Multiclass Text Classification with

Feed-forward Neural Networks and Word Embeddings

First, we will do some initialization.

In [ ]:
```
import random
import torch
import numpy as np
import pandas as pd
from tqdm.notebook import tqdm

# enable tqdm in pandas
tqdm.pandas()

# set to True to use the gpu (if there is one available)
use_gpu = True

# select device
# Se selecciona el gpu envés del cpu para el procesamiento del código
device = torch.device('cuda' if use_gpu and torch.cuda.is_available() else 'cpu')
print(f'device: {device.type}')

# random seed
seed = 1234

# set random seed
if seed is not None:
    print(f'random seed: {seed}')
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
```

```
device: cuda
random seed: 1234
```

We will be using the AG's News Topic Classification Dataset. It is stored in two CSV files: `train.csv` and `test.csv`, as well as a `classes.txt` that stores the labels of the classes to predict.

First, we will load the training dataset using pandas and take a quick look at how the data.

In [ ]:
```
train_df = pd.read_csv('/kaggle/input/ag-news/train.csv', header=None)
train_df.columns = ['class index', 'title', 'description']
train_df = train_df.sample(frac=0.8,random_state=42)
train_df
```

Out[ ]:

	class index	title	description
71787	3	BBC set for major shake-up, claims newspaper	London - The British Broadcasting Corporation,...
67218	3	Marsh averts cash crunch	Embattled insurance broker #39;s banks agree t...
54066	2	Jeter, Yankees Look to Take Control (AP)	AP - Derek Jeter turned a season that started ...
7168	4	Flying the Sun to Safety	When the Genesis capsule comes back to Earth w...
29618	3	Stocks Seen Flat as Nortel and Oil Weigh	NEW YORK (Reuters) - U.S. stocks were set to ...
...	...	...	...
59228	4	Investors Flock to Web Networking Sites	Internet whiz kids Marc Andreessen, Josh Kopel...
61417	3	Samsung Electric Quarterly Profit Up	Samsung Electronics Co. Ltd. #39;s (005930.KS:...
20703	3	Coeur Still Committed to Wheaton Deal	Coeur d #39;Alene Mines Corp. said Tuesday tha...
40626	3	Clouds on horizon for low-cost airlines	NEW YORK -- As larger US airlines suffer growi...
25059	2	Furcal issues apology for DUI arrest, returns ...	NAMES Atlanta Braves shortstop Rafael Furcal r...

96000 rows × 3 columns

The dataset consists of 120,000 examples, each consisting of a class index, a title, and a description. The class labels are distributed in a separated file. We will add the labels to the dataset so that we can interpret the data more easily. Note that the label indexes are one-based, so we need to subtract one to retrieve them from the list.

In [ ]:
```
# Se asigna la clase correspondiente a cada titulo y descripcióncon base al indice de clase
labels = open('/kaggle/input/ag-news/classes.txt').read().splitlines()
classes = train_df['class index'].map(lambda i: labels[i-1])
train_df.insert(1, 'class', classes)
train_df
```

Out[ ]:

	class index	class	title	description
71787	3	Business	BBC set for major shake-up, claims newspaper	London - The British Broadcasting Corporation,...
67218	3	Business	Marsh averts cash crunch	Embattled insurance broker #39;s banks agree t...
54066	2	Sports	Jeter, Yankees Look to Take Control (AP)	AP - Derek Jeter turned a season that started ...
7168	4	Sci/Tech	Flying the Sun to Safety	When the Genesis capsule comes back to Earth w...
29618	3	Business	Stocks Seen Flat as Nortel and Oil Weigh	NEW YORK (Reuters) - U.S. stocks were set to ...
...	...	...	...	...
59228	4	Sci/Tech	Investors Flock to Web Networking Sites	Internet whiz kids Marc Andreessen, Josh Kopel...
61417	3	Business	Samsung Electric Quarterly Profit Up	Samsung Electronics Co. Ltd. #39;s (005930.KS:...
20703	3	Business	Coeur Still Committed to Wheaton Deal	Coeur d #39;Alene Mines Corp. said Tuesday tha...
40626	3	Business	Clouds on horizon for low-cost airlines	NEW YORK -- As larger US airlines suffer growi...
25059	2	Sports	Furcal issues apology for DUI arrest, returns ...	NAMES Atlanta Braves shortstop Rafael Furcal r...

