A P System based on Negative Selection for Classification

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Abstract

Artificial immune system

Membrane Computing

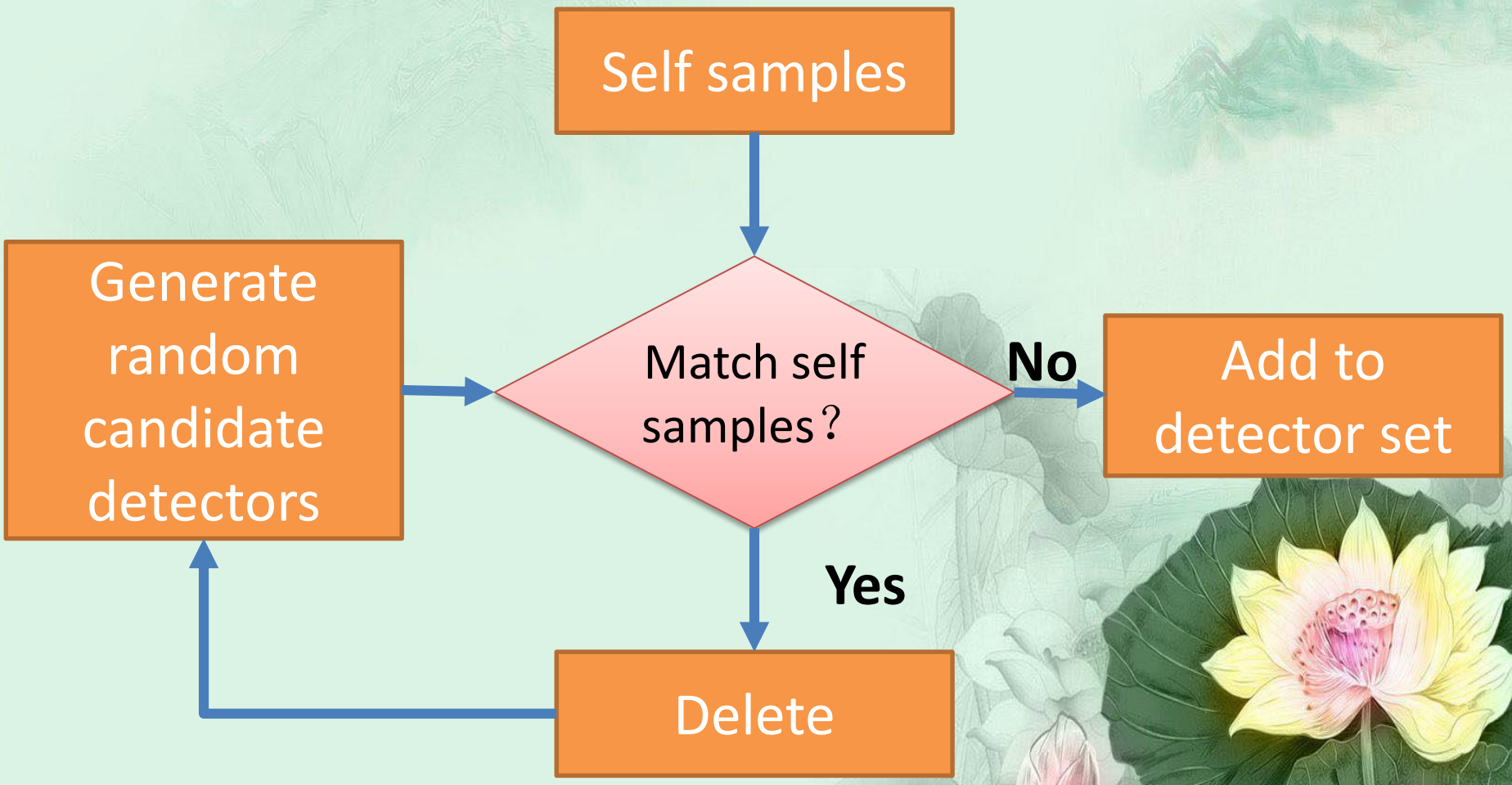
Negative selection

Cell-like system

P system： Π_{NS}

Classification

Negative selection



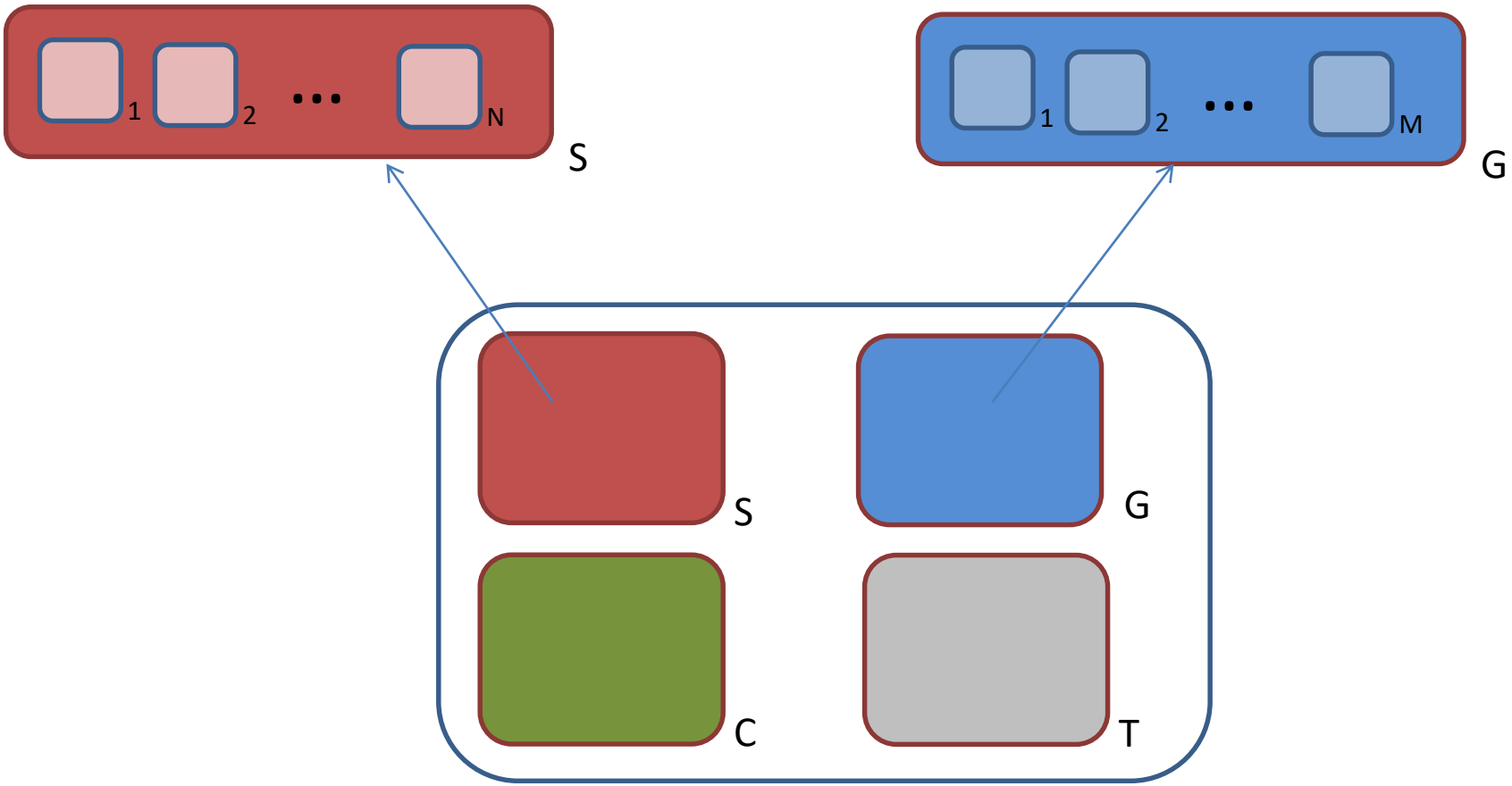
Π_{NS} for Classification

Π_{NS} for classification can defined as:

$$\Pi_{NS} = (O, \mu, \omega_1, \cdots, \omega_m, R, i_o)$$

I. O is a finite and non-empty alphabet of objects.
