Scheduling and Advertising Strategy for Channel A

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Executive Summary

This project aims to provide a schedule for TV-channel A that is designed to maximize viewership and revenue, while limiting expenses. This is done by designing and utilizing a model for making informed decisions of the scheduling of movies and the advertisement strategy, based on the available data. The model will consider the license fee for showing a movie, the possible advertisement time which can be monetized by selling ad slots to competitors, and the possible advertisement the channel can buy from said competitors. The main objective is to maximize profits for the TV-channel.

The main idea behind the created model is to first filter the movies according to their license fee and the expected view count. The filtering process was aimed to decide the most viable movie options and filter out the least profitable movies.

After getting this set of viable movie options, it needs to be decided which movies to show. This will depend on the license fees and the scaled popularity of the movies. The scaled popularity of a movie is calculated for three demographics: children, adults, and retirees. The target audience is then decided for each movie and is used to determine when a movie is shown (if it will be shown).

The increase of viewership will mainly depend on attracting viewers from other channels by buying advertisement. Whether an advertisement is bought will depend on the expected viewership and the expected viewership to be gained by buying an advertisement at that time.

A big portion of a TV channels revenue comes from selling advertisement. The choice of whether an advertisement slot should be sold to a competitor or not depends on the expected view count at that time and the price that the ad can be sold for at that time. The ad slot prices will be dynamically adjusted depending on the competitors' ad slot prices.

These decisions determine the schedule for the week. The same analysis and decision making procedure are conducted weekly for the 12-week period.

When implemented and applied, the model estimates a net profit of £110,000,000 over the 12-week period. The total revenue earned is estimated to reach £180,000,000. The model approximates the total expenses to be £70,000,000. The budget for advertisement expenditure is £3,200,000 while the licensing fees for the movies over the 12 week period will incur a cost of £66,500,000.

The analysis conducted for this report verified that the model designed earns an estimated £11,000,000 more revenue to channel A by implementing the models "buy and sell" advertisement strategy over the 12-week period, instead of just selling. Further analysis of the most profitable movie, risk modeling, and advertisement pricing are also described. Finally, suggestions for future improvements are included.

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C	Index set of competitor channels	{1,2,3}
D	Index set of days in the 12-week period	{1,2,...,84}
G	Index set of demographics	{children, adults, retirees}
M	Index set of possible movie selections	{1,2,...,5920}
T	Index set of 30-minute time slots in a day	{1,2,...,34}

Decision Variables

$x_{m,d}$	If movie m is shown on day d	binary variable
$y_{m,t,d}$	If movie m is shown in slot t on day d	binary variable
$s_{m,d}$	Start time of movie m on day d	integer variable
$e_{m,d}$	End time of movie m on day d	integer variable
$a_{m,t,c,d}$	If ad is sold to be shown during movie m in time slot t to competitor c on day d	binary variable
$b_{m,t,c,d}$	If ad is bought for movie m in time slot t from competitor c on day d	binary variable
$i_{m,c}$	Viewers gained from advertising movie m on competitor channel c	continuous variable
$z_{m,t,c,d}$	Linearization of $i_{m,c} \times a_{m,t,c,d}$	continuous variable

Parameters

r	Time slot duration in minutes	30
k	Total number of time slots on a day	34
h	Maximum runtime per day in minutes	1020
w	Total number of viewers	1,000,000
ϕ	Maximum percentage of viewers	1
τ	A total of time slots needed for an ad to be before the movie start time	4
u_d	Ad price per viewer (pre-calculated weekly)	continuous parameter
$o_{t,c,d}$	If competitor c is showing an ad in slot t on day d	binary parameter
l_m	License fee of movie m	continuous parameter
π_t	Prime time factor for time slot t	continuous parameter
$v_{g,t,d}$	Baseline view count percentage for demographic g in time slot t on day d	continuous parameter
$f_{m,g}$	Scaled popularity of demographic g for movie m	continuous parameter
n_m	Total number of time slots in movie m	integer parameter
$j_{m,t,d}$	Conversion rate of movie m in time slot t on competitor channel c on day d	continuous parameter
$q_{g,t,c,d}$	Viewership of demographic g in time slot t on competitor channel c on day d	continuous parameter
$\alpha_{t,c,d}$	Ad price in time slot t of competitor c on day d	continuous parameter
β_m	Number of ad breaks in movie m	integer parameter

1 Introduction

1.1 Problem

A major revenue stream for TV channels is selling advertisements. The price an advertisement slot can sell for is heavily determined by the viewership at the time. A natural implication for this relationship is that an increase in viewership for a TV-channel can be leveraged to command a higher price for advertisement time.

All the TV channels in this project are assumed to purely show movies as content. At any time, each channel is assumed to have a baseline viewership, and the actual viewership is determined by using this baseline viewership multiplied by the popularity of the movie shown at that time. A TV channel can increase viewership by showing more popular movies. A drawback of this is that the latter will have a higher associated streaming fee. It is therefore not a sustainable business model to purely stream the most popular movies. It will also not be appealing to viewers, as they are unlikely to be interested in watching the same movies repeatedly.

