Using Regression methods to analyse the effect of titles on YouTube videos

1. Introduction

"Clickbaiting" refers to an action on the YouTube platform, where content creators formulate the video title with specific keywords meant to capture the viewer attention and make them more likely to click on the video, hence the term "clickbait".

Despite the negative connotation, clickbait titles do have their share of usage. Namely, they show how certain keywords capture our curiosity and interest. Therefore, understanding how to use these keywords will help creators and companies choose better titles for their future videos. As long as the title is honest and relevant to the content in the video, developing a title that captures the audience's attention can have a positive impact for the creator. The application domain for the project is thus the Entertainment or Marketing industry.

This report aims to predict the effectiveness (number of views) of a video title based on video data from 5-Minute Crafts – a YouTube channel famous for its clickbaiting practice. The report is divided into 7 parts. In this introduction, we have briefly discussed the concept of clickbaiting and how video titles can have a great effect on capturing the viewer's attention. Following this section is Section 2, where we will look at the problem formulation process and provide a general description of the problem. For Section 3, the topic will shift into further details regarding the process behind this report and how the Machine Learning methods was chosen and implemented. Then, Section 4 and 5 will discuss the findings and conclusion of the report. Lastly, for the purpose of further references, Section 6 contains a list of references, and Section 7 include the code implementation of this project.

2. Problem formulation

The dataset used in this report is the "5-Minute Crafts: Video Clickbait Titles?" dataset on Kaggle, uploaded by user Shivam Bansal **[1]**. The dataset includes data from 4978 videos from 5-Minute Crafts, with 15 data columns. For this report, each video in the dataset is a data point. The features that will be examined are the videos' titles, which is a collection of English words (the feature's data type is string).

Regarding the label, since this report only studies videos from the 5-Minute Crafts channel, using the number of views as the label would not be indicative of the title's effectiveness. This is because the views can fluctuate depending on the channel's size. We cannot expect to get the same number of views on another channel by using the same title from 5-Minute Crafts. In other words, we need a rating that measures how a title performs relative to the channel size. We can obtain such rating by finding the video with the most views and use it as our reference. We can call this new number "relative rating" which is calculated as follows:

$$R_i = \frac{V_i}{\max{(V)}} \times 100$$

To put it into words, the rating of a video is equal to the number of views on that video divided by the maximum views achieved on a single video on the channel, multiplied by 100. Thus, we have a number from 0 to 100 that indicates the performance of a video relative to the channel size. This "relative rating" will be the label that we try to predict (the label's data type is float).

3. Methods

3.1. Feature selection

The data set includes 15 different columns that represent different characteristic of a video. In this report, only the “title” and “total_views” columns will be considered as they the subject of interest.

There are two main reasons why the “title” was chosen as the feature for this project. Firstly, as mentioned in the introduction, video titles have a considerable effect on capturing the audience’s attention. In fact, the title, along with the thumbnail of the video, are the two main factors that lead potential viewers to decide whether they want to watch a certain video or not. The latter of which is not available to us at the time of this report.

Secondly, video titles are easy to formulate. Different from other aspects of a video, the title only requires minimal effort from the creator. A YouTuber would only need to spend on average a few minutes to create a video title. Such minimal time effort combines with the great effect that they have on a video make the title an investment with a relatively high return on the time invested.

Thus, based on the effectiveness of video titles and the availability of the data in possession, “title” is the most suitable feature for our problem.

3.2. Data processing

Because the project at hand is related to language processing, there is a fair amount of Data processing work that must be conducted before applying the required Machine Learning methods. However, due to the page constraint and the fact that this process is not part of the grading criteria, only a brief walkthrough will be provided in order to lay out a general context. For further references, one could refer to the code appendix for more details.

First, we clean the string in the raw “title” feature by removing non-related contents such as punctuations, capitalizations, stop words, to get a string of keywords. Next, using the NLTK library, the strings are tokenized into Python lists that contain the mentioned keywords **[3]**. Finally, to continue with further analysis, each list of words is mapped to a numerical value. In other words, each title (now represented in form of list) will be given a numerical value base on the words that it contains. One logical way to approach this is to consider individual words first. If a word repeatedly exists in the titles of well-performed videos, it is likely to be a “good” word that have a positive impact on the video performance. On the contrary, if a word appeared in the titles of multiple poorly performed videos, it is likely to be a “bad” word, that is not very effective. A rather simple way to reflect the given logic is to find the mean “relative rating” of all videos that contain the word. For instance, if the word “hack” has the mean rating of 1.82, the videos that contains it have on average a 1.82 rating. After obtaining the score of each word, we only need to take the average of every word in a certain title to get its final numerical score. A visualization of the final data can be found in Figure 1.

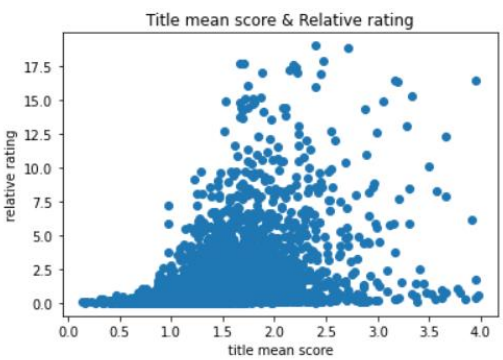


Fig. 1. Fully processed data visualization

3.3. ML Methods application

As we are trying to predict a variable that is dependent on another variable (title mean score and relative rating), this is a suitable problem for Regression models. In further details, one could even see that the label tends to increase exponentially as the feature increases. Given this relationship between features and labels, we ought to use Polynomial Regression in order to solve our given problem. Which leave one final problem that need to be solved: identifying the optimal Polynomial degree for our problem. We can find the optimal model by trying out a wide range of Polynomial degrees. This will ensure that we do not miss any potential candidates for our optimal model position and thus obtain the best model for the problem. Hence, the models that will be examine in this report are 2nd degree, 3rd degree, 5th degree, and 8th degree Polynomial Regressions.

