Identification of purchasing scenarios through eye-tracking features

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Abstract
Eye-tracking-based methods are generating a growing interest in marketing research. Nevertheless, most of the studies are focusing on intention, emotion or the evaluation of the products by the customer. The work that is presented here investigates two of the main purchasing scenarios: the routine purchasing act and the impulse purchasing act. The purpose is to propose a predictive model that best distinguishes the first scenario from the second scenario. To reach this goal, we extract statistically relevant eye-tracking descriptors. We use a supervised learning algorithm, Support Vector Machines (SVM), to build the model and reach performances of 82.5% of good identification.

Author Keywords
Eye-tracking, purchase behavior, decision-making strategy, feature selection, SVM classification.

ACM Classification Keywords
G.3: Correlation and regression analysis. H.2.1: Data models. I.2.6: Learning. J.1 : Marketing.

1. Related works in purchasing act

In this paper, we focus on two categories of purchasing acts that are defined by [Howard & Sheth 1969] and [Kollat and Willett 1969]. First, the routinized response behavior, that deals with everyday products such as food. Second, the impulse buying, that involves unplanned purchasing, such as the buying of chewing-gums in the check-out line of a supermarket, or the buying of bakeries while passing next to a shop window. This study is part of a marketing project: the ANR[†] project ORIGAMI2 ("Observation du Regard et Interprétation du geste pour une Analyse Marketing non Intrusive"). The project aims at completing an analysis of the customer's decision-making process by combining various data acquisition tools. Marketing managers want to know whether the customer hesitates in front of a product or not, between what products he hesitates, whether the purchase was planed or not, etc. They also want to quantify the impact of advertising on impulse buying. Hence the need of a predictive model that differentiates a routine purchasing scenario from an impulse purchasing scenario.

For the experimental protocol, the most difficult challenge consists in simulating the last category of purchasing acts. Three factors are involved in impulse buying. There are factors that are related to the customer himself. According to [Bonnefond & Giraud 2001] and [Cornu & De Marchi 2008], a visceral need such as hunger or thirst directly has a positive impact on impulse buying. The more possible the satisfaction of the need, the more intense the desire of buying the product: immediate availability in the selling area, a delivery service within 24 hours with on-line stores, etc. The second factors that can impact on impulse buying are atmospheric factors. [Lemoine 2003] shows that by positively influencing the degree of pleasure of the customer in store, the atmosphere of the selling area allows the customer to have a rewarding experience. The positive visible effects of a good atmosphere are the time that is spent in the selling area, the number of items purchased and the speed of the customers [Turley & Milliman 2000] [Driss et al. 2008]. The third factors that impact on impulse buying are situational factors. There are complementary results about time pressure. On the one hand, [Beatty & Ferrell 1998] and [Iyer 1989] show that the more the customer stays in the selling area, the more prone will he be to impulse buying. On the other hand, [Khamassi 2012] shows that the more in a hurry he is, the greater the proportion of impulse purchases.

The paper is motivated by the construction of a predictive model that best distinguish a routine purchase scenario from an impulse purchase scenario. The remainder of the paper falls into four sections. In the first section, the data collection phase is presented. In the second section, we describe the architecture of our approach. The third section is dedicated to several results: the search for the best statistically eye-tracking features for the final model, a global analysis of the customer's behavior and the performances of the final model.

2. Data collection

2.1 Equipment

For the experiment, a population 33 subjects is recruited. They are divided into 2 groups. The first group is dedicated to the first scenario, that is to say the routine purchasing act. There are 17 subjects. The remaining 16 subjects are in the second group and pass the second scenario, that is to say the impulse act. The subjects are granted a non-financial reward at the end of the experiment. Each of them is between 19 and 30 years old, with no ophtalmological problem. To capture

[†] Agence Nationale de la Recherche, funded by the French Ministry of Research.

Website : http://www.agence-nationale-recherche.fr/en/

the gaze position, a corneal reflection-based eye-tracker† is used. We use the head-mounted device, as it allows the subject to move freely. The glasses are connected to a computer and the experimenter can monitor the experience outside the scene, without interacting with the subject.

