Personality gaze patterns unveiled via automatic relevance determination

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Abstract. Understanding human gaze behaviour in social context, as along a face-to-face interaction, remains an open research issue which is strictly related to personality traits. In the effort to bridge the gap between available data and models, typical approaches focus on the analysis of spatial and temporal preferences of gaze deployment over specific regions of the observed face, while adopting classic statistical methods. In this note we propose a different analysis perspective based on novel data-mining techniques and a probabilistic classification method that relies on Gaussian Processes exploiting Automatic Relevance Determination (ARD) kernel. Preliminary results obtained on a publicly available dataset are provided.

Keywords: Eye movement · Gaze · Social interaction · Human behaviour · Gaussian Process · Classification · Personality · Big Five.

1 Introduction

The Latins would say 'oculus animi index' to refer the amount of personal information provided by a person's eyes. The gaze, indeed, is an important component of social interaction and a crucial non-verbal signal adopted as a basic form of communication [30]. Humans profoundly entrust on gaze cues during social and cooperative tasks with other conspecifics. This effect negatively emerges when referring to persons with autistic-like traits that may have troubles in understanding signals coming from the eye region of the other's face [1].

Eye movements are shown to be relevant and strictly related to the expression and perception of emotional states [3, 2, 29], cognitive goals [13, 48, 7], personality traits [44, 41, 36, 12, 28] and is known to play a key role in regulatory functions, as conversational turn-taking [20]. In the course of a typical face-to-face interaction, eye contact is an indicator of trustworthiness and attractiveness [6, 33], although a long direct gaze could be interpreted as a threat [34].

Neuroimaging studies of face perception confirms that direct eye contact activates specific brain areas involved in human interaction and face processing, namely the superior temporal sulcus (STS) [25]. In particular, the intraparietal sulcus (IPS) appears to specifically support the recognition of another person's gaze direction [40, 14]. These results confirm that person perception is increased when gaze is directed toward the viewer.

Having said that, and without going deeper in neurobiological details, it looks obvious that in order to realise effective and 'empathic' computational systems that naturally interacts with humans (HCI) it is necessary to understand or, at least, take into consideration the processes behind human gaze deployment. These could eventually be involved to mediate the interaction with a virtual or physical agent, in particular when dealing with humanoid robots that include eyes (for synthesis) [9], or with ones that gauge the counterpart's gaze (for recognition) [49].

In this work we will focus on the involvement of personality traits as indicator of specific gaze patterns. Personality is an information typically expressed by adopting the Big Five personality traits [23], also known as the five factor model (FFM). The five factors have been defined as agreeableness, conscientiousness, extraversion, neuroticism and openness to experience. These are assessed via standard psychological tests to the participants of an experiment.

