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Outlier Detection and Popularization of Multivariate Regression Model on HCI-Human Physiological Response

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KEYWORDS

Popularization, Multivariate model, Human physiological response, Task performance, Cognitive process

A B S T R A C T

One motivation for studying Human Computer Interaction (HCI) particularly on web applications is the need for gaining insight into how user interaction with web applications that will help in examining and regulating stress levels, not only for web applications but for other computer applications such as games. This paper is based on three modules, (a) Explore potentials of HCI-HPR modeling and develop an algorithm for determining HCI- HPR associations. (b) Identify emerging patterns in high-dimensional HCI-HPR data. (c) Provide insights into stress-related analysis via popularization of the multivariate linear regression model. The output shows significant performance of models in all popularisation stages.

Introduction

Various aspects of Human Computer Interaction (HCI) - par- ticularly on web applications - have been widely studied in recent years [11][14][21]. One motivation for such studies has been the need for gaining insight into how user interaction with computing applications may help in monitoring and controlling stress levels [9][6]. Different studies have shown that human physiology reacts to a extensive diversity of emotional events and natural indicators of stimulation have long been known to be related to mental events like constructive and destructive reactions [22][12]. Studies have therefore focused on, interalia, variations in user attention and on how user response to different stimuli on the web or online activity. This paper discusses a multivariate robust regression model [2][16] and a custom algorithm that determines potential associations between users' emotional responses to webpages. It combines aspects of HCI and human physiology. The purpose of adopting multivariate regression is to conduct a pilot investigation on the HCI-HPR to discover motivating structures in the data, the desired output is left to be discovered for each input and this sets the following research question: How can user-generated data be utilised in modelling human physiological responses to visual content of the web? To answer this question, the following objectives are set:

To identify emerging patterns in high-dimensional HCI-HPR
data.

To investigate possibilities of HCI-HPR modelling and ad- vance process for influential HCI-HPR associations.
To provide perceptions into stress-related analyses through augmentations in prospective HCI.

Robust multivariate regression

Different models are being explored to understand different phenomenal, these models could either be predictive models, regressional models etc. depending on the areas to be explored. A robust regression model can be a substitute for least median or least mean square regression when the given data are polluted with outliers and significant observations, it is mainly used for the purpose of detecting significant observations [17][18]. The model is just like a classification model except that the response are continuous [13]. We can have a single real-valued input say $xi \in R$, and a single real-valued response $yi \in R$. A regression line or curve can be fitted to a data arising from having high-dimensional inputs, outliers or non-smooth responses. The mul- tivariate regression model articulates a d-dimensional continious response vector as a linear combination of predictor instances and a vector or error instances with a multivariate normal distribution [20]. Given that $yi = (y_{i1}, \ldots, y_{id})^0$ is the response vector of instances i, i = 1, . . . , n. With a d-by-k design matrix X_i and a k-by-1 vector of coefficients β, the multivariate regression model is then given as:

$$y_i = X_i \beta + \varepsilon_i \tag{1}$$

where the d-dimensional vector of error instances follows a multivariate normal distribution,

$$\varepsilon_i \sim MVN_d(0, E) \tag{2}$$

The model assumes independence between instances, which are the error variance-covariance matrix for the n stacked d-dimensional response vectors is represented by the identity matrix

$$\mathcal{I}_n \otimes \mathcal{E} = \begin{pmatrix} \mathcal{E} & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & \mathcal{E} \end{pmatrix} \tag{3}$$

The distribution of the response vectors is then given has:

$$yi \sim MVN\, n\, d(X\beta, In \otimes E) \tag{4}$$

Where y is the nd-by-1 vector of stacked d-dimensional re-sponses, and X denotes the nd-by-k matrix of weighted strategic matrices. The Equation 1 and 2 fits multivariate regression model with a heteroscedastic or un-structured error variance-covariance matrix, E with a least median squares or maximum likelihood estimaition. The un-structure matrix are both heteroscedastic and correlated. For this paper, we try to see how we can fit a robust regression model to HCI- HPR datasets and also derived a custom model for the purpose of comparison.

