This notebook loads the dataframe as processed in the 'mvp_nlp_sentimentanalysis.ipynb' and creates a series of word clouds illustrating the trends amongst them.

> Takeaway message / recommendations:
>
> 1. Leverage the use of the word "Space." Space is commonly found within the discourse, but in congruence with other words will add significance.
> 2. Partner and collaborate with current industry leaders. Institutions like NASA and SpaceX not only have scientific headway, but they have built reputations, high esteem, and clout. Partnering with organizations of this scale will grow positive marketing schemes.
> 3. Evoke emotion. The power building an emotional response adds tremendous value to your marketing capabilities. Customers think with their hearts, and by utilizing words like "love," you are likely to create a positive sentiment around your product.

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import nltk
from nltk.tokenize import word_tokenize, sent_tokenize
from nltk.corpus import stopwords
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
nltk.download('stopwords')
stop = stopwords.words('english')

from wordcloud import WordCloud
```

```
[nltk_data] Downloading package punkt to /Users/tlipman/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /Users/tlipman/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/tlipman/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [2]:

```
pd.set_option('display.width', None)
pd.set_option('max_columns', None)
pd.set_option('max_colwidth', 200)
```

In [3]:

```
df = pd.read_csv('final_df')
df.shape
```

Out[3]:

```
(216009, 12)
```

```
In [4]: df.head()
```

Out[4]:

	Unnamed: 0	favorite_count	repost_count	text	id	polarity	pol	neg
0	0	2.0	0.0	rebel editor give give perseverance patience self awareness trusting intuition ect 2 3	66218	0.000000	{'neg': 0.105, 'neu': 0.719, 'pos': 0.176, 'compound': 0.2732}	0.105
1	1	0.0	0.0	starlinks latent china crisis could spark whole new world warcraft infosec infosec	267611	0.168182	{'neg': 0.256, 'neu': 0.625, 'pos': 0.119, 'compound': -0.4939}	0.256
2	2	0.0	1.0	littlebitprince added atom day adding right go try catch dot ada sol hold	307032	0.285714	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	0.000
3	3	0.0	0.0	databourg march 9 1934 birth soviet air force pilot cosmonaut yuri gagarin march 27 1968 fi	255943	0.000000	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	0.000
4	4	0.0	1.0	daphnedark1 mar star mind diena08950191 sadly still stick time time wasted wa suppose buildin	282555	-0.350000	{'neg': 0.333, 'neu': 0.667, 'pos': 0.0, 'compound': -0.7184}	0.333

```
In [5]: df.drop(['Unnamed: 0'], axis=1, inplace=True)
```

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

Out[6]:

	favorite_count	repost_count	text	id	polarity	pol	neg	neu	p
0	2.0	0.0	rebel editor give give perseverance patience self awareness trusting intuition ect 2 3	66218	0.000000	{'neg': 0.105, 'neu': 0.719, 'pos': 0.176, 'compound': 0.2732}	0.105	0.719	0.1
1	0.0	0.0	starlinks latent china crisis could spark whole new world warcraft infosec infosec	267611	0.168182	{'neg': 0.256, 'neu': 0.625, 'pos': 0.119, 'compound': -0.4939}	0.256	0.625	0.1
2	0.0	1.0	littlebitprince added atom day adding right go try catch dot ada sol hold	307032	0.285714	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	0.000	1.000	0.0
3	0.0	0.0	databourg march 9 1934 birth soviet air force pilot cosmonaut yuri gagarin march 27 1968 fi	255943	0.000000	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	0.000	1.000	0.0
4	0.0	1.0	daphnedark1 mar star mind diena08950191 sadly still stick time time wasted wa suppose buildin	282555	-0.350000	{'neg': 0.333, 'neu': 0.667, 'pos': 0.0, 'compound': -0.7184}	0.333	0.667	0.0

In [7]:
```
df.isnull().sum() # confirming no null values
```

Out[7]:
```
favorite_count     0
repost_count       0
text               0
id                 0
polarity           0
pol                0
neg                0
neu                0
pos                0
sil                0
cluster            0
dtype: int64
```

Word Clouds

In [8]:

```
pd.value_counts(df.cluster)
```

Out[8]:

```
2    104527
4     65686
1     35282
0      8836
3      1678
Name: cluster, dtype: int64
```

In [9]:

