```
In [1]: #Importing relevant libraries
        from pdfminer.high_level import extract_text
        import PyPDF2
        from PyPDF2 import PdfReader
        import re
        import string
         from nltk.corpus import stopwords
         from nltk.tokenize import word_tokenize
        from nltk.stem import PorterStemmer
        from nltk import download
        from gensim import corpora, models
         from gensim.models import CoherenceModel
        import os
        import statistics
        import pandas as pd
        import numpy as np
         from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from scipy.stats import pearsonr
        import matplotlib.pyplot
         import seaborn as sns
        from wordcloud import WordCloud
        import matplotlib.pyplot as plt
         from gensim.models.coherencemodel import CoherenceModel
        import tensorflow as tf
        import os
        import pdfplumber
         from gensim.corpora import Dictionary
         from gensim.models import HdpModel
         from gensim.models.ldamodel import LdaModel
         from sklearn.model_selection import KFold
        import pyLDAvis.gensim
        # Download other resources
        download('stopwords')
        download('punkt')
         [nltk_data] Downloading package stopwords to
         [nltk_data]
                       /Users/cdlacey/nltk_data...
                      Package stopwords is already up-to-date!
         [nltk_data]
         [nltk_data] Downloading package punkt to /Users/cdlacey/nltk_data...
        [nltk_data] Package punkt is already up-to-date!
        True
Out[1]:
In [2]: #Initial stats - file count
        def count_files_in_folder(folder_path):
            # Initialize a counter for files
            file_count = 0
            # Walk through the directory and count files
            for _, _, files in os.walk(folder_path):
                 file_count += len(files)
            return file_count
        folder_path = '/Users/cdlacey/TMU_DataScience/CIND820/Dataset_Sample'
         total_files = count_files_in_folder(folder_path)
        print("Total files in datasource: ", total_files)
        Total files in datasource: 25
In [3]: #Initial stats - page count
         def count_pages_and_stats(folder_path):
            total_pages = 0
            page_counts = []
            for filename in os.listdir(folder_path):
                if filename.endswith('.pdf'):
                     file_path = os.path.join(folder_path, filename)
                    with open(file_path, 'rb') as file:
                         pdf_reader = PdfReader(file)
```

```
num_pages = len(pdf_reader.pages)
                                   total_pages += num_pages
                                   page_counts.append(num_pages)
                  mean_page_count = statistics.mean(page_counts)
                  median_page_count = statistics.median(page_counts)
                  return total_pages, mean_page_count, median_page_count
            folder_path = '/Users/cdlacey/TMU_DataScience/CIND820/Dataset_Sample'
            total_pages, mean_page_count, median_page_count = count_pages_and_stats(folder_path)
            print("Total pages in all PDF files:", total pages)
            print("Mean page count per file:", mean_page_count)
            print("Median page count per file:", median_page_count)
            Total pages in all PDF files: 2113
            Mean page count per file: 84.52
            Median page count per file: 82
In [4]: # Function for preprocessing text
            def preprocess_text(text):
                  # Tokenize
                  tokens = word_tokenize(text)
                  # Remove punctuation and convert to lowercase
                  tokens = [token.lower() for token in tokens if token.isalpha()]
                  # Remove stopwords
                  stop_words = set(stopwords.words('english'))
                  french_stopwords = set(stopwords.words('french'))
                  stop_words.update(french_stopwords)
                  tokens = [token for token in tokens if token not in stop_words]
                  # Remove numbers, symbols, and certain words
                  tokens = [re.sub(r'[^a-zA-Z]', '', token) for token in tokens]
                  # Remove specific words or letters which are not useful
                       itional_stopwords = {
    'mr.', 'mrs.', 'ms.', 'speaker', 'bill', 'debate', 'hon', 'cpc', 'lib', 'bq', 'canadian',
    'act', 'amend', 'amendment', 'canada', 'house', 'public', 'honour', 'minister', 'ministry', 'gover
    'member', 'program', 'primeminister', 'would', 'people', 'chair', 'committe', 'liber', 'polici', '
    'ndp', 'government', 'conserv', 'parties', 'partisan', 's', 'b', 'c', 'e', 'f', 'g', 'h', 'j', 'k'
    'q', 'r', 't', 'u', 'v', 'w', 'x', 'y', 'z', 'am', 'pm', 'year', 'time', 'motion', 'go', 'canadians',
    'also', 'members', 'madam', 'committee', 'prime', 'senate', 'senator', 'hous',
    'one', 'govern', 'liberal', 'conservative', 'liberals', 'conservatives', 'speech', 'parliamentaria
    'secretariat', 'ii', 'iii', 'iv', 'v', 'vii', 'viii', 'viii', 'ix', 'x', 'xi', '000', '1', '3', '5',
    '15', '22', '25', '2007', '2008', '2009', '2010', '2011',
    '2012', '2013', '2014', '2015', '2016', '2017', '2018', '2019', '2020', '2021', '2022', '2023', ',
    ',Äú', ',Äù', "'",
    '......',"'s"}
ens = [token for token in tokens if token not in additional ataxwards'
                  additional_stopwords = {
                  tokens = [token for token in tokens if token not in additional_stopwords]
                  # Stemming
                  stemmer = PorterStemmer()
                  tokens = [stemmer.stem(token) for token in tokens]
                  return tokens
            # Directory path containing PDF files
            pdf_directory = '/Users/cdlacey/TMU_DataScience/CIND820/Dataset_Sample'
            # List all PDF files in the directory
            pdf_files = [os.path.join(pdf_directory, file) for file in os.listdir(pdf_directory) if file.endswith('.pd
            texts = []
            # Loop through each PDF file and extract text
            for pdf_file in pdf_files:
                  with pdfplumber.open(pdf_file) as pdf:
                        text = ""
                        for page in pdf.pages:
                             text += page.extract_text()
                        texts.append(text)
            # Preprocess text
            preprocessed_texts = [preprocess_text(text) for text in texts]
            # Create a dictionary from the preprocessed text
            dictionary = Dictionary(preprocessed_texts)
            # Create a corpus
            corpus = [dictionary.doc2bow(text) for text in preprocessed_texts]
```

```
In [5]: #spliting data for cross validation
          from sklearn.model_selection import train_test_split
         train_corpus, test_corpus = train_test_split(corpus, test_size=0.2, random_state=42)
In [22]: # Train the HDP model
         hdp_model = HdpModel(train_corpus, id2word=dictionary)
         #First evaluation of HDP model and number of topics identified per document)
In [23]:
          rows = []
          # Iterate through each document in the corpus
          for i, doc in enumerate(corpus):
              doc_topics = hdp_model[doc]
              # Extract topic numbers and their probabilities
              topic_numbers = [topic[0] for topic in doc_topics]
              topic_probs = [topic[1] for topic in doc_topics]
              # Append the document's topics to the rows list
              rows.append([i, topic_numbers, topic_probs])
          # Create a DataFrame from the list of rows
         doc_topics_df = pd.DataFrame(rows, columns=['Document_Index', 'Topic_Numbers', 'Topic_Probabilities'])
         # Display the DataFrame
         doc_topics_df.head(10)
Out[23]:
            Document_Index
                                              Topic_Numbers
                                                                                                       Topic_Probabilities
                         0 [0, 2, 3, 4, 5, 6, 10, 11, 13, 41, 48, 54, 71,
                                                            [0.047155762038943436, 0.01745641223716107, 0.021935941002908074,
         0
                                             88, 107, 133, 137]
                                                                                          0.08173593366511456, 0.3656592...
                                                       [14]
                                                                                                    [0.9960326922549173]
          2
                         2
                                                      [0, 4]
                                                                                [0.9826620155469378, 0.016204768081790315]
          3
                         3
                                                        [0]
                                                                                                    [0.9999601737264474]
          4
                         4
                                                        [1]
                                                                                                    [0.9999840119261535]
          5
                         5
                                                        [8]
                                                                                                    [0.9999438441800745]
         6
                         6
                                                        [7]
                                                                                                    [0.9999496279042555]
          7
                                                       [10]
                                                                                                    [0.9999406441139107]
                                                              [0.3406484096690997, 0.037426905142720464, 0.2210325621217866,
          8
                         8
                                  [0, 2, 4, 8, 10, 13, 14, 60, 66, 83]
                                                                                       0.12818298433928554,\, 0.0114204199...
                         a
                                                                                                    [0.9999365625262497]
         a
                                                        [11]
In [24]: # To find an approximate number of total topics identified within the HDP model, I found it easiest to tra
         #LDA model on the HDP model.
          # Here we'll train an LDA model using the HDP model as a training mechanism
         lda_model_t = hdp_model.suggested_lda_model()
          # Get the topic distributions for each document
         doc_topics = [lda_model_t.get_document_topics(doc) for doc in corpus]
          # Count the number of unique topics
         unique_topics = set()
          for doc_topics in doc_topics:
              unique_topics.update([topic[0] for topic in doc_topics])
         num_topics_identified = len(unique_topics)
         print(f"Number of topics identified by HDP model: {num_topics_identified}")
         Number of topics identified by HDP model: 19
 In [9]: #From the Literature Review, the ideal topics for LDA was found to be 7.
         from gensim.models import LdaModel
          # Train the LDA model
         lda_model = LdaModel(train_corpus, id2word=dictionary, num_topics=7, update_every=1, chunksize=10, passes=
In [10]: #Evaluating LDA topic coherance values.
         # Calculate coherence values for each topic
          coherence_values = {}
         for topic_num in range(lda_model.num_topics):
```

```
topic_words = [term for term, _ in topic_terms]
             coherence_model = CoherenceModel(topics=[topic_words], texts=preprocessed_texts, dictionary=dictionary
             coherence_values[topic_num] = coherence_model.get_coherence()
         # Create a table of coherence values
         print("Topic\tCoherence Value")
         for topic_num, coherence_value in coherence_values.items():
             print(f"{topic_num}\t{coherence_value}")
         Topic
                 Coherence Value
         0
                 0.45736087529776065
                 0.874373060072404
         2
                 0.3963513104929659
         3
                 0.660325208683177
         4
                 0.3978611926676396
                 0.5498209228613706
         5
                 0.40954532370489627
In [11]: # Finding the overall LDA model coherance value
         topics = lda_model.show_topics(num_topics=-1, formatted=False)
         # Calculate coherence values for each topic
         coherence_model_lda = CoherenceModel(model=lda_model, texts=preprocessed_texts, dictionary=dictionary, coh
         coherence_lda = coherence_model_lda.get_coherence()
         print("Coherence Score for LDA model:", coherence_lda)
         Coherence Score for LDA model: 0.410306025057182
In [25]: #Evaluating HDP topic coherance values, which were found to have a range below as well as above the LDA mo
         hdp_topics = hdp_model.show_topics(num_topics=19, formatted=False) # Get the top topics
         # Extract topic words for each topic
         topic_words = [[word for word, _ in topic] for topic_id, topic in hdp_topics]
         # Calculate coherence values for each topic
         coherence_values = {}
         for topic_num, words in enumerate(topic_words):
             coherence_model = CoherenceModel(topics=[words], texts=preprocessed_texts, dictionary=dictionary, cohe
             coherence_values[topic_num] = coherence_model.get_coherence()
         # Create a table of coherence values
         print("Topic\tCoherence Value")
         for topic_num, coherence_value in coherence_values.items():
             print(f"{topic_num}\t{coherence_value}")
         Topic Coherence Value
         0
                 0.35378889730765517
                 0.5815620435360508
         1
         2
                 0.46758620014278823
                 0.3644140581503076
         3
         4
                 0.409021556616043
                 0.23868174880719942
         5
         6
                0.3441902705045204
         7
                 0.35631095661923473
         8
                 0.4597742834083295
         9
                 0.40607332438045696
         10
                 0.2690057186740486
         11
                 0.4200206196641586
         12
                 0.4300083454633025
         13
                 0.3283835875737579
         14
                 0.3461376859783381
         15
                 0.7456783408159909
         16
                 0.7116339792674294
         17
                 0.7325777676665787
         18
                 0.7453307669425714
In [26]: # Finding the overall coherhance value for HDP model
         hdp_topics = hdp_model.show_topics(num_topics=19, formatted=False) # Get the top topics
         # Extract topic words for each topic
         topic_words = [[word for word, _ in topic] for topic_id, topic in hdp_topics]
         # Calculate coherence values for each topic
         coherence_values = {}
         for topic_num, words in enumerate(topic_words):
             coherence_model = CoherenceModel(topics=[words], texts=preprocessed_texts, dictionary=dictionary, cohe
```

topic_terms = lda_model.show_topic(topic_num)

```
coherence_values[topic_num] = coherence_model.get_coherence()

# Compute the average coherence value
avg_coherence_value = sum(coherence_values.values()) / len(coherence_values)

print("Overall Coherence Value for HDP model:", avg_coherence_value)
```

Overall Coherence Value for HDP model: 0.4584305342904611

```
In [14]: #Generate df with dominant topics, the topic contribution and topic keywords for LDA model
         def format_topics(ldamodel=None, corpus=None, texts=None):
             # Initialize an empty list to store rows
             rows = []
             # Iterate through each document in the corpus
             for i, row_list in enumerate(ldamodel[corpus]):
                 row = row_list[0] if ldamodel.per_word_topics else row_list
                 row = sorted(row, key=lambda x: (x[1]), reverse=True)
                 # Extract dominant topic, its contribution, and keywords
                 for j, (topic_num, prop_topic) in enumerate(row):
                     if j == 0: # Dominant topic
                         wp = ldamodel.show_topic(topic_num)
                         topic_keywords = ", ".join([word for word, prop in wp])
                         row_data = [int(topic_num), round(prop_topic, 4), topic_keywords, texts[i]]
                         rows.append(row_data)
                         break
             # Create df
             topics_df = pd.DataFrame(rows, columns=['Dominant_Topic', 'Perc_Contribution', 'Topic_Keywords', 'Text
             return topics_df
         df_topic_keywords = format_topics(ldamodel=lda_model, corpus=corpus, texts=preprocessed_texts)
         df_topic_keywords.head(10)
```

Out[14]:	Dominant_Topic	Perc_Contribution	Topic_Keywords	Text
	0	0.9961	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia
	1 (0.9056	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia
	2	0.5588	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia
	3	1.0000	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia
	4 5	0.9952	tax, carbon, yea, agre, commonsdeb, mass, nay,	[common, debat, volum, number, session, parlia
	5	1.0000	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia
	6	1.0000	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia
	7	0.9999	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia
	8	0.9937	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia
	9	0.6940	right, work, want, make, need, know, order, li	[common, debat, volum, number, session, parlia

```
axis=0)

# Reset Index
topics_sorteddf_mallet.reset_index(drop=True, inplace=True)

# Format DF
topics_sorteddf_mallet.columns = ['Topic_Num', "Topic_Perc_Contrib", "Keywords", "Representative Text"]

topics_sorteddf_mallet.head(10)
```

```
Out[15]:
               Topic_Num Topic_Perc_Contrib
                                                                                 Keywords
                                                                                                                                Representative Text
                                                        right, work, want, make, need, know,
                                                                                                 [common, debat, volum, number, session, parliament,
            0
                                           1.0000
                          0
                                                                 order, like, support, import
                                                                                                        offici, report, hansard, monday, novemb, hon...
                                                       tax, carbon, yea, agre, commonsdeb,
                                                                                                 [common, debat, volum, number, session, parliament,
                          5
                                           0.9952
                                                             mass, nay, sidhu, brison, fraser
                                                                                                           offici, report, hansard, thursday, june, hon...
```

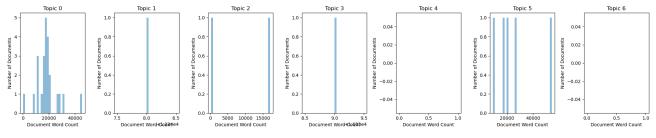
```
In [20]: #Generate df with dominant topics, the topic contribution and topic keywords for HDP model
         def topics_sentences(ldamodel=None, corpus=None, texts=None):
             # Initialize an empty list to store rows
             rows = []
             # Iterate through each document in the corpus
             for i, topics in enumerate(ldamodel[corpus]):
                 # Sort topics by contribution
                 topics = sorted(topics, key=lambda x: (x[1]), reverse=True)
                 # Extract dominant topic, its contribution, and keywords
                 for j, (topic_num, prop_topic) in enumerate(topics):
                     if j == 0: # Dominant topic
                         topic_keywords = ", ".join([word for word, prop in ldamodel.show_topic(topic_num)])
                         row_data = [int(topic_num), round(prop_topic, 4), topic_keywords, texts[i]]
                         rows.append(row_data)
                         break
             # Create df
             topics_df = pd.DataFrame(rows, columns=['Dominant_Topic', 'Perc_Contribution', 'Topic_Keywords', 'Text
             return topics_df
         df_topic_keywords = topics_sentences(ldamodel=hdp_model, corpus=corpus, texts=preprocessed_texts)
         df_topic_keywords.head(10)
```

	Dominant_Topic	Perc_Contribution	Topic_Keywords	Text	
0	6	0.3377	elect, ontario, qubec, offic, elector, vote, parliamentari, make, chief, voter, young, britishco	[common, debat, volum, number, session, parliament, offici, report, hansard, friday, februari, h	
1	8	0.9960	thedeputyspeak, pension, plan, chambr, thursday, follow, tabl, excel, messagefromthesen, permiss	[common, debat, volum, number, session, parliament, offici, report, hansard, thursday, decemb, h	
2	7	0.9999	vessel, amend, work, translat, english, abandon, commonsdeb, make, commun, issu, protect, like,	[common, debat, volum, number, session, parliament, offici, report, hansard, friday, februari, h	
3	2	1.0000	first, nation, commonsdeb, commun, make, right, work, issu, know, order, want, develop, question	[common, debat, volum, number, session, parliament, offici, report, hansard, thursday, novemb, h	
4	0	1.0000	tax, need, know, want, work, carbon, make, like, commonsdeb, go, say, agre, get, english, budget	[common, debat, volum, number, session, parliament, offici, report, hansard, thursday, june, hon	
5	4	0.9999	trade, agreement, hondura, privileg, right, countri, import, work, question, want, commonsdeb, f	[common, debat, volum, number, session, parliament, offici, report, hansard, monday, march, hono	
6	1	1.0000	commonsdeb, work, order, want, countri, make, need, develop, right, support, say, english, impor	[common, debat, volum, number, session, parliament, offici, report, hansard, tuesday, octob, hon	
7	3	0.6305	right, want, need, issu, make, care, medic, work, commun, import, decis, know, indigen, court, I	[common, debat, volum, number, session, parliament, offici, report, hansard, friday, januari, ho	
8	2	0.3875	first, nation, commonsdeb, commun, make, right, work, issu, know, order, want, develop, question	[common, debat, volum, number, session, parliament, offici, report, hansard, thursday, octob, ho	
9	2	0.9999	first, nation, commonsdeb, commun, make, right, work, issu, know, order, want, develop, question	[common, debat, volum, number, session, parliament, offici, report, hansard, thursday, june, hon	

Out[20]:

Out[27]:		Topic_Num	Topic_Perc_Contrib	Keywords	Representative Text
	0	0	1.0000	tax, need, know, want, work, carbon, make, like, commonsdeb, go, say, agre, get, english, budget	[common, debat, volum, number, session, parliament, offici, report, hansard, thursday, june, hon
	1	1	1.0000	commonsdeb, work, order, want, countri, make, need, develop, right, support, say, english, impor	[common, debat, volum, number, session, parliament, offici, report, hansard, tuesday, octob, hon
	2	2	1.0000	first, nation, commonsdeb, commun, make, right, work, issu, know, order, want, develop, question	[common, debat, volum, number, session, parliament, offici, report, hansard, thursday, novemb, h
	3	3	1.0000	right, want, need, issu, make, care, medic, work, commun, import, decis, know, indigen, court, l	[parliament, session, common, debat, offici, report, hansard, volum, monday, octob, honour, anth
	4	4	0.9999	trade, agreement, hondura, privileg, right, countri, import, work, question, want, commonsdeb, f	[common, debat, volum, number, session, parliament, offici, report, hansard, monday, march, hono
	5	5	0.9999	ontario, qubec, resourc, commun, crime, support, parliamentari, develop, project, children, firs	[common, debat, volum, number, session, parliament, offici, report, hansard, friday, novemb, hon
	6	6	0.9999	elect, ontario, qubec, offic, elector, vote, parliamentari, make, chief, voter, young, britishco	[common, debat, volum, number, session, parliament, offici, report, hansard, friday, februari, h
	7	7	0.9999	vessel, amend, work, translat, english, abandon, commonsdeb, make, commun, issu, protect, like,	[common, debat, volum, number, session, parliament, offici, report, hansard, friday, februari, h
	8	8	0.9960	thedeputyspeak, pension, plan, chambr, thursday, follow, tabl, excel, messagefromthesen, permiss	[common, debat, volum, number, session, parliament, offici, report, hansard, thursday, decemb, h

```
In [28]: #Ploting document word count against nubmer of documents for LDA model
          fig, axes = plt.subplots(nrows=1, ncols=7, figsize=(20, 4))
          for i in range(7):
              word_counts = []
              for doc in corpus:
                  # Get the topic distribution for the document
                  doc_topics = lda_model.get_document_topics(doc)
                  # Check if the current topic is the dominant topic for the document
                  for topic, prob in doc_topics:
                      if topic == i:
                           # Calculate the word count of the document and add it to the list
                           word_count = sum(count for _, count in doc)
                           word_counts.append(word_count)
                           break
              axes[i].hist(word_counts, bins=30, alpha=0.5)
              axes[i].set_title(f'Topic {i}')
              axes[i].set_xlabel('Document Word Count')
axes[i].set_ylabel('Number of Documents')
          plt.tight_layout()
          plt.show()
```

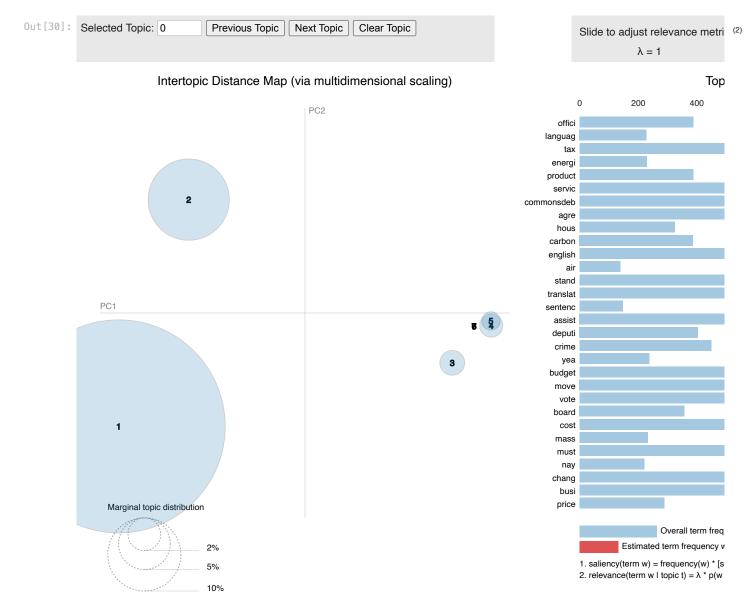


In [29]: #Ploting document word count against nubmer of documents for HDP model
fig, axes = plt.subplots(nrows=3, ncols=5, figsize=(20, 12))

```
for i in range(10):
      word_counts = []
      for doc in corpus:
             doc_topics = hdp_model[doc]
             for topic, prob in doc_topics:
                   if topic == i:
                         word_count = sum(count for _, count in doc)
                          word_counts.append(word_count)
                          break
      # Determine the position of the subplot in the grid
      row_index = i // 5
      col_index = i % 5
      axes[row_index, col_index].hist(word_counts, bins=30, alpha=0.5)
      axes[row_index, col_index].set_title(f'Topic {i}')
      axes[row_index, col_index].set_xlabel('Document Word Count')
axes[row_index, col_index].set_ylabel('Number of Documents')
plt.tight_layout()
plt.show()
                Topic 0
                                                                                                                        Topic 3
                                                                                                         1.75
 1.75
                                                                      1.75
[ 1.50
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```
In [30]: #Exploring the relevant terms for each topic of the LDA Model

pyLDAvis.enable_notebook()
vis = pyLDAvis.gensim.prepare(lda_model, corpus, dictionary=dictionary)
vis
```



In [31]: #Exploring the relevant terms for each topic of the HDP Model
 pyLDAvis.enable_notebook()
 vis = pyLDAvis.gensim.prepare(hdp_model, corpus, dictionary=dictionary)
 vis

