```
In [1]: import numpy as np
  import pandas as pd
  import os
  import re
```

## Model

This portion of the notebook borrows extensively from fast.ai's notebook for lesson 10 in their deep learning course part two.

```
In [2]: import collections
import html
from fastai.text import *
```

/home/paperspace/anaconda3/envs/fastai/lib/python3.6/site-packages/sklearn/en semble/weight\_boosting.py:29: DeprecationWarning: numpy.core.umath\_tests is a n internal NumPy module and should not be imported. It will be removed in a f uture NumPy release.

from numpy.core.umath\_tests import inner1d

LANGUAGE\_MODEL\_PATH.mkdir(exist\_ok = True)

Define the directories we'll be using

You'll need to download tweet sentiment data from kaggle - <a href="https://www.kaggle.com/c/twitter-sentiment-analysis2/data">https://www.kaggle.com/c/twitter-sentiment-analysis2/data</a>) - and put it in the twitter/orignal directory

```
In [3]: BOS = 'xbos' # beginning-of-sentence tag
FLD = 'xfld' # data field tag

# path to our original tweet data from kaggle
DATA_PATH = Path("data/")

In [4]: # path to our classification data
CLASSIFICATION_PATH = Path('data/twitter_classification/')
CLASSIFICATION_PATH.mkdir(exist_ok = True)

# path to our language model
LANGUAGE MODEL PATH = Path('data/twitter language model/')
```

start prepping our tweet data from kaggle

```
In [5]: CLASSES = ['neg', 'pos']
```

```
In [6]: df = pd.read_csv(DATA_PATH/'celebrity_train.csv', encoding='latin1')

# shuffle rows and throw out item id column
df = df.drop('ItemID', axis=1)
df = df.sample(frac=1)

# rename columns
df.columns = ['labels', 'text']

# split datafram into train and validation sets for later
split_index = int(df.shape[0] * .9)
train_df, test_df = np.split(df, [split_index], axis=0)

train_df.shape
```

Out[6]: (89990, 2)

#### saving our current progress

```
In [7]: # save to classification directory
        train_df.to_csv(CLASSIFICATION_PATH/ 'train.csv', header=False, index=False, e
        ncoding='utf-8')
        test df.to csv(CLASSIFICATION PATH/ 'test.csv', header=False, index=False, enc
        oding='utf-8')
        f = open(CLASSIFICATION_PATH/'classes.txt', 'w', encoding='utf-8')
        f.writelines(f'{c}\n' for c in CLASSES)
        f.close()
        # save to language model directory
        # we should be adding in the test.csv from the kaggle competition here because
         the language model doesn't care about labels
        # but in the interest of time I'm opting to just use the training set for the
         language model
        train df.to csv(LANGUAGE MODEL PATH/'train.csv', header=False, index=False, en
        coding='utf-8')
        test_df.to_csv(LANGUAGE_MODEL_PATH/ 'test.csv', header=False, index=False, enc
        oding='utf-8')
```

