Associative Learning

What's old is new again

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Navy Center for Applied Research in Artificial Intelligence

Associative Learning

Associative Learning

- Cross-cutting concern

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- Cross-cutting concern
    - Embodiment

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- Cross-cutting concern
  - Embodiment
  - Top/down perception

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  - Long-term learning

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- Cross-cutting concern
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- **Context is king!**

Associative Learning

- Cross-cutting concern
    - Embodiment
    - Top/down perception
    - Long-term learning
    - Memory for goals
    - Humanoid fire-fighter
    - IED bomb dogs
- **Context is king!**
    - **Yet it can't be learned**

What do we need?

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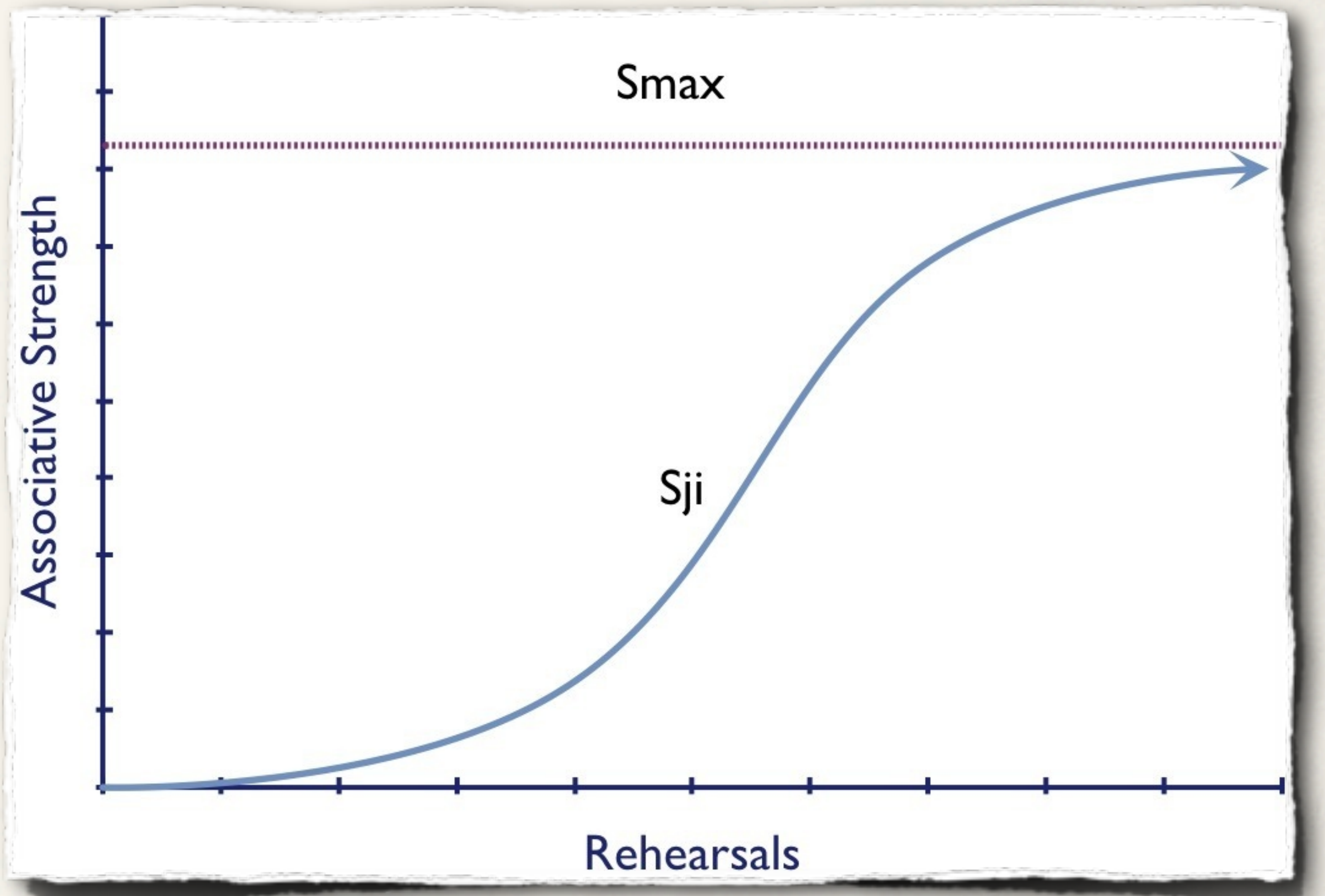
- Associations should be defined by model's behavior



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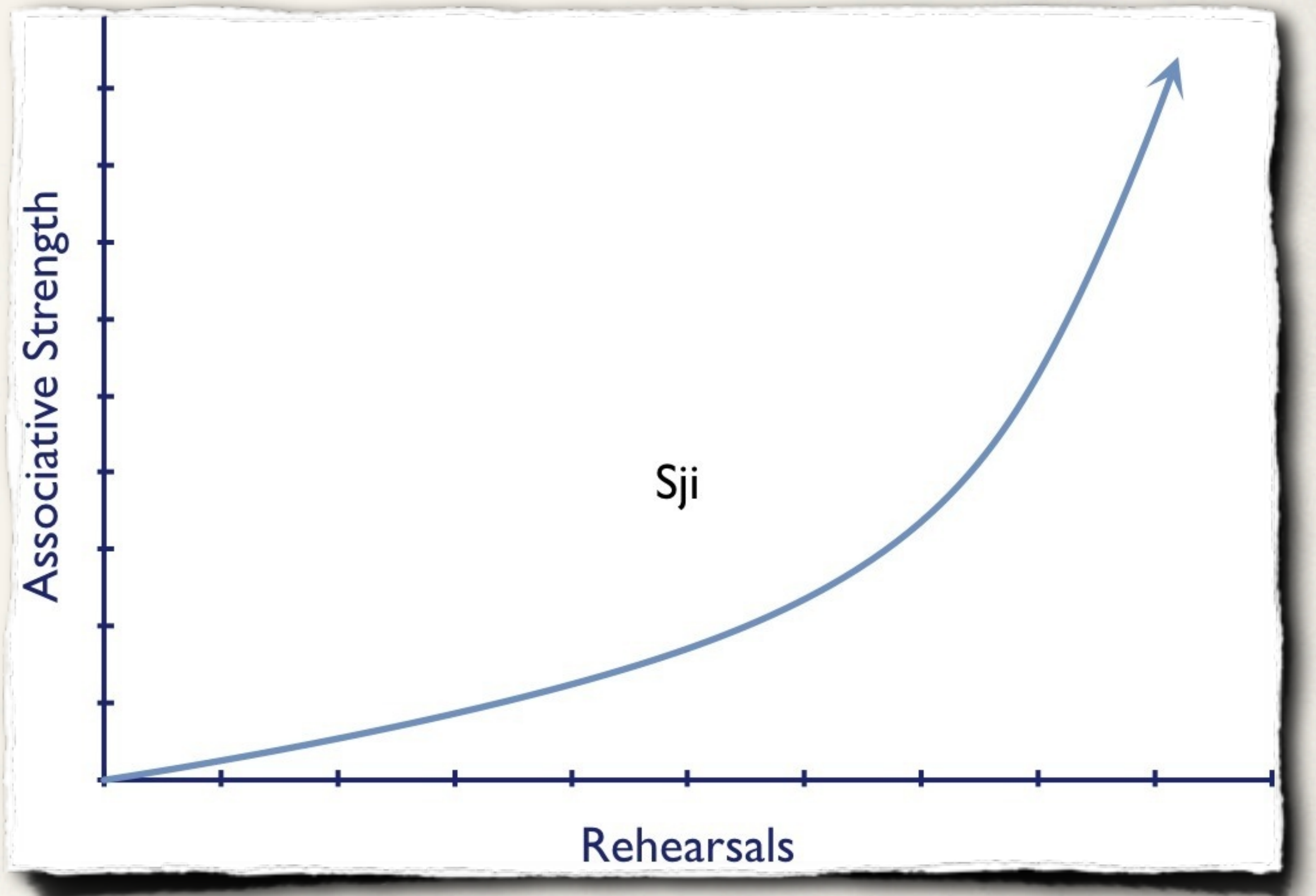
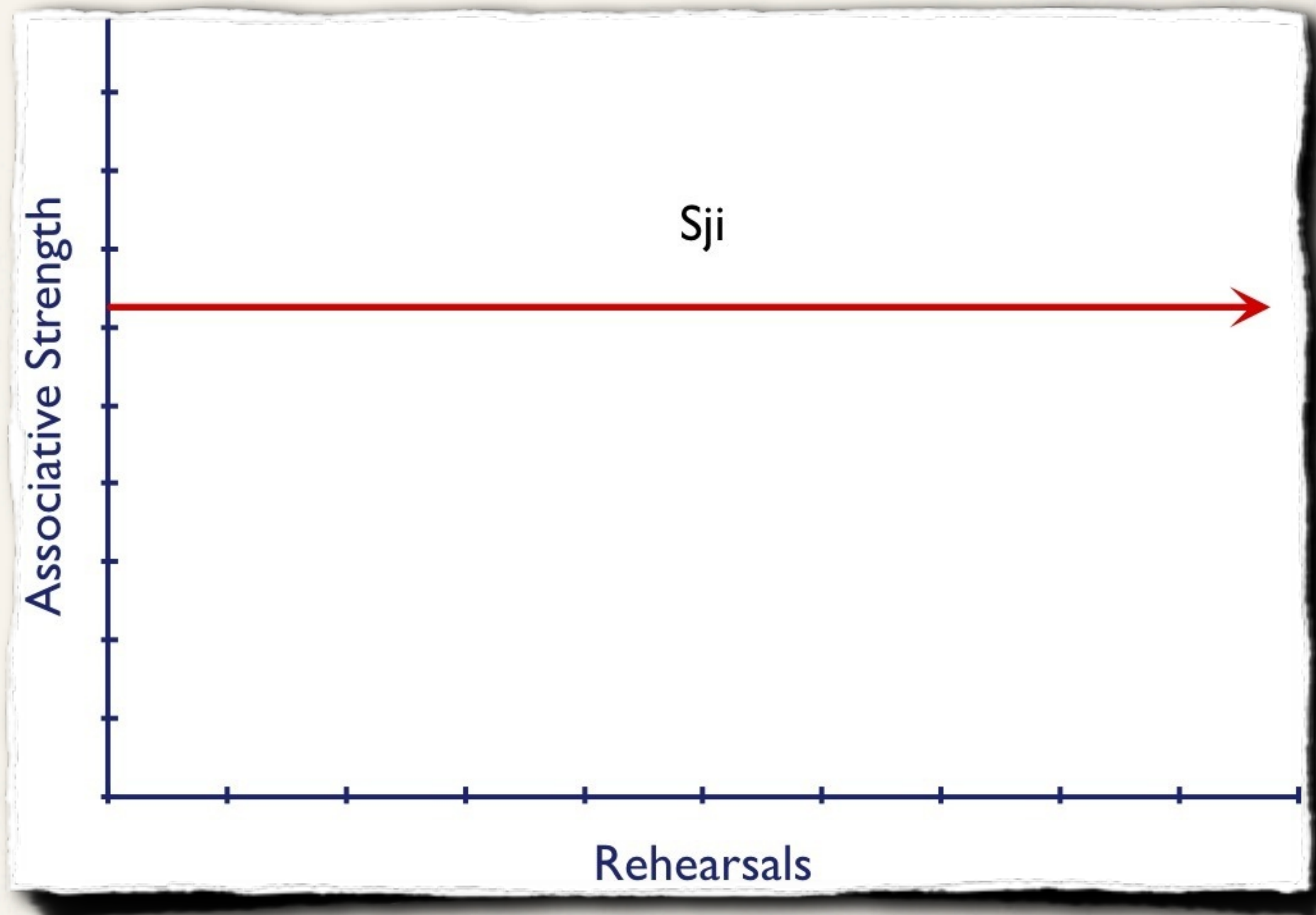
- Associations should be defined by model's behavior
- Associations should strengthen with exposure



