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1 Infersent

For this practicle we were instructed to implement 4 models as described in [1].

- Baseline: BoW model by averaging the word embeddings of the sentence.
- Uni-LSTM: An unidirectional LSTM model to encode the words in sequence into a fixed size representation. The last hidden state is used.
- Bi-LSTM: An bi directional LSTM model to encode the words in foward and backward sequence into a fixed size representaiton. The last hidden state is used.
- Bi-LSTM with Max pooling: Here callend Max-LSTM. A bi-directional LSTM model to encode the words in forward and backward sequence. Instead of the last hidden state, the max value of each dimension is used as representation.

Idealy the implementation should reproduce the results of the paper.

The word embeddings were taken from GloVe [2] 840B of 300 dimensions. The labeled data set used was the SNLI from Stanford [3].

[1] https://arxiv.org/abs/1705.02364
[2] https://nlp.stanford.edu/pubs/glove.pdf
[3] https://nlp.stanford.edu/pubs/snli_paper.pdf

The following cells contail *utils* functions and the imports necessary for the rest of the notebook to work.

```
In [1]: import numpy as np
        import pandas as pd
        import scipy
        import matplotlib as plt
        import seaborn as sns
        import infer
        from IPython.display import display
        import PIL

        from utils import load_classifier, load_encoder
        from data_2 import load_data

        %matplotlib inline
```

```
        #loss rescaling due to different number of batches.
        l_correction = 549367/9842 #train size/dev_size
```

In [2]:
```
def no_spaces(string):
    """replaces spaces by underscores of a string"""
    string = string.split()
    string = "_".join(string)
    return string

def plot_n_save(df, title='', xlabel = 'Epochs', ylabel='Accuracy'):
    """make a nice looking plot and save it as png image.
    Input:
        df: (pd.DataFrame) containing the data organized in columns. Series will be pl
            dataframe.
        title: (str) the title of the plot.
        xlabel, ylabel (str) the labels in the respective axis.
    Output:
        Display an pyplot image.
        Save an image using the title as name.
        """
    #set nice background and good size.
    sns.set(rc={'figure.figsize':(8,5)})

    #makes the plot
    ax = sns.lineplot(data = df)
    ax.set_title(title)
    ax.set_ylabel(ylabel)
    ax.set_xlabel(xlabel)
    fig = ax.get_figure()

    #parse the title so to have no spaces
    title = no_spaces(title)

    #save image
    fig.savefig(title + ".png")
```

In [3]:
```
def parse_sts(sts_dict, sts_keys = ["STS12", "STS13", "STS14", "STS15", "STS16"]):
    """parse the STSXX results to make it easier to show them in a table.
    Input:
        sts_dict (the dictionary format that comes out of the SentEval toolkit), must
        sts_keys: (list(str)), list of keys with the STSXX results to be parsed.
    Output:
        dict(dict(float)) containing the parsed data. Ready to use in pd.DataFrame.fro
    for k1 in sts_keys:
        for k2 in sts_dict[k1]:
            new_key = k1 +" "+ k2
            if type(sts_dict[k1][k2]) == dict:
                d = {}
```

```
                        for k3 in sts_dict[k1][k2]:

                            #parses tuples
                            if (type(sts_dict[k1][k2][k3]) == tuple) | (type(sts_dict[k1][k2][
                                d[k3] = sts_dict[k1][k2][k3][0]
                                d[k3+'-p'] = sts_dict[k1][k2][k3][1]

                            #parses dictionaries
                            elif (type(sts_dict[k1][k2][k3]) == dict):
                                for k4 in sts_dict[k1][k2][k3]:
                                    if k4 == "mean":
                                        d[k3] = sts_dict[k1][k2][k3][k4]
                                    else:
                                        d[k3 + " " + k4] = sts_dict[k1][k2][k3][k4]

                        #include parsed dict into the sts_dict
                        sts_dict[new_key] = d

                    else:
                        #treats edge cases
                        sts_dict[new_key] = sts_dict[k1][k2]

                #delete key from dictionary
                sts_dict.pop(k1)
            return sts_dict

In [4]: def display_row_images(list_im, title=None, save=False):
            """Display the Images in a row as ordered in list_im.
            cotersy of: https://stackoverflow.com/a/30228789/4614404
            Input:
                list_im: (iterable(str)), an iterable containing the paths to the images and t
                    extension.
                title: (str), a title to be displayed above the image. It is also used as name
                save: (bool), True to save image and False not to save it.
            Ouput:
                The images displayed in a row.
                If save, the images are saved into one single image.
            """
            #open all images
            imgs    = [ PIL.Image.open(i) for i in list_im ]

            # pick the image which is the smallest, and resize the others to match it (can be
            min_shape = sorted( [(np.sum(i.size), i.size ) for i in imgs])[0][1]
            imgs_comb = np.hstack( (np.asarray( i.resize(min_shape) ) for i in imgs ) )

            #puts the arrays into an image again.
            imgs_comb = PIL.Image.fromarray( imgs_comb)
```

```
            if save:
                if not title:
                    print("Cannot save image without a title")
                else:
                    # save that beautiful picture
                    imgs_comb.save(no_spaces(title)+".png")

            if title:
                print(title)

            display(imgs_comb)
```

```
In [5]: def gimme_image_list(path='./grad flow/', encoder='mean', entension='.png', max_epochs=
            """returns an list with image paths.
            Input:
                path: (str), folder path.
                encoder: (str), name of the encoder used. Options are 'mean', 'unilstm', 'bils
                entension: (str), entension of the saved images.
                max_epochs: (int), the number of saved images for the encoder.
                num_images: (int), number of images in the outputed list.
            Ouput:
                list_im: (list(str)), list with the file names concatenated in the order:
                    path + encoder + epoch + entension
                    len(list_im) = num_images.
                    epochs: (list(int)), the epochs used for in list_m.
            """

            #loWeR case to avoid user issues.
            encoder = encoder.lower()

            #define the step
            num_images = num_images -1
            step = int(max_epochs/num_images)

            #select the epochs
            epochs = [i for i in range(0, max_epochs+1, step)]

            #make a list with the the file names
            list_im = [path + encoder + str(i) + entension for i in epochs]

            return list_im, epochs
```

1.1 Choice of Architecture

As to make the model modular and flexible and easy to extend, the model is made of an *encoder* and of an *classifier*, they are specified in the files encoder.py and model.py respectively. The classifer, however, has to be used together with the encoder used to train it when in test time. This choice makes the model easy to be used in diferent contexts, only the classifier has to be called,

and the encoder is then called in the forward pass of the classifier, away from the user.

After having the premise (p) and the hypothesis (h) encoded the classifier concatenates the vectors _[p,h,|p-h|p*h]_ before proceeding with the forward pass through the fully connected layers.

An example of how to call the model is given bellow:

```
prediction = model.forward((batch_of_premises, array_of_premise_lenghts),
(batch_of_hypothesis, array_of_hypothesis_lenghts))
```

```
In [6]: #Example of Model archtecture

        #load embeddings
        _, text_f, _ = load_data()
        #uncoment this to load the model.

        model = load_classifier(text_f.vocab.vectors)
        model

What a fabulous weather, it is pool time!


Out[6]: InferClassifier(
          (encoder): MaxLSTM(
            (bi_lstm): LSTM(300, 2048, bidirectional=True)
          )
          (embeddings): Embedding(42632, 300)
          (classifier): Sequential(
            (0): Linear(in_features=16384, out_features=512, bias=True)
            (1): Linear(in_features=512, out_features=3, bias=True)
          )
        )
```

1.2 Baseline

The following regards the training evolution and the results in the SentEval tool kit by encoding sentences as the average of the word's embeddings.

1.2.1 Training evolution

The evolution of the training is shown in the following cells.

It seems very odd that the accuracy on the training set is lower than the accuracy on the development set throughout the training process. For as far as I can tell, the examples in the development set are only being used for evaluation and the model does not learn from them. It is also cause of suspision the model's accuracy on the test set is higher than on the training and development set. The test set is only shown to the model in the end of the training process and is completelly untouched data until then. I could not find a plausible explanation nor flaw in the code that could lead to those results. There are two possibilities to explain the results: * The model is somehow learning from dev and test examples in the training loop and what causes that could not be spoted. * The examples in the dev and the test sets are on average easier to classify than the examples in the training set.

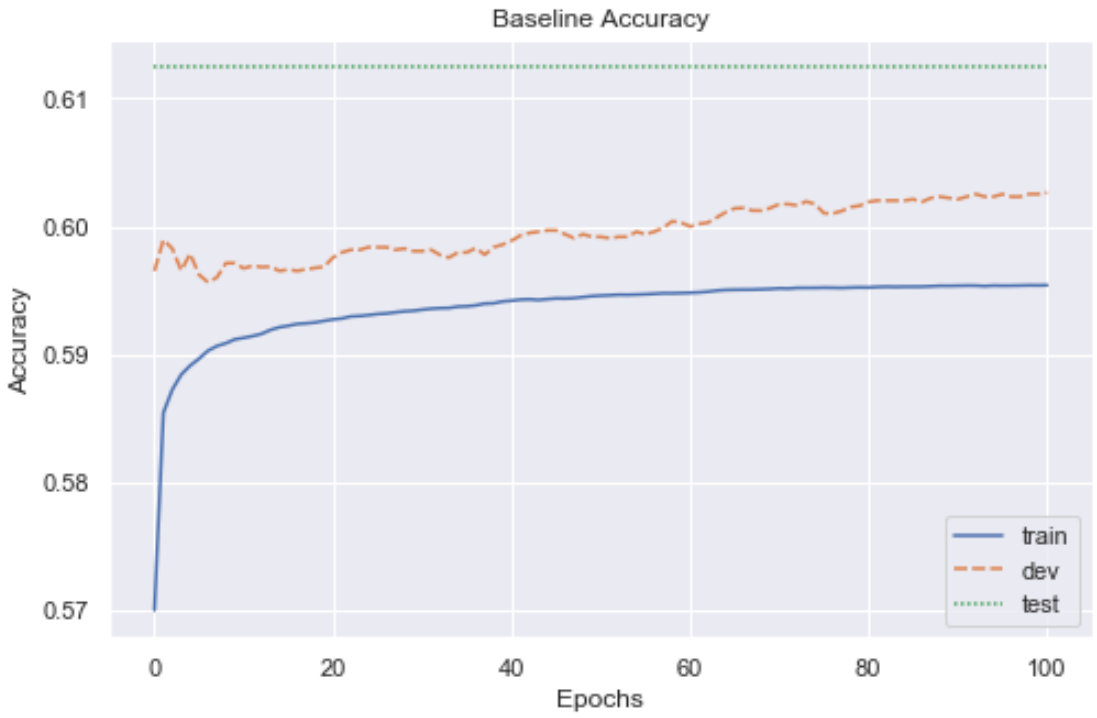
The final on test set is of accuracy of 61.2%.

```
In [7]: #Display encoder
        encoder = load_encoder(enc_name='mean')
        encoder
```

```
Hey, I am your baseline. I am not good, I am not bad, I just average!
```

