INTITUTO POLITÉCNICO NACIONAL
ESCUELA SUPERIOR DE CÓMPUTO
EVOLUTIONARY COMPUTING

Artificial Immune System

An emerging computational tool to solve complex problems

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3CV8

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Resume

- Definitions.
- Pseudocode.
- Mathematical interpretation.
- Some implementations.
- Application Areas.
- Conclusions.

Biological Immune System

The Immune System (IS) is a set of cells, molecules and organs that represent an **identification mechanism** capable of perceiving and fighting infections in our own cells and the action of external infectious microorganisms.

Biological Immune System

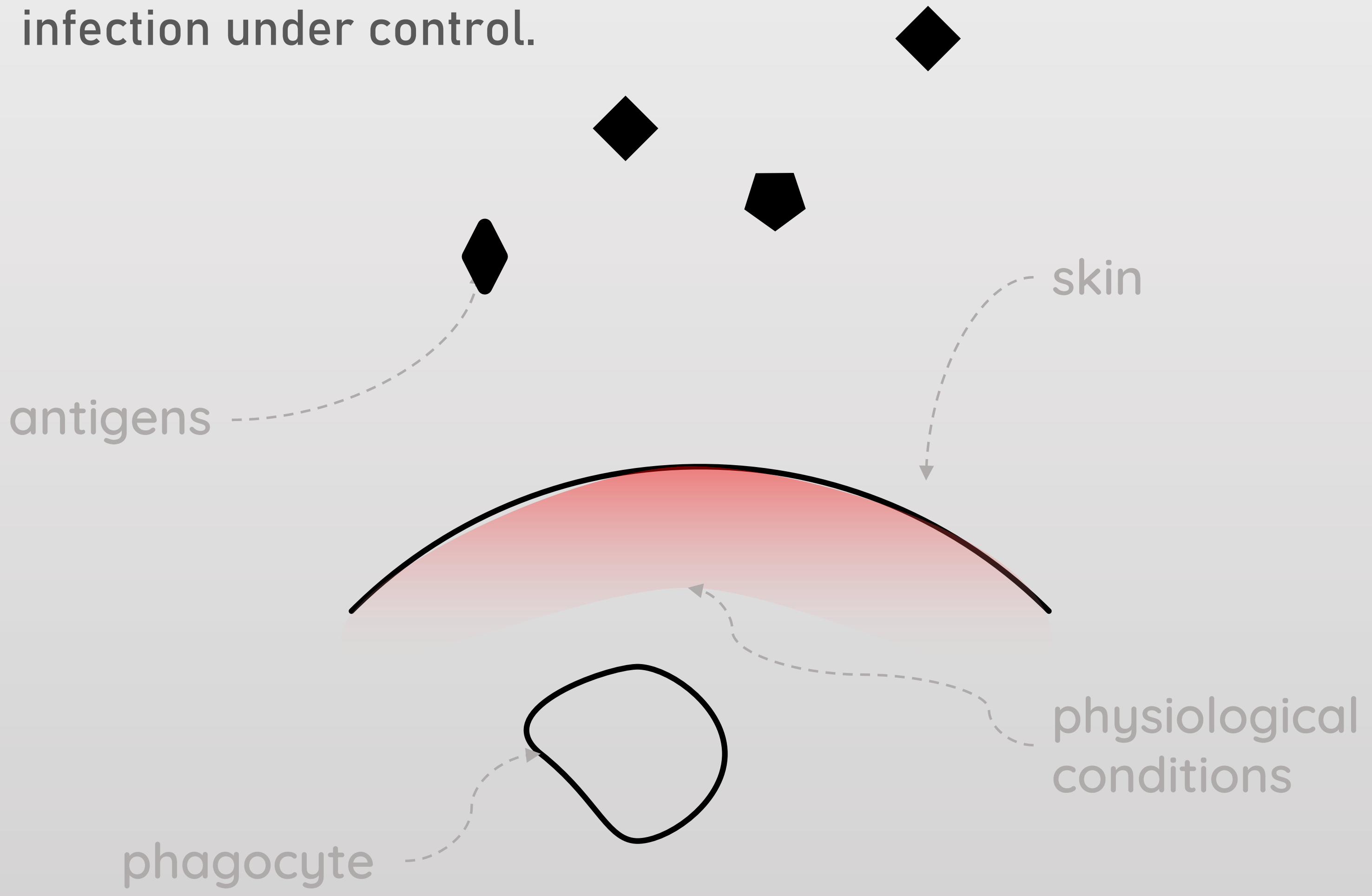
IS

Innate immune response

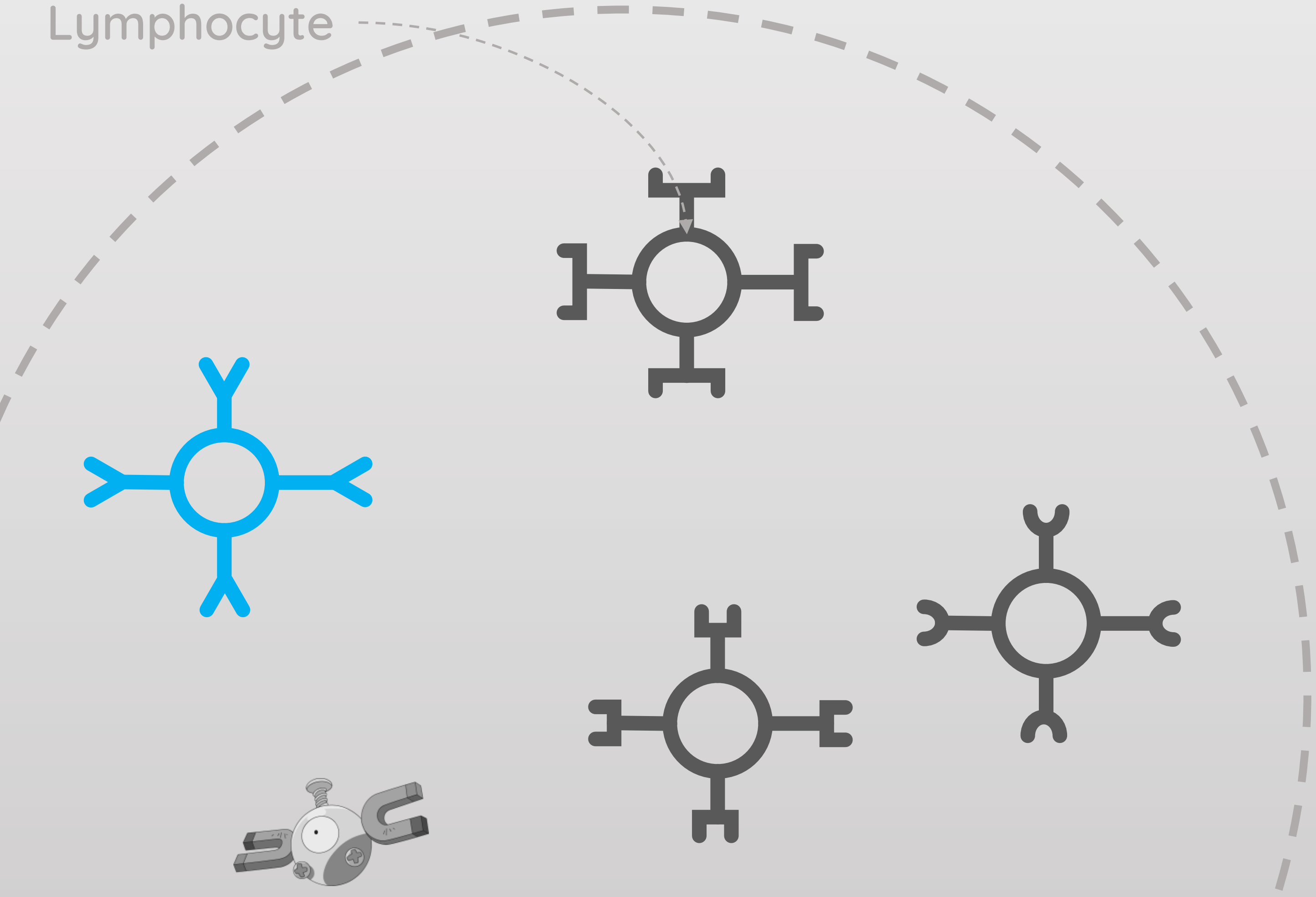
Adaptive immune response

Innate immune response

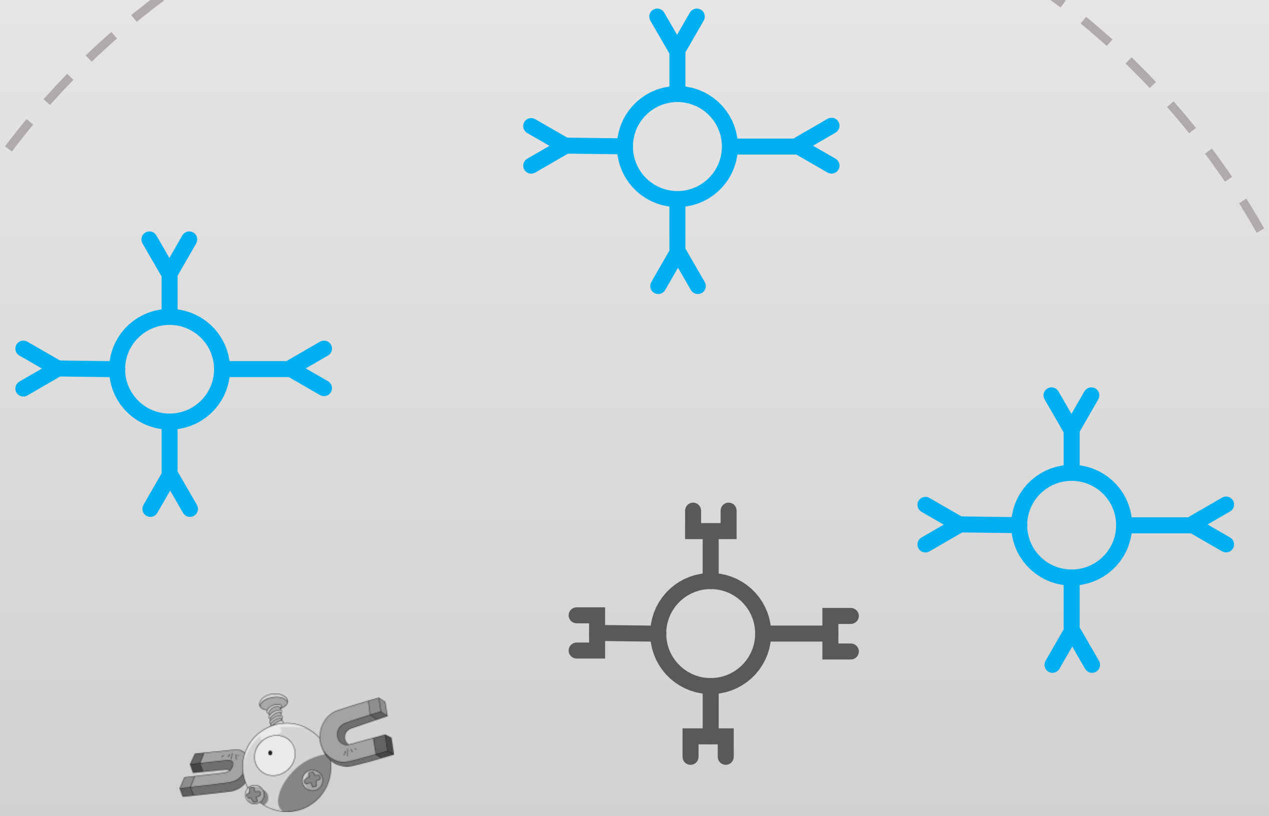
Provides a rapid first line of defense, to keep early infection under control.



Adaptive immune response



The **primary response** is slow, it takes up to three weeks to completely clear the infection



Adaptive immune response

