# Modelling In-Store Consumer Behaviour Using Machine Learning and Digital Signage Audience Measurement Data

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**Abstract.** Audience adaptive digital signage is a new emerging technology, where public broadcasting displays adapt their content to the audience demographic and temporal features. The collected audience measurement data can be used as a unique basis for statistical analysis of viewing patterns, interactive display applications and also for further research and observer modelling. Here, we use machine learning methods on real-world digital signage viewership data to predict consumer behaviour in a retail environment, especially oriented towards the purchase decision process and the roles in purchasing situations. A case study is performed on data from a small retail shop where demographic and audience data of 1294 store customers were collected, manually verified and analysed. Among all customers, 246 store customers were involved in a buying process that resulted in an actual purchase. Comparison of different machine learning methods shows that by using support vector machines we can predict with 88.6 % classification accuracy whether a customer will actually make a purchase, which outperforms classification accuracy of a baseline (majority) classifier by 7.5 %. A similar approach can also be used to predict the roles of an individual in the purchase decision process. We show that by extending the audience measurement dataset with additional heuristic features, the support vector machines classifier on average improves the classification accuracy of a baseline classifier by 15 %.

## 1 Introduction

Digital signage systems are nowadays primarily used as public information interfaces. They display general information, advertise content or serve as media for enhanced customer experience [1–4]. The ability to adapt and change broadcasting content in real time -'on the fly'- as well as access to wide audience have made interactive public displays today a highly active and interdisciplinary area of research.

In order to display engaging content and understand interaction of users with digital signage systems, various interaction techniques and case studies


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were performed [5,6]. Different interaction modalities were proposed including hand gestures, gaze, touch, body and face posture [7–10]. Interaction design studies show that the interaction level of users with digital signage systems will increase, including also the mobility of users around the display, if using an unconventional user interface, i.e. the *curiosity object* [11,12]. Müller et al. performed a field study where they observe how passers-by notice and respond to interactivity of digital signage displays. Their observations show that silhouettes which mirror users tend to be the most effective user representation and that it takes time (approximately 1.2s) to notice the interactivity [13]. In parallel to interaction research, audience measurement studies show that also demographic features and varying broadcasting scenarios influence temporal parameters of user attention [14–16].

Since digital signage systems can have a significant effect on commerce, they are also rapidly permeating shopping centers and retail stores. Retail generalization studies reveal that in-store digital signage increases customer traffic and sales [17,18]. Customers seem to be the most responsive to the broadcasting content that relates to the task at hand and their immediate interest. Pantano and Naccarato present retail digital signage systems as an effective way and advantage for retailers to improve the point of sale [19]. Besides being a new communication channel, digital signs present an effective stimulus that improves the image of shopping malls and create a positive influence on consumers shopping experience [20].

In this interdisciplinary paper, we use our custom-developed computer vision enhanced digital signage system capable of collecting audience measurement data to model and predict customer behaviour in an exemplary setup of a small apparel retail store, being able to achieve 88.6 % classification accuracy in predicting the outcome of a purchase process. Using real-world demographic and temporal audience measurement data, which is additionally annotated with retail purchase decision features, we demonstrate a machine learning model that is capable of predicting whether a person is prone to make a purchase or not. The outline of the paper is as follows: Sect. 2 elaborates the purchase decision process, Sect. 3 presents the real-world in-store consumer behaviour dataset, Sect. 4 denotes machine learning results and Sect. 5 provides final conclusions.

## 2 Purchase Decision Process and Digital Signage System for Retail Behaviour

Purchase decision process describes the sequence of actions performed by a customer when deciding to purchase a particular product or service [21]. It can also be described as a process of problem solving, where a consumer satisfies his needs after thoughtful consideration. The outcome of a purchase decision process is a decision whether a customer will buy a given product or service or not.

Purchase decision process can be described with five stages [22]. The first stage is problem recognition where consumer recognizes a problem or a need. The second stage is search for information via heightened attention of consumer towards information about a certain product, which can even resolve in actual proactive search for information. The third stage represents the evaluation of alternatives, which usually involves a comparison between various options and features based on the models of the expected value and beliefs. In the fourth stage of the purchase decision process a provider, place, time, value, type and quantity of the selected product or service are determined. The fifth and final stage describes the post purchase use, behavior and actions.