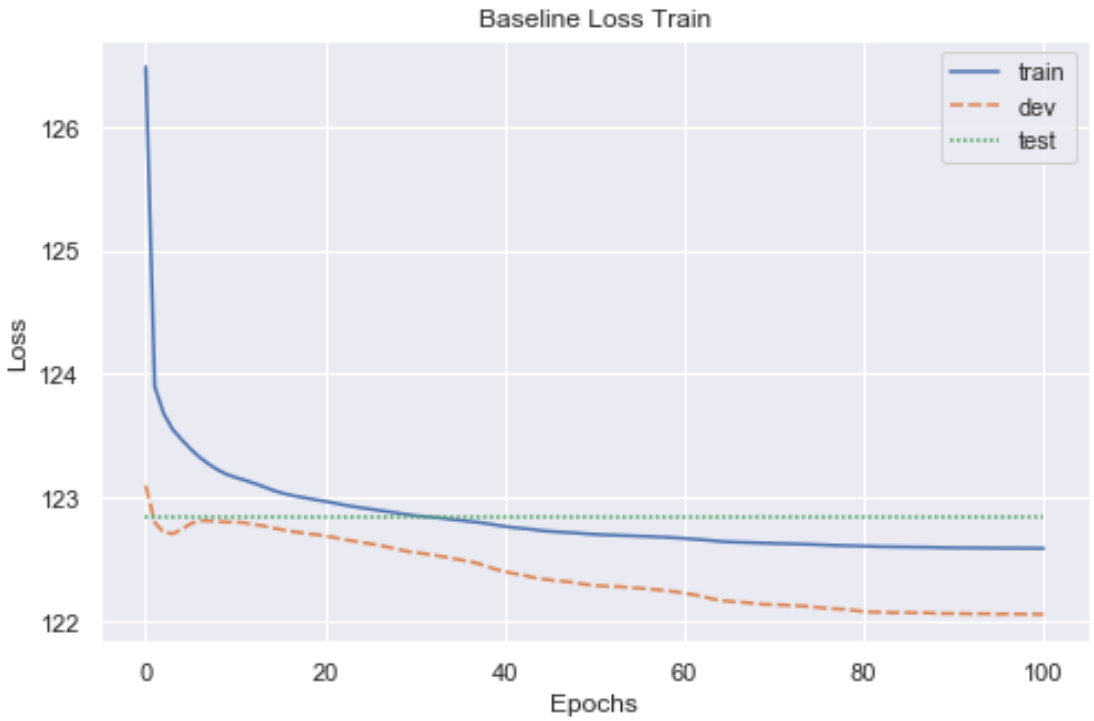
```
Out[7]: MeanEncoder()
```

```
In [8]: path = "./train/baseline/20190420/"

        df_acc = pd.DataFrame(data = None, columns = ["train", "dev", "test"])
        df_acc["train"] = np.load(path + "train_accmean.npy")
        df_acc["dev"] = np.load(path + "dev_accmean.npy")
        df_acc["test"] = np.load(path + "test_accmean.npy")

        plot_n_save(df = df_acc,
                    title = "Baseline Accuracy",
                    xlabel = "Epochs",
                    ylabel = "Accuracy")

        #stores results for later comparison
        performance = {"Mean": [df_acc.iloc[-1]["train"], df_acc.iloc[-1]["dev"], df_acc.iloc[
```



The loss curves show a similar trend as seen in the accuracy. However, the test loss is the highest, which was to be expected.

```
In [9]: path = "./train/baseline/20190420/"

        df_loss = pd.DataFrame(data = None, columns = ["train", "dev", "test"])
        df_loss["train"] = np.load(path + "train_lossmean.npy")
        df_loss["dev"] = np.load(path + "dev_lossmean.npy") * l_correction
        df_loss["test"] = np.load(path + "test_lossmean.npy") * l_correction

        plot_n_save(df = df_loss,
                    title = "Baseline Loss Train",
                    xlabel = "Epochs",
                    ylabel = "Loss")
```



Gradient Flow To get an understading of how the model is learning across epochs I modified this function [4] to save the gradient flow at each epoch. In the image we see the max in light green and the average in blue of the gradient flow at each layer of the model.

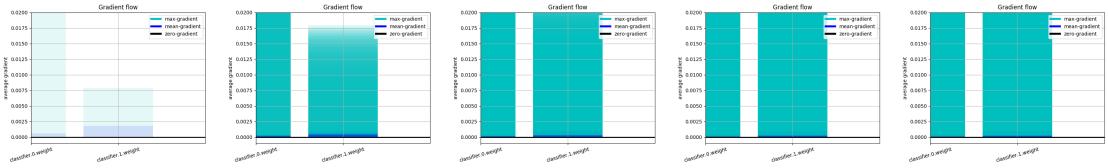
Against my intuition, the gradient flow is not the strongest in the early epochs, but later in the training. The trend was the same across models.

It is interesting to see that the layer closer to the input receives less gradient then the layer closer to the output, which is expected.

[4] https://discuss.pytorch.org/t/check-gradient-flow-in-network/15063/10

```
In [10]: #display the gradient flow across epochs

         #get list of images
         list_im, epochs = gimme_image_list(path = './grad flow/mean/',
                                            encoder = 'mean',
                                            entension = '.png',
                                            max_epochs = 100,
                                            num_images = 5)

         #Make a nice looking title
         title = "Gradient flow in epochs " + str(epochs)

         #Dislplay all images.
         display_row_images(list_im = list_im,
                            title = title,
                            save = False)
```

```
Gradient flow in epochs [0, 25, 50, 75, 100]
```



1.2.2 Transfer Learning

The model was used to encode sentences for other tasks by using the SentEval toolkit. The resultes encontered in the paper [1] were partially reproduced. All the results are shown in two tables in the cells below.

- Task: Courneaut et al. resutls ~ my results
- MR: 78.7 > 76.93
- CR: 78.5 ~ 78.36
- SUBJ: 91.6 ~ 91.18
- MPQA: 87.6 ~ 87.66
- SST: 79.8 ~ 79.68
- TREC: 83.6 > 82.6
- MRPC: 72.1/80.9 < 73.16/81.69
- SICK R: 0.8 > 0.79
- SICK E: 78.6 < 78.69
- STS14: .54/.56 ~ 0.54/0.56

```
In [11]: #load data
         path = "./train/baseline/transfer/"
```

```
file = "transfer_task_all_mean.npy"

transfer_scores = np.load(path+file)
transfer_scores = transfer_scores[()]

tasks = list(transfer_scores.keys())
transfer_scores['Length']

#take the of STSXX, SSTX and SICK out of the dictionary for the sake of simplicity
problematic_keys = ["STS12", "STS13", "STS14", "STS15", "STS16", "STSBenchmark", "SIC
sts_dict = {}
for key in problematic_keys:
    sts_dict[key] = transfer_scores.pop(key)

#make a table with the most comprehensible part of the results
df_transfer = pd.DataFrame.from_dict(transfer_scores, orient='index')
df_transfer
```

Out[11]:

	devacc	acc	ndev	ntest	f1
BigramShift	50.35	50.01	10000	10000	NaN
CR	79.84	78.36	3775	3775	NaN
CoordinationInversion	53.61	53.60	10002	10002	NaN
Depth	30.85	30.16	10000	10000	NaN
Length	58.18	59.32	9996	9996	NaN
MPQA	87.43	87.66	10606	10606	NaN
MR	77.67	76.93	10662	10662	NaN
MRPC	73.55	73.16	4076	1725	81.69
ObjNumber	75.72	76.46	10000	10000	NaN
OddManOut	50.44	49.75	10000	10000	NaN
SICKEntailment	81.00	78.69	500	4927	NaN
SUBJ	91.61	91.18	10000	10000	NaN
SubjNumber	79.37	77.99	10000	10000	NaN
TREC	73.59	82.60	5452	500	NaN
Tense	85.50	83.66	10000	10000	NaN
TopConstituents	61.44	61.55	10000	10000	NaN
WordContent	74.87	74.77	10000	10000	NaN

In [12]:
```
#parse the STSXX keys into an comprehensible dict
sts_dict = parse_sts(sts_dict)

#takes the mean of yhat,
sts_dict['SICKRelatedness']['yhat'] = sts_dict['SICKRelatedness']['yhat'].mean()
sts_dict['STSBenchmark']['yhat'] = sts_dict['STSBenchmark']['yhat'].mean()

#make a table with the results missing in the df_transfer table
df_sts = pd.DataFrame.from_dict(sts_dict, orient='index')
df_sts
```

