

# An Architecture for Learning Context-based Value Systems

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## Abstract

As cyberphysical systems become increasingly autonomous, it must be assured that their behaviour is aligned with human values. Insights from Social Science reveal that human value systems depend on context. In this *extended abstract* we introduce a representation for contextual value systems and propose a model for learning them from examples.

## Introduction

The value alignment problem (Russell 2022) states that decisions taken by AI systems must obey ethical principles and human values. A way to achieve this is to endow them with explicit representations of human values and value reasoning abilities. *Context dependency* is key in such *value-aware* AI systems (Osman and d’Inverno 2024): e.g., the importance of the values of “privacy” and “efficiency” may vary when evaluating the same alternative in different contexts.

Given the difficulty of modelling values manually, approaches like Axies (Liscio et al. 2021) and moral value detection (Rink, Lobachev, and Vorontsov 2024) apply context-sensitive value learning through text analysis but cannot reason about value preferences. The work by (Holgado-Sánchez et al. 2025) can infer value representations and value systems (value preferences) as reward functions using inverse reinforcement learning (Ng and Russell 2000), but does not account for context dependency in these representations. The contribution of this paper is twofold: it extends the aforementioned framework with context-sensitivity, and presents the architecture of a computational framework for context-based value learning.

## Representing Context-Based Value Systems

We set out from a set of  $m$  values  $V = \{v_1, \dots, v_m\}$  in an environment with a set of decision alternatives called *entities*  $E$ . Each entity  $e \in E$  is described by a feature vector  $\phi(e) \in \Phi$ . For example, values that guide decision-making in route choice (Prato 2009) may include *ecology* and *security*, entities to choose from are the alternative routes, and features include *route length* or *average speed*. A value

$v \in V$  acquires a particular meaning by *grounding* it in environment features. *Value alignment functions* allow for computing the level of alignment of alternatives with values:

### Definition 1 (Value alignment function/Grounding)

Given a value  $v$ , the function  $\mathcal{A}_v : E \rightarrow \mathbb{R}$  is a **value alignment function** for  $v$ . Then, the **grounding** for  $V$ ,  $G_V : E \rightarrow \mathbb{R}^m$ , is  $G_V = (\mathcal{A}_{v_1}, \dots, \mathcal{A}_{v_m})$  in  $E$ .

In our route choice example, the grounding of the value *ecology* may refer to the expected  $CO_2$  consumption of a certain route  $e$ , that can be estimated from the features *route length* and *average speed*. While we assume that groundings are socially-agreed upon in a society, each agent  $j$  may hold its own *value system*. We model the latter as a preference relation  $\preceq_{j, G_V}$  over entities in  $E$  based on a grounding  $G_V$ . Furthermore, we characterise a context  $c$  by a series of features  $\psi(c) \in \Psi$  that influence agent preferences. E.g, a context may comprise features that determine whether a route is to be chosen for a leisure or for a business trip.

**Definition 2 (Contextual value system)** Let  $G_V$  a grounding. The **contextual value system** of an agent  $j$  is a mapping from contexts to value systems:  $VS_{j, G_V}(c) = \{\preceq_{j, G_V}^c\}$ .

Contextual value system functions are defined by importance weights for each value  $v_i$  based on which, for each context, the degrees of alignment of an entity  $e$  with  $v_i$  are linearly aggregated, so as to represent the corresponding value system.

### Definition 3 (Contextual value system function)

Let  $VS_{j, G_V}$  be the contextual value system of agent  $j$ . The function  $\mathcal{A}_{j, G_V} : C \times E \rightarrow \mathbb{R}$  is the **contextual value system function** of  $j$  assuming the grounding  $G_V$ , defined as  $\mathcal{A}_{j, G_V}(c, e) = W_j^c \cdot G_V(e)$ , where  $W_j^c = (w_j^{v_1}(c), \dots, w_j^{v_m}(c))$  represents the value weights reflecting  $j$ ’s value system at context  $c \in C$ .

As in previous work, we assume that the weights  $W_j^c$  are restricted to  $[0, 1]^m$  and that their sum across values is 1, so that agents cannot be opposed to the promotion of a value or be completely unaware of all of them.

With this representation model we can redefine the *value system learning* problem (Holgado-Sánchez et al. 2025), adapting for context-dependency.

**Definition 4 (Contextual value system learning)** The **contextual value system learning problem** consists of (i)

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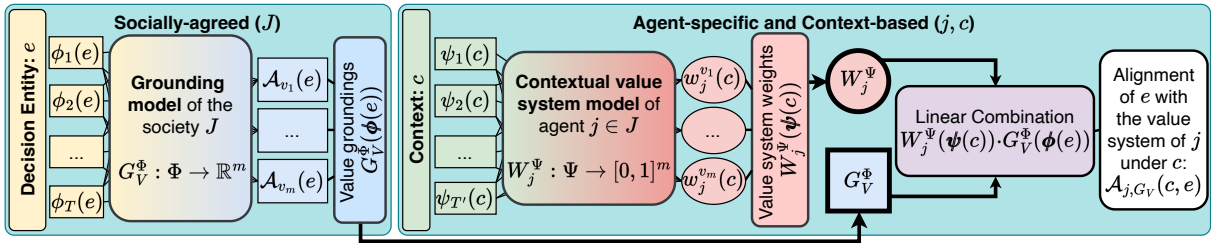


Figure 1: The proposed architecture applicable to learning agent-specific and context-based value systems.

inferring a socially-agreed grounding  $G_V : E \rightarrow \mathbb{R}^m$  that represents value alignment for a society of agents  $J$ , and (ii) learning a contextual value system function  $A_{j, G_V} : C \times E \rightarrow \mathbb{R}$  for each agent  $j \in J$  based on  $G_V$ , which reduces to finding the corresponding contextual value system weights  $W_j^c \in [0, 1]^m$ .