We distinguish between three different types of purchase decisions. They differ in value and frequency of purchase, covering different intensity levels of involvement and time invested in the purchase decision [23]: (i) routine response behaviour (for frequently purchased, low involvement products and services), (ii) limited decision-making (unfamiliar brand choices in the known category of products and services), and (iii) extensive decision-making (high involvement, high value and low frequency of purchasing). There are several factors affecting buying behaviour, such as cultural, social and personal decision elements. Cultural factors include cultural context and belonging to a certain social class or subculture. Social factors are defined with position and role of the individual, his family and reference groups, which have a direct or indirect impact on buying behavior. Personal factors are determined with individual's lifestyle, occupation, property status, personality and self-esteem [22,23].

Purchase decision process can involve one or more persons. A set of people that are involved in a single purchase decision is called a buying unit or group. Each member of the group can take up different roles in the purchase decision process [22]:

1. An initiator is the person who recognizes the need and starts with finding the solution by requesting purchase of a product or service. The initiator may be the actual user of the product or he/she could be any other member of the buying group.
2. An influencer is the person whose opinion or position has significant effect on the purchase decision, usually by providing information on product characteristics and evaluation of possible alternatives.
3. A user is the person who will use the product or service. Typically, the user is involved in defining the required product/service characteristics.
4. A decider takes the final decision when choosing between different products. The decision is based on the required characteristics of a product or service.
5. A purchaser has the formal authority to pay for goods or services. Purchaser also determines the terms of purchase, such as the payment method.
6. A passive influencer or a companion is a person who is a member of the purchase group, but is not actively involved in the buying process.

We should comment that the list of roles in the buying group varies throughout the literature; however, the above introduced initiator, influencer, user, decider and purchaser are the key roles, which are used in most of the definitions [22,23]. Note that the role of a passive influencer is not among the commonly defined roles but is introduced in this paper because of the digital signage audience measurement observations. Passive influencers do not actively participate in purchase process and would otherwise be excluded from further analysis.

A real-world experiment was performed in order to obtain retail audience measurement data. A 24 inch Sony Vaio VPCL135FX/B camera-enhanced computer display was positioned into a small clothing boutique in a city center of Ljubljana (capital of Slovenia, EU). A small retail shop was selected on purpose, to be able to cover the entire retail floor with a single camera unit. The shop's goods were mostly premium priced sports fashion clothing and apparel, which sets the demographic and behaviour characteristics of collected audience measurement data. The experiment was performed within 23 daily sessions, collecting a total of 214 hours of video recordings. Computer display acquired demographic (gender, age group) and temporal features (presence time, in-view time, attention time) of N = 1294 store customers. The experiment was primarily focused in viewership and attention statistics. The analysis reveals that 35 % of visitors *looked-at* the display, having the average attention time of 0.7s. Gender comparison shows that men (1.2s) were more responsive to digital signage than women (0.4s). Significant difference in attention time was also noted when observing age group of observers and broadcasting content. A more detailed description of demographic and temporal audience measurement features as well as results of attention analysis were already published and are available in [15].

For modelling of retail behaviour we relate the collected audience measurement data with additional data on the purchase decision process. The following consumer group features were added: *group-number* which indicates the sequential number of the buying group a person belongs to, *group-size* denotes the total number of people in a given buying group, and a binary parameter *purchase* that describes whether a group made a purchase or not. If the buying group made a purchase, the roles in the purchase decision process of each group member were also denoted, resulting in 6 additional features: *initiator*, *influencer*, *user*, *decider*, *purchaser* and *passive influencer*. The collected data was verified with manual verification of all automatically obtained data (temporal and demographic features) by two human reviewers. They reviewed the recordings and added additional purchase-oriented features to original audience measurement data. In case of disagreement between reviewers, mutual decision was accepted after discussion during the annotation assessment.

## 3 Observed Retail Behaviour Dataset

In our digital signage based experiment of retail behaviour, N = 1294 people visited the store in the time of the experiment, out of which $N_{buy} = 246$ persons were involved in a buying process that resulted in 140 purchases. The distribution of purchase decisions based on demographic features and group size is presented in Table 1. With $n_{all}$ we denote the total number of people whose characteristic meet the given criterion. With $n_{buy}$ we assign the number of persons who meet the selected criterion and have also been involved in the purchase