#### lets start cleaning some text

```
In [9]: df.shape
```

Out[9]: (99989, 2)

```
In [10]: ## functions pulled from the fast.ai notebook for text tokenization
         re1 = re.compile(r' +')
         def fixup(x):
              '''some patterns identified by the fast.ai folks that spacy doesn't accoun
             x = x.replace('#39;', "'").replace('amp;', '&').replace('#146;', "'").repl
         ace(
                 'nbsp;', ' ').replace('#36;', '$').replace('\\n', "\n").replace('quo
         t;', "'").replace(
                 '<br />', "\n").replace('\\"', '"').replace('<unk>','u_n').replace('
          @.@ ','.').replace(
                  ' @-@ ','-').replace('\\', ' \\ ')
             return rel.sub(' ', html.unescape(x))
         def get texts(df, n lbls=1):
             labels = df.iloc[:,range(n_lbls)].values.astype(np.int64)
             texts = f' \setminus BOS {FLD} 1 ' + df[n lbls].astype(str)
             for i in range(n_lbls+1, len(df.columns)): texts += f' {FLD} {i-n_lbls} '
         + df[i].astype(str)
             texts = list(texts.apply(fixup).values)
             tok = Tokenizer().proc all mp(partition by cores(texts))
             return tok, list(labels)
         def get all(df, n lbls):
             '''tokenize the text'''
             tok, labels = [], []
             for i, r in enumerate(df):
                 tok_, labels_ = get_texts(r, n_lbls)
                 tok += tok_;
                 labels += labels
             return tok, labels
In [11]: # grab our dataframes from earlier
         train_df = pd.read_csv(LANGUAGE_MODEL_PATH/'train.csv', header=None, chunksize
         val df = pd.read csv(LANGUAGE MODEL PATH/ 'test.csv', header=None, chunksize=c
         hunksize)
In [12]: # tokenize the tweets
         train_tokens, train_labels = get_all(train_df, 1)
         val tokens, val labels = get all(val df, 1)
In [21]: #make temporary directory
         os.mkdir(LANGUAGE MODEL PATH/'tmp')
In [22]: # save our tokens
         np.save(LANGUAGE_MODEL_PATH/'tmp/tok_trn.npy', train_tokens)
         np.save(LANGUAGE MODEL PATH/'tmp/tok_val.npy', val_tokens)
In [23]: # load back in
         train tokens = np.load(LANGUAGE MODEL PATH/'tmp/tok trn.npy')
         val tokens = np.load(LANGUAGE MODEL PATH/'tmp/tok val.npy')
```

```
In [24]: # lets take a look at our most common tokens
         freq = Counter(token for tokens in train tokens for token in tokens)
         freq.most common(25)
Out[24]: [('1', 90578),
          ('\n', 90001),
          ('xbos', 89990),
          ('xfld', 89990),
          ('i', 59573),
          ('.', 48209),
          ('!', 47040),
          (',', 29222),
          ('you', 27076),
          ('the', 26915),
          ('to', 26704),
          ('a', 20717),
          ('it', 20012),
          ('t up', 19450),
          ('?', 17512),
          ('and', 14741),
          ('that', 13064),
          ('&', 12953),
          ('...', 12921),
          ('my', 12449),
          ('is', 11447),
          ('for', 11277),
          ('/', 10948),
          ('in', 10717),
          ("'s", 10717)]
```

looks about right, quick note to keep in mind - the "t\_up" token isn't in the text its self, it is a marker indicating the following token is all uppercase.

fast.ai recommends that you only keep the 60,000 or so most common tokens. Reason being low frequency tokens don't help you learn a lot about a language.

We don't have that many tokens for our tweets, but it makes me feel good to put in anyways ...

```
In [25]: max_vocab = 60000
         min freq = 2
         int to token = [o for o, c in freq.most common(max vocab) if c > min freq]
         int_to_token.insert(0, '_pad_')
         int_to_token.insert(0, '_unk_')
In [26]: token_to_int = collections.defaultdict(lambda: 0, {v: k for k, v in enumerate(
         int to token)})
         len(int_to_token)
Out[26]: 20133
In [27]: train_lm = np.array([[token_to_int[o] for o in p] for p in train_tokens])
         val_lm = np.array([[token_to_int[o] for o in p] for p in val_tokens])
In [28]: # saving our progress
         np.save(LANGUAGE MODEL PATH/'tmp/trn ids.npy', train lm)
         np.save(LANGUAGE MODEL PATH/'tmp/val ids.npy', val lm)
         pickle.dump(int to token, open(LANGUAGE MODEL PATH/'tmp/itos.pkl', 'wb'))
```

```
In [29]: # loading back in
    train_lm = np.load(LANGUAGE_MODEL_PATH/'tmp/trn_ids.npy')
    val_lm = np.load(LANGUAGE_MODEL_PATH/'tmp/val_ids.npy')
    int_to_token = pickle.load(open(LANGUAGE_MODEL_PATH/'tmp/itos.pkl', 'rb'))

In [30]: num_twitter_tokens = len(int_to_token)
    num_twitter_tokens, len(train_lm)

Out[30]: (20133, 89990)
```

