Measuring the Influence of Mere Exposure Effect of TV Commercial Adverts on Purchase Behavior based on Machine Learning Prediction Models

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Abstract

In order to effectively test the short-term effectiveness of television advertisements on customer purchase behavior, there is a need to perform an analysis using new methodology and larger samples, which are lacking in previous research. In response to this, we apply machine learning algorithms to construct a number of prediction models based on the time spent exposed to adverts during a period of 3 months, and examined the predictability of change in Purchase Intention and Actual Purchase behaviors of 3000 customers across 38 different product advertisements using television usage data and product purchase behavior survey samples provided by the Nomura Research Institute, Ltd. With this data, we trained SVM and XGBoost models to analyze the change in predictability before and after 3 months of advertisements, both to observe predictable products with plausibly effective adverts, and to observe the number of predictable customers, possibly having been influenced by the adverts.

Highlights. Prediction of Purchase Intention behavior based on advert exposure time was achieved for a fourth of the population, as well as for 8 products from the total of 38. Actual Purchase behavior was completely unpredictable in any of our models.

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1. Introduction

It is generally thought that in order for companies to increase sales, they must somehow increase the purchase intention of their potential customers [1]. Historically this has been approached through many channels, but since the successful introduction of the television to the general public, it has been largely attempted via television commercial advertisements, and many companies invest heavily on these efforts. However, most studies to prove the effectiveness of these advertisements have been conducted on small sample groups, usually introducing a customer to a commercial advertisement and measuring their intentions to purchase a product before and after watching the advertisement with a survey [e.g. 2]. Another study on the predictability of purchase from purchase intention data points out how many of these analyses have very differing results [1], presumably because of a small and non-representative sample.

We propose a machine learning approach to this problem, with a large database of the television usage timelines of surveyed individuals and their answers regarding recent purchase intentions and actual purchase recalls at two points in time separated by 3 months, provided by the Nomura Research Institute, Ltd.

Now, following the traditional train of thought of the effects of mere exposure [3], we propose collecting the accumulated number of seconds that a user has viewed a commercial advert related to a certain product and observe its effects on the users. With this data we propose training a model to predict the purchase intention and purchase recall of users based on the amount of accumulated seconds of being exposed to the advertisement for the related product in the survey. We propose to do this by unit of product, to observe the difference in marketing success from product to product, and by unit of user, to observe the rate of population that was potentially influenced by advertisements. This introduces both granularity, as we are using precise television viewing time and observing effects over time, and the potential of generalizing our prediction model to unknown new users or products after training.

2. Related Work

In previous research, there have been attempts to measure the effects of advertisements on brand recognition and perception fluency [4]. The "processing fluency" model [5], states that repeated exposure leads to a more readily accessibility of the target brand in memory, which in turn must have an effect on the ability to recognize a brand in the future. Most of the related research has arrived to a consensus that there is a positive influence [6, 7]. More recent research, however, explores further whether these effects in memory are strictly related to positive emotional judgment on the brands or if they can also imply negative judgements based on the main objective of a product. [8]. Other research regarding the effects of advertisements has used brain imaging in order to explore the short-term and long-term memory effects of TV commercials [9]. It should be noted that, as is to be expected in a brain imaging experiment, the participants observed the advert directly and more consciously than in mere exposure experiments.

However, a common problem with these studies and others in television advertisement effects is the size of the sample for which the experiments take place. Ranging from a few tens to maybe two or three hundred participants, these studies have limitations when it comes to analysing actual purchasing behavior effects of advertisement. In order to solve this limitation, our research is based in data science analysis methodology, such as machine learning algorithms trained from large samples of data. Big data analysis on advertising is mostly focused on online advertisements, [10] where, with the advance of current technology, a user is exposed to adverts placed near to the the content they are currently consuming which are specifically targeting their interests [e.g. 11, 12], catching their attention (which is no longer mere exposure, but direct interaction), or a user is incentivised to watch an advertisement by blocking completely the content they were consuming until the advertisement is finished playing on screen. While most of the research in this area is focused on new ways to create online advertisements targeted to a user's interests, reducing the need of mere exposure advertisement while online, there is no research using these technologies to test the effectiveness of the mere exposure effect based advertisements which are still in use in other traditional means, such as billboards, or as we analyze in our study, television advertisement. In addition to this, to the extent of our research, most studies are done on the pretense that advertisement, be it targeted or not, has an observable effect via the mere exposure effect on customer purchase behavior, since that has been the consensus for so long without dispute.

