

A Context-Aware Adaptability Model for Service Robots

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Abstract

This article presents a context-aware, adaptable service selection model for a social robot, giving it the ability to estimate the user’s *expectation*, assess the degree of *satisfaction* and use it as feedback to improve subsequent interactions. We established specific measures for expectation and satisfaction, estimated using Bayesian inference and used to control the human-robot interaction. This work is proposed to overcome the fact that service robots are usually designed to perform within a very strict operational envelope, sometimes requiring all knowledge to be known and locally pre-programmed. The model was tested in demanding simulated scenarios, showing promising results, and also in exploratory experiments with users.

1 Introduction

In the past few years, we have witnessed an increased interest from the research community on developing intelligent robotic systems, such as the Social Robots and Companion Robots used in applications of Ambient Assisted Living. Such systems can be used as a technical solution to support our society and organizations to tackle the challenge posed by the continuously growing fraction of elderly population in developed countries. Several solutions have been devised and successfully tested. However, these solutions tend to depend greatly in previous knowledge and are unable to interact with the user in an adaptable way.

In this work, we aim to contribute towards *autonomy in interaction* of a service-providing Social Robot. More specifically, we tackle the issue of autonomously selecting the service that should be performed to a user in order to ensure their *satisfaction*. We argue that satisfaction can be fulfilled when the action that is performed matches the user’s *expectation*. These two concepts are used to perform a limited form of interaction regulation.

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The remainder of this work is organized as follows. Section 2 presents a short review of recent work on User Adaptability. Section 3 presents the proposed model. Section 4 presents our experiments, including the particular instantiation of the model used in them and the results we have obtained. These results are then discussed in Section 5, followed by our concluding remarks and notes on future work, in Section 6.

2 Related Work

In this section we present works involving robotic systems that are User Adaptable, a characteristic here defined as the system’s ability to automatically adapt its interaction to its users. There have been studies on how users can coexist with robots and on what characteristics these should exhibit in order for the user to accept them as a social entities [de Graaf *et al.*, 2015][de Graaf and Ben Allouch, 2013][Fischinger *et al.*, 2014]. These studies show that humans are indeed capable, and willing to, attribute a social role to robots and to perceive them as part of their social circle. More importantly for this work, [Heerink, 2011] shows that users of social robot systems prefer system-controlled to user-controlled adaptation, although they do prefer to maintain a sense of control.

Focusing on children as end-users, the authors of [Kanda *et al.*, 2004] and [Kanda *et al.*, 2007] present the results of long-term trials involving child students, during which the robots were able to adapt their behaviors using a “pseudo development” system, in accordance with the interactions that they experienced with the children. The authors of [Ros *et al.*, 2014] and [Magyar and Vircikova, 2015] focus on solutions for robotic dance tutors for children, with the first focusing on learning the policy of a Wizard of Oz, and the second on implementing a system that adapts based on previous interactions and a user model.

The authors of [Baraka and Veloso, 2015] also take a step towards long-term cohabitation of robots and humans, by presenting a system that aims at autonomously adapting to the user’s preferences over a long-term period where several interactions occur. In order to aid in the adaptation, the authors explicitly rely on the user providing a rating of the robot’s behavior, which is then used to learn the parameters of the model employed.

A number of works make use of the user’s personality [Eysenck, 1991] to achieve higher levels of adaptation,

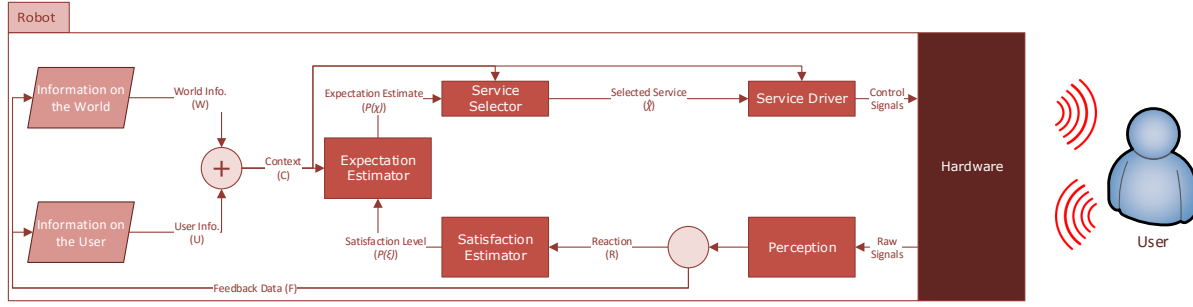


Figure 1: A pictorial overview of the composition and basic functionality of the envisioned system. The rectangles represent data processing modules, the parallelograms represent data sources and memory, and the dark rectangle represents all of the robot’s hardware.

either by performing personality matching [Tapus and Aly, 2011], synthesizing adapted behavior based on the user’s personality traits [Aly and Tapus, 2013].

The authors of [Khaoula *et al.*, 2015] present a work where the robot, a sociable dining table, develops a personalized communication protocol with the user. The robot responds to knocks on the table by knocking back, constructing a personalized protocol with the user, leading to increased acceptance.

A number of works focus on providing assistance to the user, such as the Paro robot [Wada and Shibata, 2006], able to adapt to its user by learning the name that the user prefers to use to call it, with its reinforcement learning system allowing it to gradually adapt to the user’s preferred behaviors. Similarly, Autom, the weight-loss assistant robo[Kidd and Breazeal, 2008] performs the function of aiding a person to lose weight, adapting to the user by keeping track of their progress and adjusting interaction accordingly. Robots are also able to adaptively assist users in other ways, such as by organizing shelves according to user preferences [Abdo *et al.*, 2015][Hoefinghoff *et al.*, 2015], or helping them get dressed taking into account their upper limb mobility [Gao *et al.*, 2015] or monitoring their physical limitations [Klee *et al.*, 2015].

Current works are able to adapt their paths to the presence of users [Kim and Pineau, 2015], employing the theory of Proxemics [Rios-Martinez *et al.*, 2015], and to plan the motion of robotic arms taking into account the presence of a user, be it through crowd-sourcing path scores [Menon *et al.*, 2015], using Gaussian Mixture Models to model interaction primitives [Ewerton *et al.*, 2015] or by employing Game Theory [Li *et al.*, 2015].

Lastly, we regard certain forms of human-in-the-loop control as User Adaptability. For example, in [Lam *et al.*, 2015] the authors model the interaction between the user and the vehicle they are driving in order to perform human-in-the-loop control of a moving vehicle. The system adapts to the state of the user and acts only when necessary, depending on the state of the user. In an earlier example, the authors of [Zhang and Nakamura, 2006] propose a system where a robotic arm is used to assist an impaired person in feeding themselves, employing a controller based on a Neural Network, which is automatically adjusted for each user, such that the robotic arm

compensates and assists the user’s movements.

User Adaptability exists in many forms and in systems that far exceed the boundaries of Robotics itself. The goal of this work is to contribute to the field of adaptable robotic systems by introducing the concepts of expectation and satisfaction as governing metrics of interaction, aiming to increase the autonomy of service robot. These are modelled and functionally implemented using Bayesian Programs [Ferreira and Dias, 2014] for their estimation. Results indicate that the proposed models can be used to endow social robots with new levels of autonomy in interaction.

3 The Adaptability Model

3.1 Problem Statement and Rationale

Let us assume that a service robot is interacting with a person, on one-on-one interaction. How can the robot provide a service that is *pertinent, appropriate and adjusted to the context* that the robot and the user are immersed in? More formally, given a discrete set of actions $x_i \in \chi : \chi_{1 \times n} = [x_1 \ x_2 \ \dots \ x_n]$, where χ corresponds to the space of the actions that the robot can perform, how can the robot determine which action should be performed in a given situation? By grounding our problem in the domain of service-providing Social Robotics, we establish that each action corresponds to a service that the robot can provide. We assume that the user is consistent in their service preferences, *i.e.* that they always prefer the same service in a given context.

We propose that the interaction between a robot and a human agent can be made adaptable through the application and exploitation of two concepts: *expectation* and *satisfaction*. The user *expects* the robot to perform a task, and when the robot performs this task, the user is *satisfied* to a certain degree. *The estimation of these measures and the associated decision making model are the main focus of this work and are formally defined in the following sections.*

3.2 Functional Description

Let C be the Context of the interaction as the robot perceives it. Contextual information is divided into two types: information on the user $U_{1 \times m} = [u_1 \ u_2 \ \dots \ u_m]$ and on the world $W_{1 \times l} = [w_1 \ w_2 \ \dots \ w_l]$. Variable u_i pertains to the user while

w_i is a variable containing information that does not relate to the user. Thus, context $\mathbf{C}$ is given by:

$$\mathbf{C}_{1 \times (m+l)} = [\mathbf{U} \ \mathbf{W}] \quad (1)$$

which, as will be defined later on, contains information such as the user's emotional status and/or the robot's localization in the world. This information is used to estimate the user's *expectation*. We aim to determine the *probability distribution* of user expectation, $\hat{\chi}$, as a function of the current context and user *satisfaction level* ξ , such that:

$$\hat{\chi} = f(\xi, \mathbf{C}) \quad (2)$$

Knowing this distribution will allow for the selection of an action which is most likely to match the user's expectation and achieve satisfaction, as formulated in the following section.

Every time a service is rendered, the user reacts to it. This reaction is measured by the robot's sensors, generating new signals which are processed by the *Perception* module, generating the *user's reaction* variable, $\mathbf{R}$. The user's reaction is then used as a means to estimate their satisfaction level, ξ , which aims to describe how well the user accepts the robot's actions. It is mapped into the $[0, 1]$ range, where $\xi = 1$ indicates that the user is maximally satisfied. A pictorial description of this process can be found in Fig. 1.

3.3 Model Specification

Decomposition

We employ Bayesian estimators for estimating ξ and χ , which are implemented using Bayesian Programming [Ferreira and Dias, 2014]. The Satisfaction Estimator provides an estimate of the user's satisfaction level (ξ) using the user's reaction ($\mathbf{R}$) as input. $\mathbf{R}$ is a vector of the form $[r_1 \ r_2 \ \dots \ r_z]$, where r_i is a component of the user's reaction. We propose to estimate the user's satisfaction level as $\hat{\xi} = P(\xi|\mathbf{R})$, yielding:

$$\hat{\xi} = P(\xi|\mathbf{R}) \propto P(\xi)P(\mathbf{R}|\xi). \quad (3)$$

Assuming that, in $\mathbf{R}$, all of the variables are statistically independent, we obtain

$$P(\mathbf{R}|\xi) = \prod_k P(r_k|\xi). \quad (4)$$

Since we have no prior information on user satisfaction, $P(\xi)$ is defined as a uniform distribution.

The *Expectation Estimator's* objective is to determine which of the action categories known by the robot is the most likely to correspond to the user's current expectation. By applying Bayes' Rule, we obtain:

$$P(\chi|\xi, \mathbf{C}) \propto P(\chi)P(\xi, \mathbf{C}|\chi). \quad (5)$$

Which, applying the Chain Rule to the term $P(\xi, \mathbf{C}|\chi)$, yields:

$$P(\chi|\xi, \mathbf{C}) \propto P(\chi)P(\mathbf{C}|\chi)P(\xi|\mathbf{C}, \chi). \quad (6)$$

The service is selected by the *Service Selector* through the expression

$$\hat{\chi} = \underset{x}{\operatorname{argmax}} \ P(\chi|\xi = 1, \mathbf{C}), \quad (7)$$

i.e. by finding the action that maximizes the probability of user satisfaction given the current context.

Expectation and Satisfaction Estimators

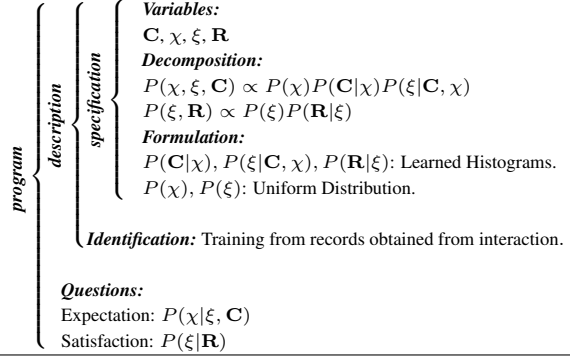


Figure 2: Bayesian Program for performing satisfaction and expectation estimation.

Inference

Regarding the estimation of satisfaction, the $P(\mathbf{R}|\xi)$ factor in Eq. 3 encodes our learning process and is described using a static stochastic matrix. In order to learn this distribution, we can perform a number of observations, where each observation produces a record of the form $\{Reaction, Satisfaction\}$, and in which the user's satisfaction level ξ is known, and the $P(r_k|\xi)$ terms can be determined by operating over the records:

$$b_{i,j} = P(r_k = i|\xi = j) = \frac{1}{N}N(r_k = i) \quad (8)$$

where N is the number of available records, and $N(U_k = i)$ is the number of records where $U_k = i$, j can be either 0 or 1, and i represents the i -th possible state of U_k . An example of these matrices can be seen in Fig. 3.

Regarding the estimation of expectation, all of the right-hand side terms in Eq. 6 can also be described using stochastic matrices. These are recalculated on every interaction, every time a service is rendered, based on the record of the form $\{Expectation, Context, Satisfaction\}$ that is produced, which constitutes our expectation learning mechanism. The recalculation of these distributions, and the way they influence the decisions the module takes, are the key to our model's adaptability. This process is described as a Bayesian Program in Fig. 2.

Because the user is assumed to maintain their preferences under equal context information, the Markov assumption is employed. Therefore, we assume that the previously estimated expectation distribution, at each time step, can be used as the prior distribution for the subsequent steps, taking care to penalize erroneous decisions when the Satisfaction level is low by reducing the probability of the erroneous action in the prior distribution injected in the next step. *i.e.* for a time instant k :

$$P(\chi_k|\xi_{k-1}, \mathbf{C}_k) \propto P(\chi_{k-1})P(\xi_{k-1}, \mathbf{C}_{k-1}|\chi_{k-1}), \quad (9)$$

a detail we have omitted from previous equations for the sake of readability. This corresponds to a computational implementation of the inference described by Eq. 5. χ_k is com-

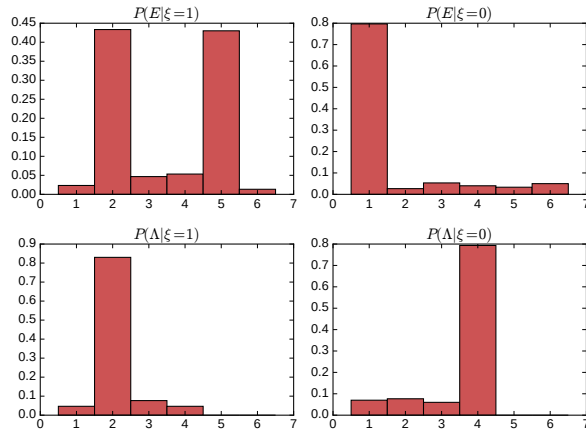


Figure 3: An example of the probability distributions produced during the training of the Satisfaction Estimator, and that can be used to generate the simulated user’s reactions.

puted synchronously every time a service is rendered and a reaction is observed.

4 Experiments

In order to demonstrate the functionality of our system, we have designed a number of experiments, divided between simulated scenarios and trials with real users. We have implemented the models using ROS [Quigley *et al.*, 2009] modules and the ProBT [Ferreira and Dias, 2014] probabilistic calculation library, which will be released on the GrowMeUp project webpage¹.

4.1 Experimental Set-Up and Model Instantiation

For these trials, we have instantiated the model as follows. $\mathbf{U}$ is constituted by both the user’s current action and displayed emotion (see the following equation).

$$\begin{aligned} \mathbf{U} &= [u_1 \ u_2], \text{ with} \\ u_1 \in \mathbf{E} : \mathbf{E} &\equiv \{sad, happy, angry, \\ &\quad scared, joyful, neutral\} \\ u_2 \in \mathbf{\Lambda} : \mathbf{\Lambda} &\equiv \{wave, nod, walk, \\ &\quad shake\ head\}, \end{aligned} \quad (10)$$

and $\mathbf{W}$ is composed by the user and robot’s location and the time of day

$$\mathbf{W} = [w_1 \ w_2 \ w_3] \quad (11)$$

where w_1 and w_2 contain the user’s and robot’s location, respectively, and w_3 contains the current time of day.

In this work, the user’s reaction is conveyed by a different materialization of the same set of variables as $\mathbf{U}$, although there is no strict need for this to be the case.

$$\mathbf{R} \equiv \mathbf{U} \quad (12)$$

In what regards the simulated scenarios, we strove to design experiments that were as realistic as possible, namely by

¹www.growmeup.eu



Figure 4: A user interacting with the robot.

the injection of uncertainty in most of the steps of the process. In order to perform these tests, we have implemented a module which emulated the “human” component in the system, which probabilistically generates an appropriate reaction to the stimuli it receives, depending on whether the value received corresponds to the “correct”. This module implemented a *person profile*, which was used to define the distributions from which the signals that were injected into the system during the tests were generated. Essentially, a profile is defined by the distribution $P(\mathbf{R}|\xi)$ and a set of constant, coherent rules that allow us to establish a connection between $\mathbf{C}$ and χ , which are unknown to the rest of the system. For example, a profile may be constituted by the distribution illustrated in Fig. 3 and the rule “when the robot and the user are in the same location, the user wants to be entertained”.

Two types of short-term tests were conducted:

- using constant $\mathbf{W}$ -context;
- using randomly-varying $\mathbf{W}$ -context.

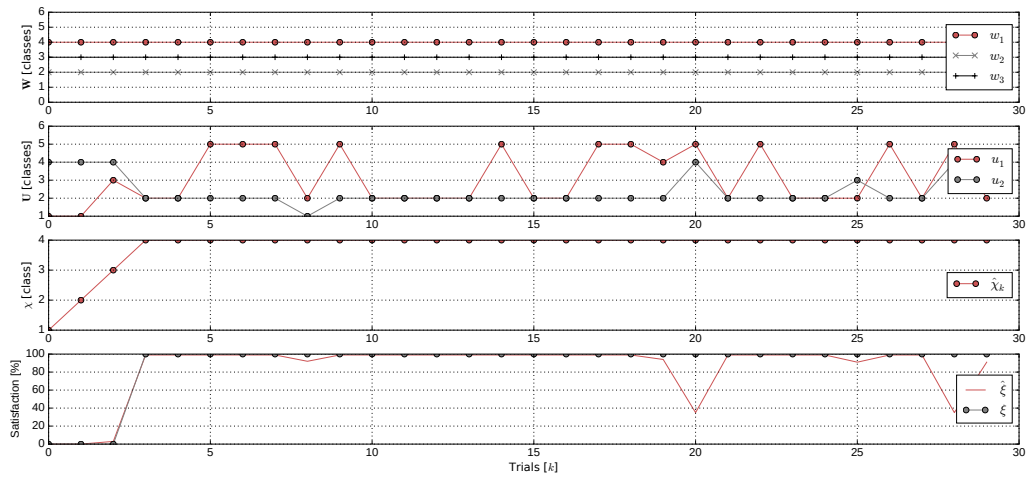
The first test had the goal of determining if the system was able to converge to the correct solution, and how quickly; the second type of test aimed to study how the system could adapt to constant changes in the environment. We have also measured the average number of cycles needed to converge to the correct solution when starting with no knowledge. The Satisfaction Estimator was trained with 300 examples drawn from the aforementioned distribution, and no training was given to the Expectation Estimator, except where noted.

Long-term simulation tests were also conducted, in order to observe the system’s ability to converge to correct solutions given enough time to study the user. In these tests, the $\mathbf{W}$ -context was varied as before, but the system was allowed to run for a much longer time, ranging from 1000 to 10000 trials.

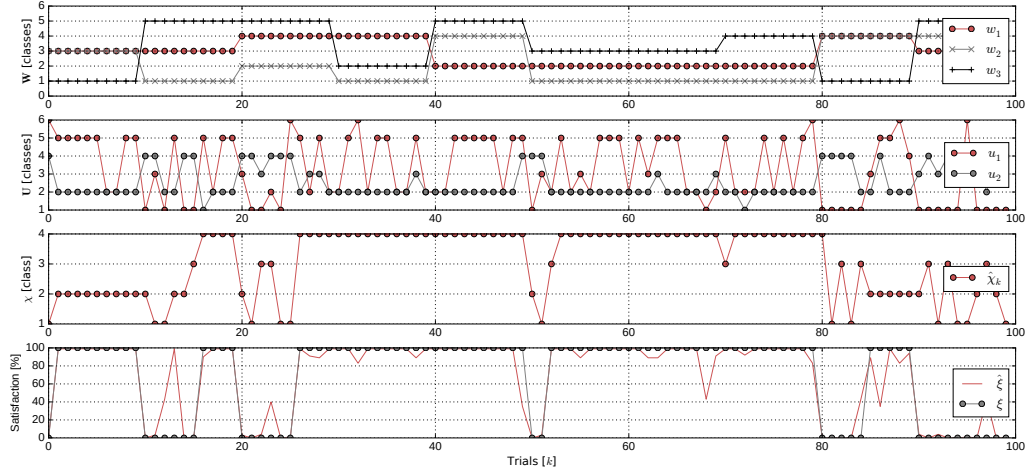
Regarding the tests with users, we have implemented a number of services on the GrowMu robot [Martins *et al.*, 2015], ultimately instantiating the χ vector as

$$\chi = [follow \ go_to \ entertain \ do_nothing]. \quad (13)$$

As a general way of measuring the level of adaptability of the system, we have calculated the error rate, *i.e.* the ratio of the number unsatisfactory trials over the number of satisfactory ones. This was done both cumulatively, *i.e.* for all



(a) Results obtained during simulated system testing with constant $\mathbf{W}$ -context.



(b) Results obtained during simulated system testing with randomly-varying $\mathbf{W}$ -context.

Figure 5: The results obtained from the short-term simulation trials.

of the previous samples obtained, as well as within a sliding window that progresses through the results of the tests.

The tests with users, pictured in Fig. 4, were conducted over two “days”, being run in simulated time, *i.e.* by manipulating the robot’s timekeeping primitives to allow for more testing in less real time. The two users that participated in the test were instructed to act according to a “user profile”, which guaranteed that there was consistency in the way the users expressed their expectation. Additionally, the satisfaction of these users was not estimated from their reaction, and they were instead asked to state their satisfaction explicitly. The advantages of this set-up for tests of this nature is twofold: it allowed us to gauge the system’s effectiveness in the absence of satisfaction estimation error, and, more practically, to avoid having the robot perform actions that the user was not interested in, thus greatly expediting the process.

