Youtube Video Statistics Data Science Project 📹📊

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About Dataset

This dataset contains two files with statistics on 1,881 YouTube videos and their comments.

video-stats.csv

- **Title:** Video Title
- **Video ID:** The Video Identifier.
- **Published At:** The date the video was published in YYYY-MM-DD.
- **Keyword:** The keyword associated with the video.
- **Likes:** The number of likes the video received. If this value is -1, the likes are not publicly visible.
- **Comments:** The number of comments the video has. If this value is -1, the video creator has disabled comments.
- **Views:** The number of views the video got.

comments.csv:

- **Video ID:** The Video Identifier.
- **Comment:** The comment text.
- **Likes:** The number of likes the comment received.
- **Sentiment:** The sentiment of the comment. A value of 0 represents a negative sentiment, while values of 1 or 2 represent neutral and positive sentiments respectively.

Purpose

The purpose of analyzing this dataset was to explore what makes a "good" video and see if we could predict whether a video performed well or poorly based on its video and comment statistics. A good video and a bad video were determined besed upon its like to view ratio (`like_conversion_rate`). We thought this would be the best way to determine the quality of the video because it does depend on viral status or high view count to determine the quality of the video. Before we began the project we knew we would have some limitations with the dataset and would need more metrics to fit an accurate model. For example, we knew that you can only like a video once where as you can watch the video multiple times. With that being said, another one of our goals was to be able to add features that are highly correlated to `like_conversion_rate` to the dataset that would help improve the overall accuracy of our model and assist in determining what is a good, nuetral, or bad video.

Importing Libraries

In [1]:

```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib as plt
import datetime as dt
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import warnings
warnings.filterwarnings('ignore')

import nltk
from nltk.corpus import stopwords
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('stopwords')
nltk.download('vader_lexicon')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/adambrenner/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /Users/adambrenner/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Out[1]:

```
True
```

Loading & Descibing Datasets

In [2]:
```python
videos = pd.read_csv("videos-stats.csv")
comments = pd.read_csv("comments.csv")
```

In [3]:
```python
videos.head()
```

Out[3]:

	Unnamed: 0	Title	Video ID	Published At	Keyword	Likes	Comments	Views
0	0	Apple Pay Is Killing the Physical Wallet After...	wAZZ-UWGVHI	2022-08-23	tech	3407.0	672.0	135612.0
1	1	The most EXPENSIVE thing I own.	b3x28s61q3c	2022-08-24	tech	76779.0	4306.0	1758063.0
2	2	My New House Gaming Setup is SICK!	4mgePWWCAmA	2022-08-23	tech	63825.0	3338.0	1564007.0
3	3	Petrol Vs Liquid Nitrogen | Freezing Experimen...	kXiYSI7H2b0	2022-08-23	tech	71566.0	1426.0	922918.0
4	4	Best Back to School Tech 2022!	ErMwWXQxHp0	2022-08-08	tech	96513.0	5155.0	1855644.0

In [4]:
```python
comments.head()
```

Out[4]:

	Unnamed: 0	Video ID	Comment	Likes	Sentiment
0	0	wAZZ-UWGVHI	Let's not forget that Apple Pay in 2014 requir...	95.0	1.0
1	1	wAZZ-UWGVHI	Here in NZ 50% of retailers don’t even have co...	19.0	0.0
2	2	wAZZ-UWGVHI	I will forever acknowledge this channel with t...	161.0	2.0
3	3	wAZZ-UWGVHI	Whenever I go to a place that doesn’t take App...	8.0	0.0
4	4	wAZZ-UWGVHI	Apple Pay is so convenient, secure, and easy t...	34.0	2.0

In [5]:
```python
videos.describe()
```

Out[5]:

	Unnamed: 0	Likes	Comments	Views
count	1881.000000	1.879000e+03	1879.000000	1.879000e+03
mean	940.000000	1.700610e+05	7863.331559	1.161292e+07
std	543.142247	7.962293e+05	37879.964926	1.084450e+08

	Unnamed: 0	Likes	Comments	Views
min	0.000000	-1.000000e+00	-1.000000	2.500000e+01
25%	470.000000	2.672500e+03	199.000000	8.451500e+04
50%	940.000000	1.478700e+04	814.000000	5.917210e+05
75%	1410.000000	6.090600e+04	3377.500000	2.804978e+06
max	1880.000000	1.644556e+07	732818.000000	4.034122e+09

In [6]:

```
comments.describe()
```

Out[6]:

	Unnamed: 0	Likes	Sentiment
count	18409.000000	18409.000000	18409.000000
mean	9204.000000	1040.019447	1.493998
std	5314.364888	10651.366148	0.709928
min	0.000000	0.000000	0.000000
25%	4602.000000	5.000000	1.000000
50%	9204.000000	29.000000	2.000000
75%	13806.000000	190.000000	2.000000
max	18408.000000	891372.000000	2.000000

In [7]:

```
videos.drop(columns="Unnamed: 0", axis=1, inplace=True)
comments.drop(columns="Unnamed: 0", axis=1, inplace=True)
```

In [8]:

```
videos.columns = videos.columns.str.lower().str.replace(" ", "_")
comments.columns = comments.columns.str.lower().str.replace(" ", "_")
```

In [9]:

```
videos.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1881 entries, 0 to 1880
Data columns (total 7 columns):
```

