Selecting physiological features for predicting bidding behavior in electronic auctions

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Abstract

Affective processes play an important role in determining human behavior in auctions. While previous research has shown that physiological measurements provide insights into these processes, it remains unclear which of the many features that can be computed from physiological data are particularly useful in predicting human behavior. Identifying these features is important for gaining a better understanding of affective processes in electronic auctions and for building biofeedback systems. In this study, we propose a new approach to identify physiological features for predicting auction behavior. We apply an Evolutionary Algorithm in combination with either the Multiple Linear Regression or Artificial Neural Network models to select physiological features and assess their predictive power. To test the approach, we use a unique dataset of participants' auction decisions and their synchronously recorded electrocardiography data. Our results show that the approach is able to identify subsets of physiological features that consistently outperform other physiological features.

1. Introduction

The quality of economic decision-making, such as decisions in auctions, is not only dependent on the decision-maker's knowledge of the domain and experience. An increasing number of studies have revealed the correlation of a decision-maker's affective processes and the quality of decisions, where quality can be measured using various metrics such as accuracy, number of errors, or divergence from theoretically optimal behavior (e.g., [1]–[5]).

However, due to the unconscious nature of one's own affective processes, it is especially difficult to be fully aware of one's own current emotional state and to utilize this valuable information [6]. Driven by the autonomous nervous system (ANS), physiological responses to environmental factors are outside of one's conscious control and, therefore, they provide an unaltered insight into a decision-maker's affective processes. Using training and decision support systems for actively increasing the awareness of one's current state has been shown to improve and de-bias decision-making (e.g., [7]–[9]). Although unlocking access to a decision-maker's emotional state and the information hidden within could also be of important interest at a team or corporate level–e.g., a financial firm putting together a trading team (i.e., trading floor) [10]–the implementation of this in a real-world information system (IS) and its integration in day-to-day use is still a long way off.

Even though the necessary tools (i.e., measurement devices and data analytic capabilities) for implementing such an IS have become ubiquitous during the past years, even for consumers [11], one particular problem remains: The immense variety of different measurements and their appropriateness to a given context. Derived from medical practice and research, every measurement of a human body's physiological activity (such as electrocardiography (ECG), electrodermal activity (EDA), and electroencephalography (EEG)) can be assessed using several different approaches. In ECG data, for example, the measurements range from simple calculation of beats per minutes (bpm) to computational complex frequency and special geometrical analysis. In addition, since those measurements are mathematical transformations of electrical signals, they also allow for a multitude of parameterizations, e.g., (i) the time window used for calculation, (ii) the values used for normalization, or (iii) the offset to an event used to detect changes in the measurement, resulting in a large amount of possible physiological features. Especially in a non-clinical environment, such as an auction, where participants are not continuously observed for days or weeks but hours or even less, it is very challenging to derive meaning from existing standard measures [12, 13].

In addition to the immense variety of different measurements and features, analyzing physiological

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data is also challenging due to the fact that physiological data is usually very noisy (i.e., measurement limitations and disturbances) and multiple measurements are likely to be correlated (e.g., heart rate and respiration). This increases computational efforts and requires more fuzzy approaches that are able to perform well under such restrictions.

Using an Evolutionary Algorithm (EA), we propose a new approach to address the above-described problem. EAs have been proven to perform exceptionally well in situations where (i) there are too many possible solutions, (ii) there is no single best solution, and (iii) the solutions are heavily constrained [14]. Since there is no theory-based answer indicating which subsets of physiological measurements and measurement parameterizations would provide outperforming predictive power, we combine an EA with two different prediction models: Multiple Linear Regression (MLR) and Artificial Neural Network (ANN). Both, MLR and ANNs, are commonly used prediction models in a broad range of research areas for analyzing linear and non-linear relations, respectively (see [15]–[17] and references therein).

2. Dataset

To test and demonstrate our approach, we make use of a unique dataset built in previously conducted studies by [18], in which the authors investigated a phenomenon known as auction fever in the context of an ascending clock auction. This auction format is one of the most used in today's retail and professional environments. In an ascending clock auction, the standing price increases automatically by a fixed time interval and participants only have the option to exit the auction (without the option of reentering) when the current standing price exceeds their personal reservation price. Other interactions, either with the auction system or with other participants, are not available to the participants. The auction ends when the second last participant exits it, leaving the last participant in the auction as the winner at the current standing price. Therefore, measuring auction time and auction prices is equivalent in this auction setting.