**Table 1.** Buying process distribution for a given demographic and buying group size feature.

| Feature | Value | $n_{all}$ | $n_{buy}$ | $p_n$ | $p_{buy}$ | $p_{all}$ |
|---|---|---|---|---|---|---|
| Gender | Male | 504 | 92 | 0.39 | 0.37 | **0.18** |
| | Female | 790 | 154 | 0.61 | 0.63 | **0.20** |
| Age group | 1–14 | 95 | 20 | 0.07 | 0.08 | 0.21 |
| | 15–24 | **133** | **12** | **0.10** | **0.05** | **0.09** |
| | 25–34 | 258 | 54 | 0.20 | 0.22 | 0.21 |
| | 35–44 | 323 | 60 | 0.25 | 0.24 | 0.19 |
| | 45–54 | 251 | 53 | 0.19 | 0.22 | 0.21 |
| | 55–64 | 153 | 30 | 0.12 | 0.12 | 0.20 |
| | 65+ | 81 | 17 | 0.06 | 0.07 | 0.21 |
| Group size | 1 | 438 | 57 | 0.34 | 0.23 | **0.13** |
| | 2 | 618 | 124 | 0.48 | 0.50 | **0.20** |
| | 3 | 165 | 57 | **0.13** | **0.23** | **0.35** |
| | 4 | 68 | 8 | 0.05 | 0.03 | 0.12 |
| | 5 | 5 | 0 | 0.004 | 0.0 | 0.0 |
| Overall | | 1294 | 246 | | | |

decision-making process which resulted in a purchase. Probability $p_n$ is defined as the ratio between the occurrence of a given criterion and the total number of participants $p_n = n_{all}/\mathrm{N}$. We also define the occurrence probability within the people who have actually made the purchase process as $p_{buy} = n_{buy}/\mathrm{N}_{\mathrm{buy}}$. Considering the distribution within a single feature space we also define normalized probability $p_{all}$ as $p_{all} = n_{buy}/n_{all}$.

Among all shop visitors, there were 61 % female customers ($p_n = 0.61$) which represent 63 % of people making purchase during observed period ($p_{buy} = 0.63$). Men present 39 % of all customers ($p_n = 0.39$) and 37 % of all people making purchase ($p_{buy} = 0.37$). Gender comparison of normalized probability ($p_{all}$) shows that the probability to be involved in the buying process and eventually made the purchase is approximately the same for both men and women (∼20 %).

Age comparison shows certain degree of balance between age groups as almost all normalized probability ($p_{all}$) are around 20 %. The only deviant exception is the age group between 15 and 24 years with $p_{all} = 0.09$.

Group size analysis reveals that during the experiment there were 438 customers who visited the store alone, 618 in buying groups of two, 165 in buying groups of three, 68 in buying groups of four and 5 in group of five customers. We observe an interesting pattern which shows that the size of the buying group importantly affects the probability of purchase. Out of 438 individual customers, only 13 % ($p_{all} = 0.13$) made a purchase decision. 618 persons, representing buying groups of two, have a normalized purchase probability of $p_{all} = 0.20$. The highest purchase probability have three-person groups with $p_{all} = 0.35$.

**Table 2.** The distribution of roles in purchase decision process for a given demographic and buying group size feature.

| Feature | Value | $n_{init}$ | $n_{inf}$ | $n_{dcdr}$ | $n_{prch}$ | $n_{usr}$ | $n_{pssv}$ | $p_{init}$ | $p_{inf}$ | $p_{dcdr}$ | $p_{prch}$ | $p_{usr}$ | $p_{pssv}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Gender | Male | 48 | 7 | 53 | 56 | 57 | 28 | 0.52 | **0.08** | 0.58 | 0.61 | 0.62 | **0.30** |
| | Female | 106 | 60 | 93 | 85 | 76 | 12 | 0.69 | **0.39** | 0.60 | 0.55 | 0.49 | **0.08** |
| Age group | 1–14 | 1 | 0 | 1 | 1 | 1 | 19 | 0.05 | **0.0** | 0.05 | 0.05 | 0.05 | **0.95** |
| | 15–24 | 5 | 2 | 5 | 4 | 5 | 5 | 0.42 | 0.17 | 0.42 | 0.33 | 0.42 | **0.42** |
| | 25–34 | 39 | 18 | 35 | 36 | 33 | 1 | 0.72 | 0.33 | 0.65 | 0.67 | 0.61 | 0.02 |
| | 35–44 | 41 | 18 | 39 | 41 | 33 | 5 | 0.68 | 0.30 | 0.65 | 0.68 | 0.55 | 0.08 |
| | 45–54 | 40 | 16 | 36 | 31 | 32 | 4 | 0.76 | 0.30 | 0.68 | 0.59 | 0.60 | 0.08 |
| | 55–64 | 18 | 9 | 19 | 20 | 18 | 3 | 0.60 | 0.30 | 0.63 | 0.67 | 0.60 | 0.10 |
| | 65+ | 10 | 4 | 11 | 8 | 11 | 3 | 0.59 | 0.24 | 0.65 | 0.47 | 0.65 | 0.18 |
| Group size | 1 | 57 | 2 | 56 | 55 | 50 | 0 | 1.0 | 0.04 | 0.99 | 0.97 | 0.88 | **0.0** |
| | 2 | 73 | 47 | 68 | 64 | 63 | 14 | 0.59 | 0.38 | 0.55 | 0.52 | 0.51 | **0.11** |
| | 3 | 22 | 16 | 20 | 20 | 18 | 23 | 0.39 | 0.28 | 0.35 | 0.35 | 0.32 | **0.40** |
| | 4 | 2 | 2 | 2 | 2 | 2 | 3 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | **0.38** |
| Overall | | 154 | 67 | 146 | 141 | 133 | 40 | 0.63 | **0.27** | 0.59 | 0.57 | 0.54 | **0.16** |

