Aspect/Modifier Classification Analysis

Project Links

Below is the link for the GitHub project page.

Github link (https://github.com/ddey117/ABSA_Project_4)

Import research papers for developement of parser logic. Includes pdf links for spaCy research paper as well as VADER sentiment intensity analyzer. Much work has been done on aspect based sentiment analysis. Please feel free to check out some previous work in the link below.

Research Papers (https://github.com/ddey117/ABSA_Project_4/tree/main/research_papers)

For another way to navigate of my overall project, please feel free to check out a HTML version of my project overview at the link below. There is also a link in this directory to see an example of what exactly a Turk worker was looking at when they were labeling data for this project.

html project directory (https://github.com/ddey117/ABSA_Project_4/tree/main/html)

Overview

```
The target for this project is an established e-commerce business w
ith a large amount of review data, such as Amazon.com or other onli
ne retailers. The goal of this project is to take advantage of tech
nology and models provided by Spacy combined with a pretrained sent
iment intensity classifier provided by the NLTK toolkit in order to
perform more fine grained sentiment analysis at scale in an efficie
nt manner. This project takes advantange of the parsing and part of
speech tagging capabilites of Spacy's pipeline in order to extract
 aspect/opinion/sentiment triplets. After the aspects are identifie
d, they can be grouped using unsupervised machine learning clusteri
ng techniques; in this case k-means clustering for model speed and
 simplicity. The buisness can use the finished product to quickly t
ransform a large amount of informal review data (text data from rev
iews that may ramble for pages) and transform it into helpful graph
s in order to tune into a small number of categories and help funne
l resources into areas where they are most needed. Amazon Turk was
 taken advantage of to crowd source human labels to analyze the per
formance of the model.
```

Data Exploration Notebook

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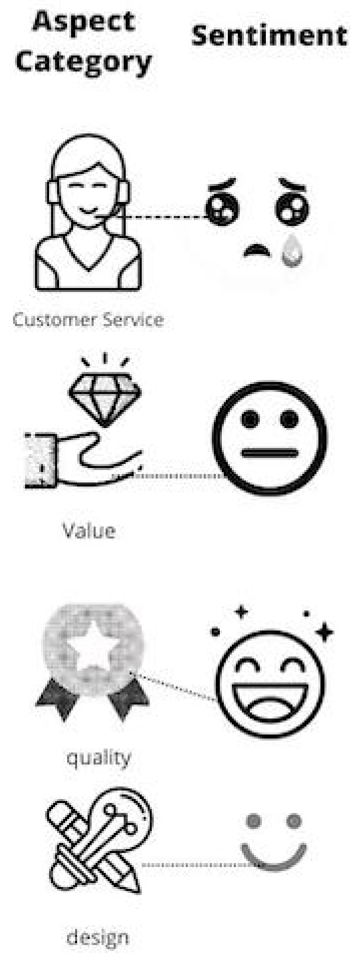
Buisness Problem


Aspect
Category
Sentiment
Customer Service
Value
quality
design

```
Sentiment analysis involves computationally identifying and categor
izing the sentiment expressed by an author in a body of text. It ha
s a wide range of applications in industry from stock speculation u
sing sentiment expressed in news and blogs, to identifying customer
satisfaction from their reviews and social media posts.
Today, most e-commerce website designs include a section where thei
r customers can post reviews for products or services. Customers ar
e free to write how they feel about fine grained aspects of a produ
ct at length. From a business perspective, very valuable informatio
n can be extracted from this section, such as customers' opinion on
a product, understanding of a product, etc..
 On Amazon.com the rating can be between 1 and 5 where 1 is the wor
st and 5 is the best. A customer can leave as lengthy of a review a
s they wish about a product to explain why a given rating was poste
d.  For example, a customer may give a product a low rating because
they didn't like someone they spoke to in customer service but like
d everything else about the product.  In typical sentiment analysi
s, these kinds of nuances would be missed since it could only be de
termined  if the overall body of the review contained positive, neu
tral, or negative sentiment. Valuable information would be left on
 the table.
 There is potentially a disconnect from the amazon review ratings,
 and the overall sentiment of the body text explaining the review,
 especially if you begin to break down the text into smaller aspect
s. Thus, Aspect Based Sentiment Analysis (ABSA) was chosen to see i
f a deeper understanding of each product can be gained by breaking
 down each review into aspect categories to be paired with predicte
d sentiment, which will then be compared with the overall rating (1
-5).
 It is often difficult to efficiently get useful data from a large
 collection of text data. A lot of e-commerce websites have thousan
ds of reviews and more incoming all of the time. Thousands of revie
ws with hundreds of words of mostly unhelpful information seems fai
rly unmanageable to most companies. While the reviews are rather in
formal, if they are carefully broken down there is information wort
h saving before generalizing again for efficiency. Aspect Based Sen
timent Analysis can transform a messy collection of thousands of in
formal reviews into a neat and manageable collection of a few aspec
t categories, in this case 4 different categories using the out of
 box  Aspect/Opinion/Sentiment Triplet Extractor. Each category wil
l have an associated degree of sentiment related to it, and therefo
re graphics can easily be prepared and presented to digest more pre
cisely what it is that customers do and do not like about a product
in a quickly digestible format in real time. By breaking it down in
to these categories, say for example Product Design, Value, Qualit
y, and Customer Support, the mass of text data has now been transfo
rmed into a numerical representation of sentiment towards broad cat
egories of a product that can be directly improved upon by the comp
any. If a product scores very high sentiment for value and design b
```

```
ut lower scores for customer support, then a company knows it doesn
t need to invest more money into improving the product and actually
needs to focus on improving how its forward facing employees intera
ct with customers.
```

The Data

Helpful links:

ReadMe file for Amazon Product Reviews (https://s3.amazonaws.com/amazon-reviews-pds/readme.html) | MetaData (https://s3.amazonaws.com/amazon-reviews-pds/tsv/index.txt)

The Amazon Customer Reviews (Product Reviews) contains over 130+ million customer reviews available to researchers in TSV files in the amazon-reviews-pds S3 bucket in AWS US East Region, as per the provided readme file. The reviews were collected from 1995 to 2015. See the provided link for associated metadata. This project focuses on the dataset given by pulling "https://s3.amazonaws.com/amazon-reviews-pds/tsv/amazon_reviews_us_Electronics_v1_00.tsv.gz" (https://s3.amazonaws.com/amazon-reviews-pds/tsv/amazon_reviews_us_Electronics_v1_00.tsv.gz%E2%80%9D) from the S3 bucket.

Product_id "B0001FTVEK" (https://www.amazon.com/Sennheiser-RS120-Wireless-Headphones-Charging/dp/B0001FTVEK) was chosen to showcase the triplet extractor as it had a large amount of verified reviews and a pair of headphones seemed like a reasonable choice for aspect based sentiment analysis.

Clean Data

Text data trends towards exponential growth with increasing dataset size. Therefore, text cleaning and preprocessing was a major considersation of this project. Please refer to my Text Preprocessing Toolset (https://github.com/ddey117/preprocess_ddey117) that I created to use for this and other projects that involve text data preprocessing.

Unlabeled Data Created Through Unsupervised Learning

This project showcases an out of box product for extracting opinon/aspect/sentiment triplets from a large amount of messy text data and converting it into a neat set of categories for analysis. To do this, however, it takes advantage of some simple clustering techniques from the sklearn cluster library. For this project, kmeans clustering was chosen for speed and simplicity. Error analysis will be discussed later in more detail in regards to how the model performs with clustering the reviews appropriately into categories and what issues it may run into when parsing internet language. Error analysis for the SentimentIntensityClassifier (https://www.nltk.org/howto/sentiment.html) offered by the Natural Language ToolKit (NLTK library) will be tested against this 'newly' generated data from my unsupervised learning will be performed by comparing to a seperate set of hand labeled aspect/modifier pairs by humans in an expiremental setting.

experimental setup

Using the following Turk_Form_HTML (html/Turk_Instructions.html) I crowdsourced some labels from humans using Amazon Mechanical Turk to compare to my model using the SentimentIntensityAnalyzer for each aspect/modifier pair extracted from the Amazon reviews. Amazon Mechanical Turk works by quickly dispersing large amounts of data to a large number of people in order to complete simple tasks for a reward. This experiment was set up to reward a penny for each aspect/modifier pair labeled for sentiment from very negative to very positive with an option for NA from a drop down menu (see html above for reference). In total, 410 workers submitted 6107 non-null aspect/opinion pairs for sentiment intensity pertaining to 1438 unique aspects. Duplicate pairs of aspect/opinion pairs were included to inspect variance of submission from human labels and machine labels for each opinion pair. No qualifications or screening was put in place before the workers were chosen, but I did review sections of the data and accept or reject what seemed reasonable.

All labels were generated using my triplet extractor on the dataset describing Product_id "B0001FTVEK" (https://www.amazon.com/Sennheiser-RS120-Wireless-Headphones-Charging/dp/B0001FTVEK) and randomized for different aspect/modifier pairs before sending out to humans for rating for sentiment.