A TV-channel can also increase its viewership by showing advertisements on competitor channels. By showing advertisements, there is a possibility of attracting new customers. This approach typically involves promoting an upcoming movie of a similar genre to the one currently airing on the TV channel where an ad is bought from. However, it also comes with a risk of not being diligent enough with the specification of genre such that the advertisements are not reaching the relevant audience.

The aim of this report is to provide strategic advice to TV-channel A on maximizing its viewership and profits by implementing an intelligent scheduling process and a cost-effective advertising strategy.

1.2 Data

To solve this problem, a dataset of movies and their related information have been presented, which contains:

Movie Title Title of the movie	**IMDb Average Vote (1-10)** Average rating on IMDb, on a scale from 1 to 10	**Vote Count** Total number of votes received on IMDb
Release Date of movie Date when the movie was released	**Revenue (Box Office)** Total earnings from the box office	**Run Time of the movie** Duration of the movie
Budget of the movie Total production cost of the movie	**Genre(s)** Categories the movie belongs to	**Number of Ad Breaks** Number of ad slots available during the movie
Runtime with Ads Total runtime including advertisements	**Children Scaled Popularity** Popularity among children relative to other age groups	**Adults Scaled Popularity** Popularity among adults relative to other age groups
Retirees Scaled Popularity Popularity among retirees relative to other age groups		

Channel A has presented a dataset for its own schedule, which contains the following information.

Three different age demographics Children, Adults, and Retirees
Datetime The date time divided into time slots (in 5-minute intervals)
The primetime factor More viewership is expected during the prime time

Channel A has 3 competitors: Channel 1, Channel 2, and Channel 3. For these three competitors, the dataset for their schedule contains:

Date time The date time divided into time slots (in 5-minute intervals)
The type of content shown on each specific time slot Could either be movie or advert
The popularity score among different demographics The popularity score among children, adults and retirees
Advertisement breaks The number of slots available for showing ads during a movie
The primetime factor More viewership is expected during the prime time
The view count for the children, adult and the retiree demographic The view count data is structured as the baseline view count, the expected view count and the true count from 1 to 9. The true count is expected view count plus Gaussian noise.
The price of an ad slot A fixed price plus a margin where the primetime factor is taken into account

Channel A has also presented a dataset for the conversion rates of its competitors. In this dataset, the columns represent each genre in the movie catalog. This conversion matrix shows the likelihood that advertising on a competitor's channel during a particular movie will positively convert viewers to channel A.

All the TV-Channels (including Channel A) will announce their TV schedule for the next week before the beginning of the week. This information is provided for a 12-week period. This data will be used to train the model. By assumption, the data represents any arbitrary future 12-week period.

2 Modeling approach

2.1 Objective Function

The objective is to maximize profit. The objective function can be divided into two parts, revenue and costs. The profit is from the revenue subtracting the costs, making the objective to maximize the revenue while minimizing the cost.

2.1.1 Revenue

1. **Selling Ads -** The revenue from selling ads can be calculated from the number of viewers at the time the ad airs. The latter can be calculated by summing all viewers in each demographic and multiplying that by the scaled popularity of the movie for that demographic. Then, to get the revenue, the number of viewers is multiplied by the ad price per viewer. The "sold ad slots" variable is also multiplied here to filter only the ad slots that are sold.
$$\sum_{g \in G} \sum_{m \in M} \sum_{t \in T} \sum_{c \in C} \sum_{d \in D} v_{g,t,d} \times \pi_t \times f_{m,g} \times a_{m,t,c,d} \times u_d \times w \tag{1}$$

2. **Increased Viewers -** When buying ads, the number of viewers on the channel increases. The extra revenue is from these gained viewers on the sold ad slots. The "gained viewership revenue" is calculated the same way as the base viewers. However, having increased viewers multiplied by the sold ad slots will be a quadratic function. Hence, variable z is introduced to change that quadratic function to a linear one. Since z already means increased viewers s multiplied by the sold ad slots a, the revenue can be shown as below.
$$\sum_{m \in M} \sum_{t \in T} \sum_{c \in C} \sum_{d \in D} z_{m,t,c,d} \times u_d \times w \tag{2}$$

2.1.2 Costs

1. **Licensing Fee -** To show a movie, the licensing fee needs to be paid. The cost of the licensing fee can be calculated from summing up the licensing fee for all movies shown.
$$\sum_{m \in M} \sum_{d \in D} l_m \times x_{m,d} \tag{3}$$

2. **Buying Ads -** The movies shown can have advertisements for them before the show time. The viewers can be gained from advertising the movies on the competitors' channels. The cost of advertising is the "bought ad

slots" multiplied by the cost of that bought slot.

$$\sum_{m\in M}\sum_{t\in T}\sum_{c\in C}\sum_{d\in D} b_{m,t,c,d} \times \alpha_{t,c,d} \tag{4}$$

2.2 Model Constraints

2.2.1 Constraints for Movie Selection

- Each time slot can show at most one movie at a time.

$$\sum_{m\in M} y_{m,t,d} \leq 1, \quad \forall t \in T,\ \forall d \in D \tag{5}$$

- The number of time slots used for a movie shown is the same as the number of time slots needed for that movie.

$$\sum_{t\in T} y_{m,t,d} = x_{m,d} \times n_m, \quad \forall m \in M,\ \forall d \in D \tag{6}$$

- The total number of time slots used for all movies shown in a day could not exceed the total time slots in a day.