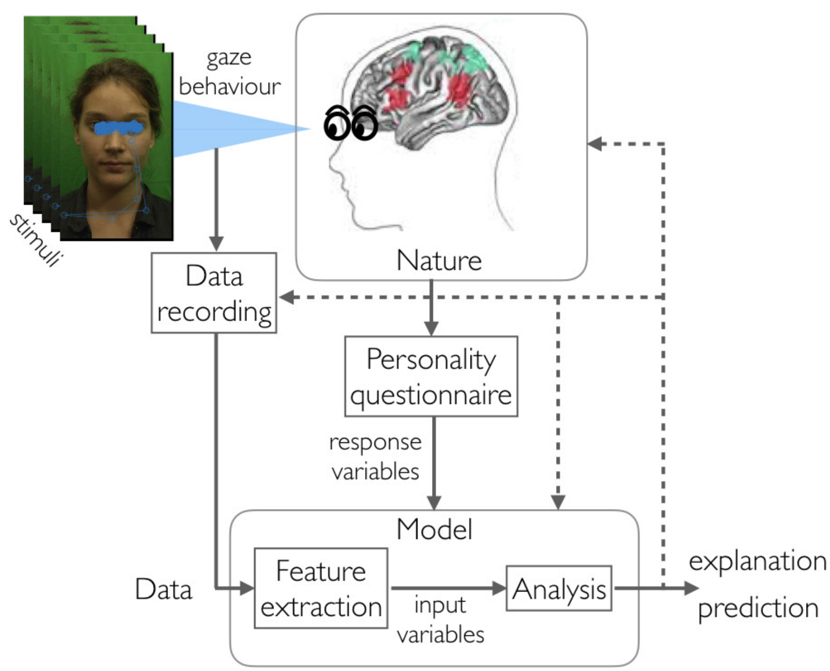


Fig. 1. Investigating subject's personality traits from gaze behaviour in face-to-face interaction (time-varying face stimuli). Full arrows highlight the *Data* $\rightarrow$ *Model* road to explanation and prediction; dashed arrows trace the feedback information to meet the quest for suitable predictor variables, model revision and experimental design.

Previous results suggest that personality influences visual information processing and social gazing, but most of these approaches present some drawbacks, such as small dataset size [12], focus on very specific personality traits [28], adoption of non-natural stimulus [44] and in general, for the analysis, they all rely on classical statistical methods applied to spatial and temporal gaze features extracted from raw data.

As to the latter point, here we offer a different perspective. It has been argued [21] that statistical rituals striving for an unthinking "search for statistical significance" have led to to "irrelevant theory, questionable conclusions, and has kept statisticians from working on a large range of interesting current problems" [10]. Breiman, in particular has acknowledged that beyond classic data analyses, algorithmic modeling has developed rapidly in realms outside statistics (involving complex prediction problems such as speech recognition, image recognition, nonlinear time series prediction), and it has gained currency since it can be used both on large complex data sets and as a more accurate and informative alternative to data modelling on smaller data sets [10]. In this view the classic data modelling approach starts with assuming a treatable model relating predictor variables to response variables (e.g., a linear regression model) and model validation is performed through classical tests (goodness-of-fit, residual examination, etc). In contrast, machine learning-based modelling relies upon an algorithm that operates on input data (usually in the form of a feature vector) to predict the responses; here, model validation is in terms of measured predictive accuracy. However, these two "cultures" [10] need not be mutually exclusive options. After all statistics starts with data and builds models (cfr. Fig. 1) in order to be able to: i) forecast what the responses are going to be to future input variables (prediction level); ii) to derive information about how nature is associating the response variables to the input variables (explanation level). The roots of statistics, as in science, lie in working with data and checking theory against data [10]. If focus is brought back on actually solving the problem, then in many complex and concrete cases this attitude is likely to lead to the adoption of a hybrid methodology. It is worth mentioning that, though algorithmic models can give better predictive accuracy than data models, it is often objected that an emphasis on predictive accuracy leads to complex, uninterpretable models that generalise poorly and offer little explanatory insight. However, the trade-off between predictive accuracy and interpretability is less grievous than deemed [26]. Indeed, it has been shown in the machine learning field that by searching for parsimonious versions of the adopted model (in the Occam's sense), it is possible to achieve predictive performance close to optimal, while gaining explanatory insights into the relevant mechanisms of the phenomenon under consideration [26].

Such a synergistic perspective is the methodological rationale behind the work presented here and it is summarised at a glance in Fig. 1. Techniques coming from different research areas will be adopted, both for feature extraction and classification. In particular, we show how the Automatic Relevance Determination (ARD) approach, which has been originally conceived in the Bayesian machine-learning framework as an effective tool for pruning large numbers of irrelevant features [37], is suitable to lead to a sparse subset of predictor variables. These bear explanatory value, while avoiding cumbersome classic statistical procedures for selecting features, or even more complex machine learning-based approaches (e.g., [5], for the specific case of gaze analysis).

Results obtained on a public dataset [19] acquired during a face-to-face experiment will provide additional levels of explanation of gaze behaviours adopting a probabilistic approach. An overview of the method is given in Section 2, while Section 3 presents the simulation results, and a conclusive discussion is given in Section 4.

2 Method

Gaze shifts are the result of two main oculomotor actions (as shown in Fig. 2): fixations and saccades. The former are concerned with bringing onto the fovea salient objects of a scene, while the latter are rapid transitions of the eye that permit to jump from spotting one location of the viewed scene to another. It is worth noting that the saliency of an object is in principle strictly related to a given task [47]. The study presented here relies on eye-tracking data collected from subjects along a free-viewing (no external task) experiment. Though this choice might be questionable in general [47], in our case the free-viewing condition is suitable for dynamically inferring the history of their "internal" selection goals and motivation, and thus their personal idiosyncrasies, as captured by the resulting attentive behaviour.

