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Kernel Modeling for Synthetic Personality*

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***Abstract*— The paper proposes a kernel approach to the modeling of synthetic personalities. Each kernel, corresponding to a personality trait, is a collection of probability distributions suitable to describe how sensor data maps into features associated with personality traits. The linear combination of human personality traits, sometimes referred in the literature as being able to generate the richness of human personality, has a counterpart in the linear combination of the kernel modeled traits proposed in the paper. People detection data from a social robot in a real environment is used to demonstrate the estimation of the kernels.**

***Index Terms*— Social Robots, Synthetic Personality, Kernel Models.**

I. Introduction

Robots are here and will evolve regardless the barriers imposed by humans, e.g., those resulting from data protection regulations, namely in the social context. Therefore, concerns related to social acceptance, e.g., safety and usefulness, are becoming omnipresent in the research on social robots. The connections with social sciences, namely in what relates to social behaviors, and hence personality studies, are clear and hence the need to explore scientific frameworks that can handle them.

In general, a social robot will have to adapt its behaviors to acceptable environment standards (in some sense adapt to the personality of the social environment) and hence the increased importance in the study of estimation and formation of synthetic personalities.

This work is part of an ongoing research effort on frameworks to synthesize personality in artificial agents. The complexity of interactions (that even a simple social robot needs to manage when acting in a realistic social context) makes clear the need of alternative approaches that can be used to reduce the complexity of shaping robot behaviors.

Personality and emotions have been at the center of research in intelligent robotics and, jointly or separately, have been included in architectures for intelligent robots. Both are key examples on concepts originating in social sciences that are being used in social robotics. Personality is defined as a relatively stable pattern of thoughts, feelings, and behaviors that explains individual differences in a wide range of important life outcomes, [18]. This means that, for purposes of synthetic personality synthesis, a personality trait is a collection of behaviors, e.g., motor behaviors, involving physical action on the environment, or data behaviors, involving some particular computational strategies/methods.

Given a set of personality traits, one may consider that all of them compete to be active (i.e., to be able to execute one of their associated behaviors). As behaviors become activated and act on the environment response events are generated and can be observed through sensors. The observation of such events provides information on the personality of the agent's actions that induced those same events (along with sensor noise and disturbances induced by all sort of exogenous sources existing in a social environment).

As personality models predict, humans are a complex composition of personality traits (as suggested for instance in [3] and [21]). Therefore, a sequence of observed behaviors is likely to contain events generated by behaviors associated to multiple traits. In general, identical events can be generated by different behavior/traits and hence the mapping trait $\mapsto$ events is surjective. Often such maps are stochastic processes and hence the identification of traits from events may not be a simple task. A sequence of stochastic events can be modeled by a probability distribution over relevant random variables, e.g., the time between events. Without loosing generality, a similar principle can be applied to synthetic personality, i.e., it can be formed by a collection of simpler traits, with each trait being associated to specific events and their dynamics.

In Psychology, the identification of personality is also made by observing a selection of events (often estimated from answers to questionnaires, [3], ch.7, [1], or by focusing a direct observation on some temporal window). The full personality is a combination of traits, i.e., of those traits compatible with the chosen personality model, e.g., the Big-Five, [23], or the 16PF, [4].

Identifying formal models for global personality and/or individual traits from sensor data amounts thus to fit observation data (the aforementioned stochastic sequences of events) to some predefined model, e.g., a probability distribution or a collection of distributions, combined in some suitable form, for example as a linear combination (see ahead). This forms the core idea of the paper, i.e., using a kernel approach to represent data containing information on the personality of

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some entity.

The paper is organized as follows. Section II briefly reviews the main concepts on personality and the argument supporting linear combination of traits. Section III discusses a kernel estimation framework to model the linear composition of traits, each being represented by a collection of probability distributions. The concepts developed are exemplified using real data obtained with a social robot in a public space. Section IV makes final remarks and discusses prospective directions for development of the ideas in the paper.

II. From Natural to Synthetic Personality

Research on human personality has proposed numerous models (see for instance [4], [10], [2]). However, the so called Big-Five model, [23], [11], [15], has been referred as suitable for computational purposes, [16].

Linear combination has been argued to be a valid form of generating complex traits from simpler ones. As an example, [20] (quoted in [21], p.409), defined compound personality trait as a linear combination of narrower personality traits.

