

Understanding Understanding In General, and in Large Language Models

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@ DFKI Berlin Colloquium

2023-07-20

These slides:

<https://clp.ling.uni-potsdam.de/talks>

Structure

- Part I: “Understanding Understanding”
 - Our Research Programme
 - Some Systematic Insights
 - Some Recent Projects
- Part II: Probing Chat-Optimized LLMs Through Gameplay
 - Games & Capabilities
 - clemgame
 - clembench

2000 – 2003		formal dialogue pragmatics	SDRT, theorem proving, probabilistic models
2007 – 2012	DFG (ENP)	Inpro: incrementalizing the representation building process (ASR, NLU, DM, NLG, TTS; turn-taking)	HMMs, SVMs, prob. parsing, ...
2012 – 2016		Inpro II: situated incremental processing (vision, gaze, gestures, embodiment)	graphical models
2015 – 2017	DFG/ ANR	DUEL: incremental disfluency detection	RNNs
2016 – 2019		concept learning / grounded lexical semantics	CNNs, RNNs
2018 – 2022	VW	knowledge- grounded closed-domain chat	LLMs + KGs
2019 –		MetaNLP / Methodology / The BIG Picture	words
2019 – 2023		Neur- Inpro & State Tracking	RNNs, transformers, LLMs
2019 – 2024	DFG	RECOLAGE: incremental instruction generation	RL, symb <-> NN transf.
2020 – 2024	SFB 1287	Limits of Pragmatic Variability in LLMs	LLMs
2022 – 2025	BMBF	COCOBOTS: construction concept learning, robot arm	code gen models
2023 –		Foundation Models: What Are They Good For?	LLMs
2024 –		Reasonable AI: Giving and Asking for Reasons	

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2015 – 2017	DFG/ ANR	DUEL: incremental dialogue systems	domains (multimodal assistance, tutoring, ...)
2016 – 2019		concept learning / grounded lexical semantics	CNNs, RNNs
2018 – 2022		Understanding Understanding — domain chat	LLMs + KGs
2019 – 2023		the process by which interlocutors create shared understanding (sufficient for current purposes)	RNNs, transformers, LLMs
2019 – 2024	DFG	RECOLAGE: incremental instruction generation	RL, symbol, N transf.
2020 – 2024	SFB 1287	ASR lexical semantics computer vision robotics	LLMs
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Representation Formalisation

moar!!!!
moar!!!!
moar!!!!

{ data | models
compute |
layers }

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2023 – 2023		Foundation Models: What Are They Good For?	Representation Learning
2024 – 2024		Reasonable AI: Giving and Asking for Reasons	NLP



Wh

P?

- Always been engineering
- 2019, became to think (a

Dialogue Games for Benchmarking Language Understanding: Motivation, Taxonomy, Strategy

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Abstract

How does one measure “ability to understand language”? If it is a person’s ability that is being measured, this is a question that almost never poses itself in an unqualified manner: Whatever formal test is applied, it takes place on the background of the person’s language use in daily social practice, and what is measured is a specialised variety of language understanding (e.g., of a second language; or of written, technical language). Computer programs do not have this background. What does that mean for the applicability of formal tests of language understanding? I argue that such tests need to be complemented with tests of language use embedded in a practice, to arrive at a more comprehensive evaluation of “artificial language understanding”. To do such tests systematically, I propose to use “Dialogue Games”—constructed activities that provide a situational embedding for language use. I describe a taxonomy of Dialogue Game types, linked to a model of underlying capabilities that are tested, and thereby giving an argument for the *construct validity* of the test. I close with showing how the internal

and greets them with “next time”; the reply comes immediately: “drinks?”

The subfield of “Natural Language Understanding” (NLU) within the field of Natural Language Processing (NLP) uses tests of the first kind—written responses to written material—to measure the degree to which a technical artefact can be said to possess the *ability* of understanding natural language. More recently, NLP has expanded towards tackling more situated and less abstracted cases of language use—as in the second part of the story, if not quite as social—, under the headings “language and vision (navigation)” or “embodied AI” (Duan et al., 2022; Gu et al., 2022; Sundar and Heck, 2022),¹ with evaluation practices not yet fully established.

This paper aims to systematise already ongoing efforts in this direction and to support future ones, by first asking how these kinds of language understanding settings—formal, and situated—relate. Coming to the conclusion that Situated Language Understanding (SLU) requires different testing approaches, and that NLU evaluation has proceeded

Where's the *theory of NLP*?

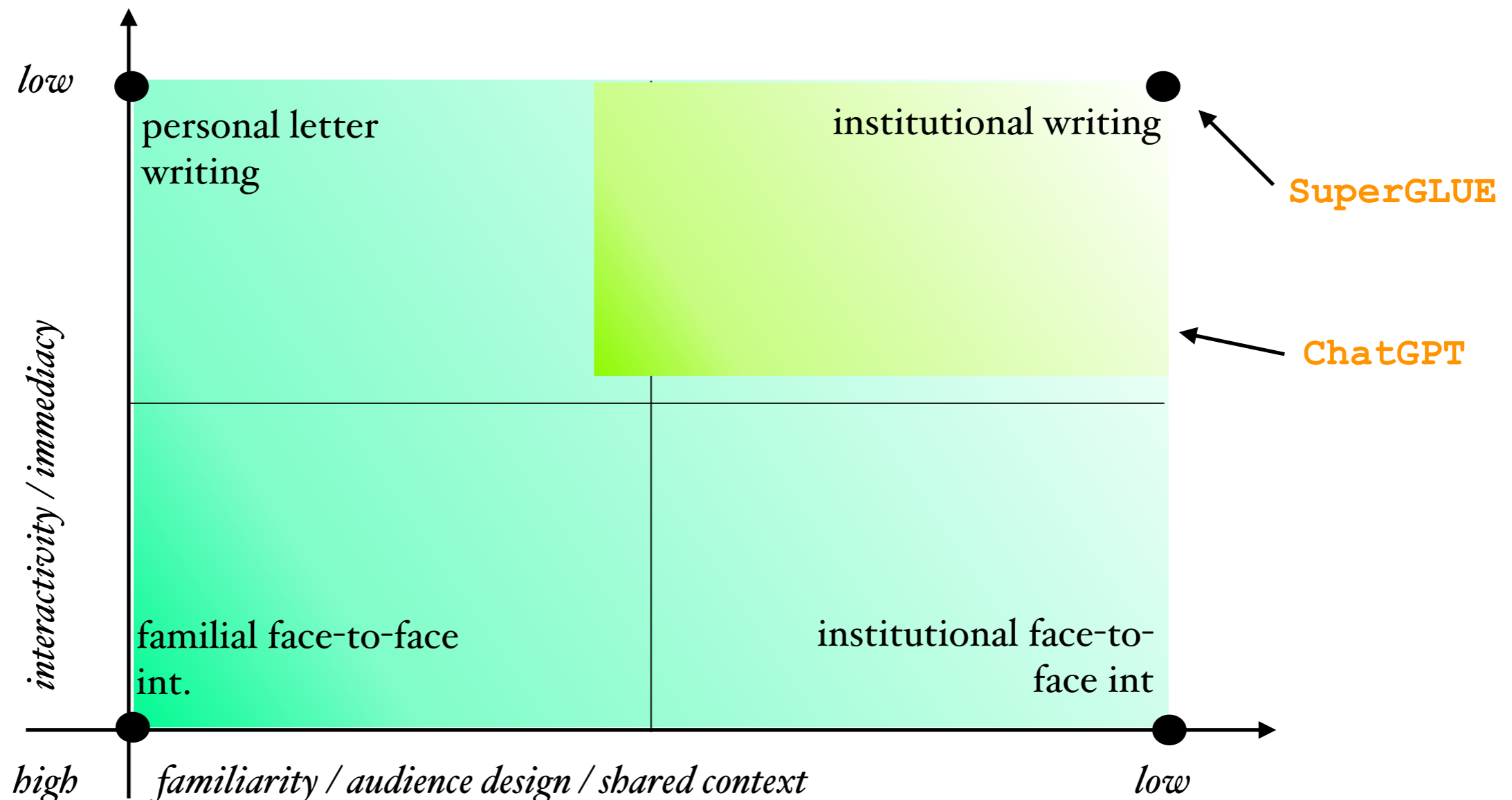
- Always been puzzled by lack of coherence. (Science when feeling fancy, engineering when challenged...)
- 2019, became “Professor of the Foundations of CL” — I’m now officially allowed to think (and write) about this!
 - (Schlangen 2019a, 2019b, 2021 ACL, 2022, 2023a, 2023b)

Where's the *theory of NLP*?

