A Probabilistic Approach to the Anxious Home for Activity Monitoring

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Abstract

This paper describes an approach to representing normal activities in a smart house based on the concept of anxiety. Anxiety is computed as a function of time and is kept low by interactions of an occupant with the various devices in a house. Abnormality is indicated by a lack of activity or the wrong activity which will cause anxiety to rise ultimately raising an alarm, querying the occupant and/or alerting a carer in real-time. Anxiety is formulated using probabilistic models that describe how people interact with devices in combinations. These models can be learnt interactively as the smart house acts pessimistically enquiring of the occupant if what they are doing is normal. Results are presented for a number of kitchen scenarios and for different formulations of anxiety.

1 Introduction

There is a growing demand for techniques to help elderly and infirm people live in their own homes safely. This paper explores the issue of dealing with hazards in a home generated by numerous appliances such as the stove being unattended, the front door being left open, or the bath being left running. The research makes extensive use of simple sensors such as pressure pads, reed switches, current sensors, simple flow sensors and control of devices via the X10 protocol.

The solution to modelling hazards requires the fusion of the interaction of the occupant with the many sensing devices. This involves learning typical patterns of activity of the occupant which is complex because patterns of activity have much variation in the sequence and sub-sequences of events and because these can be interwoven. The question is how to quantify such activities such that hazardous situations can be detected and the occupant warned. A novel approach is proposed that does not model sequences directly but is focussed on regarding devices as hazardous and passive and measuring the *anxiety* for each hazardous device and, potentially, groups of devices as well as for the whole house (the anxious home). We use statistical models to represent the interaction of the occupant with (1) the device (e.g. switching it on, opening the door), and (2) with other devices while a particular device is in a potentially hazardous state (e.g. while it is on).

The overall anxiety is computed in a probabilistic framework that uses cumulative distributions for the expected periods between interactions with devices. The significance of this approach is that it can detect multiple hazards without the normal combinatorial explosion in state space. It can also accommodate interwoven activities and activities in which there is a lot of variability in the order of the sub-activities.

The layout of the paper is as follows. First we review relevant background material, followed by the rationale behind this approach. We then formulate the statistical model used to represent the state of the devices and the house. Finally our simulated smart house is described and experimental results presented for a number of simulated scenarios. We show how different interactions with devices can be used to alter the anxiety for other devices in meaningful and useful ways.

2 Background

There has been much research in the area of smart house technology. Some very simple devices have been developed such as the Stove Guard[1] that has current and motion sensors and can turn off the stove after a certain time if it is on (detects current) and is unattended (no motion). Many other simple sensors have been used for recognising activity in houses [8, 2, 5]. Glascock and Kutzik [3] use a small number of infra-red sensors for coarse activity monitoring that is mainly suited for making sure someone has taken medication, eaten etc. which only requires events to be reported at two hour intervals. GE has described a system [4] that uses many standard sensors (window and door sensors)

[1] www.absoluteautomation.com/stoveguard — accessed Feb'05.

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and a form of anxiety that rises if there is little activity in the house compared with learnt activities. This differs from the work presented here in that we are interested in the interactions of various devices enabling richer semantics to be inferred and monitored in real time enabling prompt responses to abnormal behaviour. Anxiety is an emotion in the human sense and recently, much work has been carried out into emotional computing [7], mainly to enable computers to communicate with humans. It is argued that decision making by humans requires emotions and useful decision making by computers requires similar attributes. We believe that anxiety is an important emotion for decision making and especially for a smart house.

Activity recognition can be regarded as the recognition of patterns in multi-modal time sequences. Much research has focussed on using various forms of Markov model [1, 6]. In these methods, a model for an activity is constructed from many sequences of events (learning). HMMs model the temporal changes in state, and can accommodate variations in the durations of each activity. However they are sensitive to changes in the order of sub activities and the interleaving of events.