## Contextual Value System Learning Architecture

In this section, we describe our second contribution: an architecture for contextual value system learning. It consists of two modules. The first module (Figure 1, left) features the model  $G_V^\Phi : \Phi \rightarrow \mathbb{R}^m$  that represents the socially-agreed grounding  $G_V$  and is based on the entity features  $\Phi$ . The second module (right) is agent-specific (for each  $j \in J$ ) and also context-dependent, as it includes the learnable model  $W_j^\Psi : \Psi \rightarrow [0, 1]^m$  that estimates the weights  $W_j^c$  from the features of the context  $c$ . Then, with the linear combination of the weights and the groundings, an estimation of the contextual value system alignment function of the agent is derived:  $A_{j, G_V}(c, e) = W_j^\Psi(\psi(c)) \cdot G_V^\Phi(\phi(e))$ .

While the context feature space can be infinite or dense, the space of possible contextual value systems should not, at least for a human. E.g., if the time of day is a context feature,  $W_j^\Psi$  might assign different weights at 9:00 AM than at 9:01 AM. To prevent these unreasonable predictions, we suggest limiting the number of contexts that trigger different value systems and, if possible, make the relationship between contexts and value system interpretable. To do so, we suggest implementing clustering (Chakraborty et al. 2024), rule-based (Veronese et al. 2024) or meta-heuristic (Bruns, Dunkel, and Seremet 2023) approaches in the contextual value system model architecture.

Given the architecture, we propose a learning setting to ground Definition 4. Let an environment in which for each agent  $j \in J$  we observe a dataset  $\mathcal{D}_j = \{(e_k, e'_k, y_k^j, c_k)\}_{k=1}^K$ , where  $y_k^j \in [0, 1]$  captures  $j$ 's relative preference for entity  $e_k$  over  $e'_k$  at context  $c_k$  according to  $j$ 's value system. Consider also another dataset from domain experts, namely,  $\mathcal{D}_V = \{(e_l, e'_l, y_l^{v_1}, \dots, y_l^{v_m})\}_{l=1}^L$  where  $y_l^{v_i} \in [0, 1]^1$  is the annotated degree of preference of  $e_l$  over  $e'_l$  regarding their alignment with value  $v_i$ .

<sup>1</sup>Though they are defined generally as quantitative measures in  $[0, 1]$ , both  $y_l^{v_i}$  and  $y_k^j$  may represent qualitative preferences if they are restricted to  $\{0, 1.0, 0.5\}$ , to indicate that  $e_k/e_l$  is preferred over  $e'_k/e'_l$ , the inverse relation, or indifference, respectively.

Additionally, let  $\mathcal{L}_{G_V^\Phi}(\mathcal{D}_V)$  and  $\mathcal{L}_{W_j^\Psi | G_V^\Phi}(\mathcal{D}_j)$  be two loss functions. The first measures the error of approximating  $y^{v_i}$  from  $G_V^\Phi(e)$ , and the second, the error of approximating  $y^j$  from  $A_{j, G_V}(c, e) = W_j^\Psi(\psi(c)) \cdot G_V^\Phi(\phi(e))$ . Minimizing these two losses in a structured way (Definition 5), we obtain optimal models  $(G_V^\Phi)^*$  and  $(W_j^\Psi)^*$  that maximally represent the preferences in the datasets, solving the two tasks from Definition 4. To define these losses, inspiration can be taken from RLHF (Christiano et al. 2017).

**Definition 5** The contextual value system learning problem consists of solving the bi-level optimization problem:

$$(W_j^\Psi)^* = \arg \min_{W_j^\Psi} \sum_{j \in J} \mathcal{L}_{W_j^\Psi | (G_V^\Phi)^*}(\mathcal{D}_j)$$

subject to  $(G_V^\Phi)^* \in \arg \min_{\theta_V} \mathcal{L}_{G_V^\Phi}(\mathcal{D}_V)$ .

Approaching this bi-level optimization problem requires prioritizing approximating the value dataset  $\mathcal{D}_V$  over the value system ones  $\{\mathcal{D}_j | j \in J\}$ . To do that, and assuming differentiable loss functions and learning our models through gradient descent, we can use a weighting factor  $\lambda > 0$  to treat the loss  $\mathcal{L}_{G_V^\Phi}$  as a soft constraint and minimize a global loss  $\mathcal{L}(\mathcal{D}_j, \mathcal{D}_V) = \sum_{j \in J} \mathcal{L}_{W_j^\Psi | (G_V^\Phi)^*}(\mathcal{D}_j) + \lambda \mathcal{L}_{G_V^\Phi}(\mathcal{D}_V)$ . It is also possible to estimate a suitable value for  $\lambda$  during optimization (Cotter, Jiang, and Sridharan 2019). An alternative to differentiable approaches could be techniques from the field of operations research, employed in the related problems of finding maximally-aligned normative systems (Serramia et al. 2018) and aggregating value-based preferences of multiple agents (Lera-Leri et al. 2022).

## Applicability and Future Work

The proposed approach will allow us to estimate the value system of new agents, recommend alternatives for custom preference weights, or predict agent preferences in simulated contexts. Potential application domains include route choice (Zhao and Liang 2023) or value-aware recommender systems (De Biasio et al. 2023).

In future work, we will implement and evaluate the proposed architecture with real-world datasets on route choice, extending synthetic experiments in (Holgado-Sánchez et al. 2025). This will require extending the context model to sequential decision-making. Other challenges include the recognition of trends in the diverse value systems of a full society of agents, and support for heterogeneous value groundings (context or agent-based).

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