Then the molecular pattern of the type of antigen that caused the infection is stored in memory.

This information generates a much faster and more efficient secondary response.

Artificial Immune System

The artificial immune systems (AIS), inspired by nature immune systems are an emerging type of soft computing methods. With the pattern recognition features, anomaly detection, data analysis and machine learning

Artificial Immune System

Clonal selection.

Immune-networks.

Danger Theory.

Negative-selection.

Negative-selection.

Definition and Pseudocode

Negative selection

Negative-selection.

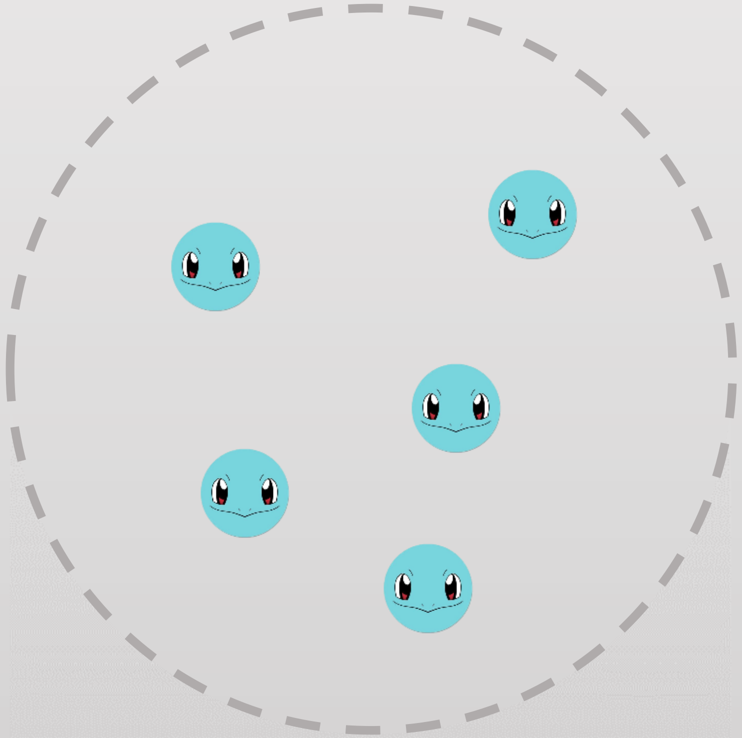
Pseudocode for detector generation.

```
GenarateDetectorsRepertoire(   ):
        Return (      )
```

Negative-selection.

Pseudocode for detector generation.

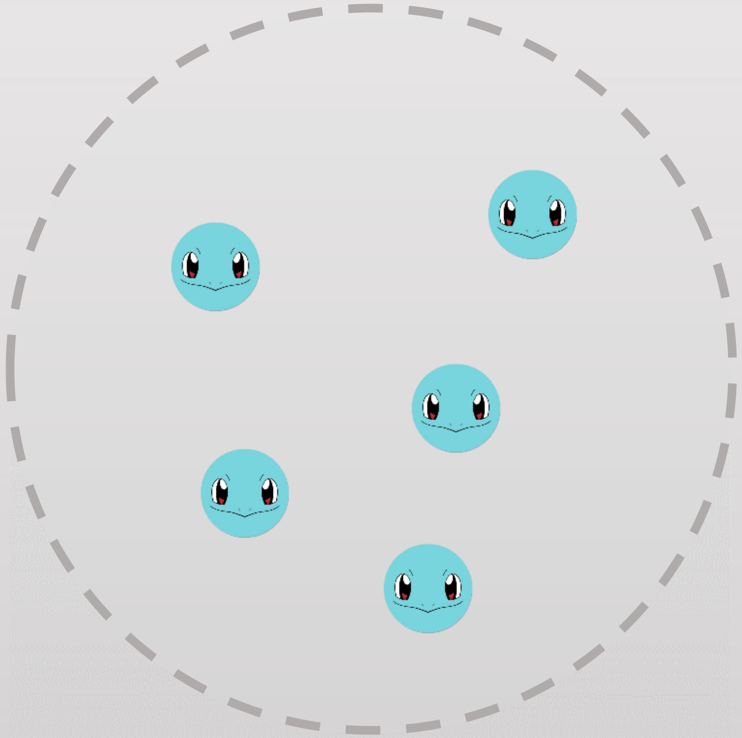
```
GenarateDetectorsRepertoire(selfData):

          Return (      )
```



Negative-selection.

Pseudocode for detector generation.

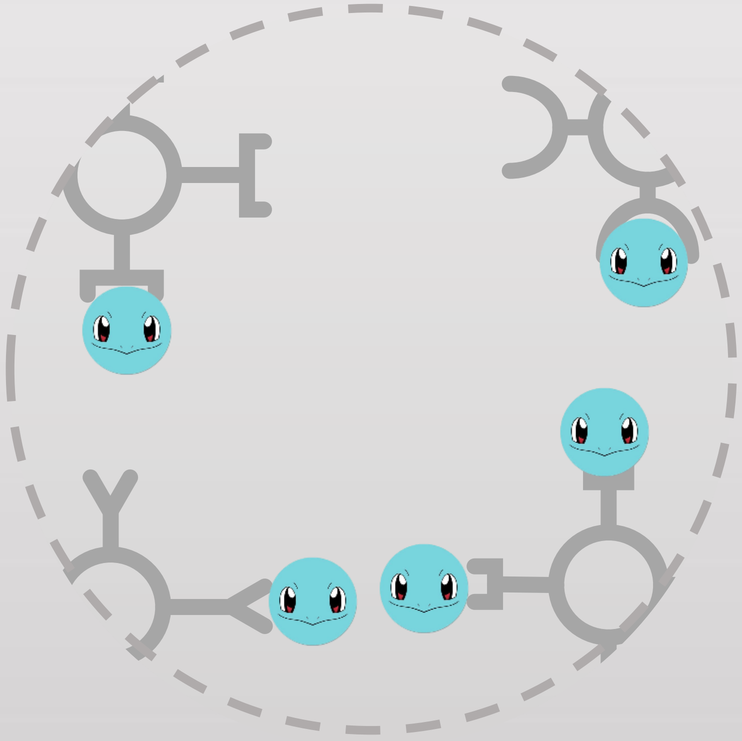
```
GenarateDetectorsRepertoire(selfData):
        repertoire = []









        Return (       )
```



Negative-selection.