Linear combinations of Big-Five traits were also used by [7] to approximate scores of complex personalities.

Furthermore, linear and quadratic regressions were used by [8] to predict income from personality traits.

Convolutional Neural Networks were used in [13] to predict Big-Five personality traits from audio, video, and text data. Though CNNs implement complex maps, the intrinsic structure is that of a linear combination of complex features (obtained from the convolutional layer).

Estimates of traits scores/ranks can be mapped into probabilities and used for decision making and/or behavior activation (and hence generation of events) and can be considered a basic tool for behavioral control of a social robot. However, such probabilities will be, in general, imprecise and hence decision making may have to rely on bounds. As an example, dependability is a highly desirable property for any artificial system humans must rely on. Personality traits relevant for dependability must thus be subject, by design, to some form of bounding on performance.

Personality (either natural or synthetic), which, as aforementioned, is tightly linked to behaviors, can then be framed in terms of the relations between behaviors and dependability. (a simple example is the behavior – or the composition of behaviors – that preserves – maximizes – the dependability of a social robot). This maps easily into an important problem in social robotics, i.e., what is the personality that best preserves dependability (or that best adapts to some environment).

The framework of credal sets introduces the concept of possibility to describe an imprecise probability. A set of possibilities is said to be consistent if the corresponding probabilities are upper bounded by their Possibilities (or *Plausabilities*), [12]. The possibilistic framework introduces also lower bounds for probability frameworks. *Beliefs* represent lower bounds. Both plausabilities/beliefs can be used instead of probabilities, namely if they are easier to estimate, though the so called *principle of minimum specificity*, [9], which specifies that anything not known to be impossible must be accounted for when estimating a possibility distribution) may lead to optimistic/conservative decisions. A survey on the construction of possibility distributions from data is presented in [9].

Estimating personality from sensed data as a kernel estimation problem, with each kernel (or some collection of kernels) representing individual traits is a form of linear combination, thus fully compliant with the possibilistic framework (assuming that each kernel is itself compliant).

Kernels can be selected according to the type of data available and bounding requirements. Instead of using common kernels, e.g., Gaussian, or uniform, in this context the estimation problem may have to use other functions, selected according both objective and subjective criteria (recall that the domain of social robotics embeds numerous subjectivities) can be used. For example, kernels used in machine learning are non-negative, integrable, and even, functions, [5]. Given the nature of personality traits evenness may be relaxed to allow the use of, for example, of exponential distributions.

III. Experiments

Current legislation on data privacy is very restrictive on the type of data a social robot can acquire from the environment, e.g., imaging sensing is often subject to very strict rules. Informed consent (IC) procedures are often used to circumvent such constraints. However, the expectations created by the act of filling an IC easily bias any assessment. Moreover, even if cameras are switched off, their simple presence easily triggers privacy fears and, it is likely that people feels some inhibition in interacting with a robot (this happens even with depth imaging). Therefore, Lidar data is used for leg detection (the specific detector used is characterized by having low false negatives and relatively high false positives).

The time between leg detection events contains information relevant to characterize the dynamics of the environment, and is correlated with personality aspects. For example, if a static social robot is measuring a low occurrence of short intervals between people detections and once it starts to move this occurrence increases significantly, then it may be an indication that the robot is behaving nervously (or, in terms of the big-five model, anxiously). Alternatively, other sensory signals can be used, namely verbal and non-verbal sounds (the importance of verbal interaction, namely for socializing purposes, is well documented in the literature).

Figures 1, 2, 3 illustrate (in the lefthand plots) the evolution of the parameters for three probability distributions along a period of 3 months, for the time between people detection by a social robot. Each point in the horizontal axis corresponds to a single experiment of variable duration (between 1 and 8 days, totaling 34 datasets). These distributions were selected as they often model sequences of time intervals (see for instance [24]).

Selecting which on is more suitable to model the real data can be done using a variety of criteria, e.g., by checking how the distribution of the real data per quantiles fits the compound distribution formed with the three distributions. This however does not give information on the relative weights of the different trait, i.e., each of them simply represent modeling choices and no decomposition in simpler traits can be inferred. Nevertheless, useful information can be obtained, as the evolution of parameters in all three distributions consistently shows periods that stand out from what can be considered as a main trend, as, for example, between samples 15 and 20. Matlab density estimators were used to obtain the values in these plots.