Beyond fixations and saccades, in the presence of moving objects (that are likely to occur in dynamic scenes) an additional action arises, called smooth pursuit. This is typically associated with fixations since the focus remain on the same stimulus, but in this case a movement of the eyes is required.

Recent research has shown that the pupil signal from video-based eye trackers contains an additional event, namely post-saccadic oscillations (PSOs). These are very important for a precise temporal classification of the events. PSOs in fact, have shown to influence fixation and saccade durations by at least 20 ms [35].

In the following we will refer to a visual scan path as the result of a stochastic process; namely a time series defined as $\{(r_1, t_1), (r_i, t_i), \cdots\}$, where $r_i = (x_i, y_i)$ identifies a specific gaze location at time t_i in presence of a natural scene $\mathcal{I}$.

$$\mathcal{I} \mapsto \{(r_1, t_1), (r_i, t_i), \cdots\} \tag{1}$$

A classification step [39] is eventually required to distinguish between the four oculomotor actions presented above. This allows to parse the raw data time series into a higher level representation of events: fixations $\mathbf{f} = (r, t^s, t^e)$, saccades $\mathbf{s} = (r^s, r^e, t^s, t^e)$, smooth pursuits $\mathbf{p} = (r^s, r^e, t^s, t^e)$ and PSO $\mathbf{o} = (r^s, r^e, t^s, t^e)$. In the case of saccades, smooth pursuits and PSO, r^s and r^e represent respectively the start and end gaze location. Likewise t^s and t^e stand for start and end time of the event.

2.1 Feature extraction

Considering a given scan path $\mathcal{W} = \{(\mathbf{f_i}, \mathbf{s_i}, \mathbf{p_i}, \mathbf{o_i})\}_{i=1}^{N}$, with N the number of events, we derive features related to the spatial and temporal properties of specific events. Given the stochastic nature of eye movements, these too can be seen as random variables (RVs) generated by an underlying random process. Such properties include fixation duration, saccade amplitude, saccade direction and event frequency.

Saccade amplitudes and directions are important because lie at the heart of systematic tendencies or "biases" in oculomotor behaviour. These can be thought of as regularities that are common across all instances of, and manipulations to, behavioural tasks [45, 46]. One remarkable example is the amplitude distribution of saccades and that typically exhibit a positively skewed, long-tailed shape [47, 45, 46]. Other paradigmatic examples of systematic tendencies in scene viewing are: initiating saccades in the horizontal and vertical directions more frequently than in oblique directions; small amplitude saccades tending to be followed by long amplitude ones and vice versa [45, 46]. Indeed, biases affecting the manner in which we explore scenes with our eyes are well known in the psychological literature (see [31] for a thorough review), and have been exploited in computational models of eye guidance [4, 17, 32] providing powerful new insights for unvealing covert strategies about where to look in complex scenes.

As an additional property we also take into consideration the pupil dilation. This information is typically adopted for emotion-related tasks, in particular to assess the level of arousal [8]. To the best of our knowledge, this is the first time pupillometric data are adopted to study personality traits.

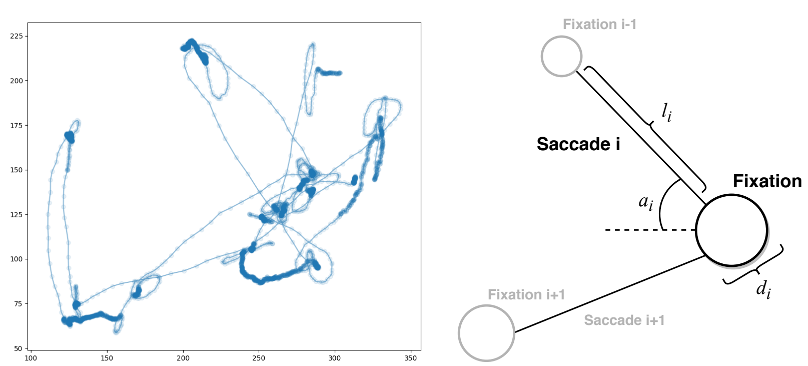


Fig. 2. (Left) Visualisation of a typical visual scan path record. (Right) Sequence of three fixations with indication of extracted features: fixation duration (d_i), saccade amplitude (l_i) and saccade direction (a_i).

