Automotive Persona

This persona is much into autombiles especially cars, it has huge interest towrds automobile parts, sales, repairs, engines and diffenrt brands associated with them. They know everything about automiles, tehir reveiews and mostly use terms related to automobiles, most of the population in this category range between ages 18-30 yrs and drive a lot, they spend most of their time on road driving differnt vechicles and in the remaining time they research about new cars and modify the existing ones. They like luxury cars but are more into sporty or performance vechiles.They spen a significant amount of money on cars and their parts.

Overview

In this project we compare any given sentence with persona and display the words and respective scores which are of least and highest interest to these people, with the help of which the sentences can be framed to attract these people.

Using the platform

We made this platform with precision and keeping our user in mind, easy to use and you could get everything you need within a matter of seconds.

Follow these two simple steps

1.Enter the text you would like to ask this persona and press enter 2.Enter the number of positive or negative words you want to see and press enter

In [1]:
```
#importing necessary packages
import nltk
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from scipy import spatial
from sklearn.feature_extraction.text import CountVectorizer
from nltk.tokenize import RegexpTokenizer
#IPython.display import
```

In [5]:
```
#personality of the persona is defined here
```

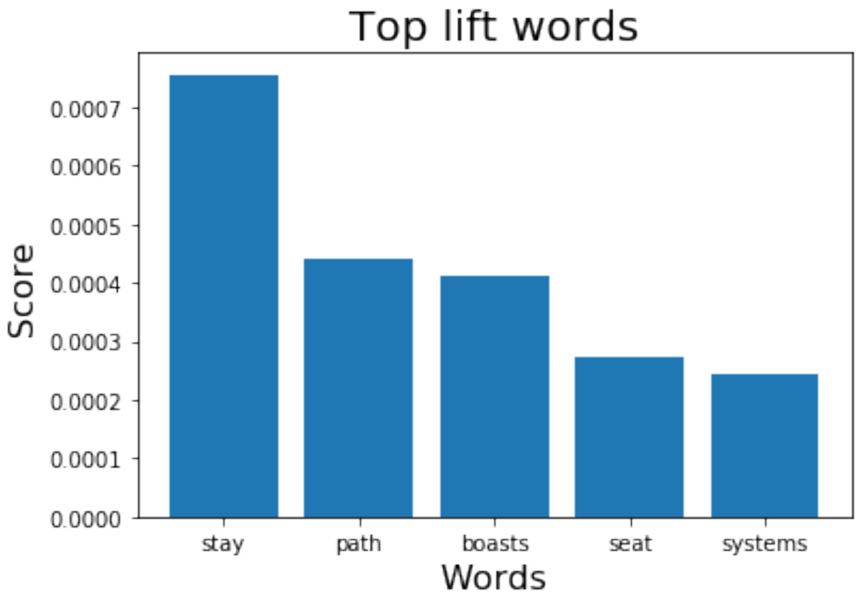
```
data_corpus="5-speed 6-speed acclaimed advanced affordable agile all-w
heel drive astonishing automatic automotive beyond compare engines int
erior classic crash-tested custom-built custom-designed customized dis
tinctive drivetrain functional futuristic engine high-agility hybrid i
nnovative legendary limitless low-emission luxurious luxury manual mor
e new noteworthy performance-inspired pinpoint powerful progressive dy
namic easy-to-drive economical effective electric elegant engineered e
nhanced environmentally-friendly ergonomic expensive extreme family-fr
iendly fast faster four-wheel drive front-wheel drive fuel-efficient r
eady-for-action reinforced safe scientific sleek sluggish speedy sport
y standard stylish top-dollar top-level tuned ultimate ultra unparalle
d used versatile  acceleration accessories adventure agility air injec
tion alloys automobile boxer engine brake pad car carbon fiber comfort
construction control convertible coupe crash rating cruise control int
erior luxury make mile mileage model motor motorcycle options passenge
r perfection performance power precision pricing profile quality refin
ement drafting driver driving elegance emission engine engineering exc
ellence experience exterior feature feeling form function handling hor
sepower incentive innovation road road contact safety sedan sophistica
tion specs speed sportiness sportster standard style styling system te
chnology throttle transmission trims vehiclebuild control cruise drive
engineer rev rev the engine ride shift speed fly go handle maximize pe
rform test drive transport turn zoom Audi BMW Buick Cadillac Chevrolet
Chrysler Dodge Ferrari Ford GM GEM GMC Honda Hummer Hyundai Infiniti I
suzu Jaguar Jeep Kia Lamborghini Land Rover Lexus Lincoln Lotus Mazda
Mercedes-Benz Mercury Mitsubishi Nissan Oldsmobile Peugeot Pontiac Por
sche Regal Saab Saturn Subaru Suzuki Toyota Volkswagen Volvo"



def token(text):
    """
    converting the text to lower case and tokenizing it
    """
    text=text.lower()
    tokenizer = RegexpTokenizer(r'\w+')
    token =tokenizer.tokenize(text)
    return token

def core_cosine_similarity(vector1, vector2):
    """
    measure cosine similarity between two vectors
    :vector1:
    :vector2:
    :return: 0 < cosine similarity value < 1
    """
    return 1  - spatial.distance.cosine(vector1, vector2)

def _sentence_similarity(sent1, sent2, stopwords=None):
    """
```