Materials and Methods

Data collection was carried out by conducting experiment (ethical approal number CS77) based on usability and evaluation testing, using physiological measures (Skin conductance response (SCR), Pupil dilation (PD), Skin temperature (ST) and Eye movement). The eye movement data was collected with an eye tracker that also records pupil dilation. The experiment involve 44 participants interacting with 6 webpages. Each of these page either has the contents deactivated or active.

The method for data analysis was approached by extracting features with a custom algorithm that helps to detect increase in stress level based on the average amplitude response detected for each webpage and the response duration. The steps for the algorithm is stated below (Figure 1). Feature extraction was considered based on significant variables often used in literature, when considering a multimodal approach such as combining eye tracking data and physiological measures [23][5], the novel approach involves appending saccade-size of fixations to the custom model and compare its performance to both original and a derived model. The diagram by the right illustrates the features used. Each participant's baseline differs and thus increase in amplitude depends on variations in the medain threshold for extracting event correlates as a matrix Z(m, n). Each participant generate instances based on the number of webpages viewed.

Savistsky filter [19] Eq 5 was applied for removal of noise and other artifacts of physiological measures. The baseline (skin conductance level (SCL)) was estimated based on point interpo- lation moving average technique (Eq 6). Peaks on the SCR were detected using a given threshold that corresponds to a participant's median SCR.

$$(Y_k)_s = \frac{\sum_{i=-n}^{n} Y_{k+1}}{\sum_{i=n}^{n} A_i} \tag{5}$$

Y_{k+1} = A_0 + A_1 x +A_2 x^2+ …+ A_n x^n
A_i = Coefficients (Scalers)
x_i = Scaler Variables

Here Y_{k+1} are the smoothen SCR response.

$$Y_k = T_k\left(\sum_{i=-n}^{n} \frac{Y_k}{2_{n+1}}\right) \tag{6}$$

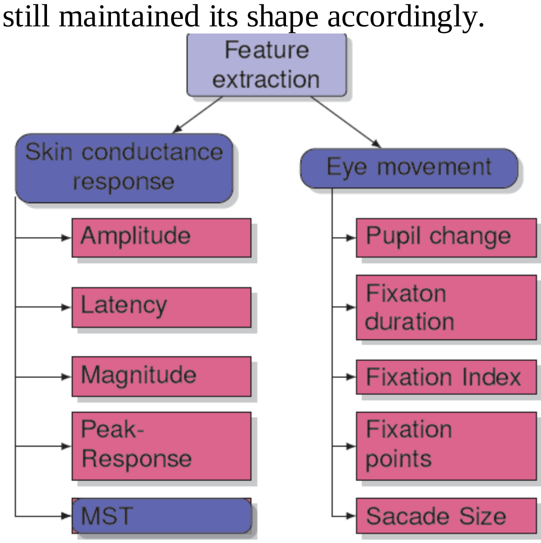
Fig.1 Data preparation module to detect stress level and associate HCI- HPR events

Algorithm: Physiological correlates $X(r1, 1)$, to web contents $Y(r!, c!)$ of url I

```
input: physiological data X(r1, c1), fixations Y(r2, c2), web image/url I
output: higher dimension matrix Z(m, n)
i = 1
j = 1
for all input matrix X(t, s) do
   Ij ↔ Xi(t, s)
compute SCL of SCR by applying filter  SCL (Xi) = sgolayfilter(SCR)
determine maximum peak responses  peaks pk(Xi) = findpeaks(SCRi,' threshold', 3)
    determine SCR baseline b(Xi) = mean(minima(SCRi, ... , SCRn))
        compute SCR magnitude mg(Xi) = sqrt((SCRi)² + ··· + (SCRi)²)
        determine SCR amplitude a(Xi) = max(SCR) − min(SCR)
        compute the mean Skin temperature MST(Xi) = mean (STi, ... , STn)
              compute the pupil size P(Xi) = mean(PSi, ... , PSn)
          for all input matrix Y(r2, c2) do
             Ij ↔ Y(r2, c2)
        compute mapped fixation in x-coordinate of Ij
        MPFX(Yi) = mean(C21, ... , C2n)
          compute mapped fixation in y-coordinate of
        Ij MPFY(Yi) = mean(r21, ... , r2n) computer fixation duration of ti
         FD(Yi) = mean(Ti21, ... , Ti2n)
for all k = 1:length(X) do
  if k == length(X);
    k+1 == 0;
  else
  X X= [X(k,1),Y(k,1);X(k+1,1),Y(k+1,1)];
 saccade(k) = pdist(XX,'euclidean');
  end if
end for
        end for
        determine stress levels Si, Ni, Ri
         if pk(Xi) > threshold and Time(ti) > 3
           stress level = Si
         elseif  pk(Xi) < threshold and pk(Xi) > mean of b(Xi)
           stress level = Ni
         else
           stress level = Ri
         update output Z(m, n)

         end if
              end for
         next i
             next j
```

