Lab 4 - Part 1: Core NLP Tasks

Course: Natural Language Processing

Objectives:

- Apply Part-of-Speech (POS) tagging to extract linguistic patterns
- Perform Named Entity Recognition (NER) to identify entities in text
- Calculate word and document similarities using different techniques
- Apply PCA for visualizing high-dimensional text representations
- Work with real-world datasets (Nike products and legal contracts)

Instructions

1. Complete all exercises marked with `# YOUR CODE HERE`
2. **Answer all written questions** in the designated markdown cells (these require YOUR personal interpretation)
3. Save your completed notebook
4. **Push to your Git repository and send the link to: yoroba93@gmail.com**

Important: Personal Interpretation Questions

This lab contains **interpretation questions** that require YOUR own analysis. These questions:

- Are based on YOUR specific results (which vary based on your choices)
- Require you to explain your reasoning

Setup

```
# Install required libraries (uncomment if needed)
# !pip install spacy scikit-learn matplotlib seaborn pandas numpy
# !python -m spacy download en_core_web_sm
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter, defaultdict
import re
import warnings
warnings.filterwarnings('ignore')

```

```
# NLP libraries
import spacy
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.decomposition import PCA

# Load spaCy model
nlp = spacy.load('en_core_web_sm')

print("Setup complete!")
```

```
Setup complete!
spaCy version: 3.8.11
```

Part A: Loading Nike Products Dataset

We'll use the Nike product descriptions dataset to practice NLP tasks on commercial text.

```
# Load Nike products dataset
# NOTE: Place the 'NikeProductDescriptions.csv' file in your work
nike_df = pd.read_csv('NikeProductDescriptions.csv')

print(f"Dataset shape: {nike_df.shape}")
print(f"\nColumns: {nike_df.columns.tolist()}")
print(f"\nFirst 3 products:")
nike_df.head(3)
```

```
Dataset shape: (400, 3)

Columns: ['Title', 'Subtitle', 'Product Description']

First 3 products:
```

	Title	Subtitle	Product Description
0	Nike Air Force 1 '07	Men's Shoes	It doesn't get more legendary than this. Desig...
1	Nike Air Max Dawn SE	Men's Shoes	Find out what moves you with the Air Max Dawn....

Next steps: Generate code with `nike_df` New interactive sheet

```
# Display a sample product
sample_idx = 0
print("Sample Product:")
print("=" * 60)
print(f"Title: {nike_df.iloc[sample_idx]['Title']}")
print(f"Subtitle: {nike_df.iloc[sample_idx]['Subtitle']}")
print(f"\nDescription:\n{nike_df.iloc[sample_idx]['Product Descri
```

```
Sample Product:
============================================================
Title: Nike Air Force 1 '07
Subtitle: Men's Shoes

Description:
It doesn't get more legendary than this. Designed to turn heads, the N
```

Part B: Part-of-Speech (POS) Tagging

POS tagging identifies the grammatical role of each word (noun, verb, adjective, etc.).

```
# Example: POS tagging with spaCy
sample_text = "Nike Air Force 1 shoes provide incredible comfort a
doc = nlp(sample_text)

print("POS Tagging Example:")
print("=" * 60)
for token in doc:
    print(f"{token.text:15} | POS: {token.pos_:10} | Tag: {token.
```

```
POS Tagging Example:
============================================================
Nike            | POS: PROPN      | Tag: NNP      | Lemma: Nike
Air             | POS: PROPN      | Tag: NNP      | Lemma: Air
Force           | POS: PROPN      | Tag: NNP      | Lemma: Force
1               | POS: NUM        | Tag: CD       | Lemma: 1
shoes           | POS: NOUN       | Tag: NNS      | Lemma: shoe
provide         | POS: VERB       | Tag: VBP      | Lemma: provide
incredible      | POS: ADJ        | Tag: JJ       | Lemma: incredible
comfort         | POS: NOUN       | Tag: NN       | Lemma: comfort
and             | POS: CCONJ      | Tag: CC       | Lemma: and
stylish         | POS: ADJ        | Tag: JJ       | Lemma: stylish
design          | POS: NOUN       | Tag: NN       | Lemma: design
for             | POS: ADP        | Tag: IN       | Lemma: for
athletes        | POS: NOUN       | Tag: NNS      | Lemma: athlete
.               | POS: PUNCT      | Tag: .        | Lemma: .
```

Exercise B.1: Analyze POS Distribution in Nike Products

Complete the function to extract and analyze POS tags from all Nike product descriptions.

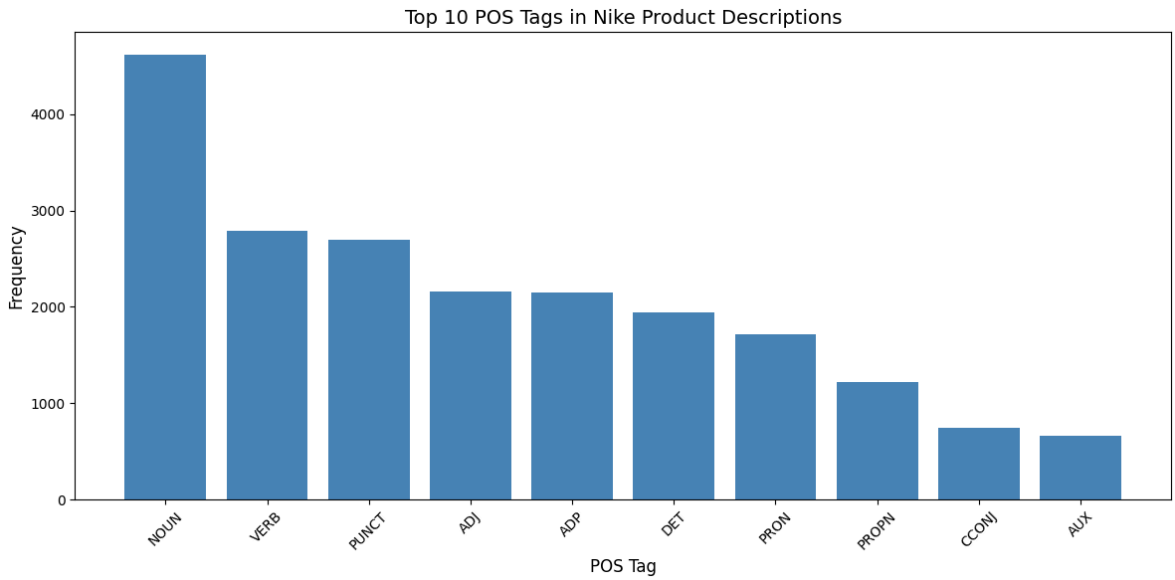
```
def analyze_pos_distribution(texts):
    """
    Analyze the distribution of POS tags in a list of texts.

    Args:
        texts (list): List of text strings