Out[12]:

	devpearson	pearson	spearman	mse	yhat	\

SICKRelatedness	0.797253	0.799244	0.718258	0.367680	3.536806
SST2	NaN	NaN	NaN	NaN	NaN
SST5	NaN	NaN	NaN	NaN	NaN
STS12 MSRpar	NaN	0.425039	0.451449	NaN	NaN
STS12 MSRvid	NaN	0.662090	0.675039	NaN	NaN
STS12 SMTeuroparl	NaN	0.491290	0.587659	NaN	NaN
STS12 all	NaN	0.522271	0.532783	NaN	NaN
STS12 surprise.OnWN	NaN	0.570257	0.610555	NaN	NaN
STS12 surprise.SMTnews	NaN	0.462677	0.339214	NaN	NaN
STS13 FNWN	NaN	0.382086	0.365692	NaN	NaN
STS13 OnWN	NaN	0.472033	0.525691	NaN	NaN
STS13 all	NaN	0.496034	0.507557	NaN	NaN
STS13 headlines	NaN	0.633982	0.631286	NaN	NaN
STS14 OnWN	NaN	0.577094	0.643466	NaN	NaN
STS14 all	NaN	0.545982	0.556325	NaN	NaN
STS14 deft-forum	NaN	0.300157	0.347216	NaN	NaN
STS14 deft-news	NaN	0.649471	0.645587	NaN	NaN
STS14 headlines	NaN	0.586721	0.551003	NaN	NaN
STS14 images	NaN	0.624048	0.612733	NaN	NaN
STS14 tweet-news	NaN	0.538402	0.537942	NaN	NaN
STS15 all	NaN	0.562578	0.592183	NaN	NaN
STS15 answers-forums	NaN	0.367109	0.369810	NaN	NaN
STS15 answers-students	NaN	0.640669	0.682521	NaN	NaN
STS15 belief	NaN	0.452195	0.527847	NaN	NaN
STS15 headlines	NaN	0.662032	0.661991	NaN	NaN
STS15 images	NaN	0.690884	0.718748	NaN	NaN
STS16 all	NaN	0.514083	0.578758	NaN	NaN
STS16 answer-answer	NaN	0.401168	0.425265	NaN	NaN
STS16 headlines	NaN	0.613820	0.658837	NaN	NaN
STS16 plagiarism	NaN	0.544246	0.558996	NaN	NaN
STS16 postediting	NaN	0.539033	0.717631	NaN	NaN
STS16 question-question	NaN	0.472147	0.533059	NaN	NaN
STSBenchmark	0.732429	0.647852	0.629638	1.569542	2.929311

	ndev	ntest	devacc	acc	pearson-p	\
SICKRelatedness	500.0	4927.0	NaN	NaN	NaN	
SST2	872.0	1821.0	79.59	79.68	NaN	
SST5	1101.0	2210.0	43.96	43.80	NaN	
STS12 MSRpar	NaN	NaN	NaN	NaN	2.949501e-34	
STS12 MSRvid	NaN	NaN	NaN	NaN	8.704721e-96	
STS12 SMTeuroparl	NaN	NaN	NaN	NaN	2.916342e-29	
STS12 all	NaN	NaN	NaN	NaN	NaN	
STS12 surprise.OnWN	NaN	NaN	NaN	NaN	6.617653e-66	
STS12 surprise.SMTnews	NaN	NaN	NaN	NaN	1.468185e-22	
STS13 FNWN	NaN	NaN	NaN	NaN	5.788063e-08	
STS13 OnWN	NaN	NaN	NaN	NaN	1.790617e-32	
STS13 all	NaN	NaN	NaN	NaN	NaN	
STS13 headlines	NaN	NaN	NaN	NaN	1.466553e-85	

STS14	OnWN	NaN	NaN	NaN	NaN	8.246970e-68
STS14	all	NaN	NaN	NaN	NaN	NaN
STS14	deft-forum	NaN	NaN	NaN	NaN	8.028866e-11
STS14	deft-news	NaN	NaN	NaN	NaN	2.501625e-37
STS14	headlines	NaN	NaN	NaN	NaN	1.437343e-70
STS14	images	NaN	NaN	NaN	NaN	3.406219e-82
STS14	tweet-news	NaN	NaN	NaN	NaN	1.352693e-57
STS15	all	NaN	NaN	NaN	NaN	NaN
STS15	answers-forums	NaN	NaN	NaN	NaN	2.084384e-13
STS15	answers-students	NaN	NaN	NaN	NaN	6.766778e-88
STS15	belief	NaN	NaN	NaN	NaN	2.676178e-20
STS15	headlines	NaN	NaN	NaN	NaN	9.159563e-96
STS15	images	NaN	NaN	NaN	NaN	1.756353e-107
STS16	all	NaN	NaN	NaN	NaN	NaN
STS16	answer-answer	NaN	NaN	NaN	NaN	3.070326e-11
STS16	headlines	NaN	NaN	NaN	NaN	3.571648e-27
STS16	plagiarism	NaN	NaN	NaN	NaN	3.901867e-19
STS16	postediting	NaN	NaN	NaN	NaN	8.605847e-20
STS16	question-question	NaN	NaN	NaN	NaN	5.313944e-13
STSBenchmark		1500.0	1379.0	NaN	NaN	NaN

		spearman-p	pearson wmean	spearman wmean
SICKRelatedness		NaN	NaN	NaN
SST2		NaN	NaN	NaN
SST5		NaN	NaN	NaN
STS12	MSRpar	6.152520e-39	NaN	NaN
STS12	MSRvid	6.995979e-101	NaN	NaN
STS12	SMTeuroparl	5.754737e-44	NaN	NaN
STS12	all	NaN	0.531901	0.549506
STS12	surprise.OnWN	8.202285e-78	NaN	NaN
STS12	surprise.SMTnews	3.354224e-12	NaN	NaN
STS13	FNWN	2.285939e-07	NaN	NaN
STS13	OnWN	3.494075e-41	NaN	NaN
STS13	all	NaN	0.541674	0.558329
STS13	headlines	1.235344e-84	NaN	NaN
STS14	OnWN	6.851317e-89	NaN	NaN
STS14	all	NaN	0.553229	0.562342
STS14	deft-forum	3.395967e-14	NaN	NaN
STS14	deft-news	9.145783e-37	NaN	NaN
STS14	headlines	8.921957e-61	NaN	NaN
STS14	images	1.662435e-78	NaN	NaN
STS14	tweet-news	1.756349e-57	NaN	NaN
STS15	all	NaN	0.600809	0.628022
STS15	answers-forums	1.347131e-13	NaN	NaN
STS15	answers-students	6.036131e-104	NaN	NaN
STS15	belief	2.739740e-28	NaN	NaN
STS15	headlines	9.493580e-96	NaN	NaN
STS15	images	3.458572e-120	NaN	NaN

```
STS16 all                          NaN       0.514433        0.579383
STS16 answer-answer       1.407604e-12            NaN             NaN
STS16 headlines           2.242227e-32            NaN             NaN
STS16 plagiarism          2.641409e-20            NaN             NaN
STS16 postediting         6.720940e-40            NaN             NaN
STS16 question-question   9.672437e-17            NaN             NaN
STSBenchmark                       NaN            NaN             NaN
```

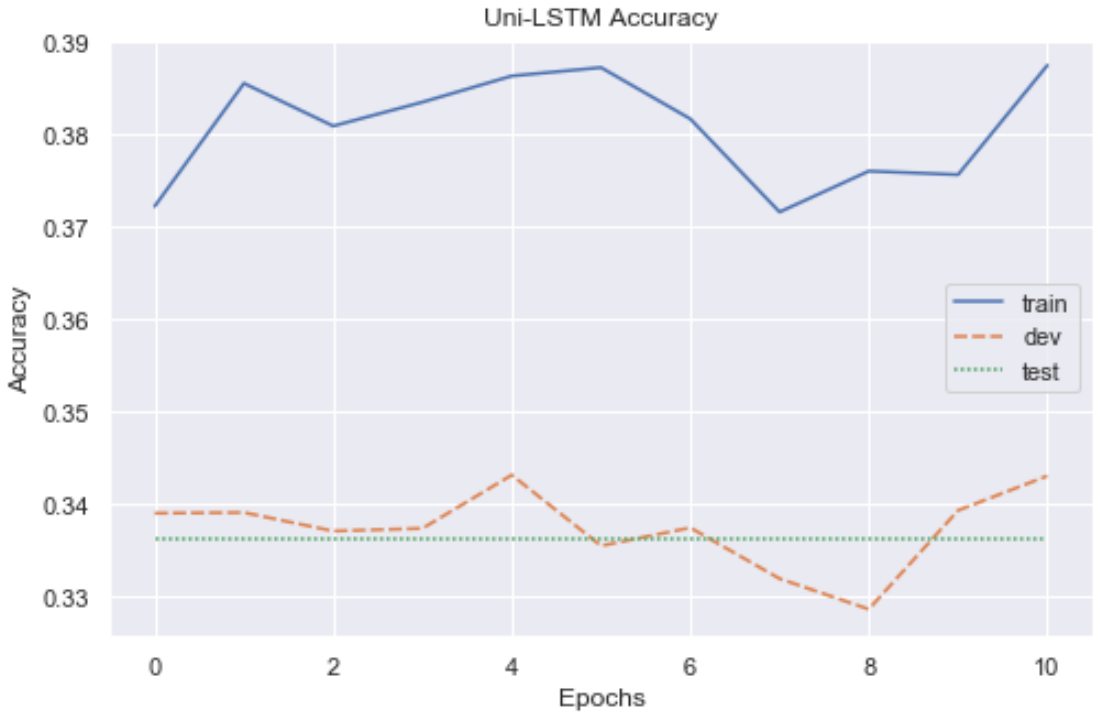
1.3 Uni LSTM

Unfortunatelly, I could not make the Uni-LSTM nor the Bi-LSTM work. I could not spot whatever is wrong in their logic, the Baseline and the Max-LSTM give ok results, they all share the same archtecture, which suggests that the problem is located in the forward pass of the Uni-LSTM, but I could not find a solution to make the encoder learn sentence representations.

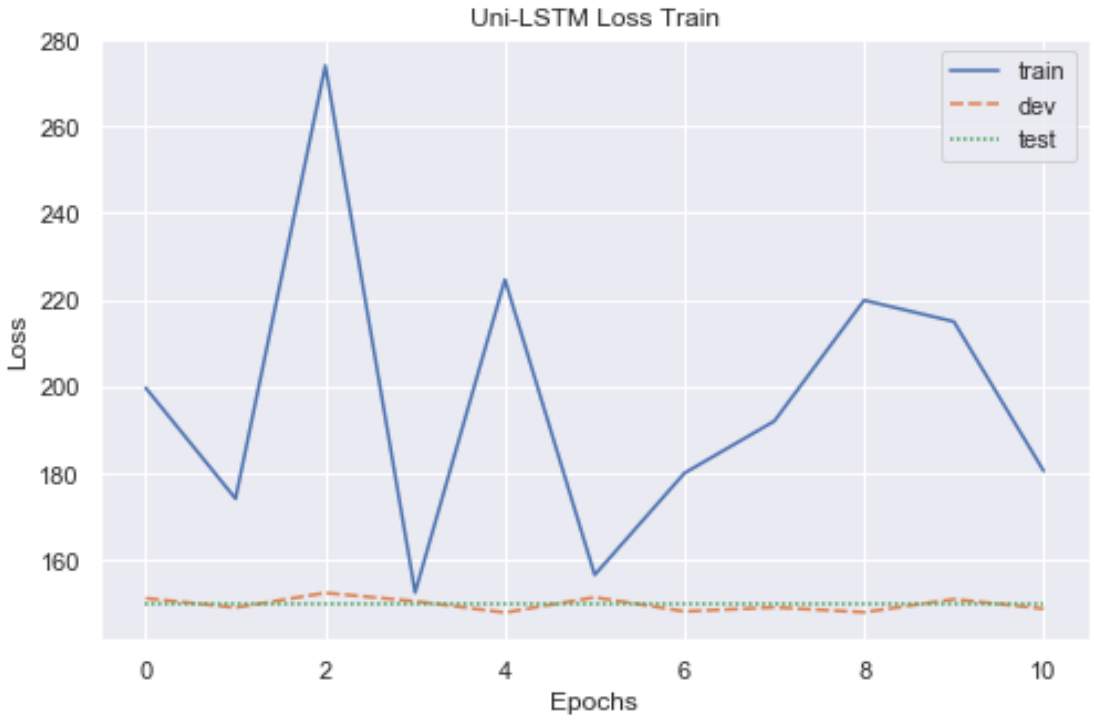
The result below is similar for feeding the padded batch into the LSTM or by using the pack-padded sequence.