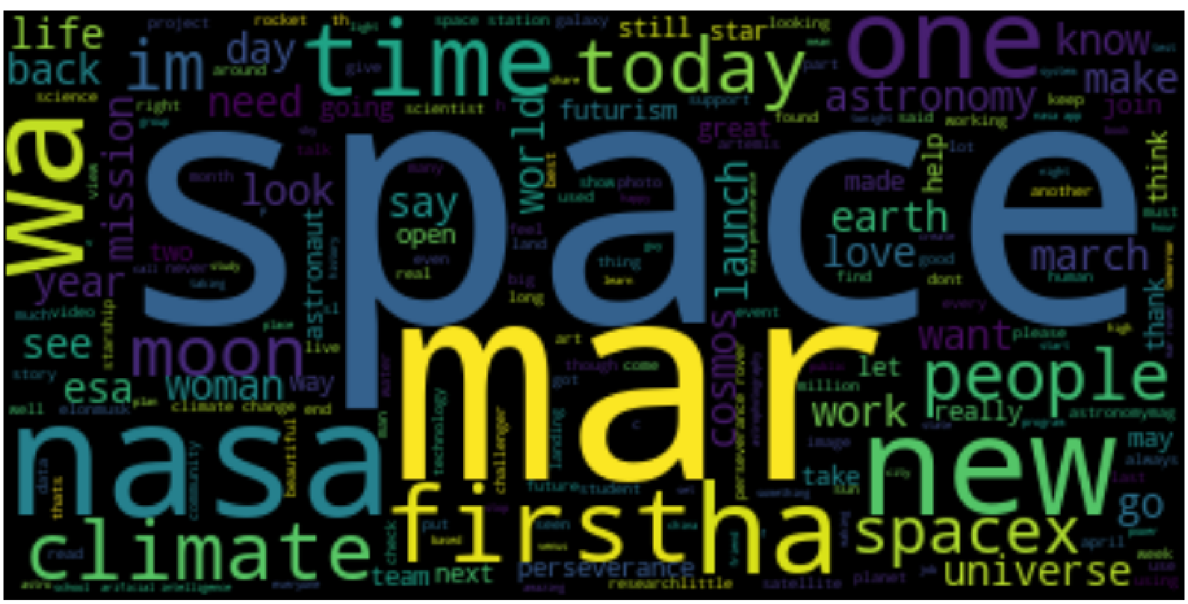
```
# creating multiple dataframes with clusters
unique_clusters = df['cluster'].unique()
cluster_4 = df.loc[df['cluster'] == unique_clusters[0]]
cluster_2 = df.loc[df['cluster'] == unique_clusters[1]]
cluster_1 = df.loc[df['cluster'] == unique_clusters[2]]
cluster_0 = df.loc[df['cluster'] == unique_clusters[3]]
cluster_3 = df.loc[df['cluster'] == unique_clusters[4]]
```

In [10]:

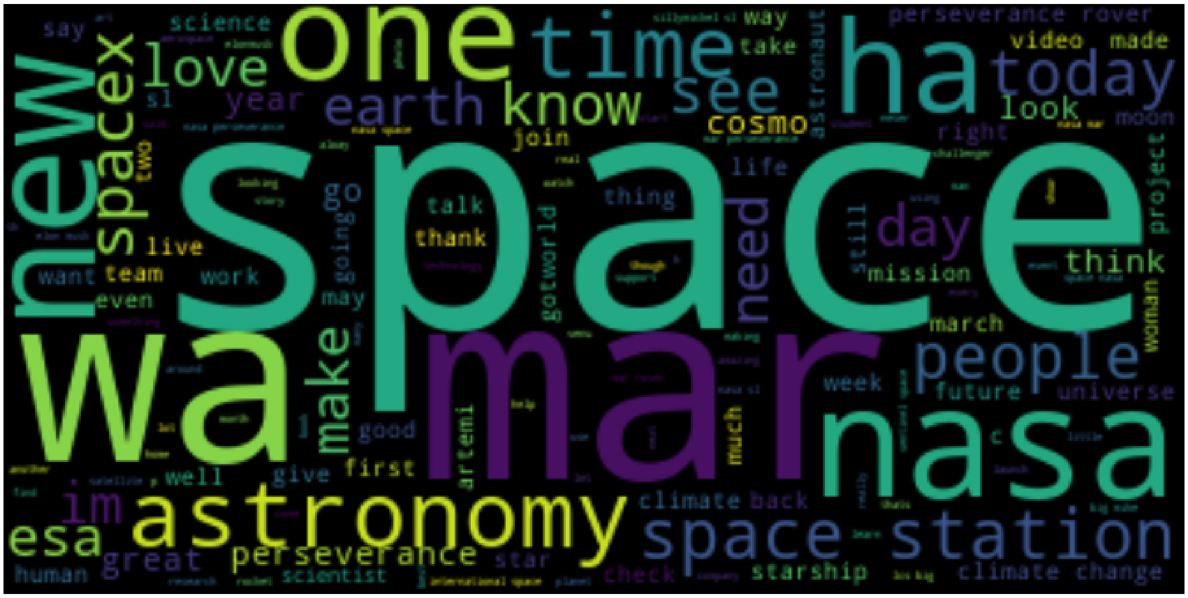
```
word_counts_0 = ' '.join(cluster_0['text'].tolist())
word_counts_1 = ' '.join(cluster_1['text'].tolist())
word_counts_2 = ' '.join(cluster_2['text'].tolist())
word_counts_3 = ' '.join(cluster_3['text'].tolist())
word_counts_4 = ' '.join(cluster_4['text'].tolist())
```