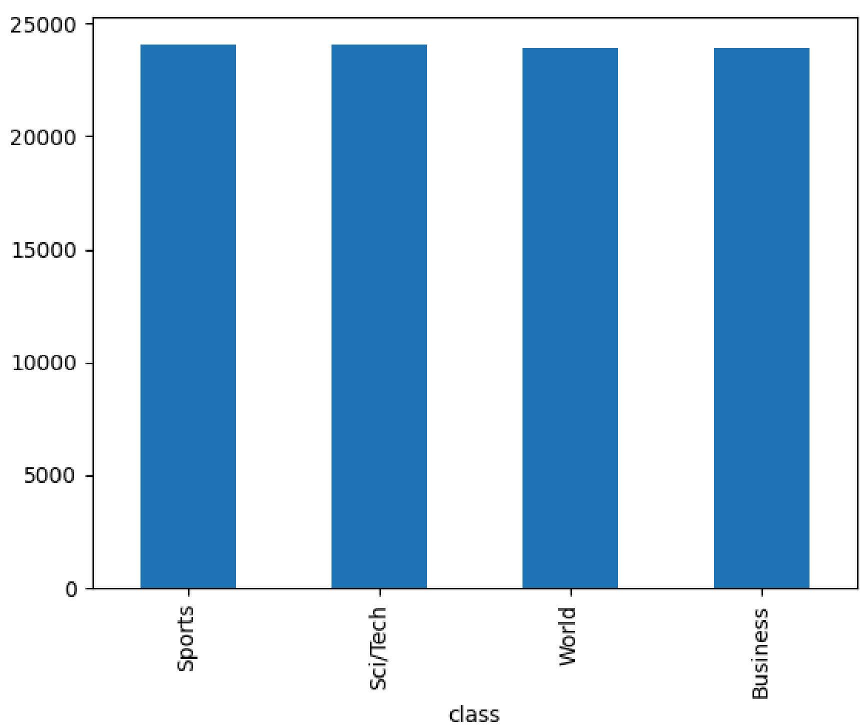
96000 rows × 4 columns

Let's inspect how balanced our examples are by using a bar plot.

In [ ]:
```
pd.value_counts(train_df['class']).plot.bar() # Verificar que todas las clases tengan la misma cantidad de datos para evitar
# sesgos y mejorar el resultado del modelo
```

```
/tmp/ipykernel_31/1846183183.py:1: FutureWarning: pandas.value_counts is deprecated and will be removed in a future version. Use p
d.Series(obj).value_counts() instead.
  pd.value_counts(train_df['class']).plot.bar() # Verificar que todas las clases tengan la misma cantidad de datos para evitar
```

Out[ ]:
```
<Axes: xlabel='class'>
```



The classes are evenly distributed. That's great!

However, the text contains some spurious backslashes in some parts of the text. They are meant to represent newlines in the original text. An example can be seen below, between the words "dwindling" and "band".

In [ ]:
```
print(train_df.loc[0, 'description'])
```

```
Reuters - Short-sellers, Wall Street's dwindling\band of ultra-cynics, are seeing green again.
```

We will replace the backslashes with spaces on the whole column using pandas replace method.

In [ ]:
```python
# Creamos una nueva columna que es la union entre el titulo y la descripción,
# remplazamos \ que representan salto de lineas a espacios para mejorar la
# tokenización de las oraciones así como pasar a minusculas todas las palabras
train_df['text'] = train_df['title'].str.lower() + " " + train_df['description'].str.lower()
train_df['text'] = train_df['text'].str.replace('\\', ' ', regex=False)
train_df
```

Out[ ]:

	class index	class	title	description	text
71787	3	Business	BBC set for major shake-up, claims newspaper	London - The British Broadcasting Corporation,...	bbc set for major shake-up, claims newspaper l...
67218	3	Business	Marsh averts cash crunch	Embattled insurance broker #39;s banks agree t...	marsh averts cash crunch embattled insurance b...
54066	2	Sports	Jeter, Yankees Look to Take Control (AP)	AP - Derek Jeter turned a season that started ...	jeter, yankees look to take control (ap) ap - ...
7168	4	Sci/Tech	Flying the Sun to Safety	When the Genesis capsule comes back to Earth w...	flying the sun to safety when the genesis caps...
29618	3	Business	Stocks Seen Flat as Nortel and Oil Weigh	NEW YORK (Reuters) - U.S. stocks were set to ...	stocks seen flat as nortel and oil weigh new ...
...	...	...	...	...	...
59228	4	Sci/Tech	Investors Flock to Web Networking Sites	Internet whiz kids Marc Andreessen, Josh Kopel...	investors flock to web networking sites intern...
61417	3	Business	Samsung Electric Quarterly Profit Up	Samsung Electronics Co. Ltd. #39;s (005930.KS:...	samsung electric quarterly profit up samsung e...
20703	3	Business	Coeur Still Committed to Wheaton Deal	Coeur d #39;Alene Mines Corp. said Tuesday tha...	coeur still committed to wheaton deal coeur d ...
40626	3	Business	Clouds on horizon for low-cost airlines	NEW YORK -- As larger US airlines suffer growi...	clouds on horizon for low-cost airlines new yo...
25059	2	Sports	Furcal issues apology for DUI arrest, returns ...	NAMES Atlanta Braves shortstop Rafael Furcal r...	furcal issues apology for dui arrest, returns ...