What do we need?

- Associations should be defined by model's behavior
- Associations should strengthen with exposure
- Not be **defined** solely by **symbolic structure**



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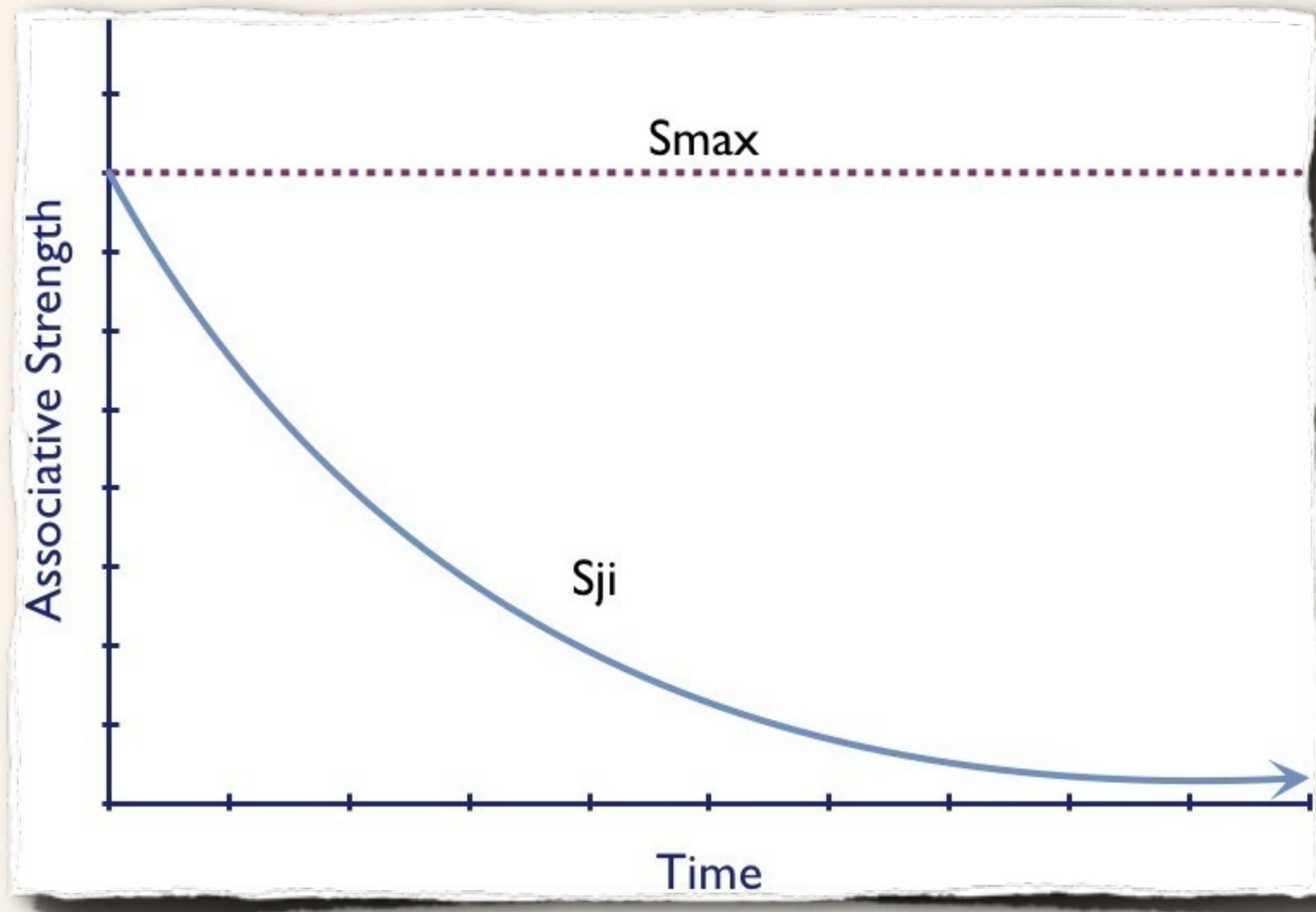
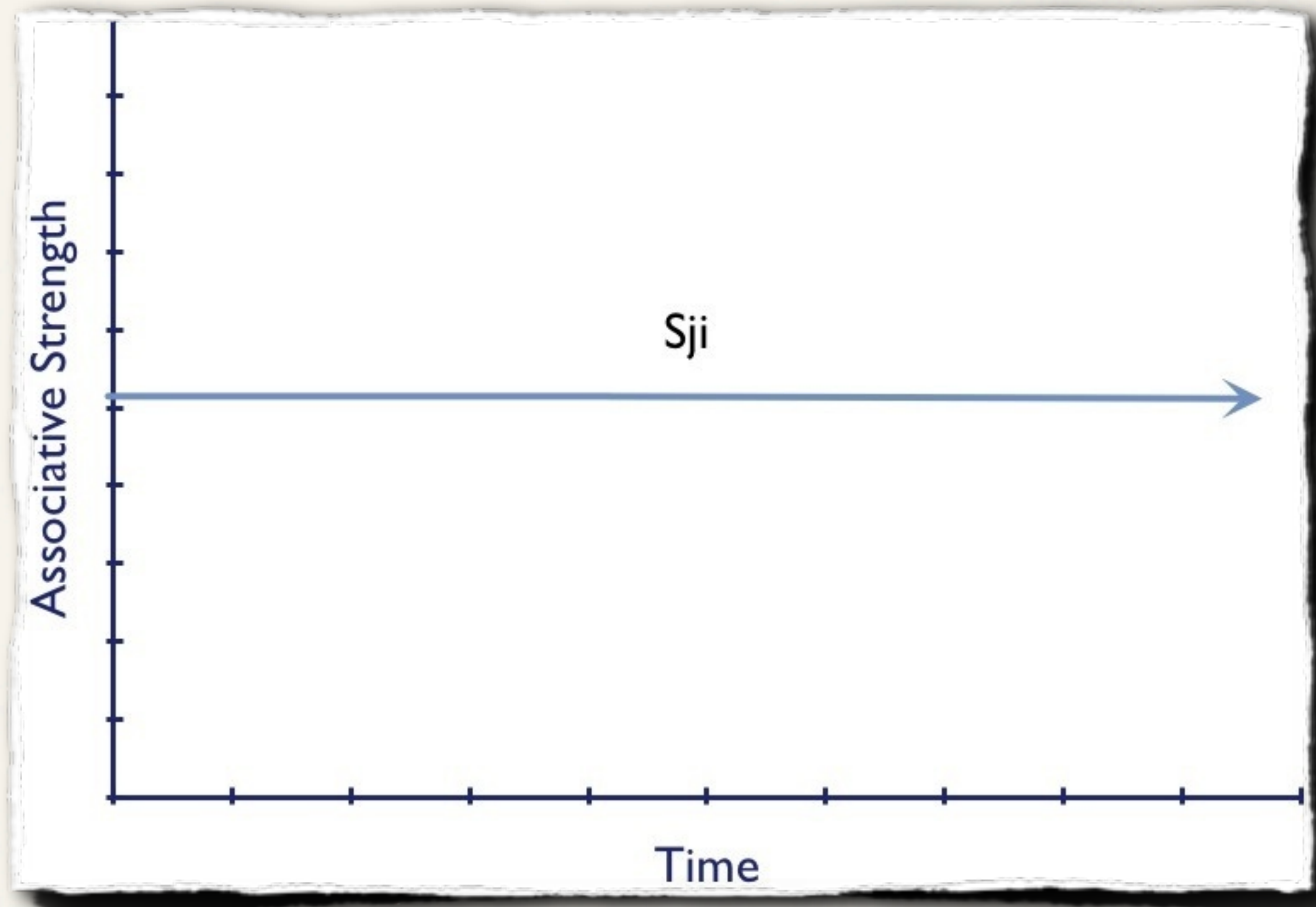
- Associations should be stable or decay with time