Fixation duration The duration of the *i-th* occurrence of the identified fixations measures the time spent spotting a specific location and it is obtained as $d_i =$

$t_i^e - t_i^s$. These durations $D = \{d_i\}_{i=1}^N$ can be seen as gamma-distributed random variables $D \sim \Gamma(a, b)$, whose probability density function (pdf) is defined as

$$f(d \mid a, b) = \frac{1}{b^a \Gamma(a)} d^{a-1} \exp\left(\frac{-d}{b}\right) \tag{2}$$

Here $\Gamma(\cdot)$ is the gamma function; the parameters of shape $D_a = a$, that closely approximates a normal distribution when large, and scale $D_b = b$ are fitted via maximum likelihood estimation (MLE).

Saccade amplitude For what concern saccades, one of the properties taken in consideration is their amplitude. This measure the absolute length of the eye movement and is obtained as the Euclidean distance between the start and end locations of each saccade, $l_i = \sqrt{(x_i^s - x_i^e)^2 + (y_i^s - y_i^e)^2}$ where $r_i^s = (x_i^s, y_i^s)$, $r_i^e = (x_i^e, y_i^e)$ and $(r_i^e, r_i^s) \in \mathbf{s}_i$. In this case, the amplitudes $L = \{l_i\}_{i=1}^N$ are assumed to be sampled from an α-stable distribution $L \sim f(\boldsymbol{\xi}; \alpha, \beta, \gamma, \delta)$. These form a four-parameter family of continuous probability densities [22], where the parameters are the skewness β (measure of asymmetry), the scale γ (width of the distribution), the location δ and the characteristic exponent α, or index of the distribution that specifies the asymptotic behavior of the distribution as $l^{-1-\alpha}$. Thus, relatively long gaze shifts are more likely when α is small. For $\alpha \geq 2$ the usual random walk (Brownian motion) occurs; if $\alpha < 2$, the distribution of lengths is "broad" and the so called Leývy flights take place. Such distributions have been shown to suitably capture the statistical behaviour of gaze shift amplitudes [11, 4], and, more generally, brain activities occurring in the attention network [18]. There is no closed-form formula for f, which is often described by its characteristic function $E\left[\exp(itx)\right] = \int_{\mathbb{R}} \exp(itx) dF(x)$, F being the cumulative distribution function (cdf). Explicitly,

$$E\left[\exp(itx)\right] = \begin{cases} \exp(-|\gamma t|^\alpha (1 - i\beta \frac{t}{|t|}) \tan(\frac{\pi\alpha}{2}) + i\delta t) \\ \exp(-|\gamma t| (1 + i\beta \frac{2}{\pi} \frac{t}{|t|} \ln |t|) + i\delta t) \end{cases}$$

the first expression holding if $\alpha \neq 1$, the second if $\alpha = 1$. Special cases of stable distributions whose pdf can be written analytically, are given for $\alpha = 2$, the normal distribution $f(x; 2, 0, \gamma, \delta)$, for $\alpha = 1$, the Cauchy distribution $f(x; 1, 0, \gamma, \delta)$, and for $\alpha = 0.5$, the Lévy distribution $f(x; 0.5, 1, \gamma, \delta)$; for all other cases, only the characteristic function is available in closed form, and numerical approximation techniques must be adopted for parameter estimation, e.g., [15], which will be used here.

Saccade direction The second property obtained from saccades, and usually overlooked, is the direction of successive eye movements. This property, called saccade direction, measures the angular direction between the start and end location of a saccade. Recalling that a saccade is represented as $\mathbf{s}_i = (r_i^s, r_i^e, t_i^s, t_i^e)$, we define its angular direction as $a_i = \texttt{arctan2}(y_i^e - y_i^s, x_i^e - x_i^s)$, where $\texttt{arctan2}$ is a function that extends the definition of $\arctan(y/x)$ to the four quadrants $(-\pi, \pi]$, taking in consideration the sign combinations of y and x.