Amazon Product Reviews ReadME (https://s3.amazonaws.com/amazon-reviews-pds/readme.html) | Amazon Product Reviews MetaData (https://s3.amazonaws.com/amazon-reviews-pds/tsv/index.txt) | Sennheiser-RS120-Wireless-Headphones (https://www.amazon.com/Sennheiser-RS120-Wireless-Headphones-Charging/dp/B0001FTVEK)

In [1]:

```python
#import necessary libraries

import pandas as pd
import numpy as np
# import dataframe_image as dfi
import string
import re
from matplotlib import pyplot as plt
import seaborn as sns
from nltk.corpus import stopwords
from nltk import FreqDist, word_tokenize
# from nltk.tokenize import TweetTokenizer
from nltk.stem import WordNetLemmatizer
# from wordcloud import WordCloud, STOPWORDS
import re,string
import unidecode
import html

import preprocess_ddey117 as pp


import requests
import os
import csv
import urllib.request
import gzip
import sys
import spacy
import json
# import boto3
# from boto.s3.connection import S3Connection

from collections import defaultdict
from sklearn import cluster
import seaborn as sns

import nltk
# nltk.download('vader_lexicon')

import spacy
nlp = spacy.load("en_core_web_lg")

from nltk.sentiment.vader import SentimentIntensityAnalyzer
sid = SentimentIntensityAnalyzer()

# from nltk.collocations import *
# bigram_measures = nltk.collocations.BigramAssocMeasures()
# trigram_measures = nltk.collocations.TrigramAssocMeasures()
# fourgram_measures = nltk.collocations.QuadgramAssocMeasures()
```

```
/Users/dylandey/anaconda3/envs/learn-env/lib/python3.6/site-packages/te
nsorflow/python/framework/dtypes.py:518: FutureWarning: Passing (type,
1) or '1type' as a synonym of type is deprecated; in a future version o
f numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/Users/dylandey/anaconda3/envs/learn-env/lib/python3.6/site-packages/te
```

```
nsorflow/python/framework/dtypes.py:519: FutureWarning: Passing (type,
1) or '1type' as a synonym of type is deprecated; in a future version o
f numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/Users/dylandey/anaconda3/envs/learn-env/lib/python3.6/site-packages/te
nsorflow/python/framework/dtypes.py:520: FutureWarning: Passing (type,
1) or '1type' as a synonym of type is deprecated; in a future version o
f numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/Users/dylandey/anaconda3/envs/learn-env/lib/python3.6/site-packages/te
nsorflow/python/framework/dtypes.py:521: FutureWarning: Passing (type,
1) or '1type' as a synonym of type is deprecated; in a future version o
f numpy, it will be understood as (type, (1,)) / '(1,)type'.
```

A large collection of amazon reviews that fall under the "electronics" category. For this project, product_id ["B0001FTVEK" (https://www.amazon.com/Sennheiser-RS120-Wireless-Headphones-Charging/dp/B0001FTVEK)](https://www.amazon.com/Sennheiser-RS120-Wireless-Headphones-Charging/dp/B0001FTVEK) was chosen as it had a large amount of verified reviews and a pair of headphones seemed like a reasonable choice for aspect based sentiment analysis.

In [2]:

```
# df = pd.read_csv('data/df_electronics.tsv', sep='\t')
# df.groupby('product_id').count().sort_values(by='star_rating').tail(2
```

In [4]:

```
df = pd.read_csv('data/df_electronics.tsv', sep='\t')
df.groupby('product_id').count().sort_values(by='star_rating').tail(20)
```

Out[4]:

product_id	marketplace	customer_id	review_id	product_parent	product_title	product_category	star_rating	helpful_votes	total_votes	vine	verified_purcl
B004LTEUDO	3997	3997	3997	3997	3997	3997	3997	3997	3997	3997	[illegible]
B004HHICKC	4213	4213	4213	4213	4213	4213	4213	4213	4213	4213	[illegible]
B0[illegible]	[illegible]	[illegible]	4773	4773	4773	4773	4773	4773	4773	4773	[illegible]
B001TH7GSW	4866	4866	4866	4866	4866	4866	4866	4866	4866	4866	[illegible]
B008KVUAGU	5015	5015	5015	5015	5015	5015	5015	5015	5015	5015	[illegible]
B003WGRUQQ	5072	5072	5072	5072	5072	5072	5072	5072	5072	5072	[illegible]
B002MAPT7U	5295	5295	5295	5295	5295	5295	5295	5295	5295	5295	[illegible]
B001GTT0VO	5580	5580	5580	5580	5580	5580	5580	5580	5580	5580	[illegible]
B0052SCU8U	5756	5756	5756	5756	5756	5756	5756	5756	5756	5756	[illegible]
B00316263Y	5813	5813	5813	5813	5813	5813	5813	5813	5813	5813	[illegible]
B00D5Q75RC	6062	6062	6062	6062	6062	6062	6062	6062	6062	6062	[illegible]
B004QK7HI8	6536	6536	6536	6536	6536	6536	6536	6536	6536	6536	[illegible]
B00F5NE2KG	6688	6688	6688	6688	6688	6688	6688	6688	6688	6688	[illegible]
B0019EHU8G	7586	7586	7586	7586	7586	7586	7586	7586	7586	7586	[illegible]
B000WYVBR0	7835	7835	7835	7835	7835	7835	7835	7835	7835	7835	[illegible]
B0001FTVEK	8793	8793	8793	8793	8793	8793	8793	8793	8793	8793	[illegible]
B0012S4APK	9359	9359	9359	9359	9359	9359	9359	9359	9359	9359	[illegible]
B003EM8008	9766	9766	9766	9766	9766	9766	9766	9766	9766	9766	[illegible]
B0002L5R78	11166	11166	11166	11166	11166	11166	11166	11166	11166	11166	[illegible]
B003L1ZYYM	15334	15334	15334	15334	15334	15334	15334	15334	15334	15334	[illegible]

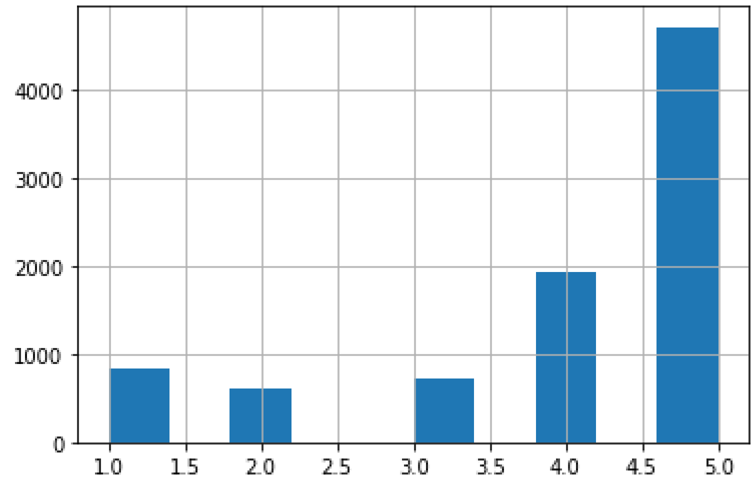
click to scroll output; double click to hide

In [3]:
```
#testing other dataframes not shown in this notebook



# df_hp1 = df.loc[df['product_id'] == 'B003EM8008'].copy()
# df_hp1.reset_index(drop=True, inplace=True)
# df_hp2 = df.loc[df['product_id'] == 'B0001FTVEK'].copy()
# df_hp2.reset_index(drop=True, inplace=True)
# df_hp3 = df.loc[df['product_id'] == 'B004RKQM8I'].copy()
# df_hp3.reset_index(drop=True, inplace=True)
# df_hp4 = df.loc[df['product_id'] == 'B0038W0K2K'].copy()
# df_hp4.reset_index(drop=True, inplace=True)

# df_sb1 = df.loc[df['product_id'] == 'B00D5Q75RC'].copy()
# df_sb1.reset_index(drop=True, inplace=True)
# df_sb2 = df.loc[df['product_id'] == 'B00F5NE2KG'].copy()
# df_sb2.reset_index(drop=True, inplace=True)

# df_mp1 = df.loc[df['product_id'] == 'B00020S7XK'].copy()
# df_mp1.reset_index(drop=True, inplace=True)
# df_mp2 = df.loc[df['product_id'] == 'B002MAPT7U'].copy()
# df_mp2.reset_index(drop=True, inplace=True)

# #dropping uneccessary columns

# columns_td = ['marketplace', 'customer_id',  'product_id',
#                'product_parent', 'product_title', 'product_category',
#                'helpful_votes', 'total_votes', 'vine', 'verified_purch
#                'review_headline', 'review_date']

# df2.drop(columns=columns_td, inplace=True)

#saving dataframe with chosen product for quick loading time

# df2.to_csv('data/df_electronics_example.csv', index=False)
```

In [4]:
```
#display important information about dataset
#Almost 9000 reviews, mostly 4 or 5 stars.

df = pd.read_csv("data/df_electronics_example.csv")
display(df.head())
print("\n")
print('star rating value counts')
display(df.star_rating.value_counts())
display(df.star_rating.hist())
df.info()
print("\n")
print("distribution of star rating")
```

	review_id	star_rating	review_body
0	R17U6AU06HR16Q	5	Great product.
1	R31Y01GPXH7P64	4	work great sounds amazing
2	RG40FO7CNWOG7	5	Works tremendously well.
3	R2CI6TXIGZR6RU	5	THEY WORK GREAT
4	R37KF8VRBUZNQD	5	Works fine

```
star rating value counts

5    4715
4    1924
1     829
3     724
2     601
Name: star_rating, dtype: int64

<AxesSubplot:>

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8793 entries, 0 to 8792
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   review_id    8793 non-null   object
 1   star_rating  8793 non-null   int64 
 2   review_body  8793 non-null   object
dtypes: int64(1), object(2)
memory usage: 206.2+ KB


distribution of star rating
```



Function Definition

In [5]:

```python
#I wrote a library for taking care of many common tasks for data langua
#However, since this project must load spaCy for parsing the aspect/opi
#Some of the major processing will be handled by spaCy

#simple processing such as removing emails, html tags, urls
#accented characters and counting all words in the dataset
#are handled with my own toolset

def master_preprocess(df):
    df['wordcounts'] = df['review_body'].apply(lambda x: pp.get_wordcou
    df['review_body'] = df['review_body'].apply(lambda x: pp.remove_ema
    df['review_body'] = df['review_body'].apply(lambda x: pp.remove_url
    df['review_body'] = df['review_body'].apply(lambda x: pp.remove_htm
    df['review_body'] = df['review_body'].apply(lambda x: pp.remove_acc
    return df
```