Pseudocode for detector generation.

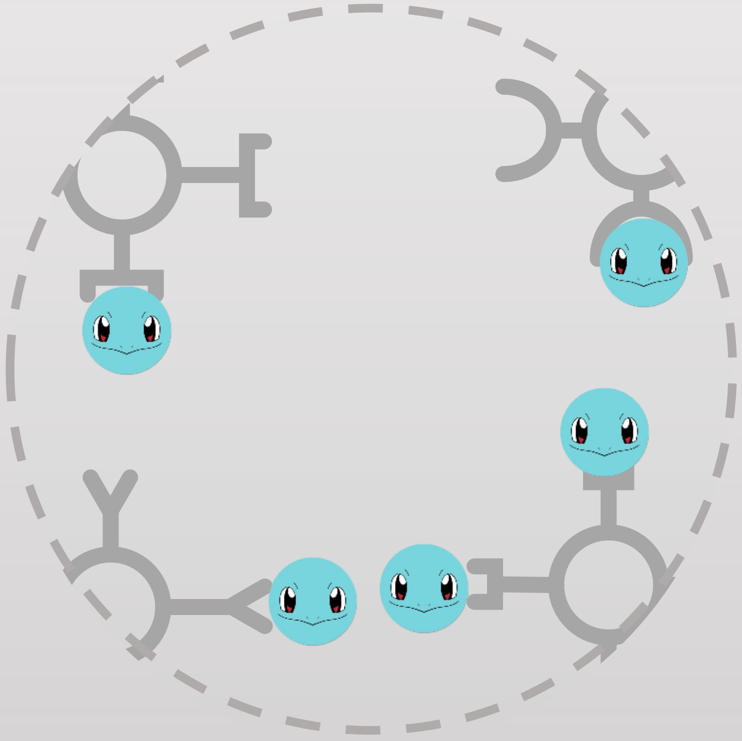
```
GenarateDetectorsRepertoire(selfData):
        repertoire = []

                detectors = GenerateRandomDetectors()







        Return (        )
```



Negative-selection.

Pseudocode for detector generation.

```
GenarateDetectorsRepertoire(selfData):
        repertoire = []

                detectors = GenerateRandomDetectors()
                for detector_i in detectors:
                        if not(matches(detector_i, selfData)):
                                repertoire.append(detector_i)
                        #end_if
                #end_for

        Return (        )
```



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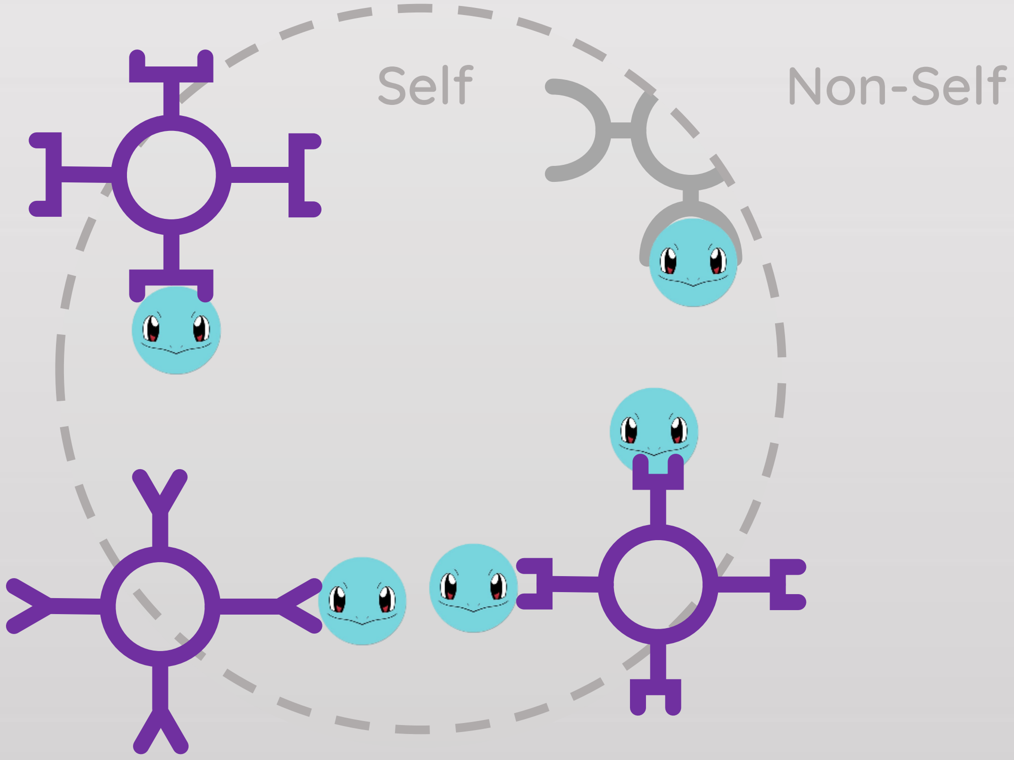

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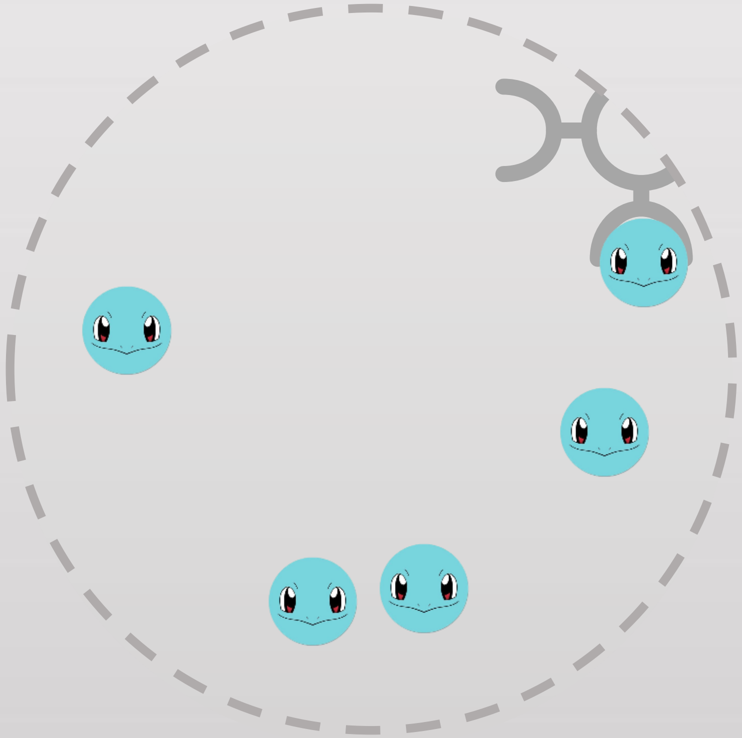
                        #end_if
                #end_for

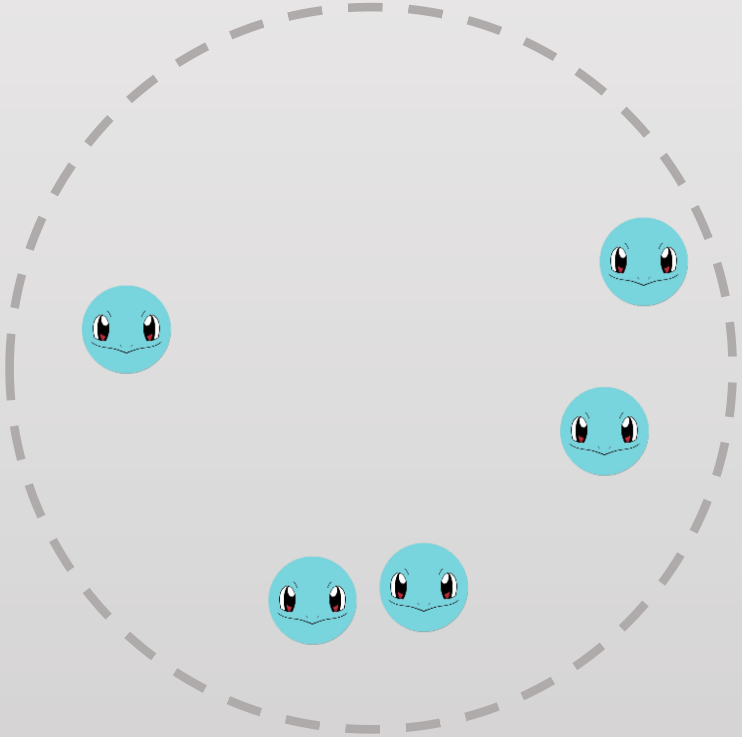
        Return (        )
```



Negative-selection.

Pseudocode for detector generation.