$$\sum_{m\in M} n_m \times x_{m,d} \leq k, \quad \forall d \in D \tag{7}$$

- The same movie cannot be shown more than once within the same week.

$$\sum_{d\in D} x_{m,d} \leq 1, \quad \forall m \in M \tag{8}$$

2.2.2 Constraints for Movie Start Time and End Time

- The end time and the start time of a movie should be the same as the total number of time slots needed for that movie.

$$e_{m,d} - s_{m,d} = x_{m,d} \times n_m, \quad \forall m \in M,\ \forall d \in D \tag{9}$$

- The end time should be at least the last time slot in which the movie is shown.

$$e_{m,d} \geq (t+1) \times y_{m,t,d}, \quad \forall m \in M,\ \forall t \in T,\ \forall d \in D \tag{10}$$

- If the movie is shown in the time slot t, then, the start time should not exceed that time slot. Otherwise, it could be any other value less than the maximum time slot.

$$s_{m,d} \leq t \times y_{m,t,d} + (1 - y_{m,t,d}) \times k, \quad \forall m \in M,\ \forall t \in T,\ \forall d \in D \tag{11}$$

2.2.3 Constraints for Selling Ads

- The total ad slots sold for each movie on each day should not exceed the total ad breaks in that movie.

$$\sum_{c\in C}\sum_{t\in T} a_{m,t,c,d} \leq x_{m,d} \times \beta_m, \quad \forall m \in M,\ \forall d \in D \tag{12}$$

- In one time slot of the movie shown, the ad can be sold to only one of the competitors.

$$\sum_{c\in C} a_{m,t,c,d} \leq y_{m,t,d}, \quad \forall m \in M,\ \forall t \in T,\ \forall d \in D \tag{13}$$

2.2.4 Constraints for Buying Ads

- An ad can only be bought if that competitor is selling an ad in that time slot.

$$b_{m,t,c,d} \leq o_{t,c,d} \times x_{m,d}, \quad \forall m \in M,\ \forall t \in T,\ \forall c \in C,\ \forall d \in D \tag{14}$$

- An ad can be bought for movie m if and only if it is at least τ time slots before the start time of that movie. $d \times k$ is to expand the "days" dimension of the variable into the "time slots" dimension.

$$s_{m,d} + (d \times k) \geq b_{m,t,c,d} \times (t + (d \times k) + \tau), \quad \forall m \in M,\ \forall t \in T,\ \forall c \in C,\ \forall d \in D \tag{15}$$

- The increased viewership is from buying ads on the competitors' channels. It is calculated by the expected viewership at the ad time of each competitor's channel multiplied by the conversion rate. The bought ad slot b is multiplied to calculate only for the ad that is actually bought.

$$i_{m,c} = \sum_{g \in G} \sum_{t \in T} \sum_{d \in D} b_{m,t,c,d} \times q_{g,t,c,d} \times j_{m,t,d}, \quad \forall m \in M,\ \forall c \in C \tag{16}$$

- Each ad slot can be bought only once, i.e. for only one movie.

$$\sum_{m \in M} b_{m,t,c,d} \leq 1, \quad \forall t \in T,\ \forall c \in C,\ \forall d \in D \tag{17}$$

- A movie can only be advertised on each competitor's channel once. This is to simplify the conversion rate, since multiple advertisements for the same movie should not convert to a linear increase in viewers.

$$\sum_{t \in T} \sum_{d \in D} b_{m,t,c,d} \leq 1, \quad \forall m \in M,\ \forall c \in C \tag{18}$$

2.2.5 Constraints for Linearizing Increased Viewership and Sold Ads

In the objective function, there is a term where the increased viewers $i_{m,c}$ is multiplied by the sold ad slots $a_{m,t,c,d}$, making it a quadratic function. This variable $z_{m,t,c,d}$ is introduced to change the objective function into a linear function, which significantly reduces the computational power to run the model.

- This constraint limits the maximum value of $z_{m,t,c,d}$ so that it will not go over $i_{m,c}$.

$$z_{m,t,c,d} \leq i_{m,c}, \quad \forall m \in M,\ \forall t \in T,\ \forall c \in C,\ \forall d \in D \tag{19}$$

- following that, if the ad is not sold in that time slot, the value of z will be 0, matching the definition of $i_{m,c} \times a_{m,t,c,d}$. Otherwise, it will be limited by the maximum percentage of viewers ϕ.

$$z_{m,t,c,d} \leq \phi \times a_{m,t,c,d}, \quad \forall m \in M,\ \forall t \in T,\ \forall c \in C,\ \forall d \in D \tag{20}$$

- Then if the ad is sold in that time slot, the lower bound of $z_{m,t,c,d}$ is limited to be the value of $i_{m,c}$. Otherwise, it could be any other value.

$$z_{m,t,c,d} \geq i_{m,c} - \phi \times (1 - a_{m,t,c,d}), \quad \forall m \in M,\ \forall t \in T,\ \forall c \in C,\ \forall d \in D \tag{21}$$

- Finally, the lower limit of $z_{m,t,c,d}$ is set to be zero such that it cannot become a negative value.

$$z_{m,t,c,d} \geq 0, \quad \forall m \in M,\ \forall t \in T,\ \forall c \in C,\ \forall d \in D \tag{22}$$

Combining all constraints, if an ad is sold in that time slot (i.e. $a_{m,t,c,d} = 1$), $z_{m,t,c,d}$ is limited by the constraints 19 and 21, where 19 and 21 are both $i_{m,c}$, making $z_{m,t,c,d}$ a value of $i_{m,c}$. On the other hand, if that ad slot is not sold, the value of $z_{m,t,c,d}$ is limited by the constraints 20 and 22, whose values are both zero, making $z_{m,t,c,d}$ zero.