In [6]:

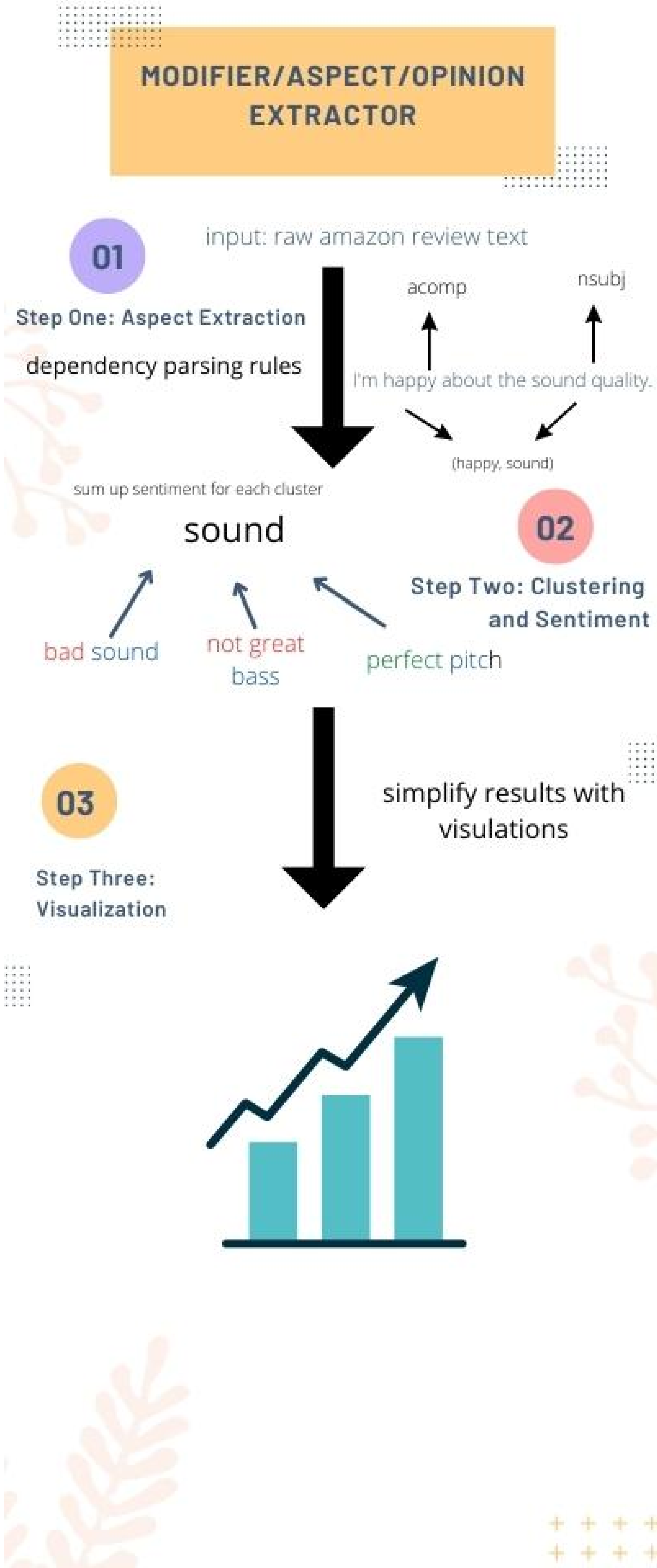
```python
df = master_preprocess(df)
```

In [7]:
```
#Looking at the statistics for wordcounts below
#The median length for a amazon review
#for this particular set of headphones is about 50 words
#ranging from 1 to 1565 words for each review
#Thus showing the wide range of informal data that is
#allowed in the review body and how unmanageable it can
#become
#With this dataset the total amount of words
#has already reached over half of a million words


display(df.describe())
df.wordcounts.sum()
```

	star_rating	wordcounts
count	8793.000000	8793.000000
mean	4.034346	74.089730
std	1.318899	91.416481
min	1.000000	1.000000
25%	4.000000	23.000000
50%	5.000000	47.000000
75%	5.000000	92.000000
max	5.000000	1565.000000

Out[7]: 651471

Explaining The Parser


MODIFIER/ASPECT/OPINION EXTRACTOR
01
input: raw amazon review text
acomp
nsubj
Step One: Aspect Extraction
dependency parsing rules
I'm happy about the sound quality.
(happy, sound)
sum up sentiment for each cluster
sound
02
Step Two: Clustering and Sentiment
bad sound
not great bass
perfect pitch
simplify results with visulations
03
Step Three: Visualization

Clustering and Polarity

A large number of amazon reviews produce a large number of aspect-modifier pairs. These pairs ultimately seemed to diverge to common topics, and therefore it would make sense to use machine learning to automatically figure out these categories for us. This leads to a better summation of insight from the total pool of customers who were kind enough to leave a review. Polarity scores are also averaged out of every cluster to give a quantifiable explanation to opinion to distinct categories of a given product.

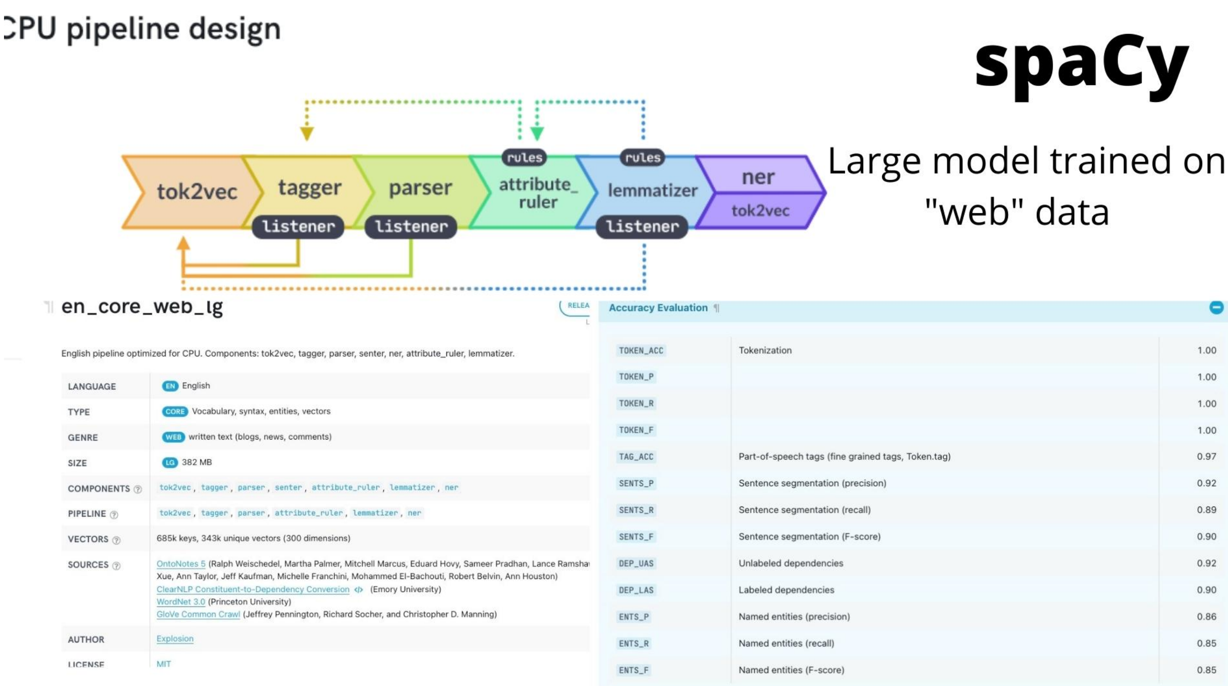
Word Vectors and Clustering

In order to work with any amazon review data, first the text data must be converted into something that a machine can recognize. The most famous implementation of words vectors is the word2vec project. However, spaCy vectorization was chosen for this projec as it provides fast and easy access to over a million unique word vectors, and its multi-task CNN model is trained on 'web' data and not 'newspaper' data as in other libraries like NLTK.

The word vectors were then grouped using K-Means clustering algorithm in Scikit-Learn. Other clustering algorithms such as DBSCAN were tested. However, K-Means gave optimal results with four clusters. The clusers were labeled with input from a user after suggesting the top most common word for each cluster.

Below Is the pipeline design for spaCy and a description for the size and sources for the model loaded to run this project and parse the amazon reviews.

[en_core_web_large (https://spacy.io/models/en#en_core_web_lg)](https://spacy.io/models/en#en_core_web_lg)



English pipeline optimized for CPU. Components: tok2vec, tagger, parser, senter, ner, attribute_ruler, lemmatizer.

