

On a role for competitions in computational neuroscience

Stephen J Eglen (1), Catherine Cutts (1), JJ Johannes Hjorth (1),
David C Sterratt (2), David J Willshaw (2)

(1) University of Cambridge

(2) University of Edinburgh

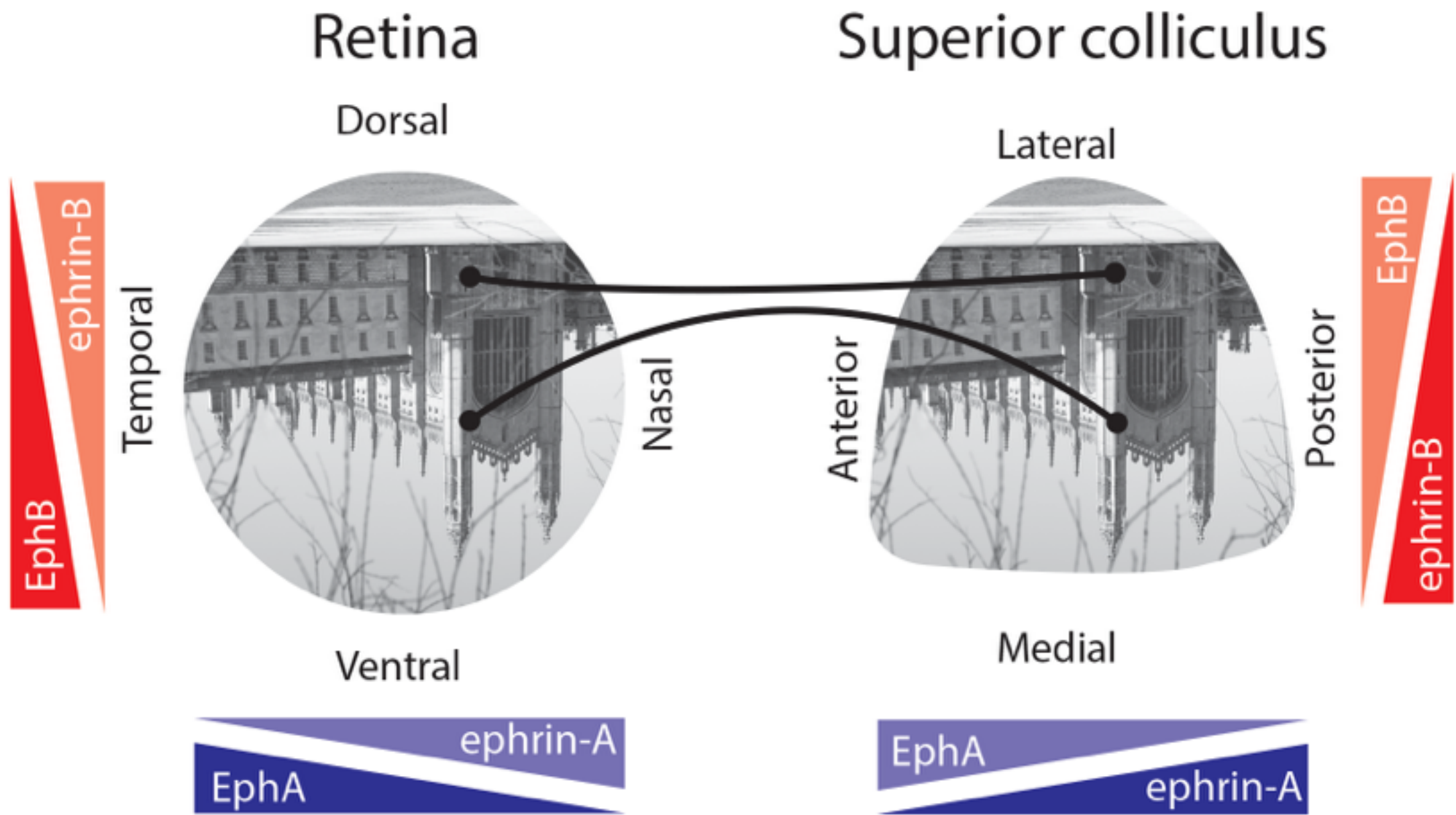
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On a role for competition in the formation of patterned
neural connexions

BY M. C. PRESTIGE AND D. J. WILLSHAW†



Which model works best?

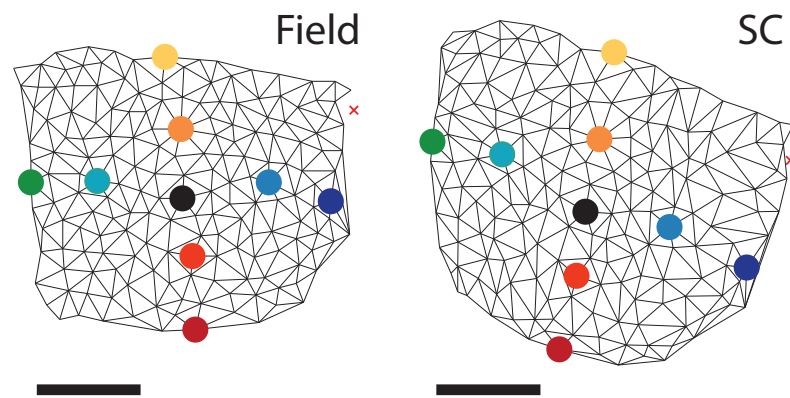
- Marker induction (Willshaw, 2006)
- Activity and gradients (Whitelaw and Cowan, 1981)
- Gradients and competition (Gierer, 1983)
- Activity and gradients (Triplett, Koulakov et al. 2011)

