

Theory of Complex Systems: Assignment

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1 Modelling the activity of a single neuron

- (a) Can you plot the distribution $P(\tau)$ of the time intervals τ between successive spikes? Check that there is indeed a refractory period, i.e., a time interval τ_0 after each spike, during which the neuron doesn't spike again. What is the duration τ_0 for this time interval?
☐
- (b) Can you check that the decay of the distribution $P(\tau)$ of inter-spike intervals is indeed exponential? Measure the corresponding decay rate λ
☐
- (c) Can you deduce an analytical expression for the distribution of inter-spike time interval $P(\tau)$ of the delayed Poisson process as a function of λ and τ_0 ? Compare your model distribution to the one obtained from the data.
☐
- (d) Using your model, can you generate another 1000 (spike times) datapoints?
☐
- (e) What is the average spiking rate f of the neuron in the data? How is f analytically related to τ_0 and λ that you have previously measured?
☐

2 Modelling binary data with the Ising model

2.A Pairwise spin model

- (a) How many terms are in the sum over the pair (i, j) ? Can you deduce what is the number of parameters in the vector $g = (h_1, \dots, h_n, J_{1,2}, \dots, J_n)$? Can you re-write the sum over the pair (i, j) as a double sum over i and j (without counting twice each pair)?
☐
- (b) Can you write down explicitly the terms in the exponential of Eq. (1) for a system with $n = 3$ spins?
☐
- (c) In Eq. (1), we can recognize the Boltzmann distribution, in which the parameter $\beta = 1/(k_B T)$ was taken equal to 1 (more precisely, the constant k_B was taken equal to 1, and the temperature parameter T was absorbed in the parameters h_i and J_{ij}). What is the energy function associated with the Boltzmann distribution in that case? What is the partition function and what is its general expression?
☐

- (d) Take a spin s_i : if h_i is positive, which direction will s_i tend to turn to, i.e., which direction of s_i will minimize the associated energy $-h_i s_i$? Take a pair of spins s_i and s_j : if J_{ij} is positive, which configurations of (s_i, s_j) minimize the coupling energy $-J_{ij} s_i s_j$?

Assume that we have inferred the best parameters h_i and J_{ij} for the US supreme court dataset discussed in section 2. How would you interpret the sign of the inferred parameters h_i and J_{ij} in this context?



2.B Observables

- (a) Given a stationary probability distribution of the state $p_{g(s)}$, what are the definitions of $\langle s_i \rangle$ and of $\langle s_i s_j \rangle$?



- (b) Consider a dataset \hat{s} composed of N independent observations of the spins: $\hat{s} = (s^{(1)}, \dots, s^{(N)})$. Let us denote by $\langle s_i \rangle_D$ and $\langle s_i s_j \rangle_D$ the empirical averages of s_i and of $s_i s_j$ respectively (i.e., their average values in the dataset). How would you compute $\langle s_i \rangle_D$ and $\langle s_i s_j \rangle_D$ from the data?



- (c) Assume that the data is stationary and that each datapoint has been randomly sampled from $p(s)$. Can you show that the empirical averages, $\langle s_i \rangle_D$ and $\langle s_i s_j \rangle_D$, converge to the model averages, respectively $\langle s_i \rangle$ and $\langle s_i s_j \rangle$, as the number N of datapoints goes to infinity? (very large dataset)



2.C Maximum Entropy models

- (a) Consider a spin system with stationary probability distribution $p(s)$. Can you recall the definition of the Shannon entropy $S[p(s)]$? As mentioned above for the Boltzmann distribution, we will take $k_b = 1$.

The Ising model in Eq. (1) can be seen as a *Maximum Entropy Model*, constrained to reproduce the data local magnetisation and local correlation, i.e., constrained to reproduce all the data averages $\langle s_i \rangle_D$ and $\langle s_i s_j \rangle_D$ (for all spins s_i and s_j). We also want $p(s)$ to be normalised, which introduces the additional constraint $\sum_s p(s) = 1$. To summarise, we are looking for the set of 2^n probabilities $p(s)$ such that $S[p(s)]$ is maximal, and such that

$$\sum_s p(s) = 1 \quad \text{and} \quad \sum_s p(s) s_i(s) = \langle s_i \rangle_D \quad \text{and} \quad \sum_s p(s) s_i(s) s_j(s) = \langle s_i s_j \rangle_D \quad (1)$$

where $\langle s_i \rangle_D$ and $\langle s_i s_j \rangle_D$ are constants that are computed from the data for all distinct s_i and s_j . Note that to be more precise, we wrote $s_i(s)$ (instead of just s_i) to specify that this is the value of s_i in the state s (this will help with the next questions).



- (b) How many constraints are there in total?

To find the shape of the distributions $p(\mathbf{s})$ that maximises the entropy while satisfying these constraints, we introduce an auxiliary function:

$$U[p(\mathbf{s})] = S[p(\mathbf{s})] + \lambda_0 \left(\sum_{\mathbf{s}} p(\mathbf{s}) - 1 \right) + \sum_{i=1}^n \alpha_i \left(\sum_{\mathbf{s}} p(\mathbf{s}) s_i(\mathbf{s}) - \langle s_i \rangle_D \right) + \sum_{\text{pair}(i,j)} \eta_{ij} \left(\sum_{\mathbf{s}} p(\mathbf{s}) s_i(\mathbf{s}) s_j(\mathbf{s}) - \langle s_i s_j \rangle_D \right) \quad (2)$$

where we have introduced a parameter in front of each constraint we want to impose. These parameters (λ_0 , α_i , and η_{ij}) are called Lagrange multipliers. To find $p(\mathbf{s})$ one must maximise this auxiliary function with respect to the 2^n probabilities $p(\mathbf{s})$.



- (c) Let us fix a choice of a state \mathbf{s} . The probability $p_{\mathbf{s}} = p(\mathbf{s})$ is a parameter of $U[\mathbf{p}]$ where \mathbf{p} is the vector of the 2^n probabilities. Can you show that:

$$\frac{\partial U[\mathbf{p}]}{\partial p_{\mathbf{s}}} = -\log(p_{\mathbf{s}}) - 1 + \lambda_0 + \sum_{i=1}^n \alpha_i s_i(\mathbf{s}) + \sum_{\text{pair}(i,j)} \eta_{ij} s_i(\mathbf{s}) s_j(\mathbf{s}) \quad (3)$$



- (d) Can you show that the most general expression of $p_{\mathbf{s}}$ with maximal entropy that satisfying the constraints in Eq. (2) is Eq. (1)? Give the relation between λ_0 and the partition function Z . How are the parameters α_i or η_{ij} related to the parameters h_i and J_{ij} ?



2.D Statistical inference: model with no couplings

- (a) ☐
- (b) ☐
- (c) ☐

2.E Statistical inference: maximising the log-likelihood function

- (a) ☐
- (b) ☐

3 Application to the analysis of the US supreme Court

- (a) ☐
- (b) ☐
- (c) ☐
- (d) ☐
- (e) ☐

(f) ☐

(g) ☐

(h) ☐

(i) ☐