- Some points
 - now that things kind of work, kind of in a general way, the domain theory aversion is coming back to haunt NLP, as problems with *measurement*
 - the type of language use represented by NLP-NLU is not the only one, and not even the paradigmatic one
 - it makes sense to analyse the task of understanding as
 - requiring *knowledge*,
 - which is applied in (update) *processes*,
 - some of which are single-minded ones, other are interactive ones
 - this makes clearer the relation btw NLP-NLU & SLU (as tasks, and methodologically)

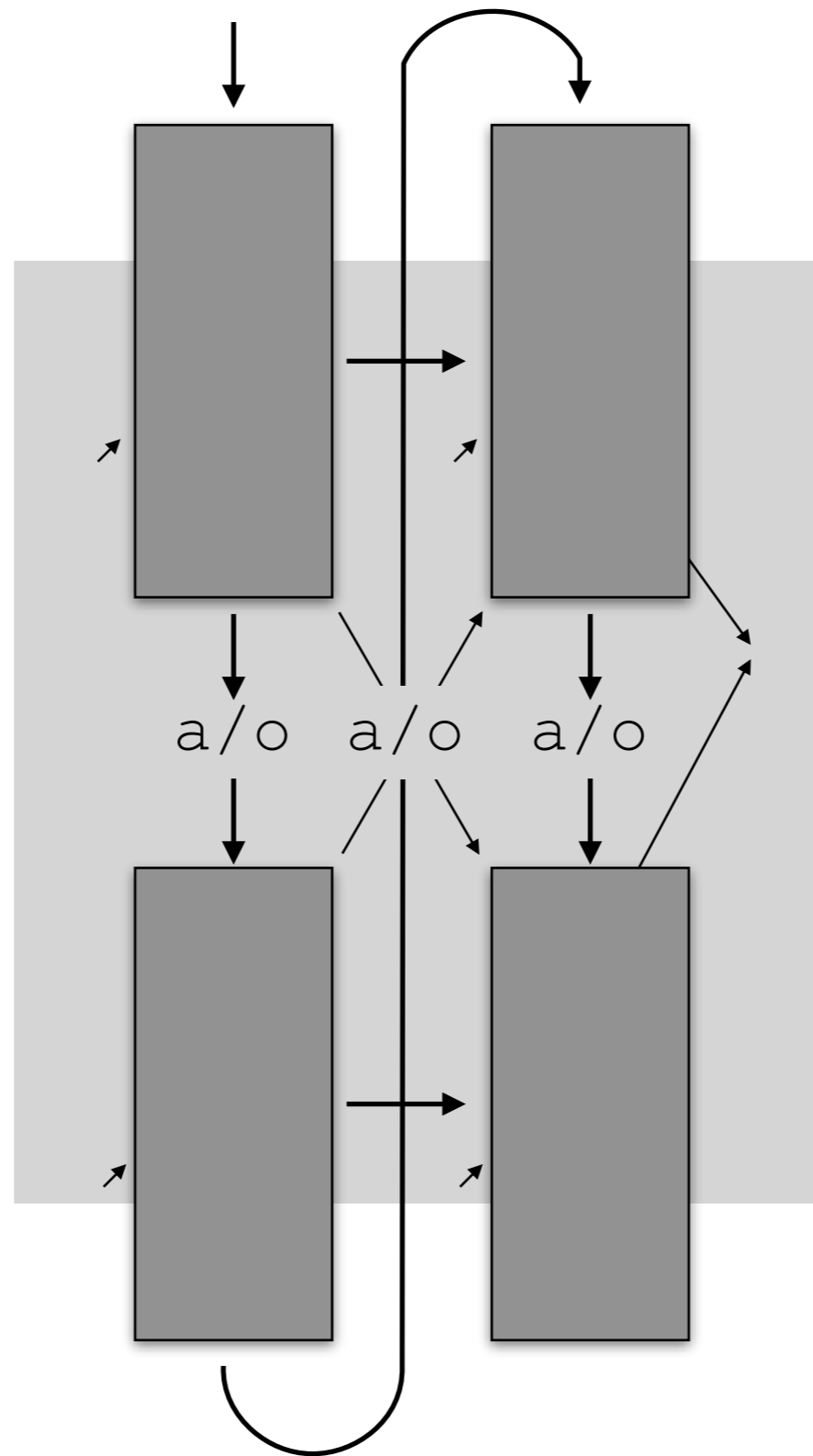
I. Types of Language Use

- the type of language use represented by NLP-NLU is not the only one, and not even the paradigmatic one



II. Task of LU has Structure

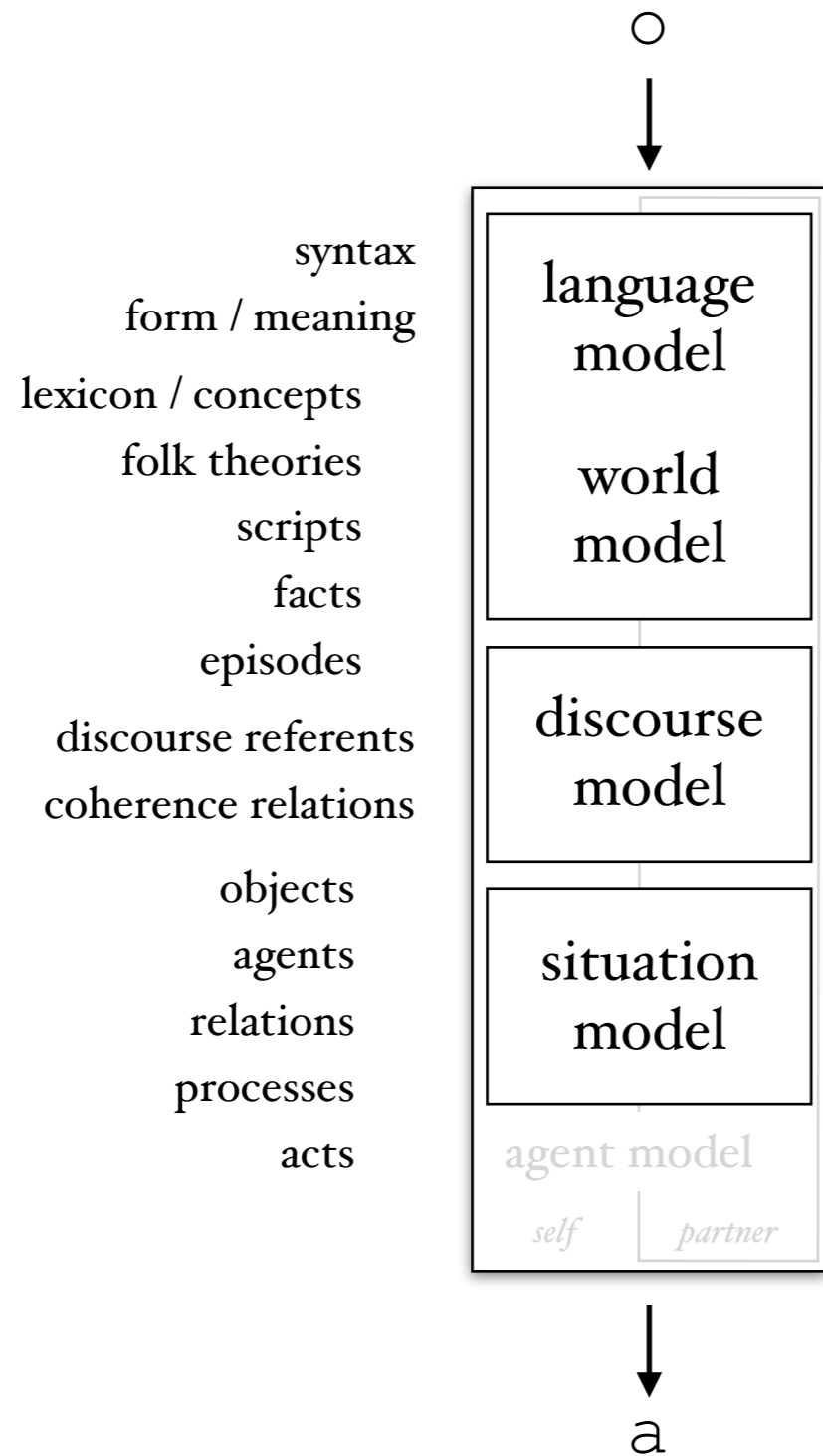
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NLP-NLU



NLP-NLU



The trophy didn't fit into the suitcase because it was too small

The trophy didn't fit into the suitcase because it was too big

(Levesque *et al.* 2012)