The right hand plots illustrate the evolution of the variance for each of the distributions. Again, a temporal consistency between similar evolution windows is visible among all three plots.

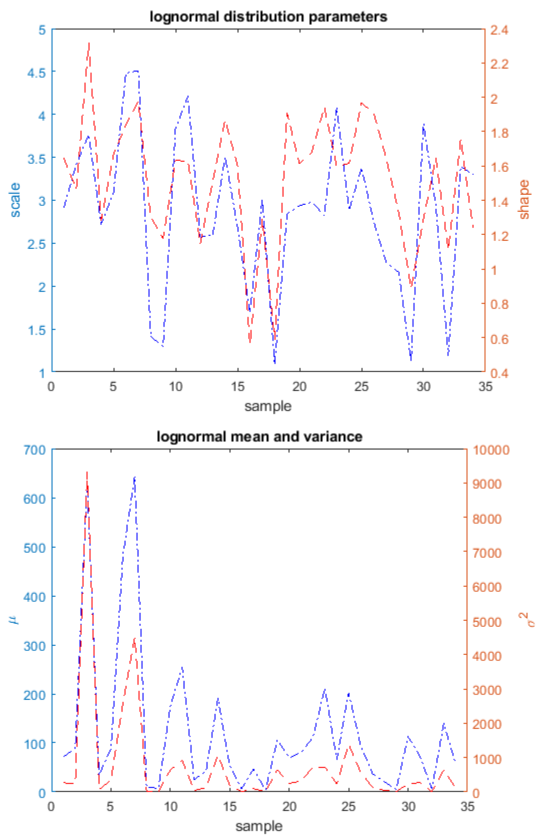


Fig. 1. Lognormal distribution parameters and moments

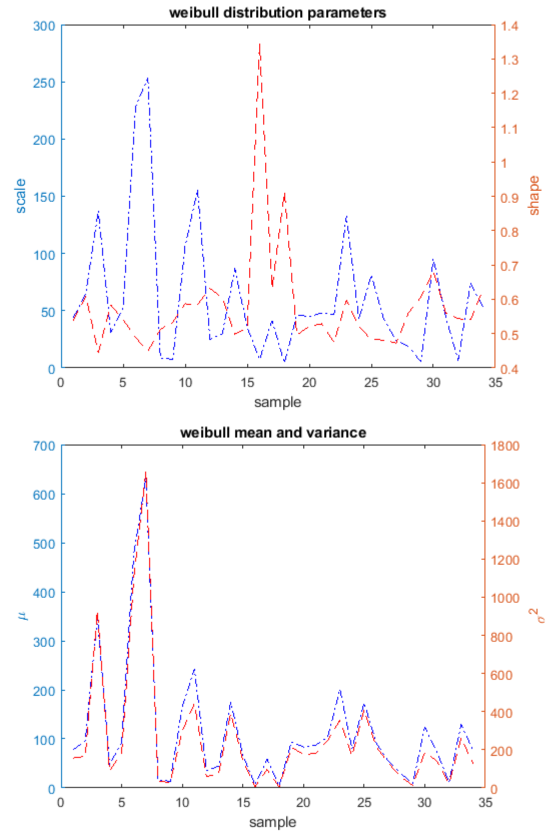


Fig. 2. Weibull distribution parameters and moments

A. *Kernel estimation*

Within kernel models multiple possibilities are available. In general, it is assumed that the choice of the kernel is critical for the success of the estimation (see for example the comments in [6]). However, according to [22] (quoted in [14]) statistically the type of kernels used is not that important and hence to test kernel based modeling a set of three kernels will be used.

From the perspective of synthetic personality, the main goal is to obtain kernel models that can generate sequences of events which resemble, from a statistical perspective, real datasets. This means that, potentially, using a "wrong" type of kernel in some regions of the input space may not be harmful. In a sense, this agrees with Silverman's remark above.

