Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

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DEEP LEARNING FOR LANGUAGE AND SPEECH

Introduction

Structure of the seminar

- Welcome to the seminar ”Deep Learning for Language and Speech”!
- Introduction tutorial, teaching you Tensorflow and how to train your neural network models, hands on, 5-6 sessions (now)
- Working in teams on training deep neural networks for NLP or speech problems, starting December
- At the end of the seminar: present your work, hand in small report (max. 8 pages)

Structure of the seminar

- Before we continue:
- E-mail: milde@informatik.uni-hamburg.de, please send me an e-mail with the title ”DL Seminar”
- Also, slides will be available here:
  `http://ltdata1.informatik.uni-hamburg.de/lt_deeplearning_seminar_WS1819/`
  (User: student Password: dl_seminar_1718)

Structure of the seminar

- Who knows Python/numpy? There will be additional reading material if you're new to the language
- Tutorial is hands on - **you need to bring your laptop**
- Easiest installation of all required software is under Linux, e.g. Ubuntu
- But Windows/Max OS X is also possible

Introduction

- TensorFlow started as DistBelief at Google Brain in 2011
- Publicly released as open source software on November 9, 2015
- Written in C++, Python bindings for rapid prototyping (best documented interface)
- Other bindings exist: Java, Scala, C♯, Rust, Go, Haskell, JavaScript, ...
- Similar projects exist: e.g. Theano, PyTorch, Dynet. All share the idea of using computation graphs.

Main concepts

- TensorFlow computations are expressed as stateful dataflow graphs
- Graphs contain operations (ops) on Tensors
- In TensorFlow lingu, a tensor is any n-d array. A scalar is a tensor of rank 0, a vector of rank 1, a matrix of rank 2.
- A Tensorflow rank is not the same as a matrix rank!
- The shape of a tensor with rank 2 is a tuple of dimensions, e.g. (128, 256) is a 128 x 256 matrix.
- Tensors of rank 3 are heavily used in feed forward networks, an example is a tensor with shape (128, 128, 256)

Layer based APIs vs. Graphs based

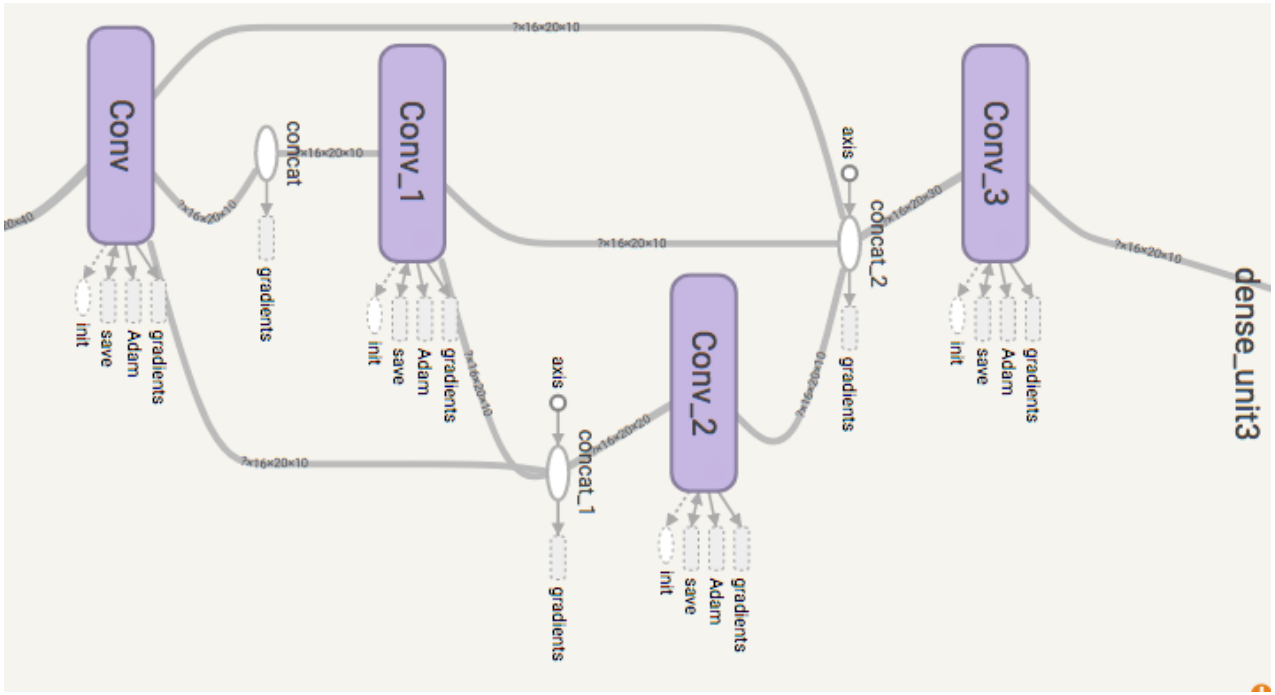
A typical layer API (not TensorFlow code):

```
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
```

