00_analyze_method_similarity_new

October 12, 2024

1 Imports

[8]:
```
import json
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from transformers import CLIPTokenizer, CLIPModel
from sentence_transformers import SentenceTransformer
import Levenshtein
import numpy as np
import torch
```

2 Load data

[9]:
```
with open('../data/pwc/methods.json', 'r') as f:
    methods_data = json.load(f)
```

[10]:
```
methods_data[0]
```

[10]:

```
{'url': 'https://paperswithcode.com/method/sig',
 'name': 'SIG',
 'full_name': 'Sliced Iterative Generator',
 'description': 'The **Sliced Iterative Generator (SIG)** is an iterative
generative model that is a Normalizing Flow (NF), but shares the advantages of
Generative Adversarial Networks (GANs). The model is based on iterative Optimal
Transport of a series of 1D slices through the data space, matching on each
slice the probability distribution function (PDF) of the samples to the data. To
improve the efficiency, the directions of the orthogonal slices are chosen to
maximize the PDF difference between the generated samples and the data using
Wasserstein distance at each iteration. A patch based approach is adopted to
model the images in a hierarchical way, enabling the model to scale well to high
dimensions. \r\n\r\nUnlike GANs, SIG has a NF structure and allows efficient
likelihood evaluations that can be used in downstream tasks. While SIG has a
```

deep neural network architecture, the approach deviates significantly from the
current deep learning paradigm, as it does not use concepts such as mini-
batching, stochastic gradient descent, gradient back-propagation through deep
layers, or non-convex loss function optimization. SIG is very insensitive to
hyper-parameter tuning, making it a useful generator tool for ML experts and
non-experts alike.',
 'paper': {'title': 'Sliced Iterative Normalizing Flows',
  'url': 'https://paperswithcode.com/paper/sliced-iterative-generator'},
 'introduced_year': 2000,
 'source_url': 'https://arxiv.org/abs/2007.00674v3',
 'source_title': 'Sliced Iterative Normalizing Flows',
 'code_snippet_url': 'https://github.com/biweidai/SIG',
 'num_papers': 15,
 'collections': [{'collection': 'Generative Models',
   'area_id': 'computer-vision',
   'area': 'Computer Vision'}]}

3 Filter data

For the analysis I use the 'name' and 'description' of the mathods that belong to exactly one collection and that collection is not 'General'

[11]:
```
flat_data = []
for item in methods_data:
    if len(item["collections"]) == 1:
        area = item["collections"][0]["area"]
        if area != 'General':
            flat_data.append({
                "name": item["name"],
                "description": item["description"],
                "area": area
            })
```

[12]:
```
len(flat_data)
```

[12]: 1064

[13]:
```
df = pd.DataFrame(flat_data)
```

This is the final amount of data left after filtering

[14]:
```
df['area'].value_counts()
```

[14]:
```
area
Computer Vision                665
Natural Language Processing    119
Graphs                         104
```

```
Reinforcement Learning         88
Sequential                     53
Audio                          35
Name: count, dtype: int64
```

4 Define the embeddings

TF-IDF

[15]:
```
def compute_tfidf(text_list):
    vectorizer = TfidfVectorizer(stop_words='english', max_features=3000,␣
 ↪sublinear_tf=True)
    vectors = vectorizer.fit_transform(text_list)
    return vectors.toarray()
```

Sentence-BERT embedding

[16]:
```
model_bert = SentenceTransformer('all-MiniLM-L6-v2')

def compute_sentence_embeddings(text_list, batch_size=256):
    embeddings = []
    text_list = [text.strip() for text in text_list]

    for i in range(0, len(text_list), batch_size):
        batch = text_list[i:i + batch_size]
        batch_embeddings = model_bert.encode(batch)
        embeddings.append(batch_embeddings)

    # Concatenate all batch embeddings
    return np.vstack(embeddings)
```

```
/home/jenifer/.local/lib/python3.10/site-
packages/transformers/tokenization_utils_base.py:1617: FutureWarning:
`clean_up_tokenization_spaces` was not set. It will be set to `True` by default.
This behavior will be deprecated in transformers v4.45, and will be then set to
`False` by default. For more details check this issue:
https://github.com/huggingface/transformers/issues/31884
  warnings.warn(
```