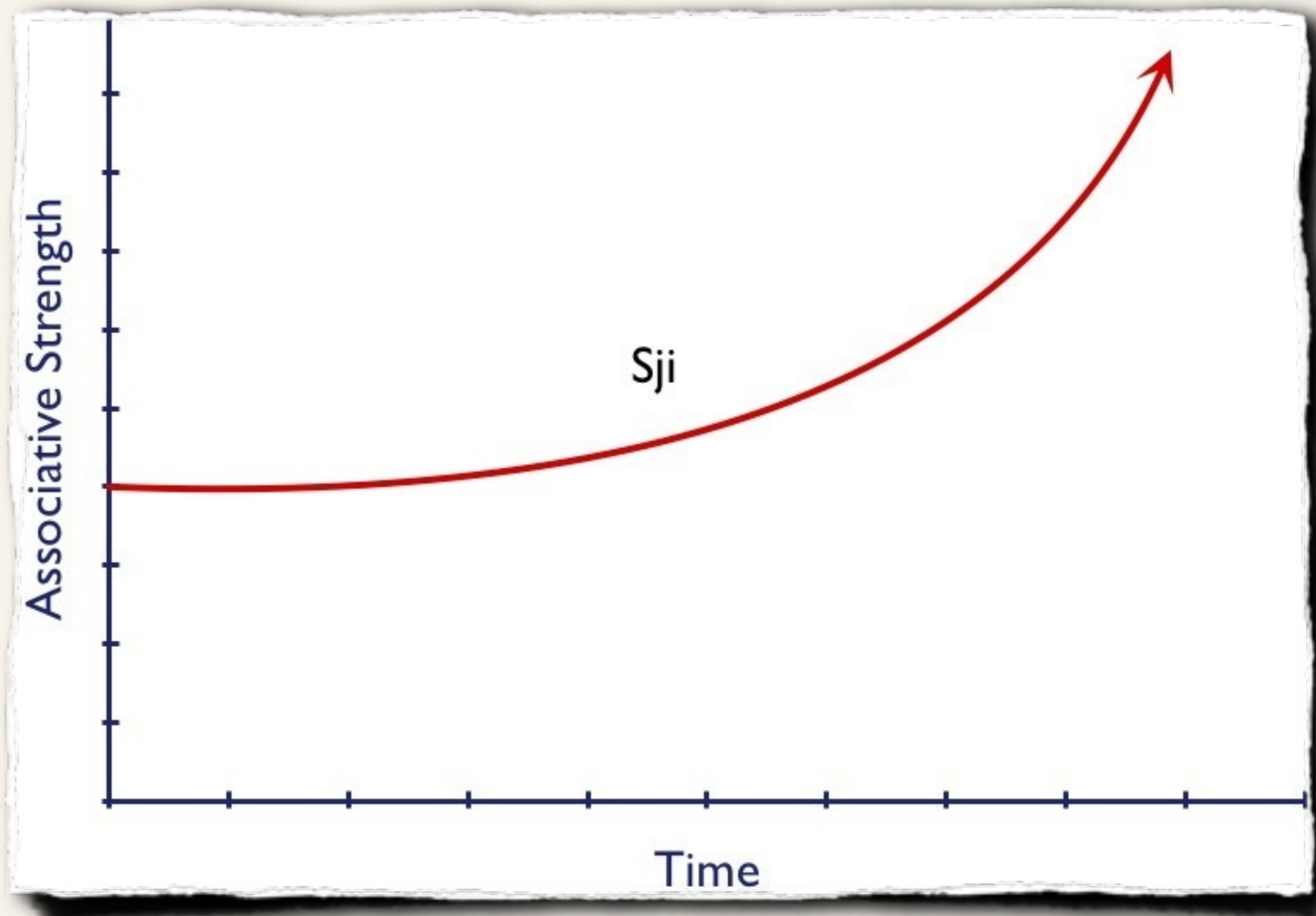
What do we need?

- Associations should be stable or decay with time
- All other things being equal



What do we need?

- Associations should be stable or decay with time
- All other things being equal
- Never **strengthen sans rehearsal**



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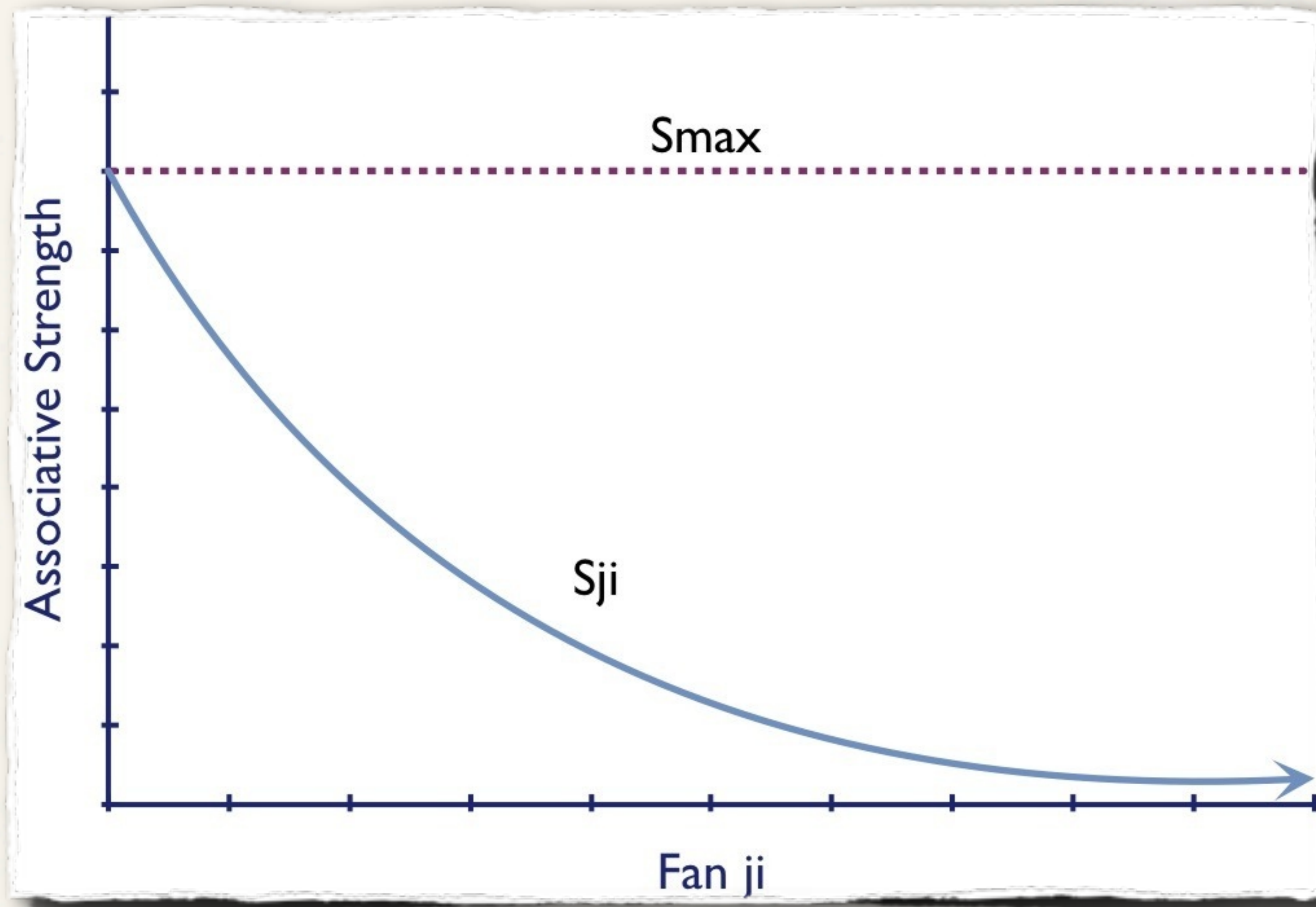
- Associations that weaken with fanji