3 Rationale

The main objective of this research is to model normality i.e. the normal activities of an occupant in their house. What we desire is a measure that will be below a threshold for normal activity but rises above the threshold for abnormal activities. Importantly we do not want to model abnormality directly. Abnormality, almost by definition, is not modellable because abnormal events rarely occur and would not be statistically meaningful. The essential idea proposed in this paper is that a device, when on, is in a hazardous state until it is switched off. Such devices are stoves, baths and fridges. The longer each device is left *unattended* the more hazardous it should become e.g. leaving a stove on for eight hours could be dangerous. We introduce the concept of *anxiety* here to represent the time a device is left unattended. When a device is turned on, its anxiety is zero, but rises over time if it is not attended by the occupant. Eventually when it reaches some threshold, some action should be taken. An important issue is what is meant by attended. This can be modelled in two ways; (1) the device is directly interacted with (settings changed or occupant adjacent e.g. standing on a pressure pad next to the device), and (2) the device is observed from close range e.g. opening the fridge that is near the cooker means the occupant can check on the state of the stove easily or can get to the stove within a reasonable time to interact with it.

Each of these should mean the anxiety of the device reduces instantaneously by some amount and then starts to rise again. The second model can be thought of as a function of whether (1) the device is normally interacted with, and (2) how far away it is. By normally interacted with, we mean that, for example, when the stove is on, it is normal to visit the fridge regularly. By how far away the device is, we mean that interaction with near devices is more reassuring than with devices far away. For example, interacting with the fridge that is near means it is easy to observe the stove and the occupant can get to the stove quickly. Interacting with the bath would mean it would take longer to reach the stove and, normally, it would be difficult to observe the stove from the bathroom.

To further illustrate the concept, consider a breakfast scenario consisting of the following sequence of events:

- Occupant opens cupboard, takes cereal from cupboard, closes cupboard, puts cereal on table.
- Occupant opens fridge door, takes egg and milk from fridge, puts milk on table, put egg on stove to cook, closes fridge door.
- Occupant sits down at table, eats breakfast.
- Occupant gets egg from stove, turns off stove, sits down, eats egg.

There are two potentially hazardous situations here. The first is leaving the stove on to boil the egg dry and then melt the pan. The second is leaving the fridge open which would spoil the food, use electricity and possible burn out the motor. There are also interleaved activities here i.e. the stove is turned on while the fridge is open. Once the stove is turned on, its anxiety will start to rise. The fact that the occupant is nearby (by the table) should mean the anxiety should not rise as fast as, say, if the occupant leaves the kitchen. As long as the occupant checks on the stove regularly or finishes eating their cereal in time, the anxiety shouldn't reach the alarm level. When the occupant turns off the stove, the anxiety for the stove should go to zero as it is not in a hazardous state anymore. Once the occupant leaves the fridge door open, the anxiety for the fridge should rise and reach the alarm state. If the door is closed before it reaches this state then anxiety reduces to zero and no alarm is signalled.

Note the kitchen could have an anxiety based on the anxiety of all the hazardous devices present in the kitchen. If both the stove and fridge are in hazardous states and not attended to, then the kitchen anxiety should be some form of combination of these anxieties.

From the above description, it can be inferred that a number of parameters are needed to describe how anxiety works. We take a learning approach to this through interacting with the occupant as initially, only the occupant (or carer) will really understand what is normal and abnormal. In this paper we take a pessimistic approach to anxiety and choose the worst case scenario. Such a scenario can occur when

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someone is standing in the kitchen for a long period of time or has collapsed on the floor. Given that we are using device activities to infer intent, these two scenarios cannot be separated so we assume the worst — they have collapsed. Pessimistically, if we ask the occupant (or carer) if the anxiety is okay (normal) when it exceeds a threshold, we can use the information about the event to update the parameters.

4 Statistical Model for Anxiety

To formulate anxiety, we divide devices into two classes. The first class consists of hazardous devices such as stoves, the bath, the fridge. These devices have to be attended to while they are in a hazardous state. The second class consists of passive devices such as pressure pads and reed switches on other devices. They usually belong to devices for which there is no hazardous state. For example, a reed switch on a cupboard is a passive device if it doesn't matter if the cupboard is left open or closed. A pressure pad would not, by itself, have a hazardous state. Some hazardous devices can be regarded as passive devices. For example, in the context of the stove, the fridge is a passive device as it is used to signal to the stove where the occupant is.

We have a number of statistical representations for the devices:

For each hazardous device we have a statistical model (called the Self Interaction Duration model: SID) in which $p^{d_i}_{\mathit{SID}}(t)$ denotes the probability density distribution of the time intervals between interaction with the device d_i where t is the time between interactions[2]. For example, if someone is cooking pasta, a occupant would check the stove every minute or so. The resulting distribution would show a peak around one minute. They would be less likely to check every 10 seconds or every five minutes. From this distribution, a cumulative distribution can be determined which represents the probability $P^{d_i}_{\mathit{SID}}(t_0, t)$ that the device *should* have been interacted with between the time of last interaction t_0 and the time now t. The closer this probability gets to 1.0 without interaction, the more anxious the device d_i becomes.