The saccade directions are typically non-uniformly distributed, with most saccades in the horizontal and vertical directions than in oblique [45]. This circular data can be modelled by adopting a von Mises distribution, whose pdf is symmetric and unimodal, and is given by

$$f(a \mid \mu, \kappa) = \frac{\exp(\kappa \cos(a - \mu))}{2\pi I_0(\kappa)}, \tag{3}$$

where $I_0(\cdot)$ is the zero-th order modified Bessel function. Its parameters are the mean direction μ and the dispersion, captured by a concentration parameter κ. For large values of κ, the distribution is concentrated around the μ direction, while for $\kappa = 0$ the pdf is a uniform distribution.

For heterogeneous data, as in the case of saccade directions, a single von Mises distribution does not provide an adequate fit, so it will be discarded in favour of a mixture of two von Mises distributions. Its parameters $A_\mu = [\mu_1, \mu_2]$ and $A_\kappa = [\kappa_1, \kappa_2]$ are estimated using an Expectation-Maximization scheme [27].

Event frequency An additional information about the gaze patterns is provided by the frequency of each of the four classified events. These are normalised adopting a classical softmax approach, so that $E_j = \frac{e_j}{(e_1 + \cdots + e_4)}$, with $j = 1, \ldots, 4$.

Pupil dilation For what concerns pupil dilation, we consider its absolute percentage variation v_i with respect to the average size in an initial window of 250ms. In this case $V = \{v_i\}_{i=1}^N$ is assumed to be sampled from an half-normal distribution, whose pdf is given by

$$f(v \mid \sigma) = \frac{\sqrt{2}}{\sigma\sqrt{\pi}} \exp\left(-\frac{v^2}{2\sigma^2}\right) \tag{4}$$

and its unique parameter $V_\sigma = \sigma$ estimated via MLE.

Eventually, the gaze behavior of each subject in the dataset is represented by a feature vector,, namely the random vector $\mathcal{X} = [D_a, D_b, L_\gamma, L_\delta, A_\mu, A_\kappa, E, V_\sigma]$ (cfr. Fig. 3). A realisation $\mathcal{X} = \mathbf{x}_i$, summarising the gaze behaviour of subject i on the observed facial stimuli, will represent the observed input of a probabilistic classifier presented below.

2.2 Personality trait classification

The classification stage aims at finding a possible nonlinear mapping between a subset of salient features contained in $\mathcal{X}$ and the levels of personality traits $\mathcal{Y}$ acquired in the dataset (the response variables). In the binary case, as the one described in Section 3, the model is defined as

$$p(y_i \mid \mathcal{X} = \mathbf{x}_i) = \varPhi(y_i f(\mathbf{x_i})), \tag{5}$$

where $\mathbf{x}_i$ represents the realisation of the random vector $\mathcal{X}$ for the i-th subject, and the $y_i \in \{-1, 1\}$ is the result of a *probit regression* approach that maps

