

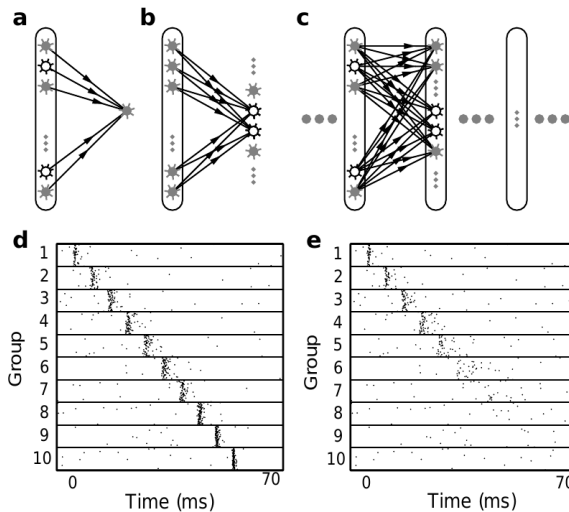
# Pulse Packets & Synfire Chains (Part 2)

Alejandro F. Bujan

Bernstein Center Freiburg

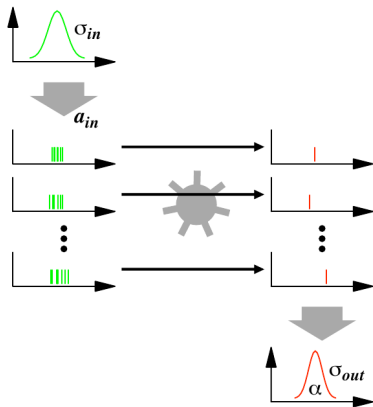
Models of Neurons and Networks, November 26, 2013

# Synfire chains and propagation through synchrony



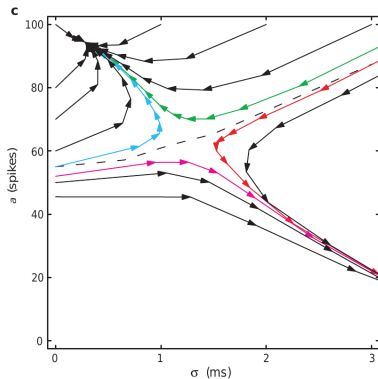
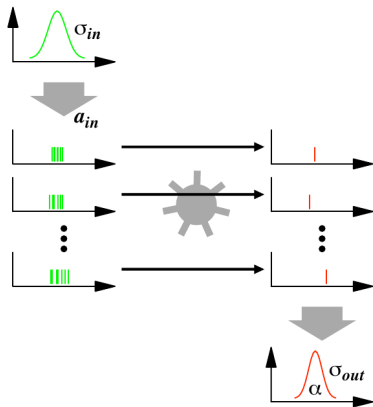
Diesmann, Gewaltig & Aertsen, 1999