Regarding the loss function, we can observe that the above data is quite closely clustered and evenly distributed. In other words, there is no separate outlier with significantly large value. According to this given insight, we don't need to use Huber loss or other similar methods to negate the effect of outliers. In addition, it is reasonable to give the data points with high "relative rating" an accordingly greater impact on our model, as those videos are the rare videos that achieve high number of views. Thus, the Mean Squared Error (MSE) loss function is a suitable loss function to use for this model. As the problem is a Polynomial Regression problem, there is no need for an additional function to evaluate the model (such as 0/1 loss for classification problems). For Regression problems, it is rather common to use the same loss function for training and evaluating the model. Therefore, MSE will be used both for training and validating the model.

For the construction of training, validation, and test sets, we will reserve 10% for testing as this is relatively common size choice for the test set. Using only 10% for testing will ensure that we can use most of the data for training and validating our model to achieve better performance. For training and validation set, we will make use of K-fold cross validation in order to estimate the model's validation error more accurately, as it ensures each data point will be included in the validation set once. One problem with K-fold is that it is computationally demanding for large data sets **[4]**. However, for our given data set of roughly 5000 data points, K-fold will not give us any significant computational burden. There will be 5 iterations of K-fold, as this effectively make the train-validation split ratio an 8:2 split for each iteration. Meaning, for each iteration, 20% of the 90% total data we have will be include in the validation set, and the other 80% will go into training the model. This ratio is optimal as it saves the majority of data for training and thus ensure the model is well-trained in each iteration. It is also worth mentioning that for validating and testing the models, the 8:2 split ratio is a rather common ratio to use in the field as well, therefore it should be a relatively reliable choice for the current project.

4. Results

After applying the methods, it is evidenced that a 3rd degree Polynomial Regression gives the best result, compared to the other Polynomial degrees. Figure 2 gives a list of training errors as well as validation errors for all the Polynomial degrees. As indicated, 3rd degree Polynomial have the lowest validation error of 4.22. It can also be seen from the Figure that the validation error is increasing from degree 3 onwards, evidenced by the fact that degree 5 and 8 have a higher validation error than the 3rd degree model. It is also quite likely that the 5th and 8th degree models are overfitted, since we can observe that despite the training error decreases, the validation error still becomes increasingly higher compared to 3rd degree model. Therefore, given these facts, 3rd degree Polynomial is the best method out of the 4 models that we have examined, and consequently will be use as our final chosen method.

```
For degree 2, average training error = 4.226235
    average validation error = 4.237403

For degree 3, average training error = 4.191956
    average validation error = 4.220556

For degree 5, average training error = 4.187900
    average validation error = 4.239863

For degree 8, average training error = 4.184781
    average validation error = 4.265005
```

Fig. 2. Validation errors of all Polynomial degrees

For the last step, we need to find the testing error using the test set mentioned earlier in Section 3.3. After training the 3rd degree Polynomial on the other data, we use the test set, which contains unseen data, to predict and calculate the test error. The result is a test error of 3.86, which is relatively low for a data set that span from 0 to 20. The plot of the final model and the test set can be seen in Figure 3.

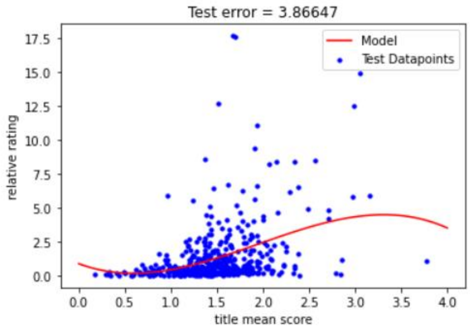


Fig. 3. The previously trained model and the test Datapoints

5. Conclusion

The report has illustrated a potential application of Machine Learning in predicting the YouTube videos' views. As evidenced by the current result, the trained model seems to have a relatively good reliability considering the test error.

However, it is worth noting that one peculiar aspect about the current findings is that there seems to exist a point of diminishing return at the "title mean score" around 3.2, as indicated by the decreasing of the plot in the visualization. At the moment, it is unclear what could cause this phenomenon, but one possible theory is that there are not enough data points in that region for the model to properly learn from. Since high-viewed videos are far rarer than low-viewed ones, low-viewed videos have higher probability to appear than their high-viewed counterpart. This causes a sampling error to arise, meaning that given a small sample size, the sample is unlikely to accurately represent the whole population **[5]**.

It is known that the larger the sample size, the better representation it is for the population. Therefore, the sampling error is often negated if a large amount of data points is present, as seen in the middle region of the plot where the model performs well. However, when the data is scarce, similar to the rightmost region beyond the 3.2 mark, it is highly likely that the sample will fail to reflect the true nature of the total population. Thus, given this observation, the most important aspect to consider for further improvement of the project is to collect more datapoints. Having more data will ensure that the model properly learn and reflect the relationship of the feature and the label population, without being subjected to the effect of sampling error that a small sample size inherently exhibit.