The selling area is reconstructed in laboratory, and has a dimension of a square with 4-meter sides. Two perpendicular tables are provided. The first one, in front of the subject, is the exhibition stand, on which are placed the products. The other table, on the left of the subject, is the trolley. Thus, every time the subject chooses a product in front of him, he has to put it on his left. A camera on tripod films the scene. The stimuli are everyday food products: biscuits, chocolate, cheese. We choose several products so as study the customer in front of several buying situations with several kind of information.

2.2 Experimental design

2.2.1 Routine purchasing scenario

Each subject of the first group has to pass four sequences: 'a)', 'b)', 'c)', 'd)'. In each one the subject has to choose one and only one product among four products. These tasks stand for the most frequent situations the consumer may face in a selling area: the differences from on task to another are not only in the nature of the products, but also in the amount of information that are given to the subject. In sequence 'a)', the choice is made only thanks to the texture of the product. Each of the possible choices (or alternatives) is placed in a different plate: there are four plates on the exhibition stand. In sequence 'b)', the choice is made thanks to the packaging and only the packaging. In sequence 'c)', only the price is available; just like in sequence 'a)', the four products are placed in four separate plates. In sequence 'd)', the choice is made thanks to the packaging and the price. Table 1 displays the content of each sequence, and Figure 1 displays the visual field of the subject. The images come from the frontal camera that is fixed on the head-mounted eye-tracker.

	Conditions		products
a)	Without packaging	Without price	Biscuits
b)	With packaging	Without price	Chocolate
c)	Without packaging	With price	Biscuits
d)	With packaging	With price	Cheese

Table 1. Composition of the sequences. Here is the instruction that is given to each subject of the first group: *"In front of you there is the exhibition stand; at your left the trolley. You have to buy a food product. Please make a decision depending on the information available. Once your choice is made, please take the product on the exhibition stand and put it on the trolley".*

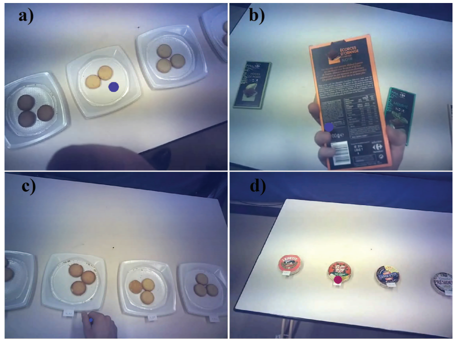

Figure 1. Visual field of the subject, for each sequence.

† Website : http://www.smivision.com/en/gaze-and-eye-tracking-systems

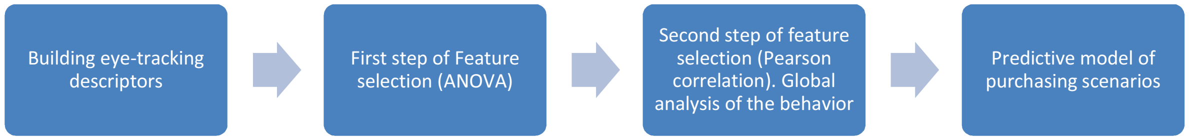

Figure 2. Architecture of our approach.

2.2.2 Impulse purchasing scenario

The impulse buying act is simulated thanks to two factors: time pressure [Khamassi 2012] and the subject's emotional state [Bonnefond & Giraud 2001] [Cornu & De Marchi 2008]. The time pressure stands in the fact that the subject only has 20 seconds to make his choice. As it is said in the introduction, most of the impulse purchasing acts are related to the desire of satisfying a immediate need: hence the opportunity for the subject to leave with the product he finally chooses.

2.2.3 Several sequences per scenario

The first advantage in varying the number of sequences per subjects is that we can change the amount of information that are available to the subjects. This leads to a better representation of all the possible situations that can be seen in a selling area. The second advantage is that we increase the database for the final predictive model. Each subject generates four samples in the database.

3. Proposed approach

So as to build the model, a procedure, which is given in Figure 2, must be followed.

3.1 Building eye-tracking descriptors from fixation and saccade data

The first part of the approach consists in building eye-tracking features, according to several areas of interests (AOI). In our experiments, there are eight areas of interest: from AOI1 to AOI7. AOI1, AOI2, AOI3 and AOI4 stand for each one of the plates or products on the exhibition stand, from the left to the right of the customer. AOI5 stands for the reunion of the price zones: AOI5 is activated when the looks at one of the four price zones. AOI6 stands for the trolley, on the left of the subject. AOI7 is the customer's hand. Typically, AOI7 is activated when the customer grabs the product for further investigation: reading the ingredients, checking the expiry date, or putting the product in the trolley. Eventually, AOI8 stands for the rest of the space that is not related to the products: we call it the "empty space".