# Synfire chains are synchrony generators



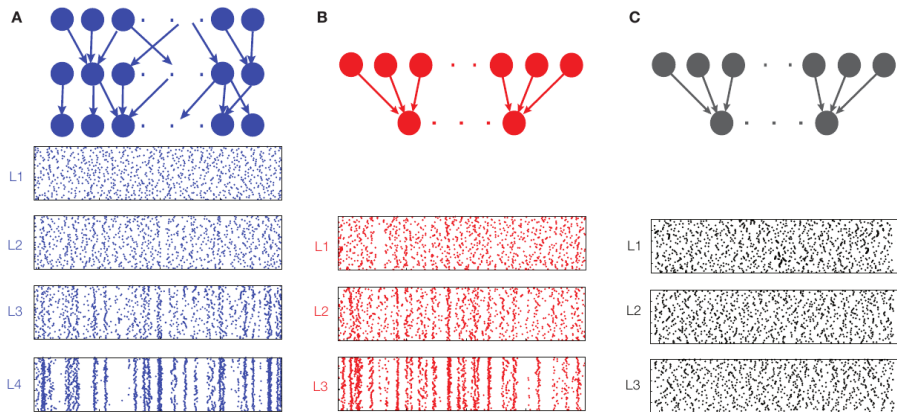
Diesmann, Gewaltig & Aertsen, 1999

# Synfire chains are synchrony generators



Diesmann, Gewaltig & Aertsen, 1999

# But how do they correlate?



Rosembaum et al., 2011

## But how do they correlate?

- Shared inputs

## But how do they correlate?

- Shared inputs
- Pooling

## But how do they correlate?

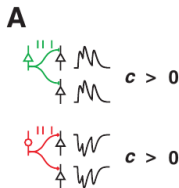
- Shared inputs
- Pooling
- (Resonance)



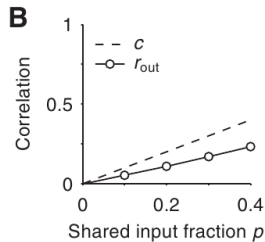
## But how do they correlate?

- Shared inputs
- Pooling
- (Resonance)

# But how do they correlate?

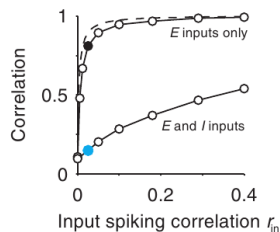
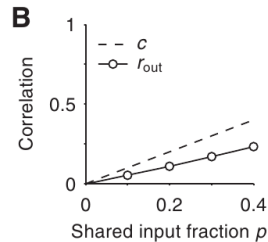
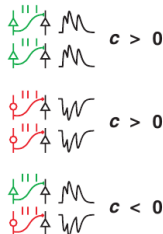
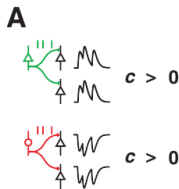


- Shared inputs
- Pooling
- (Resonance)

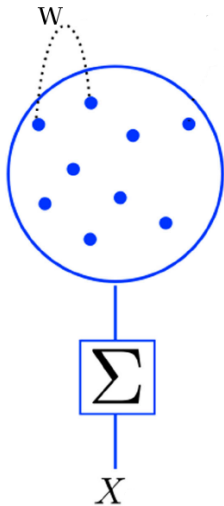


# But how do they correlate?

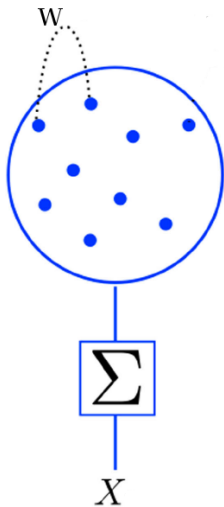
- Shared inputs
- Pooling
- (Resonance)



# The pooling effect

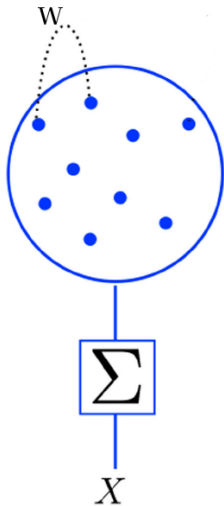


# The pooling effect



$$X = \sum_i^N x_i$$

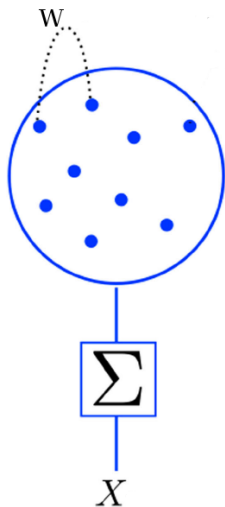
# The pooling effect



$$X = \sum_i^N x_i$$

$$W \simeq \hat{W} = \left\langle \frac{\text{cov}[x_i, x_j]}{\sqrt{\text{var}[x_i] \text{var}[x_j]}} \right\rangle_{N(N-1)}$$