LANGUAGE	EN English
TYPE	CORE Vocabulary, syntax, entities, vectors
GENRE	WEB written text (blogs, news, comments)
SIZE	LG 382 MB
COMPONENTS	tok2vec, tagger, parser, senter, attribute_ruler, lemmatizer, ner
PIPELINE	tok2vec, tagger, parser, attribute_ruler, lemmatizer, ner
VECTORS	685k keys, 343k unique vectors (300 dimensions)
SOURCES	OntoNotes 5 (Ralph Weischedel, Martha Palmer, Mitchell Marcus, Eduard Hovy, Sameer Pradhan, Lance Ramsha Xue, Ann Taylor, Jeff Kaufman, Michelle Franchini, Mohammed El-Bachouti, Robert Belvin, Ann Houston) ClearNLP Constituent-to-Dependency Conversion (Emory University) WordNet 3.0 (Princeton University) GloVe Common Crawl (Jeffrey Pennington, Richard Socher, and Christopher D. Manning)
AUTHOR	Explosion
LICENSE	MIT

TOKEN_ACC	Tokenization	1.00
TOKEN_P		1.00
TOKEN_R		1.00
TOKEN_F		1.00
TAG_ACC	Part-of-speech tags (fine grained tags, Token.tag)	0.97
SENTS_P	Sentence segmentation (precision)	0.92
SENTS_R	Sentence segmentation (recall)	0.89
SENTS_F	Sentence segmentation (F-score)	0.90
DEP_UAS	Unlabeled dependencies	0.92
DEP_LAS	Labeled dependencies	0.90
ENTS_P	Named entities (precision)	0.86
ENTS_R	Named entities (recall)	0.85
ENTS_F	Named entities (F-score)	0.85

"spaCy uses the terms **head** and **child** to describe the words connected by a single arc in the dependency tree. The term **dep** is used for the arc label, which describes the type of syntactic relation that connects the child to the head. As with other attributes, the value of .dep is a hash value. You can get the string value with .dep_." [Navigating The Parse Tree (https://spacy.io/usage/linguistic-features#navigating)](https://spacy.io/usage/linguistic-features#navigating)

First Rule of Dependency Parser: The Aspect (A) token is a subject noun with a child modifier (M) that has a relation of amod (adjectival modifier). This just means that the aspect and opinion share a simple adjective/noun relationship that can be extracted. However, there are certain caveats that need to be kept in mind when parsing the tree for this rule.

- First, it is important to check to see if there is an additional adverbial modifier that could adjust the intensity of the sentiment implied by the adjective and adverb combination in regards to the subject/aspect. This is important to keep in mind as we are taking advantage of NLTK vader sentiment intensity analyzer which can make use of additional adverbs to get a better understanding of sentiment.
- Another important thing to keep in mind when parsing for this rule is to be aware of the possibility of negating the adjective with 'no' as a determiner.

First Rule Examples

Example1: The comfortable headphones.

Example2: The most comfortable headphones.

Example3: No comfortable features.

- det = determiner
- A = aspect
- M = modifier
- amod = adjectival modifier

Second Rule of Dependency Parser: The aspect (A) is a child of something with a relation of nominal subject (nsubj.) while the modifier (M) is a child of the same something with a relationship of direct object. In this case, the adjective would be acting as the determiner of the clause. For simplicity's sake, it was determined to assume that each verb will have only one NSUBJ and DOBJ. This is a fair assumption for the application of this project, because even if there are multiple subjects, they will both be reviewing the same thing and will likely share the same opinion as it is written as a single review. For example, if an author were to say "My wife and I bought the awesome headphones", we still only want to extract the keywords 'awesome' and 'headphones.' If this sounds confusing, hopefully the example below will help clarify.

Second Rule Example

Example: I bought the awesome headphones.

- nsubj = nominal subject
- dobj =headphones
- det= awesome

Third Rule of Dependency Parser: The modifier (M) is a child of something with a relation of an adjectival complement (acomp), while the aspect (A) is a child of that same something with a relation of nominal subject (nsubj).

- This rule needs to handle special cases in which the child is tagged as a modal verb with an auxiliary dependency. This would flag for phrases such as “the sound of the speakers could be better.” For special cases like this, the parser will add a negative prefix before scoring the aspect/modifier pairs for sentiment.

Third Rule Examples

Example1: Barb is happy about the sound quality.

Example2: This could be better.

Example2 would be extracted as A= "this" and M= "not better"

- A = aspect
- M = modifier

Fourth Rule of Dependency Parser: The aspect (A) is a child of something with a relationship of passive nominal subject (nsubjpass) while the modifier (M) is a child of that same something with a relationship of adverbial modifier (advmod). In other words, the modifier is an adverbial modifier to a passive verb.

- nsubjpass: A passive nominal subject is a noun phrase which is the syntactic subject of a passive clause.
- This step of the parser will also check to add a negative prefix before extracting and scoring for sentiment if necessary

Fourth Rule Examples

Example1: The headphones died quickly.

- A = aspect
- M = modifier

Fifth Rule of Dependency Parser: The aspect (A) is a child of the modifier with a relationship of nominal subject, while the modifier has a child with a relation of copula(cop). Here the parser is looking for the complement of a copular verb. An often used copula verb is the word “is,” as in the phrase “Bill is big."

- Assumption - A verb will have only one NSUBJ and DOBJ
- cop: copula A copula is the relation between the complement of a copular verb and the copular verb. (We normally take a copula as a dependent of its complement.

Fifth Rule Example

Example1: The sound is awesome.

- A = aspect
- M = modifier

Sixth Rule of Dependency Parser: Aspect/modifier are children of an interjection

- NTJ (interjections like bravo, great etc)

Sixth Rule Example

Example1: Bravo, headphones.

- A = aspect
- M = modifier

Seventh Rule of Dependency Parser: This rule is similar to rule 5, but makes use of the attr (attribute) tag instead. It seems to function similarly, in which an attribute is considered a noun phrase following a copular verb

- ATTR - link between a verb like 'is/seem/appear/became' and its complement

Seventh Rule Example

Example1: This is garbage.

- A = aspect
- M = modifier

For all Parsing: SpaCy has a large library of named entities it can recoginize and tag. This logic is added for each step in the model.

In [8]:
```
spacy.explain('acomp')
```

Out[8]: 'adjectival complement'

Please feel free to review the following sections above under the spaCy documentation for pos_tagging if you would like to get an understanding of how the parser was designed in spaCy. Each link should be a direct link to the appropriate topic.

Dependecy Parsing with spaCy (https://spacy.io/usage/linguistic-features#dependency-parse)

Navigating The Tree (https://spacy.io/usage/linguistic-features#navigating)

Named Entity Recognition (https://spacy.io/usage/linguistic-features#named-entities)

Hutto, C.J. & Gilbert, E.E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor, MI, June 2014.

VADER sentiment (https://www.researchgate.net/publication/275828927_VADER_A_Parsimonious_Rule-based_Model_for_Sentiment_Analysis_of_Social_Media_Text)

The reasearch paper was published on release of the VADER intensity sentiment analyzer. Please feel free to read to get a better understanding of how this tool was developed before being taken advantage of in this project.

Detecting Product Aspects

In [9]:
```
display(spacy.explain('nsubjpass'))
display(spacy.explain('cop'))
display(spacy.explain('INTJ'))
spacy.explain('attr')
```

'nominal subject (passive)'

'copula'

'interjection'

Out[9]: 'attribute'

TABLE OF REFERENCE:
AMOD
adjectival modifier
ADVMOD
adverbial modifier
example: Genetically Modified Food, Less often
NSUBJ
"Nominal subject (nsubj) is a nominal which is the syntactic subject and the proto-agent of a clause. That is, it is in the position that passes typical grammatical test for subjecthood, and this

argument is the more agentive, the do-er, or the proto-agent of the clause. This nominal may be headed by a noun, or it may be a pronoun or relative pronoun or, in ellipsis contexts, other things such as an adjective." Taken from the documentation.
example: Genetically Modified Food, Less often

DOBJ
The direct object of a VP is the noun phrase which is the (accusative) object of the verb

DET
Determiner. "The English DET covers most cases of Penn Treebank DT, PDT, WDT. However, when a Penn Treebank word with one of these tags stands alone as a noun phrase rather than modifying another word, then it becomes PRON." Taken from the documentation.

ACOMP
Adjective complement. A phrase that modifies an adjective.

cop
"A cop (copula) is the relation of a function word used to link a subject to a nonverbal predicate, including the expression of identity predication (e.g. sentences like “Kim is the President”). It is often a verb but nonverbal (pronominal) copulas are also frequent in the world’s languages. Verbal copulas are tagged AUX, not VERB. Pronominal copulas are tagged PRON or DET." From the documentation.

INTJ
interjection. An interjection is a word that is used most often as an exclamation or part of an exclamation.