96000 rows × 5 columns

Now we will proceed to tokenize the title and description columns using NLTK's word_tokenize(). We will add a new column to our dataframe with the list of tokens.

In [ ]:
```python
from nltk.tokenize import word_tokenize

# Se tokenizan tanto el titulo como la descripción y se crean los vectores de los tokens
train_df['tokens'] = train_df['text'].progress_map(word_tokenize)
train_df
```

```
  0%|          | 0/96000 [00:00<?, ?it/s]
```

Out[ ]:

	class index	class	title	description	text	tokens
71787	3	Business	BBC set for major shake-up, claims newspaper	London - The British Broadcasting Corporation,...	bbc set for major shake-up, claims newspaper l...	[bbc, set, for, major, shake-up, ,, claims, ne...
67218	3	Business	Marsh averts cash crunch	Embattled insurance broker #39;s banks agree t...	marsh averts cash crunch embattled insurance b...	[marsh, averts, cash, crunch, embattled, insur...
54066	2	Sports	Jeter, Yankees Look to Take Control (AP)	AP - Derek Jeter turned a season that started ...	jeter, yankees look to take control (ap) ap - ...	[jeter, ,, yankees, look, to, take, control, (...
7168	4	Sci/Tech	Flying the Sun to Safety	When the Genesis capsule comes back to Earth w...	flying the sun to safety when the genesis caps...	[flying, the, sun, to, safety, when, the, gene...
29618	3	Business	Stocks Seen Flat as Nortel and Oil Weigh	NEW YORK (Reuters) - U.S. stocks were set to ...	stocks seen flat as nortel and oil weigh new ...	[stocks, seen, flat, as, nortel, and, oil, wei...
...	...	...	...	...	...	...
59228	4	Sci/Tech	Investors Flock to Web Networking Sites	Internet whiz kids Marc Andreessen, Josh Kopel...	investors flock to web networking sites intern...	[investors, flock, to, web, networking, sites,...
61417	3	Business	Samsung Electric Quarterly Profit Up	Samsung Electronics Co. Ltd. #39;s (005930.KS:...	samsung electric quarterly profit up samsung e...	[samsung, electric, quarterly, profit, up, sam...
20703	3	Business	Coeur Still Committed to Wheaton Deal	Coeur d #39;Alene Mines Corp. said Tuesday tha...	coeur still committed to wheaton deal coeur d ...	[coeur, still, committed, to, wheaton, deal, c...
40626	3	Business	Clouds on horizon for low-cost airlines	NEW YORK -- As larger US airlines suffer growi...	clouds on horizon for low-cost airlines new yo...	[clouds, on, horizon, for, low-cost, airlines,...
25059	2	Sports	Furcal issues apology for DUI arrest, returns ...	NAMES Atlanta Braves shortstop Rafael Furcal r...	furcal issues apology for dui arrest, returns ...	[furcal, issues, apology, for, dui, arrest, ,,...

96000 rows × 6 columns

Now we will load the GloVe word embeddings.

In [ ]:

```
from gensim.models import KeyedVectors
# Se usan los embeddings de GloVe que ya han sido preentrenados con varios corpus
# y se utiliza para estimar nuestra tokanizacion
glove = KeyedVectors.load_word2vec_format("/kaggle/input/glove6b300dtxt/glove.6B.300d.txt", no_header=True)
glove.vectors.shape
```

Out[ ]:

```
(400000, 300)
```

The word embeddings have been pretrained in a different corpus, so it would be a good idea to estimate how good our tokenization matches the GloVe vocabulary.