This is fine (and very readable!) for models that can be described by stacking individual layers

Layer based APIs vs. Graphs based

Disadvantage: Difficult to express structures like these:



Increasing evidence that these kind of deeply connected networks are very useful.

Layer based APIs vs. Graphs based

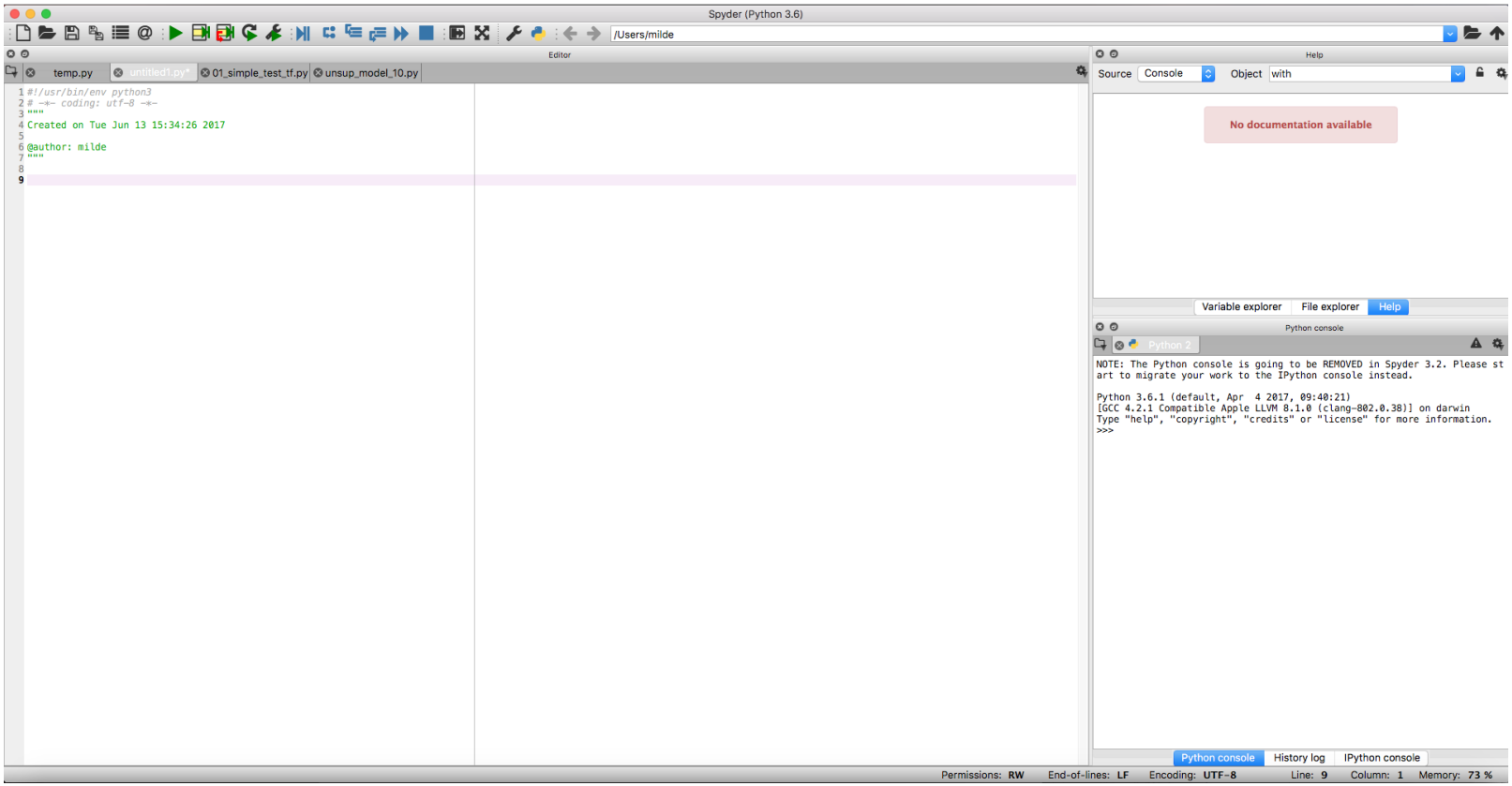
- Since Tensorflow uses computation graphs, the declaration of the model allows for a higher expressivity
- Has a steeper learning curve in the beginning
- In the newer versions of Tensorflow, you can also mix layer-like APIs (e.g. TF-Slim, Keras) with the computation graph
- We will focus on not using any short cuts, as this has a higher learning effect and we will only make use of standard Tensorlfow ops in the beginning