```
GenarateDetectorsRepertoire(selfData):
        repertoire = []
        while not(stopCondition()):
                detectors = GenerateRandomDetectors()
                for detector_i in detectors:
                        if not(matches(detector_i, selfData)):
                                repertoire.append(detector_i)
                        #end_if
                #end_for
        #end_while
        Return (        )
```



Negative-selection.

Pseudocode for detector generation.

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        while not(stopCondition()):
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                for detector_i in detectors:
                        if not(matches(detector_i, selfData)):
                                repertoire.append(detector_i)
                        #end_if
                #end_for
        #end_while
        Return (repertoire)
```
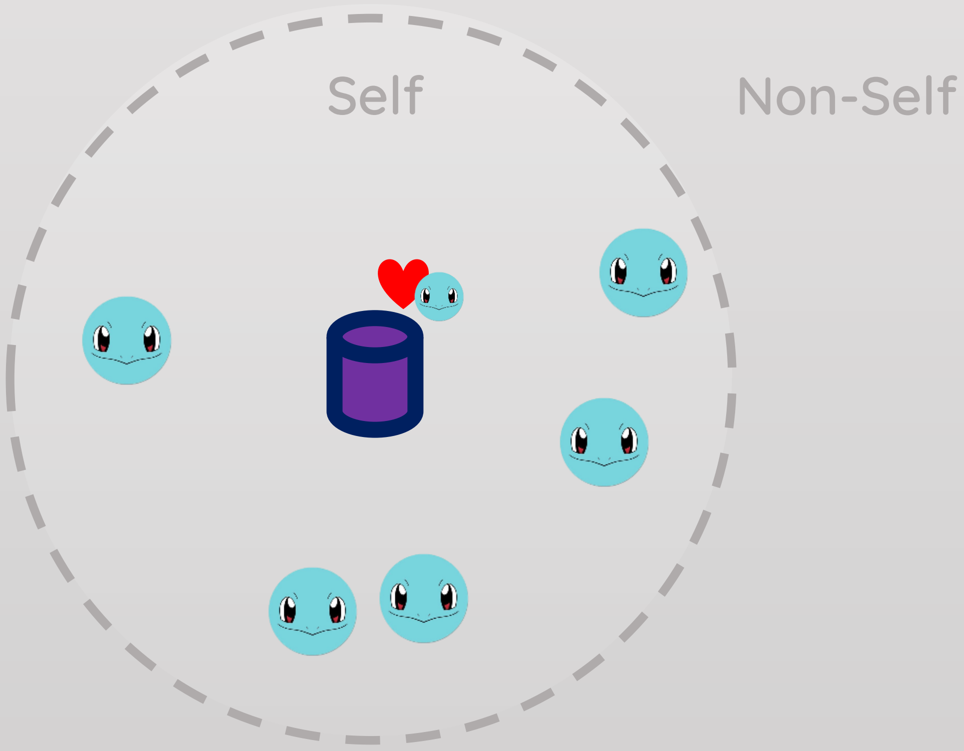
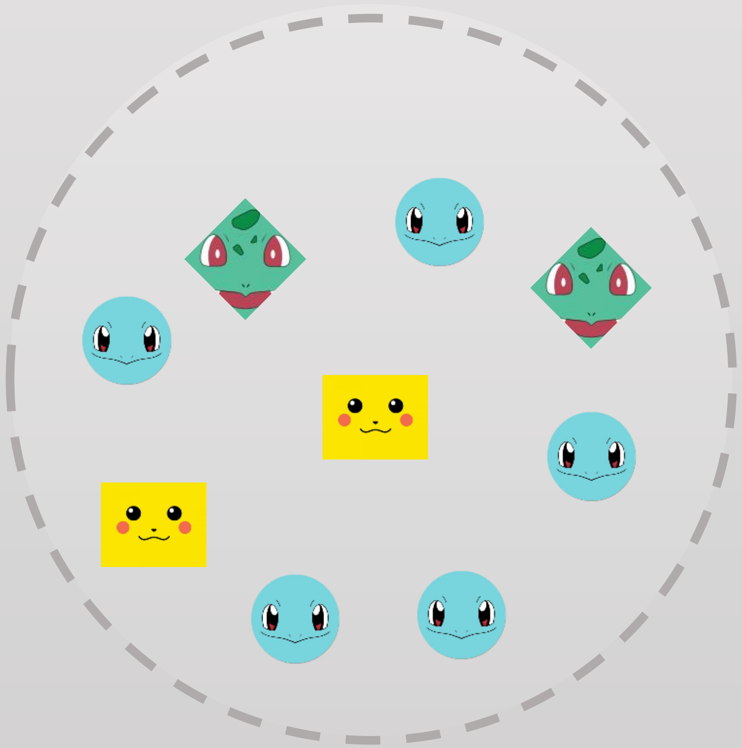



Negative-selection.

Pseudocode for detector aplication.

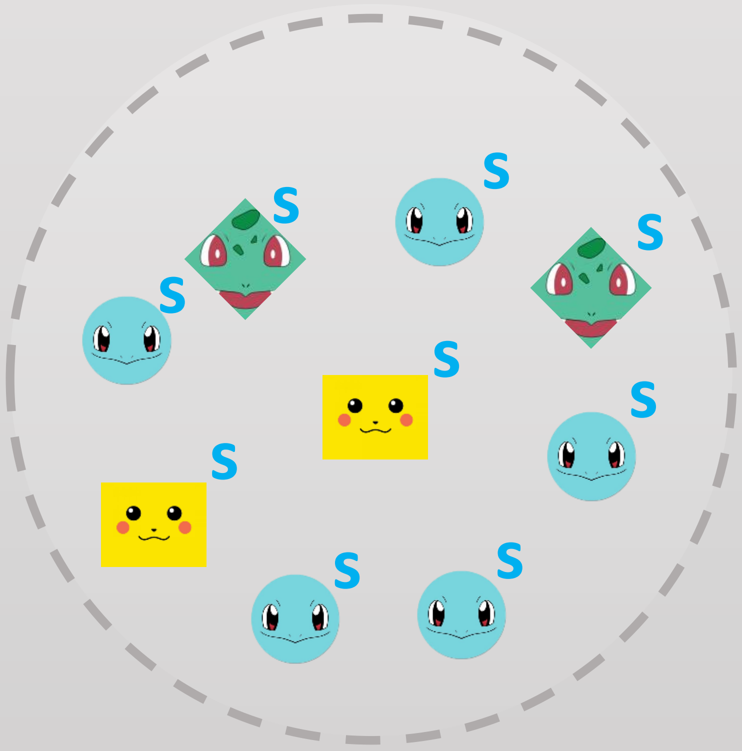
1. **Detection(inputsSamples, repertoire):**



Negative-selection.

Pseudocode for detector aplication.

```
Detection(inputsSamples, repertoire):
        for input in inputsSamples:
                input.class = self
        #end_for
```



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Pseudocode for detector aplication.

