# While you are waiting...

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# Simulating Language
# Lecture 6: Learning bias

Kenny Smith

kenny.smith@ed.ac.uk

# Summary - from evolution to learning

- A big difference between animal signalling and human language
  - Animals typically are born with the relationship between meanings and signals given innately in their genes (as a first approximation)
  - Humans *acquire* this relationship during development

- In our model, the relationship between meanings and signals is represented by connection weights in a network
  - Our animal model has these fixed in each agent, with the possibility of biological evolution
  - Our human model is born with all weights set to zero, with the possibility of changing them in response to hearing utterances (i.e. learning)

# How good is our model at learning?

- What does it mean for something to be ‘good’ at learning?
  - One answer: will two agents given the same data be able to **communicate**? Will a learner be able to communicate with its teacher?
  - Another answer: given some training data, can it **recall** that data?
  - A third answer: given some training data, can it **generalise** correctly to unseen data?

- **Which of these do you think is the most important sense of ‘good at learning’ for human language?**
- **A:** Communication

  **B:** Recall

  **C:** Generalisation

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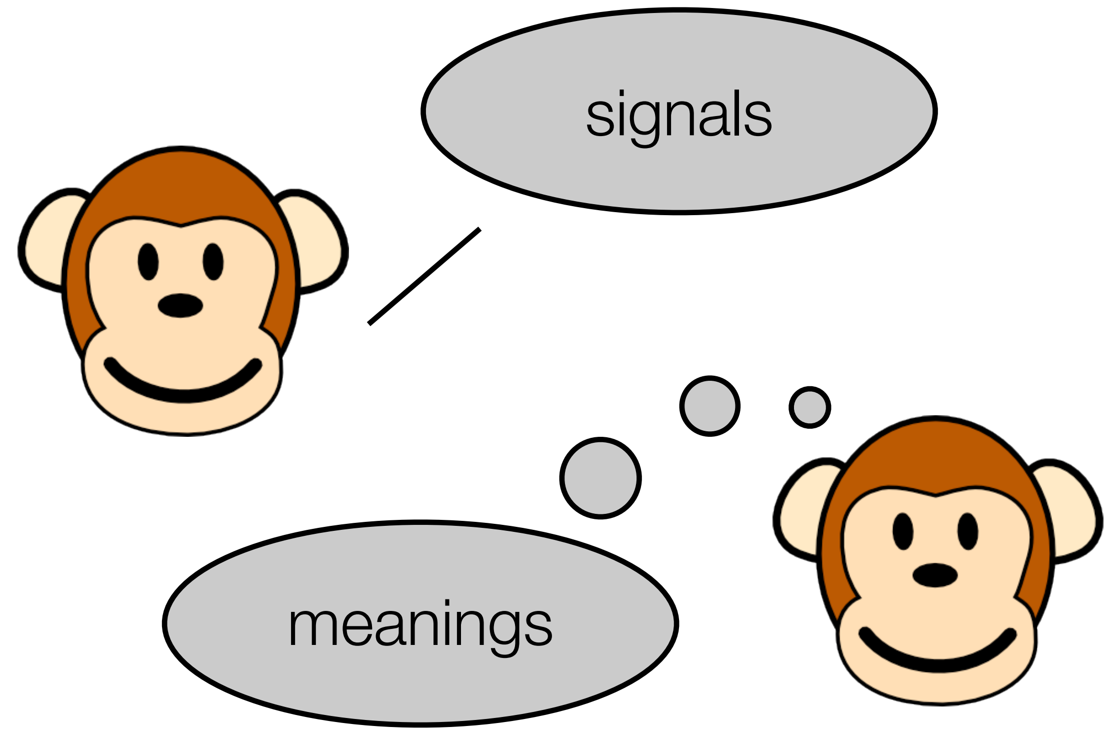
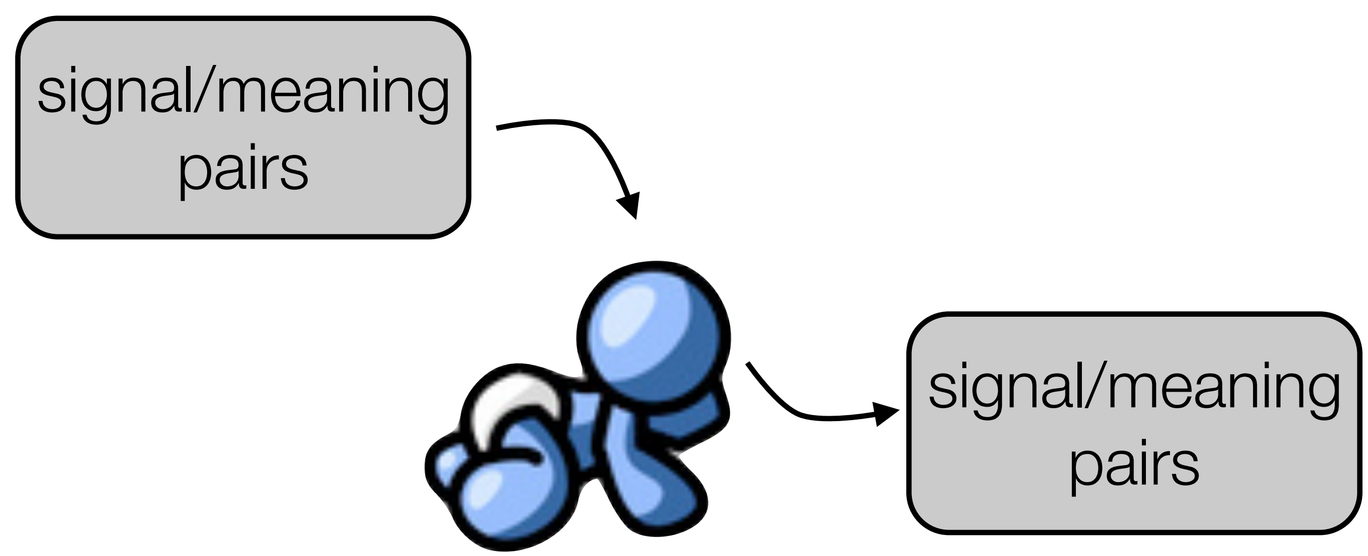
  - Another answer: given some training data, can it **recall** that data?
  - A third answer: given some training data, can it **generalise** correctly to unseen data?
- Our training data is meaning-signal pairs, so an obvious test is whether meanings correctly map to signals (and vice versa) after learning
- So, some kinds of learner will be good at learning, and others will be bad, right?
- Not as simple as that... **it will depend on what is being learned**