$O=\{\Psi_1, \Psi_2, \beta, \gamma, \gamma', \lambda, \delta, \phi, \phi_s, \phi_{ss}, \phi_c, \phi_{cc}, \eta, \eta_0, \eta', \eta_i, \eta_{ii}\}$
$\cup\{\xi_i, 0 \leq i \leq 26\}\cup\{a_j, b_j, \cdots, z_j, 1 \leq j \leq k\}$

Initial membrane structure



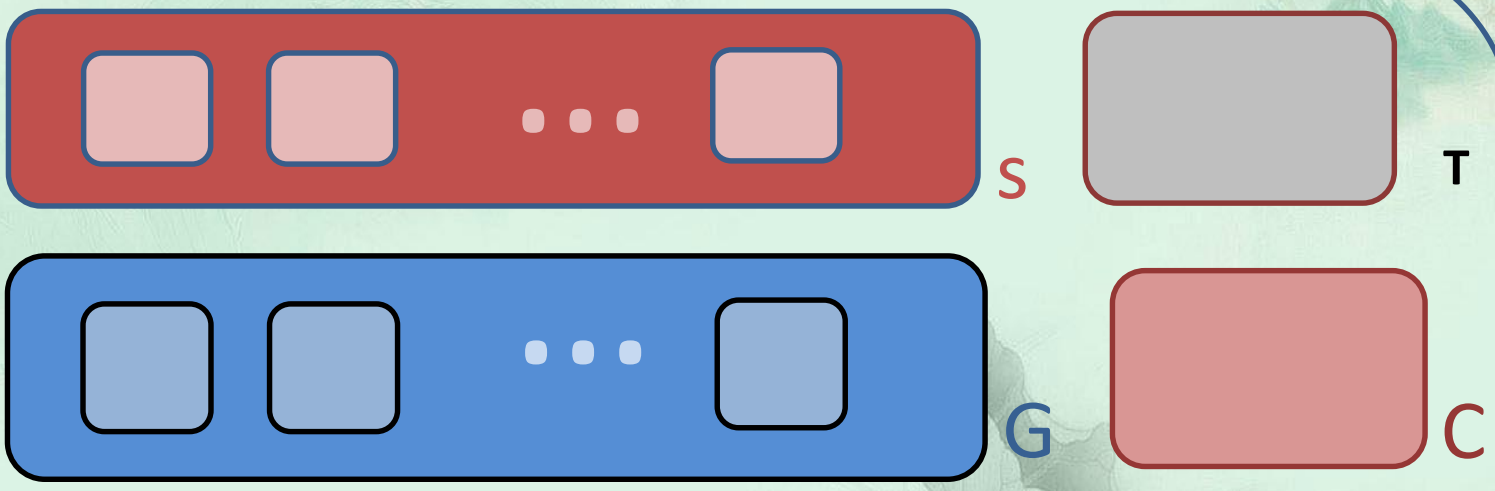
M	**the number of attributes in the data set, its max value is 26.**
N	The number of self cells. ($N=2^K-1$)

Algorithm implementation

Π_{NS} contains three important phases:

- Generate the candidate detectors randomly;
- Calculate the affinity of the detector, it will be deleted or converted into immune cell in classifier;
- Test the performance of the classifier.