```
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   title         1881 non-null   object
 1   video_id      1881 non-null   object
 2   published_at  1881 non-null   object
 3   keyword       1881 non-null   object
 4   likes         1879 non-null   float64
 5   comments      1879 non-null   float64
 6   views         1879 non-null   float64
dtypes: float64(3), object(4)
memory usage: 103.0+ KB
```

In [10]:
```
comments.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18409 entries, 0 to 18408
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   video_id   18409 non-null  object
 1   comment    18408 non-null  object
 2   likes      18409 non-null  float64
 3   sentiment  18409 non-null  float64
dtypes: float64(2), object(2)
memory usage: 575.4+ KB
```

Dealing with Null Values

As shown above, the videos DataFrame has two rows with missing values and the comments DataFrame has one. Since there are minimal null values in the DataFrame, we decided to drop these rows.

In [11]:
```
videos = videos.dropna()
comments = comments.dropna()
```

In [12]:
```
videos.isnull().sum()
```

Out[12]:
```
title           0
video_id        0
published_at    0
keyword         0
likes           0
comments        0
```

```
views          0
dtype: int64
```

In [13]:

```
comments.isnull().sum()
```

Out[13]:

```
video_id      0
comment       0
likes         0
sentiment     0
dtype: int64
```

Dealing with Duplicate Values

While exploring the videos DataFrame we discovered that there were 12 records that had repeated values in the video_id column. For every duplicated record every value was the same besides the keyword column. Since only 12 out of 1881 values were duplicates, we decided to drop the duplicate records that showed up second.

In [14]:

```
videos.loc[videos.video_id.duplicated(keep=False), :].sort_values("video_id")
```

Out[14]:

	title	video_id	published_at	keyword	likes	comments	views
1714	Vikram Vedha Movie Teaser Review | KRK | #krkr...	2FYvHn12pOQ	2022-08-24	movies	-1.0	105.0	1541874.0
1055	Vikram Vedha Movie Teaser Review | KRK | #krkr...	2FYvHn12pOQ	2022-08-24	reaction	29728.0	8832.0	405791.0
2	My New House Gaming Setup is SICK!	4mgePWWCAmA	2022-08-23	tech	63825.0	3338.0	1564007.0
88	My New House Gaming Setup is SICK!	4mgePWWCAmA	2022-08-23	gaming	63825.0	3338.0	1564007.0
1501	Computer Scientist Explains Machine Learning i...	5q87K1WaoFI	2021-08-18	computer science	42940.0	1735.0	1407319.0
1832	Computer Scientist Explains Machine Learning i...	5q87K1WaoFI	2021-08-18	machine learning	15137.0	181.0	906372.0
1762	Python Machine Learning Tutorial (Data Science)	7eh4d6sabA0	2020-09-17	data science	7555.0	442.0	295344.0
1835	Python Machine Learning Tutorial (Data Science)	7eh4d6sabA0	2020-09-17	machine learning	1237.0	16.0	32605.0

	title	video_id	published_at	keyword	likes	comments	views
1554	🚨 DÉPÊCHEZ-VOUS 🚨 Ces PROMOS disparaissent bie...	96mrgd8-3yE	2022-08-24	nintendo	406.0	57.0	13184.0
1595	🚨 DÉPÊCHEZ-VOUS 🚨 Ces PROMOS disparaissent bie...	96mrgd8-3yE	2022-08-24	xbox	406.0	57.0	13184.0
319	20 Minecraft Block Facts You Maybe Didn't ...	LeC5yJq4tsI	2022-08-21	tutorial	57526.0	1115.0	1204024.0
1220	20 Minecraft Block Facts You Maybe Didn't ...	LeC5yJq4tsI	2022-08-21	minecraft	57527.0	1115.0	1204024.0
423	How to Solve a Rubik's Cube | WIRED	R-R0KrXvWbc	2019-09-05	cubes	339759.0	32717.0	29905105.0
225	How to Solve a Rubik's Cube | WIRED	R-R0KrXvWbc	2019-09-05	how-to	339758.0	32718.0	29905105.0
1041	BLACKPINK - 'Pink Venom' DANCE PRACTICE VIDEO	RFMi3v0TXP8	2022-08-24	reaction	3001265.0	110162.0	23836066.0
916	BLACKPINK - 'Pink Venom' DANCE PRACTICE VIDEO	RFMi3v0TXP8	2022-08-24	music	3001232.0	110160.0	23836066.0
1229	I OPENED MY OWN ARCADE SHOP	WBK2_ID7KGA	2022-08-24	minecraft	298445.0	15610.0	3773387.0
91	I OPENED MY OWN ARCADE SHOP	WBK2_ID7KGA	2022-08-24	gaming	298406.0	15609.0	3773387.0
891	Lofi For Reading 📚 Lofi Hip Hop | Study Music ...	ZgeorpjGJC0	2022-08-24	music	329.0	29.0	14336.0
1077	Lofi For Reading 📚 Lofi Hip Hop | Study Music ...	ZgeorpjGJC0	2022-08-24	lofi	329.0	29.0	14341.0
682	The History Of Chess: A Reflection Of Us	kkOweffr3lI	2022-08-21	history	2546.0	173.0	51885.0
472	The History Of Chess: A Reflection Of Us	kkOweffr3lI	2022-08-21	chess	2546.0	173.0	51885.0
848	ASMR Gaming 😴 Fortnite 1 Kill = 1 Trigger Rela...	mqc6QqoGNWI	2022-08-24	asmr	563.0	86.0	14537.0
129	ASMR Gaming 😴 Fortnite 1 Kill = 1 Trigger Rela...	mqc6QqoGNWI	2022-08-24	gaming	563.0	85.0	14537.0

In [15]:

```
videos = videos.drop_duplicates(subset=['video_id'])
```

In [16]:

```
videos.video_id.duplicated().sum()
```

Out[16]: 0

We also discovered that the dataset had -1 values for records that disabled likes or comments on the video. In order to keep our data consistent, we dropped these records from our DataFrame.

In [17]:

```
print(videos[videos.likes == -1].shape)
print(videos[videos.comments == -1].shape)
```

```
(6, 7)
(2, 7)
```

In [18]:

```
videos = videos[videos.likes != -1]
videos = videos[videos.comments != -1]
```

Feature Engineering

Feature Engineering Summary:

After cleaning and analyzing our dataset we decided to add some variables that might be useful in our ML model. We added these variables because we thought they might have an impact on the like conversion rate of videos.

- **avg_comm_len:** Average comment length for each video
- **title_len:** Title length
- **avg_comm_sent:** Average comment sentiment score for each video
- **sent_title:** Title sentiment score
- **month:** Month in numerical form (1 being January, 2 being February, etc.)
- **like_conversion_rate:** Percent of likes per view
- **like_conversion_cat:** Like conversion rate assigned a certain category based on value (Bad, Neutral, or Good)

Average Comment Length:

In [19]:

```
comments["comment_len"] = comments.comment.str.split().apply(lambda x: len(x))
avg_com_len = comments.groupby("video_id")["comment_len"].mean()
videos = pd.merge(videos, avg_com_len, how="inner", on=["video_id"]).rename(columns={'comment_len':'avg_comm_le
```

Title Length:

In [20]:
```
videos['title_len'] = videos['title'].str.split().apply(lambda x: len(x))
```

Remove Stopwords and Get Sentiment Score Functions:

In [21]:
```
def remove_stopwords(title):
    title = title.lower()
    temp_title = title.split(' ')
    temp_title = [i for i in temp_title if i not in stopwords.words('english')]
    return ' '.join(temp_title)
```

In [22]:
```
sid = SentimentIntensityAnalyzer()
```

In [23]:
```
def get_sent(sentence):
    sentiment_ = sid.polarity_scores(sentence)
    return sentiment_['compound']
```

Comment Sentiment Score:

In [24]:
```
comments['comment'] = comments['comment'].apply(remove_stopwords)
```

In [25]:
```
comments['comm_sent'] = comments['comment'].apply(get_sent)
```

In [26]:
```
avg_sent = comments.groupby('video_id')['comm_sent'].mean()
videos = pd.merge(videos, avg_sent, how="inner", on=["video_id"]).rename(columns={'comm_sent':'avg_comm_sent'})
```

Title Sentiment Score:

In [27]:
```
videos['title'] = videos['title'].apply(remove_stopwords)
```

In [28]:
```
videos['sent_title'] = videos['title'].apply(get_sent)
```

Month:

In [29]:
```
videos['published_at'] = videos['published_at'].apply(pd.to_datetime)
```

In [30]:
```
videos['month'] = videos['published_at'].apply(lambda x: x.month)
```

Like Conversion Rate:

In [31]:
```
videos['like_conversion_rate'] = videos.apply(lambda x: (x['likes'] / x['views'])*100, axis=1 )
```

Like Conversion Rate Categorical Value:

In [32]:
```
pd.qcut(videos.like_conversion_rate, 3).value_counts().sort_index()
```

Out[32]:
```
(-0.001, 1.908]    620
(1.908, 3.76]      619
(3.76, 21.858]     620
Name: like_conversion_rate, dtype: int64
```

In [33]:
```
like_cat = pd.qcut(videos.like_conversion_rate, 3, labels=["Bad", "Neutral", "Good"])
videos["like_conversion_cat"] = like_cat
```

In [62]:
```
videos_final = videos.copy()
videos_final.head()
```

Out[62]:

	title	video_id	published_at	keyword	likes	comments	views	avg_comm_len	title_len	avg_comm_sent	se
0	apple pay killing physical wallet eight years ...	wAZZ-UWGVHI	2022-08-23	tech	3407.0	672.0	135612.0	36.6	18	0.39121	
1	expensive thing own.	b3x28s61q3c	2022-08-24	tech	76779.0	4306.0	1758063.0	44.6	6	0.69465	
2	new house gaming setup sick!	4mgePWWCAmA	2022-08-23	tech	63825.0	3338.0	1564007.0	29.4	7	0.35491	

	title	video_id	published_at	keyword	likes	comments	views	avg_comm_len	title_len	avg_comm_sent	se
3	petrol vs liquid nitrogen | freezing experimen...	kXiYSI7H2b0	2022-08-23	tech	71566.0	1426.0	922918.0	12.7	16	0.20926	
4	best back school tech 2022!	ErMwWXQxHp0	2022-08-08	tech	96513.0	5155.0	1855644.0	77.3	6	0.81395	

EDA

Heatmap:

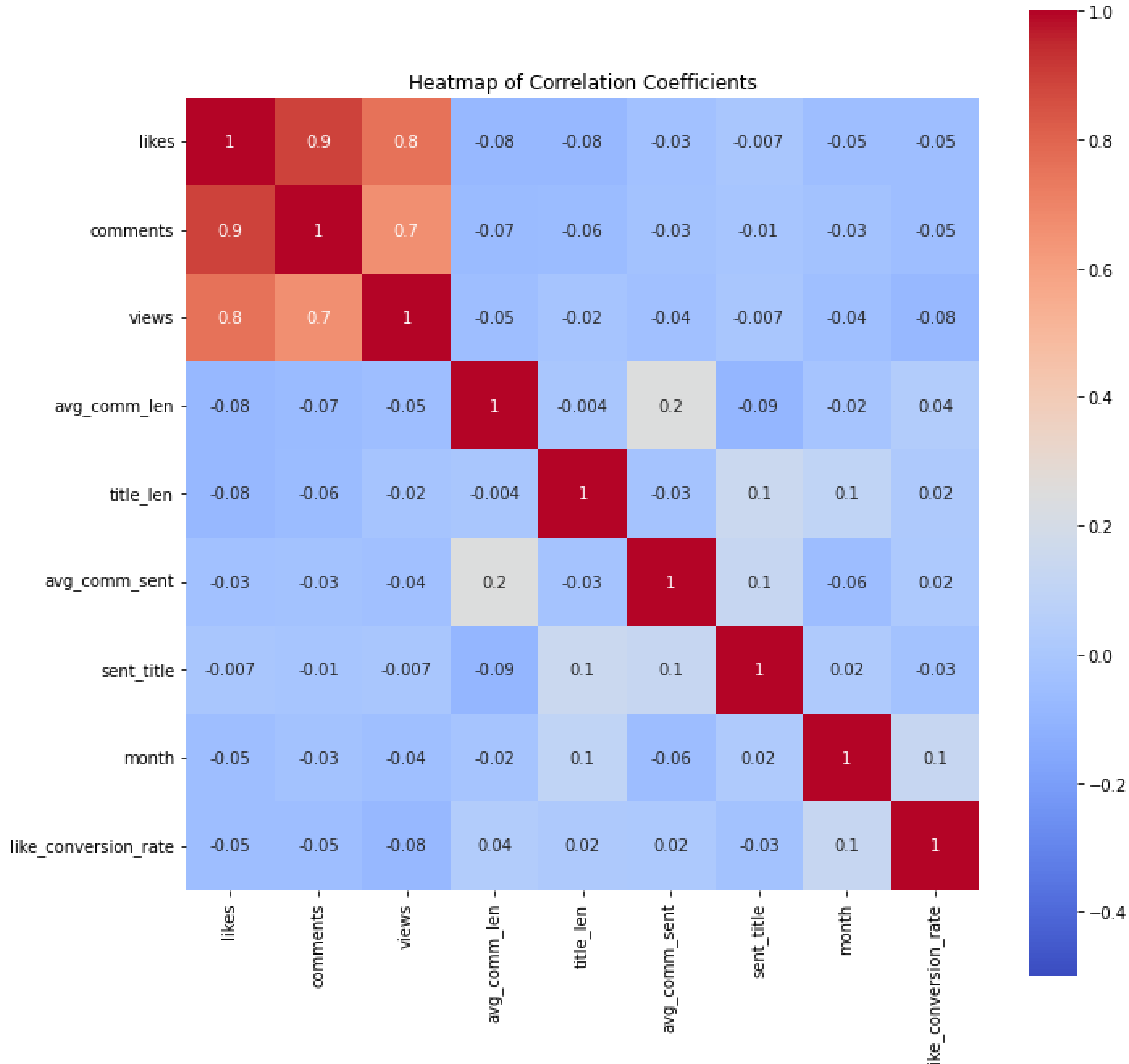
- Variables like views, comments, and likes have high correlation
- Most variables have little to no correlation

In [35]:

```
correlation_df = videos_final
df = pd.DataFrame(correlation_df.corr().unstack().sort_values(ascending=False, key=abs))
x = df[df[0] != 1].drop_duplicates().reset_index()
```

In [36]:

```
plt.figure(figsize=(11, 11))
sns.heatmap(correlation_df.corr(), cmap="coolwarm", annot=True, fmt="0.1g", vmin=-0.5, vmax=1, square=True)
plt.title('Heatmap of Correlation Coefficients')
plt.show()
```



EDA for Title Length:

- Most titles seem to be around 7-13 in length no matter the like conversion rate

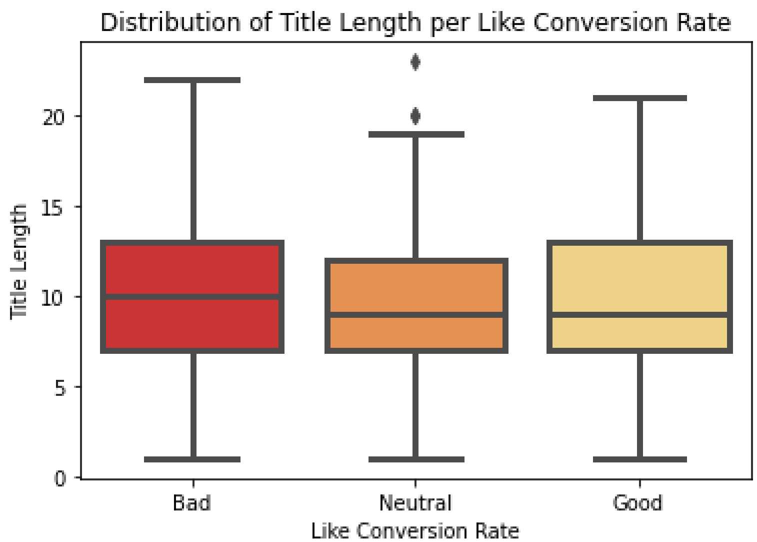
- Videos with a neutral conversion rate have a smaller distribution of title length
- Videos on either end have similar distribution

In [37]:

```
ax = sns.boxplot(data=videos_final, x="like_conversion_cat", y="title_len", linewidth=3, palette='YlOrRd_r')
plt.title('Distribution of Title Length per Like Conversion Rate')
plt.xlabel("Like Conversion Rate")
plt.ylabel("Title Length")
```

Out[37]:

```
Text(0, 0.5, 'Title Length')
```



EDA for Average Comment Length:

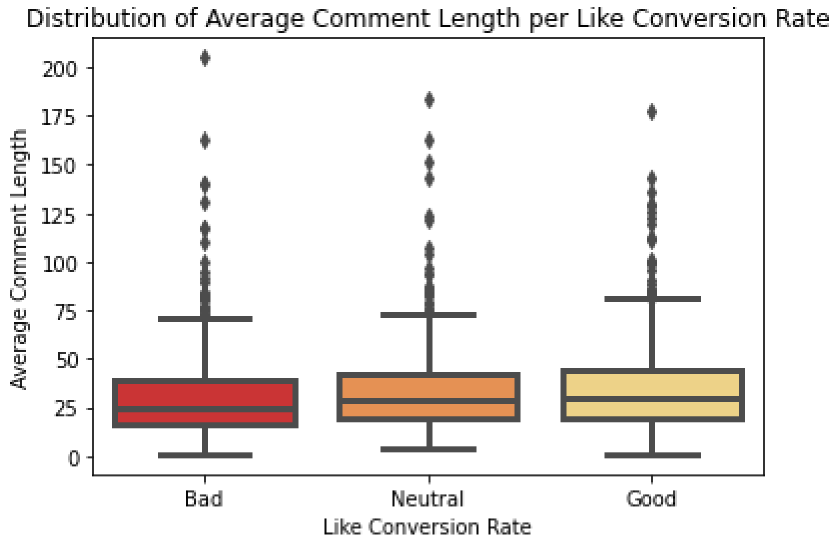
- When looking at the title sentiment score, the distribution for the average comment length between the three categories are similar

In [38]:

```
ax = sns.boxplot(data=videos_final, x="like_conversion_cat", y="avg_comm_len", linewidth=3, palette='YlOrRd_r')
plt.title('Distribution of Average Comment Length per Like Conversion Rate')
plt.xlabel("Like Conversion Rate")
plt.ylabel("Average Comment Length")
```

Out[38]:

```
Text(0, 0.5, 'Average Comment Length')
```



EDA for Average Comment Sentiment Score:

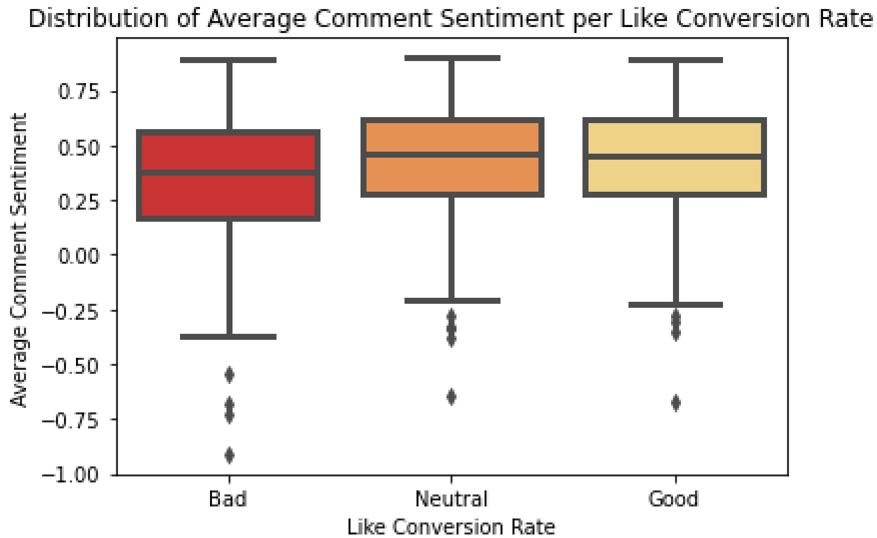
- When looking at the average comment sentiment score, videos in the bad like conversion rate category have a wider distribution
- The other two categories have similar distributions

In [39]:

```
ax = sns.boxplot(data=videos_final, x="like_conversion_cat", y="avg_comm_sent", linewidth=3, palette='YlOrRd_r'
plt.title('Distribution of Average Comment Sentiment per Like Conversion Rate')
plt.xlabel("Like Conversion Rate")
plt.ylabel("Average Comment Sentiment")
```

Out[39]:

```
Text(0, 0.5, 'Average Comment Sentiment')
```

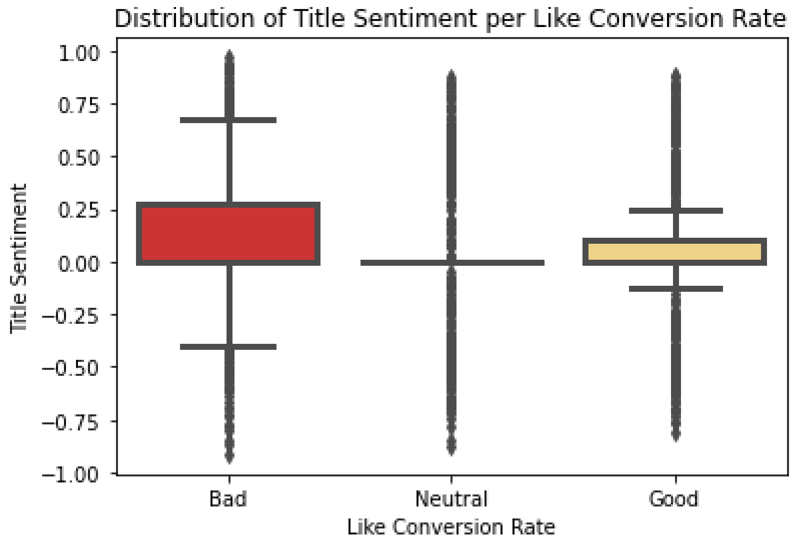


EDA for Title Sentiment Score:

- When looking at the title sentiment score the three distributions are significantly different
- Videos with a bad like conversion rate have a wide distributions
- Videos with a neutral like conversion rate have title sentiment scores that are too spread out to generate a boxplot
- Videos with a good like conversion rate have a smaller distribution

In [40]:
```
ax = sns.boxplot(data=videos_final, x="like_conversion_cat", y="sent_title", linewidth=3, palette='YlOrRd_r')
plt.title('Distribution of Title Sentiment per Like Conversion Rate')
plt.xlabel("Like Conversion Rate")
plt.ylabel("Title Sentiment")
```

Out[40]:
```
Text(0, 0.5, 'Title Sentiment')
```

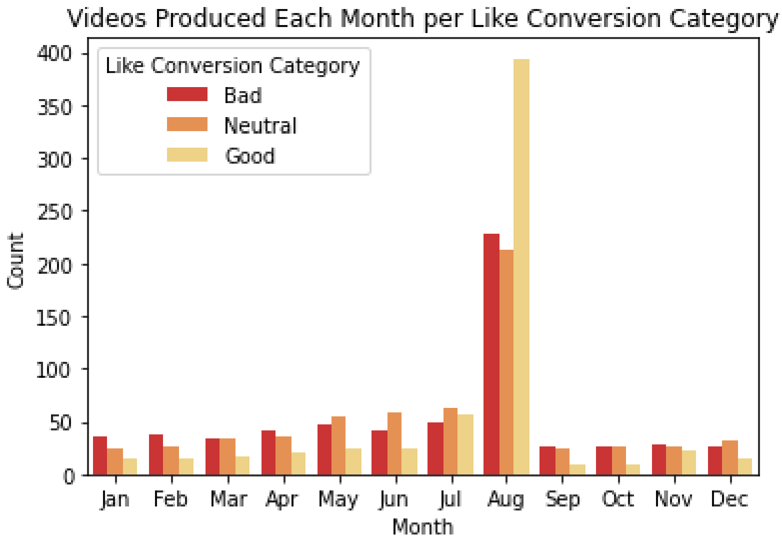


EDA for Month:

- There is a lot of videos from the dataset created in August
- A high proportion of the videos produced in August are in the good like conversion category
- The rest of the months do not follow this pattern

In [41]:

```
ax = sns.countplot(data=videos_final, x="month", hue="like_conversion_cat",palette='YlOrRd_r')
plt.xlabel("Month")
plt.ylabel("Count")
plt.title("Videos Produced Each Month per Like Conversion Category")
plt.legend(title="Like Conversion Category")
ax.set_xticklabels(('Jan','Feb','Mar','Apr','May','Jun','Jul','Aug', 'Sep', 'Oct', 'Nov', 'Dec'))
plt.show()
```

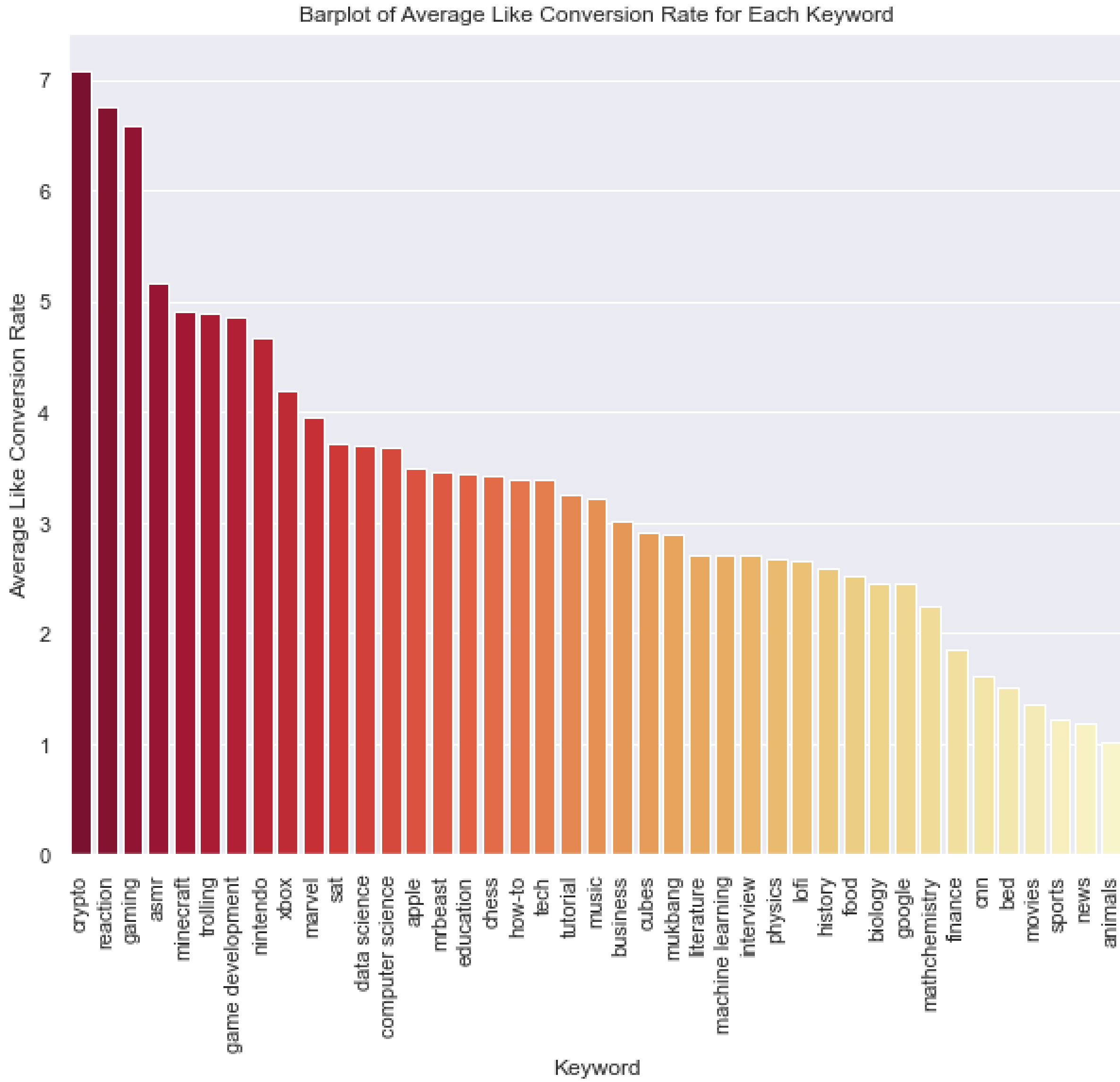


EDA for Keyword:

- There is a wide range of like conversion rate values per Keyword
- Crypto, Reaction, and Gaming are the top three by almost a full percent
- Some of the more broad topics like sports, news, and animals are towards the bottom

In [68]:

```
viz6 = videos_final.groupby('keyword')['like_conversion_rate'].mean().sort_values(ascending=False)
viz6 = pd.DataFrame(viz6).reset_index()
sns.barplot(data=viz6, x='keyword', y='like_conversion_rate', palette='YlOrRd_r')
plt.xticks(rotation=90, ha='center')
sns.set(rc={'figure.figsize': (10, 8)})
plt.xlabel('Keyword')
plt.ylabel('Average Like Conversion Rate')
plt.title("Barplot of Average Like Conversion Rate for Each Keyword")
plt.show()
```



Importing Machine Learning Libraries

In [43]:

```
from sklearn import manifold
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
```

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_moons, make_circles, make_classification
from sklearn.neural_network import MLPClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
```

Machine Learning

Linear Regression Model

In [44]:

```
videos_final = videos.copy()
videos_final.drop(["title", "video_id", "likes", "views", "published_at", "like_conversion_cat"], axis=1, inpla
```

Stratified Shuffle Split

We decided to use a stratified shuffle split on the keyword column because during the EDA section we discovered that there was a vast range of average like conversion rates given a keyword value. Since there are no more than 50 rows of each keyword value, we decided it was necessary to complete a stratified shuffle split to make sure the train and test data sets have an accurate distribution of the different keywords.

In [45]:

```
videos_final.keyword.value_counts()
```

Out[45]:

```
physics             50
```

```
tutorial              50
game development      50
cnn                   50
data science          50
trolling              50
crypto                50
mrbeast               50
interview             50
cubes                 49
marvel                49
reaction              49
sports                49
history               49
asmr                  49
sat                   49
computer science      48
food                  48
minecraft             48
tech                  48
xbox                  48
how-to                48
nintendo              48
chess                 47
biology               47
music                 46
business              46
machine learning      46
literature            46
mukbang               44
google                44
bed                   44
apple                 42
gaming                42
movies                41
lofi                  40
news                  39
finance               39
animals               38
education             24
mathchemistry         15
Name: keyword, dtype: int64
```

In [46]:

```
from sklearn.model_selection import StratifiedShuffleSplit

sss = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in sss.split(videos_final, videos_final['keyword']):
    strat_train_set = videos_final.iloc[train_index]
    strat_test_set = videos_final.iloc[test_index]
```

```
display(strat_train_set.shape, strat_test_set.shape)
```

```
(1487, 8)
(372, 8)
```

In [47]:
```
X = strat_train_set.drop('like_conversion_rate', axis=1)
y = strat_train_set['like_conversion_rate']

num_attribs = ['comments', 'avg_comm_len', 'sent_title', 'title_len', 'avg_comm_len']

cat_attribs = ['keyword', 'month']
```

In [48]:
```
full_pipeline = ColumnTransformer([
        ("num", StandardScaler(), num_attribs),
        ("cat", OneHotEncoder(), cat_attribs),
    ])

prep = full_pipeline.fit_transform(X)
```

In [49]:
```
lm = LinearRegression()
lm.fit(prep, y)
lm.score(prep, y)
```

Out[49]:
```
0.3651258191235991
```

Linear Regression Score

Our Linear Regression model has an R^2 coefficient of 0.365, indicating that around 36.5% of the variability observed in the like conversion rate value can be explained by the regression model.

In [50]:
```
test_y = strat_test_set['like_conversion_rate']
test_X = strat_test_set.drop('like_conversion_rate', axis=1)

test_prep = full_pipeline.transform(test_X)
```

In [51]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(test_y, lm.predict(test_prep))
mse
```

Out[51]: 3.9065527570492597

In [52]:

```
rmse = np.sqrt(mse)
rmse
```

Out[52]: 1.9765001282694772

In [53]:

```
videos_final.like_conversion_rate.describe()
```

Out[53]:

```
count    1859.000000
mean        3.364707
std         2.569841
min         0.000000
25%         1.522041
50%         2.755826
75%         4.450807
max        21.857510
Name: like_conversion_rate, dtype: float64
```

Root Mean Squared Error

Our root mean squared error value came out to 1.976, which means that on average our predictions from the linear regression model of like conversion rate deviate from the actual value by 1.976. This value falls slightly below the standard deviation of the like conversion rate distribution at 2.569. While the model isn't extremely accurate, it performs slightly better on average than picking a random value from the distribution.

Classification Models

In [54]:

```
videos_final = videos.copy()
videos_final.drop(["title", "video_id", "likes", "views", "published_at", "like_conversion_rate"], axis=1, inpl
```

In [55]:

```
sss = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in sss.split(videos_final, videos_final['keyword']):
    strat_train_set = videos_final.iloc[train_index]
    strat_test_set = videos_final.iloc[test_index]

X_train = strat_train_set.drop('like_conversion_cat', axis=1)
y_train = strat_train_set['like_conversion_cat']
```

