Multiclass Text Classification with¶

Feed-forward Neural Networks and Word Embeddings¶

First, we will do some initialization.

np.random.seed(seed)
torch.manual_seed(seed)

In [9]:

```
import random
import torch
import numpy as np
import pandas as pd
from tqdm.notebook import tqdm
# Habilita tqdm en pandas
tqdm.pandas()
# Pones en True para poder usar la gpu (Si hay una disponible)
use_gpu = True
# Seleciona un device
device = torch.device('cuda' if use_gpu and torch.cuda.is_available() else 'cpu')
print(f'device: {device.type}')
# Semilla random
seed = 1234
# Seleciona una semilla random
if seed is not None:
  print(f'random seed: {seed}')
  random.seed(seed)
```

device: cpu

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 [10]:

train_df = pd.read_csv('/kaggle/input/agnews-pytorch-simple-embed-classif-90/AG_NEWS/train.csv', header=**None**) # leer el dataset que se usara train_df.columns = ['class index', 'title', 'description'] # Crear las columnas que se usaran train_df = train_df.sample(frac = 0.7, random_state = 42) # Elejir una fraccion de los datos train_df

Out[10]:

		class index	title	description
71787	3		BBC set for major shake-up, claims newspaper	London - The British Broadcasting Corporation,

		class index	title	description
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
53857	1		FDA Accused of Silencing Vioxx Warnings	WASHINGTON - The Food and Drug Administration
111476	2		Buckeyes won #39;t play in NCAA or NIT tourneys	COLUMBUS, Ohio Ohio State has sanctioned its m
6343	3		Rate hikes by Fed work in two ways	If you #39;ve noticed that the price of everyt
20736	4		NASA Administrator Offers Support for Kennedy	The following is a statement from NASA Adminis

		class index	title	description
34378	2		Twins make it 3 straight	The Minnesota Twins clinched on a bus in 1991

84000 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 [11]:

labels = open('/kaggle/input/classes/classes.txt').read().splitlines() # Crear lables para almacenar todos los nombres de las clases

classes = train_df['class index'].map(**lambda** i: labels[i-1]) # Crear clases para almacenar todos los nombres de las clases

train_df.insert(1, 'class', classes) # Insertar los nombres de las clases en el data frame train_df

Out[11]:

	class index	class	title	description
71787	3	Business	BBC set for major shake-up, claims	London - The British Broadcasting

	class index	class	title	description
			newspaper	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
53857	1	World	FDA Accused of Silencing Vioxx Warnings	WASHINGTO N - The Food and Drug Administration
111476	2	Sports	Buckeyes won #39;t play in NCAA or NIT tourneys	COLUMBUS, Ohio Ohio State has sanctioned its m

	class index	class	title	description
6343	3	Business	Rate hikes by Fed work in two ways	If you #39;ve noticed that the price of everyt
20736	4	Sci/Tech	NASA Administrator Offers Support for Kennedy	The following is a statement from NASA Adminis
34378	2	Sports	Twins make it 3 straight	The Minnesota Twins clinched on a bus in 1991

84000 rows × 4 columns

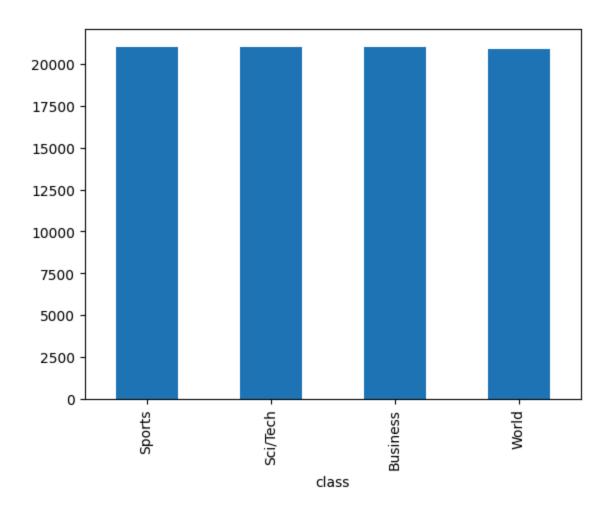
Let's inspect how balanced our examples are by using a bar plot.

In [12]:

pd.value_counts(train_df['class']).plot.bar() # Se grafica pra ver como estan los resultados

/tmp/ipykernel_30/1245903889.py:1: FutureWarning: pandas.value_counts is deprecated and will be removed in a future version. Use pd.Series(obj).value_counts() instead. pd.value_counts(train_df['class']).plot.bar()

<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".