The first experiment considers exponential kernels, with different rate values. The rational behind this test is that in a realistic environment it can be expected that several "classes" of people exist (e.g., staff, or visitors) each of which can be represented by some (simple) distribution. However, the group behavior also contains thee effects of the interactions between these groups of people and hence a mixture of distributions is selected (these were selected as distributions typical of processes involving time between events). Consider

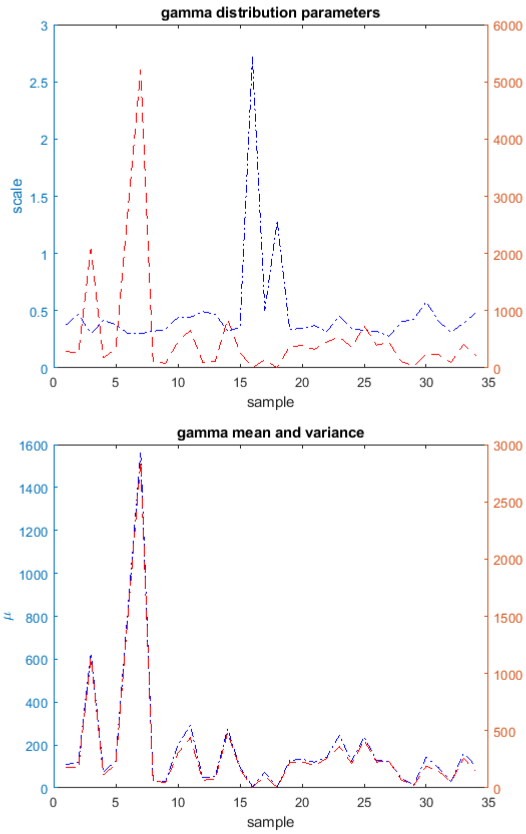


Fig. 3. Gamma distribution parameters and moments

the rates $\lambda_{1,2,3} = 1/4000, 1/8000, 1/15000$, which, from an empirical analysis can be representative of different dynamical conditions for the environment, i.e., somewhat agitated, regular, and low dynamics, when a social robot is either (i) static in a place of social movements, or (ii) wandering, autonomously, in the environment.

Therefore, the selected probability density modeling the time between detection of people, z is estimated as

$$f(z) = \begin{cases} \sum_{i=1}^{N} K_i \begin{pmatrix} \lambda_1 \exp^{-\lambda_1(z-x_i)} + \ldots \\ +\lambda_2 \exp^{-\lambda_2(z-x_i)} + \ldots \\ +\lambda_3 \exp^{-\lambda_3(z-x_i)} \end{pmatrix}, \\ \qquad\qquad\qquad\qquad z - x_i \geq 0 \\ 0, \quad \text{otherwise} \end{cases} \tag{1}$$

with N the number of "regions" where the kernels are spread into, each centered at x_i, and the K_i constants to be estimated specific of each "region", such that,

$$\sum_{i=1}^{N} K_i \left(\lambda_1 \exp^{\lambda_1 x_i} + \lambda_2 \exp^{\lambda_2 x_i} + \lambda_3 \exp^{\lambda_3 x_i}\right) = 1 \tag{2}$$

and x_i the points used to the relative placement among the kernels.

This differs from the usual Parzen-Rosenblatt estimator as each kernel is formed by three sub-kernels, and different scalings are used for each of the kernels.

Given the $z_1, \ldots, z_M$ points, corresponding to the real observations, i.e., the datasets obtained from the experiment, and computing $f(z_1), \ldots, f(z_M)$ points, for some hypothesis distribution, $f(\cdot)$, the $K_i, = 1, \ldots, N$ can be computed from,

$$\begin{aligned} &[f(z_1), \ldots, f(z_M)] = \\ &\quad [K_1, \ldots, K_N] \cdot \\ &\quad \cdot \begin{bmatrix} \sum_{j=1}^{3} \lambda_j \exp(-\lambda_j(z_1 - x_1)), \ldots, \\ \quad \sum_{j=1}^{3} \lambda_j \exp(-\lambda_j(z_M - x_1)) \\ \vdots \\ \sum_{j=1}^{3} \lambda_j \exp(-\lambda_j(z_1 - x_N)), \ldots, \\ \quad \sum_{j=1}^{3} \lambda_j \exp(-\lambda_j(z_M - x_N)) \end{bmatrix} \end{aligned} \tag{3}$$

according to some optimization strategy, e.g., least squares.