Rules of the game

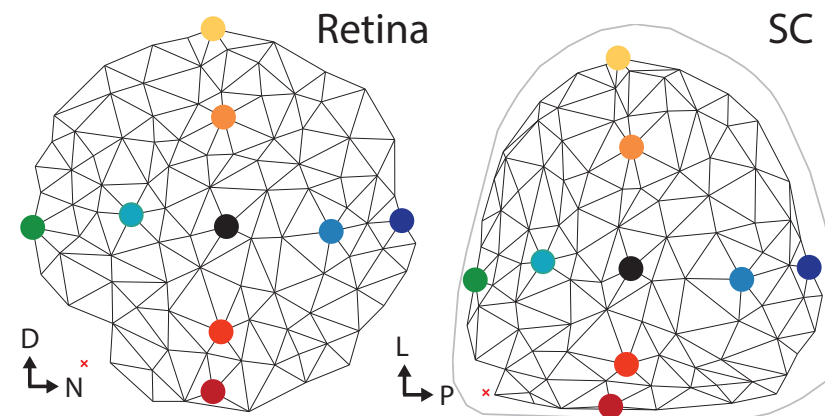
- Model parameters optimised for one condition.
- Model evaluated on multiple experimental conditions.
- Where possible, experimental and simulated data analysed in same way (e.g. virtual anterograde injections).