Y_k are the resulted data points by resampling the smoothen SCR, taking a moving average of 2n + 1 window size on each points in Y_k, in each time interval T_k. The smoothen data still maintained its shape accordingly.



Each physiological measure undergoes this process depending on how noisy the data. The eye movement data obtained includes PD and fixations captured by the eye tracker. The derivative parameter here is the saccade-size D that gives the Euclideen distance between two points (x_n, y_n) and (x_m, y_m).

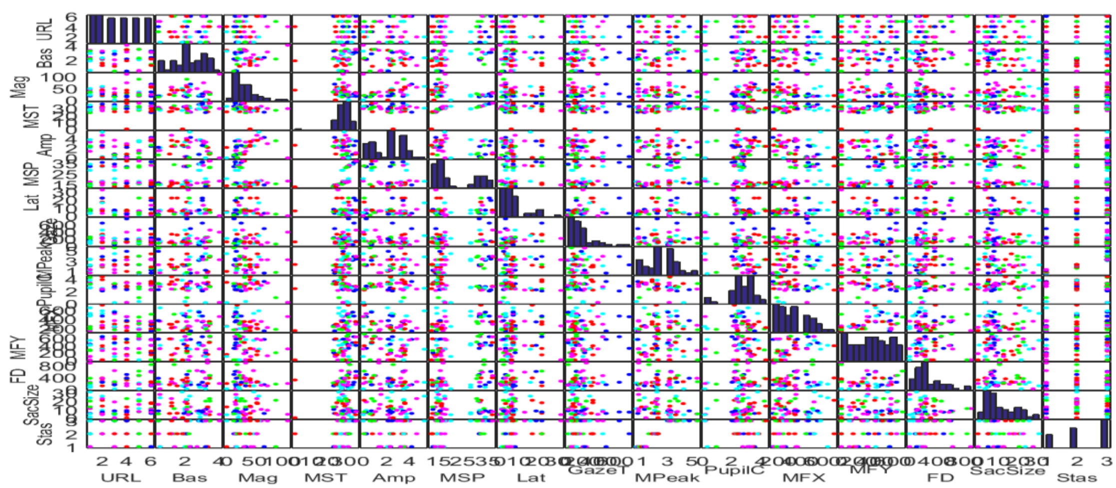
$$\mathcal{D} = \sqrt{(x_1 - y_1)^2 + ... + (x_m - y_m)^2} \qquad (7)$$

Where x_n, y_n are fixation points on the vertical plain of a webpage and x_m, y_m are the fixations on the horizontal plain.

A participant is at the tonic phase if SCR falls below median range. Increase in amplitude that exceeds the median level, indicates the participant is either stressed or excited. Given the nature of the task the former is the classified affect state. Hence we integrated between "Stress", "Neutral", and "Relaxed" state of users. The SCR is the physiological measure that serves as the major constant response for this case and appeared in all the dataset used for the model. This based on its ability in detecting spontaneous and evoked reaction in literature. The algorithm (Figure 1) detects each increase in amplitude and predicts the maximum SCR (peak) within the interval that correspond to a particular event.

The output data result into a higher dimensional dataset Z(m, n) for the purpose of modelling. The multivariate regression model (Equation 1) was applied to identify interesting patterns in the integrated multimodal data. The custom algorithm was able to detect affects corresponding to events during interaction with a performance of 80%. This was determined by the error estimate as the rate or ratio of the magnitude of baseline reaction $\mathsf{M}_{\mathrm{min-Index}}$ to the magnitude of SCR (M_R).

