

# Semantic Theory

## Week 11 – Incremental Meaning Construction

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Noortje Venhuizen  
Harm Brouwer

Universität des Saarlandes

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# Distributional Formal Semantics

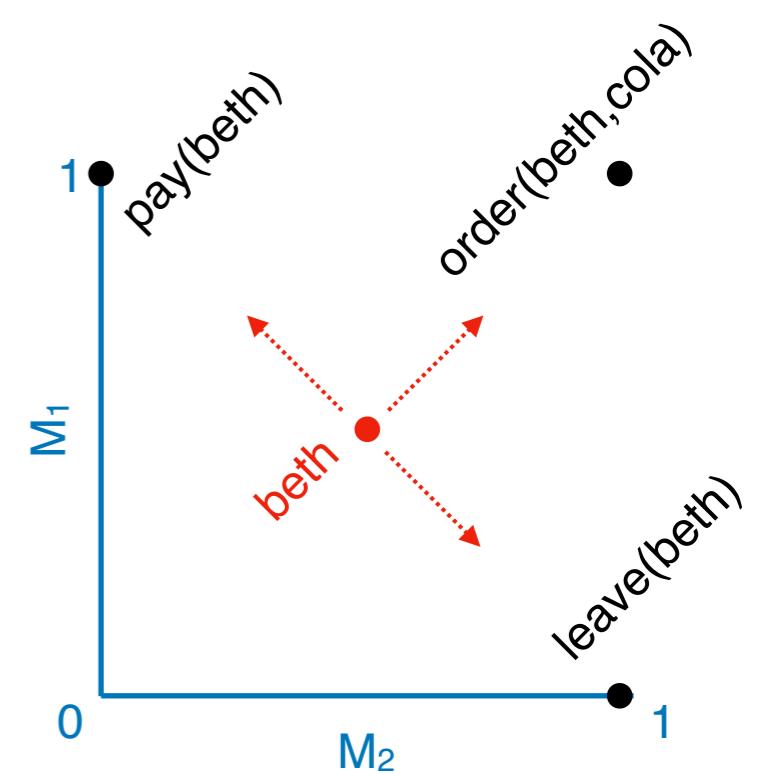
- A set of logical models  $\mathcal{M}$  that truth-conditionally and probabilistically capture the state of the world
- A set of **atomic** propositions  $\mathcal{P}$  — e.g., `order(beth,cola)`, `enter(thom,bar)`
- The meaning of a (complex) proposition  $p$  is defined by a vector  $v(p)$  in  $S_{\mathcal{M} \times \mathcal{P}}$ , reflecting its truth/falsehood relative to each model in  $\mathcal{M}$
- Fully compositional at the propositional level

Q: What about sub-propositional meaning? — e.g., ‘beth’, ‘ordered’

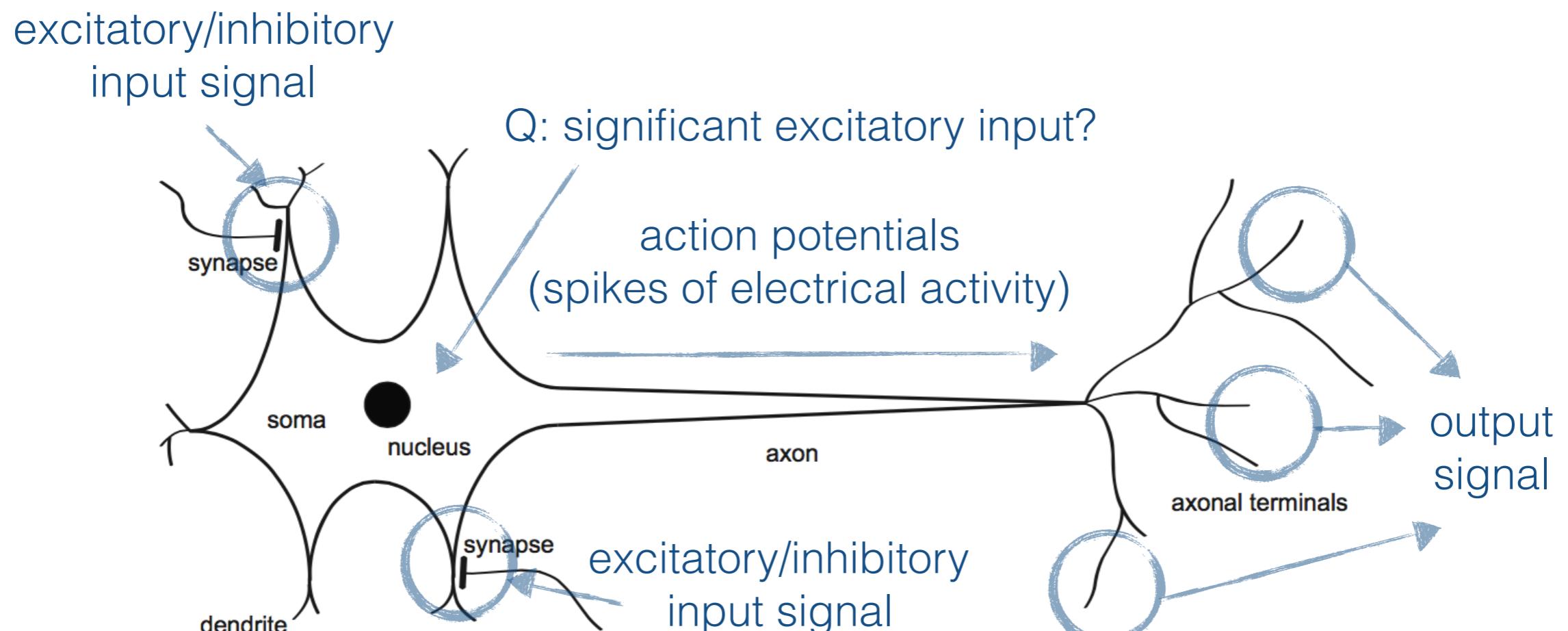
# Distributional Formal Semantics (ct'd)