In [11]:

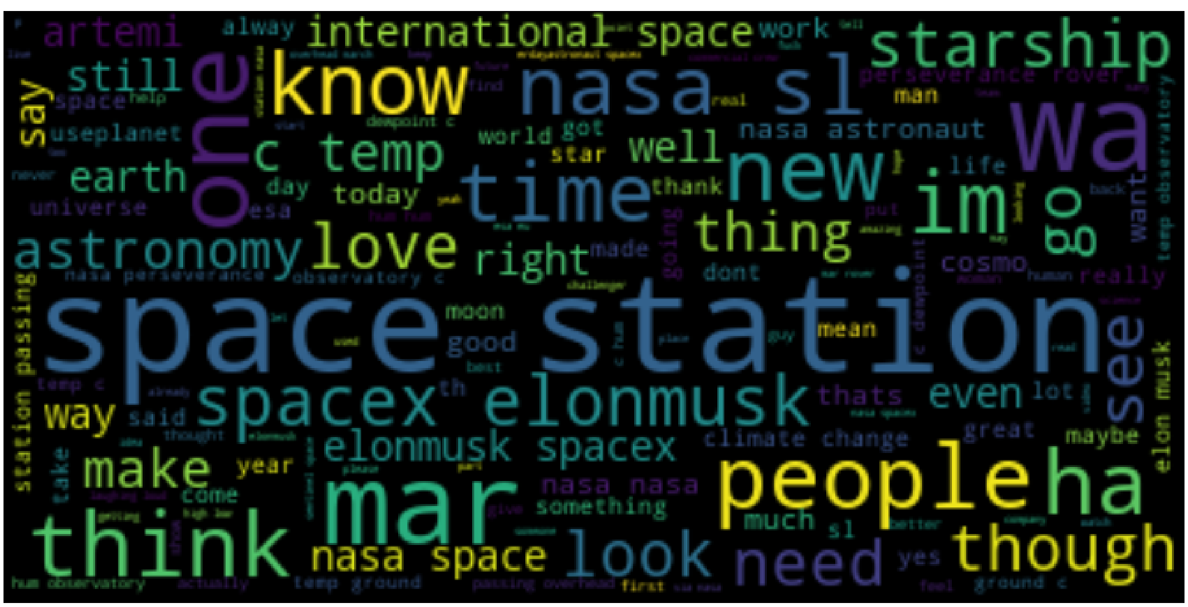
```
# CLUSTER 0
wordcloud = WordCloud().generate(word_counts_0)
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```



In [12]:
```python
# CLUSTER 1
wordcloud = WordCloud().generate(word_counts_1)
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```