2.3 Data Processing

2.3.1 Filtering Methods

It can be seen that solving linear programming problems using the simplex method will require 2m to 3m iterations, where m is the row dimension, and at worst, visit every single vertex (Nocedal et al., 1999). Consequently, obtaining a solution is computationally too heavy, and some simplification is required. The problem has two main dimensions: the total time slots (every time slot considered) and the input movies. The time slots cannot be reduced or sequentially calculated. The number of movies can be filtered based on their viability to the algorithm. Noted that in the actual modeling, the variables might have more than two dimensions stated above but most of them could be ignored since their size is small (i.e. days could be merged with time slots while demographics and competitors are only in a size of three).

Movie filtering was implemented using viability metrics, which were calculated based on two factors: the movie's popularity and its licensing fee. Only an arbitrary percentage of movies will be fed to the linear programming model. A simple experiment has been conducted to calculate the lowest percentage still viable to put in the model.

2.3.2 Penalty Factors

By assumption, no rational person would be interested in watching the same movies repeatedly. Therefore, a penalty has been implemented using a decay function to prevent the model from picking the same movies from week to week.

Decay functions were used to simulate said effect. This was partially inspired by the "Reddit Hotness Algorithm" (bsimpson63, n.d.). In Reddit's case, an exponential function was used to weigh the older contents down, but in this case, the opposite is needed, a movie that was just shown will need to be weighed down. The decay function will scale down the popularity of the movie that was just shown. This will make the decay more organic than just setting a set time or constraints for movies, making the weekly movies more randomized. Consequently, the penalty will affect both the filtering and the model solution. This can make viable movies, that have recently been shown, to have a lower viability score and hence, may get filtered out by the movie filter. Those movies also will have a low ad revenue in the objective function, thus lowering the chance of being picked, if it did not get filtered out. This will help get more variety in the week-by-week scheduling.

2.3.3 Dynamic Pricing

The pricing for each advertisement in channel A needs to be set. The traditional way of setting pricing in this setting is usually tied with viewership (Google, n.d.; Meta, n.d.). The pricing is calculated weekly and should be lower than the competitors' to attract the most buyers. As a result, dynamic pricing has been implemented, where the lowest price per viewer is picked from among the competitors and is reduced by an arbitrary percentage. To make the pricing more robust to outliers, a minimum price was introduced, which was calculated from data analysis.

Figure 1: Dynamic Pricing Strategy for Weekly Ad Pricing

2.3.4 Risk Modeling

The expectation of viewership is not an accurate assessment of the future. The solution will be more robust and reliable if the upper and lower bounds are taken into account. This would provide the worst and best case of the algorithm. In this case, an 80% upper and lower interval has been implemented.

Since both expected and actual view count were provided, a simple stochastic model can be made to simulate and test whether the model accurately describes reality. This approach is superior to respected testing with random true values. The approach can simulate both the upper and lower bounds of channel A's and competitors' data without having to "refit" the model. A normal distribution was assumed as a correct distribution of noise $\epsilon \sim N(\mu, \sigma^2)$. Normal distribution requires two parameters, mean and variance. Mean μ was assumed to be equal to the expected view count, or in other words, the noise is symmetric. Variance, then, is the only parameter that is needed to be fit.

Another assumption was made that variances are constant or is relative to the mean where $\sigma^2 = \lambda \cdot \mu$. A simple linear regression with an intercept was used to find the variance by setting $y = \beta_1 + \beta_2 x$ where y is equal to the actual variance σ^2 and x is equal to expected view. By assumption the coefficients of x are not significant, and in that case, the stochastic model will have a constant variance, or else, the stochastic model's variance will change with the mean (James et al., 2023, pp. 61–63). This may suggest that the distribution is a Poisson or a Quasi-Poisson distribution, but with big enough data, it will converge to Gaussian. It was found that variance changed with the mean, so with variance $\hat{\sigma}^2 = \beta_2$. A function that can take in a percentage and view count, and output lower and upper bound can then be constructed. Given bound $= m \pm \left(m \cdot z \cdot \sqrt{v\hat{a}r}\right)$ where $z = \frac{1}{\mathrm{CDF}(p)}$. After testing this Stochastic model with the real data, with 80% applied to the estimated view count, true view lies in this bound 0.8033 out of 1 time. This will be used to construct any value's bound in this report. Note that to apply the bound to any value, another two assumptions were needed. First, said value has to be in a multiplicative relationship with the view count or $A = \lambda \cdot B$ where A is equal to values of interest and B equals to expected view count (Murphy et al., 2022, pp. 66-70) and second, the causal variable of the noise will affect all movies roughly the same, e.g. if something causes 20% drop in viewership in Bee Movie, it will affect 20% viewership decrease in 2001: A Space Odyssey as well.