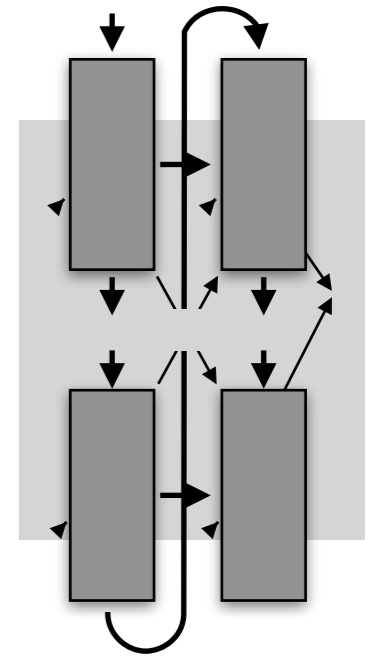
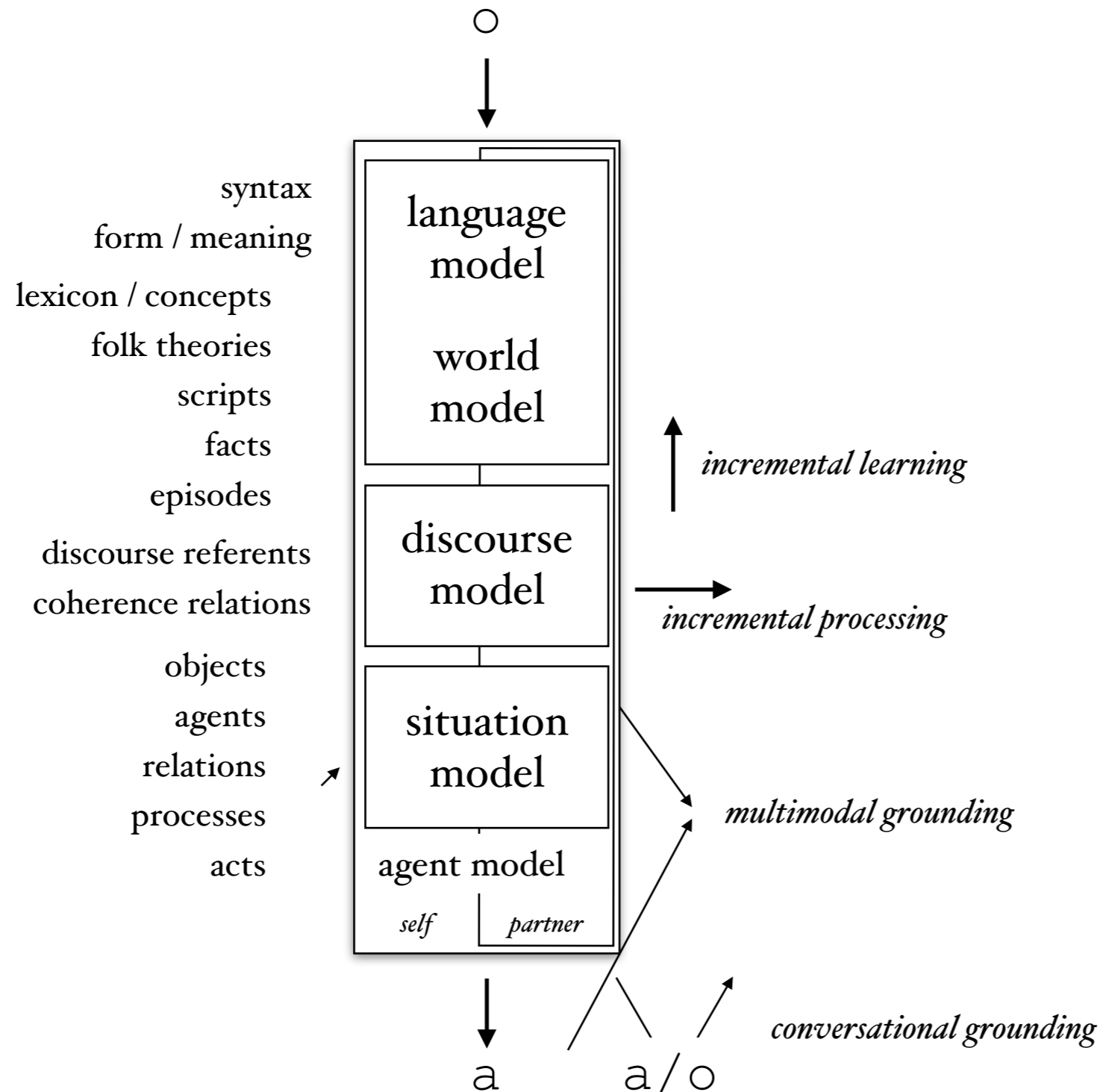
(Wang *et al.* 2019)

(Ribeiro *et al.* 2020)

(Dunietz *et al.* 2020)

work on *representation probing*

situated NLU

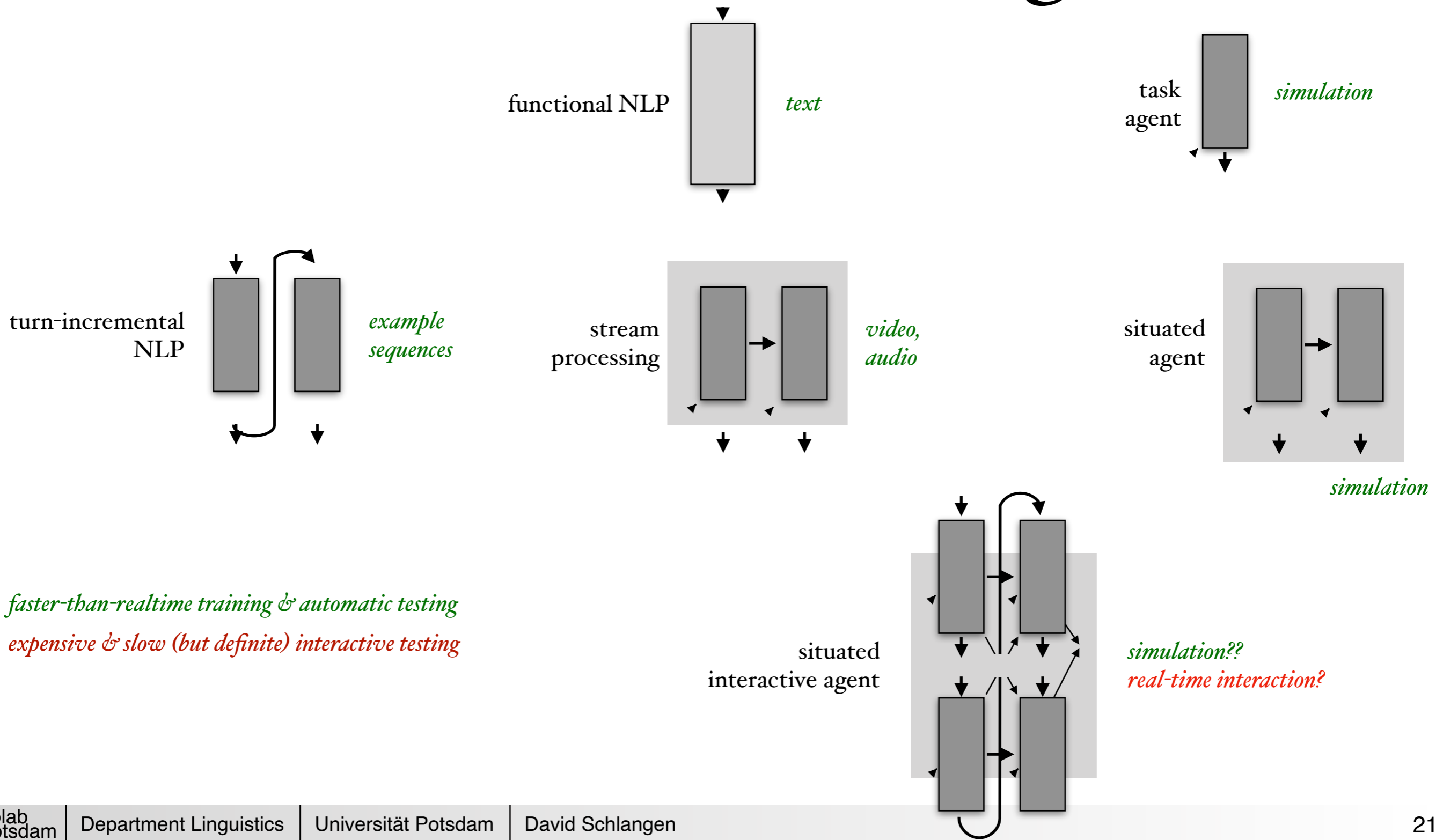


(Schlangen 2023b)

III. Relations btw NLP-NLU & SLU

- this makes clearer the relation btw NLP-NLU & SLU (as tasks, and methodologically)

from NLP-NLU to situated interactive agents



Where's the *theory of NLP*?