# The pooling effect

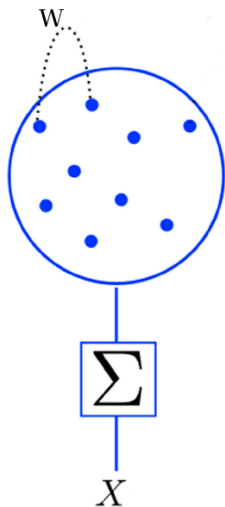


$$X = \sum_i^N x_i$$

$$W \simeq \hat{W} = \left\langle \frac{\text{cov}[x_i, x_j]}{\sqrt{\text{var}[x_i]\text{var}[x_j]}} \right\rangle_{N(N-1)}$$

$$\text{var}[X] = \sum_{i=1}^N \text{var}[x_i] + \sum_{i=1}^N \sum_{\substack{j=1 \\ j \neq i}}^N \text{cov}[x_i, x_j]$$

# The pooling effect



$$X = \sum_i^N x_i$$

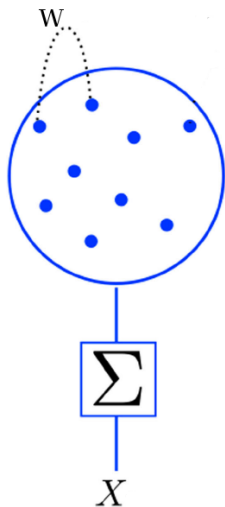
$$W \simeq \hat{W} = \left\langle \frac{\text{cov}[x_i, x_j]}{\sqrt{\text{var}[x_i]\text{var}[x_j]}} \right\rangle_{N(N-1)}$$

$$\text{var}[X] = \sum_{i=1}^N \text{var}[x_i] + \sum_{i=1}^N \sum_{\substack{j=1 \\ j \neq i}}^N \text{cov}[x_i, x_j]$$

$$\text{var}[x_1] = \text{var}[x_2] = \dots = \sigma^2$$



# The pooling effect



$$X = \sum_i^N x_i$$

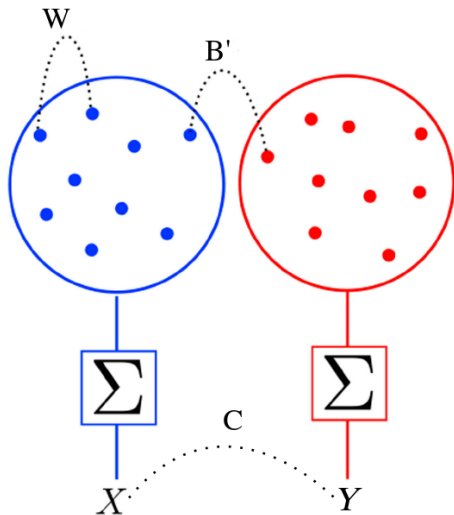
$$W \simeq \hat{W} = \left\langle \frac{\text{cov}[x_i, x_j]}{\sqrt{\text{var}[x_i]\text{var}[x_j]}} \right\rangle_{N(N-1)}$$

$$\text{var}[X] = \sum_{i=1}^N \text{var}[x_i] + \sum_{i=1}^N \sum_{\substack{j=1 \\ j \neq i}}^N \text{cov}[x_i, x_j]$$

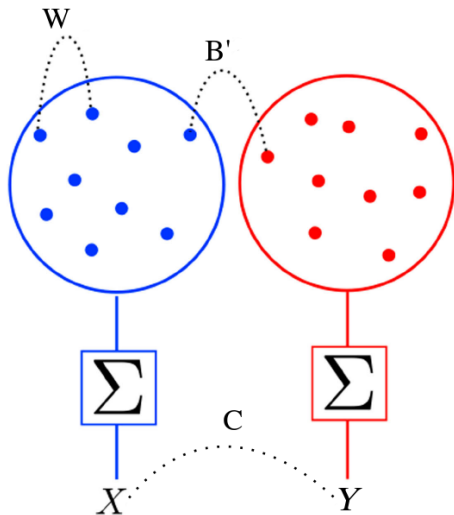
$$\text{var}[x_1] = \text{var}[x_2] = \dots = \sigma^2$$