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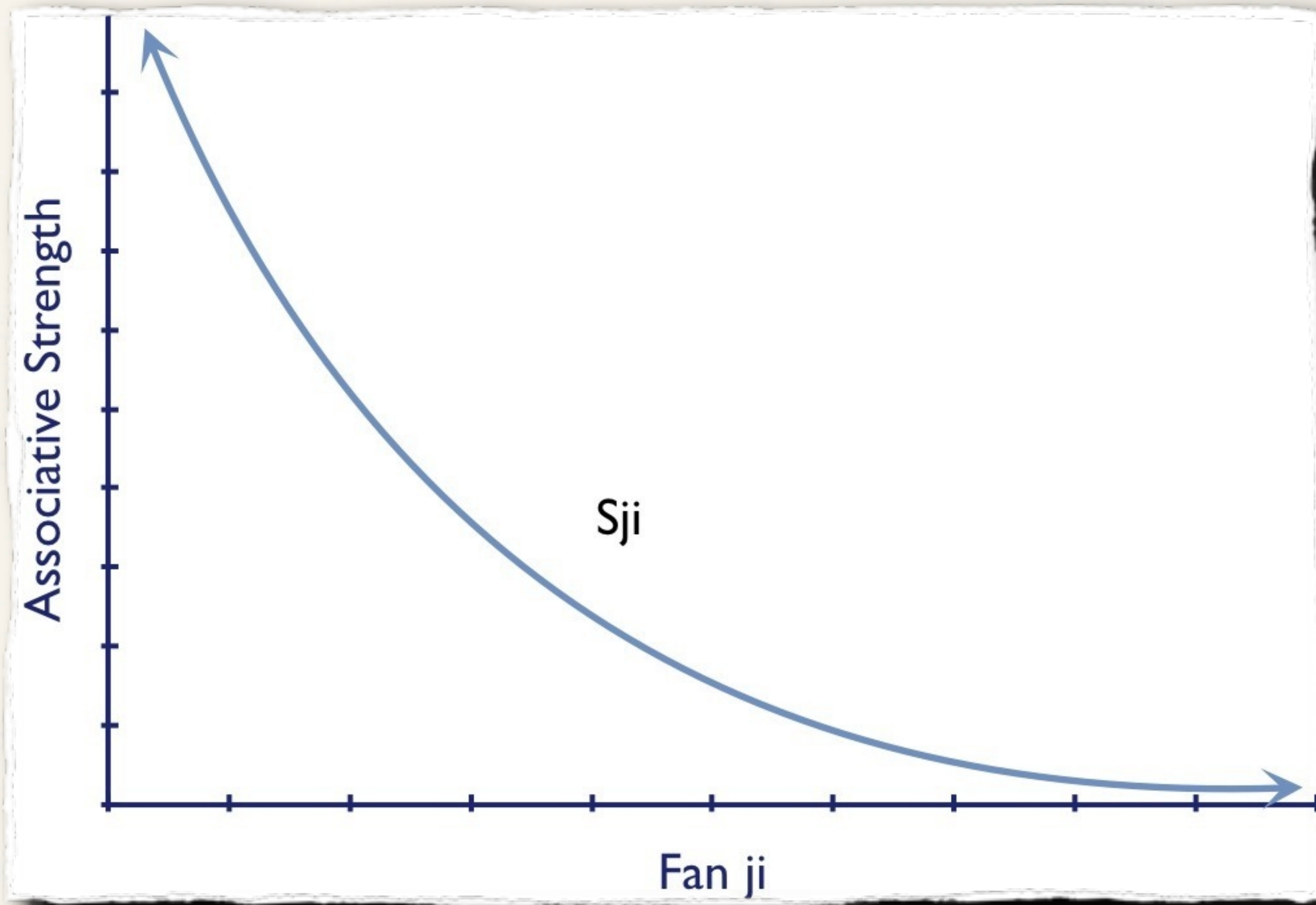
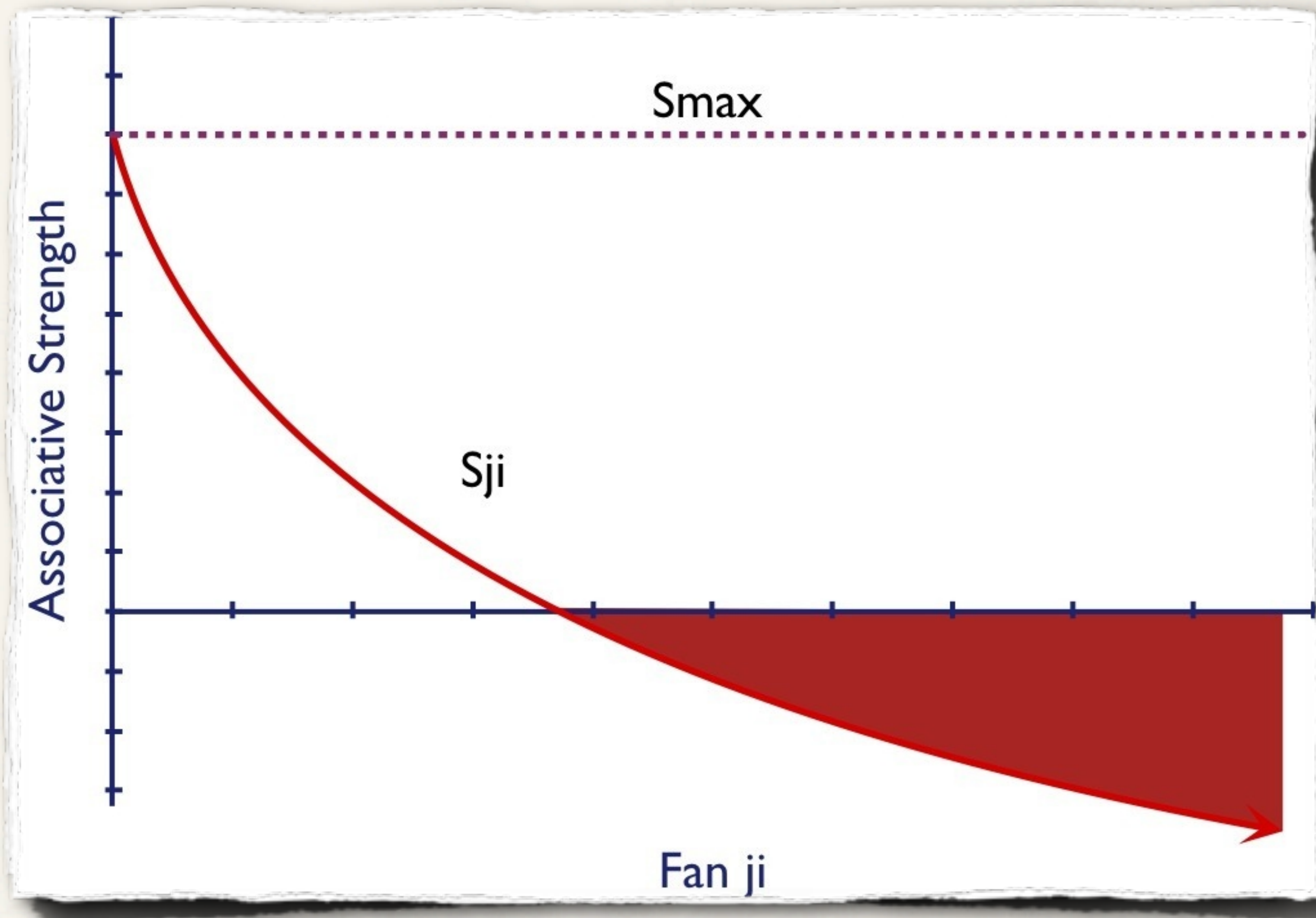


What do we need?

- Associations that weaken with fanji
- Never be **inhibitory** (unless desired)



ACT-R 6.0

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$$\frac{P(N_i|C)}{P(\bar{N}_i|C)} = \frac{P(N_i)}{P(\bar{N}_i)} \prod_j \frac{P(C_j|N_i)}{P(C_j|\bar{N}_i)}$$

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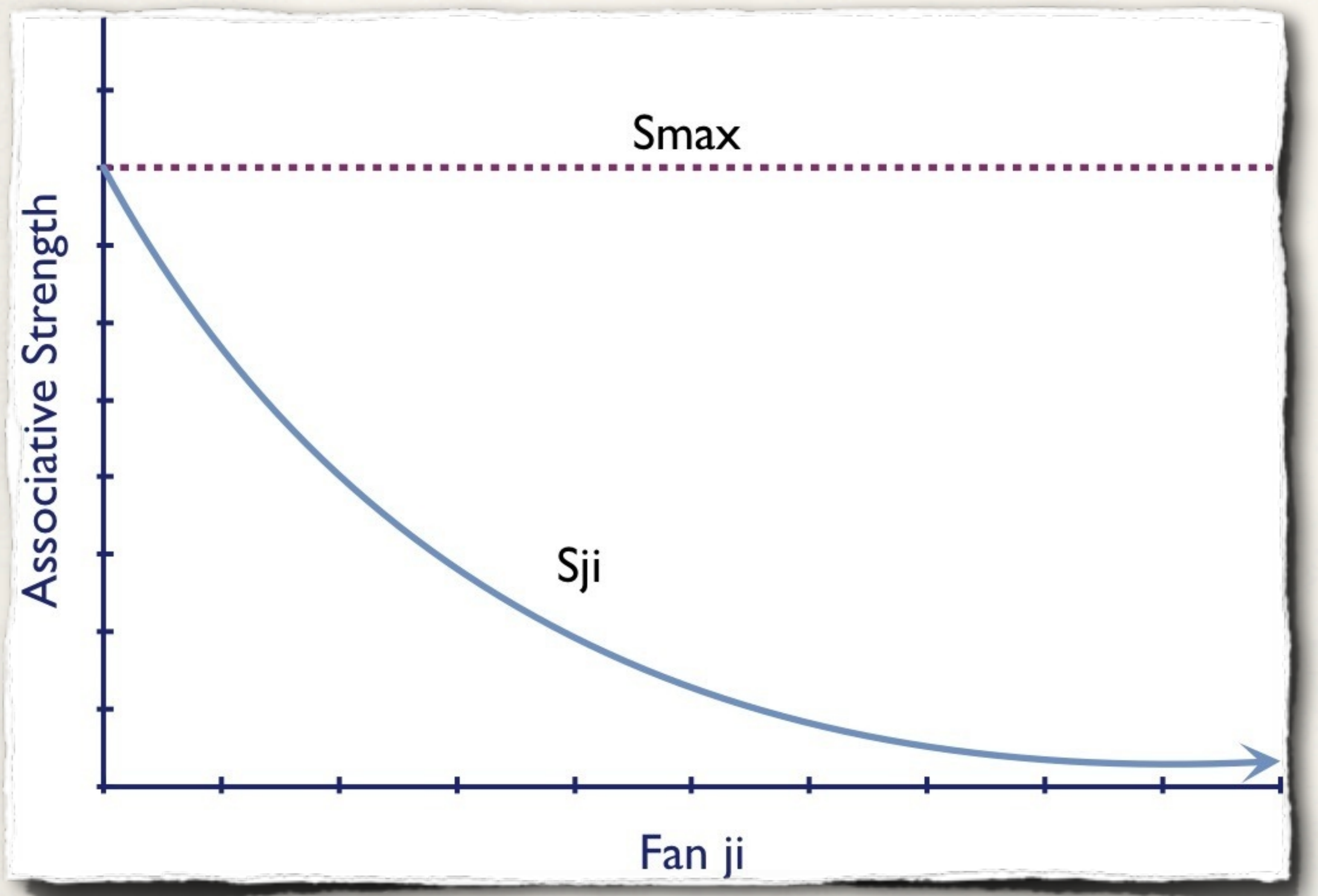