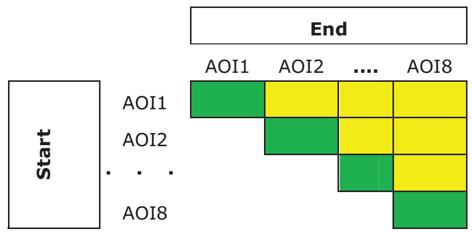

Figure 3. The incoming saccades (yellow) jump from an AOI to another AOI, whereas stagnant saccades (green) stay in the same AOI.

Given these AOIs, eye-tracking descriptors can be defined. Three groups of descriptors are built for each subject, from fixations and saccades data :

- The first group is only made of fixation data
- The second group is made of incoming saccades (in yellow in Figure 3)
- The third group is made of stagnant saccades (in green in Figure 3)

Table 2 lists the descriptors that are built from eye-tracking fixations. D1 is the total duration of the sequence. It is the time between the beginning of the sequence and the end of the sequence. An alternative is defined by one the the four possible choices, that is to say from AOI1 to AOI4. We analyze behaviors not only towards the chosen alternative, but also towards the three most observed alternatives. For each alternative, we extract: (i) the sum of all the fixation durations, (ii) the mean duration of a fixation, (iii) the ratio between the previous descriptor and (iv) the total duration of the task, and the percentage of time that is awarded to the alternative. The descriptors that are related to the chosen alternative are D2 to D5. The descriptors that are related to the three most observed alternatives are D6 to D17. In addition to these seventeen descriptors, we build descriptors related to AOI8: D18 and D19.

D1, D2, D3, D6, D7, D10, D11, D14, D15, and D18 are either temporal data or spatial data. The other descriptors are calculated relatively to the previous list; they are printed in bold. These descriptors typically do not depend on the main experimental factor: time. It will be interesting for the global analysis of the behavior, to look at the relevancy of the descriptors without standardized units of measure. From now, a distinction is made between the two kinds of descriptors: those with standardized units of measure are called "absolute descriptors"; the other are "relative descriptors”.

D1	Total time : time between the beginning of the task to the end of the task
D2	Time spent on the chosen alternative
D3	Mean fixation duration on the chosen alternative
D4	**D3/D1**
D5	**Percentage of time spent on the chosen alternative**
D6	Time spent on the 1st most observed alternative
D7	Mean fixation duration on the 1st most observed alternative
D8	**D7/D1**
D9	**Percentage of time awarded to the 1st most observed alternative**
D10	Time awarded to the 2nd most observed alternative
D11	Mean fixation duration on the 2nd most observed alternative
D12	**D11/D1**
D13	**Percentage of time awarded to the 2nd most observed alternative**
D14	Time awarded to the 3rd most observed alternative
D15	Mean fixation duration on the 3rd most observed alternative
D16	**D15/D1**
D17	**Percentage of time awarded to the 3rd most observed alternative**
D18	Time awarded to the non-information areas
D19	**Percentage of time awarded to the non-information area**

Table 2. Fixation based eye-tracking descriptors. In bold: relative descriptors (without standardized unit of measure). In thin line: absolute descriptors (with standardized unit of measure)

After a presentation of the first group of descriptors, let us see the second and the third group of descriptors that come from saccades data, on Table 3. Over the list of 88 descriptors, 33 are relative descriptors; the other descriptors are absolute descriptors. D25 to D56 are related to incoming saccades. From D25 to D56, there is a list of 8 descriptors that are similarly calculated either for the products (AOI1 to AOI5), or the hand (AOI7), or the trolley (AOI6) or the empty space (AOI8).

