

```

1 !pip install pyLDAvis
2 !pip install gensim
3 !pip install --upgrade numpy
4 !pip install pandas==1.5.3

```

1/2 1. Data acquisition, description, and preparation 2. Research Question

The research question I aim to explore with topic modeling is: **"How did regional parties in the UK, along with UKIP, adapt and respond to the realities of Brexit post-referendum?"** I would like to delve into the understanding of the thematic shifts and focuses in party manifestos and communications during a critical point in UK politics. In using the Latent Dirichlet Allocation (LDA) by examining the frequency and co-occurrence of words across various texts, the LDA can reveal the dominant themes and concerns in these political manifestos. My dataset, comprising of seven party platforms from 2017-2019 of UKIP, SNP, Plaid Cymru (Party of Wales), and DUP, provides a good and varied dataset for this analysis. I have chosen to go with regional parties and UKIP together to see how all parties tried to take a positive spin of Brexit regional and UKIP after the referendum. The chosen time frame captures the immediate aftermath of the Brexit referendum, a period likely to be ripe with Scottish independence desire, fear in Northern Ireland over a hard border, worries in all regions about economic impacts of Brexit and UKIP's push for more sovereignty being a tying theme for all the parties.

▼ Import Libraries

```

1 import os
2 import pandas as pd
3 import re
4 import numpy
5 import gensim
6 import pyLDAvis
7 import pyLDAvis.gensim_models
8 import matplotlib.pyplot as plt
9 from gensim.models import LdaModel
10 from gensim.corpora import Dictionary
11 from nltk.tokenize import word_tokenize
12 from nltk.corpus import stopwords
13 import string
14 import nltk
15 from sklearn.feature_extraction.text import TfidfVectorizer
16 nltk.download('punkt')
17 nltk.download('stopwords')

```

```

/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Deprecat
and should_run_async(code)
[nltk_data] Downloading package punkt to /root/nltk_data...

```

```
[nltk_data] Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
True
```

▼ Preprocessing and Document Matrix

```
1 def preprocess_text(text):
2     text = text.lower()
3     text = re.sub(r'\W', ' ', text)
4     text = re.sub(r'\s+[a-zA-Z]\s+', ' ', text)
5     text = re.sub(r'\^[a-zA-Z]\s+', ' ', text)
6     text = re.sub(r'\s+', ' ', text, flags=re.I)
7     return text
8
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Deprecat
and should_run_async(code)
```

```
1 folder_path = '/content/Data'
2
3 all_texts = pd.DataFrame(columns=['text'])
4
5 for filename in os.listdir(folder_path):
6     if filename.endswith('.csv'):
7         file_path = os.path.join(folder_path, filename)
8         manifesto = pd.read_csv(file_path, usecols=[0], header=0)
9         manifesto.columns = ['text']
10        manifesto['processed_text'] = manifesto['text'].apply(preprocess_text)
11        all_texts = pd.concat([all_texts, manifesto], ignore_index=True)
12
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Deprecat
and should_run_async(code)
```

```
1 all_texts['text'] = all_texts['text'].apply(preprocess_text)
2
3 tfidf_vectorizer = TfidfVectorizer(stop_words='english')
4 tfidf_matrix = tfidf_vectorizer.fit_transform(all_texts['text'])
5 tfidf_df = pd.DataFrame(tfidf_matrix.toarray(), columns=tfidf_vectorizer.get
6 tfidf_df
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Deprecat
and should_run_async(code)
```

	00	000	000per	049	067	10	100	1000	100bn	108	...	ynys	young	y
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	

4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
...
6237	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
6238	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
6239	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
6240	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
6241	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0

6242 rows x 7395 columns

Tokenization

```

1 stop_words = set(stopwords.words('english'))
2
3 def tokenize_and_preprocess(text):
4     tokens = word_tokenize(text)
5     tokens = [token for token in tokens if token not in stop_words]
6     tokens = [token for token in tokens if token not in string.punctuation]
7     tokens = [token for token in tokens if token.isalnum()]
8     return tokens
9
10 all_texts['tokens'] = all_texts['processed_text'].apply(tokenize_and_preproc
    /usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Deprecat
    and should_run_async(code)

```

LDA

3

LDA analyzes words and phrases across documents (for example political manifestos) and identifies clusters of terms that frequently appear together, which it then interprets as topics.

In executing this model for the analysis, I made critical choices regarding its configuration. One such choice was the number of topics to extract, I've have set at five. This defines how many distinct themes you expect to find in the collection of documents. Choosing fewer topics might lead to a simplistic view where distinct themes of the manifestos are merged, while too many topics can fragment the analysis, leading to overly specific topics. Another key parameter was the number of 'passes' the LDA model makes over the data, set at 25 in my case. More passes typically lead to more refined and accurate topic assignments but require more computational resources and time.

Topic modeling is a statistical model for analyzing the latent structure of a collection of documents. It is a type of unsupervised machine learning. The most common type of topic modeling is Latent Dirichlet Allocation (LDA). LDA is a generative stochastic model that assumes each document is a mixture of a certain number of topics, and each topic is a mixture of words. The goal of LDA is to discover the topics in a collection of documents and to estimate the probability of each word appearing in each topic.

These choices significantly influence how effectively the model can evaluate the research question: "How did the regional parties, along with UKIP, attempt to reconcile with the reality of Brexit post-referendum?" By opting for five topics, the goal was to strike a balance between capturing a broad spectrum of themes and maintaining analytical clarity.

Corpus for LDA

```
1 dictionary = Dictionary(all_texts['tokens'])
2 corpus = [dictionary.doc2bow(tokens) for tokens in all_texts['tokens']]
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Deprecat
and should_run_async(code)
```

Train LDA Model and Print Topics

```
1 num_topics = 5
2
3 lda_model = LdaModel(corpus, num_topics=num_topics, id2word=dictionary, pass
4
5 topics = lda_model.print_topics(num_topics=num_topics, num_words=10)
6 for topic_number, topic_words in topics:
7     print(f"Topic {topic_number + 1}: {topic_words}")
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Deprecat
and should_run_async(code)
Topic 1: 0.018*"people" + 0.012*"system" + 0.008*"house" + 0.006*"health" +
Topic 2: 0.018*"eu" + 0.017*"ireland" + 0.017*"northern" + 0.012*"uk" + 0.0
Topic 3: 0.021*"ukip" + 0.011*"energy" + 0.010*"britain" + 0.008*"new" + 0.
Topic 4: 0.018*"scotland" + 0.015*"government" + 0.011*"uk" + 0.008*"snp" +
Topic 5: 0.015*"government" + 0.014*"uk" + 0.011*"tax" + 0.011*"snp" + 0.00
```

pyLDavis

```
1 pyldavis_data = pyLDavis.gensim_models.prepare(lda_model, corpus, dictionary
2 pyLDavis.display(pyldavis_data)
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Deprecat
and should_run_async(code)
/usr/local/lib/python3.10/dist-packages/pandas/core/dtypes/cast.py:1641: De
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs for mo
return np.find_common_type(types, [])
```

Selected Topic:

Intertopic Distance Map (via multidimensional scaling)



5. Societal Systems and Brexit Implications (Topic 1)

In Topic 1 the data reveals an interpretation by regional parties such as UKIP and the DUP of Brexit's ramifications on societal infrastructures. The prevalent terms - "people," "system," "house," "health" - underscore a deep-seated concern for the holistic well-being of citizens within the post-Brexit context. The focus on "health," "ukip," "united," and "services" reflects that there was a critical discourse on the reconfiguration of national healthcare and service frameworks, adapting to new socio-political realities. Furthermore, the incorporation of terms like "diesel" and "single" an awareness of environmental and economic challenges.

Geopolitical Dynamics and Regional Identities (Topics 2 and 4)

Topics 2 and 4 encapsulate the intricate geopolitical and regional identity shifts in the Brexit epoch. Topic 2, with its emphasis on "eu," "ireland," "northern," and "uk," brings to light pivotal issues such as the Northern Ireland border dilemma and the UK's redefined relationship with the EU. This analysis elucidates concerns over international security, global positioning, and financial resilience in a post-Brexit world. Simultaneously, Topic 4 offers insights into Scotland and Wales' strategic positioning, with terms like "scotland," "government," "snp," and "wales." The prominence of "westminster" and "parliament" in this discourse suggests a critical engagement with power dynamics and autonomy within the UK, highlighting regional parties' advocacy for increased self-governance post-Brexit.

Economic and Environmental Strategies (Topic 3)

Topic 3's is characterized by "ukip," "energy," "britain," and "new," indicates a strategic redirection towards economic and environmental issues. The inclusion of "animal," "local," "jobs," and "cost" points to a strategic balance between economic growth, environmental conservation, and animal welfare. This implies that regional parties are proactively adapting to Brexit-induced economic transformations while also prioritizing sustainable, community-oriented policies.

Governance and Fiscal Policies (Topic 5):

Topic 5 centers around governance and fiscal management, with key terms like "government," "uk," "tax," and "snp." The analysis highlights a focus on reorganizing government spending and taxation strategies in the post-Brexit scenario. The mention of "women" in this context indicates a recognition of gender-sensitive policy-making.

Conclusion Overall, the topic modeling analysis portrays how UK regional parties and UKIP are strategically navigating the complex challenges in post-Brexit Britain. Their approaches, encompassing societal, healthcare, geopolitical, economic, and governance aspects, demonstrate a concerted effort to address regional nuances alongside broader national concerns within an evolving political and economic framework while trying to focus on

moving forward past brexit onto other policy topics.