ANSWERS – JEAN DEGEORGE

2.

Using the orthogonality and the properties of the trace, prove that, for X and Y two matrices:

$\left|\left|WX - Y\right|\right| = tr((WX - Y)(XW^t - Y^t))$

$= tr(YY^t) + tr(WXX^tW^t) - 2tr(YX^tW^t)$

$= tr(YY^t) + tr(XX^t) - 2tr(YX^tW^t)$ because W is orthogonal

$= tr(YY^t) + tr(WXX^tW^t) - 2tr(YX^tW^t)$

So minimizing $\left|\left|WX - Y\right|\right|$ is equivalent to maximizing:

$= tr(YX^tW^t)$

$Let\ U, \Sigma, V\ bet\ be\ the\ lemetns\ of\ the\ SVD\ decomposition\ of\ YX^t. Then$:

$tr(YX^tW^t) = tr(U\Sigma V^tW^t)$

$= tr(\Sigma V^tW^tU)\ \ Then, let\ Z = V^tW^tU$

$= tr(\Sigma Z) = \Sigma\left(Z_{i,i}\Sigma_{i,i}\right) \leq \Sigma\left(\Sigma_{i,i}\right)$

The last inequality is true since Z is orthonormal and $\Sigma\left(\Sigma_{i,i}^2\right) = 1,\ \ Z_{i,i} \leq 1$

If Z=I the maximum is attained so $W=UV^t$

3.

What is your training and dev errors using either the average of word vectors or the weighted-average?

For idf=False:
The training error is 1.409.
The dev error is: 1.524.

For idf=True:
The training error is 1.4327.
The dev error is 1.6013**.**

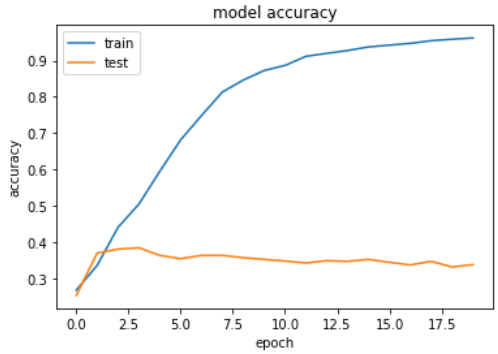
4.

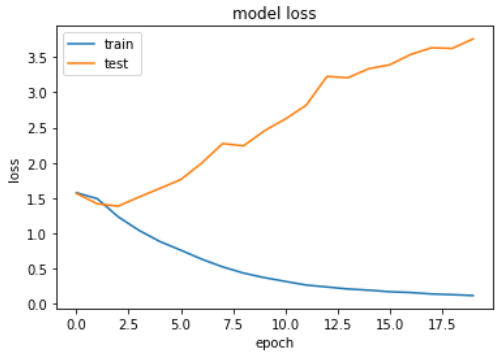
Which loss did you use? Write the mathematical expression of the loss you used for the 5-class classification.

$$L(\theta) = -\Sigma_{i=1}^{5}[p_i log(q_i)]$$

p is the "true" probability and q is the predicted probability.
For all i from 1 to 5: p_i is the probability that an observation belongs to category i. Same for q_i.

Plot the evolution of train/dev results w.r.t the number of epochs.





We can see that the test accuracy does not increase after 4 training epochs. The loss follows a symmetric path. There is even a slight decrease from epoch 4 due to overfitting.

Be creative: use another encoder. What are your motivations for using this other model?

I used the encoder that was developed in question 1 to give each sentence a word2vec representation (idf weighted average). I believed this was would give the model more information than a plain one-hot encoding but the results were not as satisfying as the original model. Other methods were used such as using a "hashing-trick" encoder provided by Keras but that didn't give better results. My final model though, adding a 1D convolutional layer, yielded a 36% accuracy (1 point more than the base model).

nlp_project

March 28, 2018

1 Deep Learning for NLP - Project

RULES:

- Do not create any additional cell
- Fill in the blanks
- All cells should be runnable (modulo trivial compatibility bugs that we'd fix)
- 4 / 20 points will be allocated to the clarity of your code
- Efficient code will have a bonus

DELIVERABLE:

- this notebook
- the predictions of the SST test set

DO NOT INCLUDE THE DATASETS IN THE DELIVERABLE..

```
In [1]: import io
        import os
        import numpy as np
        import scipy
        import operator
        import math
```

```
In [2]: PATH_TO_DATA = "/Users/Jean/Desktop/Deep Learning/nlp_project/data/"
```