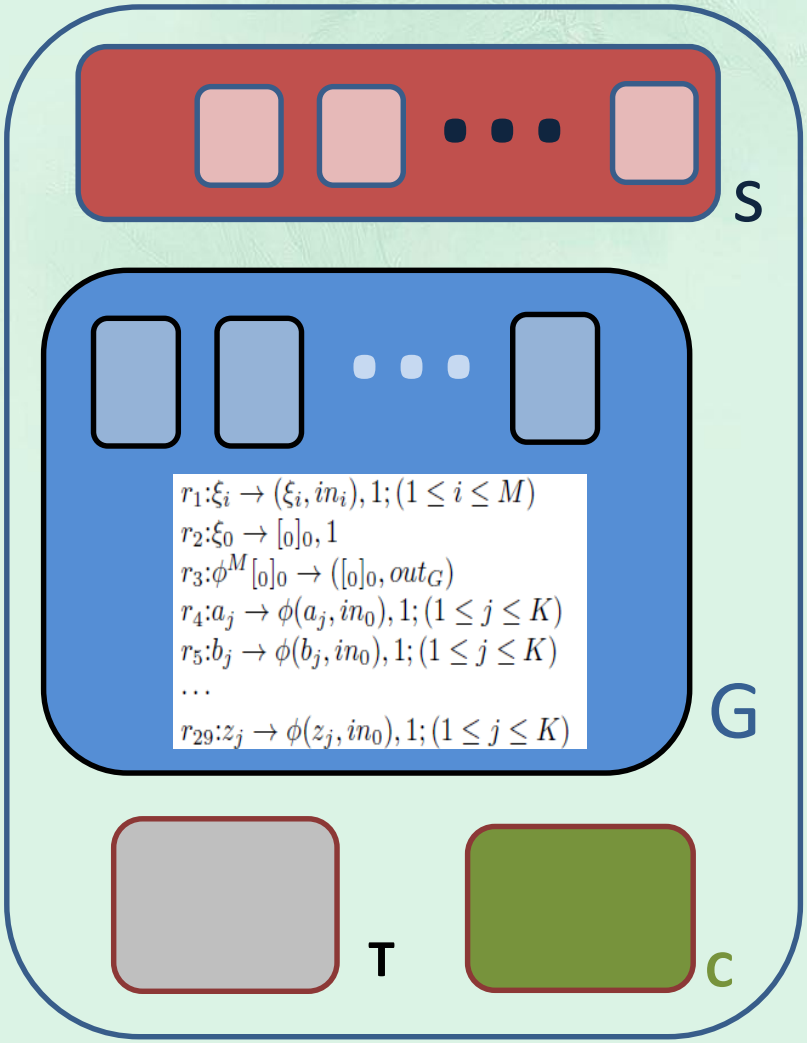
Rules in the skin membrane

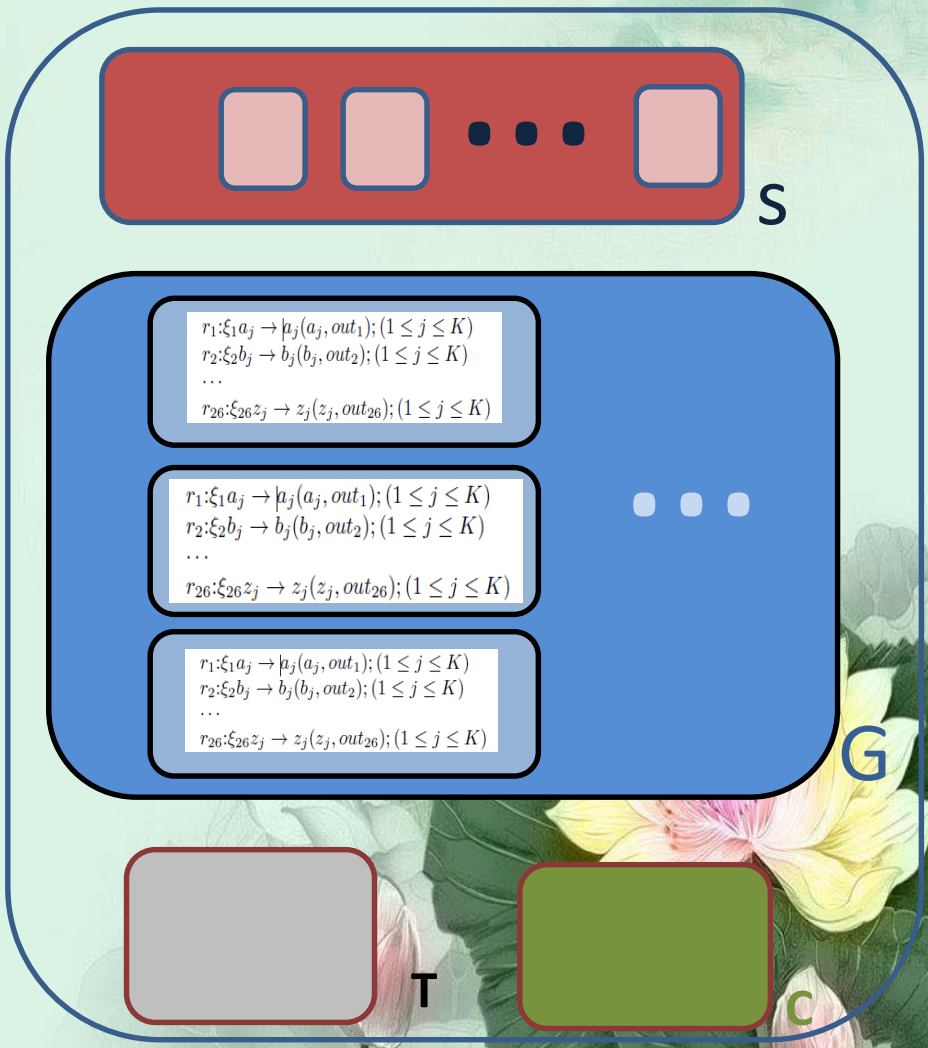


$$r_1{:}\Psi_1 \to \phi^N(\xi_0\xi_1\cdots\xi_M, in_G)$$
$$r_2{:}\phi[0]_0 \to \phi_s[0]_0[0]_0$$
$$r_3{:}\phi_s^N \to \phi_{ss}^N$$
$$r_4{:}\phi_{ss}^N[0]_0 \to (\eta[0]_0, in_s)$$
$$r_5{:}\gamma \to \gamma'\Psi_1([0]_0, in_G), 2$$
$$r_6{:}\gamma'^L\Psi_1 \to \sharp, 1$$
$$r_7{:}\beta \to \Psi_1(\eta'', in_0)$$

$$r_8{:}\Psi_2[T]_T \to \phi^{L-1}[T]_T[u]_u$$
$$r_9{:}\phi[u]_u \to \phi_c[u]_u[u]_u, 2$$
$$r_{10}{:}\phi_c^{L-1} \to \phi_{cc}^L$$
$$r_{11}{:}\phi_{cc}[u]_u \to (\eta_0[u]_u, in_C)$$
$$r_{12}{:}a_j \to (a_j, in_u), 1; (1 \le j \le K)$$
$$r_{13}{:}b_j \to (b_j, in_u), 1; (1 \le j \le K)$$
$$\cdots$$
$$r_{37}{:}z_j \to (z_j, in_u), 1; (1 \le j \le K)$$

