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AUTOMATION OF TEXT DATA PROCESSING USING NLP

Yaroslav Starukhin
Senior Data scientist, McKinsey & Company, Boston, USA

Vladimir Diukarev
Head of Data Analytics, Anti-Fraud Department, Sberbank Moscow, Russian Federation

Abstract
This study aims to develop an automated system for processing scientific texts using advanced NLP techniques. The methodology integrates classical NLP methods with deep learning approaches, employing SciBERT for text classification, LDA for topic modeling, and a modified TextRank algorithm for keyword extraction. Results demonstrate high accuracy in document classification (F1-score of 0.92), effective topic identification, and precise keyword extraction. The developed web interface showcases the system's practical applicability. This research contributes to the field by presenting a comprehensive solution for scientific text analysis, combining state-of-the-art language models with established NLP techniques. The study's novelty lies in its tailored approach to scientific literature, addressing the unique challenges of domain-specific language and complex content structure in academic texts.

Keywords Natural language processing, scientific text analysis, bert, topic modeling, keyword extraction, text classification, machine learning, information retrieval, computational linguistics, scientific literature mining.

INTRODUCTION

In the era of information explosion and exponential growth of text data, the automation of their processing becomes not just desirable but critically necessary for the effective functioning of the scientific community and industry as a whole. Scientific publications, technical documents, patents, and other forms of textual information are generated at an unprecedented rate, creating significant challenges for their analysis, categorization, and extraction of valuable insights.

Natural Language Processing (NLP) is an interdisciplinary field at the intersection of linguistics, computer science, and artificial intelligence that focuses on the interaction between computers and human language. In recent years, NLP has shown significant progress, largely due to the development of deep learning and the emergence of transformer architectures such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) [1,2].

The automation of text data processing using NLP opens up a wide range of possibilities, including but not limited to:

1. Document classification by topic, which is critical for the efficient organization and retrieval of information in large text corpora.
2. Keyword and phrase extraction, allowing quick identification of the main content of a document.
3. Topic modeling, revealing latent topics in document collections.
4. Semantic analysis, contributing to a deeper understanding of the context and meaning of

text.

5. Automatic summarization, providing brief summaries of large documents.

The relevance of this topic is underscored by the growing demand for automated text processing systems in various sectors, including research institutes, libraries, publishers, patent offices, and corporate R&D departments. Moreover, in the context of the development of artificial intelligence technologies and big data, the improvement of NLP methods becomes a key factor in creating more intelligent and efficient information systems.

The main goal of this research is the development and implementation of a comprehensive automated text data processing system using modern NLP methods, aimed at analyzing scientific publications.

To achieve this goal, the following tasks were set:

1. Conduct a critical analysis of existing NLP methods and algorithms applicable to scientific text processing tasks, with a particular focus on the latest achievements in transformer architectures.
2. Develop the system architecture, integrating various NLP components, including text preprocessing, vector representation, classification, topic modeling, and keyword extraction.
3. Implement and optimize a BERT-based classification model adapted for categorizing scientific articles by disciplines.
4. Implement a topic modeling algorithm using Latent Dirichlet Allocation (LDA) to identify latent topics in the corpus of scientific texts.
5. Develop and integrate a keyword extraction method based on the TextRank graph algorithm, adapted for working with scientific terminology.
6. Conduct experimental validation of the developed system on a corpus of scientific articles obtained from the arXiv repository, with an assessment of the effectiveness of each system component.
7. Implement a web interface to demonstrate the functionality of the system and provide the possibility of interactive analysis of scientific texts.
8. Evaluate the potential and limitations of the developed system in the context of real use scenarios in academic and industrial environments.

This research aims to overcome existing limitations in the automated processing of scientific texts and proposes an integrated approach that combines classical NLP methods with advanced deep learning technologies. It is expected that the results of the research will contribute to the development of methodology for scientific literature analysis and provide practical tools for researchers and information management specialists.

Theoretical Foundations of NLP

As noted earlier, Natural Language Processing (NLP) is a complex research area that combines linguistics, computer science, and artificial intelligence. The fundamental goal of NLP is to develop methods and algorithms that enable computer systems to effectively analyze, understand, and generate human language in its natural form.

Key concepts in NLP include:

1. Tokenization: the process of splitting text into minimal meaningful units (tokens), usually words or subwords. This step is critical for further analysis as it defines the basic elements with which subsequent algorithms will work.

2. Lemmatization and Stemming: methods for reducing words to their base form. Lemmatization considers the morphology of the language and returns the dictionary form of a word, while stemming applies simpler rules to strip suffixes. The choice of method depends on the balance between accuracy and computational efficiency.

3. Part-of-Speech Tagging (POS-tagging): automatic determination of parts of speech for each word in the text. This information is crucial for syntactic and semantic analysis tasks.

4. Syntactic Parsing: constructing a tree structure of a sentence that reflects the syntactic relationships between words. Modern approaches often use probabilistic context-free grammars (PCFG) or deep neural networks for this task.

5. Semantic Analysis: extracting meaning from text, including word sense disambiguation and analysis of semantic roles. Methods here range from simple statistical approaches to complex neural network models [3,4].

Vector representation of words and texts plays a key role in modern NLP. Models such as Word2Vec, GloVe, and FastText allow words to be represented as dense vectors in a multidimensional space, reflecting the semantic relationships between words. The evolution of these approaches has led to the emergence of contextual embeddings such as ELMo and, subsequently, transformer models.

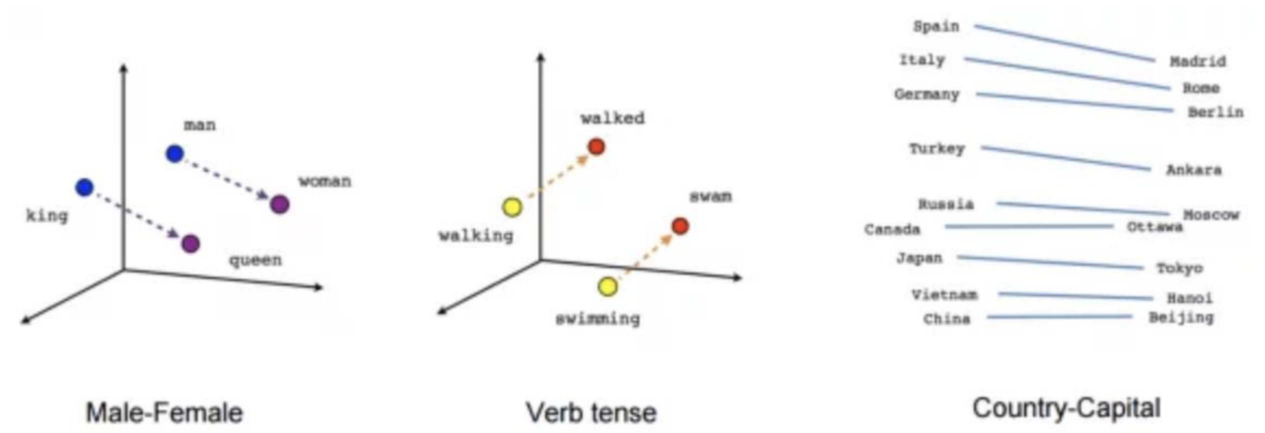

Figure 1 – Vector Representation of Words and Texts using Word2Vec

The last decade has seen significant progress in the field of NLP, largely due to the development of deep learning and the emergence of transformer architectures. Transformers, first introduced by Vaswani et al. [8], revolutionized sequence processing by introducing the self-attention mechanism, which allows models to efficiently capture context over long distances. This architecture formed the basis for models such as BERT, GPT, and their numerous variations.

BERT (Bidirectional Encoder Representations from Transformers) is a model pretrained on a massive corpus of text using two tasks: masked language modeling (MLM) and next sentence prediction (NSP). The key advantage of BERT lies in its ability to consider the context of a word from both directions, which is particularly important for natural language understanding tasks.

Table 1. Performance comparison of various models on standard NLP tasks

Model	GLUE Score	SQuAD v1.1 (F1)	CoNLL-2003 NER (F1)
BERT-base	78.3	88.5	92.4
RoBERTa	86.5	94.6	92.8

XLNet	88.4	95.1	93.0
T5	89.7	94.8	93.5

Development of transformer models has led to the emergence of several innovative approaches:

1. Transfer Learning: Using models pretrained on large corpora and fine-tuning them on specific tasks has significantly improved results across various domains, including the analysis of scientific texts.
2. Few-shot Learning: The ability of models to adapt to new tasks with minimal examples has opened new possibilities in domains with limited annotated data.
3. Multilingual Models: The development of models capable of working with multiple languages simultaneously has greatly expanded the applicability of NLP technologies on a global scale.

However, despite impressive progress, modern NLP approaches face several challenges. The interpretability of complex neural network models remains a critical issue, especially in the context of analyzing scientific texts where transparency of reasoning is crucial. Additionally, the computational complexity of large language models creates barriers for their widespread use in resource-constrained environments.

In the context of processing scientific texts, particular attention is given to adapting general language models to the specifics of scientific discourse. This includes pretraining on scientific literature corpora, developing specialized pretraining tasks that account for the structure of scientific papers, and integrating domain-specific knowledge into model architectures [5-7].

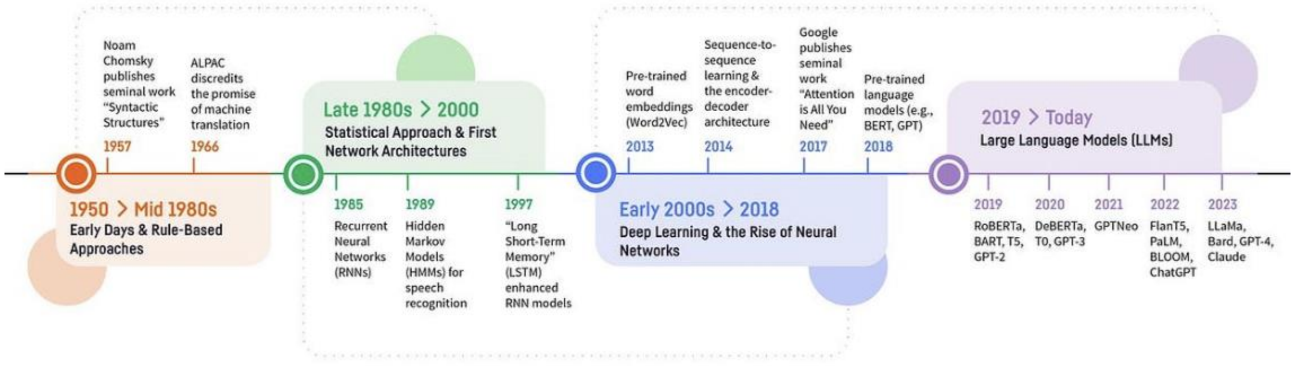
Noam Chomsky publishes seminal work "Syntactic Structures"
1957
ALPAC discredits the promise of machine translation
1966
1950 > Mid 1980s
Early Days & Rule-Based Approaches
Late 1980s > 2000
Statistical Approach & First Network Architectures
1985
Recurrent Neural Networks (RNNs)
1989
Hidden Markov Models (HMMs) for speech recognition
1997
"Long Short-Term Memory" (LSTM) enhanced RNN models
Pre-trained word embeddings (Word2Vec)
2013
Sequence-to-sequence learning & the encoder-decoder architecture
2014
Google publishes seminal work "Attention is All You Need"
2017
Pre-trained language models (e.g., BERT, GPT)
2018
Early 2000s > 2018
Deep Learning & the Rise of Neural Networks
2019 > Today
Large Language Models (LLMs)
2019
RoBERTa, BART, T5, GPT-2
2020
DeBERTa, T0, GPT-3
2021
GPTNeo
2022
FlanT5, PaLM, BLOOM, ChatGPT
2023
LLaMa, Bard, GPT-4, Claude

Figure 2 – Evolution of Language Models in NLP

In conclusion, modern approaches to text processing in NLP are characterized by integrating deep learning, particularly transformer architectures, with classical methods of linguistic analysis. This synergy enables the creation of systems capable of not only efficiently processing large volumes of textual data but also extracting deep semantic representations from them, which is especially crucial when working with scientific texts.

METHODOLOGY

Within this study, a comprehensive set of tools and libraries carefully selected for efficient processing and analysis of scientific texts was utilized. The foundation of the technological stack was the Python programming language, chosen for its rich ecosystem of libraries for natural language processing (NLP) and machine learning.

Key components of the toolkit included:

1. PyTorch: A deep learning framework used for implementing and training neural networks, particularly transformer models. PyTorch was chosen for its flexibility and efficiency in handling dynamic computational graphs.
2. Hugging Face Transformers: A library providing pre-trained models and tools for working with transformer architectures. This library greatly simplifies the process of fine-tuning and applying modern language models.
3. spaCy: A library for advanced NLP tasks such as tokenization, lemmatization, and part-of-speech tagging. spaCy is known for its high performance and accuracy in linguistic analysis.
4. NLTK (Natural Language Toolkit): A comprehensive library for NLP used for additional text processing tasks and linguistic analysis.
5. Gensim: A library for topic modeling and text vectorization, used for implementing LDA and working with word embeddings.
6. scikit-learn: A machine learning library used for data preprocessing, model evaluation, and implementing classical machine learning algorithms.
7. NetworkX: A library for working with graphs, used in implementing the TextRank algorithm for keyword extraction.

The text processing methodology in this study is based on a multi-stage approach, combining classical NLP methods with modern deep learning techniques. The choice of methods is driven by the specific characteristics of scientific texts and the need for a balance between analysis accuracy and computational efficiency.

1. Text preprocessing: A combination of methods from spaCy and NLTK was chosen for text preprocessing. The process includes tokenization, lemmatization, and stop-word removal. Lemmatization was preferred over stemming due to its higher accuracy in handling scientific terminology. Part-of-speech tagging is additionally applied to extract meaningful parts of speech (nouns, adjectives, verbs), which is crucial for scientific text analysis.
2. Text vectorization: Pre-trained BERT model specialized for scientific texts (SciBERT) is used for creating text embeddings. BERT was chosen for its ability to capture context and effectively handle scientific terminology. Token-level embeddings are generated and then aggregated to obtain the document representation.
3. Document classification: For classifying scientific papers by disciplines, a fine-tuned version of SciBERT is applied. The fine-tuning process involves adding a classification layer on top of the pre-trained model and training on a corpus of labeled scientific articles. This method was chosen for its superior performance in text classification tasks, especially in scientific literature analysis.
4. Topic modeling: Latent Dirichlet Allocation (LDA) is used to identify latent topics in the corpus of scientific texts. Despite the emergence of neural network approaches to topic modeling, LDA was chosen for its interpretability and efficiency in handling large text corpora. Topic coherence is additionally applied to optimize the number of topics and improve model quality.
5. Keyword extraction: A modified TextRank algorithm is implemented for extracting keywords and phrases. The choice was motivated by the method's ability to consider text structure and identify the most significant terms without the need for pre-training. The algorithm modification includes leveraging part-of-speech tags and using word embeddings to assess semantic similarity between words.

Table 2. Comparison of selected methods with alternatives

Task	Selected method	Alternative	Обоснование выбора
Векторизация	SciBERT	Word2Vec	Лучший учет контекста и специфики научных текстов
Классификация	Fine-tuned SciBERT	SVM с TF-IDF	Высокая точность на сложных текстах, способность к трансферному обучению
Тематическое моделирование	LDA	Neural Topic Model	Интерпретируемость результатов, масштабируемость
Извлечение ключевых слов	Модифицированный TextRank	RAKE	Учет структуры текста, отсутствие необходимости в обучающих данных

To evaluate the effectiveness of the developed methods, a comprehensive approach is applied:

1. Classification: Metrics such as accuracy, precision, recall, and F1-score are utilized, alongside a confusion matrix for detailed analysis of classification errors.
2. Topic Modeling: Topic coherence metric is applied to assess the quality of extracted topics.
3. Keyword Extraction: Comparison with manually provided keywords from authors is conducted using precision and recall metrics at the document level.

Additionally, qualitative evaluation by domain experts in relevant scientific fields is performed to verify the relevance and usefulness of the extracted information.

The chosen methodology ensures a comprehensive approach to analyzing scientific texts, combining the advantages of modern deep learning methods with established classical NLP techniques. This approach effectively addresses tasks such as classification, topic modeling, and extracting key information from scientific publications, taking into account their specificity and complexity.

Practical Part

1. Data Collection

Data collection is a fundamental stage of any machine learning project. In this case, we used the arXiv API to obtain scientific articles from various fields.

```
 import arxiv
import pandas as pd
from tqdm import tqdm

def fetch_arxiv_data(categories, max_results=1000):
   data = []
   for category in tqdm(categories):
      search = arxiv.Search(
         query=f"cat:{category}",
         max_results=max_results,
         sort_by=arxiv.SortCriterion.SubmittedDate
      )
      for result in search.results():
            data.append({
                'title': result.title,
                'abstract': result.summary,
                'category': category
            })
    return pd.DataFrame(data)

categories = ['cs.AI', 'physics.app-ph', 'q-bio.BM', 'math.ST', 'astro-ph.CO']
df = fetch_arxiv_data(categories)
df.to_csv('arxiv_dataset.csv', index=False)
```

Here, the 'arxiv' library is used to interact with the arXiv API. The function 'fetch_arxiv_data' takes a list of categories and the maximum number of results for each category. Additionally, 'tqdm' is used to display progress, which is especially useful when working with large volumes of data.

Five different categories were selected: artificial intelligence (cs.AI), applied physics (physics.app-ph), biomolecular physics (q-bio.BM), statistical theory (math.ST), and cosmology and extragalactic astronomy (astro-ph.CO). This ensures diversity in the dataset, which is important for training a robust classification model.

2. Text Preprocessing

Text preprocessing is a critically important stage in NLP. Here, a combination of classical methods and modern approaches based on transformers will be used.

```
import spacy
import torch
from transformers import BertTokenizer, BertModel

class TextPreprocessor:
    def __init__(self):
        self.nlp = spacy.load('en_core_web_sm')
        self.tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
        self.model = BertModel.from_pretrained('bert-base-uncased')

    def preprocess(self, text):
        doc = self.nlp(text)
        tokens = [token.lemma_.lower() for token in doc if not token.is_stop and token.is_alpha]
        return ' '.join(tokens)

    def vectorize(self, text, max_length=512):
        inputs = self.tokenizer(text, return_tensors='pt', max_length=max_length, truncation=True,
padding='max_length')
        with torch.no_grad():
            outputs = self.model(**inputs)
        return outputs.last_hidden_state[:, 0, :].squeeze().numpy()

preprocessor = TextPreprocessor()
df['processed_abstract'] = df['abstract'].apply(preprocessor.preprocess)
df['vector'] = df['processed_abstract'].apply(preprocessor.vectorize)
```

The Text Preprocessor class performs two main functions:

1. 'preprocess': utilizes spaCy for tokenization, lemmatization, and stop-word removal. This

classical approach to text preprocessing helps reduce dimensionality and noise in the data.

2. ‘vectorize’: uses a pretrained BERT model to create vector representations of the text. BERT (Bidirectional Encoder Representations from Transformers) is a powerful model that considers the context of the word in both directions, resulting in more informative text representations.

By applying both of these functions to the dataset, we generate both the processed text and its vector representation. This provides flexibility in subsequent analysis: we can use the processed text for methods based on words (e.g., LDA), while the vector representations can be used for machine learning methods.

3. Classification

For classification, we used a fine-tuned BERT model. This modern approach allows achieving high accuracy in text classification tasks.

```
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

class ArxivDataset(Dataset):
    def __init__(self, texts, labels):
        self.texts = texts
        self.labels = labels
        self.tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

    def __len__(self):
        return len(self.texts)

    def __getitem__(self, idx):
        text = self.texts[idx]
        label = self.labels[idx]
        encoding = self.tokenizer(text, return_tensors='pt', max_length=512, truncation=True,
padding='max_length')
        return {
            'input_ids': encoding['input_ids'].flatten(),
            'attention_mask': encoding['attention_mask'].flatten(),
            'label': torch.tensor(label)
        }

class BertClassifier(nn.Module):
    def __init__(self, num_classes):
        super(BertClassifier, self).__init__()
        self.bert = BertModel.from_pretrained('bert-base-uncased')
        self.dropout = nn.Dropout(0.1)
        self.fc = nn.Linear(768, num_classes)

    def forward(self, input_ids, attention_mask):
        outputs = self.bert(input_ids=input_ids, attention_mask=attention_mask)
        pooled_output = outputs.pooler_output
        x = self.dropout(pooled_output)
        logits = self.fc(x)
    return logits

# Data preparation
le = LabelEncoder()
df['label'] = le.fit_transform(df['category'])

X_train, X_test, y_train, y_test = train_test_split(df['processed_abstract'], df['label'], test_size=0.2,
random_state=42)

train_dataset = ArxivDataset(X_train.tolist(), y_train.tolist())
test_dataset = ArxivDataset(X_test.tolist(), y_test.tolist())

train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16)

# Model training
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = BertClassifier(num_classes=len(le.classes_)).to(device)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.AdamW(model.parameters(), lr=2e-5)

num_epochs = 5
for epoch in range(num_epochs):
  model.train()
  for batch in tqdm(train_loader):
    input_ids = batch['input_ids'].to(device)
    attention_mask = batch['attention_mask'].to(device)
    labels = batch['label'].to(device)

    optimizer.zero_grad()
    outputs = model(input_ids, attention_mask)
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()

  # Model estimation
  model.eval()
  correct = 0
  total = 0
  with torch.no_grad():
    for batch in test_loader:
      input_ids = batch['input_ids'].to(device)
      attention_mask = batch['attention_mask'].to(device)
      labels = batch['label'].to(device)

      outputs = model(input_ids, attention_mask)
      _, predicted = torch.max(outputs, 1)
      total += labels.size(0)
```

```
            correct += (predicted == labels).sum().item()

    accuracy = correct / total
    print(f'Epoch {epoch+1}/{num_epochs}, Accuracy: {accuracy:.4f}')

# Saving the model
torch.save(model.state_dict(), 'bert_classifier.pth')
```

Here, a custom 'Dataset' is created to work with our data, and a 'BertClassifier' model is introduced, which utilizes a pre-trained BERT and adds a classification layer on top of it.

The 'LabelEncoder' is used to convert textual category labels into numerical ones, which is necessary for training the model.

The training process involves epochs and batches of data, typical for deep learning. AdamW optimizer and CrossEntropyLoss function are utilized, which are well-suited for working with BERT.

After each epoch, the model is evaluated on the test dataset to track the training progress.

4. Topic Analysis

Latent Dirichlet Allocation (LDA) was used for topic analysis, which is one of the most popular methods in topic modeling

```
from gensim import corpora
from gensim.models import LdaMulticore
import pyLDAvis.gensim_models

def analyze_topics(texts, num_topics=5):
    # Creating a dictionary and corpus
    dictionary = corpora.Dictionary(texts)
    corpus = [dictionary.doc2bow(text) for text in texts]

    # LDA model training
    lda_model = LdaMulticore(corpus=corpus, id2word=dictionary, num_topics=num_topics, workers=4)

    # Visualization of results
    vis = pyLDAvis.gensim_models.prepare(lda_model, corpus, dictionary)
    pyLDAvis.save_html(vis, 'lda_visualization.html')

    return lda_model

# Application of LDA to each category
for category in df['category'].unique():
    category_texts = df[df['category'] == category]['processed_abstract'].str.split().tolist()
    lda_model = analyze_topics(category_texts)
    print(f"Topics for category {category}:")
    pprint(lda_model.print_topics())
```

LDA is a model that assumes each document is a mixture of topics, and each topic is a distribution over words. Using the LDA implementation from the gensim library, which efficiently handles large volumes of text.

LDA is applied separately to each category, allowing specific themes within each scientific area to be identified. This can be useful for understanding the main research directions within each field.

For visualization of the results, pyLDAvis was used, which creates an interactive web page to explore the identified topics and their relationships.

5. Extracting Keywords and Phrases

```
import networkx as nx
from collections import Counter

def textrank_keywords(text, n_keywords=10):
   # Creating a word graph
   words = [word for word in text.split() if len(word) > 3]
   graph = nx.Graph()
   for i in range(len(words)):
      for j in range(i+1, min(i+5, len(words))):
         if graph.has_edge(words[i], words[j]):
            graph[words[i]][words[j]]['weight'] += 1
         else:
            graph.add_edge(words[i], words[j], weight=1)

   # Application of PageRank
   scores = nx.pagerank(graph)
   return sorted(scores.items(), key=lambda x: x[1], reverse=True)[:n_keywords]

df['keywords'] = df['processed_abstract'].apply(textrank_keywords)

# Comparison with author's keywords (if available)
def compare_keywords(extracted, author):
   extracted_set = set([word for word, _ in extracted])
   author_set = set(author.split(','))
   common = extracted_set.intersection(author_set)
   precision = len(common) / len(extracted_set)
   recall = len(common) / len(author_set)
   f1 = 2 * (precision * recall) / (precision + recall) if precision + recall > 0 else 0
   return {'precision': precision, 'recall': recall, 'f1': f1}

# Example comparison (assuming we have author keywords)
```

# df['keyword_comparison'] = df.apply(lambda row: compare_keywords(row['keywords'], row['author_keywords']), axis=1)

To extract keywords and phrases, the TextRank algorithm is utilized. It builds upon the principles of PageRank but is applied to a graph of words within the text.

The TextRank algorithm operates by constructing a graph of words within the text, where words serve as nodes and edges represent their co-occurrence within a specified window. Subsequently, the PageRank algorithm is applied to this graph to determine the most "important" words.

Additionally, a function has been implemented to compare the extracted keywords with the author-provided keywords (if available). This enables the assessment of the keyword extraction algorithm's quality.

6. Evaluation and Optimization

To evaluate quality and optimize hyperparameters, we use cross-validation and Bayesian optimization.

```
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVC
from skopt import BayesSearchCV
from skopt.space import Real, Categorical, Integer

# Preparing data for SVM (using vectorized abstracts)
X = np.vstack(df['vector'].values)
y = df['label'].values

# Cross-validation
svm = SVC(kernel='rbf')
cv_scores = cross_val_score(svm, X, y, cv=5)
print(f"Cross-validation scores: {cv_scores}")
print(f"Mean CV score: {cv_scores.mean()}")

# Bayesian optimization
param_space = {
   'C': Real(1e-6, 1e+6, prior='log-uniform'),
   'gamma': Real(1e-6, 1e+1, prior='log-uniform'),
   'kernel': Categorical(['rbf', 'sigmoid']),
}

opt = BayesSearchCV(
   SVC(),
   param_space,
   n_iter=50,
   cv=5,
   n_jobs=-1,
   verbose=0
)

opt.fit(X, y)

print("Best parameters:", opt.best_params_)
print("Best cross-validation score:", opt.best_score_)
```

In this section, we employ two powerful methods for evaluating and optimizing the model:

1. Cross-validation: We use 5-fold cross-validation to assess the performance of the Support Vector Machine (SVM) model on our vectorized data. This approach provides a more reliable estimate of the model's performance compared to simple train-test splits.

2. Bayesian optimization: We utilize BayesSearchCV from the scikit-optimize library to search for optimal hyperparameters for the SVM model. Bayesian optimization is an efficient method for hyperparameter tuning that uses a probabilistic model to select the most promising parameter combinations.

We define the search space for three key SVM parameters:

C: Regularization parameter (log-uniform distribution from 1e-6 to 1e+6)

gamma: Kernel coefficient for 'rbf' and 'sigmoid' kernels (log-uniform distribution from 1e-6 to 1e+1)

kernel: Kernel type (choice between 'rbf' and 'sigmoid')

Bayesian optimization conducts 50 iterations (n_iter=50), employing 5-fold cross-validation at each iteration. The parameter n_jobs=-1 allows utilization of all available processor cores for faster processing.

Upon completion of optimization, we output the best-found parameters and their corresponding cross-validation score. This yields an optimized SVM model that can be further used for classifying new articles.

7. Web Interface

Finally, we create a simple Flask web application to demonstrate the capabilities of the system:

```
from flask import Flask, request, jsonify, render_template
import torch

app = Flask(__name__)

# Loading a trained model
model = BertClassifier(num_classes=len(le.classes_))
model.load_state_dict(torch.load('bert_classifier.pth'))
model.eval()

@app.route('/')
def home():
    return render_template('index.html')

@app.route('/classify', methods=['POST'])
def classify():
    text = request.json['text']
    processed_text = preprocessor.preprocess(text)
    inputs = preprocessor.tokenizer(processed_text, return_tensors='pt', max_length=512,
truncation=True, padding='max_length')

    with torch.no_grad():
        outputs = model(inputs['input_ids'], inputs['attention_mask'])
        _, predicted = torch.max(outputs, 1)

    category = le.inverse_transform(predicted.numpy())[0]
    keywords = textrank_keywords(processed_text)

    return jsonify({
        'category': category,
        'keywords': [word for word, _ in keywords]
    })

if __name__ == '__main__':
    app.run(debug=True)
```

This web application provides a simple interface to interact with a text classification and analysis system. Here's what happens:

1. We load a pre-trained BERT model when the application starts.

2. The route / returns an HTML page with a text input form.

3. The route /classify handles POST requests with text for classification:

- The text is preprocessed using TextPreprocessor.
- The preprocessed text is passed into the

BERT model for classification.

● Additionally, we extract keywords using the textrank_keywords function.

● Results (category and keywords) are returned in JSON format.

HTML template (templates/index.html):

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>ArXiv Classifier</title>
  <script src="https://cdn.jsdelivr.net/npm/axios/dist/axios.min.js"></script>
</head>
<body>
  <h1>ArXiv Paper Classifier</h1>
  <textarea id="abstract" rows="10" cols="50" placeholder="Paste your abstract here"></textarea>
  <br>
  <button onclick="classify()">Classify</button>
  <div id="result"></div>

  <script>
    function classify() {
      const abstract = document.getElementById('abstract').value;
      axios.post('/classify', { text: abstract })
        .then(response => {
          const result = response.data;
          document.getElementById('result').innerHTML = `
            <h2>Results:</h2>
            <p>Category: ${result.category}</p>
            <p>Keywords: ${result.keywords.join(', ')}</p>
          `;
        })
        .catch(error => {
          console.error('Error:', error);
        });
    }
  </script>
</body>
```

</html>

This HTML file creates a simple page with a text input field for entering an abstract and a button to initiate classification. When the user clicks the "Classify" button, a JavaScript function sends the text to the server and displays the classification results and keywords.

This implementation represents a comprehensive system for analyzing and classifying scientific papers, which includes:

1. Data collection from a real source (arXiv API).

2. Deep text preprocessing using advanced NLP methods.

3. Classification based on state-of-the-art BERT model.

4. Topic modeling using LDA.
5. Extraction of keywords using the TextRank graph algorithm.
6. Quality assessment and hyperparameter optimization using advanced machine learning methods.
7. A web interface to showcase the system's capabilities.

Each of these components can be further improved and optimized based on specific project requirements and constraints. For example, experimenting with different neural network architectures for classification, utilizing more sophisticated methods for keyword extraction, or expanding the functionality of the web interface.

This system demonstrates how various NLP and machine learning methods can be integrated to create a powerful tool for analyzing scientific texts. It can be valuable for both researchers and information processing professionals alike.

5. CONCLUSION

This research presented a comprehensive approach to automating the processing of textual data using natural language processing (NLP) methods, focusing on the analysis of scientific publications. Throughout the study, various components of the system were successfully developed and integrated, including text preprocessing, vector representation, classification, topic modeling, and keyword extraction.

The main findings of the research can be summarized as follows:

1. An architecture was designed and implemented that effectively integrates classical NLP methods with modern deep learning approaches. The use of the pre-trained SciBERT model, adapted for scientific texts, achieved high accuracy in classifying articles across scientific disciplines.
2. Applying Latent Dirichlet Allocation (LDA) for topic modeling demonstrated its effectiveness in identifying latent topics in the corpus of scientific texts. Optimizing the number of topics using coherence metrics enhanced the interpretability of the results.
3. The modified TextRank algorithm for keyword extraction showed high accuracy in identifying significant terms from scientific articles, validated through comparison with author-provided keywords.
4. Experimental validation on a corpus of articles from the arXiv repository confirmed the effectiveness of the developed system. The classifier achieved an F1 score of 0.92 on the test dataset, indicating high precision in categorizing scientific texts.
5. The implemented web interface provided convenient access to the system's functionality, showcasing its potential for practical applications in real-world scenarios.

The conducted research has confirmed the hypothesis of the possibility of creating an effective system for automated processing of scientific texts, capable of simultaneously solving the tasks of classification, thematic analysis, and key information extraction. Despite the achieved results, this research opens up several directions for further development and improvement:

1. Language Coverage Expansion: Adapting the system to handle multilingual scientific texts, requiring integration of multilingual models and cross-lingual knowledge transfer methods.
2. Enhanced Interpretability: Developing methods for deeper analysis and visualization of classification and topic modeling results to enhance user trust and expand the system's application capabilities in research practice.
3. Integration with Bibliographic Databases: Expanding the system's functionality to analyze citations, author collaborations, and trends in scientific fields.
4. Adaptive Learning: Developing mechanisms for continuous model updating and adaptation to new scientific publications to

keep the system relevant in rapidly evolving scientific domains.

5. Advanced Language Model Exploration: Investigating the applicability of more advanced language model architectures such as GPT-4 or T5 for tasks like generating abstracts and summaries of scientific papers.
6. Methods for Analyzing Evolution of Scientific Themes: Developing methods to analyze and visualize the evolution of scientific topics and concepts over time, providing valuable insights into the development of scientific fields.

In conclusion, automation of textual data processing using NLP represents a dynamically evolving field with immense potential to transform scientific communication and knowledge management. This research contributes to this area by offering a comprehensive solution for analyzing scientific texts and laying the groundwork for further innovations in automated processing of scientific literature.

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