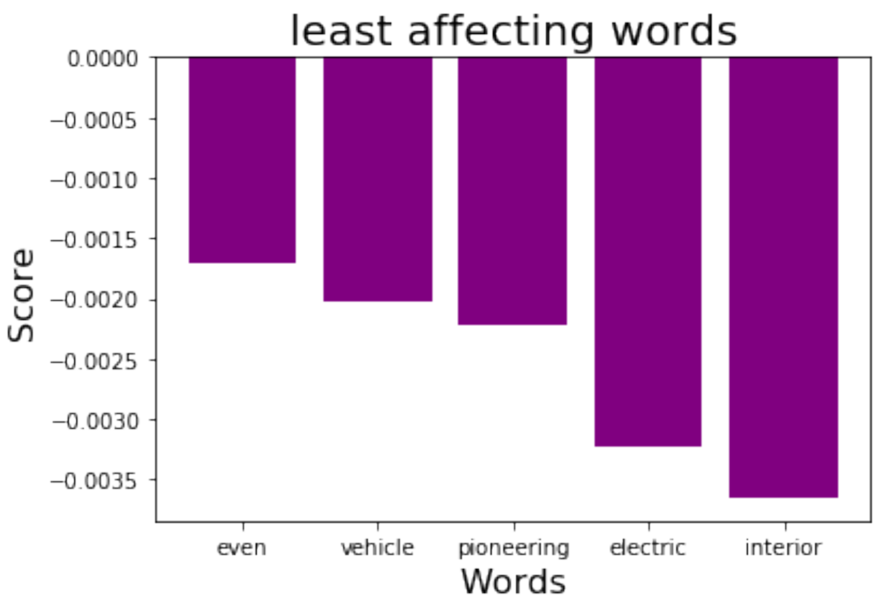
```
    compares two sentences and computes their cosine similarity
    """
    if stopwords is None:
        stopwords = []

        sent1 = [w.lower() for w in sent1]
        sent2 = [w.lower() for w in sent2]

        all_words = list(set(sent1 + sent2))

        vector1 = [0] * len(all_words)
        vector2 = [0] * len(all_words)

        # build the vector for the first sentence
        for w in sent1:
            if w in stopwords:
                continue
            vector1[all_words.index(w)] += 1

        # build the vector for the second sentence
        for w in sent2:
            if w in stopwords:
                continue
            vector2[all_words.index(w)] += 1

        return core_cosine_similarity(vector1, vector2)


def sentences_rel(data,num):
    """
    each word in a sentence is removed and been compared to the
    corpus to calculate similarity score and top and least similar
    sentences are displayed
    """
    a = []
    s = []
    d = []
    e = []

    cor = token(data)
    corp = [c for c in cor if c.isalpha()]
    stop_words = set(stopwords.words('english'))
    words = [w for w in cor if w not in stop_words]
    bs = np.array(_sentence_similarity(data_corpus,data))
    print("\nBaseline score is:",bs)
    s.append(data)
    a.append(bs)


    for i in words:
```

```
        j = data.replace(i,"")
        c = np.array(_sentence_similarity(data_corpus,j))
        e.append(c-bs)
        s.append(words)
        a.append(c)
        d.append(i)
    d = pd.DataFrame(d)
    e = pd.DataFrame(e)
    df_1 = pd.DataFrame(s)
    a = pd.DataFrame(a)
    df_1 = pd.concat([df_1,a,d,e], axis =1)
    df_1.columns = ['sentence', 'score','word','lift']
    df_2=df_1.drop_duplicates(subset=['word'])
    df_2= df_2[:-1]
    top_sentences = df_2.sort_values(by='lift', ascending=False)


    top_sentences1=top_sentences.head(num)
    least_sentences=top_sentences.tail(num)

    print("\nTop",num,"contributing lift words are:\n",top_sentences1[
['word', 'lift']])
    print("\nLeast",num,"contributing lift words are:\n",least_sentenc
es[['word', 'lift']])

    #plotting the top scores and words
    fig = plt.Figure()
    plt.bar(top_sentences1.word, top_sentences1.lift)
    plt.title('Top lift words', fontsize=20)
    plt.xlabel('Words', fontsize=16)
    plt.ylabel('Score', fontsize=16)
    plt.show()

    #plotting the least scores and words

    plt.bar(least_sentences.word, least_sentences.lift,color='purple')
    plt.title('least affecting words', fontsize=20)
    plt.xlabel('Words', fontsize=16)
    plt.ylabel('Score', fontsize=16)
    plt.show()