$$\text{var}[X] = N\sigma^2 + N(N-1)W\sigma^2$$

# The pooling effect

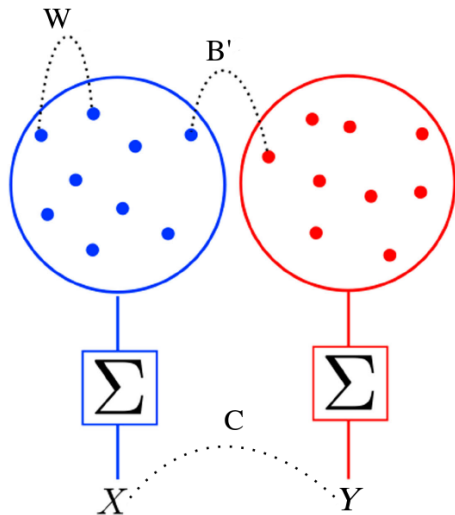


# The pooling effect



$$C = \frac{B'}{W + \frac{1}{N}(1 - W)}$$

# The pooling effect

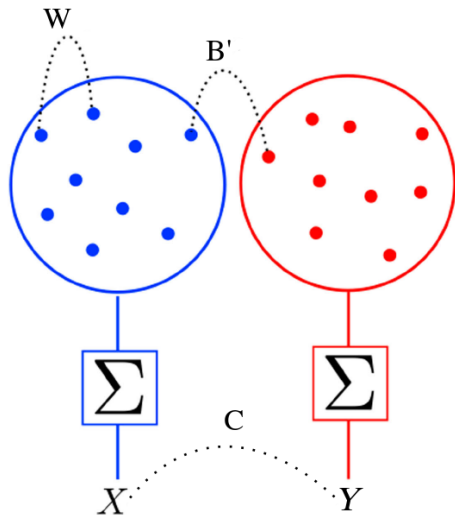


$$C = \frac{B'}{W + \frac{1}{N}(1 - W)}$$

$$= \frac{B'}{W} - \mathcal{O}\left(\frac{1}{N}\right)$$

Bedenbaugh & Gernstein, 1997  
Rosebaum et al., 2010

# The pooling effect



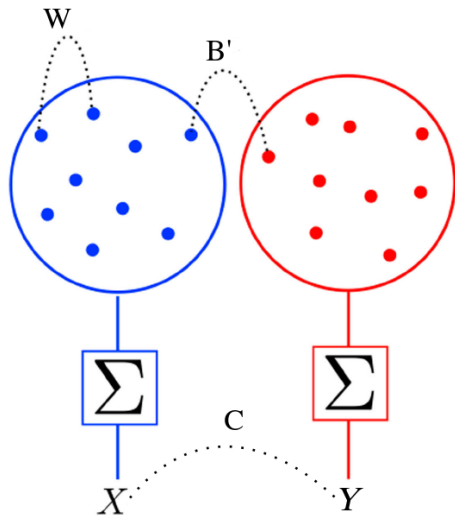
$$C = \frac{B'}{W} - \mathcal{O}\left(\frac{1}{N}\right)$$

Bedenbaugh & Gernstein, 1997

Rosembaum et al., 2010

- Amplification:  $C \geq B'$

# The pooling effect



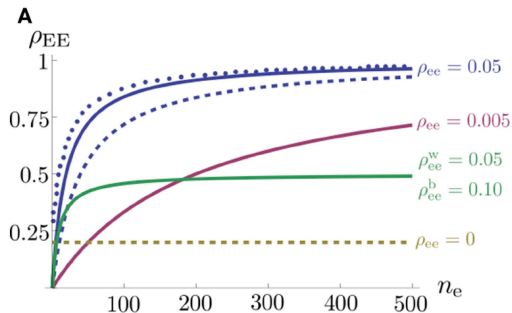
$$C = \frac{B'}{W} - \mathcal{O}\left(\frac{1}{N}\right)$$

