Etape 3 : Construction d'un modèle amélioré exploitant les sections

Pluôt que de prendre brutalement les embeddings des textes comme dans l'étape 2, nous faisons le travail suivant sur le text:

- pour chaque section, on chunk des phrases de tailles < input du LLM
- on réalise les embeddings de section par mean pooling des embeddings des phrases de section
- on réalise l'embedding du brevet par mean pooling des embeddings des sections

```
import json
import matplotlib.pyplot as plt
from tqdm import tqdm
import numpy as np
import warnings
warnings.filterwarnings("ignore")
import pickle

from sentence_transformers import SentenceTransformer
from sentence_transformers.util import cos_sim
from sentence_transformers.quantization import quantize_embeddings
from sentence_transformers import losses
from sentence_transformers.readers import InputExample
from torch.utils.data import DataLoader
from transformers import AutoTokenizer
```

Creation des embeddings par groupe de phrases sur le brevet entier

On divise chaque section du brevet en phrases de nb_tokens < 512 pour réaliser les embeddings des phrases. Puis on moyenne les embeddings

```
In [2]: with open('../data/dataset_patent_sections.json', 'r') as outfile:
    dataset_patent_section = json.load(outfile)
    outfile.close()

In [3]: def get_text_sentences_from_tokenizer(text, tokenizer, dimensions = 512):
        Recuperation de la liste de phrases qui ont une taille inferieure a la consection -- str, le texte dont on veut recuperer la liste de phrases
        list_tokens = tokenizer.tokenize(text)
        list_sentences = []
        for i in range(int(len(list_tokens)/dimensions)+1):
            sentence = ' '.join(list_tokens[dimensions*i:dimensions*(i+1)])
            list_sentences.append(sentence)
```

```
return list_sentences
         def get patent text sentences from tokenizer(patent, tokenizer, dimensions =
             Recuperation de la list de phrases constituant le brevet. Ici le brevt e
             patent -- list, representation du dictionnaire en sections
             list_sentences = []
             for i in range(len(patent)):
                 text = patent[i]['content']
                 list_sentences_text = get_text_sentences_from_tokenizer(text,
                                                                          tokenizer,
                                                                          dimensions =
                 list_sentences += list_sentences_text
             return list sentences
In [82]: # Calcul des embeddings de tous les brevets comme moyenne des embeddings de
         # model_name = "mixedbread-ai/mxbai-embed-large-v1"
         model name = 'intfloat/e5-small-v2'
         tokenizer = AutoTokenizer.from pretrained(model name)
         dimensions = 512
         model = SentenceTransformer(model name, truncate dim=dimensions, revision=Nd
         dataset_patent_section_embeddings = {}
         for i in tqdm(range(len(dataset_patent_section)), desc ="Calcul des embeddir
             dataset_patent_section_embeddings[str(i)] = {}
             for key in ['pos', 'negative']:
                 list sentences = get patent text sentences from tokenizer(dataset pa
                                                                            tokenizer,
                                                                            dimensions
                 embeddings = model.encode(list sentences)
                 patent embedding = np.mean(embeddings, axis=0)
                 dataset_patent_section_embeddings[str(i)][key] = patent_embedding
        tokenizer config.json:
                                 0%|
                                              | 0.00/314 [00:00<?, ?B/s]
                                  | 0.00/232k [00:00<?, ?B/s]
        vocab.txt:
                     0%|
        tokenizer.json:
                          0%|
                                       | 0.00/711k [00:00<?, ?B/s]
        special_tokens_map.json:
                                   0%|
                                                | 0.00/125 [00:00<?, ?B/s]
        modules.json:
                                     | 0.00/387 [00:00<?, ?B/s]
                      0%|
        README.md:
                     0%|
                                  | 0.00/67.8k [00:00<?, ?B/s]
        sentence_bert_config.json: 0%|
                                                  | 0.00/57.0 [00:00<?, ?B/s]
        config.json: 0%|
                                    | 0.00/615 [00:00<?, ?B/s]
        model.safetensors:
                                          | 0.00/133M [00:00<?, ?B/s]
                             0%|
        1_Pooling/config.json:
                                0%|
                                              | 0.00/200 [00:00<?, ?B/s]
                                          0%|
        Calcul des embeddings initiaux:
        | 0/499 [00:00<?, ?it/s]Token indices sequence length is longer than the spe
        cified maximum sequence length for this model (587 > 512). Running this sequ
        ence through the model will result in indexing errors
        Calcul des embeddings initiaux: 100%
                        || 499/499 [34:36<00:00, 4.16s/it]
```

```
embeddings = model.encode(list sentences)
             patent embedding = np.mean(embeddings, axis=0)
             dataset_patent_section_embeddings[str(i)]['query'] = patent_embedding
        Calcul des embeddings des query: 100%
                        | 499/499 [00:10<00:00, 46.99it/s]
In [88]: with open('../data/patent_sections_embeddings_e5-small-v2.pickle', 'wb') as
             pickle.dump(dataset patent section embeddings, fh)
             fh.close()
 In [4]: with open('../data/patent_sections_embeddings_e5-small-v2.pickle', 'rb') as
             dataset patent section embeddings = pickle.load(fh)
             fh.close()
 In [5]: # Performances -- classification
         nb good embeddings = 0
         for i in range(len(dataset_patent_section_embeddings)):
             embeddings = [
                 dataset patent section embeddings[str(i)]['query'],
                 dataset patent section embeddings[str(i)]['pos'],
                 dataset_patent_section_embeddings[str(i)]['negative']
             similarities = cos sim(embeddings[0], embeddings[1:])
             sim_pos, sim_neg = similarities.flatten()
             if sim_pos > sim_neg :
                 nb good embeddings+=1
         perc_good_embeddings = round(100*nb_good_embeddings/len(dataset_patent_secti)
         print('Embeddings de documents compatibles avec la query: {}, {} %'.format(r
        Embeddings de documents compatibles avec la guery: 450, 90.18 %
In [10]: # Performances -- top_K_accuracy
         list_all_embeddings = []
         for i in range(len(dataset patent section embeddings)):
             emb query = dataset patent section embeddings[str(i)]['query']
             emb pos = dataset patent section embeddings[str(i)]['pos']
             emb neg = dataset patent section embeddings[str(i)]['negative']
             list_all_embeddings.append([emb_query, emb_pos, emb_neg])
         def compute top K accuracy score(list embeddings, K=5):
             Fonction pour calculer le top_K_accuracy score a partir d'une liste d'en
             [[emb query, emb pos, emb neq]...]
             list_embeddings -- list, list des embeddings des query, positive, negati
             K -- int, le top K accuracy
             list embeddings query = [list embeddings[i][0] for i in range(len(list a
             list embeddings pos = [list embeddings[i][1] for i in range(len(list all
             list_embeddings_neg = [list_embeddings[i][2] for i in range(len(list_all
             nb_pos = 0
             nb_neg = 0
             for idx in tqdm(range(len(list embeddings query)), desc ="Calcul du top"
```

```
query = list_embeddings_query[idx]
                similarities pos = cos sim(query, list embeddings pos).flatten().tol
                similarities_pos = [('pos_{}'.format(i), similarities_pos[i]) for i
                similarities_neg = cos_sim(query, list_embeddings_neg).flatten().tol
                similarities_neg = [('neg_{}'.format(i), similarities_neg[i]) for i
                similarities = similarities pos+similarities neg
                similarities = sorted(similarities, key = lambda x: -x[1])
                top_K_ids = [similarities[i][0] for i in range(K)]
                if 'pos_{}'.format(idx) in top_K_ids:
                    nb pos += 1
                if 'neg_{}'.format(idx) in top_K_ids:
                    nb_neg+=1
            acc_K_pos = nb_pos/len(list_embeddings)
            acc_K_neg = nb_neg/len(list_embeddings)
            return acc_K_pos, acc_K_neg
        acc_K_pos, acc_K_neg = compute_top_K_accuracy_score(list_all_embeddings, K=5
        print('acc_K_pos : {} (a maximiser)'.format(acc_K_pos))
        print('acc_K_neg : {} (a minimiser)'.format(acc_K_neg))
       Calcul du top_K_accuracy score: 100%
                     499/499 [00:43<00:00, 11.55it/s]
       acc K pos : 0.9338677354709419 (a maximiser)
       acc K neg : 0.4168336673346693 (a minimiser)
In [ ]:
```