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 [14]:

train_df['text'] = train_df['title'].str.lower() + " " + train_df['description'].str.lower() # Combina las
columnas description y titulo, las juntas en un nueva cokumna llamada text y las pasas a
minusculas
train_df['text'] = train_df['text'].str.replace('\\', ' ', regex=False) # Quita los \ y los pone por
espacios en blanco
train_df

Out[14]:

		class index	class	title	description	text
71787	3		Business	BBC set for major shake-up, claims newspaper	London - The British Broadcastin g Corporation	bbc set for major shake-up, claims newspaper I

		class index	class	title	description	text
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
•••						
53857	1		World	FDA Accused of Silencing Vioxx Warnings	WASHINGT ON - The Food and Drug Administrati on	fda accused of silencing vioxx warnings washin
111476	2		Sports	Buckeyes won #39;t	COLUMBU S, Ohio	buckeyes won #39;t

		class index	class	title	description	text
				play in NCAA or NIT tourneys	Ohio State has sanctioned its m	play in ncaa or nit tourney
6343	3		Business	Rate hikes by Fed work in two ways	If you #39;ve noticed that the price of everyt	rate hikes by fed work in two ways if you #39;
20736	4		Sci/Tech	NASA Administrat or Offers Support for Kennedy	The following is a statement from NASA Adminis	nasa administrat or offers support for kennedy
34378	2		Sports	Twins make it 3 straight	The Minnesota Twins clinched on a bus in 1991	twins make it 3 straight the minnesota twins c

84000 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.

from nltk.tokenize import word_tokenize

train_df['tokens'] = train_df['text'].progress_map(word_tokenize) # Tokenizacion de palabras y los almacena en una nueva columna train_df

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Out[15]:

	clas inde	Clace	title	descripti on	text	tokens
71787	3	Business	BBC set for major shake-up , claims newspap er	London - The British Broadcas ting Corporati on,	bbc set for major shake-up , claims newspap er l	[bbc, set, for, major, shake-up, ,,, claims, ne
67218	3	Business	Marsh averts cash crunch	Embattle d insurance broker #39;s banks agree t	marsh averts cash crunch embattle d insurance b	[marsh, averts, cash, crunch, embattle d, 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	When the	flying the	[flying,

	class index	class	title	descripti on	text	tokens
			Sun to Safety	Genesis capsule comes back to Earth w	sun to safety when the genesis caps	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
53857	1	World	FDA Accused of Silencing Vioxx Warnings	WASHIN GTON - The Food and Drug Administr ation	fda accused of silencing vioxx warnings washin	[fda, accused, of, silencing, vioxx, warnings,
111476	2	Sports	Buckeyes won #39;t play in NCAA or NIT tourneys	COLUMB US, Ohio Ohio State has sanctione d its m	buckeyes won #39;t play in ncaa or nit tourney	[buckeye s, won, #, 39, ;, t, play, in, ncaa, o
6343	3	Business	Rate hikes by Fed work in two ways	If you #39;ve noticed that the price of everyt	rate hikes by fed work in two ways if you #39;	[rate, hikes, by, fed, work, in, two, ways, if

	class index	class	title	descripti on	text	tokens
20736	4	Sci/Tech	NASA Administr ator Offers Support for Kennedy	The following is a statemen t from NASA Adminis	nasa administr ator offers support for kennedy	[nasa, administr ator, offers, support, for, ke
34378	2	Sports	Twins make it 3 straight	The Minnesot a Twins clinched on a bus in 1991	twins make it 3 straight the minnesot a twins c	[twins, make, it, 3, straight, the, minnesot a,

84000 rows × 6 columns

Now we will load the GloVe word embeddings.

In [16]:

from gensim.models import KeyedVectors
glove =

KeyedVectors.load_word2vec_format("/kaggle/input/glove-fasttext-embedding-for-medium-articles/glove.6B.300d.txt", no_header=**True**) # *Importamos el dataset de glove* glove.vectors.shape

(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 [17]:

```
from collections import Counter
# Funcion que cuenta las palabras desconocidas (no incluidas en el vocabulario) en el dataset
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
# Encuentra la cantidad de veces que cada token desconocido aparece en el corpus
c = count unknown words(train df['tokens'], glove.key to index)
# Encuentra el número total de tokens en el corpus
total_tokens = train_df['tokens'].map(len).sum()
# Calcula estadísticas sobre la aparición de tokens desconocidos
unk tokens = sum(c.values())
percent_unk = unk_tokens / total_tokens
distinct tokens = len(list(c))
# Imprime las estadísticas del corpus
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}')
```

total number of tokens: 3,691,911 number of unknown tokens: 46,427

number of distinct unknown tokens: 18,956 percentage of unknown tokens: 1.26%

top 50 unknown words:

