gmail-data-analysis

April 17, 2023

1 Gmail data analysis

1.0.1 Exploring more than 5 years of Gmail messages

I learned recently that Google allows its users to download metadata for all the messages sent and received through Gmail. This leads to interesting insights to be found in the data: *What are the most common people I have been in touch with? What days of the week or time of the day have the highest trafic?* In order to explore these and other questions I decided to request my data and perform the present analysis.

The first step is requesting the data. There is data available for several Google services, only the Gmail data is used here. Depending on the amount of data the request can take several hours (my file is 1.2GB). Once we are notified that the file is ready to be downloaded, the data will come in a special format called `mailbox`. After importing some useful modules we can clean and explore the data.

1.1 Requirements

[1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[2]:
```
import mailbox
import pandas as pd
import csv
import unicodedata
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(rc={'figure.facecolor':'white'})

# For better quality plots use
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('pdf', 'svg')

from time import time
from collections import Counter
```

```
<ipython-input-2-036d9073cc2f>:12: DeprecationWarning: `set_matplotlib_formats`
is deprecated since IPython 7.23, directly use
`matplotlib_inline.backend_inline.set_matplotlib_formats()`
  set_matplotlib_formats('pdf', 'svg')
```

1.2 Data preprocessing

One of the most important steps before analyzing the data is its proper cleaning, which refers to removing unnecessary data, dealing with missing values, grouping fields that appear different for the machine but that refer to the same items, etc. We begin by saving the data file `gmail_data.mbox` in a directory called `data` (for privacy reasons, this file is absent from the GitHub repository). The file can be loaded using the `mailbox` module

[3]:
```
file_path = '/content/drive/MyDrive/Colab Notebooks/Self practice projects/
 ↪Gmail/All mail Including Spam and Trash.mbox'
mbox = mailbox.mbox(file_path)
print('samples:', len(mbox))
```

```
samples: 14601
```

The file contains 14601 samples. Even though these are mostly email messages, many other entry types are counted, such as drafts and chats. These can be removed by filtering by Gmail label. The file contains the following fields

[4]:
```
# print fields
for i, key in enumerate(mbox[0].keys()):
    print(i+1, key)
```

```
1 X-GM-THRID
2 X-Gmail-Labels
3 Delivered-To
4 Received
5 X-Google-Smtp-Source
6 X-Received
7 ARC-Seal
8 ARC-Message-Signature
9 ARC-Authentication-Results
10 Return-Path
11 Received
12 Received-SPF
13 Authentication-Results
14 Return-Path
15 DKIM-Signature
16 X-MSFBL
17 Received
18 From
19 Subject
20 Date
21 To
```

```
22 Reply-To
23 MIME-Version
24 X-mailer
25 Message-ID
26 List-Unsubscribe
27 Content-Type
```

We find that there are several section of little interest. In order to avoid loading unnecessary information, we can extract the fields of interest and put them into a `pandas` dataframe for further processing. We are interested in the following fields: `subject`, `from`, `to`, `date`, and `Gmail-label`.

[5]:
```
t0 = time()
subject = []
from_ = []
to = []
date = []
label = []
for i, message in enumerate(mbox):
    try:
        if i%2000 == 0:
            print(i, end=' ')
        subject.append(message['subject'])
        from_.append(message['from'])
        to.append(message['to'])
        date.append(message['date'])
        label.append(message['X-Gmail-Labels'])
    except:
        print(i, end=' ')
        print('subject', subject[i])
        print('from', from_[i])
        print('to', to[i])
        print('date', date[i])
        print('label', label[i])
print('\ntime: {:.1f} min'.format((time()-t0)/60))
```

```
0 2000 4000 6000 8000 10000 12000 14000
time: 0.7 min
```

[6]:
```
df = pd.DataFrame()
df['subject'] = subject
df['from'] = from_
df['to'] = to
df['date'] = date
df['label'] = label
```

[7]:
```
df[['subject', 'date', 'label']].head()
```

[7]:
```
                                             subject  \
0  =?windows-1252?Q?Here=92s_a_smart_way_to_inves…
1  Jaykumar, your application was sent to Fero Pa…
2                          Grow Your Earnings on Fiverr
3  Take advantage of BITS Pilani's open eligibili…
4  =?utf-8?B?VGltZSB0byBsZXZlbCB1cCDwn5SdIFlvdXIg…

                                 date                              label
0        Wed, 12 Apr 2023 22:31:37 +0800          Inbox,Category Updates
1  Sat, 15 Apr 2023 03:17:12 +0000 (UTC)  Inbox,Important,Category Updates
2  Thu, 13 Apr 2023 03:32:10 +0000 (UTC)        Inbox,Category Promotions
3        Fri, 14 Apr 2023 10:23:42 -0600        Inbox,Category Promotions
4        Sat, 15 Apr 2023 05:30:21 +0000          Inbox,Category Updates
```

