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Show Me How You Drive and I'll Tell You Who You Are Recognizing Gender Using Automotive Driving Parameters

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Abstract

The recognition and utilization of user-specific information is of increasing importance in relation to modern recommender systems and adaptive user interfaces. Associated with this trend is the increased need for privacy protecting measures in personalized systems. This work demonstrates the possibility to recognize user-gender from automotive driving data with high accuracy in an identity protecting manner. The analysis shows that variables in relation to acceleration, gas pedal actuation as well as situation dependent driving speed are especially informative about driver gender. The results and implications are discussed in relation to possible applications in adaptive user interfaces and personalized systems.

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Keywords: gender recognition; machine learning; personalization; adaptive user interface; user behavior, human factors;

1. Introduction

Nomenclature

AG	German for "inc."
AUC	Area under the curve
LASSO	Least Absolute Shrinkage and Selection Operator

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The capability to distinguish between both genders is an important ability in order to interpret gender-sensitive social information and develops at an age of approximately four [1]. Humans utilize a series of cues to identify other peoples gender. Amongst other features such as clothing and voice, humans recognize gender from visual features like the face or body structures [2]. Furthermore, these and other features have been intensively studied in order to train statistical classifiers for automatic gender recognition [3–6]. Besides the characteristics described above, people also infer others gender through observation of natural behavior for which gender differences have been reported in various areas such as risk taking [7] aggression [8], and most frequently in spatial abilities [9]. Gender differences in behavior can be partially explained by biological as well as evolutionary and socio-cultural factors. However, the missing consent concerning this topic is reflected in the still ongoing nature-nurture debate [10].

Analysis of user behavior for statistical recognition of demographics as well as psychometrics has recently gained popularity, especially with regard to computer and internet technology. This development is directly related to great advances in mobile computing technology and human computer interaction. Modern ubiquitous web and sensor technology exists in many every-day objects and makes it possible to unobtrusively collect large amounts of behavioral data. Some researchers even refer to this new approach as Psychoinformatics [11] or Computational Social Science [12]. In a previous study they used web browsing data to predict gender and age [13]. Others utilized various data from mobile phones to predict a multitude of demographic attributes[14]. Results of other researchers suggest that certain smartphone user behaviors as well as facebook likes can be used to even infer self reported big five personality traits [15,16] such as extraversion [17].

However, the analysis of behavioral driving data in the automotive context has been largely neglected for the purpose of gender recognition. In relation to driving behavior, previous research showed that traffic related mortality is higher for men than for females in the majority of countries worldwide [18,19]. These results are supported by other reports showing that although young men describe themselves as better drivers they drive riskier, use less safety equipment, and reported more risky driving behavior in comparison with females [20–22]. Whereas analysis of automotive driving parameters (speed, acceleration, steering angle etc) previously focused on aspects like fuel consumption, exhaust emissions and mobility patterns [23–27], the implications of individual differences in relation to automotive driving parameters have mostly been investigated as predictors for unsafe or risky driving [28–30].

The only data (known to us) related to gender specific driving behavior, recorded at a technical parameter level, was collected in two studies by [24,25] and an earlier investigation by [31]. All of these studies investigated the influence of several factors (among them gender) on driving parameters especially fuel consumption. Redsell et al. [31]noted that especially in changing environmental conditions (transition between street types) the individual driver characteristics increasingly influenced fuel consumption. Ericsson [24] discovered that the average acceleration was generally higher for men compared to women. This pattern was especially pronounced on a low speed street type. Average speed was not different between both genders, except on one street type where men drove faster in comparison with women. The author interpreted acceleration and velocity interaction effects with different street types as an indication for alternations in the street environment to trigger most gender or driver specific variation in driving parameters. In a bulletin Ericsson [25]again investigated the influence of human factors on automotive driving patterns. In addition to differences in acceleration patterns, they also found that in average, females drove at lower speed in comparison with men. However, it is difficult to generalize results of these studies due to small sample sizes (n=6, n=12, n=29 families), as well as in one case the fact that only the influence of an subject with no regard to a specific variable (gender) was investigated [31]. Furthermore, family samples (data from cars labeled as either male or female if more than 75% of the total driving was done by one gender) were used.