Our study is unique in that, using data from television advertisement and not online ads, we apply data science methodology to explore with a larger sample if there is an effect caused by mere exposure advertisement at all, and to what extent this effect happens if there is.

3. Methodology

As explained above, our approach is to train machine learning models based on the number of seconds of advertisement exposure, to predict the effect on the customers purchase decisions.

Our proposed method is explained in detail in the following sections.

3.1. Survey Data Analysis

3.1.1. Purchase Intention and Actual Purchase

From the survey data provided by Nomura Research Institute Ltd., we can examine 3000 customer samples, of which we can extract the Purchase Intention and Actual Purchase answers at two points in time, one in January 2017, and another in March 2017, for 200 different products. Each time, the surveys inquire the customer if they have recently had an intention or desire to purchase a certain product (regardless of action on this desire), which corresponds to Purchase Intention; likewise, it inquires if they have recently had purchased a product, corresponding to the Actual Purchase element. We will inspect the effect of adverts on these two elements of a customer's purchase decisions and observe their change with time on the span of three months.

3.1.2. Data Categorization

In order to explore the different effects commercial adverts may have on the purchase decisions of customers based on their answers from two different points in time, we have labeled each user in regard to each product with 6 categories (from 0 to 5), describing several patterns of behavior. For example, let's examine customers who answered they had purchased a product in January and then not in March, corresponding to category 0, in comparison to customers who purchased the product in March, corresponding to category 4: It is possible that, had category 0 customers were exposed to adverts in greater quantity than other users who still purchased the product and weren't exposed to as many adverts on the span of 3 months, this could mean that the advert was at least not effective, or in a worse scenario, off-putting. On the other hand, if the amount of advert exposure was minimal with category 0 customers and at the same time, customers in category 4 who actually recall having purchased the product in the March survey had been exposed to a large amount of adverts, it would prove to be an effective commercial advert campaign.

Although our approach for analysis is different, the above is a simple example of the importance of this distinction between behavior categories. The six categories for each element are explained in detail in Table 1 and Table 2.

3.2. Advert Viewing Time Calculation

Now, on the other side of our analysis, observing the relation between the previously explained data and the effectiveness of commercial adverts on television, we extract the viewing time for adverts of each product for each customer from the television viewing data provided by Nomura Research Institute Ltd.

Table 1: Category definition for Actual Purchase element

Category	January Actual Purchase	March Actual Purchase
0	Yes	No
1	No	No
2	No	Yes
3	Yes	Yes
4	Not Considered	Yes
5	Not Considered	No

Table 2: Category definition for Purchase Intention element

Category	January Purchase Intention	March Purchase Intention
0	Yes	No
1	No	No
2	No	Yes
3	Yes	Yes
4	Not Considered	Yes
5	Not Considered	No

Now the data provided tells us if a user had the television on at the moment of a certain show. Using the information provided of which commercial advert was shown during which television show and how long they lasted, we extracted the number of accumulated seconds a user had the television on for the adverts of each product, and organized them into different weekdays and time slots. We did this to further analyze whether the time period regularly described as "Primetime" had any different influence than other time slots. The final data for each user and product included the elements described in Table 3. We created different datasets so that the viewing time of one element never repeated in a later one. Because of this, the total viewing time was analyzed on its own.