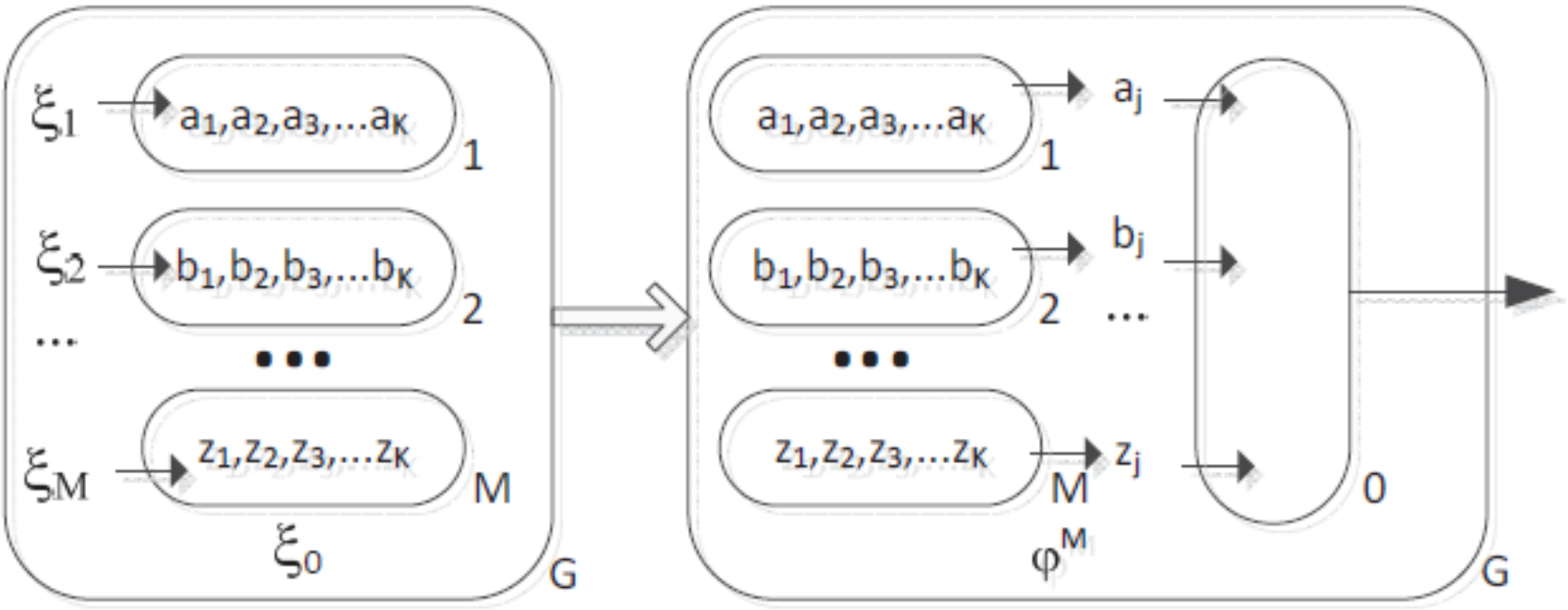
Step1:Generate the candidate detectors randomly





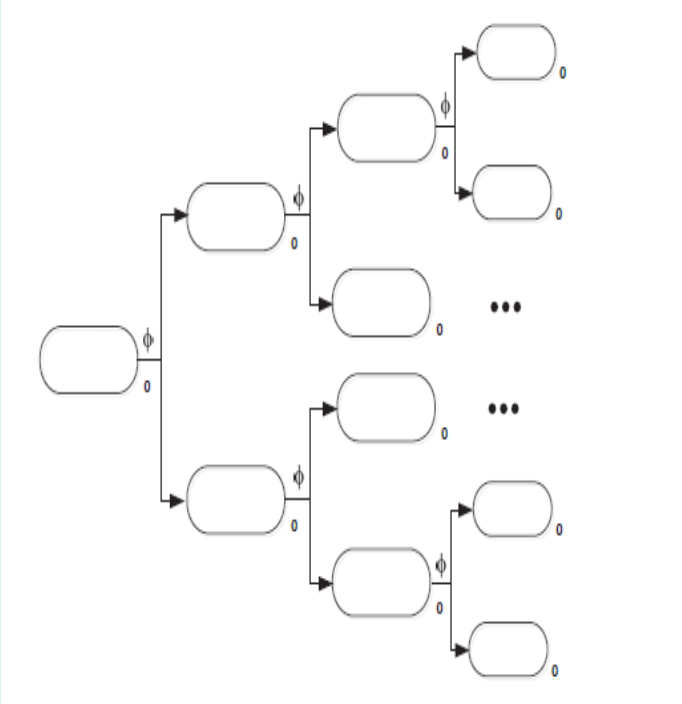
K	K represents the count of each attribute

