Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

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TENSORFLOW – DNNS

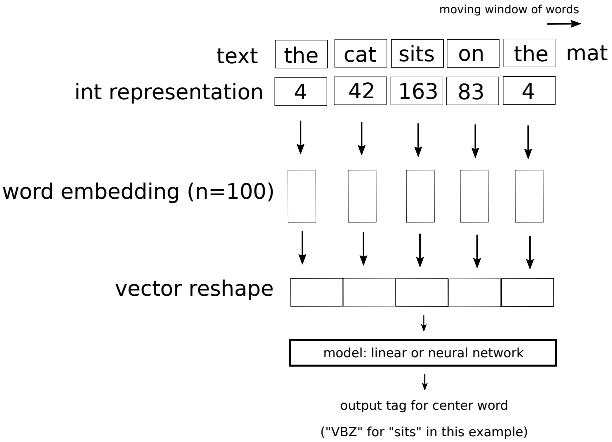
Introduction

A POS tagger with DNNs

```
>>> pos_tag(["The","cat","sits","on","the","mat"])
[('The', 'DT'), ('cat', 'NN'), ('sits', 'VBZ'),
 ('on', 'IN'), ('the', 'DT'), ('mat', 'NN')]
```

- A POS-tagger is labeling words with Part-Of-Speech (POS) tags
- Important building block in many NLP applications
- We will create a POS-tagger using Deep Neural Networks (DNN) and word embeddings, step by step
- Sequence labeling

Sketch of a simple POS tagger model



Embedding layer

Sparse encoding of one-hot values

[“A”, “short”, “example”] $\rightarrow$ [3011, 291, 14]

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Does not handle unseen values

Can be used directly to compute the (softmax) cross entropy loss

```
tf.nn.sparse_softmax_cross_entropy_with_logits(
    labels=y_train, logits=pred)
```

y_train is expected to be an array of Integers

Embeddings

Embedding layer:
$emb : V \rightarrow \mathbb{R}^d$

Embedding matrix:
$|V| \times d$ matrix

Embedding matrix

The embeddings matrix is a variable that we want to optimize:

```
embeddings = tf.Variable(
tf.random_uniform([vocabulary_size,
embedding_size], −1.0, 1.0))
```

Embedding lookup

```
embed = tf.nn.embedding_lookup(embeddings, train_inputs)
```

e.g. If your list of sentences is: $[[0, 1], [0, 3]]$ (sentence 1 is $[0, 1]$, sentence 2 is $[0, 3]$, the function will compute a tensor of embeddings, which will be of shape $(2, 2, \text{embedding\_size})$ and will look like:

$$[[\text{embedding0, embedding1}], [\text{embedding0, embedding3}]]$$

Flatten a sequence of inputs

$$\begin{bmatrix} 0 & 0 & 0 & 1 & 0 \end{bmatrix} \times \begin{bmatrix} 17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ 10 & 12 & 19 \\ 11 & 18 & 25 \end{bmatrix} = \begin{bmatrix} 10 & 12 & 19 \end{bmatrix}$$

- tf.nn.embedding_lookup does a sparse matrix multiplication for the lookup

Flatten a sequence of inputs

$$\begin{pmatrix} x_{1,1} & \cdots & x_{1,embedding\_size} \\ \vdots & & \vdots \\ x_{n,1} & \cdots & x_{n,embedding\_size} \end{pmatrix}$$

$\rightarrow$

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$\rightarrow$

$$\begin{pmatrix} x_{1,1} & \ldots & x_{1,embedding\_size} & \ldots & x_{n,1} & \ldots & x_{n,embedding\_size} \end{pmatrix}$$

Tensorflow has `tf.reshape` to do that

Flatten a sequence of embeddings

Input: tensor of rank 3 ([examples, seq_len, embedding_size])
Output: tensor of rank 2 ([examples, embedding_size*seq_len])

```
# tensor 't' is [[[0.344, 1.12], [-0.12, 0.11]],
#                [[0.344, 1.12], [3.1, -1.78]]]
# tensor 't' has shape [2, 2, 2]
# (2 examples of length 2 with embeddings of dim 2)
reshape(t, [2, 4]) ==> [[0.344, 1.12, -0.12, 0.11],
                        [0.344, 1.12, 3.1, -1.78]]
```