2 1) Monolingual (English) word embeddings

```
In [3]: class Word2vec():
            def __init__(self, fname, nmax=100000):
                self.load_wordvec(fname, nmax)
                self.word2id = dict.fromkeys(self.word2vec.keys())
                self.id2word = {v: k for k, v in self.word2id.items()}
                self.embeddings = np.array(self.word2vec.values())
```

```
            def load_wordvec(self, fname, nmax):
                self.word2vec = {}
                with io.open(fname, encoding='utf-8') as f:
                    next(f)
                    for i, line in enumerate(f):
                        word, vec = line.split(' ', 1)
                        self.word2vec[word] = np.fromstring(vec, sep=' ')
                        if i == (nmax - 1):
                            break
                print('Loaded %s pretrained word vectors' % (len(self.word2vec)))

            def most_similar(self, w, k=5):
                # k most similar words: self.score  -  np.argsort
                trainingSet = list(self.word2vec.keys())
                distances = []
                for x in range(len(trainingSet)):
                    dist = self.score(w, trainingSet[x])
                    distances.append((trainingSet[x], dist))
                distances.sort(key=operator.itemgetter(1), reverse=True)
                neighbors = []
                for x in range(1, k+1):
                    neighbors.append(distances[x][0])
                return neighbors

            def score(self, w1, w2):
                # cosine similarity: np.dot  -  np.linalg.norm
                v1 = self.word2vec[w1]
                v2 = self.word2vec[w2]
                x = np.dot(v1, v2)/(np.linalg.norm(v1)*np.linalg.norm(v2))
                return x

In [4]: w2v = Word2vec(os.path.join(PATH_TO_DATA, 'crawl-300d-200k.vec'), nmax=60000)

        # You will be evaluated on the output of the following:
        for w1, w2 in zip(('cat', 'dog', 'dogs', 'paris', 'germany'), ('dog', 'pet', 'cats', '
            print(w1, w2, w2v.score(w1, w2))
        for w1 in ['cat', 'dog', 'dogs', 'paris', 'germany']:
            print(w2v.most_similar(w1))

Loaded 60000 pretrained word vectors
cat dog 0.6716836662792491
dog pet 0.6842064029669219
dogs cats 0.7074389328052404
paris france 0.7775108541288561
germany berlin 0.7420295235998392
['cats', 'kitty', 'kitten', 'feline', 'kitties']
['dogs', 'puppy', 'Dog', 'doggie', 'canine']
['dog', 'Dogs', 'doggies', 'canines', 'puppies']
```

```
['france', 'Paris', 'london', 'berlin', 'europe']
['europe', 'german', 'berlin', 'france', 'italy']
```

```
In [4]: class BoV():
            def __init__(self, w2v):
                self.w2v = w2v
                #self.idf = self.build_idf(sentences)

            def encode(self, sentences, idf=False):
                # takes a list of sentences, outputs a numpy array of sentence embeddings
                # see TP1 for help
                sentemb = []
                idf_dict = self.build_idf(sentences)
                #return
                for sent in sentences:
                    if idf is False:
                        # mean of word vectors
                        sentemb.append(np.mean([w2v.word2vec[w] for w in sent if w in w2v.word
                        #assert False, 'TODO: fill in the blank'
                    else:
                        # idf-weighted mean of word vectors
                        sentemb.append(np.average([w2v.word2vec[w] for w in sent if w in w2v.wo
                                                   axis=0, weights=[idf_dict[w] for w in sent i
                        #assert False, 'TODO: fill in the blank'
                return np.vstack(sentemb)

            def most_similar(self, s, sentences, idf=False, k=5):
                # get most similar sentences and **print** them
                #keys = self.encode(sentences, idf)
                #query = self.encode([s], idf)
                # k most similar words: self.score  -  np.argsort
                distances = []
                for x in range(len(sentences)):
                    dist = self.score(s, sentences[x])
                    distances.append((sentences[x], dist))
                distances.sort(key=operator.itemgetter(1), reverse=True)
                neighbors = []
                for x in range(1, k+1):
                    neighbors.append(distances[x][0])
                print([" ".join(neighbors[i]) for i in range(len(neighbors))])

            def score(self, s1, s2, idf=False):
                # cosine similarity: use   np.dot  and  np.linalg.norm
                s1 = self.encode([s1]).reshape(300) #change that
                s2 = self.encode([s2]).reshape(300)
                x = np.dot(s1, s2)/(np.linalg.norm(s1)*np.linalg.norm(s2))
                return x
```

```
            def build_idf(self, sentences):
                # build the idf dictionary: associate each word to its idf value
                idf = {}
                for sent in sentences:
                    for w in set(sent):
                        idf[w] = idf.get(w, 0) + 1

                for word in idf.keys():
                    idf[word] = max(1, np.log10(len(sentences) / (idf[word])))

                return idf
```

```
In [6]: w2v = Word2vec(os.path.join(PATH_TO_DATA, 'crawl-300d-200k.vec'), nmax=10000)
        s2v = BoV(w2v)

        # Load sentences in "PATH_TO_DATA/sentences.txt"
        sentences = []
        with open(PATH_TO_DATA + 'data/sentences.txt') as f:
            for i, line in enumerate(f):
                sent = line.rstrip().split()
                sentences.append(sent)
        print('Found %s sentences' % len(sentences))

        # Build idf scores for each word
        idf = False

        # You will be evaluated on the output of the following:
        s2v.most_similar('' if not sentences else sentences[10], sentences, idf)  # BoV-mean
        print(s2v.score('' if not sentences else sentences[7], '' if not sentences else senten

        idf = True
        s2v.most_similar('' if not sentences else sentences[10], sentences, idf)  # BoV-idf
        print(s2v.score('' if not sentences else sentences[7], '' if not sentences else senten
```

```
Loaded 10000 pretrained word vectors
Found 150736 sentences
['girl smiling on roller coaster .', 'a boy smiles underwater .', 'two girlfriends smiling .',
0.593603544417741
['girl smiling on roller coaster .', 'a boy smiles underwater .', 'two girlfriends smiling .',
0.593603544417741
```

