preprocessing

March 27, 2025

1 Task 1

1.0.1 Import libraries and load data

[ ]:
```
# Import libraries
import pandas as pd
import numpy as np
import re
from cleantext import clean
import matplotlib.pyplot as plt
import nltk
#nltk.download('all')
from nltk.probability import FreqDist
import ast
```

[2]:
```
# Load data as data frame
corpusSample = pd.read_csv("250_rows.csv")
```

1.0.2 Clean content variable

[3]:
```
# The function clean_text() does this:
#   - all words will be lowercased
#   - tabs, new lines and multiple white spaces will be set to single white␣
 ↪space
#   - numbers, dates, emails, and URLs will be replaced by "\<NUM>", "\<DATE>",␣
 ↪"\<EMAIL>" AND "\<URL>", respectively.
def clean_text(data):

  # Set dates with format DD/MM/YYYY or MM/DD/YYYY to "<date>"
  data = re.sub("[0-9]{1,2}/[0-9]{1,2}/[0-9]{4}", "<date>", data)

  # Set dates with the format DD/MM/YY or MM/DD/YY to "<date>"
  data = re.sub("[0-9]{1,2}/[0-9]{1,2}/[0-9]{2}", "<date>", data)

  # Set dates with the format DD/MM/YYYY or MM/DD/YYYY to "<date>"
  data = re.sub("[0-9]{1,2}-[0-9]{1,2}-[0-9]{4}", "<date>", data)

  # Set dates with the format DD/MM/YY or MM/DD/YY to "<date>"
```

```
    data = re.sub("[0-9]{1,2}-[0-9]{1,2}-[0-9]{2}", "<date>", data)

    # Consider adding other date formats, like "Sept 6", "September 6, 2019", etc.

    # Use clean() for remaining cleaning
    cleaned = clean(data,
        fix_unicode=False,          # fix various unicode errors
        to_ascii=False,             # transliterate to closest ASCII␣
↪representation
        lower=True,                 # lowercase text
        no_line_breaks=True,        # fully strip line breaks as opposed to only␣
↪normalizing them
        no_urls=True,               # replace all URLs with a special token
        no_emails=True,             # replace all email addresses with a special␣
↪token
        no_phone_numbers=False,     # replace all phone numbers with a special␣
↪token
        no_numbers=True,            # replace all numbers with a special token
        no_digits=False,            # replace all digits with a special token
        no_currency_symbols=False,  # replace all currency symbols with a␣
↪special token
        no_punct=False,             # remove punctuations
        replace_with_punct="",      # instead of removing punctuations you may␣
↪replace them
        replace_with_url="<URL>",
        replace_with_email="<EMAIL>",
        replace_with_phone_number="<PHONE>",
        replace_with_number="<NUM>",
        replace_with_digit="0",
        replace_with_currency_symbol="<CUR>",
        lang="en"                    # set to 'de' for German special handling
    )
    return cleaned
```

[4]:

```
content_sample_cleaned = corpusSample['content'].apply(clean_text)
```

1.0.3 Tokenize content variable

[5]:

```
# Import libraries
from nltk.tokenize import word_tokenize
from nltk.tokenize import MWETokenizer

# This is to make sure that "<num>", "<date>", "<email>" and "<url>" are
# single tokens - and not "<", "num" and ">" etc.
multiWordsTokenizer = MWETokenizer([('<', 'num', '>'), ('<', 'date', '>'),␣
↪('<', 'email', '>'), ('<', 'url', '>')], separator='')
```

[6]:
```python
# Function that tokenize a string
def tokenize(data_string):

    # Word tokenize
    data_string = word_tokenize(data_string)

    # MAKE '<', 'NUM' and '>' into '<NUM>'. Same for <DATE>, <EMAIL> and <URL>:
    data_string = multiWordsTokenizer.tokenize(data_string)

    return data_string
```

[7]:
```python
content_sample_tokenized = content_sample_cleaned.apply(tokenize)
```

1.0.4 Remove stop words

[8]:
```python
# Import libraries
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
```

[9]:
```python
# Function that removes stop words from a string
def removeStopWords(words):
    filteredWords = []

    for w in words:
        if w not in stop_words:
            filteredWords.append(w)
    return(filteredWords)
```

[10]:
```python
# Remove stop words
content_sample_no_stop_words = content_sample_tokenized.apply(removeStopWords)
```

1.0.5 Perform stemming on content variable

[11]:
```python
# Import libraries
from nltk.stem import PorterStemmer
stemmer = PorterStemmer()
```

[12]:
```python
# Function that performs stemming on a string
def stemming(words):

    stemmedWords = []
    for w in words:
        stemmedWords.append(stemmer.stem(w))

    return(stemmedWords)
```

[13]:
```python
content_sample_stemmed = content_sample_no_stop_words.apply(stemming)
```

1.0.6 Reduction rates

[14]:
```
# Using FreqDist() we can see the vocabulary as well as the frequence of each␣
↪token
tokens_after_tokenization = [x.strip("'") for l in content_sample_tokenized for␣
↪x in l]
tokens_after_tokenization_vocab = FreqDist(tokens_after_tokenization)

tokens_after_removing_stop_words = [x.strip("'") for l in␣
↪content_sample_no_stop_words for x in l]
tokens_after_removing_stop_words_vocab =␣
↪FreqDist(tokens_after_removing_stop_words)

tokens_after_stemming = [x.strip("'") for l in content_sample_stemmed for x in␣
↪l]
tokens_after_stemming_vocab = FreqDist(tokens_after_stemming)

print(f"Size of vocabulary after tokenization:␣
↪{len(tokens_after_tokenization_vocab)}\n")

print(f"Size of vocabulary after removal of stop words:␣
↪{len(tokens_after_removing_stop_words_vocab)}\n")

print(f"Size of vocabulary after stemming:␣
↪{len(tokens_after_stemming_vocab)}\n")

print(f"Reduction rate of the vocabulary size after removing stopwords:␣
↪{round((len(tokens_after_tokenization_vocab)
                                    -␣
↪len(tokens_after_removing_stop_words_vocab)) /
                                    len(tokens_after_tokenization_vocab) * 100,␣
↪2)}\n")

print(f"Reduction rate of the vocabulary size after stemming:␣
↪{round((len(tokens_after_removing_stop_words_vocab)
                                    - len(tokens_after_stemming_vocab)) /
                                    len(tokens_after_removing_stop_words_vocab)␣
↪* 100, 2)}\n")
```

```
Size of vocabulary after tokenization: 16887

Size of vocabulary after removal of stop words: 16752

Size of vocabulary after stemming: 11590

Reduction rate of the vocabulary size after removing stopwords: 0.8
```

```
Reduction rate of the vocabulary size after stemming: 30.81
```

[15]:
```python
# Add preprocessed 'corpus' variable to corpus sample:
corpusSamplePreprocessed = corpusSample
corpusSamplePreprocessed['content'] = content_sample_stemmed
```

2 Task 2

2.0.1 Initial clean up: Remove non-relevant features, remove rows with invalid values and remove row duplicates

[ ]:
```python
# Load data as data frame. Load either full corpus or sample with 15,000 rows.

corpus = pd.read_csv("995,000_rows.csv")
#corpus = pd.read_csv("15,000_rows.csv")
```

[17]:
```python
# Keep only potentially usefull features
corpus = corpus[['domain','type', 'scraped_at', 'content', 'title', 'authors',␣
↪'meta_description']]
```

[18]:
```python
# Remove data points where 'type' is '2018-02-10 13:43:39.521661', since
# this type is not classifiable as fake/reliable
corpus = corpus.drop(corpus[corpus['type'] == '2018-02-10 13:43:39.521661'].
↪index)
```

[19]:
```python
# Remove data points where 'type' is 'unknown', since this type is not
# classifiable as fake/reliable
corpus = corpus.drop(corpus[corpus['type'] == 'unknown'].index)
```

[20]:
```python
# Remove articles written in russian, french or dutch
corpus = corpus.drop(corpus[corpus['domain'] == 'pravda.ru'].index)
corpus = corpus.drop(corpus[corpus['domain'] == 'legorafi.fr'].index)
corpus = corpus.drop(corpus[corpus['domain'] == 'speld.nl'].index)
```

[21]:
```python
# Remove data points where either 'type' or 'content' is NaN
corpus = corpus[corpus['type'].notna() & corpus['content'].notna()]
```

[22]:
```python
# Remove duplicates - there are 66.232 duplicated rows in full dataset.
corpus = corpus.drop_duplicates()
```

2.0.2 Preprocessing: Clean, tokenize, remove stop words and perform stemming

[23]:
```python
# Clean 'content' and save data frame as .csv file
corpus['content'] = corpus['content'].apply(clean_text)
corpus.to_csv('corpus_cleaned.csv', index=False)
```

[24]:
```
# Tokenize 'content' and save data frame as .csv file
corpus['content'] = corpus['content'].apply(tokenize)
corpus.to_csv('corpus_tokenized.csv', index=False)
```

[25]:
```
# Remove stop words from 'content' and save data frame as .csv file
corpus['content'] = corpus['content'].apply(removeStopWords)
corpus.to_csv('corpus_no_stop_words.csv', index=False)
```

[26]:
```
# Perform stemming on 'content' and save data frame as .csv file
corpus['content'] = corpus['content'].apply(stemming)
corpus.to_csv('995,000_rows_preprocessed.csv', index=False)
#corpus.to_csv('15,000_rows_preprocessed.csv', index=False)
```

3 Task 3 - exploring preprocessed dataset

[ ]:
```
# Load preprocessed corpus (if you want to skip the preprocessing steps above).
# Load either full preprocessed dataset or the preprocessed sample with 15,000␣
↪rows.

#corpus = pd.read_csv("15,000_rows_preprocessed.csv")
corpus = pd.read_csv("995,000_rows_preprocessed.csv")
```

[ ]:
```
# After loading the .csv file as dataframe remember to convert the data type of
# 'content' from string back to list:

corpus['content'] = corpus['content'].apply(ast.literal_eval)
```

3.0.1 Looking into 'domain'

[27]:
```
print(f"Number of unique values in 'domain': {len(set(corpus['domain']))}")
```

```
Number of unique values in 'domain': 555
```

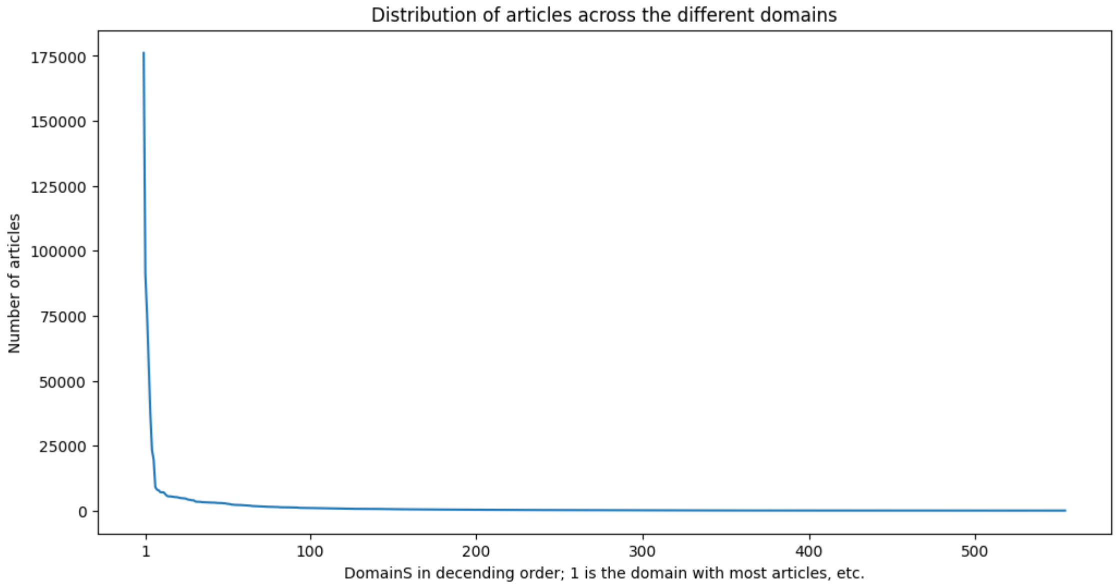
[28]:
```
# Here we see that all texts from a particular domain is of the same type
boolian_value = True
for x in set(corpus['domain']):
    df_subset = corpus[corpus["domain"] == x]
    if(len(set(df_subset['type']))) != 1:
        print(x)
        boolian_value = False

if boolian_value:
    print("All texts from a particular domain is of the same type!")
```

```
All texts from a particular domain is of the same type!
```

[29]:
```
# Here is the number of news texts for each domain
counts_domain = corpus['domain'].value_counts()
counts_domain_df = counts_domain.rename_axis('unique_values').
 ↪reset_index(name='counts')

# The domains with the most articles
print(f"The 10 domains with the most articles:\n{counts_domain_df[0:10]}\n")

# The domains with the fewest articles
print(f"The 10 domains with the fewest articles:\n{counts_domain_df[-10:]}")
```

```
The 10 domains with the most articles:
              unique_values  counts
0               nytimes.com  176144
1          beforeitsnews.com   90925
2               dailykos.com   75812
3              express.co.uk   55904
4            sputniknews.com   37171
5              wikileaks.org   23301
6         abovetopsecret.com   19566
7              lifezette.com    9005
8   investmentwatchblog.com    8041
9            dailycaller.com    7807

The 10 domains with the fewest articles:
                        unique_values  counts
545                  dailynews10.com       1
546                  madpatriots.com       1
547                       uspoln.com       1
548              dailypoliticsusa.com       1
549                  bighairynews.com       1
550                     news4ktla.com       1
551              firearmscoalition.org       1
552  elelephantintheroom.blogspot.com       1
553            usafirstinformation.com       1
554                  newsmagazine.com       1
```

[30]:
```
# Plot of the distribution of articles across the different domains
plt.figure(figsize=(12,6))
plt.xlabel('DomainS in decending order; 1 is the domain with most articles, etc.
 ↪')
plt.ylabel('Number of articles')
plt.title('Distribution of articles across the different domains')
plt.xticks([1,100,200, 300, 400, 500, 600])
plt.plot(counts_domain_df.index, counts_domain_df['counts'])
plt.show()
```

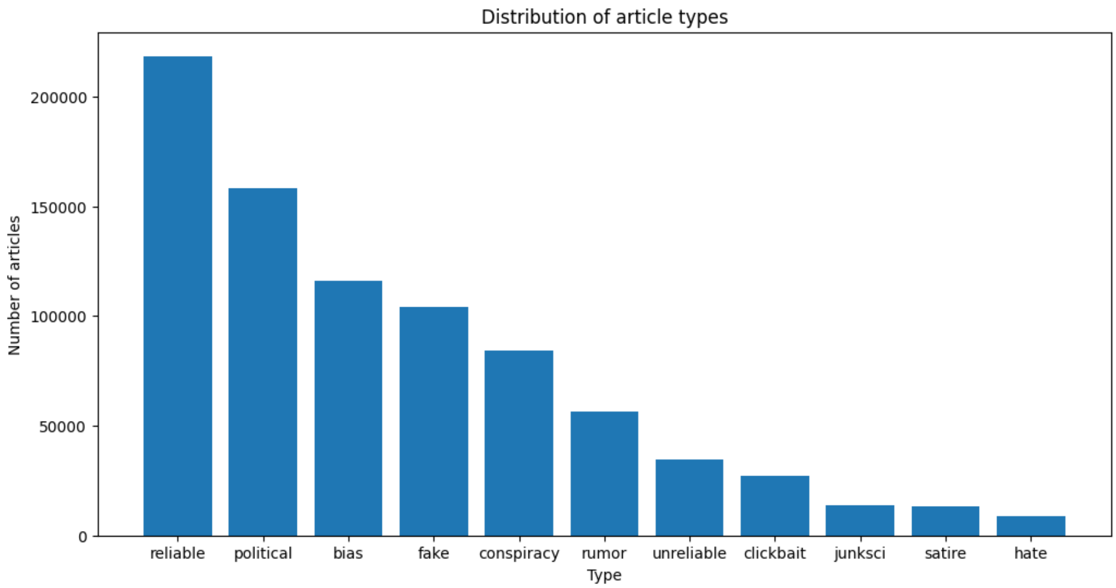


3.0.2 Looking into 'type'

[31]:
```
print(f"Number of unique values in 'type': {len(set(corpus['type']))}\n")

# Here is the number of news texts for each domain
counts_type = corpus['type'].value_counts()
counts_type_df = counts_type.rename_axis('unique_values').
↪reset_index(name='counts')

print(f"Distribution of articles type:\n{counts_type_df}")
```

```
Number of unique values in 'type': 11

Distribution of articles type:
   unique_values  counts
0       reliable  218452
1      political  158061
2           bias  115959
3           fake  104155
4     conspiracy   84069
5          rumor   56366
6     unreliable   34792
7      clickbait   27003
8        junksci   13577
9         satire   13082
10          hate    8742
```

[32]:
```
# Plot of the distribution of articles across the different types
plt.figure(figsize=(12,6))
plt.title('Distribution of article types')
plt.xlabel('Type')
plt.ylabel('Number of articles')
plt.bar(counts_type_df['unique_values'], counts_type_df['counts'])
plt.show()
```



3.0.3 Looking into 'content'

[33]:
```
# Calculate lengths of 'content' strings
corpus['content_length'] = corpus.content.str.len()
```

[34]:
```
content_length = corpus['content_length'].sort_values(ascending=False)
print(f"The articles with most tokens has {content_length.iloc[0]} tokens.")
print(f"The articles with fewest tokens has {content_length.iloc[-1]} tokens.")
```

```
The articles with most tokens has 21730 tokens.
The articles with fewest tokens has 2 tokens.
```

[35]:
```
print(f"Only 5,000 articles (or {round(5000/corpus.shape[0] * 100, 2)}% of the␣
↪articles) has more than {content_length.iloc[5000]} tokens.")
```

```
Only 5,000 articles (or 0.6% of the articles) has more than 2653 tokens.
```

[ ]:
```
print(f"Only 5,000 articles (or {round((corpus.shape[0]-5000)/corpus.shape[0] *␣
↪100, 2)}% of the articles) has {content_length.iloc[-5000]} or less tokens.")
```

```
Only 5,000 articles (or 99.4% of the articles) has more than 7 tokens.
```

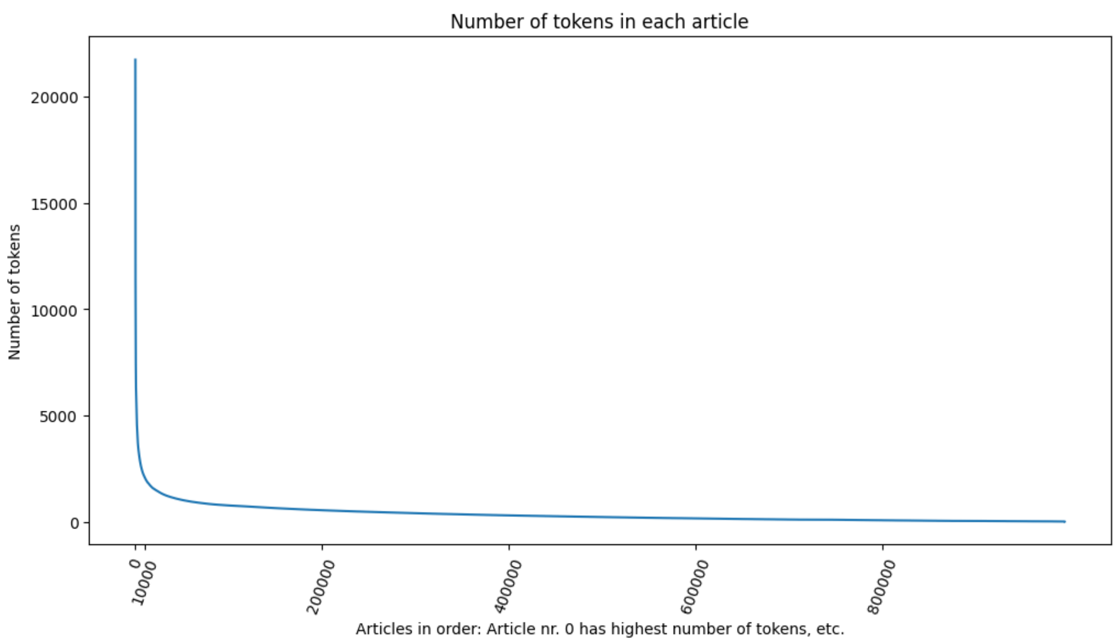
[36]:
```python
print(f"Average tokens per article is {round(content_length.mean(), 2)}")
```

```
Average tokens per article is 350.56
```

[43]:
```python
print(f"The median token count is {content_length[len(content_length)/2]}")
```

```
The median token count is 212
```

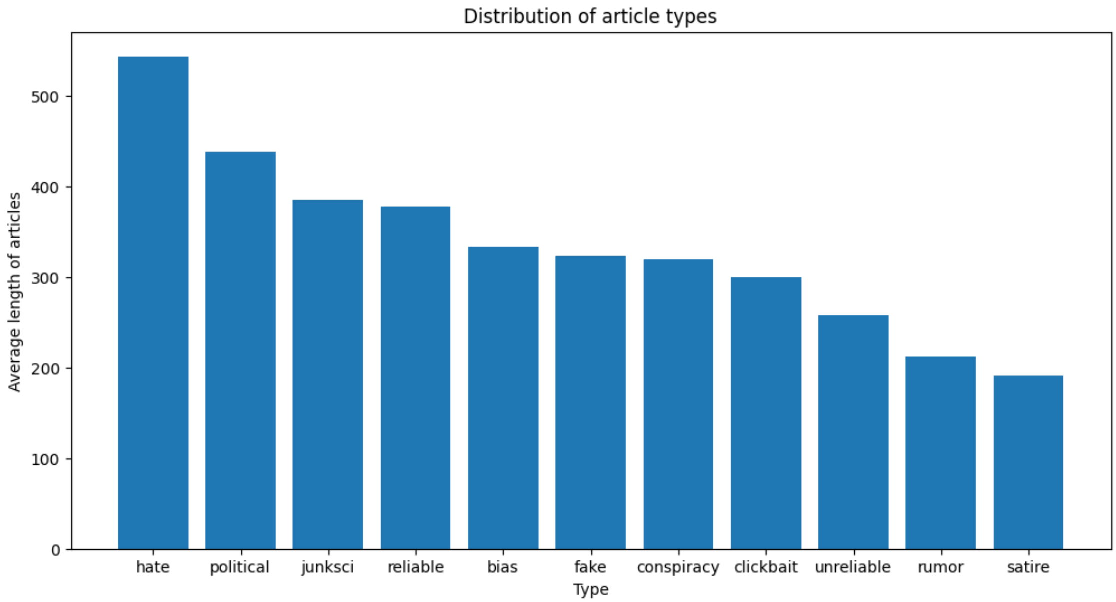
[37]:
```python
# Plot of the number tokens in each article
plt.figure(figsize=(12,6))
plt.title('Number of tokens in each article')
plt.xlabel('Articles in order: Article nr. 0 has highest number of tokens, etc.
 ↪')
plt.ylabel('Number of tokens')
plt.xticks([0,10000, 200000,400000, 600000, 800000])
plt.xticks(rotation=70)
plt.plot(corpus.index, corpus['content_length'].sort_values(ascending=False))
plt.show()
```



[38]:
```python
# Find average length of articles (token count) for each article type.
types = set(corpus['type'])
types_df = pd.DataFrame(types)
types_df.columns = ['type']
types_df["average_token_count"] = np.nan


for index, row in types_df.iterrows():
```

```
    df_temp = corpus.loc[corpus['type'] == row['type']]
    types_df.at[index, 'average_token_count'] = sum(df_temp['content_length'])/
 ↪df_temp.shape[0]

types_df = types_df.sort_values("average_token_count", ascending=False)
```

[39]:
```
# Plot the average length of articles (the token count) for each article type.
plt.figure(figsize=(12,6))
plt.title('Distribution of article types')
plt.xlabel('Type')
plt.ylabel('Average length of articles')
plt.bar(types_df['type'], types_df['average_token_count'])
plt.show()
```



4 Task 4

4.0.1 Should we shuffle before split?

Lets first try splitting without shuffling first. We sort data by 'scraped_at' before splitting.

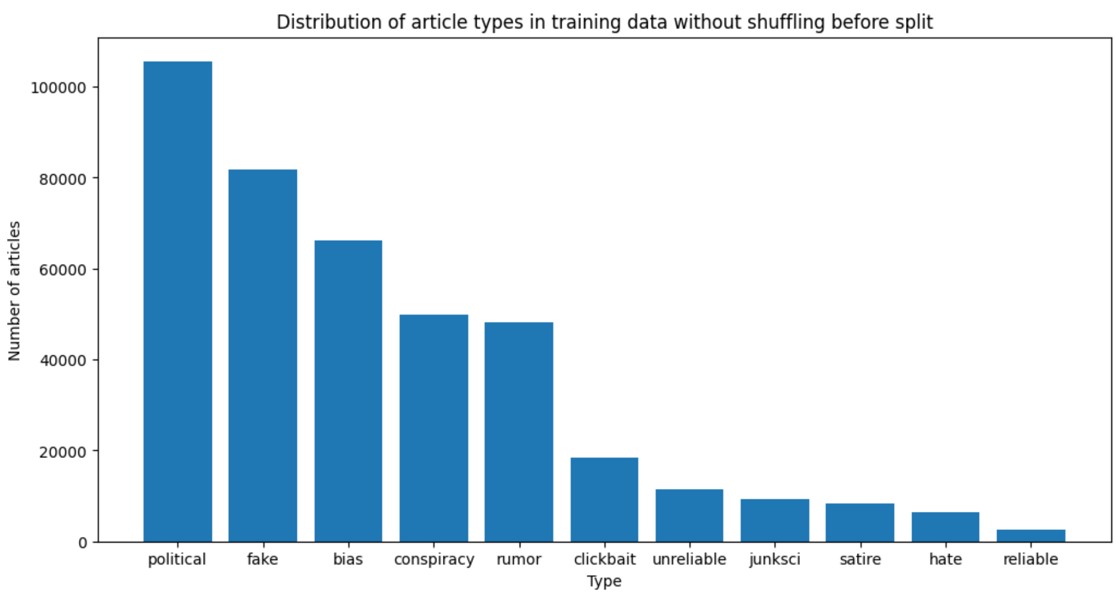
[44]:
```
# Sort data based on scrape date.

# Note that 'coerce' results in NaN for entries that can't be converted.
# This throws away many of the article, expecially articles of type 'reliable'.
# Still, this will indicate whether the distribution is somewhat even in
# in train, validation and test data without shuffling before splitting.
corpus.scraped_at = pd.to_datetime(corpus.scraped_at,errors='coerce')
```

```
corpus = corpus[corpus.scraped_at.notnull()]

corpus = corpus.sort_values('scraped_at')
```

[ ]:
```
# No shuffling before split
train, valid, test = np.split(corpus, [int(0.8*len(corpus)), int(0.
↪9*len(corpus))])
```

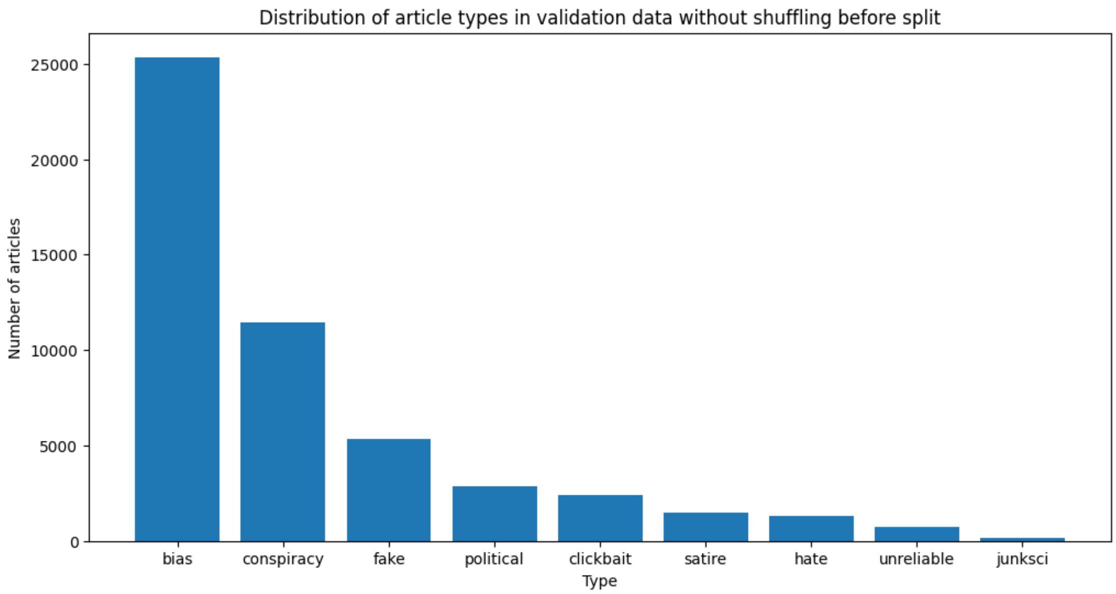
Now lets see the distribution among article types in training, validation and test data.

[46]:
```
# Find the number of news texts for each domain in training data
counts_type = train['type'].value_counts()
counts_type_df = counts_type.rename_axis('unique_values').
↪reset_index(name='counts')

# Plot of the distribution of articles across the different types
plt.figure(figsize=(12,6))
plt.title('Distribution of article types in training data without shuffling␣
↪before split')
plt.xlabel('Type')
plt.ylabel('Number of articles')
plt.bar(counts_type_df['unique_values'], counts_type_df['counts'])
plt.show()
```

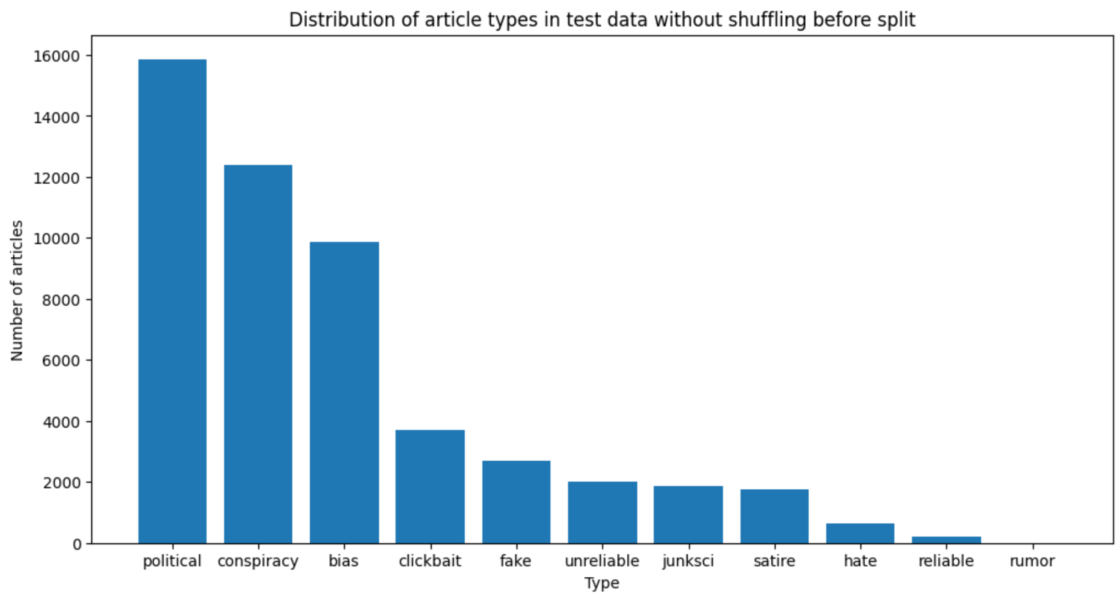


[47]:
```
# Find the number of news texts for each domain in validation data
counts_type = valid['type'].value_counts()
counts_type_df = counts_type.rename_axis('unique_values').
↪reset_index(name='counts')
```

```
# Plot of the distribution of articles across the different types
plt.figure(figsize=(12,6))
plt.title('Distribution of article types in validation data without shuffling␣
↪before split')
plt.xlabel('Type')
plt.ylabel('Number of articles')
plt.bar(counts_type_df['unique_values'], counts_type_df['counts'])
plt.show()
```



[48]:
```
# Find the number of news texts for each domain in test data
counts_type = test['type'].value_counts()
counts_type_df = counts_type.rename_axis('unique_values').
↪reset_index(name='counts')

# Plot of the distribution of articles across the different types
plt.figure(figsize=(12,6))
plt.title('Distribution of article types in test data without shuffling before␣
↪split')
plt.xlabel('Type')
plt.ylabel('Number of articles')
plt.bar(counts_type_df['unique_values'], counts_type_df['counts'])
plt.show()
```



4.0.2 Okay, splitting without shuffling seems like a bad idea since distribution of article types is very uneven among train, validation and test.

[50]:
```
# Shuffling before split
train, valid, test = np.split(corpus.sample(frac=1, random_state=42), [int(0.
↪8*len(corpus)), int(0.9*len(corpus))])
```

[51]:
```
#train.to_csv('15,000_rows_preprocessed_train.csv', index=False)
#valid.to_csv('15,000_rows_preprocessed_valid.csv', index=False)
#test.to_csv('15,000_rows_preprocessed_test.csv', index=False)
train.to_csv('995,000_rows_preprocessed_train.csv', index=False)
valid.to_csv('995,000_rows_preprocessed_valid.csv', index=False)
test.to_csv('995,000_rows_preprocessed_test.csv', index=False)
```