

# **The Dynamics of Probabilistic Population Protocols\***

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## Population Protocols

[Angluin, Aspnes, Diamandi, Fischer, Peralta, 04]

**Finite set of States**  $Q = \{q_1, \dots, q_k\}$

$n$  agents (population)

$n_i = \#$  agents in state  $q_i$

Let  $x_i = \frac{n_i}{n}$

**Configuration**,  $C$ : A map from the population to the states

**Population state at time  $t$**

$x(t) = (x_1(t), \dots, x_k(t))$

## Transition function

$\_ : Q \times Q \rightarrow Q \times Q$

**Probabilistic Population Protocols (PPP)**,  
[Angluin, et al]

(all pairs interactions) (Fairness)

We generate  $C_{t+1}$  from  $C_t$  by (1) drawing an ordered pair  $(i, j)$  of agents **independently** and **uniformly**.

(2) Applying  $\_$  to  $(C_k(i), C_k(j))$

(3) Updating the states of  $i, j$ , accordingly,  
to form  $C_{k+1}$

**Example** (Rules of  $\_$ )

$$(q_1, q_2) \rightarrow (q_3, q_2)$$

$$(q_3, q_1) \rightarrow (q_1, q_2)$$

$$(q_2, q_3) \rightarrow (q_2, q_1)$$

(else no change)

How can we study systematically the (eventual) **stability** of such a system?

**Our proposal:** Use nonlinear dynamics of continuous time  $\dot{x}_i = f_i(x)$   $i = 1 \dots \_$

Example:

$$(q_1, q_2) \rightarrow (q_3, q_2)$$

$$(q_3, q_1) \rightarrow (q_1, q_2)$$

$$(q_2, q_3) \rightarrow (q_2, q_1)$$

By inspection then

$$x_1 = x_1 x_3 + x_2 x_3 - x_1 (x_2 + x_3)$$

$$x_2 = x_1 x_3 + x_1 x_2 + x_2 x_3 - x_2 (x_1 + x_3)$$

$$x_3 = x_1 x_2 - x_3 (x_1 + x_2)$$

**Output rate** of a state  $i$

$$o_i(x) = x_m(t)$$

where  $(q_i, q_m) \rightarrow (q_r, q_)$

or  $(q_m, q_i) \rightarrow (q_r, q_)$

## Compare with the general Lotka-Volterra equation for 3 species

$$\dot{x}_i = x_i \left( r_i + \sum_{j=1}^3 x_j a_{ij} \right)$$

$i = 1, 2, 3$

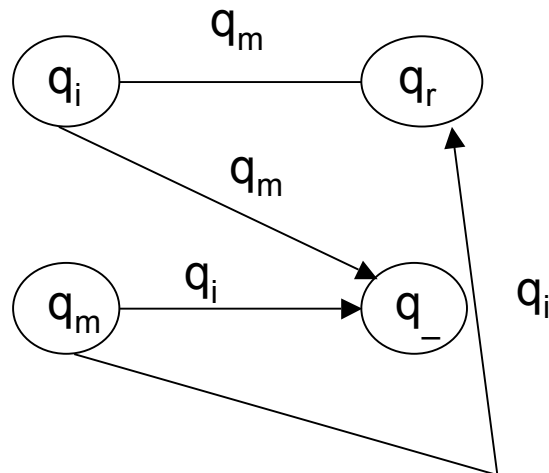
Here  $r_i = -\mu_i$  and by setting  $a_{ij}$  equal to 1 or 0 we get a special case of the dynamics of probabilistic population protocols, in which  $q_i$  must be present in the left hand of a rule when it is present on the right.

- When are they equivalent?

**Note that we can represent**

$$(q_i, q_m) \rightarrow (q_r, q_-)$$

as the following graph  
(forgetting orders in the pair)



This produces a digraph  $G(\_)$

## Remark

Sources (and sinks) in  $G(\_)$  are **transient** states in the sense that their population always decreases (increases) and then we can omit them from the differential equations approach, as far as eventual stability is concerned.

# I. When can we form such a system of differential equations?

[N. Wormald, 06] : In many cases

Note  $n_i(t)$  are random variables

(i)  $\exists$  Constant  $K : |n_i(t+1) - n_i(t)| < K$

(they don't change too quickly)

(ii)  $E(n_i(t+1) - n_i(t) \mid \text{history})$

$$= f_i\left(\frac{t}{n}, x_1, \dots, x_k\right) + o(1)$$

(we know the **expected** rate of change)

(iii)  $f_i$  is continuous and satisfies a Lipschitz condition.

Notice that the study of the rules of  $\_$ , with (nonlinear) differential equations, cannot not be always applied.

For example, a probabilistic population protocol whose outcome depends on e.g.  $n_1(t)$  being odd/even is impossible to be studied in this way.

Let  $Z_i(t) = \frac{n_i(t)}{n(t)}$ , a stochastic process.