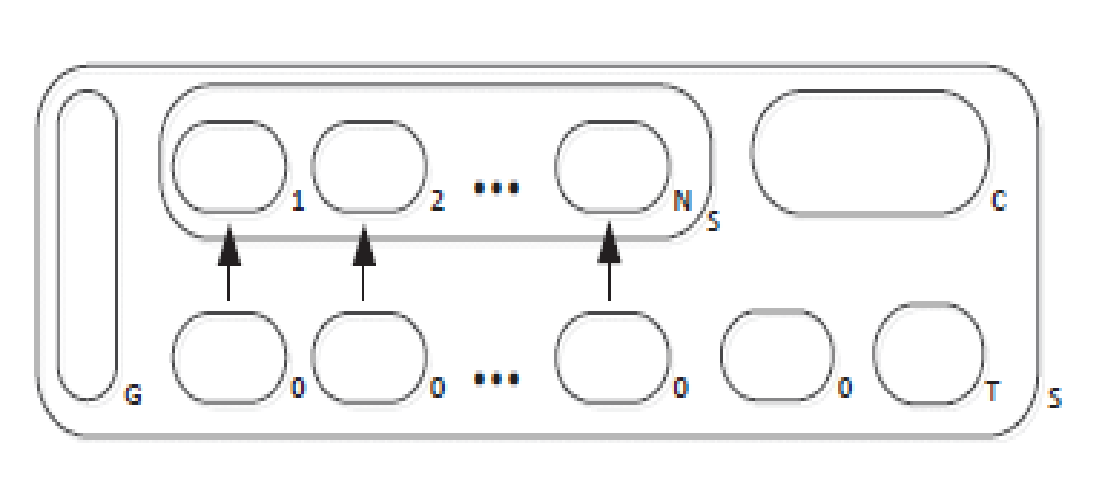
Generate a candidate cell



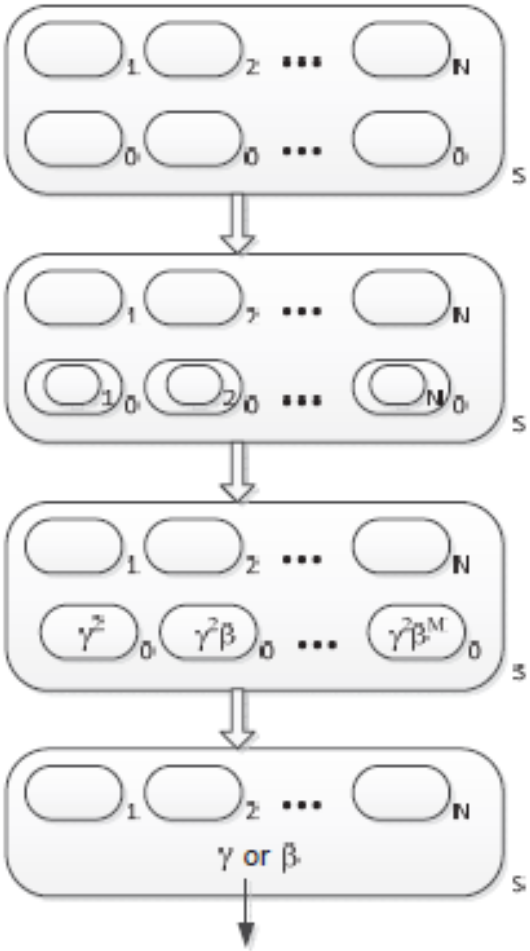
Membrane replication

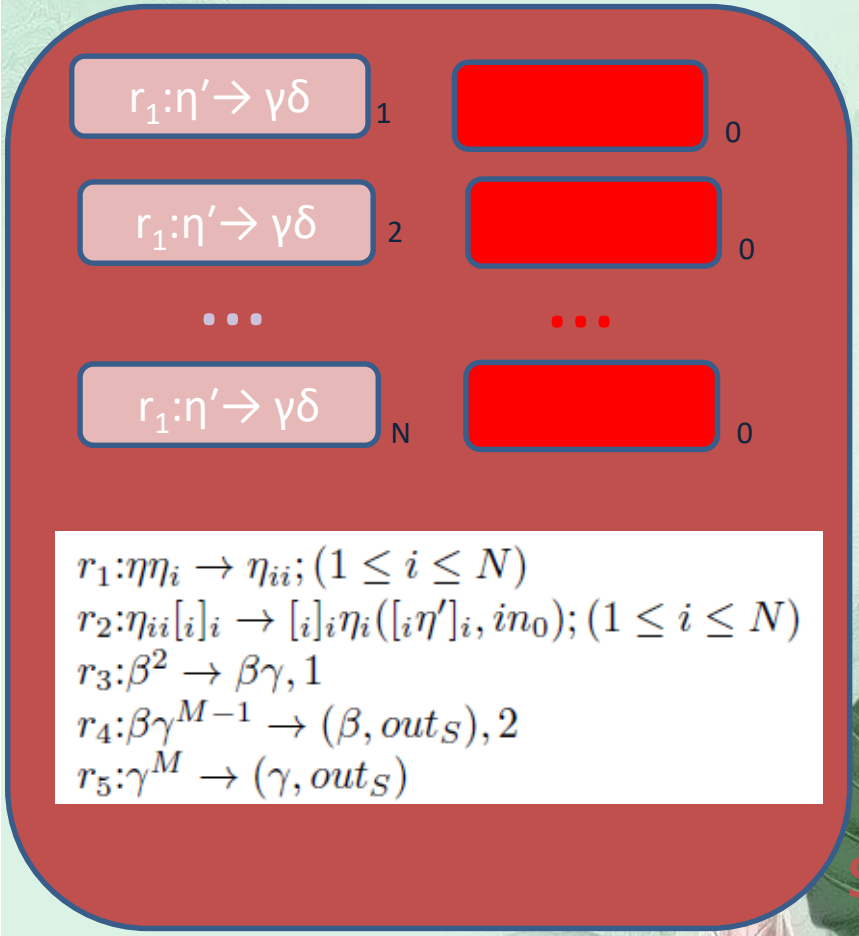
- Membrane separation



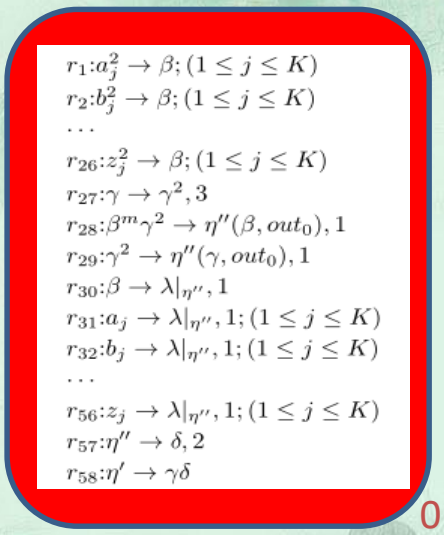


Step 2： Calculate the affinity of the detector



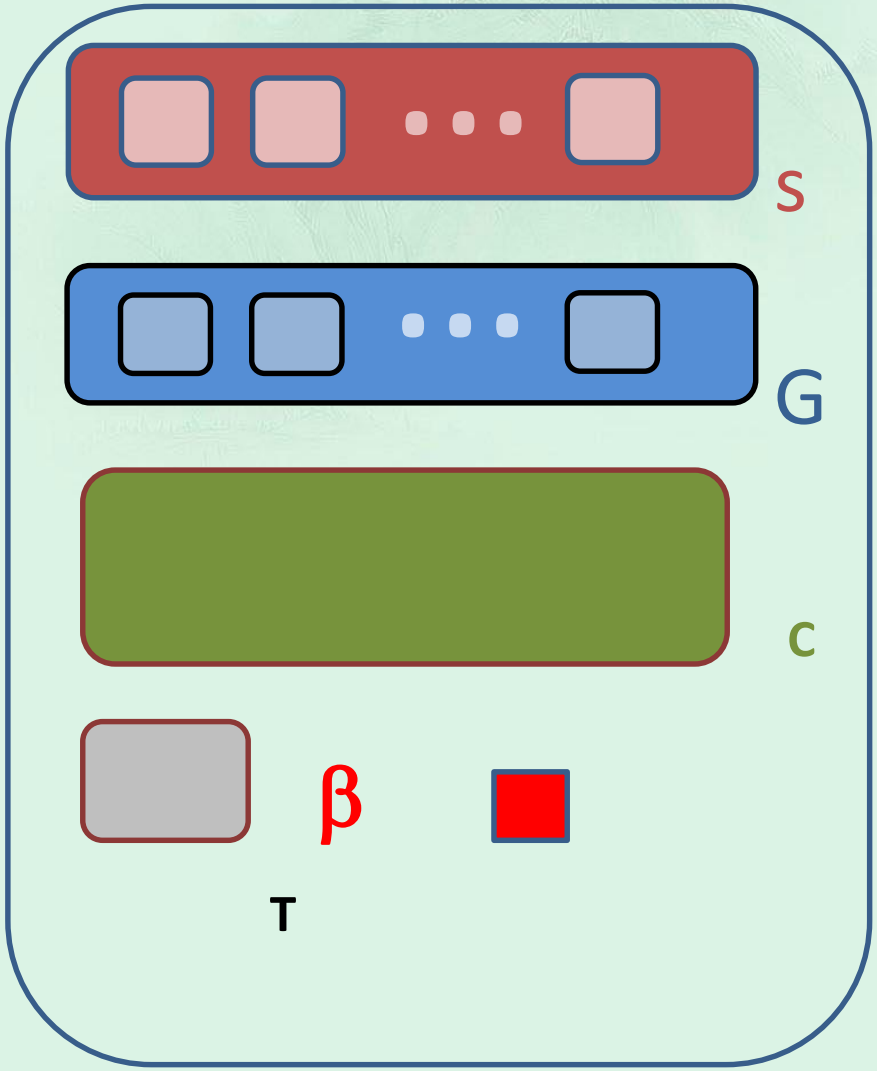


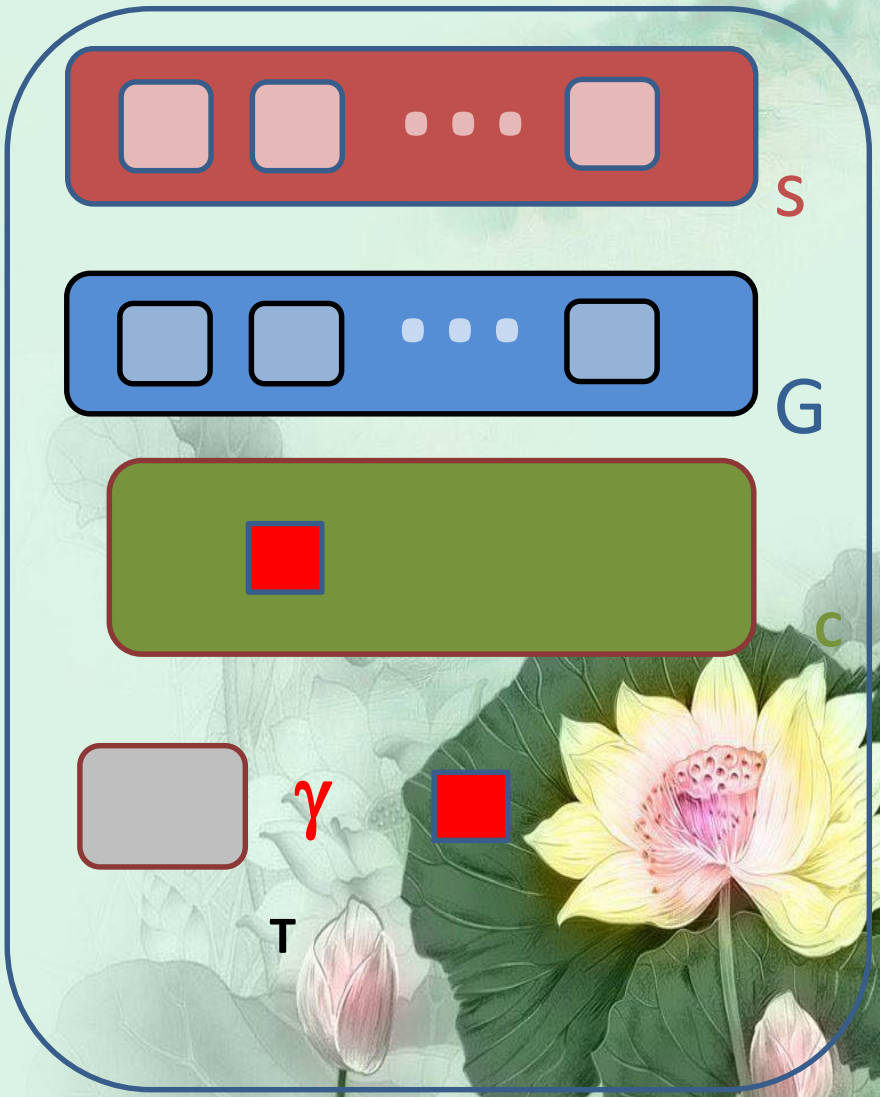