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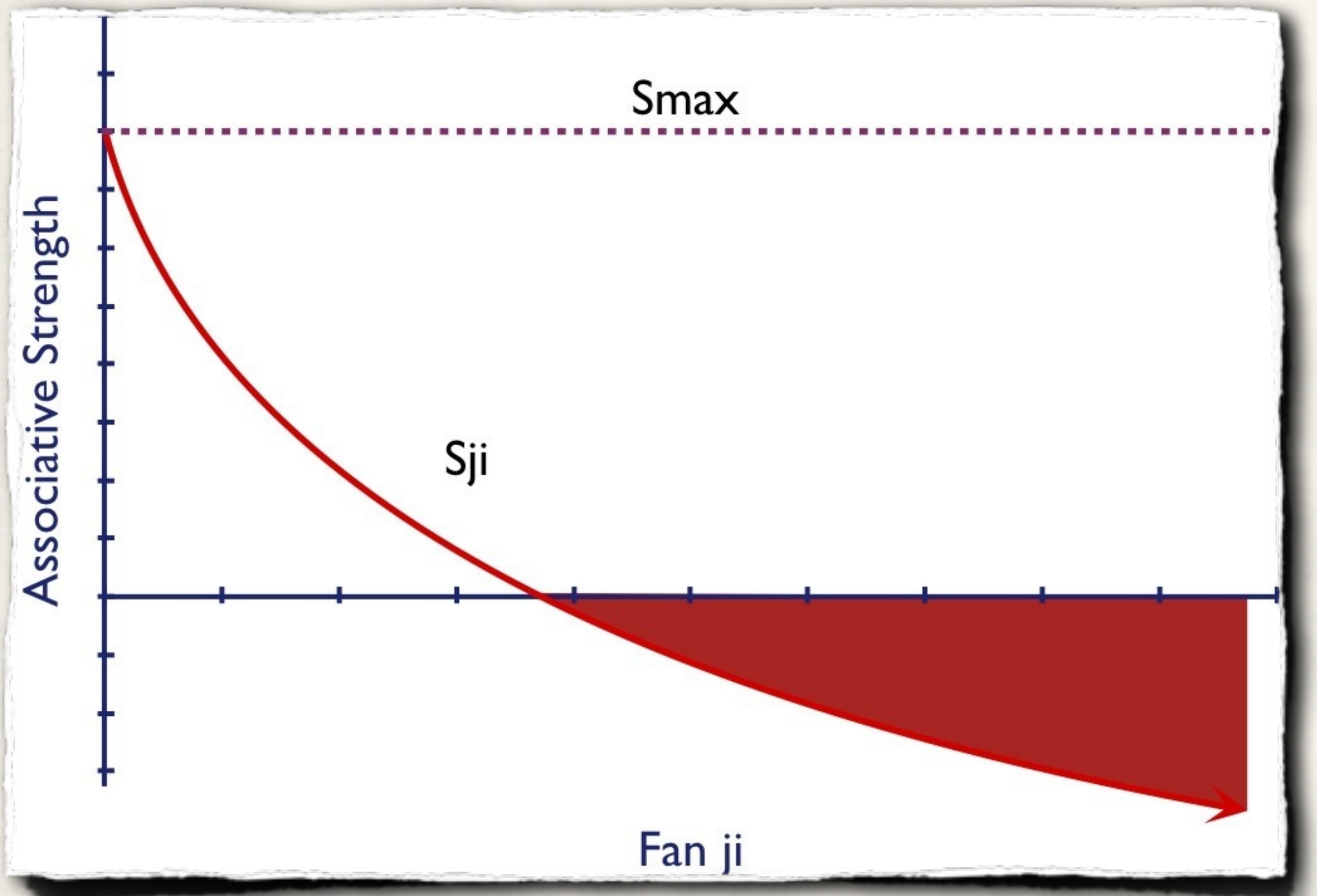
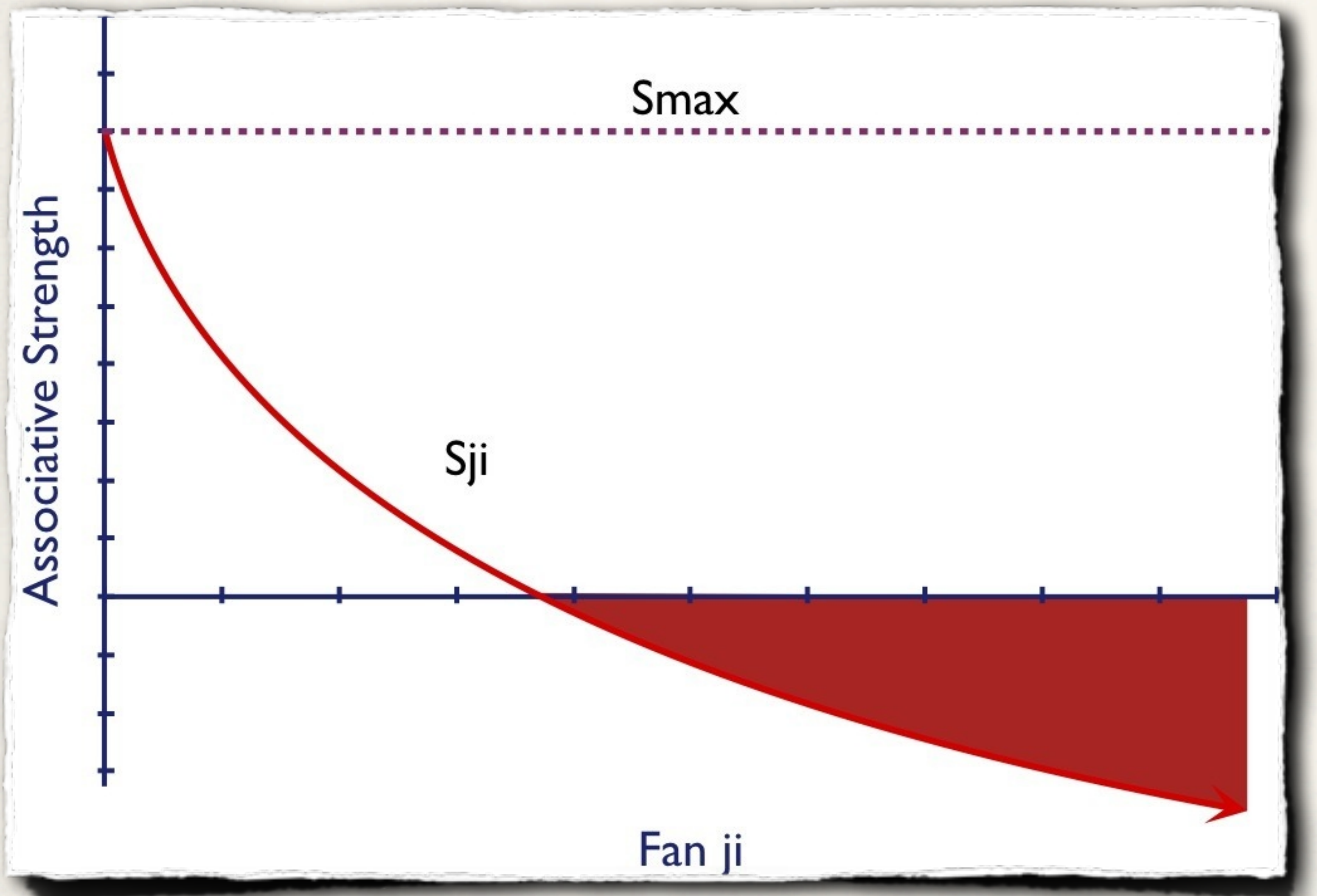


- Fanji growth is unbounded

ACT-R 6.0



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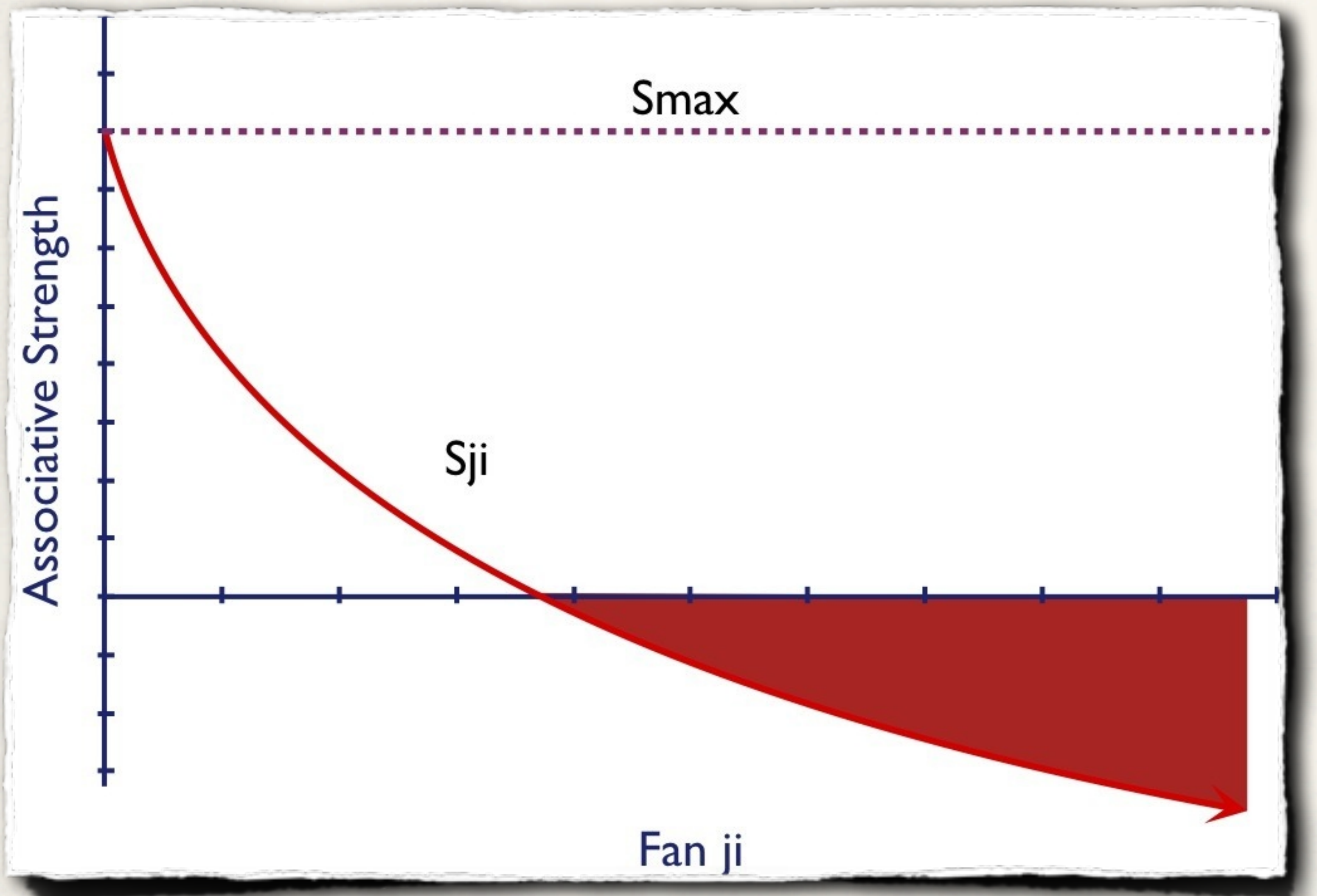