- Some points
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 - it makes sense to analyse the task of understanding as
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knowledge & process

Language Model

(Chomsky 1957)

World Model

(Murphy 2002; Margolis & Laurence 2015)

Situation Model

(Johnson-Laird 1983, van Dijk & Kintsch 1983)

Discourse Model

(Kamp 1981, Heim 1983, Asher & Lascarides 2001)

Agent Model

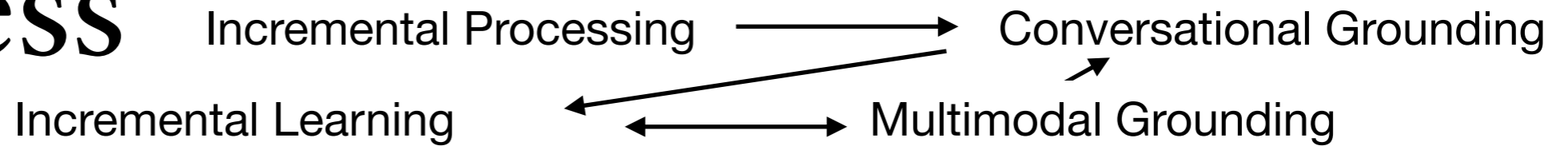
(Bratman 1987, Cohen *et al.* 1990, Clark 1996)

ALARM! Is this not just 20th century AI??

Observations certainly not new.
(This combination may be?)

But the claim is not that these should be modelled symbolically (representations + rules), just that it makes sense to pay attention to these aspects of knowledge and knowledge dynamics.

knowledge & process



Language Model

(Levinson 2010)
(Christianson & Chater 2016)

(H. Clark 1996)

(Bowles &
Gintis 2011)

World Model

(Harris 2015)
(E. Clark 2003)

Situation Model

(Fernández *et al.* 2011)
(Hoppitt & Laland 2013)

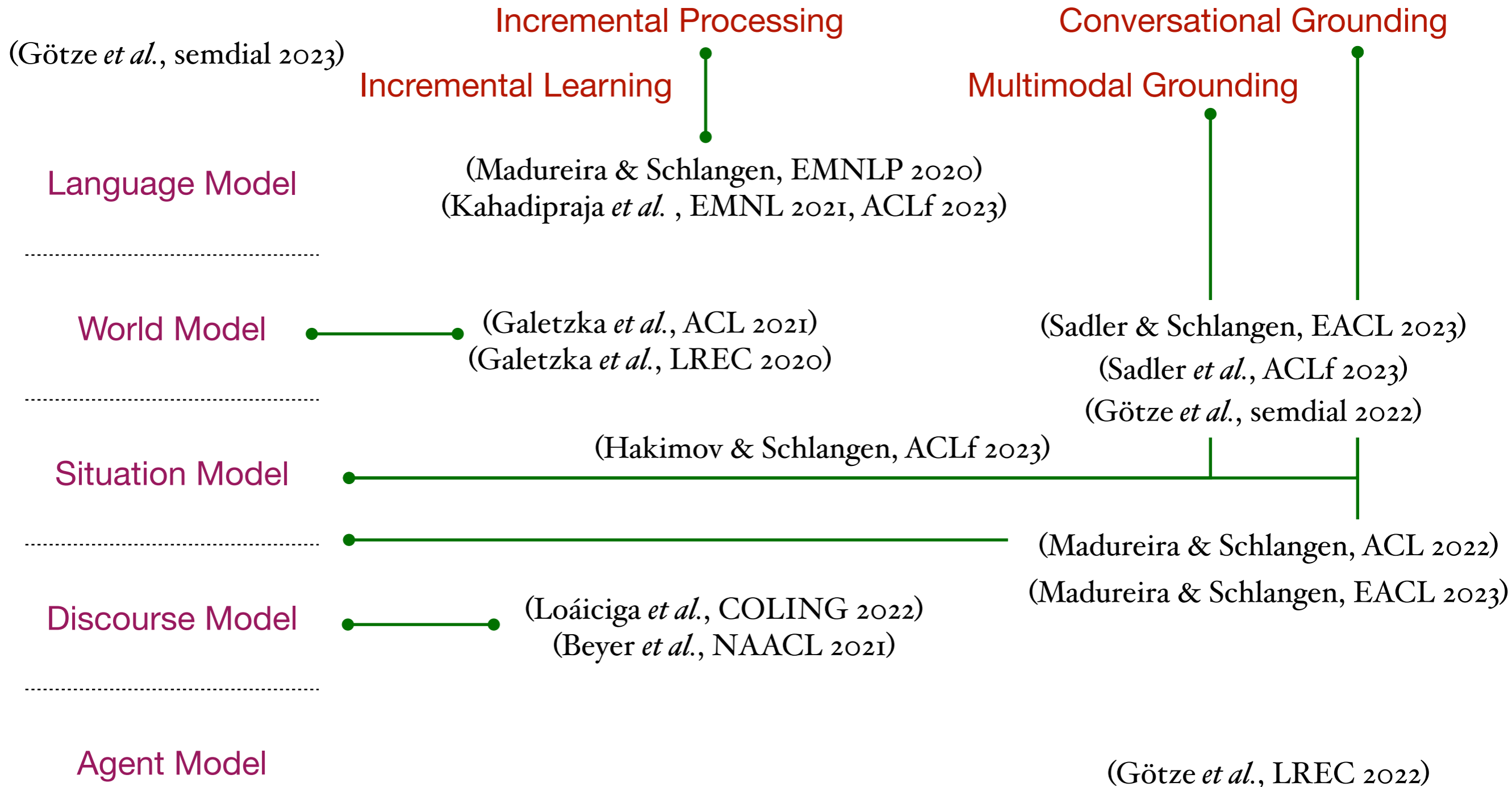
(Harnad 1990)
(Holler & Levinson 2019)
(McNeill 1992; Kendon 2004)

Discourse Model

Schlangen (forthcoming)

Agent Model

Research Programme



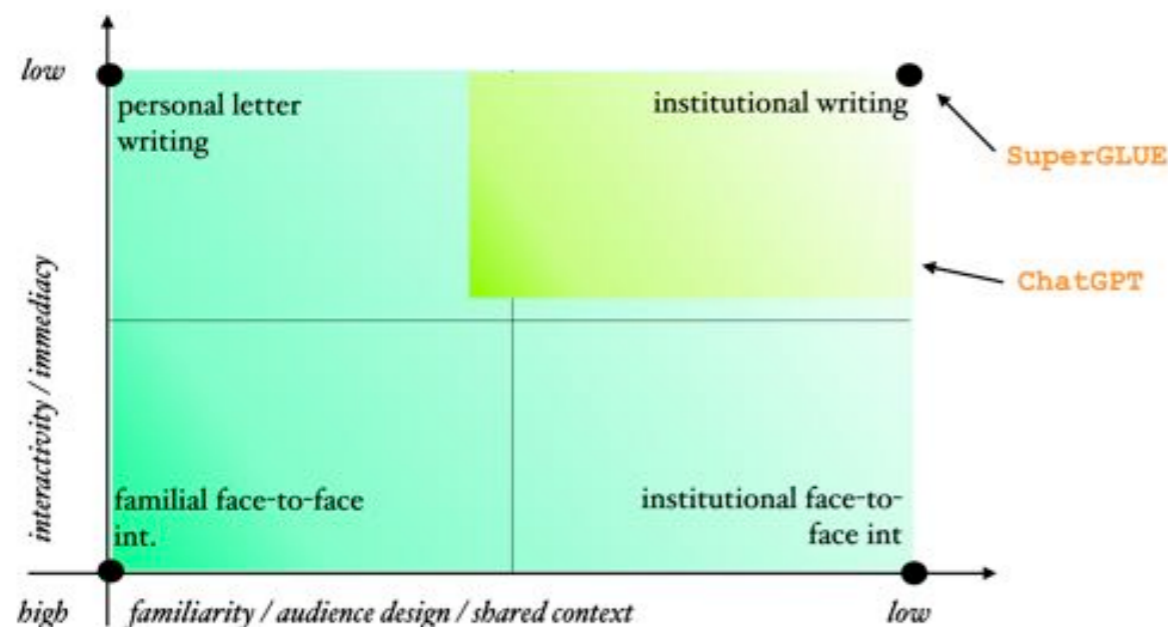
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The New Kids on the Block: chat-optimised LLMs (cLLMs)



- We know how to evaluate it NLP-NLU style.
- That's not all of NLU.
- We've said that *Dialogue Games* offer a principled way to evaluate "language understanding / use in context".
- Can we evaluate cLLMs with Dialogue Games?
 - (Ideally, even in self-play / faster-than-real time & w/o human involvement.)

