Embedding)	(None, 100, 100)	1000000
flatten_3 (Flatten)	(None, 10000)	0
dense_4 (Dense)	(None, 32)	320032
dense_5 (Dense)	(None, 1)	33
Total params: 1,320,065		=======:

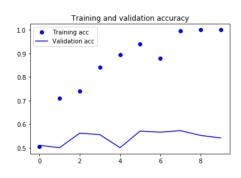
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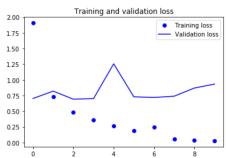
Load and Freeze the Embedding Layer

```
model.layers[0].set weights([embedding matrix])
model.layers[0].trainable = False
model.compile(optimizer='rmsprop',
              loss='binary crossentropy',
              metrics=['acc'])
history = model.fit(x train, y train,
                    epochs=10,
                    batch size=32,
                    validation data=(x_val, y_val))
model.save weights('pre trained glove model.h5')
```

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Validation Accuracy of 57%





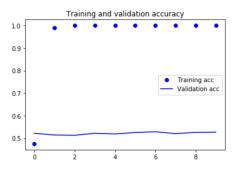
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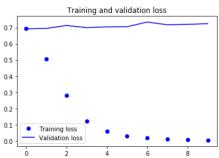
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Without the Pre-Trained Word Embeddings

Layer (type)	Output Shape	Param #
embedding_5 (Embedding)	(None, 100, 100)	1000000
flatten_4 (Flatten)	(None, 10000)	0
dense_6 (Dense)	(None, 32)	320032
dense_7 (Dense)	(None, 1)	33
Total names, 1 330 005		

Validation Accuracy of 52%





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