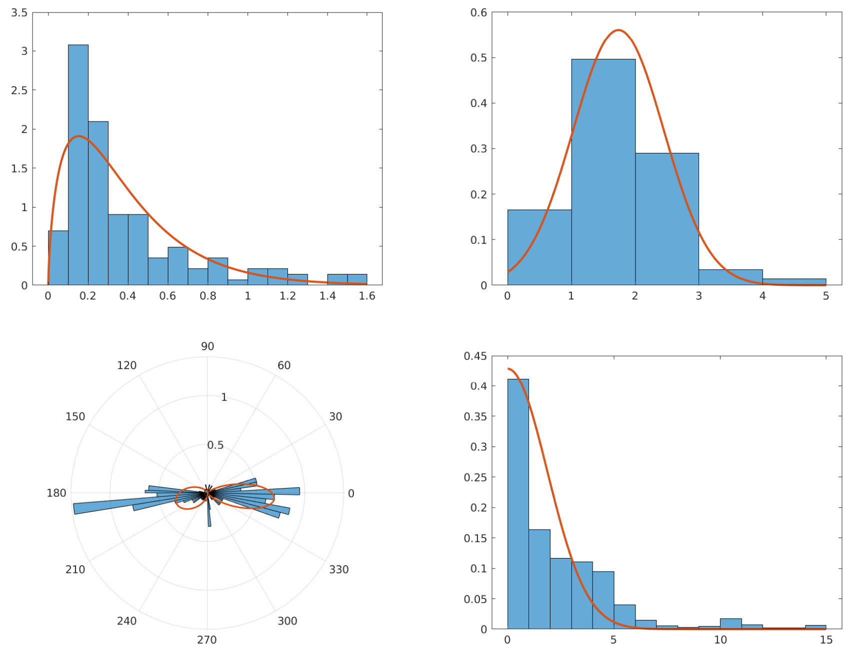


Fig. 3. Fitting of the features extracted from a sample of raw gaze data. (Top) Histogram of fixations durations, fitted via Gamma distribution and saccades amplitudes via the α-stable distribution. (Bottom) Saccade directions fitted with a mixture of von Mises distributions and histogram of pupil dilations overlaid with the half-normal distribution fit.

the output of a regression model into a class probability, namely the cumulative density function of a standard normal distribution $\Phi(z) = \int_{-\infty}^{z} \mathcal{N}(x \mid 0, 1)dx$. The function f in Eq. 5 is sampled from a Gaussian Process,

$$f \sim \mathrm{GP}(\cdot \mid 0, k) \tag{6}$$

that assumes prior probability over functions $p(\mathbf{f}(\mathbf{X})) = p(f(\mathbf{x}_1), \ldots, f(\mathbf{x}_N))$ to be jointly Gaussian with mean function $\mu(\mathbf{x}) = 0$ and covariance matrix $\mathbf{K}$. The latter is usually chosen as a positive definite kernel function $\mathbf{K}_{ij} = k(\mathbf{x}_i, \mathbf{x}_j; \theta)$, θ being the hyperparameters of the kernel function. Such function constrains similar inputs $(\mathbf{x}_i, \mathbf{x}_j)$ to have similar output values (but refer to Rasmussen and Williams [43] for an in-depth and wide introduction).

Often, in going from data to models, there are many possible inputs that might be relevant to predicting a particular output. Thus, we need algorithms that automatically decide which inputs are relevant. In the framework of Gaussian Processes one such tool is naturally provided by automatic relevance determination (ARD) kernels [37].

The adopted ARD kernel is a more general form of the squared exponential kernel for multi-dimensional inputs, that can be defined as

$$k(\mathbf{x}, \mathbf{x}'; \theta) = \sigma^2 \exp\left[-\frac{1}{2}\sum_{d=1}^{D}\left(\frac{x_d - x_{d'}}{w_d}\right)^2\right], \tag{7}$$

with hyperparameters $\theta = \{\sigma^2, w_1 \cdots w_D\}$. Here σ^2 is a scale parameter that determines the variation of function values from their mean. Most important, a different weight w_d, namely the length scale of the function along input dimension d, is assumed for each value x_d of the d-th feature in $\mathcal{X}$. This controls the horizontal length scale over which the function varies. In other terms, w_d determines the relevancy of input feature d to the classification problem: x_d is not relevant if $1/w_d$ is small.

The ARD formulation is usually exploited at the training stage, in terms of an automatic Occam's razor, in order to prune irrelevant dimensions, thus helping towards automatically finding the structure of complex models. In our scenario this will help us identifying predictive features for a specific personality trait.

3 Data analysis and results

Analysis has been conducted on a large public available dataset [19]. This includes gaze recordings from 403 participants (202 males, 201 females) watching videos of another person, initially gazing toward the bottom, then gazing up at the participant. A 10-item personality questionnaire based on the Big Five personality inventory [42] has been submitted to each participant, to define values for each of the five classes: agreeableness, conscientiousness, extraversion, neuroticism and openness to experience. They have been assessed through two items, going from 5 to 1, so that the lowest score ($p = 2$) is high in that trait, while highest score ($p = 10$) is low in that trait. It is worth mentioning that to the best of our knowledge this is the only public dataset the provides gaze recordings and personality traits values.

In order to highlight the behavioural differences of each personality trait, a binary classification approach with k-fold cross-validation was adopted ($k = 10$). The classes were formed by separating the highest ($C_1 = \{2 \le p \le 5\}$) and the lowest ($C_2 = \{7 \le p \le 10\}$) levels of each trait. The neutral value ($p = 6$) has been excluded because considered not relevant.