2.3.5 Implementation

The algorithm was only used for calculating weekly results, but a twelve-week period was considered. A greedy approach was used to determine the best solutions. The model will iterate through the twelve-weeks, using the best solutions for the first week, then the best for the second week, and repeat this process for the remaining weeks. The model was also designed to expect failure, since it requires a huge computational power, so it can continue where it dropped off. There were some data re-calculation in between each week as well. The general idea of the process is as follows:

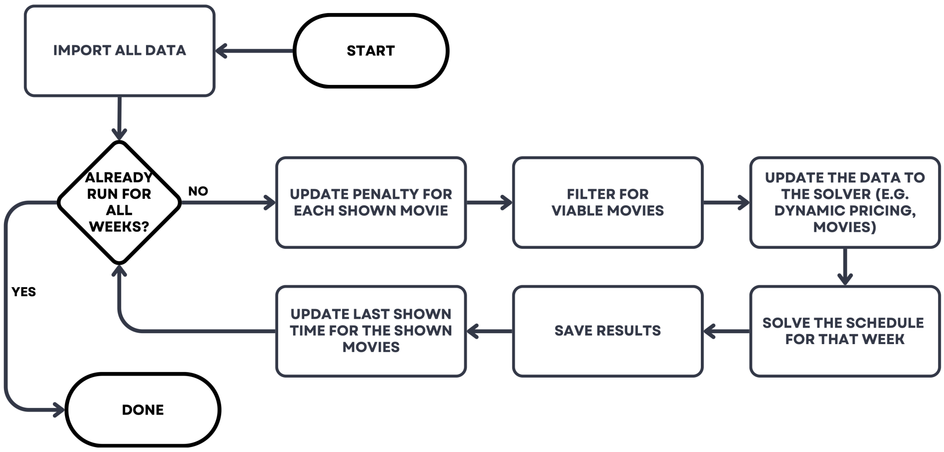

Figure 2: Weekly Scheduling Algorithm

3 Results

By executing the model over the 12-week period, Channel A can expect to generate a total revenue of £180,000,000. This revenue projection is based on optimized movie selections, strategic ad placement, and carefully planned scheduling to maximize viewership. According to the model's recommendations, Channel A should allocate a budget of £3,200,000 to cover advertising expenses.

Furthermore, the model estimated that £66,500,000 should be reserved for movie licensing fees. This allows Channel A to acquire movies that appeal to its viewers throughout the 12-week period. The total estimated expenses for Channel A over the 12-week period are approximately £70,000,000. After accounting for these costs, channel A can expect a net profit of £110,000,000.

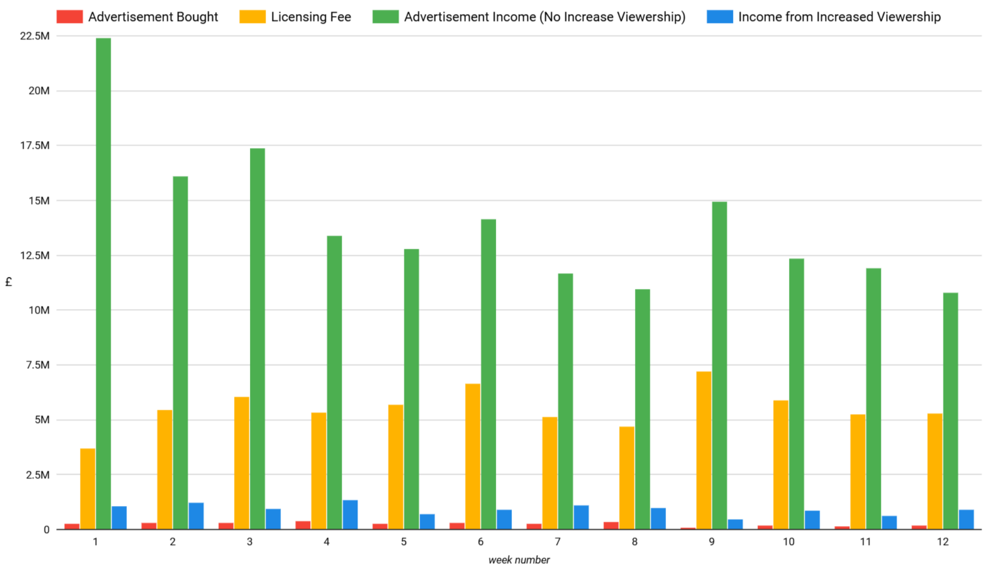

Figure 3: Revenue and expenses over 12 weeks

4 Analysis

4.1 Initial Analysis

The model estimates £110,000,000 in profit during the 12-week period for Channel A.