My Gmail data contains mostly messages in English; however, there is plenty of Spanish and German, which introduce special characters that can lead to encoding issues. For this reason, it is better to encode special characters such as ñ and letters with accents and umlauts

[8]:
```python
def remove_accents(text):
    text = str(text)
    nfkd_norm = unicodedata.normalize('NFKD', text)
    text = nfkd_norm.encode('ASCII', 'ignore').decode('utf-8')
    return text
```

[9]:
```python
df['subject'] = df['subject'].map(remove_accents)
```

After cleaning the `subject` field, we can get a general overview of the integrity of different fields

[10]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14601 entries, 0 to 14600
Data columns (total 5 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   subject  14601 non-null  object
 1   from     14601 non-null  object
 2   to       14592 non-null  object
 3   date     14601 non-null  object
 4   label    14601 non-null  object
dtypes: object(5)
memory usage: 570.5+ KB
```

We find that `to`, one of the most relevant fields, contains some null entries. Which has to be removed.

[11]:
```python
len(df[df['to'].isnull()])
```

[11]: 9

[12]:
```python
# delete null rows
df = df[df['to'].notnull()]
len(df)
```

[12]:
```
14592
```

The next goal is to transform the class type: dates are given as strings

[13]:
```python
df[['date']].head()
```

[13]:
```
                                    date
0        Wed, 12 Apr 2023 22:31:37 +0800
1  Sat, 15 Apr 2023 03:17:12 +0000 (UTC)
2  Thu, 13 Apr 2023 03:32:10 +0000 (UTC)
3        Fri, 14 Apr 2023 10:23:42 -0600
4        Sat, 15 Apr 2023 05:30:21 +0000
```

These string dates can be converted into timestamps using the converted available for dataframes

[14]:
```python
df['date'] = df['date'].apply(lambda x: pd.to_datetime(x, errors='coerce',␣
↪utc=True))
```

Some dates have unappropriate shape for conversion (these are drafts of spam messages), which can be simply removed

[15]:
```python
df = df[df['date'].notnull()]
```

Given that the date is now a timestamp, messages can be easily sorted by date, after which the dataframe index must be reset

[16]:
```python
df = df.sort_values(['date'], ascending=False)
df = df.reset_index(drop=True)
```

The most recent messages are the following

[17]:
```python
df[['subject', 'date', 'label']].head(8)
```

[17]:
```
                                             subject  \
0  Aadhaar XXXX XXXX 9211: Authentication  Succes…
1  Aadhaar XXXX XXXX 9211: Authentication  Succes…
2  =?UTF-8?Q?There=E2=80=99s_a_connection_request…
3  =?utf-8?B?VGltZSB0byBsZXZlbCB1cCDwn5SdIFlvdXIg…
4  =?UTF-8?Q?Tyke_Digest_-_Elon_Musk_to_Challenge…
5        View: Account update for your HDFC Bank A/c
6  Aye Finance is coming again with Aye Finance A…
7                  Bourge Men's Loire-z3 Running…

                       date                                      label
0 2023-04-15 05:48:59+00:00  Inbox,Important,Opened,Category Personal
```

```
1 2023-04-15 05:47:00+00:00   Inbox,Important,Opened,Category Updates
2 2023-04-15 05:46:47+00:00             Inbox,Opened,Category Social
3 2023-04-15 05:30:21+00:00                    Inbox,Category Updates
4 2023-04-15 05:10:51+00:00                    Inbox,Category Updates
5 2023-04-15 05:00:21+00:00   Inbox,Important,Opened,Category Updates
6 2023-04-15 04:56:18+00:00          Inbox,Important,Category Updates
7 2023-04-15 03:19:06+00:00                 Inbox,Category Promotions
```

where the most recent message is the notification from Gmail to download the data used here. The oldest messages are

[18]:
```
df[['subject', 'date', 'label']].tail(9)
```

[18]:
```
      subject                      date               label
14543         2020-07-17 10:51:17+00:00  Archived,Sent,Opened
14544     pdf 2020-07-17 08:43:52+00:00  Archived,Sent,Opened
14545         2020-07-07 13:41:33+00:00  Archived,Sent,Opened
14546    Re:  2020-07-06 18:44:57+00:00           Sent,Opened
14547         2020-06-28 09:56:17+00:00  Archived,Sent,Opened
14548     pdf 2020-06-23 08:53:39+00:00  Archived,Sent,Opened
14549     pdf 2020-06-22 10:25:34+00:00  Archived,Sent,Opened
14550     pdf 2020-06-22 09:17:04+00:00  Archived,Sent,Opened
14551     pdf 2020-06-22 05:33:05+00:00  Archived,Sent,Opened
```

Finally, there are many messages in the `Drafts` folder that should also be removed

[19]:
```
df = df[df['label'] != 'Drafts']
```

The same applies for `Spam` messages. Unfortunately, this label does not appear alone so it must be searched in the `label` column

[20]:
```
cnt = 0
idx_to_remove = []
for i, lab in enumerate(df['label']):
    if 'Spam' in str(lab):
        idx_to_remove.append(i)