3.3. Support Vector Machine

Support Vector Machines (later abbreviated SVM) are supervised machine learning models used in regression and classification problems [13]. Supervised learning meaning that the model trains on previously labeled data, and establishes a way to match the labels as accurately as possible for new unlabeled data to be analyzed. In a binary classification problem, also called a Support Vector Classifier (SVC), previously established binary labels are matched with a p-dimensional vector of input data. Each column or dimension in the vector expresses a feature in the input data, and each row of the vector is a different data point. After each data point is matched with a label, an SVM uses an algorithm to determine a (p-1)-dimensional hyperplane that separates the p-dimensional space in a way that minimizes error in classification, by maximizing the distance between the hyperplane and the nearest point in either classification. A two-dimensional example is shown in Fig. 1.

In our study we used the linear kernel for our SVC, defined by the formula (1) below, where x is the input vector, w is the weight vector, and b is the bias vector. The dimensions of these vectors are such that $f(x)$ and b are the size of the sample size, and w is the size of the amount of features. The sign of the value of $f(x)$ determines which classification label y is applied, as shown in the

Table 3: Viewing time analysis elements

Viewing Time	Notes
Monday	Monday Primetime only, Non Primetime only, and Total.
Tuesday	Tuesday Primetime only, Non Primetime only, and Total.
Wednesday	Wednesday Primetime only, Non Primetime only, and Total.
Thursday	Thursday Primetime only, Non Primetime only, and Total.
Friday	Friday Primetime only, Non Primetime only, and Total.
Saturday	Saturday Primetime only, Non Primetime only, and Total.
Sunday	Sunday Primetime only, Non Primetime only, and Total.
Weekday	Five Weekdays Primetime only, Non Primetime only, and Total.
Weekend	Saturday and Sunday Weekend. Primetime only, Non Primetime only, and Total.
Holidays	Weekdays that are also Holidays. Primetime only, Non Primetime only, and Total.
Rest Day	Weekday Holidays and Weekends together. Primetime only, Non Primetime only, and Total.
Primetime	All days included, total Primetime advert viewing.
Non Primetime	All days included, total Non Primetime advert viewing.
Total	Total amount of accumulated seconds viewed of adverts.

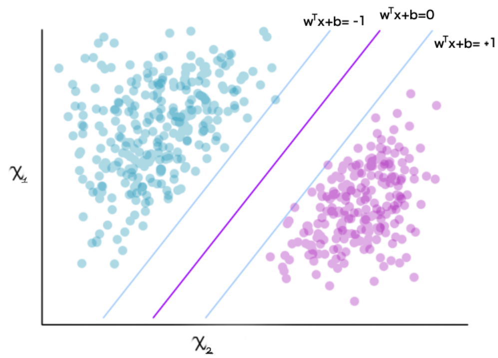

Figure 1: Two dimensional example of an SVM classification problem

formulas (2) and (3).

$$f(x) = w^\top x + b \tag{1}$$

$$f(x) \geq 0 \rightarrow y = +1 \tag{2}$$

$$f(x) \leq 0 \rightarrow y = -1 \tag{3}$$

The algorithm consists of, starting with a weight and bias vector comprised of zeroes, a randomly placed hyperplane is drawn. Each data point is tested for correct classification, and if the classification fails, the value of w is changed by a value of α as follows (4). Finally the distance to the nearest points, the support vectors, in either classification, called the margin, is calculated.

$$w \leftarrow w + \alpha sign(f(x_i))x_i \tag{4}$$

This process is repeated so that the margin is maximized and the number of erroneous classifications are minimized.

Now, in order to measure the effectiveness of the training process and data, we perform what is called a K-fold cross validation. This means that after randomly shuffling and splitting our training data in k equal parts, k-1 of those

Table 4: Prediction outcomes

	Prediction is Correct	**Prediction is Incorrect**
Prediction is Positive	True Positive	False Positive
Prediction is Negative	True Negative	False Negative

parts are used for training, while the remaining one part is used in validation. Using the trained SVM, a prediction is made, and it is decided if such a prediction is correct or not, and counted and grouped as a True Positive, True Negative, False Positive or False Negative prediction. This is explained in Table 4.