All in all, the project indicates that there is a high potential for further research and implementation of Machine Learning in the YouTube space, especially in view prediction. As a matter of fact, there are a large variety of other aspects that forms a YouTube video apart from the title. Which indicates that there is a fair number of potential subjects for further discoveries in the future.

6. References

[1] Shivam Bansal (2021), 5-Minute Crafts: Video Clickbait Titles?. https://www.kaggle.com/shivamb/5minute-crafts-video-views-dataset
[2] Department of Computer Science, Aalto University, “CS–C3240 – Machine Learning D course”, 2022.
[3] Steven Bird, Ewan Klein, and Edward Loper (2009). Natural Language Processing with Python. O’Reilly Media Inc. https://www.nltk.org/book/
[4] DANB (2018), Cross-Validation. https://www.kaggle.com/dansbecker/cross-validation
[5] Statistic Canada organization (2021), Sampling error. https://www150.statcan.gc.ca/n1/edu/power-pouvoir/ch6/sampling-echantillonage/5214807-eng.htm

7. Code appendix

YouTube video titles' views prediction - Code implementation

March 31, 2022

[1]:
```
# import the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

import nltk
## in case haven't download yet, only need to do once per run
# nltk.download('punkt')
# nltk.download('stopwords')

from nltk.corpus import stopwords
import string
from nltk.tokenize import word_tokenize
from collections import Counter
```

1 Processing the data

[2]:
```
# read the data from the file '5-Minute Crafts.csv'
df = pd.read_csv('5-Minute Crafts.csv')

# check by printing the first 5 data points
df.head(5)
```

[2]:
```
        video_id                                              title  \
0  v=XHTofu5wbbM  SUPER LAZY LIFE HACKS || Cool Hacks To Make Yo…
1  v=HGxxOumIQvk  YUM! EASY SMART FOOD HACKS || Tasty Recipes Fo…
2   v=Tt4RMk3Ih04                   HELPFUL LIFE HACKS FOR YOUR HOUSE
3  v=A2MTydM5e58  USEFUL HACKS FOR YOUR HOME || Simple Tips That…
4  v=_halJ4yrmGQ  ARE YOU A CRAFTY MOM? Amazing Parenting Hacks …

   active_since_days  duration_seconds  total_views  num_chars  num_words  \
0                 22               623       295614         60         12
1                  1               739       130544         87         17
```

```
2                       1              960       17834         33          6
3                      30              833     3128867         66         12
4                      15             3600     4210362         56         10

   num_punctuation  num_words_uppercase  num_words_lowercase  num_stopwords  \
0                2                    4                    0              2
1                4                    5                    0              3
2                0                    6                    0              2
3                2                    5                    0              3
4                1                    5                    0              4

   avg_word_len  contain_digits  startswith_digits  title_sentiment
0      5.000000               0                  0         0.144444
1      5.117647               0                  0         0.086905
2      5.500000               0                  0         0.000000
3      5.500000               0                  0         0.058333
4      5.600000               0                  0         0.500000
```

1.1 Create relative rating column

From the column total_views, we will calculate the 'relative rating', a scale from 1-100 to indicate how well the video do as respect to the highest viewed video (refer to the report for more information).

[3]:
```
maxViews = df["total_views"].max()
df = df.assign(relative_rating = df["total_views"] / maxViews * 100)
```

1.2 Clean the video titles

Since the title is essentially just a list of words, we will try to turn it into such form for easier manipulation. We need to remove stop words, punctuation, capitalization, and other symbols from the title to get a sentence of clean text. Then, we tokenize the clean sentence into a list of words for later manipulation. We will make use of the NLTK library for this process.

[4]:
```
# function to tokenize and clean a sentence
def tokenize_and_clean(x):
    # turn x into lower case
    x = x.lower()
    # tokenize x
    tokens = word_tokenize(x)

    # filter out the stop words
    clean_tokens = [word for word in tokens if not word in stopwords.words()]
    # filter out the punctuation
    clean_tokens = [word for word in clean_tokens if not word in string.
 ↪punctuation]
```

```
    # filter out non-alphabetical words (numbers, special characters, etc),␣
↪only leave normal words
    clean_tokens = list(filter(lambda token: token.isalpha() == True,␣
↪clean_tokens))

    return clean_tokens
```

[5]:
```
# apply the function to all titles in 'title' column, to create a new column␣
 ↪'clean_token'
# Note that this will take quite a long time to run
df['clean_token'] = df['title'].apply(lambda x : tokenize_and_clean(x))
```

[6]:
```
# get the final data
data = df[['clean_token','relative_rating']]
data.head(5)
```

[6]:

	clean_token	relative_rating
0	[super, lazy, life, hacks, cool, hacks, make, …	0.104446
1	[yum, easy, smart, food, hacks, tasty, recipes…	0.046124
2	[helpful, life, hacks, house]	0.006301
3	[useful, hacks, home, simple, tips, work, extr…	1.105485
4	[crafty, mom, amazing, parenting, hacks, crafts]	1.487597

Now we have sucessfully turn our data into a more manageable form. Next let's take a look at how we can make use of the text data in the video titles for our Machine Learning problem.

1.3 Transform the text data into numerical values

Since we have not learnt much regarding analyzing using text data in the course, we need a way to transform the word lists from the tokens above into numerical values that we can do our analytics on. In other words, the problem is "given a certain list of words, assign a score to that list of words base on the data that we have".

Intuitively, one way to approach this is to give each word a 'score' value, base on how well the videos that contained it performed. For example, if the word 'hacks' often appear in videos with high relative rating, we want to give it a higher score value. By contrast, if the word 'electromagnetism' often appear in videos with low relative rating, we want to give it a lower score value.

