Friedrich-Alexander-Universität
Technische Fakultät

Pattern Recognition Lab

Modeling Hippocampus in context of language

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Friedrich-Alexander-Universität Erlangen-Nürnberg

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Agenda

1. Hippocampus

2. Successor Representation

3. Goal of the thesis

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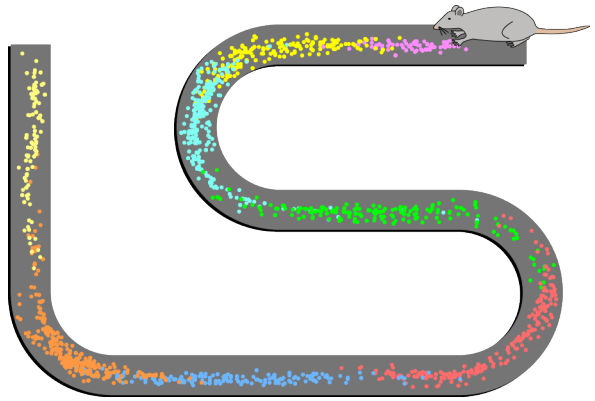

Figure: Different colors represent different place cells (= states)

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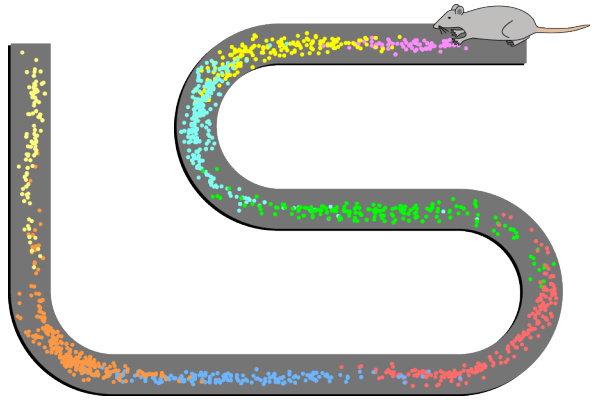
  - Grid cell: lattice-like arranged, fires continuously



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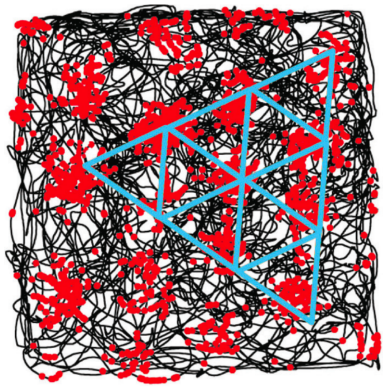

Figure: Grid cells can describes as triangulation

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- Column *j*: High value in component *i* means state *j* is visited regularly after starting at state *i*

