Coevolution of Lexical Meaning and Pragmatic Use

Thomas Brochhagen, Michael Franke & Robert van Rooij

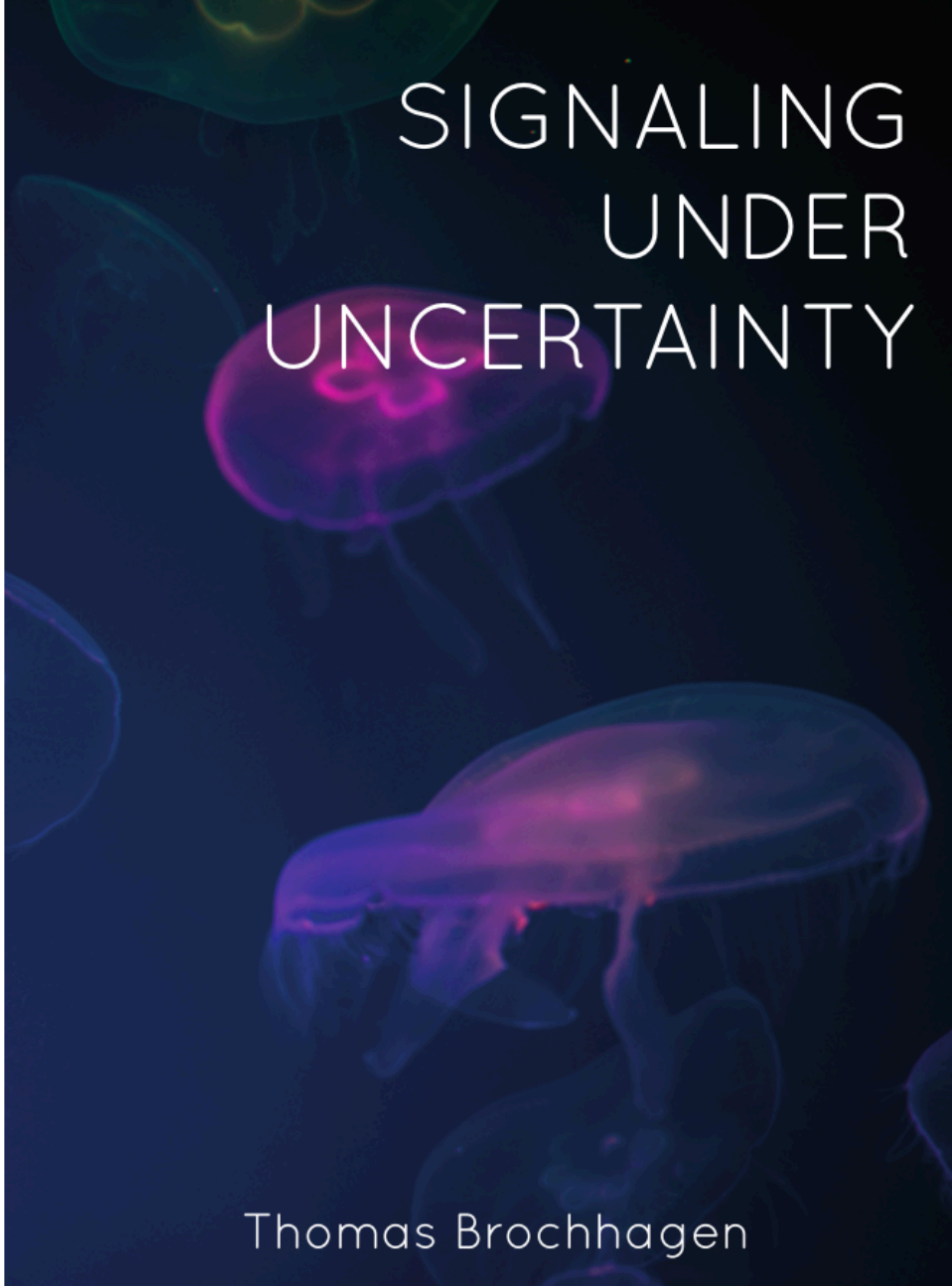
COEVOLUTION OF SEMANTICS AND PRAGMATICS

evolutionary dynamics with linguistic agents

fitness-based selection **AND**
agent-level learning

meaning as **mental representation**

Thomas Brochhagen, Michael Franke, Robert van Rooij (2018)
"Coevolution of Lexical Meaning and Pragmatic Use"
Cognitive Science



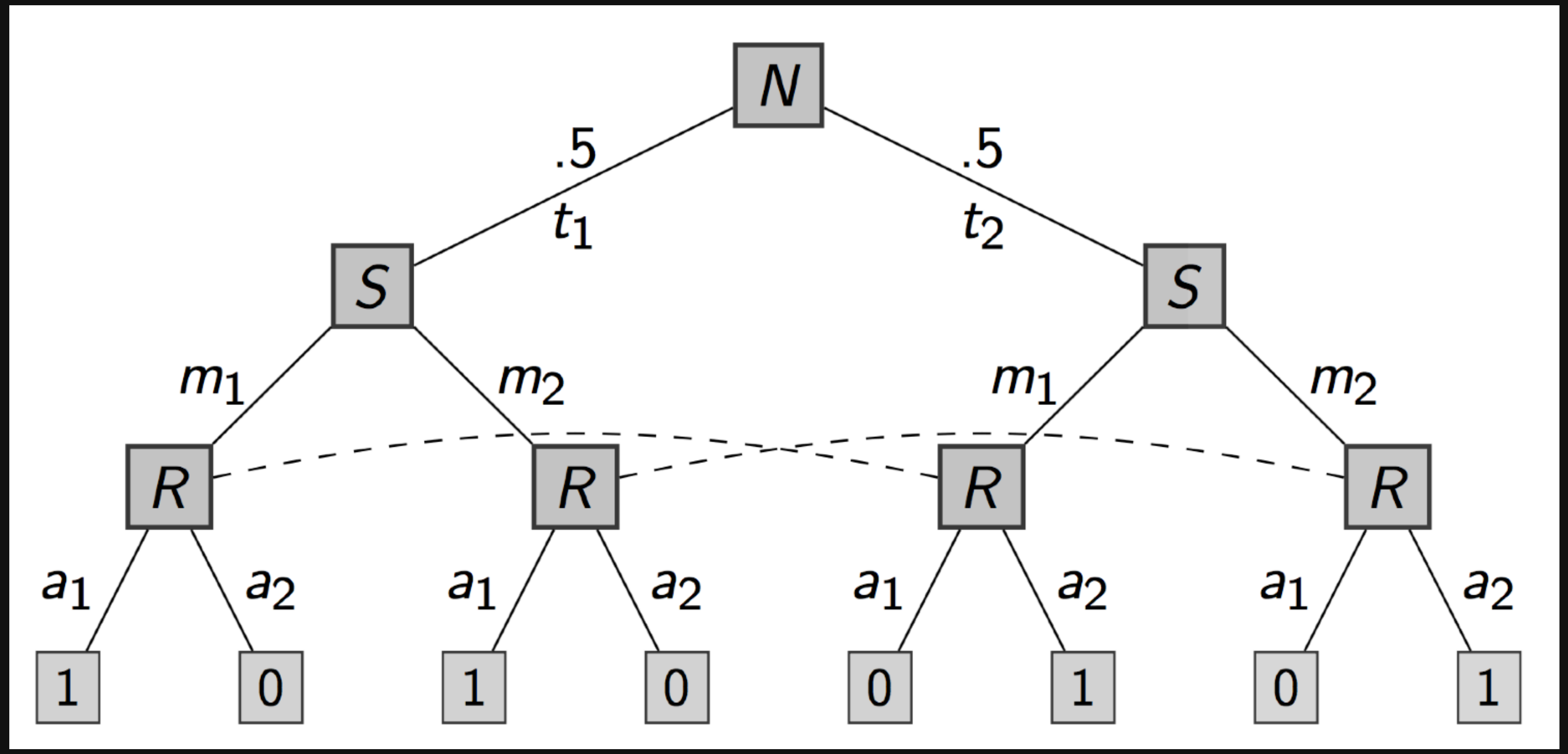
recap

We can hardly suppose a parliament of hitherto speechless elders meeting together and agreeing to call a cow a cow and a wolf a wolf. The association of words with their meanings must have grown up ***by some natural process****, though at present the nature of the process is unknown.*