# A new kind of question

- Previously, we were interested in how good two innate signalling systems were for communication




- Now, we want to know what kinds of errors a particular learner makes with a particular language



# An aside: how to do this with our code

- Use **train** to train a particular network with a set of data. e.g.:

```
>>> net = [[0, 0, 0], [0, 0, 0], [0, 0, 0]]
>>> train(net, [[0, 0], [1, 1], [2, 1]])
>>> net
[[1, 0, 0], [0, 1, 0], [0, 1, 0]]
```

- Then you can test what the resulting network's reception/production behaviour is using **wta** in combination with **production_weights** and **reception_weights**. e.g.:

```
>>> wta(production_weights(net, 0))
0
>>> wta(production_weights(net, 2))
1
>>> wta(reception_weights(net, 2))
0
```

# What about our learner?

- How well does it learn?
- Given an optimal language, it learns well:

TRAINING

m1→s1
m2→s2
m3→s3

| | s1 | s2 | s3 |
|---|---|---|---|
| m1 | 0 | 0 | 0 |
| m2 | 0 | 0 | 0 |
| m3 | 0 | 0 | 0 |

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| | s1 | s2 | s3 |
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| m1 | 1 | 0 | 0 |
| m2 | 0 | 1 | 0 |
| m3 | 0 | 0 | 1 |

RESULT

m1 → s1
m2 → s2
m3 → s3

# What about our learner?

- How well does it learn?
- Given a language with synonymy?

**A:** s1 only

**B:** s2 only

**C:** s1 and s2, in a 1:2 ratio

**D:** s1 and s2, with equal frequency

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TRAINING

m1→s1
m1→s2
m1→s2

| | s1 | s2 | s3 |
|---|---|---|---|
| m1 | 0 | 0 | 0 |
| m2 | 0 | 0 | 0 |
| m3 | 0 | 0 | 0 |

# What about our learner?

- How well does it learn?
- Given a language with synonymy, production behaviour depends on frequency of items in training:

TRAINING

m1→s1
m1→s2
m1→s2

| | s1 | s2 | s3 |
|---|---|---|---|
| m1 | 1 | 2 | 0 |
| m2 | 0 | 0 | 0 |
| m3 | 0 | 0 | 0 |

RESULT

m1→s2 only

# What about our learner?

- How well does it **generalise**?
- Unable to correctly generalise an optimal language:

TRAINING

m1→s1
m2→s2
~~m3→s3~~

| | s1 | s2 | s3 |
|---|---|---|---|
| m1 | 1 | 0 | 0 |
| m2 | 0 | 1 | 0 |
| m3 | 0 | 0 | 0 |

RESULT

# What about our learner?

- How well does it **generalise**?
- Unable to correctly generalise an optimal language:

TRAINING

m1→s1
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| | s1 | s2 | s3 |
|---|---|---|---|
| m1 | 1 | 0 | 0 |
| m2 | 0 | 1 | 0 |
| m3 | 0 | 0 | 0 |

RESULT

m1→s1
m2→s2
m3→s1, s2, s3

# What about our learner?

- How well does it **generalise**?
- Unable to correctly generalise to a maximally ambiguous language:

TRAINING

m1→s1
m2→s1
~~m3→s1~~

| | s1 | s2 | s3 |
|---|---|---|---|
| m1 | 1 | 0 | 0 |
| m2 | 1 | 0 | 0 |
| m3 | 0 | 0 | 0 |