I started studing the gradient flow when to try to find the problem with the models, but, as shown below, there is gradient being back propagated. This sugests that something is fundametaly wrong with my implementation of the forward pass, however, my efforst were not sufficient to spot it.

```
In [13]: encoder = load_encoder(enc_name='unilstm')
         encoder

Get yourself a direction and don't even look back.


Out[13]: UniLSTM(
           (uni_lstm): LSTM(300, 2048)
         )

In [14]: path = "./train/UniLSTM/20190422/"

         df_acc = pd.DataFrame(data = None, columns = ["train", "dev", "test"])
         df_acc["train"] = np.load(path + "train_accunilstm.npy")
         df_acc["dev"] = np.load(path + "dev_accunilstm.npy")
         df_acc["test"] = np.load(path + "test_accunilstm.npy")

         plot_n_save(df = df_acc,
                     title = "Uni-LSTM Accuracy",
                     xlabel = "Epochs",
                     ylabel = "Accuracy")

         #stores results for later comparison
         performance["UniLSTM"] = [df_acc.iloc[-1]["train"], df_acc.iloc[-1]["dev"], df_acc.ilo
```

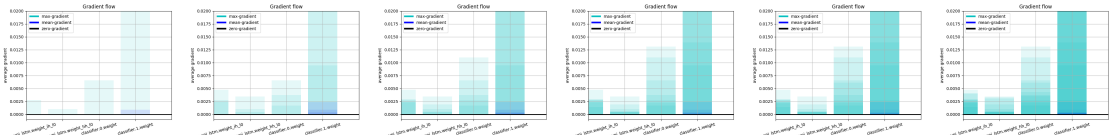



```
In [15]: df_loss = pd.DataFrame(data = None, columns = ["train", "dev", "test"])
         df_loss["train"] = np.load(path + "train_lossunilstm.npy")
         df_loss["dev"] = np.load(path + "dev_lossunilstm.npy") * l_correction
         df_loss["test"] = np.load(path + "test_lossunilstm.npy") * l_correction

         plot_n_save(df = df_loss,
                     title = "Uni-LSTM Loss Train",
                     xlabel = "Epochs",
                     ylabel = "Loss")
```



In [16]:
```
#display the gradient flow across epochs

        #get list of images
        list_im, epochs = gimme_image_list(path='./grad flow/unilstm/',
                                           encoder='unilstm',
                                           entension='.png',
                                           max_epochs=10,
                                           num_images=5)

        #Make a nice looking title
        title = "Gradient flow in epochs " + str(epochs)

        #Dislplay all images.
        display_row_images(list_im = list_im,
                           title = title,
                           save = False)
```

```
Gradient flow in epochs [0, 2, 4, 6, 8, 10]
```



1.3.1 Transfer Learning

As for the base line, the uni-LSTM was used encode sentences for other tasks by using the SentEval toolkit. All the results are shown in two tables in the cells below. The results, however, do not deserve much attention as the encoder fail to capture the semantics of the sentences in the training phase.

In [17]:
```
#load data
path = "./train/unilstm/transfer/"
file = "transfer_task_all_unilstm.npy"

transfer_scores = np.load(path+file)
transfer_scores = transfer_scores[()]

tasks = list(transfer_scores.keys())
transfer_scores['Length']

#take the of STSXX, SSTX and SICK out of the dictionary for the sake of simplicity
problematic_keys = ["STS12", "STS13", "STS14", "STS15", "STS16", "STSBenchmark", "SIC
sts_dict = {}
for key in problematic_keys:
    sts_dict[key] = transfer_scores.pop(key)

#make a table with the most comprehensible part of the results
df_transfer = pd.DataFrame.from_dict(transfer_scores, orient='index')
df_transfer
```

Out[17]:

	devacc	acc	ndev	ntest	f1
BigramShift	50.35	50.01	10000	10000	NaN
CR	79.84	78.36	3775	3775	NaN
CoordinationInversion	53.61	53.60	10002	10002	NaN
Depth	30.85	30.16	10000	10000	NaN
Length	58.18	59.32	9996	9996	NaN
MPQA	87.43	87.66	10606	10606	NaN
MR	77.67	76.93	10662	10662	NaN
MRPC	73.55	73.16	4076	1725	81.69
ObjNumber	75.72	76.46	10000	10000	NaN
OddManOut	50.44	49.75	10000	10000	NaN
SICKEntailment	81.00	78.69	500	4927	NaN
SUBJ	91.61	91.18	10000	10000	NaN
SubjNumber	79.37	77.99	10000	10000	NaN
TREC	73.59	82.60	5452	500	NaN
Tense	85.50	83.66	10000	10000	NaN
TopConstituents	61.44	61.55	10000	10000	NaN
WordContent	74.87	74.77	10000	10000	NaN

In [18]:
```
#parse the STSXX keys into an comprehensible dict
sts_dict = parse_sts(sts_dict)

#takes the mean of yhat,
sts_dict['SICKRelatedness']['yhat'] = sts_dict['SICKRelatedness']['yhat'].mean()
sts_dict['STSBenchmark']['yhat'] = sts_dict['STSBenchmark']['yhat'].mean()

#make a table with the results missing in the df_transfer table
df_sts = pd.DataFrame.from_dict(sts_dict, orient='index')
df_sts
```

Out[18]:

	devpearson	pearson	spearman	mse	yhat	\
SICKRelatedness	0.797253	0.799244	0.718258	0.367680	3.536806	
SST2	NaN	NaN	NaN	NaN	NaN	
SST5	NaN	NaN	NaN	NaN	NaN	
STS12 MSRpar	NaN	0.425039	0.451449	NaN	NaN	
STS12 MSRvid	NaN	0.662090	0.675039	NaN	NaN	
STS12 SMTeuroparl	NaN	0.491290	0.588050	NaN	NaN	
STS12 all	NaN	0.522271	0.532781	NaN	NaN	
STS12 surprise.OnWN	NaN	0.570257	0.610555	NaN	NaN	
STS12 surprise.SMTnews	NaN	0.462677	0.338812	NaN	NaN	
STS13 FNWN	NaN	0.382086	0.365692	NaN	NaN	
STS13 OnWN	NaN	0.472033	0.525691	NaN	NaN	
STS13 all	NaN	0.496034	0.507555	NaN	NaN	
STS13 headlines	NaN	0.633982	0.631281	NaN	NaN	
STS14 OnWN	NaN	0.577094	0.643466	NaN	NaN	
STS14 all	NaN	0.545982	0.556325	NaN	NaN	
STS14 deft-forum	NaN	0.300157	0.347216	NaN	NaN	
STS14 deft-news	NaN	0.649471	0.645587	NaN	NaN	
STS14 headlines	NaN	0.586721	0.551004	NaN	NaN	
STS14 images	NaN	0.624048	0.612733	NaN	NaN	
STS14 tweet-news	NaN	0.538402	0.537942	NaN	NaN	
STS15 all	NaN	0.562578	0.592181	NaN	NaN	
STS15 answers-forums	NaN	0.367109	0.369810	NaN	NaN	
STS15 answers-students	NaN	0.640669	0.682521	NaN	NaN	
STS15 belief	NaN	0.452195	0.527847	NaN	NaN	
STS15 headlines	NaN	0.662032	0.661978	NaN	NaN	
STS15 images	NaN	0.690884	0.718748	NaN	NaN	
STS16 all	NaN	0.514083	0.578758	NaN	NaN	
STS16 answer-answer	NaN	0.401168	0.425265	NaN	NaN	
STS16 headlines	NaN	0.613820	0.658837	NaN	NaN	
STS16 plagiarism	NaN	0.544246	0.558996	NaN	NaN	
STS16 postediting	NaN	0.539033	0.717631	NaN	NaN	
STS16 question-question	NaN	0.472147	0.533059	NaN	NaN	
STSBenchmark	0.732429	0.647852	0.629638	1.569542	2.929311	

	ndev	ntest	devacc	acc	pearson-p	\
SICKRelatedness	500.0	4927.0	NaN	NaN	NaN	

SST2	872.0	1821.0	79.59	79.68	NaN
SST5	1101.0	2210.0	43.96	43.80	NaN
STS12 MSRpar	NaN	NaN	NaN	NaN	2.949501e-34
STS12 MSRvid	NaN	NaN	NaN	NaN	8.704721e-96
STS12 SMTeuroparl	NaN	NaN	NaN	NaN	2.916342e-29
STS12 all	NaN	NaN	NaN	NaN	NaN
STS12 surprise.OnWN	NaN	NaN	NaN	NaN	6.617653e-66
STS12 surprise.SMTnews	NaN	NaN	NaN	NaN	1.468185e-22
STS13 FNWN	NaN	NaN	NaN	NaN	5.788063e-08
STS13 OnWN	NaN	NaN	NaN	NaN	1.790617e-32
STS13 all	NaN	NaN	NaN	NaN	NaN
STS13 headlines	NaN	NaN	NaN	NaN	1.466553e-85
STS14 OnWN	NaN	NaN	NaN	NaN	8.246970e-68
STS14 all	NaN	NaN	NaN	NaN	NaN
STS14 deft-forum	NaN	NaN	NaN	NaN	8.028866e-11
STS14 deft-news	NaN	NaN	NaN	NaN	2.501625e-37
STS14 headlines	NaN	NaN	NaN	NaN	1.437343e-70
STS14 images	NaN	NaN	NaN	NaN	3.406219e-82
STS14 tweet-news	NaN	NaN	NaN	NaN	1.352693e-57
STS15 all	NaN	NaN	NaN	NaN	NaN
STS15 answers-forums	NaN	NaN	NaN	NaN	2.084384e-13
STS15 answers-students	NaN	NaN	NaN	NaN	6.766778e-88
STS15 belief	NaN	NaN	NaN	NaN	2.676178e-20
STS15 headlines	NaN	NaN	NaN	NaN	9.159563e-96
STS15 images	NaN	NaN	NaN	NaN	1.756353e-107
STS16 all	NaN	NaN	NaN	NaN	NaN
STS16 answer-answer	NaN	NaN	NaN	NaN	3.070326e-11
STS16 headlines	NaN	NaN	NaN	NaN	3.571648e-27
STS16 plagiarism	NaN	NaN	NaN	NaN	3.901867e-19
STS16 postediting	NaN	NaN	NaN	NaN	8.605847e-20
STS16 question-question	NaN	NaN	NaN	NaN	5.313944e-13
STSBenchmark	1500.0	1379.0	NaN	NaN	NaN

