Deep Learning LAB Assignment-2

Introduction

The main aim of this task is to implement text classification using the CNN with different data

Objectives

- o To Display the graph in the Tensor Board using tensor flow
- Switch the hyperparameter from one value to other value and note the reports
- Compare the reports and examine the difference

Approaches/Methods

Convolutional Neural Networks are identical to Neural networks which are inclusive of neurons with measurable weight and bias.

This consists of layers

- Convolutional Layer
- Pooling Layer
- Fully-Connected Layer

Convolutional Layer

This layer is important building block of CNN which performs computational huge lifting **Pooling Layer**

- This layer is fitted between ConvNet architecture.
- o This layer works very independent on depth of slice with MAX operation.
- Works on volume size having W×H×D

Fully-Connected Layer

This have full of connections with complete activations with prior layers and that is done with matrix multiplications

Workflow

- o Required libraries are to be imported such as Numpy, Pandas, text CNN
- Parameters are considered for Data, Model and Training
- Data to be used for pre-processing
- o Load the wanted data and build vocabulary then shuffle randomly
- Splitting is done as the test and train data
- Cross validation must be done after training the data
- Train the procedure
- Note the reports for gradient and sparsity
- Summarize the loss and accuracy
- Note the checkpoints
- Train the loop for every set
- Evaluate parameters
- Epoch number of operations
- Tensor Boards graphs are displayed

Datasets

O Consumer complaints dataset with total number of 11 classes.

Parameters

Parameters:
ALLOW_SOFT_PLACEMENT=True
BATCH_SIZE=64
CHECKPOINT_EVERY=100
DEV_SAMPLE_PERCENTAGE=0.01
DROPOUT_KEEP_PROB=0.5
EMBEDDING_DIM=128
EVALUATE_EVERY=100
FILTER_SIZES=3,4,5
L2_REG_LAMBDA=0.0
LOG_DEVICE_PLACEMENT=False