df = df.drop(df.index[idx_to_remove])
df = df.reset_index(drop=True)
```

At this point, and given the time used for cleaning the data file, it is a good idea to export it as a `csv` file for future use without the need of redoing the preprocessing above.

[21]:
```
df.to_csv('/content/drive/MyDrive/Colab Notebooks/Self practice projects/Gmail/
 ↪gmail_data_preprocessed.csv',
          encoding='utf-8', index=False)
```

2 Data exploration

We can now begin exploring the data set.

[22]:
```
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Self practice projects/
↪Gmail/gmail_data_preprocessed.csv')
len(df)
```

[22]:
```
14535
```

Since the data was loaded from a `csv` file, the dates are back as `str` so they must be converted into `timestamp` again

[23]:
```
df['date'] = df['date'].apply(lambda x: pd.to_datetime(x))
```

2.1 1. Incoming vs. outgoing messages

For simplicity, all messages written by me or sent to me can be labeled by the string `me` instead of my email address. This will make the identification of incoming and outgoing emails easier. For this the following helper function returns `me` my email address is found and leaves the text unchanged, otherwise:

[24]:
```
def rename_me(txt):
    txt = str(txt).lower()
    if('jaykumar' in txt or
       '25012001' in txt):
        txt_out = 'me'
    else:
        txt_out = txt
    return txt_out
```

[25]:
```
df['from'] = df['from'].apply(rename_me)
df['to'] = df['to'].apply(rename_me)
```

[26]:
```
df[['subject', 'to', 'date', 'label']].head(4)
```

[26]:
```
                                             subject  to  \
0  Aadhaar XXXX XXXX 9211: Authentication  Succes…  me
1  Aadhaar XXXX XXXX 9211: Authentication  Succes…  me
2  =?UTF-8?Q?There=E2=80=99s_a_connection_request…  me
3  =?utf-8?B?VGltZSB0byBsZXZlbCB1cCDwn5SdIFlvdXIg…  me

