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Combining eye tracking, pupil dilation and EEG analysis for predicting web users click intention

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ABSTRACT

In this paper a novel approach for analyzing web user behavior and preferences on a web site is introduced, consisting of a physiological-based analysis for the assessment of a web users' click intention, by merging pupil dilation and electroencephalogram (EEG) responses.

First, we conducted an empirical study using five real web sites from which the gaze position, pupil dilation and EEG of 21 human subjects were recorded while performing diverse information foraging tasks. We found the existence of a statistical differentiation between choice and not-choice pupil dilation curves, specifically that fixations corresponding to clicks had greater pupil size than fixations without a click.

Then 7 classification models were proposed using 15 out of 789 pupil dilation and EEG features obtained from a Random Lasso feature selection process. Although good results were obtained for Accuracy (71,09% using Logistic Regression), the results for Precision, Recall and F-Measure remained low, which indicates that the behaviour we were studying was not well classified.

The above results show that it is possible to create a classifier for web user click intention behaviour based on merging features extracted from pupil dilation and EEG responses. However we conclude that it is necessary to use better quality instruments for capturing the data.

1. Introduction

From the very beginning of the Web, one main question has captured the attention of researchers and web site developers: What is the optimum structure and content of a web site for attracting the web users interest and preferences? [1]. The answer is not easy and many efforts have been developed over the years. One thing that has become clear is that the Web and the web user are dynamic, which means any currently successful structure and content on a web site has no guarantee of continued success even in the near future. In a few words, the web site must undergo continuous improvement, always based on what the web user needs and desires.

Traditionally, web user behaviour on the Web has been studied by using web usage mining techniques [2,3], where the web log files, which contain records of web user activities, are processed to extract information and knowledge about their navigation and content preferences. This new knowledge is normally used by the web master for improving site structure and content and in a more advanced sense, to provide online navigation recommendations through an automatic recommendation system [4].

Studying web user behaviour on a web site by solely using the web log file would be a great idea if we could exactly reconstruct the session and know what the user is seeing on each visited page. However the real situation is quite different, web logs contain a lot of noise, and it is usually not possible to either directly identify a web user session, or to know the sequence of web objects seen and the time spent on each page by the web user. Several previous efforts to reconstruct the web user session and preferences during web site navigation have been realized [5–8], but always from the approximation point of view, i.e., without being clear about the set of web objects visited, sequence, time spent, etc.

Better approximations about web user session reconstruction have been developed by using data originating in measurements of web user pupil dilation and eye movement on a web site [9–12]. In fact, it is possible to know for certain the web page sequence, the object seen and the time spent on each web object by the web user. The problem is that the technology used for capturing those physiological variables, the eye-tracking system, is very invasive and in any case does not actually yield real web user

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behaviour. Since it is scientific experimental simulation, it is not real navigation [13]. However a good approximation of web user behaviour can be realized by combining the data originating in web logs with the physiological ones [14].

In the present work we propose a physiological-based analysis for the assessment of Web users' click intention as a mechanism to analyse web user behaviour on a web site. This approach is interesting, since diverse physiological responses could be attributed to emotions or cognitive states worthy of investigation in the context of the Web. Pupil size, for instance, changes according to the presented visual stimulus and it has been used both to measure mental effort during cognitive tasks [15,16] and is also related with emotional arousal [17]. Similarly, EEG has been used to describe different cognitive and emotional states [18,19], and its activity patterns are involved in the execution and association of movements [20].

Based on this information, in our previous work we intended to study the pupil dilation response of users while performing different choice tasks on a web site adaptation [21], with positive results suggesting that in a more realistic environment at least the same behaviour could be obtained.

In order to achieve our objective, an experiment was conducted where the physiological responses of 21 subjects were recorded while performing several information foraging tasks on five different real Web sites.

The paper is organized as follows, first we present some related research, and then describe our approach for assessing the Web user click intention based on the physiological responses of subjects' pupil dilation and EEG. After specifying the experimental set-up, we explain the data processing, feature engineering and selection process. Next, results are shown along with the pertinent discussion, and finally we conclude our study and propose future work.