Comprehensively, these findings indicate that behavioral gender differences might be reflected in individual driving parameters and could possibly influence variables like fuel consumption and emission exhaust. The recording of automotive driving parameters in real world settings is costly and bears financial and actuarial difficulties. Virtual driving simulators are frequently used in industrial and academic settings for research and evaluations. Furthermore, modern driving simulators offer the possibility to record individual driving behaviors in a highly standardized, safe and cost-effective manner [32]. Although the external validity of driving simulator results has to be questioned [33], large sample studies are almost infeasible without initial leads from simulated driving studies. With this work we intend to investigate the possibility to infer driver-gender from automotive driving parameters. In relation to [24,25,31]previous research describing gender related differences in driving behavior, we expect variables in accordance to acceleration and speed to be good statistical predictors of drivers gender.

Furthermore meaningful information with regard to gender could possibly be extracted in driving situations where the type of driving situation is changing (e.g. change from a rural road to a highway, or at intersections).

Therefore we hypothesize that data related to vehicle acceleration at changing driving situations will be predictive for gender recognition. Nonetheless, a major part of this investigation was to identify possible additional meaningful predictors in an exploratory fashion (see the Method section for details). Aims of this study were the accurate statistical recognition of driver gender, based on automotive driving parameters as well as the identification of promising gender sensitive parameters beyond those identified in previous research. In addition, we also wanted to describe the data with aninterpretable model in order to better understand dependences between gender and driving parameters.

2. METHOD

2.1. Participants

A total of 182 subjects participated in the virtual driving simulation. All participants were haphazardly recruited from the pool of AUDI employees in Ingolstadt, Germany. Since some participants (n=37) experienced heavy symptoms of simulator sickness, they had to stop the simulation and their data were excluded from the sample. A final sample of 145 (N=145) participants remained for statistical analysis. Gender was not totally equally distributed in our sample with 83 men and 62 women. The mean age of all participants was 32 years. Most participants (n=65;44.8%) were between 18 and 28 years old, 50 participants (34.5%) were between 29 and 39 years old, 25 participants (17.2%) were between 40 and 50 years old and 5 participants (3.4%) were 51 or older. The sample was skewed in terms of education, as 71.7% of all participants had college or university education. Data collection and experimental procedures were coordinated between the AUDI AG workers committee and the Ludwig-Maximilians-Universität München in order to be conducted in a most privacy protecting and non-invasive manner.

2.2. Apparatus& Procedures

The driving task took place in a driving simulator of the AUDI AG in Ingolstadt, Germany. The used driving simulator consists of a circular 2.6m^2 x 13.3m^2 250° frontal and side projection surface, with 16 million pixels as well as a 6m^{2}x3m^2 projection surface with 4.6 million pixels, located behind the car mockup. A visual refresh-rate of 60Hz and a data collection rate of 25Hz were used during the experiment. A specifically designed test track was used during the experiment. Various sections including straights, crossroads, roundabouts, lane changes and highways were implemented in the track. During these sections, variables in relation to speed, lane departure, braking force, gas pedal pressure, steering angle were collected. The drive along the 23.7km test track took approximately 20 minutes.

Participants arrived at the laboratory and received a standardized written instruction with general information about the experimental procedures, as well as a short demographic questionnaire. On completion of the questionnaire, participants were guided to the driving simulator mockup. Once in the car, participants were verbally instructed about the interactions they had to perform during the experiment as well as possible effects of simulator sickness. During the drive, participants were verbally navigated along the route. Although participants were alone in the car mockup during the complete duration of the experiment, verbal communication with the experimenters was possible at all times.