### load in a pretrained language model trained on wikipedia text

run this line to download wikipedia model

```
In [23]: # ! wget -nH -r -np -P {PATH} http://files.fast.ai/models/wt103/
In [31]: # some stats from the wikepedia model
         embedding size, num_hidden, num_layers = 400,1150,3
In [35]: PRE_PATH = Path("/home/paperspace/data/twitter/lm/models")
         PRE LM PATH = Path(PRE PATH/"lm tt.h5")
         wgts = torch.load(PRE_LM_PATH, map_location = lambda storage, loc: storage)
         enc_wgts = to_np(wgts["0.encoder.weight"])
         row m = enc wgts.mean(0)
         itos2 = pickle.load((PRE PATH/"itos tt.pkl").open("rb"))
         stoi2 = collections.defaultdict(lambda:-1, {v:k for k,v in enumerate(itos2)})
         new_w = np.zeros((num_twitter_tokens, embedding_size), dtype=np.float32)
         for i,w in enumerate(int to token):
             r = stoi2[w]
             new_w[i] = enc_wgts[r] if r>=0 else row_m
         wgts['0.encoder.weight'] = T(new w)
         wqts['0.encoder with dropout.embed.weight'] = T(np.copy(new w))
         wgts['1.decoder.weight'] = T(np.copy(new_w))
In [25]: # PRE PATH = Path('data/aclImdb/models/wt103')
         # # PRE LM PATH = PRE PATH/'fwd wt103.h5'
In [26]: # grab the weights from the encoder
         # weights = torch.load(PRE LM PATH, map location=lambda storage, loc: storage)
```

The mean of the weights from layer 0 can be used to assign weights to tokens that exist in the wikipedia dataset but not in the twitter dataset

```
In [27]: # encoder_weights = to_np(weights['0.encoder.weight'])
# # row_m = enc_wgts.mean(0)
# encoder_mean = encoder_weights.mean(0)
```

```
In [28]: # wiki_int_to_token = pickle.load(open(PRE_PATH/'itos_wt103.pkl', 'rb'))
# wiki_token_to_int = collections.defaultdict(lambda: -1, {v:k for k, v in enu
    merate(wiki_int_to_token)})
```

We need to assign mean weights to tokens that exist in our twitter dataset that dont in the wikipedia dataset the pretrained model was trained on.

We now need to put the new weights into the pretrained model

The weights between the encoder and decoder also need to be tied together

```
In [30]: # weights['0.encoder.weight'] = T(new_weights)
# weights['0.encoder_with_dropout.embed.weight'] = T(np.copy(new_weights))
# weights['1.decoder.weight'] = T(np.copy(new_weights))
```

### Retraining the wikipedia language model

```
In [36]: wd=1e-7 # weight decay
    bptt=70 # ngram size. i.e. the model sees ~70 tokens and then tries to predic
    t the 71st
    bs=52 # batch size
    opt_fn = partial(optim.Adam, betas=(0.8, 0.99)) # optimazation function
```

Here we define a special fastai data loader, the LanguageModelLoader, to feed the training data into the model whilst training.

We can then use those to instanciate a LanguageModelData class that returns a fastai model we can train

```
In [37]: train_dl = LanguageModelLoader(np.concatenate(train_lm), bs, bptt)
    val_dl = LanguageModelLoader(np.concatenate(val_lm), bs, bptt)

md = LanguageModelData(DATA_PATH, 1, num_twitter_tokens, train_dl, val_dl, bs= bs, bptt=bptt)
```

```
In [38]: # the dropouts for each layer.
drops = np.array([0.25, 0.1, 0.2, 0.02, 0.15])*0.7
```

The last embedding layer needs to be tuned first so the new weights we set for the pretrained model get tuned properly.