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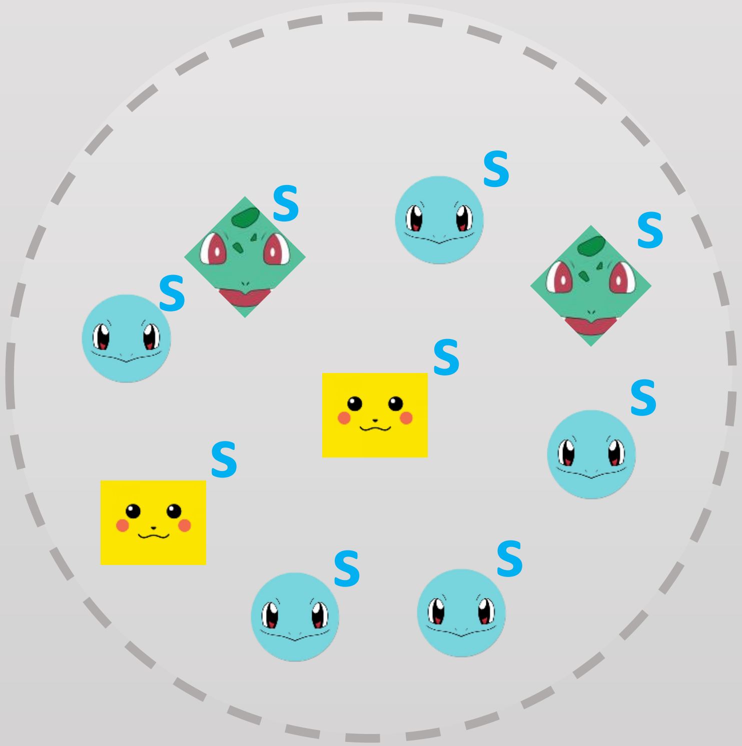
Detection(inputsSamples, repertoire):
        for input in inputsSamples:
                input.class = self
                for detector in repertoire:

                #end_for
        #end_for
```



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        for input in inputsSamples:
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                #end_for
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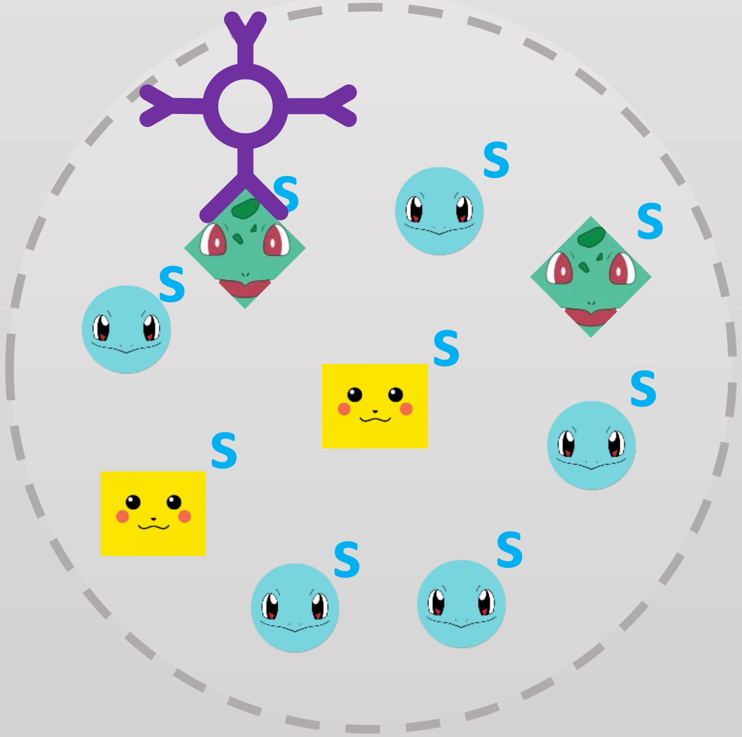
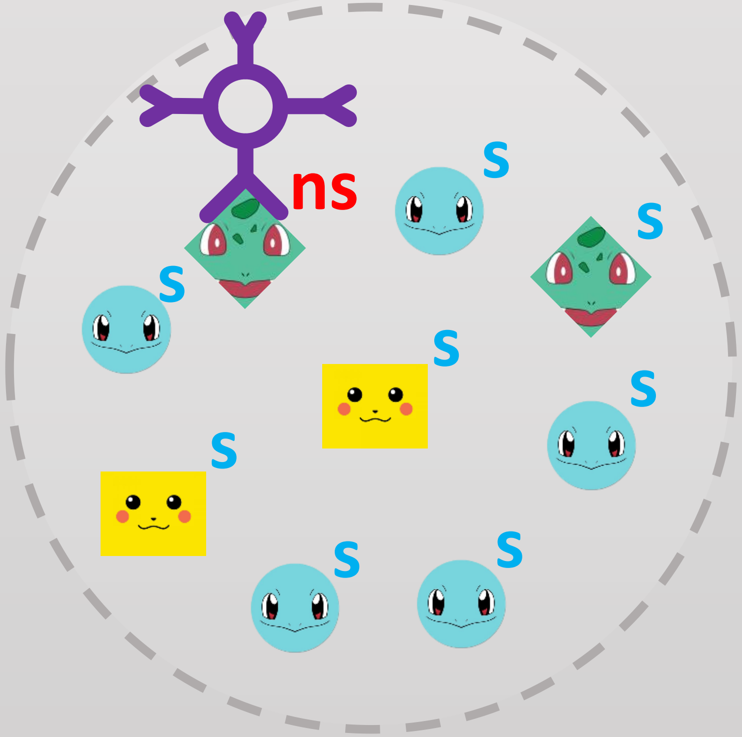


Negative-selection.

Pseudocode for detector aplication.

```
Detection(inputsSamples, repertoire):
    for input in inputsSamples:
        input.class = self
        for detector in repertoire:
            if matches(detector, input):
                input.class = nonSelf
                break
            #end_if
        #end_for
    #end_for
```



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    #end_for
```
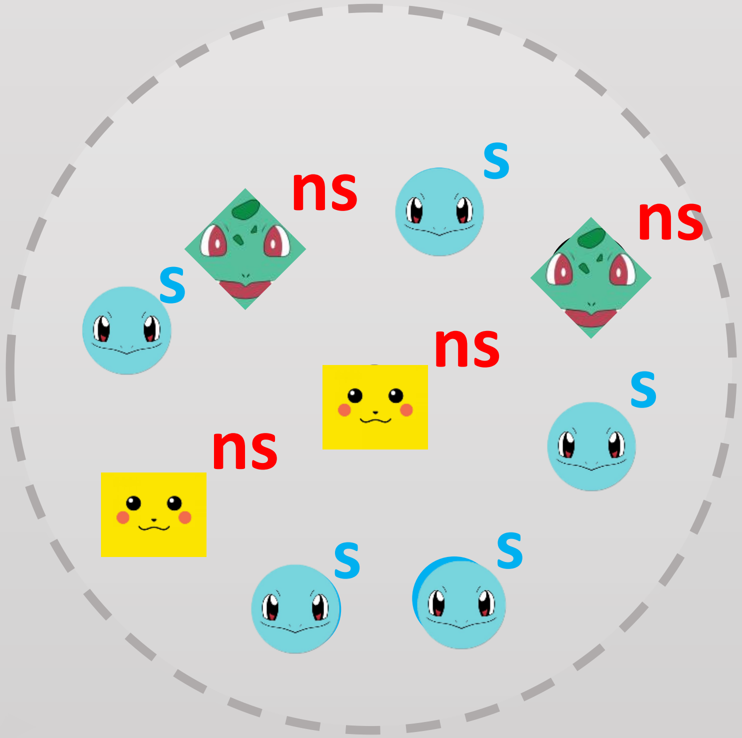
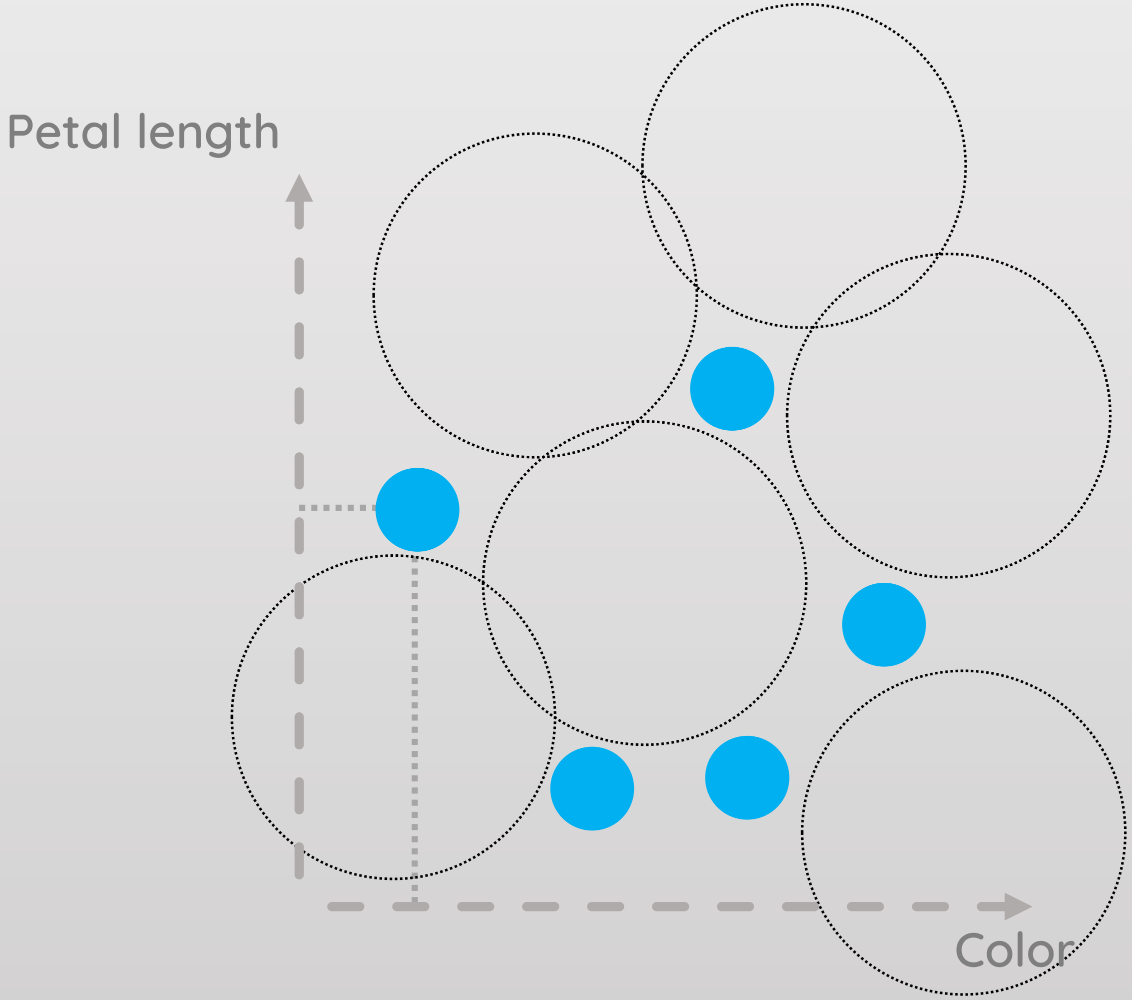