(a note in advance)

- On ArXiv (Chalamalasetti *et al.* 2023) & github [<https://github.com/clp-research/clembench>]
- but may or may not also be under review
- consider it not being advertised here...

clembench: Using Game Play to Evaluate Chat-Optimized Language Models as Conversational Agents

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Brielen Madureira, Philipp Sadler, David Schlangen *
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University of Potsdam, Germany
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Abstract

Recent work has proposed a methodology for the systematic evaluation of “Situating Language Understanding Agents”—agents that operate in rich linguistic and non-linguistic contexts—through testing them in carefully constructed interactive settings. Other recent work has argued that Large Language Models (LLMs), if suitably set up, can be understood as (simulators of) such agents. A connection suggests itself, which this paper explores: Can LLMs be evaluated meaningfully by exposing them to constrained game-like settings that are built to challenge specific capabilities? As a proof of concept, this paper investigates five interaction settings, showing that current chat-optimized LLMs are, to an extent, capable to follow game-play instructions. Both this capability and the quality of the game play, measured by how well the objectives of the different games are met, follows the development cycle, with newer models performing better. The metrics even for the comparatively simple example games are far from being saturated, suggesting that the proposed instrument will remain to have diagnostic value. Our general framework for implementing and evaluating games with LLMs is available at <https://github.com/clp-research/clembench>.

#	A	Game Master	B
1		[A] The word you need to describe is "expedition". The taboo words are "expedition", "journey", "discovery", "exploration".	
2	[A] CLUE: A trip taken for a specific purpose.		
3		[B] [valid]	
4		[B] CLUE: A trip taken for a specific purpose	
5		[B] GUESS: Journey	
6		[B] [valid, wrong]	
7		[A] GUESS: journey	
8	[A] CLUE: A planned and organized trip with a specific goal in mind.		
9		[B] [valid]	
10		[B] CLUE: A planned and organized trip with a specific goal in mind	
11		[B] GUESS: expedition	
12		[B] [correct]	

Figure 1: An episode of the taboo word game

interaction-tuned language models such as ChatGPT and GPT-4 (OpenAI, 2023).^{1,2} While the public discussion is dominated by what amounts to an unguided breadth-first search of tasks that can be “done” by these models (seeing “sparks” of generality in the process, (Bubeck et al., 2023)), systematic

Why Dialogue Games?

goal-*directed* activity (provides purpose to language)

clear definition of what counts as legal move (formal constraints)

A *Dialogue Game* is a constructed activity with a clear beginning and end, in which *players* attempt to reach a predefined *goal state* primarily by means of producing and understanding linguistic material.

(Schlangen 2019a, 2023)

multi-turn (provides context to language)