After each word have a respective score value, for each list of words we just need to take the average of all the scores of the words it contains to get our final score of the video title.

[7]:
```
# First we need a dictionary of all the words and their frequency,
# a Counter object will be suitable for this purpose
Word_Freq = Counter()
# iterate through each token in 'clean_token' collumn
for token in data['clean_token']:
    # iterate through each word in the token
    for word in token:
```

```
        # increase the count for the word in the dictionary
        Word_Freq[word] += 1

# print out the 10 most common words to check
Word_Freq.most_common(10)
```

[7]:
```
[('hacks', 2436),
 ('life', 863),
 ('ideas', 659),
 ('crafts', 468),
 ('tricks', 444),
 ('make', 438),
 ('diy', 426),
 ('easy', 377),
 ('cool', 329),
 ('know', 306)]
```

[8]:
```
Word_Total_Score = {}# dictionary to hold words and their total relative rating␣
 ↪from all videos that include the word
# iterate through each row in the data
for i in range(len(data)) :
    # iterate through each word in the token
    for word in data.loc[i, 'clean_token']:
        # if the current word doesn't exist yet in the dictionary, add it
        if(word not in Word_Total_Score):
            Word_Total_Score[word] = data.loc[i, 'relative_rating']
        else: # otherwise add the current video's relative rating to the word's␣
 ↪total score
            Word_Total_Score[word] += data.loc[i, 'relative_rating']
```

After having the frequency of each word and the total relative rating of all the videos that include it, we can divide Word_Total_Score by Word_Freq to get the average score of each word.

[9]:
```
Word_mean_score = {}# dictionary to hold the mean score of a word
# iterate through each (unique) word in both dictionary
for word in Word_Freq:
    # calculate the mean score and add it to the Word_mean_score dictionary
    Word_mean_score[word] = Word_Total_Score[word] / Word_Freq[word]

# print out the mean score of the word 'hacks' to check
print("The mean score of the word 'hacks' is: ", Word_mean_score['hacks'])
```

```
The mean score of the word 'hacks' is:  1.8266621093803712
```

From the score above we can see that although the word ‘hacks’ appear the most, videos that contain it does not seem to perform well on average.

Some further checking, let us find the word with the highest score.

[10]:
```
best_word = max(Word_mean_score, key=Word_mean_score.get)
print("The word with highest mean score is '{word}', \
with the score of {score}".format(word = best_word,score =␣
↪Word_mean_score[best_word]))
```

```
The word with highest mean score is 'ouch', with the score of 24.103273043388317
```

Given this result, we can depict that on average, videos with the word 'ouch' perform really well.

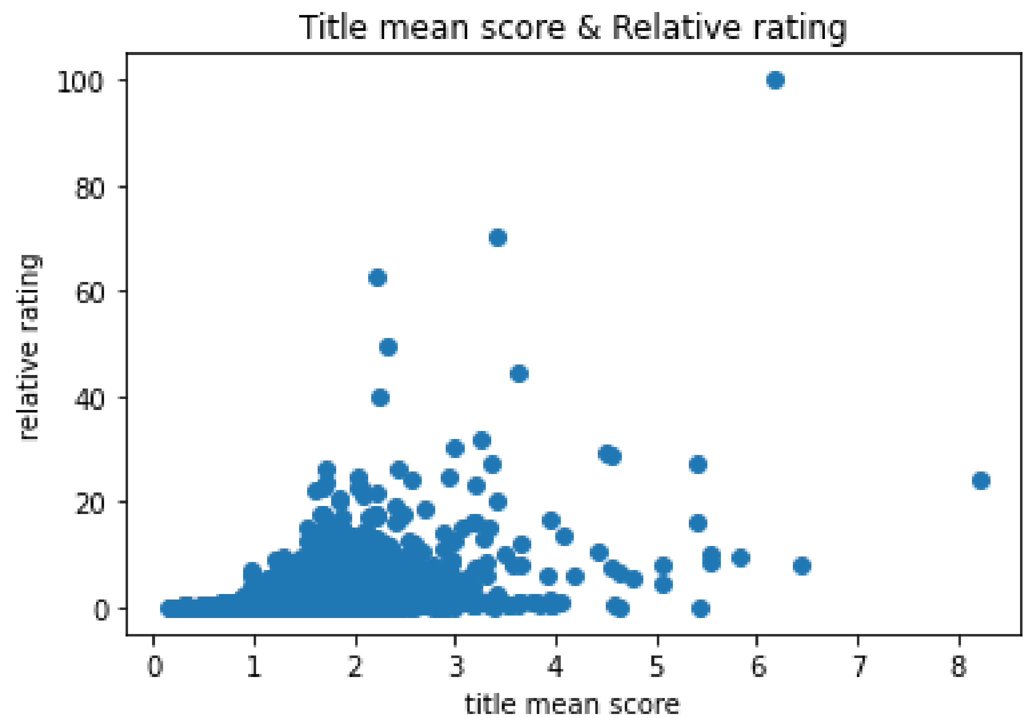
1.4 Construct the feature and label vectors

Now that we have a score for each word, we just need to take the average of the words in a certain title to obtain the title's score