2055 /b 1502 href= 1501 /a

1280 //www.investor.reuters.com/fullquote.aspx

1280 target=/stocks/quickinfo/fullquote

417 /p

356 newsfactor 340 cbs.mw 300 color= 291 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 [18]:

Valores de cadena que corresponden a los nuevos embeddings unk_tok = '[UNK]' pad_tok = '[PAD]'

```
# Inicializa los valores para los nuevos embeddings
unk_emb = glove.vectors.mean(axis=0)
pad_emb = np.zeros(300)
# Agrega los nuevos embeddings al modelo glove
glove.add_vectors([unk_tok, pad_tok], [unk_emb, pad_emb])
# Obtiene los IDs de los tokens correspondientes a los nuevos embeddings
unk_id = glove.key_to_index[unk_tok]
pad_id = glove.key_to_index[pad_tok]
unk_id, pad_id
                                                                                     Out[18]:
(400000, 400001)
                                                                                      In [19]:
from sklearn.model selection import train test split
train_df, dev_df = train_test_split(train_df, train_size=0.8) # Elejir una fraccion de los datos
train_df.reset_index(inplace=True) # Reinicia los índices en los dataframes para que
comiencen desde 0 después de la división
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 [20]:

```
threshold = 10
tokens = train_df['tokens'].explode().value_counts() # Cuenta la frecuencia de cada token en la
columna de tokens
vocabulary = set(tokens[tokens > threshold].index.tolist()) # Crea el vocabulario con los tokens
que supere la frecuencaia
print(f'vocabulary size: {len(vocabulary):,}') # Imprime los resultados
vocabulary size: 14,309
                                                                                         In [21]:
# Encuentra la logitud más larga de la lista de tokens
max_tokens = train_df['tokens'].map(len).max()
# Retorna unk id para los tokens infrecuentes
def get id(tok):
   if tok in vocabulary:
     return glove.key_to_index.get(tok, unk_id)
     return unk_id
# Función que recibe una lista de tokens y devuelve una lista de ids de tokens,
# agregando padding según la longitud máxima establecida
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
# Añade la nueva columna al data frame
train_df['token ids'] = train_df['tokens'].progress_map(token_ids)
train_df
```

	index	class index	class	title	descri ption	text	token s	token ids
0	10927 5	4	Sci/Te ch	Mmo2, Lucent to deploy conver ged fixed- mobile 	UK mobile operat or Mmo2 and US teleco ms equip m	mmo2, lucent to deploy conver ged fixed- mobile 	[mmo2 , ,, lucent, to, deploy , conver ged, fixed	[12259 7, 1, 15725, 4, 8169, 21252, 40000 0, 849
1	89047	3	Busine ss	Spitze r Plans to Sue Insure r	New York Attorn ey Gener al Eliot Spitze r will f	spitzer plans to sue insurer new york attorn ey	[spitze r, plans, to, sue, insurer , new, york,	[12185 , 559, 4, 6415, 10646, 50, 196, 1223, 21
2	11805 0	1	World	Britain Canno t Detain Terror Suspe cts Indefin i	Nine Law Lords ruled in favour of a group of m	britain cannot detain terror suspe cts indefin i	[britain , can, not, detain, terror, suspe cts,	[695, 86, 36, 14097, 1974, 2330, 9595, 45, 202
3	10681 3	1	World	Belgra de attack #39;w as	A feared assas sinatio n	belgra de attack #39;w as	[belgra de, attack, #, 39, ;, was,	[4038, 436, 2749, 3403, 89, 15,

	index	class index	class	title	descri ption	text	token s	token ids
				road rage #39;	attemp t on Serbia #39;s	road rage #39; a fear	road, rage, 	586, 9012, 274
4	84844	3	Busine ss	Arctic Thaw Threat ens Peopl e, Polar Bears	OSLO (Reute rs) - Global warmi ng is heatin g th	arctic thaw threat ens people , polar bears osl	[arctic, thaw, threat ens, people, ,,, polar, be	[7574, 20189, 6805, 69, 1, 10158, 4509, 6737,
								•••
67195	67493	3	Busine ss	Jeans Maker VF Sees Earns Up 24 Perce nt (Reute rs)	Reuter s - VF Corp , the world' s largest \jeans	jeans maker vf sees earns up 24 percen t (reute.	[jeans, maker, vf, sees, earns, up, 24, percen	[40000 0, 2737, 40000 0, 3109, 12803, 60, 795, 7
