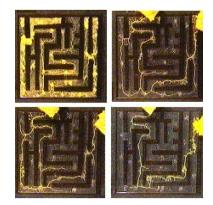
Computational Aspects of Spiking Neural Networks

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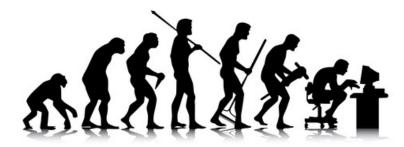
Natural Algorithm



slime system [NYT00, TKN07, BMV12]



bird flocking [Cha12, Cha09]



Evolution [LP16, LPR+14]

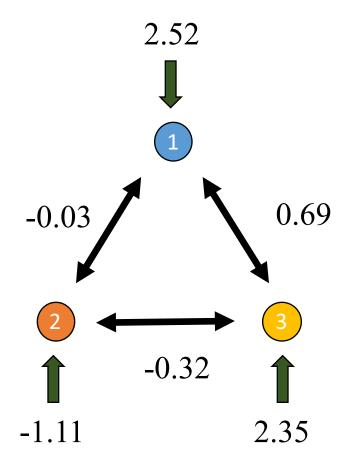


sandpile model [CV12]

``understanding and explaining algorithms observed from natural systems and dynamics''

Spiking Neural Networks (SNN) Dynamics

- Neuron i has a time-varying **potential** $\mathbf{u}_i(t)$.
- External charging rate $I = (I_1, I_2, ..., I_n)$.
- Firing threshold $\eta > 0$: neuron *i fires* a spike if $\mathbf{u}_i(t) > \eta$ or $\mathbf{u}_i(t) < \eta$.
- **Spike** causes inhibition or exhibition: When neuron i fires a spike, neighbors' $\mathbf{u}_{j}(t)$ decrease by C_{ij} .



Motivation

• Mathematical models to **explain** and **predict** the behaviors of different neuron systems. (e.g., [I+03, Adr26, Lap07])

$$\frac{d\mathbf{u}(t)}{dt} = -C\mathbf{s}(t) + \mathbf{I}dt$$

• Barrett et al. [BDM13]: *spike firing rate* can be characterized as optimal solution of quadratic optimization problem (least square problem).

$$\min_{\mathbf{x}} \mathbf{x}^{\mathrm{T}} C \mathbf{x} - 2 \mathbf{I}^{\mathrm{T}} \mathbf{x}$$

• Shapero et al. [SRH13,SZHR14]: SNN dynamics as algorithm for solving sparse optimization problems, e.g., Lasso.

First Convergence Result

Theorem (discrete SNN to linear system)

For any
$$\epsilon>0$$
, take $\eta=\lambda_{\max}$, the step size $\Delta t<\frac{\sqrt{\lambda_{\min}}}{12\cdot\sqrt{n}\|\mathbf{x}^*\|_{A^{\mathrm{T}}A}}$, and the

discrete time
$$T \geq \frac{2\kappa(A^{\mathrm{T}}A)\cdot n}{\epsilon}$$
, we have $\|\hat{\mathbf{x}}(T) - \mathbf{x}^*\|_{A^{\mathrm{T}}A} \leq \epsilon \cdot \|\mathbf{x}^*\|_{A^{\mathrm{T}}A}$.

Key Observation

Conservation argument:

$$\frac{\mathbf{u}(T) - \mathbf{u}(0)}{T \cdot \Delta \mathbf{t}} = -A^{\mathrm{T}} A \hat{\mathbf{x}}(T) + A^{\mathrm{T}} \mathbf{b}$$

Bounded potential

Lemma (bounded potential)

For any
$$t > 0$$
, take $\eta = \lambda_{\max}$ and step size $\Delta t < \frac{\sqrt{\lambda_{\min}}}{12 \cdot \sqrt{n} \|\mathbf{x}^*\|_{A^T A}}$, we have $\|\mathbf{u}(t)\|_{(A^T A)}^+ \le 2\sqrt{\kappa(A^T A) \cdot \lambda_{\max} \cdot n}$.

Q: What Solution does SNN converges to?

• Observed that a simple SNN dynamics may solve the basis pursuit problem (a.k.a. ℓ_1 minimization problem).

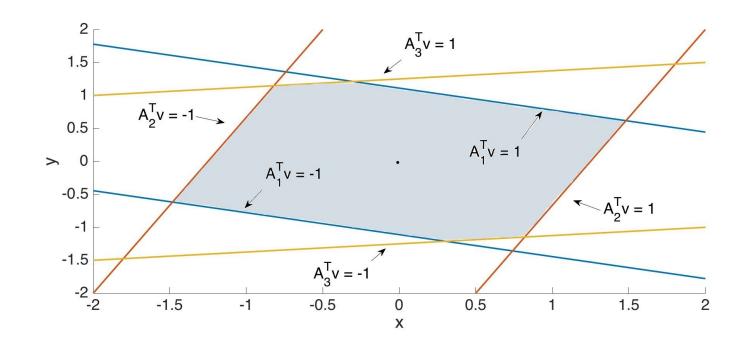
minimize
$$\|\mathbf{x}\|_1$$
 subject to $A\mathbf{x} = \mathbf{b}$,

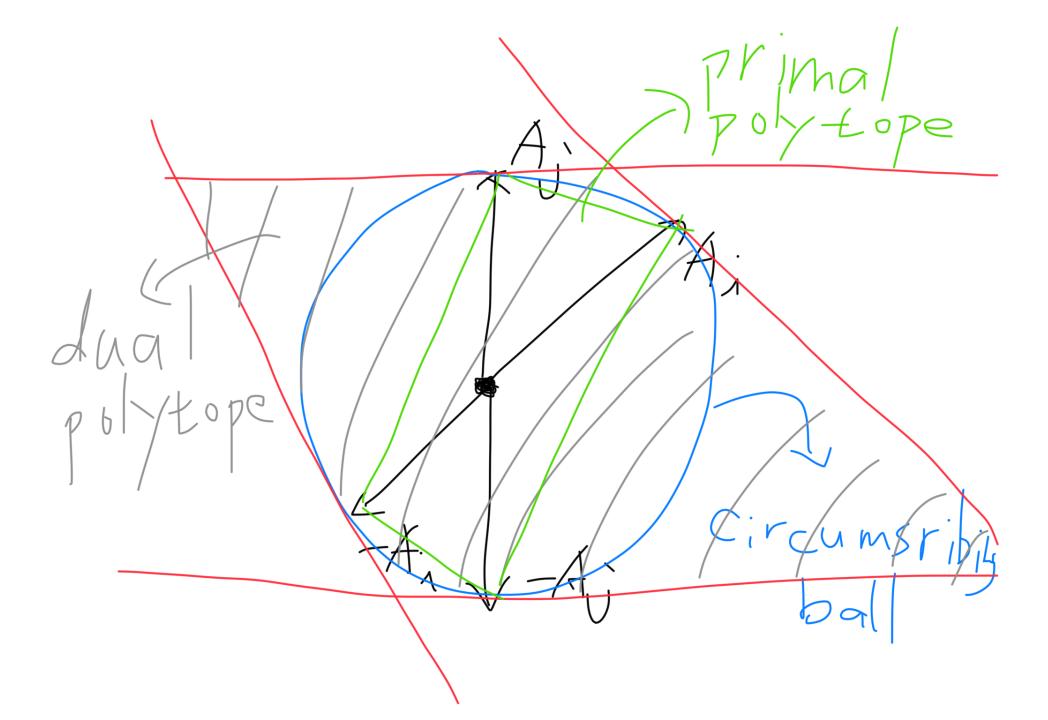
where $C = A^{T}A$ and $I = A^{T}b$.

- Interpret SNN as a natural algorithm for solving its dual linear programming.
- Seems a new algorithm for the ℓ_1 minimization problem.

Dual Interpretation of SNN Dynamics

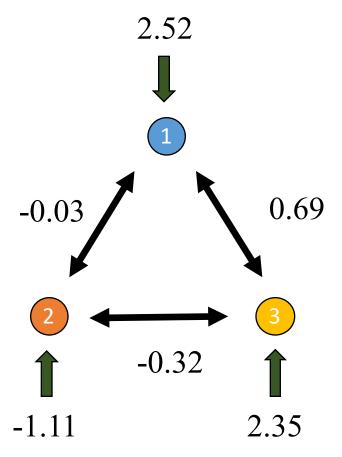
- Dual **potential**: $\mathbf{v}(t)$ where $\mathbf{u}(t) = A^{\mathrm{T}}\mathbf{v}(t)$.
- External charging rate b where $I = A^T b$: walk along b direction.
- Spike when hit a ``wall'' $\{\mathbf{v}: A_i^{\mathsf{T}}\mathbf{v} = \eta\}$, and $\mathbf{v}(t)$ is bounced back by A_i .





Peculiar features of SNN algorithms

- Simple dynamics solves non-trivial optimization problems
- Distributed algorithm with extremely simple communication
- Solutions encoded as spike firing rate, not potential
- Potential practical efficiency for sparse optimization problem



Research questions

Complexity of SNN:

Prove convergence rate of firing rate to optimal solution.

Algorithms behind SNN:

Understand the underlying algorithmic ideas.

Power of SNN:

Understand the class of optimization problems solvable by SNN

Efficiency of SNN:

Understand practical efficiency of SNN as optimization solver.