2.3. Statistical Analysis

To create features for statistical modeling we used combinations of various standard driving parameters with the current driving situation, resulting in a set of 370 predictors. Both descriptive measures (mean and standard deviation) as well as distributional measures (percentage of time in certain value ranges) were used for model creation. An overview of the recorded driving parameters as well as the driving situations is provided in Table 1. As linear models are sensitive to predictor noise and missing values we removed near zerovariance variables, and two cases containing missing values were removed from the data set (p=74).Although the elastic net is capable of dealing with correlated variables we still removed, highly correlated predictors (p=106) (if r >0.80) to achieve better predictive performance[34]. After pre-processing, 189 of the initial 370 predictor variables remained in the data set. For modeling, the data set was randomly split into a training (94/65%) and a testing set (n=49/35%).Considering the high number of predictors (P=189) in relation to our sample size we used binomial elastic net regularization to statistically classify driver gender using a subset of most contributory predictors.

Table 1. Overview of all parameters available in the data set. Actual features were created through combination of driving situations with all the other parameters. E.g.: cross1_gas_SD (Standard deviation of the gas pedal actuation in crossing 1)

Velocity	km/h	**Brake Pedal actuation**	
	M/SD		M/SD
% of time	0-15 km/h	% of time	0-25%
% of time	15-30 km/h	% of time	25-50%
% of time	30-50 km/h	% of time	50-75%
% of time	50-70 km/h	% of time	75-100%
% of time	>70 km/h		
Steering Wheel Angle	rad	**Acceleration/Deceleration**	m/s2
	M/SD		M/SD
% of time	< -5	% of time	< -2.5
% of time	-5 >< -3	% of time	- 2.5 >< -1.5
% of time	-3 >< -1	% of time	- 1.5 >< -1.0
% of time	-1 >< 0	% of time	- 1.0 >< -0.5
% of time	0 >< 1	% of time	- 0.5 >< 0.0
% of time	1 >< 3	% of time	- 0.0 >< 0.5
% of time	3 >< 5	% of time	0.5 >< 1.0
% of time	> 5	% of time	1.0 >< 1.5
Gas Pedal actuation		% of time	1.5 >< 2.5
	M/SD	% of time	> 2.5
% of time	0-25%	**Situations**	
% of time	25-50%	Start of the drive	Roundabouts
% of time	50-75%	Straight sections	Highway on-ramp
% of time	75-100%	Crossings	

The elastic net model represents a combination of the ridge regression and the LASSO (Least Absolute Shrinkage and Selection Operator), especially suitable for p > n problems [35] and is capable to perform both shrinkage of correlated predictors and grouped variable selection. This perfectly fitted our case, as we included more predictors than subjects with correlation between them. The model was trained with 10 fold 10 times repeated cross validation in order to avoid overfitting. During each resampling iteration the respective sample was centered and scaled.

3. Results

We chose to maximize specificityof the final model, in order to prevent the algorithm from predominately predicting the majority class (men). The elastic net model with parameters α=0.1 and λ=0.1showed a test set AUC (Area under the curve)of 0.89 (95% $CI_{(Auc)}$=[0.80,0.99]). See Table 2 for the performance measures of the model. The comparison of the lower specificity 0.65 and high sensitivity 0.97 shows that the model is more successful in classification of males (positive class) in comparison with females. This imbalance was most likely induced due to disproportional ratios of men an women in the sample.

Table 2. Performance Statistics of the Elastic Net Model

Measure	Value
AUC	0.89
95% CI $_{(Auc)}$	[0.80,0.99]
Accuracy (Acc)	0.84
95% CI $_{(Acc)}$	[0.70, 0.93]
No Information Rate (NIR)	0.59
P-Value [Acc > NIR]	0.0002
Kappa	0.65
Sensitivity	0.97
Specificity	0.65
Balanced Accuracy	0.81
Positive Class	Men

3.1. Variable importance

The final model included 116 non-zero predictors. In addition to the direction of the effect we also notice that certain types of measures are more often present in the 40 top ranked predictors than others. Most notably, almost half of all variables are associated with acceleration (18), while only two predictors are related to actuation of the braking pedal. Roughly the same amount of variables related to steering wheel angle (8), velocity (7) and gas pedal actuation were ranked among the top predictors. Furthermore, it is interesting that especially distributional variables were predictive in our model. Although it would be interesting to describe more of the important variables in our model with further detail, we do not elaborate on this aspect as this would go beyond the scope of this paper.