67196	58333	3	Busine ss	Temas ek Makes S\\$7.4 Bln Profit, Gets Top AAA	Temas ek Holdin gs Pte earne d S\\$7.4 billion (\\$	temas ek makes s \$7.4 bln profit, gets top aaa	[temas ek, makes , s, \$, 7.4, bln, profit, ,, ge	[40000 0, 907, 1534, 80, 14321, 17494, 1269, 1,

	index	class index	class	title	descri ption	text	token s	token ids
67197	11255 4	3	Busine ss	Local gamer: Grand Theft Auto #39; steals the	Just how excite d is Justin Field about the new	local gamer : grand theft auto #39; steals the	[local, gamer, :, grand, theft, auto, #, 39, ;	[250, 40000 0, 45, 1063, 6539, 2612, 2749, 3403
67198	11684 0	3	Busine ss	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
67199	34067	3	Busine ss	Export Cut to China Seen as Clever Strate gy on	Yukos, the Russia n oil giant, is playin g a wea	export cut to china seen as clever strateg y on	[export, cut, to, china, seen, as, clever, str	[2467, 611, 4, 132, 541, 19, 11114, 1747, 13,

67200 rows × 8 columns

más larga dev_df['token ids'] = dev_df['tokens'].progress_map(token_ids) # Agrega una nueva columna al data frame con los ids de tokens

dev_df

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Out[22]:

	index	class index	class	title	descri ption	text	token s	token ids
0	11135 2	4	Sci/Te ch	Canon loses printer recycli ng case	Refillin g, reselli ng cartrid ges doesn' t violat	canon loses printer recycli ng case refillin g,	[canon, loses, printer, recycling, case, refil	[9579, 7233, 13568, 12520, 305, 40000 0, 1, 400
1	10205 3	4	Sci/Te ch	'EICU' Lets Doctor s Monito r Many Patien ts (AP)	AP - Your next doctor could be keepin g an eye	'eicu' lets doctor s monito r many patient s (ap)	['eicu, ', lets, doctor s, monito r, many, patie	[40000 0, 57, 8235, 1768, 3933, 109, 1615, 23,
2	50868	4	Sci/Te ch	Yahoo CEO Sees No Need	Reuter s - In an era of wides	yahoo ceo sees no need	[yahoo , ceo, sees, no, need,	[6600, 3695, 3109, 84, 408, 4,

	index	class index	class	title	descri ption	text	token s	token ids
				to Join Media Merge r Fr	pread media\ consol 	to join media merge r fr	to, join, media, 	1429, 493, 3176
3	27469	2	Sports	Sports view: Charg ers Are Surpri se Winne rs (AP)	AP - So the San Diego Charg ers shock ed the NFL	sports view: charge rs are surpris e winner s (ap)	[sports view, :, charge rs, are, surpris e, winne	[40000 0, 45, 12104, 32, 2661, 2945, 23, 1582,
4	66091	3	Busine ss	Stocks Fall on J.P. Morga n Chase and Oil	NEW YORK (Reute rs) - U.S. stocks fell on Wedn.	stocks fall on j.p. morga n chase and oil new	[stock s, fall, on, j.p., morga n, chase, and, o	[895, 807, 13, 12227, 3123, 4212, 5, 316, 50,
16795	10969 1	1	World	Forme r Marine Testifi es to Atrociti es in Iraq	A former U.S. Marine staff sergea nt testifie d	former marine testifie s to atrociti es in iraq	[forme r, marine , testifie s, to, atrociti es, in	[157, 2266, 27149, 4, 8088, 6, 233, 7, 157, 99

	index	class index	class	title	descri ption	text	token s	token ids
16796	35541	4	Sci/Te ch	Bloggi ng the Story Alive	Blogg ers force CBS News to admit to a seriou s	bloggi ng the story alive blogge rs force cbs ne	[bloggi ng, the, story, alive, blogge rs, force,	[30031 , 0, 523, 2977, 19305, 352, 3286, 172, 4
16797	10613 5	3	Busine ss	Gettin g your report	Consumers in Arizon a and 12 other Weste rn stat	getting your report consu mers in arizon a and 1	[gettin g, your, report, consu mers, in, arizon a	[881, 392, 255, 2034, 6, 2203, 5, 421, 68, 556
16798	61875	3	Busine ss	GM report s poor quarte rly profits	DETR OIT: Gener al Motors Corp posted on Thurs da	gm report s poor quarte rly profits detroit: gen	[gm, report s, poor, quarte rly, profits, detroi	[2907, 687, 992, 6206, 2243, 2369, 45, 216,
16799	40321	3	Busine ss	For Cingul ar, Beco ming No. 1	The union of Cingul ar and AT T	for cingul ar, becoming no. 1 also	[for, cingul ar, ,, becoming, no, .,	[10, 31779, 1, 1663, 84, 2, 176,

index	class index	class	title	descri ption	text	token s	token ids
			Also Poses Risks	Wirele ss would	poses risks 	1, also, p	52, 9734, 334

16800 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 [23]:

from torch.utils.data import Dataset