[11]:
```
features = [] # list of features
labels = [] # list of labels
n = 0
# iterate through each row in the data
for i in range(len(data)):
    token = data.loc[i, 'clean_token']
    relative_rating = data.loc[i, 'relative_rating']

    words_sum_score = 0
    # iterate through each word in the token
    for word in data.loc[i, 'clean_token']:
        # add the score of the current word to the total
        words_sum_score += Word_mean_score[word]

    # calculate the mean score of the title
    title_score = words_sum_score / len(token)

    # add the current title score to the features list
    features.append(title_score)
    # add the current relative rating to the labels list
    labels.append(relative_rating)
    n = n + 1

X_all = np.array(features).reshape(n,1)
Y_all = np.array(labels)

# print out the shape of X and Y vector to check
print("number of datapoints:",n)
print("the shape of the feature matrix is: ",X_all.shape)
print('the shape of the label vector is: ',Y_all.shape)
```

```
number of datapoints: 4978
the shape of the feature matrix is:  (4978, 1)
the shape of the label vector is:  (4978,)
```

[12]:
```python
# visualize the processed features and labels
figure = plt.figure()

axis = figure.add_subplot(1, 1, 1) #add an axes object to the figure

axis.scatter(X_all,Y_all) # draw scatterplot based on the two vectors
axis.set_xlabel('title mean score') # graph label for X
axis.set_ylabel('relative rating') # graph label for Y
axis.set_title('Title mean score & Relative rating')

plt.show()
```



Some observations, we can see that there are some corelation between the title score we calculated and the relative rating. However, our data contain a few outliers. These are mainly videos that are unusually popular or trendy due to the YouTube algorithm. It is still unclear to the public how the YouTube algorithm works, it sometimes make seemingly "random" suggestion and views on that video will sky rocketed. As we are not intended to make sense of the YouTube algorithm in this report, one valid way according to the course for dealing with these outliers is to remove them from the data set. Since there are only a few outliers, removing them will not have a large effect on the general representation of the data set.

We can see from the plot that the majority of our data has features and labels in the interval $0 \leq X \leq 4$, and $0 \leq Y \leq 20$.

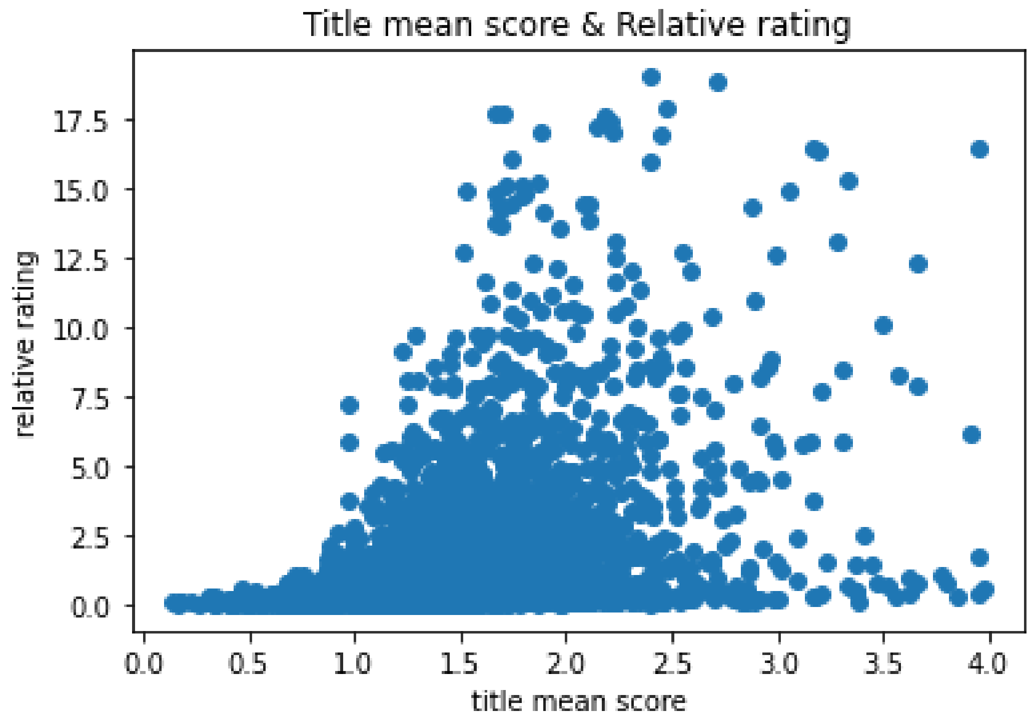
Therefore, we can use this fact to our advantage and filter out the points that fall outside these ranges. This would still leave us with a large amount of data that we can use for training and testing.

[13]:
```python
# First, we need to zip the two vectors into a single list of tuples
# that represent points (Xi,Yi)
points = list(zip(X_all,Y_all))

# Then, we filter out all points
# that have X > 4 or Y > 20
no_outlrs_points =  filter(lambda point: (point[0] > 4 or point[1] > 20) ==␣
 ↪False, points)

# Next, we can split the filtered points into two X and Y vectors again
unzipped_points = list(zip(*no_outlrs_points))
X_list = list(unzipped_points[0])
Y_list = list(unzipped_points[1])
X = np.array(X_list).reshape(len(X_list),1)
Y = np.array(Y_list)

# print out the shape of X and Y vector to check
print("the shape of the feature matrix is: ",X.shape)
print('the shape of the label vector is: ',Y.shape)
```

```
the shape of the feature matrix is:  (4932, 1)
the shape of the label vector is:  (4932,)
```

The number of datapoints is 4932, which is approximately 99% of the data. Thus, this new X and Y vectors is still a good representation of the original data set.