$r_1{:}\eta\eta_i \rightarrow \eta_{ii}; (1 \le i \le N)$
$r_2{:}\eta_{ii}[_i]_i \rightarrow [_i]_i\eta_i([_i\eta']_i, in_0); (1 \le i \le N)$
$r_3{:}\beta^2 \rightarrow \beta\gamma, 1$
$r_4{:}\beta\gamma^{M-1} \rightarrow (\beta, out_S), 2$
$r_5{:}\gamma^M \rightarrow (\gamma, out_S)$



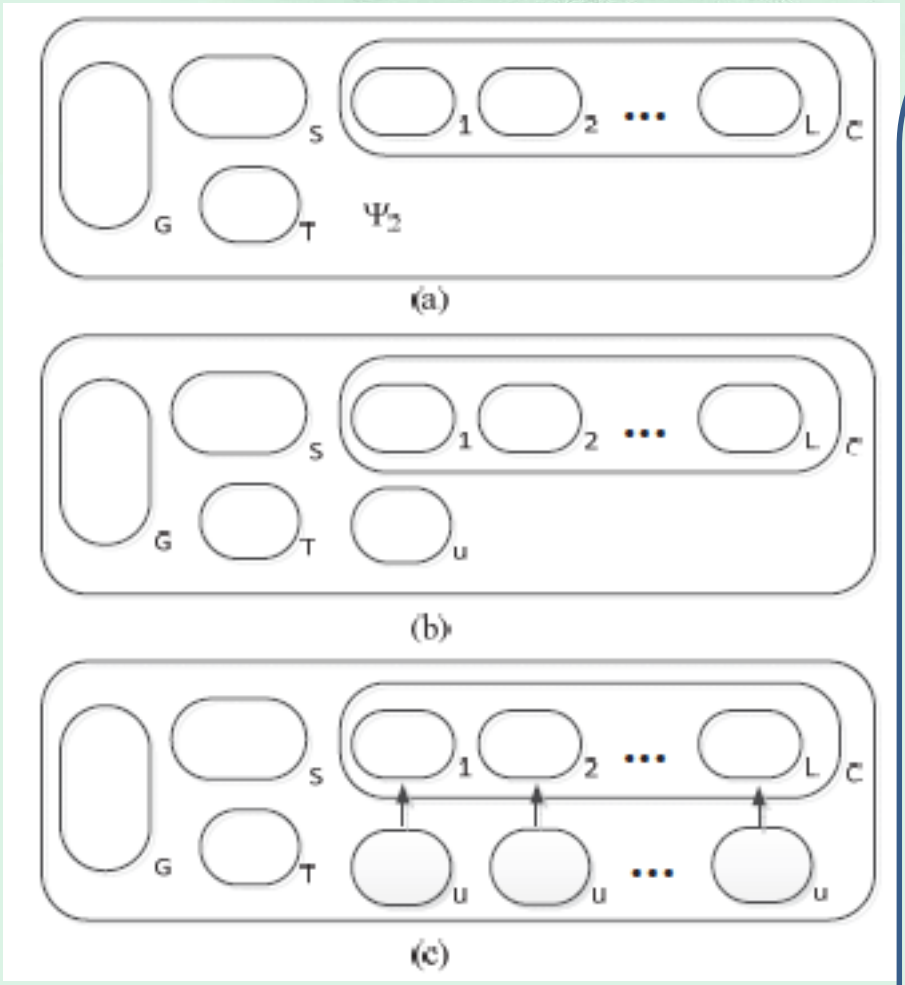
β	the corresponding attribute from the two cells are matched.
γ	the two cells are not matched