Bedenbaugh & Gernstein, 1997

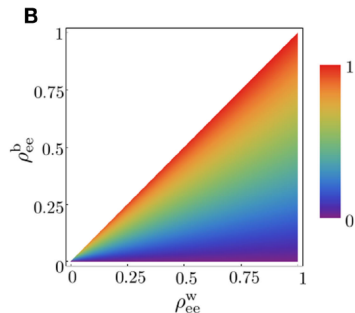
Rosembaum et al., 2010

- Amplification:  $C \geq B'$
- Bound: since  $C \leq 1$ , then  $B' \leq W - \mathcal{O}\left(\frac{1}{N}\right)$

# The pooling effect

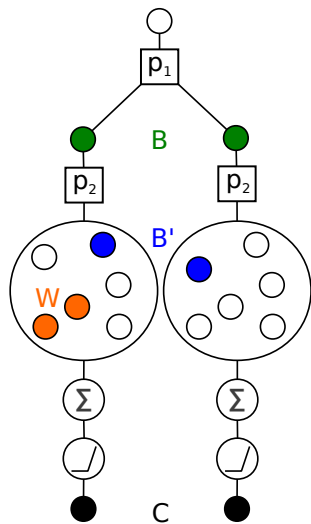


$$C = \frac{B'}{W} - \mathcal{O}\left(\frac{1}{N}\right)$$



Rosembaum et al., 2010

# Generating B and W correlations



$$p_1 = B$$

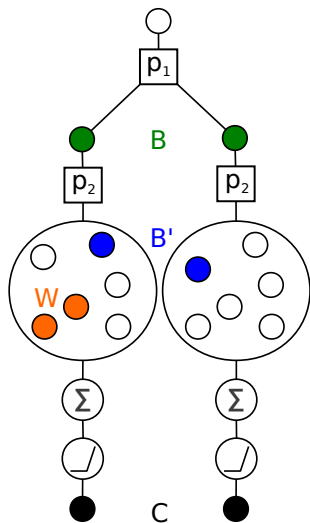
$$p_2 = W$$

$$B' = BW$$

Kuhn et al., 2003  
Yim et al., 2011  
Bujan et al., in prep.



# Generating B and W correlations



$$p_1 = B$$

$$p_2 = W$$

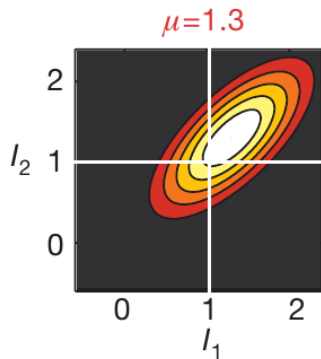
$$B' = BW$$

For large  $N$ :

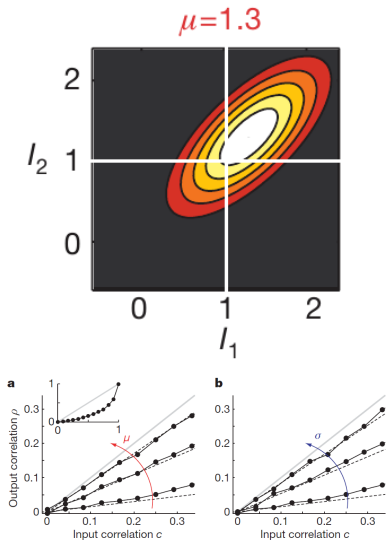
$$C \rightarrow B'/W = B$$

Kuhn et al., 2003  
Yim et al., 2011  
Bujan et al., in prep.

