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Document history

Version	Date	Author (Unit)	Description
v0.3	1/9 2014		First draft finished

1 Executive summary

2 Introduction

3 Preliminaries

4 Preliminary Models

4.1 Daimler Models

Introduction

The static OOBN

The dynamic OOBN

The above described static OOBN is able to detect a maneuver 0.6s before execution. The goal is to extend the prediction horizon for manoeuvre recognition at least to 1-2 seconds (max. 4-5 seconds ahead) before the actual lane marking crossing, which is of advantage for the adaptive cruise control. Most precisely, and as indicated in the Use Case 8 on the Requirement Analysis, the area under the ROC curve (AUC) should be greater than 0.96 for 1 second and greater than 0.9 for 2 seconds.

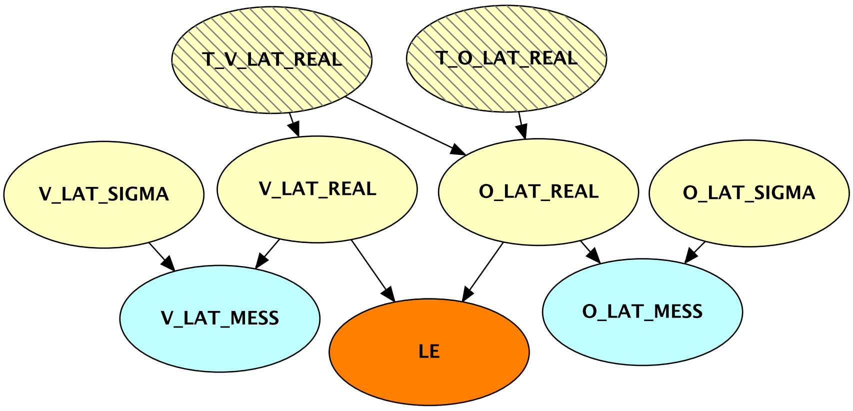
Figure [timedetection] shows the evolution on time for velocity and offset in an EGO_CutOut manoeuvre. The vertical bar indicates the moment in which the manoeuvre has been recognised by the static OOBN. By taking the temporal properties of the data into account on the model, we should be able to predict the manoeuvre earlier on time.

Each manoeuvre can be considered as a process, developing in time, i.e., as data stream given by a time sequence of the transition from lane follow into lane change manoeuvre. The dynamic extension involves copies of the static OOBN for different number of time steps in the time window (e.g. see Fig. 1 where the two top nodes are temporal clone defining the share belief state between consecutive time steps creating a first order Markov process), if also the requirement on earlier prognostics of maneuver is to be satisfied.

1. **Dynamics on Lateral Evidence (LE)** A good starting point to model the dynamics of the data involves the variables that capture the lateral evidence for the different vehicles, given its relevance and simplicity. The dynamic BN (DBN) incorporates the trend of change for the real values, where their physics relations are represented as causal dependencies between the time steps dt, e.g. in Fig. 1 the transition function of O_LAT at time t, O(t), is modeled as a Gaussian distribution. Its mean is affected by O(t-1), and by V_LAT at time $t-1$, $v(t-1)$:

$$O(t) = O(t-1) + v(t-1)dt + N \tag{1}$$

Figure 1: Daimler Temporal Model



where N denotes a white noise $N(0, \sigma^2)$ due to possible acceleration term $(adt2)/2$, which is assumed to be small for a time step in the order of 102 milliseconds.

The shaded nodes represent the development of the real values of observations over several time steps in the time window. Thus, their trend estimation contributes to the prediction of probability of transition from a lane follow to a lane change manoeuvre.