RESULT

m1→s1
m2→s1
m3→s1, s2, s3

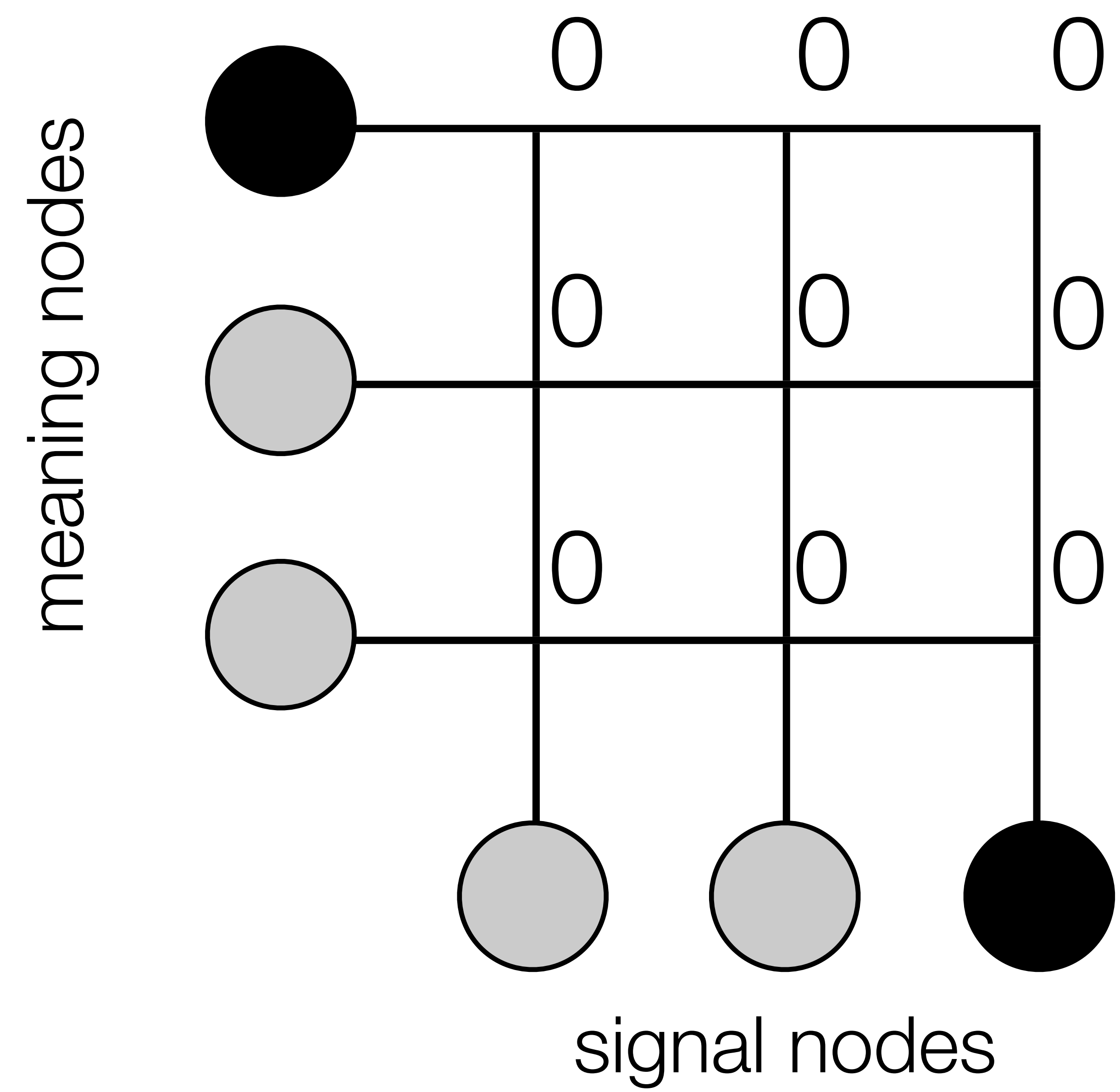
# Bias

- Our learner is not a completely “blank slate”. It responds differently to different training sets
    - In this case: it struggles with synonyms, but is otherwise faithful to its data (to the extent that it misses ‘obvious’ generalisations)
- Where does this behaviour come from?
- Features of the architecture of the model create an inherent *learning bias* which may favour some languages over others
    - Cf. Christiansen & Devlin (1997): a very different kind of neural network making the same point: learning bias means some languages are more learnable than others
- What features could we modify to manipulate bias?
- One possibility: the way we update the weights...

# Our weight-update rule

- If signal node and meaning node are active, increase connection weight by one

Observation:
m1↔s3



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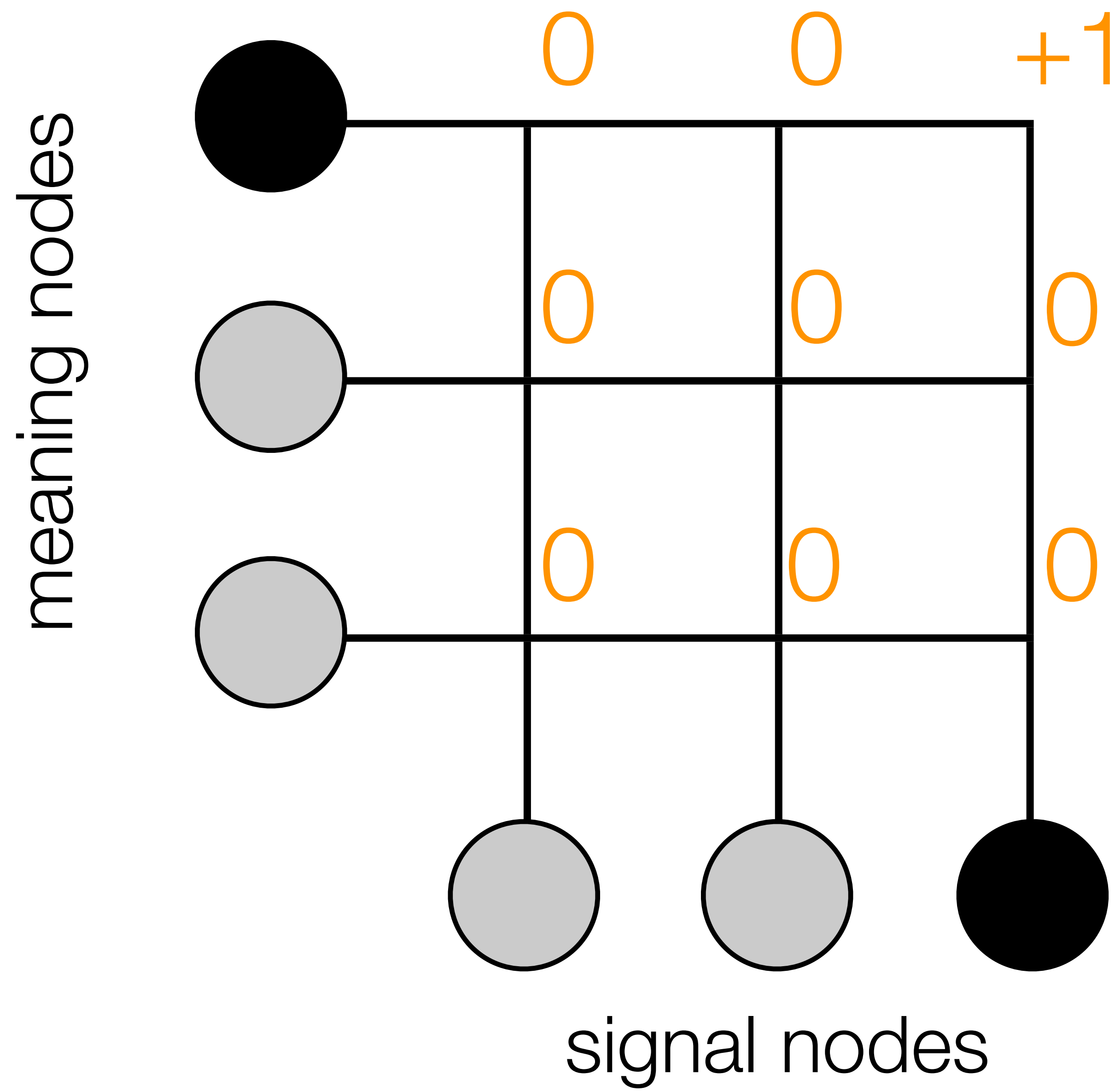