    #return "top 5 sentence with highest similarity are:",top_sentence
s[:5],"least 5:",top_sentences.tail(5)

def vector(text):
    """
    input text is vectorized with respect to corpus and
    average score is generated
    """
```

```
    vectorizer=CountVectorizer()

    a=token(data_corpus)
    text=[text]
    vocabulary=vectorizer.fit(a)
    X= vectorizer.transform(text)
    a=X.toarray()
    b=a.tolist()
    c=np.mean(a)
    b=vocabulary.get_feature_names()
    return "The baseline score is:",c


if __name__ =='__main__':
    """
    input is taken from the user and all functions are run here
    """

    data = input("Enter any string to calculate the lift score with pe
rsona: ");
    num=int(input("Enter how many top and lest lift words you want: ")
)

    c=sentences_rel(data,num)
```

```
Enter any string to calculate the lift score with persona: Elon Musk
might say some crazy stuff, but he's right about at least one thing:
his electric vehicles have changed the world. When the Model S launc
hed in 2012, it was the first long-range, widely desired electric ve
hicle, and mainstream automakers have been struggling to catch up ev
er since. The Model S is still impressive—it now has an EPA-estimate
d 373 miles of range in its Long Range variant—but for all its focus
on autonomous technology, over-the-air updates, and Easter eggs, Tes
la's interiors and build quality can sometimes fall short of expecta
tions. Better-established luxury automakers are finally getting in o
n the EV game—Porsche's Taycan is aimed directly at the Model S, for
example—and Tesla will need all its Silicon Valley pivot-power to st
ay ahead of the pack.  The seven-seat Volvo XC90 is another luxury m
idsize SUV that boasts pioneering technology. It comes standard with
high-tech safety systems that help you stay alert, detect people and
large animals in your path, and even handles some of the driving wit
h its semiautonomous Pilot Assist. Shoppers who favor heart-pumping
over a lavish interior should take a Porsche Cayenne out for a spin.
This five-seat SUV's potent powertrains launch it from zero to 60 mp
h in as little as 3.9 seconds, while its smartly tuned suspension tr
eats passengers to a comfortable ride.
Enter how many top and lest lift words you want: 5

Baseline score is: 0.9564541220919766

Top 5 contributing lift words are:
        word     lift
76      stay  0.000756
103     path  0.000440
87    boasts  0.000412
80      seat  0.000271
95   systems  0.000245

Least 5 contributing lift words are:
           word      lift
104        even -0.001709
23      vehicle -0.002020
88   pioneering -0.002218
10     electric -0.003227
115    interior -0.003659
```