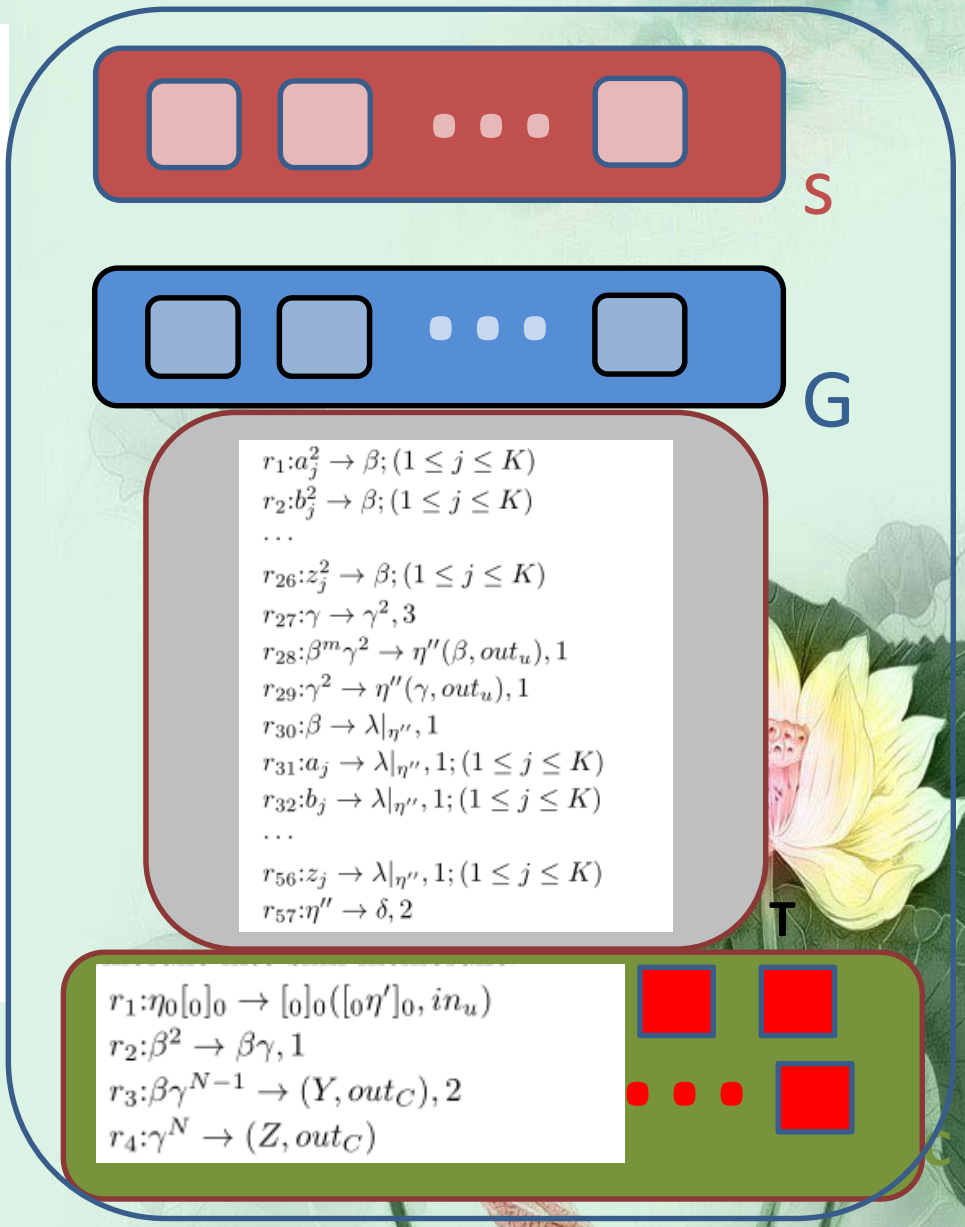
Be deleted or be converted into immune cell in classifier;

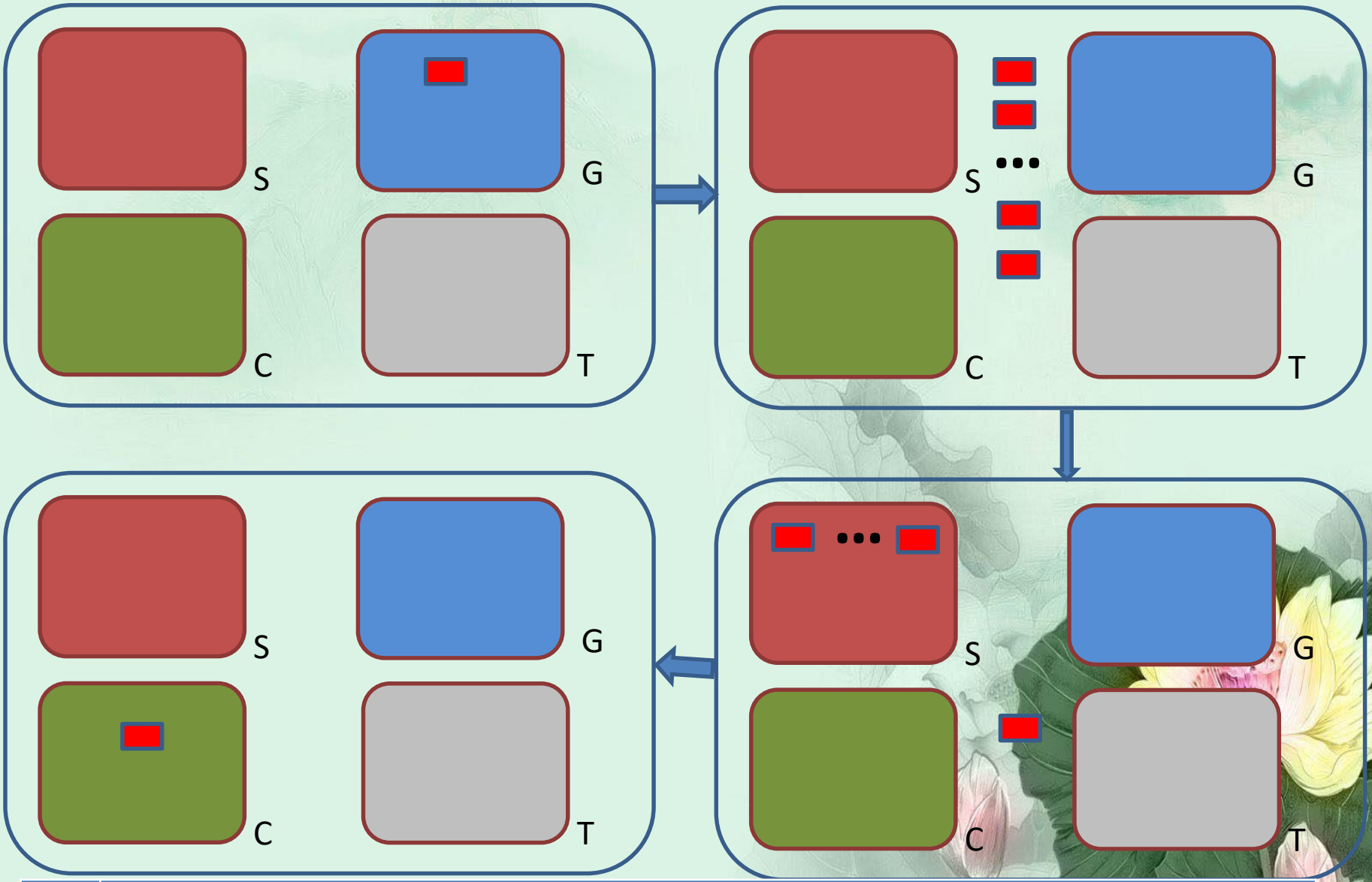




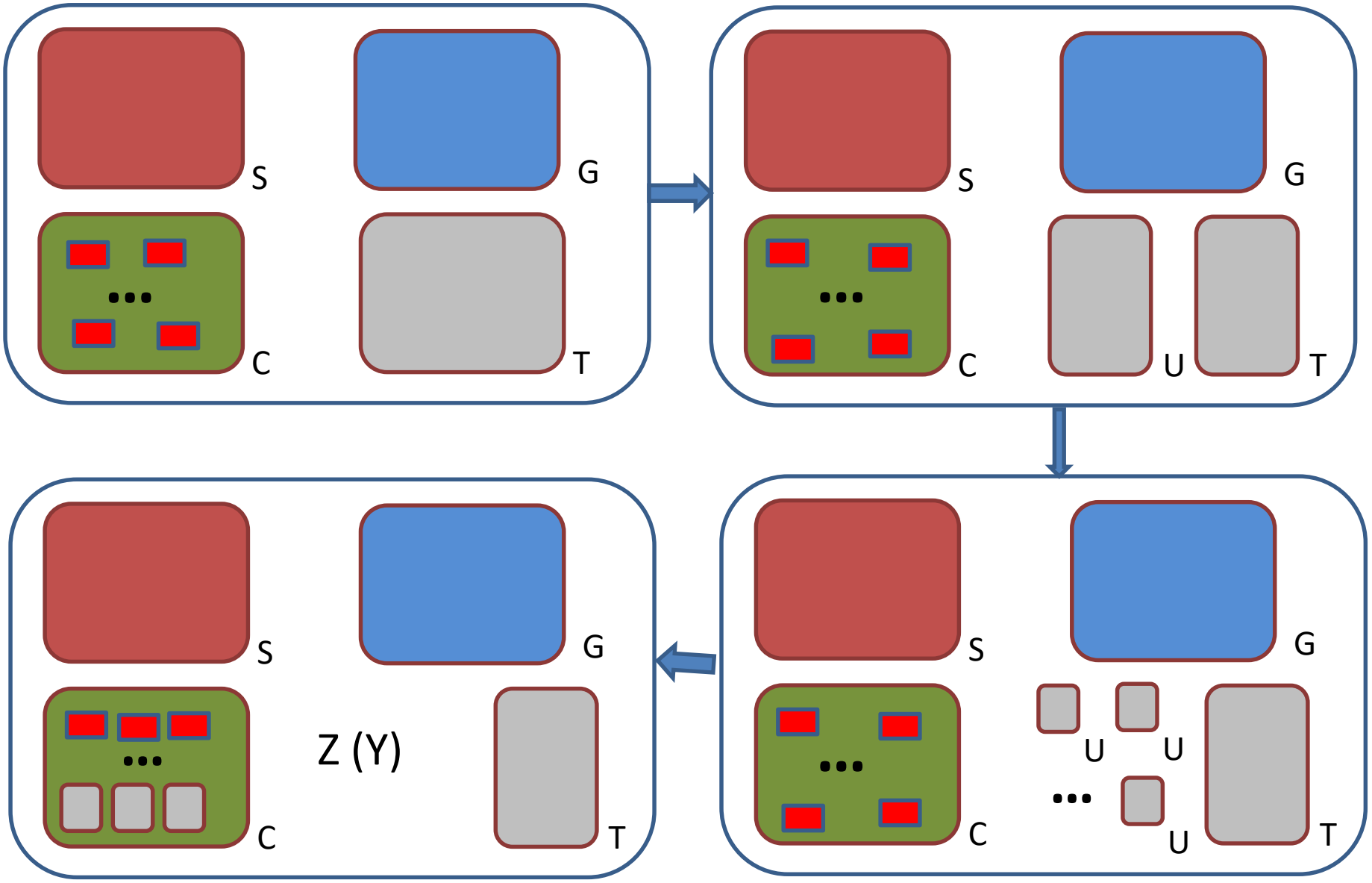
Step3: Test the performance of the classifier







m	the affinity of the two cells,1 to M
L	Number of detectors to be generated



Z	Self cell
Y	Non-self cell

System validation

The classification accuracy

$$accuracy(T) = \frac{\sum_{i=1}^{|T|} assess(t_i)}{|T|}, t_i \in T$$

$$assess(t) = \begin{cases} 1, & if \quad classify(t) = t.c \\ 0, & otherwise \end{cases}$$

Table 2. setosa as self total 47 records

Number of detectors	first time	second time	third time	forth time	five time	average	accuracy
8	32	14	18	15	14	19	40.4%
16	23	32	30	42	25	30	63.8%
32	41	38	38	37	39	39	83.0%
64	47	47	43	46	47	46	97.9%
128	47	47	47	47	47	47	100%

Table 3. Versicolour as self total 47 records

Number of detectors	first time	second time	third time	forth time	five time	average	accuracy
8	38	35	38	33	31	35	74.5%
16	37	35	36	39	38	37	78.7%
32	39	45	43	42	38	41	87.2%
64	47	47	47	46	43	46	97.9%
128	47	47	47	47	47	47	100%

Table 4. Virginica as self total 47 records

Number of detectors	first time	second time	third time	forth time	five time	average	accuracy
8	28	23	15	30	16	22	47.7%
16	33	30	34	18	17	26	55.3%
32	40	44	40	39	33	39	83.0%
64	46	47	47	46	46	46	97.9%
128	47	47	47	47	47	47	100%

The End

Thanks