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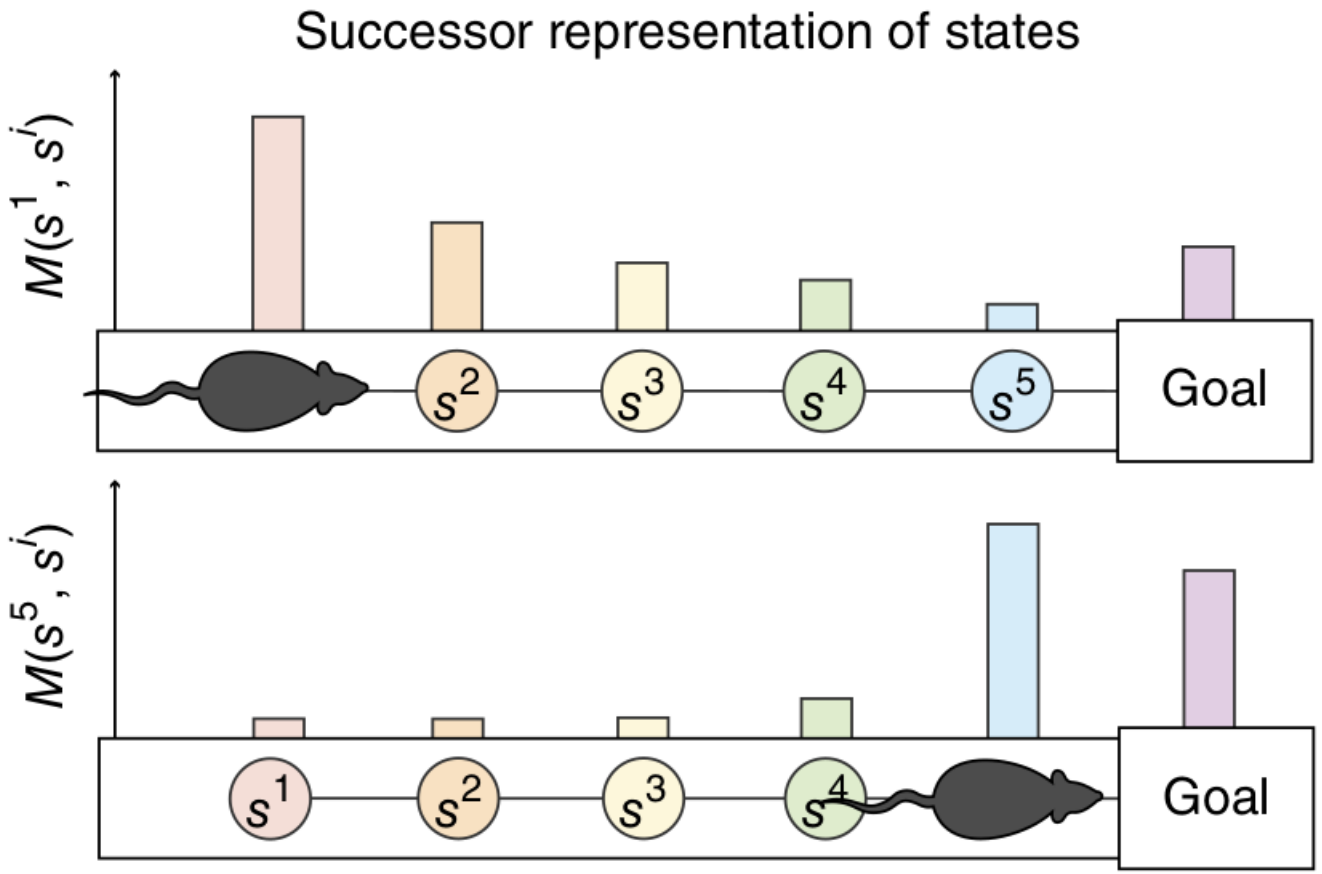

Superscript means index not power

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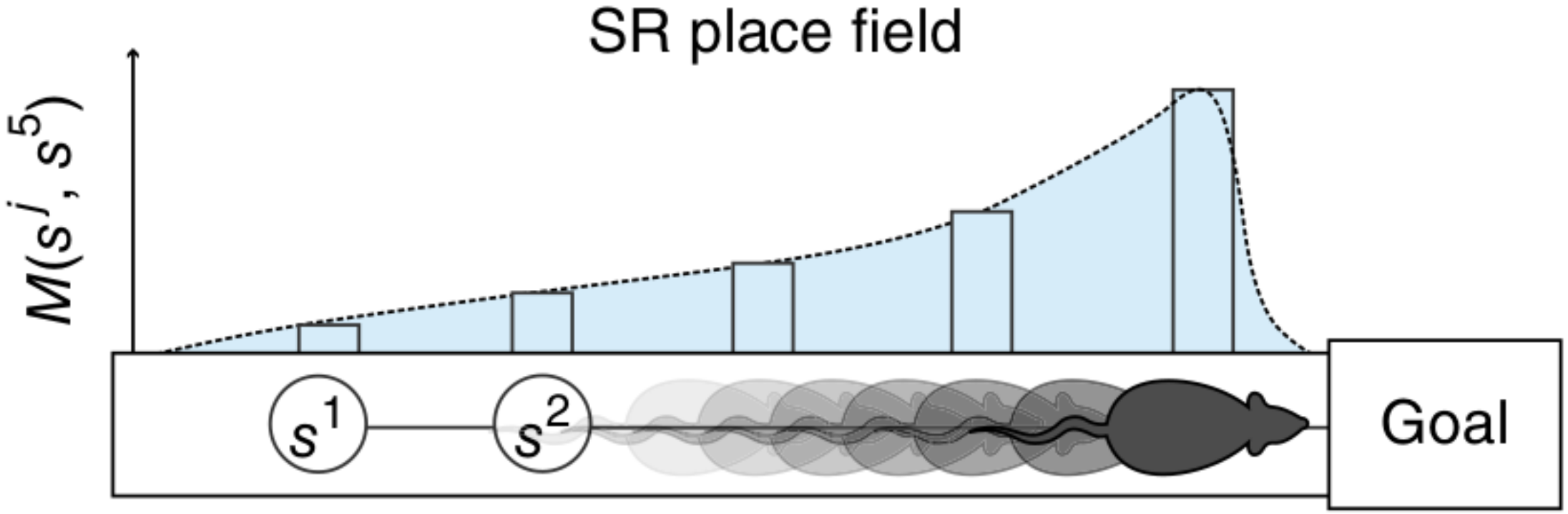
Example 2/2 of interpreting a SR matrix *M*