The selection of the x_i is determined by the width of the data region to be covered. Given the full dataset, the standard deviation provides a measure of the dispersion of the data and hence it can be used to estimate them (in the paper $N = 5$).

The selection of the z_i can be made by establishing a grid covering a region of interest. The resolution of this grid is determined by the amount of computational resources available.

In a sense, solving the kernel estimation problem (3) is very similar to solving the so called kernel-based perceptron algorithm (see [17]). A set of model parameters is fitted so that the model generates data similar to a real dataset. Instead of using a perceptron-like adaptation of the parameters, the estimation of these parameters is formulated as an optimization problem. No computational constraints were assumed in this study.

B. Bounds for beliefs

Expression (3) defines the estimator architecture, and hence must contribute to the estimation errors. The optimization strategy, in this example the least squares, is the other contributor to estimation errors.

In this expression, the lefthand side represents an hypothesis on the real probability density (pdf) of the observed data (possibly a pignistic pdf) whereas the righthand side represents the kernel hypothesis.

From a design perspective, the righthand side is an *a priori* choice, the selection of which may occur based on knowledge of the adequate models for simpler personality traits. As for the lefthand side, it is assumed to be the defined after possibly subjective, but rational (pignistic), considerations.

Within the probabilistic framework, multiple bounds are available (see for instance [19]) that can also be used to create a consistency concept. Using probability bounds on the lefthand side replaces the explicit dependence on the knowledge of the specific distribution by the knowledge on a few parameters.

In the case considered in this paper, the hypothesis of the real pdf is a lognormal distribution, selected after the single pdf estimates (see figures 1, 2, and 3). These experiments suggest that the environment may contain periods of fast and slow dynamics and hence uncertainties may be also affected.

Using Markov inequality on (3),

$$\int_{-\infty}^{x} \left(K_\tau^f \, A_\tau\right) \, d\tau \geq 1 - \frac{\mu^f}{x} \tag{4}$$

where the superscript f expresses the dependency of the pignistic pdf f, A_τ is the kernel structure (the columns of the righthand matrix in (3)), and μ^f is the first moment of f.

Given an estimated kernel, with weights K, expression (4) provides a lower bound that can be used to define a form of consistency. Moreover, μ^f becomes a design parameter that allows a consistency interpretation. Given some dataset and a pignistic density f, (4) determines a belief that can be used for decision making purposes.

C. Experiments with people detection data

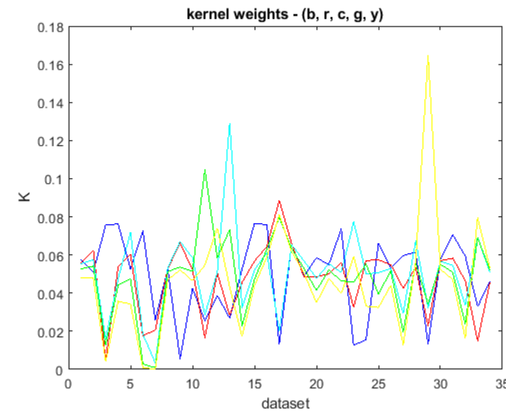
Experiments in a non-lab context will easily generate huge amounts of data and hence the estimation problem is bound to a dimensionality issue (for example, the mean value between people detections over a time span of 2 weeks is approximately 45 seconds – measured from one of the datasets obtained – and hence for an experiment of several months the amount of data is very large).

Detrending removes any values below the threshold from the dataset used to estimate the kernel weights. Though this process may remove valid people detections, it also removes false positives (due, for example to problems in the laser readings, or simply to software mishaps) and multiple detections from people standing in front of the robot. Moreover, this highlights the relevant events (for instance, short values may indicate repeated detections of people which are not considered in this paper (though the time a person stands in front of a social robot is a relevant indicator to assess interaction and personality). A different kind of people detector would be required to acquire datasets containing fast dynamics. Nevertheless, this refers only to data acquisition. The whole estimation process is not affected

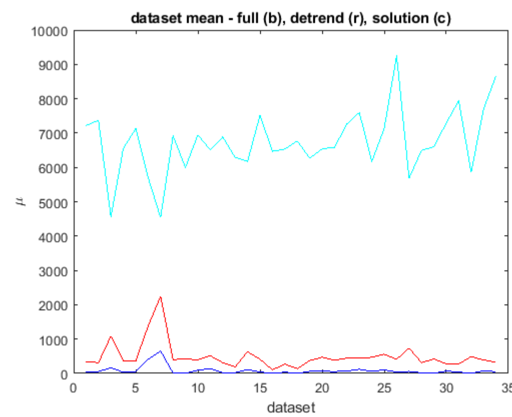
The pignistic pdf is selected as a lognormal density. Recall that the role of such density is to fit the dataset as if it would be better modeled by a single density (with no kernel modeling).

