

# Novelty Gated Episodic Memory Formation for Robot Exploration

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**Abstract**— This paper presents a method for novelty and familiarity detection, aiming at inferential use of episodic memories for modeling behavior in novel situations. The method is based on the simulation of the hippocampal function, especially on its aspects, that relate to the memory formation in spatial context as: (1) the sensory, perceptual, and behavioral correlates of the episodic memory formation, (2) its involvement in novelty/familiarity detection and inferential reuse of old memories, and (3) the natural way to relate the internal hippocampal and abstract spatial representations. The study differs substantially from the existing models, that relate the hippocampal function and robot exploration, since it focuses on flexible reuse of experienced episodes rather than on navigation. The model is build on the experimentally supported hypothesis of the novelty/familiarity discrimination function of the hippocampal area CA1.

**Index Terms**— Episodic memory, navigation, robotics, novelty detection.

## I. INTRODUCTION

Although the aim of robotics diverges with its advancement, in its core it remains to be an attempt to create machines, that act as living organisms, and are able to replace humans in performing different tasks. The tasks can vary from accomplishing domestic or industrial functions; making artificial organs that keep the integrity of a living being, e.g., it can both read neuronal (motor) output and provide sensory input to brain structures; to even simulating the functionality of the complete human brain for the purposes of experimental neuroscience.

At present, the robots are able to perform tasks with different degree of autonomy. Experimental robotics has shown, that autonomous systems can be build by simulating insect-like behaviors. We aim at higher level of intelligent behavior, which has as a bottom line flexibility - the use of its old experiences in novel situations. At present, even higher forms of intelligence, derived from imitation learning, is an object of robotics applications [1]. Since the actual processes underlying this type of behavior are understood on a very coarse level only, it does not meet our present research objectives.

The so stated scope puts forward memory based behavior, which includes remembering of past events, distinguishment of what is novel at present, in order to perform selective encoding, and familiarity detection to facilitate the ability to infer appropriate behavior in a novel environment or for performing a novel task.

Therefore, discrimination of novelty and familiarity is a central aspect of this work. Novelty is a known factor that gates learning in natural and artificial systems (for a recent review see [2]). Definitions of novelty vary widely, due to the many perspectives within the considered multi-disciplinary research area. In this paper, the novelty and familiarity discrimination problem is approached from the perspective of an embodied agent, which imposes two important aspects: first, that the novelty has to be considered in relation to behavior; and second, that the information, that has to be judged for novel or familiar is derived by the experienced episodes of events.

The relation between novelty and behavior has received much attention by experimental neuroscientists [3], [4], [5]. From robotics point of view the behavioral correlates of novelty determine a system that receives input from sensory and behavioral pool of information.

The second aspect of novelty discrimination implies that the embodied creature continuously gathers information about the surrounding world through experiencing sequences of events. The organisms, which are capable of making mental representation encode such a subjective sequences (episodes). This capability arises with the availability of a limbic system (e.g. in rats).

The analysis and modeling viewed trough this aspect have the following specificity. Many models in computer science and robotics exploit the characteristics of the semantic memory - memory for facts; Actually, memory for events and their relatedness is the way higher organisms build their knowledge; moreover, episodic memory copes naturally with the sensory, perceptual and behavioral character of learning of an embodied agent.

In our study, novelty is considered as a gating factor for forming episodic memories during learning and familiarity as a mechanism for inferential use of episodic memories while behaving in a novel environment. We construct a model of the hippocampus, a part of the brain that is involved in episodic memory formation, novelty detection, and spatial behavior. The model is meant to be illustrated through a robotic implementation. It has the potential to go beyond the state of the art robotic applications since it intrinsically accounts for the following aspects:

- Robots interact with the environment through a continuous stream of sensory information, eventually forming an internal representation and acting accordingly. The hippocampus processes sequentially incoming information by combining various sensory and memory experiences in a representation that is possibly modulated by behavioral feedback.
- Many experimental studies suggest the involvement of

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the hippocampal formation in novelty and familiarity detection [6], [7] and inferential reuse of old episodes [8], [9].

- Extensive modeling has created a consistent computational framework that connects the internal hippocampal and spatial representations.

- Experimental evidence has shown that the pyramidal cells in hippocampal area CA1 code for spatial location in terms of environmental queues and memorized episodes; moreover, it provides a novelty/familiarity distinguishment.