clear metric for whether / how well goal has been reached

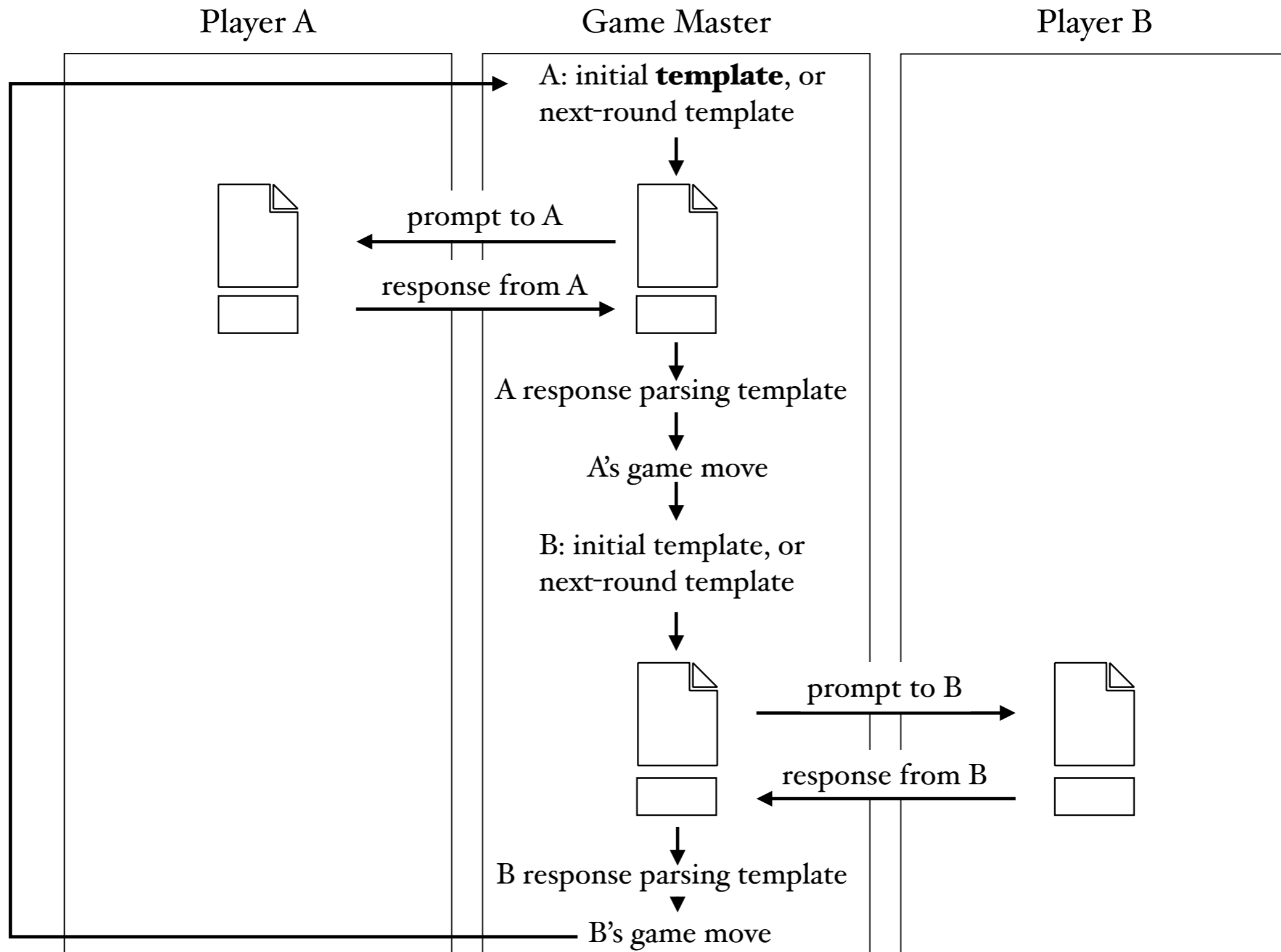
goal & rules provide

control over type of context that is relevant

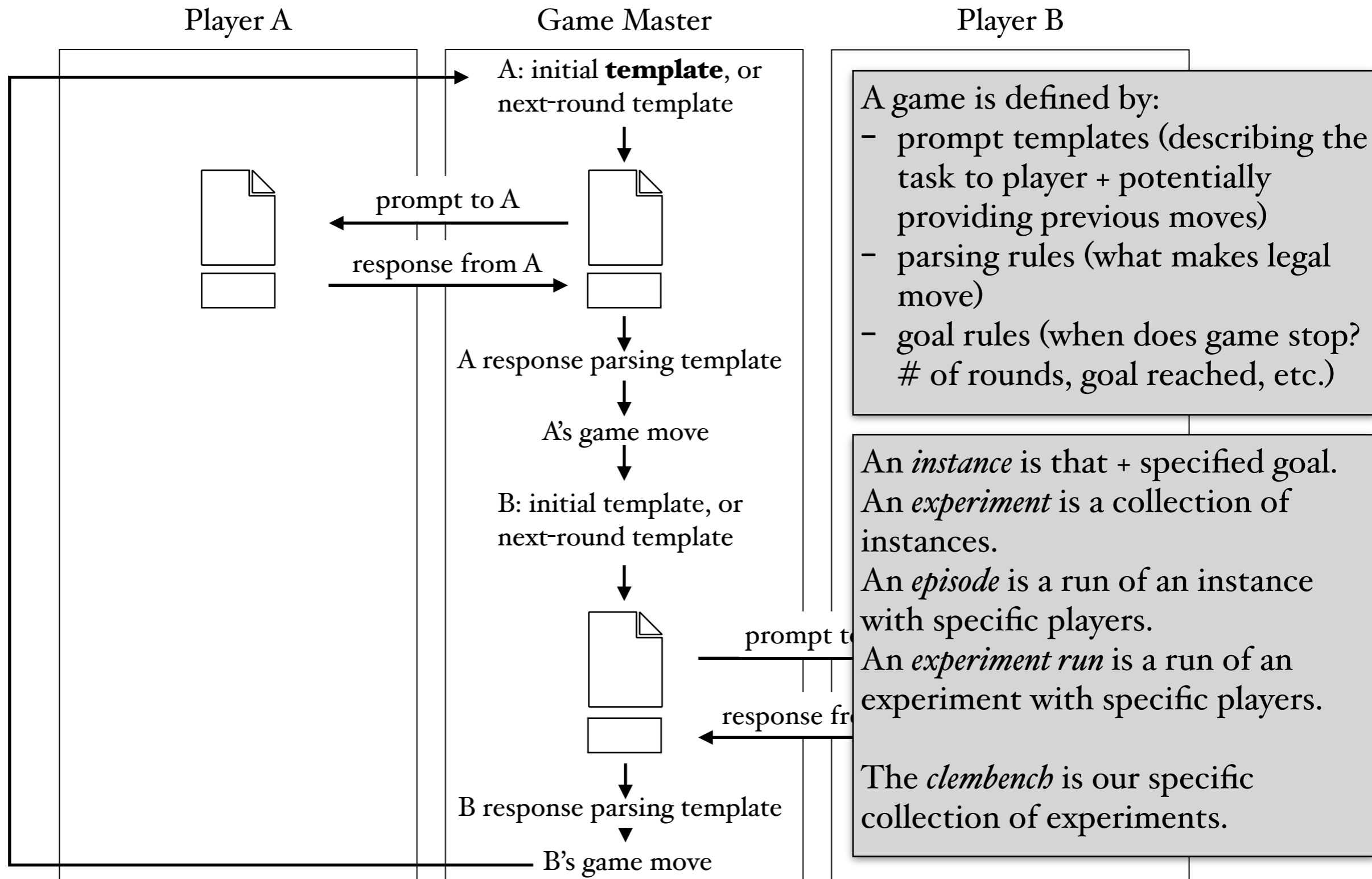
control over type of knowledge that is relevant

nice technical property: game instances unlikely to be even in internet-scale training data; easy to generate more

c1emgame Principles



clemgame Principles



A game is defined by:

- prompt templates (describing the task to player + potentially providing previous moves)
- parsing rules (what makes legal move)
- goal rules (when does game stop? # of rounds, goal reached, etc.)

An *instance* is that + specified goal.
An *experiment* is a collection of instances.

An *episode* is a run of an instance with specific players.
An *experiment run* is a run of an experiment with specific players.

The *clembench* is our specific collection of experiments.

Example: Taboo

TEMPLATE C.1.1

You are playing a collaborative game in which you have to describe a target word for another player to guess.

Rules:

(a) You have to reply in the form of a short description of the target word. Guesses from the other player are accepted with GUESS.

(b) You cannot use the target word or parts or morphological variants of the target word in your description.

(c) In addition, the same rule applies to related words which are provided.

End conditions:

(i) If you use the target word or parts of the target word in your description, then you lose.

(ii) If the other player can guess the target word in \$N\$ tries, you both win.

Let us start.

This is the target word that you have to describe and that the other player has to guess:

\$TARGET_WORDS\$

Related words are:

\$REL_WORDS\$

Important: You are under time pressure. Here are some short descriptions that are to be avoided:

#	A	Game Master	B
1		[A<GM] The word you need to describe is "expedition". The taboo words are "expedition", "journey", "discovery", "exploration".	
2	[A)GM] CLUE: A trip taken for a specific purpose.		
3		[GM GM] [valid]	
4		[GM)B] CLUE: A trip taken for a specific purpose	
5		[GM(B] GUESS: Journey	
6		[GM GM] [valid, wrong]	
7		[A<GM] GUESS: journey	
8	[A)GM] CLUE: A planned and organized trip with a specific goal in mind.		
9		[GM GM] [valid]	
10		[GM)B] CLUE: A planned and organized trip with a specific goal in mind	
11		[GM(B] GUESS: expedition	
12		[GM GM] [correct]	

.2

g a collaborative word guessing game in which you have to guess a target word that the other player describes to you.

one guess at each trial. You win when you guess the target word. You lose when you use a taboo word in \$N\$ tries.

Each trial you will get a new hint from the Game Master which starts with CLUE.

Guesses are accepted by just saying the word using the form: GUESS: <a word>

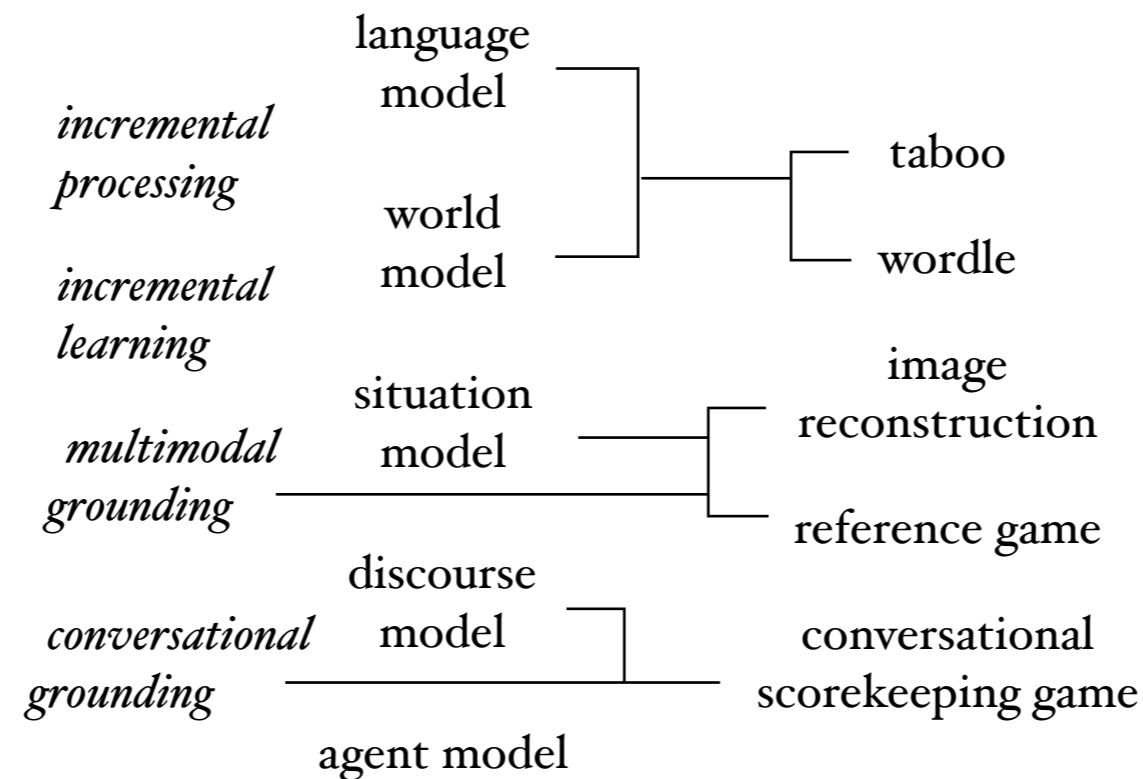
Evaluation criteria:

- has the game been played to the end (n tries)? *instruction following*
- has the instance been solved? *game success*

Why care?

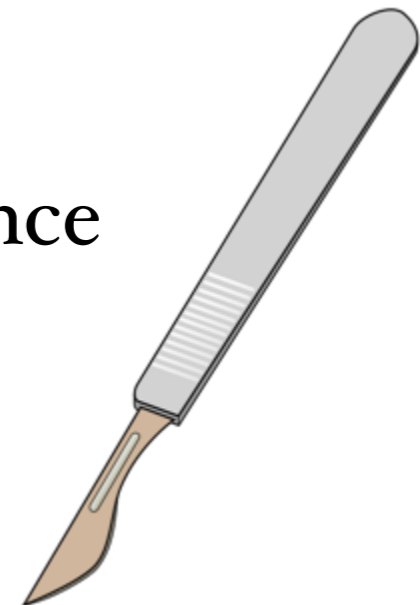
The game challenges core parts of the overall skill of "understanding".

