Evolution of Anime: a Statistical Analysis of Anime's Success Factors

I) Introduction

Under globalization, Japanese animation (anime) has become a form of entertainment for different races at different ages. The establishment of the World Wide Web (or in a broader sense, the Internet) boosts its popularity. Even if you are not a fan of anime, you may have read over news, novels, movies or memes related to it.

Source: We Heart It. (2019).[1]

The success of anime industry under globalization has spillover effect on other industries, bringing positive effect to the Japanese economy (which is probably still in lost. Nevertheless, we are not going to drill into the topic of liquidity trap). Notable examples such as Fate and One Piece successfully build different “eco-systems” in animes, toys, comics, movies, and games etc.

However, as the success of an anime is world-based nowadays, it is no longer solely determined by the taste or preference of local (young) people in Japan. In light of this, producers should pay attention to the key success factors of anime. Since lots of animes are produced based on original comics/light novels, this may help the producers to select the next One Piece or Fate. In the simplest case, this should help the producers to avoid incident like Kemono Friends 2 (けものフレンズ2),

[1]Both are downloaded using baidu.com. The original link was not accessible.

which attracted a considerable number of anger and hatred in different countries online (赵建波, 2019; IMDb, 2019).

While researchers commonly agree that anime is economically and culturally powerful (Ruble & Lysne, 2010; Fennell et. al., 2013; José Andrés Santiago Iglesias, 2018), previous research focused on the qualitative aspect of an individual anime (Ruble & Lysne, 2010) or the anime industry (Fennell et. al., 2013). In this essay, we would like to bridge this gap in anime research. By understanding the statistical properties of successful animes, we could help improve the production as well as the eco-system of anime.

The remaining sections of this paper are as follows: Section II outlines potential data sources for future researches and presents a novel approach in analyzing the data. Section III presents some preliminary results and attempt to explain with developed theories. Section IV concludes.

II) Data and Methodology

To analyze anime quantitatively, the most important thing is not to pick the right model. Rather, it is to retrieve quality anime data[2]. Currently, most anime databases are built and maintained by fans. Notable databases include MyAnimeList, Bangumi, AniDB etc. As a result, there are some problems that we should be aware of:

Firstly, the database may be highly localized. Since notable databases are mostly maintained by fans, the nationality of users may influence or even bias the statistical data in a particular database. For instance, MyAnimeList, which is commonly used by English speaker, has higher anime rating on average compare with Bangumi, which composes of mainly Chinese speaker. To deal with this issue, we should normalize the data using standard score or 0-to-1 scale.

Secondly, the database may be influenced by media mix. If we want to investigate the popularity/success of anime, we should exclude or separate cases where other medias bring up the popularity of original anime. Nevertheless, this is difficult to handle statistically because it involves qualitative data. Text mining would be required, which we will not cover in this essay.

Thirdly, the database may be influenced by transnational cultural flows. Under globalization, it is not rare that some animes were not popular in Japan originally but “re-discovered” by fans in other countries. The most recent example is the Overlord series, which is very popular in the mainland China (to be specific, on Bilibili). Comments on Bilibili (2019) shows that the sales of Overlord Blu-

[2] This is to avoid “garbage-in-garbage-out”.

ray disc was boosted by fans in the mainland after the online air of the first season. As a result, rumors on Bilibili (2019) guess that the series has two more seasons mostly because of Chinese fans. Ultimately, this may boost the popularity of the series in other countries. Treatment of this problem is similar to that of media mix.

Last but not least, the database may contain behavioral bias. Since the databases are constructed by human, behavioral bias is unavoidable. Common one includes survivorship and anchoring, which has been shown to affect decision making (Barberis & Thaler, 2003). To tackle this problem, we shall compare the cost and benefit of adjusting for the biases. Behavioral literature provides a lot of solutions in this aspect.