	spearman-p	pearson wmean	spearman wmean
SICKRelatedness	NaN	NaN	NaN
SST2	NaN	NaN	NaN
SST5	NaN	NaN	NaN
STS12 MSRpar	6.152520e-39	NaN	NaN
STS12 MSRvid	6.995979e-101	NaN	NaN
STS12 SMTeuroparl	4.896945e-44	NaN	NaN
STS12 all	NaN	0.531901	0.549512
STS12 surprise.OnWN	8.202285e-78	NaN	NaN
STS12 surprise.SMTnews	3.569453e-12	NaN	NaN
STS13 FNWN	2.285939e-07	NaN	NaN
STS13 OnWN	3.494075e-41	NaN	NaN
STS13 all	NaN	0.541674	0.558326
STS13 headlines	1.241023e-84	NaN	NaN
STS14 OnWN	6.851317e-89	NaN	NaN

```
STS14 all                          NaN       0.553229        0.562342
STS14 deft-forum          3.395967e-14            NaN             NaN
STS14 deft-news           9.145783e-37            NaN             NaN
STS14 headlines           8.917978e-61            NaN             NaN
STS14 images              1.662435e-78            NaN             NaN
STS14 tweet-news          1.756349e-57            NaN             NaN
STS15 all                          NaN       0.600809        0.628019
STS15 answers-forums      1.347131e-13            NaN             NaN
STS15 answers-students   6.036131e-104            NaN             NaN
STS15 belief              2.739740e-28            NaN             NaN
STS15 headlines           9.607065e-96            NaN             NaN
STS15 images             3.458552e-120            NaN             NaN
STS16 all                          NaN       0.514433        0.579383
STS16 answer-answer       1.407604e-12            NaN             NaN
STS16 headlines           2.242227e-32            NaN             NaN
STS16 plagiarism          2.641409e-20            NaN             NaN
STS16 postediting         6.720940e-40            NaN             NaN
STS16 question-question   9.672437e-17            NaN             NaN
STSBenchmark                       NaN            NaN             NaN
```

1.4 Bi-LSTM

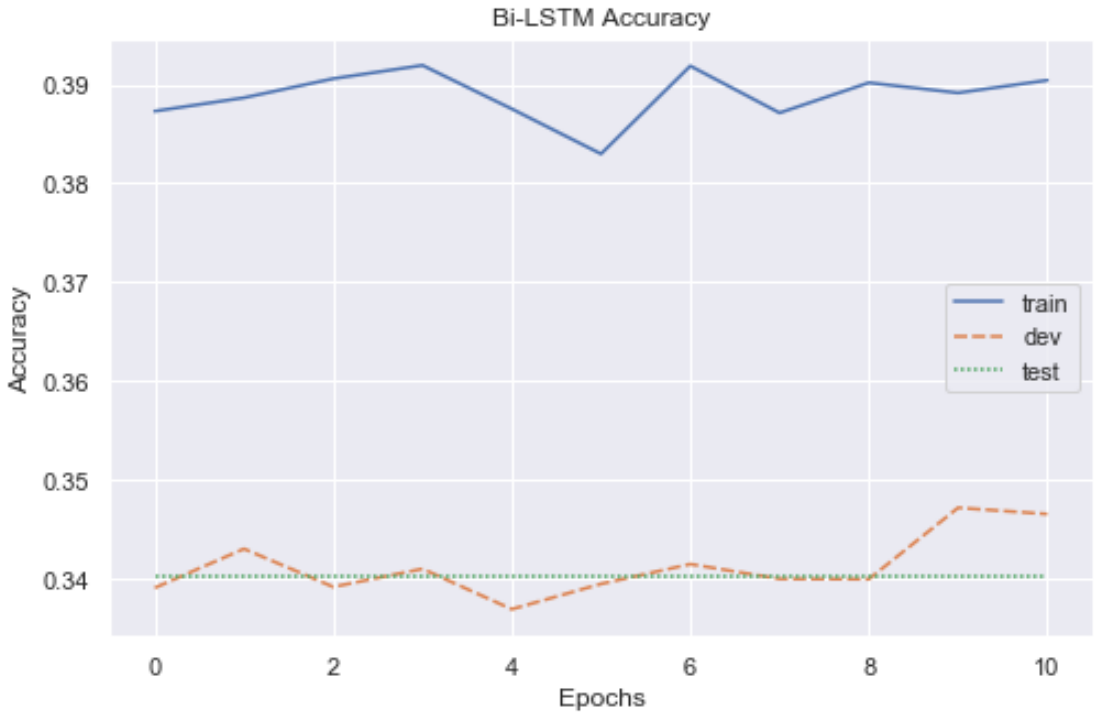
As for the Uni-LSTM, I could not make the Bi-LSTM work.

```
In [19]: encoder = load_encoder(enc_name='bilstm')
         encoder
```

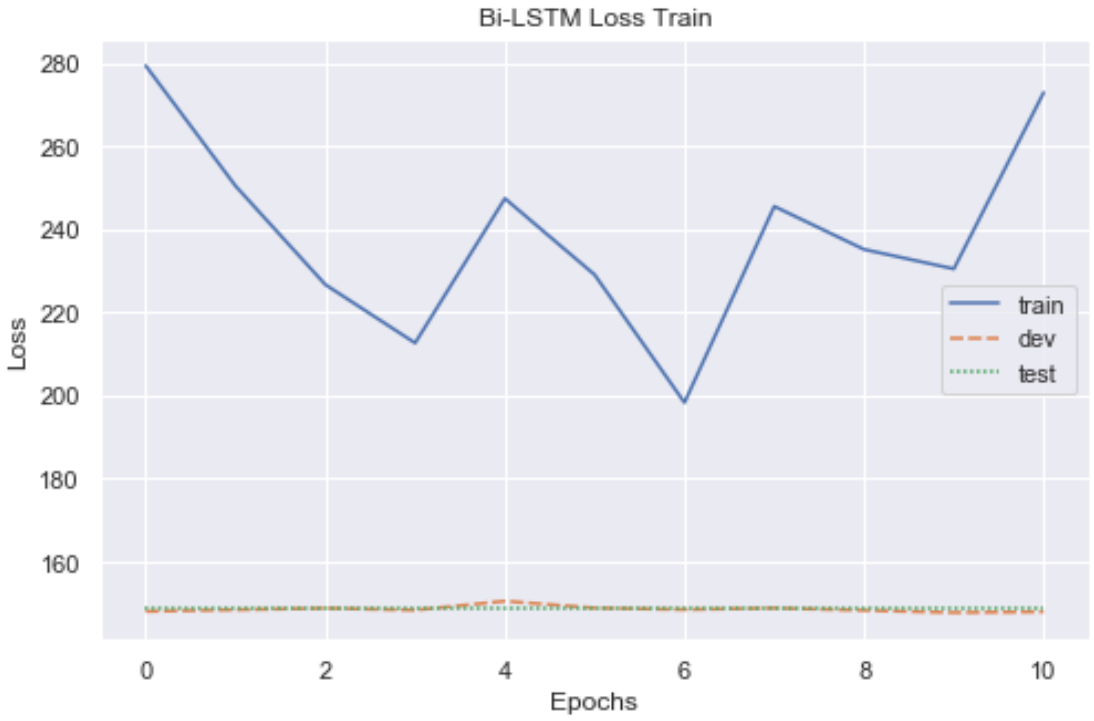
```
When crossing the road, it is important to look both sides.
```

```
Out[19]: BiLSTM(
           (bi_lstm): LSTM(300, 2048, bidirectional=True)
         )
```

```
In [20]: path = "./train/BiLSTM/20190422/"

         df_acc = pd.DataFrame(data = None, columns = ["train", "dev", "test"])
         df_acc["train"] = np.load(path + "train_accbilstm.npy")
         df_acc["dev"] = np.load(path + "dev_accbilstm.npy")
         df_acc["test"] = np.load(path + "test_accbilstm.npy")

         plot_n_save(df = df_acc,
                     title = "Bi-LSTM Accuracy",
                     xlabel = "Epochs",
                     ylabel = "Accuracy")

         #stores results for later comparison
         performance["BiLSTM"] = [df_acc.iloc[-1]["train"], df_acc.iloc[-1]["dev"], df_acc.iloc
```

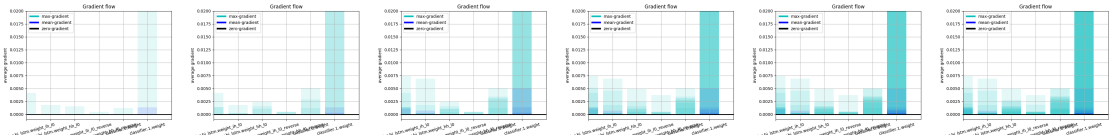



```
In [21]: df_loss = pd.DataFrame(data = None, columns = ["train", "dev", "test"])
         df_loss["train"] = np.load(path + "train_lossbilstm.npy")
         df_loss["dev"] = np.load(path + "dev_lossbilstm.npy") * l_correction
         df_loss["test"] = np.load(path + "test_lossbilstm.npy") * l_correction

         plot_n_save(df = df_loss,
                     title = "Bi-LSTM Loss Train",
                     xlabel = "Epochs",
                     ylabel = "Loss")
```



In [22]:
```
#display the gradient flow across epochs

        #get list of images
        list_im, epochs = gimme_image_list(path='./grad flow/bilstm/',
                                           encoder='bilstm',
                                           entension='.png',
                                           max_epochs=10,
                                           num_images=5)

        #Make a nice looking title
        title = "Gradient flow in epochs " + str(epochs)

        #Dislplay all images.
        display_row_images(list_im = list_im,
                           title = title,
                           save = False)
```

```
Gradient flow in epochs [0, 2, 4, 6, 8, 10]
```



1.4.1 Transfer Learning

As for the base line, the Bi-LSTM was used encode sentences for other tasks by using the SentEval toolkit. All the results are shown in two tables in the cells below. The results, however, do not deserve much attention as the encoder fail to capture the semantics of the sentences in the training phase.