- ▶ Vectors representing (combinations of) propositions are binary, reflecting truth/falsehood relative to each model
- ▶ But the meaning space  $S_{M \times P}$  is itself **continuous**
- ▶ The sub-propositional meaning of an expression  $e$  is a real-valued vector defining a point in  $S_{M \times P}$  lying in between the propositions that  $e$  pertains to
  - The derivation of the meaning of an expression  $w_1 \dots w_i$  is a trajectory through  $S_{M \times P}$
  - We can model this derivation using a Simple Recurrent artificial neural Network (SRN)

Next: A primer on Artificial Neural Networks



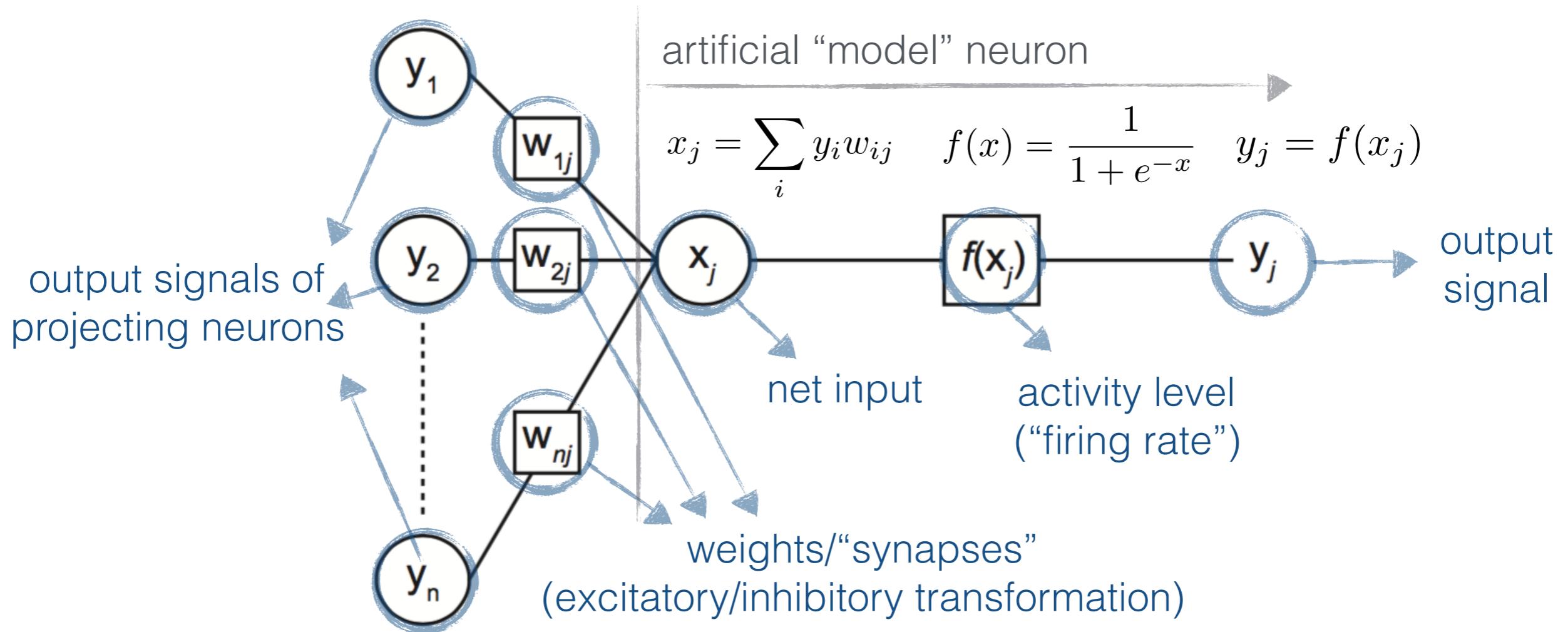
# Biological Neurons



**Figure A.1 | Schematic overview of a biological neuron (or nerve cell).**

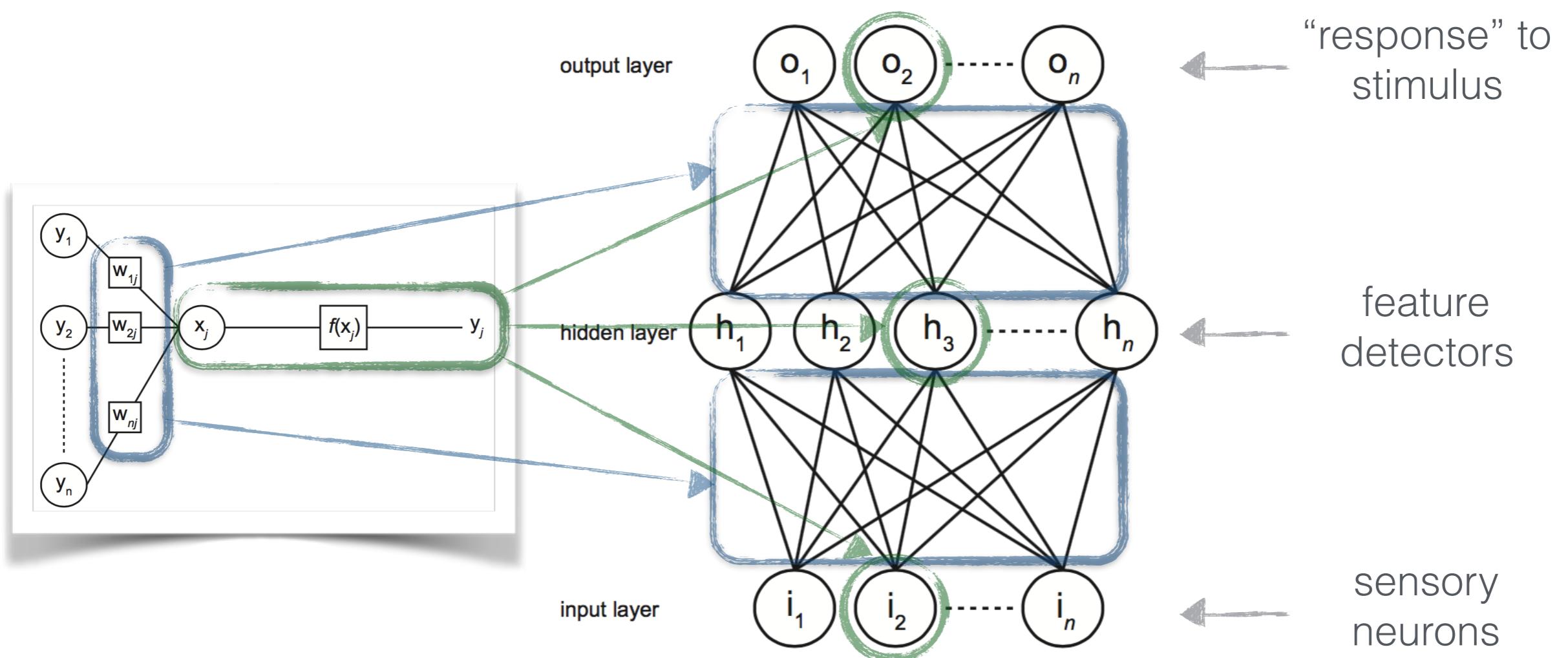
> synapses transform action potentials into an excitatory or inhibitory chemical signal

# Artificial “Model” Neurons



**Figure A.2 |** Schematic overview of a unit (or model neuron). The activation level of the unit is a non-linear combination of its net input. The unit's net input, in turn, is the weighted sum of the activation levels of all units that signal to this unit.