First steps - Install required software

- Detailed installation instructions: `http://ltdata1.informatik.uni-hamburg.de/lt_deeplearning_seminar_WS1819/`
- TL;DR basic installation with Linux: pip3 install tensorflow numpy matplotlib spyder3
- You may need to install pyqt5 bindings for spyder with: sudo apt-get install pyqt5
- (If you have a CUDA-enabled Nvidia GPU in your laptop, install tensorflow-gpu instead of the tensorflow package)
- For Mac Os X: install python3 and pip3 with brew (see http://brew.sh)
- For Windows: install Anaconda

First steps - Lets open spyder

type spyder3 in the console:



First steps - Necessary imports

```
import numpy as np
import tensorflow as tf
```

- Outside of graph computations, we usually store data in Numpy arrays.
- Numpy arrays are the main objects to transfer data to inputs of the graph and from outputs of the graph.
- Numpy arrays are also an abstraction for (homogeneous) multidimensional arrays.

Generating some random data

```
#some random test data
a_data = np.random.rand(256)
b_data = np.random.rand(256)
```

- Now a and b contain vectors of length 256 with random floats. E.g. print(a_data) returns:

```
[ 0.54976368  0.87790201  0.96528541 ...,
  0.05281365  0.48556404  0.46848266]
```

Declare the computation graph

```
#construct the graph
a = tf.placeholder(tf.float32, [256])
b = tf.placeholder(tf.float32, [256])

x = a+b
```

- The placeholders can later be used to input data to the computation graph
- The operation x = a+b does not immediately add something, it creates a graph.
- In fact, print(x) returns:

```
Tensor("add:0", shape=(256,), dtype=float32)
```

A session on a computation device

```
with tf.device('/cpu'):
    with tf.Session() as sess:
        x_data = sess.run(x, {a: a_data, b: b_data})
        print(x_data)
```

- This fills the inputs a and b with a_data and b_data (our random data), runs the computation graph and retrieves the results of x in x_data
- Obviously not terrible useful as is, but you could run the operation easily on a gpu by changing tf.device('/cpu') to tf.device('/gpu:1'). Copying data to and from the GPU is handled automatically for you.

Small warm up exercise!

- Calculate the matrix multiplication of a and b. We also change a and b to random matrices:

```
a = np.random.rand(256, 128)
b = np.random.rand(128, 512)
```

- Calculate the resulting matrix of shape (256, 512) in TensorFlow.