In [ ]:

```
from collections import Counter

# Se cuentan cuantas palabras no se conocen del vocabulario lo cual nos ayuda a comparar con el embedding importado para
# ver que tan bueno es nuestra tokenización para identificar las palabras.
def count_unknown_words(data, vocabulary):
    counter = Counter()
    for row in tqdm(data):
        counter.update(tok for tok in row if tok not in vocabulary)
    return counter

# find out how many times each unknown token occurrs in the corpus
c = count_unknown_words(train_df['tokens'], glove.key_to_index)

# find the total number of tokens in the corpus
total_tokens = train_df['tokens'].map(len).sum()

# find some statistics about occurrences of unknown tokens
unk_tokens = sum(c.values())
percent_unk = unk_tokens / total_tokens
distinct_tokens = len(list(c))

# Se hace una comparacion entre las palabras desconocidas contra las palabras totales para calcular la presición de
# la tokenizacion
print(f'total number of tokens: {total_tokens:,}')
print(f'number of unknown tokens: {unk_tokens:,}')
print(f'number of distinct unknown tokens: {distinct_tokens:,}')
print(f'percentage of unkown tokens: {percent_unk:.2%}')
print('top 50 unknown words:')
for token, n in c.most_common(10):
    print(f'\t{n}\t{token}')
```

```
  0%|          | 0/96000 [00:00<?, ?it/s]
```

```
total number of tokens: 4,218,415
number of unknown tokens: 52,899
number of distinct unknown tokens: 20,979
percentage of unkown tokens: 1.25%
top 50 unknown words:
        2379    /b
        1708    href=
        1707    /a
        1461    //www.investor.reuters.com/fullquote.aspx
        1461    target=/stocks/quickinfo/fullquote
        450     /p
        396     newsfactor
        380     cbs.mw
        344     color=
        332     face=
```

Glove embeddings seem to have a good coverage on this dataset -- only 1.25% of the tokens in the dataset are unknown, i.e., don't appear in the GloVe vocabulary.

Still, we will need a way to handle these unknown tokens. Our approach will be to add a new embedding to GloVe that will be used to represent them. This new embedding will be initialized as the average of all the GloVe embeddings.

We will also add another embedding, this one initialized to zeros, that will be used to pad the sequences of tokens so that they all have the same length. This will be useful when we train with mini-batches.

In [ ]:

```
# Para compensar por las palabras desconocidas se utilizan el promedio de todos los embeddings para llenar esos datos faltantes
# string values corresponding to the new embeddings
unk_tok = '[UNK]'
pad_tok = '[PAD]'

# initialize the new embedding values
unk_emb = glove.vectors.mean(axis=0)
pad_emb = np.zeros(300)

# add new embeddings to glove
glove.add_vectors([unk_tok, pad_tok], [unk_emb, pad_emb])

# get token ids corresponding to the new embeddings
unk_id = glove.key_to_index[unk_tok]
pad_id = glove.key_to_index[pad_tok]

unk_id, pad_id
```

Out[ ]:

```
(400000, 400001)
```

In [ ]:

```
from sklearn.model_selection import train_test_split

train_df, dev_df = train_test_split(train_df, train_size=0.8)
train_df.reset_index(inplace=True)
dev_df.reset_index(inplace=True)
```

We will now add a new column to our dataframe that will contain the padded sequences of token ids.

In [ ]:

```
threshold = 10
tokens = train_df['tokens'].explode().value_counts() # Se cuenta la cantidad de repetición de las palabras
vocabulary = set(tokens[tokens > threshold].index.tolist()) # Se crea un vocabulario solo con palabras que se
# repitan más de 10 veces
print(f'vocabulary size: {len(vocabulary):,}')
```

```
vocabulary size: 15,451
```

In [ ]:

```
# find the length of the longest list of tokens
max_tokens = train_df['tokens'].map(len).max()

# return unk_id for infrequent tokens too
def get_id(tok):
    if tok in vocabulary:
        return glove.key_to_index.get(tok, unk_id)
    else:
        return unk_id

# function that gets a list of tokens and returns a list of token ids,
# with padding added accordingly
def token_ids(tokens):
    tok_ids = [get_id(tok) for tok in tokens]
    pad_len = max_tokens - len(tok_ids)
    return tok_ids + [pad_id] * pad_len

# add new column to the dataframe
# Se crea una nueva columna que contiene el id del token
```

```
train_df['token ids'] = train_df['tokens'].progress_map(token_ids)
train_df
```

```
  0%|          | 0/76800 [00:00<?, ?it/s]
```

Out[ ]:

	index	class index	class	title	description	text	tokens	token ids
0	41480	3	Business	Unrest forces oil prices higher	Oil futures have jumped to their highest closi...	unrest forces oil prices higher oil futures ha...	[unrest, forces, oil, prices, higher, oil, fut...	[4615, 340, 316, 468, 609, 316, 3081, 33, 3450...
1	112119	4	Sci/Tech	Old News.... REALLY Old News!	The video archives of Pathe News are online, c...	old news.... really old news! the video archiv...	[old, news, ..., ., really, old, news, !, the,...	[167, 172, 434, 2, 588, 167, 172, 805, 0, 974,...
2	75220	2	Sports	Ace in the Hole	General Manager Theo Epstein said the Red Sox ...	ace in the hole general manager theo epstein s...	[ace, in, the, hole, general, manager, theo, e...	[7588, 6, 0, 2924, 216, 865, 15599, 17434, 16,...
3	111911	2	Sports	UNDATED: 14 points.	Tiffany Porter-Talbert scored 24 points, and W...	undated: 14 points. tiffany porter-talbert sco...	[undated, :, 14, points, ., tiffany, porter-ta...	[5833, 45, 657, 226, 2, 15956, 400000, 878, 79...
4	80697	2	Sports	Flatley, Rogers on bench for Australia for rug...	Back from injury, Elton Flatley and Mat Rogers...	flatley, rogers on bench for australia for rug...	[flatley, ,, rogers, on, bench, for, australia...	[400000, 1, 5638, 13, 4530, 10, 603, 10, 2707,...
...	...	...	...	...	...	...	...	...
76795	110136	2	Sports	Gerrard aiming high	Steven Gerrard insists he #39;ll not accept q...	gerrard aiming high steven gerrard insists he ...	[gerrard, aiming, high, steven, gerrard, insis...	[15773, 7584, 152, 4411, 15773, 4971, 18, 2749...
76796	112554	3	Business	Local gamer: Grand Theft Auto #39; steals the ...	Just how excited is Justin Field about the new...	local gamer: grand theft auto #39; steals the ...	[local, gamer, :, grand, theft, auto, #, 39, ;...	[250, 400000, 45, 1063, 6539, 2612, 2749, 3403...
76797	116840	3	Business	Sprint, Nextel Agree To Merge	The deal, valued at $35 billion, will create ...	sprint, nextel agree to merge the deal, valued...	[sprint, ,, nextel, agree, to, merge, the, dea...	[5514, 1, 17774, 2137, 4, 9194, 0, 435, 1, 595...
76798	34067	3	Business	Export Cut to China Seen as Clever Strategy on...	Yukos, the Russian oil giant, is playing a wea...	export cut to china seen as clever strategy on...	[export, cut, to, china, seen, as, clever, str...	[2467, 611, 4, 132, 541, 19, 11114, 1747, 13, ...
76799	34374	2	Sports	Clough: A genuine original	Although Brian Clough retired from management ...	clough: a genuine original although brian clou...	[clough, :, a, genuine, original, although, br...	[35035, 45, 7, 7231, 929, 376, 2789, 35035, 16...

76800 rows × 8 columns

In [ ]:

```
max_tokens = dev_df['tokens'].map(len).max()
dev_df['token ids'] = dev_df['tokens'].progress_map(token_ids)
dev_df
```

```
  0%|          | 0/19200 [00:00<?, ?it/s]
```

Out[ ]:

	index	class index	class	title	description	text	tokens	token ids
0	96457	1	World	House G.O.P. Leader Hails Ethics Panel's Rebuk...	Tom DeLay of Texas claimed vindication today a...	house g.o.p. leader hails ethics panel's rebuk...	[house, g.o.p, ., leader, hails, ethics, panel...	[166, 400000, 2, 329, 15244, 5321, 1908, 9, 19...
1	65284	2	Sports	Pittsburgh Steelers Notes	Bill Cowher is no longer 0-for-Texas. He beat ...	pittsburgh steelers notes bill cowher is no lo...	[pittsburgh, steelers, notes, bill, cowher, is...	[3576, 9841, 2142, 480, 400000, 14, 84, 1078, ...
2	48958	1	World	US, Iraq control Samarra	SAMARRA, Iraq - US and Iraqi forces in Samarra...	us, iraq control samarra samarra, iraq - us an...	[us, ,, iraq, control, samarra, samarra, ,, ir...	[95, 1, 233, 424, 19877, 19877, 1, 233, 11, 95...
3	78606	4	Sci/Tech	Novel Approach Targets Alzheimer #39;s Develop...	A new technique may someday be able to stop Al...	novel approach targets alzheimer #39;s develop...	[novel, approach, targets, alzheimer, #, 39, ;...	[1999, 1587, 2666, 11533, 2749, 3403, 89, 1534...
4	68705	1	World	EU #39;s Prodi ready to stay on if new Brussel...	European Commission head Romano Prodi would be...	eu #39;s prodi ready to stay on if new brussel...	[eu, #, 39, ;, s, prodi, ready, to, stay, on, ...	[644, 2749, 3403, 89, 1534, 400000, 1188, 4, 1...
...	...	...	...	...	...	...	...	...
19195	105060	4	Sci/Tech	Sun buys IT services company to help HP/IBM fight	Sun Microsystems is buying IT services company...	sun buys it services company to help hp/ibm fi...	[sun, buys, it, services, company, to, help, h...	[1662, 9911, 20, 522, 128, 4, 275, 400000, 838...
19196	93591	2	Sports	Raps down and out in LA	The Raptors have to be reminded sometimes that...	raps down and out in la the raptors have to be...	[raps, down, and, out, in, la, the, raptors, h...	[36092, 135, 5, 66, 6, 1047, 0, 15873, 33, 4, ...
19197	97615	2	Sports	South Africa in strong position Kanpur Test	KANPUR: Andrew Halls unbeaten knock of 78 help...	south africa in strong position kanpur test ka...	[south, africa, in, strong, position, kanpur, ...	[139, 637, 6, 562, 704, 42148, 728, 42148, 45,...
19198	11883	3	Business	Oil Rebounds After Iraq Pipeline Attack	LONDON (Reuters) - Oil prices rose on Friday ...	oil rebounds after iraq pipeline attack londo...	[oil, rebounds, after, iraq, pipeline, attack,...	[316, 4697, 49, 233, 4523, 436, 516, 23, 10851...
19199	7378	1	World	Impoverished families of Nepal hostages in Ira...	AFP - Relatives of 12 Nepalese workers missing...	impoverished families of nepal hostages in ira...	[impoverished, families, of, nepal, hostages, ...	[6793, 915, 3, 3759, 4005, 6, 233, 5317, 10, 1...

19200 rows × 8 columns

Now we will get a numpy 2-dimensional array corresponding to the token ids, and a 1-dimensional array with the gold classes. Note that the classes are one-based (i.e., they start at one), but we need them to be zero-based, so we need to subtract one from this array.

In [ ]:
```
from torch.utils.data import Dataset

# Se crea la clase del dataset para crear objetos usando el formato de tensors de torch
class MyDataset(Dataset):
    def __init__(self, x, y):
        self.x = x
        self.y = y

    def __len__(self):
        return len(self.y)

    def __getitem__(self, index):
        x = torch.tensor(self.x[index])
        y = torch.tensor(self.y[index])
        return x, y
```

Next, we construct our PyTorch model, which is a feed-forward neural network with two layers:

In [ ]:
```
from torch import nn
import torch.nn.functional as F

# Se crea la estructura del modelo en forma de feed-foward
class Model(nn.Module):
    def __init__(self, vectors, pad_id, hidden_dim, output_dim, dropout):
        super().__init__()
        # Se prepara los datos y se transforman para ser interpretados por el modelo
        # embeddings must be a tensor
        if not torch.is_tensor(vectors):
            vectors = torch.tensor(vectors)
        # keep padding id
        self.padding_idx = pad_id
        # embedding layer
        self.embs = nn.Embedding.from_pretrained(vectors, padding_idx=pad_id)
        # feedforward layers
```

```
        self.layers = nn.Sequential( # Es un modelo secuencial
            # La primera capa reinicia a cero ciertos inputs
            nn.Dropout(dropout),
            # Primera capa oculta lineal con función de activación ReLU
            nn.Linear(vectors.shape[1], hidden_dim),
            nn.ReLU(),
            # Otra capa de reinicio para evitar overfitting
            nn.Dropout(dropout),
            # Capa de salida lineal
            nn.Linear(hidden_dim, output_dim),
        )

    def forward(self, x):
        # get boolean array with padding elements set to false
        not_padding = torch.isin(x, self.padding_idx, invert=True)
        # get lengths of examples (excluding padding)
        lengths = torch.count_nonzero(not_padding, axis=1)
        # get embeddings
        x = self.embs(x)
        # calculate means
        x = x.sum(dim=1) / lengths.unsqueeze(dim=1)
        # pass to rest of the model
        output = self.layers(x)
        # calculate softmax if we're not in training mode
        #if not self.training:
        #    output = F.softmax(output, dim=1)
        return output
```

Next, we implement the training procedure. We compute the loss and accuracy on the development partition after each epoch.

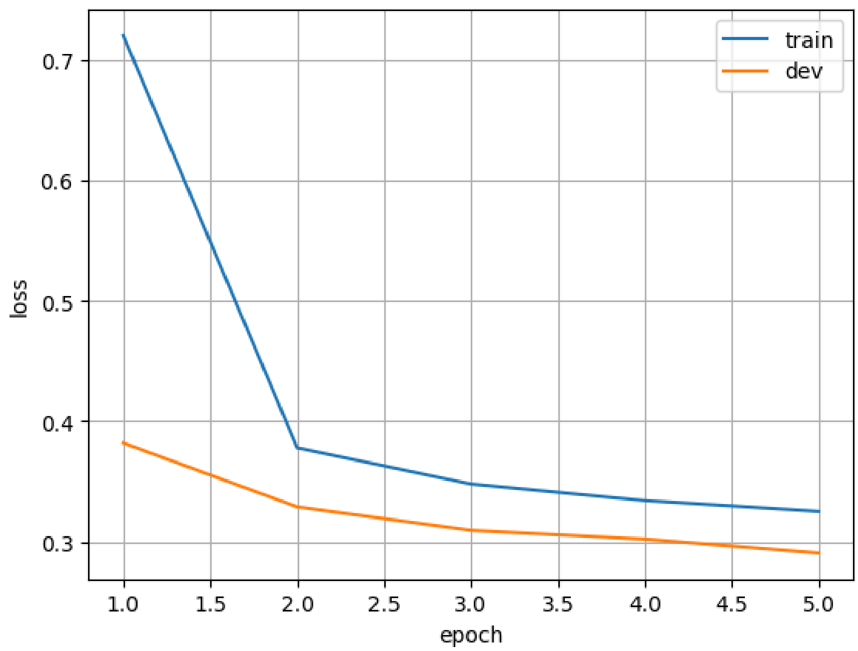
In [ ]:
```
from torch import optim
from torch.utils.data import DataLoader
from sklearn.metrics import accuracy_score

# Definimos los hiperarametros iniciales para el entrenamiento del modelo
# hyperparameters
lr = 1e-3
weight_decay = 0
batch_size = 500
shuffle = True
n_epochs = 5
hidden_dim = 50
output_dim = len(labels)
dropout = 0.1
vectors = glove.vectors

# Se inicializa el modelo con la estructura definida previamente, se utiliza la función de pérdida de CrossENtropy ya que
# es un clasificador multiclase
# Se usa el optimizador adam el cual es el más utilizado y se cargan los datos de entrenamiento
# initialize the model, loss function, optimizer, and data-loader
model = Model(vectors, pad_id, hidden_dim, output_dim, dropout).to(device)
loss_func = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=lr, weight_decay=weight_decay)
train_ds = MyDataset(train_df['token ids'], train_df['class index'] - 1)
train_dl = DataLoader(train_ds, batch_size=batch_size, shuffle=shuffle)
dev_ds = MyDataset(dev_df['token ids'], dev_df['class index'] - 1)
dev_dl = DataLoader(dev_ds, batch_size=batch_size, shuffle=shuffle)

train_loss = []
train_acc = []

dev_loss = []
dev_acc = []

# Se entrena el modelo con los datos definidos previamente con el gpu y se procesa la pérddida usando
# el cpu para ahorro de recursos
# train the model
for epoch in range(n_epochs):
    losses = []
    gold = []
    pred = []
    model.train()
    for X, y_true in tqdm(train_dl, desc=f'epoch {epoch+1} (train)'):
        # clear gradients
        model.zero_grad()
        # send batch to right device
        X = X.to(device)
        y_true = y_true.to(device)
        # predict label scores
        y_pred = model(X)
        # compute loss
        loss = loss_func(y_pred, y_true)
        # accumulate for plotting
```

```
            losses.append(loss.detach().cpu().item())
            gold.append(y_true.detach().cpu().numpy())
            pred.append(np.argmax(y_pred.detach().cpu().numpy(), axis=1))
            # backpropagate
            loss.backward()
            # optimize model parameters
            optimizer.step()
        train_loss.append(np.mean(losses))
        train_acc.append(accuracy_score(np.concatenate(gold), np.concatenate(pred)))

        model.eval()
        with torch.no_grad():
            losses = []
            gold = []
            pred = []
            for X, y_true in tqdm(dev_dl, desc=f'epoch {epoch+1} (dev)'):
                X = X.to(device)
                y_true = y_true.to(device)
                y_pred = model(X)
                loss = loss_func(y_pred, y_true)
                losses.append(loss.cpu().item())
                gold.append(y_true.cpu().numpy())
                pred.append(np.argmax(y_pred.cpu().numpy(), axis=1))
            dev_loss.append(np.mean(losses))
            dev_acc.append(accuracy_score(np.concatenate(gold), np.concatenate(pred)))
```

```
epoch 1 (train):   0%|          | 0/154 [00:00<?, ?it/s]
epoch 1 (dev):   0%|          | 0/39 [00:00<?, ?it/s]
epoch 2 (train):   0%|          | 0/154 [00:00<?, ?it/s]
epoch 2 (dev):   0%|          | 0/39 [00:00<?, ?it/s]
epoch 3 (train):   0%|          | 0/154 [00:00<?, ?it/s]
epoch 3 (dev):   0%|          | 0/39 [00:00<?, ?it/s]
epoch 4 (train):   0%|          | 0/154 [00:00<?, ?it/s]
epoch 4 (dev):   0%|          | 0/39 [00:00<?, ?it/s]
epoch 5 (train):   0%|          | 0/154 [00:00<?, ?it/s]
epoch 5 (dev):   0%|          | 0/39 [00:00<?, ?it/s]
```

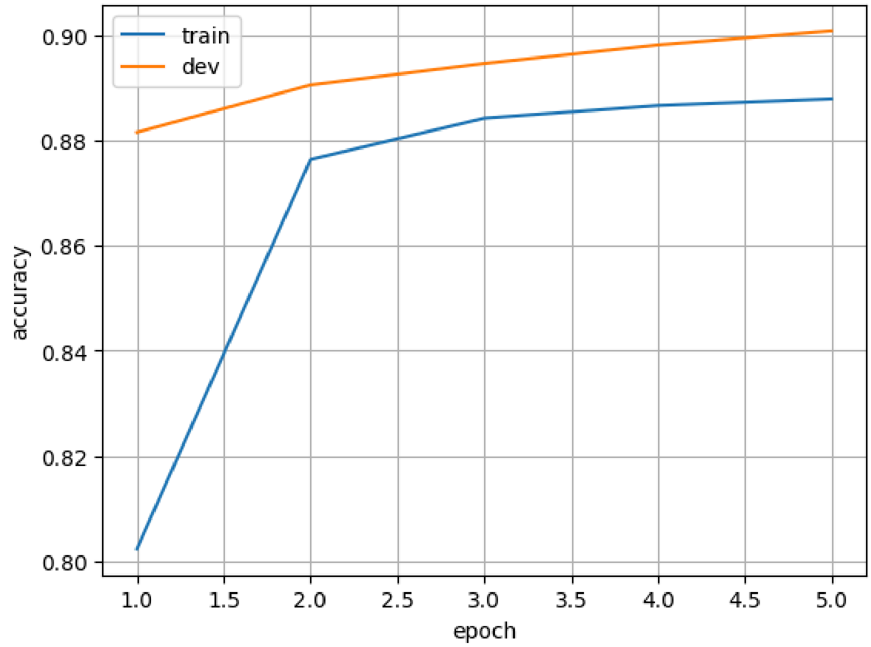
Let's plot the loss and accuracy on dev:

In [ ]:
```
import matplotlib.pyplot as plt
%matplotlib inline

x = np.arange(n_epochs) + 1

plt.plot(x, train_loss)
plt.plot(x, dev_loss)
plt.legend(['train', 'dev'])
plt.xlabel('epoch')
plt.ylabel('loss')
plt.grid(True)
```



In [ ]:
```
plt.plot(x, train_acc)
plt.plot(x, dev_acc)
plt.legend(['train', 'dev'])
plt.xlabel('epoch')
```

```
plt.ylabel('accuracy')
plt.grid(True)
```



Next, we evaluate on the testing partition:

In [ ]:
```
# repeat all preprocessing done above, this time on the test set
# Se repite el mismo procedimiento de limpieza, tokenización y creación de tensor
test_df = pd.read_csv('/kaggle/input/ag-news/test.csv', header=None)
test_df.columns = ['class index', 'title', 'description']
test_df['text'] = test_df['title'].str.lower() + " " + test_df['description'].str.lower()
test_df['text'] = test_df['text'].str.replace('\\', ' ', regex=False)
test_df['tokens'] = test_df['text'].progress_map(word_tokenize)
max_tokens = dev_df['tokens'].map(len).max()
test_df['token ids'] = test_df['tokens'].progress_map(token_ids)
```

```
  0%|          | 0/7600 [00:00<?, ?it/s]
  0%|          | 0/7600 [00:00<?, ?it/s]
```

In [ ]:
```
from sklearn.metrics import classification_report

# set model to evaluation mode
model.eval()

dataset = MyDataset(test_df['token ids'], test_df['class index'] - 1)
data_loader = DataLoader(dataset, batch_size=batch_size)


# don't store gradients
with torch.no_grad():
    y_pred = []

    for X, _ in tqdm(data_loader):
        X = X.to(device)
        # predict one class per example
        y = torch.argmax(model(X), dim=1)
        # convert tensor to numpy array (sending it back to the cpu if needed)
        y_pred.append(y.cpu().numpy())
        # print results
    print(classification_report(dataset.y, np.concatenate(y_pred), target_names=labels))

# Se predice en las distintas categorías y se obtienen las métricas de precisión con los valores reales de pruebas
```

```
  0%|          | 0/16 [00:00<?, ?it/s]
              precision    recall  f1-score   support

       World       0.92      0.88      0.90      1900
      Sports       0.95      0.97      0.96      1900
    Business       0.85      0.85      0.85      1900
    Sci/Tech       0.86      0.87      0.87      1900

    accuracy                           0.89      7600
   macro avg       0.89      0.89      0.89      7600
weighted avg       0.89      0.89      0.89      7600
```

In [1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:

```
# Exportar a HTML
!jupyter nbconvert --to html "/content/drive/MyDrive/Colab Notebooks/notebookdb7084fa45.ipynb"
```