Configuration

Pycharm

Python: 2.7.13 Tensor Flow

Evaluation & Discussion

Code snippet

```
③ 🛊 🔯 👫 🎼 CNN.py. × 🖟 text_cnn.py × 🖟 train.py × 🎉 parsers.py × 🕮 consumer_complaints.csv × 🖟 data_helper.py × 📡 belling_the_cat.bst ×
> Dim graph

# belling_the_cat.txt
                                                 * Data loading params of the training data to use for validation") tf.flags.DEFINE_float("day_mample_percentage", .1, "Percentage of the training data to use for validation") tf.flags.DEFINE_fring("positive_data_file", "./data/t-tpolaritydata/t-tpolarity_now,") "Data source for the r
   CNN.py
   consumer_complaints.csv
  data_helper.py
                                                 # Model Hyperparameters

f Model Hyperparameters

tf.flags.DEFINE_interper("embedding_dim", 128, "Dimensionality of character embedding (default: 128)")

tf.flags.DEFINE_tring("eilte_size", "3.4.5, "Norman-sepations there is included a size (default: 128, "1,5")

tf.flags.DEFINE_tlack("default: 128)")

tf.flags.DEFINE_tlack("dropout_leabour, 0.5, "Dropout keep probability (default: 0.5)")

tf.flags.DEFINE_tlack("dropout_leabour, 0.5, "Dropout keep to default: 128)")
   rnn_words.py
   text_cnn.py
train.py
                                                  # Training parameters

if.flags.DEFINE integer("hatch_size", 64, "Batch Size (default: 64)")

if.flags.DEFINE integer("num_epochs", 200, "Number of training spochs (default: 200)")

if.flags.DEFINE integer("evaluate every", 100, "Evaluate model on dev set after this many steps (default: 100

if.flags.DEFINE integer("checkpoint every", 100, "Save model after this many steps (default: 100)")

if.flags.DEFINE integer("num_checkpoints", 5, "Number of checkpoints to store (default: 5)")

if.flags.DEFINE integer("num_checkpoints", 5, "Number of checkpoints to store (default: 5)")
                                                 tf.flags.DEFINE_boolean("allow_soft_placement", True, "Allow device soft device placement")
tf.flags.DEFINE_boolean("log_device_placement", False, "log placement of ops on devices")
                                                 FIAGS = +f flags FIAGS
 # Build vocabulary
 max_document_length = max([len(x.split(" ")) for x in x_text])
 vocab processor = learn.preprocessing.VocabularyProcessor(max document length)
 x = np.array(list(vocab_processor.fit_transform(x_text)))
 # Randomly shuffle data
 np.random.seed(10)
 shuffle_indices = np.random.permutation(np.arange(len(y)))
 x_shuffled = x[shuffle_indices]
 y_shuffled = y[shuffle_indices]
 # Split train/test set
 # TODO: This is very crude, should use cross-validation
 dev_sample_index = -1 * int(FLAGS.dev_sample_percentage * float(len(y)))
 x_train, x_dev = x_shuffled[:dev_sample_index], x_shuffled[dev_sample_index:]
 y_train, y_dev = y_shuffled[:dev_sample_index], y_shuffled[dev_sample_index:]
 del x, y, x_shuffled, y_shuffled
 print("Vocabulary Size: {:d}".format(len(vocab processor.vocabulary )))
 print("Train/Dev split: {:d}/{:d}".format(len(y_train), len(y_dev)))
 # Training
 with tf.Graph().as_default():
  def train_step(x_batch, y_batch):
         A single training step
         feed_dict = {
           cnn.input_x: x_batch,
           cnn.input_y: y_batch,
           cnn.dropout keep prob: FLAGS.dropout keep prob
        _, step, summaries, loss, accuracy = sess.run(
              [train_op, global_step, train_summary_op, cnn.loss, cnn.accuracy],
              feed dict)
         time str = datetime.datetime.now().isoformat()
         print("{}: step {}, loss {:g}, acc {:g}".format(time_str, step, loss, accuracy))
         train_summary_writer.add_summary(summaries, step)
  def dev_step(x_batch, y_batch, writer=None):
         Evaluates model on a dev set
         feed dict = {
           cnn.input_x: x_batch,
            cnn.input_y: y_batch,
           cnn.dropout_keep_prob: 1.0
         step, summaries, loss, accuracy = sess.run(
                [global_step, dev_summary_op, cnn.loss, cnn.accuracy],
```

```
A CNN for text classification.
                      Uses an embedding layer, followed by a convolutional, max-pooling and softmax layer.
                      def init (
                         self, sequence_length, num_classes, vocab_size,
                         embedding_size, filter_sizes, num_filters, 12_reg_lambda=0.0):
                             # Placeholders for input, output and dropout
                             self.input_x = tf.placeholder(tf.int32, [None, sequence_length], name="input_x")
                             self.input_y = tf.placeholder(tf.float32, [None, num_classes], name="input_y")
                             self.dropout_keep_prob = tf.placeholder(tf.float32, name="dropout_keep_prob")
                             # Keeping track of 12 regularization loss (optional)
