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Attempting to Bring Order to Chaos: Clustering Medium Article Titles with DistilBERT

Tarek · Follow

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In this blog post, we'll introduce you to "DistilBERT," a variant of BERT, and show you how to combine it with Gaussian Mixture Models to cluster medium article titles. We will use real examples from popular publications like "Towards Data Science" and "The Startup," you'll gain a better understanding of how this powerful technique can be used to automatically organize titles.

What is DistilBERT?

DistilBERT is a lightweight version of BERT (Bidirectional Encoder Representations from Transformers), a pre-trained language model that uses a transformer architecture to understand the context of words in a sentence. DistilBERT was created by compressing the original BERT model, resulting in a smaller and faster model that maintains its accuracy and effectiveness.

Although DistilBERT may not match BERT's performance in more complex language tasks, it should suffice for title clustering purposes.

What is Gaussian Mixture Models (GMM)?

Gaussian Mixture Models (GMM) is a clustering algorithm that is used to group data points into clusters based on their similarity. The algorithm is based on the assumption that the data points in a cluster are normally distributed, and the algorithm tries to find the parameters that define these distributions.

Combining DistilBERT and GMM for Title Clustering

By combining DistilBERT and GMM, we can automate the process of categorizing article titles. We first use DistilBERT to extract meaningful representations of each title, which can then be used by GMM to cluster the titles based on their similarity.

To demonstrate this process, we will use a dataset of medium article titles from two publications “Towards Data Science”, “UX Collective” and “The Startup.”

Running DistilBERT to Extract Title Embeddings

```
import torch
import numpy as np
from transformers import AutoTokenizer, AutoModel

model_name = 'distilbert-base-cased'
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModel.from_pretrained(model_name)

title_embeddings = []
for title in titles:
    encoding = tokenizer.encode_plus(
        title,
        add_special_tokens=True,
        max_length=128,
        pad_to_max_length=True,
        return_attention_mask=True,
        return_tensors='pt'
    )
    with torch.no_grad():
        embedding = model(encoding['input_ids'], encoding['attention_mask'])[0][
        title_embeddings.append(embedding.numpy())
title_embeddings = np.array(title_embeddings).squeeze()
```

In this code, we utilize the DistilBERT model to generate embeddings for a list of medium article titles. It first tokenizes each title using the model’s tokenizer, and generates an embedding for each title using the DistilBERT model. The resulting embeddings can be used for various natural language processing tasks, such as clustering similar article titles which we will do next.

Clustering the Titles

```
from sklearn.mixture import GaussianMixture
clusters = GaussianMixture(n_components=3).fit_predict(title_embeddings)
```

This Python code uses the Gaussian Mixture Model (GMM) algorithm to cluster the embeddings generated by DistilBERT. The code first specifies the number of clusters to generate using the GMM algorithm. It then fits the GMM algorithm to the title embeddings, generating cluster assignments for each title. These assignments are added to a list, which can be used for various natural language processing tasks, such as grouping similar article titles together.

Next, we assign each title to its cluster list using the following code:

```
title_clusters = []
for i in range(len(np.unique(clusters))):
    cluster_titles = []
    for j, title in enumerate(titles):
        if clusters[j] == i:
            cluster_titles.append(title)
    title_clusters.append(cluster_titles)
```

Results

To get a sense of the clustering quality, we can inspect the first 5titles in each cluster:

```
for idx, cluster in enumerate(title_clusters):
    print(f'Cluster {idx}:')
    print('\n'.join(np.random.choice(cluster, 5)))
    print()
```

This will return:

```
Cluster 0: [Seems to be related to Towards Data Science topics]
Visualized Linear Algebra to Get Started with Machine Learning: Part 2
Hacking Causal Inference: Synthetic Control with ML approaches
Performance Estimation Techniques for Machine Learning Models
Claymorphism in user interfaces
How I Address Direct Questions on My Competitors as a 1-Man Consultant

Cluster 1: [Seems to be related to UX Collection topics]
Screen time: the next plastic?
Google wants you to test LaMDA; how UX research can help it outperform
The Vignelli Canon: A design classic from the last of the modernists
Standing at the crossroads of authenticity and career advancement
Product design is going down a weird path, but we can still save it

Cluster 2: [Seems to be related to The Startup topics]
I Tried Substack for a Month, You Won't Believe What Happened
What I'm Doing as the Recession Gets Worse (To Avoid Going Broke)
Your Results Will Only Change When You Do
5 New Side Hustles You Didn't Even Know Existed
4 Easy Tips To Make the Most Out of LinkedIn as a Newbie Writer
```