Lattice analysis

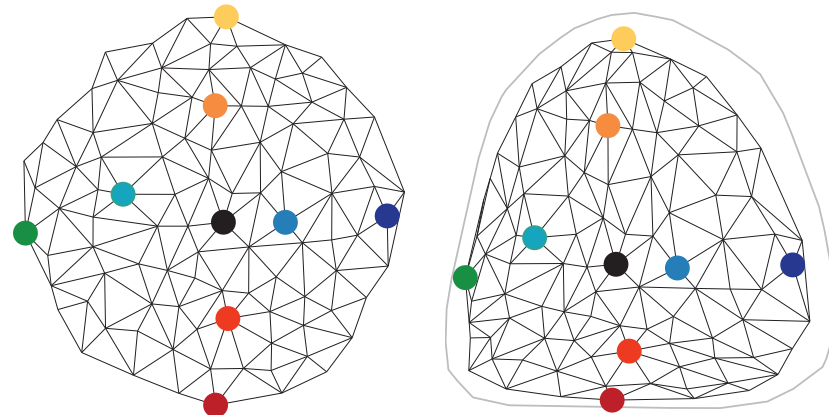
A Wild type



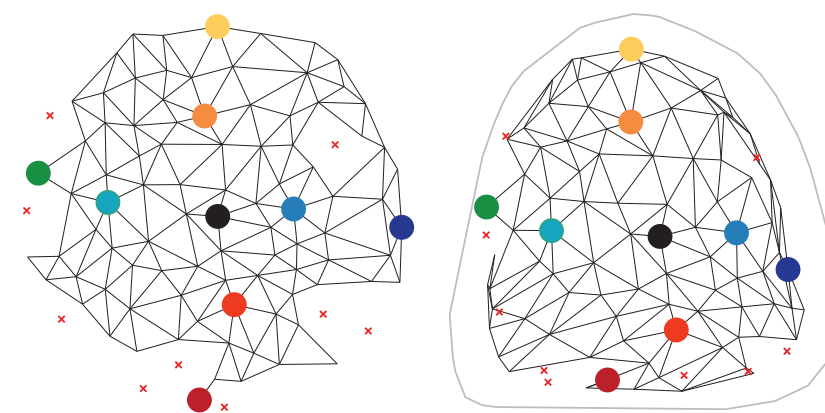
B Gierer



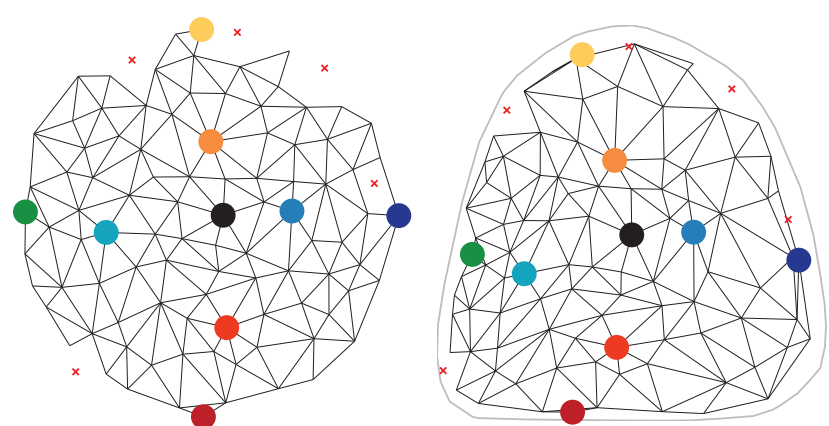
C Koulakov



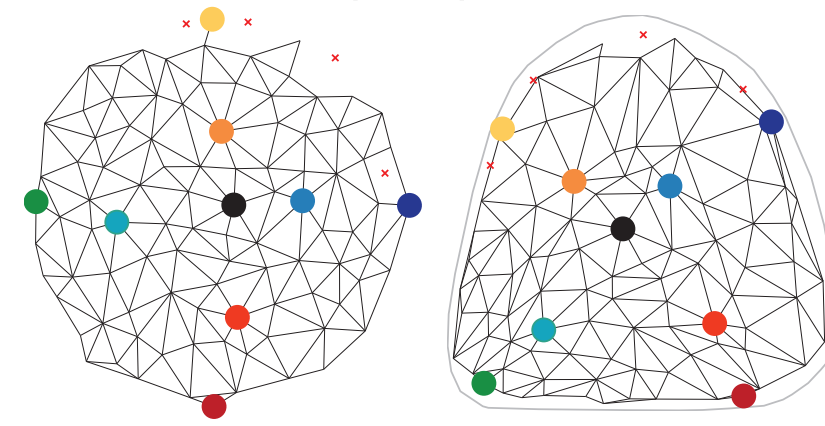
D Whitelaw



E Willshaw (early)

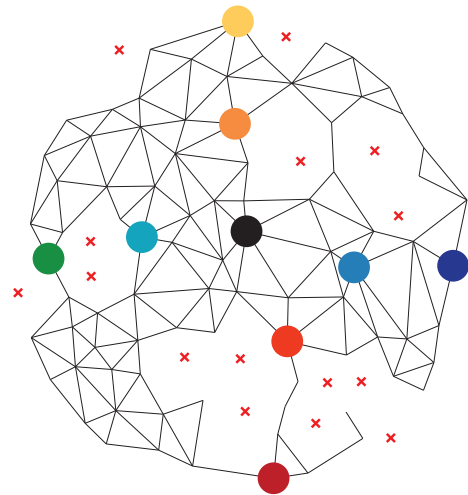


F Willshaw (late)

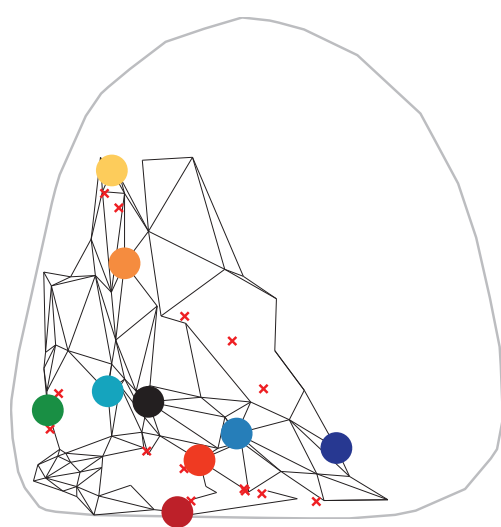


Math5 KO

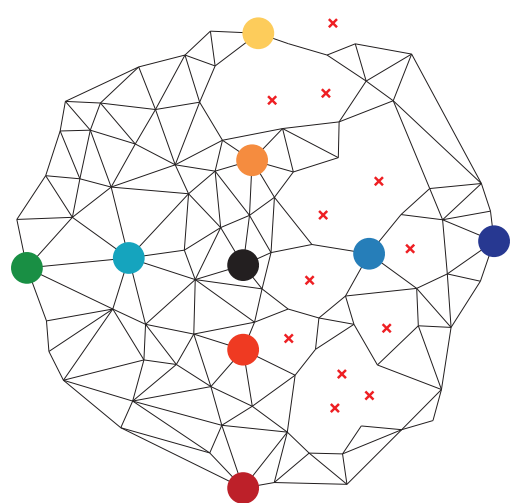
A Gierer



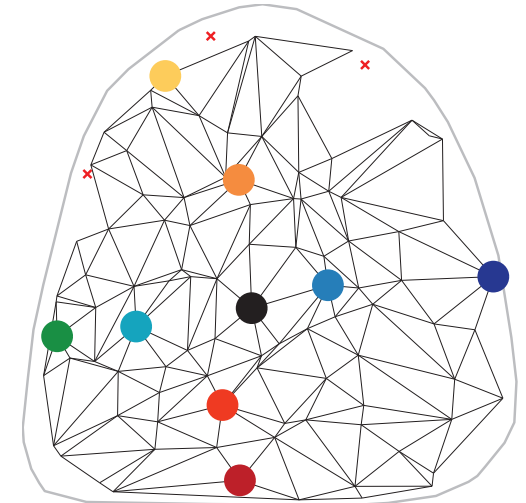
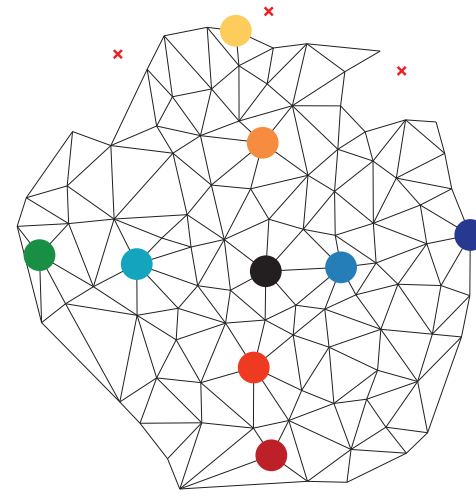
B Koulakov



