Baseline Model: BOW, Linear Regression

Load Data

In [1]:
```
import pandas as pd
```

In [2]:
```
gb = pd.read_csv('GB_youtube_trending_data.csv')
print('GB dataset shape: ' + str(gb.shape))

us = pd.read_csv('US_youtube_trending_data.csv')
print('US dataset shape: ' + str(us.shape))

df = pd.concat([gb,us])
print('total dataset shape: ' + str(df.shape))
```

```
GB dataset shape: (93395, 16)
US dataset shape: (93391, 16)
total dataset shape: (186786, 16)
```

In [3]:
```
df.sample(3)
```

Out[3]:

	video_id	title	publishedAt	channelId	channelTitle	categoryId	trending_date
51637	AuXmuhmtwz4	How Difficult is it to Ride a Penny Farthing?	2021-04-30T10:25:27Z	UCIRiWCPZoUyZDbydIqitHtQ	Mike Boyd	24	2021-05-01T00:00:00Z
43099	cU6cnHHX4LM	펜타곤 (PENTAGON) - 'DO or NOT' Official Music Video	2021-03-15T09:00:09Z	UCw4NcAAtRsjL-cGlBrUnMTQ	PENTAGON 펜타곤 (Official YouTube Channel)	10	2021-03-19T00:00:00Z
55413	Z189RXBXfGg	The NBA Arrives In Fortnite	2021-05-19T14:31:09Z	UClG8odDC8TS6Zpqk9CGVQiQ	Fortnite	20	2021-05-20T00:00:00Z

Create BOW Embedding

In [4]:
```
# We need all the titles in our dataset

titles = df['title']
titles
```

Out[4]:
```
0         I left youtube for a month and THIS is what ha...
1              TAXI CAB SLAYER KILLS 'TO KNOW HOW IT FEELS'
2         Apex Legends | Stories from the Outlands – “Th...
3                            Nines - Clout (Official Video)
4                        i don't know what im doing anymore
                               ...                        
93386      Hermitcraft 8 | Ep.9: ANTI BOATEM DEFENCE FORCE!
93387     The AFTERMATH of listing all 40 cars for sale ...
93388       When a kid thinks he’s to smart for his grade :
93389           Minecraft Manhunt, But Trash Gives OP Items
93390                       Volcano of the Dead! - DayZ Mod
Name: title, Length: 186786, dtype: object
```

In [5]:
```
# Now we can use CountVectorizer to build our embeddings
from sklearn.feature_extraction.text import CountVectorizer

# Since this is our baseline model, we will use the default perameters for the vectorizer
# This means that there will be very limited pre-processing to the tokens, simply just lowercase
embedder = CountVectorizer()
embedder.fit(titles)
embedder
```

Out[5]:
```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                lowercase=True, max_df=1.0, max_features=None, min_df=1,
                ngram_range=(1, 1), preprocessor=None, stop_words=None,
                strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                tokenizer=None, vocabulary=None)
```

In [6]:

```
# Let's test the embedder
sample_title = titles.sample()
sample_title

sample_title, embedder.transform(sample_title).toarray()
```

Out[6]:

```
(37465    CHAOS AGENT SKIN IS BACK IN FORTNITE!
 Name: title, dtype: object, array([[0, 0, 0, ..., 0, 0, 0]], dtype=int64))
```

In [7]:

```
# Let's make it into a function so we can use it on a dataframe later

def embed(text):
    return embedder.transform([text]).toarray()
```

Creating the Dataset

In [8]:

```
# We want to predict the view count with our embedded vector,
# so we are going to need both our embeddings and the correspoding
# view counts

embeddings = embedder.transform(df['title'])
views = df['view_count'].to_numpy()

embeddings.shape, views.shape
```

Out[8]:

```
((186786, 21290), (186786,))
```

Linear Regression Model

In [9]:

```
# For the baseline model, let's use the default perameters

from sklearn.linear_model import LinearRegression

lr = LinearRegression()
```

In [10]:

```
# Let's use cross validation to see how it performs

from sklearn.model_selection import cross_validate

cv_results = cross_validate(lr, embeddings, views, cv=10, n_jobs=10, scoring=['neg_mean_squared_erro
r', 'r2'])
cv_results
```

Out[10]:

```
{'fit_time': array([114.62855554, 112.26919603,  88.20360994, 105.9631753 ,
        121.70671296, 115.17542791, 118.67543674, 104.6194272 ,
         90.04736018, 105.69755459]),
 'score_time': array([0.        , 0.        , 0.01563025, 0.        , 0.        ,
        0.        , 0.01563001, 0.        , 0.        , 0.        ]),
 'test_neg_mean_squared_error': array([-5.44779079e+13, -4.85260855e+13, -4.53427376e+13, -8.52897
952e+13,
        -4.70751785e+13, -6.57873941e+13, -4.54969001e+13, -4.50817466e+13,
        -8.17742714e+13, -5.53059799e+13]),
 'test_r2': array([-0.52038537, -1.68848746, -0.36493162, -0.10816334, -0.39682136,
        -0.21117885, -0.47231531, -0.22454227,  0.21555149, -0.2086462 ])}
```