This partitioning led, in some cases, to unbalanced classes that were treated using the ADASYN oversampling technique [24] inside each fold of the cross-validation, in order to avoid possible overfitting problems. ADASYN is a novel extension of SMOTE [16] method that aims at creating, via linear interpolation, new examples from the minority class next to the bound with the majority one.

Classification results, shown in Figure 4, include a comparison with a linear discriminant analysis (LDA) and a support vector machine (SVM) with radial basis function kernel. It shows how the GP classifier outperforms, in general, the other two methods and is able to correctly guess the personality class, apart from neuroticism, for the $\geq 73\%$ of cases (chance level is 50%). To provide an overall quantitative evaluation, the mean value of the accuracy and the values of other three metrics for each personality trait, over 10 cross-validation folds of GP classification, are provided in Table 1.

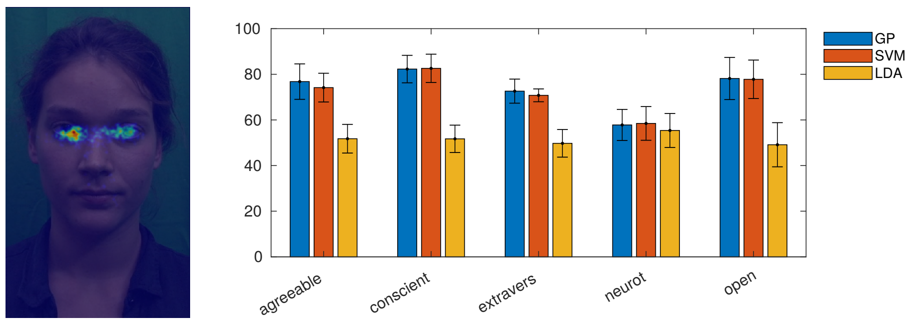
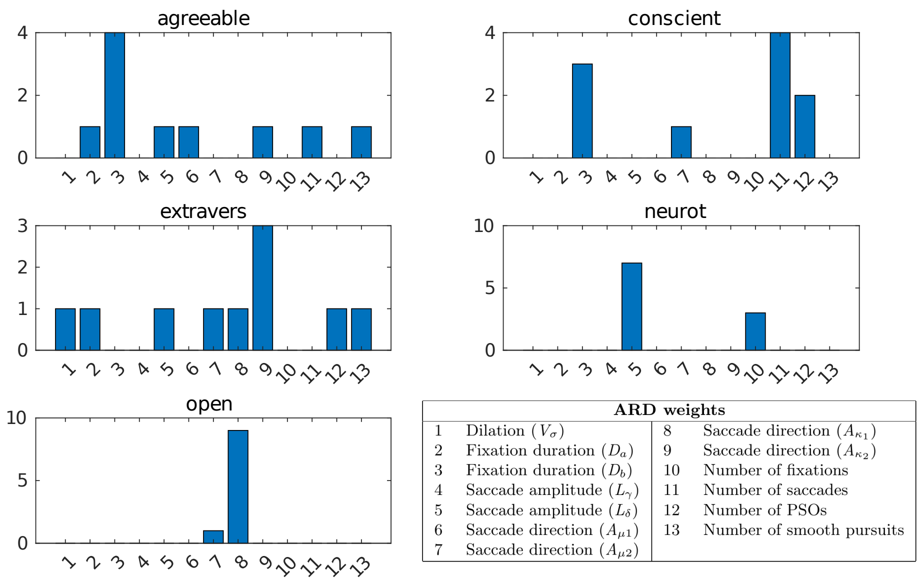


Fig. 4. (Left) Heatmap visualisation of fixations recorded from a subject during the experiment. (Right) Mean classification accuracy (and standard dev.) for each personality trait obtained with GP classification, SVM with Gaussian kernel and LDA.

Table 1. Mean value (and standard dev.) of the accuracy, precision, recall and F-measure for each personality trait obtained with Gaussian process classifier.