In [18], the participants compete for a virtual good in every auction. The good's value (i.e., resale value) is described by a commonly known discrete and uniform distribution with a predefined range and an expected value at one-half of the range's length. The actual value of a good in each auction is randomly drawn from the distribution after a winner is announced and, therefore, is unknown ex ante. A profit is only gained by the winning participant, if the randomly drawn value is higher than the winning price. Otherwise, the participant generates a loss.

The studies were conducted as a series of laboratory experiments at Karlsruhe Institute of Technology, Germany, in a controlled environment (e.g., consistent experimental protocol, controlled temperature and humidity levels, and limited participant interactions). Student participants were recruited to compete in a series of auctions at a time and the participants were incentivized using a monetary payoff related to their experiment performance. Three participants competed in an auction, whereby a random stranger (re-)matching approach was applied after each completed auction. Using this random stranger matching approach ensures that the groups of participants change between every auction and, therefore, participants cannot adapt to the strategy of a specific competitor. This reduces participant-specific learning effects and increases inter-auction independency. The participants had no further knowledge against whom of the other participants they were competing. Using a full factorial and between-subjects design, the authors used two treatment variables (time pressure and social competition) to vary the degree of auction fever to which the participants were exposed. In the first of the two reported studies in [18], the auction environment was implemented using zTree [19] and the participants competed in 15 adjacent auctions. During these auctions, behavioral data (i.e., how long participants stay in the auction) as well as physiological data of the participants were simultaneously recorded. This unique combination of synchronized behavioral and physiological data comprises the dataset we use in this study (for further information on the dataset see [18]).

In addition to the behavioral and physiological data, the dataset comprises demographic data on the participants, such as gender and risk aversion, as well as detailed information on the conducted auction. In the following, the behavioral and physiological data is described in more detail.

2.1. Behavioral data

The behavioral data is based on the interactions of participants during the auctions. Fig. 1 outlines the auction timeline including its main events.

Each auction starts with a rest period of 1 minute (in addition to an initial cool down period of 5 minutes preceding the first auction), which is used to establish the baseline of a participant's current physiological state. This baseline is later used to normalize physiological features, in order to reduce between-subject variability and, therefore, increase generalizability of results. The subsequent auction has

five main events: (i) the auction start, (ii) the start of the resale value range, (iii) the expected value, (iv) the auction exit, and (v) the auction end. Given the design of an ascending clock auction, only the first and last events (the auction start and auction end) are recorded for every participant and every auction. The remaining events do not occur for every participant in every auction, since they depend on the time of a participant's auction exit. If a participant chooses to exit the auction before the resale value range or the expected value is reached, then these events cannot be recorded. Similarly, if a participant wins an auction, no auction exit is recorded, since the participant wins the auction by being the last participant in it. The auction start event is used as a reference point for all later events of an auction, which are measured in milliseconds relatively to their current auction start (i.e., $t_s = 0 < t_r < t_v < t_e$).

In our analysis, we focus on the prediction of participants' auction exit t_x, which provides us with a dataset of 677 observations (only data entries, which include an auction exit event) from 60 participants of one treatment (M=11.28 [SD=3.05] observations per participant). If recorded, t_x occurs between the auction start and auction end ($t_s < t_x < t_e$).

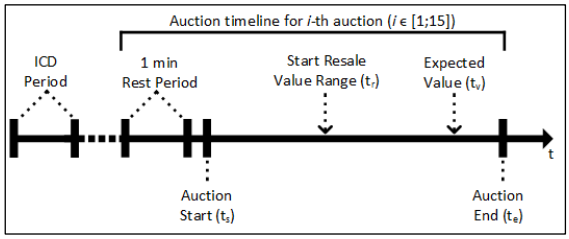

Fig. 1 An auction timeline showing the Initial Cool Down (ICD) Period, Rest Period (RP) and 4 auction events: t_s=Auction Start, t_r= Start Resale Value Range, t_v=Expected Value, and t_e=Auction End.

2.2. Physiological data

The physiological data consists of electrical activity measurements of the heart by means of a 3-lead electrocardiogram. The ECG signal was continuously recorded for each participant with a sampling frequency of 1 kHz. Before the data was used in this study, it was preprocessed to assure signal quality as well as proper heartbeat and inter-beat interval (IBI) detection. The IBI describes the time (in milliseconds) between two adjacent peaks in a heartbeat signal and it is the basis for most heart rate-based physiological features.