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                        [0.344, 1.12, 3.1, -1.78]]
```

Special value -1: If one component of shape is the special value -1, the size of that dimension is computed so that the total size remains constant. [...] At most one component of shape can be -1.

https://www.tensorflow.org/api_docs/python/tf/reshape

Multinomial logistic regression

Softmax function

$\sigma(\mathbf{z})_\mathbf{j} = \frac{\mathbf{e}^{\mathbf{z}_\mathbf{j}}}{\sum_{\mathbf{k}=1}^{\mathbf{K}} \mathbf{e}^{\mathbf{z}_\mathbf{k}}}$ for "j" = 1, ..., "K".

- Transforms the vector z, so that all values add up to one
- Can be used as a probability distribution over outputs (=classes)
- Commonly used in neural networks as output function for classification tasks

Cross entropy

Cross-entropy (for C classes):

$$-\sum_{i=1}^{n}\sum_{c=1}^{C} y_{ic} \log p_{ic}$$

$p_i p_i$ is the true label
Note: For two classes this is binary-crossentropy

Softmax and cross entropy in Tensorflo

```
tf.nn.softmax_cross_entropy_with_logits(
labels=y_train, logits=pred)
```

vs.

```
tf.nn.sparse_softmax_cross_entropy_with_logits(
labels=y_train, logits=pred)
```

- Difference is how y_train is given:
- e.g. $\left[[00010],[00001]\right]$ vs. $[3,4]$ or $[0,0,1,0]$ vs. $[2]$

Hands on: A simple POS tagger

A POS tagger (Brown corpus)

- use an embedding layer
- predict the POS tag given the embeddings of the target word and *n* context words

Getting the predicted class

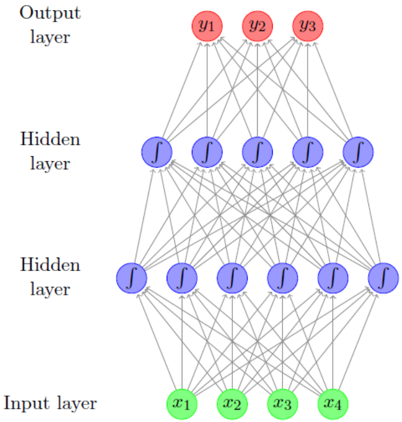
- Getting the class index:
  `tf.argmax` returns the index of the largest value in a tensor

Getting the predicted class

- Getting the class index:
  `tf.argmax` returns the index of the largest value in a tensor
- Getting the class names:
  Use `.inverse_transform` of a LabelEncoder to transform sparse one-hot encodings back to non-numeric labels

Deep Feed-Forward Networks

A feed-forward DNN



Multiple layers

First approach: just add layers

```
last_dim = input_dim
for dim in [100, 100]:
    hidden = tf.Variable(tf.random_uniform(
        [last_dim, dim], -0.1, 0.1, dtype=tf.float32))
    b = tf.Variable(tf.random_uniform(
        [dim], -0.1, 0.1, dtype=tf.float32))
    x = tf.add(tf.matmul(x, hidden), b)
    last_dim = dim
```

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    last_dim = dim
```

Won't add anything to the models capacity:
as each layer is just a linear function this is just composing linear functions – the result is a linear function

Adding non-linearities

Different choices: Sigmoid, tanh, ReLU (Rectified Linear Unit)