Games & Understanding



Games as benchmarking instrument

- coarse-grained: one number, to weigh and rank
($\text{quality} * \frac{\text{completed}}{\text{attempted}}$)
- finer-grained: look at quality and %-completed separately
- even finer: look at performance by game
- very fine-grained: fine analysis of game performance (additional metrics), qualitative analysis



The games in clembench-1.0

- **taboo**: word guessing game with word constraints
- **wordle**: word guessing game with letter-based constraints
 - **wordle+clue**: additionally, content-based clue
 - **wordle+clue+critic**: other player needs to agree with choice
- **image reconstruction game**: A gets B to reconstruct ASCII grid image
- **reference game**: A describes one (out of three) ASCII images to B, who “sees” them in different order. (Single shot.)
- **conv. scorekeeping game**: A provides information from list to B, but is privately asked by GM about what they “think” B knows.

Example: wordle

#	A	Game Master	B
1	[A GM] guess: hello explanation: This is a common five-letter English word, and I am starting my guess with this word.		hello
2	[A GM] guess_feedback: h<red> e<yellow> l<yellow> l<red> o<yellow>		
3	[A GM] guess: world explanation: The feedback indicates that the letters "e" and "o" are correct but in the wrong position. The word "world" has these letters in the correct positions, so I am guessing this word.		worl d
4	[A GM] guess_feedback: w<red> o<green> r<red> l<yellow> d<yellow>		
5	[A GM] guess: swirl explanation: The feedback indicates that the letters "o" is correct and in the correct position. The letter "l" is correct but in the wrong position. The word "swirl" has these letters in the correct positions, so I am guessing this word.		swirl
6	[A GM] <continues for remaining attempts>		
7	[GM GM] attempts: 6 target_word = model guess: clerk guess_feedback: c<red> l<yellow> e<yellow> r<red> k<red>		
8	[GM GM] game_result = LOSS		

Example: image game

#	A	Game Master	B
1		[A(GM) [initial prompt...] □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ L L L L L □ □ □ □ □ What is your next instruction?	
2	[A(GM) Instruction: Put L in the fourth row in all columns.		
3		(GM)(B) [initial prompt...] Instruction: Put L in the fourth row in all columns.	
4		(GM)(B) □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ L L L L L □ □ □ □ □	
5		[A(GM) What is your next instruction?	
6	[A(GM) Instruction: DONE		

(a) Successful gameplay from both players

#	A	Game Master	B
1		[A(GM) [initial prompt...] □ □ V □ □ □ □ V □ □ □ □ V □ □ □ □ V □ □ □ □ V □ □ What is your next instruction?	
2	[A(GM) Instruction: Put a V in every cell of the second column.		
3		(GM)(B) [initial prompt...] Instruction: Put a V in every cell of the second column.	
4		(GM)(B) □ V □ □ □ □ V □ □ □ □ V □ □ □ □ V □ □ □ □ V □ □ □	
5		[A(GM) What is your next instruction?	
6	[A(GM) Instruction: DONE		

(b) Player A fails in generating the correct instruction (points to second column instead of third as in the target grid)

Example: conv. scorekeeping

#	A	Game Master	B
1		[A<GM] [initial prompt]	
2		[GM<B] What class do you prefer?	
3	[A)GM] ANSWER: Economy.		
4		[GM<B] Which means of transportation do you prefer?	
5	[A)GM] ANSWER: Train.		
6		[GM<B] Please inform your destination.	
7	[A)GM] ANSWER: Stuttgart.		
8		[GM<B] What is the origin of your trip?	
9	[A)GM] ANSWER: London.		
10		[GM<B] When is the trip?	
11	[A)GM] ANSWER: In May.		

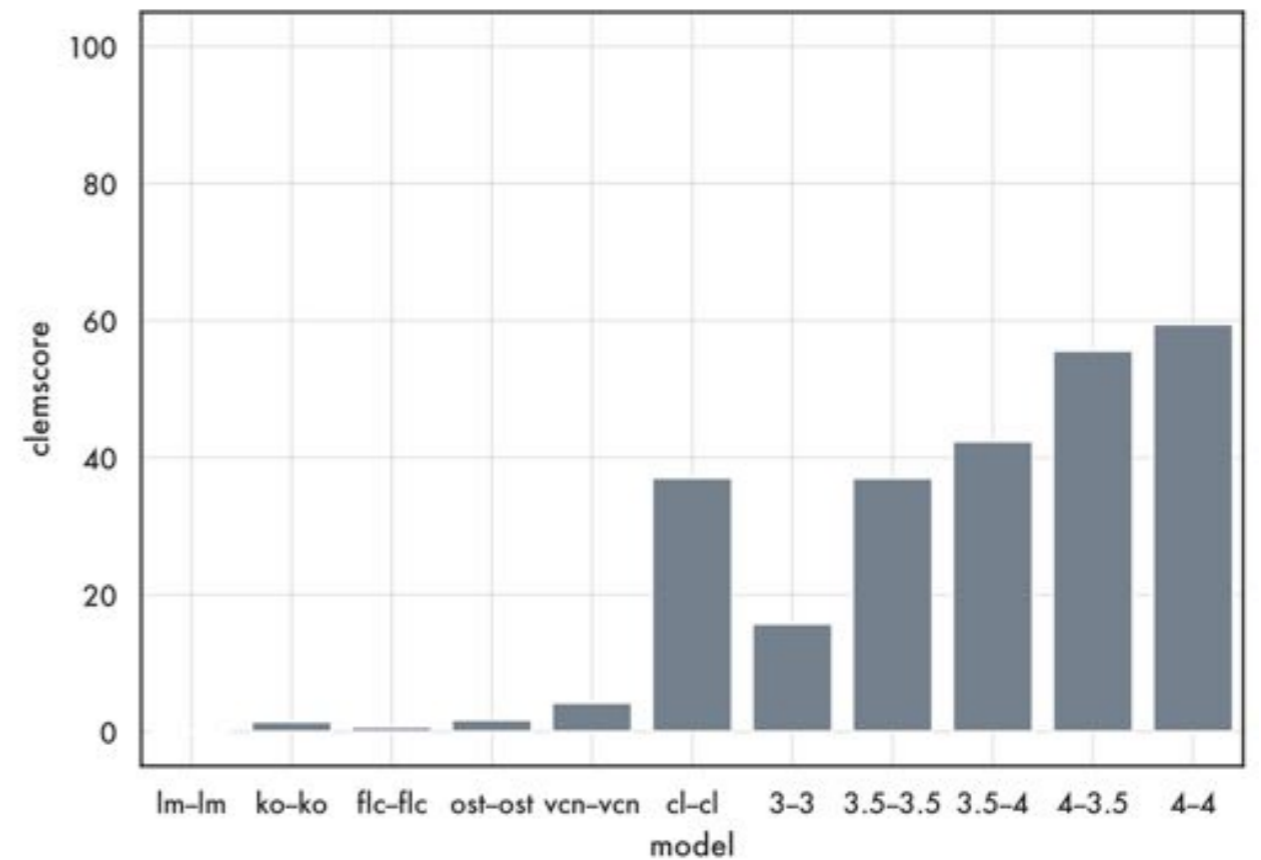
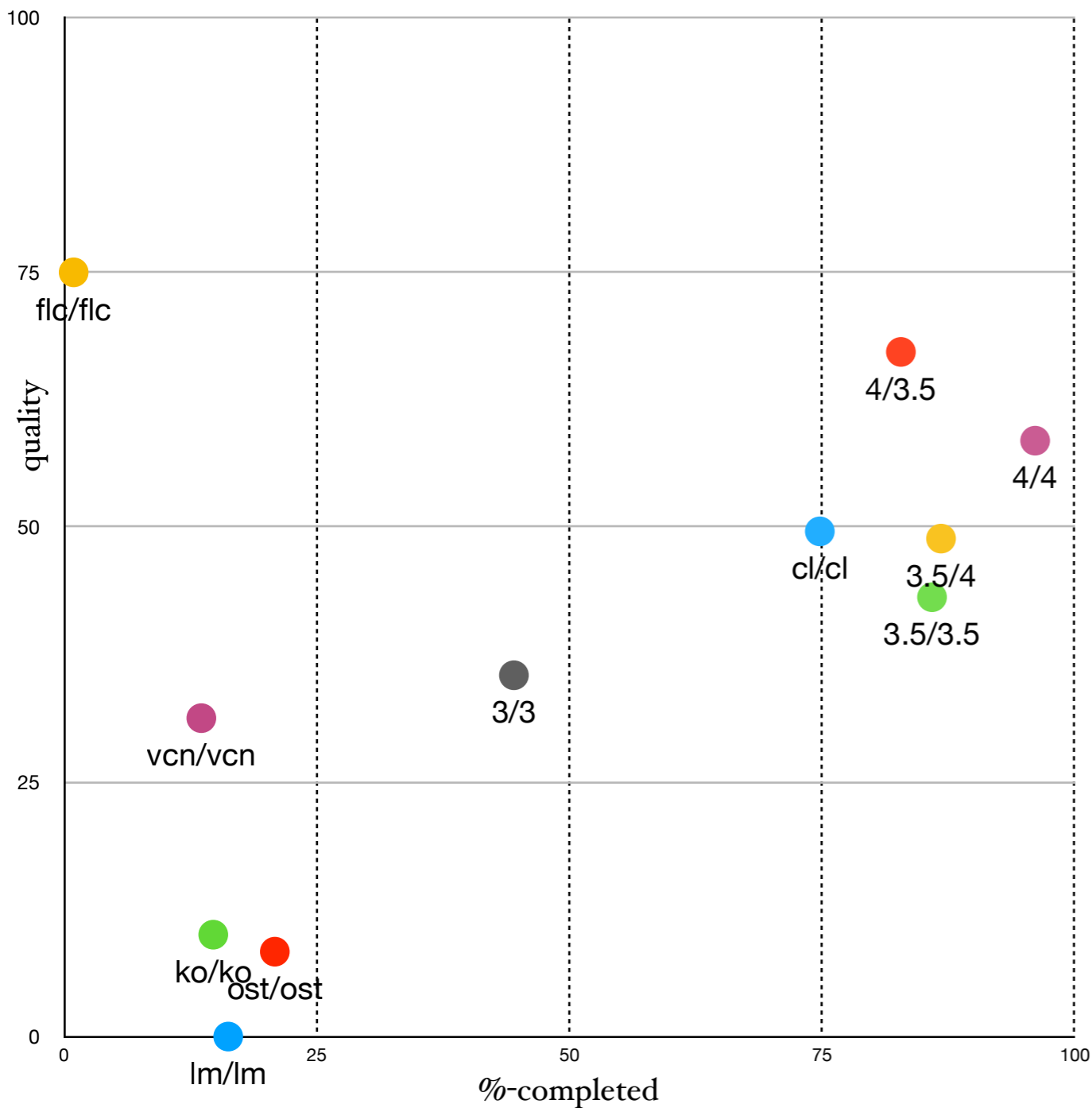
#	A	Game Master	B
1		[A<GM] ME: Do you think the travel agent knows where you depart from? Please answer yes or no.	
2	[A)GM] ASIDE: No.		
3		[A<GM] ME: Do you believe that the travel agent is aware of where you are going? Please answer yes or no.	
4	[A)GM] ASIDE: Yes.		
5		[A<GM] ME: Does the travel agent know how you wish to travel? Please answer yes or no.	
6	[A)GM] ASIDE: No.		
7		[A<GM] ME: Have you informed the travel agent about your class preference? Please answer yes or no.	
8	[A)GM] ASIDE: Yes.		
9		[A<GM] ME: Is the travel agent aware of the dates of your trip? Please answer yes or no.	
10	[A)GM] ASIDE: No.		