	All saccades	Incoming	Stagnant
	Codes for the saccade-based descriptors		
Number of saccades	D20		
Scanpath length	D21		
Mean length of a saccade	D22		
Sum of all the durations of the saccades	D23		
Mean duration of a saccade	D24		
Number of saccades on one of the products (AOI1 to AOI5)		D25	D57
Scanpath length on one of the products (AOI1 to AOI5)		D26	D58
Mean length of a saccade on one of the products (AOI1 to AOI5)		D27	D59
Sum of all the durations of the saccades on one of the products (AOI1 to		D28	D60
Mean duration of a saccade on one of the products (AOI1 to AOI5)		D29	D61
Ratio between the number of saccades on one of the products		**D30**	**D62**
Ratio between the scanpath length on one of the products and		**D31**	**D63**
Ratio between the mean length of a saccade on one of the		**D32**	**D64**
Same list as D25 to D32, replacing the products with the hand (AOI7)		D33 to D40	D65 to D72
Same list as D25 to D32, replacing the products with the empty space		D41 to D48	D73 to D80
Same list as D25 to D32, replacing the products with the trolley (AOI6)		D49 to D56	D81 to D88

Table 3. Saccade based eye-tracking descriptors. In bold: relative descriptors (without standardized unit of measure). In thin line: absolute descriptors (with standardized unit of measure)

D57 to D88 are related to the second group of saccade data: stagnant saccades. As for the case of incoming saccades, the same list of 8 descriptors is extracted, considering the products, the hand, the trolley and the empty space. Overall, we define a list of 69 descriptors from saccade data. There are 24 relative descriptors from the saccade data: D30 to D32, D38 to D40, D46 to D48, D54 to D56, D62 to D64, D70 to D72, D78 to D80, D86 to D88.

In general, all the descriptors do not bring the same amount of information. They can also be correlated each other. For instance, the higher the duration of the task (D1), the greater the number of saccades (D20). Thus, it is necessary, before building the predictive models, to select the most statistically relevant descriptors and to minimize the redundancy of the information.

3.2 Feature selection using ANOVA and PCA

Feature selection goes through three steps. In the first step, the goal is to select the descriptors according to their ability to separate efficiently people of the routine purchasing scenario from people of the impulse purchasing scenario. Two spaces of descriptors are formed. The first space is the space of relevant descriptors. The second space is the space of non-relevant descriptors.

In the second step of feature selection, a Principal Component Analysis is performed on the second space. This leads to a new space of the same size. PCA organizes the data so as to minimize the redundancy of the information from one component to another. In the third step, an ANOVA is performed on the space that is calculated from the PCA: we only keep the components that are statistically relevant. The final space of descriptors is the concatenation of this list of relevant components with the first list of relevant descriptors from the first step.

3.3 A global analysis of the customer's behavior

The main idea in this part of our approach is to analyze the spread of the final list of features, according to the main factor of the experiment protocol: time pressure. In other words, we want to know how strong is correlated each descriptors to the duration of the sequence. A correlation threshold is defined: 0.232, with a p-value of 0.01. The descriptors, which correlation coefficient with the duration of the sequence is greater than 0.232, are considered as dependent from the experiment protocol. The others are considered as independent from the experiment protocol. Typically, we have four areas in a 2-D space, as it is represented (see Figure 4 in section 4.2).

3.4 Predictive model of purchasing scenarios with Support Vector Machines

Let us take into account a learning set $S = \{(\boldsymbol{x_1}, f(\boldsymbol{x_1})), \dots, (\boldsymbol{x_n}, f(\boldsymbol{x_n}))\} \subset X \times Y$. X is the space of the descriptors, of dimension p (here, inferior or equal to 19). Y is the output space, that is to say {'routine','impulse'}. Support Vector Machines (SVM) is a supervised learning algorithm. If the problem is linear, it can be shown that the class of each new data $\boldsymbol{x}$ is given by:

$$f(\boldsymbol{x}) = \frac{1}{n}\sum_{i=1}^{n} \lambda_i^* y_i \langle \boldsymbol{x} | \boldsymbol{x_i} \rangle + b^* \qquad (2a)$$

λ_i^* and b^* are proportional to Lagrange multipliers

What is important to emphasize with SVM, in the linear case and the non linear case, is that : (i) the problem can be solved using only the dot products between the data, (ii) the solution is calculated considering only a few set of data that are called support vectors. For further information about SVM, one can refer to the works of Rivas-Perea, P. et al (2013). The SVM method is used here for its robustness against noise and the possibility of dealing with data that are not linearly separable in their representation space.