Top lift words
Score
0.0007
0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
stay
path
boasts
seat
systems
Words


least affecting words
Score
0.0000
−0.0005
−0.0010
−0.0015
−0.0020
−0.0025
−0.0030
−0.0035
even
vehicle
pioneering
electric
interior
Words

Sample input

Elon Musk might say some crazy stuff, but he's right about at least one thing: his electric vehicles have changed the world. When the Model S launched in 2012, it was the first long-range, widely desired electric vehicle, and mainstream automakers have been struggling to catch up ever since. The Model S is still impressive—it now has an EPA-estimated 373 miles of range in its Long Range variant—but for all its focus on autonomous technology, over-the-air updates, and Easter eggs, Tesla's interiors and build quality can sometimes fall short of expectations. Better-established luxury automakers are finally getting in on the EV game—Porsche's Taycan is aimed directly at the Model S, for example—and Tesla will need all its Silicon Valley pivot-power to stay ahead of the pack.

The seven-seat Volvo XC90 is another luxury midsize SUV that boasts pioneering technology. It comes standard with high-tech safety systems that help you stay alert, detect people and large animals in your path, and even handles some of the driving with its semiautonomous Pilot Assist. Shoppers who favor heart-pumping over a lavish interior should take a Porsche Cayenne out for a spin. This five-seat SUV's potent powertrains launch it from zero to 60 mph in as little as 3.9 seconds, while its smartly tuned suspension treats passengers to a comfortable ride.

Future scope

1 Month

We would improve the charts, inculcate the whole program on a web server and diplay on a website so only the input box is visible.

3 Months

Find better algorithms to increase precision and also increase knowledge of the model, will also try to add more features and personas to the platform which would help users benefit.

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Appendices

def process(data,num): """ both the corpus and data are been processed and each word of the text input is compared with the corpus to compute lift score and display charts and words with highest and least similarity """ #Formatting the input data cor = word_tokenize(data) cor = [c for c in cor if c.isalpha()] stop_words = set(stopwords.words('english')) words = [w for w in cor if w not in stop_words] lem = [WordNetLemmatizer().lemmatize(i) for i in words] y =[] w = [] #comparing each word with corpus for i in lem: w.append(i) x = _sentence_similarity(data_corpus,i) y.append(x) df = pd.DataFrame(w) y = pd.DataFrame(y) df = pd.concat([df,y], axis =1) df.columns = ['word', 'score'] basescore=df['score'].sum() print("\nThe base score is: ",basescore) #sorting and storing top and least scores top_words = df.sort_values(by='score', ascending=False) top_words1=top_words.head(num) least_words1=top_words.tail(num) print("\nTop",num,"contributing words are:\n",top_words.head(num)) print("\nleast",num,"contributing words are:\n",top_words.tail(num)) #plotting the top scores and words fig = plt.Figure() plt.bar(top_words1.word, top_words1.score) plt.title('Top similar words', fontsize=20) plt.xlabel('Words', fontsize=16) plt.ylabel('Score', fontsize=16) plt.show() #plotting the least scores and words low_words=top_words.tail(num) plt.bar(low_words.word, low_words.score,color='purple') plt.title('least similar words', fontsize=20) plt.xlabel('Words', fontsize=16) plt.ylabel('Score', fontsize=16) plt.show() #return # return " top 5 words improving score are:",top_words[:5],"least impacting words are:",top_words.tail(5)

For any further clarifications please feel free to reach me out at kaja.s@husky.neu.edu