This paper is structured as follows: Section II attempts to bring a more global framework that makes a parallel between the robot's representation and hippocampal encoding; On this basis a hypothesis is made in Section III. The framework is further developed in Section IV to lay a computational ground for further modeling. The actual model and results are shown in Section V. Section VI offers a discussion of the state of the research and its perspectives.

## II. SPIRAL MODEL OF THE ORGANISM-ENVIRONMENT INTERPLAY

Sensed information, together with the memory experiences, goals, and anticipations, form perception in the brain which in turn determines the behavior of the animal [10]. The expression of the behavior is a concrete action. This relation can be expressed as a cycle with two connecting points: the organism and the environment. The organism gets sensory information from the environment, and acts upon it. The world changes continuously, so every other action is applied on a changed environment. The new sensation forms a perception in the changed mind, since the preceding percept might have changed the expectations, the understanding, the certainty of the mental representation etc., i.e., the brain has changed as well. Therefore, the interplay between perception and behavior connects two changing systems: the mind and the environment. If expressed graphically, this interplay can be represented by a spiral, as shown in Figure 1.

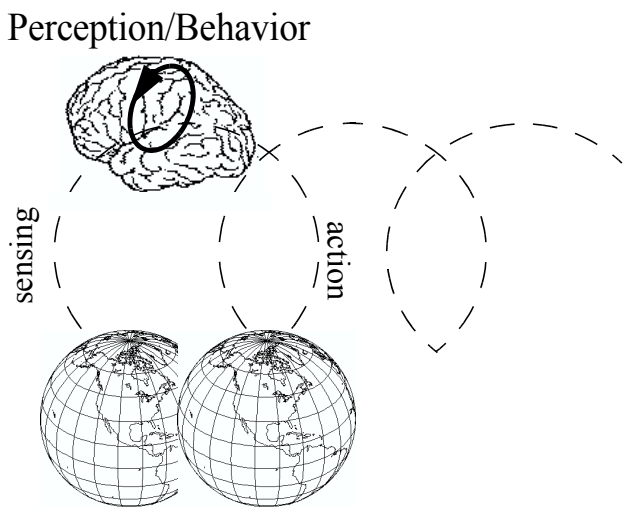


Fig. 1. Spiral model of organism-environmental interaction.

Since the difference between two perceptions is usually small or none, it is easy to reuse the old model of the world by only distinguishing which is the changed (novel) part.

One possible intersection point of the past and present of the two systems is to be found in the episodic memory, where the new experiences are encoded in sequences of events. The mammals, who are able to form episodic memories, and especially humans can remember some information for the whole life span. This fact suggests, that the episodic memory encoding is an efficient process, i.e. together with the encoding a decision of the content and importance of the encoded information is taken. We consider the novelty as the only gating factor for learning, i.e., the only factor that determines what to be encoded. In the spiral model (Figure 1), the novelty is measured by the change of environmental representation between two perceptions. This discretization is formalized in Section IV.

## III. HYPOTHESIS

It is widely known that the hippocampus encodes episodic memories. In particular, the CA1 area, to which projections of sensory-bound stimuli come together with formed episodes of recent memories is an area of interest [6], [7], [11]. Recent analysis of the data from rat experiments [11] has shown a bi-modal structure of the theta rhythm, a brain rhythm which appears when exploratory behavior takes place. The authors conclude, that a possible reason for bimodality is the different nature of information that comes at the same time to CA1 area - sensory and episodic, and the different time it needs to be projected to this area. Other studies suggest, the function of CA1 as a comparator [6], [7]. There are slight variations of how exactly the comparison takes place, but in general they agree in the following mechanism: the same sensory-bound pattern is transferred through the direct and the indirect pathway from the entorhinal cortex (EC) to CA1 area (as illustrated in Figure 2). During the indirect path the pattern passes DG and CA3 areas, where orthogonalization, and episodic memory encoding take place.

The interaction of the information from the learned episode from CA3 and the sensory-bound information coming directly from EC forms a pattern that controls the upcoming behavior. At the same time the comparison between the two patterns produces a novelty signal which indicates whether encoding has to take place, or the episode is familiar already.