```
# Creas las clase de MyDataset
class MyDataset(Dataset):
    def __init__(self, x, y):
        self.x = x
        self.y = y

# Devuelve la longitud del dataset
    def __len__(self):
        return len(self.y)

# Obtiene el elemento en la posición index y lo convierte en un tensor de PyTorch
    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 [24]:

```
from torch import nn
import torch.nn.functional as F
# Creas la clase Model
class Model(nn.Module):
  def __init__(self, vectors, pad_id, hidden_dim, output_dim, dropout):
     super(). init ()
     # Verifica si 'vectors' es un tensor, de lo contrario, lo convierte
    if not torch.is tensor(vectors):
       vectors = torch.tensor(vectors)
     # Almacena el ID del padding
     self.padding idx = pad id
     # Crea la capa de embeddings a partir de los vectores preentrenados
     self.embs = nn.Embedding.from pretrained(vectors, padding idx=pad id)
     # Define las capas feedforward en una secuencia
     self.layers = nn.Sequential(
       nn.Dropout(dropout),
       nn.Linear(vectors.shape[1], hidden_dim),
       nn.ReLU(),
       nn.Dropout(dropout),
       nn.Linear(hidden_dim, output_dim),
    )
  def forward(self, x):
     # Obtiene un arreglo booleano donde los elementos de padding son marcados como
False
    not_padding = torch.isin(x, self.padding_idx, invert=True)
    # Calcula las longitudes de los ejemplos (excluyendo el padding)
    lengths = torch.count_nonzero(not_padding, axis=1)
    # Obtiene los embeddings para la entrada
    x = self.embs(x)
    # Calcula la media de los embeddings
    x = x.sum(dim=1) / lengths.unsqueeze(dim=1)
     # Pasa el resultado al resto del modelo
     output = self.layers(x)
```

```
# Calcula softmax si no estamos en modo de entrenamiento
#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 [25]:

```
from torch import optim
from torch.utils.data import DataLoader
from sklearn.metrics import accuracy score
```

```
# Hiperparámetros

Ir = 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
```

```
# Inicializa el modelo, la función de pérdida, el optimizador y el cargador de datos 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)
```

```
# Listas para almacenar pérdidas y precisiones de entrenamiento y desarrollo train_loss = [] train_acc = []
```