In [10]:

```
def apply_extraction(row,nlp=nlp,sid=sid):
    review_body = row['review_body']
#     review_id = row['review_id']
#     review_marketplace = row['marketplace']
#     customer_id = row['customer_id']
#     product_id = row['product_id']
#     product_parent = row['product_parent']
#     product_title = row['product_title']
#     product_category = row['product_category']
#     date = str(row['review_date'])
#     star_rating = row['star_rating']
#     url = add_amazonlink(product_id)



    doc=nlp(review_body)


    ## FIRST RULE OF DEPENDANCY PARSE -
    ## M - Sentiment modifier || A - Aspect
    ## RULE = M is child of A with a relationshion of amod(adjectival 
    ner_heads = {ent.root.idx: ent for ent in doc.ents}
    rule1_pairs = []
    for token in doc:
        A = "999999"
        M = "999999"
        if token.dep_ == "amod" and not token.is_stop:
            M = token.text
            if token.head in ner_heads:
                A = ner_heads[token.head].text
            else:
                A = token.head.text

            # add adverbial modifier of adjective (e.g. '*most* comfor
            M_children = token.children
            for child_m in M_children:
                if(child_m.dep_ == "advmod"):
                    M_hash = child_m.text
                    M = M_hash + " " + M
                    break

            # negation in adjective, the "no" keyword is a 'det' of th
            A_children = token.head.children
            for child_a in A_children:
                if(child_a.dep_ == "det" and child_a.text == 'no'):
                    neg_prefix = 'not'
                    M = neg_prefix + " " + M
                    break

        if(A != "999999" and M != "999999"):
            rule1_pairs.append((A, M,sid.polarity_scores(token.text)['

    ## SECOND RULE OF DEPENDANCY PARSE -
    ## M - Sentiment modifier || A - Aspect
    #Direct Object - A is a child of something with relationship of ns
    # M is a child of the same something with relationship of dobj
```

```
    #Assumption - A verb will have only one NSUBJ and DOBJ
#     ner_heads = {ent.root.idx: ent for ent in doc.ents}
    rule2_pairs = []
    for token in doc:
        children = token.children
        A = "999999"
        M = "999999"
        add_neg_pfx = False
        for child in children :
            if(child.dep_ == "nsubj" and not child.is_stop):
                if child.idx in ner_heads:
                    A = ner_heads[child.idx].text
                else:
                    A = child.text
                # check_spelling(child.text)

            if((child.dep_ == "dobj" and child.pos_ == "ADJ") and not
                M = child.text
                #check_spelling(child.text)

            if(child.dep_ == "neg"):
                neg_prefix = child.text
                add_neg_pfx = True

    if (add_neg_pfx and M != "999999"):
        M = neg_prefix + " " + M

        if(A != "999999" and M != "999999"):
            rule2_pairs.append((A, M,sid.polarity_scores(M)['compound'


    ## THIRD RULE OF DEPENDANCY PARSE -
    ## M - Sentiment modifier || A - Aspect
    ## Adjectival Complement - A is a child of something with relation
    ## M is a child of the same something with relationship of acomp
    ## Assumption - A verb will have only one NSUBJ and DOBJ
    ## "The sound of the speakers would be better. The sound of the sp


    rule3_pairs = []

    for token in doc:

        children = token.children
        A = "999999"
        M = "999999"
        add_neg_pfx = False
        for child in children :
            if(child.dep_ == "nsubj" and not child.is_stop):
                if child.idx in ner_heads:
                    A = ner_heads[child.idx].text
                else:
                    A = child.text
                # check_spelling(child.text)

            if(child.dep_ == "acomp" and not child.is_stop):
                M = child.text
```

```python

            # example - 'this could have been better' -> (this, not be
            if(child.dep_ == "aux" and child.tag_ == "MD"):
                neg_prefix = "not"
                add_neg_pfx = True

            if(child.dep_ == "neg"):
                neg_prefix = child.text
                add_neg_pfx = True

        if (add_neg_pfx and M != "999999"):
            M = neg_prefix + " " + M
                #check_spelling(child.text)

        if(A != "999999" and M != "999999"):
            rule3_pairs.append((A, M, sid.polarity_scores(M)['compound

    ## FOURTH RULE OF DEPENDENCY PARSE -
    ## M - Sentiment modifier || A - Aspect

    #Adverbial modifier to a passive verb - A is a child of something
    # M is a child of the same something with relationship of advmod

    #Assumption - A verb will have only one NSUBJ and DOBJ

    rule4_pairs = []
    for token in doc:


        children = token.children
        A = "999999"
        M = "999999"
        add_neg_pfx = False
        for child in children :
            if((child.dep_ == "nsubjpass" or child.dep_ == "nsubj") an
                if child.idx in ner_heads:
                    A = ner_heads[child.idx].text
                else:
                    A = child.text
                # check_spelling(child.text)

            if(child.dep_ == "advmod" and not child.is_stop):
                M = child.text
                M_children = child.children
                for child_m in M_children:
                    if(child_m.dep_ == "advmod"):
                        M_hash = child_m.text
                        M = M_hash + " " + child.text
                        break
                #check_spelling(child.text)

            if(child.dep_ == "neg"):
                neg_prefix = child.text
                add_neg_pfx = True

        if (add_neg_pfx and M != "999999"):
            M = neg_prefix + " " + M
```

```

        if(A != "999999" and M != "999999"):
            rule4_pairs.append((A, M,sid.polarity_scores(M)['compound'


    ## FIFTH RULE OF DEPENDANCY PARSE -
    ## M - Sentiment modifier || A - Aspect

    #Complement of a copular verb - A is a child of M with relationshi
    # M has a child with relationship of cop

    #Assumption - A verb will have only one NSUBJ and DOBJ

    rule5_pairs = []
    for token in doc:
        children = token.children
        A = "999999"
        buf_var = "999999"
        for child in children :
            if(child.dep_ == "nsubj" and not child.is_stop):
                if child.idx in ner_heads:
                    A = ner_heads[child.idx].text
                else:
                    A = child.text

                # check_spelling(child.text)

            if(child.dep_ == "cop" and not child.is_stop):
                buf_var = child.text
                #check_spelling(child.text)

        if(A != "999999" and buf_var != "999999"):
            rule5_pairs.append((A, token.text,sid.polarity_scores(toke


    ## SIXTH RULE OF DEPENDENCY PARSE -
    ## M - Sentiment modifier || A - Aspect
    ## INTJ (interjections like bravo, great etc)


    rule6_pairs = []
    for token in doc:
        children = token.children
        A = "999999"
        M = "999999"
        if(token.pos_ == "INTJ" and not token.is_stop):
            for child in children :
                if(child.dep_ == "nsubj" and not child.is_stop):
                    M = token.text
                    if child.idx in ner_heads:
                        A = ner_heads[child.idx].text
                    else:
                        A = child.text
                    # check_spelling(child.text)

        if(A != "999999" and M != "999999"):
            rule6_pairs.append((A, M,sid.polarity_scores(M)['compound'
```

```python


    ## SEVENTH RULE OF DEPENDENCY PARSE -
    ## M - Sentiment modifier || A - Aspect
    ## ATTR - link between a verb like 'be/seem/appear' and its comple
    ## Example: 'this is garbage' -> (this, garbage)

    rule7_pairs = []
    for token in doc:
        children = token.children
        A = "999999"
        M = "999999"
        add_neg_pfx = False
        for child in children :
            if(child.dep_ == "nsubj" and not child.is_stop):
                if child.idx in ner_heads:
                    A = ner_heads[child.idx].text
                else:
                    A = child.text
                # check_spelling(child.text)

            if((child.dep_ == "attr") and not child.is_stop):
                M = child.text
                #check_spelling(child.text)

            if(child.dep_ == "neg"):
                neg_prefix = child.text
                add_neg_pfx = True

        if (add_neg_pfx and M != "999999"):
            M = neg_prefix + " " + M

        if(A != "999999" and M != "999999"):
            rule7_pairs.append((A, M,sid.polarity_scores(M)['compound'



    aspects = []

    aspects = rule1_pairs + rule2_pairs + rule3_pairs +rule4_pairs +ru
    prod_pronouns = ['it', 'this', 'they']

    # replace all instances of "it", "this" and "they" with "product"
    aspects = [(A,M,P,r) if A not in prod_pronouns else ("product",M,P

#     dic = {"review_id" : review_id , "aspect_pairs" : aspects, "revi
#     , "customer_id" : customer_id, "product_id" : product_id, "produ
#     "product_title" : product_title, "product_category" : product_ca


    return aspects



def remove_digits(x):
    return " ".join([t for t in x.split() if not t.isdigit()])