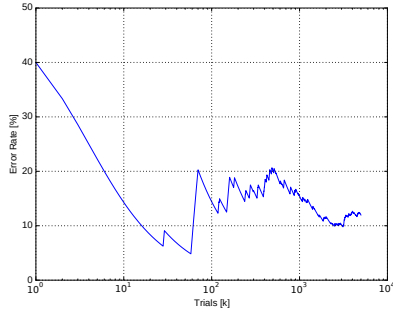
4.2 Results

Fig 5 shows the simulation results we have obtained, both for constant (5a) and varying (5b) $\mathbf{W}$ -context. The model took,

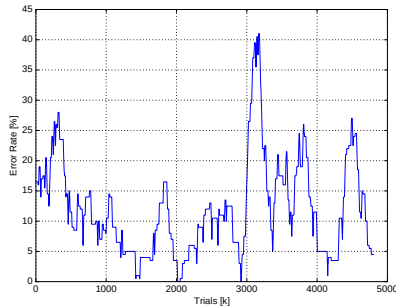
on average, 3.85 iterations to converge on a “typical” trial such as the one presented in Fig. 5.

Fig 6 shows the results of the long-term tests. We can observe, in Fig. 6a that the error rate that the system experiences tends to stabilize around 15%, but that despite its initial general decreasing trend, does not reach a negligible value. We can also observe, in Fig. 6b, that in the later stages of the experiment, the error rate is rather unstable, exhibiting significant variation.

Lastly, the tests with users yielded the following results. When training the system, it displayed a behavior similar to that of the first few trials in Fig. 6a, with relatively unstable error rates. Once the system was trained, and in the absence of the Satisfaction Estimator, it exhibited null error rates, inferring the user’s preferences from context perfectly every time it was asked to do so. In other words, the error rate of the system tends to zero once enough information on the user is gathered.



(a) Error rate calculated cumulatively for the whole experiment window. Please note the logarithmic scale on the x-axis, used to evidence the high initial error rate observed during the training process.



(b) Error rate calculated using a sliding window with a width of 100 trials.

Figure 6: Error rate progression observed during the experiments.

5 Discussion

In Fig. 5, we can observe that the system exhibits the main characteristics we envisioned: it is able to effectively explore the solution space for the correct one, as seen in Fig 5a. When found, it tends to maintain that decision, as seen in Fig 5b. In the same figure, we can observe that it is also able, to some degree, to deal with possible errors in the estimation of the user’s satisfaction.

In the long-term tests, depicted in Fig. 6 We can observe that the error rate does not stabilize in the case of the sliding window analysis, although it does show a clear tendency in the cumulative case. We attribute this observation to the fact that, in both cases, the user’s satisfaction is generated and estimated by probabilistic models, such as the one pictured in Fig. 3. Although it is not explicitly measured in this work, the satisfaction estimator suffers from a significant error rate itself, which tends to induce the expectation estimator in error.

Furthermore, we can observe that the system converges to a low error rate rather early in the test, showing that it does not need an exceedingly large amount of information to be able to operate well.

In the tests with real users, where the Satisfaction Estimator was replaced by the user’s explicit answer, and where we observed that the system can converge to a null error rate, we can conclude that the system is able to achieve a full knowl-

edge of the user’s preferences in the contexts under inspection.

6 Conclusions and Future Work

In this work, we have introduced a probabilistic system that aims at learning the user’s preferences in what regards the services they would like a robot to perform. We have performed simulated tests, which show the functionality of our technique, and demonstrative tests with human users, illustrating the system’s ability to regulate a real interaction and its ability to adapt to its users. Our results show that our system can operate well given a substantial enough amount of training data and that it is able to adapt to real users, albeit within a restricted environment.

We can now envision a number of improvements that can be made to our system. Firstly, there is room for improvement when it comes to convergence speed, an issue we can mitigate, for instance, by intelligently propagating the information gathered across contexts, obtaining a more context-invariant but still context-aware representation of the user’s preferences. Secondly, our tests with users are also relatively demonstrative, and could likely be improved with the analysis of a larger, more varied population of both expert and non-expert users. Lastly, we are interested in progressing beyond the service-based paradigm. As such, we will now focus taking steps toward the design, implementation and testing of a full *interaction regulation* system which should be able to achieve full interaction autonomy by automatically learning and optimizing its actions, not only services, in order to better fit the user’s preferences, moods and characteristics.

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