Subsequently, during recall, the perforant path input initially has a stronger influence on activity in CA1. However, for familiar stimuli, the pattern of activity arriving from region CA3 via the Schaffer collaterals will dominate within region CA1, allowing output from region CA3 to drive neurons which had previously been associated with the particular activity pattern in region CA3.

Our hypothesis is, that the CA1 area of the mammal hippocampus is one possible place where sensory and memory-related information comes together to form a representation. This representation determines the future behavior, and indicates the familiarity/novelty of the upcoming in-

formation. It therefore determines what has to be encoded or what can be ignored.

Based on this hypothesis we refine the computational scheme as shown in Figure 2. This scheme accentuates on the CA1 area, as a physical component with comparative function.

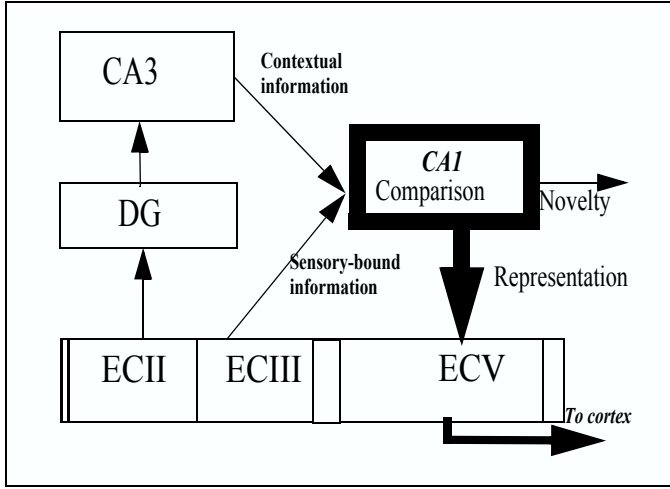


Fig. 2. Working scheme of the hippocampal formation, accentuating on the comparative role of the CA1 area. CA1-3 denote the pyramidal cells in areas 1-3 of cornu ammonis, the ECII-V denote the entorhinal cortex. The sensory bound and episodic memory related representations are compared to indicate the familiarity.

The information from the learned episode from CA3 area and the sensory-bound information coming directly from EC forms the pattern that controls the upcoming behavior. At the same time the comparison between the two patterns produces a novelty signal which indicates whether encoding has to take place, or the episode is familiar already.

Several studies have established the opinion, that the parahippocampal area is responsible for novelty detection and management, while the hippocampus is involved in encoding relational memory. Recently a series of new experimental and neuroimaging evidences [12], [13], [14], [9], [15] confirmed that the hippocampal formation contributes similarly to declarative memory tasks that require relational or familiarity processing. Therefore, the use of the scheme shown in Figure 2 appears a plausible one.

#### IV. EPISODIC MEMORY FORMALISM WITHIN THE ROBOTICS FRAMEWORK

Episodic and autobiographical memories have intrinsic relation with sensory, perceptual, and behavioral events. By a definition, given by Conway [16], which extends the widely accepted definition of Tulving [17], the episodic memory has event specific, sensory-perceptual details of recent experiences that lasted for comparatively short periods of time (in the range of a few minutes to a few hours).

Basing our reasoning on the proposed spiral model of organism-environmental interaction we argue, that episodic memory has behavioral correlates as well:

- There is not a clear separation between action and perception. Every sensory-perceptual event causes behavior,

which in turn either changes the environment or reflects the changes that occurred independently of its action;

- Episodic memory is formed during specific experienced sequence of events, and every event consists of sensing, binding the sensed information into a coherent perception, acting accordingly;
- Episodic encoding consists of organizing abstract knowledge derived from goals active during experience.
- Episodic memory represents short time slices, possibly determined by changes in goal-processing. Goal and action processing are tightly related.

The computational approach that has been taken in this work requires a formalization of the episodic memory task. The computational approach that has been taken in this work requires a formalization of the episodic memory task. Let us assume that an episode evolves under the action of the sensory, perceptual and behavioral competing influences. Therefore formally an episode  $E$  is a set of  $n$  discrete events defined by a considerable difference in the event representations

$$E = \{e_t\}, t \in [1, \dots, n]. \quad (1)$$

A single event  $e$  is defined by

$$e = \{s, p, b\}, \quad (2)$$

where sensory component  $s$  introduces the influence from the external world and constitutes by feedforward connections. Perceptual component  $p$  represents the internal influences, and is performed by the lateral connections. Behavioral component  $b$  represents the influence, that the previous action has brought on the current event. All three components are multidimensional vectors. The change from one to another event requires a change in at least one component, that is bigger than an internal threshold, indicating the detection of a novel event. The distinguishment among sensory and perceptual influences is very delicate, since the perception includes sensory as well as memory related, anticipatory and behavioral components. In our notation an artificial division between the two is made, by assuming that perception is a result of changes in internal state only.