Heart rate, among other physiological features, provides a direct and quick insight into a person's current physiological as well as emotional state [20]. By reflecting the activities of the ANS, physiological features reveal information that usually cannot be influenced by conscious control and is outside of conscious awareness [21]. The ANS is responsible for balancing the so-called "fight or flight" reflex on the one hand (sympathetic nervous system), and digestion and recreation on the other hand (parasympathetic nervous system). In recent years, this circumstance has successfully inspired the use of physiological features in other, non-clinical research areas, such as IS research (NeuroIS) [21, 22].

Heart rate in particular has been shown to accurately reflect the arousal dimension of a person's current emotional state [24]–[26]. It increases in stressful situations and can influence (economic) decision-making [18].

After identifying commonly used heart rate-based physiological features and normalization methods from the literature [27], we implemented those physiological features using the Matlab *HRV tools* [28]. For each participant, 37 physiological features have been derived from their IBI data. Table 1 shows an overview of the physiological features and additional normalizations implemented for this study.

Feature	Additional Normalization	Description
hrMean	RP, ICD, Log	Mean heart rate (HR)
ibiMean	RP, ICD, Log	Mean inter-beat interval (IBI)
hrv*X*	RP	Heart rate variability ($X \in$ ["Low Frequency (LF)," "High Frequency (HF)," "Ratio of LF/HF"])
pNN*X*	RP	Adjacent IBIs smaller than $X \in$ [12, 20, 50]
rmssd	RP	Root mean squared standard deviation of adjacent IBIs
sd*X*	RP	Standard deviations of Poincaré Plot $X \in$ [1, 2]
sd1sd2	RP	Ratio of sd1/sd2
sdnn	RP	Standard deviation of adjacent IBIs
renyi entropy*X*	-	Renyi Entropy based on $X \in$ [Ruler, Histogram]
fractal dimension	-	Fractal dimension based on IBIs

Normalization: RP=Rest Period; ICD=Initial Cool Down Period; Log=Log-Transformed

Table 1 Physiological features.

In order to calculate the physiological features listed in Table 1, an observation window has to be defined. This observation window selects the range of IBI data to be used for the calculation of a physiological feature and it is defined by three parameters: (i) window size, (ii) offset, and (iii) selection type. The window size defines the timespan (i.e., the range), which is used as input for

calculating the physiological feature. The offset defines the distance of the observation window's end to the event to which it refers (i.e., the auction start event). For example, for a given window size, an offset of zero selects an observation window, which ends exactly at the time of the event, whereas an offset of minus 10 milliseconds selects an observation window of the same window size, which ends 10 milliseconds before the time of the event (analogous using positive offsets). Lastly, the selection type of an observation window defines on what basis the selections of window size and offset are performed. In the case of heartbeats, the selection types are either millisecond-basis (such as the previous example) or heartbeat-basis (i.e., number of beats). Table 2 provides an overview of the observation window parameters.

Window Sizes	Window Offsets	Selection Types
10,000; 15,000; 20,000	[-10,000; 0] in 500ms increments	Milliseconds (ms)
10; 15; 20	[-10; 0] in 1 beat increments	Heartbeats (b)

Table 2 Observation window parameters.

By combining all physiological features and observation window parameters (e.g., hrMean, window size 15,000ms, and window offset -500ms), there are a total of $N = 5772$ possible predictors, i.e., candidate features (CFs), for our prediction models.

3. Methods

The approach is built on two elements: First, an EA to select a subset of the available CFs and, second, a prediction model to evaluate the selected subset. Our implementation is realized in Matlab (version R2015a), and, where possible, built-in functions are used to avoid reimplementation. Fig. 2 illustrates the entire approach as a flowchart.

3.1. Performance metrics

We use two performance metrics (i.e., fitness values) to evaluate the results: Minimization of the subset size S (i.e., number of selected CFs) and maximization of the prediction model's predictive power (i.e., R^2 error metric).

As the problem at hand is of high dimensionality (i.e., far more CFs than observations), it is statistically possible to select a big enough subset of CFs ($\geq$ number of observations), which almost perfectly explains the given dataset (i.e., overfitting [29, 30]). Furthermore, we seek to provide practical solutions that are applicable to real-world ISs. Therefore, a smaller subset size S is always preferable, as it directly relates to less computational effort. However, it is not possible to determine a priori the minimal (nor optimal) subset size S that provides sufficient predictive power.

To measure the predictive power of our prediction model, we have chosen the commonly used R^2 error metric. This metric determines the quality of a prediction model in relation to the naïve assumption of always predicting the observation mean. In addition, the metric is independent of the actual type of prediction models as it is not model specific. The calculation is as follows:

$$R^2 = \max(0;\ 1 - \frac{\sum\left(a - f(a)\right)^2}{\sum(a - \bar{a})^2})$$

where a represents an observation, $f(a)$ is the prediction of a for a given model, and $\bar{a}$ the mean of a of the given dataset. Values close to zero indicate poor predictive power, while increasing values indicate increasing predictive power.