In [12]:

```
# Let's get the average MSE as well as R2 score

results = {}
results['MSE'] = sum(cv_results['test_neg_mean_squared_error']) / 10
results['R2'] = sum(cv_results['test_r2']) / 10

results
```

Out[12]:

```
{'MSE': -57415799682205.35, 'R2': -0.3979920290811073}
```

In [13]:

```
# Looks like the model performs very poorly.
# A negative r^2 value means that the model performs worse than a horizontal line.
# This makes sense as it is using the most basic form of embedding,
# along with the most basic model.

# It is also very likely that the data is simply non linear, thus a linear model
# is bound to perform poorly
```

Visualizations

In [16]:

```
# Let's take a look at how the data is distributed.
# Generally, because of their sparse nature, BOW embeddings are highly compressable
# We can use SVD to compress our embeddings for visualization

# Since we are working with Sparse Matrix we can use TruncatedSVD
from sklearn.decomposition import TruncatedSVD

svd_embeddings = TruncatedSVD(n_components=2).fit_transform(embeddings)
svd_embeddings
```

Out[16]:

```
array([[ 0.26449606, -0.02101968],
       [ 0.25285891, -0.00596183],
       [ 1.82301177, -0.42374467],
       ...,
       [ 0.28342311, -0.02082473],
       [ 0.05542347, -0.01059827],
       [ 1.06479866, -0.22592808]])
```

In [22]:

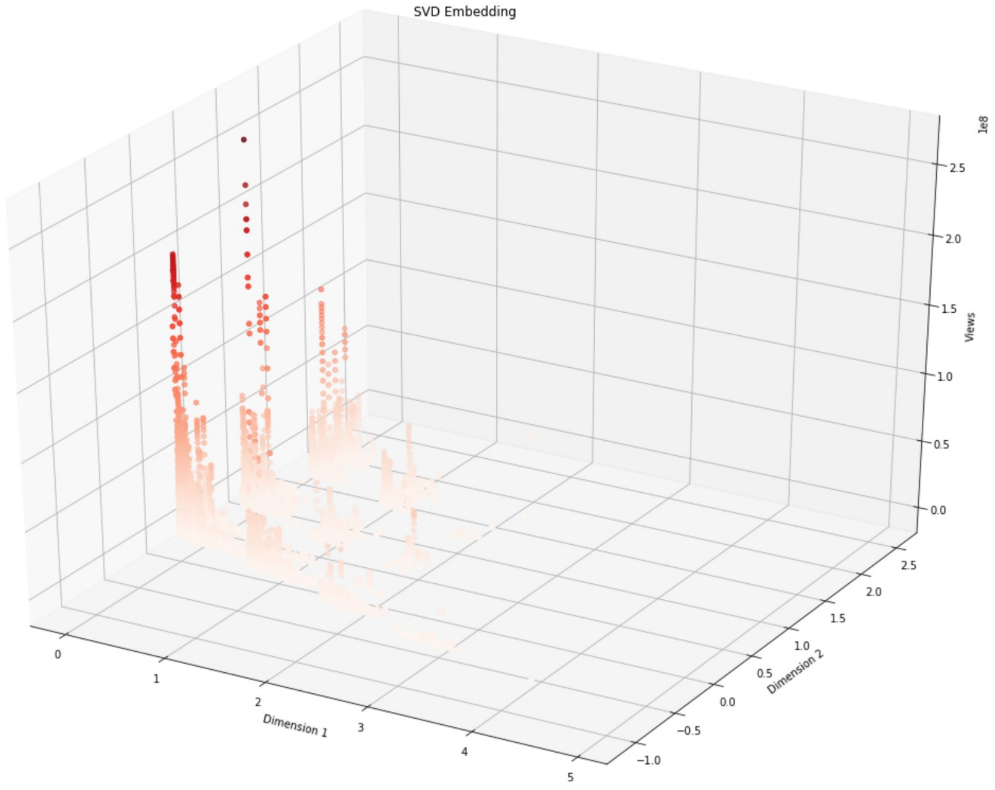
```
# Now let's make a graph where the x and y axis are our embeddings,
# and the z axis is the view count.

import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline

fig = plt.figure(figsize=(20,15))
ax = plt.axes(projection='3d')
ax.set_xlabel('Dimension 1')
ax.set_ylabel('Dimension 2')
ax.set_zlabel('Views')
ax.set_title('SVD Embedding')
ax.scatter3D(svd_embeddings[:,0], svd_embeddings[:,1], views, c=views, cmap='Reds')
```

Out[22]:

```
<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x246c1d1a248>
```



In [ ]:

```
# As seen here, the data is not very linearly seperable, there are many peaks and valleys
# We will consider this in our future models
```