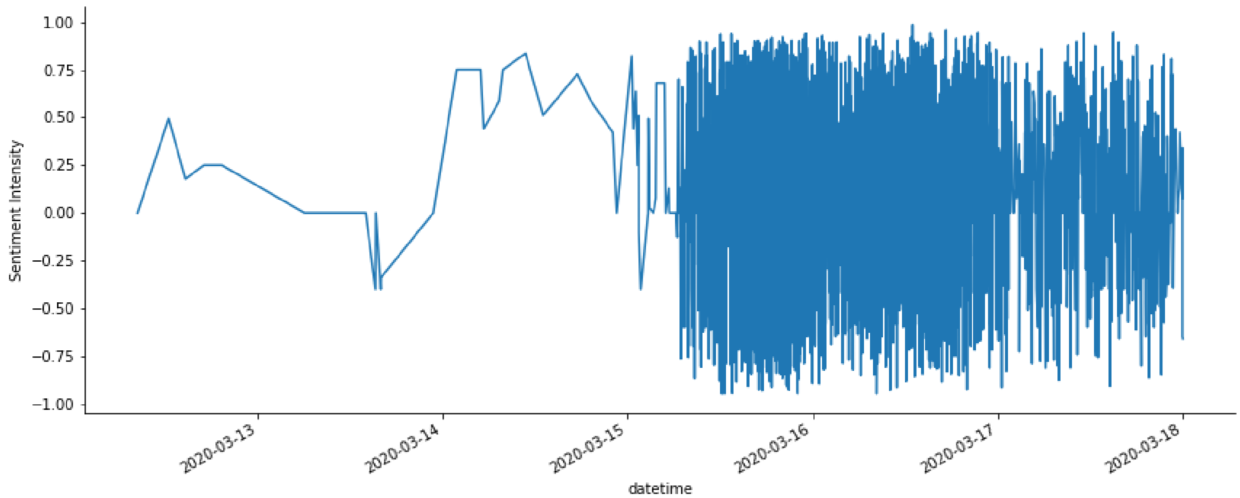
Emotional Sentiment on Twitter

A coronavirus vaccine online firestorm



The ongoing competition for a viable vaccine against coronavirus is arguably the race of the century. With its hundred millions of users, Twitter is particularly well-suited for research into sentiment and emotions running in social media.

This is how it all begun: an exercise of 'real politiks' that is likely to change dramatically the way science, politics and business colide in a pos-covid19 world. As we will see below, the 15th March 2020 will go down in history as a shift of political tone that is at odds with the collaborative, responsible and ethical behaviour of scientific research.

I collected the data scraping tweets from TwitterÕs application program inter-face (API), using TwitterScraping. Tweets were saved on a daily basis using the fol-lowing search term ÒCurevacÓ, the name of a German vaccine maker backed by Bill & Melinda Gates Foundation, and currently working on a Covid-19 vaccine. The post covers tweets from a 6-year period from March 3, 2014 to March 18, 2020 (N = 14,991).

The post covers tweets from a 6-year period from March 3, 2014 to March 18, 2020.

Results include 15,036 tweets in a wide range of languages.

In this notebook you will find examples of some of the most common NLP (Natural Language Processing) techniques used to uncover patterns of sentiment and emotion in the kind of unstructured data that is predominant in Twitter. It is organized as follows:

- Step 1: Exploratory analysis
- Step 2: Text processing

- Step 3: Sentiment analysis
- Step 4: Word frequency
- Step 5: LDA topics extraction
- Step 6: Emotion analysis

Step 1: EXPLORATORY ANALYSIS

After scrapping the Twitter API, the retained tweets were gathered in an excel file (tweets_curevac.xlsx).

Below we have the major Python packages that are required for data handling (pandas), scientific computing (numpy) and data visualization (matplotlib and seaborn).

In [1]:
```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
from collections import defaultdict
from datetime import date

import re # for regular expressions
import string
```

In [3]:
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

Importing the data

In [4]:
```
tweets = pd.read_csv('input/tweets.csv')
```

In [5]:
```
# getting the date column ready for datetime operations
tweets['datetime']= pd.to_datetime(tweets['datetime'])
```

Here is a view of the first rows:

In [6]:
```
tweets.head()
```

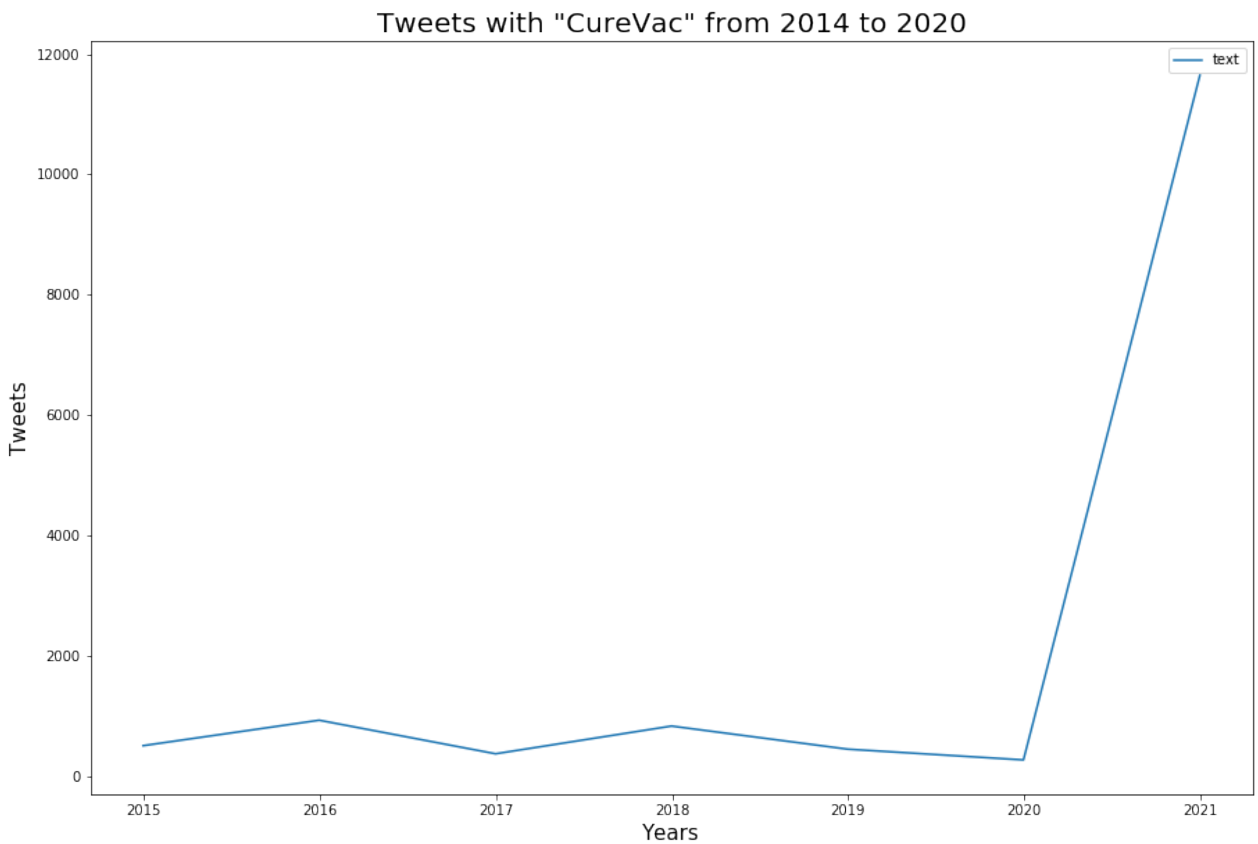
Out[6]:

	datetime	text
0	2014-03-12 18:26:59	Robert-Jan Smits at Innovation Convention 2014...
1	2014-03-13 09:50:54	First #EU #vaccine prize awarded 2 CureVac ...
2	2014-03-14 12:50:28	Congrats 2 CureVac ! 4 #EU #vaccine prize #...
3	2014-03-14 16:01:30	MT @sanofiDE CureVac Wins Two Million EUR f...

4	2014-03-14 17:44:32	CureVac wins EU's EUR2m inducement prize for ...

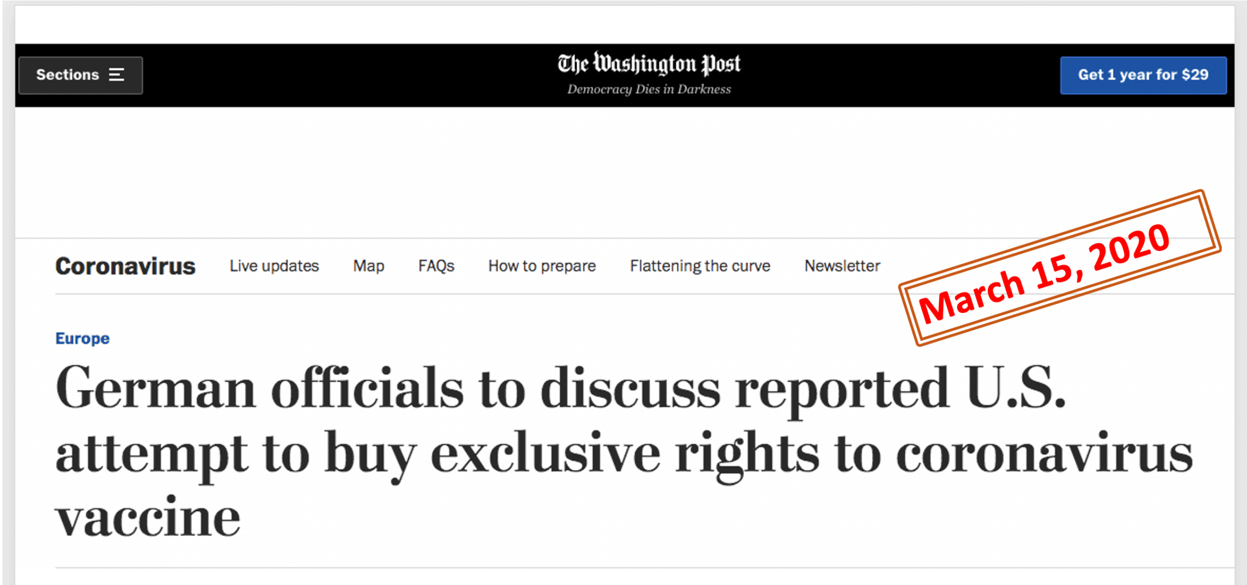
And here is a plot of the tweets with thw word "CureVac" over the past 6 years.

In [7]:
```
# A simple timeseries plot
fig = plt.figure(figsize=(15, 10))
ax = sns.lineplot(data=tweets.set_index("datetime").groupby(pd.Grouper(fre
q='Y')).count())
plt.title('Tweets with "CureVac" from 2014 to 2020', fontsize=20)
plt.xlabel('Years', fontsize=15)
plt.ylabel('Tweets', fontsize=15)
fig.savefig("images/All_Tweets_2014-2020.png")
```



For several years, the rate of tweets went on at a regular pace, until one day ... everything changed!

Digital marketing researchers call these events Òonline firestormsÓ, referring to negative word of mouth (eWOM) that suddenly attract thousands of expres-sions of support from other clients through social [1].



Let us create a column to identify this three-days event.

In [8]:
```python
# creating a column to filter the onlinestorm (from 15 and 18 March)
def make_onlinestorm_field():
    for i, row in tweets.iterrows():
        if pd.to_datetime(tweets.at[i, 'datetime']) > pd.Timestamp(date(2020,3,15)):
            tweets.at[i, 'onlinestorm'] = True
        else:
            tweets.at[i, 'onlinestorm'] = False

make_onlinestorm_field()
```

In [9]:
```python
# count tweets during the three days online storm
print('In three days, tweets went over {}, all around the world.'.format(tweets[tweets['onlinestorm']]['onlinestorm'].count()))
```

```
In three days, tweets went over 11364, all around the world.
```

Here we have them ..

In [10]:
```python
tweets[tweets['onlinestorm']]
```

Out[10]:

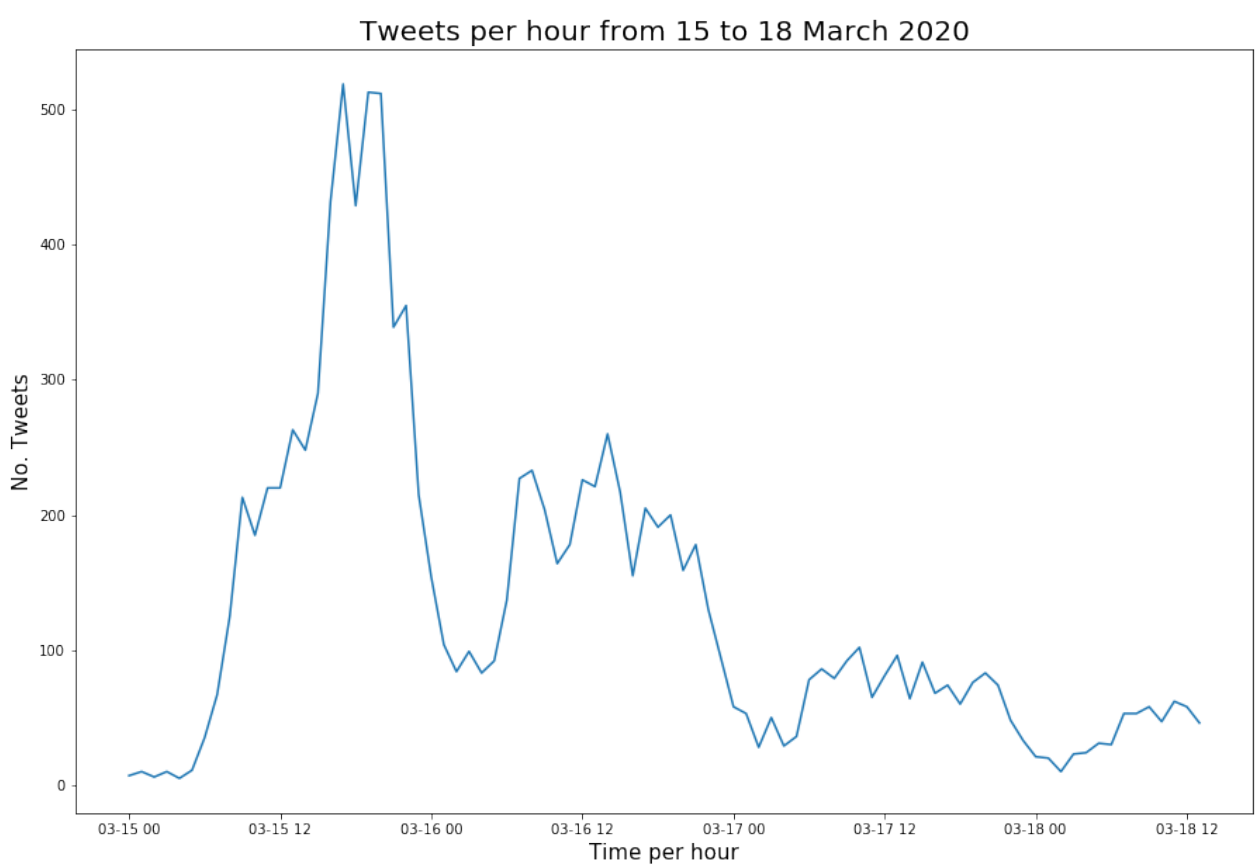
	datetime	text	onlinestorm
3627	2020-03-15 00:07:55	Germany's CureVac says low-dose coronavirus ...	True
3628	2020-03-15 00:14:42	ドイツのディ・ヴェルト紙（ネット版、3月15日）が伝えるところによると、米国政府がドイツでコ...	True
3629	2020-03-15 00:18:05	Germany's CureVac says low-dose coronavirus ...	True
3630	2020-03-15 00:30:29	A Bill & Melinda Gates funded, German Biotech ...	True

3631	2020-03-15 00:42:51	.@BillGates .@gatesfoundation .@melindagates...	True
...	...	...	...
14986	2020-03-18 13:33:33	CureVac -MiteigentŸmer: Hopp macht Hoffnung au...	True
14987	2020-03-18 13:33:36	Non, c'Žtait dans la presse allemande. L'actio...	True
14988	2020-03-18 13:35:22	Rainer Hachfeld https:// cartoonmovement.sho...	True
14989	2020-03-18 13:36:14	ドイツのバイオテクノロジー企業である CureVac が新型コロナのワクチンを秋までに開発す...	True
14990	2020-03-18 13:38:00	Trad.: "Je n'ai pas parlŽ personnellement ˆ M....	True

11364 rows × 3 columns

Let's have a look at the distribution of the tweets by the hour during the online storm.