2. Related work

How important is it to understand human Web behaviour? What are the available tools we have to do this? What biological processes drive attention and make people choose from several options within a web site? The literature provides many research approaches that try to answer these sorts of questions with different points of view and results that we analyse in this section.

2.1. Web user decision assessment

There is a large set of studies that intend to relate web user choice with different variables or behaviours. For example, in 2006, Chandon et al. [13], performed an eye-tracking (ET) experiment for analysing object choice situations associated with brands. They concluded that visual attention is relevant in a user's choice process, suggesting that those objects with low choice probability could be enhanced if they were placed next to the objects with high choice probability.

Another study was performed by Krajbich et al. [22], with the objective of relating choice process with gaze position. In particular, they developed a choice prediction model based on three main observations: the first and last fixations are *shorter* than the central ones, yet this does not affect the choice probability of each element; the last seen object has *higher* choice probability than the rest; and objects with *longer* fixations have a higher probability of being chosen.

In 2011, Reutskaja et al. [23] studied users' behaviour when choosing between objects under conditions of time pressure and overload, using eye-tracking techniques. They concluded that objects placed in the centre of the screen have a higher probability of being chosen than objects with similar characteristics placed in other screen zones. This could allow decisions to be influenced, for example by centring the object that is desired to be chosen. Additionally, they concluded that 70% of the chosen objects, had *longer* eye fixations.

Khushaba et al. [24,25] have been researching consumer neuroscience, in particular with user preferences by using electroencephalograms (EEG) and ET data. Their studies aim to find interdependencies among the EEG signals from cortical regions in a decision-making environment and also, a way to quantify the importance of different product features such as shape, colour or texture in these decisions. Results have shown there is a clear and significant change in the EEG power spectral activities that take place mainly in the frontal, temporal and occipital regions when participants indicate their preferences.

2.2. Web objects saliency

An important research line regarding the study of Web object saliency was introduced by Velasquez et al. In [26] the authors developed a methodology for identifying *Website Keywords*, defined as "a word or possibly a set of words that is used by visitors in their search process and characterizes the content of a given Web page or website", by analysing plain text. Afterwards this methodology was extended to include the analysis of other kinds of content present on web sites, such as images or videos, and *Website Objects* were defined as "any structured group of words or multimedia resource within a Web page that has metadata to describe its content". They finally defined the *Website Keyobjects* as "a Web object or group of Web objects that attract Web users' attention and that characterizes the content of a given web page or website", these objects would be the most probable elements to be chosen or clicked on the web site [3,27].

To further improve the methodology and make it more objective, Velasquez et al. incorporated an eye-tracking-based analysis for estimating the time spent on each object by each user, thus obtaining better results [14]. Finally, a pupil dilation approach was used to complement the previous work, finding that the inclusion of pupillary activity, although not conclusively, allows the extraction of a more robust Web Object classification, achieving a 14% increment in the overall accuracy [9].

Another remarkable line of salient Web object identification has been developed by Buscher et al. Their main motivation comes from the need to understand how people allocate visual attention on web pages, taking into account its relevance for both Web developers and advertisers. In the study from 2009, they implemented an eye tracking-based analysis in which 20 users were shown 361 webpages while performing information foraging and inspection tasks [28]. The main assumption was that gaze data could represent a proxy of attention. Taking that into account, they developed an analysis framework by first generating a tool that characterizes DOM elements and then maps the users' gazes to them, and second by using extracted web features in a machine-learning setting to predict the salient elements of a web page.

An extra relevant contribution by Buscher et al. is the introduction of the concept of *fixation impact*. It allows the identification of the set of elements that are under the gaze of the user at a certain time. It follows empirical studies that show that human vision is characterized by a narrow window of high acuity along with the standard gaze area. Thus, when visualizing an element, it means that other elements in the surroundings are also being considered. Therefore, given a fixation point, a DOM area is selected in order to identify every element under it. A distance score is given to each element based on its coverage, assuming a Gaussian distribution. The fixation impact is computed using this distance and also incorporating a time dimension, which means the fixation duration.