```

```python


def get_word_vectors(unique_aspects, nlp=nlp):
    asp_vectors = []
    for aspect in unique_aspects:
        # print(aspect)
        token = nlp(aspect)
        asp_vectors.append(token.vector)
    return asp_vectors


def get_aspect_freq_map(aspects):
    aspect_freq_map = defaultdict(int)
    for asp in aspects:
        aspect_freq_map[asp] += 1
    return aspect_freq_map



NUM_CLUSTERS = 4

def get_word_cluster_labels(unique_aspects, nlp=nlp):
    # print("Found {} unique aspects for this product".format(len(uniq
    asp_vectors = get_word_vectors(unique_aspects, nlp)
    # n_clusters = min(NUM_CLUSTERS,len(unique_aspects))
    if len(unique_aspects) <= NUM_CLUSTERS:
        # print("Too few aspects ({}) found. No clustering required...
        return list(range(len(unique_aspects)))

    # print("Running k-means clustering...")
    n_clusters = NUM_CLUSTERS
    kmeans = cluster.KMeans(n_clusters=n_clusters)
    kmeans.fit(asp_vectors)
    labels = kmeans.labels_
    # dbscan = cluster.DBSCAN(eps = 0.2, min_samples = 2).fit(asp_vect
    # labels = dbscan.labels_

    # print("Finished running k-means clustering with {} labels".forma
    # print(labels)
    return labels



def get_cluster_names_map(asp_to_cluster_map, aspect_freq_map):
    cluster_id_to_name_map = defaultdict()
    # cluster_to_asp_map = defaultdict()
    clusters = set(asp_to_cluster_map.values())
    for i in clusters:
        this_cluster_asp = [k for k,v in asp_to_cluster_map.items() if
        filt_freq_map = {k:v for k,v in aspect_freq_map.items() if k i
        filt_freq_map = sorted(filt_freq_map.items(), key = lambda x:
        cluster_id_to_name_map[i] = filt_freq_map

        # cluster_to_asp_map[i] = this_cluster_asp

    # print(cluster_to_asp_map)
    # print(cluster_id_to_name_map)
```

```python
    return cluster_id_to_name_map



#Two master functions below for applying above functions


def extract_aspect_sentiment_tuples(df):
    df = master_preprocess(df)
    df = df.loc[df['wordcounts'] > 10].copy()
    df.reset_index(drop=True, inplace=True)
    df['aspect_tups'] = df.apply(apply_extraction, axis=1)
    df = df.explode('aspect_tups').copy()
    df.dropna(inplace=True)
    df['asp'] = df['aspect_tups'].apply(lambda x: x[0])
    df['modifier'] = df['aspect_tups'].apply(lambda x: x[1])
    df['modifier_sentiment'] = df['aspect_tups'].apply(lambda x: x[2])
    df['rule_number'] = df['aspect_tups'].apply(lambda x: x[3])
    return df


#This function will work with input from user
#to find best possible label name for clusters
def get_cluster_name_inputs(df):
    print('loading....')
    aspect_freq_map = get_aspect_freq_map(df['asp'].values)
    unique_asp_array = df['asp'].unique()
    mapped_labels = get_word_cluster_labels(unique_asp_array)
    asp_labels_map = dict(zip(unique_asp_array, mapped_labels))
    label_names_map = get_cluster_names_map(asp_labels_map, aspect_fre

    df['asp_cluster_label'] = df['asp'].map(asp_labels_map)

    print("write misc if low counts and special characters")
    print("the top word is usually the best fit")

    display(label_names_map[0][:10])
    print("Pick a category for above words: ")
    clust_0 = input()

    display(label_names_map[1][:10])
    print("Pick a category for above words: ")
    clust_1 = input()

    display(label_names_map[2][:10])

    print("Pick a category for above words: ")
    clust_2 = input()

    display(label_names_map[3][:10])
    print("Pick a category for above words: ")
    clust_3 = input()

    clusters = [clust_0] + [clust_1] + [clust_2] + [clust_3]


    name_clust_dict = {0: clusters[0],
```

```
                      1: clusters[1],
                      2: clusters[2],
                      3: clusters[3]
                     }



    df['cluster_name'] = df['asp_cluster_label'].map(name_clust_dict)

    fig = plt.figure(figsize=(10,8))

    df_senti.groupby(by='cluster_name')['modifier_sentiment'].sum().pl

    plt.title("Clustered Aspect Sentiment Totals")

    plt.savefig('images/extractor_example1.jpg')

    return df




#function for visualizing variance in opinion for the same
#opinion/aspect couple among voters

def variance_visualizer(df, tup):
    graph_s = df[df['tup_pair'] == tup]['sentiment'].value_counts()
    fig = plt.figure(figsize=(6,4))


    ax = graph_s.plot.bar()

    #ADD TOTAL NUMBER OF VOTES
    fig.text(0.9,
             0.9,
             s=f'Total Votes: {(graph_s.sum())} \n tuple: {tup}',
             ha='center',
             va='center',
             transform=ax.transAxes,
             size=12
            )

    plt.savefig('images/variance_graph_example.jpg');




#function for visualizing variance in opinion for the same
#opinion/aspect couple among voters

def sum_squares(df, tup):
    s = df[df['tup_pair'] == tup]['sentiment'].value_counts()
#     print(f'{tup} Residual sum of squares: {(np.sum((s-s.mean())**2)
    sum_s = np.sum((s-s.mean())**2)
    return(tup,sum_s)
```

Running The Extractor

In [11]:
```
#aspect extractor ran in order to extract tuples from
#entire amazon review text body
df_senti = extract_aspect_sentiment_tuples(df)
df_senti.head()
```

Out[11]:

	review_id	star_rating	review_body	wordcounts	aspect_tups	asp	modifier	modif
0	RA8R84N9JMZLD	3	My Dad loves this, only issue is charging, it ...	32	(connection, proper, 0.0, 1)	connection	proper	
2	R1KL6IIDB77A2O	4	I would not have paid the original price for t...	58	(price, original, 0.3182, 1)	price	original	
2	R1KL6IIDB77A2O	4	I would not have paid the original price for t...	58	(bit, little, 0.0, 1)	bit	little	
2	R1KL6IIDB77A2O	4	I would not have paid the original price for t...	58	(star, how durable, 0.0, 1)	star	how durable	
2	R1KL6IIDB77A2O	4	I would not have paid the original price for t...	58	(price, lower, -0.296, 1)	price	lower	

In [12]:

```
#keep only columns of interest
df_senti_predicted = df_senti.loc[:, ['modifier', 'asp', 'modifier_sent


#convert sentiment to Categorical to compare to human labels more easil
df_senti_predicted.loc[df_senti_predicted['modifier_sentiment'] < -.5,
df_senti_predicted.loc[(df_senti_predicted['modifier_sentiment'] >= -.5
df_senti_predicted.loc[df_senti_predicted['modifier_sentiment'] == 0, '
df_senti_predicted.loc[(df_senti_predicted['modifier_sentiment'] > 0) &
df_senti_predicted.loc[df_senti_predicted['modifier_sentiment'] > 0.5,

#convert aspects back to pair insted of triplet
#for easy comparison to human labels
df_senti_predicted['tup_pair'] = list(zip(df_senti_predicted['modifier'
#drop duplicate aspect pairs
df_to_turk2 = df_senti_predicted.drop_duplicates(subset='tup_pair')

df_to_turk2.sort_values(by='asp')
```

Out[12]:

	modifier	asp	modifier_sentiment	sentiment	tup_pair
1072	Able		0.0000	Neutral	(Able,)
7660	Though bulky		0.0000	Neutral	(Though bulky,)
1900	Only negative		-0.5719	Very Negative	(Only negative,)
6809	Really disappointed		-0.4767	Negative	(Really disappointed,)
6810	Otherwise excellent		0.5719	Very Positive	(Otherwise excellent,)
...	...	...	...	...	...
5475	fake	youout	-0.4767	Negative	(fake, youout)
3941	past	yrs	0.0000	Neutral	(past, yrs)
6229	dead	zone	-0.6486	Very Negative	(dead, zone)
197	sweet	zone	0.4588	Positive	(sweet, zone)
7059	extra	~$20	0.0000	Neutral	(extra, ~$20)

17675 rows × 5 columns

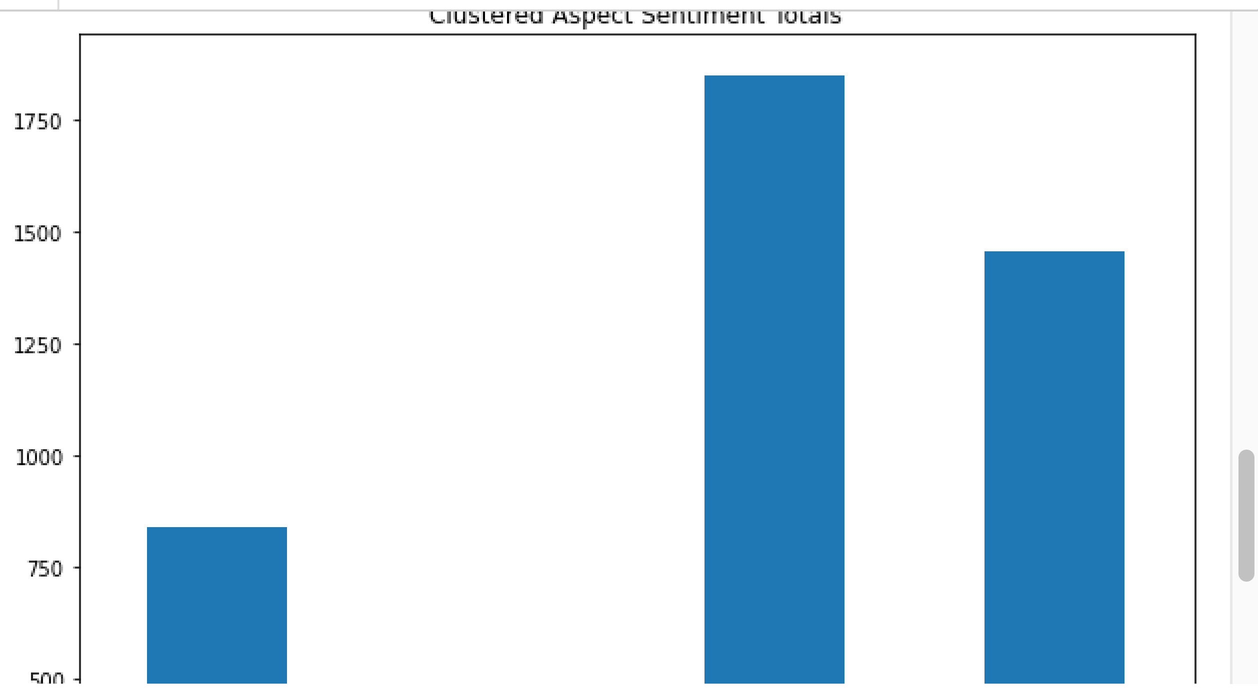
In [13]:

```
#sending data to create template
#for workers to submit labels
#using Amazon Turk
df_to_turk2 = df_senti_predicted.drop_duplicates(subset='tup_pair')
df_to_turk2.loc[:, ['modifier', 'asp']].to_csv('data/turk_data2.csv', i
```

Below is an example of the extractor being run to cluster the aspects and return a bar graph of total sentiment (total summation of negative and positive from the VADER sentiment intensity analyzer) as well as a DataFrame with cluster names for further analyses. You can see that for the product_id ["B0001FTVEK" (https://www.amazon.com/Sennheiser-RS120-Wireless-Headphones-Charging/dp/B0001FTVEK)](https://www.amazon.com/Sennheiser-RS120-Wireless-Headphones-Charging/dp/B0001FTVEK), which are RS120 Wireless

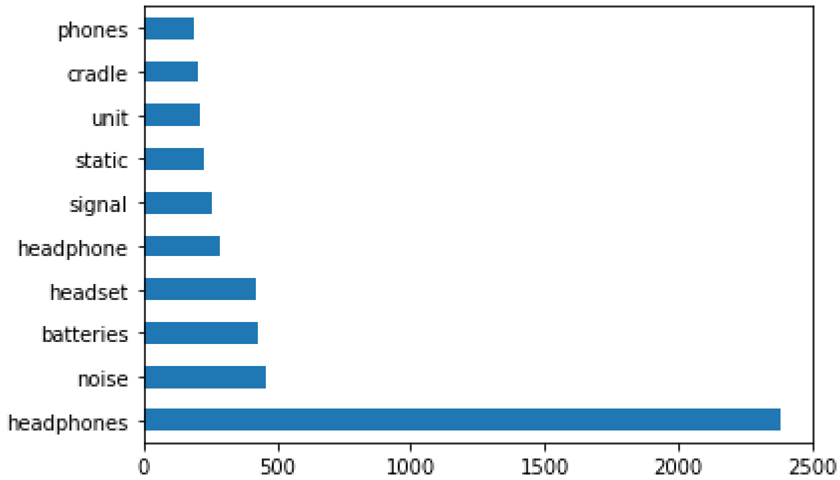
Headphones, there is a lot of positive sentiment for the value and sound_quality categories as compared to the headphone_design and hiss/tech_diff categories. The hiss category is low enough that it should be the major focus for the company to funnel resources in response to customer demand for improving their product. If they can focus first on fixing the hiss mentioned in many amazon reviews, they can also put a few extra resources into impoving some other design aspects of the headphones, such as the batteries or cradle.