In [11]:
```
# plot it
fig = plt.figure(figsize=(15, 10))
ax = sns.lineplot(data=tweets[tweets['onlinestorm'] == True].set_index("da
tetime").groupby(pd.Grouper(freq='H')).onlinestorm.count())
plt.title('Tweets per hour from 15 to 18 March 2020', fontsize=20)
plt.xlabel('Time per hour', fontsize=15)
plt.ylabel('No. Tweets', fontsize=15)
fig.savefig("images/All_Tweets_Onlinestorm.png")
```



It is time to have a first look at the content of the tweets and do some descriptive statistics. For now, I will focus only on features like hastags, mentions, urls, capital words and words in general.

In [12]:
```
# A function to count tweets based on regular expressions
def count_tweets(reg_expression, tweet):
    tweets_list = re.findall(reg_expression, tweet)
    return len(tweets_list)
```

In [13]:
```
# Creating a dictionary to hold the counts
content_count = {
    'words' : tweets['text'].apply(lambda x: count_tweets(r'\w+', x)),
    'mentions' : tweets['text'].apply(lambda x: count_tweets(r'@\w+', x)),
    'hashtags' : tweets['text'].apply(lambda x: count_tweets(r'#\w+', x)),
    'urls' : tweets['text'].apply(lambda x: count_tweets(r'http.?://[^\s]+
[\s]?', x)),
}
```

In [14]:
```
df = pd.concat([tweets, pd.DataFrame(content_count)], axis=1);df
```

Out[14]:

	datetime	text	onlinestorm	words	mentions	hashtags	urls
0	2014-03-12 18:26:59	Robert-Jan Smits at Innovation Convention 2014...	False	26	1	0	1
1	2014-03-13 09:50:54	First #EU #vaccine prize awarded 2 CureVac ...	False	23	0	4	0
2	2014-03-14 12:50:28	Congrats 2 CureVac ! 4 #EU #vaccine prize #...	False	21	0	5	0
3	2014-03-14 16:01:30	MT @sanofiDE CureVac Wins Two Million EUR f...	False	17	1	0	0
4	2014-03-14 17:44:32	CureVac wins EU's EUR2m inducement prize for ...	False	33	0	2	1
...	...	...	...	...	...	...	...
14986	2020-03-18 13:33:33	CureVac -MiteigentŸmer: Hopp macht Hoffnung au...	True	18	0	0	0
14987	2020-03-18 13:33:36	Non, cŽtait dans la presse allemande. L'actio...	True	46	0	0	1
14988	2020-03-18 13:35:22	Rainer Hachfeld https://cartoonmovement.sho...	True	42	4	2	0
14989	2020-03-18 13:36:14	ドイツのバイオテクノロジー企業である CureVac が新型コロナのワクチンを秋までに開発す...	True	39	0	0	1

14990	2020-03-18 13:38:00	Trad.: "Je n'ai pas parlŽ personnellement ˆ M....	True	62	0	0	0

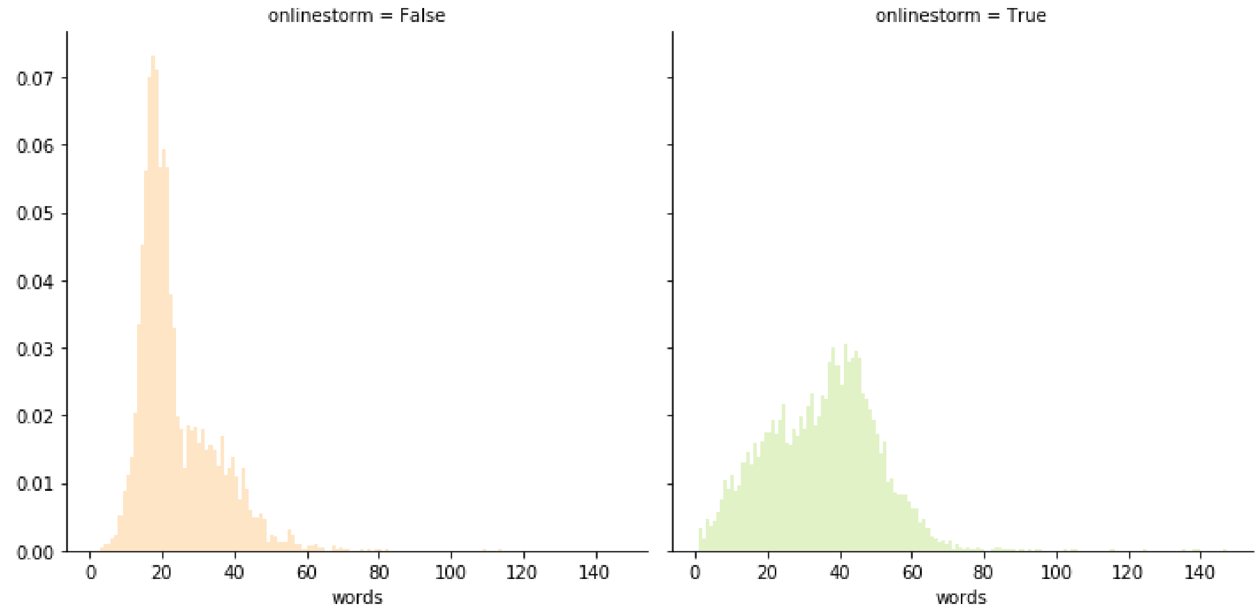
14991 rows × 7 columns

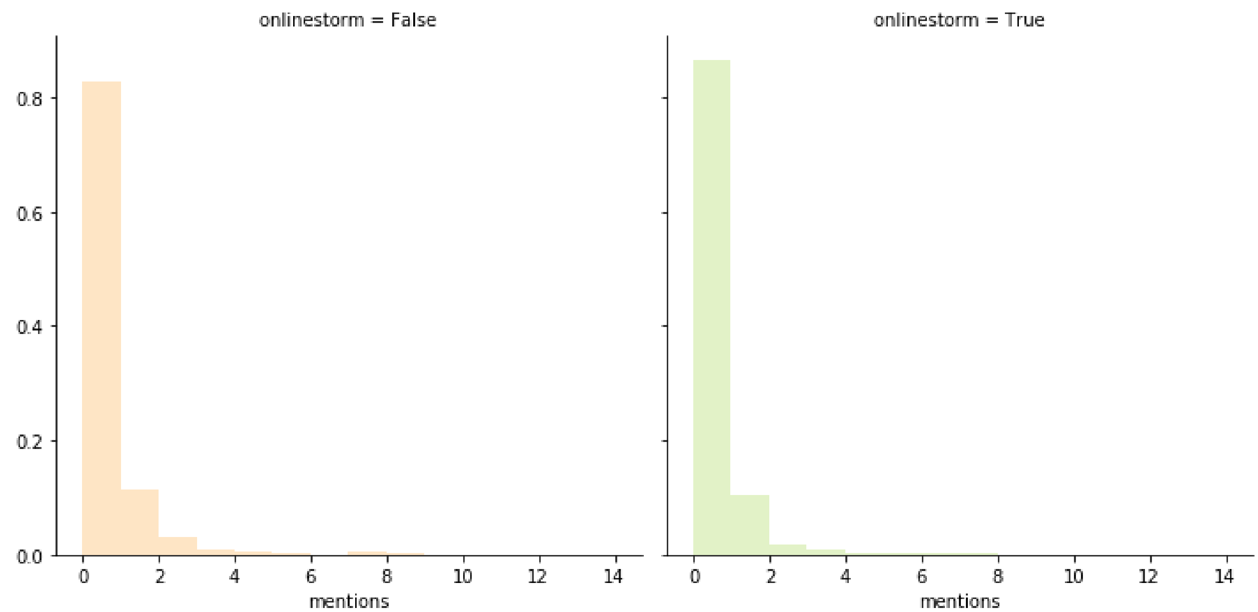
Tweets descriptive statistics

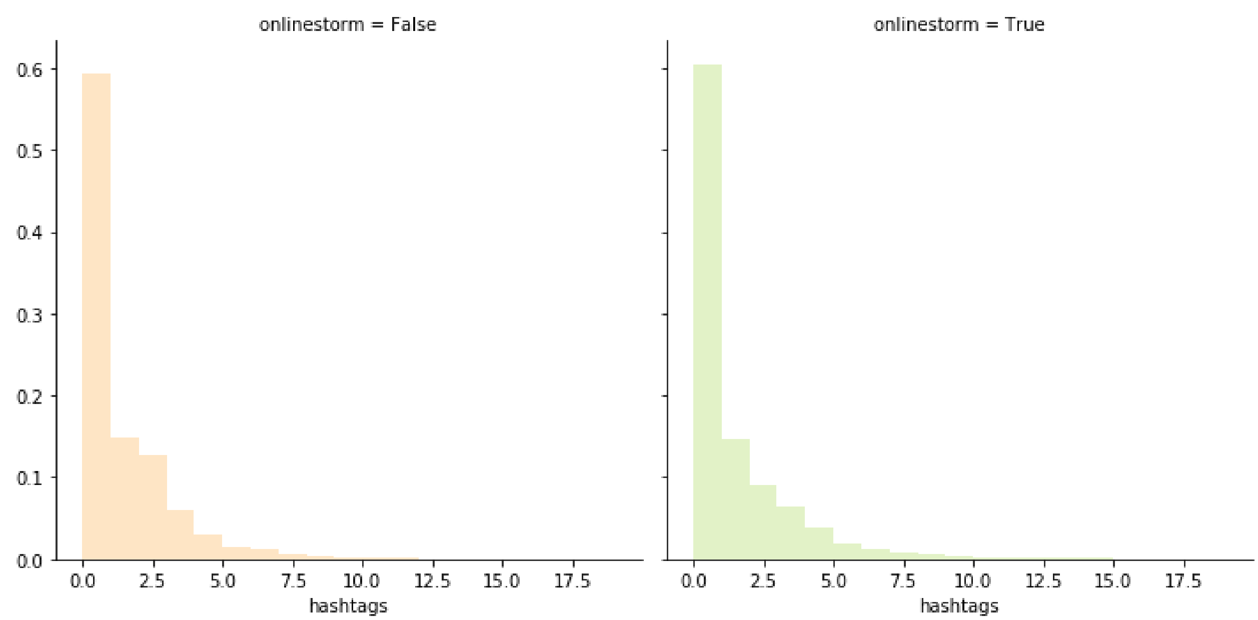
In [15]:
```
# Display some descriptive statistics
for key in content_count.keys():
    print()
    print('Descriptive statistics for {}'.format(key))
    print(df.groupby('onlinestorm')[key].describe())
```

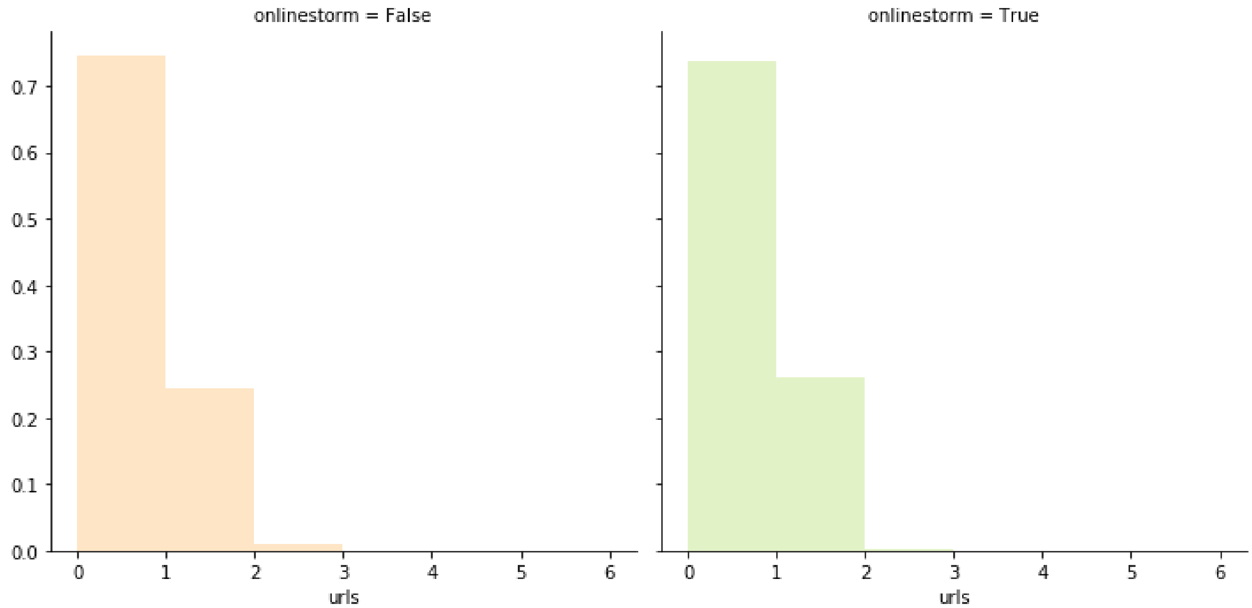
```
Descriptive statistics for words
               count       mean        std  min   25%   50%   75%    max
onlinestorm
False         3627.0  23.355390  10.731606  3.0  16.0  20.0  29.0  113.0
True         11364.0  34.571718  15.048733  1.0  23.0  36.0  45.0  147.0

Descriptive statistics for mentions
               count      mean       std  min  25%  50%  75%   max
onlinestorm
False         3627.0  0.304659  0.931811  0.0  0.0  0.0  0.0  12.0
True         11364.0  0.205297  0.694837  0.0  0.0  0.0  0.0  14.0

Descriptive statistics for hashtags
               count      mean       std  min  25%  50%  75%   max
onlinestorm
False         3627.0  0.971602  1.611123  0.0  0.0  0.0  2.0  13.0
True         11364.0  1.071454  1.923787  0.0  0.0  0.0  1.0  19.0

Descriptive statistics for urls
               count      mean       std  min  25%  50%  75%  max
onlinestorm
False         3627.0  0.267990  0.480024  0.0  0.0  0.0  1.0  6.0
True         11364.0  0.265488  0.449512  0.0  0.0  0.0  1.0  4.0
```

In [16]:
```
# Now plot them
for key in content_count.keys():

    bins = np.arange(df[key].min(), df[key].max() + 1)
    g = sns.FacetGrid(df, col='onlinestorm', height=5, hue='onlinestorm', 
palette="RdYlGn")
    g = g.map(sns.distplot, key, kde=False, norm_hist=True, bins=bins)
    plt.savefig('images/Descriptive_stats_for_' + key + '.png')
```


onlinestorm = False
onlinestorm = True
words
words


onlinestorm = False
onlinestorm = True
mentions
mentions


onlinestorm = False
onlinestorm = True
hashtags
hashtags



From the above descriptive statistics, there are no noteworthy differences in terms of mentions, hashtags or urls during the online storm. Yet, the average number of words, per tweet, increased substantially during this period.