Bertrand Russell (1921) *The Analysis of Mind* p.190

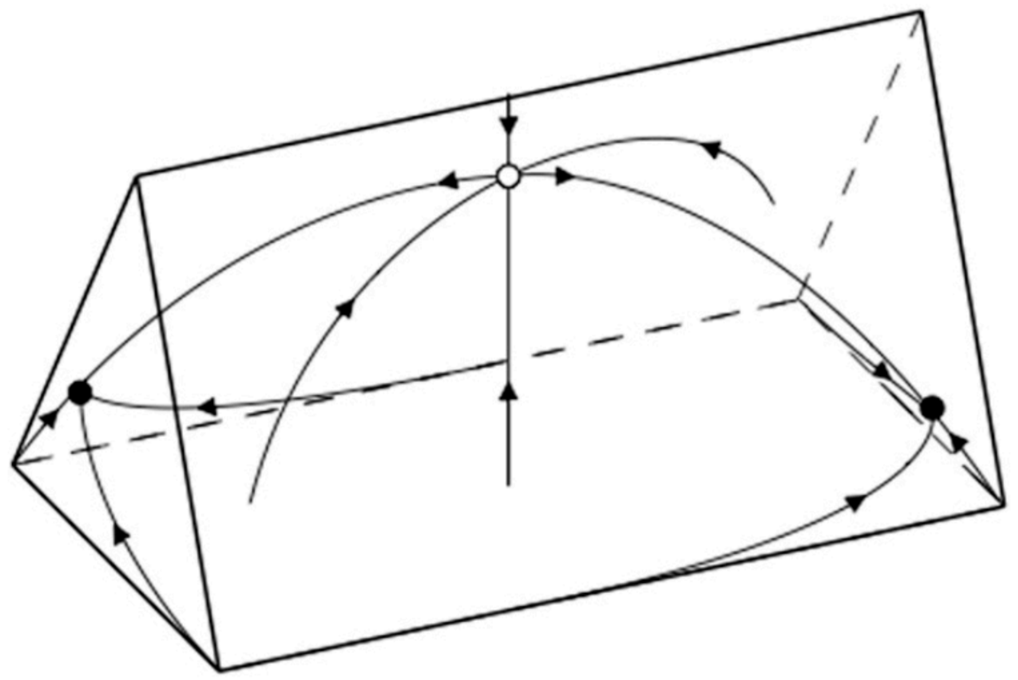
MEANING AS CONVENTION

equilibria of **signaling games**



David Lewis (1969) *Convention*

SIGNALING THEORY



evolutionary dynamics instead of equilibria

fitness-based selection **OR**
agent-level learning

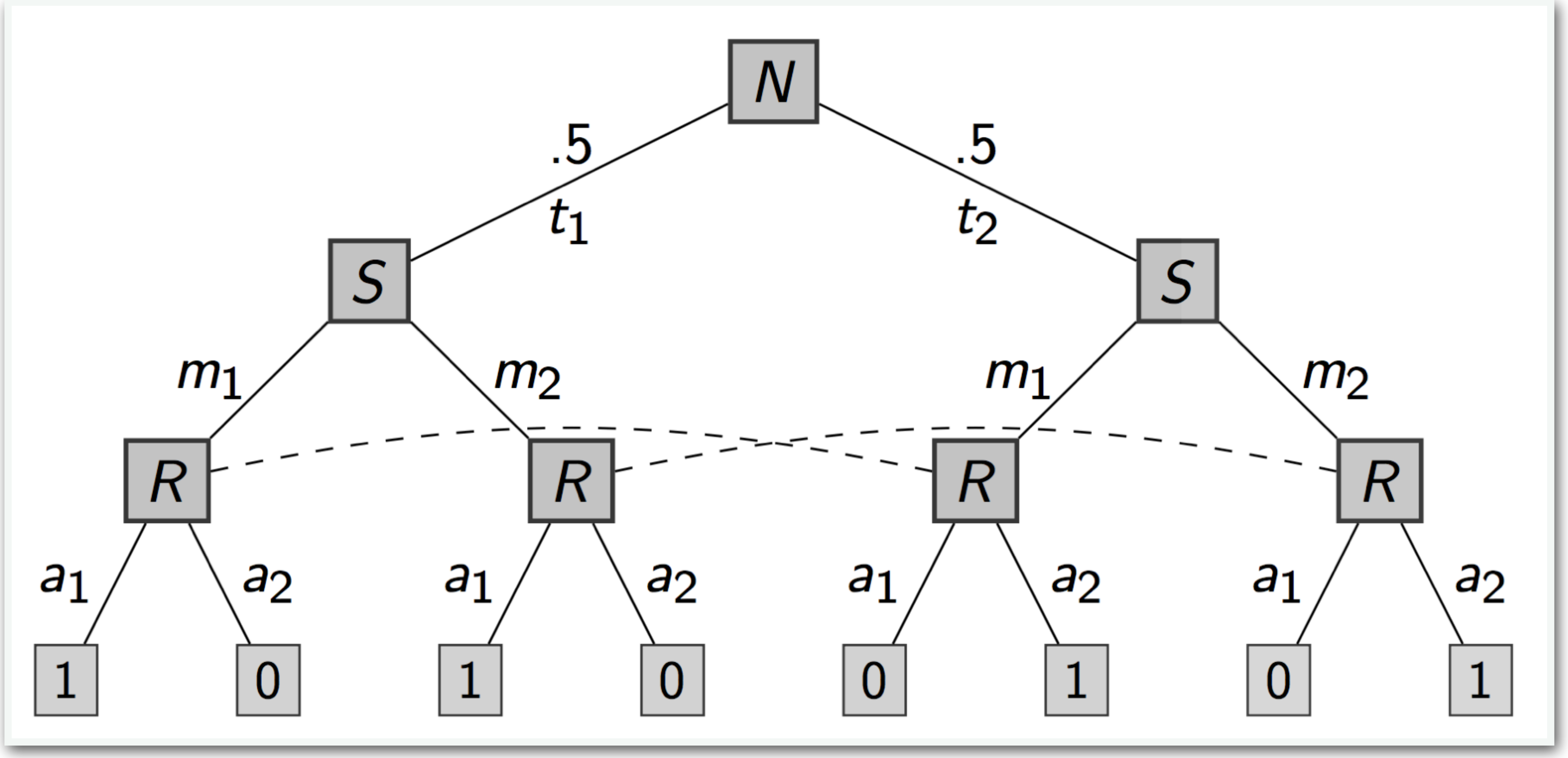
meaning as **information content**

Brian Skyrms (2010) *Signals: Evolution, Learning, and Information*