3 2) Multilingual (English-French) word embeddings

Let's consider a bilingual dictionary of size V_a (e.g French-English).

Let's define **X** and **Y** the **French** and **English** matrices.

They contain the embeddings associated to the words in the bilingual dictionary.

We want to find a **mapping W** that will project the source word space (e.g French) to the target word space (e.g English).

Procrustes : **W* = argmin || W.X - Y || s.t W^T.W = Id** has a closed form solution: **W = U.V^T where U.Sig.V^T = SVD(Y.X^T)**

In what follows, you are asked to:

In [7]:
```
# 1 - Download and load 50k first vectors of
#     https://s3-us-west-1.amazonaws.com/fasttext-vectors/wiki.en.vec
#     https://s3-us-west-1.amazonaws.com/fasttext-vectors/wiki.fr.vec

# TYPE CODE HERE

def load_wordvec(fname, nmax):
    word2vec = {}
    with io.open(fname, encoding='utf-8') as f:
        next(f)
        for i, line in enumerate(f):
            word, vec = line.split(' ', 1)
            word2vec[word] = np.fromstring(vec, sep=' ')
            if i == (nmax - 1):
                break
    print('Loaded %s pretrained word vectors' % (len(word2vec)))
    return word2vec

fr_dict = load_wordvec(os.path.join(PATH_TO_DATA, 'wiki.fr.vec'), nmax=50000)
en_dict = load_wordvec(os.path.join(PATH_TO_DATA, 'wiki.en.vec'), nmax=50000)
```

```
Loaded 50000 pretrained word vectors
Loaded 50000 pretrained word vectors
```

In [10]:
```
# 2 - Get words that appear in both vocabs (= identical character strings)
#     Use it to create the matrix X and Y (of aligned embeddings for these words)

# TYPE CODE HERE

common = list(set(list(fr_dict)).intersection(list(en_dict)))
len(common)

X = [fr_dict[x] for x in common]
Y = [en_dict[x] for x in common]
```

In [11]:
```
# 3 - Solve the Procrustes using the scipy package and: scipy.linalg.svd() and get th
#     Now W*French_vector is in the same space as English_vector

# TYPE CODE HERE

# W = U.V^T where U.Sig.V^T = SVD(Y.X^T)
```

```
from scipy.linalg import svd
temp = np.dot(np.transpose(np.matrix(X)), np.matrix(Y))
U, s, Vh = svd(temp)
W = np.dot(U, Vh)
```