Step 2: TEXT PROCESSING

For the next steps, I retained only the tweets in English, avoiding duplicates. These are contained in an excel file ('Tweets_CureVac_en.xlsx') with 6,546 tweets.

The second step of our analysis will look deeper into the content of these tweets. It is time to apply some of the basic NLP operations, such as cleaning, tokenizing and lemmatizing.

We will use NLTK (Natural Language Toolkit), one of the most popular NLP libraries for Python.

In [17]:
```
import nltk
from nltk.corpus import stopwords
from nltk.stem.snowball import SnowballStemmer
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import sent_tokenize, word_tokenize
from nltk import pos_tag
```

In [18]:
```
import string
import re  # for regular expressions
```

In [19]:
```
# I am adding my own stopwords list to the NLTK list.
# This way we can drop words that are irrelevant for text processing
MY_STOPWORDS = ['curevac','vaccine','german','mrna','biotech','cancer','li
lly','eli','ag','etherna_immuno', 'translatebio', 'mooreorless62','boehrin
ger', 'ingelheim','biopharmaceutical', 'company']
STOPLIST = set(stopwords.words('english') + list(MY_STOPWORDS))
SYMBOLS = " ".join(string.punctuation).split(" ") + ["-", "...", "”", "``"
, ",", ".", ":", "''","#","@"]
```

In [20]:
```
# The NLTK lemmatizer and stemmer classes
lemmatizer = WordNetLemmatizer()
stemmer = SnowballStemmer('english')
```

In [21]:
```
# read english selected tweets, no duplicates
tweets = pd.read_csv('input/tweets_en.csv')
```

In [22]:
```
# I use the POS tagging from NLTK to retain only adjectives, verbs, adverb
s and nouns for lemmatization.
def get_lemmas(tweet):

    # A dictionary to help convert Treebank tags to WordNet
    treebank2wordnet = {'NN':'n', 'JJ':'a', 'VB':'v', 'RB':'r'}

    postag = ''
    lemmas_list = []

    for word, tag in pos_tag(word_tokenize(tweet)):
        if tag.startswith("JJ")      \
            or tag.startswith("RB") \
            or tag.startswith("VB") \
            or tag.startswith("NN"):

            try:
                postag = treebank2wordnet[tag[:2]]
            except:
                postag = 'n'

            lemmas_list.append(lemmatizer.lemmatize(word.lower(), postag))


    return lemmas_list
```

In [23]:
```
# This function processes, cleans and filters the tokens for each tweet
def clean_tweet(tokens):

    filtered = []
    for token in tokens:
        if re.search('[a-zA-Z]', token):
            if token not in STOPLIST:
                if token[0] not in SYMBOLS:
                    if not token.startswith('http'):
                        if  '/' not in token:
                            if  '-' not in token:
                                filtered.append(token)

    return filtered
```

We will now pre-process the tweets, following a pipeline of tokenization, filtering, case normalization and lemma extraction, including an overall cleaning of html and other codes.

Prior to lemmatization, I applied POS (part-of-speech) tagging to make sure that only the adjectives, verbs, adverbs and nouns were retained.

In [24]:
```
# Starts the lemmatization process
def get_lemmatized(tweet):

    all_tokens_string = ''
    filtered = []
    tokens = []

    # lemmatize
    tokens = [token for token in get_lemmas(tweet)]

    # filter
    filtered = clean_tweet(tokens)

    # join everything into a single string
    all_tokens_string = ' '.join(filtered)

    return all_tokens_string
```

In [25]:
```
# get the lemmatized tweets and puts the result in an "edited" text column
 for future use
edited = ''
for i, row in tweets.iterrows():
    edited = get_lemmatized(tweets.loc[i]['text'])
    if len(edited) > 0:
        tweets.at[i,'edited'] = edited
    else:
        tweets.at[i,'edited'] = None
```

In [26]:
```
# After lemmatization, some tweets may have as a result the same words
# Let's make sure that we have no duplicates
tweets.drop_duplicates(subset=['edited'], inplace=True)
tweets.dropna(inplace=True)
```

With these text processing steps, and the removal of duplicates, the final sample counts 5,508 English-language tweets, with an average of 30 words (SD 12.5, ranging from 4 to 61 words).

In [27]:
```
# Using apply/lambda to create a new column with the number of words in ea
ch tweet
tweets['word_count'] = tweets.apply(lambda x: len(x['text'].split()),axis=
1)
t = pd.DataFrame(tweets['word_count'].describe()).T
t
```

Out[27]:

	count	mean	std	min	25%	50%	75%	max
word_count	5508.0	30.546659	12.499944	4.0	19.0	31.0	42.0	61.0

Here is the result of our pre-processing, showing the difference between the original tweet (column "text") and the lemmatized, cleaned, tweet (column "edited").

In [28]:
```
tweets.head()
```

Out[28]:

	datetime	text	edited	word_count
0	2020-03-16 11:13:00	Interior Minister Horst Seehofer, when asked t...	interior minister horst seehofer ask confirm r...	47
1	2020-03-16 03:34:02	CureVac said it has been in contact with many...	say contact many organization global authority...	26
2	2015-07-07 13:24:10	CureVac Announces Phase I/IIa Clinical Study ...	announces phase clinical study data immunother...	15
3	2015-11-02 13:21:08	CureVac alone has received >$100M from US fou...	alone receive us foundation gate darpa manufac...	21
4	2020-03-16 20:10:33	I hope to God CureVac doesn't cave. Trump is...	hope god n't cave trump despicable po planet	20

Step 3: SENTIMENT ANALYSIS

For sentiment analysis -- a growing sub-field of Natural Language Processing (NLP) -- I used VADER (Valence Aware Dictionary for Sentiment Reasoning), a rule-based system that performs specially well on social media data.

VADER quantifies the sentiment of a tweet based on positive, neutral and neg-ative scores, and uses a Compound score to account for the intensity of the overall sentiment of a given text. It measures the strength of sentiments by giving scores ranging from +1 to -1 with positive numbers indicate favorable atti-tudes while negative numbers indicate negative attitudes.

In this section, I will focus on a simple comparison between the sentiment (Compound score) of a 6-year period with the score over the three days of the CureVac online firestorm, from March 15 to March 18.

Let us import the VADER analyser.

In [29]:

```
from nltk.sentiment.vader import SentimentIntensityAnalyzer
```

For the puropose of the timeseries analysis, we must make sure that the tweets are all correctly sorted.

In [30]:

```
tweets['datetime']=pd.to_datetime(tweets['datetime'])
tweets.sort_values('datetime', inplace=True, ascending=True)
tweets = tweets.reset_index(drop=True)
```

In [ ]:

```

```

In [31]:

```
# Creating a column to "filter" the online storm period.
make_onlinestorm_field()
```

In [32]:

```
# To avoid repetitions in our code, here are some plottimng functions
# that will be called often ...
```

```
def plot_sentiment_period(df, info):

    # Using the mean values of sentiment for each period
    df1 = df.groupby(df['datetime'].dt.to_period(info['period'])).mean()

    df1.reset_index(inplace=True)
    df1['datetime'] = pd.PeriodIndex(df1['datetime']).to_timestamp()
    plot_df = pd.DataFrame(df1, df1.index, info['cols'])

    plt.figure(figsize=(15, 10))
    ax = sns.lineplot(data=plot_df, linewidth = 3, dashes = False)
    plt.legend(loc='best', fontsize=15)
    plt.title(info['title'], fontsize=20)
    plt.xlabel(info['xlab'], fontsize=15)
    plt.ylabel(info['ylab'], fontsize=15)
    plt.tight_layout()
    plt.savefig('images/' + info['fname'])
    return


def plot_fractions(props, title, fname):

    plt1 = props.plot(kind='bar', stacked=False, figsize=(16,5), colormap=
'Spectral')
    plt.legend(bbox_to_anchor=(1.005, 1), loc=2, borderaxespad=0.)
    plt.xlabel('Online storm', fontweight='bold', fontsize=18)
    plt.xticks(rotation=0,fontsize=14)
    #plt.ylim(0, 0.5)
    plt.ylabel('Fraction of Tweets', fontweight='bold', fontsize=18)
    plt1.set_title(label=title, fontweight='bold', size=20)
    plt.tight_layout()
    plt.savefig('images/' + fname + '.png')

    return


def plot_frequency_chart(info):

    fig, ax = plt.subplots(figsize=(14, 8))
    sns.set_context("notebook", font_scale=1)
    ax = sns.barplot(x=info['x'], y=info['y'], data=info['data'], palette=
(info['pal']))
    ax.set_title(label=info['title'], fontweight='bold', size=18)
    plt.ylabel(info['ylab'], fontsize=16)
    plt.xlabel(info['xlab'], fontsize=16)
    plt.xticks(rotation=info['angle'],fontsize=14)
    plt.yticks(fontsize=14)
    plt.tight_layout()
    plt.savefig('images/' + info['fname'])

    return
```

In [33]:

```
# Calling VADER
analyzer = SentimentIntensityAnalyzer()
```

In [34]:

```
# get VADER Compound value for sentiment intensity
```

```
tweets['sentiment_intensity'] = [analyzer.polarity_scores(v)['compound'] f
or v in tweets['edited']]
```

The output of VADER are the positive, negative, and neutral ratios of sentiment. The most useful metric in VADER is the Compound score. Basically, it is calculated by a sum of the scores of each word, normalized to yeld values between -1, the most extreme negative score, and +1, the most extreme positive.

From this normalized score, I will then create a categorical variable ("sentiment"), with an output of positive, negative and neutral ratios of sentiment, using the following thresholds:

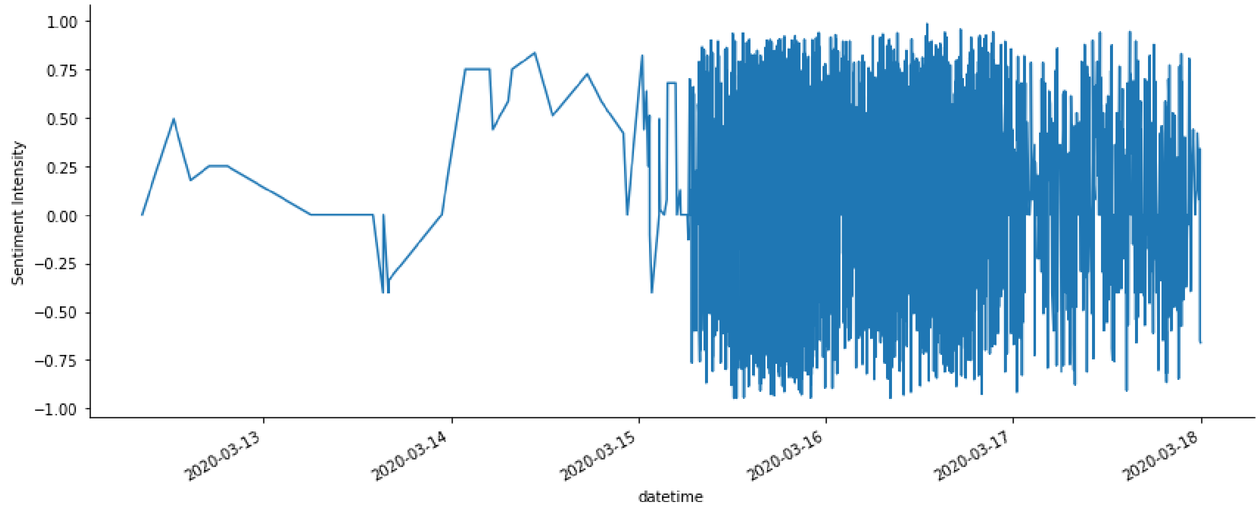
- Positive sentiment : (compound score >= 0.05).
- Neutral sentiment : (compound score > -0.05) and (compound score < 0.05).
- Negative sentiment : (compound score <= -0.05)

In [35]:
```
# This function returns the sentiment category
def get_sentiment(intensity):
    if intensity >= 0.05:
        return 'Positive'
    elif (intensity >= -0.05) and (intensity < 0.05):
        return 'Neutral'
    else:
        return 'Negative'

# Using pandas apply/lambda to speed up the process
tweets['sentiment'] = tweets.apply(lambda x: get_sentiment(x['sentiment_in
tensity']),axis=1)
```

The Online Storm

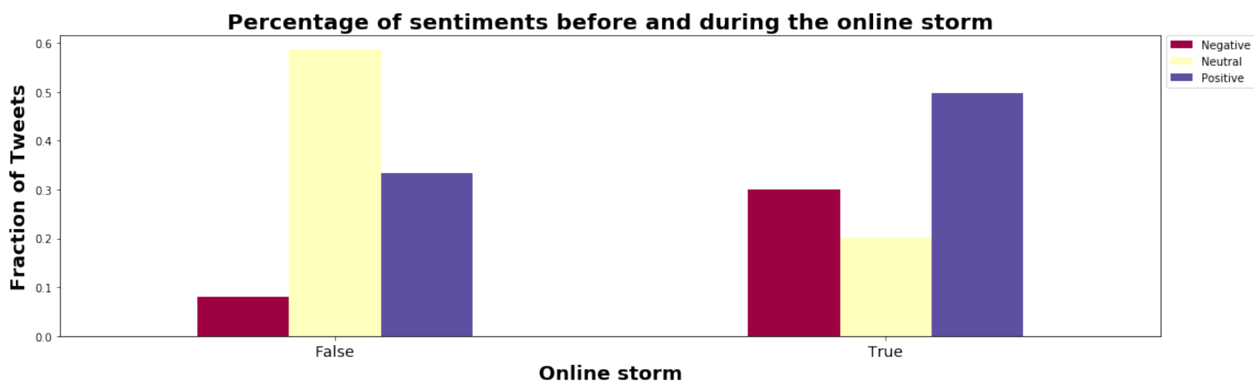
The next plot gives us a clear image of the ÒexplosionÓ of contradictory sentiments in this period:

In [36]:
```
df=tweets.loc[:,['datetime','sentiment_intensity']]
df.set_index('datetime',inplace=True)
df=df[(df.index>='2020-03-12') & (df.index<'2020-03-18')]
df.plot(figsize=(12,5));
plt.ylabel('Sentiment Intensity')
plt.legend().set_visible(False)
plt.tight_layout()
sns.despine(top=True)
plt.savefig('images/Average_sentiment_during_onlinestorm.png')
plt.show();
```



And this one will shows us a comparison of the sentiments before and during the online strom.

In [37]:
```
# Values are normalized to take into account the number of tweets in each
# of the two different periods
props = tweets.groupby('onlinestorm')['sentiment'].value_counts(normalize=
True).unstack()
plot_fractions(props,'Percentage of sentiments before and during the onlin
e storm',
               'Fraction_sentiments_before_and_during_onlinestorm')
```



In sentiment analysis and opinion mining, neutral tweets usually outnumber the negative or positive ones. This is what actually happened during the 6-year period in consideration. Moreover, research has been showing that scientists tend to use neutral language while communicating among peers, particularly in social media.

The picture clearly changed during the 3-days online storm. Sentiments become less neutral, as it is also likely that the majority of the authors come from a wider public. The percentage of positive tweets increased, suggesting increased expectations about a viable vaccine for coronavirus.

But the fraction of negative tweets increased even more during the online storm. This calls for a deeper look to the date. That is what we will do now.

Step 4: Word frequency

Now that our text is pre-processed, it is time to examine key patterns of word frequency in tweets posted before and during the online storm.