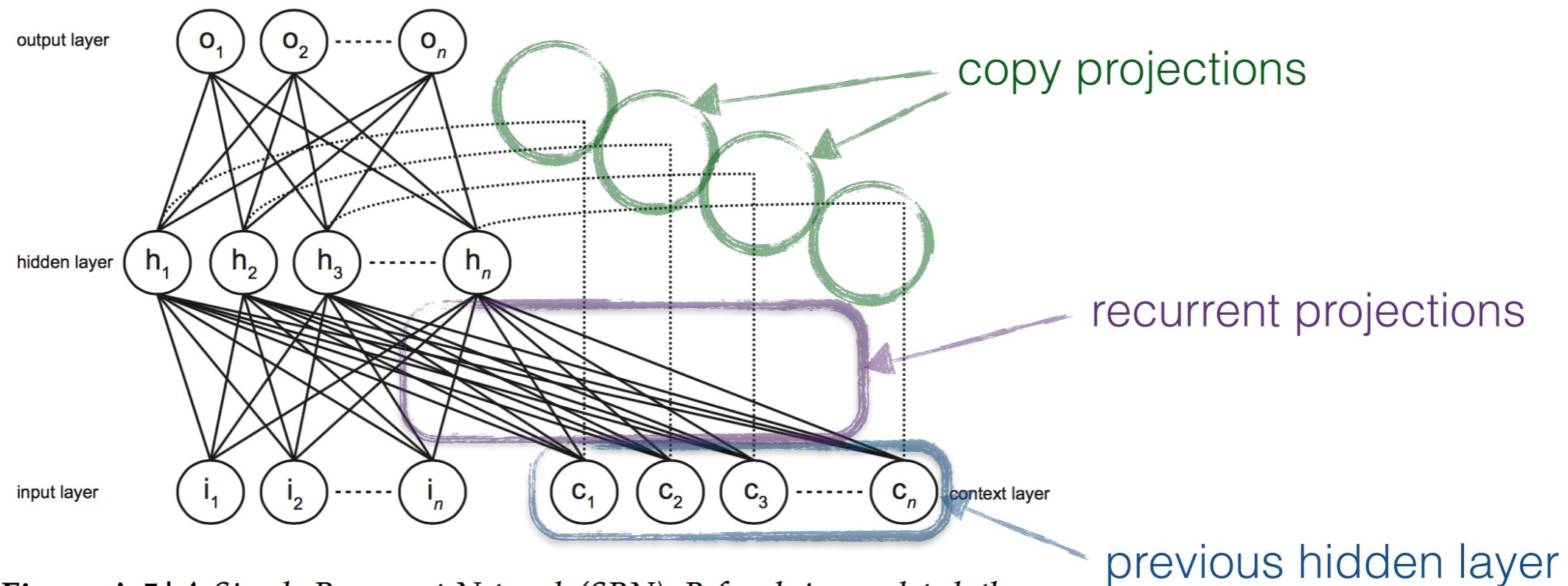
# Artificial Neural Networks



**Figure A.3 | A Feed Forward neural Network (FFN). Units in successive layers are fully connected, whereas units within layers are not.**

# Recurrence—Modeling Memory

Q: What about temporally extended stimuli (e.g., sentences)?