Since the relation and weighting of the two performance metrics (number of selected CFs and the model's predictive power) are also not known a priori, the metrics cannot be combined into a single metric (e.g., by a ratio or a scalar product). This makes the proposed research question a multi-objective optimization problem.

3.2. Evolutionary algorithm (EA)

The EA is applied as a wrapper method [17, 31] for selecting subsets of CFs. As outlined above, the proposed problem is a multi-objective optimization problem, and therefore we use the *Non-Dominated Sorting Genetic Algorithm II (NSGA-II)* [32]. Like all EAs, the NSGA-II is a population-based metaheuristic for finding solutions in a complex search space. By starting with randomly initiated solutions and evolving them over time (favoring solutions based on their fitness values), EAs are to converge to a globally optimal solution. However, the NSGA-II is specially designed for multi-objective optimization, aiming to minimize multiple performance metrics. To account for the contradiction with our performance metric R^2 (needs to be maximized), we multiply R^2 by minus one and use negative R^2 instead. The solutions computed do not consist of a single best individual (i.e., subset of CFs) but multiple feasible individuals, i.e., the Pareto front [30, 33]. Individuals qualify to be included in the Pareto front are Pareto dominant, which means that their fitness based on both the performance metrics are at least as good as the corresponding performance metrics of all other individuals, and there is at least one performance metric that strictly outperforms the corresponding

performance metric of every other individual. In addition, the NSGA-II favors solutions that are less crowded within the search space, in order to increase sparsely used areas (i.e., favor diversity). Recalling the initially proposed problem, the NSGA-II is therefore an appropriate choice for our approach. For further reading on the NSGA-II and EAs in general, see [14, 32].

The EA is implemented such that each individual (x_i) represents one subset of CFs (i.e., genotype). The subsets are modeled using a binary string approach, which means that every subset consists of N binary values–each representing one CF. If a CF is selected to be included in the following computation, it is assigned the value one, whereas zero is assigned to CFs that are excluded. Given the binary string approach, reproduction is performed using a uniform crossover operator in combination with a random flip-bit mutation operator.

Since one requirement of our approach is the applicability to real-world ISs, the limit of CFs for valid solutions is arbitrarily set to a maximum of $S_{max} = 50$ CFs per individual x_i. The individuals are all initialized with 25 randomly selected CFs ($S_{init} = 25$). Table 3 shows an overview of all settings used to parameterize the above-described EA.

Parameter	Value	Parameter	Value
Population Size	250	Selection Type	Tournament
Populations	5	Mutation Type	Random Flip (25%)
Crossover Type	Uniform (80%)	Migration Direction	Forward (1%)
Elitism	5%	Migration Interval	10

Table 3 Settings used for the NSGA-II.

3.3. Prediction models

CFs selected by the EA are used as inputs (i.e., predictors or independent variables) for the outcome variable, the auction exit (i.e., the dependent variable). We apply two different prediction models to determine the predictive power of a particular subset of CFs: MLR and ANN.

The MLR model analyzes linear relations between the model's independent variables (i.e., CFs) and the outcome variable. Although physiological measurements often show a non-linear characteristic, using a linear model is still feasible considering our CFs. By additionally using, for example, log-transformed and normalized physiological measures, we reduce the potential impact of non-linear characteristics to exhaust the strengths of a MLR model. The MLR model is formulated as follows:

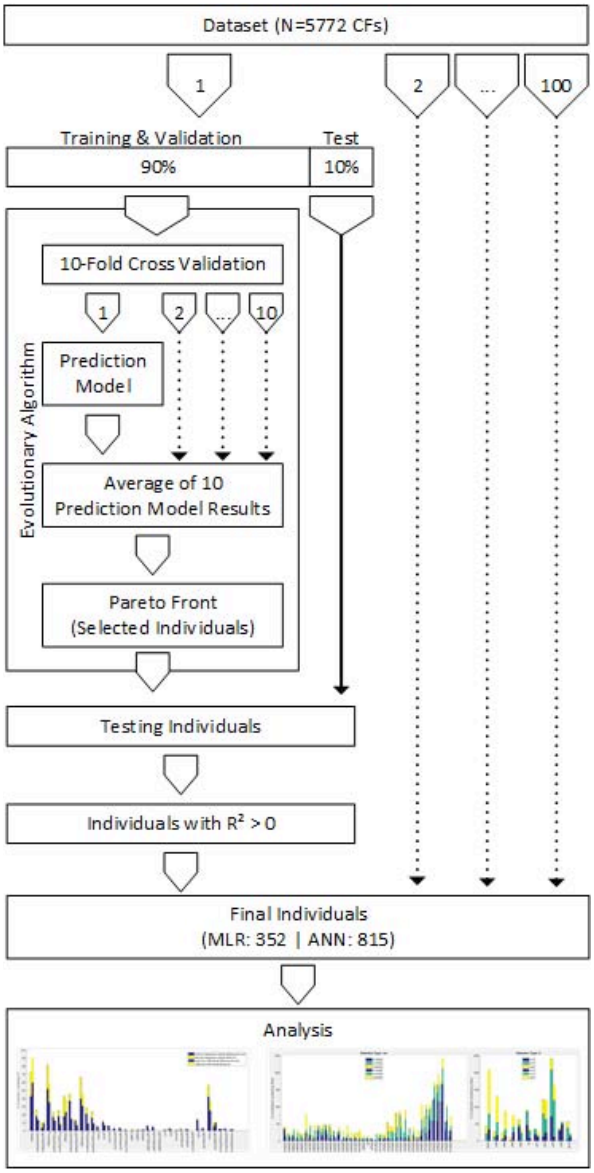

Fig. 2 A flowchart of the proposed approach.

$$y = \alpha + \sum_{i}^{S} \beta_i CF_i + \varepsilon$$

where y is the dependent variable, α the intercept, S is the size of a given subset, β_i the i-th model coefficient, CF_i the i-th CF of the given subset, and ε the model residuals. To estimate the coefficients, the standard method of least squares is used.

The nature-inspired ANN is a statistical learning method, which uses a weighted graph of inter-connected neurons to find relations (linear and non-linear) between its input neurons and a given output. Although ANNs are often referred to as a "black box" approach, their outstanding predictive power in the realm of time series forecasting and classification fostered their use in a wide area of research and

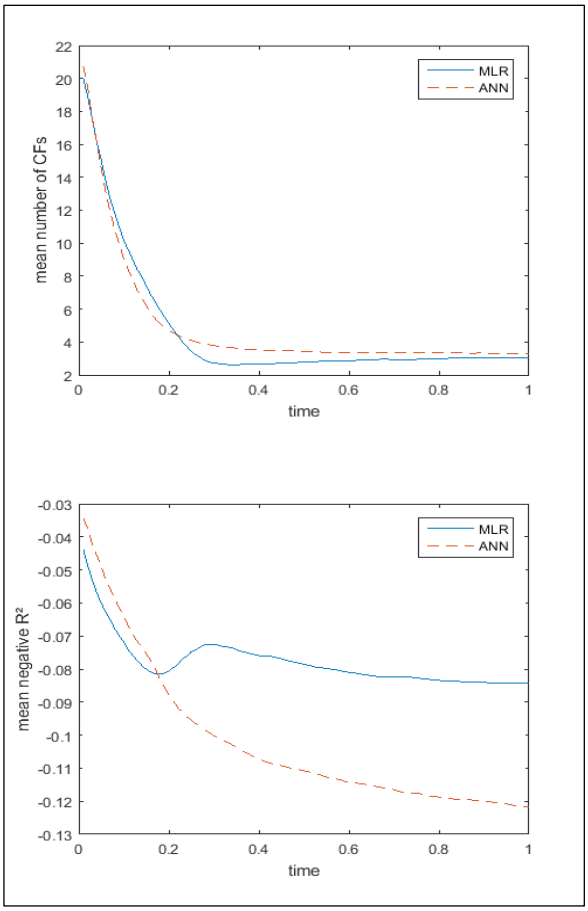

Fig. 3 Improvements of EA over time.

real-world ISs, such as in finance, health, ecology, and biology [34]. For our ANN model, we implement a basic feedforward Multilayer Perceptron, using two hidden layers and a default Levenberg-Marquardt backpropagation learning algorithm [35]. The number of neurons per layer is adjusted depending on the current subset size S. That is, the input layer has S neurons, the first hidden layer has $\lceil 2/3 * S \rceil$ neurons, the second hidden layer $\lceil 1/3 * S \rceil$, and the output layer consists of a single neuron.