                             12_loss = tf.constant(0.0)
                             # Embedding layer
                             with tf.device('/cpu:0'), tf.name scope("embedding"):
                                   self.W = tf.Variable(
                                          tf.random_uniform([vocab_size, embedding_size], -1.0, 1.0),
                                          name="W")
                                   self.embedded_chars = tf.nn.embedding_lookup(self.W, self.input_x)
                                   self.embedded_chars_expanded = tf.expand_dims(self.embedded_chars, -1)
                             # Create a convolution + maxpool layer for each filter size
                             pooled_outputs = []
                             for i, filter_size in enumerate(filter_sizes):
                                   with tf.name scope("conv-maxpool-%s" % filter size):
                             for i, filter_size in enumerate(filter_sizes):
                                    with tf.name scope("conv-maxpool-%s" % filter size):
                                            # Convolution Layer
                                           filter shape = [filter size, embedding size, 1, num filters]
                                           \underline{\underline{W}} = tf.Variable(tf.truncated_normal(filter_shape, stddev=0.1), name="\begin{align*} W" \]
                                           b = tf.Variable(tf.constant(0.1, shape=[num_filters]), name="b")
                                           conv = tf.nn.conv2d(
                                                  self.embedded_chars_expanded,
                                                  strides=[1, 1, 1, 1],
                                                  padding="VALID",
                                                  name="conv")
                                           # Apply nonlinearity
                                           h = tf.nn.relu(tf.nn.bias_add(conv, b), name="relu")
                                           # Maxpooling over the outputs
                                           pooled = tf.nn.max_pool(
                                                  h,
                                                  ksize=[1, sequence_length - filter_size + 1, 1, 1],
                                                  strides=[1, 1, 1, 1],
                                                  padding='VALID',
                                                  name="pool")
                                           pooled_outputs.append(pooled)
                             # Combine all the pooled features
                             num_filters_total = num_filters * len(filter_sizes)
                             self.h_pool = tf.concat(pooled outputs, 3)
                             self.h_pool_flat = tf.reshape(self.h_pool, [-1, num_filters_total])
         o Output
n train

2018-04-23T17;12:27,838248; step 982, loss 0.500326, acc 0.8125

2018-04-23T17;12:28.311586; step 983, loss 0.379159, acc 0.84375

2018-04-23T17;12:28.77999; step 984, loss 0.473596, acc 0.859375

2018-04-23T17;12:29.726692; step 986, loss 0.307726, acc 0.859375

2018-04-23T17;12:29.726692; step 986, loss 0.356266, acc 0.859375

2018-04-23T17;12:30.662788; step 986, loss 0.359414, acc 0.78125

2018-04-23T17;12:31.65786; step 989, loss 0.359414, acc 0.78125

2018-04-23T17;12:31.65289; step 990, loss 0.369039, acc 0.78125

2018-04-23T17;12:32.66728; step 991, loss 0.389039, acc 0.853375

2018-04-23T17;12:33.602589; step 990, loss 0.389039, acc 0.883333

2018-04-23T17;12:33.602589; step 990, loss 0.389039, acc 0.828125

2018-04-23T17;12:33.507943; step 992, loss 0.389039, acc 0.828125

2018-04-23T17;12:33.507943; step 994, loss 0.389399, acc 0.82125

2018-04-23T17;12:34.93605; step 996, loss 0.271033, acc 0.821875

2018-04-23T17;12:35.64750; step 996, loss 0.271033, acc 0.621875

2018-04-23T17;12:35.64750; step 996, loss 0.2788989, acc 0.675

2018-04-23T17;12:35.84750; step 996, loss 0.288898, acc 0.675

2018-04-23T17;12:35.84750; step 996, loss 0.388899, acc 0.675

2018-04-23T17;12:35.84750; step 996, loss 0.388899, acc 0.675

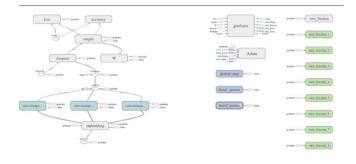
2018-04-23T17;12:35.84750; step 996, loss 0.388899, acc 0.675

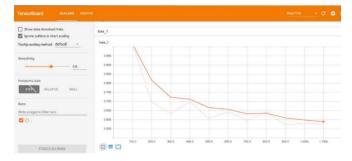
2018-04-23T17;12:35.84750; step 996, loss 0.37101, acc 0.859375

2018-04-23T17;12:35.84750; step 996, loss 0.37101, acc 0.859375

2018-04-23T17;12:35.84750; step 996, loss 0.37101, acc 0.859375
```

Tensor flow graph







Conclusion

By using tensor flow the code both deploy and debug has done.

By CNN increment of accuracy got satisfied.

There is a chance of increment in both accuracy and complexity if we use RNN's and LSTM's References

http://cs231n.github.io/convolutional-networks/