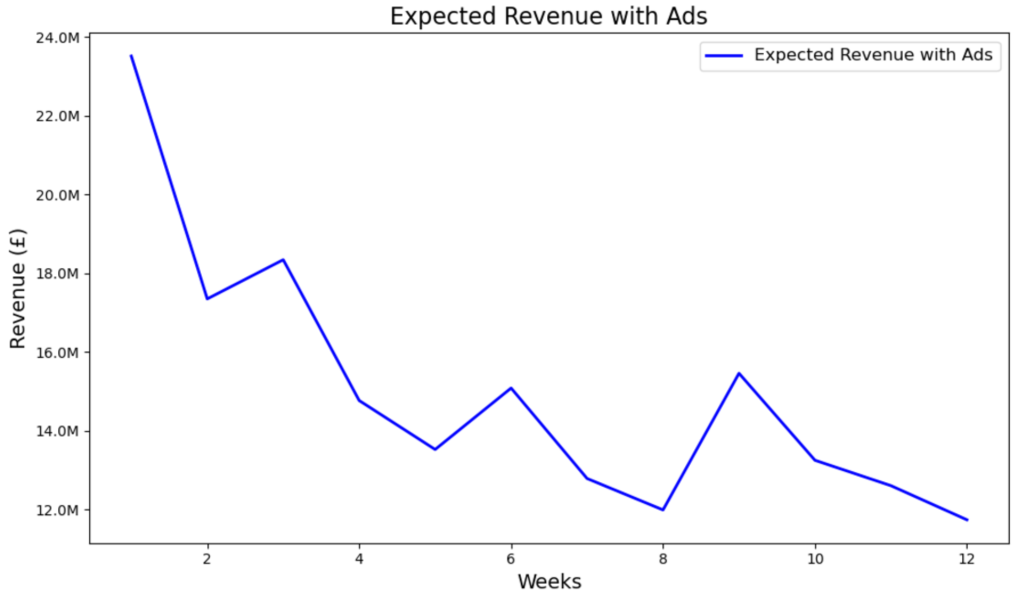

Figure 4: Expected revenue for Channel A when buying advertisements

Figure 4 illustrates that the expected revenue will steadily decrease over the weeks. This is because a of the decay rate that was implemented and explained in: 2.3.2

The penalty term affects Channel A more significantly than other channels due to the model's assumption of a loyal fan base, for which which it aims to cater. As a result, for Channel A to air a movie multiple times during the 12-week period, the movie's popularity must be high. While movies that have already been shown on competitors' channels are given more flexibility, the movie's popularity still needs to meet a certain standard to be considered airing. This penalty term reduces the popularity of the movie over time, reflecting the natural decline in viewer interest.

For the scope of this report, operational costs are not taken into consideration when calculating profits. However, for illustrative purposes, they can be assumed to be quite high. For instance, the BBC's operational costs were estimated to be 96% (BBC, 2023) of its total revenue. While these figures indicate the substantial costs involved in running a TV channel, they do not directly represent Channel A. Unlike the license fee-funded BBC (that is mandatory to have in the UK), Channel A is a channel that generates its revenue primarily from selling advertisements.

4.1.1 The Movies

After a more careful analysis of the results, it can be seen that certain kinds of movies are more profitable to show than others. From the advertisement pricing strategy and the given licensing fee calculation, it can be summarized that the profit will be proportional to:

Positive Contribution	Negative Contribution
The movie's popularity	The box office revenue The movie's budget

Movies with relatively low budgets but high returns, such as horror films like Saw or comedies like Bottoms, typically focus on one or two genres. The algorithm schedules these films at specific times: kids shows in the morning, family-oriented films in the evening, and horror movies late at night. These films are significantly more profitable than high-budget movies with broad appeal, such as The Avengers or Titanic. Although high-budget movies attract larger audiences, the licensing fees are so high that they outweigh the benefits of increased viewership.

4.1.2 The Ads

Following the implementation of dynamic ads, it can be seen that the graph, while fluctuating, is quite consistent, showing that competitors, or at least the cheapest competitor, have relatively stable pricing.

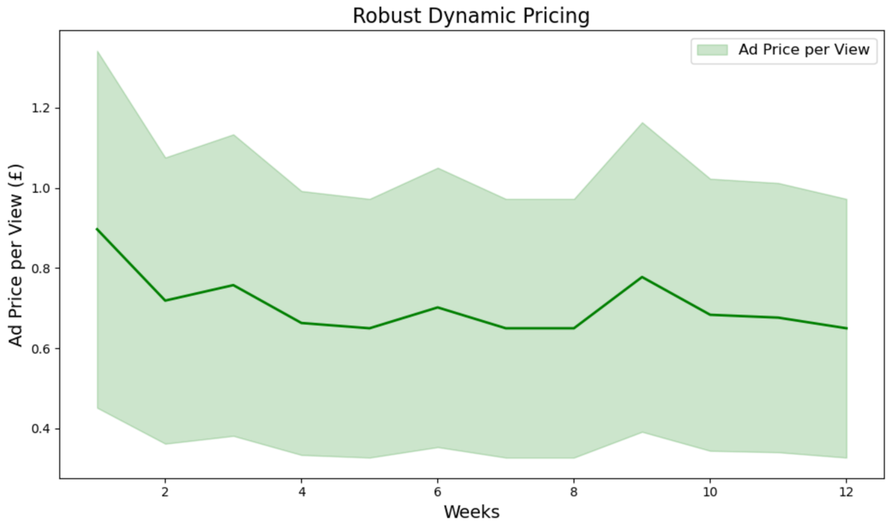

Figure 5: How advertisement pricing changes over the 12-week period

Questions might arise whether setting the price this way is leaving money on the table or not. It is a trade-off between pricing aggressively to be able to sell more advertisements or making more profit. The trade-off should be revisited after more data on how buyers' advertisements respond to the pricing strategy. For now, what is known is that even considering the lower end of the revenue bound (£375,000.00 expected and £190,000.00 on a 80% confidence bound), the revenue is enough to afford the lower price to gain the most buyers and data to build more profitable pricing later.

4.2 Sensitivity Analysis

4.2.1 Baseline

Naturally, a way to evaluate the basic effectiveness of the model is needed and using a baseline to compare is an effective way to gauge the system's effectiveness. A simple way to build a baseline model was conceived. First, instead of the viability score, which is normally used to filter movies, random sampling was used for the baseline model. Following that, sample just enough movies to be scheduled, but not enough for the system to choose an efficient distribution of movies. Together, this would simulate an inefficient system. While this would not produce a truly random model, three pieces of information were gleaned from comparing the normal model with this baseline model. First, it provides a benchmark of a competent model. If everything is working correctly, the model should massively outperform the baseline. Furthermore, if the model outperforms the baseline, which it does, it can be one of the supporting metrics that the viability scores work and that with more options for movies, the model is effective in distributing and placing movies. Finally, it can be a reference point when visualizing the system's performance.

4.3 Advertisement Purchasing

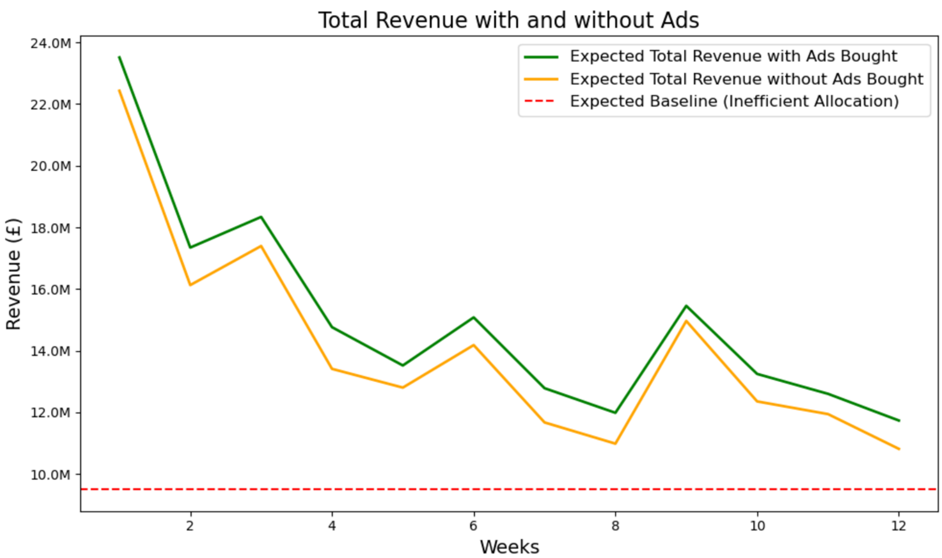

Figure 6: Total revenue with and without ads

In order to validate that buying advertisements provides a significant improvement for channel A's revenue, an analysis where the model did not buy any advertisements from competitors was conducted. This analysis was selected because it can precisely address the key insights required to get an appropriate perspective. The model was simulated in the same manner where these changes were adjusted. The simulation estimated that the revenue generated for channel A over the same period without the procurement of advertising would be £169,000,000, resulting in a net difference of £11,000,000 over the 12-week period.

Not only are the total revenue less for the entire period, but also by Figure 6, for each week, channel A will earn a higher revenue by implementing the buy-and-sell strategy for advertisements, as opposed to purely selling advertisement.

The effects of the decay function are clearly illustrated in this figure. During the initial weeks, Channel A has access to all available movies that are considered the most profitable, those that make the "cut". As a result, Channel A initially selects the movies that generate the highest revenue. However, these movies are subject to a "penalty", making them economically non-viable to re-show for a period of time.

As time progresses, Channel A shifts to selecting movies that provide the highest possible revenue potential. Since these later selections do not generate as much revenue as the initially chosen ones, the overall earnings naturally decrease. The spike observed in week 9 occurs because some of the movies that were initially penalized have now had their penalty reduced, making them economically viable to air again.

4.4 Risk Analysis

The advantage of modeling the actual view count as a continuous function becomes clearer. With it, several aspects of the system (as can be seen in pricing strategy and viewership comparison) can be tested for the worst-case scenario, enabling the system to be more robust and give more data for decision making. Furthermore, the risk modeling applies to the revenue over a 12-week period, and some interesting observations came up. First of all, the spread of revenue is quite large for 80% bounded, the spread can be between £10,000,000 - £15,000,000 , this can make a difference between profitable and unprofitable. Special care has to be taken of the factors that can affect several movies' viewership (e.g., disruption of streaming service, big sports events, and a shift in behavior). While, a shift in one movie's viewership is undesirable, a larger systematic shift could give a detrimental outcome.