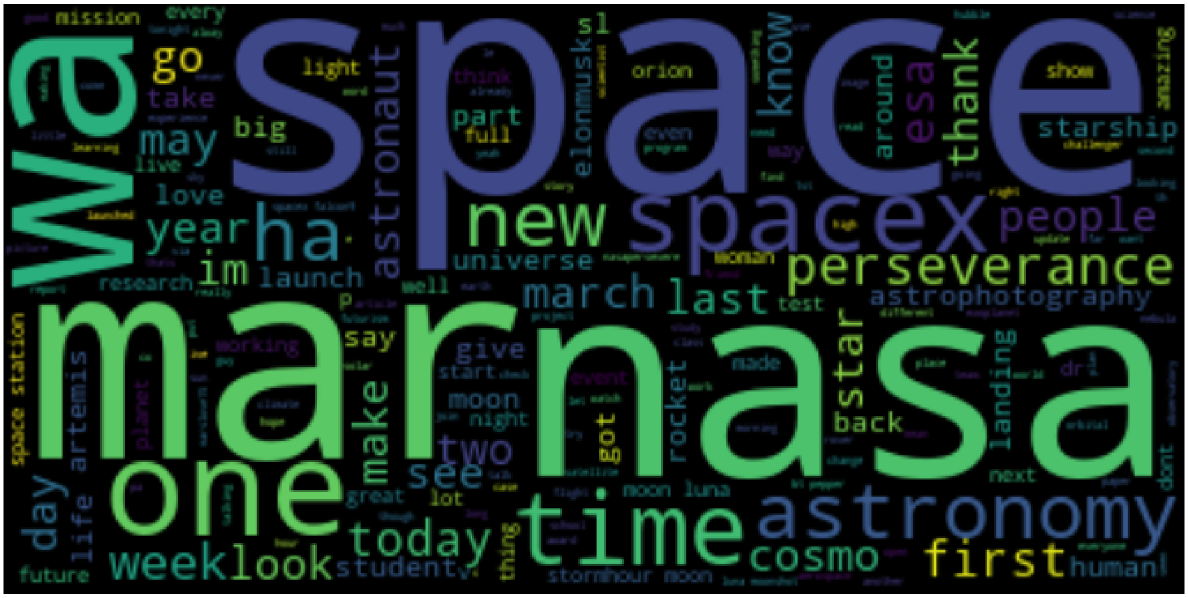


In [13]:
```python
# CLUSTER 2
wordcloud = WordCloud().generate(word_counts_2)
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```



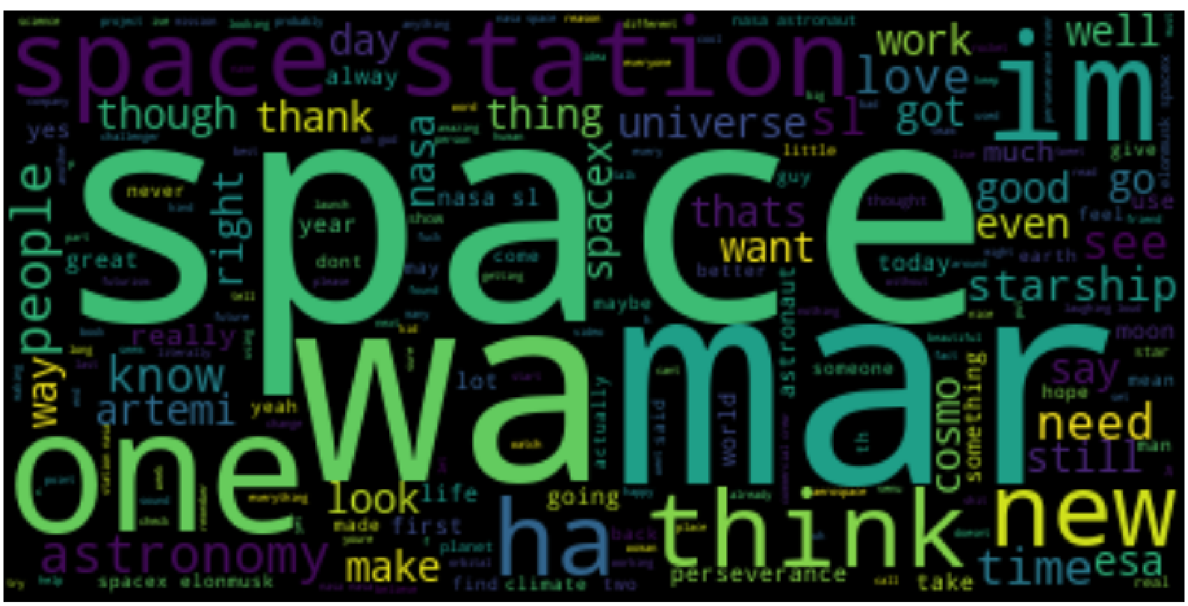
In [14]:

```
# CLUSTER 3
wordcloud = WordCloud().generate(word_counts_3)
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```