#### V. NOVELTY DETECTION AND THE HIPPOCAMPAL PARADIGM

The proposed model aims at novelty driven encoding and recall, that facilitates inferential reuse of old memories. It is based on the established theory, that the cells in the rat hippocampus fire when the rat is at particular location of the environment. Because of this feature, these cells are called also place cells. If the rat moves through the environment, at every particular place a number of place cells fire. Cells that code for places in nearest vicinity fire most strongly, while the cells that fire for more distant location fire less. The activity of the place cell firing can be modeled by a Gaussian for the open environments, where place cells show non-directional firing. Therefore, the movement of a

simulated rat at every place of the environment is characterized by a particular pattern of firing, containing of the active place cells in vicinity of the animate. The activity of each cell can be represented in the following way:

$$s_{i,t}(r) = -\frac{\|r - pc_i\|}{e^{2\sigma^2}}, \quad (3)$$

where  $pc_i$  is the location in the space of the center of the cell  $i$ -th place field,  $r$  is the position of the simulated rat, and  $\sigma$  represents the width of the place field.

Therefore, the sensory signals are encoded into constellations of active place cells. The unique pattern of activity corresponds to a certain position  $r$  of the environment. The level of activity of every place cell depends on the distance between the rat position and the place fields centers. Figure 3 shows two activation patterns from the rat route. These patterns are external-world related and are further transmitted through the direct pathway.

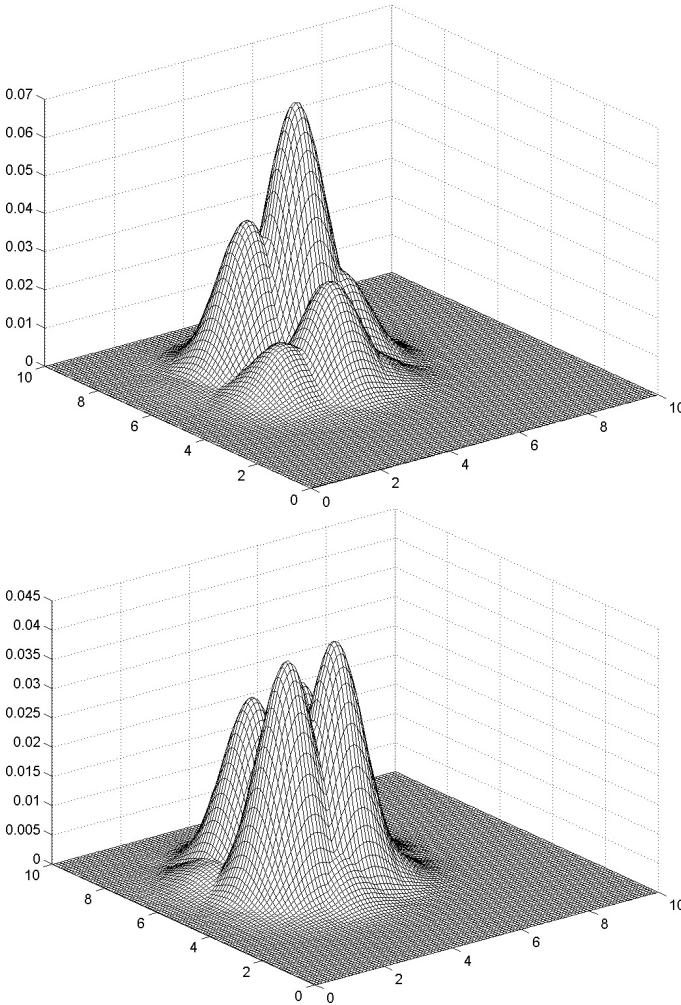


Fig. 3. Samples of sensory bound patterns.