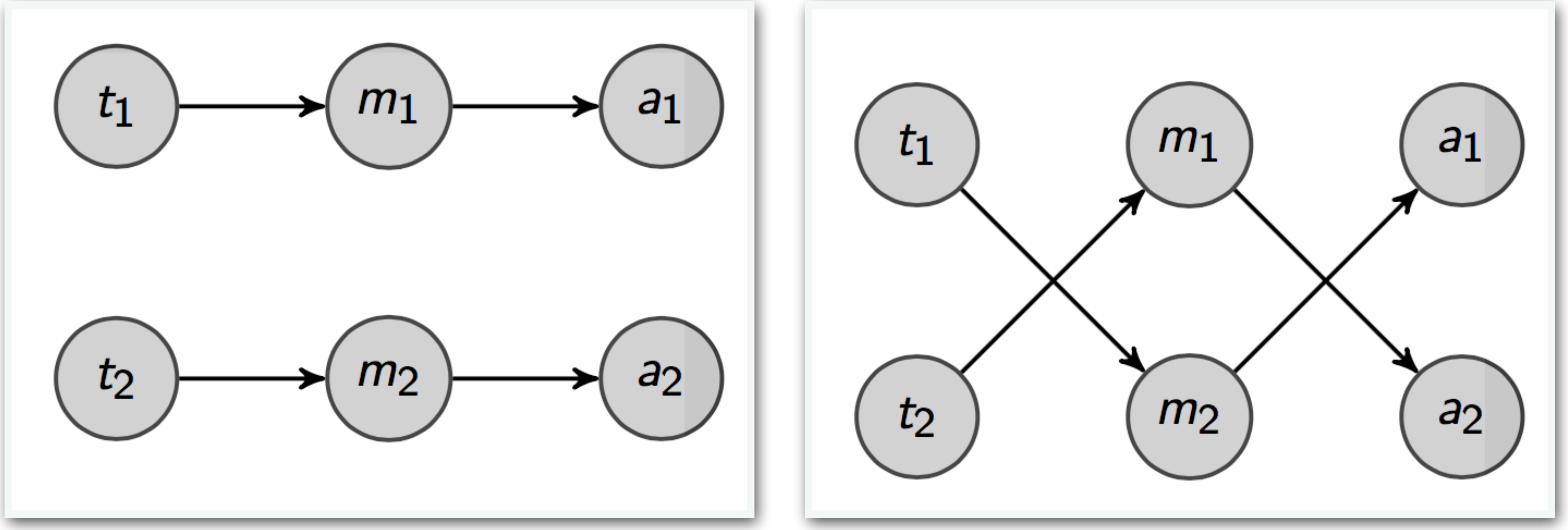
signaling theory

SIGNALING THEORY

SIGNALING GAME



EVOLUTIONARY STABLE STATES LEWIS



STRATEGIES

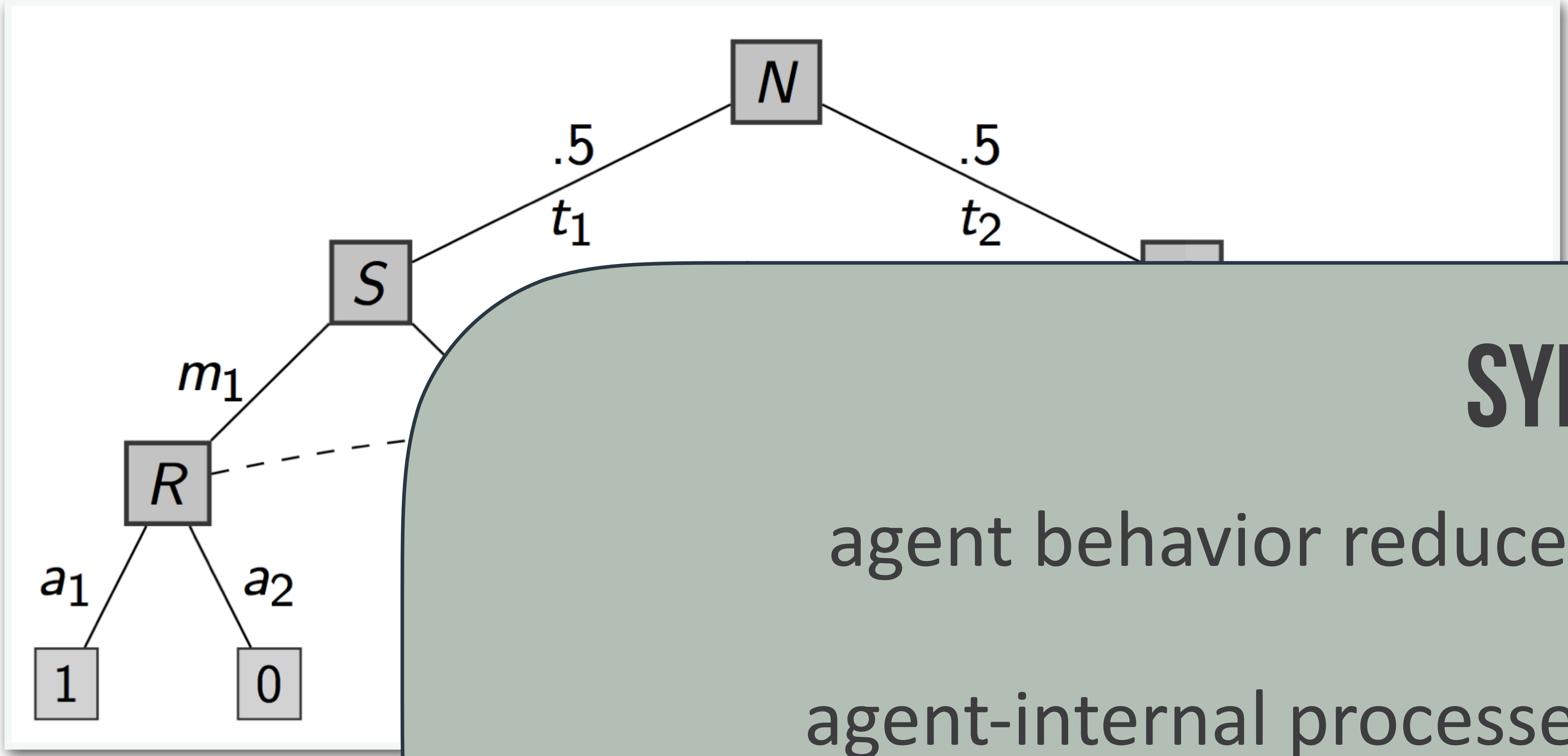
sender: $P_S(m \mid t)$ receiver: $P_R(a \mid m)$

INFORMATION CONTENT VECTOR SKYRMS

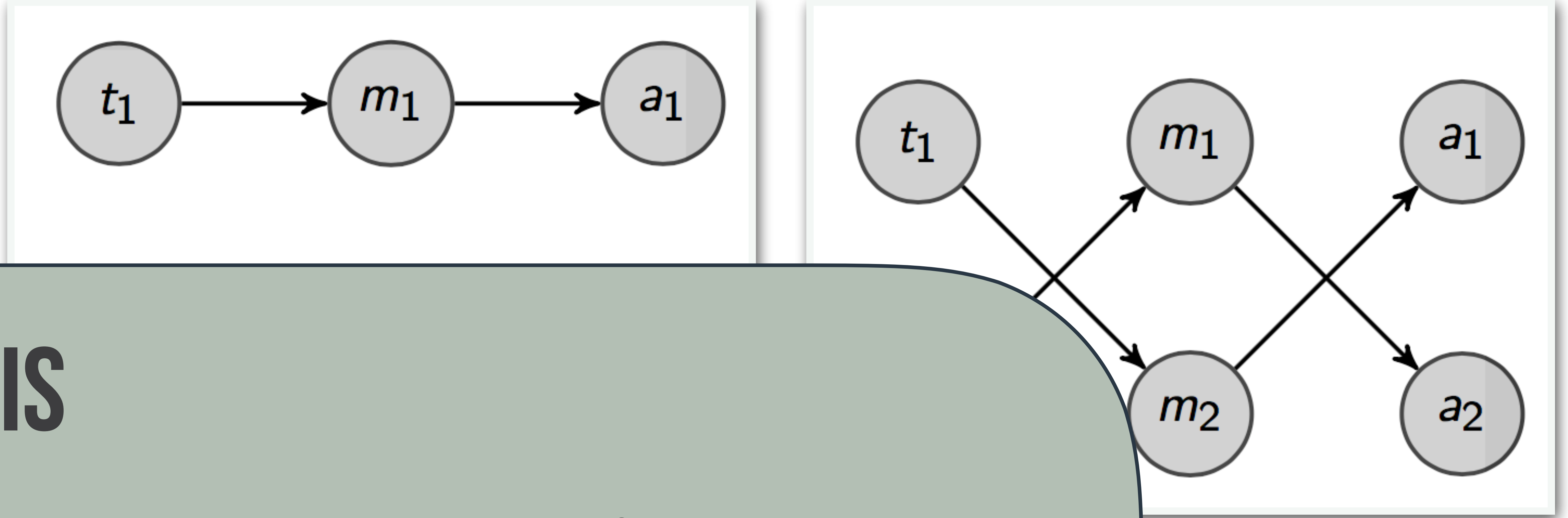
$$\text{ICV}(m) = \left\langle \log \frac{P_S(t_1 \mid m)}{P(t_1)}, \log \frac{P_S(t_2 \mid m)}{P(t_2)} \right\rangle$$

