# A general theory of learning and memory with Complex Synapses

based on work with Surya Ganguli

Subhaneil Lahiri

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April 8, 2013



Complex synapses

2013-04-08

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# Introduction

We often model synaptic plasticity as the change of a single number (synaptic weight). In reality, there is a complex dynamical system inside a synapse.

Semi-realistic models of synaptic memory have terrible storage without synaptic complexity.

We will study the entire space of a broad class of models of complex synapses to find upper bounds on their performance.





Introduction

We often model synaptic plasticity as the change of a single number (synaptic weight). In reality, there is a complex dynamical system inside a synapse.

Semi-realistic models of synaptic memory have terrible storage without synaptic complexity.

We will study the entire space of a broad class of models of complex synapses to find upper bounds on their performance.

1. amplitude of psp.
2. finite number of values.

# Outline







Outline
Why complex synapses?
Modelling synaptic complexity
Upper bounds
Envelope memory curve

1. review terrible properties of simple synapses.
2. mathematical formalism of model, quantify performance (memory decay over time)
3. upper bounds on single numbers that describe performance at all times
4. upper bounds at finite times

Section 1

# Why complex synapses?



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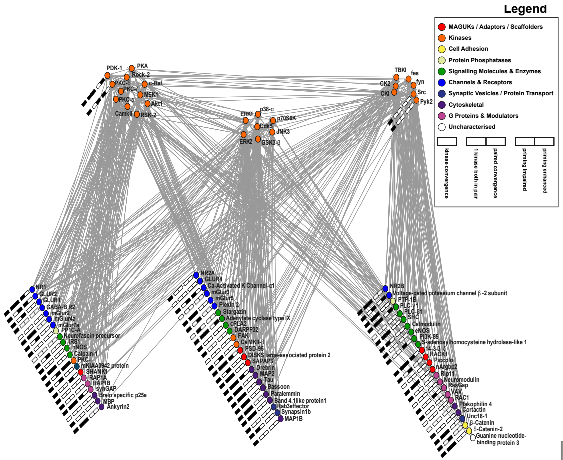
Complex synapses
└─Why complex synapses?

Section 1

Why complex synapses?

# Complex synapse

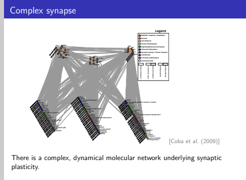



[Coba et al. (2009)]

There is a complex, dynamical molecular network underlying synaptic plasticity.







1. Does this matter?
2. Could just be the machinery for changing synaptic weight

# Storage capacity of synaptic memory

A classical perceptron (used as a recognition memory device) has a capacity $\propto N$, the number of synapses.

Requires synapses' dynamic range also $\propto N$.

If we restrict synaptic weight to a fixed, finite set of values,
$\implies$ tradeoff between learning and forgetting:
new memories overwriting old.

If we wish to store new memories rapidly, memory capacity $\sim \mathcal{O}(\log N)$.
[Amit and Fusi (1992), Amit and Fusi (1994)]

To circumvent this tradeoff, need to go beyond model of a synapse as a single number.





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# Section 2

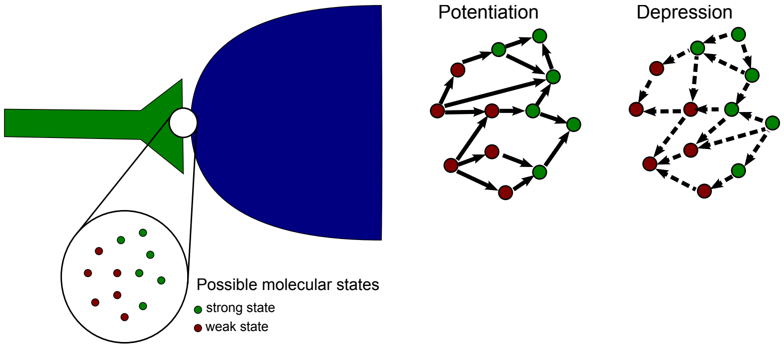
## Modelling synaptic complexity





Section 2
Modelling synaptic complexity

# Complex synapses



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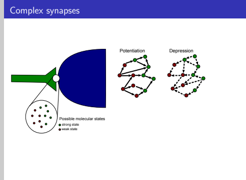
Complex synapses
└─Modelling synaptic complexity
└─Complex synapses



# Simplifying assumptions

- There are $N$ identical synapses with $M$ internal functional states.
- States of different synapses are independent of each other.
- Which synapses eligible for plasticity chosen randomly.
- Potentiating/depressing plasticity events $\sim$ Poisson processes with rates $rf^{\text{pot/dep}}$, where $f^{\text{pot}} + f^{\text{dep}} = 1$.
- Potentiation and depression are described by Markov processes with transition probabilities $\mathbf{M}^{\text{pot/dep}}$.
- Synaptic weights of the internal states are given by vector $\mathbf{w}$.
  Can only take values $\pm 1$.





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In other words, $r$ is the total rate of plasticity events per synapse and $f^{\text{pot/dep}}$ are the fraction of these events that are potentiating/depressing.

## Section 3

# Upper bounds





Section 3
Upper bounds

# Section 4

## Envelope memory curve





Section 4
Envelope memory curve

# Acknowledgements

Thanks to:

- Surya Ganguli
- Stefano Fusi
- Marcus Benna





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1. Last slide!

# References I


M. P. Coba, A. J. Pocklington, M. O. Collins, M. V. Kopanitsa, R. T. Uren, S. Swamy, M. D. Croning, J. S. Choudhary, and S. G. Grant.
"Neurotransmitters drive combinatorial multistate postsynaptic density networks".
*Sci Signal*, 2(68):ra19, 2009, PubMed:19401593.
6

D. J. Amit and S. Fusi.
"Constraints on learning in dynamic synapses".
*Network: Computation in Neural Systems*, 3(4):443–464, 1992.
7

D. J. Amit and S. Fusi.
"Learning in neural networks with material synapses".
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7




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└References


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