In [ ]:

```

```

In [38]:

```
# We need these imports for the wordcloud representation:
from PIL import Image
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
from matplotlib.colors import makeMappingArray
from palettable.colorbrewer.diverging import Spectral_4
```

In [39]:

```
from collections import Counter    # Look at the most common items in a li
st
```

In [ ]:

```

```

In [40]:

```
def display_wordcloud(tokens):

    tokens_upper = [token.upper() for token in tokens]

    cloud_mask = np.array(Image.open("images/cloud_mask.png"))
    wordcloud = WordCloud(max_font_size=100,
                          max_words=50, width=2500,
                          height=1750,mask=cloud_mask,
                          background_color="white").generate(" ".join(toke
ns_upper))
    plt.figure()
    fig, ax = plt.subplots(figsize=(14, 8))
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()

    return
```

In [41]:

```
def join_edited_string(edited_tweets):

    edited_string = ''
    for row in edited_tweets:
        edited_string = edited_string + ' ' + row

    return edited_string
```

In [42]:

```
def get_trigrams(trigrams, top_grams):

    grams_str = []
    data = []

    gram_counter = Counter(trigrams)

    for grams in gram_counter.most_common(10):
        gram = ''
        grams_str = grams[0]
```

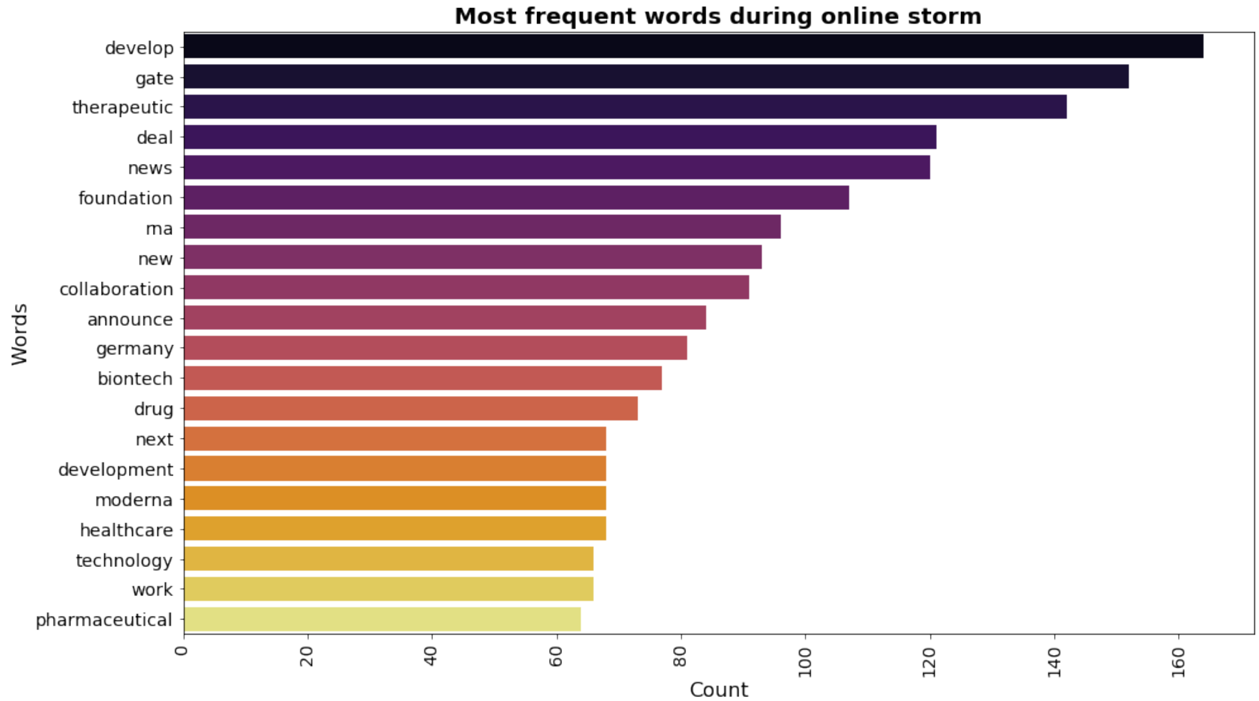
```
        grams_str_count = []
        for n in range(0,3):
            gram = gram + grams_str[n] + ' '
        grams_str_count.append(gram)
        grams_str_count.append(grams[1])
        data.append(grams_str_count)
        print(grams_str_count)

    df = pd.DataFrame(data, columns = ['Grams', 'Count'])

    return df
```

Word frequency before the online storm

LetÕs have a look at the 20 most frequent words in tweets before the online storm.

In [43]:
```
# Filtering the tweets of the 6 years before the online storm
df = tweets[tweets['onlinestorm'] == False]

# Join all the edited tweets in one single string
joined_string = join_edited_string(df['edited'])

# Get tokens
tokens = joined_string.split(' ')

# get trigrams
trigrams = nltk.trigrams(tokens)
```

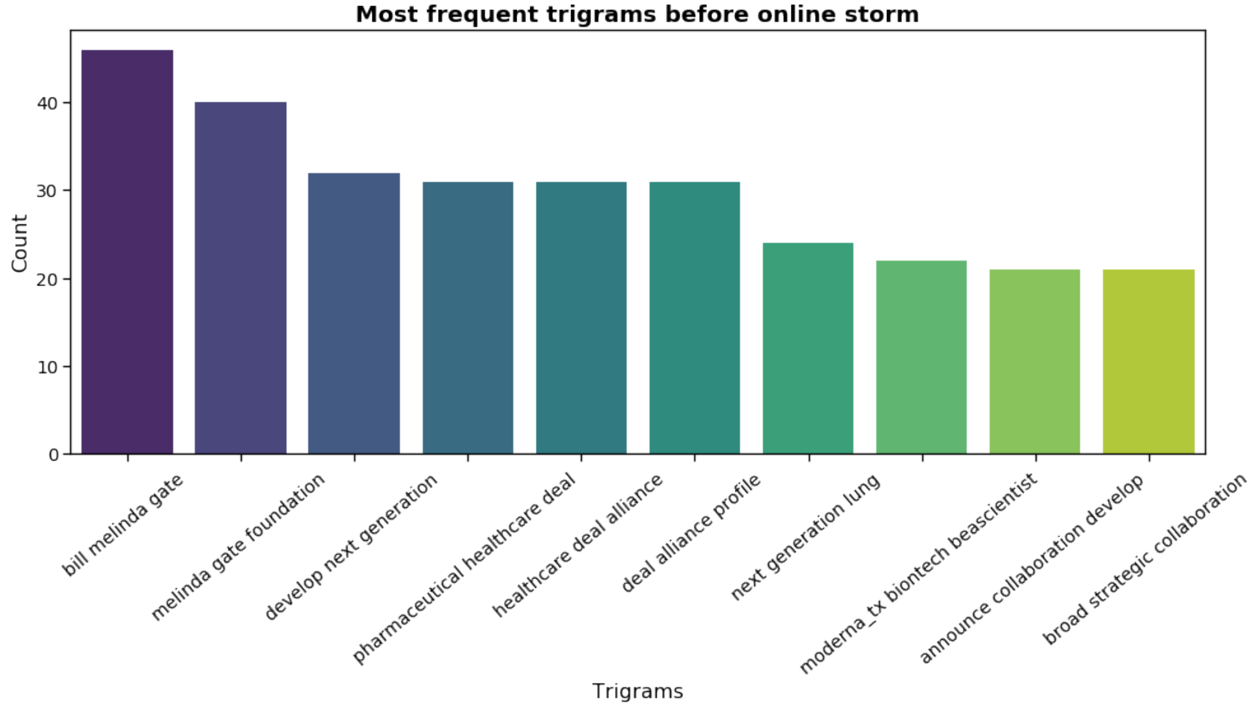
In [44]:
```
# plot word frequency during online storm
word_counter = Counter(tokens)
df_counter = pd.DataFrame(word_counter.most_common(20), columns = ['word',
 'freq'])
info = {'data': df_counter, 'x': 'freq', 'y': 'word',
       'xlab': 'Count', 'ylab': 'Words', 'pal':'inferno',
       'title': 'Most frequent words during online storm',
       'fname':'word_frequency_during_onlinestorm.png',
       'angle': 90}
plot_frequency_chart(info)
```



And now the 10 most frequent trigrams (sequences of 3 consecutive words) ...

In [45]:
```
# plot trigram frequency
df_trigrams = get_trigrams(trigrams, 10)
info = {'data': df_trigrams, 'x': 'Grams', 'y': 'Count',
        'xlab': 'Trigrams', 'ylab': 'Count', 'pal':'viridis',
        'title': 'Most frequent trigrams before online storm',
        'fname':'trigrams_frequency_before_onlinestorm.png',
        'angle': 40}
plot_frequency_chart(info)
```

```
['bill melinda gate ', 46]
['melinda gate foundation ', 40]
['develop next generation ', 32]
['pharmaceutical healthcare deal ', 31]
['healthcare deal alliance ', 31]
['deal alliance profile ', 31]
['next generation lung ', 24]
['moderna_tx biontech beascientist ', 22]
['announce collaboration develop ', 21]
['broad strategic collaboration ', 21]
```



And the wordcloud ...

In [46]:
```
display_wordcloud(tokens)
```

<Figure size 432x288 with 0 Axes>

There are some noteworthy features in these plots:

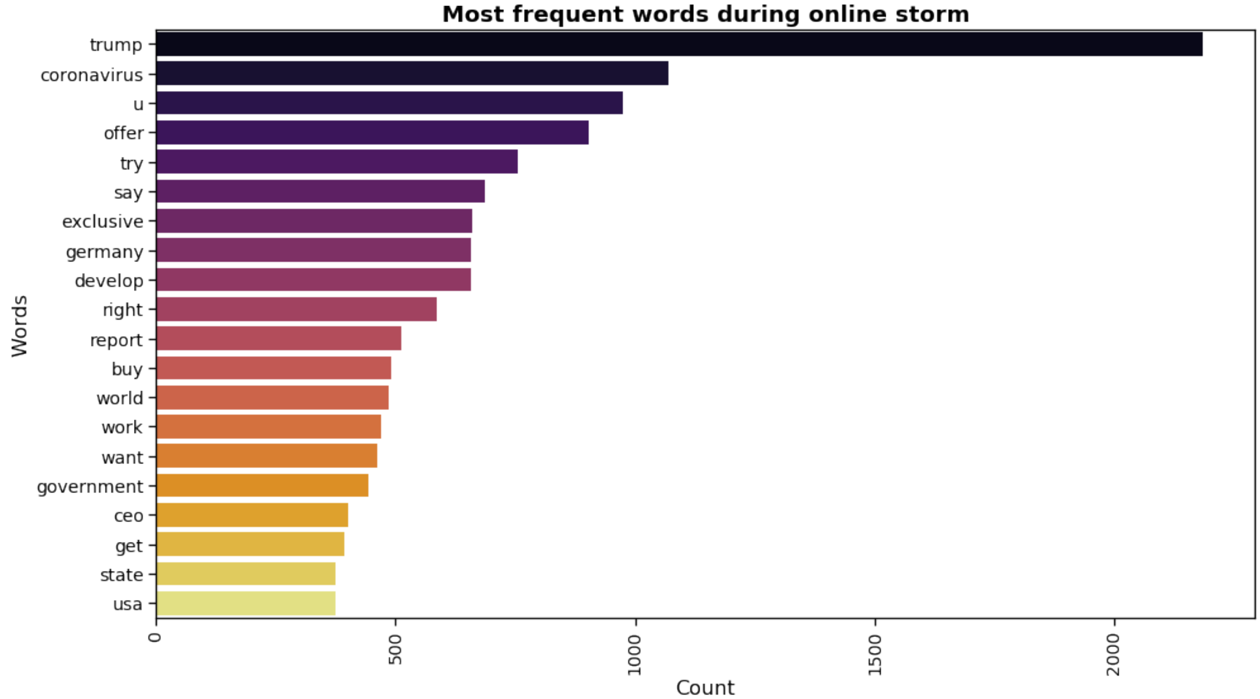
- Along with ÔgateÕ (ie., Bill Gates), the most frequent words in 6 years of tweets are ÔdevelopÕ, ÔtherapeuticÕ, ÔdealÕ and 'news'. Unsurprisingly, these were times when tweets were used mainly as public relations devices to communicate the core business of CureVac, a vaccine maker funded by the Melinda gate Foudation.
- Immediatly follows ÔCollaborationÕ, the next most frequent word, reflecting in this way the key importance of partnerships in the strategy of the company, followed by ÔnewÕ, as a evidence of CureVac's concern with innovation.
- The trigrams reinforce these trends, and with a stronger focus on collaboration. These are mainly about 'next generation in health care' and 'pharmaceutical deals' carried out in Ôbroad strategic collaborationsÕ.

Word frequency during the online storm

It is now time to examine what happened on those "stormy" three days, after the 15th March 2020 ...

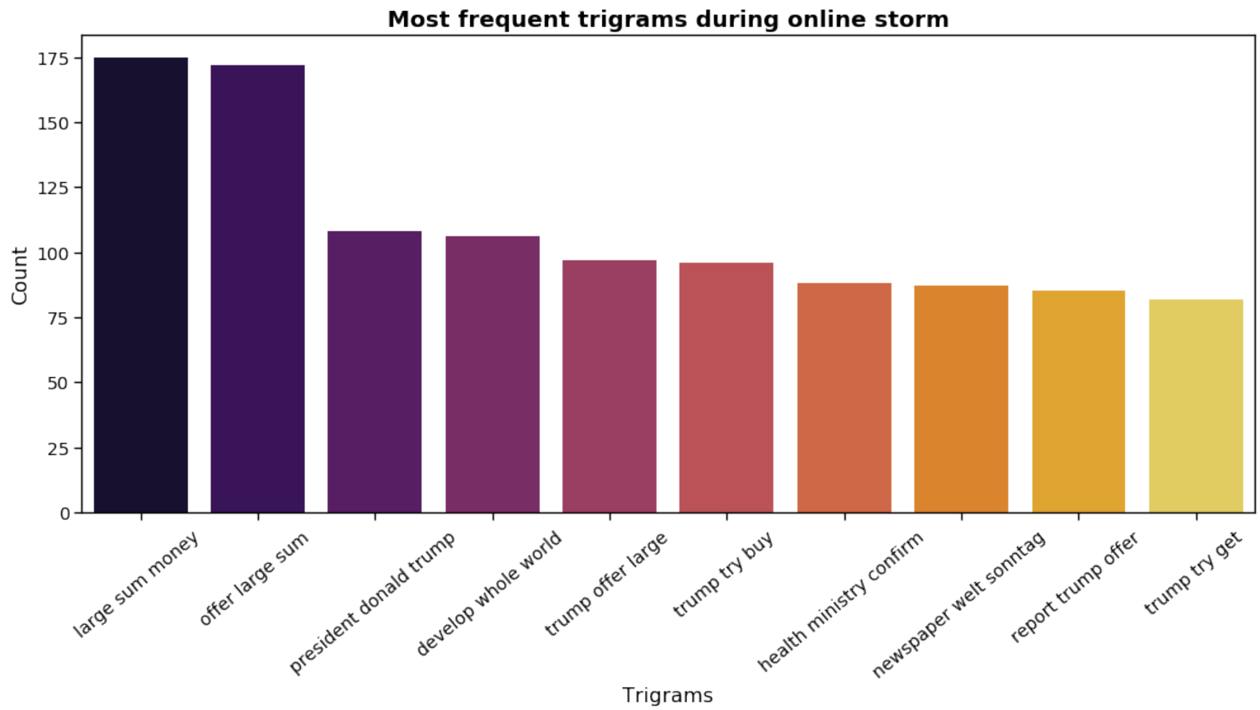
In [47]:
```
# Filtering the tweets of the 3 days of the online storm
df =tweets[tweets['onlinestorm']]

# Join all the edited tweets in one single string
joined_string = join_edited_string(df['edited'])

# Get tokens
tokens = joined_string.split(' ')

# get trigrams
trigrams = nltk.trigrams(tokens)
```

In [48]:
```
# plot word frequency during online storm
word_counter = Counter(tokens)
df_counter = pd.DataFrame(word_counter.most_common(20), columns = ['word',
 'freq'])
info = {'data': df_counter, 'x': 'freq', 'y': 'word',
        'xlab': 'Count', 'ylab': 'Words', 'pal':'inferno',
        'title': 'Most frequent words during online storm',
        'fname':'word_frequency_during_onlinestorm.png',
        'angle': 90}
plot_frequency_chart(info)
```



In [49]:
```
# plot trigrams frequency
df_trigrams = get_trigrams(trigrams, 10)
info = {'data': df_trigrams, 'x': 'Grams', 'y': 'Count',
       'xlab': 'Trigrams', 'ylab': 'Count', 'pal':'inferno',
       'title': 'Most frequent trigrams during online storm',
       'fname':'trigrams_frequency_during_onlinestorm.png',
       'angle': 40}
plot_frequency_chart(info)
```

```
['large sum money ', 175]
['offer large sum ', 172]
['president donald trump ', 108]
['develop whole world ', 106]
['trump offer large ', 97]
['trump try buy ', 96]
['health ministry confirm ', 88]
['newspaper welt sonntag ', 87]
['report trump offer ', 85]
['trump try get ', 82]
```



In [50]:
```
display_wordcloud(tokens)
```

```
<Figure size 432x288 with 0 Axes>
```

What we've seen above shows obvious differences from the main stream life of CureVac on Twitter:

- The top word is no longer ÔgateÕ but ÔtrumpÕ (ie., Donald Trump), immediately followed by 'coronavirus'.
- Gone are the days of collaboration for a next generation of new and innovative therapies. - - ÔExclusiveÕ

takes the lead, ÔcollaborationÕ is out of the league.