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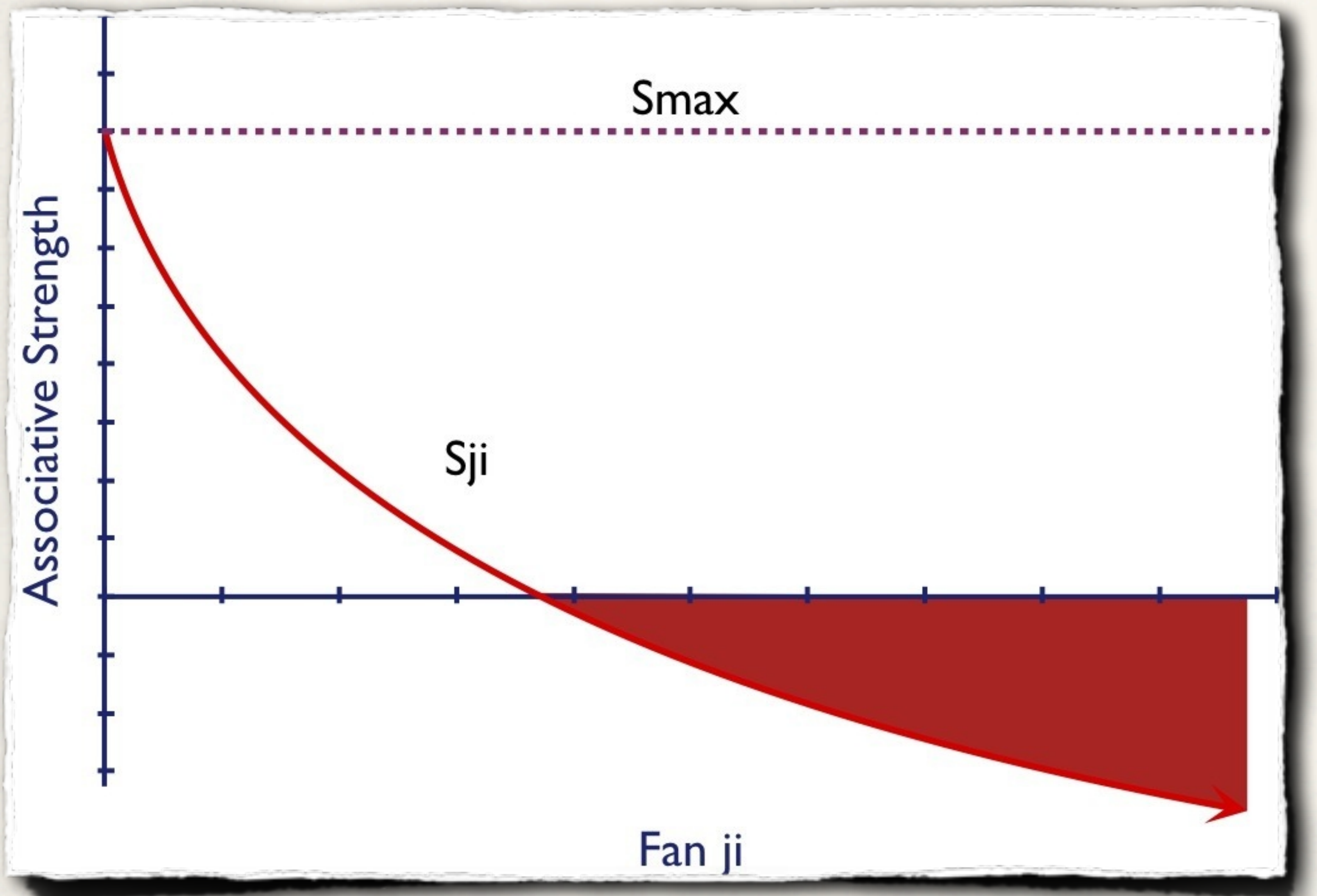
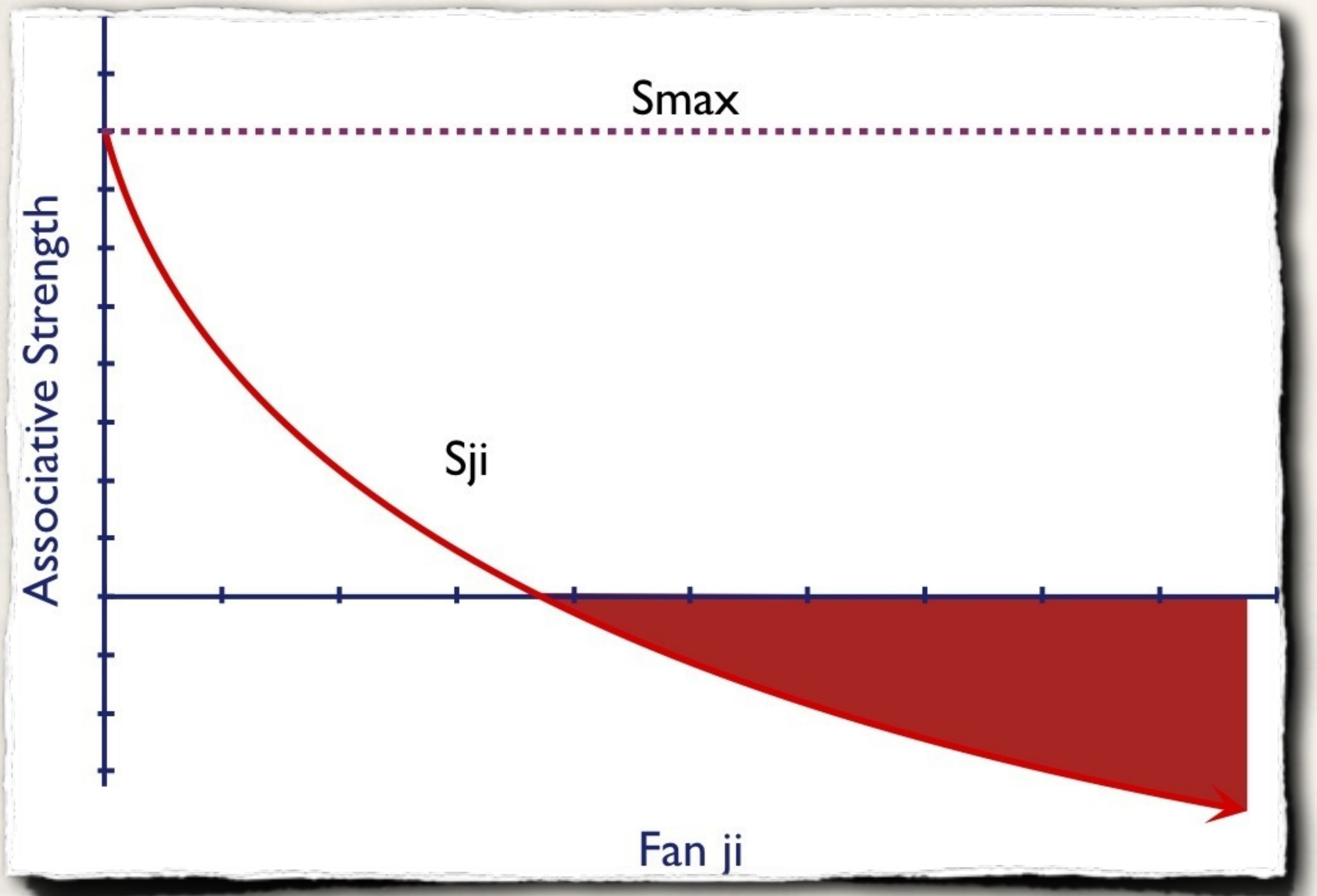
ACT-R 6.0



- Fanji growth is unbounded
- Fan can grow quite large for some chunks
  - States
  - Visual properties

ACT-R 6.0



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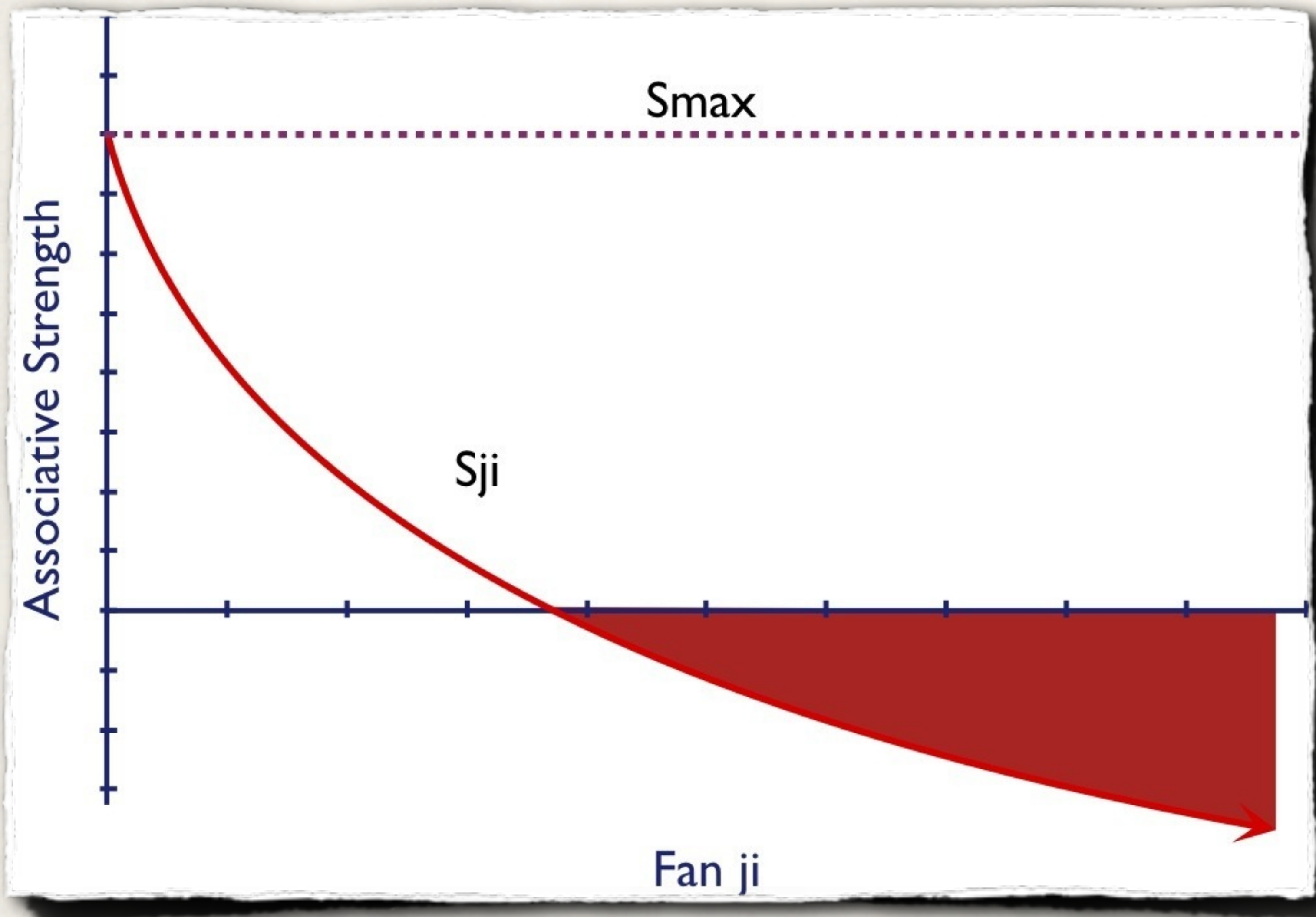