```python
X_test = strat_test_set.drop('like_conversion_cat', axis=1)
y_test = strat_test_set['like_conversion_cat']
```

In [56]:
```python
num_attribs = ['comments', 'avg_comm_len', 'sent_title', 'title_len', 'avg_comm_len']
cat_attribs = ['keyword', 'month']

full_pipeline = ColumnTransformer([
        ("num", StandardScaler(), num_attribs),
        ("cat", OneHotEncoder(), cat_attribs),
    ])

train_X_prepared = full_pipeline.fit_transform(X_train)
test_X_prepared = full_pipeline.transform(X_test)
```

In [57]:
```python
names = ["Nearest Neighbors", "Linear SVM", "RBF SVM",
         "Decision Tree", "Random Forest", "Neural Net", "AdaBoost"]

classifiers = [
    KNeighborsClassifier(3),
    SVC(kernel="linear", C=0.025),
    SVC(gamma=2, C=1),
    DecisionTreeClassifier(max_depth=5),
    RandomForestClassifier(max_depth=5, n_estimators=10, max_features=1),
    MLPClassifier(alpha=1, max_iter=1000),
    AdaBoostClassifier(),
    ]
```

In [58]:
```python
X_train = train_X_prepared
X_test = test_X_prepared

for name, clf in zip(names, classifiers):
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)

    # evaluate predictions
    accuracy = clf.score(X_test, y_test)
    print("%s Accuracy: %.2f%%" % (name,accuracy * 100.0))
```

```
Nearest Neighbors Accuracy: 50.54%
Linear SVM Accuracy: 52.42%
RBF SVM Accuracy: 47.04%
```

```
Decision Tree Accuracy: 50.27%
Random Forest Accuracy: 50.54%
Neural Net Accuracy: 59.68%
AdaBoost Accuracy: 54.03%
```

Interpreting Model Accuracy

The most accurate model we created is the neural net model which has an average accuracy of classification of 59.68%. While the model isn't extremely accurate in predicting the like conversion category, more often than not, it predicts the correct category that a video falls into. The neural net model is significantly more accurate than guessing a like conversion category at random. It is not a suprise that the neural net classifier is more accurate than the other classifiers we tried, as neural nets are much more complex models, allowing them to handle more nuanced classifications. Since we saw little correlation between most features and like conversion rate, it makes sense that the neural net classification performed the strongest at predicting like conversion categories.

The least accurate model is the RBF SVM. This is not a suprise, as our dataset does not make much sense to use with support vector machine models. Unlike the neural net classifier, these types of models perform better when there is a clear margin of seperation between classes, minimal noise, and are used on smaller data sets.

In [59]:

```
X = videos_final.drop('like_conversion_cat', axis=1)
y = videos_final['like_conversion_cat']

X_prepared = full_pipeline.fit_transform(X)
```

In [60]:

```
classifier = MLPClassifier(alpha=1, max_iter=1000)
classifier.fit(X_prepared, y)
```

Out[60]:

```
MLPClassifier(alpha=1, max_iter=1000)
```

Summary

Findings:

Throughout our EDA process we realized that not many of our variables were correlated with eachother. The heatmap shows that only a couple variables had higher than 0.2 correlation. In addition to this, the distribution of our numerical variables did not vary much between the like conversion rate categories. The only varaible that seemed significant throughout the visualizations was the keyword variable. While this was suprising at first, it caused us to reevaluate the dataset we were working with. Anyone who has access to an electronic device can access Youtube. People may not have any desire for liking or leaving a comment on a video. With that being said, our ML classification model ended up being around 60% accurate. This was suprising given the correlation of the variables. As mentioned previously, while this is not an extremely high score, it is much more accurate than guessing at random, and given the dataset we were working with, we are satisfied with the results.

We fit many different models on to our dataset and found that Neural Net Classification was the best in classifying the Youtube videos into the three categories. We also found that `crypto`, `reaction`, and `gaming` keywords have the highest `like_conversion_rate` out of all other keywords. Overall we found that many of the metrics we defined have some influence in determining a good, nuetral, or bad video. For example, we found that the higher the comment length and sentiment score the better the video performed slightly. Also, shorter title lengths on average resulted in a slightly better like conversion rate. Also, videos posted in August performed much better on average than other months. Overall, these variables were very similar to each other and in order to see major differences in the future we may have to get rid of outliers and find more evenly distributed data.

Challenges and Recommendations:

- Deciding project topic
    - We took too much time deciding on what we were going to do our project on. If we would have had a more efficient brainstorming approach it would have saved us a significant amount of time.
- Cleaning our data multiple times throughout the project
    - When we first started our project we did not do much initial EDA. A consequence of this is that we had to go back and re-clean our data multiple times throughout the project. For example, we did not realize that there were duplicate values in our dataset until we were about to create our model. If we would would have dont an throughout initial EDA then it would have saved us time.
- Inefficient feature engineering
    - When we first started feature engineering we were creating any column that came to mind. This was a waste of time and energy. We should have sat down as a time and brainstomed a list of features that might have been interesting instead of implementing them right away.
    - When creating the like_conversion_rate we should have taken into account that people can like a video only once, but are able to watch the video multiple times. This influenced our model slightly. We knew we did not want to just do like count because that might have bias toward people with more subscribers, so we should have brainstormed more about what we wanted to find to classify a good and bad video.
- Not much correlation
    - Throughout our EDA and ML model we realized that our variables did not have much correlation. Even though this is a finding in itself, it would have been more rewarding to work on a topic that had more correlation. We should have done some initial

correlation analysis on multiple datasets to find one that might be more rewarding.

In the future, for this specific project it might be useful to bring in outside data if it is accessible and merge it with this dataset. I think the model would perform a lot better if it had other metric including Video Length, Thumbnail, Dislikes, Watchtime, Play Rate, Social Shares. These are all things that go into showing whether a video will perform well or not because we know that people can only like a video once but can watch it multiple times. It would also be interesting to use Youtube's free data api to scrape for more data about each of the videos. The addition of this outside data would have gotten rid of the uncertainty and bias of people being able to watch a video multiple times while only being able to like it once. With more time and resources the accuracy for predicting the classification of the video can be improved drastically.