Similarly, Loyola [10] proposed a graph-based analysis framework to study the dynamics of visual gaze from web users, concluding that their results suggest that a graph-based analysis can capture, in a reliable way, the dynamics of user behaviour and the identification of salient objects within a web site.

Furthermore, in [12], the authors studied the relationship between location typicality and efficiency in finding target Web objects for the case of online shops, online newspapers, and company web pages. They found that a typical object placement signified fewer fixations and a faster object finding. However, some Web objects were less sensitive to location typicality if they were more visually salient and conformed to user expectations in appearance.

Additionally, in [11], Dimpfel and Morys used a combination of eye-tracking and EEG to perform an objective assessment of five commercial Web sites. The eye-tracking device was used mainly for tracking gaze movements, while diverse quantitative features were obtained from the EEG. These features tried to measure users' attention and activation and then these reactions were compared with a typical survey. The results showed that the use of EEG features could be helpful in web site analysis, but more studies are needed to confirm if this kind of research could be helpful in other scenarios, such as advertising.

Finally, in [29], the authors proposed a biological-based feature comparison for identifying salient Web objects. Several features extracted from eye-tracking and EEG data were compared to a baseline given by the mean fixation impact introduced by Buscher in [28]. Their results showed that a relationship exists between EEG features and the users' attention to objects. In particular, the longer the subjects watched an object, the less the brain signal appeared disturbed. These results suggest that EEG features could be used to identify salient objects without considering the time users spend on them, as done in previously mentioned methodologies.

2.3. Biological response analysis on the web

In 2005, Li et al. performed an eye-tracking experiment to assess the users' web page viewing behaviour, with the objective of finding some features to characterize it and proposing suggestions for web design. Their conclusions include the stability of the fixation duration distribution, the fixation duration dependency on some crowd factors and web page contents, and the fact that users' attentions were ordinal [30].

Using eye-tracking technologies, Djamasbi et al., examined the effect that pictures of faces had on the visual appeal, efficiency and trustworthiness of a web page, discovering that users believe that a page containing images of people's faces are more appealing and that it is easier to perform tasks in them, as opposed to those that do not contain them. Furthermore, the analysis revealed a strong positive correlation between trusting the informational content of a page and its visual appeal [31].

In 2010, Lee and Seo performed a usability study in which typical techniques were mixed with biosignal analysis. Specifically, they compared the results of a standard usability test using user-based evaluations (user performance measurements, keystroke analysis, satisfaction questionnaires and interviews), with the results obtained from analysing EEG and ECG data. They found that using this new biosignal-based approach was a reasonable and valuable method for web evaluation, since they obtained 70% precision in the comparison [32].

Additionally, the work of Do Amaral et al. in [33] aimed to establish a relationship between EEG signals and the users' opinion about the usability of some Facebook privacy features. Although it was a preliminary study, it showed the feasibility of using EEG data as a potential source of information to be added to software usability testing.

Similarly, in [34] the use of EEG to further improve usability testing is proposed, based on the hypothesis that learnability can be assessed by analyzing the rise and fall of specific frequency bands in electroencephalographic recordings. Authors found that their EEG-based test is applicable either as a pre-test in order to determine whether further testing is necessary, or as an augmenting method during standard usability testing.

Finally, the study presented in [35] discussed the methodology of increasing the conversion rate with an objective usability testing based on the analysis of users' EEG. As a result some improvements in the users? interface for mobile devices were proposed, which led to a threefold increase in its click-through rate.

3. Hypothesis and research questions

The main objective of this study is to predict web users' choices expressed as clicks on web site objects according to physiological responses. In pursuance of that goal, we propose an approach based on eye tracking and EEG, in which we utilize gaze position, pupil dilation and electrical brain activity for predicting click intention on web sites.