Figures 4 to 7 illustrates the evolution of the estimated kernel weights, mean, and standard deviation statistics, for a number of detrending thresholds.

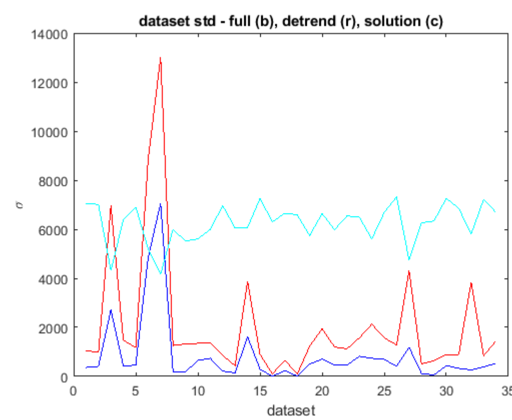
The evolution of the weights suggests a higher relative importance of the traits associated to smaller times between



(a) Estimated weights

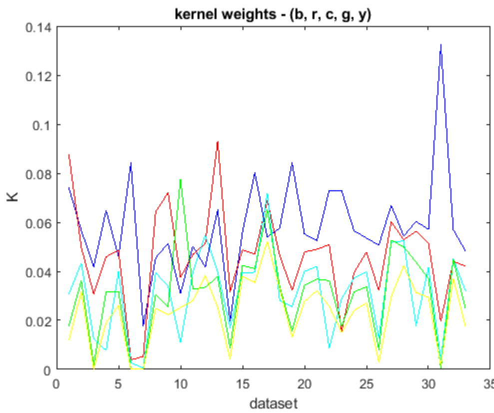


(b) 1st moment

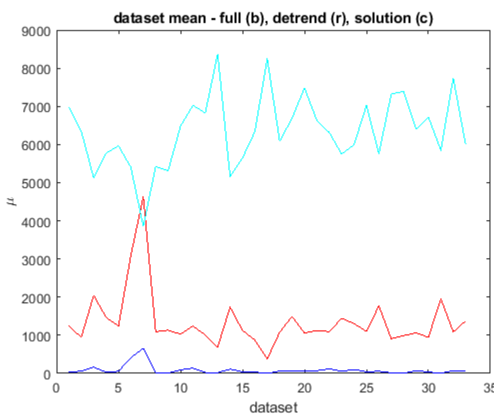


(c) 2nd moment

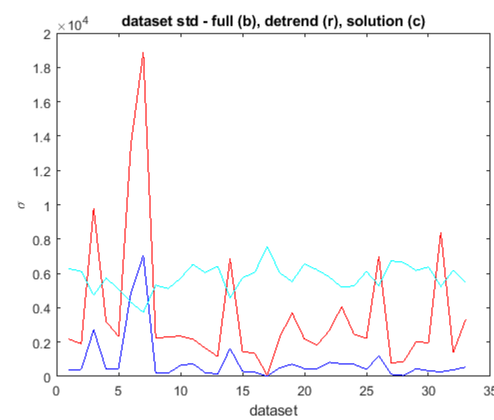
Fig. 4. Estimated distribution parameters and statistics for 50s detrending threshold



