Reinforcement Mechanism in Semantic Structure Models

Reinforcement learning models for the behavior of Semantic Structures

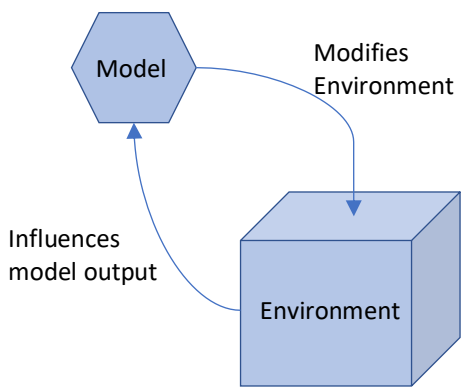
We are considering reinforcement learning models where both are true:

1) The environment influences the model
2) The model influences the environment

The model influences the environment in such a way that the environment gets conditioned to support certain interactions and encourages forming certain types of ensembles. The pertinent question here is what constitutes the environment. We will consider both a static model and dynamic model for semantic structure interactions. In both static and dynamic modeling the environment is represented by some kind of a *field* which will influence the particles entering semantic space either via inference or via parsing. The environment will condition those new particles to form certain kinds of ensembles and to associate them in a certain preferred way with the existing semantic structures.

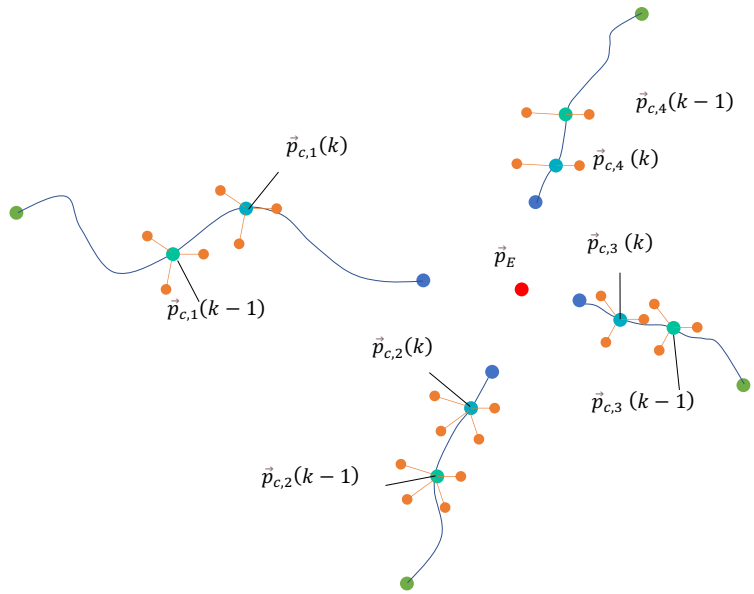
The Role of the Environment in parsing and inference of semantic structures

The model of semantic structure interactions in conjunction of the Environment determines how the incoming semantic particles will form semantic structures and how the newly formed structures will interact with the existing ones.



When structures are formed from semantic particles certain semantic paths will be reinforced by the Model while other paths will be discouraged. The reinforcement happens based on certain statistics computed for every newly formed structure. Discouragement happens when the attempt to form a semantic structure fails.

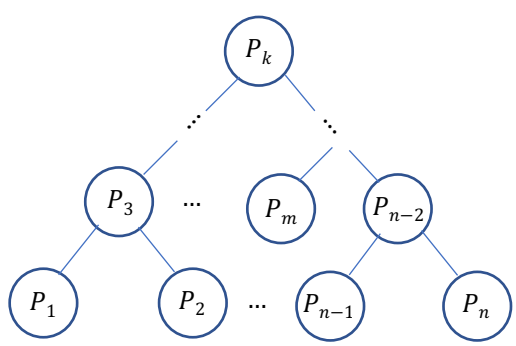
In the Figure below it is depicted an ensemble of 4 properties travelling toward their bound states. With green are depicted the in-situ positions of each of the properties. With blue are depicted the bound state positions of each of the properties. The red point in the center is the energy weighted center of mass of the ensemble $\vec{p}_E$ at the time each of the properties reach their bound states. The mass center of each property in some position between in-situ and bound state, denoted with $\vec{p}_{c,i}$, is depicted as a magenta point. The orange points connected to each magenta point represent the semantic aspects of each property. The blue lines between the in-situ and bound state positions are the trajectories (travel paths) of the mass centers (centroids) of each property.



Optimization Problems involving reinforcement learning environment

Let us have a semantic particle V which is composed of n properties as

$$V = \sum_{m=1}^{n} \left(k_{i_m} k_{j_m} \dots k_{l_m}, P_m \right) \qquad (1)$$



Instead, we would like to construct a semantic particle V^* which is composed of the same n properties but connected differently in a property tree:

$$V^* = \sum_{m=1}^{n} \left(k_{p_m} k_{q_m} \dots k_{r_m}, P_m \right) \qquad (2)$$

The question which we are going to study is - can this be achieved solely by modifying the semantic energy signatures in semantic space for the relevant aspects?
Let us elaborate on this question.

Definition: *Trajectory of semantic particle*

Definition: *Energy signature of semantic property*
Let us denote the *trajectory* of P_i from moment t_0 to t_k with $T(P_i, t_0, t_k)$. For brevity we will use the concise notation $T_{i,0,k} \equiv T(P_i, t_0, t_k)$. With $E_{i,0,k}$ we denote the *energy signature* of P_i along the trajectory $T_{i,0,k}$ that is the total energy of the set of aspects which belong to P_i when the centroid $\vec{p}_{c,i}$ follows the trajectory $T_{i,0,k}$. So, for every point $t_{i,l}$ (with $0 \leq l < k$) in semantic space which belong to the trajectory $T_{i,0,k}$ we will have a real value $E_{i,l}$ which is the total energy accumulated in P_i for the interval $\left[\vec{p}_{c,i}(l), \vec{p}_{c,i}(l+1)\right)$.

Definition: *Energy signature of primitive semantic particle*
Let V be a primitive semantic particle having M properties denoted with $P_i, i = 1..M$. Let us denote the trajectory of the particle centroid from moment t_0 to t_k with $T(V, t_0, t_k)$. For brevity we will use the concise notation $T_{0,k}(V) \equiv T(V, t_0, t_k)$. Any trajectory from t_0 to t_k in the set of the trajectories of $P_i, i = 1..M$ can be expressed as $T_{0,k}(V) + \vec{p}_i$. $E_{0,k}(V) = \sum_{i=0}^{M} E_{i,0,k}$.