As stated before, different biological processes can be attributed to physiological responses, therefore we want to use the fact that both the pupil dilation and the electrical brain activity recorded from eye trackers and EEG systems could be represented as streams of data with a time component, where diverse patterns could be derived depending on the stimuli and underlying cognitive processes.

To that end, we propose the following research hypothesis: *Changes in brain activity and pupil size over time correspond to a predictive variable of the web user's click intention*. We intend to characterize states of choice and not choice with features obtained from the mentioned physiological responses, understanding choice as the *visible act in which a subject clicks one of the objects presented through a series of web sites*. We focused on finding answers to the following research questions:

- Is there any recognizable pattern within the pupil dilation and/or the electrical brain activity response related to the choice and not-choice states?
- Is it possible to generate a model for predicting click intention according to these variables?

4. Proposed approach and experimental design

In order to validate our hypothesis an experiment was conducted considering different aspects that allowed the reproduction of user web navigation, while monitoring and recording gaze position, pupil dilation and electrical brain activity. The experimental phase took place at the Web Intelligence Centre Laboratory of the University of Chile.

4.1. Subjects

Twenty-one healthy adults participated in the study, ten females and eleven males. The ages ranged from 24 to 37 years, with an average of 26.5. All subjects declared having normal or corrected-to-normal vision and did not have any neurological or psychiatric illness. All participants signed an informed consent approved by the Ethical Committee of the Faculty of Engineering and Sciences of the University of Chile.

4.2. Task description

Five web sites were chosen to carry out the experiment. The general idea was to give users diverse information foraging tasks along with the respective web site where the information was to be found. The criteria used for selecting the web sites was the fact that in our previous study an adaptation was used having positive results, thus in the present work we aimed to use real web sites. Moreover the intended audience would be as general as possible, hoping to provide the level of heterogeneity necessary to validate the results. Due to our relationship with the Department of Industrial Engineering of the University of Chile, we selected five related web sites corresponding to several areas of the Department:

1. Centro de Estudios de Retail: www.ceret.cl
2. Educacion Ejecutiva: www.eeuchile.cl
3. MBA Ingenieria Industrial Universidad de Chile: www.mbauchile.cl
4. Centro de Inteligencia de Negocios: www.ceine.cl
5. Departamento de Ingenieria Industrial Universidad de Chile: www.dii.uchile.cl

We designed ten questions for each web site concerning the act of looking for certain information within the web site. For each question, the home page of the web site was given, thus a navigation was induced in order to obtain the requested information. A total of twenty tasks were selected randomly for each subject.

4.3. Instruments

Eye gaze and pupil dilation were recorded with the Sofey eye-tracking system at a 30Hz sampling rate. The EEG signals were acquired with the Emotiv EPOC neuroheadset, which operates with 14 electrodes at a sampling rate of 128Hz. Subjects were presented the web sites on a 23 screen at a distance of 80 cm while their chins were placed on a support in order to reduce head movements.

4.4. Data pre-processing

Using the mentioned instruments implied working with two sources of data. First, the eye tracker provided several CSV files, those being vision, mouse, keyboard and navigation. We focused on three of them: the *vision* data, which contained information related to the gaze position on the screen, pupil size and whether a saccade or blink occurred during the experiment, the *navigation* data which contained the pages each user visited and the *mouse* data, which contained the time at which each user clicked on any given object. The second source was the EEG, which contained the electrical potential of the brain cortex for 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) located according to the 10–20 International System.

The data pre-processing consisted of two separate steps in which **i)** the physiological signals were cleaned and filtered, and **ii)** the navigational sessions and observations were defined.

4.4.1. Physiological signals

The pupil dilation signal was pre-processed by linearly interpolating blinks and fixing the offset produced by saccades. Then a one-pole Butterworth low-pass 4Hz filter was applied in order to remove noise. Finally, each signal was z-scored in order to make them easier to compare because of the inter-subject variability [9], [36]. The EEG signals were filtered with a 0.5–63 Hz bandpass filter [37].

4.4.2. Navigation path and observation definition

Once physiological signals were pre-processed, we performed the second step. Initially, each subject's navigational path was constructed, determining the start and end times for each web page visited during the experiment. Then, the vertical positions given by the eye-tracking device were corrected with the mouse scrolls, taking into account the differences that could exist between fixations. Lastly, fixations were defined following a heuristic similar to [28], where a simple clustering procedure was implemented considering a time window of 600 ms and a 50-pixel radius. In other words, a fixation was considered a valid observation if gaze points between a time interval of 600 ms were close enough to be inside an area of 50 pixels of radius. For each valid fixation, mouse clicks were assigned a label with values 0 or 1, corresponding to absence and presence of click respectively.

Table 1
Frequencies corresponding to EEG Wavelet decomposition.

Decomposition levels	Frequency bands	Frequency bandwidth [Hz]
A4	Theta	0–4
D4	Delta	4–8
D3	Alpha	8–16
D2	Beta	16–32
D1	Gamma	32–64

Table 2
Feature selection results.

Method	Accuracy	Precision	Recall	F-measure
Baseline	0.6659	0.4915	**0.3074**	**0.3782**
PCA	0.6482	0.4438	0.2366	0.3074
Random Lasso	**0.6916**	**0.5104**	0.2740	0.3565

4.5. Feature engineering

In a similar manner, several features were proposed for both pupil size and EEG signals. For the case of pupil size, four features were computed for each fixation, namely maximum, minimum, average and delta, which corresponds to the difference between maximum and minimum values [29].

The EEG signals were first analysed using the Discrete Wavelet Transform (DWT) with four levels of decomposition and Daubechies order 4 wavelet function ("db4"). Table 1 shows frequencies corresponding to each decomposition level for a sampling rate of 128 Hz [38].

The following features were then computed for each frequency band and EEG channel:

- Statistics: Mean, maximum, minimum, standard deviation, power [39].
- Hjorth Features: Complexity, mobility [40].
- Petrosian Fractal Dimension [41].
- Higuchi Fractal Dimension [42].
- Approximate Entropy [43–45].
- Hurst Exponent [46].

The signal entropy was computed for each fixation and for each channel as well [39]. This resulted in a total of 789 features to work with.

4.6. Feature selection

Once the features were extracted, we tested two methods for Feature Selection, Principal Component Analysis (PCA) and Random Lasso. To compare how both performed, we attempted to classify the examples of our dataset using a Support Vector Machine (SVM) with a *RBF* kernel. Additionally, we compared both methods to the baseline of not filtering any feature. The results of this step are presented in Table 2:

For the PCA we found that the first 30 components explained more than 99% of the total variance, whereas for the Random Lasso we found that the 15 most selected features were:

Table 3
Classification.

Method	Accuracy	Precision	Recall	F-measure
SVC	0.6916	0.5104	0.2740	0.3565
Logit	**0.7109**	**0.5449**	0.2428	0.3359
Passive aggressive	0.6121	0.443	0.3417	0.3858
Ridge	0.7102	0.5391	0.2109	0.3032
Ada boost	0.6945	0.5097	0.2545	0.3395
Gradient boosting	0.7038	0.5249	0.2413	0.3306
Neural network	0.6186	0.4730	**0.3566**	**0.4066**

1. `min_area`
2. `pfd_O1_D4`
3. `hurst_O1_D2`
4. `hcom_F3_D4`
5. `hmov_T7_D1`
6. `hmov_O1_D1`
7. `hfd_T7_D1`
8. `hfd_T8_D2`
9. `hmov_P8_D2`
10. `hmov_T7_D2`
11. `hmov_F3_D1`
12. `hmov_FC5_D4`
13. `hmov_F4_D1`
14. `hcom_P8_D2`
15. `avg_area_30`

Where `min_area` represents the minimum pupil size during the fixation, `pfd_O1_D4` represents the Petrosian Fractal Dimension of the fourth detail decomposition (D4) of channel `O1`, `hurst` is the Hurst Exponent, `hcom` and `hmov` correspond to the Hjorth complexity and mobility respectively, `hfd` to the Higuchi Fractal Dimension, and `avg_area_30` to the average pupil size during the first 30 frames of the fixation.

We finally decided to use the 15 features given by the Random Lasso because of the simplicity of working with a considerably smaller feature set and the fact that both the accuracy and precision were better than those given by the baseline and the PCA.

5. Results and discussion

Once we had our data fully pre-processed and transformed, we were able to perform the proposed analysis in order to answer the research questions. For this, we first analysed the pupil dilation signal to validate our prior results corresponding to the differences between pupil size for choice and not-choice (click and not-click) states. Then, we implemented diverse classification models to discern whether a set of features implied a click or not.

5.1. General results

We computed a grand average curve for all valid fixations for all subjects with the intention of finding patterns or differences between pupil sizes related to clicks and not clicks for subjects browsing the Web. Similar to our prior work we found that for fixations corresponding to objects that were visually explored and chosen (clicked), pupil dilation was statistically greater than those than were not chosen. This could be graphically seen in Fig. 1, where the blue curve corresponds to click fixations and the red curve to not clicked. The *X* axis represents 30 time frames which depict a one-second fixation duration, and the *Y* axis expresses the z-scored pupil sizes.

Afterwards, we tested 7 different classification methods to discern whether a set of features implied a click or not. Table 3 shows the classification results, where it could be seen that the best performance in terms of Accuracy and Precision were obtained by the

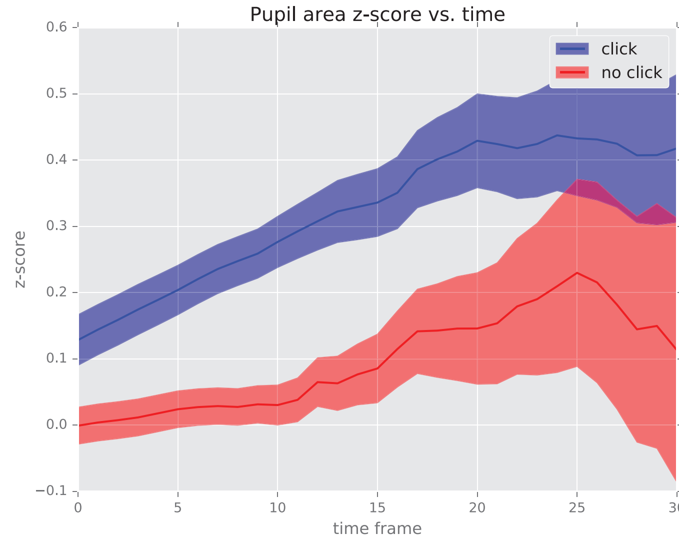

Fig. 1. Pupil dilation curves for click and not-click fixations.

Logistic Regression (71.09% and 54.49%), very close to the Ridge model (71.02% and 0.5391%). Taking into account the Recall and F-measure ratios, the best results were obtained by the Neural Network (35.66%, 40.66%) followed by the Passive Aggressive algorithm (34.17% and 38.58%). Fig. 2 displays the ROC curve for each one of the classifiers:

5.2. Analysis and discussion

The first remarkable result obtained in this work is the different pattern found in the pupil dilation curve comparison between choice and not-choice fixations. This discovery is useful to answer the first research question stated in 3. Indeed, fixations related to a choice, represented as the visible act of performing a click, revealed greater pupil sizes than fixations with no clicks at all. However, finding such a pattern within the EEG curves was not possible since its waveform is difficult to interpret for this sort of analysis.

In terms of the classification models, it is important to say that the results obtained might be due to the fact that the features we implemented were based on emotion recognition studies, hence the novelty of this analysis. It is also possible that the methods we conducted are not suitable for this kind of data and a further review ought to be done in order to achieve better performances.

Notwithstanding the results, it is worth mentioning that the totality of the models performed better than the baseline, which indicates that a phenomenon is actually able to be classified. As a result, new methodologies are proposed, such as the integration of new features for both pupil size and EEG and also new models that might have better prediction capabilities for this sort of data and situation.

Last but not least, it is possible that by reason of the low sampling rate of the instruments used in this work, particularly the eye tracker, an important amount of information could have been lost in the moment we defined the valid fixations to be employed. In this regard, we look forward to working with better quality instruments in the future in an attempt to obtain higher quality results.

6. Conclusions and future work

In this work we have explored the behaviour of web users from a physiological perspective; we have tried to assess the choice–represented as a click–intention using pupil dilation and electroencephalogram responses. For collecting the necessary data, we conducted an empirical study using five real web sites from which the

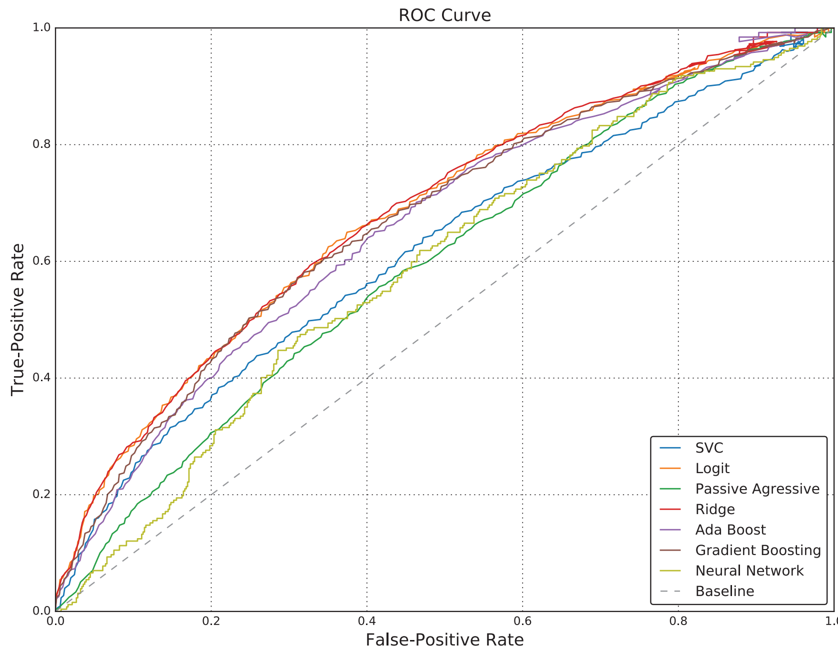

Fig. 2. ROC curve.

gaze position, pupil dilation and EEG of 21 subjects were recorded while performing diverse information foraging tasks.

Taking into account different aspects we defined the fixations through a clustering algorithm and labelled them as click and not click, using the mouse tracking information. We found the existence of a statistical differentiation between choice and not-choice pupil dilation curves, specifically that fixations corresponding to clicks had greater pupil size than fixations without a click. This fact corroborates our previous findings related to a similar study in a web site adaptation.

We also proposed 7 classification models using 15 out of 789 pupil dilation and EEG features obtained from a Random Lasso feature selection process. Although good results were obtained for Accuracy (71.09% using Logistic Regression), the results for Precision, Recall and F-measure remained low, which indicates that the behaviour we were studying was not well classified. These results show that it is possible to create a classifier for the web user click intention behaviour based on features extracted from pupil dilation and EEG responses.

As further work we propose the utilization of better quality instruments, at least for the eye tracker, whose low sampling rate might have affected the description and definition of the study basis–the fixations. On the other hand, we suggest using new features for both pupil dilation and EEG by exploring new classification or feature selection algorithms that could improve the results obtained in the present work.

Finally we contemplate performing similar studies with a larger number of subjects to capture more heterogeneity and also having a wider spectrum of web sites in terms of content. Thus we may be able to analyse different segments of users vis-a-vis their dependency on the content.

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