- The most frequent trigram is Ôtry buy exclusiveÕ. These are now times for Ôexclusive large gainÕ.
- ÔBuyÕ becames a new key word. Ôlarge sum moneyÕ and Ôoffer large sumÕ are now the top trigrams in the chart.

Step 5: LDA topics extraction

LDA (Latent Dirichlet Allocation) is an unsupervised machine learning technique that is increasingly popular in most text mining toolkits. You can find [here]() a comprehensive article on the subject, published on Medium, covering extensively the assumptions and the math behind the algorithm.

I applied LDA to the two datasets (before and during the CureVac online fire-storm) to check whether the findings corroborate the trends that we have seen in our previous analysis of the word frequency.

In [51]:
```
from sklearn.decomposition import LatentDirichletAllocation
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [52]:
```
# I am using here Susan Li's functions to get the top words of a topic:

def get_keys(topic_matrix):
    '''
    returns an integer list of predicted topic
    categories for a given topic matrix
    '''
    keys = topic_matrix.argmax(axis=1).tolist()
    return keys

def keys_to_counts(keys):
    '''
    returns a tuple of topic categories and their
    accompanying magnitudes for a given list of keys
    '''
    count_pairs = Counter(keys).items()
    categories = [pair[0] for pair in count_pairs]
    counts = [pair[1] for pair in count_pairs]
    return (categories, counts)

def get_top_n_words(n, n_topics, keys, document_term_matrix, tfidf_vectori
zer):
    '''
    returns a list of n_topic strings, where each string contains the n mo
st common
    words in a predicted category, in order
    '''
    top_word_indices = []
    for topic in range(n_topics):
        temp_vector_sum = 0
        for i in range(len(keys)):
            if keys[i] == topic:
                temp_vector_sum += document_term_matrix[i]
        temp_vector_sum = temp_vector_sum.toarray()
```

```
        top_n_word_indices = np.flip(np.argsort(temp_vector_sum)[0][-n:],0
)
        top_word_indices.append(top_n_word_indices)
    top_words = []
    for topic in top_word_indices:
        topic_words = []
        for index in topic:
            temp_word_vector = np.zeros((1,document_term_matrix.shape[1]))
            temp_word_vector[:, index] = 1
            the_word = tfidf_vectorizer.inverse_transform(temp_word_vector
)[0][0]
            try:
                topic_words.append(the_word.encode('ascii').decode('utf-8'
))
            except:
                pass
        top_words.append(", ".join(topic_words))
    return top_words
```

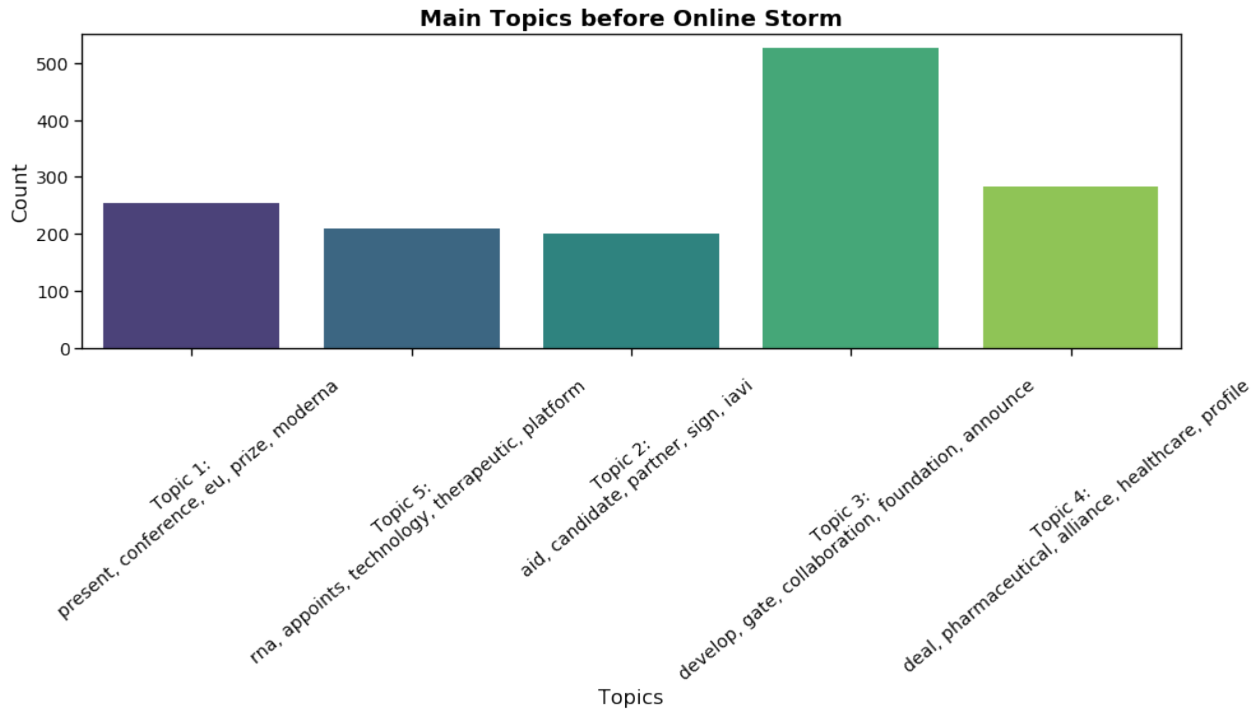
And here is a function for topics extraction using LDA, in which I end up creating a dataframe with the topics and their top words to facilitate the plotting that follows.

In [53]:
```
# LDA topics
def get_topics(edited, n_topics, n_words):

    eds = edited.values

    vec = TfidfVectorizer(use_idf=True, smooth_idf=True)
    document_term_matrix = vec.fit_transform(eds)

    model = LatentDirichletAllocation(n_components=n_topics)
    topic_matrix = model.fit_transform(document_term_matrix)

    keys = get_keys(topic_matrix)
    categories, counts = keys_to_counts(keys)
    top_n_words = get_top_n_words(n_words, n_topics, keys, document_term_m
atrix, vec)

    topics = ['Topic {}: \n'.format(i + 1) + top_n_words[i] for i in categ
ories]
    data=[]
    for i, topic in enumerate(topics):
        tmp = []
        tmp.append(topic)
        tmp.append(counts[i])
        data.append(tmp)
    df_topics = pd.DataFrame(data, columns = ['Topics', 'Count'])

    return df_topics
```

In [ ]:

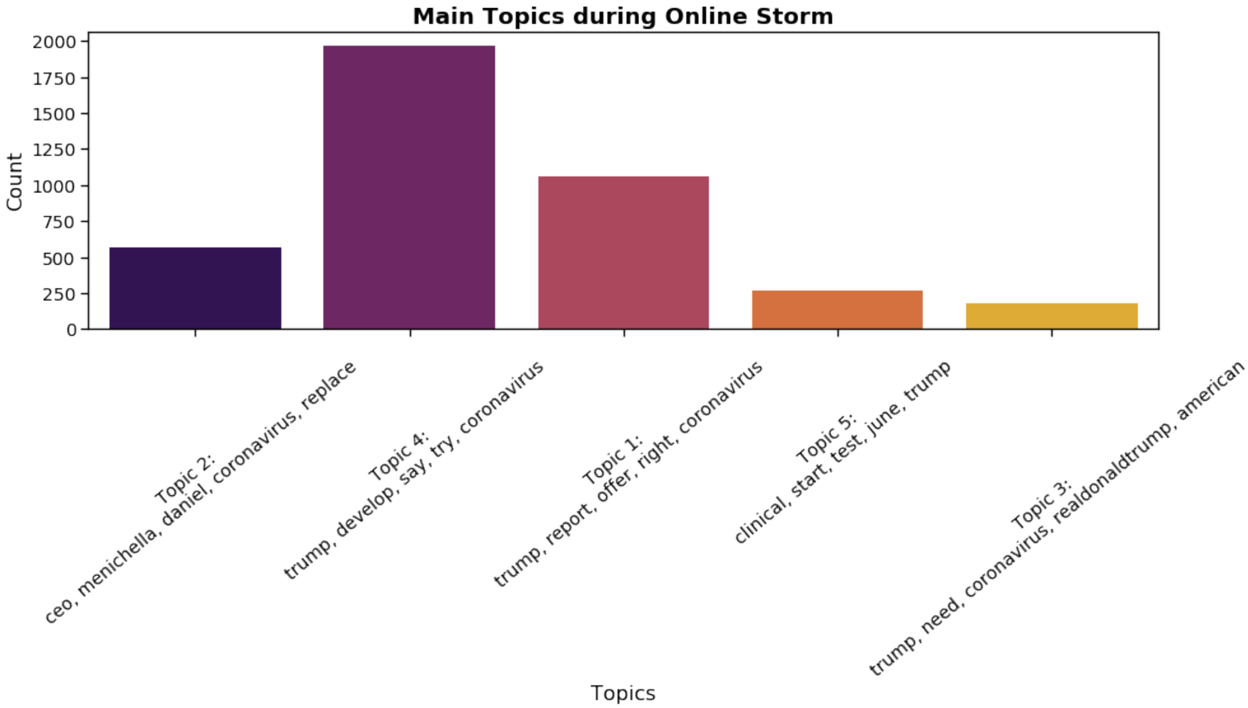
Topics before the online storm

In [54]:
```
# Filtering the tweets of the 6 years before the online storm
df = tweets[tweets['onlinestorm'] == False]

# LDA topics
df_topics = get_topics(df['edited'], 5, 5)
info = {'data': df_topics, 'x': 'Topics', 'y': 'Count',
       'xlab': 'Topics', 'ylab': 'Count', 'pal':'viridis',
       'title': 'Main Topics before Online Storm',
       'fname':'LDA_Topics_before_onlinestorm.png',
       'angle': 40}
plot_frequency_chart(info)
```



Topics during the online storm

In [55]:
```
# Filtering the tweets of the 3 days of the online storm
df =tweets[tweets['onlinestorm']]

# LDA topics
df_topics = get_topics(df['edited'], 5, 5)
info = {'data': df_topics, 'x': 'Topics', 'y': 'Count',
       'xlab': 'Topics', 'ylab': 'Count', 'pal':'inferno',
       'title': 'Main Topics during Online Storm',
       'fname':'LDA_Topics_during_onlinestorm.png',
       'angle': 40}
plot_frequency_chart(info)
```

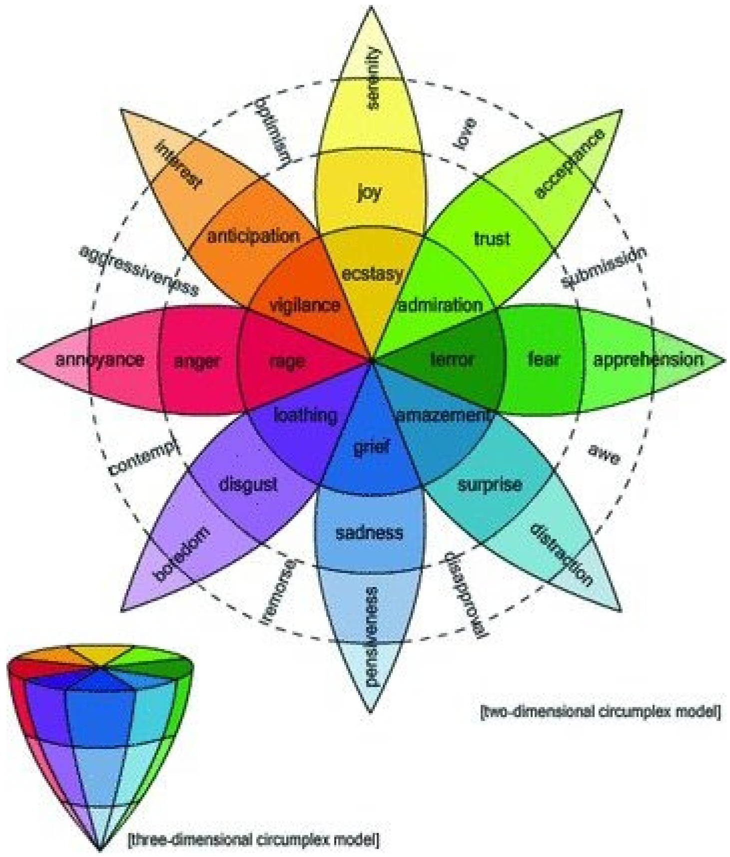


A word of caution must be exercised here. LDA topics are ÒimaginaryÓ (latent) topics, frequently overlapping, and a clear distinction is not always achievable. Nevertheless, a comparison between topics before and during the online storm leaves no doubts about contrasting trends.

For a period of six years, the major topic emerging from tweets is about collaborative developments. In contrast, during the online storm, in a period of three days, the two topics that stand out are clearly about the alleged attempt of the USA president to ensure the exclusive rights for the coronavirus vaccine.

Step 6: Emotion analysis

I drew from Robert PlutchikÕs wheel of basic emotions an attempt to uncover the presence of the seven lexical units for anger, fear, sadness, disgust, anticipa-tion, joy and surprise [4].



In [56]:
```
import termcolor
import sys
from termcolor import colored, cprint
plt.style.use('fivethirtyeight')
```

The basic approach is to create a matrix of tweets and emotions to connect each word in the tweet to one or more emotions. I applied the National Research Council Canada (NRC) lexicon, a binary matrix with 14,182 words and 10 col-umns rows, each corresponding to positive and negative sentiment plus eight emotions. For a full understanding of the NRC lexicon read this article.[5]

In [57]:
```
ncr = pd.read_csv('input/NCR-lexicon.csv', sep =';')
```

In [58]:
```
emotions = ['Anger', 'Anticipation','Disgust','Fear', 'Joy','Sadness', 'Su
rprise', 'Trust']
```

In [ ]:
```

```

In [59]:
```
# Join all the edited tweets in one single string
joined_string = join_edited_string(df['edited'])