[14]:
```python
# plot the points again
figure = plt.figure()

axis = figure.add_subplot(1, 1, 1) #add an axes object to the figure

axis.scatter(X,Y) # draw scatterplot based on the two vectors
axis.set_xlabel('title mean score') # graph label for X
axis.set_ylabel('relative rating') # graph label for Y
axis.set_title('Title mean score & Relative rating')

plt.show()
```



With the outliers removed and the graph zoomed in, we can see that the correlation between X and Y seem to be more clear.

2 Applying Machine Learning methods

As we are trying to predict a variable that is dependent on another variable (title mean score and relative rating), this is a suitable problem for Regression models. In further details, one could even see that the label tends to increase exponentially as the feature increases. Given this relationship between features and labels, we ought to use Polynomial Regression in order to solve our given problem. Which leave one final problem that need to be solved: identifying the optimal Polynomial degree for our problem. We can find the optimal model by trying out a wide range of Polynomial degrees. This will ensure that we do not miss any potential candidates for our optimal model position and thus obtain the best model for the problem. Hence, the models that will be examine in this report are 2nd degree, 3rd degree, 5th degree, and 8th degree Polynomial Regressions.

We will make use of K-fold to estimate the model's validation error more accurately, as it ensure each data point will be included in the validation set once.

[15]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split
```

Firstly, 10% of the data must be reserve for the test set.

[16]:
```
# reserve 10% of the data for testing first

# split into the test set and the remaining set
X_rem, X_test, Y_rem, Y_test = train_test_split(X,Y,test_size=0.
↪1,random_state=50)
```

Next, we performs K-fold for all the Polynomial degrees to find the optimal model.

[17]:
```
k = 5
k_fold = KFold(n_splits=k, shuffle=True, random_state=50)
```

[18]:
```
### some code lines that is use for plotting in stage 2 of the project are␣
↪commented out

# plt.figure(figsize=(50, 20))

degrees = [2, 3, 5, 8]

avg_train_errs = []
avg_val_errs = []

# iterate through all the degrees
for i, degree in enumerate(degrees):
    deg_train_errs = []
    deg_val_errs = []

    # plot_row = 0# to keep track of the plot row
    # plot_col = 0


    # iterate through all the folds
    for j, (train_indices, val_indices) in enumerate(k_fold.split(X_rem)):
        # make it so that it move on to the next line after every 2 plots
#         if (j % 2 == 0 and j != 0):
#             plot_row += 1
#             plot_col = 0

#         plt.subplot(3, k, plot_row * k + plot_col + 1)   # choose the␣
↪subplot's location
#         plot_col += 1

        X_train, Y_train, X_val, Y_val = X_rem[train_indices],␣
↪Y_rem[train_indices], X_rem[val_indices], Y_rem[val_indices]

        # fit the linear model
        regr = LinearRegression(fit_intercept=False)
        polyFeatures = PolynomialFeatures(degree=degree)
```

```
        X_train_poly = polyFeatures.fit_transform(X_train)
        regr.fit(X_train_poly, Y_train)


        # Calculate the training and validation error from the current fold
        Y_pred_train = regr.predict(X_train_poly)    # predict using the␣
↪regression model
        tr_error = mean_squared_error(Y_train, Y_pred_train)    # calculate the␣
↪training error
        X_val_poly = polyFeatures.transform(X_val)
        Y_pred_val = regr.predict(X_val_poly) # predict labels for the␣
↪validation data using the regression model
        val_error = mean_squared_error(Y_val, Y_pred_val) # calculate the␣
↪validation error

        deg_train_errs.append(tr_error)
        deg_val_errs.append(val_error)
        # plot the current fold
    #     X_fit = np.linspace(0, 4.5, 100)    # generate X interval for the␣
↪graph, from 0 to 4.5 with 100 samples
    #     plt.tight_layout()
    #     plt.plot(X_val, Y_pred_val, label="Model")    # draw the linear␣
↪regression model
    #     plt.scatter(X_train, Y_train, color="b", s=10, label="Train␣
↪Datapoints")    # draw points for train data
    #     plt.scatter(X_val, Y_val, color="r", s=10, label="Validation␣
↪Datapoints")    # draw points for validation data
    #     plt.xlabel('title mean score')    # set the label for the x/y-axis
    #     plt.ylabel('relative rating')
    #     plt.legend(loc="best")    # set the location of the legend
    #     plt.title(f'CV iteration = {j}\nTraining error = {tr_error:.
↪6}\nValidation error = {val_error:.6}')


    # calculate the average training and validation error for the current␣
↪degree, accross all fold
    avg_train_err = np.mean(deg_train_errs)
    avg_val_err = np.mean(deg_val_errs)

    avg_train_errs.append(avg_train_err)
    avg_val_errs.append(avg_val_err)

# plt.show()
```

Let's print out the training and validation errors of all the different degree Polynomial models.

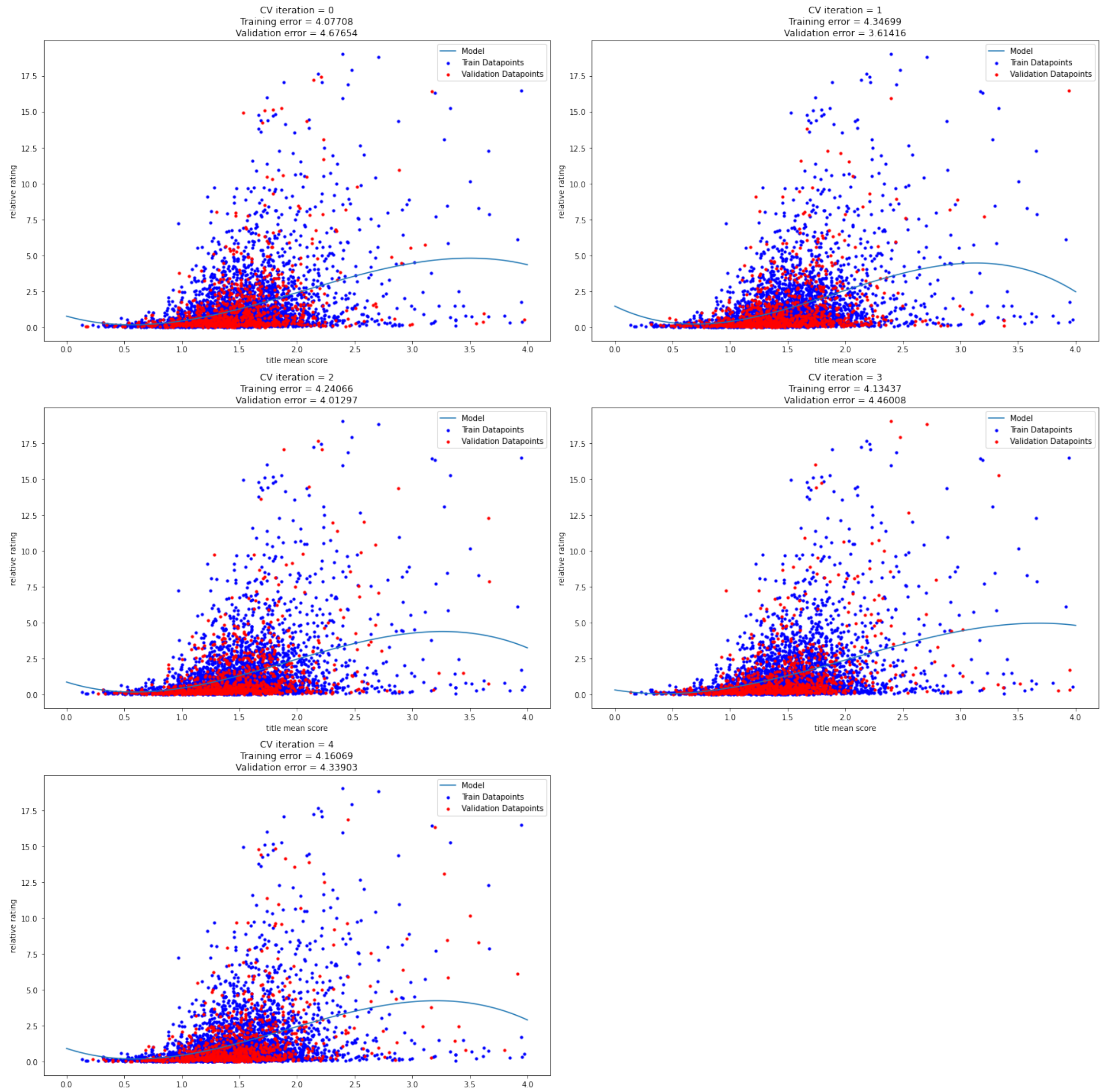
[19]:
```
for i, degree in enumerate(degrees):
    print(f"""For degree {degree}, average training error = {avg_train_errs[i]:.
 ↪6f}
    average validation error = {avg_val_errs[i]:.6f}\n""")
```

```
For degree 2, average training error = 4.226235
    average validation error = 4.237403

For degree 3, average training error = 4.191956
    average validation error = 4.220556

For degree 5, average training error = 4.187900
    average validation error = 4.239863

For degree 8, average training error = 4.184781
    average validation error = 4.265005
```

According to the average validation errors, 3rd degree Polynomial model provide the best prediction. For a quick visualization, let's plot this Polynomial implementation throughout all the K-fold iterations.

[20]:
```
plt.figure(figsize=(50, 20))


plot_row = 0# to keep track of the plot row
plot_col = 0



# iterate through all the folds
for j, (train_indices, val_indices) in enumerate(k_fold.split(X_rem)):
    # make it so that it move on to the next line after every 2 plots
    if (j % 2 == 0 and j != 0):
        plot_row += 1
        plot_col = 0

    plt.subplot(3, k, plot_row * k + plot_col + 1)    # choose the subplot's␣
 ↪location
    plot_col += 1

    X_train, Y_train, X_val, Y_val = X_rem[train_indices],␣
 ↪Y_rem[train_indices], X_rem[val_indices], Y_rem[val_indices]

    # fit the model
    regr = LinearRegression(fit_intercept=False)
    polyFeatures = PolynomialFeatures(degree=3)# make it a third degree model
    X_train_poly = polyFeatures.fit_transform(X_train)
    regr.fit(X_train_poly, Y_train)
```

```
    # Calculate the training and validation error from the current fold
    Y_pred_train = regr.predict(X_train_poly)    # predict using the regression model
    tr_error = mean_squared_error(Y_train, Y_pred_train)    # calculate the training error
    X_val_poly = polyFeatures.transform(X_val)
    Y_pred_val = regr.predict(X_val_poly) # predict labels for the validation data using the regression model
    val_error = mean_squared_error(Y_val, Y_pred_val) # calculate the validation error

    # plot the current fold
    X_fit = np.linspace(0, 4, 100)    # generate X interval for the graph, from 0 to 4.5 with 100 samples
    plt.tight_layout()
    plt.plot(X_fit, regr.predict(polyFeatures.transform(X_fit.reshape(-1, 1))), label="Model")
    plt.scatter(X_train, Y_train, color="b", s=10, label="Train Datapoints")    # draw points for train data
    plt.scatter(X_val, Y_val, color="r", s=10, label="Validation Datapoints")    # draw points for validation data
    plt.xlabel('title mean score')    # set the label for the x/y-axis
    plt.ylabel('relative rating')
    plt.legend(loc="best")    # set the location of the legend
    plt.title(f'CV iteration = {j}\nTraining error = {tr_error:.6}\nValidation error = {val_error:.6}')


plt.show()
```



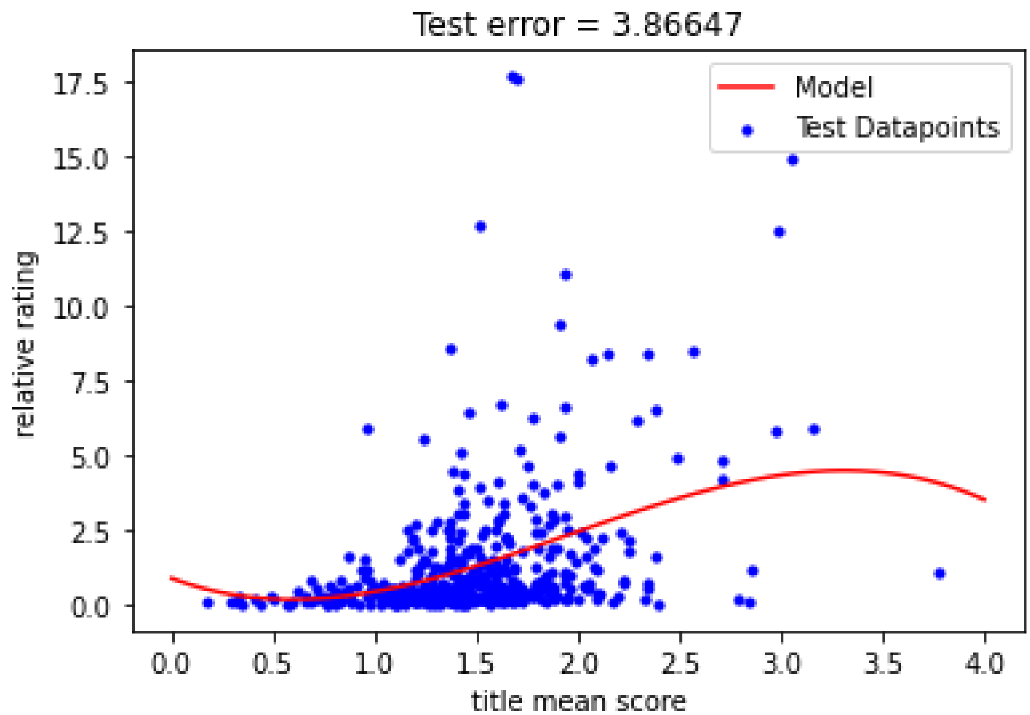
Now that we have the plots, we can observe that the result is quite interesting. It seems like there is a point of diminishing return when the tile mean score reaches 3.2.

This is rather unusual since according to common logic, using a title with higher score should give a higher relative rating. What is so special about the 3.2 mark that make the relative rating took a down turn? One possible theory is that there are not enough data points in that region for the model to properly learn from. Since high-viewed videos are far rarer than low-viewed ones, low-viewed videos have higher probability to appear than their high-viewed counterpart. This causes a sampling error to arise, meaning that given a small sample size, the sample is unlikely to accurately represent the whole population.

It is known that the larger the sample size, the better representation it is for the population. Therefore, the sampling error is often negated if a large amount of data points is present, as seen in the middle region of the plot where the model performs well. However, when the data is scarce, similar to the rightmost region beyond the 3.2 mark, it is highly likely that the sample will fail to reflect the true nature of the total population.

Finally, to wrap up the project, let's test the chosen model on the test set and obtain the final test error.

[21]:
```
# fit the model using the remaining data (the 90% data that we already seen)
regr = LinearRegression(fit_intercept=False)
polyFeatures = PolynomialFeatures(degree=3)# make it a third degree model
X_rem_poly = polyFeatures.fit_transform(X_rem)
regr.fit(X_rem_poly, Y_rem)

# Calculate the test error using the test set (the 10% unseen data)
X_test_poly = polyFeatures.transform(X_test)
Y_pred_test = regr.predict(X_test_poly)    # predict using the regression model
test_error = mean_squared_error(Y_test, Y_pred_test)    # calculate the␣
 ↪training error

# plot the current fold
X_fit = np.linspace(0, 4, 100)    # generate X interval for the graph, from 0␣
 ↪to 4.5 with 100 samples
plt.tight_layout()
plt.plot(X_fit, regr.predict(polyFeatures.transform(X_fit.reshape(-1, 1))),␣
 ↪label="Model", color="r")
plt.scatter(X_test, Y_test, color="b", s=10, label="Test Datapoints")    # draw␣
 ↪points for train data
plt.xlabel('title mean score')    # set the label for the x/y-axis
plt.ylabel('relative rating')
plt.legend(loc="best")    # set the location of the legend
plt.title(f'Test error = {test_error:.6}')

plt.show()
```



The model seems quite consistent with our training and validation process. It is worth noting that the test error is even lower than the validation error we had earlier. However, this can again be explain by the fact that our model is not very accurate from the point 3.2 onwards due to the lack of data. Thus, with the test set being randomly sampled and as we can see in the plot, this sample happen to include very few data from the rightward region. Therefore, it is normal that the model give a better result on this specific sample.

```
[ ]:
```