C Whitelaw



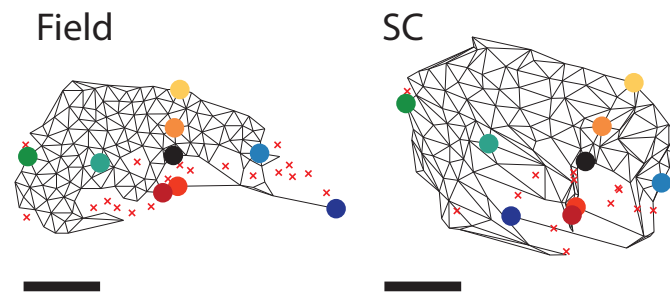
D Willshaw



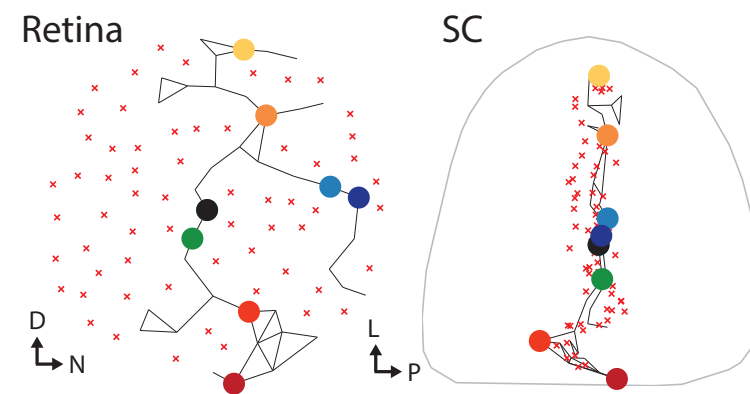
(Triplett et al. 2011)

ephrin-A2/3/5 TKO

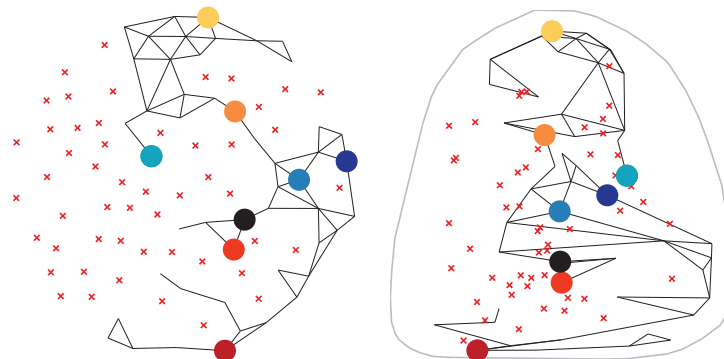
A Triple knock-out



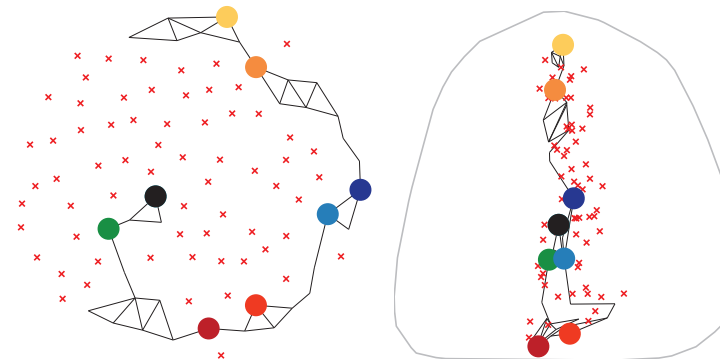
B Gierer



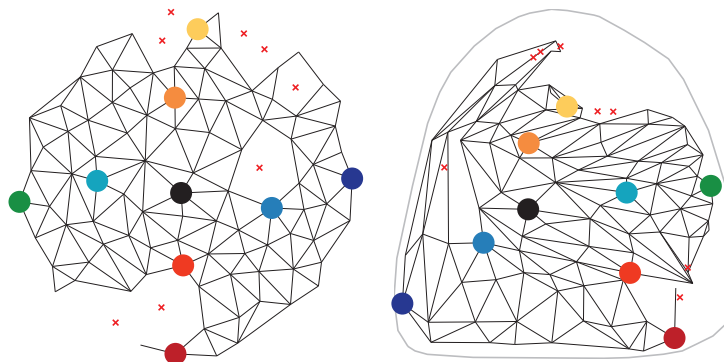
C Koulakov



D Whitelaw



E Willshaw



(Cang et al. 2008)

Summary

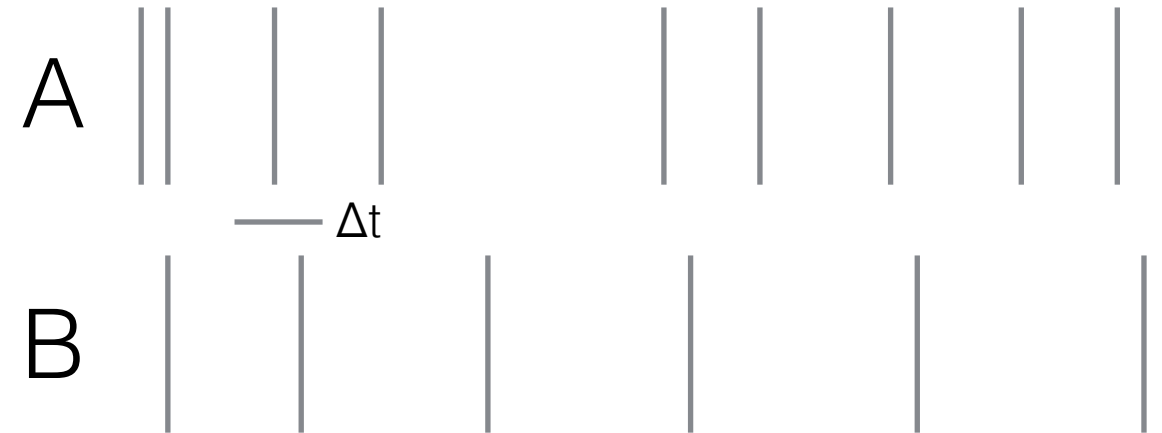
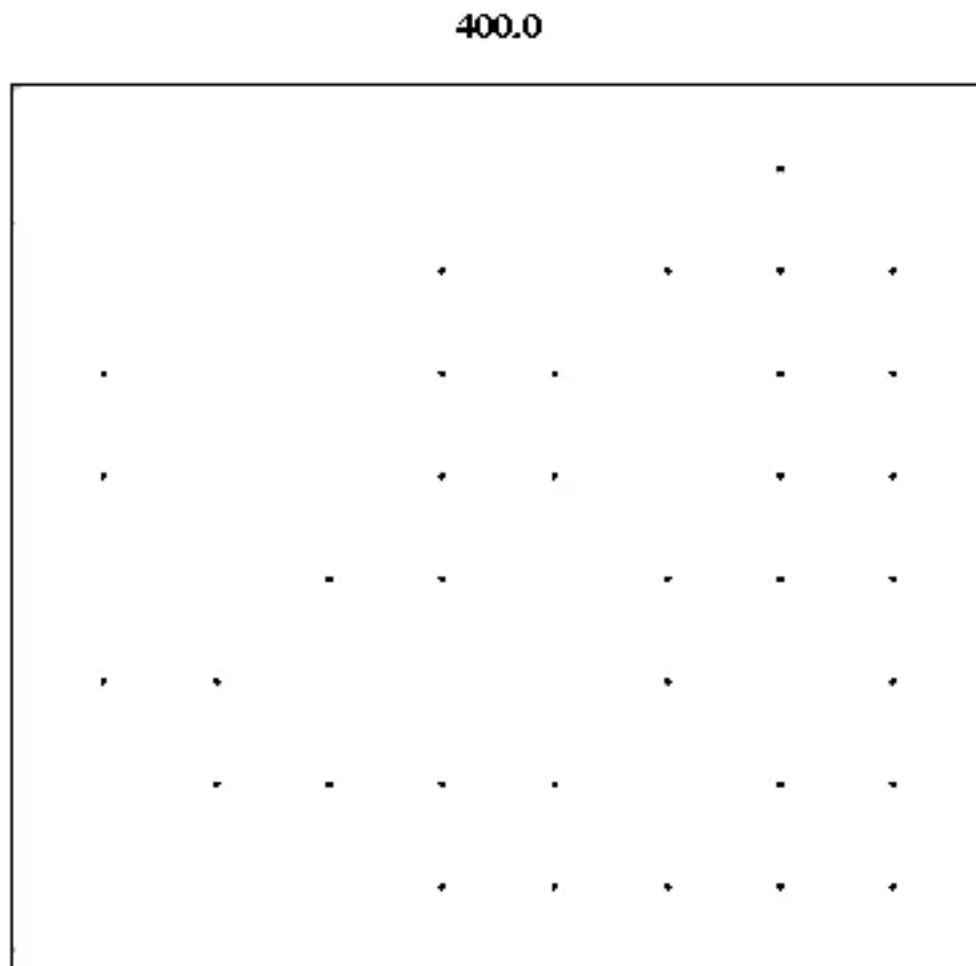
Genotype	Gierer	Koulakov	Whitelaw	Willshaw
Wild type	✓	✓	✓	* ✓
<i>Isl2-EphA3</i> ^{ki/ki}	Isl2 ⁺ misfit	Isl2 ⁺ misfit	* ✓	Isl2 ⁺ misfit
<i>Isl2-EphA3</i> ^{ki/+}	No collapse, Isl2 ⁺ misfit	* Isl2 ⁺ misfit	No collapse, Isl2 ⁺ misfit	No collapse, Isl2 ⁺ misfit
TKO (no gradient)	No patches	Patches but no global order	No patches	Global order but no polarity
TKO (weak gradient)	No patches	✓	No patches	Ordered map
<i>Math5</i> ^{-/-}	* ✓	✓	Normal map	Normal map

Asterisk (*) denotes which phenotype the model was optimized for.

Detecting correlations

Catherine Cutts (J Neurosci 2014)

Correlation index



$$c = \frac{N_{A,B}[-\Delta t, +\Delta t] T}{N_A N_B 2\Delta t}$$

(Wong et al. 1993; Demas et al. 2003)

Measuring correlation

Distance measures and cost functions

- 1 Victor and Purpura (1997)
- 2 ISI-distance (Kreuz et al., 2007a)
- 3 Hunter-Milton similarity (Hunter and Milton, 2003)
- 4 Van Rossum (2001)
- 5 SPIKE (Kreuz et al., 2013)

Cross-correlation based

- 6 Coincidence index (Pasquale et al., 2008)
- 7 Altered Coincidence index*
- 8 Cross correlation coefficient (Pasquale et al., 2008)
- 9 Schreiber et al. (2003) similarity coefficient
- 10 Altered Schreiber et al. similarity coefficient*
- 11 Kerschensteiner and Wong (2008) cross-correlation
- 12 Jimbo and Robinson index (Jimbo et al., 1999)

Synchrony not from cross-correlation

- 13 Correlation index (Wong et al., 1993)
- 14 Activity pair (Eytan et al., 2004)
- 15 Unitary events analysis (Grün et al., 2002)
- 16 Event synchronization (Kreuz et al., 2007b)*
- 17 Joris et al. (2006) correlation index

Information theory

- 18 Mutual information (Li, 1990)
- 19 Mutual information with smoothing*

Measures from shot-noise process

- 20 Coherence (at zero) (Eggermont, 2010)
- 21 Spike count correlation (Eggermont, 2010)
- 22 Smoothed spike count correlation (Kruskal et al., 2007)[‡]
- 23 Spike count covariance (Eggermont, 2010)

Measures assuming a marked point process

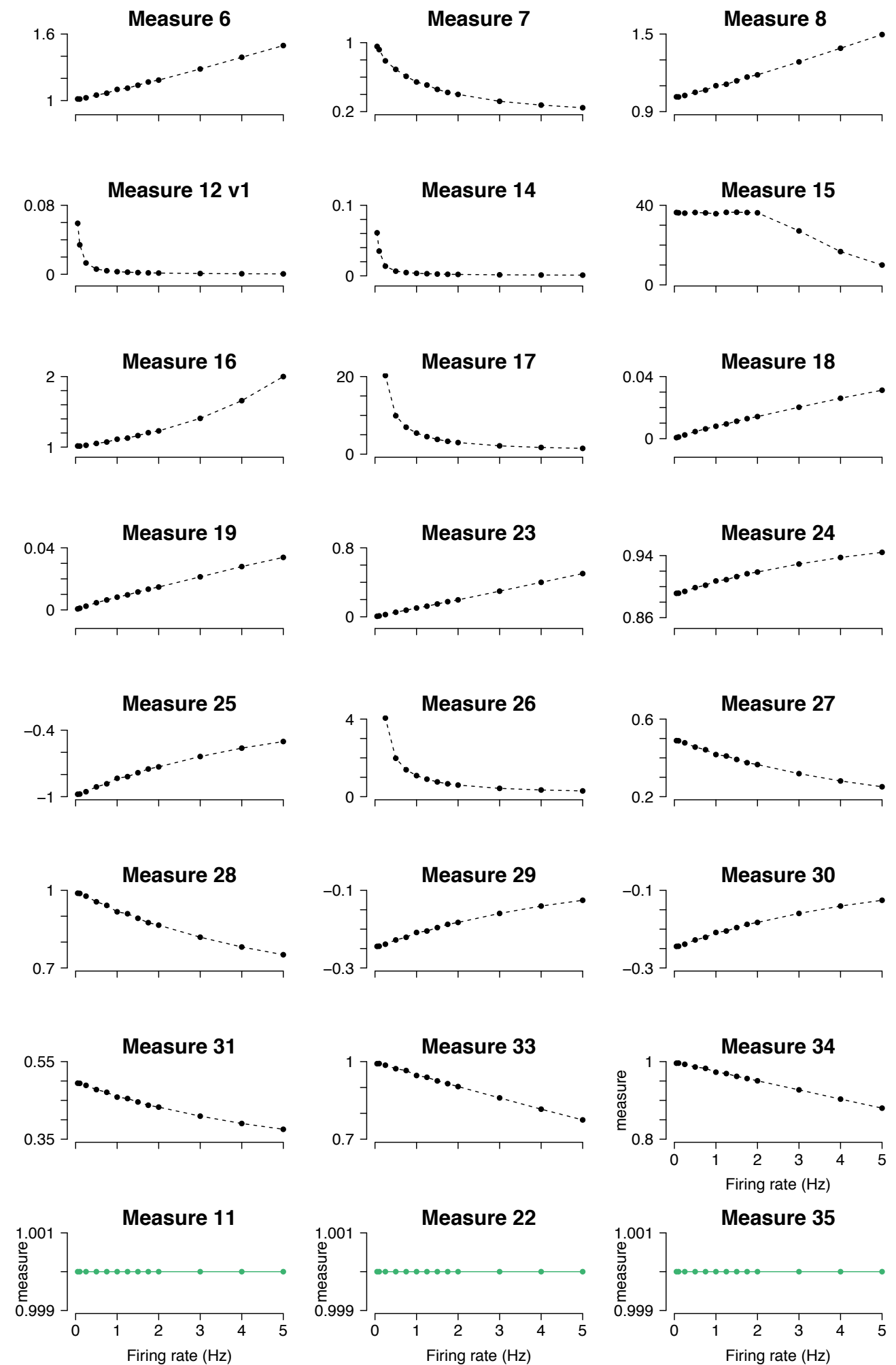
- 24 Stoyan's K_{mm} function (Stoyan and Stoyan, 1994)
- 25 Isham's mark correlation function (Isham, 1985)
- 26 Ripley's K_{mm} function (Ripley, 1976)
- 27 Simpson (1949) index
- 28 Simpson (1949) index no correction
- 29 Stoyan's mark covariance function (Stoyan, 1984)
- 30 Mark variogram (Cressie, 1993)
- 31 Mark covariance function (Cressie, 1993)
- 32 Mark conditional expectation (E ; Schlather et al., 2004)
- 33 Mark conditional variance (V ; Schlather et al., 2004)
- 34 Mark conditional standard deviation (Schlather et al., 2004)

Which method is best?

- 34 measures in literature + 1 from us => 35.
- Phase 1: six necessary properties:
 1. Symmetric
 2. Robust to variations in firing rate
 3. Robust to amount of data
 4. Bounded $[-1, +1]$
 5. Robust to variations in bin width (Δt)

Twenty-one measures
rejected as they
depend on firing rate.

(autocorrelation of
Poisson trains)



Phase 2: Desirable properties

Desirable properties:

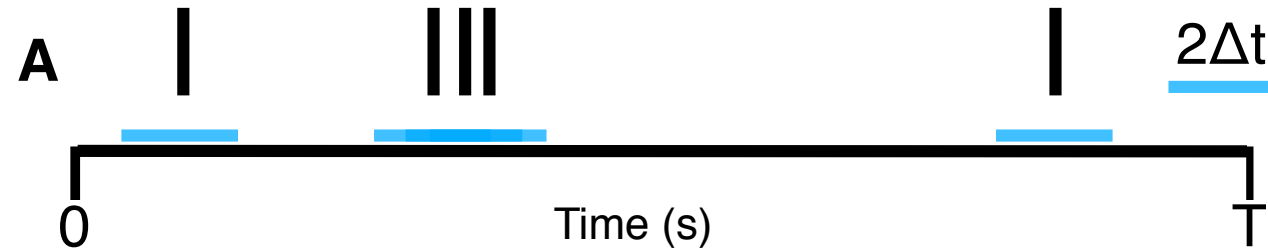
- D1: Ignore periods when both neurons are inactive.
- D2: minimal assumptions on structure.
- D3: aside from Δt , minimise number of parameters

Four methods:

- Kerschensteiner and Wong correlation (D1, D2)
- Tiling coefficient (D1, D2, D3)
- Spike count correlation (D2, D3)
- Kruskal et al. binless correlation measure (D1?, D2, D3)

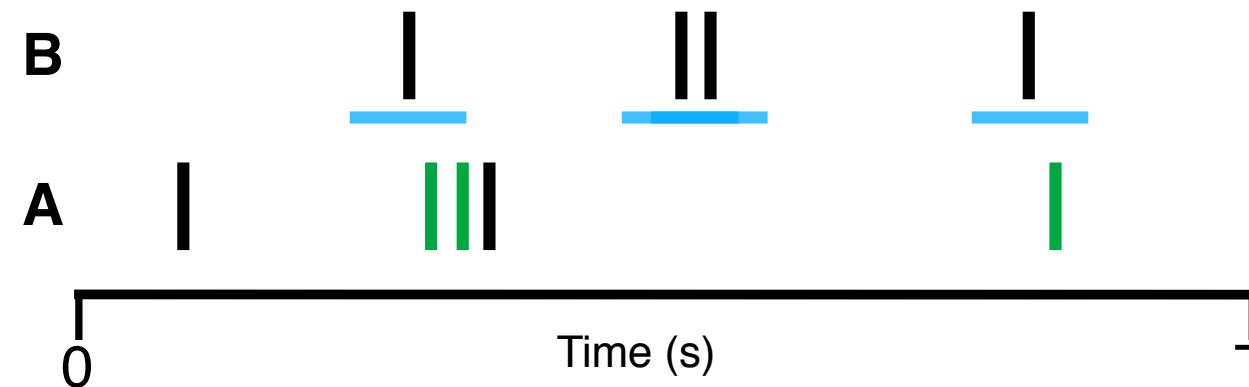
Tiling coefficient - TC

T_A : the proportion of total recording time which lies within $\pm\Delta t$ of any spike from A. T_B calculated similarly.



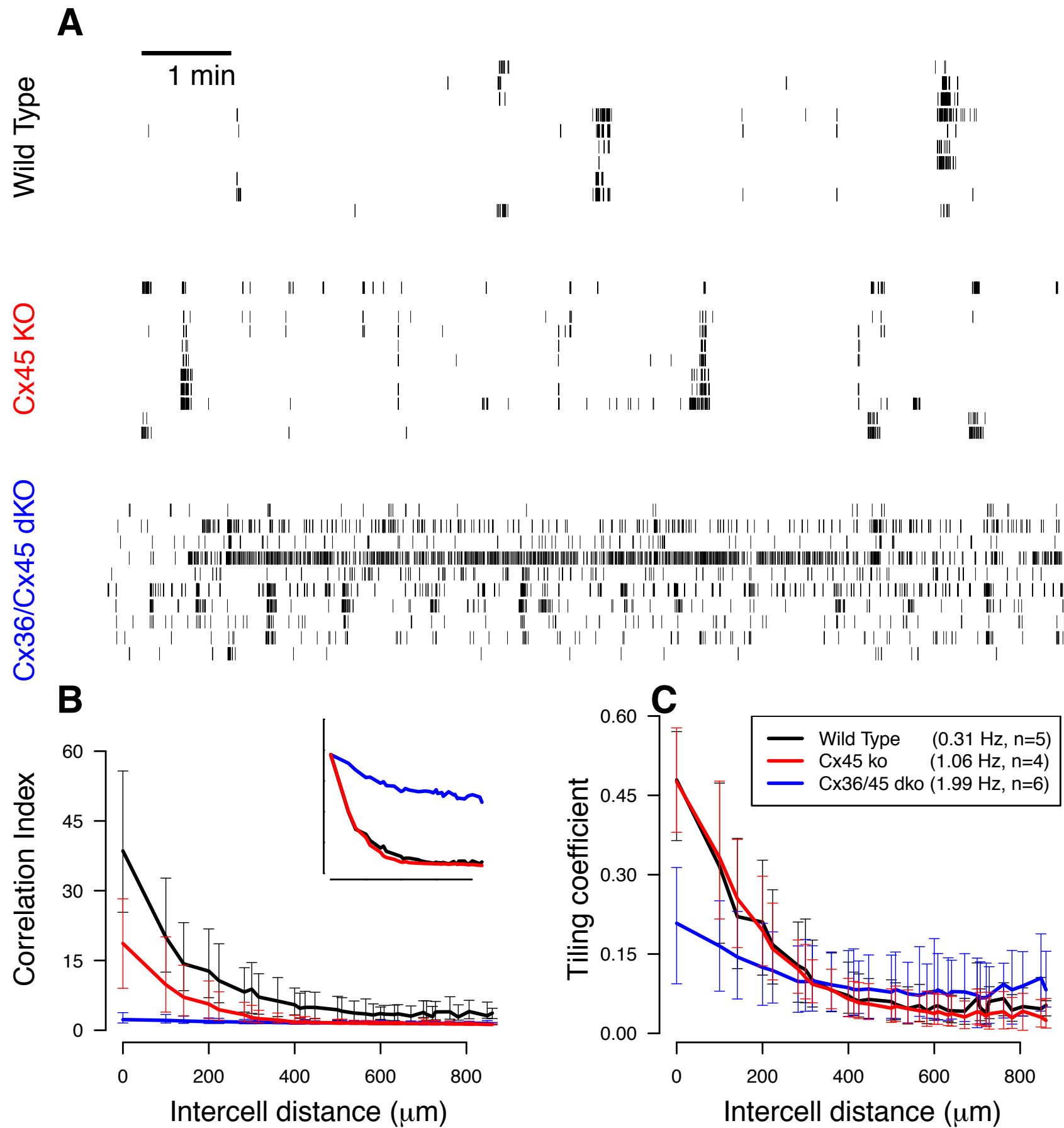
T_A is given by the fraction of the total recording time (black) which is covered (tiled) by blue bars. Here T_A is 1/3.

P_A : the proportion of spikes from A which lie within $\pm\Delta t$ of any spike from B. P_B calculated similarly.



P_A is the number of green spikes in A (3) divided by the total number of spikes in A (5). Here P_A is 3/5.

$$TC = \frac{1}{2} \left(\frac{P_A - T_B}{1 - P_A T_B} + \frac{P_B - T_A}{1 - P_B T_A} \right)$$



(Blankenship et al. 2011)

Summary

- Competitions can help frame problems in interesting ways and remove a source of bias.
- No model can account for all experimental data on mouse retinocollicular map formation.
- We now have better ways to detect correlated activity (tiling coefficient) and bursts.

Acknowledgments

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Map formation: JJJ Hjorth, CS Cutts, DC Sterratt, DJ Willshaw

Correlations: CS Cutts

Data/code: <http://damtp.cam.ac.uk/user/eglen>