OpenAI CLIP embedding

[17]:
```
model_clip = CLIPModel.from_pretrained("openai/clip-vit-base-patch32")
tokenizer = CLIPTokenizer.from_pretrained("openai/clip-vit-base-patch32")

def compute_clip_embeddings(text_list, batch_size=256):
    embeddings = []
    for i in range(0, len(text_list), batch_size):
        batch = text_list[i:i + batch_size]
```

```
        inputs = tokenizer(batch, padding=True, truncation=True,␣
↪return_tensors="pt")
        with torch.no_grad():
            batch_embeddings = model_clip.get_text_features(**inputs).cpu().
↪numpy()
        embeddings.append(batch_embeddings)
    return np.vstack(embeddings)
```

5 Calculate the embeddings

[18]:
```
names = df['name'].tolist()
descriptions = df['description'].tolist()
```

[19]:
```
names_tfidf = compute_tfidf(names)
descriptions_tfidf = compute_tfidf(descriptions)
```

[20]:
```
sentence_embeddings_names = compute_sentence_embeddings(names)
sentence_embeddings_descriptions = compute_sentence_embeddings(descriptions)
```

[21]:
```
clip_embeddings_names = compute_clip_embeddings(names)
clip_embeddings_descriptions = compute_clip_embeddings(descriptions)
```

6 Reduce dimensionality for the plot

[22]:
```
def reduce_dimensionality(embeddings, method='pca'):
    if method == 'pca':
        pca = PCA(n_components=2)
        reduced = pca.fit_transform(embeddings)
    elif method == 'tsne':
        tsne = TSNE(n_components=2, random_state=42)
        reduced = tsne.fit_transform(embeddings)
    return reduced
```

[23]:
```
reduced_names_tfids = reduce_dimensionality(names_tfidf, method='tsne')
reduced_descriptions_tfidf = reduce_dimensionality(descriptions_tfidf,␣
↪method='tsne')
```

[24]:
```
reduced_embeddings_names = reduce_dimensionality(sentence_embeddings_names,␣
↪method='tsne')
reduced_embeddings_descriptions =␣
↪reduce_dimensionality(sentence_embeddings_descriptions, method='tsne')
```

[25]:
```
reduced_clip_names = reduce_dimensionality(clip_embeddings_names, method='tsne')
```

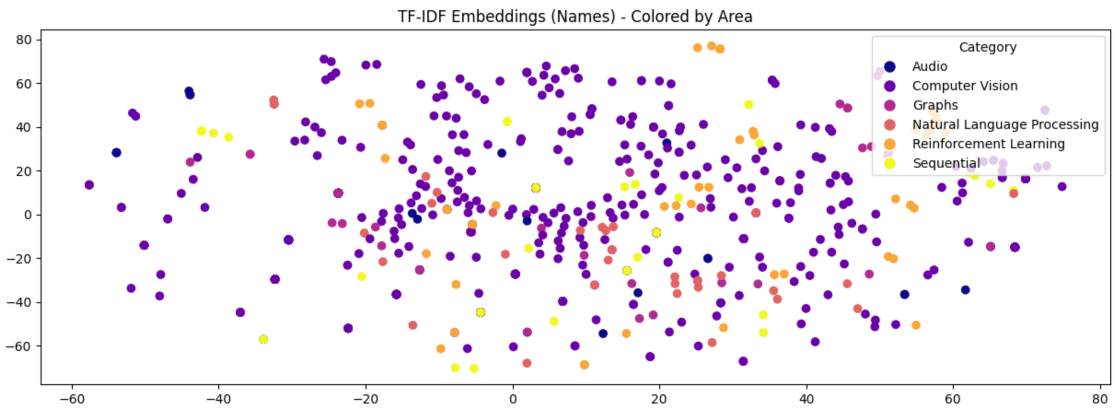
```
reduced_clip_descriptions = reduce_dimensionality(clip_embeddings_descriptions,␣
↪method='tsne')
```