```

```
    Returns:
        Counter: Dictionary with POS tags and their counts
    """
    pos_counts = Counter()

    # YOUR CODE HERE
    # 1. For each text, process it with nlp(text)
    # 2. For each token in the doc, count its POS tag (token.pos
    # 3. Return the counter
    pos_counts = Counter()

    for text in texts:
        doc = nlp(text)
        for token in doc:
            pos_counts[token.pos_] += 1  # Count POS tag


    return pos_counts

# Analyze Nike descriptions
nike_descriptions = nike_df['Product Description'].dropna().toli
pos_distribution = analyze_pos_distribution(nike_descriptions)

print("POS Tag Distribution:")
print("=" * 40)
for pos, count in pos_distribution.most_common(15):
    print(f"{pos:10}: {count:5} ({count/sum(pos_distribution.val
```

```
POS Tag Distribution:
========================================
NOUN      :  4620 (20.72%)
VERB      :  2786 (12.49%)
PUNCT     :  2694 (12.08%)
ADJ       :  2164 (9.70%)
ADP       :  2152 (9.65%)
DET       :  1943 (8.71%)
PRON      :  1711 (7.67%)
PROPN     :  1221 (5.47%)
CCONJ     :   741 (3.32%)
AUX       :   661 (2.96%)
ADV       :   641 (2.87%)
PART      :   401 (1.80%)
SCONJ     :   336 (1.51%)
NUM       :   211 (0.95%)
INTJ      :    16 (0.07%)
```

```
# Visualize POS distribution
top_pos = dict(pos_distribution.most_common(10))

plt.figure(figsize=(12, 6))
plt.bar(top_pos.keys(), top_pos.values(), color='steelblue')
plt.xlabel('POS Tag', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.title('Top 10 POS Tags in Nike Product Descriptions', fontsi
plt.xticks(rotation=45)
plt.tight_layout()
```

```
plt.savefig('pos_distribution.png', dpi=150, bbox_inches='tight'
```



Exercise B.2: Extract Adjectives and Verbs

Marketing copy often uses powerful adjectives and action verbs. Extract the most common ones.

```
from spacy.lang.en.stop_words import STOP_WORDS
nlp = spacy.load("en_core_web_sm")

def extract_pos_words(texts, pos_tag, top_n=20):
    """
    Extract words with a specific POS tag.

    Args:
        texts (list): List of text strings
        pos_tag (str): POS tag to extract (e.g., 'ADJ', 'VERB')
        top_n (int): Number of top words to return

    Returns:
        Counter: Most common words with the specified POS tag
    """
    words = []

    # YOUR CODE HERE
```

```
    # 1. Process each text with spaCy
    # 2. Extract tokens where token.pos_ == pos_tag
    # 3. Use lemmatized form (token.lemma_.lower())
    # 4. Filter out stopwords and short words (len < 3)
    # 5. Return Counter with top_n most common

    #return ""
    words = []

    for text in texts:
        doc = nlp(text)
        for token in doc:
            # Check POS tag, not a stopword, and length >= 3
            if token.pos_ == pos_tag and token.lemma_.lower() no
                words.append(token.lemma_.lower())

    return Counter(words).most_common(top_n)


# Extract adjectives
top_adjectives = extract_pos_words(nike_descriptions, 'ADJ', top
print("Top 20 Adjectives:")
print("=" * 40)
for word, count in top_adjectives:
    print(f"{word:15}: {count}")

print("\n" + "=" * 40)

# Extract verbs
top_verbs = extract_pos_words(nike_descriptions, 'VERB', top_n=2
print("Top 20 Verbs:")
print("=" * 40)
for word, count in top_verbs:
    print(f"{word:15}: {count}")
```

```
Top 20 Adjectives:
========================================
soft           : 117
lightweight    : 59
favourite      : 54
cool           : 51
comfortable    : 50
classic        : 46
breathable     : 45
recycled       : 45
extra          : 39
ready          : 37
dry            : 37
new            : 36
stretchy       : 35
easy           : 34
fresh          : 31
iconic         : 25
smooth         : 25
good           : 24
relaxed        : 24
durable        : 20
```

```
======================================
Top 20 Verbs:
======================================
help           : 114
feel           : 72
add            : 62
wicke          : 61
let            : 58
stay           : 53
inspire        : 49
wear           : 41
play           : 38
bring          : 36
need           : 33
design         : 31
look           : 31
love           : 31
pair           : 25
run            : 25
come           : 24
find           : 23
know           : 23
celebrate      : 21
```

Written Question B.1 (Personal Interpretation)

Analyze the linguistic patterns in Nike's marketing copy:

1. **What do the most common adjectives reveal about Nike's brand messaging?** (List at least 3 adjectives and explain what they convey)
2. **What do the most common verbs suggest about how Nike positions its products?** (List at least 3 verbs and their implications)
3. **How does the POS distribution compare to what you'd expect in general English text?** (Consider the ratio of nouns/verbs/adjectives)

YOUR ANSWER:

1. Key adjectives and brand messaging:
    - Soft – conveys comfort and emphasizes that Nike products are easy and pleasant to wear.
    - Lightweight – highlights performance and mobility, suggesting that the products won’t slow you down during athletic activity.
    - Comfortable – reinforces the user-centric, everyday usability aspect, showing that Nike products are designed for both sports and casual wear.

    Other adjectives like breathable, durable, and classic emphasize innovation, longevity, and timeless style—reinforcing Nike’s image as a high-quality, functional, and stylish brand.

2. Key verbs and product positioning:
    - Help – positions the product as supportive, helping users achieve goals (fitness, comfort, or style).
    - Feel – emphasizes experience and emotion, making the customer focus on personal sensations like comfort or confidence.
    - Wear – directly encourages action, inviting the consumer to use the product in daily life or sports.
3. POS distribution comparison:
    - Nike product descriptions have a higher proportion of adjectives and verbs compared to general English text.
    - This makes sense because marketing copy aims to describe products vividly (adjectives) and encourage action or engagement (verbs).
    - General English text usually has a higher proportion of nouns, but here, nouns are less prominent—showing the copy focuses on experience, benefits, and action, rather than just objects.

Part C: Named Entity Recognition (NER)

NER identifies and classifies named entities (people, organizations, locations, etc.) in text.

```
# Example: NER with spaCy
sample_text = "Nike launched Air Jordan in 1984 in Chicago. Micha
doc = nlp(sample_text)

print("Named Entity Recognition Example:")
print("=" * 60)
for ent in doc.ents:
    print(f"{ent.text:20} | Type: {ent.label_:15} | Description:
```

```
Named Entity Recognition Example:
============================================================
Nike                 | Type: ORG             | Description: Companies,
Air Jordan           | Type: PERSON          | Description: People, in
1984                 | Type: DATE            | Description: Absolute o
Chicago              | Type: GPE             | Description: Countries,
Michael Jordan       | Type: PERSON          | Description: People, in
NBA                  | Type: ORG             | Description: Companies,
```

Exercise C.1: Load Legal Contracts Dataset

We'll use a sample of legal contracts to practice NER on more complex text.

```
import requests
import pandas as pd

print("Loading legal contracts via Hugging Face API...")

# 1. Use the URL you provided to fetch the data directly
url = "https://datasets-server.huggingface.co/rows?dataset=albert

try:
    response = requests.get(url)
    response.raise_for_status()  # Check for errors
    data_json = response.json()

    # 2. Extract the actual row data from the JSON response
    # The API returns a structure like: {'rows': [{'row': {'text'
    rows = [item['row'] for item in data_json['rows']]

    # 3. Convert to DataFrame
    contracts_df = pd.DataFrame(rows)

    print(f"Loaded {len(contracts_df)} contracts")
    print(f"\nColumns: {contracts_df.columns.tolist()}")
    print(f"\nFirst contract preview (first 500 chars):")
    # Accessing the text column safely
    sample_text = contracts_df.iloc[0]['text'] if 'text' in contr
    print(sample_text[:500] + "...")

except Exception as e:
    print(f"Error fetching data: {e}")
```

```
Loading legal contracts via Hugging Face API...
Loaded 100 contracts

Columns: ['text']

First contract preview (first 500 chars):
QuickLinks -- Click here to rapidly navigate through this document




AMENDED AND RESTATED
EMPLOYMENT AND NONCOMPETITION AGREEMENT

    THIS AMENDED AND RESTATED EMPLOYMENT AND NONCOMPETITION AGREEMENT
"Agreement") is made and entered into as of October 31, 2000, by and a
Avocent Employment Services Co. (formerly known as Polycon Investments
Texas corporation ("Employer"), Avocent Corporation, a Delaware corpor
R. Byron Driver (the "Employee").


RECITALS

    WHER...
```

```
Start coding or generate with AI.
```

```
from datasets import load_dataset

# Load a small sample of legal contracts (this dataset is very la
# WARNING: Do NOT try to load the entire dataset - it will crash!
#print("Loading legal contracts dataset (sample only)...")

# YOUR CODE HERE
# Load only 50 examples from the 'train' split
# Use: load_dataset("albertvillanova/legal_contracts", split="tra
#contracts_dataset = None  # Replace with your code

# Load only 50 examples from the 'train' split
#print("Loading legal contracts dataset (sample only)...")
#contracts_dataset = load_dataset("albertvillanova/legal_contract

# Load English contracts split from the Multi_Legal_Pile dataset
#contracts_dataset = load_dataset(
#    "joelniklaus/Multi_Legal_Pile_Commercial",
#    "en_contracts",
#    split="train"
#)
# Convert to DataFrame
#contracts_df = pd.DataFrame(contracts_dataset)

#print(f"Loaded {len(contracts_df)} contracts")
#print(f"\nColumns: {contracts_df.columns.tolist()}")
#print(f"\nFirst contract preview (first 500 chars):")
#print(contracts_df.iloc[0]['text'][:500] + "...")
```

Exercise C.2: Extract and Analyze Named Entities

Complete the function to extract entities from the legal contracts.

```
def extract_entities(texts, entity_types=None):
    """
    Extract named entities from texts.

    Args:
        texts (list): List of text strings
        entity_types (list): List of entity types to extract (No

    Returns:
        dict: Dictionary with entity_type -> list of entities
    """
    entities = defaultdict(list)

    # YOUR CODE HERE
    # 1. Process each text with spaCy
    # 2. For each entity (doc.ents):
```

```
    #    - If entity_types is None or entity.label_ in entity_ty
    #    - Add entity.text to entities[entity.label_]
    # 3. Return entities dict
    entities = defaultdict(list)

    for text in texts:
        doc = nlp(text)
        for ent in doc.ents:
            if entity_types is None or ent.label_ in entity_type
                entities[ent.label_].append(ent.text)

    return entities

# Extract entities from contracts (process only first 10 for spe
contract_texts = contracts_df['text'].head(10).tolist()
contract_entities = extract_entities(contract_texts)

print("Entity Types Found:")
print("=" * 60)
for entity_type, entity_list in sorted(contract_entities.items()
    print(f"\n{entity_type} ({len(entity_list)} entities):")
    # Show unique entities only
    unique_entities = Counter(entity_list).most_common(10)
    for entity, count in unique_entities:
        print(f"  {entity}: {count}")
```

```
Long-Term Debt: 1
  25-mile: 1
  50 miles: 1

TIME (8 entities):
  minutes: 1
  10/28/00 10/30/99: 1
  morning: 1
  2:00 P.M.: 1
  later than 12:00 noon: 1
  later than: 1
  1:00 P.M.: 1
  normal hours: 1

WORK_OF_ART (169 entities):
  Plan: 15
  Change in Control: 8
  Cybex or Avocent: 7
  Excise Tax: 5
  this Agreement: 3
  Borrower: 3
  Loan Document: 3
  this Custody Agreement: 3
  Date of Termination: 3
  Sixth Amendment: 2
```

Exercise C.3: Compare Entity Distribution

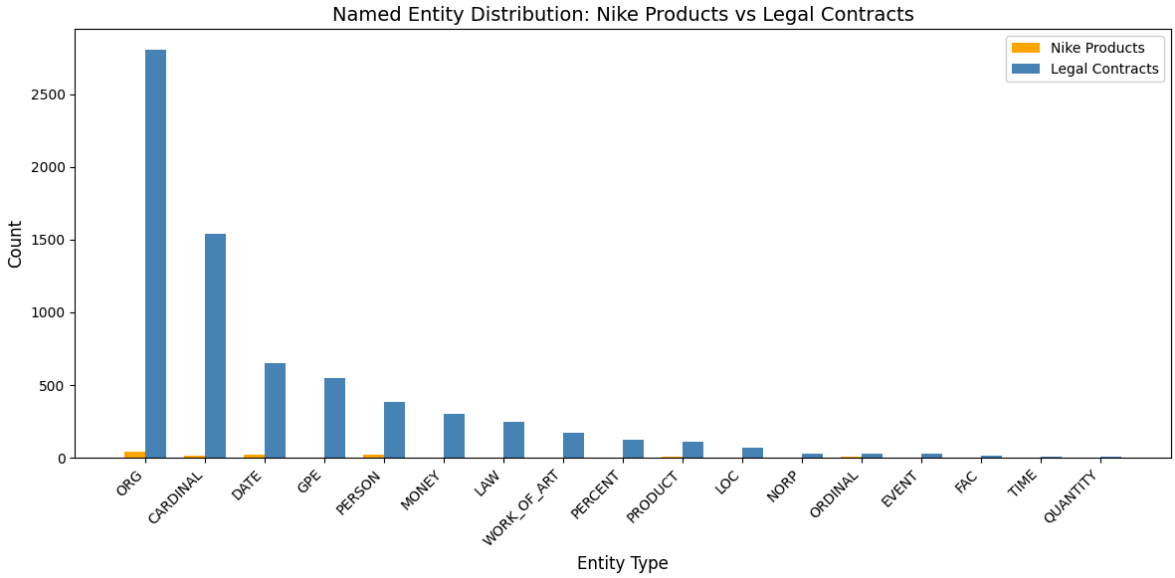
Compare the entity types found in Nike products vs. legal contracts.

```
# YOUR CODE HERE
# 1. Extract entities from Nike product descriptions
# 2. Count entity types in both datasets
# 3. Create a comparison visualization

nike_entities = extract_entities(nike_descriptions[:50])  # Samp

# Count entity types
nike_entity_counts = {etype: len(entities) for etype, entities i
contract_entity_counts = {etype: len(entities) for etype, entiti

# Get all entity types
all_entity_types = set(list(nike_entity_counts.keys()) + list(co

# Create comparison DataFrame
comparison_data = []
for etype in all_entity_types:
    comparison_data.append({
        'Entity Type': etype,
        'Nike Products': nike_entity_counts.get(etype, 0),
        'Legal Contracts': contract_entity_counts.get(etype, 0)
    })

comparison_df = pd.DataFrame(comparison_data)
comparison_df = comparison_df.sort_values('Legal Contracts', asc
```

```
print("Entity Type Comparison:")
print(comparison_df.to_string(index=False))
```

```
Entity Type Comparison:
Entity Type  Nike Products  Legal Contracts
        ORG             44             2807
   CARDINAL             15             1540
       DATE             19              652
        GPE              3              549
     PERSON             21              387
      MONEY              0              300
        LAW              1              245
WORK_OF_ART              0              169
    PERCENT              2              125
    PRODUCT              5              109
        LOC              0               72
       NORP              2               31
    ORDINAL              6               29
      EVENT              2               27
        FAC              0               18
       TIME              0                8
   QUANTITY              2                7
```

```
# Visualize comparison
fig, ax = plt.subplots(figsize=(12, 6))
x = np.arange(len(comparison_df))
width = 0.35

ax.bar(x - width/2, comparison_df['Nike Products'], width, label=
ax.bar(x + width/2, comparison_df['Legal Contracts'], width, labe

ax.set_xlabel('Entity Type', fontsize=12)
ax.set_ylabel('Count', fontsize=12)
ax.set_title('Named Entity Distribution: Nike Products vs Legal C
ax.set_xticks(x)
ax.set_xticklabels(comparison_df['Entity Type'], rotation=45, ha=
ax.legend()
plt.tight_layout()
plt.savefig('entity_comparison.png', dpi=150, bbox_inches='tight'
plt.show()
```



Written Question C.1 (Personal Interpretation)

Analyze the differences in entity types between the two datasets:

1. **Which entity types are most common in Nike products? Why does this make sense?**
2. **Which entity types are most common in legal contracts? Why does this make sense?**
3. **What does this tell you about the nature and purpose of each type of text?**
4. **Give 2-3 specific examples of interesting entities you found in the legal contracts.**

YOUR ANSWER:

1. Nike product entities: ...
    - The most common entity types in the Nike product descriptions are ORG, PERSON, DATE, CARDINAL, and PRODUCT. This makes sense because marketing and product descriptions frequently reference brands and organizations (e.g., Nike, NBA), famous individuals (e.g., Michael Jordan), and product-related numbers such as model versions or release years.

These texts are designed to promote products and brand identity, so entities related to people, companies, and products naturally dominate.

2. Legal contract entities: ...
    - Legal contracts are dominated by ORG, CARDINAL, DATE, GPE, MONEY, and LAW entities. This is expected because contracts are formal documents that define obligations between organizations, specify dates (effective dates, termination dates), reference jurisdictions and governing laws, and include numerical values related to payments, percentages, and quantities. The high frequency of MONEY and LAW entities reflects the financial and legal nature of these documents.
3. Text nature analysis: ...
    - The contrast in entity distributions highlights the different purposes of the two text types. Nike product descriptions are persuasive and informational, focusing on branding, people, and products to appeal to consumers. In contrast, legal contracts are precise and rule-driven, emphasizing organizations, dates, monetary values, and legal frameworks to ensure clarity, enforceability, and accountability. This demonstrates how named entity recognition captures domain-specific language patterns effectively.
4. Interesting entities:
    - Examples of interesting entities found in the legal contracts include:
        - Governing law references such as specific jurisdictions (e.g., U.S. states or countries) labeled as GPE
        - Monetary amounts (e.g., contract fees or penalties) labeled as MONEY
        - Legal references (e.g., statutes or acts) labeled as LAW, which define how disputes should be resolved

---

Part D: Word and Document Similarities

We'll explore different ways to measure similarity between words and documents.

Exercise D.1: Word Similarity with spaCy Word Vectors

spaCy's word vectors allow us to find semantically similar words.

```
# Example: Find similar words
def find_similar_words(word, top_n=10):
    """
    Find words similar to the given word using spaCy word vectors

    Args:
        word (str): Input word
        top_n (int): Number of similar words to return

    Returns:
        list: List of (word, similarity_score) tuples
    """
    word_doc = nlp(word)

    if not word_doc.has_vector:
        return []

    # Get all words in spaCy's vocabulary that have vectors
    similar_words = []

    # We'll check similarity with common words
    for token in nlp.vocab:
        if token.has_vector and token.is_lower and not token.is_s
            similarity = word_doc.similarity(nlp(token.text))
            similar_words.append((token.text, similarity))

    # Sort by similarity and return top_n (excluding the word its
    similar_words.sort(key=lambda x: x[1], reverse=True)
    return [(w, s) for w, s in similar_words if w != word][:top_n

# Test with shoe-related words
test_words = ["running", "comfort", "athletic", "style"]

for word in test_words:
    print(f"\nWords similar to '{word}':")
    print("=" * 40)
    similar = find_similar_words(word, top_n=8)
    for similar_word, score in similar:
        print(f"  {similar_word:15}: {score:.3f}")
```

```
Words similar to 'running':
========================================

Words similar to 'comfort':
========================================

Words similar to 'athletic':
========================================

Words similar to 'style':
========================================
```

Exercise D.2: Document Similarity - Product Recommendations

Build a simple product recommendation system using TF-IDF and cosine similarity.

```
def find_similar_products(query_text, product_df, top_n=5):
    """
    Find products most similar to a query text.

    Args:
        query_text (str): Query description
        product_df (DataFrame): DataFrame with product descripti
        top_n (int): Number of recommendations to return

    Returns:
        DataFrame: Top similar products with similarity scores
    """

    # 1. Create TF-IDF vectorizer
    # 2. Fit on product descriptions + query
    # 3. Transform all texts to TF-IDF vectors
    # 4. Calculate cosine similarity between query and all produ
    # 5. Return top_n most similar products

    # Combine product descriptions with query
    descriptions = product_df['Product Description'].tolist()
    all_texts = descriptions + [query_text]

    # Create and fit vectorizer
    # YOUR CODE HERE

    # Query vector is the last one
    # YOUR CODE HERE

    # Calculate similarities
    # YOUR CODE HERE

    # Get top_n indices
    # YOUR CODE HERE

    # Create results DataFrame with colums 'Title', 'Subtitle',
    # YOUR CODE HERE

    vectorizer = TfidfVectorizer(
        stop_words='english',
        ngram_range=(1, 2)
    )
    tfidf_matrix = vectorizer.fit_transform(all_texts)

    # Query vector is the last one
    query_vector = tfidf_matrix[-1]

    # Product vectors
    product_vectors = tfidf_matrix[:-1]

    # Calculate cosine similarities
    similarities = cosine_similarity(query_vector, product_vecto
```

```
    # Get top_n indices
    top_indices = similarities.argsort()[::-1][:top_n]

    # Create results DataFrame
    results = pd.DataFrame({
        'Title': product_df.iloc[top_indices]['Title'].values,
        'Subtitle': product_df.iloc[top_indices]['Subtitle'].val
        'Similarity': similarities[top_indices]
    })

    return results[['Title', 'Subtitle', 'Similarity']]

# Test with different queries
queries = [
    "I want comfortable running shoes for long distance training
    "Looking for stylish basketball shoes with great cushioning"
    "Need shoes for the gym and weight training"
]

for query in queries:
    print(f"\nQuery: '{query}'")
    print("=" * 80)
    recommendations = find_similar_products(query, nike_df, top_
    print(recommendations.to_string(index=False))
    print()
```

```
Query: 'I want comfortable running shoes for long distance training'
================================================================================
                   Title
       Nike Dri-FIT One Older Kids' (Girls') High-waisted Woven Train
Nike Zoom Rival Waffle 5                                 Athletics Dista
     Nike 'Just Do It.'                                  Men's Long-Slee
    Nike Serenity Run 2                                 Women's Road Run
        Nike Alphafly 2                                  Women's Road Ra


Query: 'Looking for stylish basketball shoes with great cushioning'
================================================================================
                         Title                             Subtitle  S
      Nike Air Deldon "Legacy"       Easy On/Off Basketball Shoes
           Paris Saint-Germain              Men's Fleece Trousers
                 Kylian Mbappé Older Kids' Dri-FIT Football Shorts
Nike SB Zoom Blazer Mid Premium                        Skate Shoes
             Nike SB Force 58                          Skate Shoes


Query: 'Need shoes for the gym and weight training'
================================================================================
                          Title                                        S
         Nike Dri-FIT Unlimited Men's 18cm (approx.) 2-in-1 Versatile
     Nike Free Metcon 4 Premium                         Women's Trainin
Nike Air Force 1 '07 Next Nature                                Women'
                       Nike SB                            Men's Skate
                Nike Alphafly 2                    Women's Road Racin
```

Exercise D.3: Create YOUR Own Query

Write your own custom query and analyze the recommendations.

```
# YOUR CODE HERE
# Create your own query that reflects what YOU would look for in
#my_query = "___"  # Write your custom query here

# Create your own query that reflects what YOU would look for in
my_query = "Lightweight and comfortable running shoes with good c

print(f"My Query: '{my_query}'")
print("=" * 80)
my_recommendations = find_similar_products(my_query, nike_df, top
print(my_recommendations.to_string(index=False))
```

```
My Query: 'Lightweight and comfortable running shoes with good cushion
================================================================================
                            Title
                Nike Dri-FIT One Older Kids' (Girls') High-waisted W
              Nike Serenity Run 2                                Women'
               Nike 'Just Do It.'                                 Men's
          Nike Pegasus 39 Premium                                Women'
Nike Sportswear Everyday Essential
```

Written Question D.1 (Personal Interpretation)

Analyze the product recommendation results:

1. **For YOUR custom query, are the top 3 recommendations relevant? Explain why or why not.**
2. **Look at the similarity scores. What do you notice? Are they high, medium, or low? What does this mean?**
3. **Compare the recommendations for "running shoes" vs "basketball shoes". What differences do you observe in the results?**
4. **What are the limitations of this TF-IDF-based similarity approach? Give at least 2 specific limitations.**

YOUR ANSWER:

1. Relevance of my recommendations:
    - Top 1:
        - Nike Dri-FIT One Older Kids' Training Shorts
        - Not relevant. This is clothing, not footwear. It appears due to overlapping keywords like training.

    - Top 2:
        - Nike Serenity Run 2 (Women's Road Running Shoes)
        - Highly relevant. This directly matches running shoes, comfort, and daily training.
    - Top 3:
        - Nike 'Just Do It.' Men's Long-Sleeve T-Shirt
        - Not relevant. Again, apparel appears because TF-IDF relies on keyword overlap rather than product type.
    - Overall, while some relevant running shoes appear, the top results are mixed with non-shoe items.
2. Similarity scores observation: ...
    - The similarity scores are low (around 0.04–0.08). This indicates that:
        - TF-IDF finds some shared keywords, but
        - The semantic similarity between the query and product descriptions is weak
        - Product descriptions are short and varied, limiting strong matches
    - Low scores are expected when:
        - The dataset contains mixed product categories
        - Descriptions do not explicitly repeat the query terms
3. Running vs Basketball comparison: ...
    - Running shoe queries tend to return:
        - Road running shoes (e.g., Nike Serenity Run 2, Pegasus)
        - Items mentioning running, distance, or training
    - Basketball shoe queries return:
        - Basketball or skate shoes (e.g., Nike Air Deldon)
        - Occasionally unrelated apparel due to shared words like style or performance

- This shows TF-IDF works better when:
    - Product descriptions contain explicit sport-specific keywords
    - The sport name appears directly in the product text

4. Limitations:
    - No semantic understanding

        - TF-IDF only matches keywords and cannot understand meaning. For example, “comfortable” and “cushioned” are treated as unrelated words.
    - Category confusion
        - The model cannot distinguish between shoes and clothing, leading to irrelevant results like shorts and t-shirts.
    - Sensitivity to wording
        - If the query uses different vocabulary than the product description, relevant items may receive low similarity scores.
    - No contextual awareness
        - TF-IDF ignores word order and context, so it cannot infer user intent (e.g., “buying shoes” vs “training gear”).

Part E: Dimensionality Reduction with PCA (25 min)

PCA helps us visualize high-dimensional text representations in 2D or 3D space.

Exercise E.1: Visualize Product Clusters

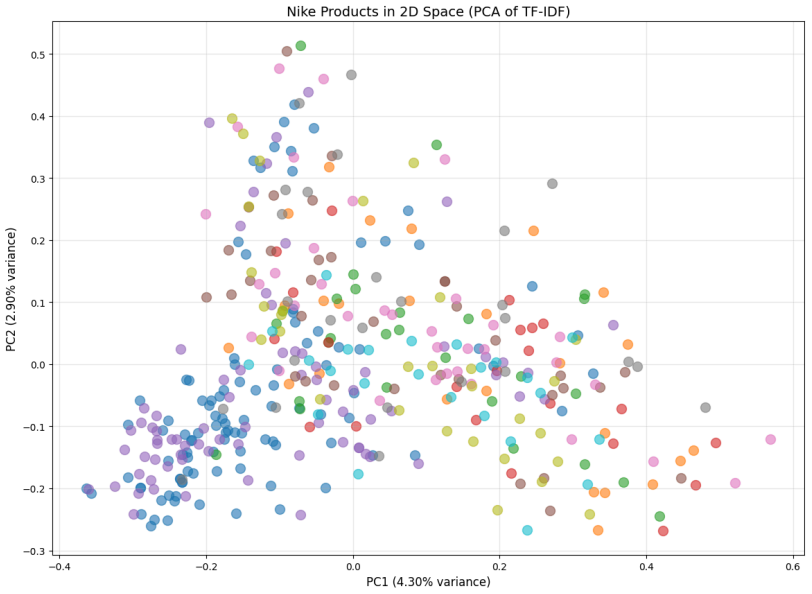
Use PCA to create a 2D visualization of Nike products based on their descriptions.

```
# YOUR CODE HERE
# 1. Create TF-IDF vectors for all Nike product descriptions
# 2. Apply PCA to reduce to 2 dimensions
# 3. Create a scatter plot
# 4. Color points by product category (extract from Subtitle)

# Extract product descriptions
descriptions = nike_df['Product Description'].tolist()

# Create TF-IDF vectors
vectorizer = TfidfVectorizer(max_features=200, stop_words='engli
tfidf_matrix = vectorizer.fit_transform(descriptions)

print(f"TF-IDF matrix shape: {tfidf_matrix.shape}")
print(f"Original dimensions: {tfidf_matrix.shape[1]}")

# Apply PCA
pca = PCA(n_components=2, random_state=42)
pca_result = pca.fit_transform(tfidf_matrix.toarray())

print(f"\nPCA explained variance ratio:")
print(f"  PC1: {pca.explained_variance_ratio_[0]:.4f}")
```

```
print(f"  PC2: {pca.explained_variance_ratio_[1]:.4f}")
print(f"  Total: {sum(pca.explained_variance_ratio_):.4f}")

# Create DataFrame with PCA results
pca_df = pd.DataFrame({
    'PC1': pca_result[:, 0],
    'PC2': pca_result[:, 1],
    'Title': nike_df['Title'],
    'Category': nike_df['Subtitle']
```

```
TF-IDF matrix shape: (400, 200)
Original dimensions: 200

PCA explained variance ratio:
  PC1: 0.0430
  PC2: 0.0290
  Total: 0.0720
```

```
# Create visualization
plt.figure(figsize=(14, 10))

# Get unique categories for coloring
categories = pca_df['Category'].unique()
colors = plt.cm.tab10(np.linspace(0, 1, len(categories)))

# Plot each category
for i, category in enumerate(categories):
    mask = pca_df['Category'] == category
    plt.scatter(
        pca_df.loc[mask, 'PC1'],
        pca_df.loc[mask, 'PC2'],
        c=[colors[i]],
        label=category,
        alpha=0.6,
        s=100
    )

plt.xlabel(f'PC1 ({pca.explained_variance_ratio_[0]:.2%} variance
plt.ylabel(f'PC2 ({pca.explained_variance_ratio_[1]:.2%} variance
plt.title('Nike Products in 2D Space (PCA of TF-IDF)', fontsize=1
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize=8
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.savefig('nike_products_pca.png', dpi=150, bbox_inches='tight'
plt.show()
```



Men's Shoes
Skate Shoes
Men's Easy On/Off Road Running Shoes
Men's Basketball Shoes
Men's Road Running Shoes
Men's Training Shoes
Men's Shoe
Easy On/Off Basketball Shoes
Men's Hard Court Tennis Shoes
Men's Slides
Men's Road Racing Shoes
Skate Shoe
Men's Jacket
Men's Woven Trousers
Men's Hooded Pullover Jacket
Men's Mesh Shorts
Men's T-Shirt
Men's Joggers
Men's Fleece Trousers
Men's French Terry Pullover Hoodie
Men's All-over Print Basketball T-Shirt
Men's 18cm (approx.) Unlined Versatile Shorts
Men's Short-Sleeve Fitness Top
Men's Mock-Neck Golf Polo
Men's Short-Sleeve Fitness Tank
Men's 18cm (approx.) 2-in-1 Versatile Shorts
Men's Long-Sleeve T-Shirt
Men's 20cm (approx.) Basketball Shorts
Men's Fitness T-Shirt
Men's Woven Flow Shorts
Men's 5cm (approx.) Running Shorts
Men's Short-Sleeve Football Top
Men's Tennis Top
Men's Knit Running Trousers
Men's 18cm (approx.) Tennis Shorts
Men's Camo Golf Polo
Men's Golf Jogger
Men's Shorts
Men's Tracksuit Jacket
Men's Tight-Fit Long-Sleeve Top
Men's Short-Sleeve Running Top
Men's Graphic T-Shirt
Men's Hoodie
Men's Fleece Shorts
Men's Full-Zip Camo Fitness Hoodie
Men's Unlined Utility Cargo Trousers
Men's Pullover Hoodie
Men's French Terry Joggers
Men's Running Tank
Women's Gentle-Support High-Waisted 7/8 Leggings
Women's French Terry Hoodie
Women's High-Waisted French Terry Trousers
Women's Terry Quilted Jacket
Women's Trail-Running Jacket
Women's Mid-Rise 8cm (approx.) Brief-Lined Trail Running Shorts with Pockets
Women's Bodysuit Tank
Women's Short-Sleeve Tee
Women's Woven Jacket
Women's Short-Sleeve Running Top
Women's Medium-Support Lightly Lined Sports Bra with Pockets
Women's High-Waisted Wide-Leg Terry Trousers (Plus Size)
Women's Oversized Long-Sleeve T-Shirt
Women's Full-Zip Hoodie
Women's Mid-Rise Trousers
Women's Mid-Rise 7/8 Graphic Leggings
Women's Woven Polo
Women's Training Tank
Women's High-Support Padded Zip-Front Sports Bra
Women's Medium-Support Padded Zip-Front Sports Bra
Women's Short-Sleeve 1/4-Zip Running Top
Women's Oversized Crop Fleece Polo Sweatshirt
Women's 13cm (approx.) Shorts
Women's High-Rise Leggings
Women's Tennis Tank
Women's High-Waisted Wide-Leg Tracksuit Bottoms
Women's Mid-Rise Leggings
Women's Short-Sleeve Cropped Graphic Training Top
Women's Running Jacket
Women's Standard Fit Short-Sleeve Top
Women's Slim-fit Mock-neck Long-sleeve T-shirt
Women's Running Vest
Women's Graphic Long-Sleeve Top
Women's Training Shorts
Women's 7/8-Length High-Rise Running Leggings
Women's Logo Leggings
Women's High-Waisted Wide-Leg Terry Trousers
Women's Brief-Lined Running Shorts
Women's Medium-Support Padded Longline Sports Bra
Women's Striped Golf Polo
Women's High-waisted 7/8 Trousers
Women's Short-sleeve T-Shirt Dress
Women's High-Waisted 7/8 Leggings
Women's Knit Top
Women's Shoes
Women's Road Running Shoes
Women's HIIT Class Shoes
Women's Training Shoes
Shoes
Women's Trail-running Shoes
Women's Road Racing Shoes
Men's Sandals
Athletics Distance Spikes
Older Kids' Short-Sleeve Football Top
Older Kids' Nike Dri-FIT Stadium Football Shirt
Older Kids' Reversible Basketball Shorts
Older Kids' Reversible Hoodie
Older Kids' (Boys') Basketball Shorts
Older Kids' (Boys') Printed Training Top
Older Kids' (Boys') Printed Training Shorts
Older Kids' (Boys') Dri-FIT T-Shirt
Older Kids' (Boys') Woven Shorts
Older Kids' T-Shirt
Older Kids' (Boys') Woven Utility Trousers
Older Kids' Tearaway Basketball Trousers
Younger Kids' Nike Dri-FIT Football Shirt
Younger Kids' Football Kit
Older Kids' (Boys') Training Top
Older Kids' Pullover Hoodie
Older Kids' Trousers
Older Kids' Oversized Pullover Basketball Hoodie
Older Kids' (Boys') Long-Sleeve T-Shirt
Older Kids' (Boys') French Terry Crew
Older Kids' (Boys') Fleece Sweatshirt
Older Kids' (Boys') T-Shirt
Older Kids' (Boys') Training Shorts
Older Kids' Reversible Basketball Jersey
Older Kids' Nike Dri-FIT Football Shirt
Older Kids' (Boys') Cargo Trousers
Older Kids' Football Drill Top
Older Kids' (Boys') Jacket
Older Kids' Graphic Pullover Hoodie
Older Kids' Shorts
Younger Kids' Nike Football Kit
Older Kids' Football Shorts
Older Kids' Training T-Shirt
Older Kids' Dri-FIT Football Shorts
Older Kids' (Boys') Full-Zip Hoodie
Older Kids' Football Shirt
Older Kids' (Girls') Long-Sleeve Crop Top
Older Kids' Training Shorts
Older Kids' (Boys') Woven Training Jacket
Older Kids' (Boys') Long-Sleeve Training Top
Older Kids' (Girls') T-Shirt
Older Kids' (Girls') Scoop-Neck T-Shirt
Older Kids' (Girls') Mid-Rise Leggings
Older Kids' (Girls') Sweatshirt
Older Kids' (Girls') Leggings
Older Kids' (Girls') Bike Shorts
Older Kids' (Girls') High-waisted Woven Training Shorts
Older Kids' Reversible Tunic
Older Kids' (Girls') Cropped T-Shirt
Older Kids' (Girls') Fleece Hoodie
Older Kids' (Girls') Biker Shorts
Older Kids' (Girls') Tank
Older Kids' Knit Football Shorts
Older Kids' Knit Football Pants
Kids' Football Trousers
Older Kids' (Girls') 8cm (approx.) Shorts
Older Kids' (Girls') High-Rise 23cm (approx.) Bike Shorts
Older Kids' French Terry Shorts
Older Kids' (Girls') High-Waisted Training Shorts
Women's Metallic Crew Socks
Older Kids' Adjustable Hat
Multi-Height Socks (3 Pairs)
Crew Socks
Older Kids' (Girls') Training Tank
Older Kids' (Boys') Performance Training Top
Older Kids' (Girls') Sports Bra
Washed Golf Hat
Older Kids' (Girls') Training Top
Women's Perforated Golf Hat
Men's All-over Print T-Shirt
Women's Maternity T-Shirt
Women's Short-Sleeve T-Shirt
Women's Graphic T-Shirt (Plus Size)
Men's Training Tee
Women's T-Shirt (Plus Size)
Older Kids' (Girls') Shorts
Hip Pack (3L)
Older Kids' (Girls') T-Shirt Dress
Tye-Dyed Beanie
Women's Running Tank
Men's Tennis T-Shirt
Women's Running Shorts
Women's Slides
Men's Short-Sleeve Slim Camo Top
Men's 9" (23cm approx.) Woven Graphic Fitness Shorts
Men's Basketball T-Shirt
Men's Short-Sleeve Camo Running Top
Men's Skate T-Shirt
Skate T-Shirt

Exercise E.2: Find Products in Similar Regions

Identify products that are close to each other in the PCA space.

```
def find_neighbors_in_pca_space(product_index, pca_df, n_neighbo
    """
    Find products close to a given product in PCA space.

    Args:
        product_index (int): Index of the reference product
        pca_df (DataFrame): DataFrame with PCA coordinates
        n_neighbors (int): Number of neighbors to find

    Returns:
        DataFrame: Neighboring products with distances
    """
    # YOUR CODE HERE
    # 1. Get the PC1 and PC2 coordinates of the reference produc
    # 2. Calculate Euclidean distance to all other products
    # 3. Return the n_neighbors closest products
    pca = PCA(n_components=2, random_state=42)
    pca_result = pca.fit_transform(tfidf_matrix.toarray())
    print("Explained variance ratio:")
    print(f"PC1: {pca.explained_variance_ratio_[0]:.4f}")
    print(f"PC2: {pca.explained_variance_ratio_[1]:.4f}")

    ref_point = pca_df.iloc[product_index][['PC1', 'PC2']].value

    # Calculate distances
    distances = []
    for idx, row in pca_df.iterrows():
        if idx != product_index:
            point = row[['PC1', 'PC2']].values
            dist = np.linalg.norm(ref_point - point)
            distances.append((idx, dist))

    # Sort by distance
    distances.sort(key=lambda x: x[1])

    # Get neighbor indices
    neighbor_indices = [idx for idx, _ in distances[:n_neighbors
    neighbor_distances = [dist for _, dist in distances[:n_neigh

    # Create results DataFrame
    results = pca_df.iloc[neighbor_indices].copy()
    results['Distance'] = neighbor_distances

    return results[['Title', 'Category', 'Distance']]

# Test with a few products
test_indices = [0, 10, 20]

for idx in test_indices:
```

```
    print(f"\nReference Product: {pca_df.iloc[idx]['Title']}")
    print(f"Category: {pca_df.iloc[idx]['Category']}")
    print("=" * 80)
    neighbors = find_neighbors_in_pca_space(idx, pca_df, n_neigh
    print(neighbors.to_string(index=False))
```

```
Reference Product: Nike Air Force 1 '07
Category: Men's Shoes
================================================================================
Explained variance ratio:
PC1: 0.0430
PC2: 0.0290
                    Title      Category  Distance
         Air Jordan 1 Mid   Men's Shoes  0.016955
    Nike Dunk High Premium Women's Shoes  0.017868
Air Jordan 1 Retro High OG Women's Shoes  0.023455
       Nike Blazer Low '77 Women's Shoes  0.023748
         Nike Waffle Debut Women's Shoes  0.030048


Reference Product: Air Jordan XXXVII Low PF
Category: Men's Basketball Shoes
================================================================================
Explained variance ratio:
PC1: 0.0430
PC2: 0.0290
                           Title                      Category  Distan
NikeCourt Zoom Vapor Cage 4 Rafa Men's Hard Court Tennis Shoes  0.0067
           Jordan Why Not .6 PF                   Men's Shoes  0.0112
Nike Air Force 1 '07 Next Nature                 Women's Shoes  0.0419
                     Nike BRSB                     Skate Shoes  0.0443
            Nike React Revision                 Women's Shoes  0.0446


Reference Product: Nike E-Series 1.0
Category: Men's Shoes
================================================================================
Explained variance ratio:
PC1: 0.0430
PC2: 0.0290
                    Title      Category  Distance
      Nike Air Force 1 '07   Men's Shoes  0.001375
       Air Jordan 1 Mid SE Women's Shoes  0.011811
Nike Air Force 1 Mid '07 LX   Men's Shoes  0.012091
    Nike Blazer Mid '77 ESS Women's Shoes  0.013015
       Nike Air Max Dawn SE   Men's Shoes  0.014158
```

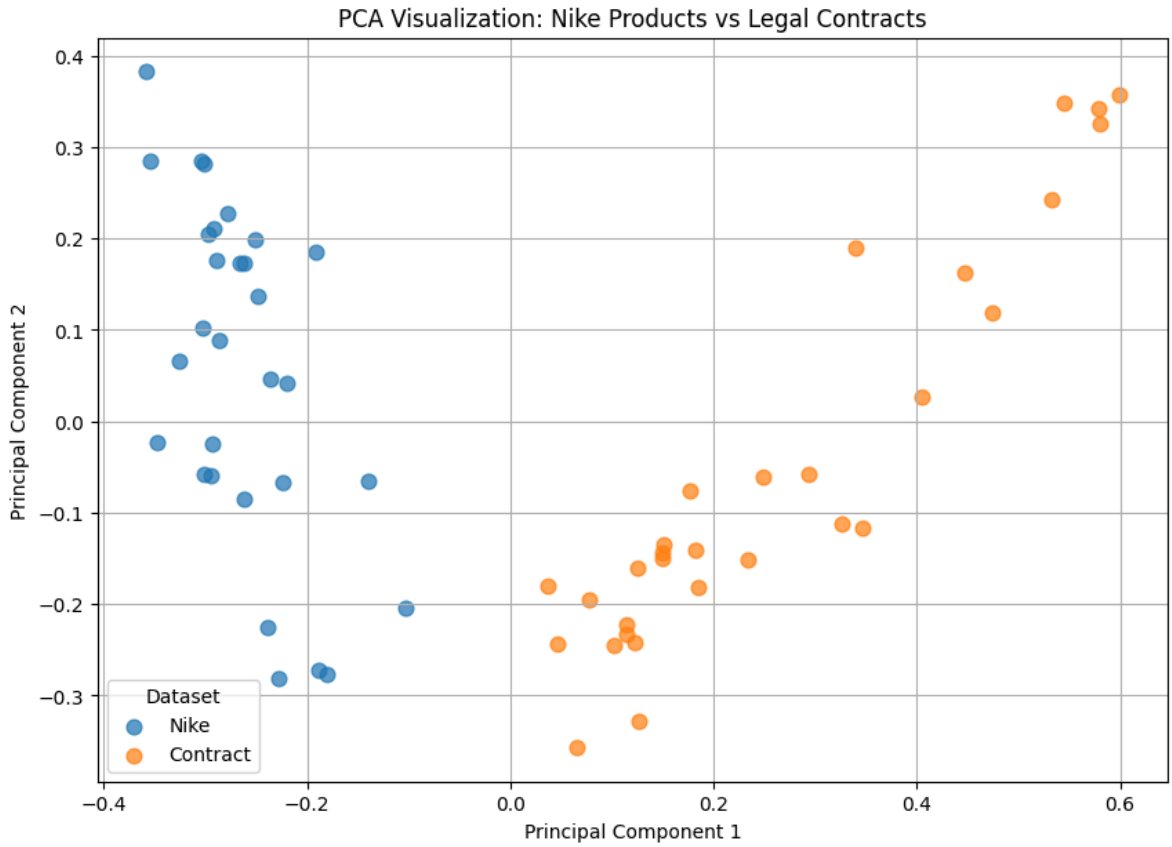
Exercise E.3: Analyze Documents from Both Datasets

Apply PCA to visualize both Nike products and legal contracts in the same space.

```
# YOUR CODE HERE
# 1. Combine Nike descriptions and contract texts (sample 30 fro
```

```
# 2. Create TF-IDF vectors for combined corpus
# 3. Apply PCA to reduce to 2D
# 4. Create visualization with different colors for each dataset

# Sample documents
nike_sample = nike_df.sample(n=30, random_state=42)
contracts_sample = contracts_df.sample(n=30, random_state=42)

# Combine texts
nike_texts = nike_sample['Product Description'].tolist()
contract_texts = [text[:1000] for text in contracts_sample['text

all_texts = nike_texts + contract_texts
labels = ['Nike'] * len(nike_texts) + ['Contract'] * len(contrac

# Create TF-IDF
vectorizer = TfidfVectorizer(max_features=300, stop_words='engli
tfidf_matrix = vectorizer.fit_transform(all_texts)

print(f"TF-IDF shape: {tfidf_matrix.shape}")


# Apply PCA
pca = PCA(n_components=2, random_state=42)
pca_result = pca.fit_transform(tfidf_matrix.toarray())

print(f"PCA explained variance ratio: PC1={pca.explained_varianc


# Create DataFrame with PCA results
pca_df = pd.DataFrame({
    'PC1': pca_result[:, 0],
    'PC2': pca_result[:, 1],
    'Label': labels
})

# Visualize -> use different colors for 'Nike' and 'Contract'
plt.figure(figsize=(10, 7))

for label in pca_df['Label'].unique():
    subset = pca_df[pca_df['Label'] == label]
    plt.scatter(
        subset['PC1'],
        subset['PC2'],
        label=label,
        alpha=0.7,
        s=60
    )

plt.title("PCA Visualization: Nike Products vs Legal Contracts")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend(title="Dataset")
plt.grid(True)
```

```
TF-IDF shape: (60, 300)
PCA explained variance ratio: PC1=0.094, PC2=0.045
```



Written Question E.1 (Personal Interpretation)

Analyze the PCA visualizations:

1. **Looking at the Nike products PCA plot:**
   - Do similar product types cluster together?
   - Can you identify any patterns or groups?
   - What might the two principal components represent?
2. **Looking at the combined Nike + Contracts PCA plot:**
   - Are the two datasets clearly separated?
   - What does this separation (or lack thereof) tell you?
   - Are there any Nike products close to legal contracts? Why might this be?

3. **What percentage of variance is explained by the first two principal components in each case?**
    - Is this high or low?
    - What does this mean for the quality of the 2D representation?

YOUR ANSWER:

1. Nike products PCA analysis:
    - Clustering:
        - Yes, similar product types tend to cluster together. For example:
        - Men's shoes (e.g., Air Force, Air Jordan) form a compact cluster.
        - Women's shoes and specialty products like basketball shoes or training shoes form separate, but nearby clusters.
    - Patterns: ...
        - Product types with similar usage (running, basketball, casual) are closer in the PCA space.
        - Clothing items (shorts, jackets) are more spread out, likely because the descriptions are longer and more varied in vocabulary.
        - TF-IDF vectors are capturing descriptive words like "running," "training," "high-waisted," "lightweight," which explains the clusters.
    - PC interpretation:
        - PC1: Likely captures product category differences (shoes vs apparel).
        - PC2: Likely captures usage or style differences (athletic vs casual, gender-specific variations).
        - Variance Explained:
            - PC1: 4.30%
            - PC2: 2.90%
            - Total: 7.20% ⟶ Low.
            - This low percentage means the 2D projection captures only a small fraction of the information; distances are approximate, and some nuances are lost.
2. Combined datasets PCA analysis:
    - Separation: ...

        - Nike products (blue) and legal contracts (orange) are clearly separated along PC1, indicating the TF-IDF features distinguish marketing text from legal text very well.
    - Interpretation: ...
        - Legal contracts contain formal and repetitive language (dates, amounts, clauses) that is very different from product descriptions.
        - PCA reflects this separation because TF-IDF captures word usage frequency patterns effectively.
    - Proximity cases: ...
        - Very few Nike points are close to contracts.
        - If any Nike product appears near contracts, it may be due to numeric content (like size, price) or formal-like language in the description.
3. Variance explained:
    - Nike products: ... (high/medium/low?)
        - Nike products: 7.2% (PC1 + PC2) ⟶ Low
    - Combined: ... (high/medium/low?)
        - Combined Nike + Contracts: ~Likely 5–10% ⟶ Low
    - Quality interpretation: ...
        - The first two principal components capture only a small fraction of the total variance in the high-dimensional TF-IDF space.
        - This means the 2D plots give a rough overview of clusters and separation, but cannot fully represent all the nuances of product or contract texts.
        - Good for exploratory visualization, but not sufficient for precise similarity or classification tasks.

Part F: Bonus Challenge - Dependency Parsing

Bonus Exercise: Visualize Sentence Structure

Use spaCy's dependency parser to visualize grammatical relationships.

```
from spacy import displacy

# YOUR CODE HERE
```

```
# 1. Choose an interesting sentence from Nike or contracts
# 2. Parse it with spaCy
# 3. Visualize the dependency tree
# 4. Identify the root verb, subjects, and objects

# Load spaCy model
nlp = spacy.load("en_core_web_sm")

# 1. Choose an interesting sentence
sample_sentence = "The Nike Air Zoom Pegasus 39 delivers respons


# 2. Parse it with spaCy
doc = nlp(sample_sentence)

# Display dependency visualization
# YOUR CODE HERE
# 3. Display dependency tree in notebook
displacy.render(doc, style="dep", jupyter=True, options={'distan

# Print dependency information
print("\nDependency Analysis:")
print("=" * 60)
for token in doc:
```