This group size also achieves a high conversion rate between $p_n = 0.13$ and $p_{buy} = 0.23$.

The distribution of roles in a group is the crucial element in the purchasing process. Every member of a buying group took up at least one of the six roles. Several members can take up the same role (e.g., there may be several users or influencers), and also oppositely, one individual can take up multiple roles. Table 2 shows the distribution of roles in the purchasing process according to the their calculated probabilities. Value $n$ denotes the number of customers in a given group and $p$ the probability of occurrence of this group. Index mark $init$ refers to the role of initiator, $inf$ to influencer, $dcdr$ to decider, $prch$ to purchaser, $usr$ to user, and $pssv$ to passive influencer.

The comparison by gender reveals a significant difference for the roles of influencer and passive observer. Only 8 % of all male customers that participated in a completed purchase ($p_{inf} = 0.08$) have taken up the role of an influencer. The probability for a female customer to take up the influencer role is 39 % ($p_{inf} = 0.39$) which is almost five times higher. The opposite observations hold for the role of a passive influencer, which men took up with probability of 30 % ($p_{pssv} = 0.30$) and women with 8 % ($p_{pssv} = 0.08$).

Age group analysis reveals that youngest age group hardly actively participated in the buying process. Customers aged between 1 and 14 years never took the role of influencer ($p_{inf} = 0.00$) and almost always took the role of passive observer ($p_{pssv} = 0.95$). A very likely explanation for this observation could be the retail's assortment targeted for adult customers.

Group size comparison shows increased correlation between the group size and the probability for its members to take up the role of a passive influencer. For the buying group of two, the probability of a group member to be a passive influencer is 11 % ($p_{pssv} = 0.11$). Probability increases to 40 % ($p_{pssv} = 0.40$) for a member in a buying group of three. As expected, the probability of roles:

**Table 3.** Comparison of machine learning algorithms for classification of decision-making process of the purchase.

| Method | CA | Sensitivity | Specificity |
|---|---|---|---|
| Maj | **0.810** | **0.000** | **1.000** |
| NB | 0.867 | 0.768 | 0.890 |
| kNN | 0.851 | 0.492 | 0.935 |
| SVM | **0.886** | **0.594** | **0.954** |
| RF | 0.873 | 0.394 | 0.986 |

initiator, decider, purchaser and user descend inversely linear with the size of the buying group.

## 4 Modelling Retail Behaviour and Purchase Decision Process

The major contribution of this paper is the finding that it is possible to *predict* the purchase decisions and roles in the purchase decision process by using machine learning methods on our digital signage audience measurement data. Audience measurement data which is additionally annotated with purchase decisions and purchase roles is used to train purchase decision classifiers. Several machine learning algorithms were used in order to compare classifiers of retail behaviour. The baseline classification accuracy for our analysis is 81 %, which corresponds to the *apriori* probability of the class distribution as there were 246 (19 %) out of 1294 consumers that made a purchase during the period of the experiment.

Table 3 shows the results of 10-fold cross-validation for different machine learning methods: the majority classifier (Maj), the naive Bayesian classifier (NB), K-Nearest Neighbor (kNN), Support Vector Machines (SVM) and Random forest (RF). Classification accuracy represents the ratio of correctly classified examples. Sensitivity (also true positive rate or recall) denotes the ratio between the correctly classified positive examples and the number of all positive examples in machine learning dataset. Similar measure is specificity (also true negative rate) which measures the ratio between correctly classified negative examples and the number of all negative examples. The target class value is set to whether a person was involved in a purchase (purchase = yes). Majority classifier reaches a 81 % classification accuracy which sets the baseline for comparison with other methods. The best classification results using 10-fold cross validation are obtained with the SVM classifier which reaches a classification accuracy of 88.6 % and improves the prediction of the majority classifier for 7.6 %. SVM also achieves best sensitivity and specificity rates of 59.4 % and 95.4 % respectively. The random forest method turns out to be the second best, reaching 87.3 % classification accuracy. Other methods of machine learning improve the baseline's classification accuracy for ∼5 %.