In [12]:
```
# 4 - After alignment with W, give examples of English nearest neighbors of some Fren
#     You will be evaluated on that part and the code above

# TYPE CODE HERE

# update fr_dict
X_new = np.matrix(list(fr_dict.values()))
X_new = np.dot(X_new, W)
X_new = [X_new[i].tolist()[0] for i in range(len(X_new))]
new_fr_dict = dict(zip(list(fr_dict.keys()), X_new))

def most_similar(trainingSet, testInstance, k=5):
    distances = []
    for x in range(len(trainingSet)):
        dist = score(testInstance, trainingSet[x])
        distances.append((trainingSet[x], dist))
    distances.sort(key=operator.itemgetter(1), reverse=True)
    neighbors = []
    for x in range(k):
        neighbors.append(distances[x][0])
    return neighbors

# French to English

def score(w1, w2):
    # cosine similarity: np.dot  -  np.linalg.norm
    v1 = new_fr_dict[w1]
    v2 = en_dict[w2]
    x = np.dot(v1, v2)/(np.linalg.norm(v1)*np.linalg.norm(v2))
    return x

for w1 in ['maman']:
    print(most_similar(list(en_dict.keys()), w1))

# English to French

def score(w1, w2):
    # cosine similarity: np.dot  -  np.linalg.norm
    v1 = en_dict[w1]
    v2 = new_fr_dict[w2]
    x = np.dot(v1, v2)/(np.linalg.norm(v1)*np.linalg.norm(v2))
    return x
```

```
        for w1 in ['dog']:
            print(most_similar(list(new_fr_dict.keys()), w1))
```

```
['grandma', 'mom', 'mommy', 'mama', 'baby']
['dog', 'chien', 'hound', 'chiens', 'chienne']
```

If you want to dive deeper on this subject: https://github.com/facebookresearch/MUSE

4 3) Sentence classification with BoV and scikit-learn

In [13]:
```
# 1 - Load train/dev/test of Stanford Sentiment TreeBank (SST)
#     (https://nlp.stanford.edu/~socherr/EMNLP2013_RNTN.pdf)

# TYPE CODE HERE

w2v = Word2vec(os.path.join(PATH_TO_DATA, 'crawl-300d-200k.vec'), nmax=10000)
s2v = BoV(w2v)


# Load train sentences in "PATH_TO_DATA/sentences.txt"
sentences = []
with open(PATH_TO_DATA + 'SST/stsa.fine.train.txt') as f:
    for i, line in enumerate(f):
        sent = line.rstrip().split()
        sentences.append(sent)
print('Found %s sentences' % len(sentences))

# Get senetences without target
target = [sentences[i][0] for i in range(len(sentences))]
sentences = [sentences[i][1:] for i in range(len(sentences))]

# Load dev sentences in "PATH_TO_DATA/sentences.txt"
dev_sent = []
with open(PATH_TO_DATA + 'SST/stsa.fine.dev.txt') as f:
    for i, line in enumerate(f):
        sent = line.rstrip().split()
        dev_sent.append(sent)
print('Found %s sentences' % len(dev_sent))

# Get senetences without target
dev_target = [dev_sent[i][0] for i in range(len(dev_sent))]
dev_sent = [dev_sent[i][1:] for i in range(len(dev_sent))]


# Load test sentences in "PATH_TO_DATA/sentences.txt"
test_sent = []
with open(PATH_TO_DATA + 'SST/stsa.fine.test.txt') as f:
```

```
            for i, line in enumerate(f):
                sent = line.rstrip().split()
                test_sent.append(sent)
        print('Found %s sentences' % len(test_sent))
```

```
Loaded 10000 pretrained word vectors
Found 8544 sentences
Found 1101 sentences
Found 2210 sentences
```

In [48]:
```
# 2 - Encode sentences with the BoV model above

# TYPE CODE HERE

idf = False
encoded = s2v.encode(sentences, idf)
dev_encoded = s2v.encode(dev_sent, idf)
test_encoded = s2v.encode(test_sent, idf)
```