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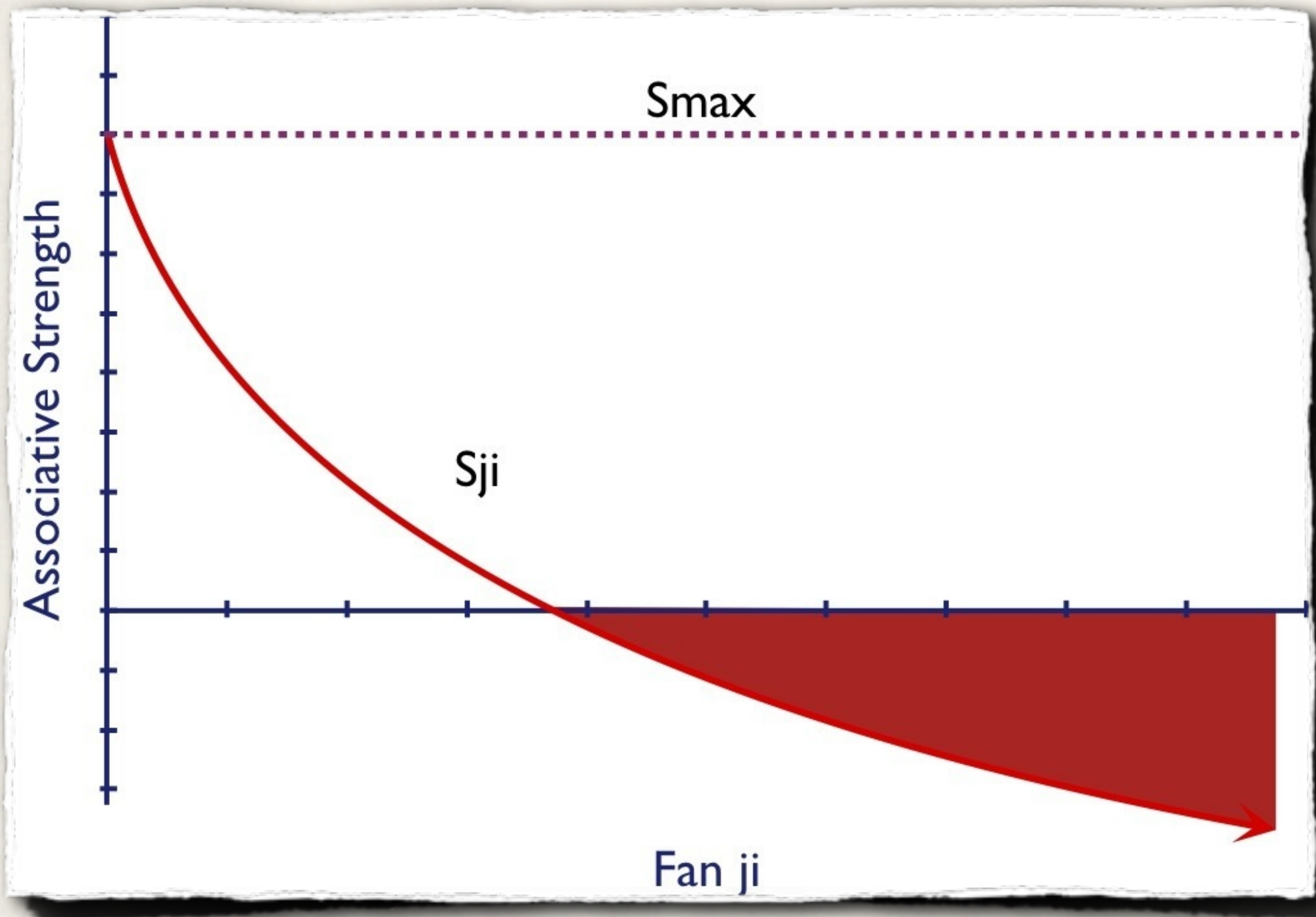

- Fanji growth is unbounded
- Fan can grow quite large for some chunks
  - States
  - Visual properties
- Sji quickly becomes inhibitory
- Can be **catastrophic**
- Smax becomes a breaking point between models

ACT-R 4

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$$\frac{P(N_i|C)}{P(\bar{N}_i|C)} = \frac{P(N_i)}{P(\bar{N}_i)} \prod_j \frac{P(C_j|N_i)}{P(C_j|\bar{N}_i)}$$

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```
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   =goal>
    isa goal
    slot1 chunkj1
    slot2 chunkj2
   =retrieval>
    isa something
```

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N*i* : Chunk *i* was *needed*
(retrieved)

```
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   slot2 chunkj2
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Needed

ACT-R 4

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N*i* : Chunk *i* was *needed* (retrieved)

C*j* : Chunk *j* in the *context* (slot value of goal)

```
(p sample
  =goal>
   isa goal
   slot1 chunkj1
   slot2 chunkj2
  =retrieval>
   isa something
```

Context — slot1 chunkj1, slot2 chunkj2

Needed — =retrieval>

ACT-R 4

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$$\frac{P(N_i)}{P(\bar{N}_i)} \prod_j \frac{P(C_j|N_i)}{P(C_j|\bar{N}_i)}$$

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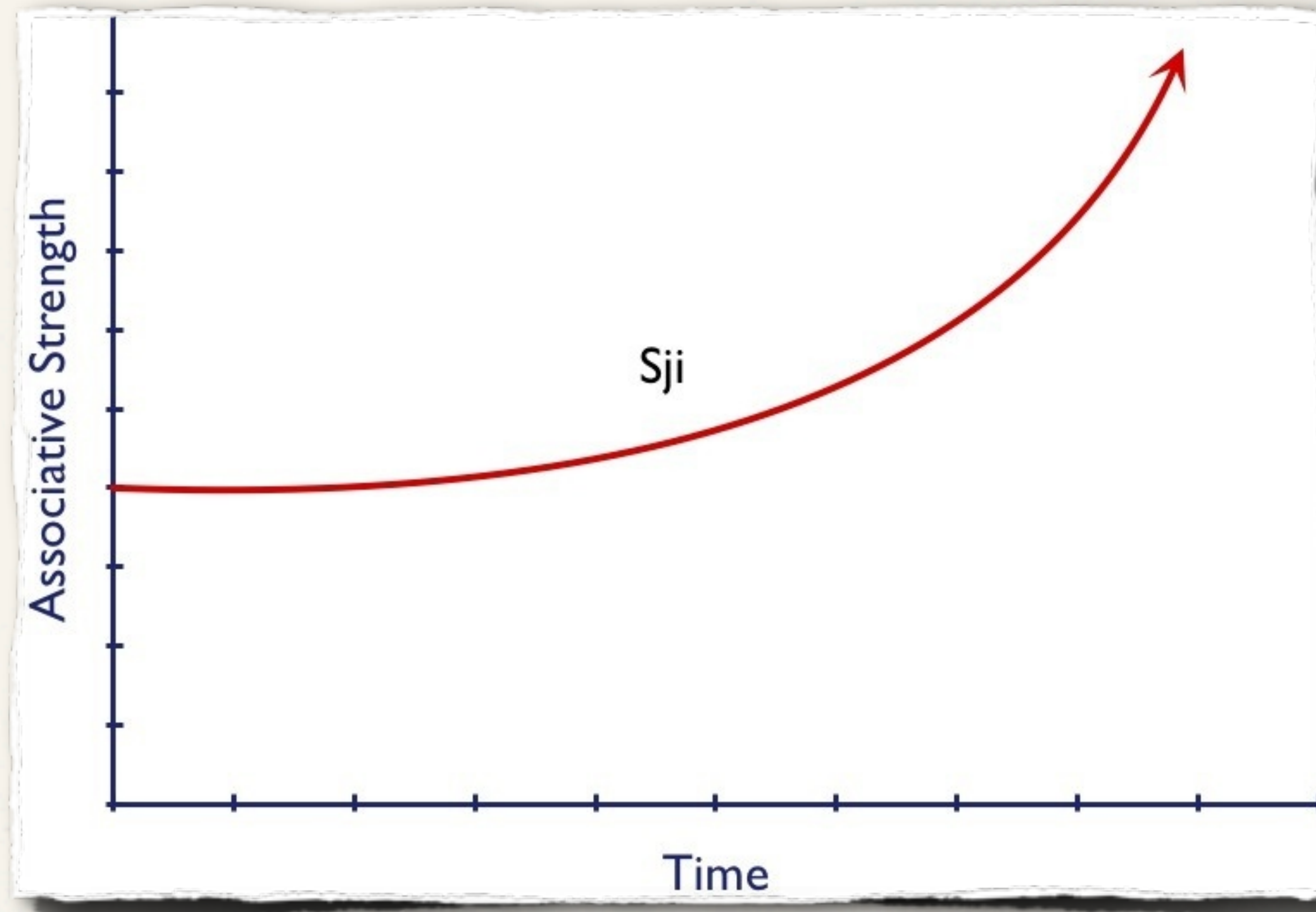

Back to the Future

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- Update 4.0 equations and mappings to match pattern 6.0

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- Associations defined by production-level co-occurrence

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  - Subsumes containment associative links

Back to the Future

- Update 4.0 equations and mappings to match pattern 6.0
- Associations defined by production-level co-occurrence
  - Subsumes containment associative links
- Have looked at associations across a single buffer (retrieval priming retrieval, ala Richard Young)

Associative Proposal

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$$\frac{P(N_i|C)}{P(\bar{N}_i|C)} = \frac{P(N_i)}{P(\bar{N}_i)} \prod_j \frac{P(C_j|N_i)}{P(C_j|\bar{N}_i)}$$

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```
(p sample
   =goal>
    isa goal
    slot1 chunkj1
    slot2 chunkj2
   =retrieval>
    isa something
    slot1 chunkj3
   =visual>
    isa visual-object
    color red
==>
```

Associative Proposal

$$\frac{P(N_i|C)}{P(\bar{N}_i|C)} = \frac{P(N_i)}{P(\bar{N}_i)} \prod_j \frac{P(C_j|N_i)}{P(C_j|\bar{N}_i)}$$

N*i* : Chunk *i* was ***needed***

(matched in **any** buffer)

Needed

Needed

Needed

```
(p sample
  =goal>
   isa goal
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   isa something
   slot1 chunkj3
  =visual>
   isa visual-object
   color red
==>
```

Associative Proposal

$$\frac{P(N_i|C)}{P(\bar{N}_i|C)} = \frac{P(N_i)}{P(\bar{N}_i)} \prod_j \frac{P(C_j|N_i)}{P(C_j|\bar{N}_i)}$$

N*i* : Chunk *i* was ***needed***
(matched in **any** buffer)

C*j* : Chunk *j* in the ***context***
(slot value of any matched chunk in **any** buffer)