# Get tokens
tokens = joined_string.split(' ')
```

In [ ]:
```

```

In [60]:
```
# We build now two dictionaries with indexes and unique words, for future
reference
```

```
unique_words = set(tokens)

word_to_ind = dict((word, i) for i, word in enumerate(unique_words))
ind_to_word = dict((i, word) for i, word in enumerate(unique_words))
```

In [ ]:

In [61]:
```
def plot_emotions_period(df, cols, period = 'h' ):

    df1 = df.groupby(df['datetime'].dt.to_period(period)).mean()

    df1.reset_index(inplace=True)
    df1['datetime'] = pd.PeriodIndex(df1['datetime']).to_timestamp()
    plot_df = pd.DataFrame(df1, df1.index, cols)

    plt.figure(figsize=(15, 10))
    ax = sns.lineplot(data=plot_df, linewidth = 3,dashes = False)
    plt.legend(loc='best', fontsize=15)
    plt.title('Emotions in Tweets with CureVac during online storm', fonts
ize=20)
    plt.xlabel('Time by ythe hour', fontsize=15)
    plt.ylabel('Z-scored Emotions', fontsize=15)
    plt.savefig('images/Emotions_during_onlinestorm.png')
    return
```

In [62]:
```
def get_tweet_emotions(df, emotions, col):

    df_base = df.copy()
    df_base.drop(['sentiment','sentiment_intensity'], axis=1, inplace=True
)

    emo_info = {'emotion':'' , 'emo_frq': defaultdict(int) }

    list_emotion_counts = []

    for emotion in emotions:
        emo_info = {}
        emo_info['emotion'] = emotion
        emo_info['emo_frq'] = defaultdict(int)
        list_emotion_counts.append(emo_info)

    #criamos um dataframe de zeros com a dimensão de df
    df_emotions = pd.DataFrame(0, index=df.index, columns=emotions)

    stemmer = SnowballStemmer("english")
    x = 0
    for i, row in df_base.iterrows():
        tweet = word_tokenize(df_base.loc[i][col])
        for word in tweet:
            word_stemmed = stemmer.stem(word.lower())
            result = ncr[ncr.English == word_stemmed]
            if not result.empty:
                for idx, emotion in enumerate(emotions):
                    df_emotions.at[i, emotion] += result[emotion]
```

```
                    if result[emotion].any():
                        try:
                            list_emotion_counts[idx]['emo_frq'][word_to_in
d[word]] += 1
                        except:
                            continue

    df_base = pd.concat([df_base, df_emotions], axis=1)

    return df_base, list_emotion_counts
```

In [ ]:

In [63]:
```
def get_words(word_list, emotions):

    words_emotion_idx = []

    for i, word in enumerate(word_list):
        word = stemmer.stem(word.lower())
        result = ncr[ncr.English == word]
        if not result.empty:
            for emotion in emotions:
                if result[emotion].any() > 0:
                    words_emotion_idx.append(i)

    return words_emotion_idx
```

In [ ]:

In [64]:
```

def get_top_emotion_words(word_counts, n = 5):

    # Passamos finalmente o dicionário para uma numpy array "words", com o
 indice da palavra e respectiva frequência
    words = np.zeros((len(word_counts), 2), dtype=int)
    for i, w in enumerate(word_counts):
        words[i][0] = w
        words[i][1] = word_counts[w]

    # A partir dos indices gerados pela função argsort, sabemos a posição
    # das "n" palavras mais frequentes na array words
    top_words_indices = np.flip(np.argsort(words[:,1])[-n:],0)

    # Com estas posições (indices), obtemos os indices que funcionam como
keys no dicionário ind_to_word,
    # e nos devolvem, como "value", as palavras como strings
    top_words = [words[ind][0] for ind in top_words_indices]

    return words, top_words, top_words_indices
```

In [ ]:

In [65]:
```
def print_colored_emotions(tweets, emotions, color, on_color):
```

```
    for tweet in tweets:

        word_list = word_tokenize(tweet)

        word_emotion_idx = get_words(word_list, emotions)

        for i, w in enumerate(word_list):
            if i in word_emotion_idx:
                w=colored(w, color=color, on_color=on_color)
            print(w, end='')
            print(' ', end='')

        print('\n')


    return
```

In [ ]:

```
```

Connecting words to emotions

In [66]:

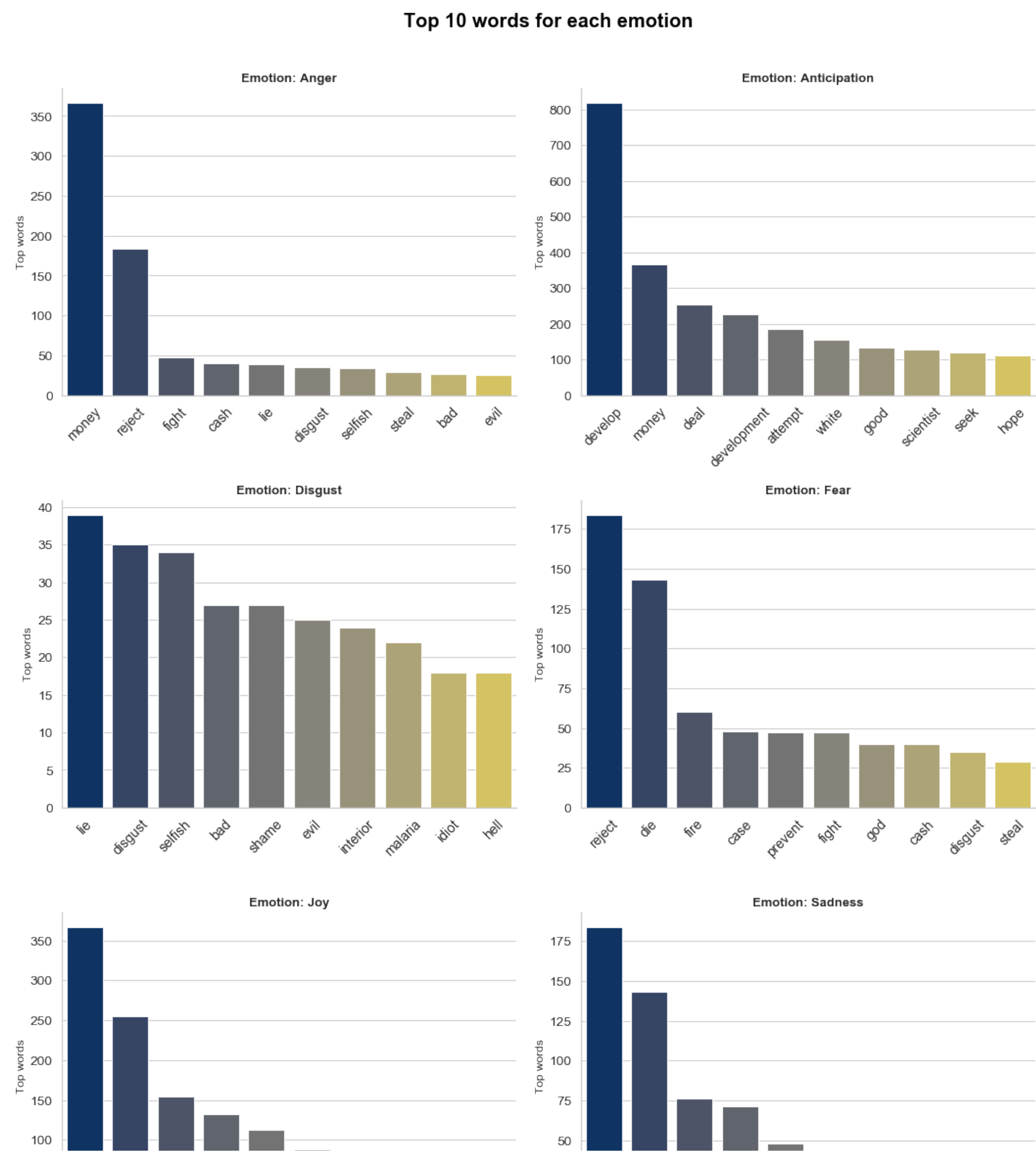
```
# We are using the NCR lexicon to associate words to emotions
# Be patient, this will take some minutes ...

df_emo, list_emotion_counts = get_tweet_emotions(tweets, emotions, 'edited
')

# Preparing for time series
df_emo['datetime']= pd.to_datetime(df_emo['datetime'])
```

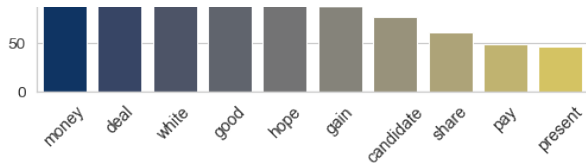
For a better understanding of the word-emotions associations, we have here the charts showing what are the 10 words that contributed the most for each of the 8 emotions.

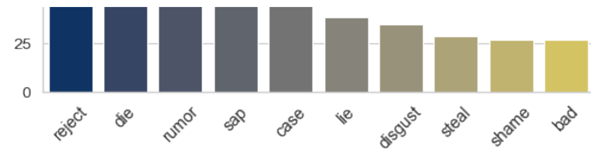
In [67]:

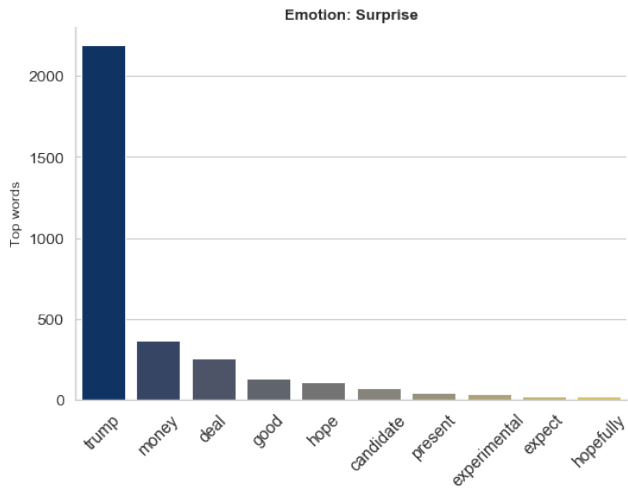
```
# Plotting the 10 words that contribute the most for each of the 8 emotion
s

fig, axs = plt.subplots(figsize=(15, 25), frameon=False)
plt.box(False)
plt.axis('off')
plt.subplots_adjust(hspace = 1.6)
counter = 0

for i, emotion in enumerate(emotions): # for each emotioin

    # This is the dict that holds the top 10 words
    words, top_words, top_words_indices = get_top_emotion_words(list_emoti
on_counts[i]['emo_frq'], 10)

    info = {'values' : [words[ind][1] for ind in top_words_indices],
                      'labels' : [ind_to_word[word] for word in top_words]
}
    sns.set(style="whitegrid")
    sns.set_context("notebook", font_scale=1.25)
```

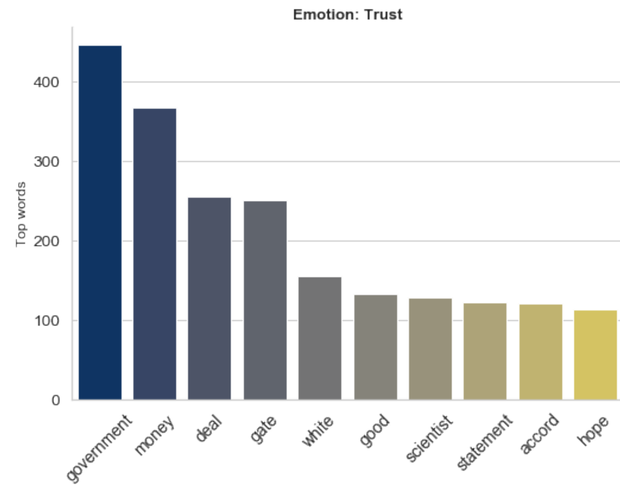
```
    ax = fig.add_subplot(4, 2, counter+1) # plot 2 charts in each of the 4
 rows
    sns.despine()
    ax = sns.barplot(x='labels', y='values', data=info, palette=("cividis"
))
    plt.ylabel('Top words', fontsize=12)
    ax.set_title(label=str('Emotion: ') + emotion, fontweight='bold', size
=13)
    plt.xticks(rotation=45, fontsize=14)
    counter += 1