**(the “real” process)**

**Definition:** The nonlinear dynamic system of equations  $\_(\_)$  corresponding to the rules of  $\_$  is **faithful** iff its solution  $x_i(t)$  satisfies.

$$(1) Z_i(0) = x_i(0)$$

(2)  $\forall \epsilon > 0$  and any integer  $T > 0$  there is a positive constant  $N_0$  so that if  $n > N_0$  then

$$\text{Prob} \{ |Z_i(t) - x_i(t)| \geq \epsilon \} < \epsilon,$$

for any  $t : 0 \leq t \leq T$  at which  $x_i(t)$  is defined.

## Remarks

(a) What are the faithful probabilistic population protocols?

(open)

(b) The faithfulness definition does not only speak about  $t \rightarrow \infty$  but requires the sample paths of the PPP model to behave “according to their expected behaviour” in the long run.

**II.** Assume that a PPP is faithful.  
What conclusions do we get about  
its asymptotic stability?

How can we easily design (and  
understand) the behaviour of  
faithful PPP?

## II.1. A proposal for “globally” specifying a faithful PPP protocol.

### The Switching Probabilistic Protocols

#### idea

- (A) Specify when each agent in  $q_i$  wants to **review** her state.
- (B) If so, specify rates (probabilities) to go from  $q_i$  to  $q_j$ .

## Switching Probabilistic Protocols (SPP)

A “simpler” dynamic system (global configurations)

(a) Each agent of state  $q_i(t)$  **reviews** her state at rate  $\lambda_i(t)$

(b) **Conditional Rates of switch**

Each agent, in state  $q_i(t)$ , **switches to** state  $q_j$  at a rate  $p_{ij}(x(t))$

If all Review / Switch rates are **Poisson**, and independent, then when  $n \rightarrow \infty$

$$\dot{x}_i = \sum_{j \in Q} x_j p_{ji}(x) \dot{e}_j(x) - x_i \dot{e}_i(x)$$

$i = 1, \dots, n$

(no Wormald needed here)

## Theorem

The differential equations of SPP include those of PPP as a special case.

(Almost by inspection)

In our example choose

$$-1 = x_2 + x_3$$

$$-2 = x_1 + x_3$$

$$-3 = x_1 + x_2$$

$$p_{21} = \frac{x_3}{x_1 + x_3} \quad p_{11} = \frac{x_3}{x_1 + x_3} \quad p_{31} = 0$$

$$p_{12} = \frac{x_3}{x_2 + x_3} \quad p_{22} = \frac{x_1}{x_1 + x_3} \quad p_{32} = \frac{x_2}{x_1 + x_2}$$

$$p_{13} = \frac{x_2}{x_2 + x_3} \quad p_{23} = p_{33} = 0$$

In our theorem we exclude sources/sinks in the graph  $G(\_)$ .

Note that, in general,  $p_{ij} \ j=1 \dots k$  is not a distribution.

What happens when  $p_{ij} \ j=1 \dots k$  is indeed a prob. distribution?

## An answer

Specs of SPP independent of time,  
(and of the configuration)

Let, for all  $i$

$$x_i(x(t)) = x_i$$

and for all  $i, j$

$$p_{ij}(x(t)) = p_{ij}$$

Then the dynamics of SPP become

$$\dot{x}_i = \sum_{j \in K} x_j \ddot{e}_j p_{ji} - \ddot{e}_i x_i$$

$$i = 1 \dots k$$

**Definition:** The Markovian Population Protocols are SPP with  $\mu_i$ ,  $p_{ij}$  independent of time and of the configuration  $x(t)$ .

Let us define “rates”  $r_{ij}$  such that

(1)  $i \neq j$        $r_{ij} = \mu_i p_{ij}$  for all  $i, j$ ,

(2)  $i = j$        $r_{ii} = \mu_i (p_{ii} - 1)$

Then ( $i = 1 \dots k$ )

$$(*) \quad \dot{x}_i(t) = r_{ij}x_j(t) + \sum_{k \neq i} r_{ki}x_k(t)$$

Note that  $x(t)$  is such that  $\sum x_i(t) = 1$  and can be seen as a prob. distribution itself!

The equations (\*) are the dynamics of a Markov Chain of  $k$  states and continuous time rates  $q_{ij}$ .

(This holds even when  $r_{ij}, p_{ij}$  are only functions of time!)

When all  $r_{ij}$  are nonzero then this Markov Chain is **irreducible** and **homogeneous**.

Then, we conclude:

- The  $\lim_{t \rightarrow \infty} x_i(t)$  always exist and are independent of  $x(0)$ .
- The limiting distribution is **unique**, and is the solution of the system

$$r_{ii}x_i + \sum_{i \neq j} r_{ij}x_i = 0$$

- The faithful PPP is always stable.

**What is the gain of  
proving that a PPP is  
faithful?**

## What is the gain?

Powerful analytic tools for asymptotic  
(in)stability  
(Can be **decided**)

Let  $f_i(x) = 0$   $i = 1 \dots n$

Let  $x^*$  = a solution of  $f_i(x) = 0$   $i = 1 \dots n$

Let  $L = [L_{ij}]$

Where  $L_{ij} = \frac{\partial f_i}{\partial x_j}(x^*)$  (Jacobian)

Let an eigenvalue  $g$  of  $L$  be  
 $g = a + iw$

## Theorem [Hartman, 60]

At  $x^*$

- (1)  $a < 0 \forall g$  then  $x(t) \rightarrow x^*$
- (2)  $\exists g : a > 0$  then  $x(t)$  **diverges**
- (3)  $\exists g \_ = 0$  then oscillations

i.e. in our case, if PPP dynamic can be written via differential equations, then we can decide **stability** in polynomial time.

**A study of a special case  
of faithful SPP, PPP.**

**Linear Viral Protocols  
(LVP)**

Assume that the rules of  $\_$  basically specify that agents adopt the state of “the first person they meet in the street” (if they adopt at all).

Formally, for all  $i, j, x(t)$

$$p_{ij}(x(t)) = x_j(t) \quad (**)$$

So, the dynamics are

$$\dot{x}_i = \sum_{j \in \mathbb{E}} x_j x_i \ddot{e}_j(x) - x_i \ddot{e}_i(x)$$

We now propose a **linear** model to capture the “immunity” that an agent (in a state) has against other agents in the population.

One can imagine **immunity** to be a measure of the degree of protection of agents when they interact.

## Assumptions (A1)

- We measure the immunity of an interacting  $(q_i, q_j)$  pair by an integer  $a_{ij}$ .
- We require  $a_{ji} = a_{ij}$   
(symmetry)  
thus

**Definition:** Let  $A = [a_{ij}]$  be a symmetric matrix of integers.

The **immunity** of an agent in state  $q_i$  is

$$t_i(x(t)) = a_{i1}x_1(t) + \cdots + a_{ik}x_k(t)$$

It is natural to assume that agents in state  $q_i$  wish to review their states more often when their immunity is low.

So we assume  
(Assumption A2)

For state  $q_i$ ,

$$t_i(x(t)) = \frac{1}{\mu_i} - \frac{1}{\mu_i} t_i(x(t))$$

where  $\mu_i, \mu_i$ , reals,  $\mu_i > 0$ , and  $t_i(x) \leq \frac{1}{\mu_i}$  always.

**Definition** (Average immunity of a population)

$$t(x) = \sum_i x_i t_i(x)$$

**Definition:** The SPP with assumptions A1, A2 are called Linear Viral Protocols (LVP).

## Lemma E.1.

The dynamics of LVP are

$$\dot{x}_i = \alpha(t_i(x) - t(x))x_i$$

i.e. they are a  $\alpha$ -rescaling of the **Replicator Dynamics** of evolutionary game theory.

So,

## Lemma E.2.

The dynamics of LVP are equivalent to the Lotka-Volterra dynamics.

Note, from Lemma E.1 that the “rest” points  $x^*$  of the dynamics (i.e. when  $\dot{x}(t) = 0$ ) must satisfy

$$t_i(x^*) = t(x^*)$$

### **Lemma E.3.**

When (if) LVP stabilizes, then the immunity of any agent is the average system immunity.

## Very Immune Rest Points

### Definition

Let  $x^*$  be a rest point of LVP.

Then  $x^*$  **is very immune** iff, for any  $x(t)$  in a region around  $x^*$  it holds:

$$t(x) < \sum_{i=1}^k x_i^* t_i(x)$$

It is intuitive to expect that the very immune rest points are stable.

To show this, we recall:

## Lyapunov's Theorem

Let  $\dot{x} = f(x)$  be a time-independent nonlinear equation.

Let  $V : \{x(t)\} \rightarrow \mathbb{R}$  be continuously differentiable. Then if in a region around  $x^*$  we have  $\dot{V} < 0$  then  $x^*$  is stable.

**$V(x)$  is called a Lyapunov Potential.**

## Lemma E.4.

Very Immune Rest Points are stable.

### Proof

Consider the relative entropy

$$E(x) = - \sum_{i=1}^k x_i^* \ln \left( \frac{x_i}{x_i^*} \right) \quad (\text{clearly } E(x^*)=0)$$

We can easily show that  $E(x) < 0$  in the region around  $x^*$  (region defined by the property “Very Immune”).

QED

## Conclusions

- (1) In many cases, PPP can be studied as systems of time –independent nonlinear 2<sup>nd</sup> degree diff. equations.
- (2) This can be used to efficiently decide stability of PPP
- (3) We can “globally specify” PPP by the Switching Protocols approach  
(since  $SPP \supseteq PPP$  when PPP are faithful).
- (4) Faithful PPP and SPP contain several well-known dynamic systems!

**Thank you!**