For each hazardous device, we also have a statistical model (called the Interaction Event model: IE) in which $P^{d_i,d_j}_{\mathit{IE}}$ denotes the probability of interaction of the occupant with another device d_j while the device d_i is in a hazardous state. That is, when the cooker is on, $P^{\mathit{stove},\mathit{fridge}}_{IE} = 0.9$ means that 90% of the times the cooker is on, the occupant interacts with the fridge. A high value means this is more likely to be a normal occurrence.

For each passive device d_j we have a statistical model (called the Inter Interaction Duration model: IID) that is a distribution $p^{d_i,d_j}_{\mathit{IID}}(t)$ that describes the time intervals between interacting with the passive device d_j and then with the hazardous device d_i given that device d_i is in a hazardous state. This is a distance function as well as a time function because, assuming intent by the occupant, the intervals will reflect the time it takes to get from one device to another or the distance between them. Learning these distributions reveals normal pathways through the house. From this distribution, a cumulative distribution can be determined which represents the probability $P^{d_i,d_j}_{\mathit{IID}}(t_0, t)$ that the device d_i *should* have been interacted with at time t given that device d_j was interacted with at time t_0. The closer this probability gets to 1.0 without interaction, the more anxious the device d_i becomes.

[2] In this paper P denotes probability, and p denotes probability density.

Table 1. Various probabilities at each time step for a simple example.

	Stove			Cupboard					Overall
Time mins	PDF cts	CDF cts	CDF norm	PDF cts	CDF cts	CDF norm	1-G	1-G*0.7	D×I
A	B	C	D	E	F	G	H	I	J
0	0	0	0						0
1	5	5	0.030						0.030
2	10	15	0.092						0.09
3	15	30	0.18						0.18
4	20	50	0.30	0	0	0	1	0.3	0.30
5	25	75	0.46	0	0	0	1	0.3	0.46
6	24	99	0.61	0	0	0	1	0.3	0.61
7	20	119	0.73	2	2	0.05	0.94	0.34	0.25
8	15	134	0.82	5	7	0.20	0.79	0.44	0.36
9	12	146	0.90	10	17	0.5	0.5	0.65	0.58
10	8	154	0.95	10	27	0.79	0.20	0.85	0.81
11	5	159	0.98	5	32	0.94	0.05	0.95	0.94
12	3	162	1	2	34	1	0	1	1
13	0	162	1	0	34	1	0	1	1
14	0	162	1	0	34	1	0	1	1
15	0	162	1	0	34	1	0	1	1
16	0	162	1	0	34	1	0	1	1
17	0	162	1	0	34	1	0	1	1
18	0	162	1	0	34	1	0	1	1
19	0	162	1	0	34	1	0	1	1
20	0	162	1	0	34	1	0	1	1

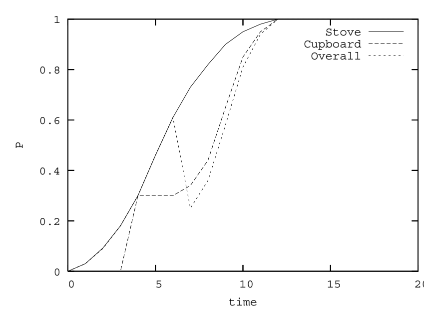

Figure 1. Graph of the main columns of Table 1 showing anxieties for the stove (column D), the cupboard (column I) and overall (column J).

How the various probabilities are used are shown in Table 1 for a period of 20 minutes (column A). Column B