In [14]:
```
df_senti = get_cluster_name_inputs(df_senti)
```



In [15]:
```
print('\nheadphone_design\n')
display(df_senti.loc[df_senti['cluster_name'] == 'design', 'asp'].value
print('\nheadphone_design\n')
df_senti.loc[df_senti['cluster_name'] == 'design', 'asp'].value_counts(
```

```
headphone_design


headphones     2382
noise           460
batteries       432
headset         425
headphone       289
signal          259
static          228
unit            213
cradle          206
phones          188
fit             150
audio           135
light           133
station         118
output          107
headsets         97
tuning           96
setup            84
device           82
frequency        81
earphones        80
Headphones       78
pads             78
transmitter      76
controls         75
channels         74
screen           65
speakers         65
battery          63
cable            54
Name: asp, dtype: int64


headphone_design
```



Loading Turk Data

The DataFrames below are batch results loaded as csv files submitted from Amazon Turk. As stated before, there are a total of 6107 non-null entries with information for 1438 unqiue aspects, submitted from a total of410 different workers from around the globe. Duplicate pairs of aspect/opinion pairs were included to inspect variance of submission from human labels and machine labels for each opinion pair.

In [16]:

```
#Read all Turk Data

df1 = pd.read_csv("data/batch1_results.csv")
df2 = pd.read_csv("data/batch2_results.csv")
df3 = pd.read_csv("data/batch3_results.csv")
df4 = pd.read_csv("data/batch4_results.csv")
# df_lab = pd.read_csv("data/locally_sourced_labels.csv")

display(df1.info())
display(df2.info())
display(df3.info())
display(df4.info())
# df_lab.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1020 entries, 0 to 1019
Data columns (total 32 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   HITId                         1020 non-null   object
 1   HITTypeId                     1020 non-null   object
 2   Title                         1020 non-null   object
 3   Description                   1020 non-null   object
 4   Keywords                      1020 non-null   object
 5   CreationTime                  1020 non-null   object
 6   MaxAssignments                1020 non-null   int64
 7   RequesterAnnotation           1020 non-null   object
 8   AssignmentDurationInSeconds   1020 non-null   int64
 9   AutoApprovalDelayInSeconds    1020 non-null   int64
 10  Expiration                    1020 non-null   object
 11  NumberOfSimilarHITs           0 non-null      float64
 12  LifetimeInSeconds             0 non-null      float64
 13  AssignmentId                  1020 non-null   object
```

In [17]:

```
#concact turk data into one dataframe
#keep only necessary columns

df_turk = pd.concat([df1,df2,df3, df4])

num_turk = len(df_turk.WorkerId.unique())
print(f'Total number of Turk Workers: {num_turk}\n')

df_turk = df_turk.loc[:, ['Input.Modifier', 'Input.Aspect',  'Answer.se
df_turk.dropna(inplace=True)

num_aspects = len(df_turk["Input.Aspect"].unique())
print(f'Total number of Unique Aspects: {num_aspects}\n')

display(df_turk.info())

#rename to differentiate human labels
df_turk.rename({'Input.Modifier': 'modifier',
                        'Input.Aspect': 'asp',
                        'Answer.sentiment.label': 'sentiment_h'
                       }, axis=1, inplace=True)



df_turk.sort_values(by='asp')
```

```
Total number of Turk Workers: 410

Total number of Unique Aspects: 1438

<class 'pandas.core.frame.DataFrame'>
Int64Index: 6107 entries, 0 to 3228
Data columns (total 3 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Input.Modifier          6107 non-null   object
 1   Input.Aspect            6107 non-null   object
 2   Answer.sentiment.label  6107 non-null   object
dtypes: object(3)
memory usage: 190.8+ KB

None
```

Out[17]:

	modifier	asp	sentiment_h
32	extra	$	Very Positive
115	more missing	1/2	Negative
646	single	1/8	Neutral
1659	stereo	1/8\\	Neutral
589	new	120s	Positive
...	...	...	...
3042	pair	years	Neutral

	modifier	asp	sentiment_h
1031	plus	years	Positive
1878	past	years	Positive
2296	fake	youout	Very Negative
299	sweet	zone	Positive

6107 rows × 3 columns

In [18]:

```
#create aspect/opinion pair to
#compare machine label vs human
df_turk['tup_pair'] = list(zip(df_turk['modifier'],df_turk['asp']))
display(df_turk.info())
df_senti_predicted.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6107 entries, 0 to 3228
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   modifier     6107 non-null   object
 1   asp          6107 non-null   object
 2   sentiment_h  6107 non-null   object
 3   tup_pair     6107 non-null   object
dtypes: object(4)
memory usage: 238.6+ KB

None

<class 'pandas.core.frame.DataFrame'>
Int64Index: 35355 entries, 0 to 7875
Data columns (total 5 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   modifier            35355 non-null  object 
 1   asp                 35355 non-null  object 
 2   modifier_sentiment  35355 non-null  float64
 3   sentiment           35355 non-null  object 
 4   tup_pair            35355 non-null  object 
dtypes: float64(1), object(4)
memory usage: 1.6+ MB
```

Results

In [19]:

```
#create merged DataFrame
#in order to compare human
#labeled aspect/opinion sentiment
#vs model aspect/opinion sentiment
#can check accuracy and precision

#how much do Turk workers agree with
#my model?

#How much do Turk workers agree with
#each other?

df_results = pd.merge(df_turk,
                      df_senti_predicted,
                      on='tup_pair',
                      how='left'
                     )

df_results.drop_duplicates(subset='tup_pair', inplace=True)
df_results.head()
```

Out[19]:

	modifier_x	asp_x	sentiment_h	tup_pair	modifier_y	asp_y	modifier_sentiment
0	old	father	Neutral	(old, father)	old	father	0.0
16	wireless	headphones	Neutral	(wireless, headphones)	wireless	headphones	0.0
748	charging	rack	Neutral	(charging, rack)	charging	rack	0.0
752	also available	headphones	Very Positive	(also available, headphones)	also available	headphones	0.0
753	impaired	husband	Negative	(impaired, husband)	impaired	husband	0.0

In [20]:

```
display(df_results.sentiment_h.value_counts())
df_results.sentiment.value_counts()
```

```
Positive         1860
Neutral          1521
Very Positive     790
Negative          692
Very Negative     223
Name: sentiment_h, dtype: int64
```

Out[20]:

```
Neutral          3309
Positive          763
Very Positive     523
Negative          397
Very Negative      88
Name: sentiment, dtype: int64
```

In [21]:

```
df_results2 = df_results.reset_index(drop=True)
df_results2.dropna(inplace=True)

matching_predictions = df_results2.loc[df_results2['sentiment_h'] == df
mismatching_predictions = df_results2.loc[df_results2['sentiment_h'] !=

display(matching_predictions.sentiment.value_counts())
mismatching_predictions.sentiment.value_counts()
```

```
Neutral          1198
Positive          394
Very Positive     187
Negative          141
Very Negative      21
Name: sentiment, dtype: int64
```

Out[21]:

```
Neutral          2111
Positive          369
Very Positive     336
Negative          256
Very Negative      67
Name: sentiment, dtype: int64
```

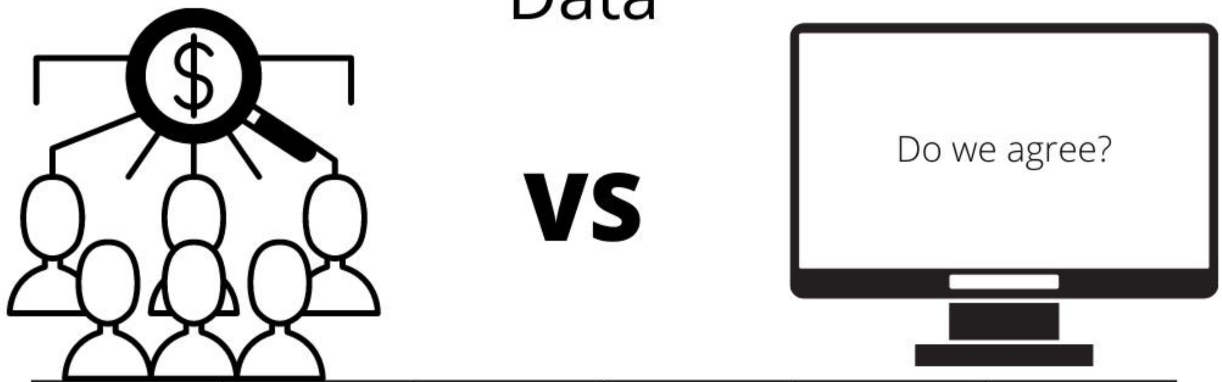
In [22]:

```
#create table to see accuracy and precision of extractor
#AS COMPARED TO MY AMAZON TURK HUMAN LABELS
#ARE MY HUMAN LABELS RELIABLE????

agree = matching_predictions.sentiment.value_counts().values
disagree = mismatching_predictions.sentiment.value_counts().values
total_arr = agree + disagree
precision = agree/total_arr
denom = 5*[5080]
accuracy = agree/denom
columns = matching_predictions.sentiment.value_counts().index
df_table = pd.DataFrame(data=[precision, accuracy], columns=columns)
df_table = df_table.apply(lambda x: round(x,4))
df_table.rename({0: 'precision', 1: 'accuracy'},
                inplace = True
               )

df_table.to_csv("data/acc_prec_table.csv", index=False)

df_table.head()
```

