DL Exercise 5: Tensorflow and Classification Challenge

Pattern Recognition Lab, Friedrich-Alexander University of Erlangen-Nürnberg

January 21, 2019

Goal of this exercise

- Get to know a widely used deep learning framework: TensorFlow
- Implement & train two widely architectures: AlexNet and ResNet18
- Classification on **real** data: Images from solar panels

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- Classification on **real** data: Images from solar panels
- **Challenge yourself & your colleagues!**

Organizational

Part I: Classification with Tensorflow - Mandatory

- Implementation & training of TensorFlow architectures
- No oral presentation, BUT: submission of trained models in submission system (later more)
- Goal: reach mean F1 score of > 0.60 for both architectures
- **Deadline: Feb. 15**

Organizational

Part II: Challenge - Optional, but highly encouraged

- Try to find & train the best architecture & model for this task!
- Compete with your colleagues!
- **Deadline: March 1**
- Announcement of winners & prices: March 4 - 8

Source: Designed by Freepik

Data set: Identification of defects in solar panels

- Solar moduls are composed of cells
- Are subject to degradation (transport, wind, hail, ...)
- Different defects, e.g., cracks or inactive regions

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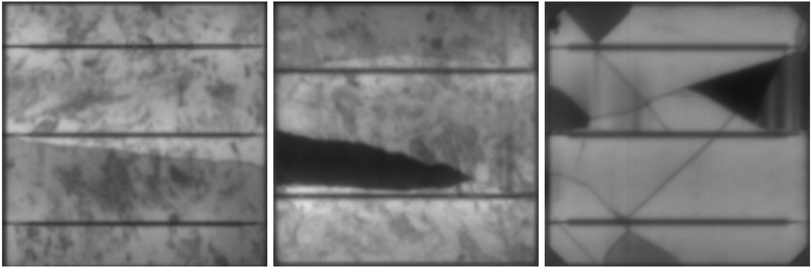

Figure: Left: Crack on a polycristalline module; Middle: Inactive region; Right: Cracks and inactive regions on a monocristalline module

TensorFlow: General introduction

- Open source software library for numerical computations
- Using data flow graphs:
  - Nodes = mathematical operations (e.g. convolutions)
  - Edges = multidimensional data arrays (=tensors)
  - Implemented in C++, different APIs
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- Python API provides higher- and lower-level functionalities
  - We suggest to go somewhat “middle-level”, e.g., tf.nn/tf.layer/tf.losses
  - Takes care of most variables definitions
  - We will handle data input, training iterations, etc. ourselves

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  - We will handle data input, training iterations, etc. ourselves
- **Online documentation**: https://www.tensorflow.org/api_docs/python/

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- Simple example:

```python
import tensorflow as tf
# We define two constant nodes (=tensors)
node1 = tf.constant(3.0, dtype=tf.float32)
node2 = tf.constant(4.0) # also tf.float32 implicitly
# And define some operation on these nodes
node3 = tf.subtract(node1, node2)
# Only now we instantiate the graph and execute it
with tf.Session() as sess:
    sess.run(node3)
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   - Freeze all values in graph
   - Compute forward pass (=prediction) for validation/test data

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8. Monitor training process using TensorBoard

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- Define interacting operations with so-called symbolic variables:
  - Placeholder for input tensors (=training or test batches of data)

```
images_placeholder =
tf.placeholder(tf.float32, shape=(batch_size, height_size,
    width_size, channels_size))
```

Step 0: TensorFlow preparations and terms

- Variables (=modifiable during training)

```
# Variable with shape [3, 3, 3, 16]
example_variable = tf.get_variable('example_var', shape=[3, 3,
    3, 16], initializer=tf.contrib.layers.xavier_initializer())
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- Variables are fed with values and evaluated during a so-called session:

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# Create a session
with tf.Session() as sess:
        # Initialize the variables
        sess.run(tf.global_variables_initializer())
        # Run this session and evaluate e.g. values which are
        # contained at the moment in the variable:
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Step 1: Data preparation

- Load data from disk and provide batches for training
- Normalization & data augmentation
- Handling of unbalanced data etc.

➔ In this exercise, this part will already be provided in `dataset.py` in the code skeleton.