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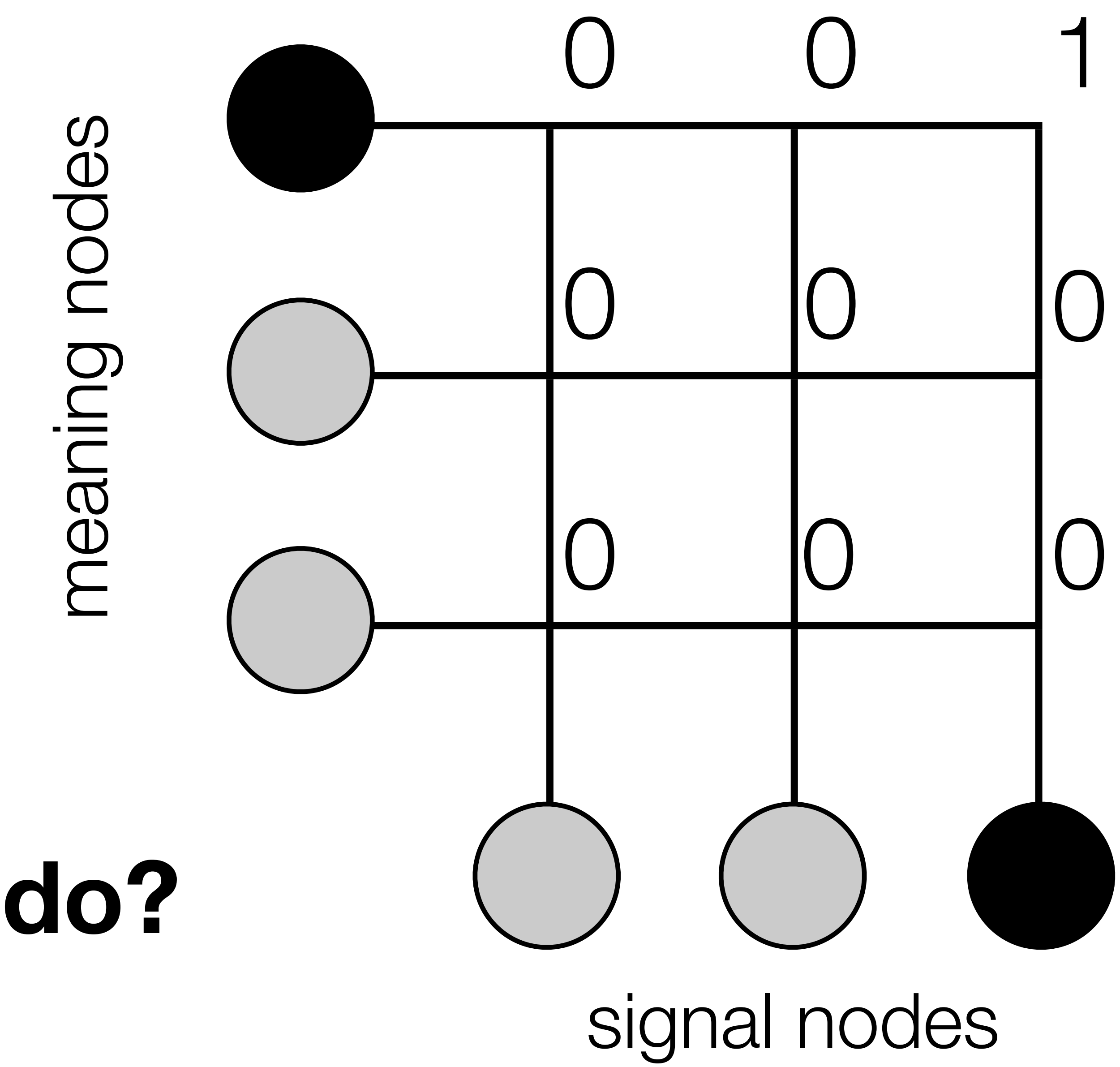
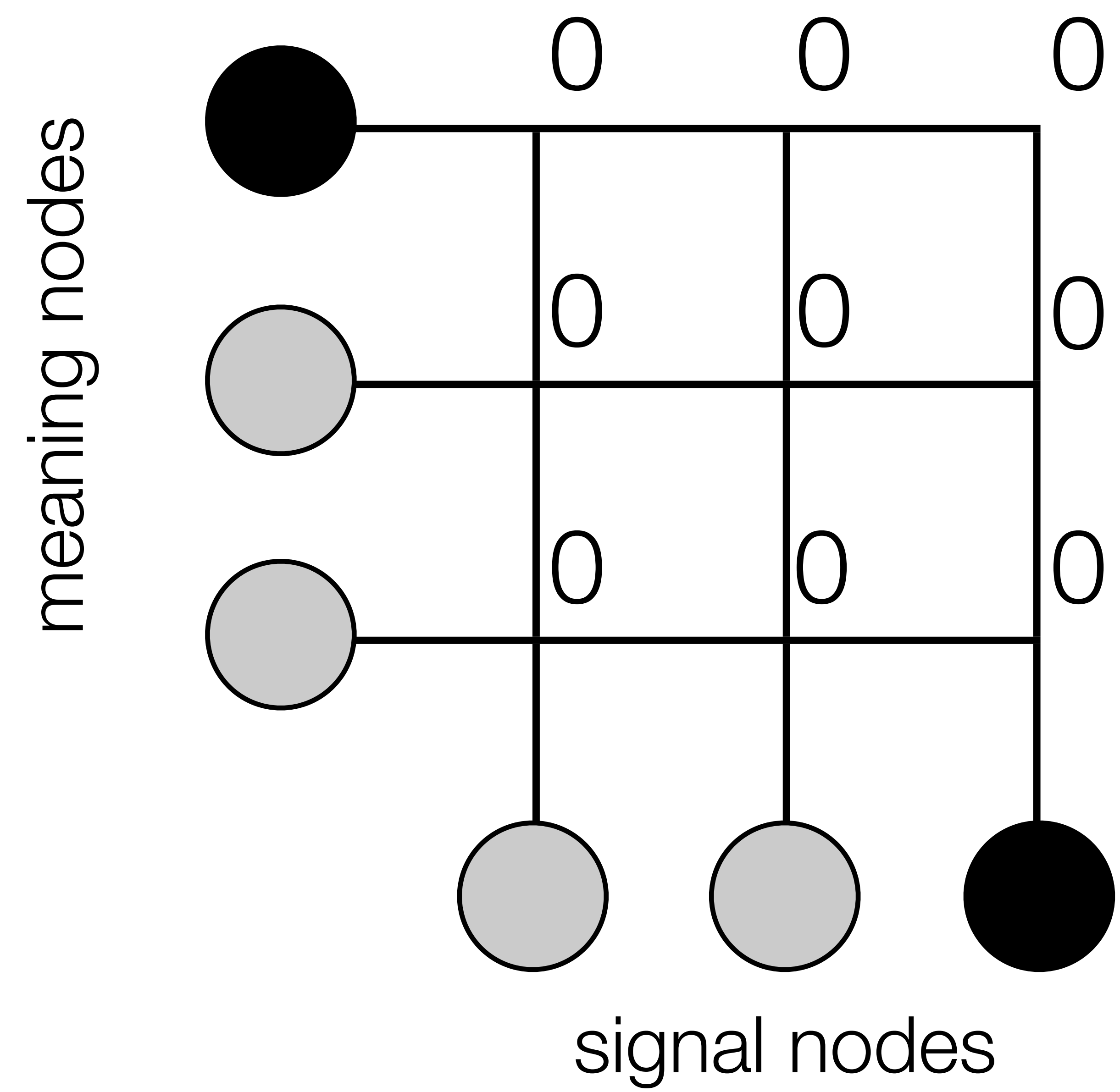