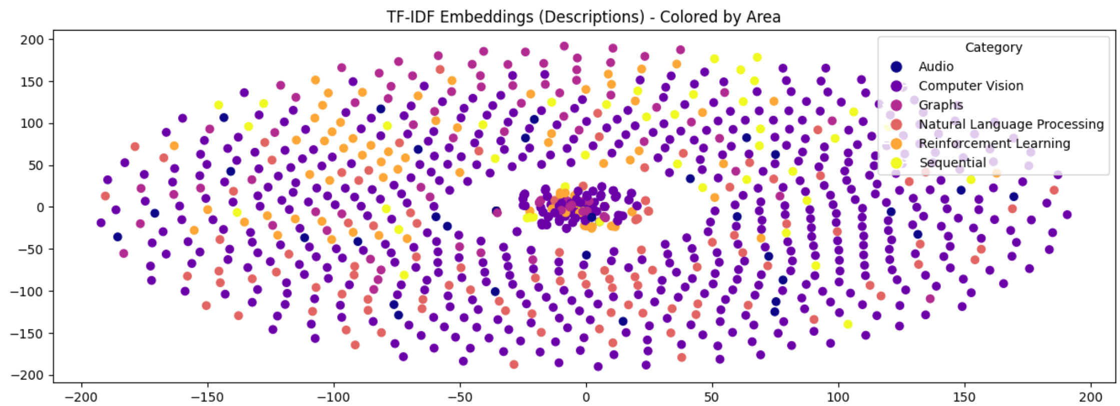
7 Plot

[26]:
```
def plot_embeddings(embeddings, color_by, title, color_map):
    plt.figure(figsize=(15, 5))

    # Convert color_by into a categorical type and get unique categories
    categories = pd.Categorical(color_by)
    category_codes = categories.codes
    category_labels = categories.categories

    # Create scatter plot
    scatter = plt.scatter(embeddings[:, 0], embeddings[:, 1], c=category_codes,␣
↪cmap=color_map)

    plt.title(title)

    # Create a custom legend
    unique_categories = np.unique(category_codes)
    legend_elements = [plt.Line2D([0], [0], marker='o', color='w',␣
↪markerfacecolor=scatter.cmap(scatter.norm(code)), markersize=10)
                       for code in unique_categories]
    plt.legend(legend_elements, category_labels, title="Category", loc="upper␣
↪right")

    plt.show()
```

7.1 Plot TF-IDF Embeddings

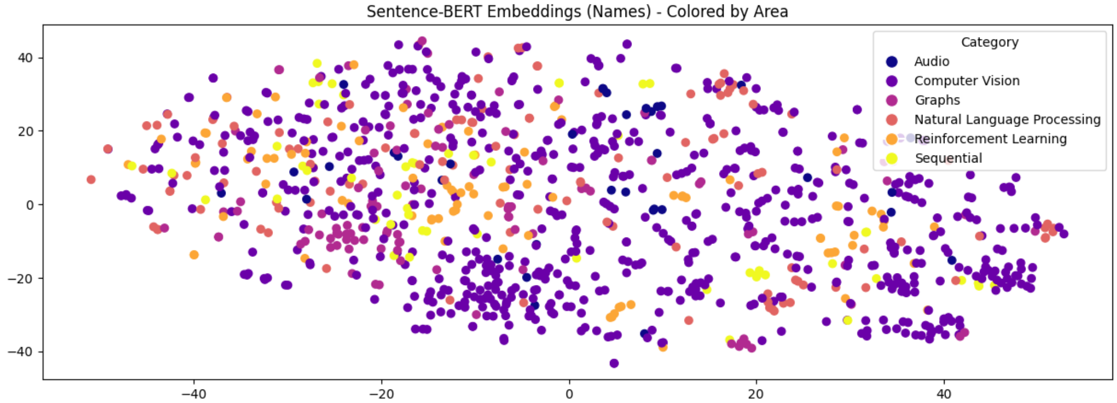
[27]:
```
plot_embeddings(reduced_names_tfids, df['area'], 'TF-IDF Embeddings (Names) -␣
↪Colored by Area', 'plasma')
plot_embeddings(reduced_descriptions_tfidf, df['area'], 'TF-IDF Embeddings␣
↪(Descriptions) - Colored by Area', 'plasma')
```