                       date                                  label
0 2023-04-15 05:48:59+00:00  Inbox,Important,Opened,Category Personal
1 2023-04-15 05:47:00+00:00   Inbox,Important,Opened,Category Updates
2 2023-04-15 05:46:47+00:00             Inbox,Opened,Category Social
3 2023-04-15 05:30:21+00:00                   Inbox,Category Updates
```

Since we want to explore the statistical distribution of messages, a useful information is a count of messages, for which a unit `count` column can be created

[27]:
```
df['count'] = [1 for _ in range(len(df))]
```

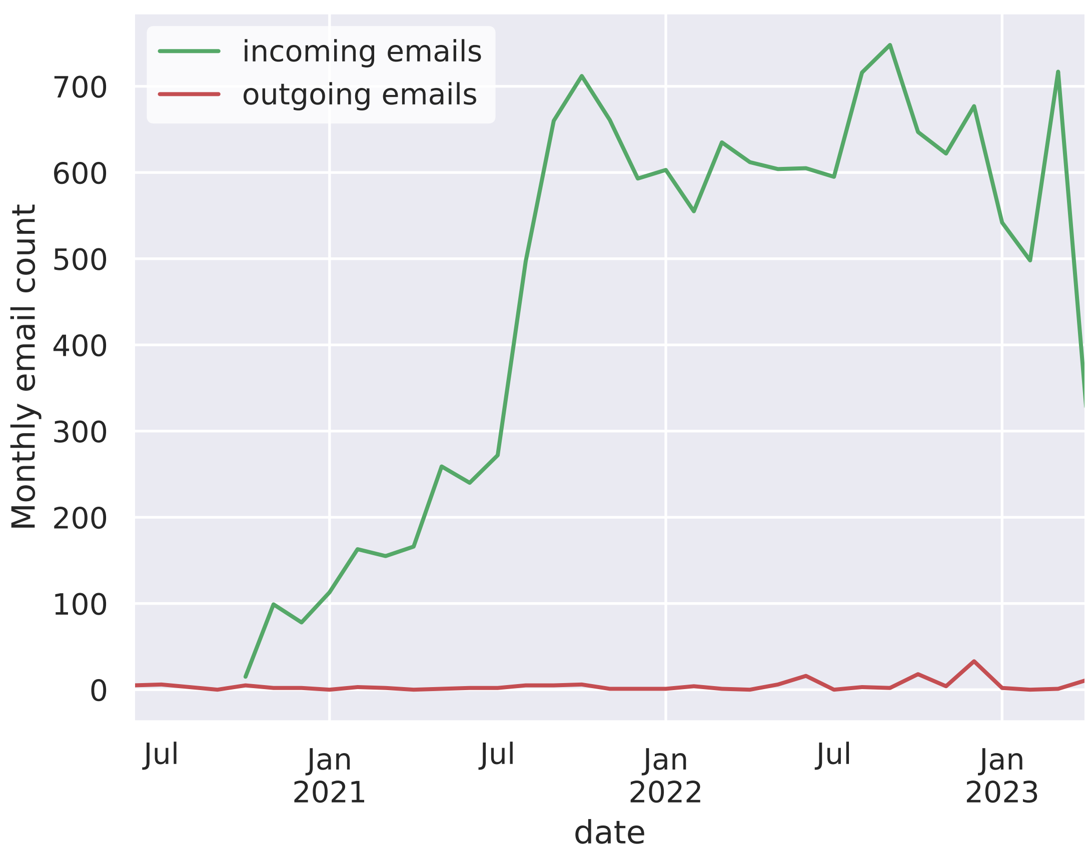
In order to keep the original data intact, we can make a copy and set the timestamp as a index, so that messages can be grouped and resampled by time periods

[28]:
```
data = df.copy()
data.set_index('date', drop=True, inplace=True)
```

Now we can identify incoming vs. outgoing emails

[29]:
```
data_in = data[data['to'] == 'me']
data_out = data[data['from'] == 'me']
```

[30]:
```
monthly_in = data_in['count'].resample('M').sum()
monthly_out= data_out['count'].resample('M').sum()
monthly_in.plot(color='g', label='incoming emails')
monthly_out.plot(color='r', label='outgoing emails')
plt.ylabel('Monthly email count')
plt.legend(loc='upper left', frameon=True).get_frame().set_color('white');
```



It can be seen that most of the time the number of received emails is greater than the number of emails sent.

2.2 2. Busy days

We can now try to identify email activity vs. day of the week. We use the `timestamp` method `weekday()`, which returns an index [0....6] corresponding to the days of the from Monday to Sunday.

[31]:
```
dow = []
for i in range(len(df)):
    dow.append(df['date'][i].weekday())
```

Create new `series` with the day of the week of the message

[32]:
```
df['dow'] = dow
df[['subject', 'date', 'dow', 'label']].head(4)
```

[32]:
```
                                             subject  \
0  Aadhaar XXXX XXXX 9211: Authentication  Succes…
1  Aadhaar XXXX XXXX 9211: Authentication  Succes…
2  =?UTF-8?Q?There=E2=80=99s_a_connection_request…
3  =?utf-8?B?VGltZSB0byBsZXZlbCB1cCDwn5SdIFlvdXIg…