Fig.2 Multivariate data of HCI-HPR



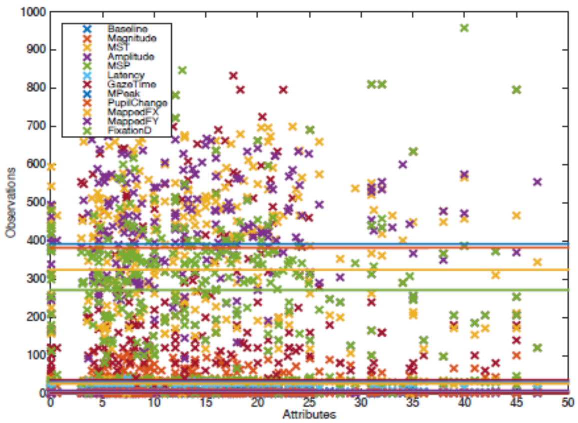
$$error = \frac{\mathcal{M}_{min-Index}}{\mathcal{M}_R} \qquad (8)$$

The next stage involves fitting the multivariate regression model [2] to the datasets, to detect outliers, significant instances and estimate parameters by solving the nonlinear minimization problem.

Data analysis

The dataset array now contains the HCI-HPR data. The response and predictor data were both initially specified for the purpose of model building. The data contains 14 physiological parameters; observations were based on the number of webpages each participants interacted with, given a total of n = 264 instances. The dimension of the response corresponds to each parameters d = 14. The predictors are the associated variables to stress indicators. Figure 2 shows a scatter plot of the multivariate data.

Fig.3 Heteroscedastic matrix for corrected instances and outliers



The multivariate regression model in (Eq 9) fits with be- tween physiological attributes concurrent correlation (Eq 10). The diagram shows that each regression has an intercept which is different from each other but have a common slope. Upon visualising, some of the lines appear to fit the data better than others. The points above the boundaries of fits are considered to be outliers. The model takes the initial form:

$$y_{ij} = \alpha_j + X_i\beta + \varepsilon_{ij} \quad i = 1, \ldots, n; j = 1, \ldots, d, \qquad (9)$$

with inter-parameters synchronized correlation, with y has the function of physiological paremeters.

$$COV(\varepsilon_{ij}, \varepsilon_{ij}) = \sigma_{jj} \quad j = 1, \ldots, d. \qquad (10)$$

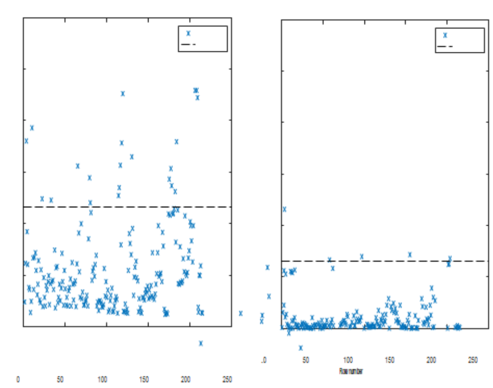
This gives k = 15 regression coefficients to be estimated by 14 intercept instances and a single slope. The model then contains a k-dimentional coefficient vector with variance-covariance matrix of the form:

$$\begin{pmatrix} \sigma_{11} & \cdots & \sigma_{1,14} \\ \vdots & \ddots & \vdots \\ \sigma_{14,1} & \cdots & \sigma_{14,14} \end{pmatrix} \text{ and } \alpha_j = (\alpha_1, \alpha_2, \ldots, \alpha_{14}, \beta)$$

To determine diagnostics of dataset and identify outliers in order to see what other problems the model presents, a leverge of the data and model is demonstrated. Figure 4a shows levarage plot of points with high influence on model performance. But this does not reveal whether the high-leverage points are outliers. Identifying points with huge margin of Cook's distance (Figure 4b) shows there are points circled in red of such instances which are identified as outliers and are removed. This initial step was carried out to prepare the model and room for exploiting significant residuals.

For us to detect multivariate outliers in the data fit to suit our purpose, a test of normality and outliers was carried out. The purpose is to look for observations further the centriod and for all observations with a p-value less than that of the significant level 0.05 are influential as influential outliers i.e the correlation between the variable for these responses are significantly different and anomalous when compared to the rest of the dataset.