For a more aesthetically pleasing summarization of each cluster, we can use word clouds:

```
def show_word_cloud(cluster):
    words = [word.lower() for title in cluster for word in title.split() if "'"
    text = " ".join(words)
    wordcloud = WordCloud(width = 800, height = 800,
```

```
                        background_color ='white',
                        stopwords = STOPWORDS,
                        min_font_size = 10).generate(text)

    plt.figure(figsize = (2, 2), facecolor = None)
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad = 0)

    plt.show()
```

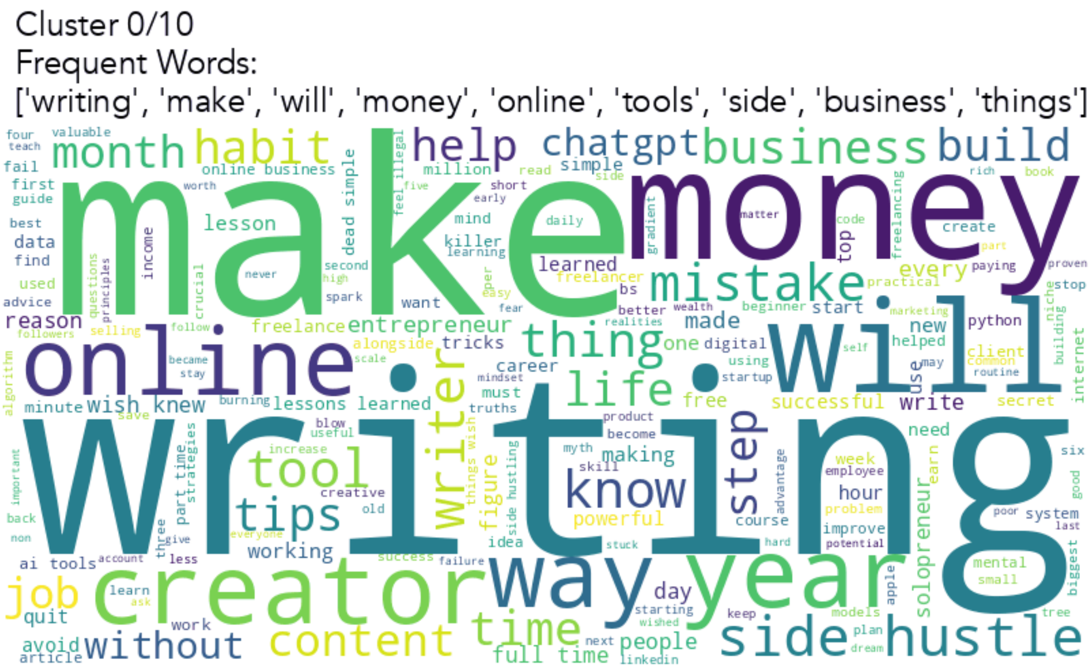
This code takes a cluster as input and plots a word cloud, here you can see all generated word clouds:

WordClouds for all three clusters.

Can you take a guess and pair each cluster with its corresponding publication? ;)

Want More Clusters?

If you would like to see how the quality changes when using more clusters? Check out this GIF that demonstrates clustering with 10 clusters.



WordClouds for 10 clusters with frequest words in each.

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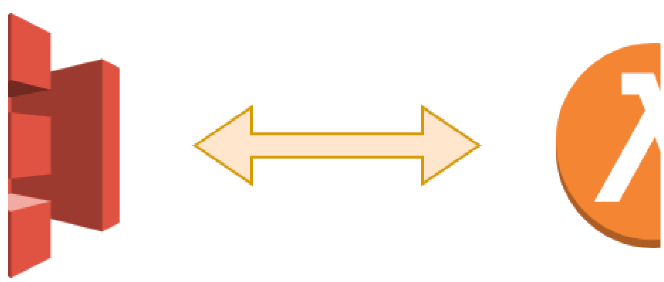

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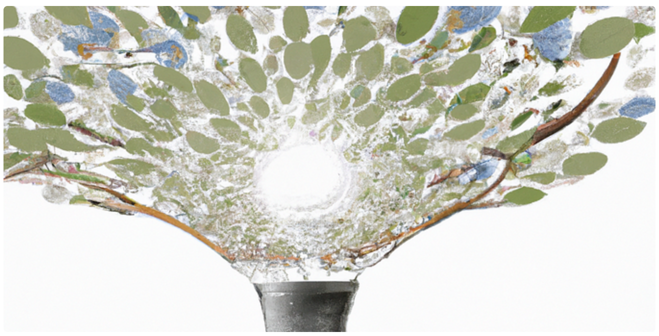

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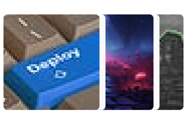

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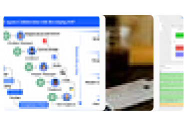

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