SIGNALING THEORY

SIGNALING GAME



EVOLUTIONARY STABLE STATES LEWIS



SYNOPSIS

agent behavior reduced to input-output mapping

agent-internal processes are abstracted away from

meaning is identified at the level of behavioral patterns

STRATEGIES

sender: $P_S(m \mid t)$ receiver: $P_R(a \mid m)$

NT VECTOR SKYRMS

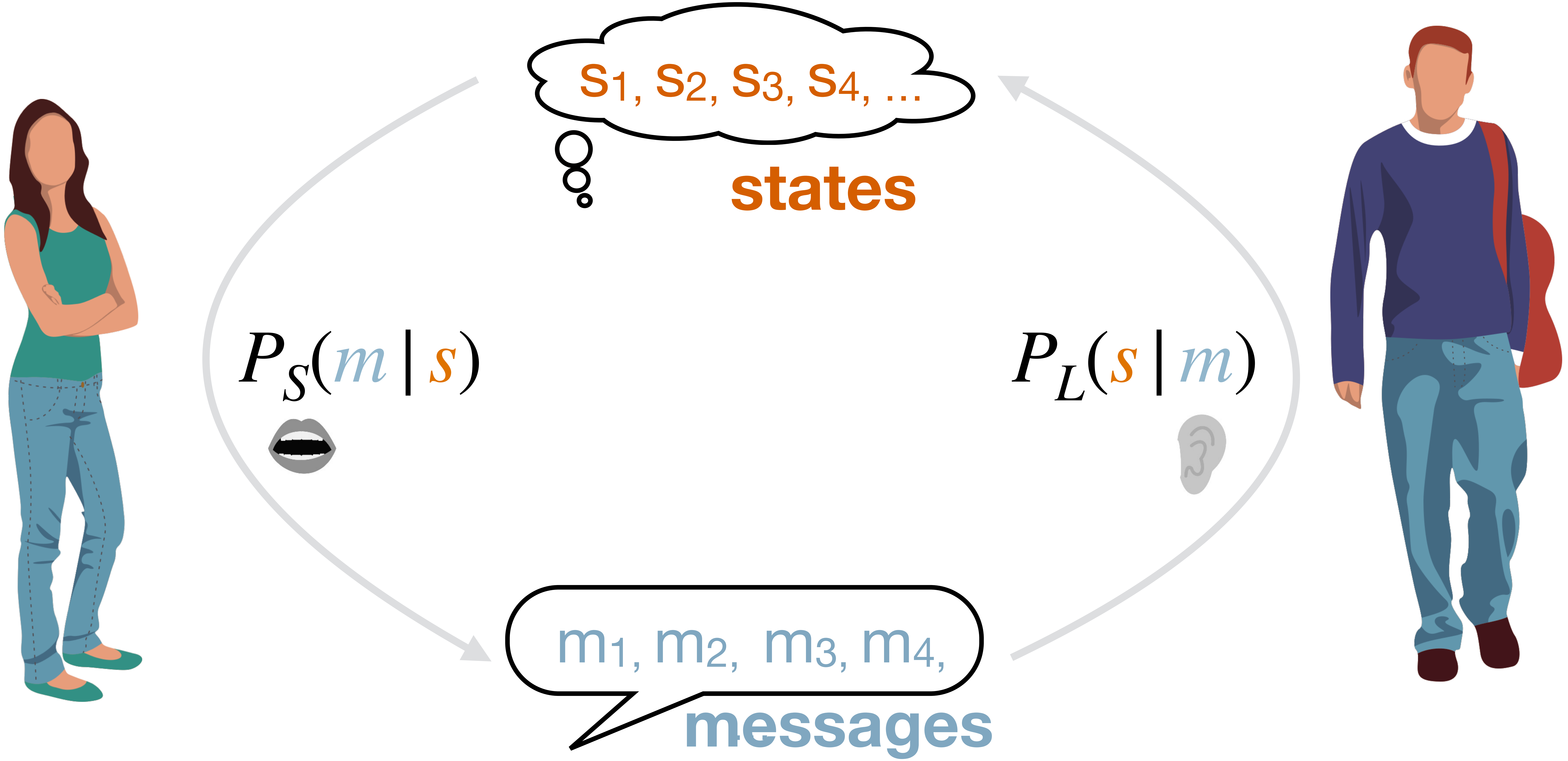
$$\text{ICV}(m) = \left\langle \log \frac{P_S(t_1 \mid m)}{P(t_1)}, \log \frac{P_S(t_2 \mid m)}{P(t_2)} \right\rangle$$

types

EVOLUTIONARY
TYPE

LEXICON

COMPREHENSION & PRODUCTION RULES


s1, s2, s3, s4, ...
states
$P_S(m \mid s)$
$P_L(s \mid m)$
m1, m2, m3, m4,
messages

RATIONAL SPEECH ACT MODELS

LITERAL INTERPRETATION — STRATEGIC DEPTH 0

$$P_{lit}(s \mid m) \propto P(s)\ L_{[s,m]}$$

GRICEAN SPEAKER — STRATEGIC DEPTH 1

$$P_S(m \mid s) \propto \exp(\alpha \log P_{lit}(s \mid m))$$

GRICEAN INTERPRETATION — STRATEGIC DEPTH 2

$$P_L(s \mid m) \propto P(s)\ P_S(m \mid s)$$

e.g. Frank & Goodman (2012), Franke & Jäger (2016)

http://www.problang.org

Probabilistic language understanding

An introduction to the Rational Speech Act framework

By Gregory Scontras, Michael Henry Tessler, and Michael Franke

The present course serves as a practical introduction to the Rational Speech Act modeling framework. Little is presupposed beyond a willingness to explore recent progress in formal, implementable models of language understanding.

Main content

The literal listener rule can be written as follows:

```
// set of states (here: objects of reference)
// we represent objects as JavaScript objects to demarcate them from utterances
// internally we treat objects as strings nonetheless
var objects = [{color: "blue", shape: "square", string: "blue square"},
               {color: "blue", shape: "circle", string: "blue circle"},
               {color: "green", shape: "square", string: "green square"}]

// set of utterances
var utterances = ["blue", "green", "square", "circle"]

// prior over world states
var objectPrior = function() {
  var obj = uniformDraw(objects)
  return obj.string
}

// meaning function to interpret the utterances
var meaning = function(utterance, obj){
  _.includes(obj, utterance)
}

// literal listener
var literalListener = function(utterance){
  Infer({model: function(){
    var obj = objectPrior();
    var uttTruthVal = meaning(utterance, obj);
    condition(uttTruthVal == true)
    return obj
  }})
}

viz.table(literalListener("blue"))
```

run

(state)	probability
blue circle	0.5
blue square	0.5

Exercises:

1. In the model above, `objectPrior()` returns a sample from a `uniformDraw` over the possible objects of reference. What happens when the listener's beliefs are not uniform over the

LITERAL VS. PRAGMATIC LANGUAGE USERS

LITERAL AGENTS STRATEGIC DEPTH 0

$$S_0(m \mid s; L) \propto \exp(\lambda \, L_{[s,m]})$$

$$H_0(s \mid m; L) \propto P(s) \; L_{[s,m]}$$

Literal Luke

PRAGMATIC AGENTS STRATEGIC DEPTH 1

$$S_1(m \mid s; L) \propto \exp(\lambda \, H_0(s \mid m; L))$$

$$H_1(s \mid m; L) \propto P(s) \; S_1(m \mid s; L)$$

Gricean Greta

minimal type space

TYPE SPACE 1: ALL 4 COMBINATIONS OF 2 LEXICA + 2 PRAGMATIC RULES

$$L_{\text{bound}} = \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array}$$

$$L_{\text{lack}} = \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{c} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \end{array}$$