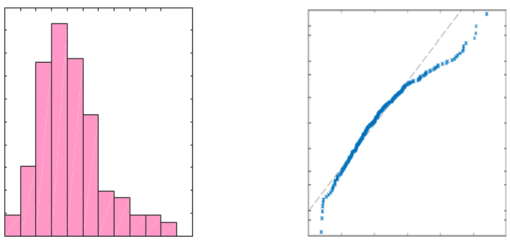
Fig.4 The leverage plot and Cook's distance of case order



(a) Leverage for case order (b) Cook's distance for case order

We determine whether removing the records with these criteria will lead to accurate effective sizes, betas (βi) or regression weight and a better model or if modifying and retaining them can still preserve the best solution. The first stage was to identify the outliers.

Fig.5 Outliers and normal probability plot of outliers

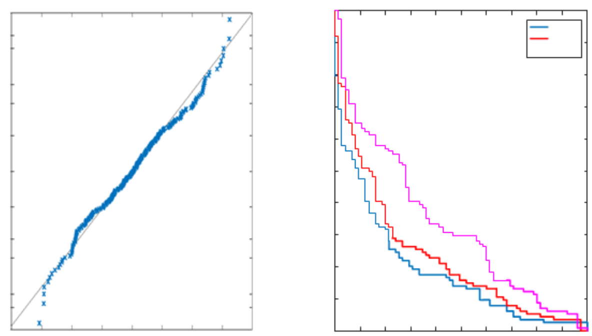


a) Histogram of residuals with potential outliers (b) Normal probability plot showing outliers

There are several ways to help identify potential outliers such as the residual and stalactite plots. This helps discover errors and correlations in the model or data. The one used here are the simplest form of residuals known as the histogram plot of residuals. It shows the series of the residuals, occurrences and analytical or probability plot of how the distribution of residuals associates to a normal distribution with corresponding variance.

The normal probability and histogram of residuals (Figure 5) shows instances of observations less than -15 and greater than 30 as possible outliers. These were observations 13, 25, and 38. For these participants, there were unusual occurrences such as they had normal latency while they looked at Search engine page. Observation 13 and 25 looked at Search engine suggest page (ASL active) with a fixation duration less than the normal interval (100ms-500ms) [4] and also a mean saccade size less than the other observations. These observations have a normal latency (0-3 secs) [1]. This is a good example of an instance with normal response to stimuli. Probably why they were picked out as outliers and due to the unique difference. Observation 38 look at a Search engine search page (ASL not active) and has latency twice that of 13 and 25 with increase in stress level while visiting the Search engine page. Observation 38 was neither stressed nor relaxed but the fixation duration was not at the normal level and likely not a good instance of response to stimulus.

Fig.6 Normally distributed data and popularization stages of regression model



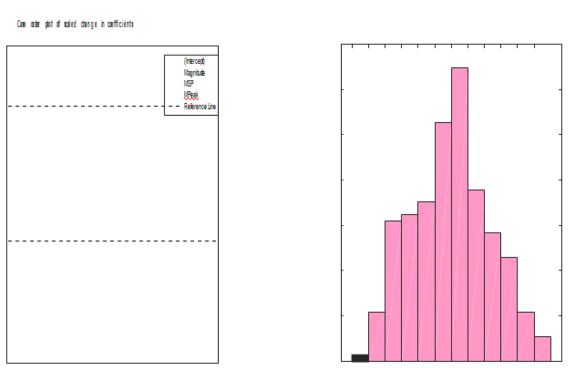
(a) Normally distributed residuals (b) Performance in polarisation stage

Echoing the model during analysis shows p-values for each parameter, the smaller the p-values, the more suitable the predic- tors are for the model [3][15]. The best predictors includes MSP, baseline, magnitude, MPeaks and fixation on the x-cordinate of a webpage and are good representation for determining the stress level of participants than the other parameters, given their p- values. The most includes the mean skin potential with ($p = 0.0002$), MPeak with ($p = 0.003$), Pupil changes with ($p = 0.004$). The variable "saccade-size" and "fixation duration" were really not a good predictor or not best for determining the stress level of users. They were reserved as the ordinal vector and best for response vectors. It is interesting to note that the predicted values are close to match the position of saccade-size and fixation duration during model simplification. The model produces a mean squared error of 0.428, which indicates a performance not close enough to the hypothesis for which the custom algorithm is based on. Further test illustrates if replacing the irrelevant variables or retaining them will help in improving the model performance from its correlation of (r2 = 0.80, $p < 0.05$). The following sections discusses the model effects and results of refining the model.