```
(p sample
  =goal>             Needed
   isa goal
   slot1 chunkj1     Context
   slot2 chunkj2     Context
  =retrieval>        Needed
   isa something
   slot1 chunkj3     Context
  =visual>           Needed
   isa visual-object
   color red         Context
==>
```

Not Quite Bayesian

approx.

Not Quite Bayesian

$$\frac{P(N_i|C)}{P(\bar{N}_i|C)} = \frac{P(N_i)}{P(\bar{N}_i)} \prod_j \frac{P(C_j|N_i)}{P(C_j|\bar{N}_i)}$$

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$$\frac{P(C_j\, N_i)\, \cancel{P(\bar{N}_i)}}{P(C_j\, \bar{N}_i)\, \cancel{P(N_i)}}$$

$$\frac{F(C_j\, N_i)}{F(C_j\, \bar{N}_i)} \xrightarrow{\text{approx.}} \frac{1}{fan_{ji}}$$

Alternatives

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$$\boxed{\frac{F(C_j\,N_i)}{F(C_j)}} \qquad \boxed{\frac{F(C_j\,N_i)}{1 + F(C_j\,\bar{N}_i)}}$$

[0-1]

Alternatives

[0-1]

$$\frac{F(C_j\ N_i)}{F(C_j)}$$

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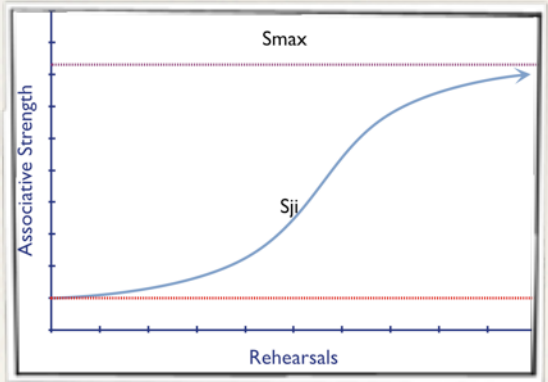

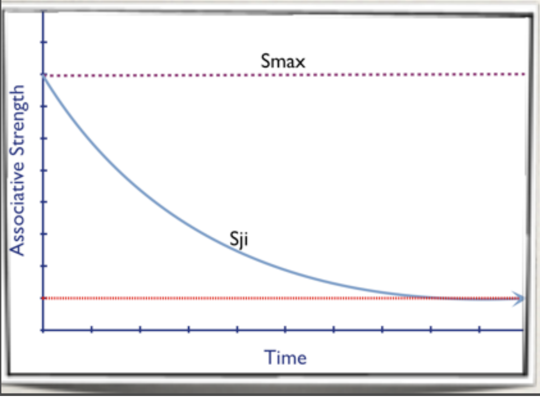

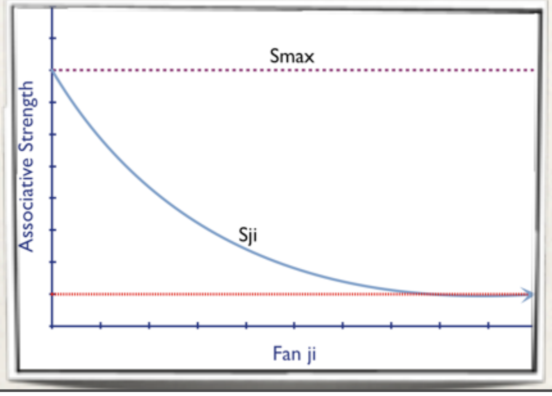

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[0-Infinity]

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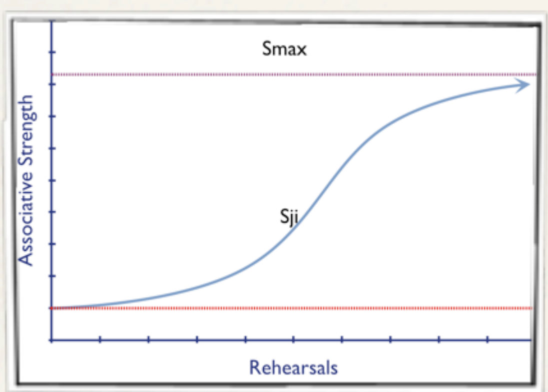

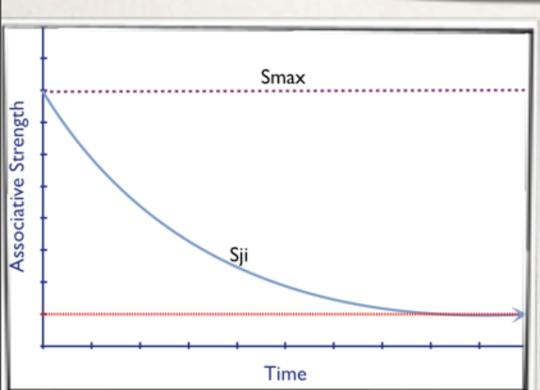

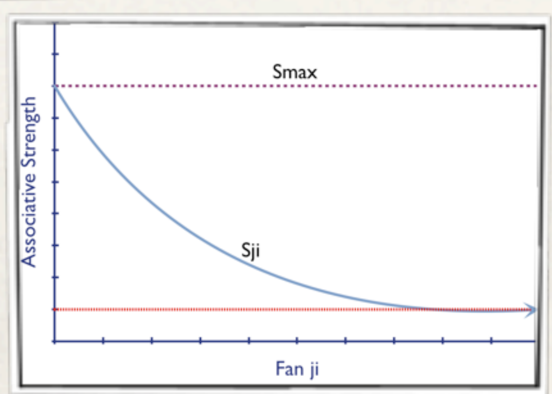

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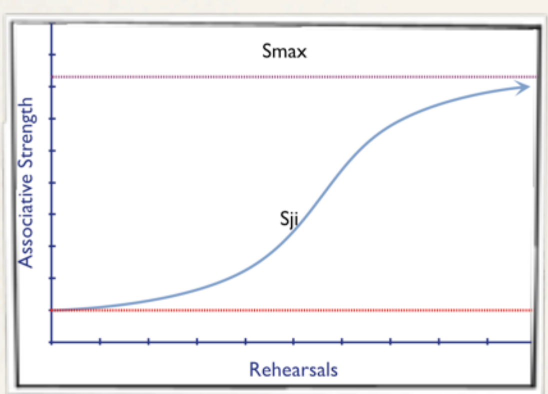

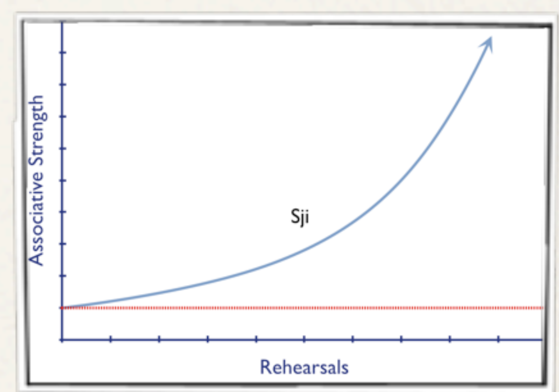

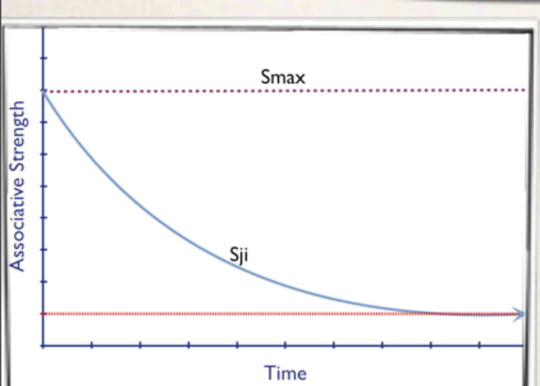

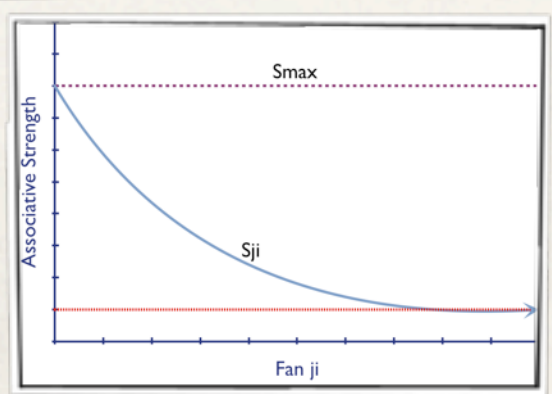

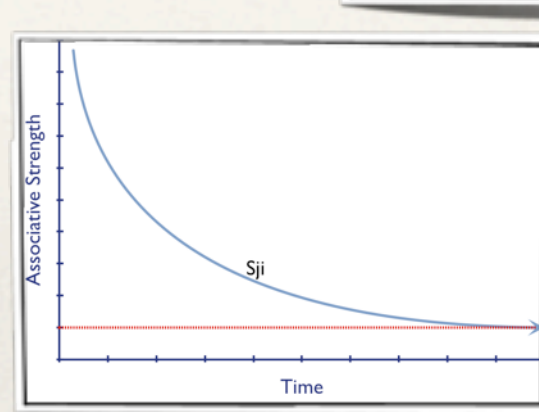

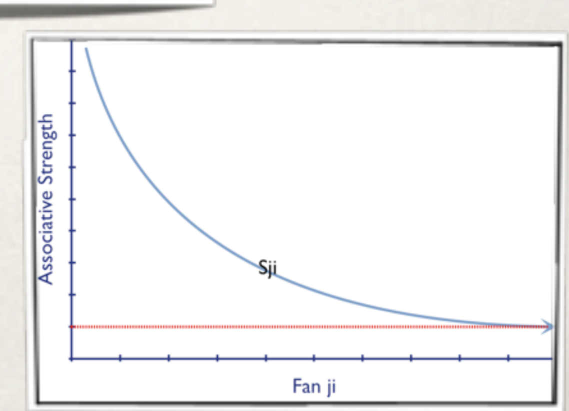

Model Fit

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  - Latency R2=0.94, RMSE=5.6ms

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- Full model
  - Perception/Action
  - Study-phase

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Questions?

Insights?

Ideas?