**What else could we do?**

# There are other possibilities

- Some of you wondered if it was possible to *reduce* connection weights between nodes that were 'competing' for the same meaning or signal

Observation:
m1↔s3



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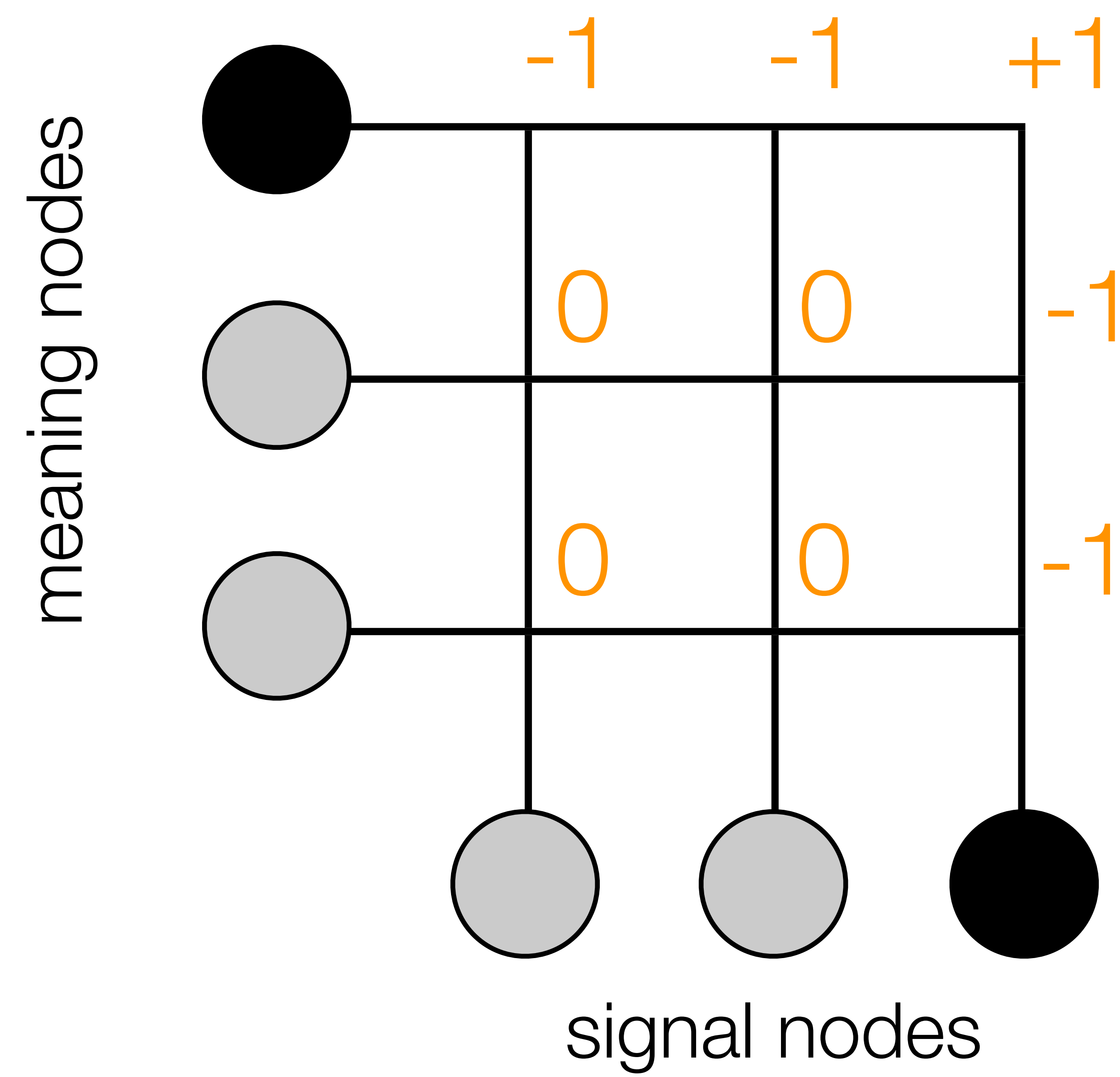