Measures of accuracy are determined from these prediction outcomes. This process is then repeated k times and the measures taken are averaged. In this study we used the F_1 score, which measure is a harmonic mean between precision and recall. Precision, described in formula (5), lets us observe the rate of correct positive predictions from all the positive predictions, while Recall, detailed in formula (6), observes the rate of correct positive predictions from the total of actual positive data. The F_1 score in formula (7) then can only be high when both of these measures are high simultaneously, and will lower substantially if they are not consistent. We use this score as it allows us to avoid overlooking data while maintaining accurate predictions.

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{5}$$

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{6}$$

$$F_1 = 2\frac{Precision * Recall}{Precision + Recall} \tag{7}$$

Table 5: Prediction Model Bases

Prediction Model Base	Description
Product Based Prediction Models	For each product from 200 available in the survey, data from 3000 users was collected and paired with their labels.
User Based Prediction Models	For each user from 3000 available, data corresponding to all 200 products available in the survey was collected and paired with their labels.

3.4. XGBoost

Originally started as a research project by Tianqi Chen [14], XGBoost is an improved and optimized application of a Gradient Boosting Machine, or GBM, also called gradient tree boosting, or gradient boosted regression tree. A Gradient Boosted Regression Tree (GBRT) works by building an ensemble model from several weak learning machines which are just above random guessing in accuracy, in this case using Decision Trees. The misclassified results from these weak predictions are then weighted and added to a final strong learning machine. This process iteratively optimizes the misclassification cost in a functional gradient descent so that the final learning machine focuses on important factors from the training data for a stronger prediction model.

4. Experiments

4.1. Prediction Models

Based on the input vector that is used, we have proposed investigating the two different configurations possible for our prediction models, as explained in Table 5.

After extracting the commercial advert viewing data using these parameters from the 3000 users that answered the survey, which includes purchase behavior

Table 6: Prediction Model experiments performed

Prediction Model	Prediction Targets	Number of Categories
Product Based CM View Time	Actual Purchase	6
Product Based CM View Time	Purchase Intention	6
User Based CM View Time	Actual Purchase	6
User Based CM View Time	Purchase Intention	6

questions from 200 products at two different points in time, only 38 products from those in the survey were linked to commercial adverts that were actually viewed by those same users. Thusly, we performed our experiments using the viewing data of 3000 users for these 38 products in the configurations explained before in Table 5.

4.2. Prediction Model Targets

Using the previously explained bases, we performed analysis for both Actual Purchase and Purchase Intention, and each variation in change explained before as categories in section 3.1.2 of this paper. With this categorization, we can observe the difference in relation between the number of seconds of advert viewing and a change in Purchase Behavior between January 2017 and March 2017. In total we performed experiments with 24 different prediction models. This can be visualized in Table 6.

4.3. Machine Learning Algorithms

Using the Prediction models explained in section 4.2 of this paper, we performed the machine learning experiments with both SVM and XGboost algorithms and then compared results from both groupings.

5. Results

We investigated the relation between viewing data and 6 different purchase behavior categories depending on their change throughout two different points in time. However, the two categories which we will focus on this paper are category 2 and 4, since they represent the customer base that either changed from not purchasing to purchasing, or also customers who continued their purchases. This would let us observe if there is any positive relation between the time spent viewing commercial adverts and the purchase decision, granting us insight to the effectiveness of the advert in its desired purpose. We present the results of our analysis in the following sections. The detailed results presented first are all from the experiments performed using the SVM algorithm. We then present the differences in results for SVM and XGBoost experiments in a later section.

5.1. Product Based Models Results

5.1.1. Product Based CM View Time · Actual Purchase Category 2

For all 38 products, we collected the data of actual purchase behavior from 3000 customers, labeling those who changed their behavior from not having purchased in January 2017 to having made a purchase in March 2017 as the positive classification, and any customer other than those as the negative classification for our SVM training data.