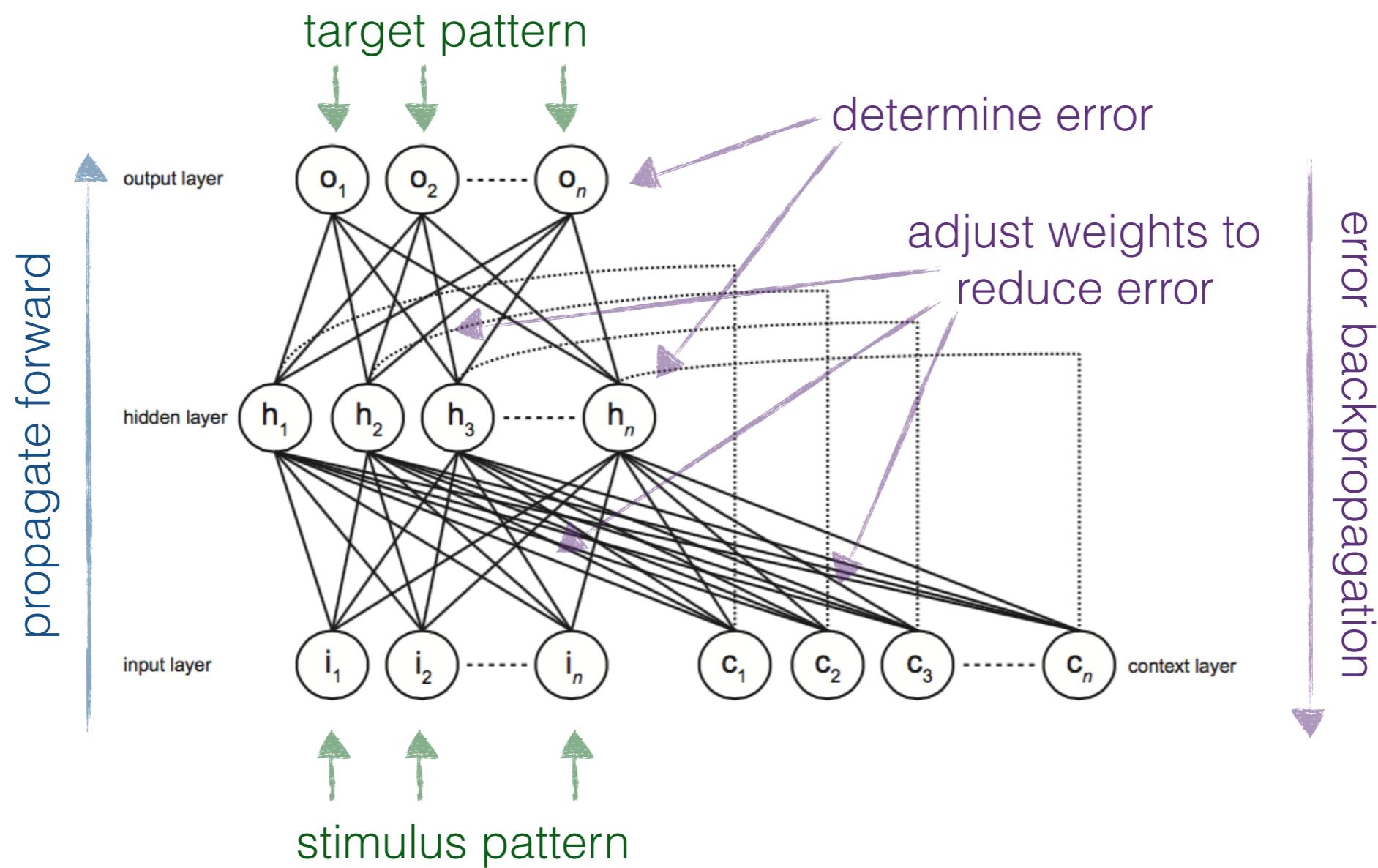


**Figure A.5 | A Simple Recurrent Network (SRN).** Before being updated, the activation values of the units in the hidden layer are copied to their corresponding unit in the context layer (the fine dotted lines represent copy connections).

> a Simple Recurrent Network (SRN) is a very powerful tool for cognitive modeling