Results and Discussion

To popularise the model, we try to obtain a simpler model with fewer responses, but with the same predictive accuracy as the orignal model using a step size 10. This improves the model with additional options specified and one or more parameter added or removed in paired arguments. For this case, step sizes were taken for each model outlier detecting process. The observation still showed outliers greater 30 (Figure 7a). Other explicit method would be to visualise the residuals in a stalactite plot that clearly indicates outliers in a stratified predictable routine based on Mahalnobis distances [8]. Figure 6a shows a normal probability plot with less residuals than Figure 5b, and this is fairly fit to the normally distributed residuals.

Fig.7 Histogram of residuals with possible residuals and model close to original model

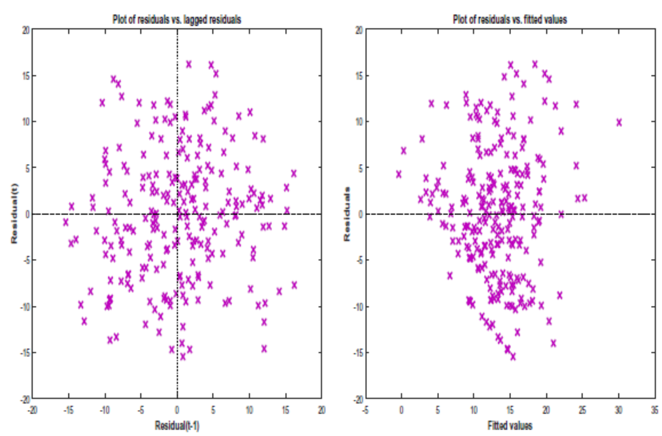


(a) Scaled residuals with outliers outside reference line. (b) Histogram of residuals with no outlier and similarity to orginal model

The residuals greater than 30 in the model (Figure 7a) were termed are as outliers and are removed. Further simplification shows residual in Figure 7b with impartially symmetric and exclu-sive of tangible hitches i.e there seem to be no obvious problem. However, the more model simplification is conducted the more performance deviates from the original model (Figure 6b), this is indicated by the difference in performance in popularisation stages. Nevertheless, there were some serial correlation among the residuals. A new plot was created to view the existing lagged effect of terms and fitted model against the residuals.

The scatter plot in Figure 8a shows a bit more crosses in the upper-left and lower-right quadrants which is also reflected in the other two quadrants, that shows symmetric correlation and indicates symmetric positive and negative constructive sequential association among the residuals and the model fit Figure 8b. There are potential issues whereby residuals are sometimes too large for some observations, but this is not the case in this current model. The crosses appear less in the third quadrant indicting more positive than negative correlation among variables.

Fig.8 Interaction among attributes both fixed and dynamic

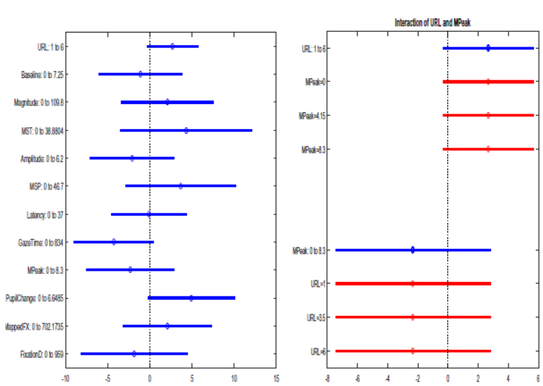


(a) Residuals vs lagged. (b) Residuals vs Model fit

A. Predictors effect

To understand the predictor effects, each predictor is assigned a regression model using two different types of effect. The predictions is based on averaging over one predictor at the same time, the other changes. This produce the confidence intervals (blue lines) for predictors. The plot in Figure 9a shows that changing the URL from Search engine suggest page (ASL active) to National rail Enquiry search page (ASL inactive) will increase the effect by about 2.9. It also shows that increase in stress level of MPeak from 0.39 to 8.3 will reduce the effect by about 2.8. The Figure 9b shows the joint interaction of two predictors (Mpeak and URL). It shows the effect of changing parameters with one parameter fixed. For stress levels, increase of mean peak count from 0.1 to 9.9 will increase ranges and have more advance on Search engine suggest (1), page (4) and National rail Enquiry search page (ASL inactive)(6). On the other hand, changing webpage from Search engine suggest page (ASL active) to National rail Enquiry search page (ASL inactive) will decrease stress level by 0.3.