The results of the F_1 score for the prediction models for each of the 38 products resulted in 0. This means that any predictions were failed and that the SVM could not find a separating (p-1)-dimensional hyperplane for the viewing data. In other words, people who changed their purchasing behavior from January to March, and people who did otherwise, were exposed to similar amounts of advert time, or that viewing time was spread indiscriminately for all users regardless of purchase decision for any of the products that we investigated separately.

5.1.2. Product Based CM View Time · Actual Purchase Category 4

Now, the results for the product based model labeling positively those who regardless of change, had actually purchased the product by March 2017; and labeling negatively any customers who did not purchase the product by March are presented in this section.

The F_1 scores for all but one of the 38 prediction models in this experiment were 0. The remaining product was the japanese bottled tea "IEMON", with an F_1 score of 0.018. Now, for a score to describe a relatively accurate prediction model, it must be at least above 0.5. This means that even though this particular product had a score slightly above 0, there is no particular relation found by the SVM that could determine the purchase behavior of customers based on the time spent viewing adverts for the related product.

5.1.3. Product Based CM View Time · Purchase Intention Category 2

Similar to our results for Actual Purchase behavior, the experiment labeling positively customers whose Purchase Intention changed from not having any intention at the first point in time to having a purchase intention at the latter, and labeling negatively those who did otherwise resulted in an F_1 score of 0 for all 38 products. This means that for any of the 38 products, advert viewing time did not have any relation to their purchase intentions changing or not in the vector space.

5.1.4. Product Based CM View Time · Purchase Intention Category 4

The results for Purchase Intention behavior, labeling positively customers whose Purchase Intention was positive at the latest point in time in the survey, regardless of their behavior before that point; and labeling negatively those who did otherwise, resulted in an F_1 score greater than 0.5 for 8 of the 38 products available in our viewing data. These prediction accuracy results are presented in Table 7. There were other 3 products which had an F_1 score between 0 and 0.5, not listed, and the remaining 27 products had an F1 score of 0.

Table 7: $F_1 > 0.5$ for Product Based CM View Time · Purchase Intention Category 4

Product	F_1
KitKat	0.863
IEMON	0.799
Ghana	0.777
Lunch Pack	0.773
Dars	0.757
Mitsuya Cider	0.737
Namacha	0.733
Jurokucha	0.709

5.2. User Based Models Results

This section shows the results from the user based experiments. These experiments calculate the number of specific users that are predictable in their Actual Purchase and Purchase Intention behaviors based on their advert viewing time.

5.2.1. User Based CM View Time · Actual Purchase Category 2

This section presents the results for the Actual Purchase behavior prediction of Category 2 users (those who didn't purchase in the first survey and changed their behavior in the second survey 3 months later). Only 30 of 3000 users had an F_1 score greater than 0.5, meaning they were fairly predictable in their behavior based on their advert viewing time. The remaining 99% was completely unpredictable. This result is shown in Figure 2.

5.2.2. User Based CM View Time · Actual Purchase Category 4

The results for the user based model in Actual Purchase Category 4, however, presents a larger amount of users, with 253 of 3000 users having been predictable, obtaining an F_1 score greater than 0.5. It is easier to predict a single purchasing behavior in their last survey, based on their viewing time from the previous 3 months, than to predict a specific change in behavior like the last experiment.

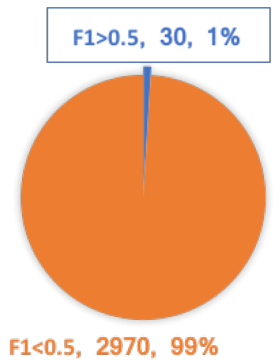

Figure 2: Prediction results for User Based CM View Time · Actual Purchase Category 2

However, there is still a 92% of users whose behavior was unpredictable with only advertisement viewing time considered. This result is shown in Figure 3.

