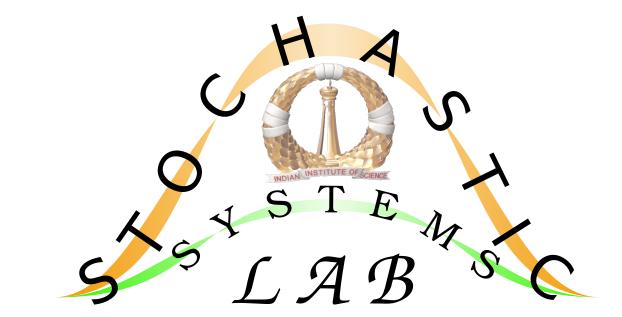
Stochastic Systems Lab
Dr. M. Narasimha Murty, Dr. Shalabh Bhatnagar, Dr. Shirish K. Shevade, Dr. V. Susheela Devi



# Research Areas

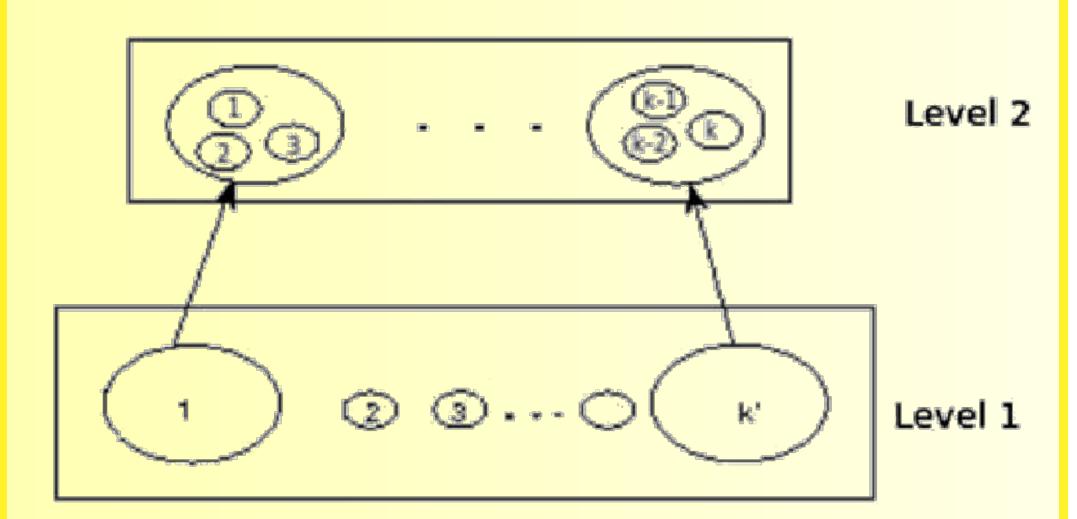
SSL lab conducts research in the area of optimization and control of stochastic dynamic systems -

- Stochastic control and optimization
- Reinforcement learning

- Multi-agent systems and stochastic games
- Machine learning and pattern recognition

- Communication and wireless networks
- Vehicular traffic control
- Data mining

# TWO-LEVEL K-MEANS CLUSTERING



### Relation between k and $\tau$ :

When k'=1, i.e. we directly cluster dataset into  $(R/\tau)^n$  clusters, we can obtain a relationship between the radius threshold  $\tau$  and the final number of clusters k. The number of distance computations required in this scenario should not be greater than the number of computations required to cluster the dataset into k clusters. Therefore, we have

$$2Nk - k^{2} \ge 2N(R/\tau)^{n} - (R/\tau)^{2n}$$

$$\Rightarrow ((R/\tau)^{n} - k)((R/\tau)^{n} + k - 2N) \ge 0$$

Since the maximum values that  $(R/\tau)^n$  and k can take are N, the expression  $((R/\tau)^n + k - 2N)$  cannot be positive. Hence, the following two inequalities must be satisfied:

$$(R/\tau)^n \le k \text{ and } (R/\tau)^n \le (2N - k)$$

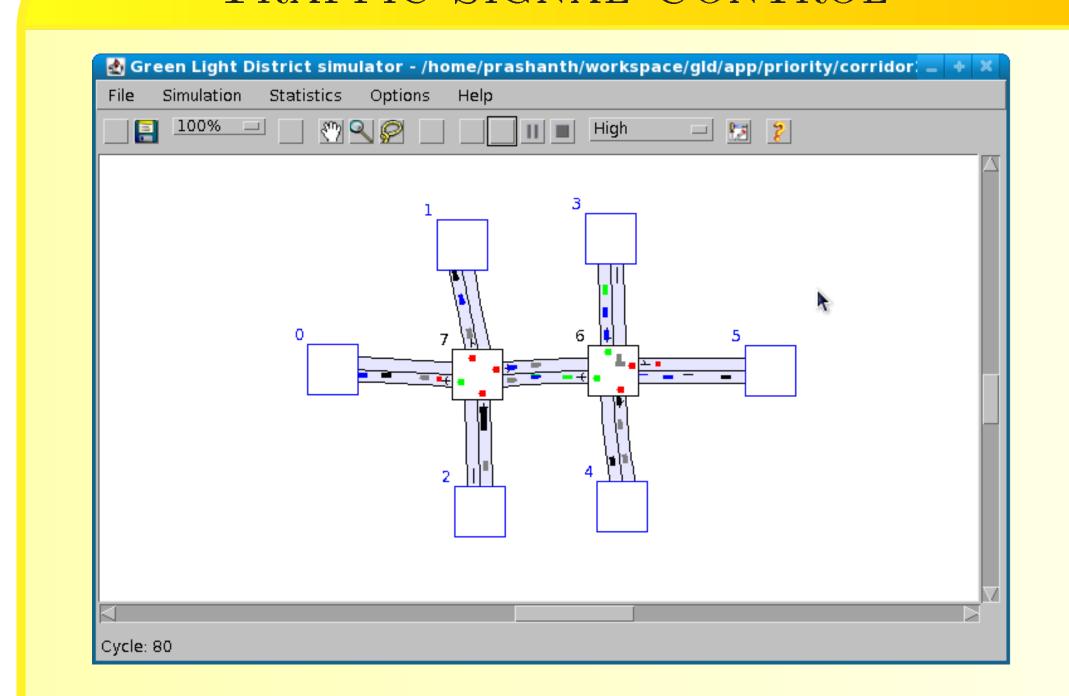
$$\Rightarrow \tau \ge R/(k)^{1/n} \text{ and } \tau \ge R/(2N - k)^{1/n}$$

This gives us the following relation between  $\tau$  and

$$max(R/(k)^{1/n}, R/(2N-k)^{1/n}) \le \tau \le R$$

Ref.: Radha Chitta and M. Narasimha Murty. "Twolevel k-means clustering algorithm for  $k-\tau$  relationship establishment and linear-time classification". Journal of Pattern Recognition, Vol. 43, pp. 796-804, Elsevier, 2010.

# TRAFFIC SIGNAL CONTROL



Traffic signal control via reinforcement learning techniques such as Q-learning.

Ref.: Prashanth L. A. and Shalabh Bhatnagar. "Q-Learning based algorithm for traffic signal control". IEEE Transactions on Vehicular Technology, Submitted 2009.

# NATURAL ACTOR-CRITIC ALGORITHM

 $f_{s_t}$ : state-features

 $\psi_{s_t,a_t} = \nabla ln\pi(s_t,a_t)$ : state-action features  $\xi_t = c\alpha_t, \beta_t = o(\alpha_t)$ 

 $\sum_{t} \alpha_{t} = \sum_{t} \beta_{t} = \infty, \sum_{t} \alpha_{t}^{2}, \sum_{t} \beta_{t}^{2} < \infty$ 

**Avg. Reward Update:**  $\hat{J}_{t+1} = (1 - \xi_t) \hat{J}_t + \xi_t r_{t+1}$ **TD Error:**  $\delta_t = r_{t+1} - \hat{J}_{t+1} + v_t^{\top} f_{s_{t+1}} - v_t^{\top} f_{s_t}$ Fisher information matrix inverse:

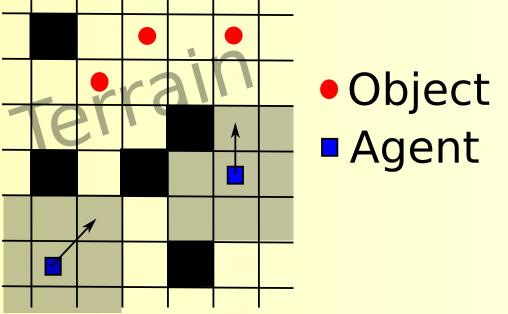
 $G_{t}^{-1} = \frac{1}{1 - \alpha_{t}} \left[ G_{t-1}^{-1} - \alpha_{t} \frac{\left( G_{t-1}^{-1} \psi_{s_{t} a_{t}} \right) \left( G_{t-1}^{-1} \psi_{s_{t} a_{t}} \right)^{\top}}{1 - \alpha_{t} + \alpha_{t} \psi_{s_{t} a_{t}}^{\top} G_{t-1}^{-1} \psi_{s_{t} a_{t}}} \right]$ 