In [23]:
```
#load data
path = "./train/bilstm/transfer/"
file = "transfer_task_all_bilstm.npy"

transfer_scores = np.load(path+file)
transfer_scores = transfer_scores[()]

tasks = list(transfer_scores.keys())
transfer_scores['Length']

#take the of STSXX, SSTX and SICK out of the dictionary for the sake of simplicity
problematic_keys = ["STS12", "STS13", "STS14", "STS15", "STS16", "STSBenchmark", "SIC
sts_dict = {}
for key in problematic_keys:
    sts_dict[key] = transfer_scores.pop(key)

#make a table with the most comprehensible part of the results
df_transfer = pd.DataFrame.from_dict(transfer_scores, orient='index')
df_transfer
```

Out[23]:

	devacc	acc	ndev	ntest	f1
BigramShift	50.49	50.20	10000	10000	NaN
CR	79.09	78.54	3775	3775	NaN
CoordinationInversion	53.73	53.52	10002	10002	NaN
Depth	30.58	30.26	10000	10000	NaN
Length	58.81	59.53	9996	9996	NaN
MPQA	84.48	84.71	10606	10606	NaN
MR	74.78	74.71	10662	10662	NaN
MRPC	72.52	68.75	4076	1725	75.26
ObjNumber	74.23	75.40	10000	10000	NaN
OddManOut	50.78	50.35	10000	10000	NaN
SICKEntailment	79.60	78.28	500	4927	NaN
SUBJ	90.30	89.97	10000	10000	NaN
SubjNumber	78.74	76.62	10000	10000	NaN
TREC	73.95	82.00	5452	500	NaN
Tense	81.25	78.47	10000	10000	NaN
TopConstituents	59.63	58.70	10000	10000	NaN
WordContent	68.25	68.27	10000	10000	NaN

In [24]:
```
#parse the STSXX keys into an comprehensible dict
sts_dict = parse_sts(sts_dict)

#takes the mean of yhat,
sts_dict['SICKRelatedness']['yhat'] = sts_dict['SICKRelatedness']['yhat'].mean()
sts_dict['STSBenchmark']['yhat'] = sts_dict['STSBenchmark']['yhat'].mean()

#make a table with the results missing in the df_transfer table
df_sts = pd.DataFrame.from_dict(sts_dict, orient='index')
df_sts
```

Out[24]:

	devpearson	pearson	spearman	mse	yhat	\
SICKRelatedness	0.790365	0.796891	0.714278	0.371666	3.540087	
SST2	NaN	NaN	NaN	NaN	NaN	
SST5	NaN	NaN	NaN	NaN	NaN	
STS12 MSRpar	NaN	0.343938	0.370770	NaN	NaN	
STS12 MSRvid	NaN	0.661899	0.674626	NaN	NaN	
STS12 SMTeuroparl	NaN	-0.061971	0.406366	NaN	NaN	
STS12 all	NaN	0.370296	0.467751	NaN	NaN	
STS12 surprise.OnWN	NaN	0.530039	0.573666	NaN	NaN	
STS12 surprise.SMTnews	NaN	0.377574	0.313329	NaN	NaN	
STS13 FNWN	NaN	0.371867	0.366239	NaN	NaN	
STS13 OnWN	NaN	0.422174	0.463114	NaN	NaN	
STS13 all	NaN	0.429739	0.443196	NaN	NaN	
STS13 headlines	NaN	0.495175	0.500235	NaN	NaN	
STS14 OnWN	NaN	0.514686	0.585370	NaN	NaN	
STS14 all	NaN	0.489733	0.514108	NaN	NaN	
STS14 deft-forum	NaN	0.271475	0.322704	NaN	NaN	
STS14 deft-news	NaN	0.567607	0.571757	NaN	NaN	
STS14 headlines	NaN	0.460501	0.477037	NaN	NaN	
STS14 images	NaN	0.635066	0.617392	NaN	NaN	
STS14 tweet-news	NaN	0.489062	0.510388	NaN	NaN	
STS15 all	NaN	0.529006	0.566300	NaN	NaN	
STS15 answers-forums	NaN	0.338489	0.331701	NaN	NaN	
STS15 answers-students	NaN	0.636575	0.688244	NaN	NaN	
STS15 belief	NaN	0.448042	0.529118	NaN	NaN	
STS15 headlines	NaN	0.531239	0.563486	NaN	NaN	
STS15 images	NaN	0.690686	0.718950	NaN	NaN	
STS16 all	NaN	0.433027	0.506599	NaN	NaN	
STS16 answer-answer	NaN	0.369180	0.387390	NaN	NaN	
STS16 headlines	NaN	0.528226	0.543000	NaN	NaN	
STS16 plagiarism	NaN	0.367021	0.456997	NaN	NaN	
STS16 postediting	NaN	0.512421	0.703280	NaN	NaN	
STS16 question-question	NaN	0.388288	0.442328	NaN	NaN	
STSBenchmark	0.699091	0.615245	0.592748	1.673554	2.936937	

	ndev	ntest	devacc	acc	pearson-p	\
SICKRelatedness	500.0	4927.0	NaN	NaN	NaN	

SST2	872.0	1821.0	79.70	79.30	NaN
SST5	1101.0	2210.0	42.14	42.49	NaN
STS12 MSRpar	NaN	NaN	NaN	NaN	2.987567e-22
STS12 MSRvid	NaN	NaN	NaN	NaN	1.029762e-95
STS12 SMTeuroparl	NaN	NaN	NaN	NaN	1.850611e-01
STS12 all	NaN	NaN	NaN	NaN	NaN
STS12 surprise.OnWN	NaN	NaN	NaN	NaN	1.475823e-55
STS12 surprise.SMTnews	NaN	NaN	NaN	NaN	5.750595e-15
STS13 FNWN	NaN	NaN	NaN	NaN	1.374846e-07
STS13 OnWN	NaN	NaN	NaN	NaN	1.179271e-25
STS13 all	NaN	NaN	NaN	NaN	NaN
STS13 headlines	NaN	NaN	NaN	NaN	1.196022e-47
STS14 OnWN	NaN	NaN	NaN	NaN	5.819401e-52
STS14 all	NaN	NaN	NaN	NaN	NaN
STS14 deft-forum	NaN	NaN	NaN	NaN	4.824505e-09
STS14 deft-news	NaN	NaN	NaN	NaN	5.542104e-27
STS14 headlines	NaN	NaN	NaN	NaN	1.223772e-40
STS14 images	NaN	NaN	NaN	NaN	6.189830e-86
STS14 tweet-news	NaN	NaN	NaN	NaN	2.359077e-46
STS15 all	NaN	NaN	NaN	NaN	NaN
STS15 answers-forums	NaN	NaN	NaN	NaN	1.665461e-11
STS15 answers-students	NaN	NaN	NaN	NaN	1.851263e-86
STS15 belief	NaN	NaN	NaN	NaN	6.473753e-20
STS15 headlines	NaN	NaN	NaN	NaN	7.584439e-56
STS15 images	NaN	NaN	NaN	NaN	2.136903e-107
STS16 all	NaN	NaN	NaN	NaN	NaN
STS16 answer-answer	NaN	NaN	NaN	NaN	1.274872e-09
STS16 headlines	NaN	NaN	NaN	NaN	2.699138e-19
STS16 plagiarism	NaN	NaN	NaN	NaN	9.619549e-09
STS16 postediting	NaN	NaN	NaN	NaN	9.748652e-18
STS16 question-question	NaN	NaN	NaN	NaN	6.273495e-09
STSBenchmark	1500.0	1379.0	NaN	NaN	NaN

	spearman-p	pearson wmean	spearman wmean
SICKRelatedness	NaN	NaN	NaN
SST2	NaN	NaN	NaN
SST5	NaN	NaN	NaN
STS12 MSRpar	7.441823e-26	NaN	NaN
STS12 MSRvid	1.026564e-100	NaN	NaN
STS12 SMTeuroparl	1.116145e-19	NaN	NaN
STS12 all	NaN	0.409947	0.490938
STS12 surprise.OnWN	7.532288e-67	NaN	NaN
STS12 surprise.SMTnews	1.543759e-10	NaN	NaN
STS13 FNWN	2.186345e-07	NaN	NaN
STS13 OnWN	3.605016e-31	NaN	NaN
STS13 all	NaN	0.452336	0.469468
STS13 headlines	9.681772e-49	NaN	NaN
STS14 OnWN	3.549456e-70	NaN	NaN

```
STS14 all                          NaN       0.497848        0.522502
STS14 deft-forum          2.297955e-12            NaN             NaN
STS14 deft-news           1.939268e-27            NaN             NaN
STS14 headlines           6.994664e-44            NaN             NaN
STS14 images              5.252448e-80            NaN             NaN
STS14 tweet-news          5.485159e-51            NaN             NaN
STS15 all                          NaN       0.562941        0.600272
STS15 answers-forums      4.416477e-11            NaN             NaN
STS15 answers-students   2.365454e-106            NaN             NaN
STS15 belief              1.930655e-28            NaN             NaN
STS15 headlines           4.604610e-64            NaN             NaN
STS15 images             2.762007e-120            NaN             NaN
STS16 all                          NaN       0.434990        0.508229
STS16 answer-answer       1.605767e-10            NaN             NaN
STS16 headlines           1.694796e-20            NaN             NaN
STS16 plagiarism          2.867038e-13            NaN             NaN
STS16 postediting         1.000692e-37            NaN             NaN
STS16 question-question   2.008524e-11            NaN             NaN
STSBenchmark                       NaN            NaN             NaN
```

1.5 Max-LSTM

For the Max-LSTM I managed to get results in the same line as in the paper, however with lower accuracies. The final test accuracy is 74.8%.

