Solving optimization problems with neural networks: The case of the travelling salesman problem

Workshop on Spins, Games and Networks

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### The travelling salesman problem



Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?

OR

What is the shortest Hamiltonian path/tour/route?





Empathy for the network



Empathy for the network hard

	А	В	С	D	E	F	
A B	$\begin{bmatrix} 0\\ 7.57 \end{bmatrix}$	7.57	$8.14 \\ 9.22$	$\begin{array}{c} 6.56 \\ 3.78 \end{array}$	$11.32 \\ 7.21$	$4.83 \\ 5.66$	total distance: 31.6
C D	8.14	9.22		5.45	6.3	4.18	
E	$\begin{array}{c} 6.56\\ 11.32\end{array}$	$3.78 \\ 7.21$	$\begin{array}{c} 5.45 \\ 6.3 \end{array}$	$\begin{array}{c} 0\\ 4.94\end{array}$	$\begin{array}{c} 4.94 \\ 0 \end{array}$	$\begin{array}{c} 2.5\\ 6.61 \end{array}$	B C C
F	4.83	5.66	4.18	2.5	6.61	0	2 4 6 8

## Setting up the neural network

A salesman has to travel through n cities. The salesman has to make n stops such that a new city appears at a every stop and the total distance travelled is minimum.



1.

Constraints for a valid tour of the salesman:

## Discrete dynamics

The dynamics takes place in the corners of a  $N^2$  dimensional hypercube for an *N*-city problem

Instead, swap columns of an initial suboptimal valid tour





=

 $1 + e^{\frac{1}{T}(E(V_a) - E(V_b))}$ 

# Simulated Annealing



Kirkpatrick et. al. 1983, 220 (4598)

### Continuous dynamics

The dynamics takes place in  $\mathbb{R}^{N^2}$  dimension for an *N*-city problem

The initial condition is kept at the centre to ensure non-convergence to bad solutions and with a tiny noise to break symmetry.

$$E = \frac{\gamma}{2} \left( \sum_{i} \left( \sum_{X} V_{X,i} - 1 \right)^2 + \sum_{X} \left( \sum_{i} V_{X,i} - 1 \right)^2 \right) + \frac{D}{2} d_{tot}$$

## Continuous version of Hopfield model

$$\frac{dU_i}{dt} = -\tau U_i - \frac{\partial E}{\partial V_i}$$
$$\frac{\partial E}{\partial V_i} = -\sum_{j \neq i} W_{ij} V_j + \theta_i$$
$$V_i = \sigma_T(U_i)$$

Hopfield, 1984, PNAS 81



# Thank you