(a) Estimated weights

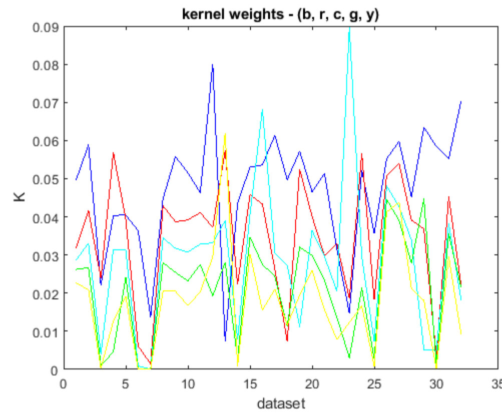


(b) 1st moment

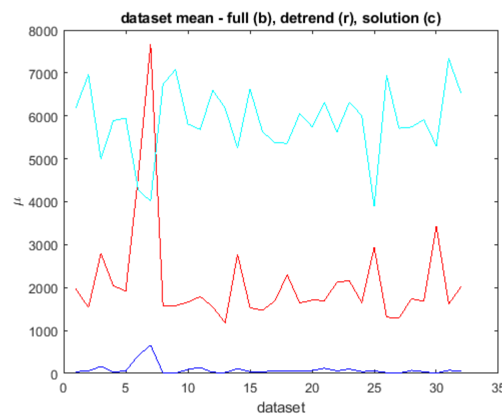


(c) 2nd moment

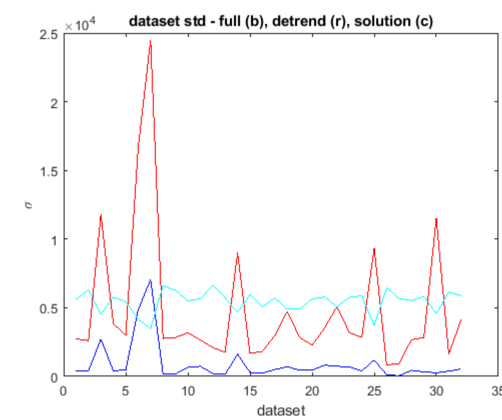
Fig. 5. Estimated distribution parameters and statistics for 300s detrending threshold



(a) Estimated weights



(b) 1st moment



(c) 2nd moment

Fig. 6. Estimated distribution parameters and statistics for 500s detrending threshold

detections, which is in agreement with the common perception for a typical public environment.

The evolution of the 1st and 2nd moments (figures 4b, 5b, 6b, 7b) suggest the existence of regions of slow and fast dynamics.

Empirical evidence, from the plots, is the fact that the effect of the detrending on the dynamics of the K_i weights is higher than the corresponding effect in the 1st and second moments. Moreover, there is a similarity between the corresponding regions for different detrending thresholds.

D. Correctedness assessment

The results in the previous section must be complemented with a correctedness test, namely by showing that the estimation procedure is able to estimate a kernel distribution that can generate data highly correlated with the data used for the estimation.

Figure 8 shows a sample test with a reference distribution formed after a pdf of the form (3) with $\lambda_1 = 1/4000, \lambda_2 = 1/8000, \lambda_3 = 1/15000$ and $K_1 = 0.5, K_2 = 0.4, K_3 = 0.3, K_4 = 0.2, K_5 = 0.1$. The kernels were located at $x_1 = 300, x2 = 300 + 10/2, x_3 = 300 + 10, x_4 = 300 + 1.5 * 10, x_5 = 300 + 20$.

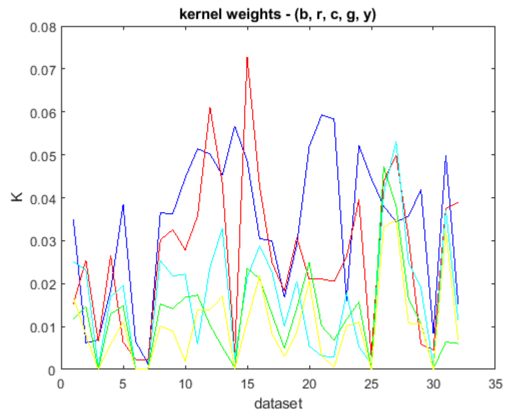
The five blue peaks in figure 8b correspond to samples that do not correlate well with the reference dataset. The reduced number of these, when compared with the one hundred total trials is a good indicator of the correctedness of the estimation process.

The test also shows the non convex nature of the problem as the estimated values for kernel weights do not need to match the reference ones (see figure 8a). A natural consequence of this feature is that a similar complex personality can occur from multiple combination of simpler traits. Though apparently naive, this remark represents well the richness of biological personality in a mathematical framework.