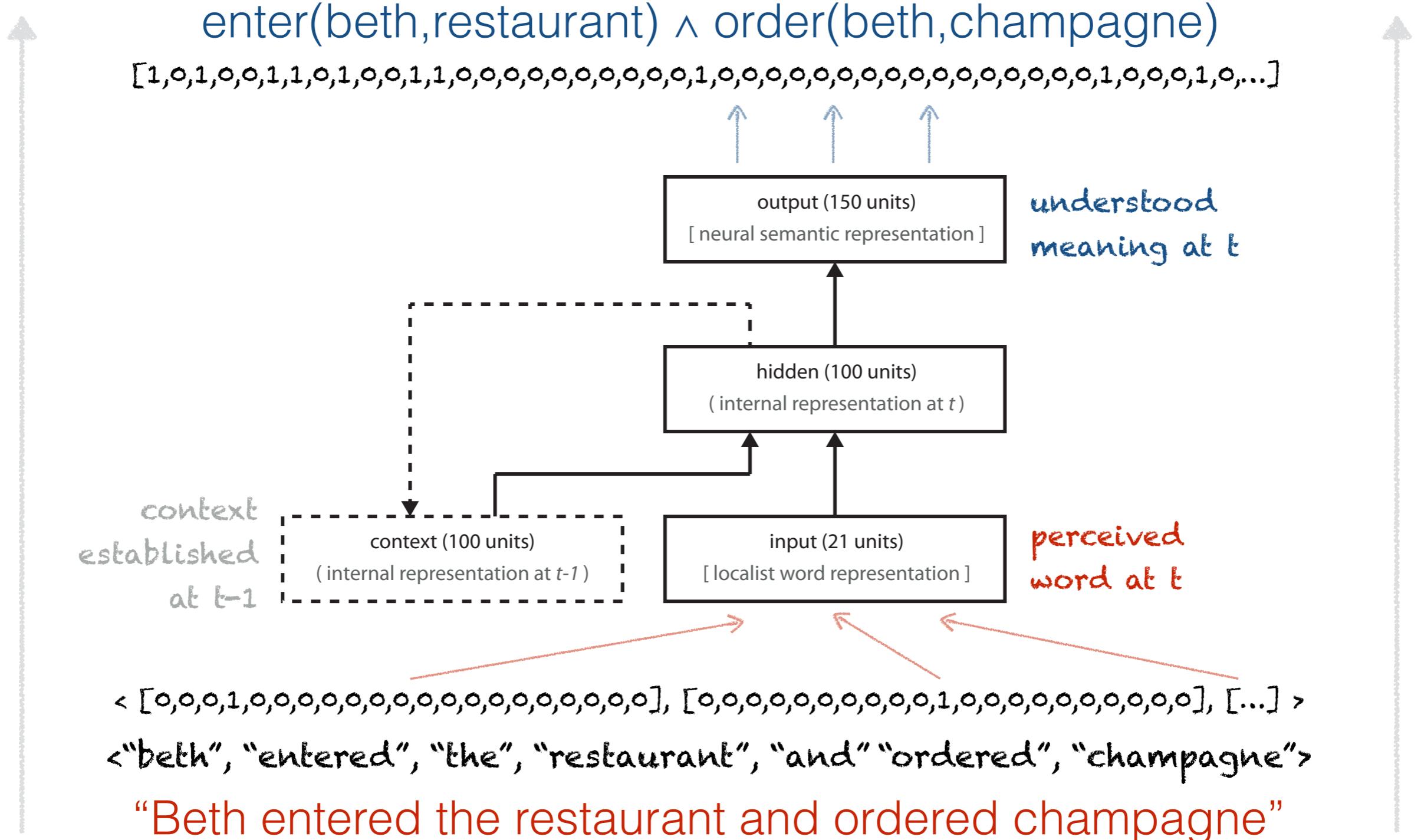
# Learning in Neural Networks

> Neural Networks learn from experience (training)



> challenge in neural network modeling is to **minimize error** for a set of stimuli