5.2.3. User Based CM View Time · Purchase Intention Category 2

Similarly to the experiment for Actual Purchase behavior, the results for Purchase Intention prediction for Category 2 users, who changed their behavior from not purchasing to purchasing between surveys, was extremely low. Only 40 of the 3000 users had a prediction score greater than 0.5. This result is shown in Figure 4.

5.2.4. User Based CM View Time · Purchase Intention Category 4

In contrast to all previous results, the user based prediction model for Purchase Intention in the last survey was more successful. 753 of 3000 users, roughly 25% of users were predictable based on their advert viewing time regarding their Purchase Intention behavior. This result is shown in Figure 5.

5.3. XGBoost Comparison to SVM

As the results shown above are all from the experiments done with SVM machine learning algorithms, we show a comparison of the experiments done with XGboost in Table 8 and Table 9, for product based models and user based models respectively.

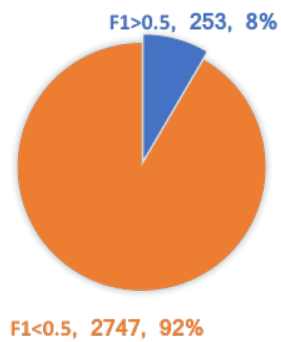

Figure 3: Prediction results for User Based CM View Time · Actual Purchase Category 4

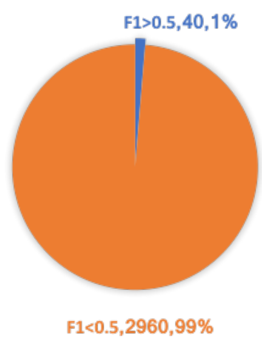

Figure 4: Prediction results for User Based CM View Time · Purchase Intention Category 2

Figure 5: Prediction Results for User Based CM View Time · Purchase Intention Category 4

Table 8: SVM and XGBoost percentage of elements with $F_1 > 0.5$ comparison for product based models

Product Based Model	SVM	XGBoost
Actual Purchase Category 2	0	0
Actual Purchase Category 4	0.08	0
Purchase Intention Category 2	0	0
Purchase Intention Category 4	0.21	0.21

Table 9: SVM and XGBoost percentage of elements with $F_1 > 0.5$ comparison for user based models

User Based Model	SVM	XGBoost
Actual Purchase Category 2	0.01	0
Actual Purchase Category 4	0.08	0.06
Purchase Intention Category 2	0.01	0
Purchase Intention Category 4	0.25	0.24

The results for SVM prediction models held a slightly higher percentage of predictable elements, but overall they both show similar results.

6. Discussion

6.1. Influence of TV adverts on Actual Purchase and Purchase Intention

In this paper, we have obtained results on the predictability of Actual Purchase and Purchase Intention customer behaviors based on the time spent exposed to TV adverts. These results are low enough that it can be said TV adverts are not a main factor in predicting whether a customer will change their purchasing behavior. While the research based on the mere exposure effect would suggest otherwise, customers are observed to decide on their purchase without much predictability. It could be said that while there is influence in the customer's knowledge of the brand, the amount of time exposed to TV adverts seems to have an indirect influence on purchasing behavior at most, if not none at all.

Other studies, using a controlled environment, have linked mere exposure with bias in consumer choice [15]. However, there is a possible explanation for these discrepancies in results. While controlled experiments show the TV adverts to their sample audience directly in most cases, in an uncontrolled environment of a customer's home, the customer is left free to ignore the advert and do something unrelated in the meanwhile [16]. In the United Kingdom, there is a widely documented phenomenon involving TV advert timing and a surge in electricity caused by the use of electric kettles for preparing tea. This phenomenon is commonly called TV pickup, and has been documented for long [17, 18]. Similar to these cases, if the customers whose data were actively ignoring the adverts, the sample for training the prediction models would contain noise, altering the results. It stands to reason that without the influence of this active aversion would have on our learning model, it might correctly predict purchasing behavior as expected. However, this is more of a problem with the current TV advertisement model than with the methodology of this study. We will discuss this further in section 6.3 of this paper.