                       date  dow                                     label
0 2023-04-15 05:48:59+00:00    5  Inbox,Important,Opened,Category Personal
1 2023-04-15 05:47:00+00:00    5   Inbox,Important,Opened,Category Updates
2 2023-04-15 05:46:47+00:00    5             Inbox,Opened,Category Social
3 2023-04-15 05:30:21+00:00    5                   Inbox,Category Updates
```

[33]:
```
df_in = df[df['to'] == 'me']
df_out = df[df['from'] == 'me']
```

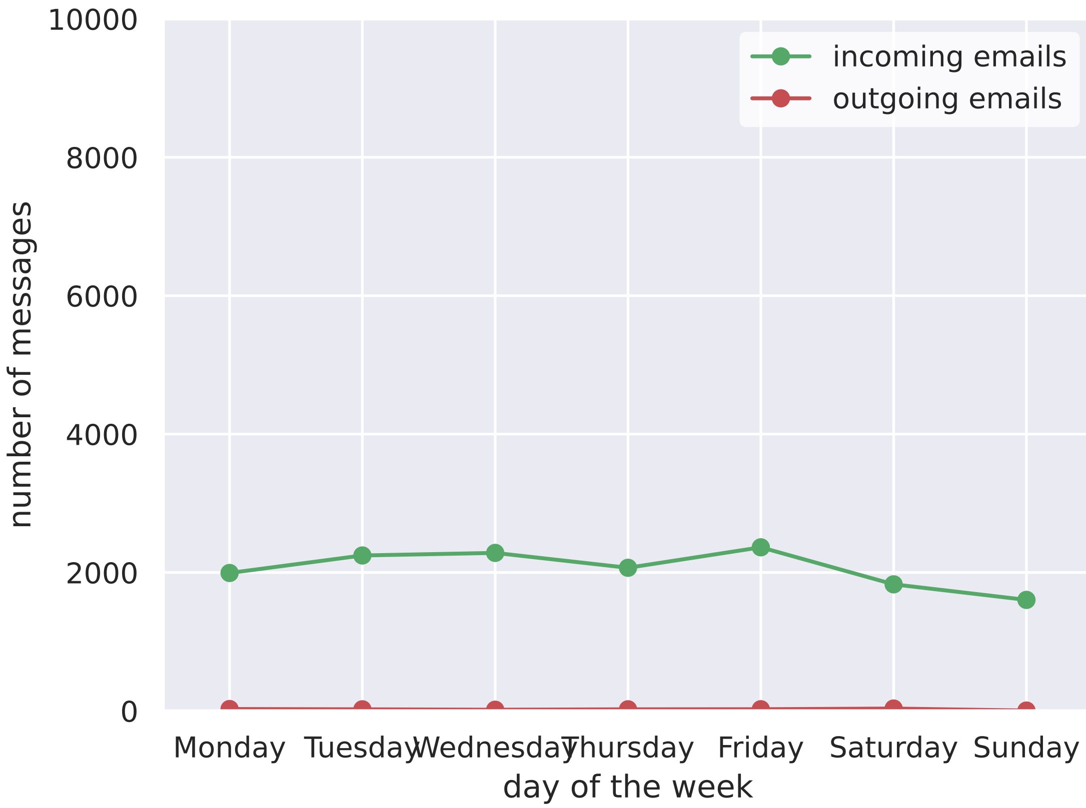
We can now get the distribution of messages per day of the week. For this a dictionary can easily capture the frequency of messages on each day

[34]:
```
dow_in, dow_out = {}, {}
for i in range(7):
    dow_in[i] = 0
    dow_out[i] = 0
for i in df_in['dow']:
    dow_in[i] += 1
for i in df_out['dow']:
    dow_out[i] += 1
```

[35]:
```
x, y_in, y_out, y_all = [], [], [], []
for key in dow_in.keys():
    x.append(key)
```

```
    y_in.append(dow_in[key])
    y_out.append(dow_out[key])
    y_all.append(dow_in[key] + dow_out[key])