axs.set_title(label='\nTop 10 words for each emotion\n',
              fontweight='bold', size=20, pad=40)
plt.tight_layout()
plt.savefig('images/Top10_words_per_emotion.png')
```











For some authors, isolated emotions might not be the best granullarity for analysis. Skillicorn (2019) and colleagues prefer to aggregate emotions into positive and negative emotions [6]. Let's try it.

In [68]:
```
# Aggregating negative and positive emotions
df_emo['neg_emotions'] = df_emo['Sadness'] + df_emo['Fear'] + df_emo['Disg
ust'] + df_emo['Anger']
df_emo['pos_emotions'] = df_emo['Joy'] + df_emo['Anticipation'] + df_emo['
Trust'] + df_emo['Surprise']
```

In [69]:
```
df_emo['total_neg_emotions'] = df_emo['neg_emotions'].apply(lambda x: x >
0)
df_emo['total_pos_emotions'] = df_emo['pos_emotions'].apply(lambda x: x >
0)
```

I use here pandas groupby feature to obtain a normalized account of the emotions as a proportion that takes into account the number of tweets in each of the two periods (before and during the online storm).

In [70]:
```
props = df_emo.groupby('onlinestorm')['total_neg_emotions'].value_counts(n
ormalize=True).unstack()
props
```

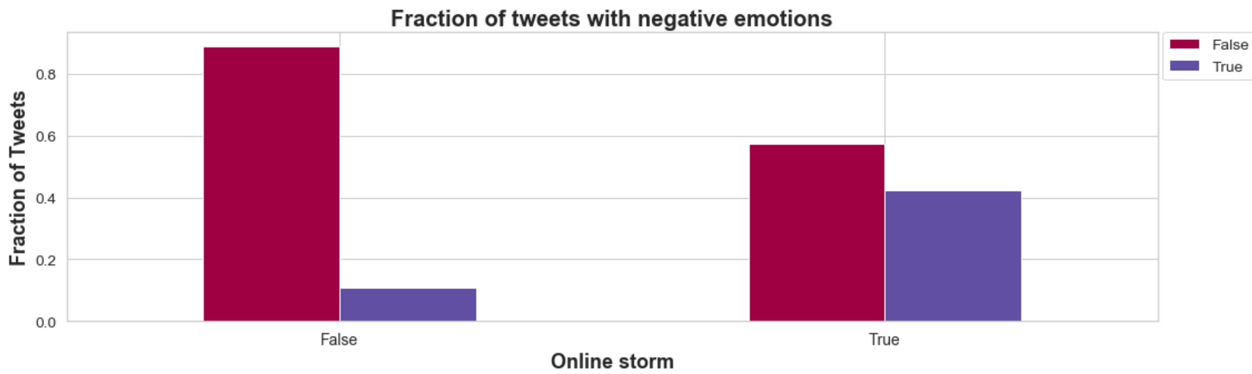
Out[70]:

total_neg_emotions	False	True
onlinestorm		
False	0.890699	0.109301
True	0.575713	0.424287

The results show that during the online storm period, negative emotions are present in 42 per cent of the tweets, whereas previously only 11% of the tweets included negative emotions.

We can spot it more clearly in the following chart ...

In [71]:
```
# plot it
plot_fractions(props,'Fraction of tweets with negative emotions','Fraction
_of_Tweets_with_negative_emotions')
```



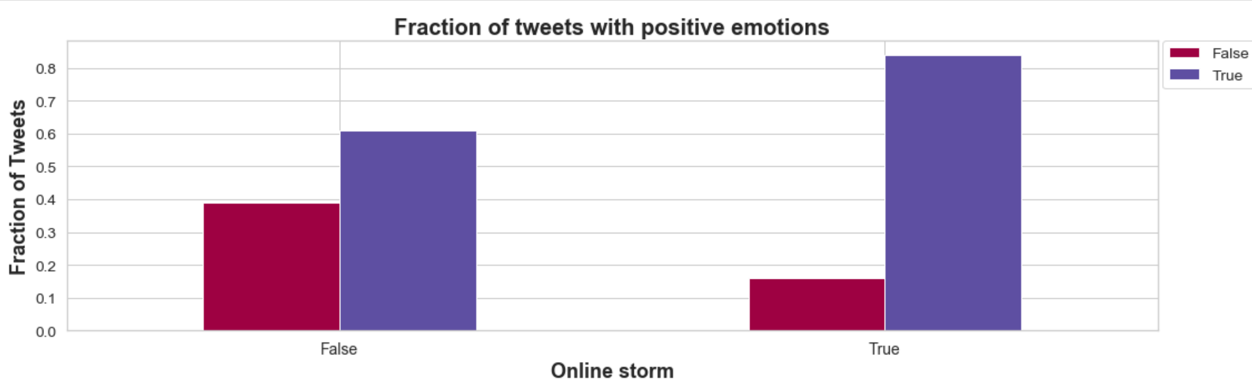
Conversely, when it comes to positive emotions, we witness also an increase in the proportion of tweets with these emotions during online storm (84 per cent). But it is not such a sharp change when compared to the 61 per cent before the online storm.

In [72]:
```
props = df_emo.groupby('onlinestorm')['total_pos_emotions'].value_counts(n
ormalize=True).unstack()
props
```

Out[72]:

total_pos_emotions	False	True
onlinestorm		
False	0.390360	0.609640
True	0.159356	0.840644

In [73]:
```
plot_fractions(props,'Fraction of tweets with positive emotions','Fraction
_of_Tweets_with_positive_emotions')
```



Word - emotion connections in the tweets

To help us have a feeling of how things work behind thew scenes, I wrote a function (print_colored_emotions) to display the words connected to negative (red) and positive (green) emotions.

It is important to acknowledge that I am not giving any kind of emotion score to the tweets (that would be another undertaking all together). I am just locating the word-emotion connections within the tweets, since a tweet may depict more than one emotion (or cluster of emotions) Ð and they usually do.

Here are some negative emotions ...

In [74]:
```
df = df_emo[df_emo['Sadness'] > 3]
print_colored_emotions(df['text'], ['Disgust','Sadness','Anger','Fear'], '
white', 'on_red')
```

```
Die Stiftung von Bill Gates investiert 52 Millionen Dollar in dt . Firma C
ureVac , die an Impfstoff gegen # Coronavirus forscht . ( Das ist die Firm
a , an der die US-Regierung großes Interesse hat aktuell , siehe : https :
 // twitter.com/AscotBlack/sta tus/1239161218398670848 ? s=19 … ) https :
//www . forbes.com/sites/matthewh erper/2015/03/05/bill-melinda-gates-foun
dation-makes-largest-ever-equity-investment-in-a-biotech-company/amp/ ? __
twitter_impression=truehttps : //www.forbes.com/sites/matthewherper/2015/0
3/05/bill-melinda-gates-foundation-makes-largest-ever-equity-investment-in
-a-biotech-company/amp/ ? __twitter_impression=true …

You created crowded conditions @ airports corralling sick w/healthy . This
 will lead to further disease spreading . Your denials & delays , along w/
ill-prepared quarter measures are going to kill many . And stop trying to
steal CureVac for U.S. only . # VaccinesForAll

@ KimStrassel @ kimguilfoyle @ seanmdav @ maggieNYT That wasn ’ t the lie
put forth by Germany . The lies was that Curevac had a cure and Trump want
ed a . Exclusive supply . You lied all about Trump/Russia and you are lyin
g again .

You are full of it . Trump has put America in danger every single day and
his mixed messages are causing confusion and eventually death . He has han
dled this Corona situation so badly and tried to bribe a German called Cur
eVac . This President is so shameful https : //www . tagesschau.de/inland/
corona- impfstoff-deutschland-usa-101.html … https : // twitter.com/GOP/st
atus/123 9342159486164998 …

News ! # CureVac CureVac Rejects Rumors of US Acquisition : CureVac Reject
s Rumors of US Acquisition http : // dlvr.it/RRzMsN Visit our site ! pic.t
witter.com/OLnwkX4Glu

Yes they have lied , but in this case no , USA Today and CureVac provide p
roof it ’ s a false story.. pick a real lie to propagate , not a fake news
 story , all that does is hurt your credibility

# COVID19 latest , 9pm GMT Cases 197,467 Deaths 7,953 Recoveries 81,691 #
Belgium to enforce lockdown from 11am GMT Wed # US cities , states announc
e piecemeal lockdowns # EU Commission Chief Ursula von der Leyen claims Ge
rman company CureVac may have # vaccine ready “ towards fall '' pic.twitte
r.com/jycIhEU0bg
```

And here some positive ones ...

In [75]:
```
df = df_emo[df_emo['Anticipation'] > 4]
print_colored_emotions(df['text'], ['Joy','Trust','Anticipation'], 'white'
, 'on_green')
```

```
UK pharma is equally likely to develop a vaccine . In fact , pharma all ov
er the world are searching for a vaccine for SARS-CoV-2 . CureVac is unlik
ely to develop one quickly enough alone . Now 's a good time for pharma to
 cooperate , rather than compete for financial gains .

It works ! It worked after 9/11 . God Bless Lee Greenwood ! God Bless Cure
Vac ! God Bless China ! God Bless Italy ! God Bless Iran ! God Bless South
 Korea ! God Bless Germany Too ! God Bless Asia , Europe , Africa , Americ
as & Australia . pic.twitter.com/dSKwPrLTeD

Glad researchers behind GER lab # CureVac have '' vetoed '' this , it s a
sign of huge progress from the times of # WorldWar . Einstein & others gav
e up their research to build d A-Bomb : if we do give up our values to mon
ey we have nothing else but # death ahead . # EU stay strong @ vonderleyen


Take Precautions . Pray Harder . Pray that something good comes out of ' C
urevac among others . Faith over Fear . This too shall pass in JESUS name
. Once again liked I posted earlier . `` Pls dont forget to lift up prayer
s over the virus '' . We are not really praying . Lets Pray Saints

1/ Yes . Human vaccine trials are already underway in the US and China . C
ureVac in Germany has two candidates and expect an experimental vaccine in
 June/July . Having said that , the expectation is , it will only be publi
cly available in about 18 months . Until then
```

In [ ]:

Fraction of emotions in relation to number of tweets, before and during the online storm

In [76]:
```
df1 = df_emo.groupby(df_emo['onlinestorm'])[emotions].apply(lambda x:( x.s
um()/x.count())*100)
```

In [77]:
```
df1.index = ['before_onlinestorm', 'during_onlinestorm']
```

In [78]:
```
df1.head()
```

Out[78]:

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	
before_onlinestorm	5.091650	54.921928	2.511881	8.689749	26.408690	5.431093	22.471147	54
during_onlinestorm	33.358116	86.270136	16.183395	31.945477	40.421314	28.178439	82.131351	8

In [79]:
```
df1.index
```

Out[79]:
```
Index(['before_onlinestorm', 'during_onlinestorm'], dtype='object')
```

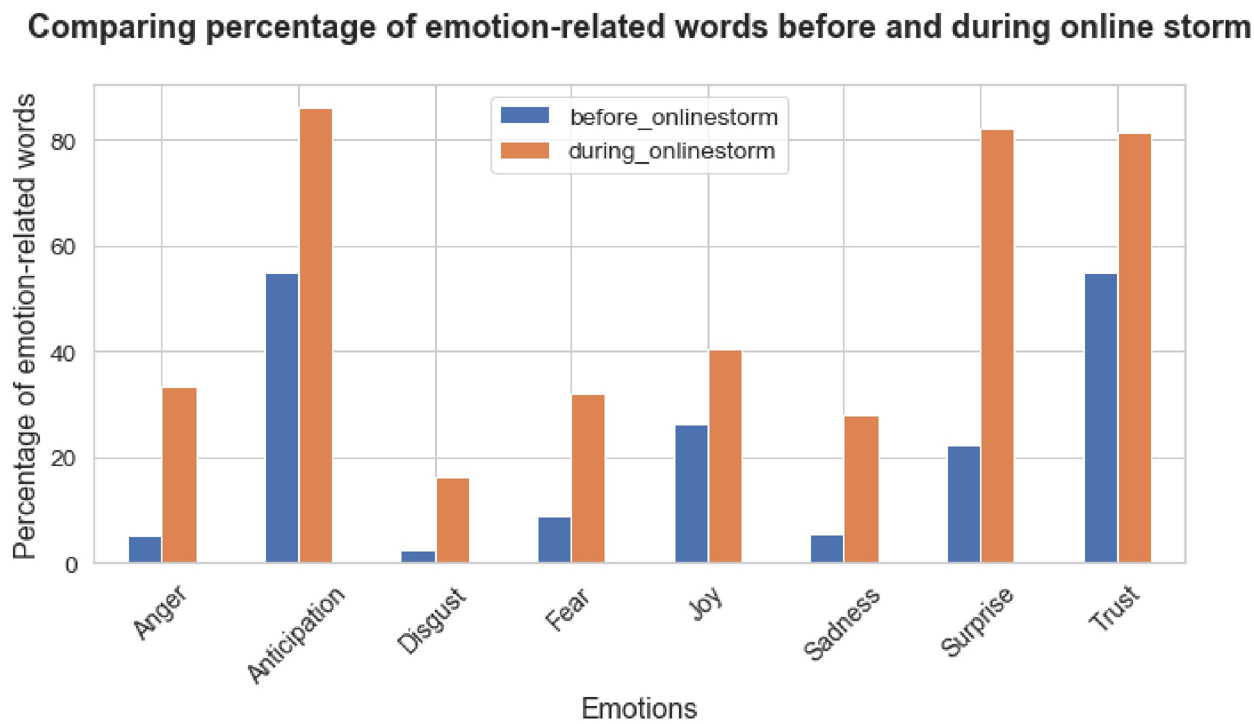
In [80]:
```
df_ =df1.T
```

In [81]:
```
df_.reset_index()
```

Out[81]:

	index	before_onlinestorm	during_onlinestorm
0	Anger	5.091650	33.358116
1	Anticipation	54.921928	86.270136
2	Disgust	2.511881	16.183395
3	Fear	8.689749	31.945477
4	Joy	26.408690	40.421314
5	Sadness	5.431093	28.178439
6	Surprise	22.471147	82.131351
7	Trust	54.989817	81.437423

In [82]:
```
fig, ax = plt.subplots(1, 1, figsize=(10, 6))
ax.set_title(label='Comparing percentage of emotion-related words before a
nd during online storm\n', fontweight='bold', size=18)
df_.reset_index().plot(
    x="index", y=["before_onlinestorm", "during_onlinestorm"], kind="bar",
 ax=ax
)