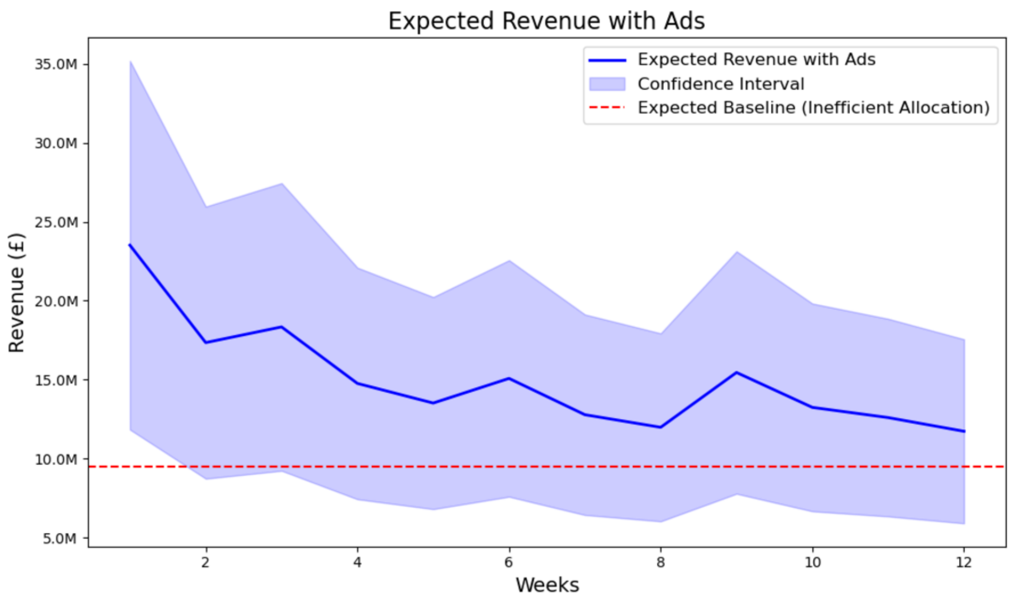

Figure 7: Total revenue with confidence bound and baseline

4.5 Profitable Movies

To conclude the analysis, a simulation has been conducted to target a movie with high popularity and a limited number of genres (e.g., horror and comedy). The only change being made to this simulation is that the total number of viewers has been increased from 1,000,000.00 to 5,000,000.00.

Viewership	Average Movie Budget ($)	Average Box-Office Return ($)
1.00×10^6	13,283,250.00	29,546,423.00
5.00×10^6	25,992,793.00	46,839,349.00

Table 1: First week schedule of viewership = 1,000,000.00 vs viewership = 5,000,000.00

As illustrated, average movies from increased view counts are much more popular and have higher licensing fees. These results are not surprising, by lifting the viewership, licensing fees are less emphasized and pure popularity is much more emphasized. So, the conclusion can be made that relatively low-budget and moderately-popular films are more desirable than high-budget and highly popular films at the current viewership level. If viewership increases, film popularity will become more and more important while licensing fees become less and less important.

5 Conclusion

The model suggests that Channel A can potentially earn an additional £11,000,000 by implementing a strategy that includes both selling and buying advertisements, instead of solely selling advertisements during the period analyzed.

Based on the analysis, niche movies with a specific appeal are more profitable to show due to their lower budgets and sufficiently large target audiences. The analysis also recommends implementing a robust dynamic pricing strategy for selling advertisements, with the flexibility to adjust as more data becomes available.

Furthermore, for channel A to continue to grow, adapt and prosper, some suggestions for future improvement are provided.

Learnable Advertising Strategy and More Buyer

Currently, the assumption is to only sell advertisements to competitors, not to the others, which leaves a lot of potential buyers out. In the long run, if channel A outperforms competitors, buyers will be less and less willing or could not afford to buy advertisements. It could be therefore interesting to simulate a model where non-competitor buyers also are allowed to buy advertisement. This could be beneficial as channel A would still earn a revenue from the advertisement, but not lose viewership (as it effectively does when it sells advertisement to its competitors)

After deploying a dynamic pricing strategy, if a high percentage of advertisement slots are sold, the price could be slowly raised. Learning elements akin to Bayesian Optimization can be employed to maximize profits. These, however, can only be done after real buyer data is gained. (Roughgarden, 2023)

Online Strategy

The rise of online channels that curate movies that are only available for a limited period of time (channels like Criterion, Mubi, or UK's own BFI) seems to be a viable alternative to the industry behemoths such as Netflix, Amazon Prime, and Apple. These operate mostly the same as movie channels but are available through the Internet. With tweaking and extensions of the model, they can be used to optimize what to show on the Internet at a given time.

Vertical Integration

After it is known which movies are profitable, becoming one's own movie distributor is a natural extension. The licensing fee incurs by far the channel's highest cost. With the rise of independent distributors (Shahzeidi, 2023), this can provide an extra income for the channel, while reducing the licensing fee. It could also provide the benefit of making films that is the right fit for channel A.

To conclude, it is highly recommended that Channel A implements this model in order to take advantage of the potential return it can expect by applying it. The model is designed with a heavy emphasis on robustness and sustainability to deal with a dynamic competitive environment where all competitors are always looking for an edge. The model has a high potential for future development due to its strong base structure and flexibility. It is believed that this model can be a strong foundation for providing channel A with a bright future.

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7 Appendix

Codes Implementation

`https://github.com/puttiwatWan/mmcs-project-uoe/tree/main`

This repository is made private, please ask either one of the authors for an access. Please also attach your Github id, email, and the repository.

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