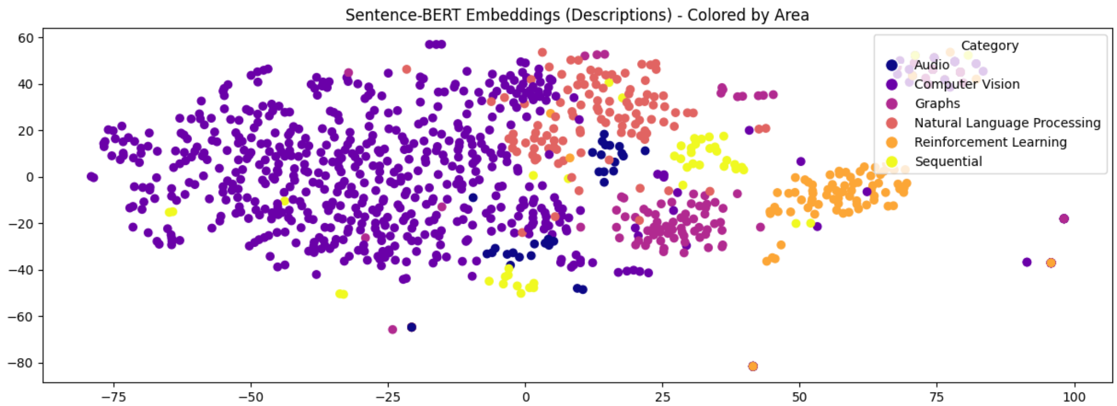




7.2 Plot Sentence-BERT Embeddings

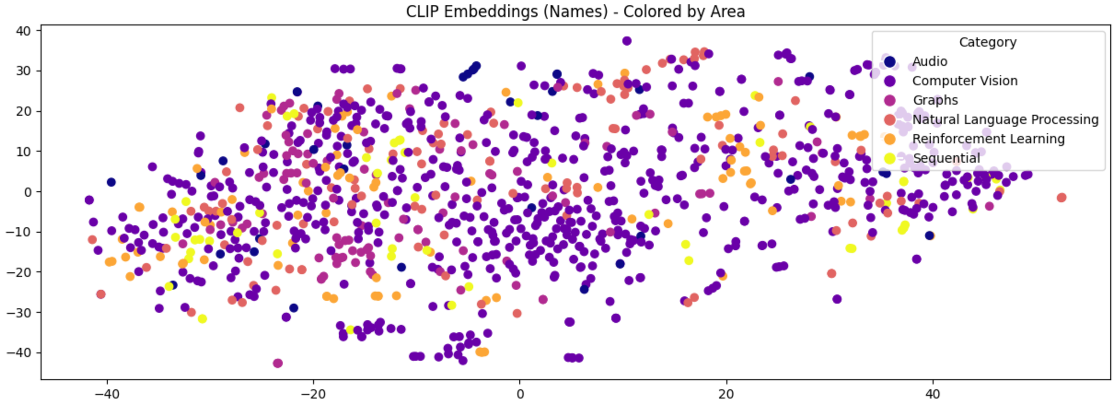
[28]:
```
plot_embeddings(reduced_embeddings_names, df['area'], 'Sentence-BERT Embeddings␣
↪(Names) - Colored by Area', 'plasma')
plot_embeddings(reduced_embeddings_descriptions, df['area'], 'Sentence-BERT␣
↪Embeddings (Descriptions) - Colored by Area', 'plasma')
```

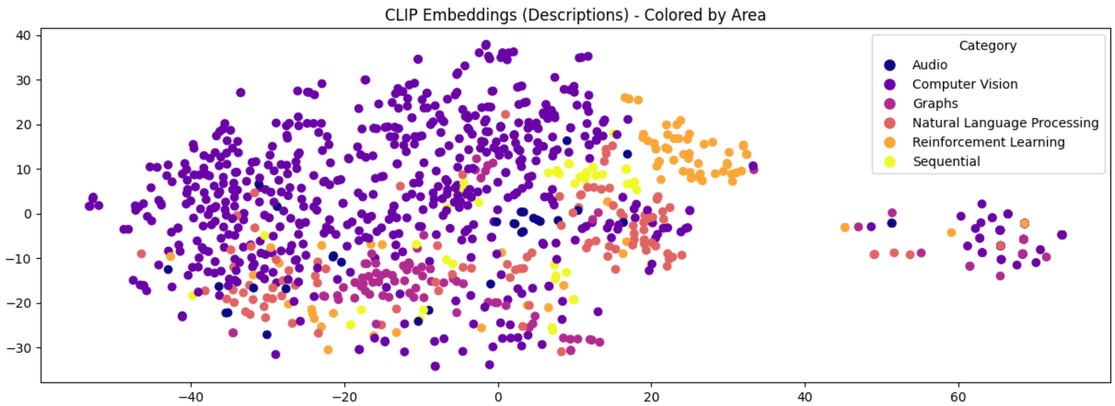




7.3 Plot CLIP Embeddings

[29]:
```
plot_embeddings(reduced_clip_names, df['area'], 'CLIP Embeddings (Names) -␣
↪Colored by Area', 'plasma')
plot_embeddings(reduced_clip_descriptions, df['area'], 'CLIP Embeddings␣
↪(Descriptions) - Colored by Area', 'plasma')
```