Fig.9 Interaction among attriutes, both fixed and dynamic



(a) Inter-attributes effect of parameters. (b) Effect of a fixed URL to MPeak

To further understand more instances of term effects, additional attributes such as the saccade size from eye movement data was appended. This helps to understand the effects of parameters in the regression model. So a new variable is created with M appedF Y ∗ Pupil Change as the added variable. The effect of interaction is based on the predictions; for every fixed number of the pupil change (1.66, 2.72, 3.8) the saccade-size is adjusted. The effect adopted an L-shaped arc on stress level over the adjusted value of the response (saccade-size).

In the model the fixed effect represents the observed quantities in terms that specify the variables, which are, treated as non- random data. This is on like random effects and mixed model where parameters are of random causes. The model helps to control unobserved heterogeneity when it is constant over time and have significant associations with the independent parameters. The presence of a significant interaction implies the effect of one parameter variable on the response variable is totally distinct at different values of the predictor variable [7][10]. A fixed effect are thus considerd, because it interprets the difference between the uniqueness of a parameter and its interaction with another.

Fig.10 Interaction of stress level on pupil changes based on prediction

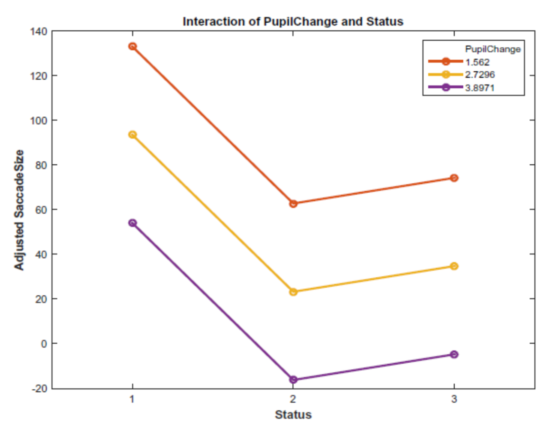


Figure 11 shows the results of fitting both Mapped FY* Saccadesize and Status to the parameters other than simply the saccade size. The diagram shows what additional improvement in the model we need to fix in order to determine whether or not the model is of any significance. The full model shows the negative effect and confident fit in red dashed lines of the points as confident of the added M appedF Y∗ Saccadesize to the regression model, with a (p-value < 0.05) (Table I). The horizontal line y (response) can be contained by the confidence bounds given the nature and hour shaped curve of the dashed lines. A zero slope could be consistent with the data given the value of the coefficient of added attributes.

Fig.11 Additional variable as Saccadesize

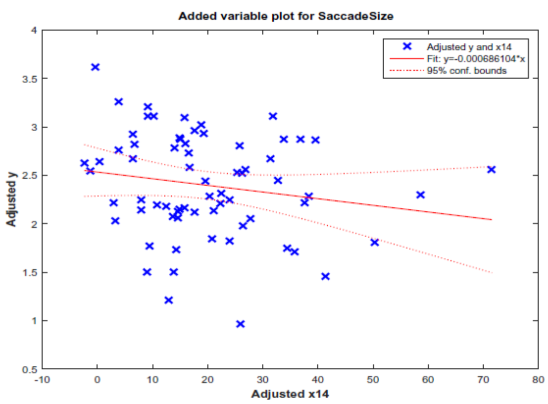


Table.I Table of regression model terms performance

Estimated Coefficients				
	Estimate	SE	tStat	pValue
(Intercept)	30.056	3.5627	8.4362	0.0034953
MappedFX	-0.083614	0.017945 7	-4.6595	0.018653
MappedFY	7 0.06875	0.014133	7 4.8646	0.016593
FixationD	0.059455	0.017968	3.309	0.045426
$Status_2$	-9.2284	2.9068	-3.1747	0.050297
$Status_3$	0.73372	1.9952	0.36774	0.73748
MSE:	**R-sqd**	**p-value**	**Adj R**	**F-stat vs. CM**
0.228	0.889	4.46e-12	0.823	11.9