fastai allows you to freeze and unfreeze model layers. So here we freeze everything but the weights in the last embedding layer

```
In [39]: learner = md.get model(
              opt fn, embedding size, num hidden, num layers, dropouti=drops[0], dropout
         =drops[1],
             wdrop=drops[2], dropoute=drops[3], dropouth=drops[4]
         )
         learner.metrics = [accuracy]
         # freeze everything except last layer
         learner.freeze to(-1)
In [41]: # load the weights
         learner.model.load_state_dict(wgts)
In [42]: | lr = 1e-3 # learning rate
         lrs = lr
         learner.fit(lrs/2, 1, wds=wd, use_clr=(32,2), cycle_len=2)
In [ ]:
           88|
                          43/515 [00:05<00:45, 10.37it/s, loss=5.32]
In [38]:
         # save our progress
         learner.save('lm_last_ft')
In [39]:
         # load back in
         learner.load('lm_last_ft')
In [40]:
         # now with our new embedding weights trained up, we can unfreeze and train all
          layers
         learner.unfreeze()
In [41]: # to find our learning rate
         learner.lr_find(start_lr=lrs/10, end_lr=lrs*50, linear=True)
         epoch
                     trn_loss
                                {\tt val\_loss}
                                            accuracy
                     4.307766
                                4.150575
             0
                                            0.321169
In [42]:
         learner.sched.plot()
            4.45
            4.40
          validation loss
            4.35
            4.30
```

4.25

4.20

4.15

 $10^{-3}$ 

learning rate (log scale)

```
# looks like 10-2 or 10-3 or so could be a good learning rate for us
In [44]:
          learner.fit(lrs, 1, wds=wd, use clr=(20,10), cycle len=1)
                     trn loss
          epoch
                                 val loss
                                             accuracy
                     3.955422
                                 3.76257
                                             0.360825
Out[44]: [array([3.76257]), 0.36082455994827406]
In [45]:
          # save our progress
          learner.save('lm1')
          learner.save_encoder('lm1_enc')
In [46]:
         # taking a look at our loss
          learner.sched.plot_loss()
           4.5
           4.4
           4.3
           4.2
           4.1
           4.0
                     100
                             200
                                     300
                                             400
                                                    500
```

## **Tweet Sentiment Classifier**

Now that we have our language model trained on tweets, we can start training our tweet sentiment classifier

To do this all we have to do is tack on a layer to our trained encoder.

```
In [48]: # do the same cleaning we did for the language model
    train_tokens, train_labels = get_all(train_df, 1)
    val_tokens, val_labels = get_all(val_df, 1)
```

```
In [ ]: # make temp directory in classifier directory
         #os.mkdir(CLASSIFICATION PATH/'tmp')
         # save tokens
         np.save(CLASSIFICATION PATH/'tmp/tok trn.npy', train tokens)
         np.save(CLASSIFICATION PATH/'tmp/tok val.npy', val tokens)
         np.save(CLASSIFICATION PATH/'tmp/trn labels.npy', train labels)
         np.save(CLASSIFICATION_PATH/'tmp/val_labels.npy', val_labels)
In [ ]: # load back in
         train tokens = np.load(CLASSIFICATION PATH/'tmp/tok trn.npy')
         val tokens = np.load(CLASSIFICATION PATH/'tmp/tok val.npy')
In [ ]: int to token = pickle.load(open(LANGUAGE MODEL PATH/'tmp/itos.pkl', 'rb'))
         token to int = collections.defaultdict(lambda: 0, {v:k for k, v in enumerate(i
         nt_to_token)})
         len(int_to_token)
In [ ]: train_classification = np.array([[token_to_int[o] for o in p] for p in train_t
         val classification = np.array([[token to int[o] for o in p] for p in val token
         s])
 In [ ]: np.save(CLASSIFICATION_PATH/'tmp/trn_ids.npy', train_classification)
         np.save(CLASSIFICATION_PATH/'tmp/val_ids.npy', val_classification)
In [ ]: # load back in
         train classification = np.load(CLASSIFICATION PATH/'tmp/trn ids.npy')
         val_classification = np.load(CLASSIFICATION_PATH/'tmp/val_ids.npy')
         train labels = np.squeeze(np.load(CLASSIFICATION PATH/'tmp/trn labels.npy'))
         val labels = np.squeeze(np.load(CLASSIFICATION PATH/'tmp/val labels.npy'))
In [ ]: # params
         bptt, embedding size, num hidden, num layers = 70, 400, 1150, 3
         num_tokens = len(int_to_token)
         opt_fn = partial(optim.Adam, betas=(0.8, 0.99))
         bs = 48
 In [ ]: train_classification[:5], train_labels[:5]
In [89]: min_label = train_labels.min()
         train_labels -= min_label
         val labels -= min label
         c = int(train labels.max()) + 1
```

```
In [91]: train ds = TextDataset(train classification, train labels)
         val ds = TextDataset(val classification, val labels)
         # the sortish sampler helps by sorting things kinda sorta by their token lengt
         h so padding isn't crazy
         train sampler = SortishSampler(train classification, key=lambda x: len(train c
         lassification[x]), bs=bs//2)
         # doesn't matter so much for the validation set
         val_sampler = SortSampler(val_classification, key=lambda x: len(val_classifica
         tion[x]))
         # get data loaders
         train dl = DataLoader(train ds, bs//2, transpose=True, num workers=1, pad idx=
         1, sampler=train sampler)
         val dl = DataLoader(val ds, bs, transpose=True, num workers=1, pad idx=1, samp
         ler=val sampler)
         # model data
         md = ModelData(DATA PATH, train dl, val dl)
In [92]: # part 1
         dps = np.array([0.4, 0.5, 0.05, 0.3, 0.1])
In [93]: # part 2
         dps = np.array([0.4, 0.5, 0.05, 0.3, 0.4])*0.5
In [94]: m = get_rnn_classifier(bptt, 20*70, c, num_tokens, emb_sz=embedding_size, n_hi
         d=num_hidden, n_layers=num_layers,
                                pad_token=1, layers=[embedding_size*3, 50, c], drops=[d
         ps[4], 0.1], dropouti=dps[0],
                                wdrop=dps[1], dropoute=dps[2], dropouth=dps[3])
In [95]: opt fn = partial(optim.Adam, betas=(0.7, 0.99))
In [96]: learn = RNN Learner(md, TextModel(to gpu(m)), opt fn=opt fn)
         learn.reg_fn = partial(seq2seq_reg, alpha=2, beta=1)
         learn.clip=25.
         learn.metrics = [accuracy]
In [97]: | lr=3e-3
         lrm = 2.6
         lrs = np.array([lr/(lrm**4), lr/(lrm**3), lr/(lrm**2), lr/lrm, lr]) # differen
         tial learning rates
In [ ]: #lrs=np.array([1e-4,1e-4,1e-4,1e-3,1e-2])
```