3.4. Robustness

To increase the robustness of our analysis, the entire dataset is randomly split by participants into three distinct segments prior to the analysis [36]. We use 90% of the dataset for training and validation, and the remaining 10% for testing. The training and validation data is then further used to generate a 10-fold cross validation dataset. This cross validation is applied to each iteration and individual, so that the R^2 of an individual per iteration is the mean of the 10-fold cross validation outcomes. After the EA computation is completed, the test dataset is applied to the selected individuals. Only those individuals are considered in the results, which also yield a $R^2 \neq 0$ using the test dataset.

Moreover, due to the stochastic nature of the EA and the high correlation of some CFs (e.g., mean heart rate of a given window size and the offset of one beat with the offset of two beats), we do not expect the result to be a single dominant individual. Given the initial random seed, which is relevant for the "random" steps of any EA, two individuals could create an equal fitness value but consist of different (but mostly similar) CFs. To counter this, we run our approach 100 times over both prediction models, each with different initial random seeds. We then statistically test all individuals for our final solution.

4. Results and discussion

Our approach results in 352 and 815 individuals for MLR and ANN, respectively. Each individual x_i represents one distinct solution. The large number of distinct individuals is a result of the high correlation among some CFs, as described above. All presented statistical results are tested against a 5% significant level.

4.1. Descriptive results

First, we inspect the process of the EA's improvements over time. Fig. 3 shows the results based on the two performance metrics, mean number of CFs (upper graph) and mean predictive power (lower graph), on a normalized time scale. Inspecting the mean number of CFs, we can see that the two prediction models have similar progress over time. For the mean predictive power metric, however, the ANN model outperforms the MLR model. Recall that an increasing value of R^2 (i.e., decrease in negative R^2) indicates improvement.

Next, we provide an overview of the predictive power of all solutions grouped by the number of CFs that each solution contains, i.e., the mean over all Pareto fronts, including standard deviations. This is shown in the upper graphs of Fig. 4. The lower graphs in Fig. 4 show the number of solutions with different numbers of CFs. These two types of graphs are shown in Fig. 4 for the MLR (on the left) as well as the ANN (on the right) models. As expected, the most powerful predictive capability is achieved by solutions containing the most CFs (CFs=20, R^2=0.1810). However, there is only one such solution. Recall that all individuals were initialized with 25 CFs and the arbitrary maximum number of CFs was 50–both are greater than the number of CFs in any solution.

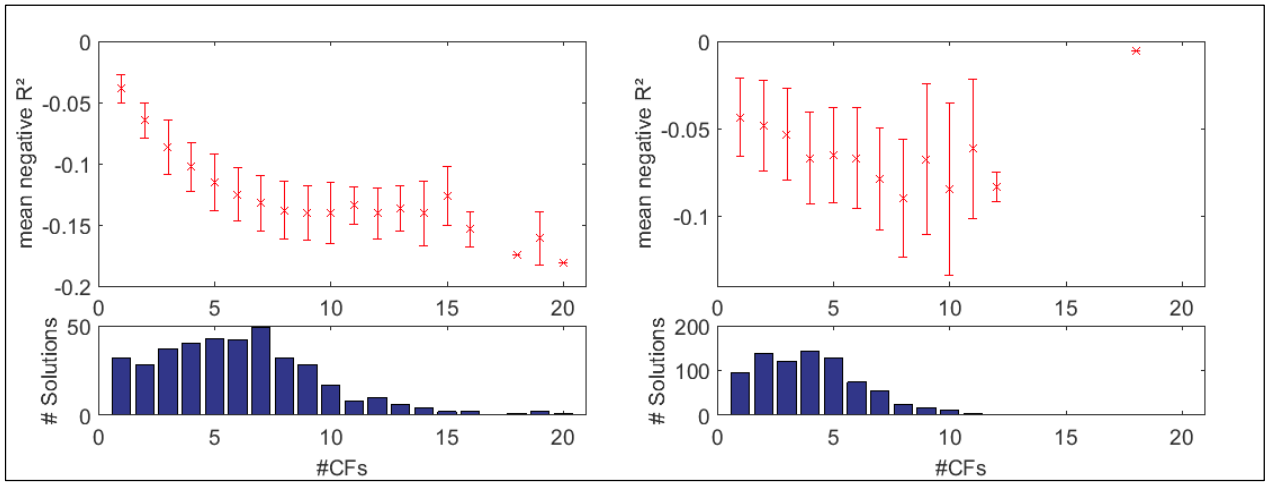

Fig. 4 Mean EA results for the MLR (left) and ANN (right) models.
Upper graph: Mean negative R² with standard deviation (y) by number of CFs (x).
Lower graph: Number of solutions (y) containing number of CFs (x).