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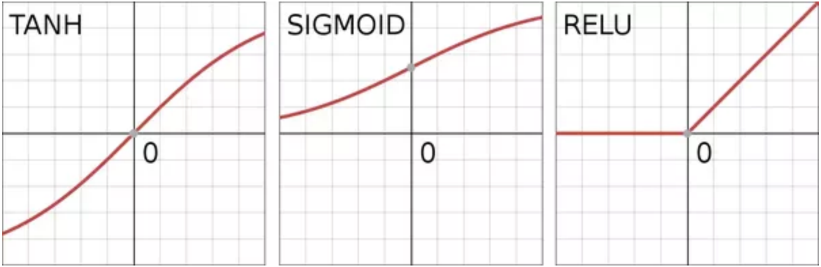
    b = tf.Variable(tf.random_uniform(
        [dim], -0.1, 0.1, dtype=tf.float32))
    x = tf.add(tf.matmul(x, hidden), b)
    x = tf.nn.relu(x)
    last_dim = dim
```

Non-linearities



tf.tanh tf.sigmoid tf.nn.relu

MLP with one hidden layer

One hidden layer is enough to create a universal approximator.

MLP with one hidden layer

One hidden layer is enough to create a universal approximator.
However:
Neural networks with more layers have been shown to learn functions better.

Example

```
last_dim = input_dim
for dim in [100, 100]:
    ### add hidden layers as before

## define the output layer
out_w = tf.Variable(tf.random_uniform(
        [last_dim, out_dim], -0.1, 0.1,
        dtype=tf.float32))
b = tf.Variable(tf.random_uniform(
    [out_dim], -0.1, 0.1, dtype=tf.float32))
out = tf.add(tf.matmul(x, out_w), b)
```

Hands on 1

Add hidden layers to the POS tagger.

Dropout

- Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." Journal of machine learning research 15.1 (2014): 1929-1958.

In Tensorflow:

```
tf.nn.dropout( x,  keep_prob, noise_shape=None,
 seed=None,   name=None)
```

Hands on 2

Extend POS tagger with a train a test set, measure accuracy. (Hint: `sklearn.metrics.accuracy_score`) Add dropout to the POS tagger and compare train and validation loss+accuracy.

Tensorboard

- Visualize loss, embeddings and much more in your browser
- You need to add a few lines of code to tell Tensorboard what to log
- Make sure train_summary_dir is a new directory for every new experiment!

```
loss_summary = tf.summary.scalar('loss', loss)
train_summary_op = tf.summary.merge_all()
summary_writer = tf.summary.FileWriter(train_summary_dir, sess.graph)
```

Tensorboard

- You need to regularly call the train_summary_op in training
- Not as often as the training step, because it will otherwise slowdown your training if you have more complex summaries

```
if current_step % 100==0 and current_step != 0:
        summary_str = sess.run(train_summary_op, feed_dict=feed_dict)
        summary_writer.add_summary(summary_str, current_step)
        summary_writer.flush()
```

Tensorboard

- Some useful statistics on tensors (e.g. neural network weights):

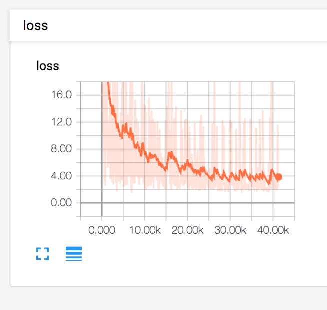
```
with tf.name_scope('x1'):
        tf.summary.scalar('mean', mean)
        with tf.name_scope('stddev'):
            stddev = tf.sqrt(tf.reduce_mean(tf.square(var - mean)))
        tf.summary.scalar('stddev', stddev)
        tf.summary.scalar('max', tf.reduce_max(var))
        tf.summary.scalar('min', tf.reduce_min(var))
        tf.summary.histogram('histogram', var)
```

Tensorboard - running it

```
tensorboard --logdir=w2v_summaries_1499773534
--host=127.0.0.1
```

or

```
python3 -m tensorboard.main --logdir=w2v_summaries_1499773534
--host=127.0.0.1
```



Tensorboard - embeddings

- Possible to nicely visualize embeddigs, see `https://www.tensorflow.org/get_started/embedding_viz`
- Also checkout `http://projector.tensorflow.org/`, live demo of pretrained embeddings