## Decorrelation due to thresholding in LIF neurons



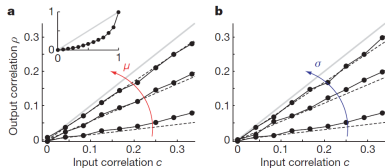
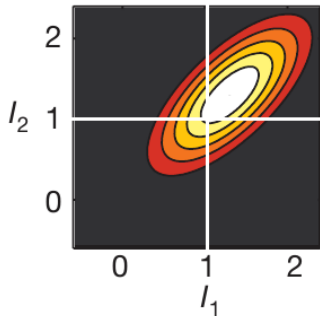
# Decorrelation due to thresholding in LIF neurons



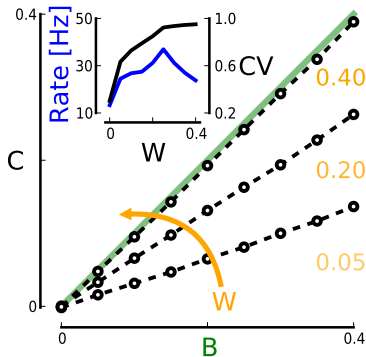
de la Rocha et al., 2007

# Decorrelation due to thresholding in LIF neurons

$\mu=1.3$

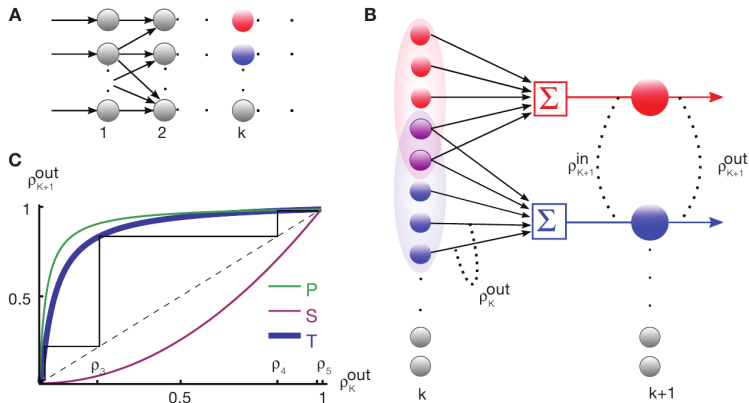


de la Rocha et al., 2007



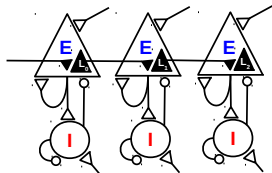
Bujan et al., in prep.

# Correlation transfer across synfire chains

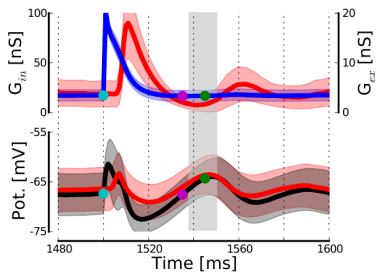
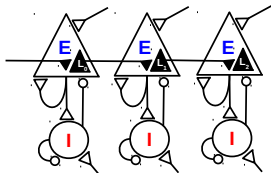


Rosebaum et al., 2011

# Synchronization through resonance

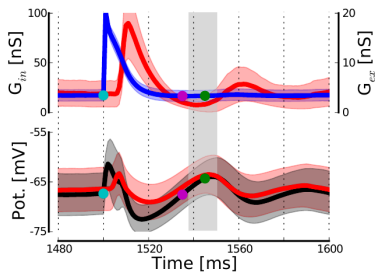
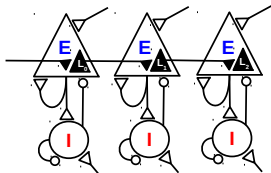


# Synchronization through resonance

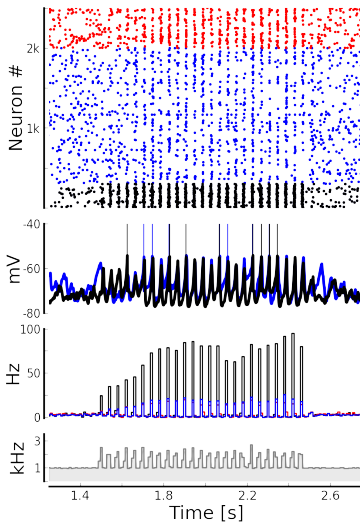


Hahn et al., in prep.