1.5.1 Training

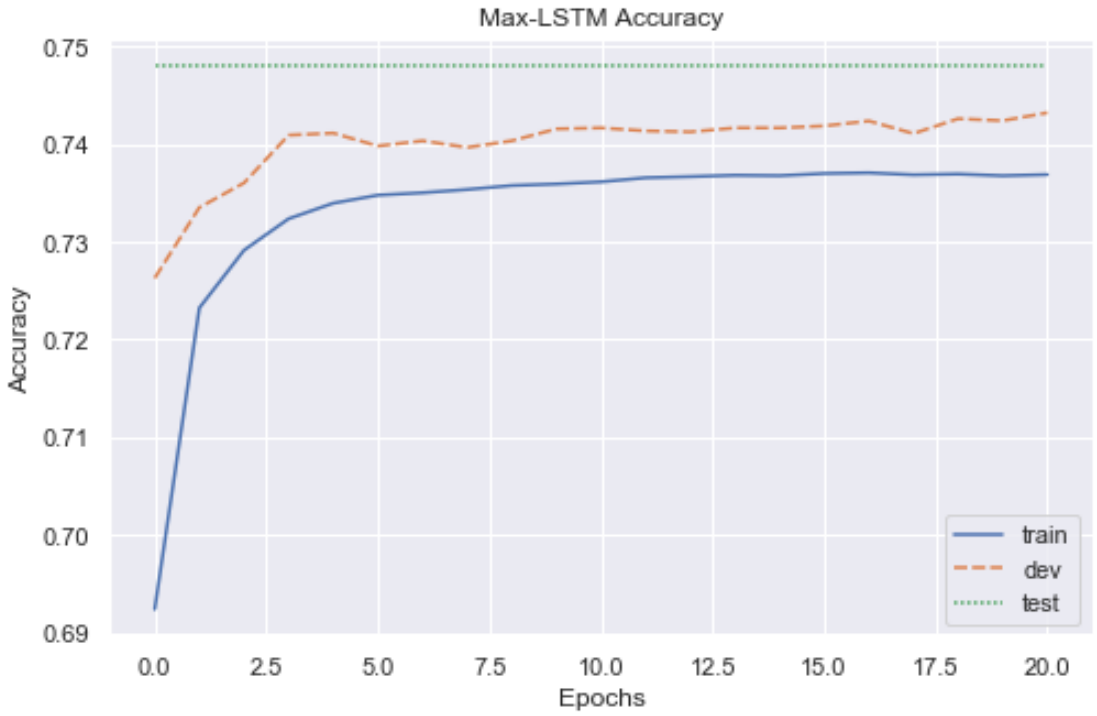
```
In [25]: #Encoder
         encoder = load_encoder(enc_name='maxlsmt')
         encoder
```

```
Three words entered a bar, or was it just one very fat and tall word?
```

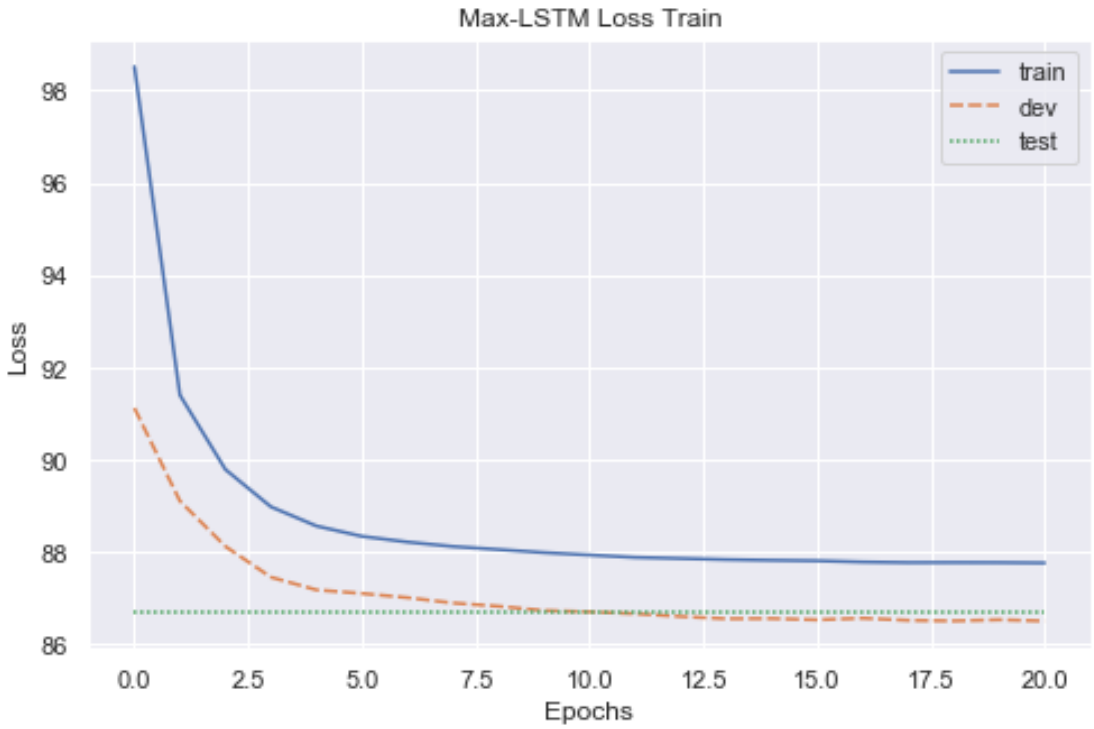
```
Out[25]: MaxLSTM(
           (bi_lstm): LSTM(300, 2048, bidirectional=True)
         )
```

```
In [26]: path = "./train/MaxLSTM/20190421/"

         df_acc = pd.DataFrame(data = None, columns = ["train", "dev", "test"])
         df_acc["train"] = np.load(path + "train_accmaxlstm.npy")
         df_acc["dev"] = np.load(path + "dev_accmaxlstm.npy")
         df_acc["test"] = np.load(path + "test_accmaxlstm.npy")

         plot_n_save(df = df_acc,
                     title = "Max-LSTM Accuracy",
                     xlabel = "Epochs",
                     ylabel = "Accuracy")
```

```
#stores results for later comparison
performance["MaxLSTM"] = [df_acc.iloc[-1]["train"], df_acc.iloc[-1]["dev"], df_acc.ilo
```

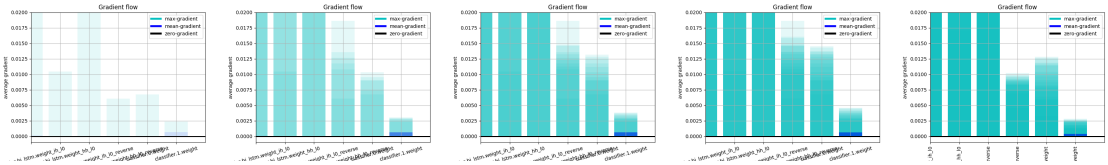


In [27]:
```
path = "./train/MaxLSTM/20190421/"

df_loss = pd.DataFrame(data = None, columns = ["train", "dev", "test"])
df_loss["train"] = np.load(path + "train_lossmaxlstm.npy")
df_loss["dev"] = np.load(path + "dev_lossmaxlstm.npy") * l_correction
df_loss["test"] = np.load(path + "test_lossmaxlstm.npy") * l_correction

plot_n_save(df = df_loss,
            title = "Max-LSTM Loss Train",
            xlabel = "Epochs",
            ylabel = "Loss")
```



In [28]:
```
#display the gradient flow across epochs

        #get list of images
        list_im, epochs = gimme_image_list(path='./grad flow/maxlstm/',
                                           encoder='maxlstm',
                                           entension='.png',
                                           max_epochs=20,
                                           num_images=5)

        #Make a nice looking title
        title = "Gradient flow in epochs " + str(epochs)

        #Dislplay all images.
        display_row_images(list_im = list_im,
                           title = title,
                           save = False)
```

```
Gradient flow in epochs [0, 5, 10, 15, 20]
```



1.5.2 Transfer learning

As for the base line, the Max-LSTM was used encode sentences for other tasks by using the SentEval toolkit. The resultes encontered in the paper [1] were partially reproduced. All the results are shown in two tables in the cells below.

- Task: Courneaut et al. resutls ~ my results
- MR: 77.5 ~ 77.17
- CR: 81.3 > 78.22
- SUBJ: 89.6 < 91.08
- MPQA: 88.7 > 87.53
- SST: 80.7 ~ 79.79
- TREC: 85.8 > 81.8
- MRPC: 73.2/81.6 < 73.04/82.09
- SICK R: 0.86 > 0.80
- SICK E: 83.4 < 78.81
- STS14: .39/.48 < 0.55/0.56

In [29]:
```
#load data
path = "./train/MaxLSTM/transfer/"
file = "transfer_task_all_maxlstm.npy"

transfer_scores = np.load(path+file)
transfer_scores = transfer_scores[()] #trick to take the dict out of a zero-dim array

#take the of STSXX, SSTX and SICK out of the dictionary for the sake of simplicity
problematic_keys = ["STS12", "STS13", "STS14", "STS15", "STS16", "STSBenchmark", "SICK
sts_dict = {}
for key in problematic_keys:
    sts_dict[key] = transfer_scores.pop(key)

#make a table with the most comprehensible part of the results
df_transfer = pd.DataFrame.from_dict(transfer_scores, orient='index')
df_transfer
```

Out[29]:

	devacc	acc	ndev	ntest	f1
BigramShift	50.40	50.04	10000	10000	NaN
CR	79.90	78.22	3775	3775	NaN
CoordinationInversion	53.61	53.48	10002	10002	NaN
Depth	30.68	29.92	10000	10000	NaN
Length	58.42	59.49	9996	9996	NaN
MPQA	87.45	87.53	10606	10606	NaN
MR	77.68	77.17	10662	10662	NaN
MRPC	73.50	73.04	4076	1725	82.09
ObjNumber	75.70	76.47	10000	10000	NaN
OddManOut	50.26	49.57	10000	10000	NaN

```
SICKEntailment          81.20  78.81    500   4927    NaN
SUBJ                    91.59  91.08  10000  10000    NaN
SubjNumber              79.34  78.03  10000  10000    NaN
TREC                    73.55  81.80   5452    500    NaN
Tense                   85.50  83.65  10000  10000    NaN
TopConstituents         61.42  61.57  10000  10000    NaN
WordContent             74.78  74.68  10000  10000    NaN
```

In [30]:
```
#parse the STSXX keys into an comprehensible dict
sts_dict = parse_sts(sts_dict)

#takes the mean of yhat,
sts_dict['SICKRelatedness']['yhat'] = sts_dict['SICKRelatedness']['yhat'].mean()
sts_dict['STSBenchmark']['yhat'] = sts_dict['STSBenchmark']['yhat'].mean()

#make a table with the results missing in the df_transfer table
df_sts = pd.DataFrame.from_dict(sts_dict, orient='index')
df_sts
```