plt.plot(x, y_in, 'o-', color='g', label='incoming emails')
plt.plot(x, y_out, 'o-', color='r', label='outgoing emails')
plt.axis([-0.5, 6.5, 0, 10000])
plt.xlabel('day of the week')
plt.ylabel('number of messages')
days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',␣
 ↪'Sunday']
plt.xticks(x, days)
plt.legend(frameon=True).get_frame().set_color('white');
```



This plot shows clearly that the activity is quite uniform during the week days and it decreases during the weekens, as sort of expected.

2.3 3. Frequent contacts

Another immediate question that can be answered with this data is regarding the most frequent contacts I have received messages from and those to whom I have written the most. Just as done earlier with my email address that was replaced by the string `me`.

For the privacy of my contacts (I prefer not to post their email address) can be protected by creating a function that can replace their contact information with a nickname.

[36]:
```
def nickname(txt, list_to_rename, new_name):
    txt = str(txt)
    for name in list_to_rename:
        if name in txt.lower():
            txt_out = new_name
            break
        else:
            txt_out = txt
    return txt_out
```

where `txt` is the text where the names on the list `list_to_rename` are been searched, if found they will be replaced by the nickname `new_name`.This is done for a few frequent contacts.

[37]:
```
df['to'] = df['to'].apply(lambda x: nickname(x, ['krutik'], 'krutik'))
df['to'] = df['to'].apply(lambda x: nickname(x, ['sakshi'], 'sakshi'))
df['to'] = df['to'].apply(lambda x: nickname(x, ['agney'], 'agney'))
df['to'] = df['to'].apply(lambda x: nickname(x, ['desai'], 'kishan'))
df['to'] = df['to'].apply(lambda x: nickname(x, ['meet'], 'meet'))
df['to'] = df['to'].apply(lambda x: nickname(x, ['meko'], 'meko'))
df['to'] = df['to'].apply(lambda x: nickname(x, ['place'], 'university'))
df['to'] = df['to'].apply(lambda x: nickname(x, ['gujuni'], 'guj university'))
```

The most frequent contacts that I have written to are

[38]:
```
df['to'].value_counts()[1:10]
```

[38]:
```
sakshi                     22
krutik                     17
guj university             12
meko                       10
agney                       6
kishan                      6
meet                        6
university                  5
undisclosed-recipients:;    4
Name: to, dtype: int64
```

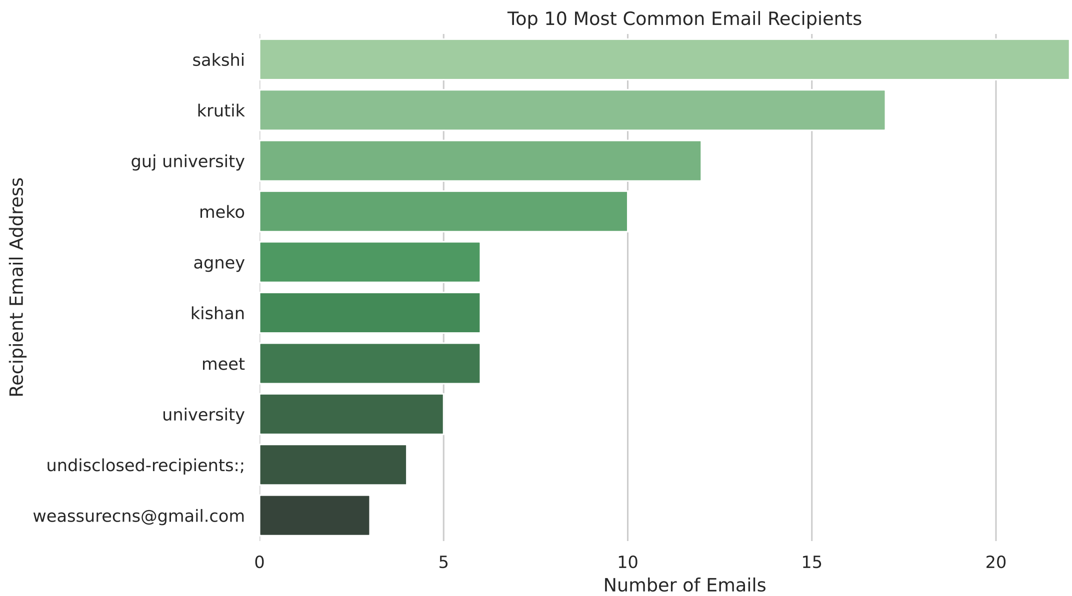
This shows the count of emails which were sent. All these results can be visualized

[39]:
```
df_top10 = df['to'].value_counts()[1:11].reset_index()
df_top10.columns = ['to', 'count']

sns.set_style("whitegrid")
```

```
sns.set_color_codes("pastel")
plt.figure(figsize=(10, 6))
sns.barplot(x='count', y='to', data=df_top10, palette='Greens_d')
plt.title('Top 10 Most Common Email Recipients')
plt.xlabel('Number of Emails')
plt.ylabel('Recipient Email Address')