The pattern, coming through the indirect pathway, represents the perceptual (memory related) influence to the representation in CA1 area. It is formed within a network structured as a two layer lattice of neurons, corresponding to the EC and CA3 layers. The feedforward connections

from a EC area, that contain patterns as the ones shown in Figure 3, to the superficial CA3 area are trained through a modified Hebbian rule:

$$\Delta w_{ij}^{CA-EC} = \alpha_1 g (EC_i CA_j - w_{ij}^{CA-EC} CA_j^2), \quad (4)$$

where  $\alpha_1$  is the learning rate,  $g$  is a gating factor, and notation  $CA-EC$  shows the starting and destination layer of the connection (coming from EC, reaching CA layer). Indices  $i$  and  $j$  denote neurons on the input and output layer, correspondingly. The CA layer is not denoted as CA1 or CA3, because the learning rule is used for EC-CA1 as well as EC-CA3 learning. The term  $w_{ij}^{CA-EC} CA_j^2$  is needed due to internal instability of the Hebbian rule.

The topological connections are predominant - the simulation is done as the neurons from the first layer project to a topologically adjacent area, in a way that every input neuron is connected to 20% of the output neurons. The lateral inhibition connections, denoted as LI have a sharpening effect on the transmitted to CA3 area activations. Equation 6, i.e. they promote self-organization

$$\Delta w_j^{LI-CA} = \alpha_2 g (LI CA_j - \alpha_3 w_j^{LI-CA} CA_j^2), \quad (5)$$

where  $\alpha_2$  and  $\alpha_3$  are learning rates and  $g$  is a gating factor.

The biological and computational plausibility of the learning process performed in Equations 4 and 5 have been shown previously in [18] where the learning parameters choices is explained in detail. A plot of a sample learned episode is given in Figure 4.

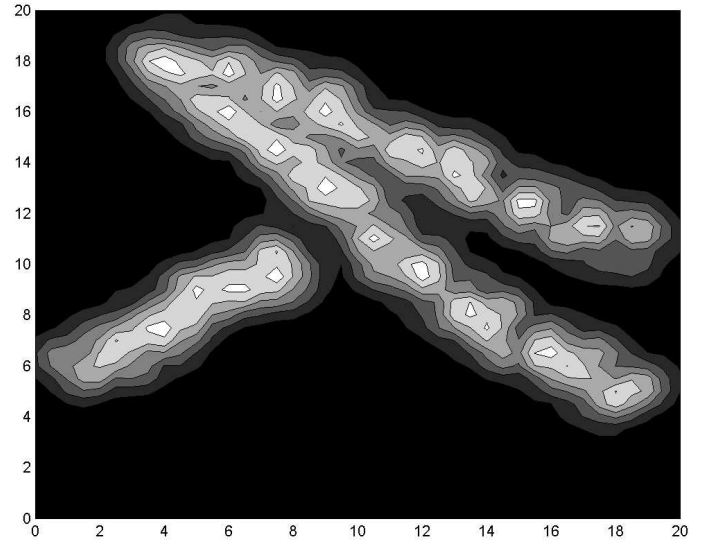


Fig. 4. Examples of 3 formed episodes in a two dimensional array of neurons.

The result of this learning process corresponds to the perceptual contribution of the proposed event definition. The behavioral influence is represented by a neuromodulator-like gating signal:

$$\Delta b_i^{CA} = \beta g \left( \frac{CA_i}{CA^d} - 1 \right), \quad (6)$$

where  $\beta$ ,  $CA_i$ , and  $CA^d$  denote correspondingly the learning rate, current, and desired state of CA1 output. Due to the scope of this paper, this influence will not be elaborated further on.

The sensory bound representation of the direct pathway, and the episodic representation of the indirect pathway, come together in CA1 area, where the comparison (novelty/familiarity judgments) takes place. Note, that at the same time, the CA1 area gets input from the current pattern of EC area and a pattern from CA3 area, which does not have processed yet (incorporated into an episode) the pattern that EC area currently projects.

For the novelty detection, similarity between the constellations as found in already encoded episodes and those of the incoming couples of sensory experiences is used. The sensory bound patterns are simplified in order to suit to the representation of the encoded episodes, some samples are shown in Figure 5. The predominant topological connections preserve the relative structure of the environment. The comparison is made by a modification of the algorithm, initially proposed in [19]. This modification preserves the connections between events within an episode and allows on-line comparison of the incoming sensory-bound patterns with those encoded into the episodes.