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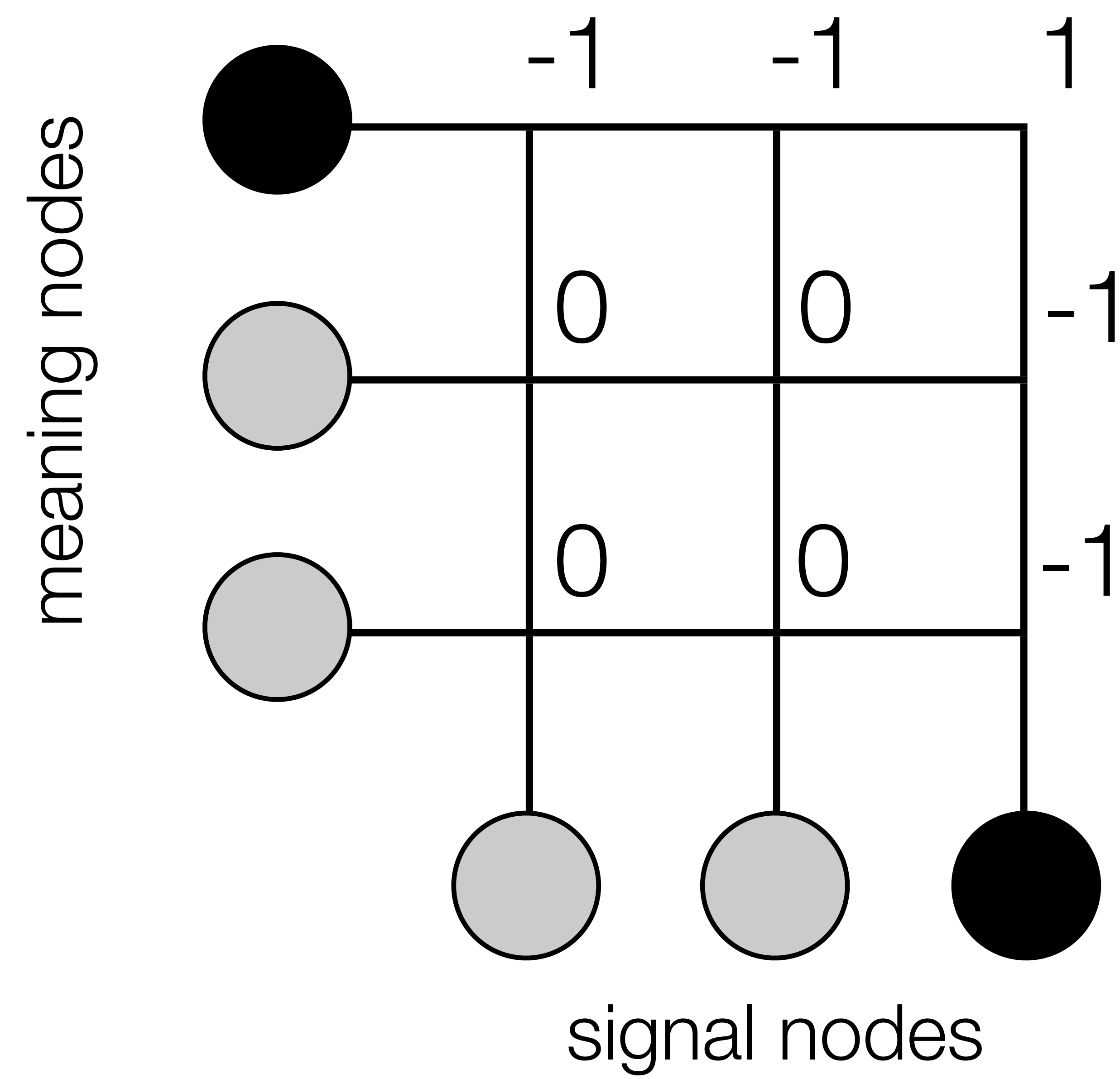

# There are other possibilities

- Maybe we should reduce connection weights between nodes that were simultaneously inactive

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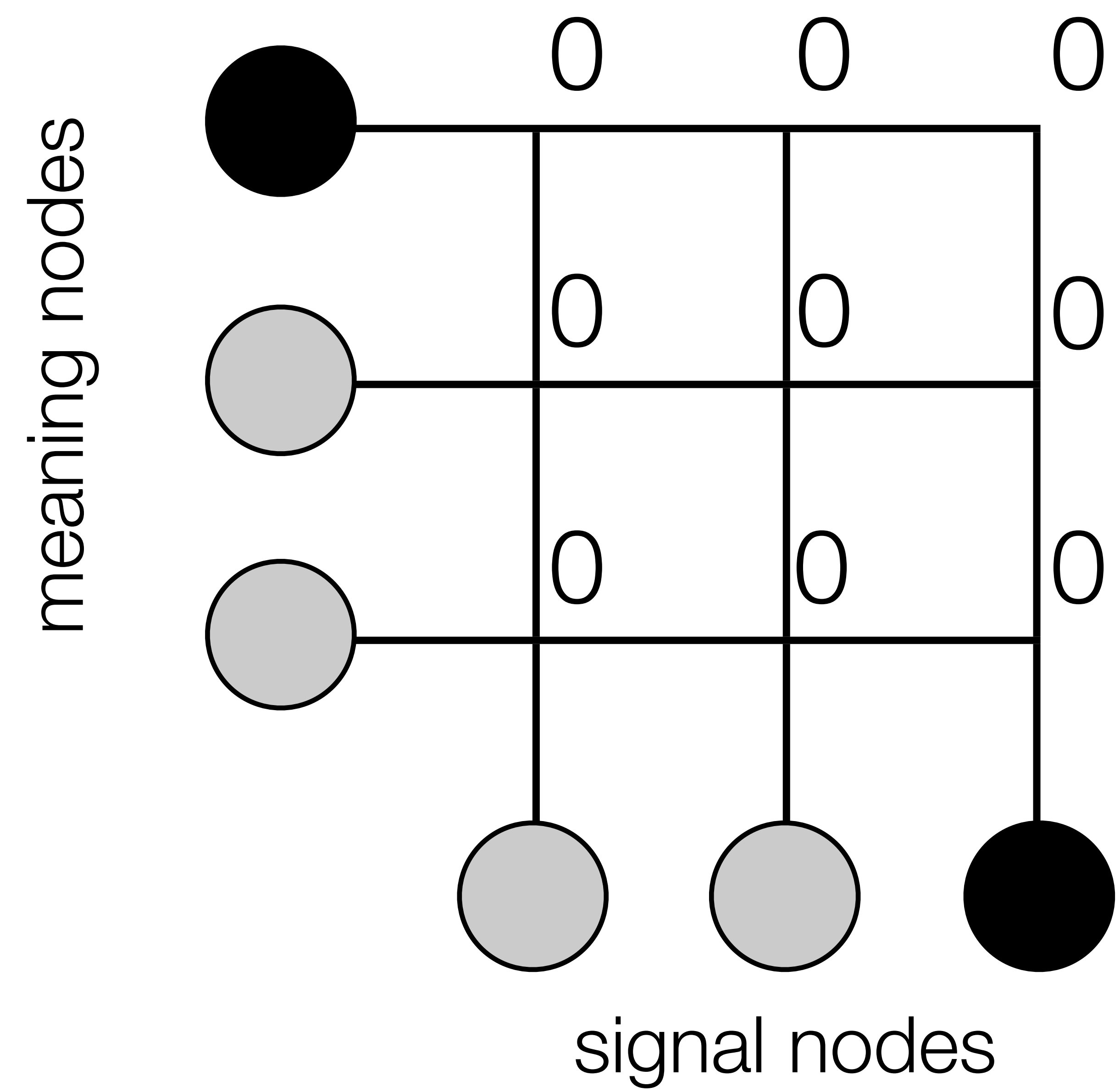