We also investigate the polarised model by performing more forward search to specify parameters one step at a time by choosing most significant parameter. Since the histogram of residual shows symmetrical behaviour and the added variable for the model shows the model is very significant, we addressed the stage of simulating new random responses, which are equal to the mean prediction and a random disturbance with equal variance as the training data used for creating the model. The model is significant enough that the bounds does not come to containing the horizontal red line. The slope β of the line is the same as the slope of the fit to the parameters projected onto their best-fitting direction or normalized coefficient vector.

Performance of models

A custom model was created based on the following term equation:

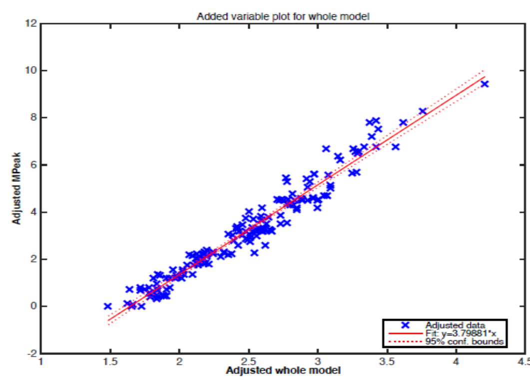
Status ∼ M SP + M appedF X : M P eak + M P eak2

Where a quadratic term was introduced to understand the curved effect on the data with the model fit. This produces a significant performance as compared to the forward search algorithm, illus-trated in the table below, which indicates the performance of all models used in the first and second polarisation stages. The model seems to perform better with each stage except for the original model which depreciates by a 0.1%, insignificant enough to be ignored. These invariably, are best solutions to the model fit.

Table.II Table with performance of models

Model Performance		
Original	Forward search	Custom model
81%	87%	89%
80%	90%	91%

Fig.12 Effect of adding variable to model



A. Simulating Response to New Data

To simulate response to new data, data are generated from the original model with a default linear model of the response Status and made to match the instances of the dataset. A set of array predictors were created from minimal, mean and maximal values or the original data. A new predicted model response is then generated and fitted with the given model formula:

SaccadeSize ~ 1 + M appedF X + M appedF Y +F ixationD + Status

The predicted responses was conducted more times to ensure no negative occurrence of predicted value. The differences between the actual response and predicted responses are computed. The fitted model can then be shared with others or within an organisation that would benefit from models based on HCI-HPR.

Conclusion

This paper examines a multivariate robust regression model and a custom algorithm that defines a dataset of HCI-HPR associations. It combines aspects of HCI and human physiology through experimental study where data are collected and features extracted to form the underlying data for the model fit. A robust multivariate regression model was used to fit the data. The model can be a substitute for least median or mean squares regression when the given data are polluted with outliers and significant observations, it mainly detects significant observations and abnormal occurrence in the data. The model is just like a classification model except that the responses are continuous. We also present a custom model with a quadratic term and represents single real-valued predictors $x_i \in \mathbb{R}$, and a single real-valued response $y_i \in \mathbb{R}$.

Interesting patterns were observed for both the interaction among terms and also the effects of terms while a given parameter is fixed. For other stress related therapies, given a stimulus as predictions, we can easily predict stress level based on thier given peak and fixations on stimulus presented. This can also tell the effect of changing a particular stimulus for a less taxing alternate stimulus of the same magnitude.

The output shows significant performance of models and de-spite the outliers detected and popularisation, the performance of the forward search algorithm diverges from the original model with a slight margin. Though the symmetric histogram of residuals shows the stability of the model.

To further understand the predictor effects we simulated responses to a new data and the results of predicted response shows close associations to the original data with no negative response value. The model can be shared and used for other stress related analyses that are not completely limited to web applications. Further work will be to test the model on new data and see if this will further stabilize the performance of the model or if further popularisation will prompt flawless prototype. Based on the results obtained, one of the future directions will also be to utilise user generated data to predict where users are likely to look at on webpages. This will prompt speedy application development and performance mangement.

Acknowledgement

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