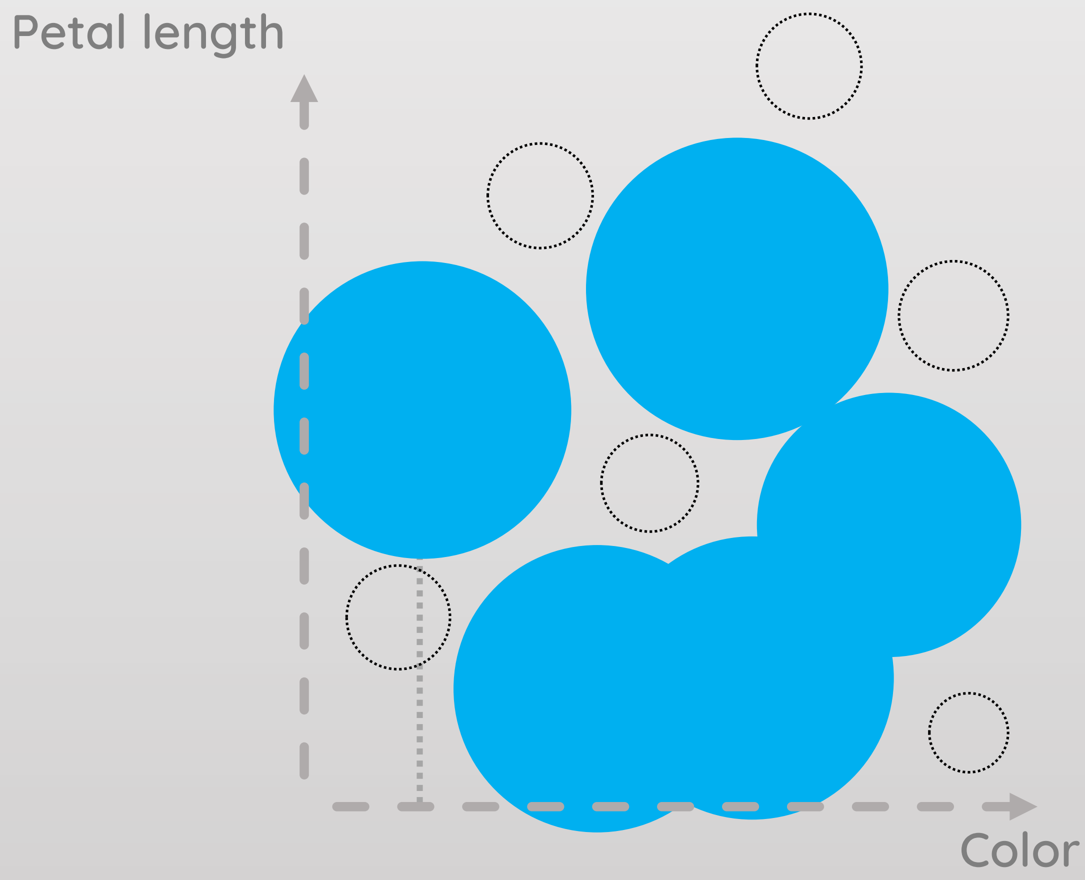
Mathematical interpretation

Negative selection

Negative-selection.



Negative-selection.



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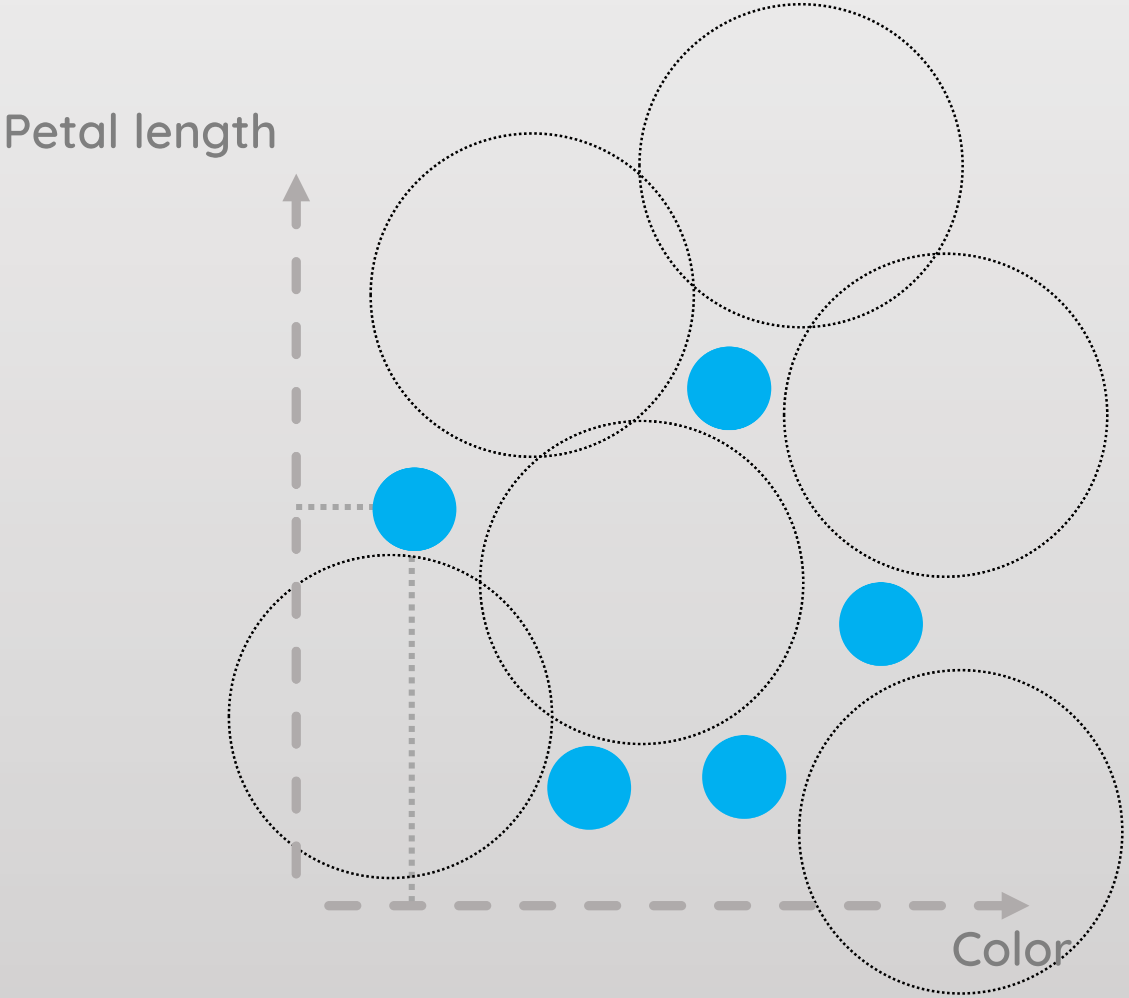
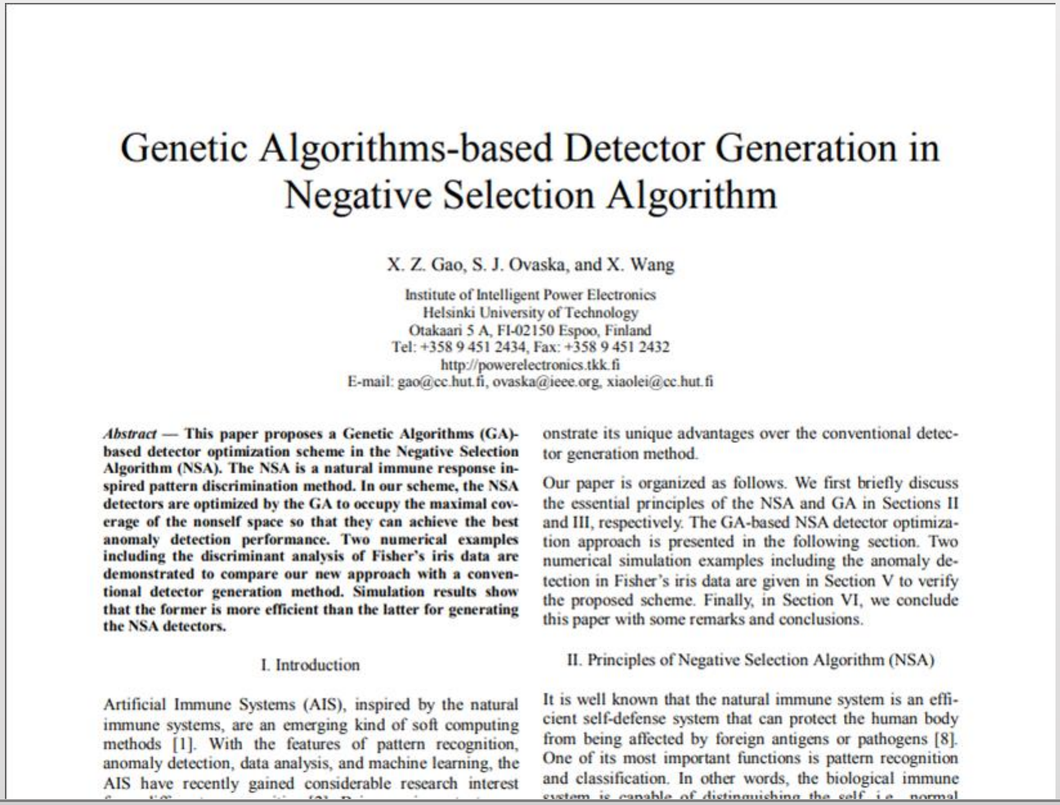