[30]:
```
from sklearn.metrics import silhouette_score, calinski_harabasz_score,␣
↪davies_bouldin_score
```

[31]:
```
def evaluate_clustering_metrics(X, y, embedding_name, source_text):
    print(f'Clustering metrics for {embedding_name} - {source_text}:')
    # Calculate metrics
    silhouette_avg = silhouette_score(X, y)
    calinski_harabasz = calinski_harabasz_score(X, y)
    davies_bouldin = davies_bouldin_score(X, y)

    # Return results in a dictionary
    metrics = {
        'Silhouette Score': silhouette_avg,
        'Calinski-Harabasz Index': calinski_harabasz,
        'Davies-Bouldin Index': davies_bouldin
    }

    table = [["Metric", "Score"]]
```

```python
    for metric, score in metrics.items():
        table.append([metric, f"{score:.4f}"])

    print(f'Clustering metrics for {embedding_name} (OvR Random Forest) -␣
↪{source_text}:')
    print(f'Silhouette Score: {silhouette_avg:.4f}')
    print(f'Calinski-Harabasz Index: {calinski_harabasz:.4f}')
    print(f'Davies-Bouldin Index: {davies_bouldin:.4f}')
```

[47]:
```python
evaluate_clustering_metrics(reduced_names_tfids, df['area'], 'TF-IDF', 'Names')
```

```
Clustering metrics for TF-IDF - Names:
Clustering metrics for TF-IDF (OvR Random Forest) - Names:
Silhouette Score: -0.0998
Calinski-Harabasz Index: 2.1983
Davies-Bouldin Index: 25.1087
```

[48]:
```python
evaluate_clustering_metrics(reduced_descriptions_tfidf, df['area'], 'TF-IDF',␣
↪'Descriptions')
```

```
Clustering metrics for TF-IDF - Descriptions:
Clustering metrics for TF-IDF (OvR Random Forest) - Descriptions:
Silhouette Score: -0.1325
Calinski-Harabasz Index: 18.9289
Davies-Bouldin Index: 9.3969
```

[49]:
```python
evaluate_clustering_metrics(reduced_embeddings_names, df['area'], 'TF-IDF',␣
↪'Names')
```

```
Clustering metrics for TF-IDF - Names:
Clustering metrics for TF-IDF (OvR Random Forest) - Names:
Silhouette Score: -0.1083
Calinski-Harabasz Index: 6.9565
Davies-Bouldin Index: 21.5425
```

[46]:
```python
evaluate_clustering_metrics(reduced_embeddings_descriptions, df['area'],␣
↪'TF-IDF', 'Descriptions')
```

```
Clustering metrics for TF-IDF - Descriptions:
Clustering metrics for TF-IDF (OvR Random Forest) - Descriptions:
Silhouette Score: 0.0169
Calinski-Harabasz Index: 14.5111
Davies-Bouldin Index: 4.5539
```

[50]:
```python
evaluate_clustering_metrics(reduced_clip_names, df['area'], 'TF-IDF', 'Names')
```

```
Clustering metrics for TF-IDF - Names:
Clustering metrics for TF-IDF (OvR Random Forest) - Names:
```

```
Silhouette Score: -0.0997
Calinski-Harabasz Index: 6.3118
Davies-Bouldin Index: 10.6563
```

[51]:
```
evaluate_clustering_metrics(reduced_clip_descriptions, df['area'], 'TF-IDF',␣
↪'Descriptions')
```

```
Clustering metrics for TF-IDF - Descriptions:
Clustering metrics for TF-IDF (OvR Random Forest) - Descriptions:
Silhouette Score: -0.0788
Calinski-Harabasz Index: 19.1802
Davies-Bouldin Index: 6.1514
```