sns.despine(left=True, bottom=True)
plt.show()
```



Now we can check from whom i received most number of emails. But the problem with the from email is duplicate email IDs. *Eg - no-reply@ncp.flipkart.com and no-reply@ncb.flipkart.com* they both are same but if we count the number of emails both the email IDs will show seperate counts. So for this we can create nicknames just the way we created for sent mails.

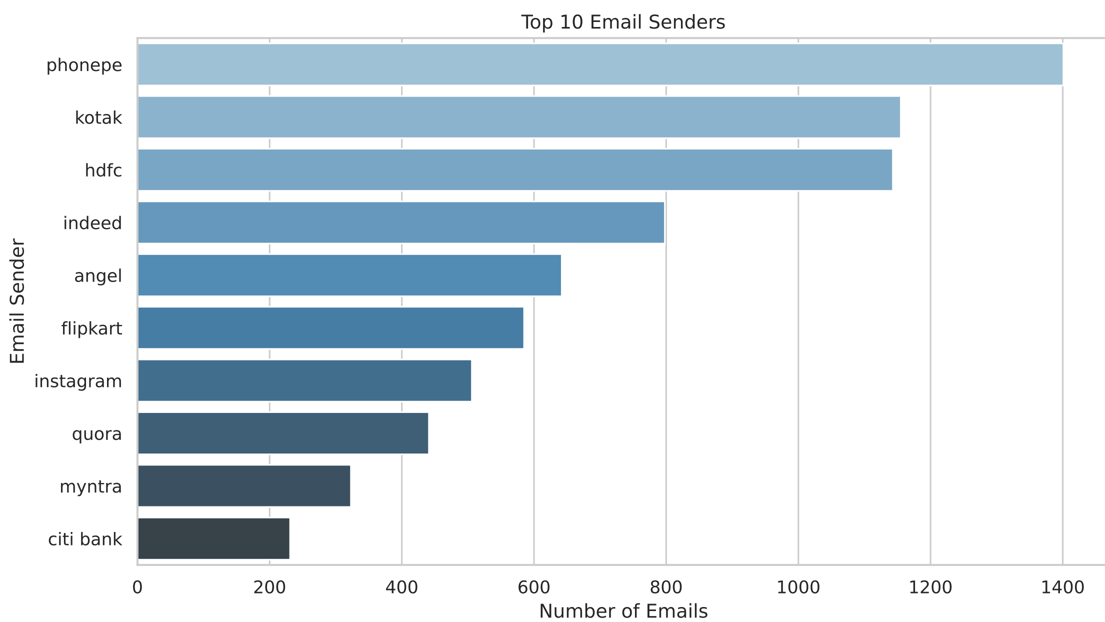
[58]:
```
df['from'] = df['from'].apply(lambda x: nickname(x, ['hdfc'], 'hdfc'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['linkedin'], 'linkedin'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['angel'], 'angel'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['indeed'], 'indeed'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['phonepe'], 'phonepe'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['instagram'], 'instagram'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['myntra'], 'myntra'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['flipkart'], 'flipkart'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['quora'], 'quora'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['kotak'], 'kotak'))
df['from'] = df['from'].apply(lambda x: nickname(x, ['citi'], 'citi bank'))
```

[59]:
```
df['from'].value_counts()[1:8]
```

[59]:
```
phonepe      1401
kotak        1155
hdfc         1143
indeed        798
angel         642
flipkart      585
instagram     506
Name: from, dtype: int64
```

This shows the count of emails which were received. All these results can be visualized

[60]:
```
df_top7 = df['from'].value_counts()[1:11]
sns.set_style('whitegrid')
plt.figure(figsize=(11,6))
sns.barplot(x=df_top7, y=df_top7.index, palette='Blues_d')
plt.xlabel('Number of Emails')
plt.ylabel('Email Sender')
plt.title('Top 10 Email Senders')
plt.show()
```



2.3.1 4. Most common topics

The content of the messages is unavailable; however, the subject of each message can clearly indicate the recurrent topics for both incoming and outgoing emails. which can be visualized in word cloud.

[43]:
```
all_wrds_in = []
for wrds in list(df['subject'][df['to'] == 'me']):
    all_wrds_in.extend(str(wrds).lower().split())

all_wrds_out = []
for wrds in list(df['subject'][df['from'] == 'me']):
    all_wrds_out.extend(str(wrds).lower().split())
```

[44]:
```
all_wrds_in[:6]
```

[44]:
```
['aadhaar', 'xxxx', 'xxxx', '9211:', 'authentication', 'successful']
```

[45]:
```
my_stopwords = ['re:', 'nan', 'none', '-', 'fwd:', 'fw:',
                '&', 'hola', 'saludos', 'order', 'amazon.com']
```

[46]:
```
import nltk
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Unzipping corpora/stopwords.zip.
```

[46]:
```
True
```

[47]:
```
from nltk.corpus import stopwords
stopwords_en = set(stopwords.words('english'))
all_stopwords = stopwords_en | set(my_stopwords)
```

[48]:
```
len(all_wrds_in), len(all_wrds_out)
```

[48]:
```
(83215, 415)
```

[49]:
```
all_wrds_in = [wrd for wrd in all_wrds_in if wrd not in all_stopwords]
all_wrds_out = [wrd for wrd in all_wrds_out if wrd not in all_stopwords]
```

[50]:
```
len(all_wrds_in), len(all_wrds_out)
```

[50]:
```
(63304, 315)
```

[51]:
```
wrds_in = Counter(all_wrds_in)
wrds_out = Counter(all_wrds_out)
```

[52]:
```
wrds_in.most_common(10)
```

[52]:
```
[('new', 1339),
 ('jobs', 1000),
 ('bank', 943),
 ('account', 917),
```