In [15]:

```
# CLUSTER 4
wordcloud = WordCloud().generate(word_counts_4)
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```



Term Frequency-Inverse Document Frequency

In [16]:
```
#function that calculates the inverse document frequency(IDF) of each wo
rd in our collection
def get_idf(class_, dataframe, stopwords_list):
    docs = dataframe[dataframe.cluster==class_].text
    class_dict = {}
    for doc in docs:
        words = set(doc.split())
        for word in words:
            if word.lower() not in stopwords_list:
                class_dict[word.lower()] = class_dict.get(word.lower(),
0) + 1
    idf_df = pd.DataFrame.from_dict(class_dict, orient='index')
    idf_df.columns = ['IDF']
    idf_df.IDF = np.log(len(docs)/idf_df.IDF)
    idf_df = idf_df.sort_values(by="IDF", ascending=True)
    return idf_df.head(40)
```

In [17]:
```
for i in range(5):
    print(get_idf(i , df, stop))
```

	IDF
space	1.895914
mar	2.320398
nasa	2.331985
ha	2.979567
wa	3.006656
new	3.015852
climate	3.065566
perseverance	3.146418
first	3.149053
one	3.170388
time	3.231518
like	3.287497
year	3.290532
spacex	3.379479
today	3.458968
2	3.510640
people	3.537513
get	3.644172
esa	3.648510
day	3.674944
im	3.688427
1	3.692962
moon	3.739482
rover	3.753871
astronomy	3.753871
image	3.763580
starship	3.768470
launch	3.768470
see	3.788272
need	3.818731
earth	3.834316
work	3.844843
make	3.860843
know	3.871654
universe	3.871654
3	3.899204
march	3.904806
world	3.927534
life	3.939095
go	3.974602

	IDF
space	1.874200
nasa	2.099655
mar	2.124723
perseverance	2.834859
spacex	2.961245
first	3.089626
wa	3.090249
new	3.144663
ha	3.184936
astronomy	3.219783
one	3.326721
esa	3.354734
like	3.355546
sl	3.362066
time	3.410652

climate	3.434101
station	3.571405
year	3.578487
2	3.611513
astronaut	3.635944
get	3.643499
rover	3.645668
people	3.666514
1	3.670958
elonmusk	3.696904
starship	3.711873
im	3.725892
day	3.741304
moon	3.754533
today	3.772860
2021	3.782773
see	3.789020
via	3.805444
know	3.833870
work	3.851055
earth	3.868540
image	3.880827
make	3.927216
launch	3.946099
universe	3.947566

	IDF
space	1.774413
nasa	1.882875
mar	2.167125
spacex	2.242590
elonmusk	2.605631
wa	2.905127
station	2.960827
like	3.048846
sl	3.217939
one	3.239923
im	3.266657
perseverance	3.267410
ha	3.318928
starship	3.333305
esa	3.338414
astronomy	3.343277
time	3.408177
new	3.448277
get	3.479754
first	3.502360
astronaut	3.535616
know	3.560883
would	3.606698
people	3.668866
climate	3.731157
see	3.739978
need	3.747659
2021	3.754583
think	3.756219
go	3.773560
1	3.782765

2	3.792480
universe	3.800150
via	3.803148
year	3.809172
moon	3.828785
make	3.828785
earth	3.846547
good	3.870121
day	3.871498

	IDF
space	2.215872
nasa	2.550161
mar	2.565545
wa	2.982707
one	3.191251
spacex	3.191251
time	3.298224
ha	3.314484
week	3.382307
moon	3.418025
perseverance	3.436374
astronomy	3.436374
new	3.455066
like	3.474114
2	3.554157
last	3.554157
today	3.618695
1	3.641168
year	3.664158
esa	3.687688
first	3.736478
get	3.761796
people	3.787772
two	3.841839
sl	3.841839
big	3.841839
day	3.870010
krisdegliatti	3.870010
march	3.870010
sherisherman732	3.898997
loragtz	3.898997
go	3.898997
may	3.928850
3	3.928850
see	3.959622
im	3.959622
look	3.959622
elonmusk	3.959622
astronaut	4.024161
know	4.024161

	IDF
space	1.900567
mar	2.228036
nasa	2.229308
spacex	2.596876
wa	2.776585
like	2.863663

im	2.956123
elonmusk	3.086940
one	3.088944
sl	3.189414
esa	3.261818
astronomy	3.281478
ha	3.309417
time	3.348071
get	3.357645
perseverance	3.421746
think	3.452037
station	3.468999
know	3.472917
starship	3.499267
would	3.501284
first	3.574034
people	3.581116
see	3.647808
cosmos	3.658975
astronaut	3.682294
new	3.699378
go	3.703077
artemis	3.703695
good	3.723040
love	3.740200
year	3.746631
need	3.758312
make	3.780088
also	3.800304
universe	3.809193
thing	3.843426
day	3.869345
really	3.901965
thats	3.906497