In [49]:
```
# 3 - Learn Logistic Regression on top of sentence embeddings using scikit-learn
#     (consider tuning the L2 regularization on the dev set)

# TYPE CODE HERE

from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectKBest, chi2, f_classif
from sklearn.cross_validation import cross_val_score
from sklearn.metrics import accuracy_score

def compute_score(clf, X, y, scoring='accuracy'):
    xval = cross_val_score(clf, X, y, cv=5, scoring=scoring)
    return np.mean(xval)

# format to numpy
X = np.array(encoded)
X_dev = np.array(dev_encoded)
X_test = np.array(test_encoded)
y = np.array(target).astype(int)
y_dev = np.array(dev_target).astype(int)

logistic = LogisticRegression(multi_class='multinomial', solver='lbfgs', C=1.0) #'lbf
logistic.fit(X, y)
print("Cross-validation accuracy score: " + str(compute_score(logistic, X, y, scoring=

# get training error
from sklearn.metrics import mean_squared_error
y_pred = logistic.predict(X)
print("Training MSE: " + str(mean_squared_error(y, y_pred)))
```

```
Cross-validation accuracy score: 0.3974732182312716
Training MSE: 1.409878277153558
```

```
In [50]: # 4 - Produce 2210 predictions for the test set (in the same order). One line = one p
         #     Attach the output file "logreg_bov_y_test_sst.txt" to your deliverable.
         #     You will be evaluated on the results of the test set.

         # TYPE CODE HERE

         y_pred = logistic.predict(X_dev)
         print("Dev accuracy: " + str(accuracy_score(y_dev, y_pred)))

         # get dev error
         print("Dev MSE: " + str(mean_squared_error(y_dev, y_pred)))

         # predict test
         y_test = logistic.predict(X_test)

         # save to file
         y_test.tofile('logreg_bov_y_test_sst.txt', sep=',')
```

```
Dev accuracy: 0.3978201634877384
Dev MSE: 1.5240690281562217
```

```
In [51]: # BONUS!
         # 5 - Try to improve performance with another classifier
         #     Attach the output file "XXX_bov_y_test_sst.txt" to your deliverable (where XXX

         # TYPE CODE HERE
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.model_selection import GridSearchCV, StratifiedKFold

         RF = RandomForestClassifier(n_estimators=100, criterion='gini')
         RF.fit(X, y)
         print("Cross-validation accuracy score: " + str(compute_score(RF, X, y, scoring='accu

         y_pred = RF.predict(X_dev)
         print("Dev accuracy: " + str(accuracy_score(y_dev, y_pred)))

         #test
         y_test = RF.predict(X_test)

         y_test.tofile('RandomForest_bov_y_test_sst.txt', sep=',')
```

```
Cross-validation accuracy score: 0.36890682111918577
Dev accuracy: 0.35240690281562215
```

5 4) Sentence classification with LSTMs in Keras

5.1 4.1 - Preprocessing

In [5]:
```
import keras
```

```
/Users/Jean/anaconda3/lib/python3.6/site-packages/h5py/__init__.py:36: FutureWarning: Conversio
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
/Users/Jean/anaconda3/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning: compiletime ve
  return f(*args, **kwds)
```

In [60]:
```
# 1 - Load train/dev/test sets of SST

# TYPE CODE HERE

w2v = Word2vec(os.path.join(PATH_TO_DATA, 'crawl-300d-200k.vec'), nmax=10000)
s2v = BoV(w2v)


# Load train sentences in "PATH_TO_DATA/sentences.txt"
sentences = []
with open(PATH_TO_DATA + 'SST/stsa.fine.train.txt') as f:
    for i, line in enumerate(f):
        sent = line.rstrip().split()
        sentences.append(sent)
print('Found %s sentences' % len(sentences))

# Get senetences without target
target = [int(sentences[i][0]) for i in range(len(sentences))]
sentences = [sentences[i][1:] for i in range(len(sentences))]

# Load dev sentences in "PATH_TO_DATA/sentences.txt"
dev_sent = []
with open(PATH_TO_DATA + 'SST/stsa.fine.dev.txt') as f:
    for i, line in enumerate(f):
        sent = line.rstrip().split()
        dev_sent.append(sent)
print('Found %s sentences' % len(dev_sent))

# Get senetences without target
dev_target = [int(dev_sent[i][0]) for i in range(len(dev_sent))]
dev_sent = [dev_sent[i][1:] for i in range(len(dev_sent))]


# Load test sentences in "PATH_TO_DATA/sentences.txt"
test_sent = []
with open(PATH_TO_DATA + 'SST/stsa.fine.test.txt') as f:
```

```
            for i, line in enumerate(f):
                sent = line.rstrip().split()
                test_sent.append(sent)
        print('Found %s sentences' % len(test_sent))
```

```
Loaded 10000 pretrained word vectors
Found 8544 sentences
Found 1101 sentences
Found 2210 sentences
```

```
In [61]: # 2 - Transform text to integers using keras.preprocessing.text.one_hot function
         #     https://keras.io/preprocessing/text/

         # TYPE CODE HERE

         from keras.preprocessing.text import one_hot

         n = 20000

         train_one_hot = [one_hot(" ".join(sentences[i]), n) for i in range(len(sentences))]
         dev_one_hot = [one_hot(" ".join(dev_sent[i]), n) for i in range(len(dev_sent))]
         test_one_hot = [one_hot(" ".join(test_sent[i]), n) for i in range(len(test_sent))]
```

Padding input data

Models in Keras (and elsewhere) take batches of sentences of the same length as input. It is because Deep Learning framework have been designed to handle well Tensors, which are particularly suited for fast computation on the GPU.

Since sentences have different sizes, we "pad" them. That is, we add dummy "padding" tokens so that they all have the same length.