Out[22]:

	Neutral	Positive	Very Positive	Negative	Very Negative
precision	0.3620	0.5164	0.3576	0.3552	0.2386
accuracy	0.2358	0.0776	0.0368	0.0278	0.0041

Comparison of Turk Data to Extractor Data



	Neutral	Positive	Very Positive	Negative	Very Negative
Precision	36.20%	51.64%	35.76%	35.52%	23.86%
Accuracy	23.58%	7.76%	3.68%	2.78%	0.41%

The precision values explain how many times the machine label correctly line up with the human labels for each aspect/opinion pair when guessing for that appropriate sentiment. That is, if the machine were to guess only for negative sentiment, it was in agreement with humans 35% of the time. The accuracy scores represent how many times the machine were right overall for the entire dataset when predicted a certain class. Due to the nature of the dataset, accuracy scores will be low for a lot of the classes strictly because of class imbalances. Therefore, precision is a better metric for judging the performance of my model. However, there were some major issues with the overal expiremental setup that need to be discussed and anaylzed.

Reliability of Experimental Setup

To quickly visualize the variance among the different Amazon Turk workers assigned to labeling the aspect/opinion pairs, a function was utilized to create a bargraph that displays the different labels each worker voted for each aspect/opinion set that appeared in the dataset more than 10 times. A more statistical approach will be carried out using sum of squares residuals further down in the notebook. It is very apparent that the Amazon turks had a lot of trouble coming to any agreement on sentiment. The task was setup to reward workers to label data as quickly as possible without much safeguard to the quality of the work being submitted other than a quick overview by myself.I am just one poorly funded individual. Without proper funding from a research grant it was dificult to setup a reliable expirement. This cast a large shadow of doubt on the reliabilty of this data to be used as a way to reliably test the accuarcy of my model. In comparison, you can see that the extractor chooses the same sentiment for a unique aspect/opinion pair every single time it shows up in the dataset. While the human data has been revealed to be severely flawed, it has brought up a shining example as to why machine learning may be a better substitute for labeling large amounts of tedius data in the first place.

In [23]:
```
#create dataframe for tuple_pairs with more than 10 votes from turk dat

multi_votes = df_turk['tup_pair'].value_counts()[df_turk['tup_pair'].va

df_turk2 = df_turk[df_turk["tup_pair"].isin(multi_votes)].copy()

df_turk2.rename({'sentiment_h': 'sentiment'},
                axis=1,
                inplace=True
               )

unique_tup = df_turk2.tup_pair.unique()



#create dataframe for tuple_pairs with more than 10 votes from extracto

multi_votes_e = df_senti_predicted['tup_pair'].value_counts()[df_senti_

df_ex = df_senti_predicted[df_senti_predicted["tup_pair"].isin(multi_vo

unique_tup_e = df_ex.tup_pair.unique()
```

Partition Sum Of Squares to Measure Disperson of Turk Data

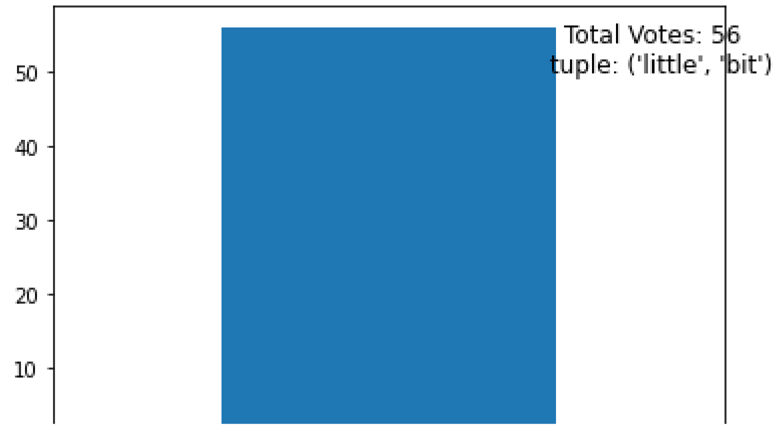
Partition Sum of Squares (https://en.wikipedia.org/wiki/Partition_of_sums_of_squares)

For simplicity, sum of square statistical measurements were calculated for each aspect in the human labeled data as well as the machine labeled data that had more than 10 votes. This was chosen over entropy as a calculation for dispersion as the "sum of squares" for these data is a close enough estimate for the variance in categorical data for this expirement. Every single human labeled aspect with multiple aspects had a non-zero value for residual sum of squares, while every machine labeled aspect had zero residual error. This shows the difference in variance statistically and mathmatically very clearly between the two and shows the unreliability of the turk data. See the figure below for the total range in the residual sum of square values for the tested aspects in each group.

In [24]:

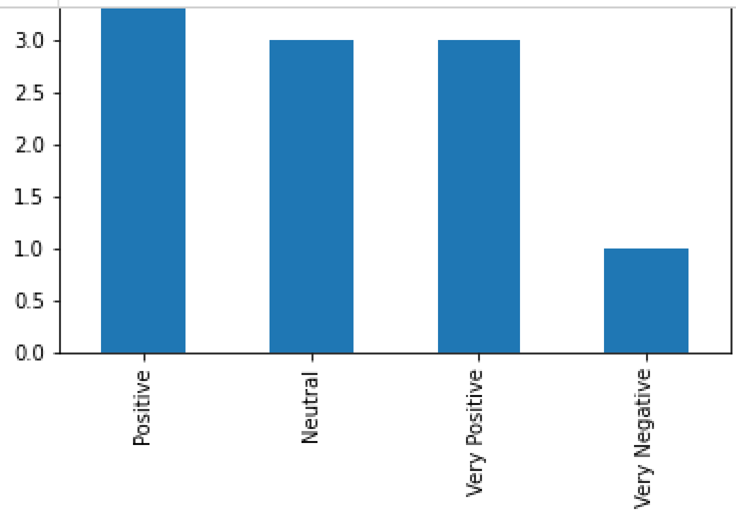
```
for tup in unique_tup_e:
    variance_visualizer(df_ex, tup)
```

```
/Users/dylandey/anaconda3/envs/learn-env/lib/python3.6/site-packages/ip
ykernel_launcher.py:426: RuntimeWarning: More than 20 figures have been
opened. Figures created through the pyplot interface (`matplotlib.pyplo
t.figure`) are retained until explicitly closed and may consume too muc
h memory. (To control this warning, see the rcParam `figure.max_open_wa
rning`).
```



In [25]:

```
for tup in unique_tup:
    variance_visualizer(df_turk2, tup)
```



In [26]:

```
for tup in unique_tup_e:
     sum_squares(df_ex, tup)
```

In [27]:

```
emp_list = []
for tup in unique_tup:
    emp_list.append(sum_squares(df_turk2, tup))


df_turk_var = pd.DataFrame(emp_list, columns=['asp', 'sum_of_squares'])
df_turk_var.to_csv('data/turk_var1.csv')

emp_list = []
for tup in unique_tup_e:
     sum_squares(df_ex, tup)

df_ex_var = pd.DataFrame(emp_list, columns=['asp', 'sum_of_squares'])
df_ex_var.to_csv('data/human_var1.csv')
```

In [28]:

```
df_turk_var
```

Out[28]:

	asp	sum_of_squares
0	(wireless, headphones)	232.750000
1	(second, set)	4.750000
2	(clear, sound)	26.000000
3	(sound, quality)	870.000000
4	(great, headphones)	19.000000
5	(second, pair)	11.200000
6	(good, sound)	60.750000
7	(rechargeable, batteries)	4.666667
8	(good, range)	16.666667
9	(great, quality)	58.750000
10	(Sound, quality)	4.500000
11	(great, product)	34.750000
12	(great, range)	18.666667
13	(great, sound)	60.666667
14	(good, quality)	83.000000
15	(long, time)	11.200000

In [29]:

```
# all values sum to zero

df_ex_var
```

Out[29]:

asp	sum_of_squares

Further Discussion and Future Work

1) Due to a lack of funding from grants and some other issues in expiremental design, I feel the most appropriate next step would be to repeat the experiment with more carefully collected labeled data. Increasing the reward per label and the requirements for submission (such as proving a proficiency in english) I believe cam substantiely improve the quality of the human labeled data and reduce the variance in this data significantly. Sourcing reliable test data is the number one priority in continuing future work for this project.

2) Integrate into AWS for scaling

3) integrate into a SQL server for data management

4) incoroprate a flash based UI for viewing results at scale

THANK YOU

[Blog (https://dev.to/ddey117)] | [GitHub (https://github.com/ddey117/ABSA_Project_4)] | [PreProcess Github (https://github.com/ddey117/preprocess_ddey117)]

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