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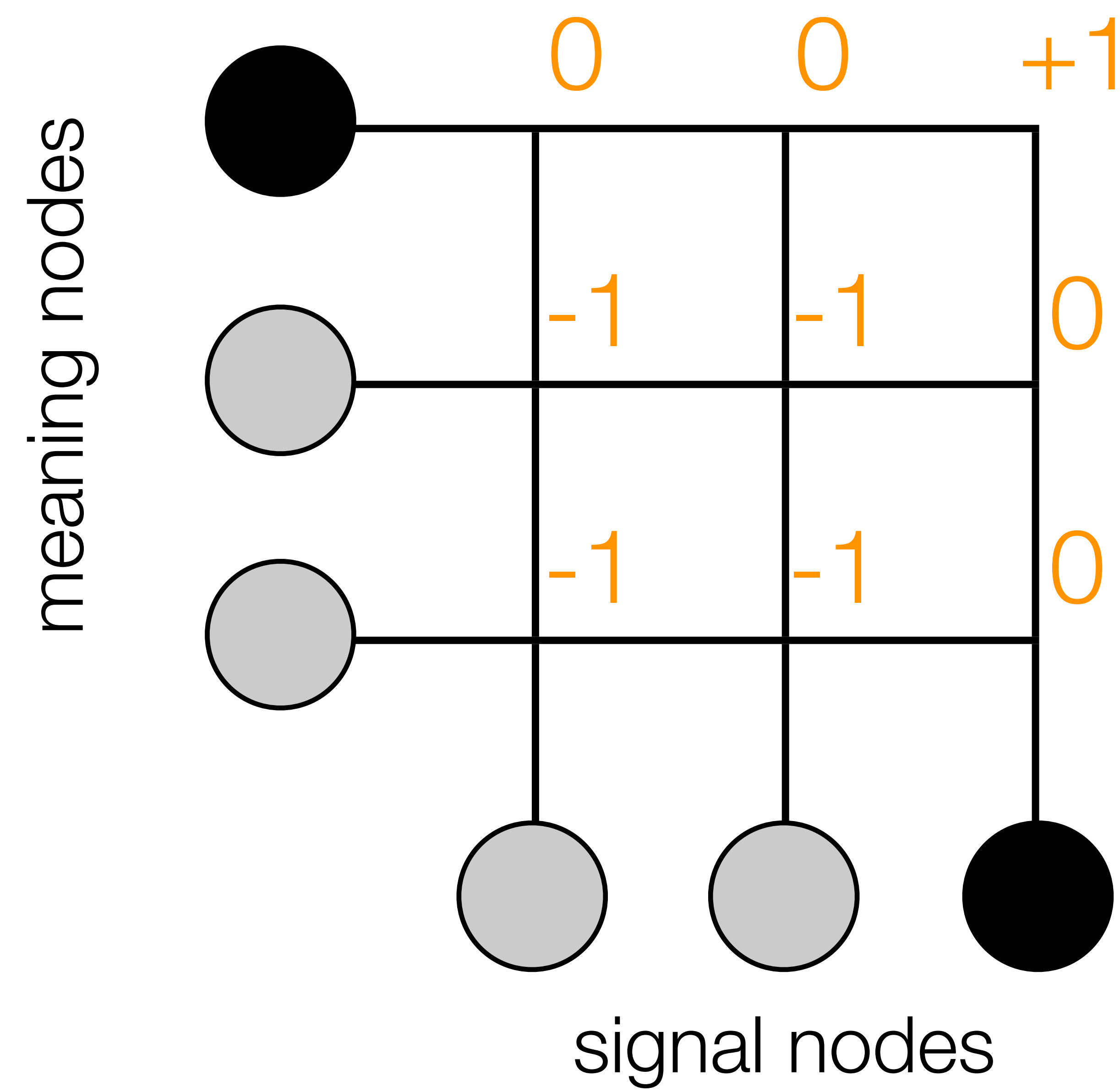