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PRAGMATIC AGENTS STRATEGIC DEPTH 1

$$S_1(m \mid s; L) \propto \exp(\lambda\, H_0(s \mid m; L))$$

$$H_1(s \mid m; L) \propto P(s)\, S_1(m \mid s; L)$$

	LEXICALIZED UPPER BOUND	TEXTBOOK MEANING	
	$$L_{\text{bound}} = \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \\ \left[\begin{array}{c} 1 \\ 0 \end{array}\right. & \left.\begin{array}{c} 0 \\ 1 \end{array}\right] \end{array}$$	$$L_{\text{lack}} = \begin{array}{c} \\ s_{\exists\neg\forall} \\ s_{\forall} \end{array} \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \\ \left[\begin{array}{c} 1 \\ 1 \end{array}\right. & \left.\begin{array}{c} 0 \\ 1 \end{array}\right] \end{array}$$	LEXICA
	$$H_0(\cdot \mid \cdot, L_{\text{bound}}) = \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \\ \left[\begin{array}{c} 1 \\ 0 \end{array}\right. & \left.\begin{array}{c} 0 \\ 1 \end{array}\right] \end{array}$$	$$H_0(\cdot \mid \cdot, L_{\text{lack}}) = \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \\ \left[\begin{array}{c} .5 \\ 0 \end{array}\right. & \left.\begin{array}{c} .5 \\ 1 \end{array}\right] \end{array}$$	STRATEGIC DEPTH 0
	$$H_1(\cdot \mid \cdot, L_{\text{bound}}) \approx \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \\ \left[\begin{array}{c} .73 \\ .27 \end{array}\right. & \left.\begin{array}{c} .27 \\ .73 \end{array}\right] \end{array}$$	$$H_1(\cdot \mid \cdot, L_{\text{lack}}) \approx \begin{array}{c} \\ m_{\text{some}} \\ m_{\text{all}} \end{array} \begin{array}{cc} s_{\exists\neg\forall} & s_{\forall} \\ \left[\begin{array}{c} .59 \\ .35 \end{array}\right. & \left.\begin{array}{c} .41 \\ .65 \end{array}\right] \end{array}$$	STRATEGIC DEPTH 1

evolutionary dynamics

- fitness-based selection
  - the better a type is at communicating, the more it will be replicated

$$f_i = \sum_j x_j \, \mathrm{EU}(t_i, t_j)$$

- learning biases
  - agents acquire/update their type by observation of others' behavior

$$Q_{ji} = \sum_{d \in D} P(d \mid t_j) \; P(t_i \mid d)$$

$$x_i' = \frac{\sum_j x_j f_j \; Q_{ji}}{\phi}$$

REPLICATOR MUTATOR DYNAMIC

e.g., Nowak (2006), Griffith & Kalish (2007), Hutteger et al. (2014)

- fitness-based selection
  - the better a type is at communicating, the more it will be replicated

$$f_i = \sum_j x_j \, \mathrm{EU}(t_i, t_j)$$

$$\left(\mathrm{RD}(\overrightarrow{x})\right)_i = \frac{x_i f_i}{\Phi}$$

REPLICATOR DYNAMIC

- learning biases
  - agents acquire/update their type by observation of others' behavior