Critic Update:  $v_{t+1} = v_t + \alpha_t \delta_t f_{s_t}$ Actor Update:  $\theta_{t+1} = \Gamma \left( \theta_t + \beta_t G_t^{-1} \delta_t \psi_{s_t a_t} \right)$ 

Ref.: Shalabh Bhatnagar, Richard S. Sutton, Mohammad Ghavamzadeh and Mark Lee. "Natural Actor-Critic Algorithms". Accepted as a Regular Paper in Automatica, 2009.

## STOCHASTIC GAMES

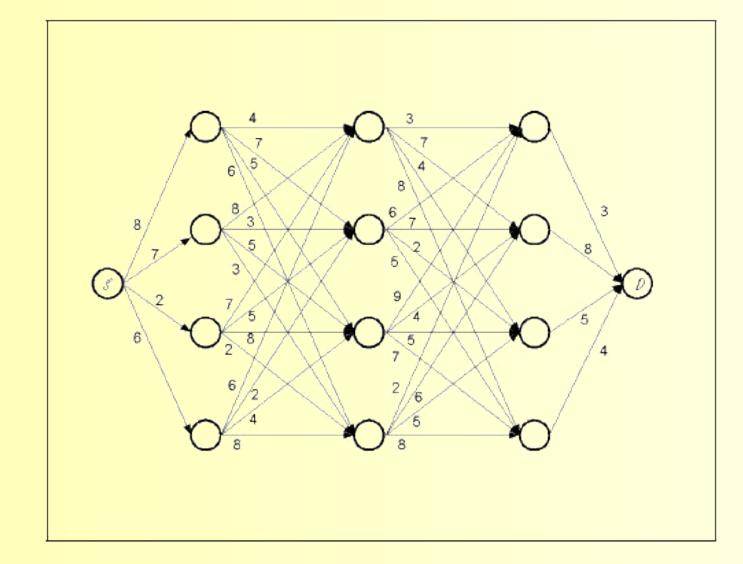
Stochastic game model of terrain exploration.



- Any gradient-descent method converges to a Nash equilibrium strategy for discounted reward stochastic games.
- Herskovits two-stage direction method with suitable modifications gives a good offline computational technique.

Ref.: Prasad H. L., S. Bhatnagar, and N. Hemachan-"A computational procedure for general-sum stochastic games". CSA, IISc, Tech. Rep. IISc-CSA-TR-2009-5, May 2009.