load our encoder from our tweet language model

```
In [98]: wd = 1e-7
wd = 0
learn.load_encoder('lm1_enc')
```

```
In [99]: # freeze all except last layer
learn.freeze_to(-1)
```

```
In [100]: # to find learning rate
           learn.lr find(lrs/1000)
           learn.sched.plot()
                            3050/3750 [00:40<00:09, 75.95it/s, loss=2.16]
             2.0
             1.8
             1.6
           validation loss
             1.4
             1.2
             1.0
             0.8
              0.6
                     10-5
                                                  10^{-1}
                                   10^{-3}
                                           10^{-2}
                                                          10°
                              learning rate (log scale)
  In [ ]: # little tough to tell here, but we'll go with what we set previously and what
            fastai used for their imdb dataset
In [101]: learn.fit(lrs, 1, wds=wd, cycle_len=1, use_clr=(8,3))
           epoch
                      trn loss
                                  val_loss
                                              accuracy
                       0.565335
                                  0.512834
                                              0.743274
Out[101]: [array([0.51283]), 0.7432743282047006]
  In [1]:
           # save our first classifier
           learn.save('clas_0')
           NameError
                                                        Traceback (most recent call last)
           <ipython-input-1-44c81e4f52fe> in <module>
                 1 # save our first classifier
           ---> 2 learn.save('clas_0')
           NameError: name 'learn' is not defined
  In [2]: # load it back in
           learn.load('clas_0')
                                                        Traceback (most recent call last)
           <ipython-input-2-608fe198f397> in <module>
                 1 # load it back in
           ---> 2 learn.load('clas_0')
          NameError: name 'learn' is not defined
In [104]: # unfreeze one more layer
           learn.freeze_to(-2)
```

In [111]: learn.fit(lrs, 1, wds=wd, cycle\_len=10, use\_clr\_beta=(32,10))

