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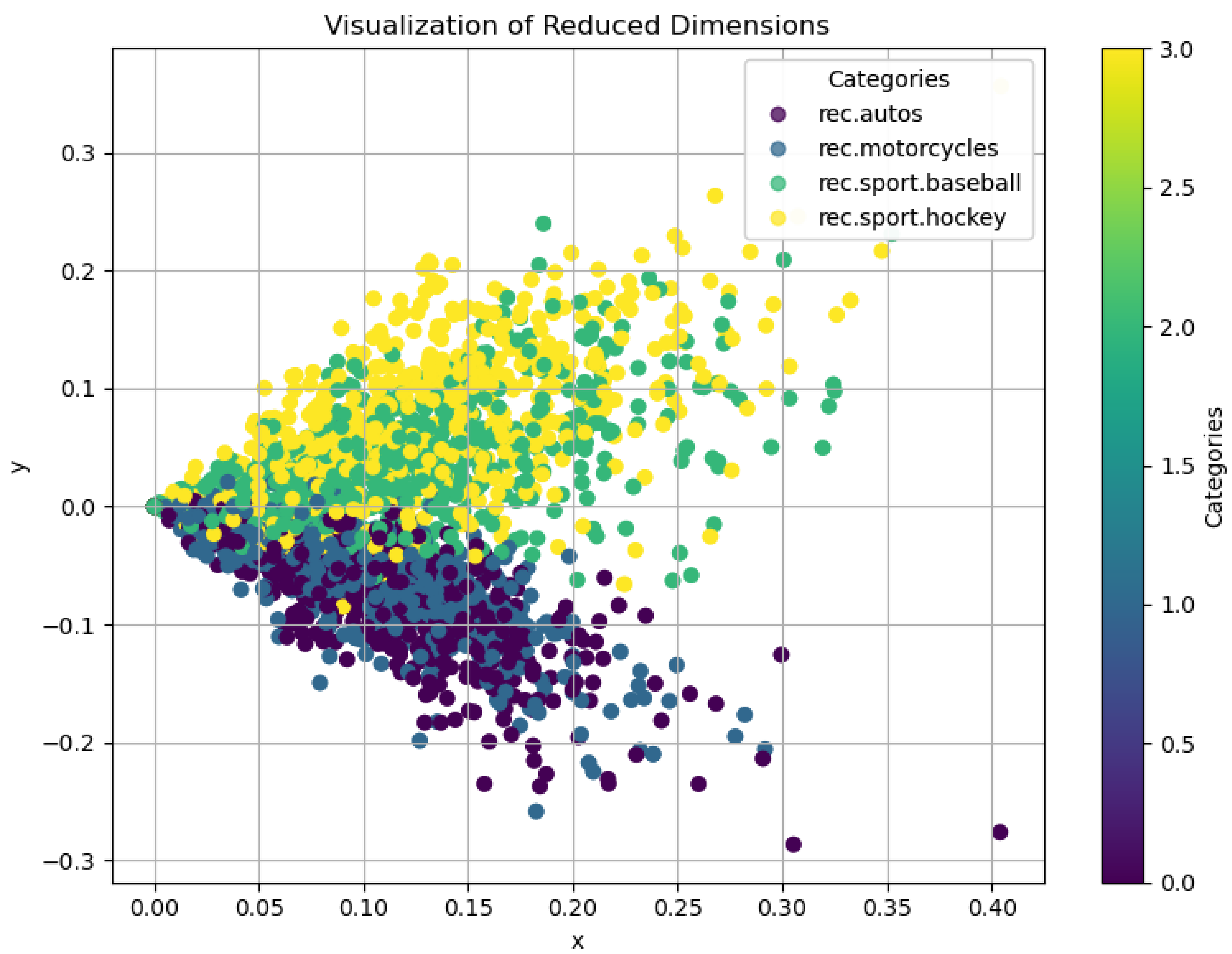
Exercise 11

DATA.STAT.840 Statistical Methods for Text Data Analysis

In [26]:

```
import nltk
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import TruncatedSVD
from sklearn.datasets import fetch_20newsgroups
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
import matplotlib.pyplot as plt
import sklearn
import sklearn.decomposition
import sklearn.manifold
nltk.download('stopwords')
import gensim
import numpy, hmmlearn, hmmlearn.hmm


stop_words = 'english'

categories = ['rec.autos', 'rec.motorcycles', 'rec.sport.baseball', 'rec.sport.hockey']

newsgroups_data = fetch_20newsgroups(subset='train', categories=categories, remove=('headers', 'footers', 'quotes'))


tfidf_vectorizer = TfidfVectorizer(stop_words=stop_words, max_features=5000)
tfidf_matrix = tfidf_vectorizer.fit_transform(newsgroups_data.data)

n_components = 100

svd = TruncatedSVD(n_components=n_components, random_state=42)
lsa_matrix = svd.fit_transform(tfidf_matrix)

num_clusters = 4
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
cluster_labels = kmeans.fit_predict(lsa_matrix)

category_names = ['rec.autos', 'rec.motorcycles', 'rec.sport.baseball', 'rec.sport.hockey']
plt.figure(figsize=(8, 6))
scatter = plt.scatter(lsa_matrix[:, 0], lsa_matrix[:, 1], c=newsgroups_data.target, cmap='viridis', alpha=0.7)


legend1 = plt.legend(handles=scatter.legend_elements()[0], labels=category_names, title='Categories', loc='upper right')
plt.gca().add_artist(legend1)

plt.scatter(lsa_matrix[:, 0], lsa_matrix[:, 1], c=newsgroups_data.target)
plt.title('Visualization of Reduced Dimensions')
plt.xlabel('x')
plt.ylabel('y')
plt.colorbar(label='Categories')

plt.grid(True)
plt.tight_layout()
plt.show()
```

```
[nltk_data] Downloading package stopwords to /home/ahmad/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
/home/ahmad/anaconda3/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of `n_i
nit` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

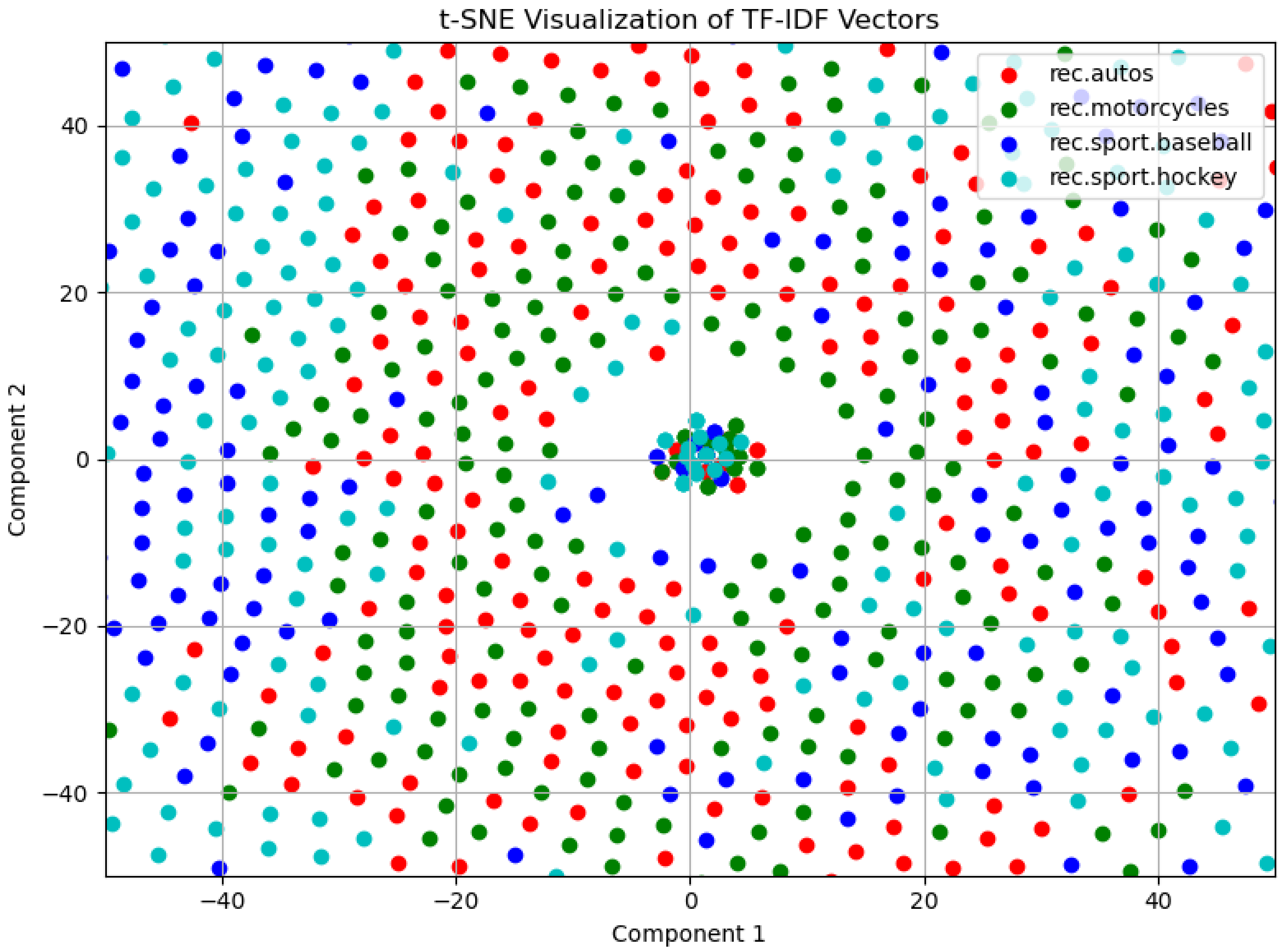


According to graph, Baseball and Hockey has correlated. Additionally, autos and motorcycles meet in same region.

Exercise 11.2: t-SNE plot of four newsgroups. Using the same data as in exercise 6.1 (four newsgroups), use the t-distributed stochastic neighbor embedding (t-SNE) method to reduce the TF- IDF vectors of the documents (as computed in exercise 6.1) to two dimensions. Plot the resulting two-dimensional vectors; plot the documents of the different four newsgroups with different colors. Discuss the results: does the t-SNE plot tell something about the distribution of the document features? You can use the Python implementation discussed on the lecture (lecture 11, slide 7), or another language/library of your choice.

In [24]:
```
subset_indices = np.random.permutation(tfidf_matrix.shape[0])[:1000]
X_small = tfidf_matrix[subset_indices, :].toarray()

tsne_model = sklearn.manifold.TSNE(n_components=2, verbose=1, perplexity=20, n_iter=400)
tsne_plot = tsne_model.fit_transform(X_small)

plt.figure(figsize=(8, 6))
colors = ['r', 'g', 'b', 'c']
for i, category in enumerate(newsgroups_data.target_names):
    indices = np.where(newsgroups_data.target[subset_indices] == i)
    plt.scatter(tsne_plot[indices, 0], tsne_plot[indices, 1], c=colors[i], label=category)

plt.title('t-SNE Visualization of TF-IDF Vectors')
plt.xlabel('Component 1')
plt.ylabel('Component 2')
plt.legend()
plt.grid(True)
plt.tight_layout()

plt.axis([-50, 50, -50, 50])

# Show the plot
plt.show()
```

```
[t-SNE] Computing 61 nearest neighbors...
[t-SNE] Indexed 1000 samples in 0.003s...
[t-SNE] Computed neighbors for 1000 samples in 0.320s...
[t-SNE] Computed conditional probabilities for sample 1000 / 1000
[t-SNE] Mean sigma: 0.000000
[t-SNE] KL divergence after 250 iterations with early exaggeration: 48.950615
[t-SNE] KL divergence after 400 iterations: 0.702027
```



Exercise 11.3: Word embedding. In this exercise we use the same data as in exercise 8.1 (provided in "hmm_sentences.txt" for that exercise, one sentence per line, and also in the current exercise package; in the current package we also provide a subdirectory "hmm_sentences" with the same data as separate files for each sentence). Note: you do not need to prune the vocabulary of these texts since it is so small already. Using the gensim library as in lecture 11 slide 24, or using another language/library of your choice, create 5-dimensional word2vec embeddings for the data. Use a window size of 3 words. Report the resulting embeddings (vectors) for the words "where", "dog", and "explain".

In [29]:
```
with open('hmm_sentences.txt', 'r') as file:
    sentences = [line.strip() for line in file.readlines()]

sentences_tokenized = [sentence.split() for sentence in sentences]

word2vec_model = gensim.models.Word2Vec(sentences=sentences_tokenized, vector_size=5, window=3, min_count=1)
words_to_check = ["where", "dog", "explain"]
for word in words_to_check:
    if word in word2vec_model.wv.key_to_index:
        print(f"Word: {word} - Embedding: {word2vec_model.wv[word]}")
    else:
        print(f"Word: {word} - Embedding: Word not found in vocabulary")
```

```
Word: where - Embedding: [-0.3539674   0.97975016  0.63945335 -0.6262694   0.7030814 ]
Word: dog - Embedding: [-0.10397124  1.0345687   0.56981754 -0.32818294  0.7225344 ]
Word: explain - Embedding: [-0.09556364  1.0061413   0.8269282  -0.29617968  0.7786528 ]
```