The input to a Keras model thus has this size : (batchsize, maxseqlen) where maxseqlen is the maximum length of a sentence in the batch.

```
In [62]: # 3 - Pad your sequences using keras.preprocessing.sequence.pad_sequences
         #     https://keras.io/preprocessing/sequence/

         # TYPE CODE HERE
         from keras.preprocessing.sequence import pad_sequences

         train_pad = pad_sequences(train_one_hot)
         dev_pad = pad_sequences(dev_one_hot)
         test_pad = pad_sequences(test_one_hot)
```

5.2 4.2 - Design and train your model

```
In [46]: # 4 - Design your encoder + classifier using keras.layers
         #     In Keras, Torch and other deep learning framework, we create a "container" whic
         #     Then we add components to this contained : the lookuptable, the LSTM, the class
         #     All of these components are contained in the Sequential() and are trained toget
```

```
        # ADAPT CODE BELOW


        from keras.models import Sequential
        from keras.layers import Embedding, LSTM, Dense, Activation, Conv1D, MaxPooling1D, Res

        embed_dim  = 32  # word embedding dimension
        nhid       = 64  # number of hidden units in the LSTM
        vocab_size = 20000  # size of the vocabulary
        n_classes  = 5

        model = Sequential()
        model.add(Embedding(vocab_size, embed_dim))
        model.add(LSTM(nhid, dropout_W=0.2, dropout_U=0.2))
        model.add(Dense(n_classes, activation='sigmoid'))
```

```
/Users/Jean/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:20: UserWarning: Update
```

```
In [47]: # 5 - Define your loss/optimizer/metrics

        # MODIFY CODE BELOW

        loss_classif     =  'categorical_crossentropy' # find the right loss for multi-class
        optimizer        =  'adam' # find the right optimizer
        metrics_classif  =  ['categorical_accuracy']

        # Observe how easy (but blackboxed) this is in Keras
        model.compile(loss=loss_classif,
                      optimizer=optimizer,
                      metrics=metrics_classif)
        print(model.summary())
```

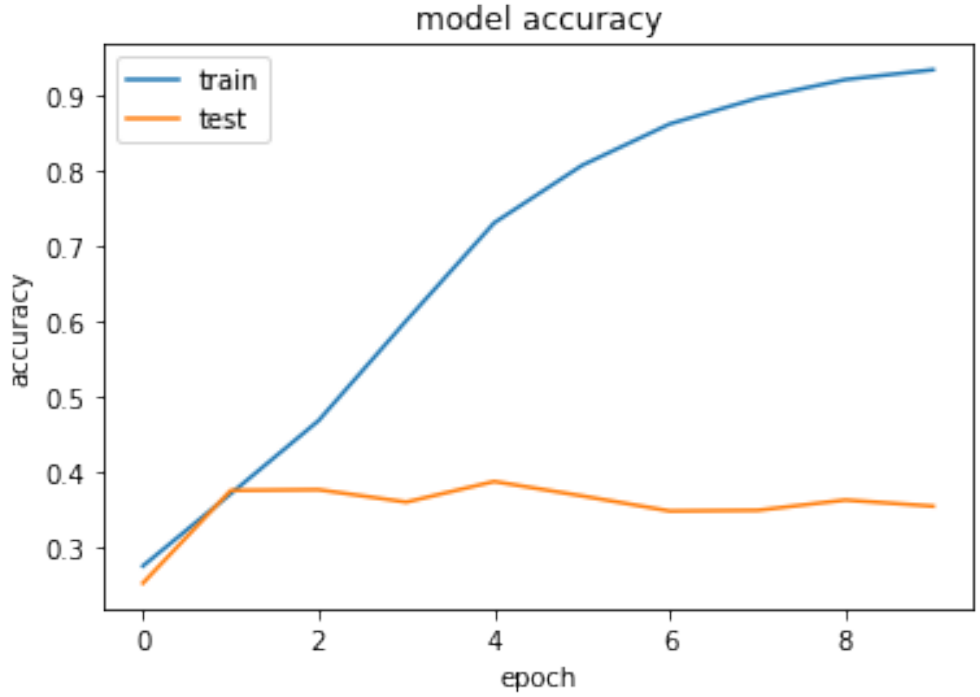
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_12 (Embedding)     (None, None, 32)          640000
_________________________________________________________________
lstm_16 (LSTM)               (None, 64)                24832
_________________________________________________________________
dense_16 (Dense)             (None, 5)                 325
=================================================================
Total params: 665,157
Trainable params: 665,157
Non-trainable params: 0
_________________________________________________________________
```

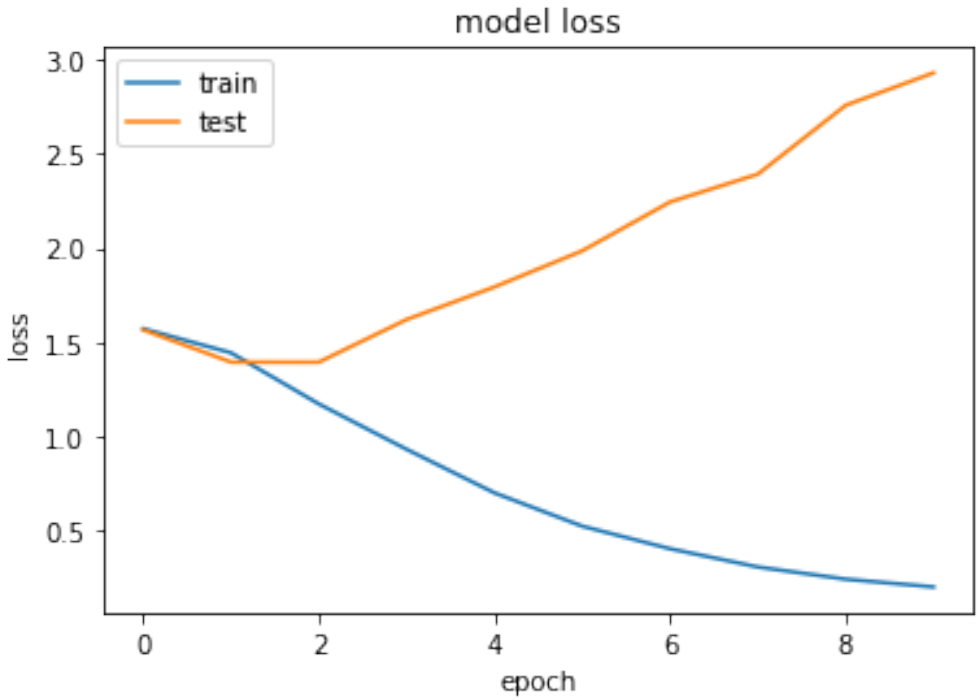
```
None
```

In [35]:
```
# 6 - Train your model and find the best hyperparameters for your dev set
#     you will be evaluated on the quality of your predictions on the test set

# ADAPT CODE BELOW

# Format
from keras.utils import np_utils
X_train = train_pad
y_train = target
y_train = np_utils.to_categorical(y_train, 5)

X_dev = dev_pad
y_dev = dev_target
y_dev = np_utils.to_categorical(y_dev, 5)

bs = 64
n_epochs = 10

history = model.fit(X_train, y_train, batch_size=bs, nb_epoch=n_epochs, validation_da
```

```
/Users/Jean/anaconda3/lib/python3.6/site-packages/keras/models.py:944: UserWarning: The `nb_epo
  warnings.warn('The `nb_epoch` argument in `fit` '


Train on 8544 samples, validate on 1101 samples
Epoch 1/10
8544/8544 [==============================] - 21s 2ms/step - loss: 1.5714 - categorical_accuracy
Epoch 2/10
8544/8544 [==============================] - 20s 2ms/step - loss: 1.4433 - categorical_accuracy
Epoch 3/10
8544/8544 [==============================] - 20s 2ms/step - loss: 1.1716 - categorical_accuracy
Epoch 4/10
8544/8544 [==============================] - 21s 2ms/step - loss: 0.9306 - categorical_accuracy
Epoch 5/10
8544/8544 [==============================] - 20s 2ms/step - loss: 0.6992 - categorical_accuracy
Epoch 6/10
8544/8544 [==============================] - 18s 2ms/step - loss: 0.5222 - categorical_accuracy
Epoch 7/10
8544/8544 [==============================] - 18s 2ms/step - loss: 0.4024 - categorical_accuracy
Epoch 8/10
8544/8544 [==============================] - 22s 3ms/step - loss: 0.3054 - categorical_accuracy
Epoch 9/10
8544/8544 [==============================] - 21s 2ms/step - loss: 0.2407 - categorical_accuracy
Epoch 10/10
8544/8544 [==============================] - 21s 2ms/step - loss: 0.1995 - categorical_accuracy
```

In [37]:
```
# 7 - Generate your predictions on the test set using model.predict(x_test)
#     https://keras.io/models/model/
#     Log your predictions in a file (one line = one integer: 0,1,2,3,4)
#     Attach the output file "logreg_lstm_y_test_sst.txt" to your deliverable.

# TYPE CODE HERE

# plot

import matplotlib.pyplot as plt
%matplotlib inline
# plot accuracy
plt.plot(history.history['categorical_accuracy'])
plt.plot(history.history['val_categorical_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# plot loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

# prediction
X_test = test_pad
y_test = model.predict(X_test)
y_classes = y_test.argmax(axis=-1)
y_classes.tofile('logreg_lstm_y_test_sst.txt', sep=',')
```


model accuracy
train
test
accuracy
epoch
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
2
4
6
8


model loss
train
test
loss
epoch
3.0
2.5
2.0
1.5
1.0
0.5
0
2
4
6
8

5.3 4.3 -- innovate !

In [63]:
```
from keras.utils import np_utils
X_train = train_pad
y_train = target
y_train = np_utils.to_categorical(y_train, 5)

X_dev = dev_pad
y_dev = dev_target
y_dev = np_utils.to_categorical(y_dev, 5)
```

In [66]:
```
# 8 - Open question: find a model that is better on your dev set
#     (e.g: use a 1D ConvNet, use a better classifier, pretrain your lookup tables ..
#     you will get point if the results on the test set are better: be careful of not
#     Attach the output file "XXX_XXX_y_test_sst.txt" to your deliverable.

# TYPE CODE HERE

embed_dim  = 32  # word embedding dimension
nhid       = 64  # number of hidden units in the LSTM
vocab_size = 20000  # size of the vocabulary
n_classes  = 5

model2 = Sequential()
model2.add(Embedding(vocab_size, embed_dim))
model2.add(LSTM(nhid, dropout_W=0.2, dropout_U=0.2)) #, return_sequences=True))
#model2.add(LSTM(nhid, dropout_W=0.2, dropout_U=0.2))
model2.add(Dense(3, activation='softmax'))
model2.add(Reshape((3, 1)))
model2.add(Conv1D(16, 2, activation='relu'))
model2.add(MaxPooling1D(pool_size=2))
model2.add(Flatten())
model2.add(Dense(n_classes, activation='softmax'))

#
loss_classif     =  'categorical_crossentropy' # find the right loss for multi-class
optimizer        =  'adam' # find the right optimizer
metrics_classif  =  ['categorical_accuracy']

# Observe how easy (but blackboxed) this is in Keras
model2.compile(loss=loss_classif,
               optimizer=optimizer,
               metrics=metrics_classif)
print(model2.summary())


bs = 64
n_epochs = 5
```

```
        history2 = model2.fit(X_train, y_train, batch_size=bs, nb_epoch=n_epochs, validation_d

        # prediction
        y_test = model2.predict(X_test)
        y_classes = y_test.argmax(axis=-1)
        y_classes.tofile('conv1d_lstm_y_test_sst.txt', sep=',')
```

```
/Users/Jean/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:15: UserWarning: Update
  from ipykernel import kernelapp as app
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_25 (Embedding)     (None, None, 32)          640000
_________________________________________________________________
lstm_33 (LSTM)               (None, 64)                24832
_________________________________________________________________
dense_34 (Dense)             (None, 3)                 195
_________________________________________________________________
reshape_14 (Reshape)         (None, 3, 1)              0
_________________________________________________________________
conv1d_16 (Conv1D)           (None, 2, 16)             48
_________________________________________________________________
max_pooling1d_16 (MaxPooling (None, 1, 16)             0
_________________________________________________________________
flatten_16 (Flatten)         (None, 16)                0
_________________________________________________________________
dense_35 (Dense)             (None, 5)                 85
=================================================================
Total params: 665,160
Trainable params: 665,160
Non-trainable params: 0
_________________________________________________________________
None
```

```
/Users/Jean/anaconda3/lib/python3.6/site-packages/keras/models.py:944: UserWarning: The `nb_epo
  warnings.warn('The `nb_epoch` argument in `fit` '
```

```
Train on 8544 samples, validate on 1101 samples
Epoch 1/5
8544/8544 [==============================] - 16s 2ms/step - loss: 1.5791 - categorical_accuracy
Epoch 2/5
8544/8544 [==============================] - 10s 1ms/step - loss: 1.5678 - categorical_accuracy
Epoch 3/5
8544/8544 [==============================] - 10s 1ms/step - loss: 1.5350 - categorical_accuracy
Epoch 4/5
```

```
8544/8544 [==============================] - 10s 1ms/step - loss: 1.4421 - categorical_accuracy
Epoch 5/5
8544/8544 [==============================] - 10s 1ms/step - loss: 1.3232 - categorical_accuracy
```