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shows $p^{d_i}_{SID}(t)$ for a stove. This is a unimodal distribution with a mean around five minutes and all interaction intervals between one and 12 minutes. Column D shows the cumulative distribution $P^{d_i}_{SID}(0,t)$ which rises from zero to a maximum at 12 minutes. Column E shows $p^{d_i,d_j}_{IID}(t-4)$ for the cupboard given the stove is in hazard. The values for time from zero to three minutes are not shown because the cupboard d_j was interacted with the fourth minute after the stove d_i was last attended. Hence $P^{d_i,d_j}_{IID}(t)$ is not relevant until the fourth minute. The distribution shows that the mean time to interact with the stove after opening the cupboard door is approximately six minutes. Column G shows the cumulative distribution $P^{d_i,d_j}_{IID}(4,t)$ which rises from zero to a maximum at 12 minutes. The probability of interacting with the cupboard when the stove is in the hazardous state P^{d_i,d_j}_{IE} is defined to be 0.7 for this example. The way the probabilities for the cupboard are used to modify the probability of the hazardous device is as follows. We want the anxiety of the stove to reduce once the cupboard has been interacted with and then rise again. The effect of the cupboard on the anxiety should be removed if no interaction with the stove has occurred. To add in the affect of the cupboard, the stove probability is modified by:

$$S^{d_i,d_j}(t) = 1.0 - (P^{d_i,d_j}_{IE}(1.0 - P^{d_i,d_j}_{IID}(t))) \qquad (1)$$

Columns H and I show the calculations for $S^{d_i,d_j}(t)$. The probabilities are incorporated as:

$$P^{d_i}_{overall}(t) = P^{d_i}_{SID}(t-t_o) \times \prod_{\forall e_j} S^{d_i,d_j}(t-t_{e_j}) \qquad (2)$$

where e_j is an event for device d_j and assuming that $e_j \forall j$ are independent of each other. One problem with this formulation is that if the occupant repeatedly interacts with a device, the anxiety for the hazardous device will keep on reducing. This can be overcome by only using the latest interaction. This can be argued for because once the latest event occurs, all the previous events are not relevant. Then the probability becomes:

$$P^{d_i}_{overall}(t) = P^{d_i}_{SID}(t-t_o) \times S^{d_i,d_j}(t-t_{e_j}) \qquad (3)$$

Figure 1 shows plots over time for the anxiety of the stove on its own, the cupboard, and the overall anxiety for the stove. The overall anxiety rises until the cupboard is interacted with after which it drops and then starts rising again. Eventually the overall anxiety levels out at a probability of 1.0 signifying that no interaction with the stove has taken place. Comparing the curves for the stove on its own and the overall reveals the cupboard interaction increased the time for a particular anxiety e.g. a value of 0.8 could be when an alarm is raised.

Given that each hazardous device has its own anxiety, there is a need to consider the overall anxiety of the house. Each anxiety has a range $0:1$ (probabilities of being anxious) and simply taking the product would result in an anxiety lower than the maximum. Ideally two device anxieties of say 0.5 should result in an overall anxiety much higher, say 0.75. Currently we take the maximum anxiety as the overall.

5 Experimental Environment

To explore these and other ideas, we developed a Smart House laboratory environment. The laboratory is populated with a number of devices to simulate those that would be found in a typical house. The house has several rooms: a kitchen, lounge and bedroom. The kitchen includes a small electric stove, microwave oven, fridge, dishwasher, cupboards, a kitchen table and chair. Each device is augmented with sensors to detect interaction by the occupant. Reed switches detect the opening and closing of doors (e.g. the fridge, dishwasher, microwave, cupboards), while pressure mats detect the proximity of the occupant to certain key locations (doorways, chairs). For hazardous devices, pressure mats are positioned on the floor in front of each device to detect interaction by the occupant.

6 Experiments and Results

To evaluate our model, we trained the system on 30 examples of a breakfast sequence with variation in the events, their duration and ordering. Note breakfast was accelerated to reduce the time to acquire the data. For testing, normal and abnormal sequences are presented and we examine how the anxiety changes over time.

Figure 2 shows a typical result. The event sequence is shown in the lower time-line. In the scenario, the occupant takes an egg from the fridge and places it in a pot on the stove. State `stove:hazard` becomes true when the occupant turns on the stove. While interacting with the stove, the state `stove:mat` is true, so `stove:unattended` does not become true until the occupant steps off the mat and begins another activity. In this scenario, the occupant uses the toaster, collects the egg from the stove and sits at the dining table to eat breakfast. Once the stove becomes unattended, the system computes the anxiety which increases over time as shown in the upper plot in Figure 2. In the absence of events, the anxiety level increases monotonically according to $P^{stove}_{SID}(t_0,t)$ (see Figure 4, top). It is modified by the occupant performing actions that are normally associated with the breakfast scenario. This results in a temporary reduction in the anxiety level following expected events. The