As a result of training two episodes given in Figure 6 have been distinguished: after the presentation of the third pattern, the novelty signal gradually increases, which results in encoding of a new episode.

## VI. DISCUSSION

This study proposes a hippocampal model applicable to behavioral simulations, that incorporates novelty gated learning and episode formation. The impact of novelty is two-fold: it allows an efficient encoding (exploration) phase and it is a basis for flexible reuse of memories in the recall (exploitation) phase. The same computational paradigm is used in both cases, which makes possible on-line implementation.

The paper accentuates on the methodological part. The simulations of episodic memory encoding and novelty detection are inspired by an algorithm as proposed in [19]. For the actual simulations, however, the algorithm has been substantially changed to cope with novelty detection between individual patterns and such that are involved in episodes. The reuse of memories based upon the familiarity principle is in an experimental phase.

Exploiting the novelty detection properties of the hippocampus for behavioral modeling and a navigation task in particular distinguishes this approach from the existing models, that relate hippocampal modeling and robot navigation tasks.

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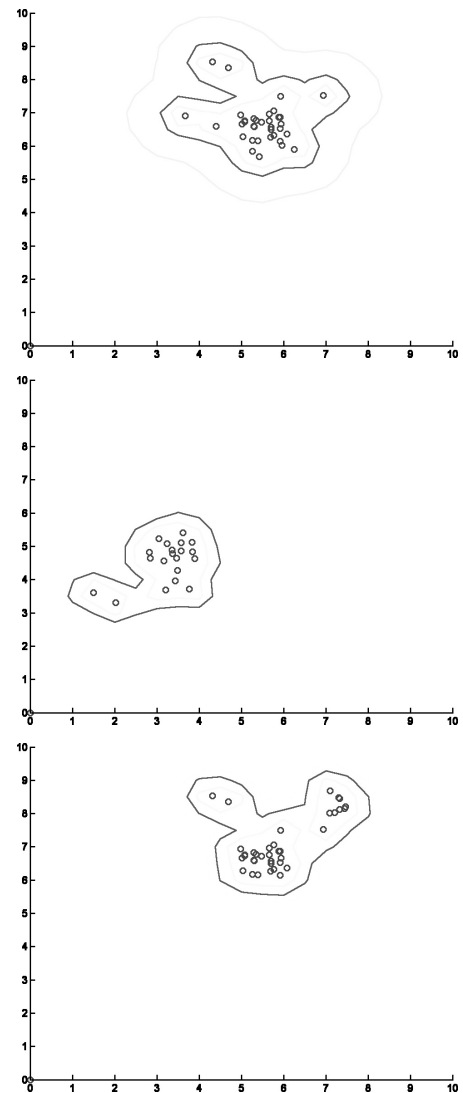


Fig. 5. Some training patterns, based on the place field activation patterns.

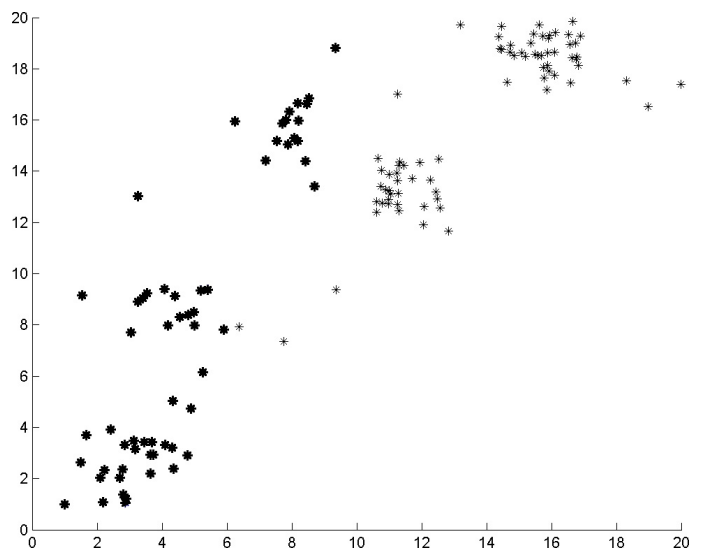


Fig. 6. Learning of two episodes with an overlap. After the two trajectories show discrepancy, the novelty signal is issued.

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