3.2. Discussion

To our knowledge, this is the first paper that investigates gender recognition based on automotive driving parameters. The goal of this paper was to investigate whether driving data based on a 20 minute drive in a simulator is sufficient for accurate prediction of driver-gender using machine learning techniques.

Our results show that although we did not use personal information such as text input or video data, it was possible to classify gender well above chance, purely based on technical driving parameters. As hypothesized, features relating to acceleration in dynamic driving situations were identified as most important predictors in the model. However, variable importance measures also illustrate that additional parameters with relation to individual acceleration behavior were contributing to the final model. Additionally, speed (velocity), gas pedal actuation and measures related to the steering wheel angle turned out to be especially predictive in our model. These gender specific patterns in acceleration, gas pedal actuation and velocity are in accordance with previous research [24,25,31]that indicated possible gender differences in automotive driving parameters. Intuitively, these differences in driving parameters could be closely related to gender differences in spatial orientation, frequently reported in previous research[18]. However, the real reasons for gender differences in driving patterns remain unclear and should be investigated prospectively[9].In consideration of the relatively short virtual test drive (20min), classification accuracy is quite impressive. Furthermore, if these results are reproducible in real life driving situations, alterations or suggestions for adaptations of systems in the car could be made possible after a very short period of time. Gender specific needs could be addressed in both usability and functionality in human-machine interaction of adaptive user interfaces. Navigational strategies for example have been reported to be different for both genders in previous studies. Whereas men mostly use Euclidian information when orienting, it was reported that women predominantly rely on landmark information [36,37]. In addition to gender sensitive interfaces for navigational tasks gender prediction while driving could also be used to account for more individual aesthetical needs in adaptive user interfaces. For example, results of a study suggest design strategies like gamification as differentially appealing to both genders [38]. Furthermore, gender-adaptive systems in vehicles could alter aspects like seat ergonomics, temperature or even interface characteristics like colors and point of interests in a map.

Especially useful might be the alteration of system adjustments that usually do not justify the installation of a button or menu entry or are not intuitively understandable to the average user. For example, steering effort is a factor that could very well be adjusted to user-specific needs in am subliminal manner [39]. Considering the wide variety of gender differences reported so far, many more adjustments in adaptive user interfaces could be explored.

The analysis of behavioral gender differences does not exactly simplify gender recognition in comparison with facial image classification [3,4]. However, it could prove as useful in situations where neither visual nor linguistic information can be collect (cars without camera, privacy violations). Gender recognition via camera might be privacy violating, as in addition to gender, an image could reveal the identity of a person.

Even though, driving data obtained in a high-end virtual driving simulation offers high degrees of standardization and does relate to real driving situations, they are not equivalent to data collected in real settings [33]. Therefore, care has to be taken generalizing these results to real driving situations. In real driving contexts, different and additional variables might be informative about driver gender. Furthermore, variables like the steering wheel angle as well as actuation of the braking pedal might yield different values once recorded in real life settings, due to the lags in the simulation [33]. In addition, the influence of factors like virtual distance perception (that have been heavily investigated outside of the automotive context) might cause deviations in virtual in comparison with in real driving behavior. For a review see [40].

3.3. Conclusions and Future Work

This work demonstrates the possibility to recognize drivers gender with high accuracy based on standard driving parameters obtained in a 20 minute virtual test drive. Automated, non-camera based gender recognition from automotive driving parameters opens new possibilities for gender adaptive systems and user interfaces in the car.

The present work acts as a starting point for further research in relation to the analysis of driving parameters in order to infer user specific characteristics. Future work should focus on more complex criteria such as the interaction between gender, age and traits such as personality. This could be promising as gender and age are known to interact with big five personality factors such as emotional stability, agreeableness [41,42] and sub-facets like assertiveness and excitement seeking [43]as well as openness to feelings. The latter ones might be reflected in individual driving behavior. The presented results do not shed light onunderlying reasons for gender differences in driving parameters.

Therefore, continuativeresearch shouldfurther investigate the cause of gender differences in the observed variables by e.g. linking them to biological or cognitive theories.In direct relation to that, the current results should be compared and validated based on driving parameters obtained in real life driving settings, a goal we intend to achieve in the near future.

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