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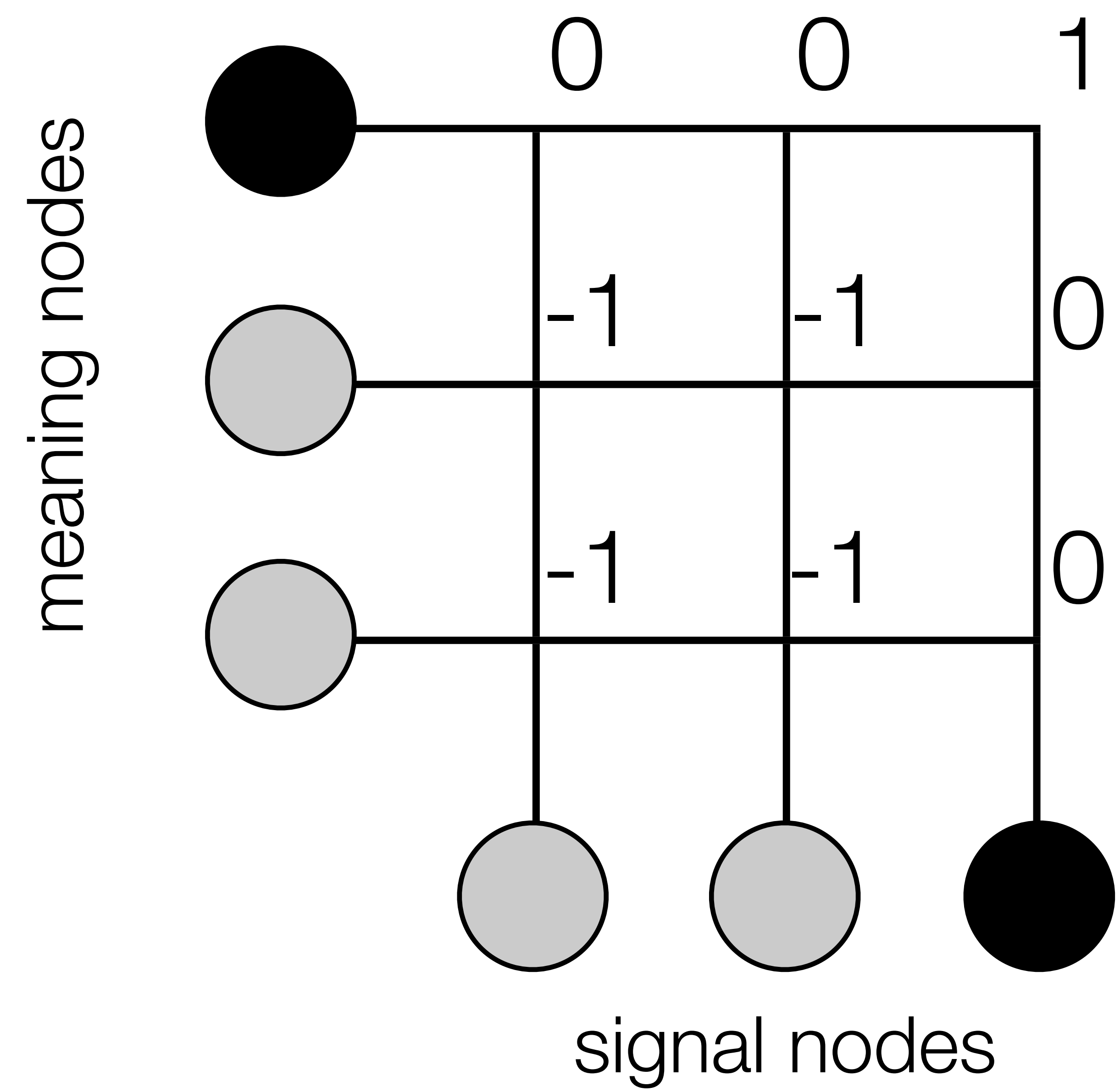

# A set of possible *weight update rules*

- We need to specify what will happen to a weight in four different situations:

$\Delta w_{m_i s_j} =$ **?** if both $m_i$ and $s_j$ are active
$\Delta w_{m_i s_j} =$ **?** if $m_i$ is active and $s_j$ is inactive
$\Delta w_{m_i s_j} =$ **?** if $m_i$ is inactive and $s_j$ is active
$\Delta w_{m_i s_j} =$ **?** if both $m_i$ and $s_j$ are inactive

# A set of possible *weight update rules*

- We need to specify what will happen to a weight in four different situations:

$\Delta w_{m_i s_j}$ = **+1** if both $m_i$ and $s_j$ are active
$\Delta w_{m_i s_j}$ = **0** if $m_i$ is active and $s_j$ is inactive
$\Delta w_{m_i s_j}$ = **0** if $m_i$ is inactive and $s_j$ is active
$\Delta w_{m_i s_j}$ = **0** if both $m_i$ and $s_j$ are inactive

Our rule

# A set of possible *weight update rules*

- We need to specify what will happen to a weight in four different situations:

$\Delta w_{m_i s_j}$ = **+1** if both $m_i$ and $s_j$ are active
$\Delta w_{m_i s_j}$ = **-1** if $m_i$ is active and $s_j$ is inactive
$\Delta w_{m_i s_j}$ = **-1** if $m_i$ is inactive and $s_j$ is active
$\Delta w_{m_i s_j}$ = **0** if both $m_i$ and $s_j$ are inactive

Another rule

# A set of possible *weight update rules*

- We need to specify what will happen to a weight in four different situations:

$\Delta w_{m_i s_j}$ = **+1** if both $m_i$ and $s_j$ are active

$\Delta w_{m_i s_j}$ = **0** if $m_i$ is active and $s_j$ is inactive

$\Delta w_{m_i s_j}$ = **0** if $m_i$ is inactive and $s_j$ is active

$\Delta w_{m_i s_j}$ = **-1** if both $m_i$ and $s_j$ are inactive

Yet another rule

# A set of possible *weight update rules*

- We need to specify what will happen to a weight in four different situations:

$\Delta w_{m_i s_j}$ = **α** if both $m_i$ and $s_j$ are active
$\Delta w_{m_i s_j}$ = **β** if $m_i$ is active and $s_j$ is inactive
$\Delta w_{m_i s_j}$ = **γ** if $m_i$ is inactive and $s_j$ is active
$\Delta w_{m_i s_j}$ = **δ** if both $m_i$ and $s_j$ are inactive

General specification of rules: [α, β, γ, δ]

# Investigation into weight update rules

- If we limit ourselves to +1, 0 or 1 for each weight update, then there are 81 different possible rules

- For each of these weight update rules we want to ask:

  - How well does it recreate the training data for certain important types of language (e.g. the optimal language, or a maximally ambiguous language)?

  - How well does it generalise to unseen data for each of these languages?

  - How well will a pair of agents with the rule communicate after being trained on these languages?

# Bias and innateness

- Each of these 81 rules may model a different *learning bias*
- What do they correspond to in reality?
    - They are a feature that an agent is born with that changes the learnability of different kinds of languages. A different kind of innateness.
- What are the consequences for language of this kind of innateness?
    - For the animal model, there's a simple relationship between genes and behaviour (i.e. signalling)
    - For the learning model, the relationship between genes and behaviour (i.e. language) is much more complex