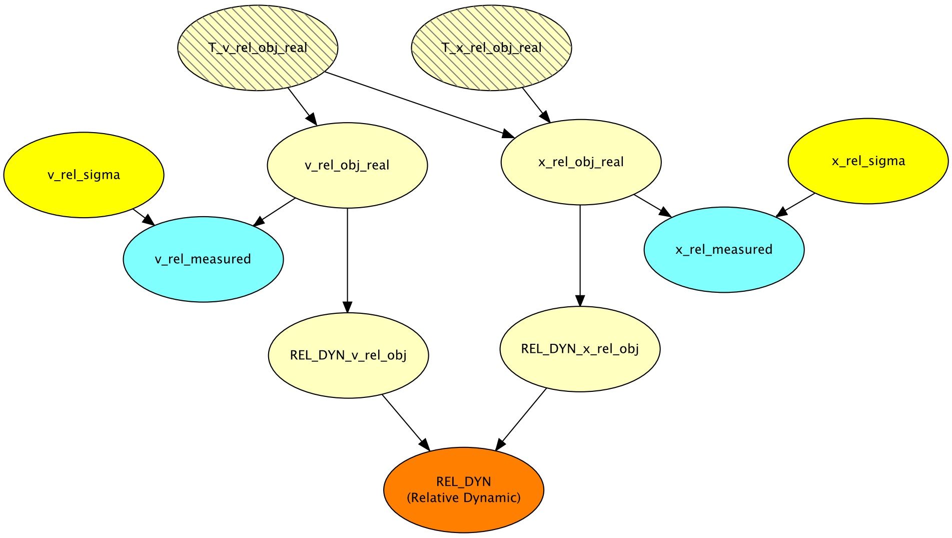
A DBN induces a number of constraints on the compilation of the network into a computational structure. One constraint relates to transferring the belief state from one time slice to the next where the belief state is the probability distribution over the variables shared by neighbouring time slices. In general, the belief state is transferred as a joint distribution. This means that approximate methods [**?**] may have to be considered for meeting the requirements of the target platform.

2. **New hypothesis: Relative Dynamics (REL_DYN)**

   Earlier prediction of manoeuvre intentions can be achieved even before any development of the trend for lateral evidence LE has been observed. A first indication of possible lane change intention can be observed through the relative dynamics between one vehicle (host or object) and the vehicles in front of it on the same lane. Once again, the goal is to further increase the prediction horizon for manoeuvre recognition (up to 5 seconds).

   We can include qualitatively new information based on driving experience, which indicates a need for a lane change if a slower vehicle is driving in front of the own vehicle on the same lane. To continue its safe driving, the approaching vehicle should either break and reduce its speed to the speed of the vehicle in front or, alternatively,,it should change to the neighbour lane, if the neighbour lane is free and no other vehicle is approaching with a higher speed than the own vehicle. A continued safe manoeuvre (of type “lane follow” or “lane change”) is modelled by

Figure 2: Daimler Temporal Model with relative dynamics



estimating the TTC (TimeToCollision) to the vehicle in front (on the same lane) or to eventually approaching vehicle (on the neighbour lane). For safe manoeuvre, TTC should be bigger than 1 second, if the own vehicle wants to change to the neighbour lane or if it needs to break to ensure safe driving on the same lane ("'lane follow") .

Figure [timedetectionRelDyn] shows the evolution on time for the velocity and distance in an EGO_CutOut manoeuvre. The vertical bar indicates the moment in which the manoeuvre has been recognised by the static OOBN. By taking the temporal properties of the relative dynamics into account on the DBN, we should be able to predict the manoeuvre even earlier on time.

By analogy to Fig. 1, the original OOBN has been extended with the hypothesis "relative dynamics" (REL_DYN), as shown in Fig.2. This BN fragment models the hypothesis REL_DYN with 3 states Left/Follow/RIGHT, utilising the independency assumption for the discrete variables V_REL_MEASSURED and X_REL_MEASSURED.

If we compare the structure of this network with that of Fig. 1, we can observe two additional nodes: REL_DYN_V_REL_OBJ and REL_DYN_X_REL_OBJ. They are the results of a modelling trick to simplify the EM-learning of parameters from data for the static BN fragment.

Note that the new REL_DYN hypothesis introduced would require two instances in the OOBN, one for the relative dynamics of the EGO with the OBJ in front, and another one for the OBJ and another OBJ in front of it. Each REL_DYN would indicate if the EGO and the OBJ cars are going to turn right, left or continue straight.