```
 ('hdfc', 679),
 ('update', 662),
 ('a/c', 612),
 ('view:', 608),
 ('job', 528),
 ('|', 482)]
```

[53]:
```
wrds_out.most_common(10)
```

[53]:
```
[('opportunity', 11),
 ('inquiry', 10),
 ('regarding', 10),
 ('job', 10),
 ('mentioned', 10),
 ('fiver', 10),
 ('ggg', 7),
 ('views', 6),
 ('resume', 6),
 ('assignment', 5)]
```

[54]:
```
from wordcloud import WordCloud, STOPWORDS
```

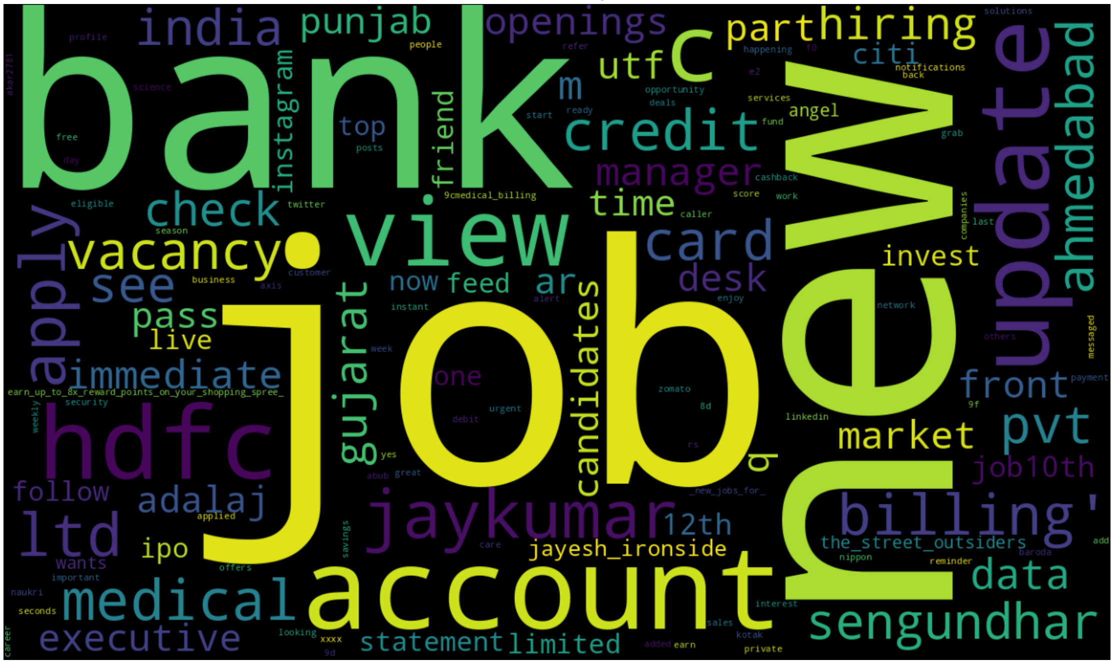
[55]:
```
words_in = ''
for t in wrds_in.most_common(150):
    for i in range(t[1]):
        words_in += t[0] + ' '

words_out = ''
for t in wrds_out.most_common(150):
    for i in range(t[1]):
        words_out += t[0] + ' '
```

3 Word cloud of incoming mails

[56]:
```
wordcloud_in = WordCloud(stopwords=STOPWORDS,
                      background_color='black',
                      width=1350, height=800,
                      collocations=False
                     ).generate(words_in)
plt.figure(figsize=(20,10))
plt.imshow(wordcloud_in)
plt.axis('off')
plt.title('WordCloud: incoming emails');
```

WordCloud: incoming emails



4 Word cloud of outgoing mails

[57]:
```
wordcloud_out = WordCloud(stopwords=STOPWORDS,
                          background_color='black',
                          width=1350, height=800,
                          collocations=False
                         ).generate(words_out)
plt.figure(figsize=(20,10))
plt.imshow(wordcloud_out)
plt.axis('off')
plt.title('WordCloud: outgoing emails');
```

WordCloud: outgoing emails