$$Q_{ji} = \sum_{d \in D} P(d \mid t_j) \, P(t_i \mid d)$$

$$(\mathrm{M}(\overrightarrow{x}))_i = (\overrightarrow{x} \cdot Q)_i$$

ITERATED LEARNING

$$x_i' = \left(\mathrm{M}\left(\mathrm{RD}(\overrightarrow{x})\right)\right)_i$$

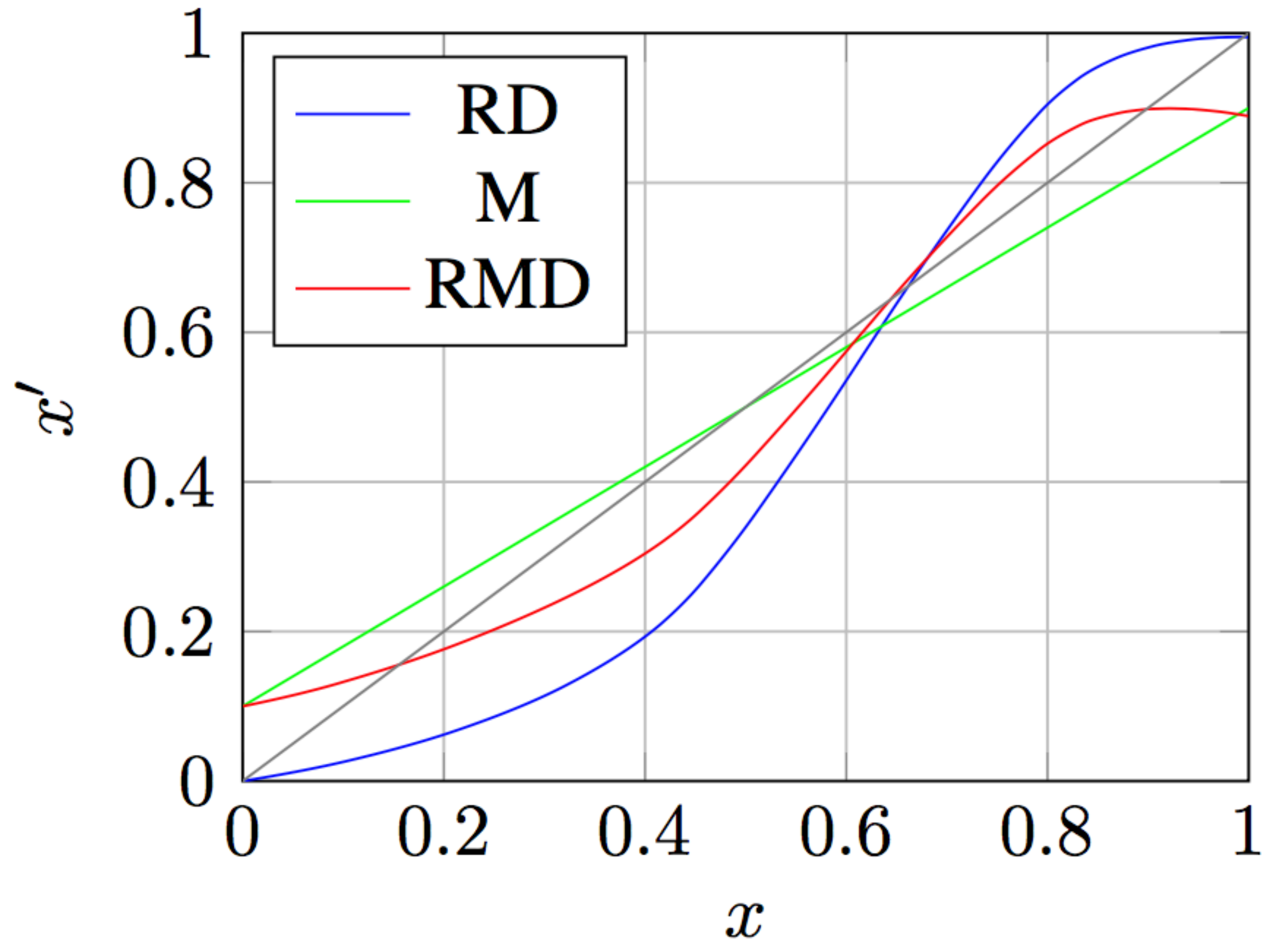
REPLICATOR MUTATOR DYNAMIC

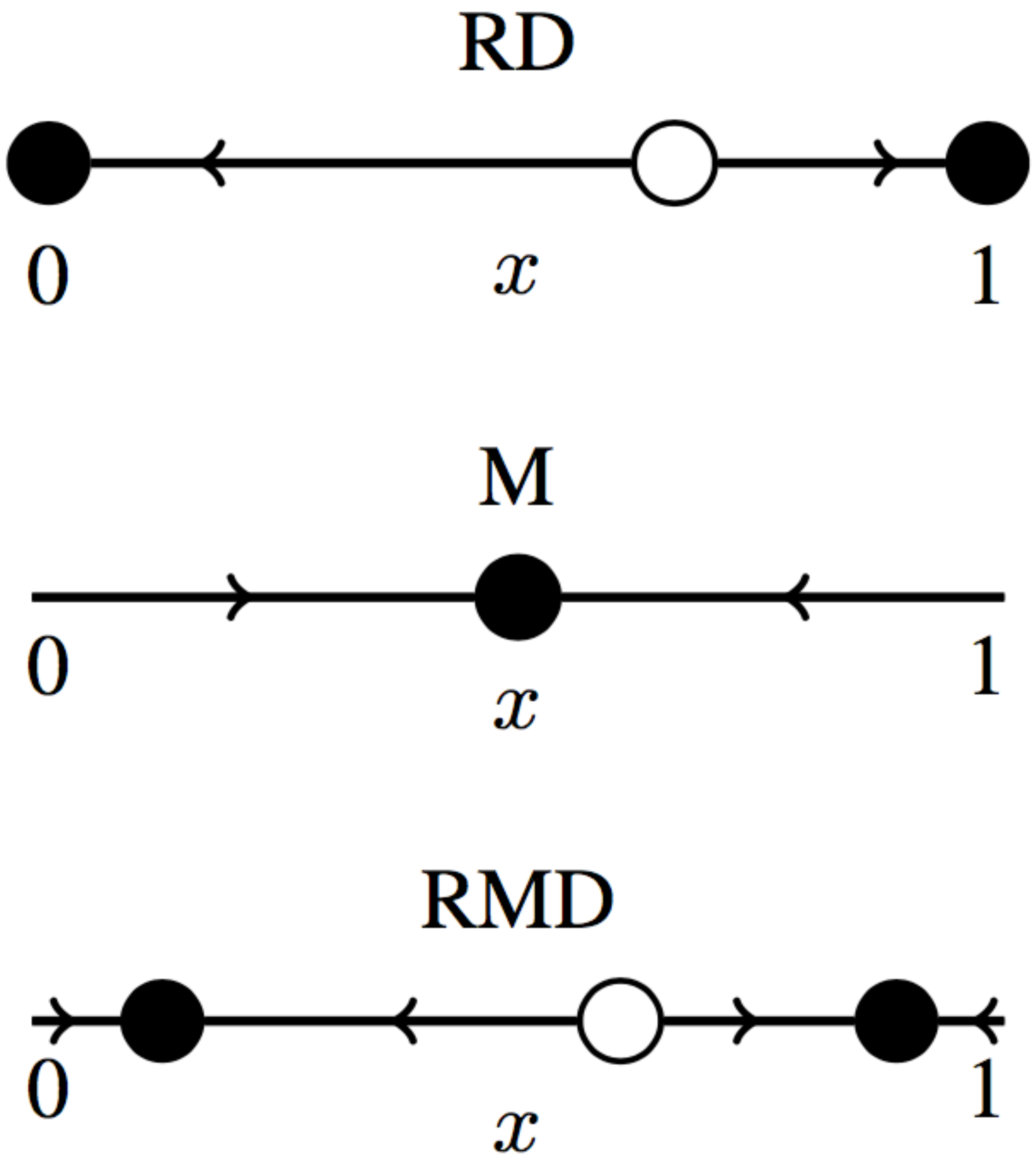
e.g., Nowak (2006), Griffith & Kalis (2007), Hutteger et al. (2014)

EXAMPLE

$$U = \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix}$$

$$Q = \begin{pmatrix} .9 & .1 \\ .1 & .9 \end{pmatrix}$$





minimal type space

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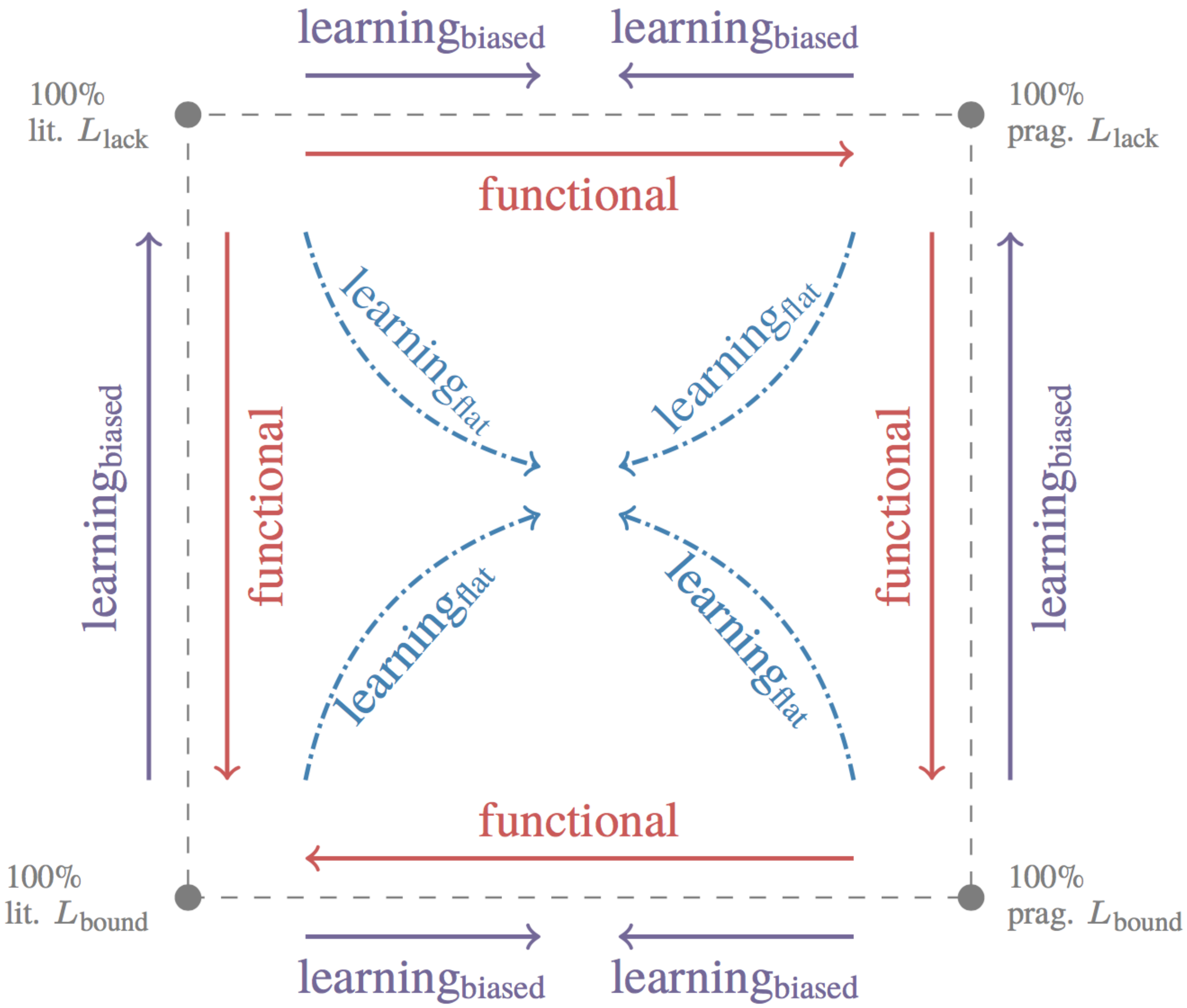
PRAGMATIC AGENTS STRATEGIC DEPTH 1

$$S_1(m \mid s; L) \propto \exp(\lambda \; H_0(s \mid m; L))$$

$$H_1(s \mid m; L) \propto P(s) \; S_1(m \mid s; L)$$

ANALYSIS



learning$_{\text{biased}}$
learning$_{\text{biased}}$
100%
lit. L_{lack}
100%
prag. L_{lack}
functional
learning$_{\text{biased}}$
functional
learning$_{\text{flat}}$
learning$_{\text{flat}}$
learning$_{\text{flat}}$
learning$_{\text{flat}}$
functional
learning$_{\text{biased}}$
functional
100%
lit. L_{bound}
100%
prag. L_{bound}
learning$_{\text{biased}}$
learning$_{\text{biased}}$

larger type space

SET UP

STATES $S = \{s_{\varnothing}, s_{\exists\neg\forall}, s_{\forall}\}$

USAGE $\mathfrak{U} = \{\text{lit}, \text{prag}\}$

LEXICA $\mathfrak{L} = R^M$

LEXICAL REPRESENTATIONS

intuitive name	$s_\emptyset$	$s_{\exists\neg\forall}$	$s_\forall$	least complex formula	complexity
"all"	0	0	1	$A \subseteq B$	3
"some but not all"	0	1	0	$A \cap B \neq \emptyset \wedge A \neq \emptyset$	8
"some"	0	1	1	$A \cap B \neq \emptyset$	4
"none"	1	0	0	$A \cap B = \emptyset$	4
"none or all"	1	0	1	$\neg(A \cap B \neq \emptyset \wedge A \neq \emptyset)$	10
"not all"	1	1	0	$\neg(A \subseteq B)$	5