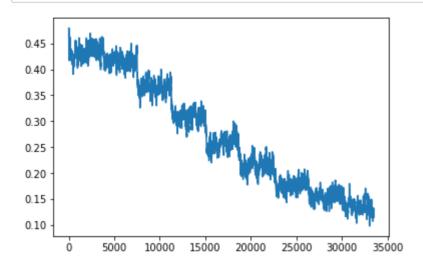
```
trn_loss
                   val_loss
epoch
                               accuracy
          0.454162
                    0.421473
   0
                               0.808981
   1
          0.432943
                     0.411333
                               0.810281
   2
          0.366563
                     0.422387
                               0.810081
   3
          0.3215
                     0.449872
                               0.814681
   4
          0.248104
                     0.49484
                               0.811581
   5
          0.224862
                     0.553132
                               0.809581
   6
                               0.80478
          0.198725
                     0.528209
   7
          0.153145
                     0.568736
                               0.806881
 93% | 3490/3750 [01:52<00:08, 30.19it/s, loss=0.121]
```

```
KeyboardInterrupt
                                           Traceback (most recent call last)
<ipython-input-111-2ce4d2f4f7f2> in <module>
---> 1 learn.fit(lrs, 1, wds=wd, cycle len=10, use clr=(32,10))
~/fastai/courses/dl2/fastai/text.py in fit(self, *args, **kwargs)
    209
    210
            def get crit(self, data): return F.cross entropy
--> 211
            def fit(self, *args, **kwargs): return super().fit(*args, **kwarg
s, seq_first=True)
    212
    213
            def save encoder(self, name): save model(self.model[0], self.get
model path(name))
~/fastai/courses/dl2/fastai/learner.py in fit(self, lrs, n cycle, wds, **kwar
gs)
    300
                self.sched = None
    301
                layer opt = self.get_layer_opt(lrs, wds)
--> 302
                return self.fit gen(self.model, self.data, layer opt, n cycle
, **kwargs)
    303
    304
            def warm_up(self, lr, wds=None):
~/fastai/courses/dl2/fastai/learner.py in fit gen(self, model, data, layer op
t, n_cycle, cycle_len, cycle_mult, cycle_save_name, best_save_name, use_clr,
use clr beta, metrics, callbacks, use wd sched, norm wds, wds sched mult, us
e_swa, swa_start, swa_eval_freq, **kwargs)
    247
                    metrics=metrics, callbacks=callbacks, reg fn=self.reg fn,
 clip=self.clip, fp16=self.fp16,
                    swa model=self.swa model if use swa else None, swa start=
    248
swa start,
--> 249
                    swa_eval_freq=swa_eval_freq, **kwargs)
    250
    251
            def get_layer_groups(self): return self.models.get_layer_groups()
~/fastai/courses/dl2/fastai/model.py in fit(model, data, n_epochs, opt, crit,
metrics, callbacks, stepper, swa model, swa start, swa eval freq, visualize,
 **kwargs)
    139
                    batch num += 1
    140
                    for cb in callbacks: cb.on_batch_begin()
                    loss = model_stepper.step(V(x),V(y), epoch)
--> 141
    142
                    avg_loss = avg_loss * avg_mom + loss * (1-avg_mom)
    143
                    debias_loss = avg_loss / (1 - avg_mom**batch_num)
~/fastai/courses/dl2/fastai/model.py in step(self, xs, y, epoch)
                if self.loss scale != 1: assert(self.fp16); loss = loss*self.
loss_scale
     56
                if self.reg fn: loss = self.reg fn(output, xtra, raw loss)
---> 57
                loss.backward()
     58
                if self.fp16: update_fp32_grads(self.fp32_params, self.m)
     59
                if self.loss_scale != 1:
~/anaconda3/envs/fastai/lib/python3.6/site-packages/torch/autograd/variable.p
y in backward(self, gradient, retain_graph, create_graph, retain_variables)
    165
                        Variable.
    166
                torch.autograd.backward(self, gradient, retain graph, create
graph, retain variables)
    168
    169
            def register hook(self, hook):
~/anaconda3/envs/fastai/lib/python3.6/site-packages/torch/autograd/__init__.p
```

y in backward(variables, grad variables, retain graph, create graph, retain v

#### KeyboardInterrupt:

# In [112]: # plot out our loss learn.sched.plot\_loss()



In [113]: # save our final classifier
learn.save('clas\_2')