Incorporating these treatments, we now turn to discuss the methodology. Complete research shall begin with retrieving dynamic data online. Taking MyAnimeList as an example, we could use the unofficial API Jikan (2019). However, for simplicity, we will illustrate with a static dataset provided by CooperUnion on Kaggle (2016), which looks like the following:

```
> raw[1:20,]
   anime_id                                                  name
1     32281                                        Kimi no Na wa.
2      5114                      Fullmetal Alchemist: Brotherhood
3     28977                                              Gintama°
4      9253                                           Steins;Gate
5      9969                                         Gintama&#039;
6     32935 Haikyuu!!: Karasuno Koukou VS Shiratorizawa Gakuen Koukou
7     11061                                    Hunter x Hunter (2011)
8       820                                  Ginga Eiyuu Densetsu
9     15335      Gintama Movie: Kanketsu-hen - Yorozuya yo Eien Nare
10    15417                              Gintama&#039;: Enchousen
11     4181                                  Clannad: After Story
12    28851                                        Koe no Katachi
13      918                                               Gintama
14     2904                       Code Geass: Hangyaku no Lelouch R2
15    28891                                 Haikyuu!! Second Season
16      199                            Sen to Chihiro no Kamikakushi
17    23273                                Shigatsu wa Kimi no Uso
18    24701                          Mushishi Zoku Shou 2nd Season
19    12355                            Ookami Kodomo no Ame to Yuki
20     1575                          Code Geass: Hangyaku no Lelouch
```

To facilitate modelling, we will focus only on TV anime and break down the textual data into binary genre (indicator which 1 stands for true and 0 stands for false on a particular anime. The summary statistics is as follows:

```
> sort(colSums(data[, 5:47]))
Hentai    Yuri    Yaoi    Dementia    Shounen Ai
0    0    0    9    24
Shoujo Ai    Josei    Thriller    Cars    Vampire
31    32    34    36    46
Police    Samurai    Demons    Psychological    Martial Arts
50    51    89    89    95
Game    Horror    Music    Space    Parody
103    113    123    123    126
Military    Harem    Super Power    Mystery    Seinen
133    175    190    222    235
Sports    Ecchi    Historical    Shoujo    Magic
240    245    275    310    353
Mecha    Supernatural    Kids    Slice of Life    School
379    431    484    562    567
Romance    Drama    Shounen    Fantasy    Sci-Fi
652    697    736    765    774
Adventure    Action    Comedy
932    1098    1870
```

From the summary statistics, we can see that producers favor genres like comedy and action. However, is it true that these attributes are well received by global audience (or at least English speaker)? To answer this question, we want to measure the impact of these factors on anime popularity/rating. A typical statistical model will be a linear factor model. As our paper is not meant to be theoretical, we shall skip the model specification. However, a factor model can partially tackle behavioral bias as our sample size helps eliminate them under the law of large number.

Since we only adopt data from a single source (MyAnimeList) for illustration, we face the problem of localization (i.e. some anime may suit English speakers' taste more and thus receive higher rating). To tackle this problem, we may use a cross referencing and take averages across different database for our response variable[3].

To handle non-linearity, we may use the popular neural network model with several layers. However, we aim to investigate the cross section of successful anime rather than predicting the successfulness of future anime. Hence, we will not drill into this model.

III) Result

We first examine the result using a linear factor model. The summary is as follows (the complete code can be found at the end of this essay):

[3]However, this cannot be done due to Internet speed and computational power concern. The writer is in a country with low Internet speed when he write this paper. Interested readers may try to browse Kaggle or use API avilable online.

```
> summary(model)

Call:
lm(formula = rating ~ ., data = train)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.6210 -0.4052  0.0356  0.4784  3.4675 

Coefficients: (3 not defined because of singularities)
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)     6.320820   0.040055 157.803  < 2e-16 ***
Action          0.191028   0.037595   5.081 4.03e-07 ***
Adventure       0.169738   0.037419   4.536 6.00e-06 ***
Cars           -0.276750   0.148440  -1.864 0.062383 .  
Comedy          0.050224   0.032857   1.529 0.126504    
`Sci-Fi`        0.029881   0.043958   0.680 0.496715    
Shounen         0.382391   0.041027   9.320  < 2e-16 ***
Mecha          -0.040030   0.057786  -0.693 0.488547    
Sports          0.331564   0.063652   5.209 2.05e-07 ***
Demons          0.306022   0.101456   3.016 0.002584 ** 
Drama           0.346351   0.040591   8.533  < 2e-16 ***
Ecchi          -0.108734   0.067912  -1.601 0.109477    
Horror         -0.206449   0.094905  -2.175 0.029697 *  
Mystery         0.378368   0.065729   5.757 9.62e-09 ***
Romance         0.290376   0.044859   6.473 1.15e-10 ***
Fantasy         0.205415   0.041082   5.000 6.12e-07 ***
Magic          -0.008618   0.055698  -0.155 0.877051    
Supernatural    0.243781   0.051925   4.695 2.81e-06 ***
`Martial Arts`  0.046249   0.103193   0.448 0.654063    
`Super Power`   0.146864   0.071988   2.040 0.041443 *  
Vampire        -0.117522   0.129455  -0.908 0.364057    
Harem          -0.059840   0.078472  -0.763 0.445792    
School          0.311295   0.045268   6.877 7.68e-12 ***
Historical      0.135779   0.060281   2.252 0.024380 *  
Kids           -0.358050   0.045544  -7.862 5.56e-15 ***
Military        0.313049   0.084719   3.695 0.000224 ***
Shoujo          0.297684   0.060767   4.899 1.03e-06 ***
Psychological   0.412833   0.104363   3.956 7.84e-05 ***
Josei           0.529918   0.155604   3.406 0.000671 ***
Music           0.123856   0.084233   1.470 0.141577    
Space           0.234289   0.089460   2.619 0.008873 ** 
Seinen          0.440454   0.066330   6.640 3.82e-11 ***
Game            0.049567   0.090808   0.546 0.585221    
Parody          0.070715   0.081950   0.863 0.388269    
Police          0.099364   0.120591   0.824 0.410033    
Samurai         0.207519   0.128914   1.610 0.107576    
Hentai                NA         NA      NA       NA    
`Slice of Life` 0.294678   0.044028   6.693 2.68e-11 ***
```

```
Dementia        0.347695   0.370616   0.938 0.348255
Thriller        0.715035   0.157563   4.538 5.94e-06 ***
`Shoujo Ai`     -0.229389   0.164316  -1.396 0.162829
Yuri                  NA         NA      NA       NA
`Shounen Ai`    -0.258593   0.178837  -1.446 0.148310
Yaoi                  NA         NA      NA       NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7286 on 2532 degrees of freedom
  (78 observations deleted due to missingness)
Multiple R-squared:  0.3018,    Adjusted R-squared:  0.2907
F-statistic: 27.36 on 40 and 2532 DF,  p-value: < 2.2e-16
```

Ignoring the statistically insignificant variable, we arrive at the final model using general-to-specific approach (Bauwens & Sucarrat, 2010):

```
> summary(model1)


Call:
lm(formula = as.formula(f), data = train)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.6142 -0.4106  0.0343  0.4857  3.4339 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   6.36416    0.02989 212.899  < 2e-16 ***
Action        0.18617    0.03543   5.254 1.61e-07 ***
Adventure     0.16994    0.03674   4.625 3.93e-06 ***
Cars         -0.29542    0.14779  -1.999 0.045719 *
Shounen       0.37812    0.03960   9.548  < 2e-16 ***
Sports        0.32720    0.06226   5.255 1.60e-07 ***
Demons        0.30860    0.10078   3.062 0.002221 **
Drama         0.33558    0.03984   8.422  < 2e-16 ***
Horror       -0.21987    0.09330  -2.356 0.018524 *
Mystery       0.37955    0.06488   5.850 5.54e-09 ***
Romance       0.26173    0.04199   6.233 5.34e-10 ***
Fantasy       0.19086    0.03898   4.897 1.03e-06 ***
Supernatural  0.22104    0.05053   4.374 1.27e-05 ***
SuperPower    0.15504    0.07006   2.213 0.026986 *
School        0.29153    0.04368   6.674 3.05e-11 ***
Historical    0.15675    0.05651   2.774 0.005576 **
Kids         -0.36801    0.04468  -8.237 2.78e-16 ***
Military      0.29923    0.08349   3.584 0.000345 ***
Shoujo        0.26903    0.05549   4.849 1.32e-06 ***
Psychological 0.42619    0.10291   4.141 3.57e-05 ***
Josei         0.55801    0.15473   3.606 0.000317 ***
```

```
Space         0.23446    0.08670   2.704 0.006890 **
Seinen        0.43242    0.06573   6.579 5.73e-11 ***
SliceofLife   0.30643    0.04322   7.091 1.72e-12 ***
Thriller      0.71010    0.15660   4.534 6.04e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7292 on 2548 degrees of freedom
  (78 observations deleted due to missingness)
Multiple R-squared:  0.2963,    Adjusted R-squared:  0.2896
F-statistic: 44.69 on 24 and 2548 DF,  p-value: < 2.2e-16
```

There are several interesting things that worth our effort to study:

Firstly, Cars, Horror and Kids record an average decrease to the rating of an anime. While we can explain horror and kids using behavioral bias (kids would use these databases less often than adults; horror has specific target audience), it remains a question why car racing anime is not popular. Upon reviewing different car racing animes included in the dataset, we can partially attribute the reason to insufficient globalization element in the anime. Successful instance such as Initial D and Capeta has many English OSTs and some are even sung by foreign singers. These songs are well received on social media, which push up popularity of the original anime.

Secondly, it is observed that popular elements such as Comedy, Action and Adventure have little or no effect on the rating. This is probably due to lack of creativity in these genres. Since they are very common, it becomes difficult to develop new settings or character prototypes. On the other hand, topics that are harder to handle, such as Thriller, Josei and Psychological, are well rewarded by fans. The high positive impact of Josei and disappearance of Harem provide insight to producers on the importance of sexual equality, which is a common topic under globalization. In other words, producers could pay more attention to global market in order to make successful anime.

Thirdly, the explanatory power of the model is not high (only ~0.3 R^2). This is easily understood as our information set is not complete. Other factors such as director and animator may also have significant predictive power.

Last but not least, we notice the positive coefficient of tags like Historical. While the reinvention of tradition/history remains a debate in the media, it seems that the general public (at least for English speaker) like this kind of topic. This supports the theory of cultural evolution and idea of cultural as a process.

IV) Recommendation

In this essay, we have discussed the importance and lack of statistical analysis of successful animes. By building quantitative models, we can understand more about the properties of animes, which may help the producer to plan their anime production and make better anime. As a start, we have illustrated the possibility of using a linear factor model and discussed some solutions to quantitative anime research using online database.

For more complete research (which was our original plan), we may try to obtain time series data to check the evolution of anime in different decades. In this case, we can truly see the impact of globalization to anime genres. For instance, we may see that more and more Sci-Fi appear as influenced by Star War and Transformer. Unfortunately, we are not able to do so due to data limitation.

While it is a pity that we cannot continue due to limited time and resources in a general education course, we believe that this essay also opens a new area for future students. For instance, student may conduct case study using linear factor model on a particular genre like Isekai. Hitherto, I sincerely hope that this course will attract insightful submission in the future.

Reference

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Appendix: R code

```
#read the data
raw = read.csv("anime.csv", header = T)
#extract unique elements of anime
tag = unique(unlist(strsplit(as.character(levels(raw[,3])), ",")))
tag = unique(gsub("^[[:space:]]*(.*?)[[:space:]]*$", "\\1", tag, perl=TRUE))
tag[5] = "SciFi"
ntag = length(tag)
#construct the dataset
data = raw[which(raw$type=="TV"),]
temp = data.frame(matrix(ncol=ntag, nrow=nrow(data)))
colnames(temp) = gsub(" ", "", tag)
data = cbind.data.frame(data$rating, data$anime_id, data$name, data$episodes, data$genre,
    temp)
colnames(data)[1:5] = c("rating", "id", "name", "episodes", "genre")
for (i in 1:nrow(data))
{
  temp = as.character(data$genre[i])
  for (j in 1:ntag)
  {
    if (length(grep(tag[j], temp)))
      data[i, j+5] = 1
    else
      data[i, j+5] = 0
  }
}
data = data[,-5]
rm(temp)
#summary statistics
sort(colSums(data[, 5:47]))
set.seed(78938)
n = nrow(data)
d = sample(1:n, 0.3*n)
```

```
train = cbind(data$rating[-d],data[-d,5:47])
test = cbind(data$rating[d],data[d,5:47])
colnames(train)[1] = "rating"
colnames(test)[1] = "rating"
model = lm(rating~., data = train)
summary(model)
x = colnames(train)[-1] #vector storing names of predictor
p = coef(summary(model))[,4][-1] #vector of p-values
while (max(p) > 0.05) #perform general to specific approach in econometrics
{
  del = which(x == names(which.max(p))) #get the index of the predictors to delete
  x = x[-del] #drop the predictor
  f = paste("rating~",paste(x, "+", sep="", collapse=""), sep="") #update formula
  f = substr(f, 1, nchar(f)-1) #drop the last + sign
  model1 = lm(as.formula(f), data = train) #train reduced model
  p = coef(summary(model1))[,4][-1] #retrive p-values
}
summary(model1)
```