LEXICAL REPRESENTATIONS

$R \to_2 R \wedge R$ $\quad$ $R \to_2 \neg R$

$R \to_1 X \subseteq X$ $\quad$ $R \to_1 X \neq \emptyset$ $\quad$ $R \to_1 X = \emptyset$

$X \to_1 \{A, B\}$ $\quad$ $X \to_1 X \cap X$ $\quad$ $X \to_1 X \cup X$

EXAMPLES OF RELEVANT TYPES OF LEXICA

L_{all}

	m_{none}	m_{some}	m_{all}
$s_\emptyset$	0	0	0
$s_{\exists\neg\forall}$	0	0	0
$s_\forall$	1	1	1

L_{bound}

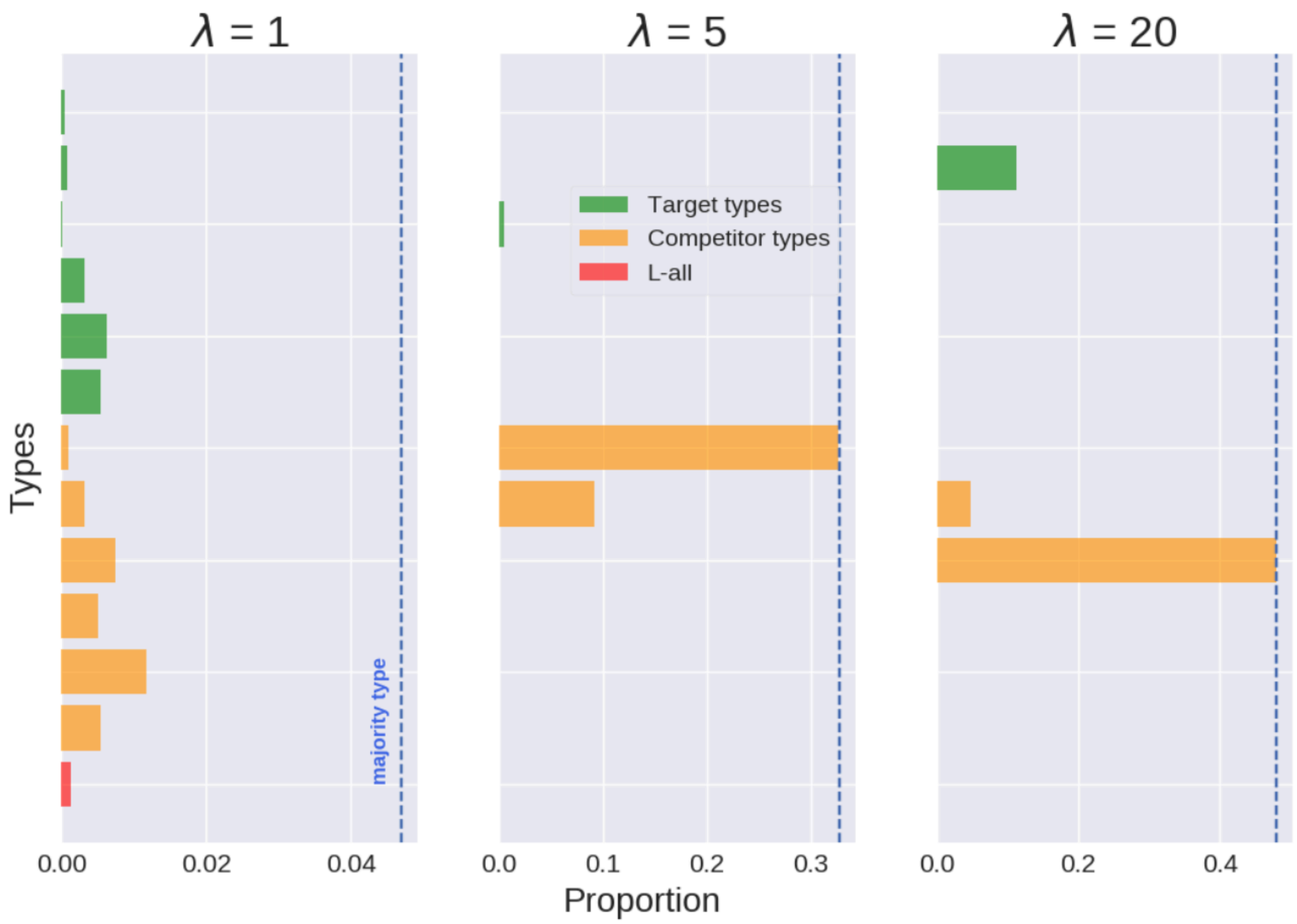
	m_{none}	m_{some}	m_{all}
$s_\emptyset$	1	0	0
$s_{\exists\neg\forall}$	0	1	0
$s_\forall$	0	0	1

L_{lack}

	m_{none}	m_{some}	m_{all}
$s_\emptyset$	1	0	0
$s_{\exists\neg\forall}$	0	1	0
$s_\forall$	0	1	1

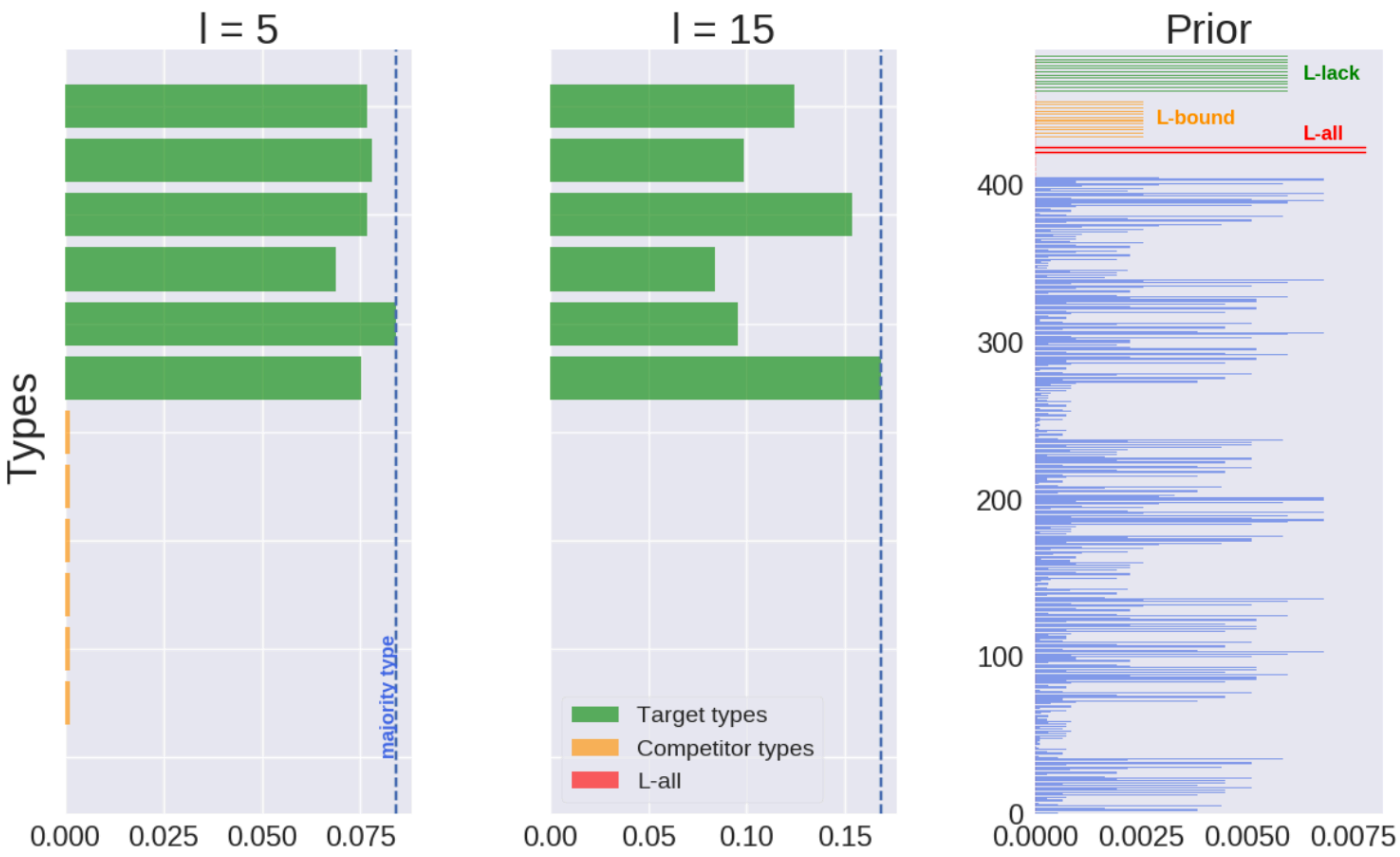
SIMULATION RESULTS ::: FITNESS-BASED SELECTION ONLY