plt.xlabel("Emotions",fontsize = 16)
plt.ylabel("Percentage of emotion-related words",fontsize = 16)
plt.xticks(rotation=45,fontsize=14)
plt.tight_layout()
plt.savefig('images/Percentage_emotions_before_and_during_onlinestorm.png'
)
```



In [ ]:

Applying a Z-score normalization

In another effort to normalize the emotion scores, I am using the Z-score, instead of the mere counts of word-emotion connections, because these are heavily affected by the number of tweets in each period in consideration.

The z-score tells us how many standard deviations an individual value is from the mean, and is calculated with following formula:

$$z = \frac{x - \mu}{\sigma}$$

I use the pandasÕ apply function to calculate the z-score of each individual value in all the 8 columns of emotions in the dataframe.

In [84]:
```
df_zscore = df_emo.groupby(df_emo['onlinestorm'])[emotions].apply(lambda x
:(x - x.mean()) / x.std())
```

In [85]:
```
df_emo = pd.concat([df_emo[['datetime','text','edited', 'onlinestorm']], d
f_zscore], axis=1)
```

In [86]:
```
df_emo.head()
```

Out[86]:

	datetime	text	edited	onlinestorm	Anger	Anticipation	Disgust	Fear	
0	2014-03-12 18:26:59	Robert-Jan Smits at Innovation Convention 2014...	smits innovation convention win Û2m inducement...	False	-0.211661	-0.764009	-0.156192	-0.261235	-0.515
1	2014-03-13 09:50:54	First #EU #vaccine prize awarded 2 CureVac ...	first eu prize award euic2014 check complex jo...	False	-0.211661	2.018154	-0.156192	2.745007	3.388
2	2014-03-14 12:50:28	Congrats 2 CureVac ! 4 #EU #vaccine prize #...	congrats eu prize euic2014 find industry contr...	False	-0.211661	-0.764009	-0.156192	-0.261235	-0.515
3	2014-03-14 16:01:30	MT @sanofiDE CureVac Wins Two Million EUR f...	mt sanofide win million eur inaugural european...	False	-0.211661	-0.764009	-0.156192	-0.261235	-0.515
4	2014-03-14 17:44:32	CureVac wins EU's EUR2m inducement prize for ...	win eu eur2m inducement prize mactive technol...	False	-0.211661	-0.764009	-0.156192	-0.261235	-0.515

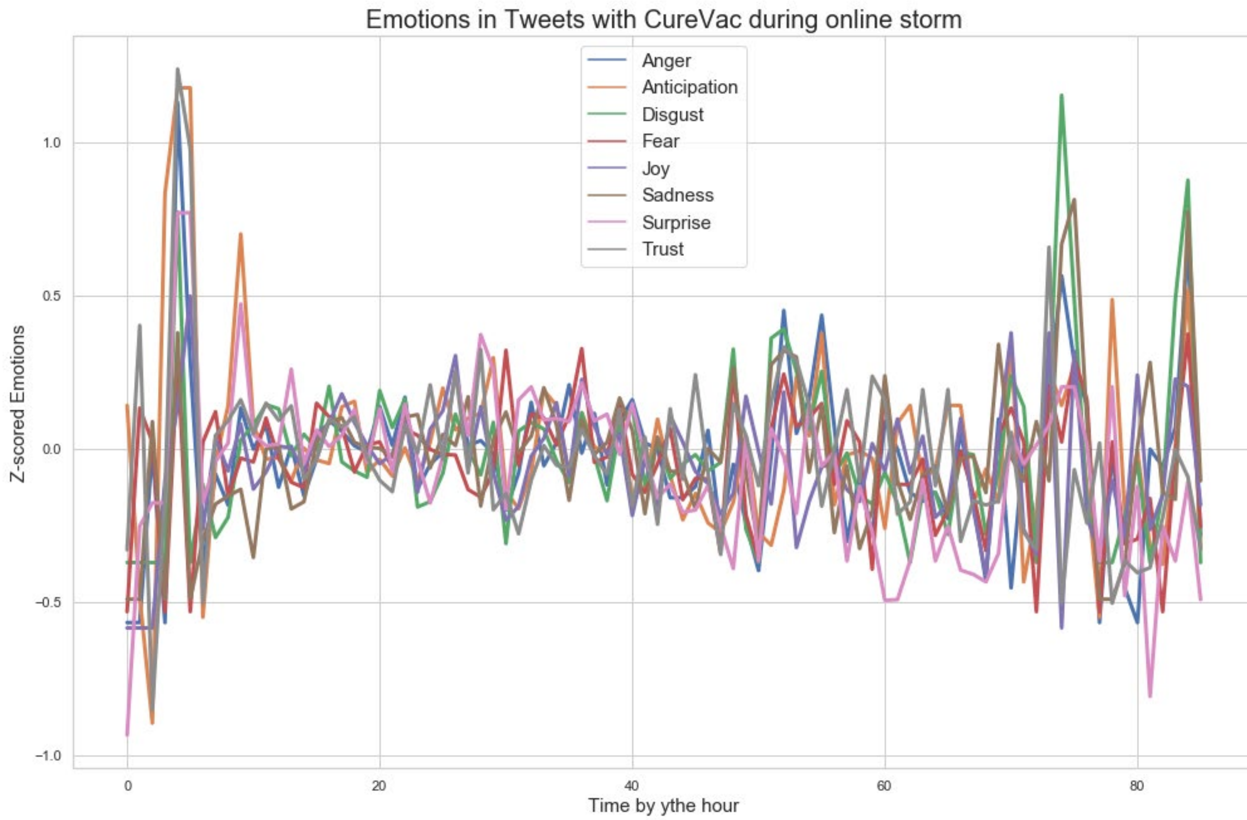
In [ ]:

The dynamics of emotions during the online storm

With our normalized values, we can now have a more precise view of the way emotions evolved, by the hour, during the 3 days of the online storm.

Here we have a mixture of all the emotions during online storm ...

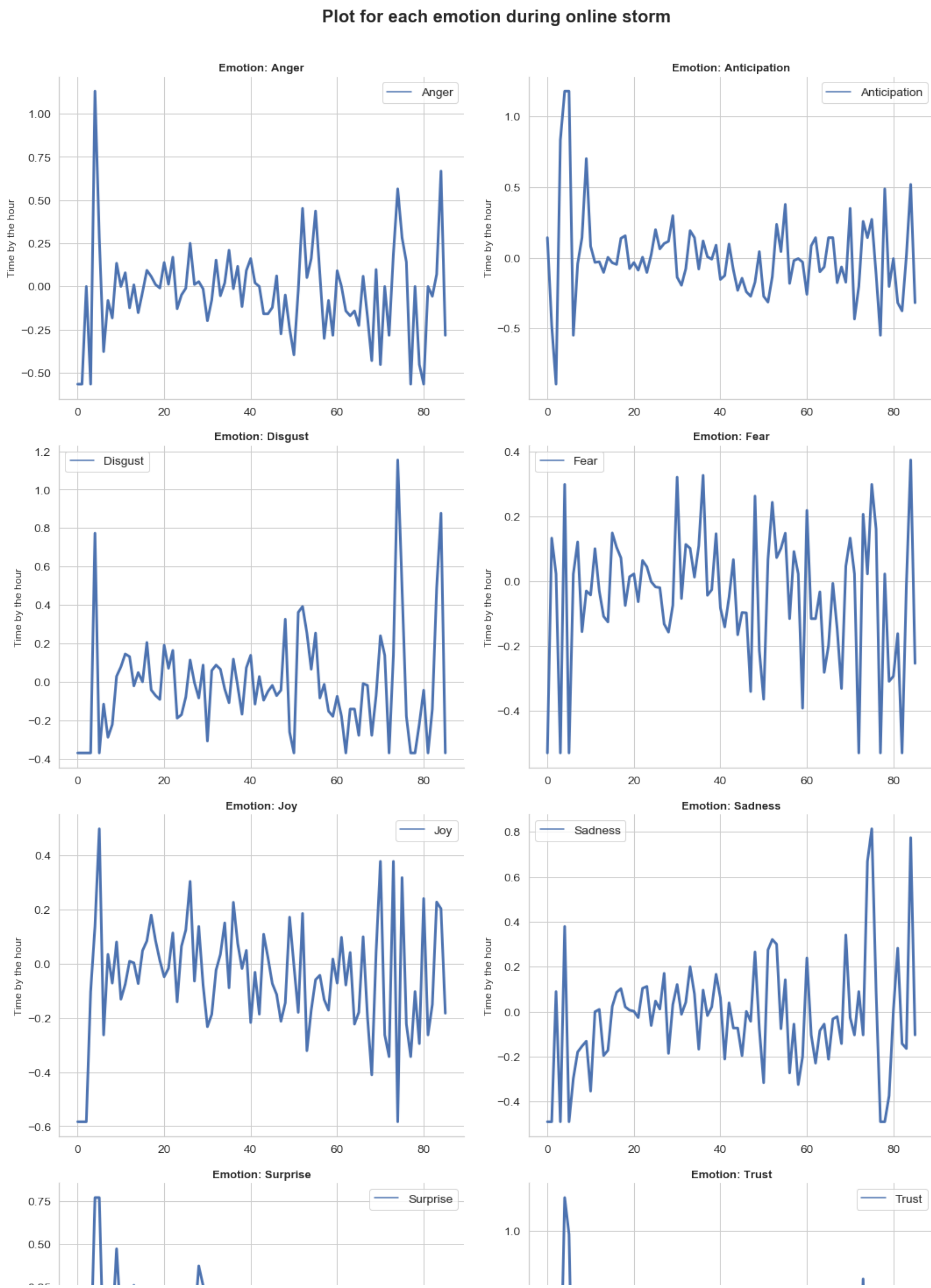
In [87]:
```
plot_emotions_period(df_emo[df_emo['onlinestorm']], emotions)
```

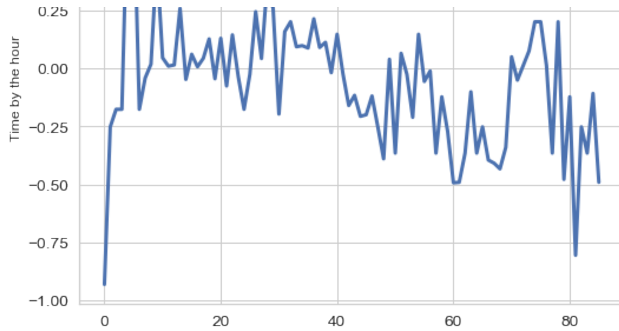


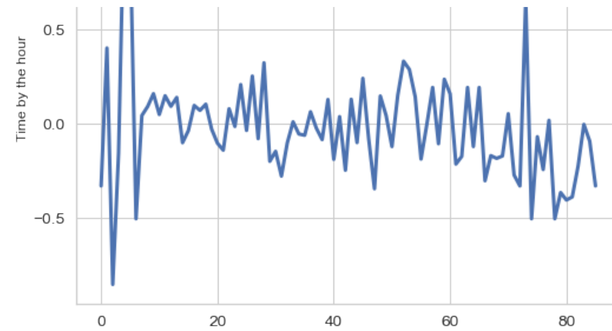
Let's see how each of the emotions evolved during this period ...

In [88]:
```
# Plotting emotions during online storm

fig, axs = plt.subplots(figsize=(15, 25), frameon=False)
plt.box(False)
plt.axis('off')
plt.subplots_adjust(hspace = 1.6)
counter = 0

df = df_emo[df_emo['onlinestorm']]
df1 = df.groupby(df['datetime'].dt.to_period('h')).mean()
df1.reset_index(inplace=True)
df1['datetime'] = pd.PeriodIndex(df1['datetime']).to_timestamp()

for i, emotion in enumerate(emotions): # for each emotion

    emo = []
    emo.append(emotion)
    plot_df = pd.DataFrame(df1, df1.index, emo)

    sns.set(style="whitegrid")
    sns.set_context("notebook", font_scale=1.25)
    ax = fig.add_subplot(4, 2, counter+1) # plot 2 charts in each of the 4
 rows
    sns.despine()
    ax = sns.lineplot(data=plot_df, linewidth = 3,dashes = False)
    plt.ylabel('Time by the hour', fontsize=12)
    ax.set_title(label=str('Emotion: ') + emotion, fontweight='bold', size
=13)
    counter += 1
```

```
axs.set_title(label='\nPlot for each emotion during online storm\n',
              fontweight='bold', size=20, pad=40)
plt.tight_layout()
plt.savefig('images/Emotions_during_onlinestorm.png')
```

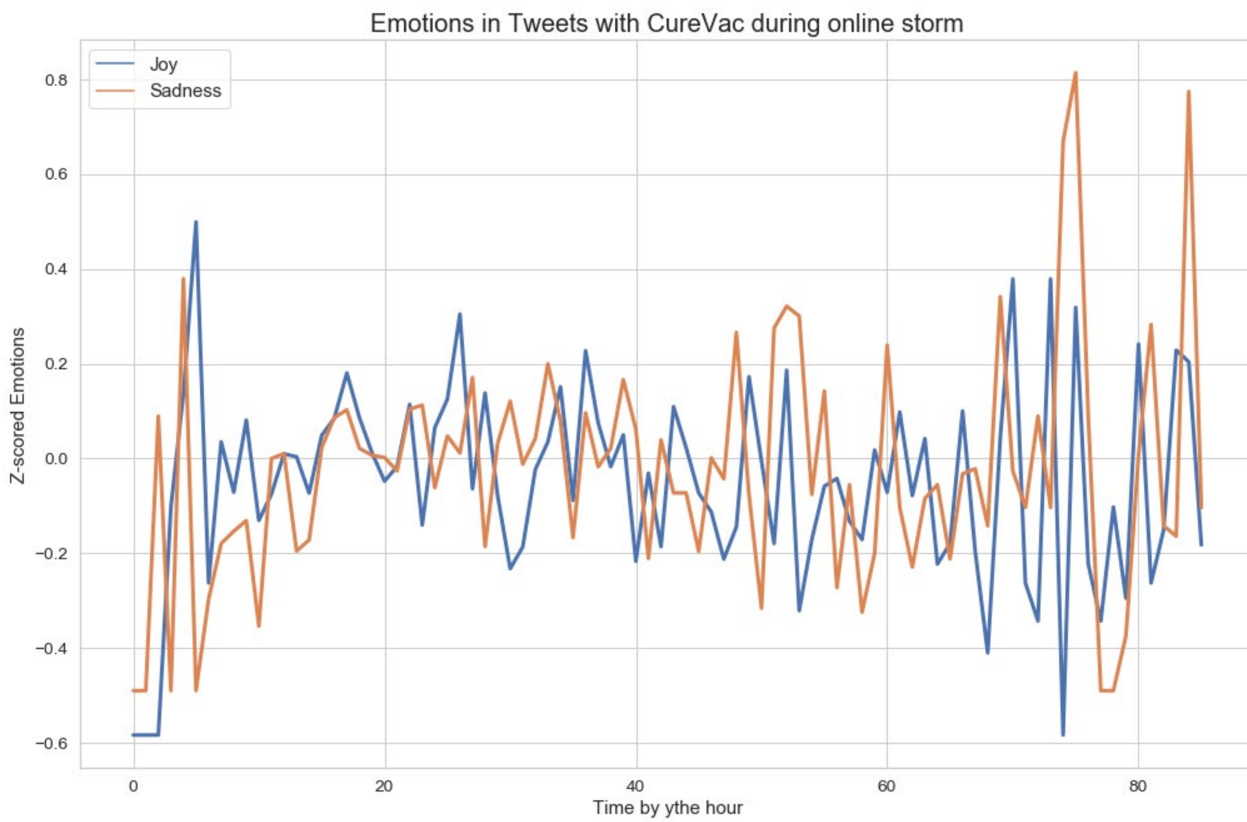






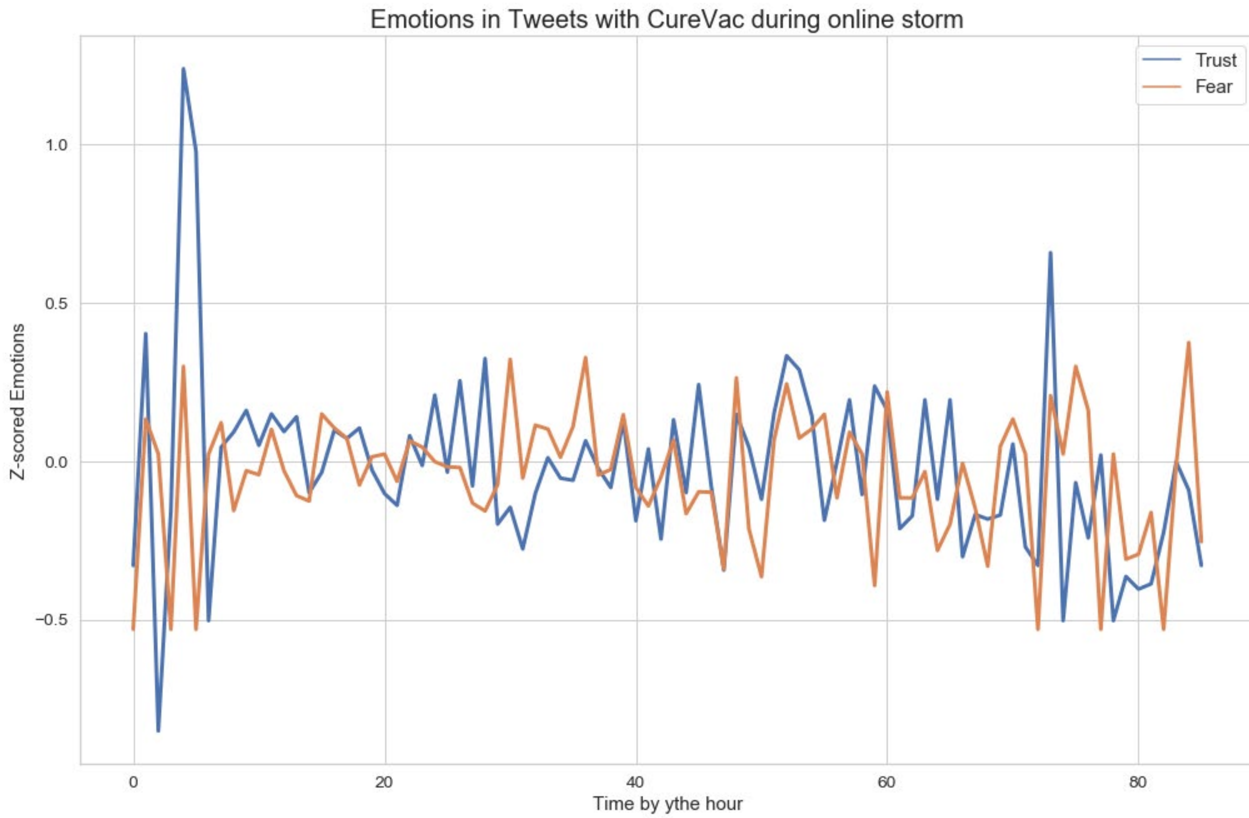
Another way of looking at it is by plotting contrasts of emotions, like joy and sadness ...

In [89]:
```
plot_emotions_period(df_emo[df_emo['onlinestorm']], ['Joy', 'Sadness'])
```



In [ ]:
```

```

In [91]:
```
plot_emotions_period(df_emo[df_emo['onlinestorm']], ['Trust', 'Fear'])
```


Emotions in Tweets with CureVac during online storm
Trust
Fear
Z-scored Emotions
1.0
0.5
0.0
−0.5
0
20
40
60
80
Time by ythe hour

In [ ]:

In [ ]:

In [ ]: