MODELS OF THE NEURON
Project 2

The TMNT • 12.06(or 08?).2017

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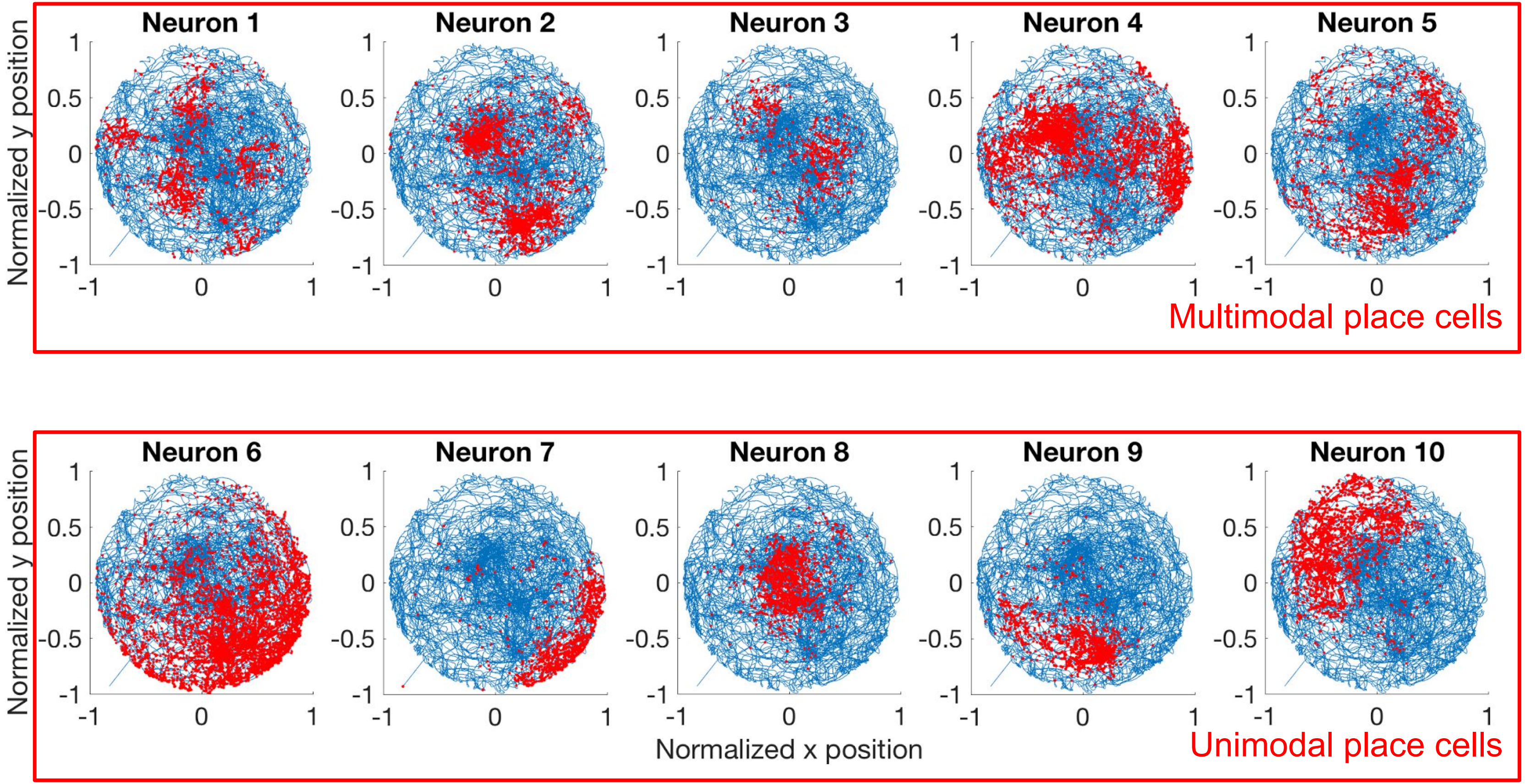
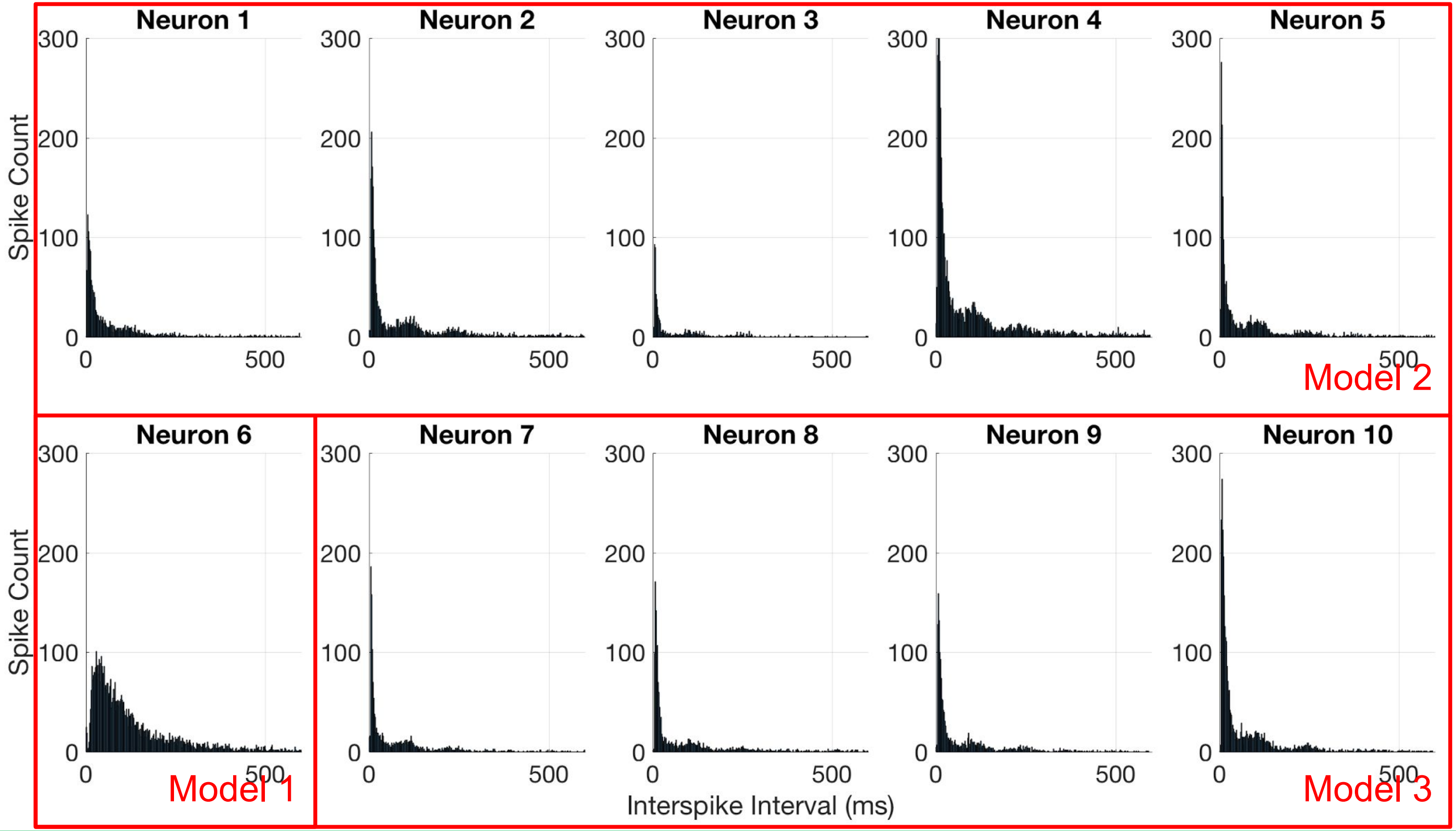
Spiking activities of unimodal and multimodal place cells



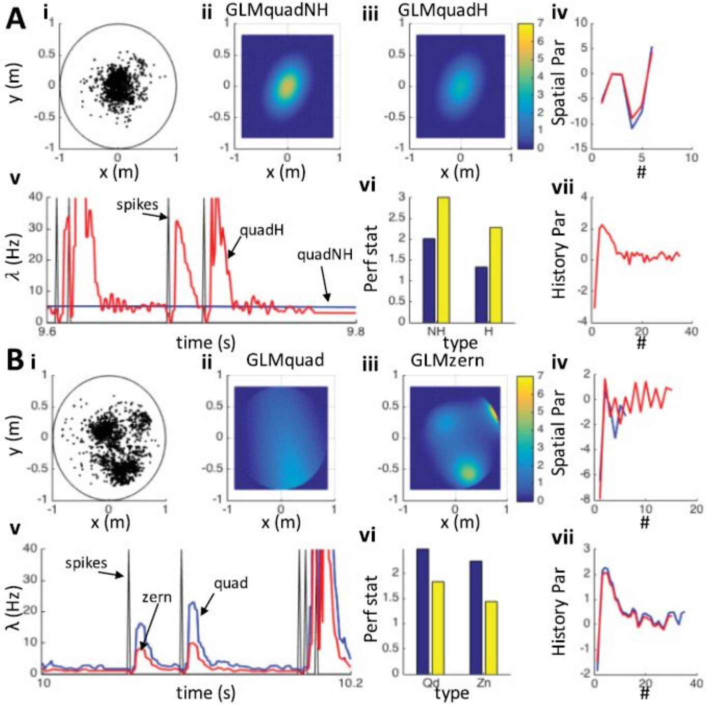
Interspike intervals of spiking activity



Base model: positional covariates + history dependence

- Quadratic GLM (GLMquad)

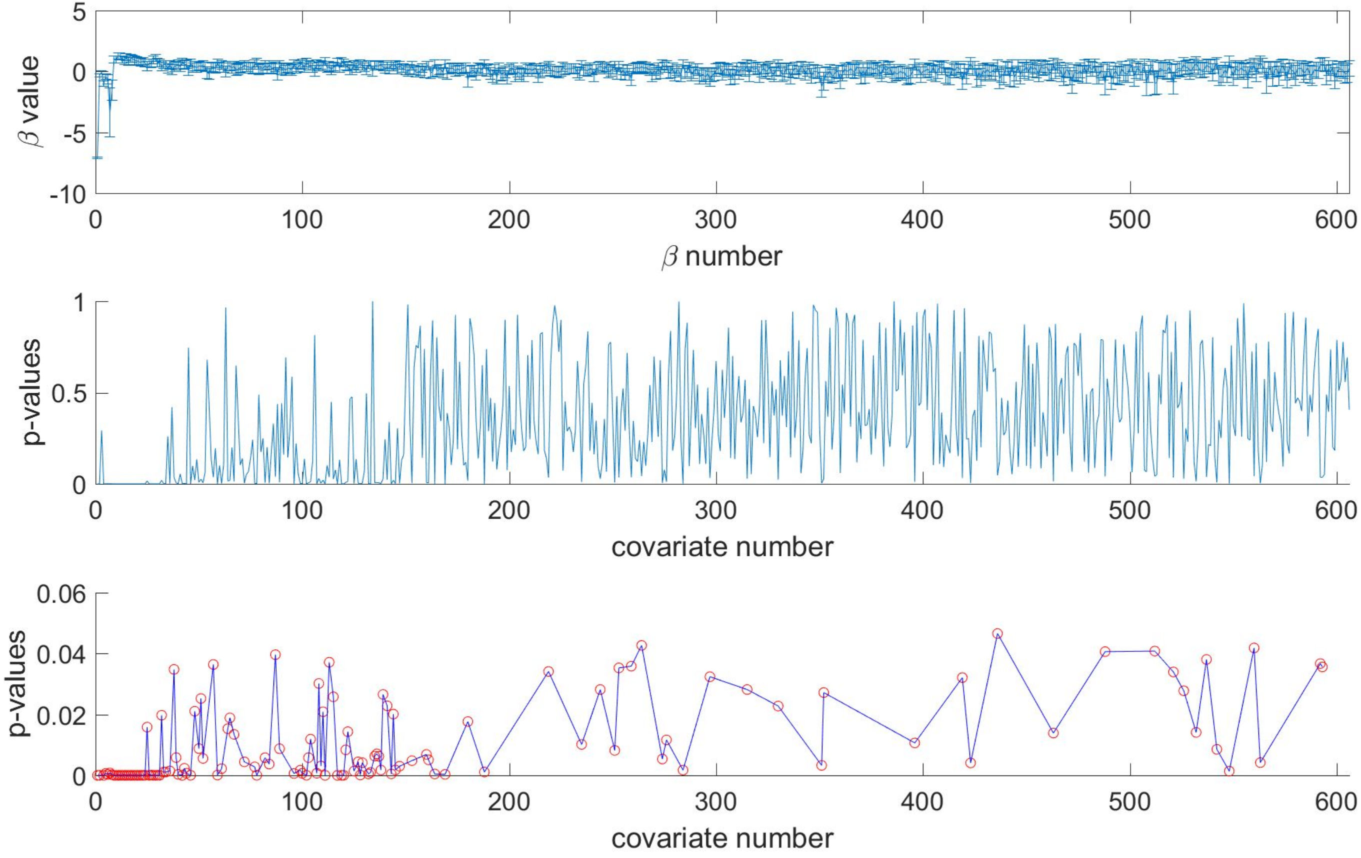
$$\log \lambda_c(t|x_t, y_t, \mathbf{h}_c(t)) = \alpha_{1c} + \underline{\alpha_{2c}x_t + \alpha_{3c}y_t + \alpha_{4c}x_t^2 + \alpha_{5c}y_t^2} + \underline{\alpha_{6c}x_t y_t} + \underline{\sum_{j=1}^{J} \beta_{jc} h_{jc}(t)} \qquad (2.4)$$



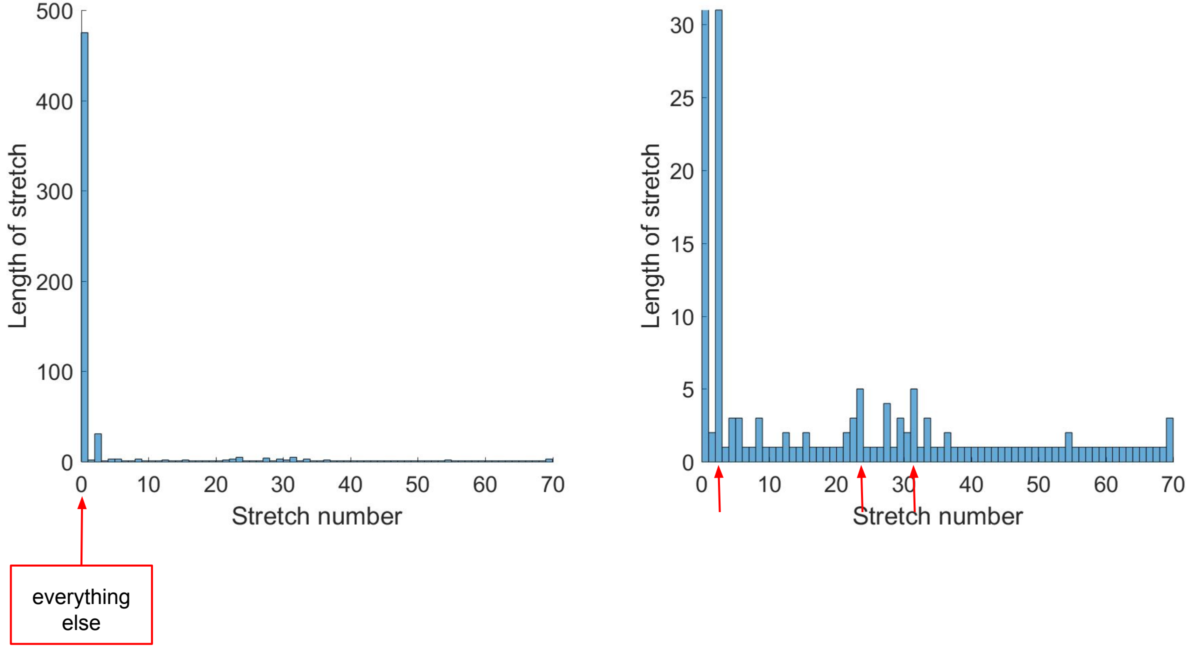
1. What is the history dependence?
2. Are there other covariates that explain spiking activity?

Agarwal et. al (2016)

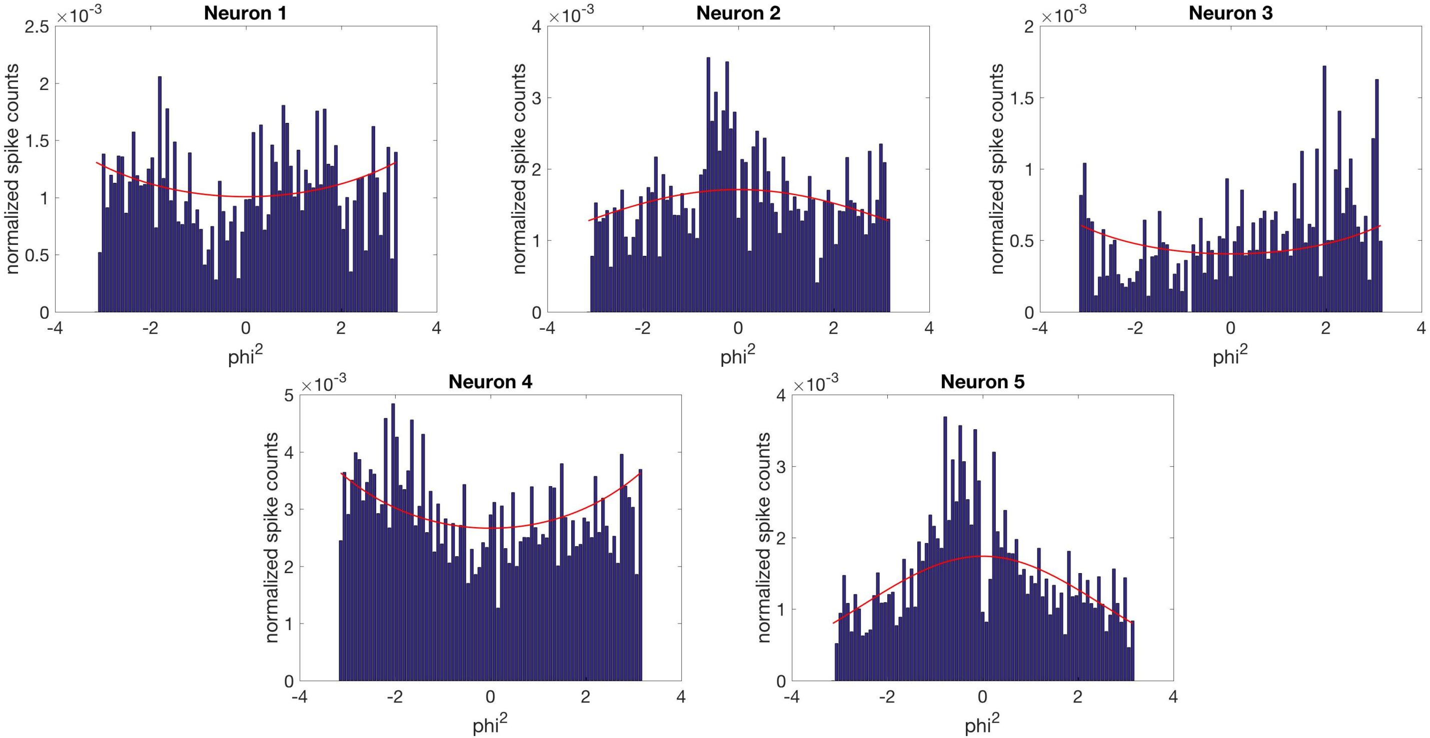
Parameterizing history dependence: significant p-values



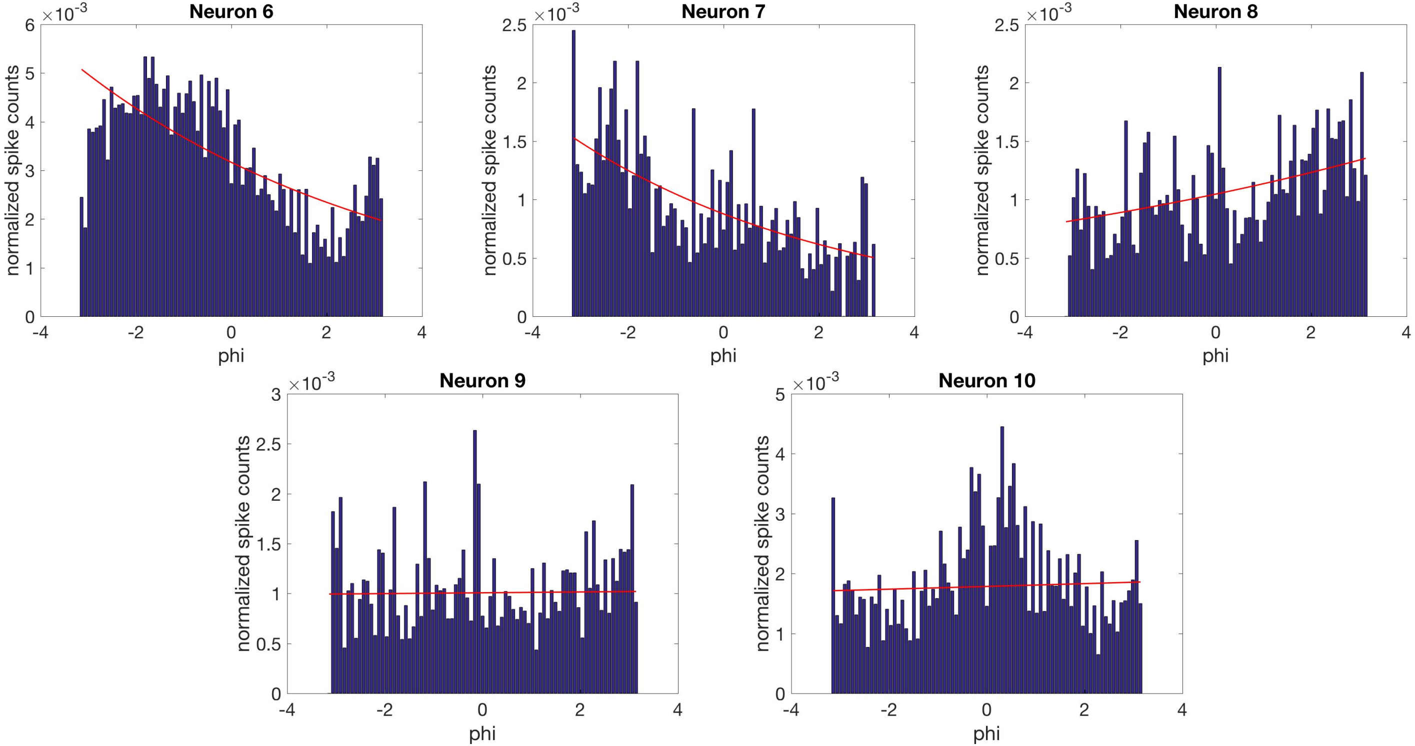
Parameterizing history dependence: stretches of significant p-values



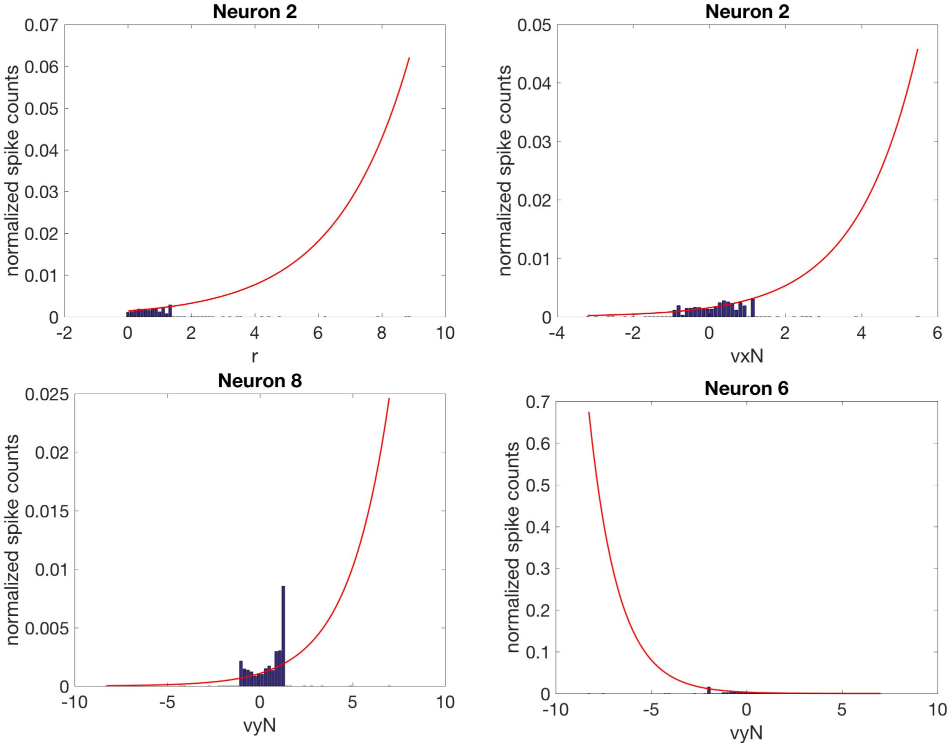
Head direction (phi) is quadratically-correlated with firing rates of multimodal cells



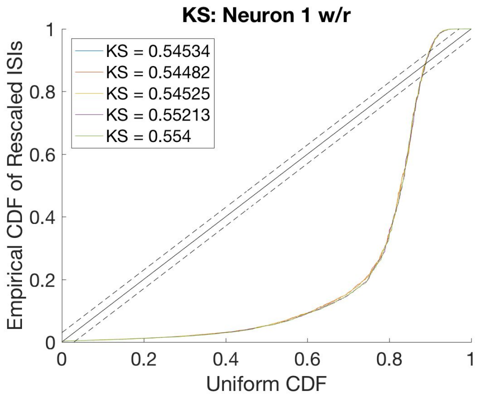
Head direction (phi) is linearly-correlated with firing rates of unimodal cells

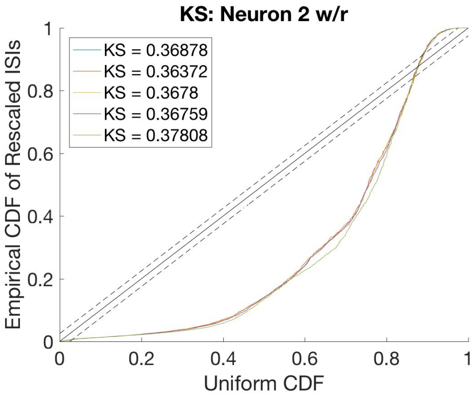


Unable to determine correlation of velocities (vxN, vyN) and speed (r) with firing rates



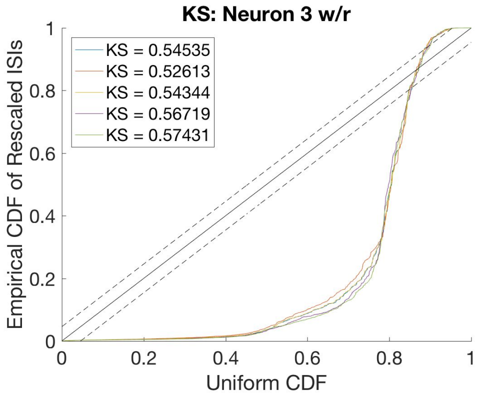
Speed (r) contributes a model in explaining multimodal cell firing

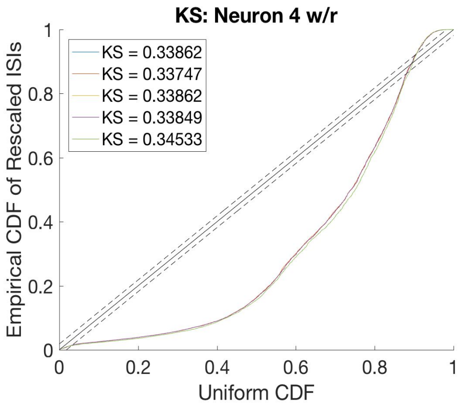


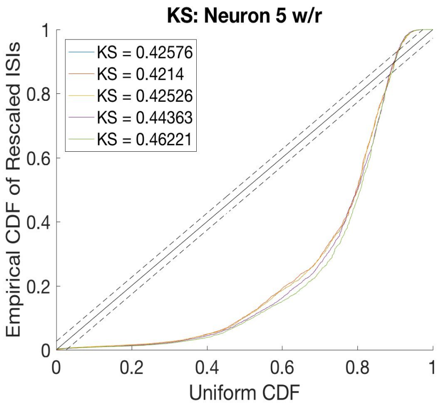


Base = xN, yN, xN2, yN2, xN*yN

- Base
- Base, r
- Base, r2
- Base -xN
- Base -xN - yN







Generalized Linear Models (GLMs)

Model 1

$$log\lambda_c(t|x_t, y_t, h_c(t)) = \alpha_{1c} + \alpha_{2c}x_t + \alpha_{3c}y_t + \alpha_{4c}x_t^2 + \alpha_{5c}y_t^2 + \alpha_{6c}x_t y_t + \alpha_{7c}v_t^y + \alpha_{8c}\phi + \sum_{j=4}^{15}\beta_{jc}h_{jc}(t) + \sum_{j=96}^{109}\beta_{jc}h_{jc}(t) + \sum_{j=140}^{146}\beta_{jc}h_{jc}(t)$$

Model 2

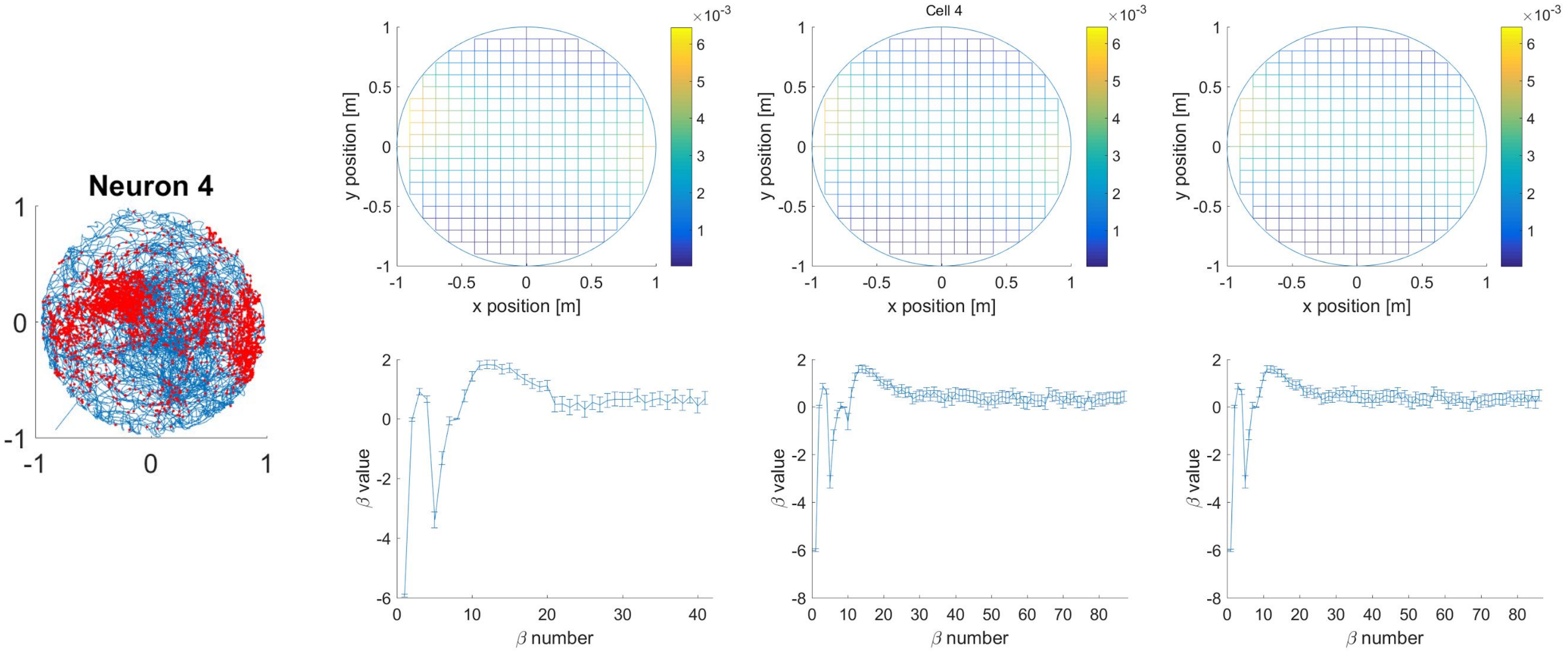
$$log\lambda_c(t|x_t, y_t, h_c(t)) = \alpha_{1c} + \alpha_{2c}x_t + \alpha_{3c}y_t + \alpha_{4c}x_t^2 + \alpha_{5c}y_t^2 + \alpha_{6c}x_t y_t + \alpha_{7c}v_t^x + \alpha_{8c}r_t + \alpha_{9c}\phi_t^2 + \sum_{j=3}^{28}\beta_{jc}h_{jc}(t) + \sum_{j=88}^{138}\beta_{jc}h_{jc}(t)$$

Model 3

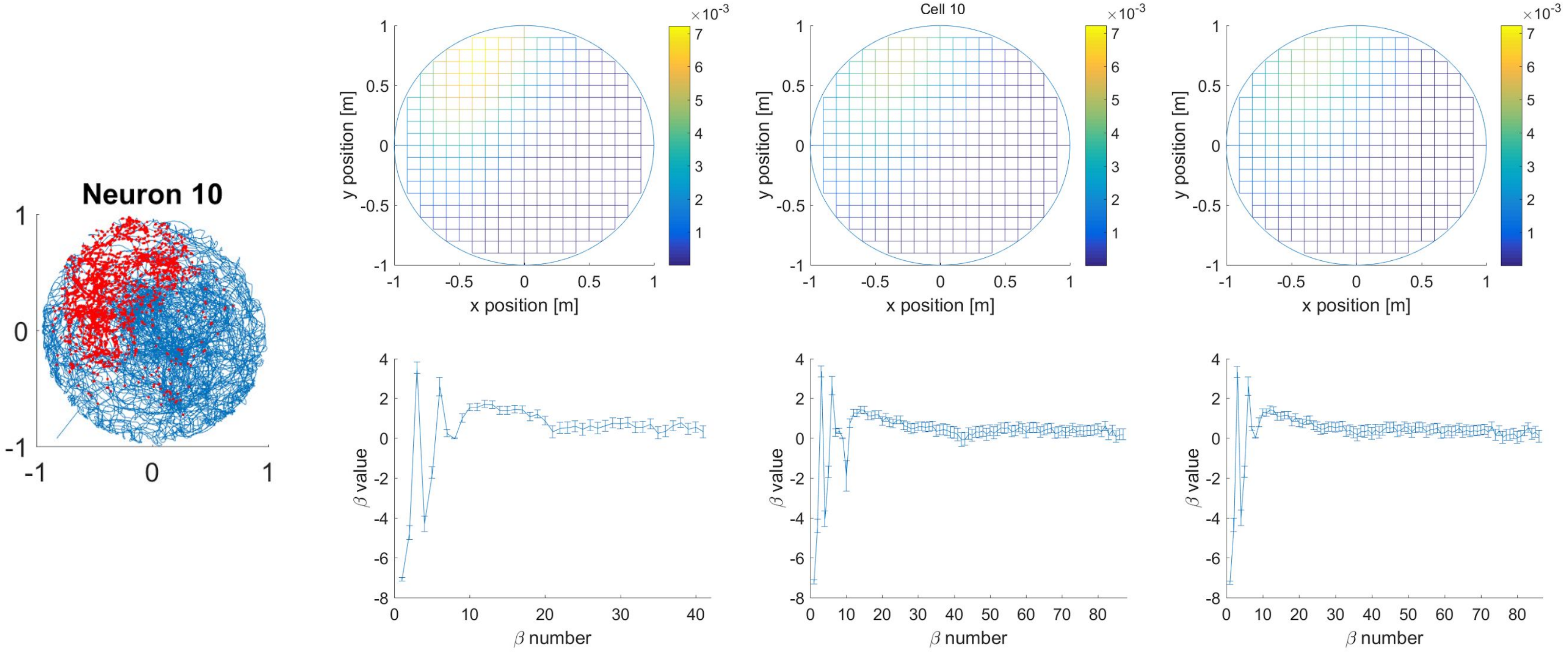
$$log\lambda_c(t|x_t, y_t, h_c(t)) = \alpha_{1c} + \alpha_{2c}x_t + \alpha_{3c}y_t + \alpha_{4c}x_t^2 + \alpha_{5c}y_t^2 + \alpha_{6c}x_t y_t + \alpha_{7c}r_t + \alpha_{8c}\phi_t + \sum_{j=4}^{30}\beta_{jc}h_{jc}(t) + \sum_{j=96}^{146}\beta_{jc}h_{jc}(t)$$

Results

High dependence on x and y coordinate and moderate dependence on short term history



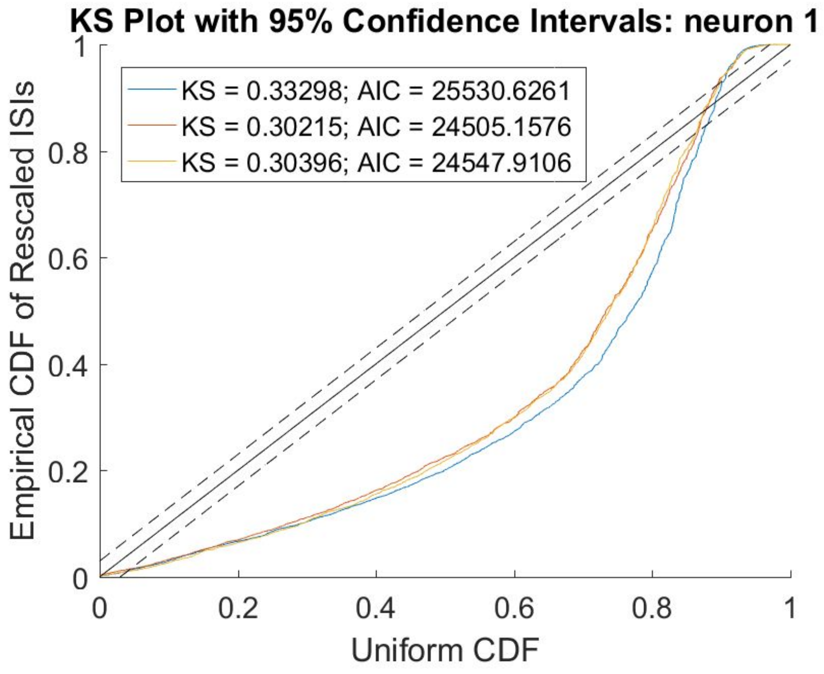
High dependence on x and y coordinate and moderate dependence on short term history

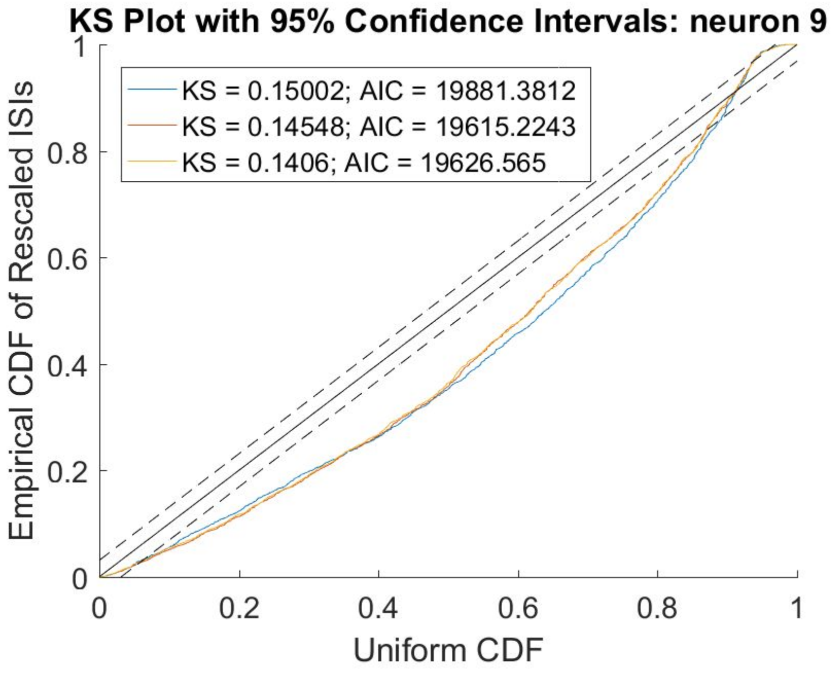


What are the cells encoding?

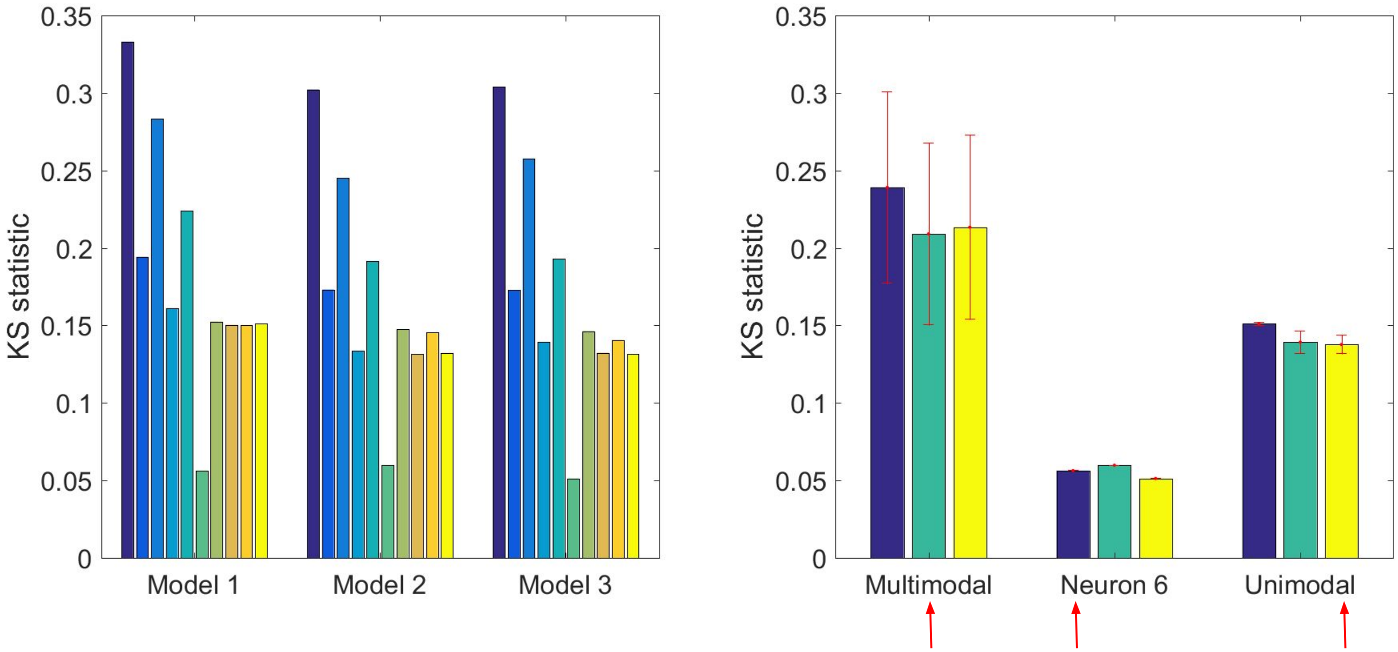
- xN: strong
- yN: strong
- xN^2: strong
- yN^2: strong
- xN·yN: strong
- Speed (r): moderate (unimodal), low (multimodal)
- Heading (phi): low (unimodal/multimodal)
- Velocity (vxN, vyN): low (unimodal/multimodal)
- Short term history (5-20 ms): moderate-to-strong
- Medium term history (90-140): low
- Long term history: very low

Models were able to better explain spiking activity of neurons they were made for

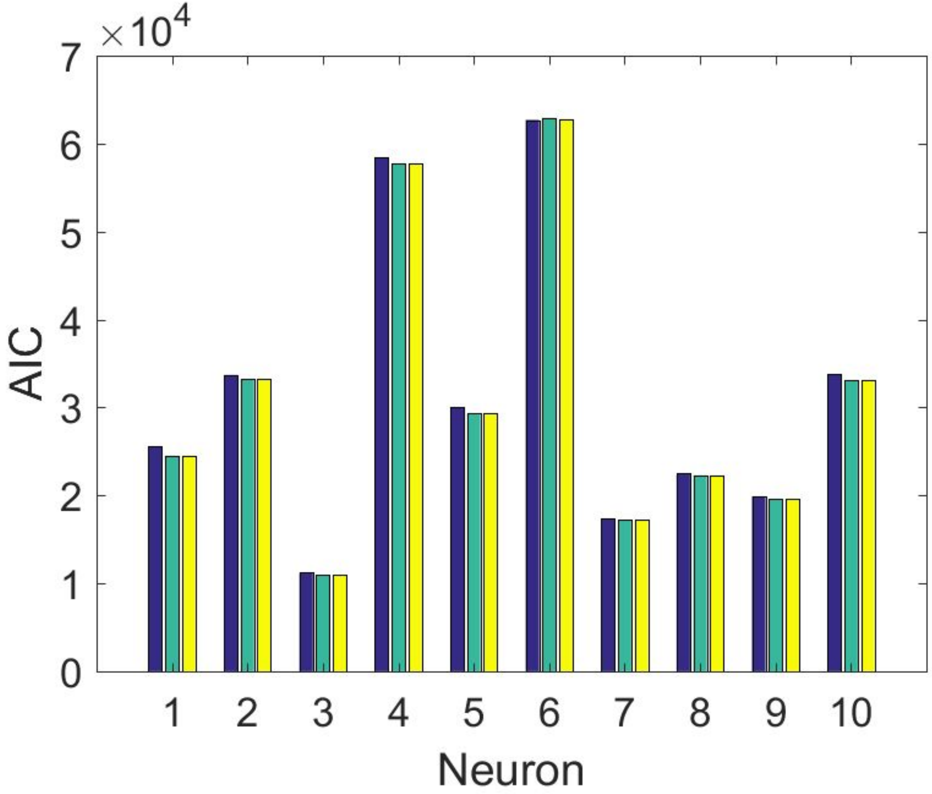




Models better explained unimodal neurons than multimodal neurons



Model 1 is relatively better in explaining the data for all neurons



Number of covariates

Model 1	39
Model 2	84
Model 3	84

Conclusions

- We constructed 3 GLMs which performed better for the neurons they were constructed for
  - Model 1 → neuron 6
  - Model 2 → neurons 1-5
  - Model 3 → neurons 7-10
- Model 1 performed best when comparing relative goodness-of-fit due to low number of covariates
- Positional covariates had the most explanatory power
- All the neurons showed some history dependence between 5-20 ms in the past as well as around 90-140 ms

References

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