# Synchronization through resonance

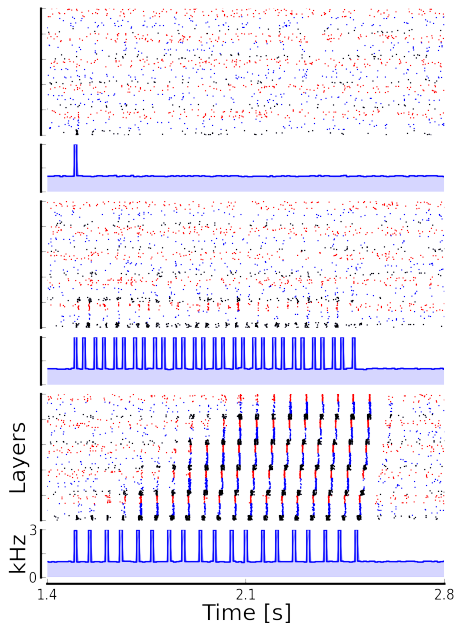


Hahn et al., in prep.





# Synchronization through resonance



Hahn et al., in prep.

# Summary

- 1 - Synfire chains propagate activity by making it more synchronous.

# Summary

- 1 - Synfire chains propagate activity by making it more synchronous.
- 2 - In classic synfire chains, synchrony arises mainly due to shared inputs and pooling.

# Summary

- 1 - Synfire chains propagate activity by making it more synchronous.
- 2 - In classic synfire chains, synchrony arises mainly due to shared inputs and pooling.
- 3 - Pooling effect is the predominance of shared fluctuations when different signals are added or pooled together.

# Summary

- 1 - Synfire chains propagate activity by making it more synchronous.
- 2 - In classic synfire chains, synchrony arises mainly due to shared inputs and pooling.
- 3 - Pooling effect is the predominance of shared fluctuations when different signals are added or pooled together.
- 4 - Periodic trains of pulse packets (or oscillations) can synchronize by exploiting the resonance frequencies of excitatory-inhibitory networks. Resonance-induced synchrony can allow the propagation of pulse packets in diluted synfire chains.

# Bibliography

- [1] P Bedenbaugh and G L Gerstein. Multiunit normalized cross correlation differs from the average single-unit normalized correlation. *Neural computation*, 9(6):1265–75, August 1997.
- [2] Jaime de la Rocha, Brent Doiron, Eric Shea-Brown, Kresimir Josić, and Alex Reyes. Correlation between neural spike trains increases with firing rate. *Nature*, 448(7155):802–806, Aug 2007.
- [3] M. Diesmann, M. O. Gewaltig, and A. Aertsen. Stable propagation of synchronous spiking in cortical neural networks. *Nature*, 402(6761):529–533, Dec 1999.
- [4] Alexandre Kuhn, Ad Aertsen, and Stefan Rotter. Higher-order statistics of input ensembles and the response of simple model neurons. *Neural Comput*, 15(1):67–101, Jan 2003.
- [5] Alfonso Renart, Jaime de la Rocha, Peter Bartho, Liad Hollender, Néstor Parga, Alex Reyes, and Kenneth D Harris. The asynchronous state in cortical circuits. *Science*, 327(5965):587–590, Jan 2010.
- [6] Robert Rosenbaum, James Trousdale, and Krešimir Josić. The effects of pooling on spike train correlations. *Front Neurosci*, 5:58, 2011.
- [7] Robert J Rosenbaum, James Trousdale, and Krešimir Josić. Pooling and correlated neural activity. *Frontiers in Computational Neuroscience*, 4, 2010.
- [8] Man Yi Yim, Ad Aertsen, and Arvind Kumar. Significance of Input Correlations in Striatal Function. *PLoS Computational Biology*, 7(11):e1002254, November 2011.