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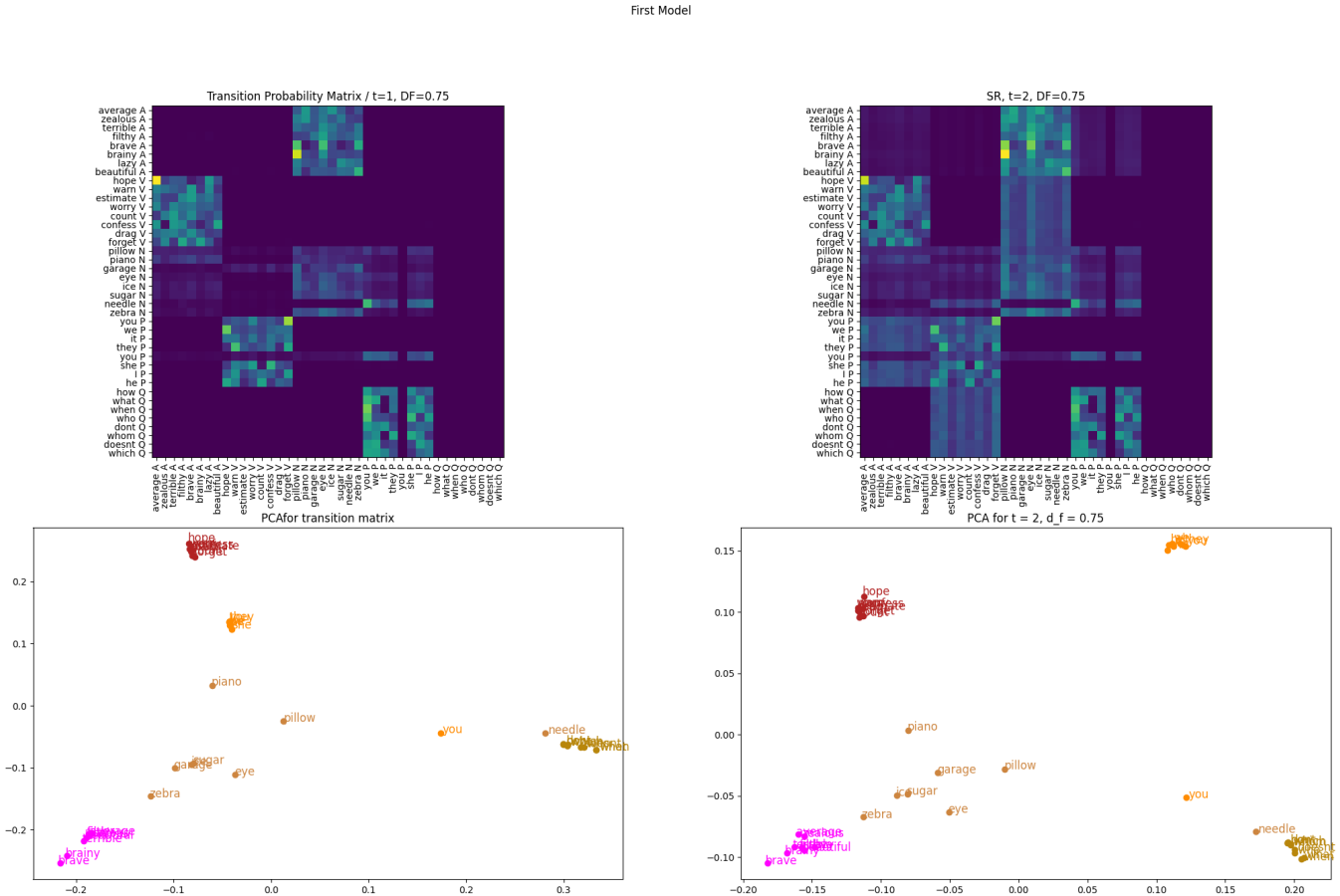
Example results for graphical model

Rules used: Question Word → Personal Pronoun, Adjective → Noun, Personal Pronoun → Verb & Verb → Adjective



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Example of word vector model