Step 2: Build architecture

Architecture of a network can consist of different layers:

- Convolution:

```
# Definition of a convolution layer
conv1_layer = tf.layers.conv2d(input_layer, filters=16, strides
    =(CONV_STRIDE_SIZE, CONV_STRIDE_SIZE), padding=PADDING,
    use_bias=True)
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Architecture of a network can consist of different layers:

- Fully connected:

```
# If e.g. the previous layer was a convolution and thus the
# input tensor is a 4-D one, we need to reshape our input
# tensor first
input_layer = tf.layer.flatten(input_layer)
# Then we can multiply the input_layer with the weights matrix
# and add a bias in a fully connected layer (tf: dense layer)
fc = tf.layers.dense(input_layer, units=n_weights_fc1,
    activation=None, use_bias=True)
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- Activation:

```
layer_output = tf.nn.relu(pre_activation)
```

Step 2: Build architecture

Architecture of a network can consist of different layers:

- Pooling:

```
pooled_output = tf.layers.max_pooling2d(input_layer, pool_size
    =(POOL_KERNEL_SIZE, POOL_KERNEL_SIZE), strides=(
    POOL_STRIDE_SIZE, POOL_STRIDE_SIZE), padding=PADDING)
```

Step 3: Build loss function and optimizer

- Loss: Compare current predictions with ground-truth labels
  - For our classification task: Cross entropy

```
norm_prediction = tf.nn.softmax(net_output)
cross_entropy = tf.losses.softmax_cross_entropy(labels=
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- Optimizer
  - E.g. Stochastic gradient descent

```
optimizer = tf.train.GradientDescentOptimizer(learning_rate)
```

Step 4: Build graph

- Compose all operations in a TensorFlow graph:

```
# We use default graph
with tf.Graph().as_default():
# Get placeholder for data
images_placeholder = tf.placeholder(tf.float32, [None,
    height_size, width_size, channels_size])
labels_placeholder = tf.placeholder(tf.float32, [None,
    NUM_CLASSES])
# Some preprocessing... e.g. mean subtraction
mean_normalized_images = tf.subtract(images_placeholder, mean)

# Define the forward pass of the model, e.g., for implemented
    alexnet
output = model.alexnet(mean_normalized_images)
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```
# Loss and training (= backward pass) for exclusive labels
loss = tf.losses.softmax_cross_entropy(labels_placeholder,
    output)
optimizer =  tf.train.AdamOptimizer(LEARNING_RATE)
train_op = optimizer.minimize(loss)

# Create summary object for TensorBoard
summary = tf.summary.merge_all()

# Initialize all variables in graph, e.g. weights in layers
init = tf.global_variables_initializer()

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saver = tf.train.Saver()
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Step 5: Create session and initialize graph

- Create and run session within the graph:

```
# Create a session
with tf.Session() as sess:
        # Run the initialization operation
        sess.run(init)
```

Step 6: Train graph

- Running a session with an operation from the graph will evaluate all operations needed for the given one:

```
# We run the session and evaluate all data in the graph
# up to the loss operation
# loss_value is the current result for the evaluated loss
# feed_dict is the current batch of data fed into the graph
_, loss_value = sess.run([train_op, loss], feed_dict=feed_dict)
```

Step 7: Validate/test graph

- Same as before: Running a session with an operation from the graph will evaluate all operations needed for the given one:

```
# For evaluation we only run the prediction operation and/or
# the loss operation
# prediction returns the prediction for the current batch
# loss_value is the current result for the evaluated loss
# feed_dict is the current batch of data fed into the graph
prediction, loss_value = sess.run([norm_prediction, loss],
    feed_dict=feed_dict)
```

Step 8: Monitoring with TensorBoard

- First serialize data during training, e.g. loss value

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# Add a scalar summary for the snapshot loss
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- After training: launch TensorBoard
  - Command: **`tensorboard - -logdir=path/to/log-directory`**
  - Navigate browser to **localhost:6006**

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- In contrast to previous exercises, there is a code skeleton

➔ First task: Make yourself familiar with the existing code

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→ First task: Make yourself familiar with the existing code

- You will have to adapt four classes for the mandatory part:
  - `train.py`: Adapt hyper parameters if necessary, add loss function
  - `train/trainer.py`: Implement actual training, validation and stopping criteria
  - `model/alexnet.py` and `model/resnet.py`: Implement architectures