# A Neural Model of Comprehension



# DP Model — Atomic propositions

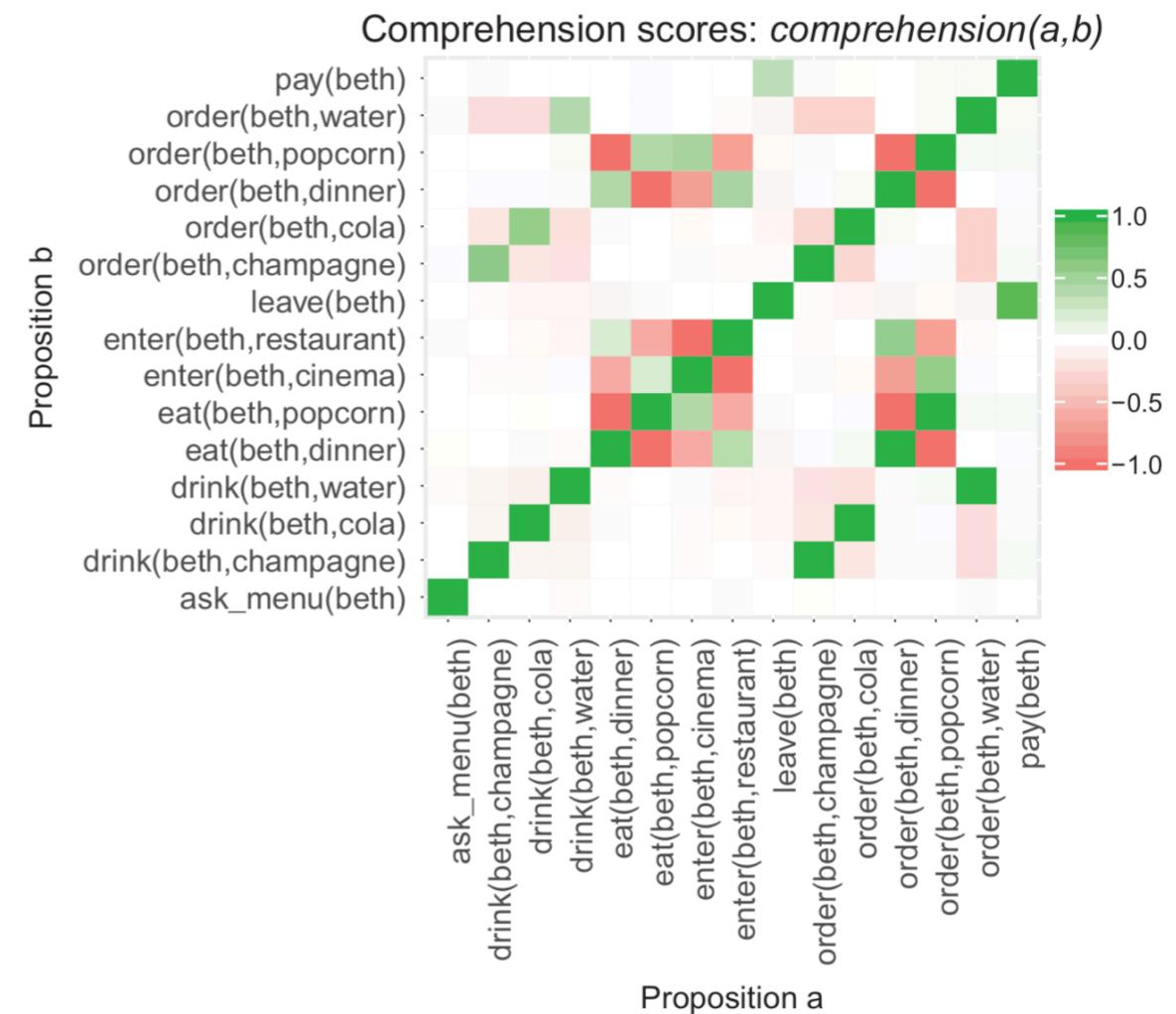
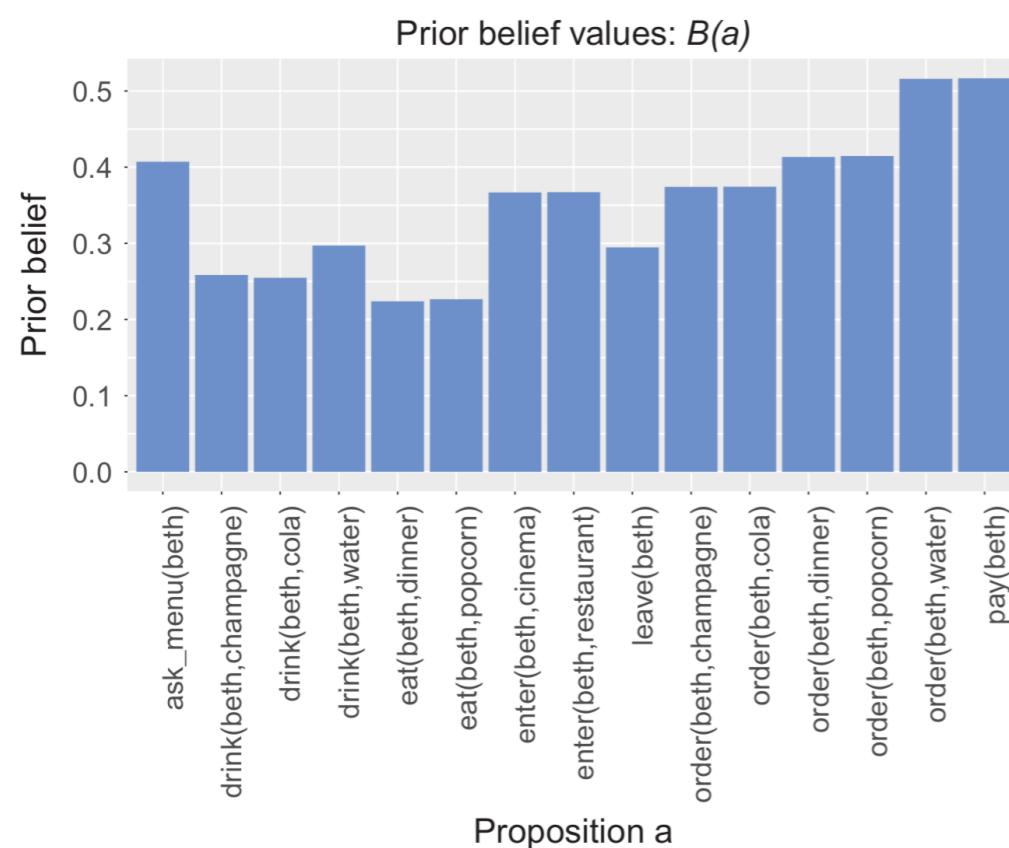
**Table 1.** Microworld concepts.