**Table 4.** Comparison of machine learning algorithms for classification of roles in purchase decision process.

| | Role in the purchase decision process | | | | | |
|---|---|---|---|---|---|---|
| Method | Initiator | Influencer | User | Decider | Purchaser | Passive Infl. |
| Maj | **0.626** | **0.728** | **0.541** | **0.593** | **0.573** | **0.837** |
| NB | 0.679 | 0.735 | 0.606 | 0.614 | 0.614 | 0.882 |
| kNN | 0.659 | 0.740 | 0.630 | 0.603 | 0.651 | 0.865 |
| SVM | **0.692** | **0.748** | **0.728** | 0.599 | **0.724** | **0.910** |
| RF | 0.651 | 0.724 | 0.611 | **0.635** | 0.653 | 0.861 |
| $NB_h$ | 0.728 | 0.736 | 0.658 | 0.719 | 0.682 | 0.857 |
| $kNN_h$ | 0.747 | 0.757 | 0.682 | 0.695 | 0.744 | 0.878 |
| $SVM_h$ | **0.793** | **0.768** | **0.731** | **0.764** | **0.755** | **0.918** |
| $RF_h$ | 0.711 | 0.724 | 0.686 | 0.670 | 0.614 | 0.846 |

The presented results show that the dataset which originated from our digital signage audience measurement data can be used for modelling the retail behaviour. Among all people that entered the store, we can predict whether they will be included in a shopping decision with a 88 % classification accuracy, based on observable demographic characteristics and the size of the buying group. We believe that such results can yield significant difference for retailers.

We use a similar approach to model the roles in the purchase decision process. Based on observations noted during the ground truth annotation of the audience measurement data, additional heuristic attributes are defined and added to the dataset. Heuristic binary feature *in-group* indicates whether a person was shopping alone or was part of a larger group. Based on presence time intervals we define a numeric heuristic feature *entered* which describes the sequence number in which group members entered the store. Additional heuristic binary feature *entered-first* is derived from it. In a similar manner, we construct also heuristic features *left* and *left-last*. A set of new heuristic features conclude the ratio between presence and in-view time, and ratio between in-view time and attention time.

The evaluation of role classifiers is performed by a 10-fold cross validation. Each algorithm is tested twice, once with retail behaviour data and the second time with added heuristic features. The classification accuracy of each algorithm is presented in Table 4. The case where heuristic features were also present in the learning dataset is denoted with index *h*.

Again, the most robust and efficient method is SVM. When evaluated on basic retail behaviour dataset (upper half of Table 4) the SVM achieves the best classification accuracy in predicting roles of: initiator (69.2 %), influencer (74.8 %), user (72.8 %), purchaser (72.4 %) and passive influencer (91.0 %). Random forest achieves best classification accuracy of 63.5 % for the role of decider. The classification accuracy of best methods in average exceeds the baseline (majority) classifier for 8.9 %.

The lower part of Table 4 represents the classification accuracy of the selected methods when evaluated on the dataset with added heuristic features. We observe that by adding heuristic features, the best classification accuracy achieved improves for all 6 roles. The best results are obtained when heuristic features are added and with the SVM classifier which outperforms the baseline classifier by 14.9 % on average.

The described in-store consumer behaviour model is based on audience measurement data closely tied to a specific broadcasting location and time when it was collected. Therefore, these results should be understood in the context of the store where our experiment took place. However, we believe that the proposed approach exposes and quantifies certain relationships and behavioural patterns that were already identified before in consumer behaviour literature. It also enables that the measurement and modelling is performed again at an arbitrary location.

## 5 Conclusion

Audience-aware public displays are currently a hot topic of research. The ability to broadcast interactive and targeted content and to collect demographic data of viewers opens the way for interdisciplinary research and broadens the application options of such advanced digital signage systems. This work introduces a new approach to automatic modelling of in-store consumer behaviour based on audience measurement data. The experimental results show that under controlled environment the viewership data can be used to predict purchase decisions. The same model with additional heuristic features can also be used to predict more distinctive characteristics, such as an individual's role in the purchase decision process. We believe that these interdisciplinary results show that digital signage audience measurement data can be used to model various user behaviour.

The presented results open new exciting routes to explore in-store consumer behaviour modelling in combination with data from other sources, such as a shop's assortment and customer database. A comparison with additional retailing audience measurement experiments could also illuminate interesting marketing and consumer behaviour phenomena. The proposed approach could also be used to model user behaviour in different situations, such as edutainment, interaction user interface design and gaming.

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