4.2 CajaMar Models

Introduction

Model Structure

From a probabilistic modeling point of view, Caja-Mar faces two different problems [][]: the prediction of the risk of defaulting of a customer in the next two years; and the extraction of profiles of "desirable" prospective customers.

The risk prediction problem has been modeled as supervised dynamic prediction problem. We are given a data base with a set of variables or predictors (some of them manually built by CajaMar's experts) describing the financial behavior of the customers and, also, whether the customer is considered as defaulter and non defaulter according to CajaMar standards (i.e. a binary class variable). The dynamic component of the problem needs to be considered because the behavior of the customers evolves over time (e.g. the account balance is continuously changing from month to another, the level of incomes, etc.) as well as the labeling as defaulter or non-defaulter customer (e.g. one customer can be creditworthy and, but after some time, be in bankrupt for becoming unemployed). More specifically, the proposed model is expected to answer the following question: which is the probability that this customer will default in some of his/her loans in two years? And this prediction has to be made only using the customer's behavior in the last 180 days [1].

The graphical structure of the dynamic probabilistic graphical model devised for this problem is given in Figure 3. The yellow square boxes "Day -180", ..., "Day-1" represents the temporal evolution of the predictor variables. The model only refers to 180 days because this is the imposed limit of days when making predictions. Similarly, the class variable "default" is assumed to evolve over time but with the relevant different that the default class sequence refers to a point in the time **two years later** than the point in the time the daily predictor variables.

Finally, in Figure 4 we further detail the structure of the predictors variables evolving over time.

[1]This limit is imposed by the Bank of Spain.

Figure 3: Caja Mar Temporal Model

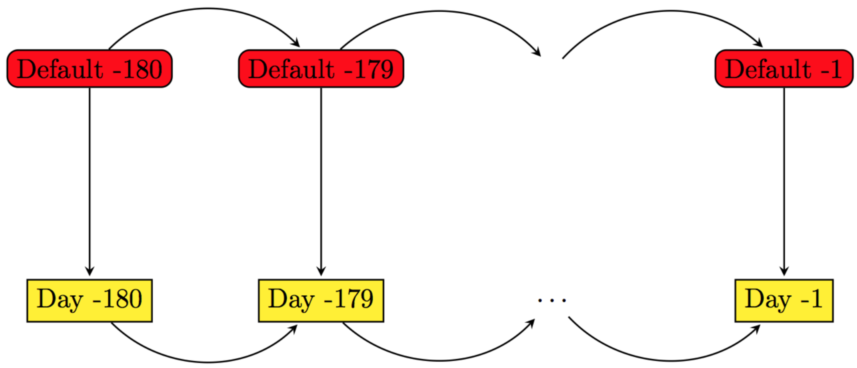
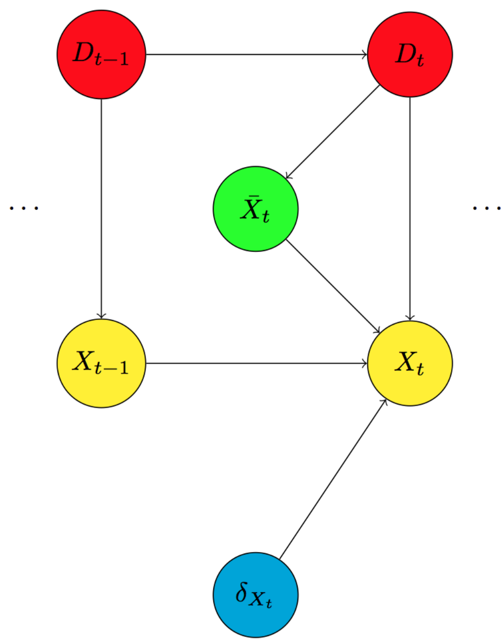


Figure 4: Basic component of the structure of the dynamic model



Data Analysis

4.3 Verdande Models

Model Structure

Data Analysis

5 AMIDST Model Class

6 Conclusions