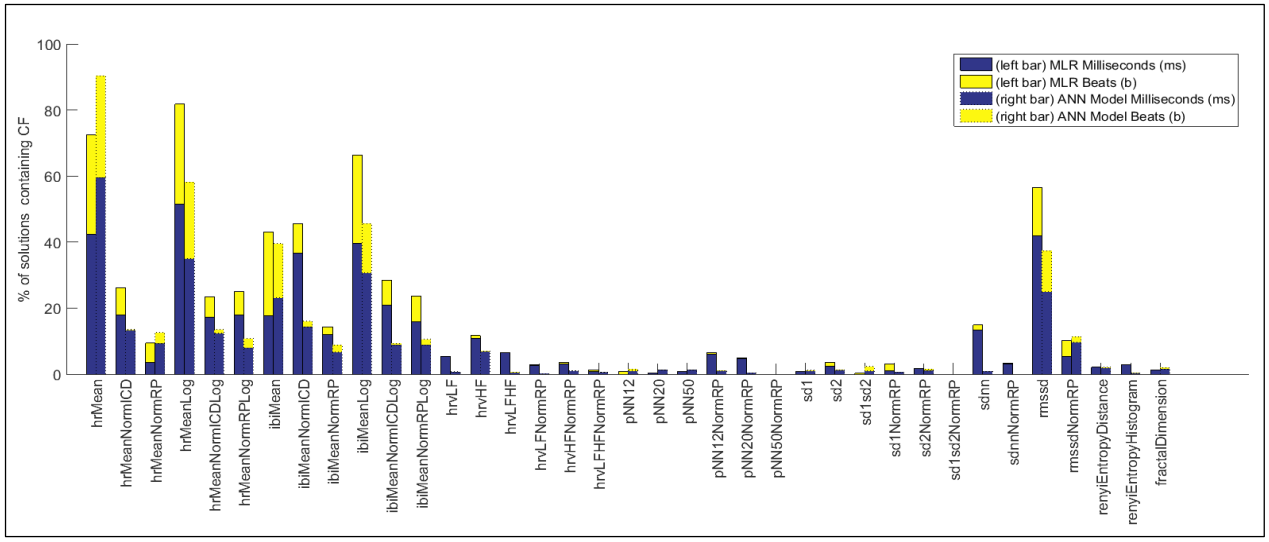

Fig 5. Occurrences of physiological features in EA solutions.
Bottom bar: selection type ms. Top bar: selection type: b. Left bar: MLR. Right bar: ANN.

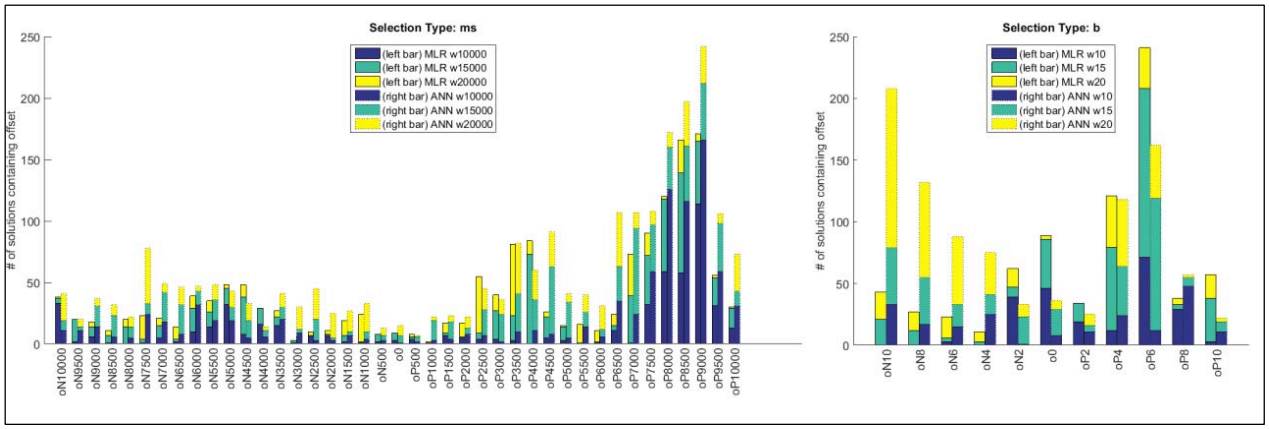

Fig 6. Occurrences of window sizes and offsets in EA solutions.
Left figure: Selection Type ms. Right figure: Selection Type b.
Left columns: MLR. Right columns: ANN.

Fig. 5 provides a summary of the physiological features that appear in the final solutions. The bars in Fig. 5 are composed of stacked bars showing the selection type *ms* (lower bar) and *beats* (upper bar). The figure shows that the selection type *ms* is more often selected than *beats*. Based on a two-tailed Mann-Whitney U test, these results are found to be significant for the MLR model (*ms* [M=42.62], *beats* [M=20.16], U=442.0, $p<.01$) as well as the ANN model (*ms* [M=63.54], *beats* [M=25.83], U=406.0, $p<.01$). In addition, Fig. 5 shows that the most often selected physiological features are heart rate and IBI-based CFs as well as rmssd. Frequency and geometric based CFs are rarely selected.

Fig. 6 provides an overview of the distribution of window sizes and offsets. It is shown that positive offsets (*oP**) are more often selected than negative offsets (*oN**) (cf. Table 4). This is to be expected because a positive offset means that the selected data is closer to the auction exit event, which we are predicting. However, the analysis also reveals that this naïve assumption does not hold in the case of selection type *beats* and ANN as well as selection type *ms* and MLR (i.e., $p>.05$).

Analyzing the selections of window sizes as shown in Fig. 6, the results indicate no significant difference for any window size (i.e., comparison of all window size tuples result in $p>.10$).

Selection Type	Model	Mean *oN**	Mean *oP**	U	*p*
Ms	MLR	7.77	18.37	2155.5	.062
	ANN	12.07	26.87	2395.0	.002
Beats	MLR	11.07	32.73	162.5	.039
	ANN	35.73	25.60	79.0	.171

Table 4 Two-tailed Mann-Whitney U test results on selection of offsets.

4.2. Limitations

Our results show that there are indications of preferences on specific CFs over others in order to gain predictive power. Of course, it is not possible to draw general conclusions based on the presented results, as the results are only valid for the given dataset and the decision-maker context it represents. However, the goal of this paper is to present an approach capable of selecting proper CFs for a given context. The CFs selected in our final solutions have to be taken with caution. We did not optimize our prediction models for the presented context but mostly relied on provided standard settings of the model implementations. It is possible that by adjusting the prediction models or introducing different models, the final solutions could further improve.

In addition, analyzing physiological data is always difficult because changes in a participant's physiology might not always be due to the observed event but external factors. We took this fact into consideration by including the data of 60 participants recorded in a controlled laboratory environment to reduce external distraction in the best possible way. Also, recent studies indicate that the source of a change in physiology (e.g., arousal) does not matter to its later impact on behavior [37, 38].

4.3. Implications and future work

The approach has been demonstrated to be able to select physiological features that can predict auction behavior. With this, utilizing physiological information is a step closer to become more feasible in real-world ISs. In combination with today's ubiquity of physiological sensors and existing theoretical models (e.g., [39, 40]), the approach can be used to enhance (existing) ISs. Such enhancements (e.g., neuro-adaptive ISs and biofeedback) can support decision-making and potentially mitigate biases in a given decision-making context [41]. Although the additional information provided by the physiological information might appear limited, in a decision-making context, such as electronic auctions, the smallest advantage over one's competitors can make the difference between being first and being out of business. For example, in high stake situations, advising a trader to avoid taking unnecessary risks can prevent excessive monetary losses.

Certainly, future work is necessary to further this research and improve the results presented in this study. Using the approach in combination with additional CFs (e.g., "arousal meter" [42]), physiological measurements (e.g., EDA) and auction events (e.g., outcome of preceding auctions) will provide promising research opportunities and more precise prediction for a given decision-making context. Especially for electronic auctions, the approach can be used to compare the role of physiological measurements in different auction settings [43, 44], in order to determine bidding behavior and modify the underlying user interface or auction design accordingly. Even new auction designs that incorporate physiological information into the auction process itself are possible. This could increase excitement, affect bidding behavior, and provide additional hedonic value to participants.

The CFs found to have more predictive power than others can also be of interest to researchers of other disciplines. Disciplines such as medicine and psychology can build on these results and investigate

further relations of the underlying processes driving a decision-maker's behavior.

5. Conclusion

We have presented a working approach for selecting physiological measurements and their parameterization in order to create real-world ISs (such as decision support systems, neuro-adaptive ISs, and education support systems), which can profit from the hidden information that physiological information provides. Especially in a fast pace environment, such as an electronic auction, where every small piece of information can have tremendous advantages, making the most out of one's own physiological information can have a significant impact.

6. Acknowledgement

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