Running the benchmark

model	version	here	P	T	I
gpt-4	0314	4	n/a	n/a	Y
gpt-3.5-turbo	0301	3.5	n/a	n/a	Y
text-davinci	003	3	175	300	Y
claude	v1.3	cl	52	n/a	Y
luminous-supreme	2023-01	lm	70	588	Y
falcon-40b-instruct	2023-06	flc	40	600	Y
vicuna-13b	2023-06	vcn	13	1.4k	Y
open-assistant-12b	2023-06	ost	12	400	Y
koala-13b	2023-06	ko	13	1.4k	Y

- Evaluated for:
 - % games played to completion
[following formal rules]
 - quality of game play (only completed games)
[reaching game-specific goal]

Running the benchmark



Running the benchmark

		all	taboo	wordle	wordle+cl	wordle+cr	drawing	reference	priv/sh
lm/lm	% played	16.24	0.0	100.0	3.33	10.34	0.0	0.0	0.0
0.00	qlty score	00.00	/	0.0 (0.0)	0.0 (-)	0.0 (0.0)	/	/	/
ko/ko	% played	14.76	0.0	86.67	16.67	0.0	0.0	0.0	0.0
1.47	qlty score	10.00	/	0.0 (0.0)	20.0 (44.72)	/	/	/	/
flc/flc	% played	0.95	0.0	0.0	3.33	3.33	0.0	0.0	0.0
0.71	qlty score	75.00	/	/	50.0 (-)	100.0 (-)	/	/	/
ost/ost	% played	20.85	0.0	100.0	16.67	14.29	0.0	15.0	0.0
1.73	qlty score	8.33	/	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	/	33.33 (51.64)	/
vcn/vcn	% played	13.58	5.08	56.67	13.33	20.0	0.0	0.0	0.0
4.24	qlty score	31.25	100.0 (0.0)	0.0 (0.0)	25.0 (50.0)	0.0 (0.0)	/	/	/
cl/cl	% played	74.76	76.92	100.0	100.0	46.43	0.0	100.0	100.0
37.06	qlty score	49.58	68.75 (38.71)	0.0 (0.0)	30.56 (40.13)	30.77 (48.04)	/	82.5 (38.48)	84.87 (18.87)
3/3	% played	44.50	28.81	66.67	36.67	23.33	57.5	82.5	16.0
15.77	qlty score	35.46	76.47 (43.72)	1.25 (5.59)	31.36 (38.99)	50.0 (50.0)	38.7 (27.78)	36.36 (48.85)	14.1 (25.21)
3.5/3.5	% played	85.86	69.49	100.0	93.33	76.67	97.5	100.0	64.0
37.02	qlty score	43.12	71.95 (44.79)	0.0 (0.0)	28.57 (46.0)	13.19 (30.16)	60.28 (25.95)	55.0 (50.38)	72.83 (13.07)
3.5/4	% played	86.75	69.49	/	/	80.0	97.5	100.0	/
42.39	qlty score	48.87	62.6 (45.15)	/	/	10.42 (17.42)	64.95 (25.45)	57.5 (50.06)	/
4/3.5	% played	82.78	66.1	/	/	100.0	65.0	100.0	/
55.61	qlty score	67.19	93.59 (23.45)	/	/	46.67 (42.92)	81.0 (21.54)	47.5 (50.57)	/
4/4	% played	96.06	94.92	100.0	100.0	100.0	77.5	100.0	100.0
59.48	qlty score	61.93	76.19 (37.45)	3.67 (8.4)	49.67 (42.09)	49.11 (38.46)	89.06 (22.28)	75.0 (43.85)	90.79 (8.2)

What does it all mean?

- Still room to grow. (Compare to human / human play.)
- Performance seems to increase as a function of size (parameter count, training data, instruction tuning)
- Performance of better models not bad even for image game, scorekeeping
- Pure wordle very hard, even for GPT₄
- Open models not quite there yet

What does it all mean?

- But what did the scalpel dissect?
 - At the moment, a bit hard to see trees for the forrest...
 - More fine-grained analyses to come. (But see paper.)
 - E.g., explanations in wordle mostly not consistent with decision made by model.

Where to?

- This was just a proof-of-concept of the instrument
- Much remains to be done:
 - Deeper analysis of performance on games
 - Additional games (e.g., more modalities; multi-linguality)
 - Clearer argument for correlation btw game performance and (useful) task performance
 - Investigate performance as function of model parameters (checkpoint, parameter size, etc.): Is performance linear? “Emergence”? Etc.
 - Continuous testing... new models to test every day...
- Open source — easy to get involved! <https://github.com/clp-research/clembench>

Structure

- Part I: “Understanding Understanding”
 - Our Research Programme
 - The *task* of LU has internal structure
 - Realising this is useful (at the very least) for benchmarking
 - Some Systematic Insights
 - Some Recent Projects
- Part II: Probing Chat-Optimized LLMs Through Gameplay
 - Games & Capabilities
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- There's more to LU than NLU
- The *task* of LU has internal structure
- Realising this is useful (at the very least) for benchmarking
- Also sketches path from NLP-NLU to SLU

- cLLMs do go some steps towards handling context-dependent language use
- using formal constraints to rein in LLMs might be worthwhile strategy for more (real-)task-oriented SIAs...

Thank you.

Questions, Comments?

Acknowledgements: Many thanks to my current & former grad students (<https://clp.ling.uni-potsdam.de/people/>) & colleagues w/ whom I have discussed related ideas in recent years.

**clmbench: Using Game Play to Evaluate
Chat-Optimized Language Models as Conversational Agents**

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Gratefully acknowledged: Funding by DFG (project “RECOLAGE”; CRC “Limits of Variability”, project Bo6); BMBF (project “COCOBOTS”)

List of References for the Talk “Understanding Understanding”

All of our publications can be found at: <https://clp.ling.uni-potsdam.de/publications/>.

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