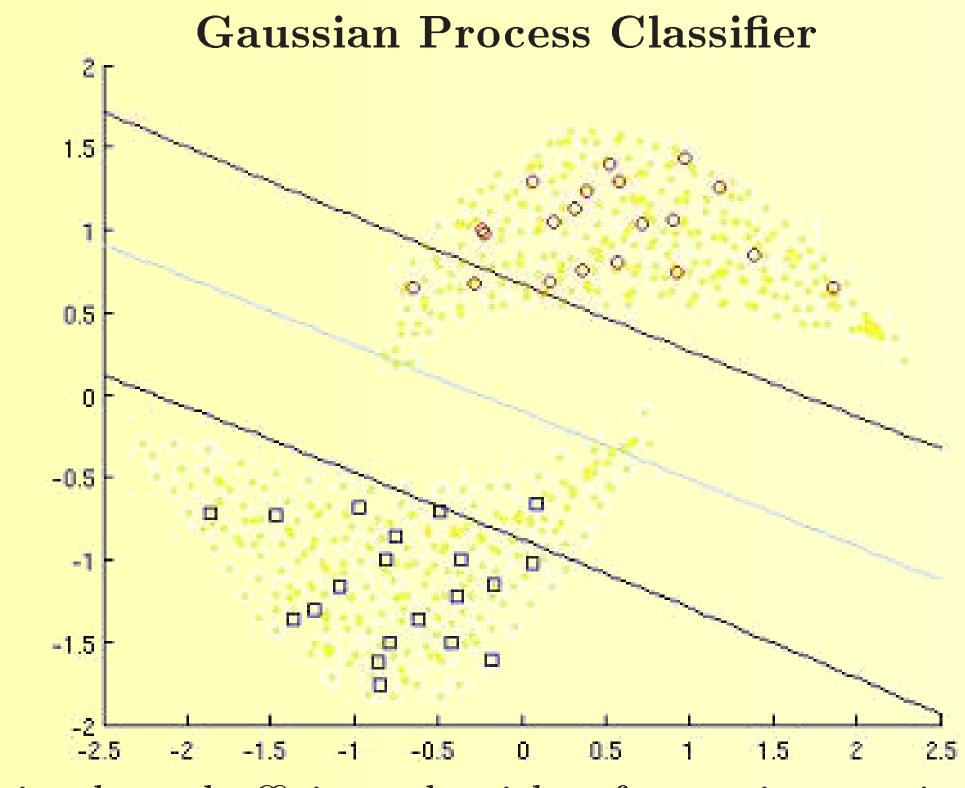
# ANT COLONY OPTIMIZATION

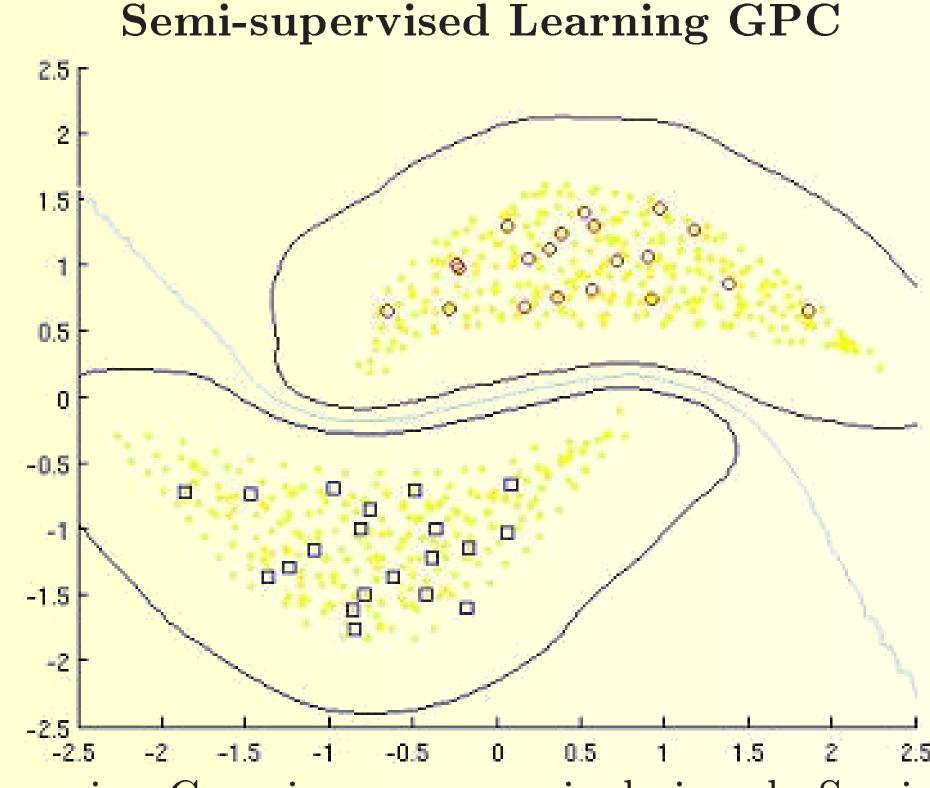


$$T_{ij}^{k}(t+1) = (1-\rho)T_{ij}^{k}(t) + \rho QR_{ij}^{k}(t)$$
$$X_{ij}^{k}(t+1) = X_{ij}^{k}(t) + a(t)X_{ij}^{k}(t)T_{ij}^{k}(t+1)$$

Ref.: Sudha Rani K., Lakshmanan K. and S. Bhatnagar. "Ant Colony Optimization Algorithms for Shortest Path Problems". Proceedings of Second Workshop on NET-COOP, LNCS 5425, pp.37-44, Springer, 2008.

# Semi-supervised Learning





A simple and efficient algorithm for semi-supervised learning using Gaussian processes is designed. Semisupervised learning uses unlabelled data along with labeled data to improve generalization performance of classifier.

Ref.: Amrish Patel, S. Sundararajan and Shirish Shevade. "Semi-supervised Classification using Sparse Gaussian Process Regression". International Joint conference on Artificial Intelligence (IJCAI), 2009