Negative-selection.

Some implementations

Negative selection

Negative Selection



Genetic Algorithms-based Detector Generation in Negative Selection Algorithm

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***Abstract* — This paper proposes a Genetic Algorithms (GA)-based detector optimization scheme in the Negative Selection Algorithm (NSA). The NSA is a natural immune response inspired pattern discrimination method. In our scheme, the NSA detectors are optimized by the GA to occupy the maximal coverage of the nonself space so that they can achieve the best anomaly detection performance. Two numerical examples including the discriminant analysis of Fisher's iris data are demonstrated to compare our new approach with a conventional detector generation method. Simulation results show that the former is more efficient than the latter for generating the NSA detectors.**

I. Introduction

Artificial Immune Systems (AIS), inspired by the natural immune systems, are an emerging kind of soft computing methods [1]. With the features of pattern recognition, anomaly detection, data analysis, and machine learning, the AIS have recently gained considerable research interest

onstrate its unique advantages over the conventional detector generation method.

Our paper is organized as follows. We first briefly discuss the essential principles of the NSA and GA in Sections II and III, respectively. The GA-based NSA detector optimization approach is presented in the following section. Two numerical simulation examples including the anomaly detection in Fisher's iris data are given in Section V to verify the proposed scheme. Finally, in Section VI, we conclude this paper with some remarks and conclusions.

II. Principles of Negative Selection Algorithm (NSA)

It is well known that the natural immune system is an efficient self-defense system that can protect the human body from being affected by foreign antigens or pathogens [8]. One of its most important functions is pattern recognition and classification. In other words, the biological immune

Genetic Algorithms-based Detector Generation in Negative Selection Algorithm

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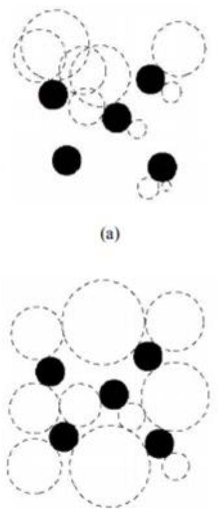

(a)

(b)

Fig. 3. Detector generation in NSA

(a) self samples and randomly generated detectors,

according to *a prior* knowledge. Table 1 shows the number of specimens of the setosa and virginica detected by the randomly generated detectors. The anomaly detection results of our GA optimized detectors are given in Table 2. It should be pointed out that the figures in the tables are the averages of 100 runs. The anomaly detection rate is calculated as the ratio between the number of specimens detected and 50. Comparing the two tables, we can conclude that the detection rates for both setosa and virginica have been considerably increased by the GA optimized detectors, i.e., 21% *vs.* 74% and 26% *vs.* 37%, which implies these detectors have a much better anomaly detection performance than the randomly generated ones.

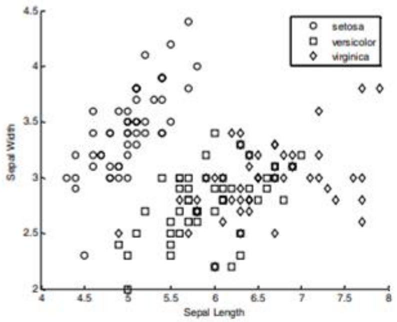

Fig. 4. Distribution of Fisher's iris data in sepal length-sepal width

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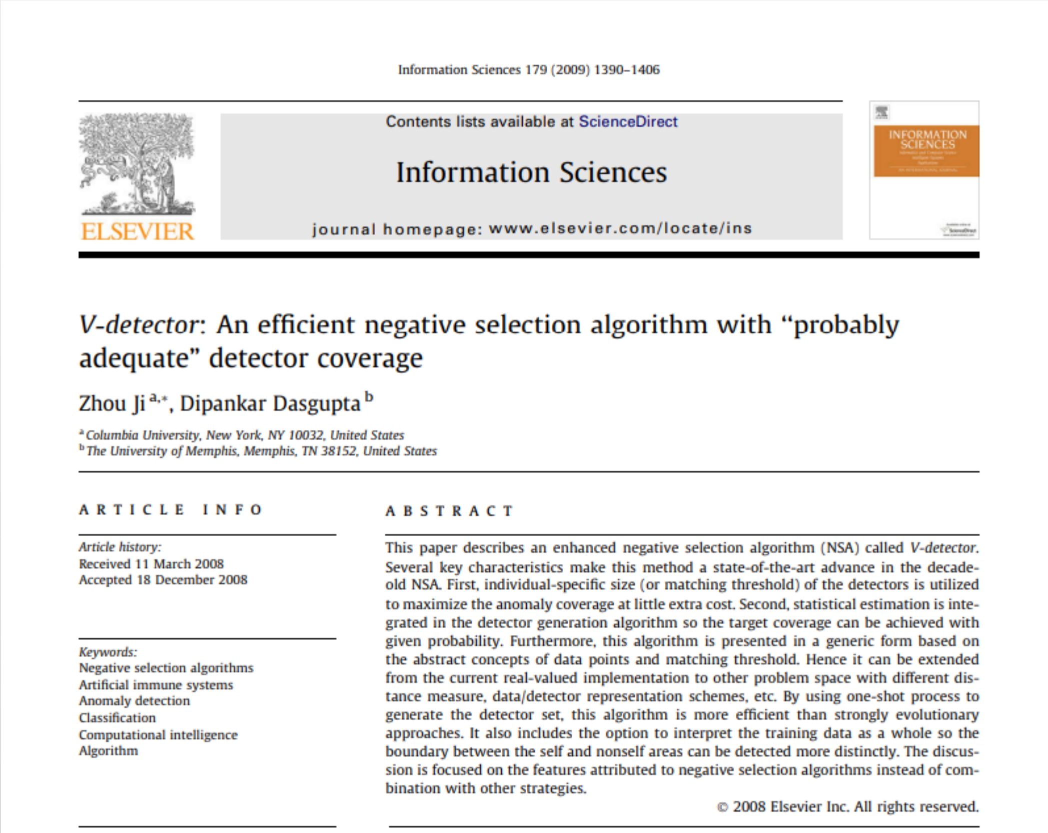

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V-detector: An efficient negative selection algorithm with "probably adequate" detector coverage

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ABSTRACT

This paper describes an enhanced negative selection algorithm (NSA) called *V-detector*. Several key characteristics make this method a state-of-the-art advance in the decade-old NSA. First, individual-specific size (or matching threshold) of the detectors is utilized to maximize the anomaly coverage at little extra cost. Second, statistical estimation is integrated in the detector generation algorithm so the target coverage can be achieved with given probability. Furthermore, this algorithm is presented in a generic form based on the abstract concepts of data points and matching threshold. Hence it can be extended from the current real-valued implementation to other problem space with different distance measure, data/detector representation schemes, etc. By using one-shot process to generate the detector set, this algorithm is more efficient than strongly evolutionary approaches. It also includes the option to interpret the training data as a whole so the boundary between the self and nonself areas can be detected more distinctly. The discussion is focused on the features attributed to negative selection algorithms instead of combination with other strategies.

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Negative Selection

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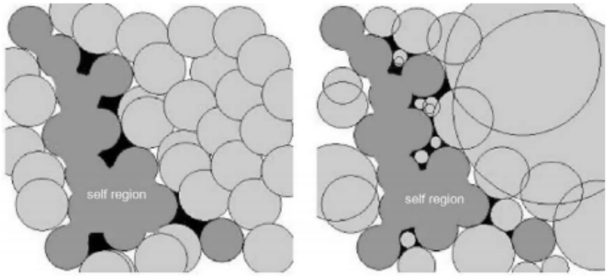

(a) Constant-sized detectors (b) Variable-sized detectors

Fig. 3. Main concept of detectors with variable properties.

numbers, but basically we only regard the samples we already see as normal. We call an interpretation that does not allow much variability an "aggressive interpretation".

At the first look, it seems that in an extremely aggressive interpretation like Fig. 4b, no generalization could happen. That does not have to be the case. Fig. 5 shows a group of three self sample points. Even if we do not take any circular surrounding area of a single self sample as normal, we can still generalize to a self region by considering the neighboring self points together, as shown in Fig. 5c. Compared with Fig. 5a or b, this is more aggressive to detect anomaly, but only to the outside of the perceived "self region".

Naturally, each self sample point can be interpreted as an evidence that its vicinity is self region. On the other hand, we can fairly assume that the self samples can be drawn anywhere over the entire self region. There is no reason to exclude the points that are close to the boundary between self and nonself regions no matter what kind of matching rule or distance measure is used.

Fig. 6 illustrates the "boundary dilemma", the scenario that the self samples close to the boundary inevitably extend the actual self region due to the variability allowed by the algorithm. In this figure, the shaded area is the "real" self region; the dots are the self samples and the circles are their generalization. If the self threshold is too small, the space between self samples could not be represented. In other words, more samples are needed to train the system properly. On the other hand, if the self threshold is large, the false self region represented by the boundary samples may be too large to accept.

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Negative Selection

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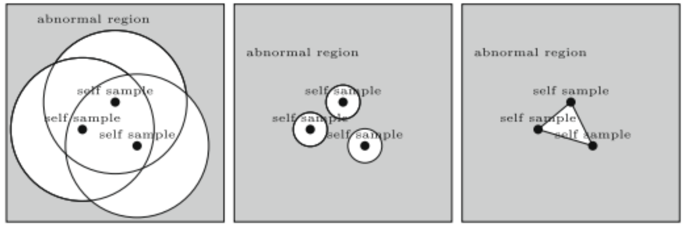
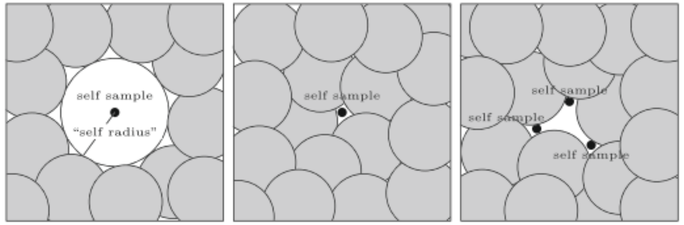


(a) Large threshold (b) Small threshold (c) As a collection

Fig. 5. Possible interpretations of a group of self samples.



(a) Conservative (b) Aggressive (c) Boundary-aware

Fig. 7. Detectors enclosing the perceived "self region".

V-detector: An efficient negative selection algorithm with "probably adequate" detector coverage.

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Columbia University, The University of Memphis [3]

A Feedback Negative Selection Algorithm to Anomaly Detection

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Abstract

Negative selection algorithm (NSA) lacks adaptability and needs a large number of self elements to build the profile of the system and train detectors. In order to overcome these limitations and build an appropriate profile of the system in a varying self and nonself condition, this paper presents a feedback negative selection algorithm, which is referred to FNSA algorithm, and its applications to anomaly detection. The proposed approach uses the feedback technique, which adjusts the self radius of self elements, the detection radius of detectors and the number of detectors, to adapt the varieties of self/nonself space and build the appropriate profile of the system based on some of self elements

typical applications include change detection, fault detection, function optimization [2], especially, network security [3-5] and the NSA is believed to have distinct process from alternative methods and be the most effective algorithm available [6]. However, there are some problems to prevent the AIS and the NSA from being applied extensively.

Firstly, the low-level representation of detectors prevents the extraction of meaningful domain knowledge. It is difficult to map back to problem space, e.g. binary representation [7].

Secondly, because the cost for the detectors training is exponentially related to the size of self set [8], it is impossible to use a large number of self elements for the detectors training.

Thirdly, Self and nonself space often vary over time,

A Feedback Negative Selection Algorithm to Anomaly Detection

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Sichuan University [4]

Application Areas

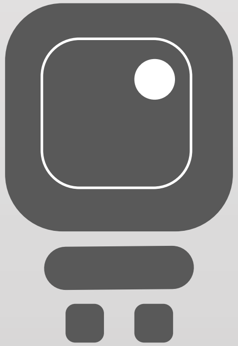
Negative selection

Clustering/classification

Anomaly detection

Kim, J., & Bentley, P. (1999, July). Negative selection and niching by an artificial immune system for network intrusion detection. [5]

Computer security



Hofmeyr, S. A., & Forrest, S. (1999). An immunological model of distributed detection and its application to computer security. [6]

Data mining

Gobinath, R., & Hemalatha, M. (2014). A negative association rules for web usage mining using negative selection algorithm. [7]

Conclusions

Conclusions

The negative selection algorithm is a new and still emerging tool in the field of classification / grouping.

Most of the implementations presented conclude that the algorithm, although reasonably successful on a narrow range of problems, they do not add sufficient value over and above that which is offered by other paradigms to make them anything other than another tool in the engineers application tool-box.

Although from some points of view, any tool is a worthwhile addition, I believe there is still a wealth of unexploited potential in the AIS domain.

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Table 1. Comparison between FNSA and V-detector using Fisher's Iris dataset

Training Data	Algorithm	Detection Rate	False Alarm Rate	Number of Detectors
setosa (50%)	V-detector	99.43%	3.68%	10
	FNSA	99.63%	3.24%	10
setosa (100%)	V-detector	99.14%	0.00%	10
	FNSA	99.35%	0.00%	7
versicolor (50%)	V-detector	70.13%	5%	50
	FNSA	89.52%	1.88%	48
versicolor (100%)	V-detector	60.63%	0.00%	50
	FNSA	89.09%	0.00%	40
verginica (50%)	V-detector	87.39%	16.96%	40
	FNSA	92.41%	8.64%	39
verginica (100%)	V-detector	80.53%	0.00%	40
	FNSA	92.33%	0.00%	35

Source : [4]

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versicolor (100%)	V-detector	60.63%	0.00%	50
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	FNSA	92.41%	8.64%	39
verginica (100%)	V-detector	80.53%	0.00%	40
	FNSA	92.33%	0.00%	35

Source : [4]

Table 1. Anomaly detection in Fisher's iris data with randomly generated detectors.

Species	Specimens Detected	Detection Rate
Setosa	10.5	21%
Virginica	13.1	26%

Table 2. Anomaly detection in Fisher's iris data with GA optimized detectors.

Species	Specimens Detected	Detection Rate
Setosa	36.9	74%
Virginica	18.4	37%

Source : [2]

For Hart and Timmis in [8], the following is a list of features that bring together some of the discussions above and which they believe point the way forward for AIS.

- They will be incarnated.
- They will exhibit homeostasis.
- They will benefit from the interactions between the innate and adaptive immune models.
- They will be required to undertake lifelong learning.

Thanks for your attention

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Clonal selection.

Immune-networks.

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Danger Theory.