```
dev_loss = []
dev_acc = []
# Entrena el modelo
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)'):
     # Limpia los gradientes
    model.zero_grad()
     # Envía el lote al dispositivo correcto
    X = X.to(device)
    y_true = y_true.to(device)
     # Predice las puntuaciones de las etiquetas
    y_pred = model(X)
     # Calcula la pérdida
    loss = loss_func(y_pred, y_true)
     # Acumula para graficar
    losses.append(loss.detach().cpu().item())
     gold.append(y_true.detach().cpu().numpy())
     pred.append(np.argmax(y_pred.detach().cpu().numpy(), axis=1))
     # Realiza el backpropagate
    loss.backward()
     #Optimiza los parámetros del modelo
     optimizer.step()
  train_loss.append(np.mean(losses))
  train_acc.append(accuracy_score(np.concatenate(gold), np.concatenate(pred)))
  model.eval() # Establece el modelo en modo de evaluación
  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))
     # Almacena la pérdida y precisión promedio para el conjunto de desarrollo
     dev_loss.append(np.mean(losses))
     dev_acc.append(accuracy_score(np.concatenate(gold), np.concatenate(pred)))
```

epoch 1 (train): 0% | 0/135 [00:00<?, ?it/s] | 0/34 [00:00<?, ?it/s] epoch 1 (dev): 0%| epoch 2 (train): 0%| | 0/135 [00:00<?, ?it/s] | 0/34 [00:00<?, ?it/s] epoch 2 (dev): 0%| | 0/135 [00:00<?, ?it/s] epoch 3 (train): 0% epoch 3 (dev): 0% | 0/34 [00:00<?, ?it/s] epoch 4 (train): 0% | 0/135 [00:00<?, ?it/s] | 0/34 [00:00<?, ?it/s] epoch 4 (dev): 0%| epoch 5 (train): 0% | 0/135 [00:00<?, ?it/s]

Let's plot the loss and accuracy on dev:

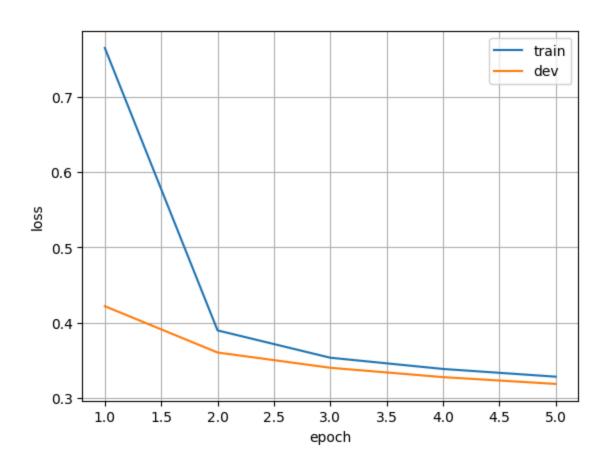
| 0/34 [00:00<?, ?it/s]

epoch 5 (dev): 0%|

In [26]:

Se crean graficas para ver los resultados de train_loss y dev_loss x = np.arange(n_epochs) + 1

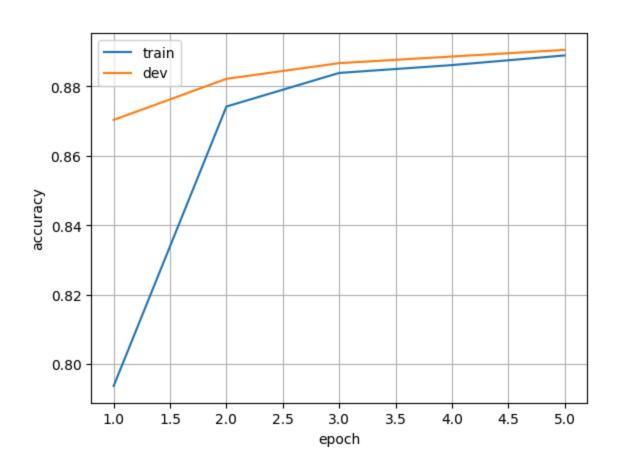
plt.plot(x, train_loss)
plt.plot(x, dev_loss)
plt.legend(['train', 'dev'])
plt.xlabel('epoch')
plt.ylabel('loss')
plt.grid(**True**)



In [27]:

Se crean graficas para ver los resultados de train_acc y dev_acc 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:

```
test df =
pd.read_csv('/kaggle/input/agnews-pytorch-simple-embed-classif-90/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 [29]:
from sklearn.metrics import classification_report
# Se pone el modelo en modo evaluacion
model.eval()
dataset = MyDataset(test_df['token ids'], test_df['class index'] - 1)
data_loader = DataLoader(dataset, batch_size=batch_size)
y_pred = []
# No se guardan los gradientes
with torch.no grad():
  for X, _ in tqdm(data_loader): # Itera sobre los lotes en el DataLoader
     X = X.to(device) # Envía los datos al dispositivo (CPU o GPU)
     # Predice la clase más probable para cada ejemplo en el lote
     y = torch.argmax(model(X), dim=1)
     # Convierte el tensor en un array numpy (y lo envía de regreso a la CPU si es necesario)
     y_pred.append(y.cpu().numpy())
     # Imprime los resultados
  print(classification_report(dataset.y, np.concatenate(y_pred), target_names=labels))
```

0%| | 0/16 [00:00<?, ?it/s]

		£4	
precision	recall	T1-score	support

World	0.92	0.87	0.90	1900
Sports	0.95	0.97	0.96	1900
Business	0.83	0.86	0.85	1900
Sci/Tech	0.87	0.86	0.86	1900

accuracy	0.8	9 760	00	
macro avg	0.89	0.89	0.89	7600
weighted avg	0.89	0.89	0.89	7600