Personality trait	**Accuracy**	**Precision**	**Recall**	**F-measure**	
	0.77 ± 0.08	0.79	0.96	0.87	GP
agreeableness	0.74 ± 0.06	0.78	0.93	0.85	SVM
	0.52 ± 0.06	0.78	0.54	0.64	LDA
	0.82 ± 0.06	0.86	0.94	0.90	GP
conscientiousness	0.82 ± 0.06	0.86	0.94	0.90	SVM
	0.52 ± 0.06	0.86	0.53	0.65	LDA
	0.73 ± 0.05	0.74	0.96	0.84	GP
extraversion	0.71 ± 0.03	0.75	0.92	0.82	SVM
	0.50 ± 0.06	0.71	0.54	0.62	LDA
	0.58 ± 0.07	0.48	0.44	0.45	GP
neuroticism	0.58 ± 0.07	0.45	0.14	0.22	SVM
	0.55 ± 0.07	0.45	0.53	0.49	LDA
	0.78 ± 0.09	0.82	0.95	0.88	GP
openness	0.78 ± 0.08	0.82	0.93	0.87	SVM
	0.49 ± 0.10	0.78	0.53	0.63	LDA

For what concerns the ARD weights learned during the GP training, these have been aggregated adopting a ‘winner-takes-all’ approach. In other terms, for each fold have been considered only the most prominent feature with respect to each personality trait. Final results are shown in Figure 5.



ARD weights			
1	Dilation (V_σ)	8	Saccade direction ($A_{\kappa 1}$)
2	Fixation duration (D_a)	9	Saccade direction ($A_{\kappa 2}$)
3	Fixation duration (D_b)	10	Number of fixations
4	Saccade amplitude (L_γ)	11	Number of saccades
5	Saccade amplitude (L_δ)	12	Number of PSOs
6	Saccade direction ($A_{\mu 1}$)	13	Number of smooth pursuits
7	Saccade direction ($A_{\mu 2}$)		

Fig. 5. The ARD weights resulting after training the GP classifiers. The x-axis indicates each of the extracted features $\mathcal{X} = [V_\sigma, D_a, D_b, L_\gamma, L_\delta, A_\mu, A_\kappa, E]$, while y-axis reports the number of 'wins' in the cross-validation.

Beyond the predictive accuracy gained by the model, it is remarkable to note how ARD weights, automatically derived along the training procedure, provide insights with respect to the most relevant features that characterise, according to this analysis, the different personality traits. For example, extraversion and openness to experience are best described in terms of saccade directions; conscientiousness is mostly accounted for by the number of saccades and fixation duration, while the latter is prevalent in explaining agreeablenes. The neuroticism trait, though more difficult to predict than others, is however clearly related to exploratory behaviour represented by saccade amplitude.

4 Discussion

We presented a novel approach for the analysis of gaze patterns in relation to personality traits. We adopted a probabilistic classifier based on Gaussian processes that achieves good results in the recognition of levels of personality traits.

In particular, the adoption of an ARD kernel that considers different weights for each feature, allows to automatically detect the most prominent ones in relation to each trait. Indeed, the motivating rationale behind this study was not only to attain predictive performance in terms of classification accuracy, but also to show how machine learning-based modelling could be used for gaining explanatory insights into relevant mechanisms of the studied phenomenon. This explanatory gain could be further exploited in subsequent and more focused refinements of experimental design. For instance, as shown in Figure 5, it results that the saccades directions, a typically overlooked feature, are a discriminating factor between subject with high and low levels of openness and extraversion.

As a final specific remark, the reasons behind the low accuracy of the neuroticism trait are probably to be found in the nature of the experiment and in the definition of neuroticism. It is not known, in fact, whether the subjects present clinical conditions. This could result into an overlapping between measures of neuroticism addressed via the self-report questionnaire and symptoms of common mental disorders. Moreover, as pointed in [38], does exist a lack of consensus on the optimal conceptualization of neuroticism and they suggest to see it as a mutable score that reflects a person's level of negative affect during a particular period.

Finally, as a general remark, must be kept in mind that, as noted in [19]: *many aspects of the experimental design might have influenced the results* [. . .] *The actors we used were all Caucasian between 20 and 40 years old with a neutral expression and did not speak - all factors that could have influenced observers strategies.*

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