4. Results

4.1 A global analysis of the customer's behavior under the time pressure factor

Figure 4 illustrates the customer's behavior on the 2D space that is introduced in section 3.3. There are 9 descriptors, 8 descriptors, 25 descriptors and 3 descriptors in, respectfully Zone1, Zone2, Zone3 and Zone4. The aim of the analysis trough the time pressure factor is to determine what kind of descriptor best represents each one of the four zones

Let us call P_{ir}, P_{ia}, P_{if} and P_{is} respectfully the proportions of relative descriptors, absolute descriptors, fixation based descriptors and saccade based descriptors, in Zonei. They are given by the following formulas:

$$P_{ir} = \frac{\#of\ relative\ descriptors\ in\ Zonei}{\#\ of\ descriptors\ in\ Zonei} * \frac{\#\ of\ descriptors}{\#\ of\ relative\ descriptors}$$

$$P_{ia} = \frac{\#of\ absolute\ descriptors\ in\ Zonei}{\#\ of\ descriptors\ in\ Zonei} * \frac{\#\ of\ descriptors}{\#\ of\ absolute\ descriptors}$$

$$P_{if} = \frac{\#of\ fixation\ based\ descriptors\ in\ Zonei}{\#\ of\ descriptors\ in\ Zonei} * \frac{\#\ of\ descriptors}{\#\ of\ fixation\ based\ descriptors}$$

$$P_{ir} = \frac{\#of\ saccade\ based\ descriptors\ in\ Zonei}{\#\ of\ descriptors\ in\ Zonei} * \frac{\#\ of\ descriptors}{\#\ of\ saccade\ based\ descriptors}$$

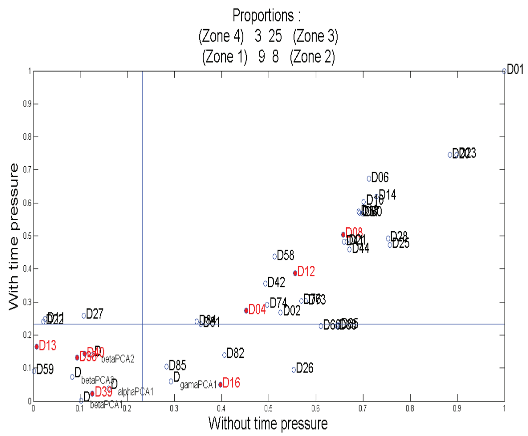

Figure 4. 2D space for a global analysis of the customer's behavior. The red descriptors stand for the relative descriptors ; the black descriptors stand for the absolute descriptors.

P_{ir} is proportional to the percentage of relative descriptors in Zonei; it is weighted by the inverse of the proportion of relative descriptors that remains after the first step of feature selection (8 relative descriptors).

The calculations for P_{ia}, P_{if} and P_{is} follow the same rules. The proportions of the descriptors in each zone are given by the following matrixes:

$$P_{*r} = \begin{bmatrix} 0 & 0.7 \\ \mathbf{1.3} & \mathbf{1.4} \end{bmatrix}, P_{*a} = \begin{bmatrix} \mathbf{1.2} & \mathbf{1.1} \\ 0.7 & 0.6 \end{bmatrix}$$

$$P_{*f} = \begin{bmatrix} \mathbf{0.9} & \mathbf{1.13} \\ 0.9 & 0.7 \end{bmatrix}, P_{*s} = \begin{bmatrix} \mathbf{0.9} & 0.8 \\ \mathbf{1.2} & \mathbf{1.2} \end{bmatrix}$$

In Zone1, the subject is more represented by relative descriptors than absolute descriptors: 1.25 against 0.68. Zone1 is also more represented by saccade based descriptors than fixation based descriptors: 1.2 against 0.9. Let us remind that Zone1 stands for the descriptors that do not depend on the duration of the task, whether there is a time pressure or not. This means that it is necessary to take into account saccade based data and relative descriptors. In Zone3, it logical to notice that absolute descriptors are more represented than relative descriptors: 1.1 against 0.7. This idea is illustrated by the following example. We found that the more people have time, the higher the sum of the durations of all the saccades (D23), and the greater the number of saccades (D41). The more people have time, the lower the jumps that reach a product (D59): in other words, people tend to maximize the distances when they are purchasing in a hurry.