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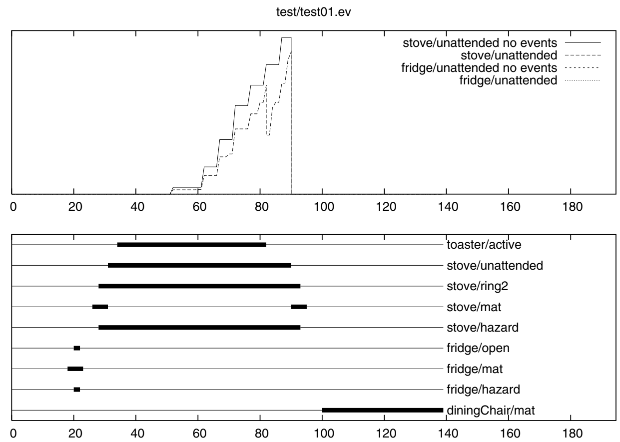

Figure 2. Anxieties for an example of normal breakfast behaviour (using all events).

degree of reduction is determined by the probability of the event P_{IE}^{stove,d_j}. The effect tapers off over time, according to the learned distribution of the lag between the event and the stove being attended $P_{IID}^{stove,d_j}(t_0,t)$ (see Figure 4, bottom).

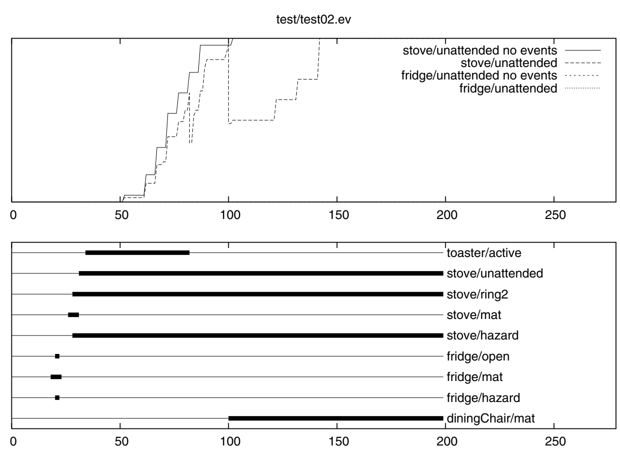

Figure 3. Anxieties for an example of abnormal breakfast behaviour (using all events).

Figure 3 shows a hazardous scenario. Here, the timeline is as before, but the occupant neglects to turn off the stove. Sitting in the dining chair is an event that sometimes occurs when the stove is in use, but the system knows the distribution of the time lag between this event (`diningChair/mat`) and the stove being attended. After this time has elapsed, the contribution of this event expires and the anxiety reaches its maximal level of 1.0. If the

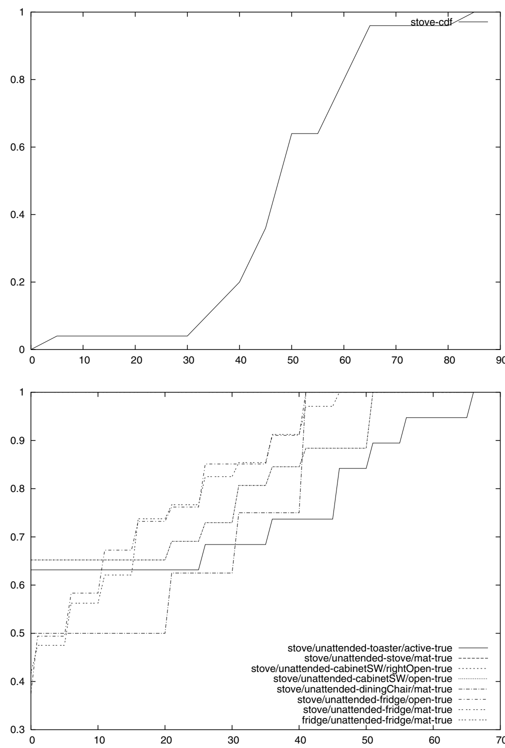

Figure 4. Cumulative distribution function $P_{SID}^{stove}(t_0,t)$ for the stove (top), and for interaction with other devices $P_{IID}^{stove,d_j}(t_0,t)$ while the stove is in hazard (bottom).

stove is running for a long time, it is normal for the occupant to periodically attend to it. This pattern is shown in Figure 5. At approximately 90 seconds, the occupant returns to check the stove, which resets the `stove:unattended` state and hence resets the anxiety level.

In the presence of many events, the reduction in the anxiety level can be significant. We explored two models which vary the influence of events (see Section 4 and equations 2 and 3). Figure 6 shows the results for the two models. In the upper plot, all events are considered. In the lower plot, only the most recent event is considered. As expected using only the latest event results in a higher anxiety as including all events reduces the anxiety for each event considered.

7 Conclusions

This paper has described an emotive solution to deciding if a device, house and ultimately the occupant are in abnormal states. Anxiety is used as a measure of normality and represented with a number of statistical models that are combined together to integrate interactions with haz-

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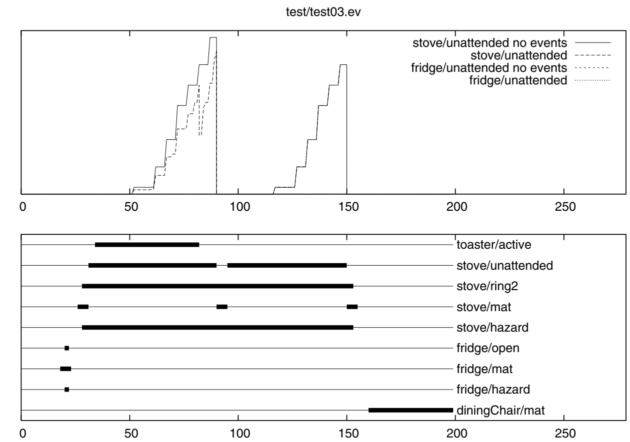

Figure 5. Anxieties for the stove managed by repeated attention.

ardous devices (stove, fridge) as well as other passive devices (doors, chairs) to compute anxiety as it varies with time. The complexity of interactions of all devices has been reduced by considering each hazardous device individually and using interactions with other devices to determine anxiety. Looking at combinations of the anxieties of different devices and rigid sequencing of activities and events is avoided. Currently the anxiety for the house is simply taken as the maximum for the active devices.

Results show that for some reasonably well defined scenarios in the kitchen, the anxiety model produces meaningful results. Importantly all the statistical models used are learnt from real scenarios which are assumed to be normal. The important issue is to acquire enough data to be reliable. Given that we are using a pessimistic approach to the monitoring process, we will learn the parameters incrementally for a particular occupant and house interactively by asking the occupant if things are normal for each time a high anxiety is detected.

The next objective of this research is to run the methods for a large time period in a real environment. To this end we have been capturing video of people in kitchens and will analyse to get the sequence of events for normal behaviour.

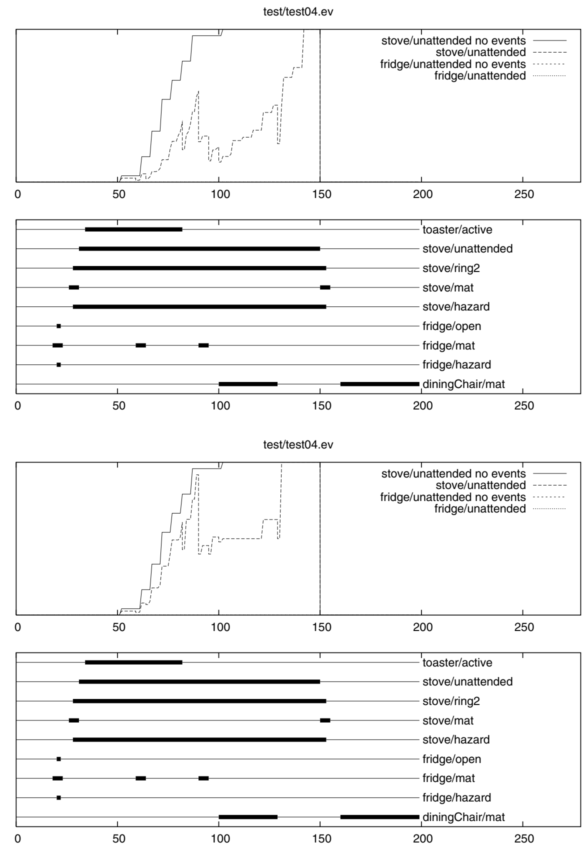

Figure 6. Anxieties (top) for including all events (see equation 2), and (bottom) for only including the last event (see equation 3).

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