Out[30]:

	devpearson	pearson	spearman	mse	yhat	\
SICKRelatedness	0.796940	0.799365	0.718504	0.367487	3.536771	
SST2	NaN	NaN	NaN	NaN	NaN	
SST5	NaN	NaN	NaN	NaN	NaN	
STS12 MSRpar	NaN	0.425039	0.451449	NaN	NaN	
STS12 MSRvid	NaN	0.662090	0.675038	NaN	NaN	
STS12 SMTeuroparl	NaN	0.491290	0.587953	NaN	NaN	
STS12 all	NaN	0.522271	0.532823	NaN	NaN	
STS12 surprise.OnWN	NaN	0.570257	0.610555	NaN	NaN	
STS12 surprise.SMTnews	NaN	0.462677	0.339118	NaN	NaN	
STS13 FNWN	NaN	0.382086	0.365692	NaN	NaN	
STS13 OnWN	NaN	0.472033	0.525691	NaN	NaN	
STS13 all	NaN	0.496034	0.507556	NaN	NaN	
STS13 headlines	NaN	0.633982	0.631284	NaN	NaN	
STS14 OnWN	NaN	0.577094	0.643466	NaN	NaN	
STS14 all	NaN	0.545982	0.556319	NaN	NaN	
STS14 deft-forum	NaN	0.300157	0.347179	NaN	NaN	
STS14 deft-news	NaN	0.649471	0.645587	NaN	NaN	
STS14 headlines	NaN	0.586721	0.551003	NaN	NaN	
STS14 images	NaN	0.624048	0.612733	NaN	NaN	
STS14 tweet-news	NaN	0.538402	0.537942	NaN	NaN	
STS15 all	NaN	0.562578	0.592176	NaN	NaN	
STS15 answers-forums	NaN	0.367109	0.369810	NaN	NaN	
STS15 answers-students	NaN	0.640669	0.682523	NaN	NaN	
STS15 belief	NaN	0.452195	0.527847	NaN	NaN	
STS15 headlines	NaN	0.662032	0.661954	NaN	NaN	
STS15 images	NaN	0.690884	0.718748	NaN	NaN	
STS16 all	NaN	0.514083	0.578758	NaN	NaN	
STS16 answer-answer	NaN	0.401168	0.425265	NaN	NaN	

STS16 headlines	NaN	0.613820	0.658837	NaN	NaN
STS16 plagiarism	NaN	0.544246	0.558996	NaN	NaN
STS16 postediting	NaN	0.539033	0.717631	NaN	NaN
STS16 question-question	NaN	0.472147	0.533059	NaN	NaN
STSBenchmark	0.731583	0.647061	0.628590	1.572699	2.935438

	ndev	ntest	devacc	acc	pearson-p	\
SICKRelatedness	500.0	4927.0	NaN	NaN	NaN	
SST2	872.0	1821.0	79.36	79.79	NaN	
SST5	1101.0	2210.0	43.78	43.80	NaN	
STS12 MSRpar	NaN	NaN	NaN	NaN	2.949345e-34	
STS12 MSRvid	NaN	NaN	NaN	NaN	8.704745e-96	
STS12 SMTeuroparl	NaN	NaN	NaN	NaN	2.916275e-29	
STS12 all	NaN	NaN	NaN	NaN	NaN	
STS12 surprise.OnWN	NaN	NaN	NaN	NaN	6.617384e-66	
STS12 surprise.SMTnews	NaN	NaN	NaN	NaN	1.468178e-22	
STS13 FNWN	NaN	NaN	NaN	NaN	5.788041e-08	
STS13 OnWN	NaN	NaN	NaN	NaN	1.790618e-32	
STS13 all	NaN	NaN	NaN	NaN	NaN	
STS13 headlines	NaN	NaN	NaN	NaN	1.466557e-85	
STS14 OnWN	NaN	NaN	NaN	NaN	8.246955e-68	
STS14 all	NaN	NaN	NaN	NaN	NaN	
STS14 deft-forum	NaN	NaN	NaN	NaN	8.028812e-11	
STS14 deft-news	NaN	NaN	NaN	NaN	2.501745e-37	
STS14 headlines	NaN	NaN	NaN	NaN	1.437347e-70	
STS14 images	NaN	NaN	NaN	NaN	3.406289e-82	
STS14 tweet-news	NaN	NaN	NaN	NaN	1.352696e-57	
STS15 all	NaN	NaN	NaN	NaN	NaN	
STS15 answers-forums	NaN	NaN	NaN	NaN	2.084354e-13	
STS15 answers-students	NaN	NaN	NaN	NaN	6.767002e-88	
STS15 belief	NaN	NaN	NaN	NaN	2.676109e-20	
STS15 headlines	NaN	NaN	NaN	NaN	9.159507e-96	
STS15 images	NaN	NaN	NaN	NaN	1.756342e-107	
STS16 all	NaN	NaN	NaN	NaN	NaN	
STS16 answer-answer	NaN	NaN	NaN	NaN	3.070334e-11	
STS16 headlines	NaN	NaN	NaN	NaN	3.571658e-27	
STS16 plagiarism	NaN	NaN	NaN	NaN	3.901817e-19	
STS16 postediting	NaN	NaN	NaN	NaN	8.605684e-20	
STS16 question-question	NaN	NaN	NaN	NaN	5.313858e-13	
STSBenchmark	1500.0	1379.0	NaN	NaN	NaN	

	spearman-p	pearson wmean	spearman wmean
SICKRelatedness	NaN	NaN	NaN
SST2	NaN	NaN	NaN
SST5	NaN	NaN	NaN
STS12 MSRpar	6.152520e-39	NaN	NaN
STS12 MSRvid	7.002293e-101	NaN	NaN
STS12 SMTeuroparl	5.096888e-44	NaN	NaN

```
STS12 all                          NaN       0.531902        0.549537
STS12 surprise.OnWN       8.202285e-78            NaN             NaN
STS12 surprise.SMTnews    3.404308e-12            NaN             NaN
STS13 FNWN                2.285939e-07            NaN             NaN
STS13 OnWN                3.494075e-41            NaN             NaN
STS13 all                          NaN       0.541674        0.558328
STS13 headlines           1.237234e-84            NaN             NaN
STS14 OnWN                6.851317e-89            NaN             NaN
STS14 all                          NaN       0.553229        0.562338
STS14 deft-forum          3.418558e-14            NaN             NaN
STS14 deft-news           9.145783e-37            NaN             NaN
STS14 headlines           8.921957e-61            NaN             NaN
STS14 images              1.662435e-78            NaN             NaN
STS14 tweet-news          1.756349e-57            NaN             NaN
STS15 all                          NaN       0.600809        0.628013
STS15 answers-forums      1.347131e-13            NaN             NaN
STS15 answers-students   6.025446e-104            NaN             NaN
STS15 belief              2.739740e-28            NaN             NaN
STS15 headlines           9.807620e-96            NaN             NaN
STS15 images             3.458572e-120            NaN             NaN
STS16 all                          NaN       0.514433        0.579383
STS16 answer-answer       1.407604e-12            NaN             NaN
STS16 headlines           2.241978e-32            NaN             NaN
STS16 plagiarism          2.641409e-20            NaN             NaN
STS16 postediting         6.720940e-40            NaN             NaN
STS16 question-question   9.672437e-17            NaN             NaN
STSBenchmark                       NaN            NaN             NaN
```

1.6 SNLI summary

The table below sumarizes the results obtained in the SNLI task. Unfortunatelly, I was not able to implement working versions of the Uni-LSTM and Bi-LSTM models.

```
In [31]: df_performance = pd.DataFrame.from_dict(data = performance,
                                                 orient='index',
                                                 columns= ["Train acc", "Dev acc", "Test acc"])
         df_performance

Out[31]:          Train acc   Dev acc  Test acc
         Mean      0.595390  0.602622  0.612520
         UniLSTM   0.387448  0.343060  0.336242
         BiLSTM    0.390441  0.346510  0.340300
         MaxLSTM   0.736884  0.743214  0.748072
```

2 Inference bot

Bellow you will find a well humored implementation of infer.py. Infer loads one of the pretrained models, *MaxLSTM* is the standard one. It is an interative aplication, the use is quite intuitive and

straight forward.

1. It asks for a premise. You should enter a phrase with the content. No special formatation is needed.
2. It asks for an hypothesis. You should enter the hypothesis. No special formatiation is needed.
3. It tells you if the premise entails, contradicts or is neutral to the hypothesis.
4. It asks if you want to enter a new premise. Press *n* to quit or anything else to continue.

Note, the implementation requires the bot to load the word embeddings in memory. It takes a few minutes before it asks for the premise for the first time. Once loaded, all the rest workis timelly.

Have fun!

```
In [32]: infer.main()

['While you wait... Why are there no mamals that are green?']
Let's play some pool...
['What is your premise my dear?'] >>> Francesco had coffee this morning
['Be careful with what you want to infer from the premise!'] >>> Francesco feels well

 The premise entails the hypothesis.

Do you want to keep playing? [y/n] I am very well prepared for this demo.
['Give me a premise, please.'] >>> I am very well prepared for this demo.
['What is your hypothesis my dear?'] >>> My models don't work.

 The premise contradicts the hypothesis.

Do you want to keep playing? [y/n] y
['Would you be so kind as to provide me of a premise?'] >>> I am a boy
['What do you want to infer from that?'] >>> I am not a boy.

 The premise contradicts the hypothesis.

Do you want to keep playing? [y/n] y
['Premise, NOW!'] >>> I see a robot, two goals and a football field.
['H Y P O T H E S I S !'] >>> There is a game on going.

 The premise entails the hypothesis.

Do you want to keep playing? [y/n] n
```

3 Conclusion

The practice was extremely interesting, it required good level of theoretical knowledge and a great deal of practial implementation. The taks of capturing semantics is a bottle neck in many Artificial

Intelligence aplications, NLP being a very prominent one. Through this assigment, we intended to build four models to encode sentences using GloVe word embeddings.

I presented my archtecture and the results of each model in the Inference task as well as how it performed in in the transfer learning tasks using the SentEval toolkit. The Baseline and the Max-LSTM gave results in line with what was expected.

The code can be found in my github page: https://github.com/VictorZuanazzi/Inference_Bot.git

In [ ]: