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How to mine newsfeed data and extract interactive insights in Python

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The web is an overcrowded space of data. In fact, you will find it in different shapes and formats, from simple tabular sheets like excel files to large and unstructered NoSql databases. the variety of content is overwhelming: texts, logs, tweets, images, comments, likes, views, videos, reports, news headlines. All of these are constantly produced on a real time fashion, all over the world, generating quintillions of bytes (http://www.vcloudnews.com/every-day-big-data-statistics-2-5-quintillion-bytes-of-data-created-daily/) everyday.

If you could think one second about what you could do about this and how you could make use of open-source data, you will find many applications:

- If you're a marketer, you could feel and quantify the impact of your newly released product by applying sentiment analysis on tweets. You'll then catch the uninterested/unsatisfied users and understand what made them unhappy.
- If you're into finance, you could collect stocks historical data and build statistical models to predict the future stock prices.
- You could collect your country open data and investigate different metrics (growth rate, crime rate, unemployment ...). You could even correlate your results and cross them with other data sources and come up with new insights!

In this tutorial, we will also make sense of the data for a specific use case. We will collect news feeds from 60 different sources (Google News, The BBC, Business Insider, BuzzFeed, etc). We will ingest them in a usable format. We'll then apply some machine learning techniques to cluster the articles by their similarity and we'll finally visualize the results to get high level insights. This will give us a visual sense of the grouping clusters and the underlying topics. These techniques are part of what we call topic mining.

Following the structure of the previous tutorial, I'll go through different steps and explain the code on the fly.

- I'll collect the news by requesting an external powerful REST API called newsapi. I'll connect to this service through a python script that runs in my server background every five minutes and fetches the data and stores it in a csv file.
- Once the data is collected and stored, I'll ingest it in a pandas dataframe. I'll first preprocess it using text preprocessing tokenization and the tfidf algorithm and then I'll cluster it using 2 different algorithms: K-means and Latent Dirichlet Allocation (LDA). Details below.
- Finally I'll visualize the resulting clusters using two interactive python visualization libraries. They're called Bokeh and pyldavis, they're awesome and you'll see why.

Let's get started !

Well, we'll try to learn something useful at least.

1 - Environment setup

In this tutorial, I'll be using python 3.6 One thing I recommend is downloading the Anaconda distribution for python 3.6 from this link (https://www.continuum.io/downloads). This distribution wraps python with the necessary packages used in data science like Numpy, Pandas, Scipy or Scikit-learn.

For the purpose of this tutorial we'll also have to download external packages:

- tqdm (a progress bar python utility) from this command: pip install tqdm
- nltk (for natural language processing) from this command: conda install -c anaconda nltk=3.2.2
- bokeh (for interactive data viz) from this command: conda install bokeh
- lda (the python implementation of Latent Dirichlet Allocation) from this command: pip install lda
- pyldavis (python package to visualize lda topics): pip install pyldavis

To connect to the Newsapi service you'll have to create an account at https://newsapi.org/register (https://newsapi.org/register) to get a key. It's totally free. Then you'll have to put your key in the code and run the script on your own if you want to.

You can download the data I fetched from my github account. Link below.

This post is entirely written in Jupyter notebook which is my favorite tool for data analysis and discovery. I'll post it on github so that you can download it and reproduce the results on your side.

2 - Data acquisition from Newsapi.org

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News API is a simple and easy-to-use API that returns JSON metadata for the headlines currently published on a range of news sources and blogs (70 and counting so far).

Use it to display live news headlines and images in your app or on your site!

FREAKING FAST

Everything is asynchronously cached for a super-fast response.

FREE TO USE

Just add a 'powered by' attribution link back to NewsAPI.org.

CORS ENABLED

Make requests directly from the front-end!

Get API Key

Well, this looks like something very handy. It avoids you the tedious data scrapping that you would perform on each site separately. Getting the latest news for a specific source like Techcrunch is as simple as sending a get request to this address: https://newsapi.org/v1/articles?source=techcrunch&apiKey={API_KEY} (https://newsapi.org/v1/articles?source=techcrunch&apiKey={API_KEY}) The JSON file resulting from this response is pretty straightforward:


```
{
    "status": "ok",
    "source": "techcrunch",
    "sortBy": "top",
    "articles": [{
        "author": "Khaled \"Tito\" Hamze",
        "title": "Crunch Report",
        "description": "Your daily roundup of the biggest TechCrunch stories and startup news.",
        "url": "https://techcrunch.com/video/crunchreport/ (https://techcrunch.com/video/crunchreport/)",
        "urlToImage": "https://tctechcrunch2011.files.wordpress.com/2015/03/tccrshowogo.jpg?w=500&h=200&crop=1
        "publishedAt": "2017-03-02T04:40:50Z"
    }, {
        "author": "Kate Conger, Devin Coldewey",
        "title": "Marissa Mayer forgoes bonus and equity in wake of Yahoo security incidents",
        "description": "Yahoo’s board has decided that CEO Marissa Mayer will not receive her annual b
        "url": "https://techcrunch.com/2017/03/01/marissa-mayer-forgoes-bonus-and-equity-in-wake-of-yahoo-security-in
        "urlToImage": "https://tctechcrunch2011.files.wordpress.com/2014/05/marissa-mayer3.jpg?w=764&h=400&crop
        "publishedAt": "2017-03-01T22:20:38Z"
    }, {
        "author": "Matthew Lynley",
        "title": "Snap values itself at nearly $24B with its IPO pricing",
        "description": "Snap has given a final price for its IPO, setting the company's valuation at n
        "url": "https://techcrunch.com/2017/03/01/snap-values-itself-at-nearly-24b-with-its-ipo-pricing/ (https://techcrunc
        "urlToImage": "https://tctechcrunch2011.files.wordpress.com/2016/12/8a82586a123a7429edd0ca2f65ddbeda.jp
        "publishedAt": "2017-03-01T19:49:15Z"
    }, {
        "author": "Lucas Mat y",
```

```
            "title": "Oculus co-founder talks new Rift pricing, Touch adoption and possible Mac support",
            "description": "While so many virtual reality hardware companies have been tasked only with se
            "url": "https://techcrunch.com/2017/03/01/oculus-co-founder-talks-new-rift-pricing-touch-adoption-and-possible-
            "urlToImage": "https://tctechcrunch2011.files.wordpress.com/2017/03/2016-09-14_oculus_134750-1-0022.jpg?w
            "publishedAt": "2017-03-01T18:56:02Z"
        }, {
            "author": "Matthew Lynley",
            "title": "Five burning questions that Snap’s IPO is about to answer",
            "description": "Snap will begin publicly trading tomorrow, which means that it will officially
            "url": "https://techcrunch.com/2017/03/01/five-burning-questions-that-snaps-ipo-is-about-to-answer/ (https://tec
            "urlToImage": "https://tctechcrunch2011.files.wordpress.com/2017/02/gettyimages-616058338.jpg?w=764&h=4
            "publishedAt": "2017-03-01T17:55:28Z"
        }]
    }
```


/
gist.github.com/ahmedbesbes/ee2d307e45d80d78fc8ce706f331f9bb/raw/9aef54ba0fecf20c0ede9044a37011b21f2c6551/news.js)
news.js (https://gist.github.com/ahmedbesbes/ee2d307e45d80d78fc8ce706f331f9bb#file-news-js) hosted with ♡ by **GitHub (https://github.com)**

The 'articles' object is a list of JSON files corresponding to the latest published articles. As you can see, we can not go far into the historical data to extract a large dump of articles.

One solution I came up with to get a large set of news articles was to request the address above for every source at every 5 minutes for a period of time. As for now, the script has been running for more than two weeks.

Let's get into the code to see how to manage this data acquisition:

In [2]:
```python
# import packages
import requests
import pandas as pd
from datetime import datetime
from tqdm import tqdm
from matplotlib import pyplot as plt
```

In this post, we'll be analyzing english news sources only.

In [3]:
```python
# a function to extract the sources I'll be analyzing. I'll focus on the english ones
def getSources():
    source_url = 'https://newsapi.org/v1/sources?language=en (https://newsapi.org/v1/sources?language=en)'
    response = requests.get(source_url).json()
    sources = []
    for source in response['sources']:
        sources.append(source['id'])
    return sources
```

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In [4]:
```
# Let's see what news sources we have
sources = getSources()
print('number of sources :', len(sources))
print('sources :', sources)
```

```
number of sources : 60
sources : ['abc-news-au', 'ars-technica', 'associated-press', 'bbc-news', 'bbc-sport', 'bloomb
```

Newsapi allows you to map each data source to its category. Let's use this information as an additional feature in our dataset. This may be useful later.

In [5]:
```
# a dictionary mapping each source id (from the list displayed above) to the corresponding news category
def mapping():
    d = {}
    response = requests.get('https://newsapi.org/v1/sources?language=en (https://newsapi.org/v1/sources?language=en)')
    response = response.json()
    for s in response['sources']:
        d[s['id']] = s['category']
    return d
```

In [6]:
```
# Let's check the category of reuters and techcrunch for example:
m = mapping()
print('category of reuters:', m['reuters'])
print('category of techcrunch:', m['techcrunch'])
```

```
category of reuters: general
category of techcrunch: technology
```

In [7]:
```
# Let's see what categories we have:
print('categories:', list(set(m.values())))
```

```
categories: ['music', 'entertainment', 'sport', 'gaming', 'science-and-nature', 'general', 'bu
```

The main function is getDailyNews. It will loop on each news source, request the api, extract the data and dump it to a pandas DataFrame and then export the result to csv file.

On each iteration of the loop the csv file is updated and cleaned. Redundant lines are removed. This is handled by cleanData function.

For each article we'll collect these fields:

- author
- title
- description
- url
- urlToImage
- publishedAt

And add two other features:

- category
- scraping_date : the time at which the script runs. This will help us track the data.

Here is the complete script:


```
import requests
from bs4 import BeautifulSou
```

```
import pandas as pd
from datetime import datetime
from tqdm import tqdm
from functools import reduce

def getSources():
    source_url = 'https://newsapi.org/v1/sources?language=en (https://newsapi.org/v1/sources?language=en)'
    response = requests.get(source_url).json()
    sources = []
    for source in response['sources']:
        sources.append(source['id'])
    return sources

def mapping():
    d = {}
    response = requests.get('https://newsapi.org/v1/sources?language=en (https://newsapi.org/v1/sources?language=e
    response = response.json()
    for s in response['sources']:
        d[s['id']] = s['category']
    return d

def category(source, m):
    try:
        return m[source]
    except:
        return 'NC'

def cleanData(path):
    data = pd.read_csv(path)
    data = data.drop_duplicates('url')
    data.to_csv(path, index=False)

def getDailyNews():
    sources = getSources()
    key = '[YOUR_KEY]'
    url = 'https://newsapi.org/v1/articles?source= (https://newsapi.org/v1/articles?source=){0}&sortBy={1}&apiKey={2}
    responses = []
    for i, source in tqdm(enumerate(sources)):
        try:
            u = url.format(source, 'top',key)
            response = requests.get(u)
            r = response.json()
            for article in r['articles']:
                article['source'] = source
            responses.append(r)
        except:
            u = url.format(source, 'latest', key)
            response = requests.get(u)
            r = response.json()
```

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```
            for article in r['articles']:
                article['source'] = source
            responses.append(r)

    news = pd.DataFrame(reduce(lambda x,y: x+y ,map(lambda r: r['articles'], responses)))
    news = news.dropna()
    news = news.drop_duplicates()
    d = mapping()
    news['category'] = news['source'].map(lambda s: category(s, d))
    news['scraping_date'] = datetime.now()

    try:
        aux = pd.read_csv('/home/news/news.csv')
    except:
        aux = pd.DataFrame(columns=list(news.columns))
        aux.to_csv('/home/news/news.csv', encoding='utf-8', index=False)

    with open('/home/news/news.csv', 'a') as f:
        news.to_csv(f, header=False, encoding='utf-8', index=False)

    cleanData('/home/news/news.csv')
    print('Done')

if __name__ == '__main__':
    getDailyNews()
```

ist.github.com/ahmedbesbes/4597996515e4bb7961825d4c13ea6aff/raw/7ede5a3c0323acf601d508c7aff14a7d46b37fb1/news.py)
news.py (https://gist.github.com/ahmedbesbes/4597996515e4bb7961825d4c13ea6aff#file-news-py) hosted with ♡ by **GitHub (https://github.com)**

Ok, now this script needs to run repetitively to collect the data.

To do this:

I uploaded the script to my linux server at this path /home/news/news.py then I created a crontab schedule to tell my server to run news.py every 5 minutes. To do this:

- from the terminal, type crontab -e to edit the crontab file
- add this line to the end of the file using nano or vim: */5 * * * * /root/anaconda2/bin/python /home/news/news.py (put absolute paths for your executables).

  basically what this command tells the server is: "for every 5 minutes (*/5) of every hour (*) of every day of the month (*) of every month (*) and whatever the day of the week (*), run the news.py script.
- give your script the execution permission. Otherwise, this won't work: chmod +x news.py

Now that the data has been collected, we will start anlayzing it :

- We'll have a look at the dataset and inspect it
- We'll apply some preoprocessings on the texts: tokenization, tf-idf
- We'll cluster the articles using two different algorithms (Kmeans and LDA)

- We'll visualize the clusters using Bokeh and pyldavis

3 - Data analysis

3 - 1 - Data discovery

In [8]:
```
%matplotlib inline
# pandas for data manipulation
import pandas as pd
pd.options.mode.chained_assignment = None
# nltk for nlp
from nltk.tokenize import word_tokenize, sent_tokenize
from nltk.corpus import stopwords
# list of stopwords like articles, preposition
stop = set(stopwords.words('english'))
from string import punctuation
from collections import Counter
import re
import numpy as np
```

In [9]:
```
data = pd.read_csv('./news.csv')
```

The data is now ingested in a Pandas DataFrame.

Let's see how it looks like.

In [10]:
```
data.head()
```

Out[10]:

	author	description	publishedAt	source	title
0	http://www.abc.net.au/news/lisa-millar/166890 (http://www.abc.net.au/news/lisa-millar/166890)	In the month following Donald Trump's inaugura...	2017-02-26T08:08:20Z	abc-news-au	Has R chang tone tc Donalc Trump
1	http://www.abc.net.au/news/emily-sakzewski/768 (http://www.abc.net.au/news/emily-sakzewski/768)...	A fasting diet could reverse diabetes and repa...	2017-02-26T04:39:24Z	abc-news-au	Fastin 'could revers diabet regen.
2	http://www.abc.net.au/news/jackson-vernon/7531870 (http://www.abc.net.au/news/jackson-vernon/7531870)	Researchers discover what could be one of the ...	2017-02-26T02:02:28Z	abc-news-au	Mine pollutic turning Mount river ir
3	http://www.abc.net.au/news/sophie-mcneill/4516794 (http://www.abc.net.au/news/sophie-mcneill/4516794)	Yemen is now classified as the world's worst h...	2017-02-26T09:56:12Z	abc-news-au	Austra ignore unfold humar catas..
4	http://www.abc.net.au/news/dan-conifer/5189074 (http://www.abc.net.au/news/dan-conifer/5189074)...	Malcolm Turnbull and Joko Widodo hold talks in...	2017-02-26T03:43:04Z	abc-news-au	Austra Indone agree restore

It's cool to have all these features. In this article, we will be mainly focusing on the description column.

Let's look at the data shape.

In [11]:
```
print('data shape:', data.shape)
```

```
data shape: (31009, 9)
```

Let's check the distribution of the different categories across the dataset.

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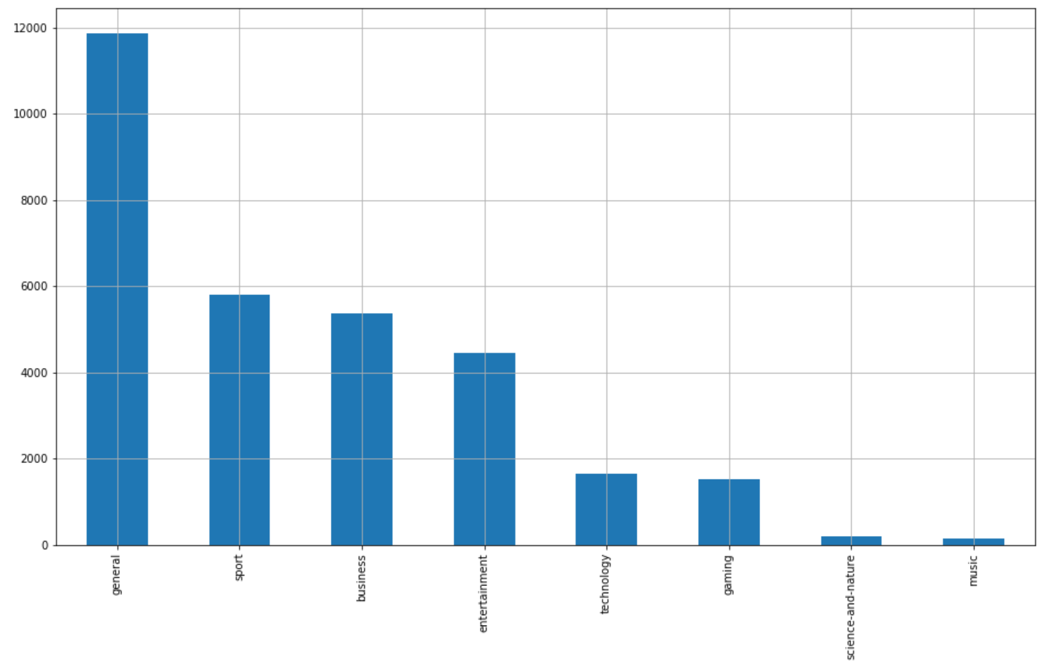
In [12]:
```
data.category.value_counts().plot(kind='bar', grid=True, figsize=(16, 9))
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7feb6b8a3c18>



Many mixed topics are included in the "general" category.

This gives us a very superficial classificaion of the news. It doesn't tell us the underlying topics, nor the keywords and and the most relevant news per each category.

To get that sort of information, we'll have to process the descriptions of each article since these variables naturally carry more meanings.

Before doing that, let's focus on the news articles whose description length is higher than 140 characters (a tweet length). Shorter descriptions happen to introduce lots of noise.

In [14]:
```
# remove duplicate description columns
data = data.drop_duplicates('description')
```

In [15]:
```
# remove rows with empty descriptions
data = data[~data['description'].isnull()]
```

In [16]:
```
data.shape
```

Out[16]: (27865, 9)

In [17]:
```
data['len'] = data['description'].map(len)
```

In [18]:
```
data = data[data.len > 140]
data.reset_index(inplace=True)
data.drop('index', inplace=True, axis=1)
```

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In [19]:
```
data.shape
```

Out[19]: (9361, 10)

We are left with 30% of the initial dataset.

3 - 2 - Text processing : tokenization

Now we start by building a tokenizer. This will, for every description:

- break the descriptions into sentences and then break the sentences into tokens
- remove punctuation and stop words
- lowercase the tokens

In [20]:
```
def tokenizer(text):
    try:
        tokens_ = [word_tokenize(sent) for sent in sent_tokenize(text)]

        tokens = []
        for token_by_sent in tokens_:
            tokens += token_by_sent

        tokens = list(filter(lambda t: t.lower() not in stop, tokens))
        tokens = list(filter(lambda t: t not in punctuation, tokens))
        tokens = list(filter(lambda t: t not in [u"'s", u"n't", u"...", u"''", u'``',
                                            u'\u2014', u'\u2026', u'\u2013'], tokens))
        filtered_tokens = []
        for token in tokens:
            if re.search('[a-zA-Z]', token):
                filtered_tokens.append(token)

        filtered_tokens = list(map(lambda token: token.lower(), filtered_tokens))

        return filtered_tokens
    except Error as e:
        print(e)
```

A new column 'tokens' can be easily created using the map method applied to the 'description' column.

In [21]:
```
data['tokens'] = data['description'].map(tokenizer)
```

The tokenizer has been applied to each description through all rows. Each resulting value is then put into the 'tokens' column that is created after the assignment. Let's check what the tokenization looks like for the first 5 descriptions:

In [22]:
```
for descripition, tokens in zip(data['description'].head(5), data['tokens'].head(5)):
    print('description:', descripition)
    print('tokens:', tokens)
    print()
```

```
description: Researchers discover what could be one of the worst cases of mine pollution in th
tokens: ['researchers', 'discover', 'could', 'one', 'worst', 'cases', 'mine', 'pollution', 'wo

description: Malcolm Turnbull and Joko Widodo hold talks in Sydney, reviving cooperation halte
tokens: ['malcolm', 'turnbull', 'joko', 'widodo', 'hold', 'talks', 'sydney', 'reviving', 'coop

description: KUALA LUMPUR, Malaysia (AP) — Malaysia's health minister said Sunday that the dos
tokens: ['kuala', 'lumpur', 'malaysia', 'ap', 'malaysia', 'health', 'minister', 'said', 'sunda

description: HANOI, Vietnam (AP) — Two women — a Vietnamese and an Indonesian — have been arre
tokens: ['hanoi', 'vietnam', 'ap', 'two', 'women', 'vietnamese', 'indonesian', 'arrested', 'al

description: NEW YORK (AP) — A trans-Atlantic wave of puzzlement is rippling across Sweden for
tokens: ['new', 'york', 'ap', 'trans-atlantic', 'wave', 'puzzlement', 'rippling', 'across', 's
```

Let's group the tokens by category, apply a word count and display the top 10 most frequent tokens.

In [23]:
```
def keywords(category):
    tokens = data[data['category'] == category]['tokens']
    alltokens = []
    for token_list in tokens:
        alltokens += token_list
    counter = Counter(alltokens)
    return counter.most_common(10)
```

In [24]:
```
for category in set(data['category']):
    print('category :', category)
    print('top 10 keywords:', keywords(category))
    print('---')
```

```
category : music
top 10 keywords: [('years', 2), ('twitter', 2), ('could', 2), ('best', 2), ('facial', 2), ('br
---
category : entertainment
top 10 keywords: [('new', 185), ('one', 120), ('first', 105), ('season', 86), ('two', 84), ('l
---
category : sport
top 10 keywords: [('league', 194), ('new', 156), ('season', 151), ('first', 135), ('team', 131
---
category : science-and-nature
top 10 keywords: [('could', 23), ('may', 16), ('help', 10), ('people', 9), ('space', 8), ('per
---
category : gaming
top 10 keywords: [('playing', 4), ('ign', 3), ('week', 3), ('comics', 3), ('gaming', 3), ('pla
---
category : general
top 10 keywords: [('trump', 1024), ('president', 886), ('said', 793), ('donald', 607), ('new',
---
category : technology
top 10 keywords: [('new', 128), ('company', 89), ('today', 89), ('one', 88), ('like', 69), ('i
---
category : business
top 10 keywords: [('trump', 230), ('president', 227), ('u.s.', 194), ('said', 191), ('donald',
---
```

Looking at these lists, we can formulate some hypotheses:

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- the sport category deals with the champions' league, the footbal season and NFL

- some tech articles refer to Google
- the business news seem to be highly correlated with US politics and Donald Trump (this mainly originates from us press)

Extracting the top 10 most frequent words per each category is straightforward and can point to important keywords.

However, although we did preprocess the descriptions and remove the stop words before, we still end up with words that are very generic (e.g: today, world, year, first) and don't carry a specific meaning that may describe a topic.

As a first approach to prevent this, we'll use tf-idf

3 - 3 - Text processing : tf-idf

tf-idf stands for term frequencey-inverse document frequency. It's a numerical statistic intended to reflect how important a word is to a document or a corpus (i.e a collection of documents).

To relate to this post, words correpond to tokens and documents correpond to descriptions. A corpus is therefore a collection of descriptions.

The tf-idf a of a term t in a document d is proportional to the number of times the word t appears in the document d but is also offset by the frequency of the term t in the collection of the documents of the corpus. This helps adjusting the fact that some words appear more frequently in general and don't especially carry a meaning.

tf-idf acts therefore as a weighting scheme to extract relevant words in a document.

$$tfidf(t,d) = tf(t,d).\, idf(t)$$

tf(t,d) is the term frequency of t in the document d (i.e. how many times the token t appears in the description d)

idf(t) is the inverse document frequency of the term t. it's computed by this formula:

$$idf(t) = log(1 + \frac{1 + n_d}{1 + df(d,t)})$$

- n_d : the number of documents
- df(d,t) : the number of documents (or descriptions) containing the term t

Computing the tfidf matrix is done using the TfidfVectorizer method from scikit-learn. Let's see how to do this:

In [25]:
```
from sklearn.feature_extraction.text import TfidfVectorizer

# min_df is minimum number of documents that contain a term t
# max_features is maximum number of unique tokens (across documents) that we'd consider
# TfidfVectorizer preprocesses the descriptions using the tokenizer we defined above

vectorizer = TfidfVectorizer(min_df=10, max_features=10000, tokenizer=tokenizer, ngram_range=(1, 2))
vz = vectorizer.fit_transform(list(data['description']))
```

In [26]:
```
vz.shape
```

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Out[26]:
```
(9361, 4194)
```

vz is a tfidf matrix.

- its number of rows is the total number of documents (descriptions)
- its number of columns is the total number of unique terms (tokens) across the documents (descriptions)

x_dt = tfidf(t,d) where x_dt is the element at the index (d,t) in the matrix.

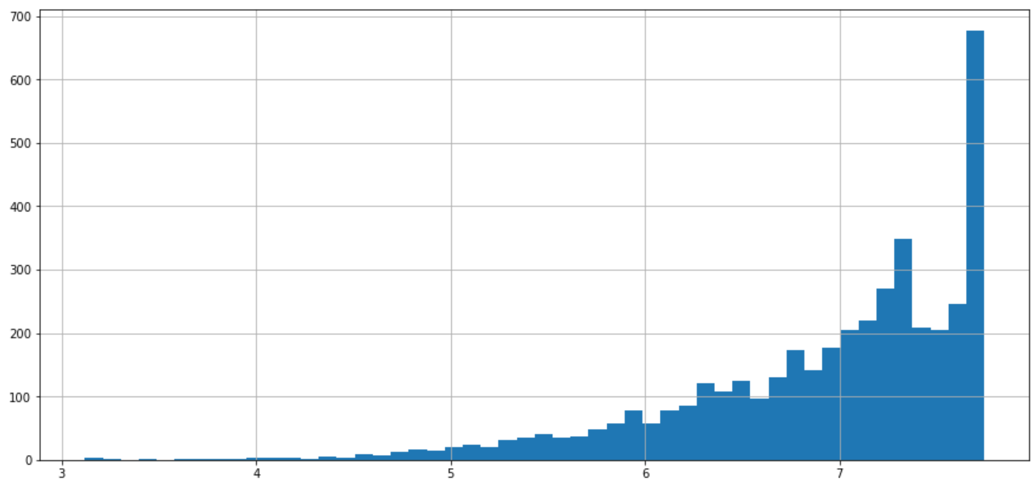
Let's create a dictionary mapping the tokens to their tfidf values

In [27]:
```
tfidf = dict(zip(vectorizer.get_feature_names(), vectorizer.idf_))
tfidf = pd.DataFrame(columns=['tfidf']).from_dict(dict(tfidf), orient='index')
tfidf.columns = ['tfidf']
```

We can visualize the distribution of the tfidf scores through an histogram

In [28]:
```
tfidf.tfidf.hist(bins=50, figsize=(15,7))
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7feb66526e80>



Let's display the 30 tokens that have the lowest tfidf scores

SHARES

In [29]:

```
tfidf.sort_values(by=['tfidf'], ascending=True).head(30)
```

Out[29]:

	tfidf
trump	3.118876
president	3.162480
said	3.180279
new	3.238661
donald	3.427819
donald trump	3.599065
one	3.697108
first	3.724419
u.s.	3.838139
president donald	3.843628
two	3.929806
house	3.974803
last	4.000229
would	4.037391
former	4.064481
ap	4.066772
people	4.085291
could	4.106543
time	4.173152
year	4.173152
years	4.178267
tuesday	4.185990
may	4.230911
government	4.303773
week	4.330284
white	4.345322
monday	4.345322
state	4.369863
back	4.391842
according	4.401411

Not surprisingly, we end up with a list of very generic words. These are very common across many descriptions. tfidf attributes a low score to them as a penalty for not being relevant. Words likes may, one, new, back, etc.

You may also notice that Trump, Donald, U.S and president are part of this list for being mentioned in many articles. So maybe this may be the limitation of the algorithm.

Now let's check out the 30 words with the highest tfidf scores.

In [30]:
```
tfidf.sort_values(by=['tfidf'], ascending=False).head(30)
```

Out[30]:

	tfidf
photographs	7.746519
u.s. stocks	7.746519
manifesto pledge	7.746519
oath	7.746519
2-year-old daughter	7.746519
attorney preet	7.746519
years later	7.746519
oval office	7.746519
client	7.746519
million income	7.746519
world's largest	7.746519
north london	7.746519
reign	7.746519
outskirts	7.746519
court heard	7.746519
produce	7.746519
manohar	7.746519
brandon	7.746519
escape	7.746519
eight years	7.746519
six muslim-majority	7.746519
fish	7.746519
ga.	7.746519
watson	7.746519
shop	7.746519
require	7.746519
flag	7.746519
missile defense	7.746519
mixed	7.746519
ratings	7.746519

We end up with less common words. These words naturally carry more meaning for the given description and may outline the underlying topic.

SHARES

As you've noticed, the documents have more than 4000 features (see the vz shape). Put differently, each document has more than 4000 dimensions.

If we want to plot them like we usually do with geometric objects, we need to reduce their dimension to 2 or 3 depending on whether we want to display on a 2D plane or on a 3D space. This is what we call dimensionality reduction.

To perform this task, we'll be using a combination of two popular techniques: Singular Value Decomposition (SVD) to reduce the dimension to 50 and then t-SNE to reduce the dimension from 50 to 2. t-SNE is more suitable for dimensionality reduction to 2 or 3.

Let's start reducing the dimension of each vector to 50 by SVD.

In [31]:
```
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components=50, random_state=0)
svd_tfidf = svd.fit_transform(vz)
```

In [32]:
```
svd_tfidf.shape
```

Out[32]:
```
(9361, 50)
```

Bingo. Now let's do better. From 50 to 2!

In [33]:
```
from sklearn.manifold import TSNE

tsne_model = TSNE(n_components=2, verbose=1, random_state=0)
tsne_tfidf = tsne_model.fit_transform(svd_tfidf)
```

```
[t-SNE] Computing pairwise distances...
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Computed conditional probabilities for sample 1000 / 9361
[t-SNE] Computed conditional probabilities for sample 2000 / 9361
[t-SNE] Computed conditional probabilities for sample 3000 / 9361
[t-SNE] Computed conditional probabilities for sample 4000 / 9361
[t-SNE] Computed conditional probabilities for sample 5000 / 9361
[t-SNE] Computed conditional probabilities for sample 6000 / 9361
[t-SNE] Computed conditional probabilities for sample 7000 / 9361
[t-SNE] Computed conditional probabilities for sample 8000 / 9361
[t-SNE] Computed conditional probabilities for sample 9000 / 9361
[t-SNE] Computed conditional probabilities for sample 9361 / 9361
[t-SNE] Mean sigma: 0.061218
[t-SNE] KL divergence after 100 iterations with early exaggeration: 1.247375
[t-SNE] Error after 300 iterations: 1.247375
```

Let's check the size.

In [34]:
```
tsne_tfidf.shape
```

Out[34]:
```
(9361, 2)
```

Each description is now modeled by a two dimensional vector.

Let's see what tsne_idf looks like.

In [35]:
```
tsne_tfidf
```

Out[35]:
```
array([[  7.69915656,  -4.98227799],
       [ 10.63074735,  -2.85524484],
       [  8.73919302,   5.31266416],
       ...,
       [ -9.07820579,   4.83042557],
       [ -1.53490535,  -8.33400456],
       [ -1.96923235, -10.07561762]])
```

We're having two float numbers per discription. This is not interpretable at first sight.

What we need to do is find a way to display these points on a plot and also attribute the corresponding description to each point.

matplotlib is a very good python visualization libaray. However, we cannot easily use it to display our data since we need interactivity on the objects. One other solution could be d3.js that provides huge capabilities in this field.

Right now I'm choosing to stick to python so I found a tradeoff : it's called Bokeh.

"Bokeh is a Python interactive visualization library that targets modern web browsers for presentation. Its goal is to provide elegant, concise construction of novel graphics in the style of D3.js, and to extend this capability with high-performance interactivity over very large or streaming datasets. Bokeh can help anyone who would like to quickly and easily create interactive plots, dashboards, and data applications." To know more, please refer to this link (http://bokeh.pydata.org/en/latest/)

Let's start by importing bokeh packages and initializing the plot figure.

In [36]:
```
import bokeh.plotting as bp
from bokeh.models import HoverTool, BoxSelectTool
from bokeh.plotting import figure, show, output_notebook
```

In [37]:
```
output_notebook()
plot_tfidf = bp.figure(plot_width=700, plot_height=600, title="tf-idf clustering of the news",
    tools="pan,wheel_zoom,box_zoom,reset,hover,previewsave",
    x_axis_type=None, y_axis_type=None, min_border=1)
```

(http://bokeh.pydata.org) BokehJS successfully loaded.

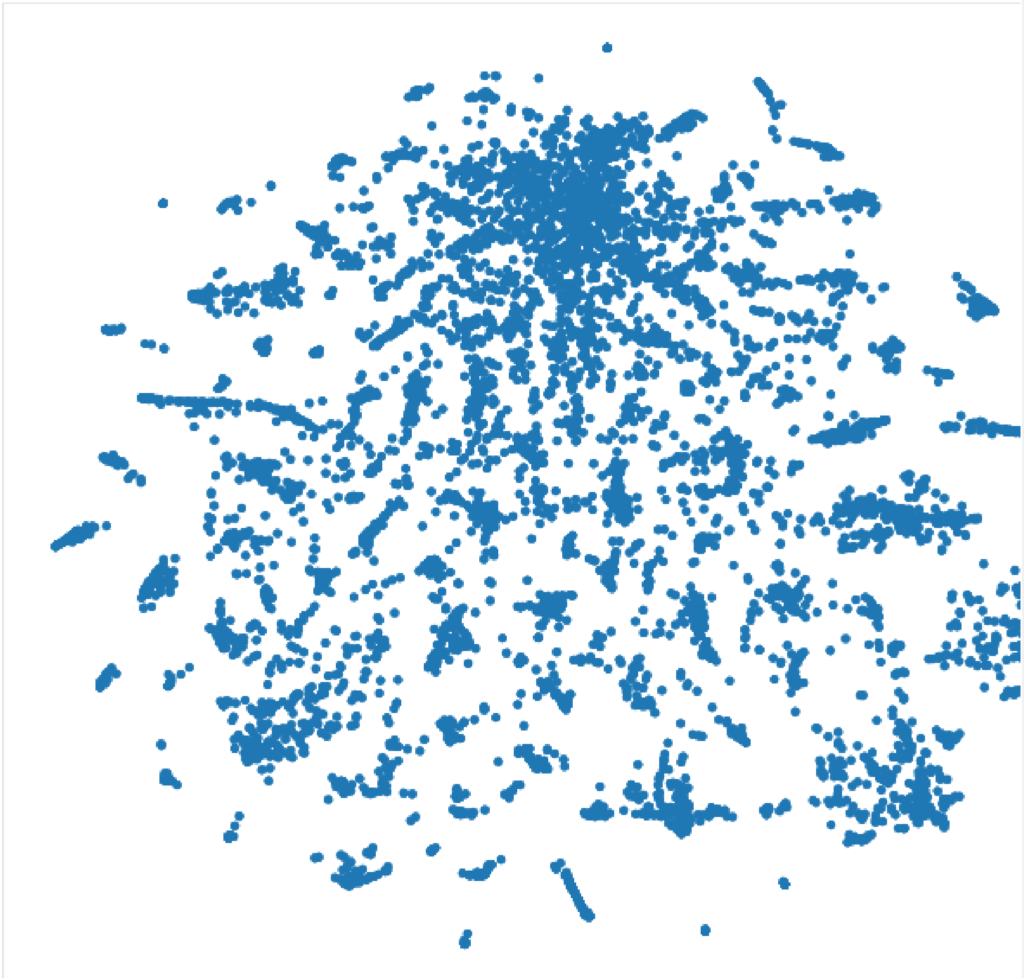
In [38]:
```
tfidf_df = pd.DataFrame(tsne_tfidf, columns=['x', 'y'])
tfidf_df['description'] = data['description']
tfidf_df['category'] = data['category']
```

Bokeh need a pandas dataframe to be passed as a source data. this is a very elegant way to read data.

SHARES

In [39]:
```
plot_tfidf.scatter(x='x', y='y', source=tfidf_df)
hover = plot_tfidf.select(dict(type=HoverTool))
hover.tooltips={"description": "@description", "category":"@category"}
show(plot_tfidf)
```

tf-idf clustering of the news



Bokeh charts offer many functionalities:

- navigating in the data
- zooming
- hovering on each data point and displaying the corresponding description
- saving the chart

When the description popup doesn't show properly you have to move the data point slightly on the left.

By hovering on each news cluster, we can see groups of descriptions of similar keywords and thus referring to the same topic.

Now we're going to use clustering algorithms on the tf-idf matrix.

4 - Clustering

SHARES

4 - 1 - KMeans

Our starting point is the tf-idf matrix vz. Let's check its size again.

In [40]:
```
vz.shape
```

Out[40]:
```
(9361, 4194)
```

This matrix can be seen as a collection of (x) high-dimensional vectors (y). Some algorithms like K-means can crunch this data structure and produce blocks of similar or "close" data points based on some similarity measure like the euclidean distance.

One thing to know about Kmeans is that it needs the number of clusters up front. This number is usually found by trying different values until the result looks satisfactory.

I found that 20 was a good number that separates the dataset nicely.

In [41]:
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

from sklearn.cluster import MiniBatchKMeans

num_clusters = 30
kmeans_model = MiniBatchKMeans(n_clusters=num_clusters, init='k-means++', n_init=1,
                         init_size=1000, batch_size=1000, verbose=False, max_iter=1000)
kmeans = kmeans_model.fit(vz)
kmeans_clusters = kmeans.predict(vz)
kmeans_distances = kmeans.transform(vz)
```

Let's see the five first description and the associated cluster

In [42]:
```
for (i, desc),category in zip(enumerate(data.description),data['category']):
    if(i < 5):
        print("Cluster " + str(kmeans_clusters[i]) + ": " + desc +
              "(distance: " + str(kmeans_distances[i][kmeans_clusters[i]]) + ")")
        print('category: ',category)
        print('---')
```

```
Cluster 3: Researchers discover what could be one of the worst cases of mine pollution in the
category:  general
---
Cluster 26: Malcolm Turnbull and Joko Widodo hold talks in Sydney, reviving cooperation haltec
category:  general
---
Cluster 14: KUALA LUMPUR, Malaysia (AP) — Malaysia's health minister said Sunday that the dose
category:  general
---
Cluster 14: HANOI, Vietnam (AP) — Two women — a Vietnamese and an Indonesian — have been arres
category:  general
---
Cluster 9: NEW YORK (AP) — A trans-Atlantic wave of puzzlement is rippling across Sweden for t
category:  general
---
```

This doesn't tell us much. What we need to look up are the "hot" keywords that describe each clusters.

SHARES

In [43]:

```
sorted_centroids = kmeans.cluster_centers_.argsort()[:, ::-1]
terms = vectorizer.get_feature_names()
for i in range(num_clusters):
    print("Cluster %d:" % i)
    aux = ''
    for j in sorted_centroids[i, :10]:
        aux += terms[j] + ' | '
    print(aux)
    print()
```

```
Cluster 0:
social media | social | media | women | posted | news | comments | fury | violence | veterans

Cluster 1:
muhammad | airport | ali | detained | jr. | questioned | month | son | lawyer | separate |

Cluster 2:
care | health | health care | plan | obamacare | care act | act | affordable | republicans | r

Cluster 3:
one | like | new | world | another | best | could | two | go | people |

Cluster 4:
ncaa tournament | tournament | ncaa | coppa | coppa italia | italia | percent | semi-final | j

Cluster 5:
energy | executive | chief | chief executive | nascar | atlanta motor | atlanta | motor | mons

Cluster 6:
white | white house | house | trump | president | donald | donald trump | president donald | s

Cluster 7:
attorney general | attorney | general | sessions | jeff | jeff sessions | general jeff | russi

Cluster 8:
league | manchester | premier | premier league | win | cup | champions | manchester united | u

Cluster 9:
new york | york | new | york ap | york city | ap | city | york times | state | trump |

Cluster 10:
originally | originally appeared | article originally | appeared | article | people.com (http://p

Cluster 11:
minister | prime | prime minister | theresa | theresa may | may | minister theresa | brexit |

Cluster 12:
years | years ago | ago | three | two years | five years | three years | two | five | four yea

Cluster 13:
turkish | netherlands | turkey | erdogan | tayyip erdogan | tayyip | diplomatic | turkish pres

Cluster 14:
korea | north | south | north korea | korean | kim | south korea | malaysia | jong | kim jong

Cluster 15:
states | united states | united | jewish | federal reserve | reserve | federal | interest | th

Cluster 16:
police | officers | man | woman | police said | said | michael brown | ferguson | found | brow

Cluster 17:
last | year | week | last year | last week | francois | fillon | francois fillon | new | frenc

Cluster 18:
home | family | died | home office | children | court | said | outside | daughter | father |

Cluster 19:
project | management | asset | asset management | billion | budget | largest | standard | woul

Cluster 20:
free | free agency | agency | sturgeon | nicola sturgeon | nicola | free agent | scottish | pe
```

SHARES

```
Cluster 21:
corbyn | labour | jeremy corbyn | jeremy | copeland | party | leader | labour leader | by-elec

Cluster 22:
season | game | well | first | finale | episode | back | contains | end | survivor |

Cluster 23:
day | women | international | women’s | international women | women day | international women’

Cluster 24:
la | best | picture | academy | la land | la la | best picture | land | awards | oscars |

Cluster 25:
mosul | state | islamic | iraqi | islamic state | forces | militants | city | iraqi forces | g

Cluster 26:
new | said | people | first | time | could | would | two | u.s. | company |

Cluster 27:
eu | brexit | lords | theresa | uk | theresa may | european | britain | may | article |

Cluster 28:
trump | president | donald | donald trump | president donald | u.s. | president trump | obama

Cluster 29:
rapoport | ian rapoport | ian | nfl | nfl network | network | insider ian | network insider |
```

Looking at these clusters you can roughly have an idea of what's going on.

Let's plot these clusters. To do this we need to reduce the dimensionality of kmeans_distances to 2.

In [44]:

```
tsne_kmeans = tsne_model.fit_transform(kmeans_distances)
```

```
[t-SNE] Computing pairwise distances...
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Computed conditional probabilities for sample 1000 / 9361
[t-SNE] Computed conditional probabilities for sample 2000 / 9361
[t-SNE] Computed conditional probabilities for sample 3000 / 9361
[t-SNE] Computed conditional probabilities for sample 4000 / 9361
[t-SNE] Computed conditional probabilities for sample 5000 / 9361
[t-SNE] Computed conditional probabilities for sample 6000 / 9361
[t-SNE] Computed conditional probabilities for sample 7000 / 9361
[t-SNE] Computed conditional probabilities for sample 8000 / 9361
[t-SNE] Computed conditional probabilities for sample 9000 / 9361
[t-SNE] Computed conditional probabilities for sample 9361 / 9361
[t-SNE] Mean sigma: 0.007932
[t-SNE] KL divergence after 100 iterations with early exaggeration: 1.349728
[t-SNE] Error after 300 iterations: 1.349728
```

Let's use a color palette to assign different colors to each cluster

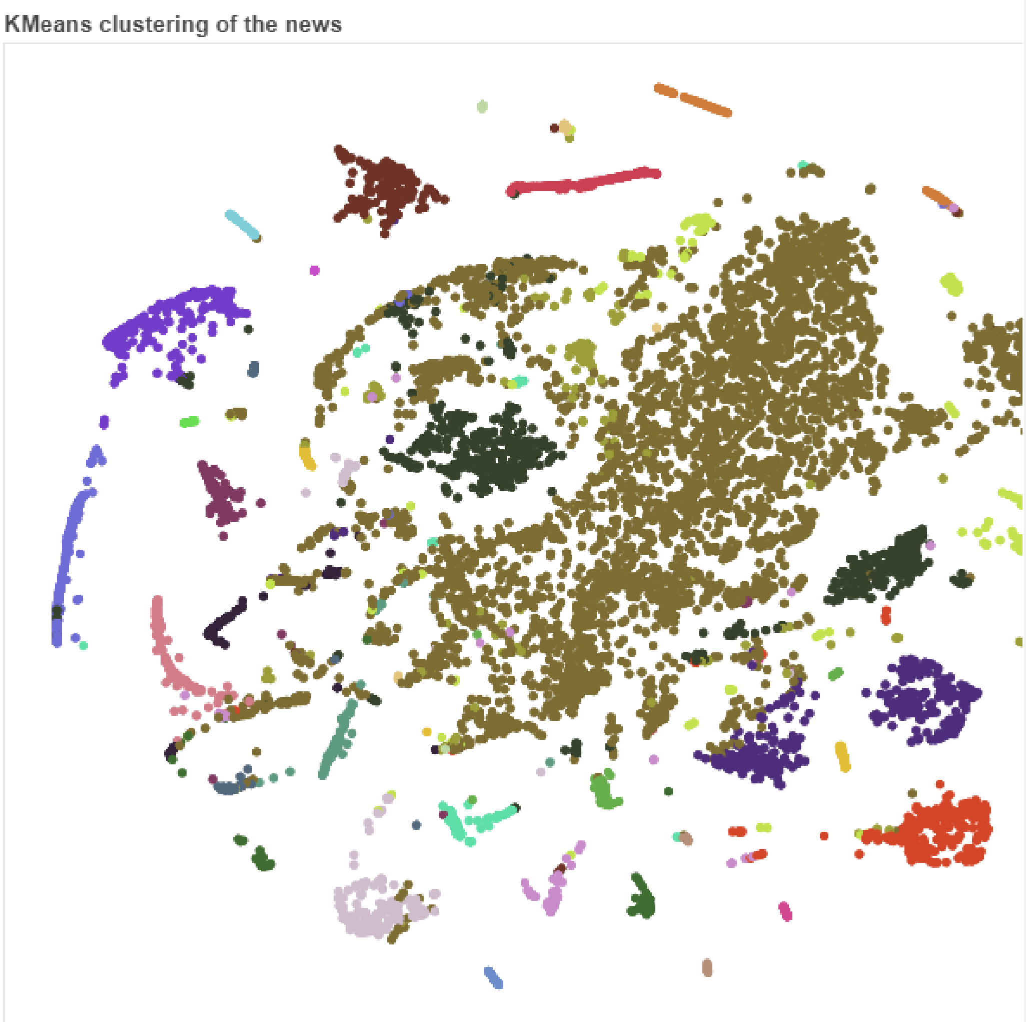
In [45]:

```
import numpy as np

colormap = np.array(["#6d8dca", "#69de53", "#723bca", "#c3e14c", "#c84dc9", "#68af4e", "#6e6cd5",
"#e3be38", "#4e2d7c", "#5fdfa8", "#d34690", "#3f6d31", "#d44427", "#7fcdd8", "#cb4053", "#5e9981",
"#803a62", "#9b9e39", "#c88cca", "#e1c37b", "#34223b", "#bdd8a3", "#6e3326", "#cfbdce", "#d07d3c",
"#52697d", "#7d6d33", "#d27c88", "#36422b", "#b68f79"])

plot_kmeans = bp.figure(plot_width=700, plot_height=600, title="KMeans clustering of the news",
    tools="pan,wheel_zoom,box_zoom,reset,hover,previewsave",
    x_axis_type=None, y_axis_type=None, min_border=1)
```

SHARES

In [46]:
```
kmeans_df = pd.DataFrame(tsne_kmeans, columns=['x', 'y'])
kmeans_df['cluster'] = kmeans_clusters
kmeans_df['description'] = data['description']
kmeans_df['category'] = data['category']
```

In [47]:
```
plot_kmeans.scatter(x='x', y='y',
                    color=colormap[kmeans_clusters],
                    source=kmeans_df)
hover = plot_kmeans.select(dict(type=HoverTool))
hover.tooltips={"description": "@description", "category": "@category", "cluster":"@cluster"}
show(plot_kmeans)
```



It looks like clusters are separated nicely. By hovering on each one of them you can see the corresponding descriptions. At first sight you could notice that they deal approximately with the same topic. This is coherent since we build our clusters using similarities between relevant keywords.

We can also notice that within the same cluster, many subclusters are isolated from one another. This gives an idea about the global topic as well as the

Kmeans separates the documents into disjoint clusters. the assumption is that each cluster is attributed a single topic.

SHARES

However, descriptions may in reality be characterized by a "mixture" of topics. We'll cover how to deal with this problem with the LDA algorithm.

4 - 2 - 1 - Latent Dirichlet Allocation (with Bokeh)

Let's apply LDA on the data set. We'll set the number of topics to 20.

In [48]:
```
import lda
from sklearn.feature_extraction.text import CountVectorizer
```

In [49]:
```
import logging
logging.getLogger("lda").setLevel(logging.WARNING)
```

In [50]:
```
cvectorizer = CountVectorizer(min_df=4, max_features=10000, tokenizer=tokenizer, ngram_range=(1,2))
cvz = cvectorizer.fit_transform(data['description'])

n_topics = 20
n_iter = 2000
lda_model = lda.LDA(n_topics=n_topics, n_iter=n_iter)
X_topics = lda_model.fit_transform(cvz)
```

In [51]:
```
n_top_words = 8
topic_summaries = []

topic_word = lda_model.topic_word_  # get the topic words
vocab = cvectorizer.get_feature_names()
for i, topic_dist in enumerate(topic_word):
    topic_words = np.array(vocab)[np.argsort(topic_dist)][:-(n_top_words+1):-1]
    topic_summaries.append(' '.join(topic_words))
    print('Topic {}: {}'.format(i, ' '.join(topic_words)))
```

```
Topic 0: may brexit said european eu theresa minister theresa may
Topic 1: said state military islamic forces mosul islamic state city
Topic 2: new new york york per ap cent city per cent
Topic 3: court states united united states federal government law immigration
Topic 4: trump president donald donald trump president donald obama white congress
Topic 5: first years time two three since second four
Topic 6: budget chancellor turkish would philip hammond tax make
Topic 7: party day minister women international election chief state
Topic 8: league live saturday champions night david champions league says
Topic 9: company new today announced google uber app service
Topic 10: one like get new it’s much way time
Topic 11: police two man years home london found woman
Topic 12: north korea south said korean north korea kim two
Topic 13: russian general attorney trump campaign attorney general sessions said
Topic 14: trump house president care health order donald trump donald
Topic 15: best la appeared sunday film awards season series
Topic 16: nfl league manchester team united season city former
Topic 17: back news one last week big day bill
Topic 18: u.s. said according spending year market billion federal
Topic 19: people could new found health say children report
```

SHARES

In [52]:
```
tsne_lda = tsne_model.fit_transform(X_topics)
```

```
[t-SNE] Computing pairwise distances...
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Computed conditional probabilities for sample 1000 / 9361
[t-SNE] Computed conditional probabilities for sample 2000 / 9361
[t-SNE] Computed conditional probabilities for sample 3000 / 9361
[t-SNE] Computed conditional probabilities for sample 4000 / 9361
[t-SNE] Computed conditional probabilities for sample 5000 / 9361
[t-SNE] Computed conditional probabilities for sample 6000 / 9361
[t-SNE] Computed conditional probabilities for sample 7000 / 9361
[t-SNE] Computed conditional probabilities for sample 8000 / 9361
[t-SNE] Computed conditional probabilities for sample 9000 / 9361
[t-SNE] Computed conditional probabilities for sample 9361 / 9361
[t-SNE] Mean sigma: 0.091730
[t-SNE] KL divergence after 100 iterations with early exaggeration: 1.470521
[t-SNE] Error after 350 iterations: 1.470521
```

In [53]:
```
doc_topic = lda_model.doc_topic_
lda_keys = []
for i, tweet in enumerate(data['description']):
    lda_keys += [doc_topic[i].argmax()]
```

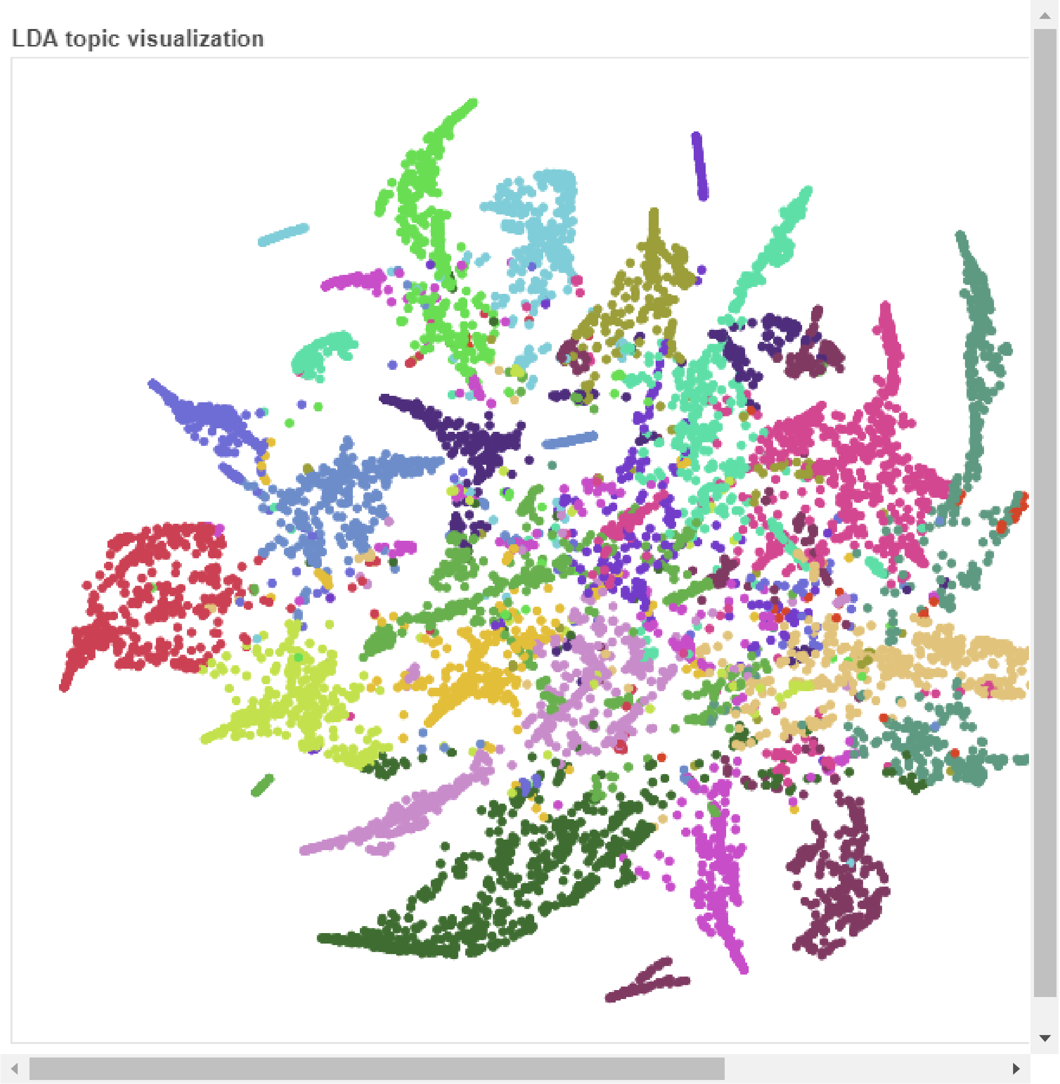
In [54]:
```
plot_lda = bp.figure(plot_width=700, plot_height=600, title="LDA topic visualization",
    tools="pan,wheel_zoom,box_zoom,reset,hover,previewsave",
    x_axis_type=None, y_axis_type=None, min_border=1)
```

In [55]:
```
lda_df = pd.DataFrame(tsne_lda, columns=['x','y'])
lda_df['description'] = data['description']
lda_df['category'] = data['category']
```

In [56]:
```
lda_df['topic'] = lda_keys
lda_df['topic'] = lda_df['topic'].map(int)
```

SHARES

In [57]:
```
plot_lda.scatter(source=lda_df, x='x', y='y', color=colormap[lda_keys])

hover = plot_lda.select(dict(type=HoverTool))
hover.tooltips={"description":"@description", "topic":"@topic", "category":"@category"}
show(plot_lda)
```



Better separation between the topics.

No more dominant topic.

4 - 2 - 2 Visualization of the topics using pyLDAvis

Now we're going to use a more convenient visualization to explore LDA topics. It's called pyldavis.

In [58]:
```
lda_df['len_docs'] = data['tokens'].map(len)
```

SHARES

In [59]:
```
def prepareLDAData():
    data = {
        'vocab': vocab,
        'doc_topic_dists': lda_model.doc_topic_,
        'doc_lengths': list(lda_df['len_docs']),
        'term_frequency':cvectorizer.vocabulary_,
        'topic_term_dists': lda_model.components_
    }
    return data
```

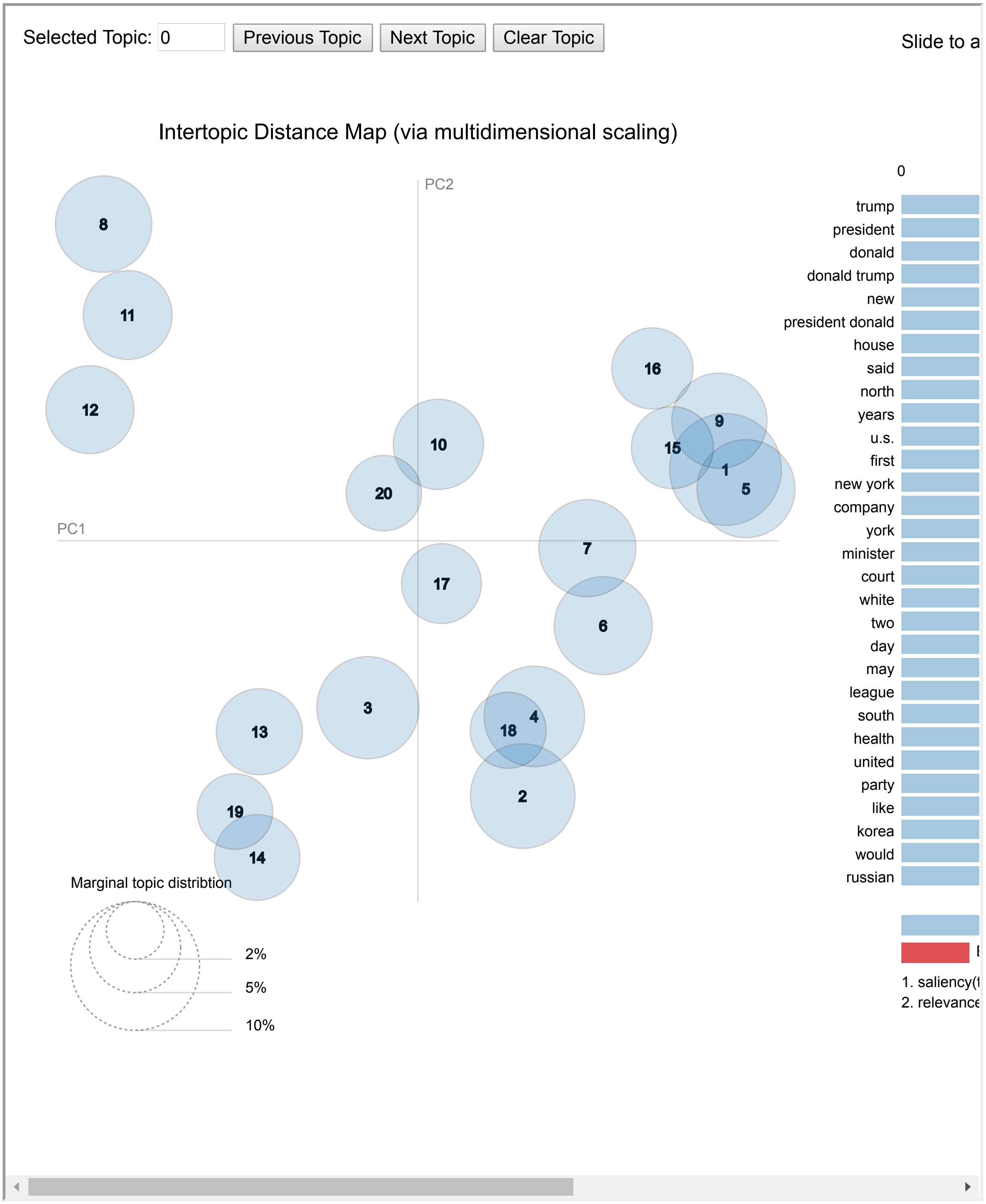
In [60]:
```
ldadata = prepareLDAData()
```

In [61]:
```
import pyLDAvis
```

In [62]:
```
pyLDAvis.enable_notebook()
```

In [63]:
```
prepared_data = pyLDAvis.prepare(**ldadata)
```

In [64]:
```
pyLDAvis.save_html(prepared_data,'./pyldadavis.html')
```



You can play with this visualization here (http://ahmedbesbes.com/pyldadavis.html).

5 - Conclusion

In this post we explored many topics.

- We set up a script to automatically extract newsfeed data from a REST API called newsapi.
- We processed the raw text by using different tools (pandas, nltk, scikit-learn)
- We applied tf-idf statistics as a natural language preprocessing technique
- We created clusters on top of the tf-idf matrix using the KMeans algorithm and visualized them using Bokeh
- We extracted topics using the Latent Dirichlet Allocation algorithm and visualized them using Bokeh and pyldavis

Different techniques have been used but I'm pretty sure there's plenty of better methods. In fact, one way to extend this tutorial could be to dive in:

- word2vec and doc2vec to model the topics
- setting up a robust way to select the number of clusters/topics up front

Thanks for reading ! Don't hesitate to comment if you have a suggestion or an improvement.

6 - References

- https://newsapi.org/ (https://newsapi.org/)
- http://scikit-learn.org/stable/modules/feature_extraction.html (http://scikit-learn.org/stable/modules/feature_extraction.html)
- https://en.wikipedia.org/wiki/Tf%E2%80%93idf (https://en.wikipedia.org/wiki/Tf%E2%80%93idf)
- http://pythonhosted.org/lda/ (http://pythonhosted.org/lda/)
- NLP post (http://nbviewer.jupyter.org/github/skipgram/modern-nlp-in-python/blob/master/executable/Modern_NLP_in_Python.ipynb#topic=3&lambda=0.87&term=)

Data science (https://ahmedbesbes.com/tag/data-science.html) Python (https://ahmedbesbes.com/tag/python.html)
tf-idf (https://ahmedbesbes.com/tag/tf-idf.html) LDA (https://ahmedbesbes.com/tag/lda.html)
Kmeans (https://ahmedbesbes.com/tag/kmeans.html) Newsapi.org (https://ahmedbesbes.com/tag/newsapiorg.html)
NLP (https://ahmedbesbes.com/tag/nlp.html) Topic mining (https://ahmedbesbes.com/tag/topic-mining.html)
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Jim McManus • 9 months ago

I enjoyed your article. Any plans for a book?

2 • Reply • Share ›

Ahmed BESBES Mod Jim McManus • 9 months ago

Thanks, not yet but i'm planning a next article soon.

• Reply • Share ›

Maritza Lara Aguillón • 3 months ago

Hi! awesome article, but tokenizer functions does not work for me, when I apply the function to the description column i get the following: UnicodeDecodeError: 'ascii' codec can't decode byte 0xe2 in position 8: ordinal not in range(128) .... do you know how can I fix this?.

Regards and congrats again!!

1 ^ | v • Reply • Share ›

Ahmed BESBES Mod → Maritza Lara Aguillón • 3 months ago

if you're using python 2, could you try this:
def tokenizer(text):
try:
# modification I made:
text = unicode(text.decode('utf-8'))
# end.
tokens_ = [word_tokenize(sent) for sent in sent_tokenize(text)]

tokens = []
for token_by_sent in tokens_:
tokens += token_by_sent

tokens = list(filter(lambda t: t.lower() not in stop, tokens))
tokens = list(filter(lambda t: t not in punctuation, tokens))
tokens = list(filter(lambda t: t not in [u"'s", u"n't", u"...", u"''", u'``',
u'\u2014', u'\u2026', u'\u2013'], tokens))
filtered_tokens = []
for token in tokens:

see more

1 ^ | v • Reply • Share ›

Maritza Lara Aguillón → Ahmed BESBES • 3 months ago

Thak you so much!!

^ | v • Reply • Share ›

Mel Flo • 5 months ago

Fantastic article!!!
thanks
I am looking forward to reading your book.

1 ^ | v • Reply • Share ›

Jamie White • 10 months ago

Great article. I struggled with visualizing k-means clusters, and I really like your solution.

1 ^ | v • Reply • Share ›

Shailaja Sampat • 10 months ago

Great! Enjoyed hands on!

1 ^ | v • Reply • Share ›

adrienR • 10 months ago

Great read! Very nice blog!

1 ^ | v • Reply • Share ›

William C Brown • 10 months ago

Excellent Article!

1 ^ | v • Reply • Share ›

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Anton Normelius • 11 days ago

Thank you for this! I was wondering if you had any idea how to update the code to work with version 2 with newsapi. I figured it wouldn't be too much hassle to do it myself but can't get it to work with their new version.

• Reply • Share ›

loks2cool A • a month ago

Great Article!, thank you so much, I tried to perform the same & I got some issue in

TypeError: object of type 'NoneType' has no len()

then I removed try & except to see actual error. It shown below error. I even added following lines " text = unicode(text.decode('utf-8'))" still no luck..

UnicodeEncodeError: 'ascii' codec can't encode character u'\u2014' in position 14: ordinal not in range(128)

Any help would be highly appeciated..

• Reply • Share ›

Sapir Shemesh • a month ago

Hi,
I have been following your code in how to mine the news feed
Which is a great post!!!

But Each time i get an error for the scatter functions:

plot_kmeans.scatter(x='x', y='y', color=colormap[kmeans_clusters], source=kmeans_df)

plot_lda.scatter(source=lda_df, x='x', y='y', color=colormap[lda_keys])

File "C:/Users/user/PycharmProjects/untitled/newsKnnModule.py", line 218, in <module>
plot_lda.scatter(source=lda_df, x='x', y='y', color=colormap[lda_keys])
File "C:\Users\user\Anaconda3\lib\site-packages\bokeh\plotting\figure.py", line 677, in scatter
return getattr(self, markertype)(*args, **kwargs)
File "fakesource", line 5, in circle
File "C:\Users\user\Anaconda3\lib\site-packages\bokeh\plotting\helpers.py", line 721, in func
_process_sequence_literals(glyphclass, glyph_ca, source, is_user_source)
File "C:\Users\user\Anaconda3\lib\site-packages\bokeh\plotting\helpers.py", line 296, in
_process_sequence_literals

see more

• Reply • Share ›

Nicole • a month ago

Hi! great article!!!! can you please upload the source code to git or something?please please please:)))

• Reply • Share ›

Ahmed BESBES Mod → Nicole • a month ago

Hello Nicole,

It's already there : https://github.com/ahmedbes...

4 • Reply • Share ›

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Nicole → Ahmed BESBES • a month ago

yes, thank a lot! I saw it :)

I meant the knn algorithm after the tokenizing in python :)))

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Faza Maula • 2 months ago

Hey Ahmed,
thanks for the great article!!,
Can you help me?
i've tried to replicate your work using different data, but i got this error when trying to visualize the k-means :

Supplying a user-defined data source AND iterable values to glyph methods is
not possibe. Either:

Pass all data directly as literals:

p.circe(x=a_list, y=an_array, ...)

Or, put all data in a ColumnDataSource and pass column names:

source = ColumnDataSource(data=dict(x=a_list, y=an_array))
p.circe(x='x', y='x', source=source, ...)

I'm using Anaconda and python 3.6 btw,
thanks!

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Sapir Shemesh → Faza Maula • a month ago

Hi, Did you solve this problem? since I'm facing similar issue with the scatter functions when trying to plot the data

Reply • Share ›

Yousra Gad • 5 months ago

Thank Ahmed for great article. I want to ask you how to evaluate LDA results?. Can you suggest evaluation method for LDA.

Reply • Share ›

Ahmed BESBES Mod → Yousra Gad • 3 months ago

Hello Yousra, I've investigated this subject a bit.
Here's an answer I found worth reading: https://www.quora.com/What-...

Reply • Share ›

Faizal Luke • 6 months ago

Hi Ahmed, I really loved what you have built here. I was looking to build a data scrapping toolkit and was going through newsapi.org and that was when I discovered your blog. Somehow being a newbie I jut can't seem to run the code. I get connection error: Max retries exceeded. I tried to have a timer to slow down the number of request but that didn't work either.

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Ahmed BESBES Mod → Faizal Luke • 3 months ago

Could you share your code? Have you registered to the API and got your own credentials?

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Udeme Ekong • 6 months ago

Hi, I am trying this using python anaconda and prepared_data = pyLDAvis._prepare(**ldadata) in line 63 has run for over 2 hours without concluding, is this expected?

^ | v • Reply • Share ›

Ahmed BESBES Mod ➦ Udeme Ekong • 3 months ago

I believe this may take one minute or two to run. I don't thnik 2 hours are expected.
Could you share your machine configuration ?

^ | v • Reply • Share ›

Brendan @ LearnDataSci • 8 months ago

Awesome article. Definitely going to start using Bokeh more often.

^ | v • Reply • Share ›

Alistair Walsh • 9 months ago

I'm using bokeh==0.12.2 and had to wrap the dataframes in this helper function before before they could be used as a source in the plotting code -

from bokeh.plotting_helpers import ColumnDataSource

plot_tfidf.scatter(x='x', y='y', source=ColumnDataSource(tfidf_df))
hover = plot_tfidf.select(dict(type=HoverTool))
hover.tooltips={"description": "@description", "category":"@category"}
show(plot_tfidf)

Not sure why, I've not used Bokeh much before

Using it without the helper function threw this error -
"
ValueError: expected an instance of type DataSource, got x y description \
0 7.972095 -5.364891 Researchers discover what could be one of the ...
1 10.563941 -0.480654 Malcolm Turnbull and Joko Widodo hold talks in...
2 8.580543 3.471753 KUALA LUMPUR, Malaysia (AP) — Malaysia's healt...

etc.
"

^ | v • Reply • Share ›

Ahmed BESBES Mod ➦ Alistair Walsh • 3 months ago

I'm not sure but I think you're using an old version of Bokeh that doesn't handle connexions with pandas dataframes;

^ | v • Reply • Share ›

Ahmed • 9 months ago

Ahmed - great post. Could you help me wrap my head around one line of code in the script at the top?

news = pd.DataFrame(reduce(lambda x,y: x+y ,map(lambda r: r['articles'], responses)))

I've been reading up on reduce(), filter(), map(), etc., and I see that reduce() takes a function and a sequence --> reduce(func, seq)

In the line above -- I see that you have:
- a lambda function that takes parameters x & y, and returns their sum
- a map() function that iterates over responses, and returns r['articles']

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I'm confused about the goal of this line of code, what is x+y adding, as it iterates over the iterable

I'm confused about the goal of this line of code. what is x+y adding, as it iterates over the iterable returned by map()? What step is this accomplishing in making the Data Frame?

^ | v • Reply • Share ›

Alistair Walsh ➦ Ahmed • 9 months ago

I wondered that too.

"functools.reduce(function, iterable[, initializer])

Apply function of two arguments cumulatively to the items of sequence, from left to right, so as to reduce the sequence to a single value. For example, reduce(lambda x, y: x+y, [1, 2, 3, 4, 5]) calculates ((((1+2)+3)+4)+5). The left argument, x, is the accumulated value and the right argument, y, is the update value from the sequence. If the optional initializer is present, it is placed before the items of the sequence in the calculation, and serves as a default when the sequence is empty. If initializer is not given and sequence contains only one item, the first item is returned."

^ | v • Reply • Share ›

yang yang • 9 months ago

Hi, could you tell me how you point your domain to s3 endpoint?

^ | v • Reply • Share ›

Joopie • 9 months ago

Why did you use a combination of Singular Value Decomposition (SVD) to reduce the dimension to 50 and then t-SNE to reduce the dimension from 50 to 2? Why not just one?

^ | v • Reply • Share ›

Ahmed BESBES Mod ➦ Joopie • 9 months ago

Applying t-sne directly was very slow and did not give good results.

I needed to feed it a matrix with lower dimension so applying SVD to first reduce to 50 dimensions was the solution.

Applying SVD to directly reduce the dimension to 2 was not a good solution either because clusters were not nicely represented. for this kind of task, t-sne is far better.

^ | v • Reply • Share ›

Curtis Miller • 10 months ago

This is great! I've been interested in topic modelling. Would you recommend a reference to learn more about topic modelling?

^ | v • Reply • Share ›

Ahmed BESBES Mod ➦ Curtis Miller • 3 months ago

I think the Gensim documentation is pretty good for starting. Have also a look at their blog:

https://rare-technologies.c...

^ | v • Reply • Share ›

Lorenzo Mainardi • 10 months ago

Why not to use a stemming algorithm on the tokens? This could help reduce dimensions and filter out couple like "years", "yearly" and so on.

^ | v • Reply • Share ›

Ahmed BESBES Mod ➦ Lorenzo Mainardi • 10 months ago

I did use stemming but for some reasons I was not really happy with the results.

Could you reproduce it and tell me how it turns out?

Thank you

Thank you.

^ | v • Reply • Share ›

William C Brown • 10 months ago

In [2] ... if your are using Python 3 it would appear reduce is been moved to functoools...so you need an additional line

form functools import reduce....

I checked Github, I didn't have time to issue pull request..sorry

^ | v • Reply • Share ›

Ahmed BESBES Mod ➦ William C Brown • 10 months ago

Thanks. Fixed.

^ | v • Reply • Share ›

gael Gégourel • 10 months ago

from python3.2, reduce moved to functools, so the script needs:
from functools import reduce

^ | v • Reply • Share ›

Ahmed BESBES Mod ➦ gael Gégourel • 10 months ago

Thanks. Fixed.

^ | v • Reply • Share ›

ALSO ON **AHMED BESBES**

Welcome to my new blog !

5 comments • a year ago

Avatar **Tony Stark** — Hi Ahmed, I also want to learn machine learning, I am following many youtube videos and blogs for past 2 months but I am not

Understanding deep Convolutional Neural Networks with a practical use-case in

9 comments • 2 months ago

Avatar **Christoph Burgdorf** — Cool! Let me know how if you need any help. We are currently in private beta which means you'll need to wait for account

Sentiment analysis on Twitter using word2vec and keras !

Welcome to my blog !

1 comment • 2 years ago

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