#### Int. Journal of Math. Analysis, Vol. 6, 2012, no. 30, 1453 - 1455

# Robot Self-Awareness: Occam's Razor for Fluents

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#### Abstract

In this paper we consider robot self-awareness from the point of view of temporal relation based data mining. In particular, we use rational function approximations and consider Occam's razor for fluents.

### Mathematics Subject Classification: 41A20

**Keywords:** robot self-awareness, Occam's razor, fluents

A robot with self-aware system has the possibility of dealing with complex novel situations more effectively than a robot without self-awareness (see e.g. [1, 2]). In [1], the authors considered robot self-awareness from the point of view of temporal relation based data mining. Temporal patterns can be expressed using fluents (see e.g. [1, 3]). A fluent is a proposition with temporal extent. For example, "drinking-coffee" can be defined as a fluent that is true whenever I am drinking coffee. This fluent can be represented as a binary time series x, where x[t] is 1 if and only if I am drinking coffee at time t. Respectively, temporal relations needed only to express relations of fluents.

To build a system of self-awareness the robot needs a system of automatic selection of fluents and prediction of values of selected fluents. Using some kind of system of self-learning and accumulation of knowledge (see e.g. [1, 3]) the

robot can obtain fluents as experimental measured dependencies. Therefore, we can use the rational function approximations for prediction of values of fluents. Since the function x[t] is given by measured data pair, the rational function approximations can be made by following manner. For every t[i],  $1 \le i \le n$ , we can write following expression  $x[t[i]] = \frac{\sum_{j=0}^{p} a_j t^j[i]}{1 + \sum_{l=1}^{r} b_l t^l[i]}$ , where x[t[i]] and t[i] are known data and  $a_j$ ,  $b_l$  are required unknown coefficients. This expression we can write in following form

$$x[t[i]] = \sum_{j=0}^{p} a_j t^j[i] - x[t[i]] \sum_{l=1}^{r} b_l t^l[i].$$

Note that we can suppose that n = p + r. Therefore,

$$(a_{0}, \dots, a_{p}, b_{1}, \dots, b_{r})^{T} = \left( \begin{pmatrix} 1 & t[1] & \dots & t^{p}[1] & -x[t[1]]t[1] & \dots & -x[t[1]]t^{r}[1] \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & t[n] & \dots & t^{p}[n] & -x[t[n]]t[n] & \dots & -x[t[n]]t^{r}[n] \end{pmatrix} \right)^{T} \cdot \left( \begin{pmatrix} 1 & t[1] & \dots & t^{p}[1] & -x[t[1]]t[1] & \dots & -x[t[1]]t^{r}[1] \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & t[n] & \dots & t^{p}[n] & -x[t[n]]t[n] & \dots & -x[t[n]]t^{r}[n] \end{pmatrix} \right)^{-1} \cdot \left( \begin{pmatrix} 1 & t[1] & \dots & t^{p}[1] & -x[t[1]]t[1] & \dots & -x[t[n]]t^{r}[n] \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & t[n] & \dots & t^{p}[n] & -x[t[n]]t[n] & \dots & -x[t[n]]t^{r}[n] \end{pmatrix} \right)^{T} \cdot \left( \begin{pmatrix} 1 & t[1] & \dots & t^{p}[1] & -x[t[1]]t[1] & \dots & -x[t[n]]t^{r}[n] \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & t[n] & \dots & t^{p}[n] & -x[t[n]]t[n] & \dots & -x[t[n]]t^{r}[n] \end{pmatrix} \right)^{T} \cdot (x[t[1]], \dots, x[t[n]])^{T} \cdot \dots + x[t[n]]t^{r}[n] \right)^{T} \cdot (x[t[1]], \dots, x[t[n]])^{T} \cdot \dots + x[t[n]]t^{r}[n] \right)^{T} \cdot (x[t[1]], \dots, x[t[n]])^{T} \cdot \dots + x[t[n]]t^{r}[n] \right)^{T} \cdot (x[t[1]], \dots, x[t[n]])^{T} \cdot \dots + x[t[n]]t^{r}[n] \right)^{T} \cdot (x[t[1]], \dots, x[t[n]])^{T} \cdot \dots + x[t[n]]t^{r}[n] \right)^{T} \cdot (x[t[1]], \dots, x[t[n]])^{T} \cdot \dots + x[t[n]]t^{r}[n] \cdot \dots + x[t[n]]t^$$

The thesis "Entities should not be multiplied beyond necessity" articulated by the 14th century logician William of Occam and known as the Occam's razor states that the simplest theory should be chosen from among all theories which equally well explain observed data [4]. Occam's razor is obviously relevant to machine learning [5]. In particular, it can be used for selection of fluents. However, the exact way it translates to this context has been subject to a long-lasting debate (see e.g. [6, 7, 8]).

Let length(z) denote the number of bits which are required for representation of z. We can consider

$$(p+r+1)\max\{\max_{0\leq j\leq p} length(a_j), \max_{1\leq l\leq r} length(b_l)\}$$

as a measure of complexity of fluent. In our model, robot automatically use a genetic algorithm to determine rational function approximations of fluents with best predictive capability. After this, robot consider a set of simplest fluents. Let  $x[t[i]] = \frac{\sum_{j=0}^{p} a_j t^j[i]}{1+\sum_{l=1}^{r} b_l t^l[i]}$  and  $y[t[i]] = \frac{\sum_{j=0}^{p} c_j t^j[i]}{1+\sum_{l=1}^{r} d_l t^l[i]}$ . Robot use the function

$$\sum_{j=0}^{p} (a_j - c_j)^2 + \sum_{l=1}^{r} (b_l - d_l)^2$$

as the measure of similarity of fluent x[t[i]] and y[t[i]]. After this, robot use the following assertion for further selection of fluents: "Models selected from a larger set of tested candidate models overfit more than those selected from a smaller set" (see e.g. [8]).

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Received: January, 2012