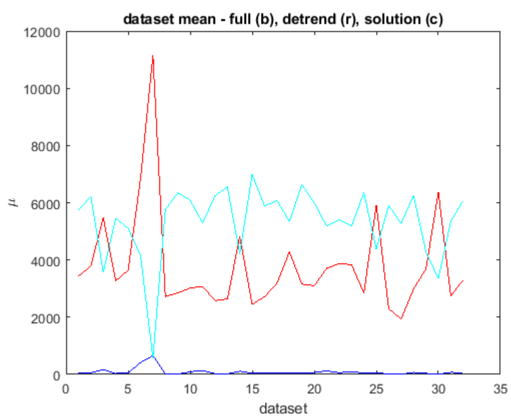
IV. Conclusions

The paper presented an architecture to model synthetic personality after linear combination of a set of individual traits. Each of the traits corresponds to a collection of pdfs selected to rationally model abstract processes that can generate data similar to the data available for the estimation of the model parameters. The overall concept is inspired in concepts and models from social sciences which are mapped into concepts common in kernel based models.

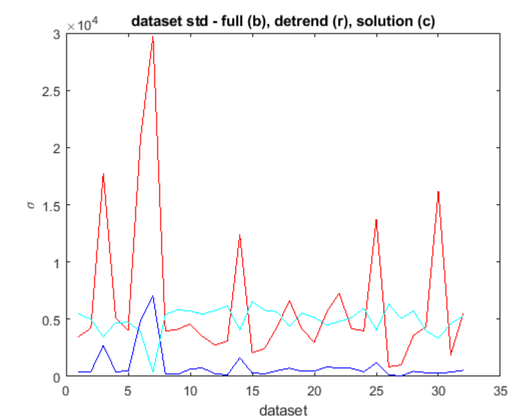
The architecture was tested with data from an experiment in social robotics that took place in a real, non-lab, environment for a period of approximately 3 months. The traits were selected without bearing any interpretation in terms of the meanings/labels used by any of the mainstream human personality models. The underlying idea was to test the estimation procedure. However, once a trait is identified with a distribution or collection of distributions, the



(a) Estimated weights

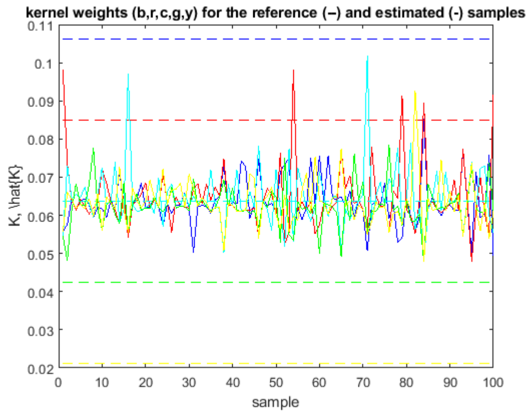


(b) 1st moment

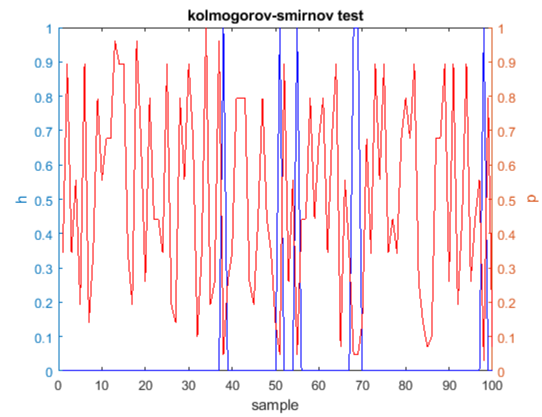


(c) 2nd moment

Fig. 7. Estimated distribution parameters and statistics for 1000s detrending threshold



(a) Weights



(b) Kolmogorov-Smirnov test

Fig. 8. Kolmogorov-Smirnov correlation test between a reference dataset and a dataset generated after the distribution estimated from the reference one

estimation process yields the corresponding weight in the complex/compound personality.

In some cases each single K_i will be interpreted in terms of a single trait. In other situations the K_i may undergo a further classification procedure such that multiple of them can be associated with single traits. Additional experiments are planned, with (i) data from different sensors, e.g., sound and touch data, and (ii) kernels matched to specific personality traits. Also, the paper also provide pointers for further technical developments, as is the case of the section on bounds.

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