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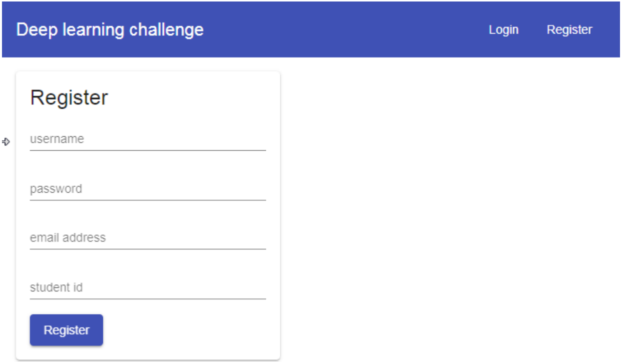
  - `train.py`: Adapt hyper parameters if necessary, add loss function
  - `train/trainer.py`: Implement actual training, validation and stopping criteria
  - `model/alexnet.py` and `model/resnet.py`: Implement architectures
- Additional important files:
  - `data/dataset.py` and associated files: Responsible for data loading and augmentation
  - `evaluation/evaluation.py` and `evaluation/measures.py`: Allows monitoring training

Submission to online tool

- After training run, model is automatically saved
- Online submission tool will be made available **by the end of the week**
- Website: https://lme156.informatik.uni-erlangen.de/dl-challenge
- **Only available from within the university network**
- Same teams (max. 2) as before allowed

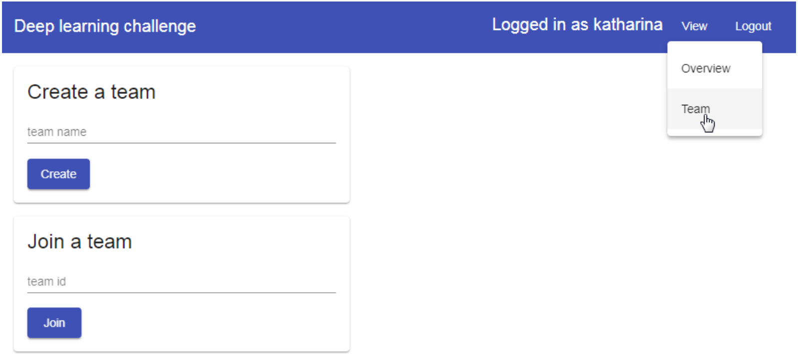
Submission to online tool: Registration

Register with your email and student id.



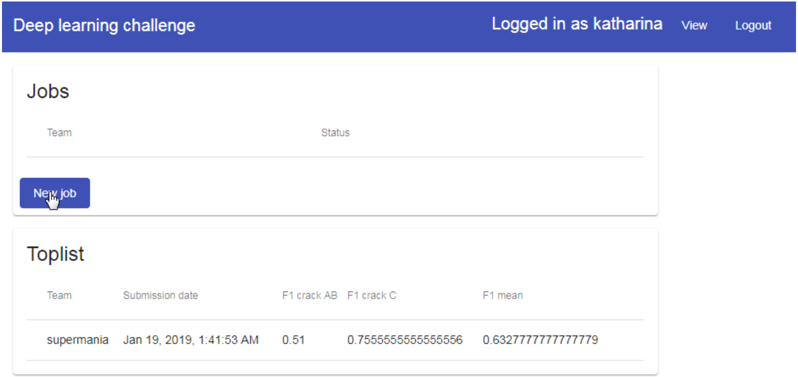
Submission to online tool: Team

If you work in a team: One of you has to create a new team, the other has to join.



Submission to online tool: Submit model

Submit trained models (zip-file generated by train.py) by uploading them. You may submit multiple models.



THE CHALLENGE

Improve on the baseline by AlexNet/ResNet:

- Adapt architectures/try out new architectures
- Pretraining ?
- Regularization ?
- Data augmentation ?
- Use your creativity!
- Best model from each team will be tested on independent data after March 01
- **Best participants will receive a winner's certificate and a prize!**

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- **Best participants will receive a winner's certificate and a prize!**
- **May the best machine learners win!**