higher act-rationality



SIMULATION RESULTS ::: ITERATED LEARNING ONLY

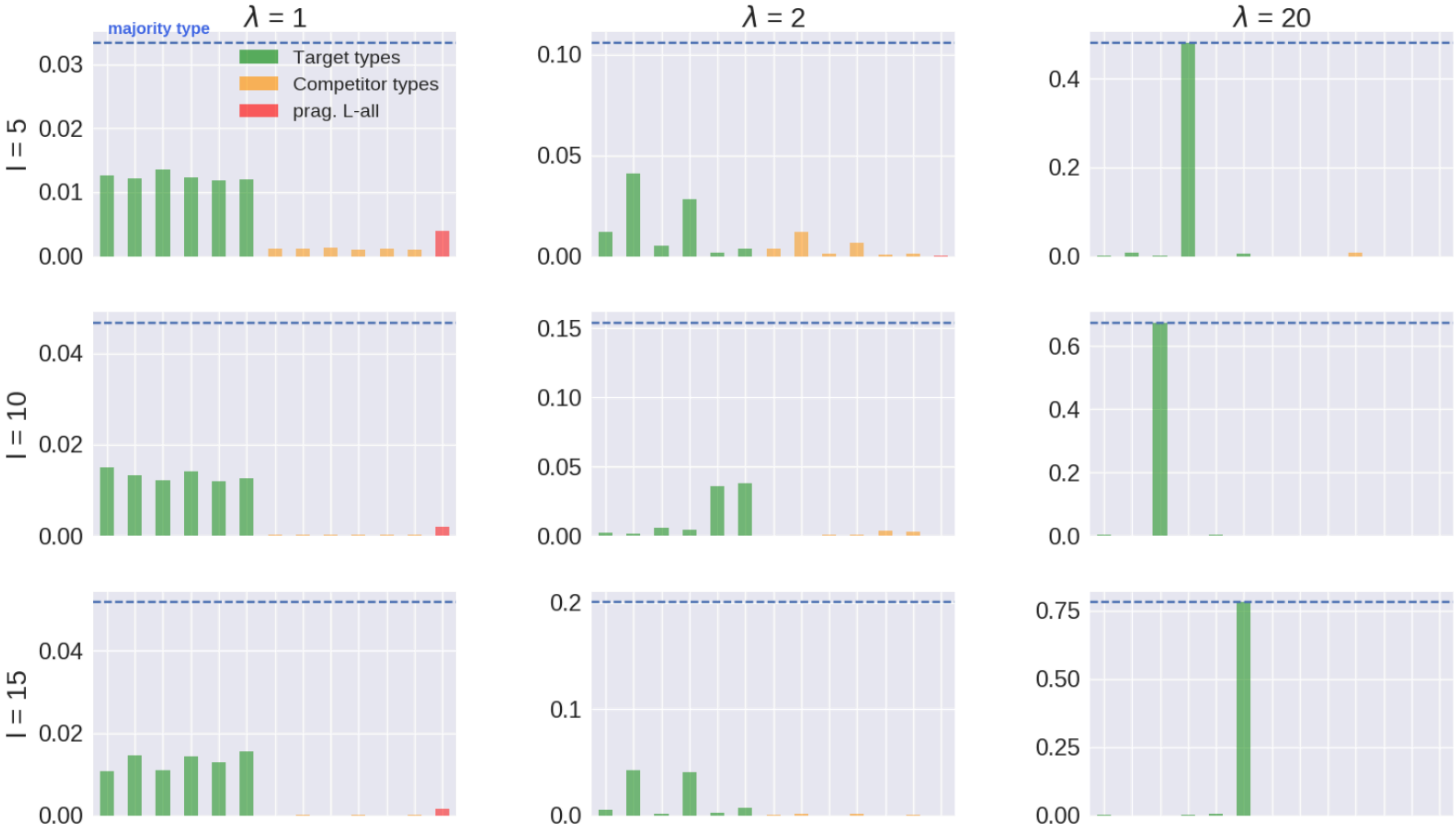
higher belief-rationality



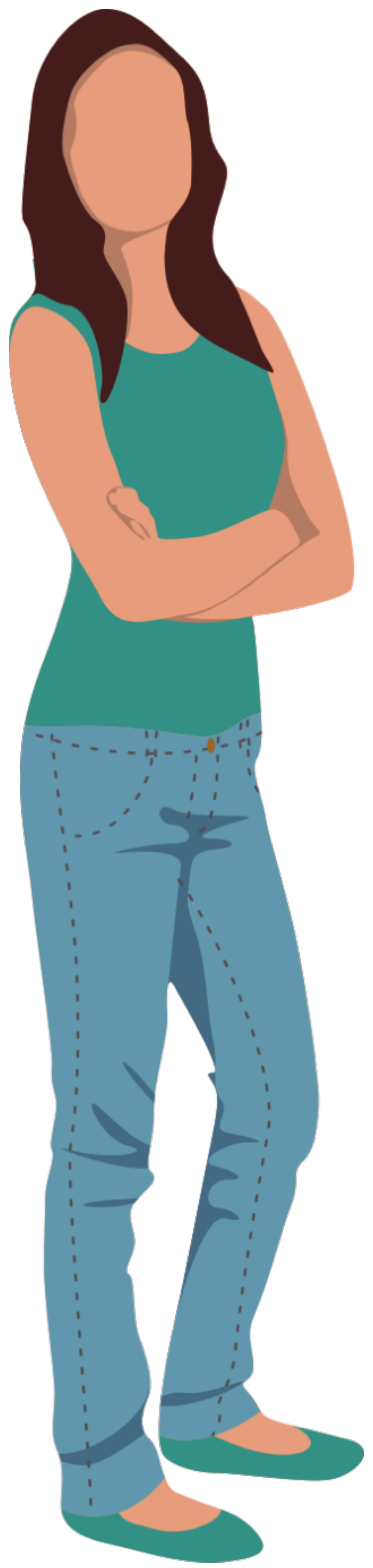
SIMULATION RESULTS ::: REPLICATOR MUTATOR DYNAMIC

higher act-rationality

higher belief-ration.



SUMMARY



- pragmatic language use with underspecified semantics can evolve
- results from interplay of two forces:
  - functional pressure towards efficient communication
  - learning bias: preference for simple mental representations

Gricean Greta

Literal Luke

conclusion

general trend

EXTENDING THE
NATURALIST PROGRAMM

TO INCORPORATE MORE
LINGUISTIC / COGNITIVE
REALISM

- role of common ground in disambiguation of meaning

ACCEPTED MANUSCRIPT

Signalling under Uncertainty: Interpretative Alignment without a Common Prior

Thomas Brochhagen

The British Journal for the Philosophy of Science, axx058, https://doi.org/10.1093/bjps/axx058

Published: 28 November 2017

- interlocutor-specific adaptation
  - from prior to passing theories

- functional rationale of vagueness

- impact of recurrent tropes on conventionalization of meaning