Let us analyze Zone1 and Zone4 through absolute and relative descriptors. When there is no time pressure and no immediate satisfaction, the subject is represented by both absolute and relative descriptors (Zone1 ∪ Zone4). When we add time pressure and immediate satisfaction, absolute descriptors become more correlated to the duration of the task than relative descriptors (Zone4). Let us analyze Zone2 and Zone3. In the first scenario, the subject is represented by both relative and absolute descriptors (Zone2 ∪ Zone3). If time pressure and immediate satisfaction are added to the protocol, the subject becomes more represented by relative descriptors in Zone3; in other words, most of the descriptors that become un-correlated to D1 are relative descriptors.

The analysis through fixation and saccade data of (Zone1 ∪ Zone4), on the one hand, and (Zone2 ∪ Zone3), on the other hand, are similar. This leads us to the following interesting result: if time pressure and immediate satisfaction are added to the experiment, fixation data and absolute descriptors generally become more correlated to the duration of the task than saccade data and relative descriptors. Zone1, Zone2 and Zone4 are more relevant than Zone3, in building a predictive model of the purchasing act. Indeed, in Zone3, the descriptors are correlated to the duration of the purchasing act. Thus, in order to build the model, it is necessary to take into account the information that come from relative descriptors and saccade based descriptors.

4.3 Classification results:

		Predicted classes		
		Routine	Impulse	all
Gold standard	Routine	82	18	
	Impulse	17	83	
	all			82.5

Table 4. Confusion matrix of the predictive classifier.

Table 4 shows the confusion matrix for the SVM with a linear kernel on our database. We use the "leave-one-out" cross-validation method (LOOCV). Given *N* observations, the LOOCV method consists in building a model on *N*-1 observations and validating it on the N^{th} observations. The process is repeated *N* times. It can be seen that 82% of the routine purchasing acts are correctly identified by the SVM classifier; only 18% of them are labeled as impulse buying acts. The accuracy on the second scenario is equivalent to the accuracy on the first scenario. Indeed, 83% of the impulse buying acts are correctly identified; 17% of them are classified in the other scenario. The global accuracy of the predictive model is satisfying, as it reach 82.5% of correct identifications.

5. Conclusion and discussion

The work that is presented in this paper is part of behavioral marketing project. It aims at proposing a predictive model that best separate the routine purchasing act from the impulse purchasing act. We have analyzed the behavior of 33 subjects. We first defined 88 eye tracking descriptors, from fixation and saccade data. A distinction is made between descriptors that have a standardized unit of measure ("absolute descriptors") and descriptors that have no unit of measure ("relative descriptors"). We perform the feature selection operation in two steps. The first step, which is the natural approach, consists in keeping descriptors that best distinguish the routine purchasing act from the impulse purchasing act ; hence the use of a combination between ANOVA and PCA. A first list of 45 descriptors is built. The second step in the feature selection operation consists in keeping the descriptors that are not correlated to the duration of the task: using Pearson correlation coefficients, 20 descriptors are selected. We find two interesting results. The first result is that whether there is time pressure and immediate satisfaction or not, the mean fixation duration on the chosen alternative remains statistically the same; this also applies to the mean fixation durations on the first most observed alternative and the third most observed alternative. For the second result, we first represent the subjects by both fixation and saccade data, and both absolute and relative descriptors. We then notice that: if time pressure and immediate satisfaction are added to the experiment, fixation data and absolute descriptors become correlated to the duration of the task than saccade data and relative descriptors. This last result leads to the fact that saccade and relative data are necessary to build a model that best separate the impulse buying scenario from the routine buying scenario. A supervised learning algorithm, SVM, is then implemented; the predicting model reaches 82.5% of good predictions.

These results are very interesting for the behavioral marketing field and lead to a better understanding of the customer's decision-making process in a purchasing act. Some extensions are being considered in future works. We are going to introduce other eye tracking descriptors, based on the saccade data, so as to improve the accuracy of the prediction. A second additional work is the introduction of other tracking devices. Indeed, the path of the client in the selling area defines the content of his basket at the end of the shopping. So, a very promising field of study would be to merge data from eye tracking devices with data from GPS data.

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