6.2. Influence of TV adverts based on Primetime

In our prediction model experiments, we used data from advertisement exposure during different time periods, days of the week and weekends. While we did this in order to observe differences in predictability for different time schedules available to different kinds of customers, especially during primetime television hours, we arrived to similarly low results for all time categories. We did not observe any difference in predictability based on Primetime television watching compared to other time periods, as well as differences in weekdays and weekends. This could be interpreted as there being little influence in time periods and changes in purchasing behavior. However, as we stated in section 6.1, the common problem with advertisements being actively ignored by customers has existed for long. Taking this problem into consideration, our results imply that the problem is constant over all the time periods, and that there is not a particular time slot that results in customers being more attentive to adverts.

6.3. Implications for the TV advert industry

Based on the low results of predictability of purchase behavior by advert exposure, it can be observed that TV adverts have a low probability of achieving their main purpose: to increase sales. As was stated in section 6.1 of this paper, there could be a large influence on this study's results from customers actively ignoring the adverts although they are being broadcast to their TVs. It is left to further discussion and research if adverts actually have the intended effect on customers when watched properly, or if this effect is not achieved anyway. In [4] it is proposed that while the mere exposure of banner advertisement increases perceptual fluency, it doesn't have an effect on actual brand recognition compared to the control groups, for example. The existence or absence of influence by perceptual fluency on a customer's purchase decision hasn't been fully explored, but the consensus in the processing fluency model is that perceptual fluency influences brand judgement on some level, although it depends on the concept if the reception is positive or not [8]. The problem with these studies and the current consensus, as has been said previously in this paper, is both that most experiments are done with relatively small sample sizes, and that there is a factor of uncertainty that comes with the physical avoidance of adverts in a customers home environment.

With these things in mind, we consider both possibilities: either customers are attentive and the adverts have the expected influence in their short and long term memories in the case of repeated exposures [9]; or the customers are inattentive of the advert and there might be some level of unconscious effect of mere exposure in their perception fluency [4]. We observed however in our results that the effect on Actual Purchase behavior is minimal. While it may be true and out of the reach of our data that the customers would have influence in their memory, there was no link observed between the time of advert exposure and the purchase decisions. This raises a concern for the TV advert industry.

Regardless of the cause of our results, the main implication of our paper is that currently, TV adverts are shown to have little to no effect on changes in Actual Purchase behavior, and only some observable effect in Purchase Intention. While thousands of billions of japanese yen are spent on TV advertisements each year [19], the effects observed in this study are negligible. Because of this, changes are necessary in the current TV advertisement model.

7. Conclusion and Future Work

In this paper we analyzed the ability to predict purchasing behavior, namely Purchase Intention and Actual Purchase based on the customers' time spent exposed to television adverts using machine learning algorithms. We analyzed the data by product and by customer, determining which specific products and which specific customers provided a better prediction model. Based on our low results for any prediction of Actual Purchase, we concluded that there must be other factors that are more strongly tied to the customer's purchasing behavior. The results for Purchase Intention were relatively higher but still low enough that only a few products, mostly tea and chocolate snacks, could be predicted, and only one fourth of the customers were predictable in their purchase intention. We discussed possible influence by deliberate avoidance of advert cuts to prepare food or tea, and while some studies focus on the effect of attentive watching of adverts, other studies focus on the mere exposure effects, which would be achieved despite physical avoidance because of advert audio and simple proximity of the television. Both scenarios are in strong contrast with the results of our study, which shows little to no predictability in purchase behavior. Points left to research in future work are a deeper analysis of the predictable customers, looking for similarities or clusters within this class, as well as using different machine learning algorithms, which weren't considered because of requiring bigger datasets.

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