Class	Variable	Class members
Persons	$x$	beth, dave, thom
Places	$p$	cinema, restaurant
Foods	$f$	dinner, popcorn
Drinks	$d$	champagne, cola, water
Predicates	-	enter, ask menu, order, eat, drink, pay, leave

**Table 2.** Basic propositions.

Proposition	$n$
enter ( $x, p$ )	6
ask menu ( $x$ )	3
order ( $x, d$ ), order ( $x, f$ )	15
eat ( $x, f$ )	6
drink ( $x, d$ )	9
pay ( $x$ )	3
leave ( $x$ )	3
Total	45

# DP Model — Meaning space



(only propositions for 'beth' are shown)

# DP Model — Grammar

**Table 3.** Grammar of the language used for training. Optional arguments are in square brackets, and different instantiations of a rule are separated using the pipe symbol. Variable  $V \in \{enter, menu, order, eat, drink, pay, leave\}$  denotes verb types.

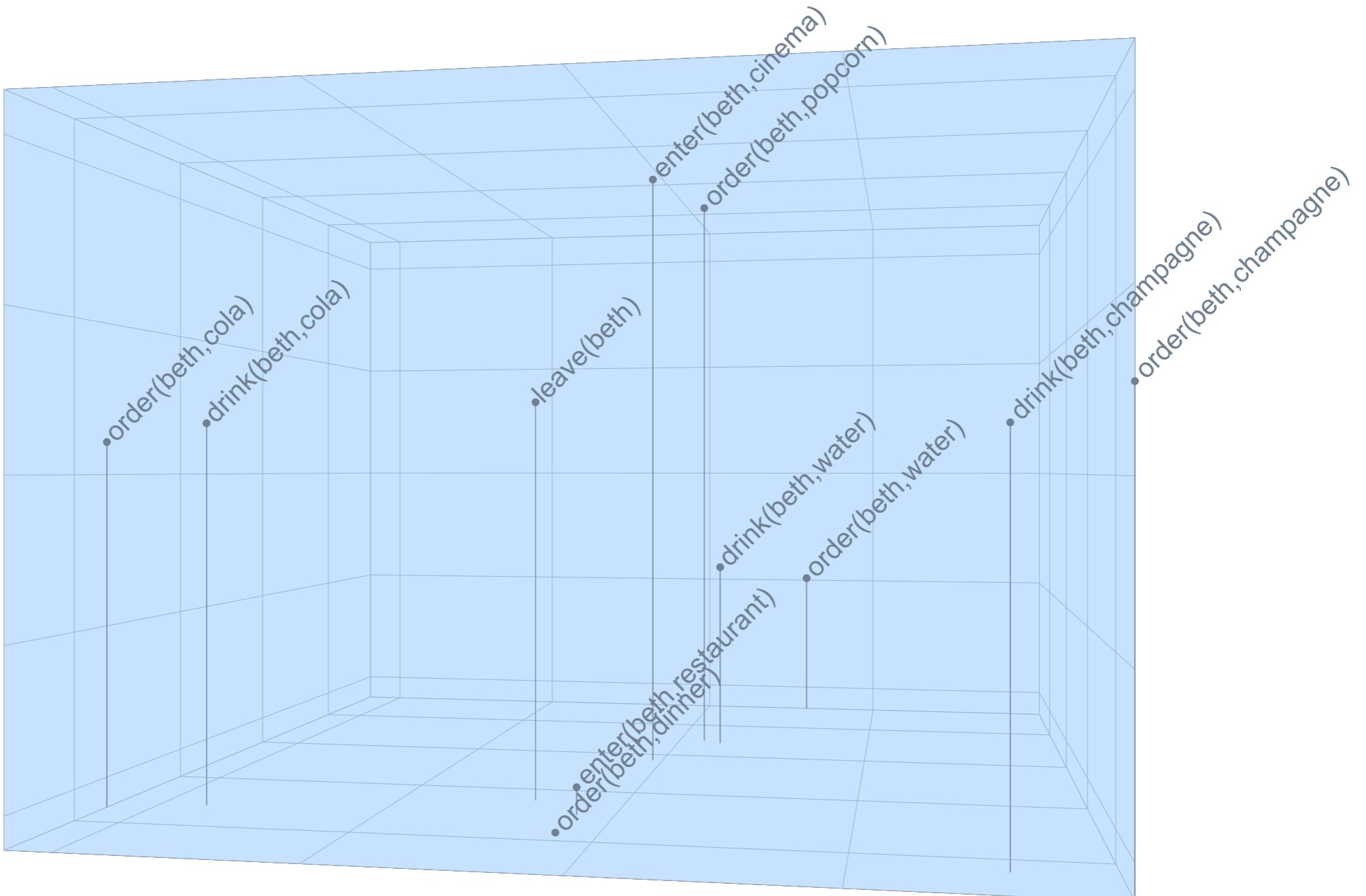
Head		Body
S	→	$NP_{person} VP_V [CoordVP_V]$
$NP_{person}$	→	beth   dave   thom
$NP_{place}$	→	the cinema   the restaurant
$NP_{food}$	→	dinner   popcorn
$NP_{drink}$	→	champagne   cola   water
$VP_{enter}$	→	entered $NP_{place}$
$VP_{menu}$	→	asked for the menu
$VP_{order}$	→	ordered $NP_{food}$   ordered $NP_{drink}$
$VP_{eat}$	→	ate $NP_{food}$
$VP_{drink}$	→	drank $NP_{drink}$
$VP_{pay}$	→	paid
$VP_{leave}$	→	left
$CoordVP_{enter}$	→	and $VP_{menu}$   and $VP_{order}$   and $VP_{leave}$
$CoordVP_{menu}$	→	and $VP_{order}$   and $VP_{leave}$
$CoordVP_{pay}$	→	and $VP_{order}$   and $VP_{leave}$

**Highly frequent (x9):** “ $NP_{person}$  ordered dinner,” “ $NP_{person}$  ate popcorn,” “ $NP_{person}$  ordered champagne,” “ $NP_{person}$  drank water”;

**Relatively frequent (x5):** “ $NP_{person}$  ordered cola,” “ $NP_{person}$  drank cola.”

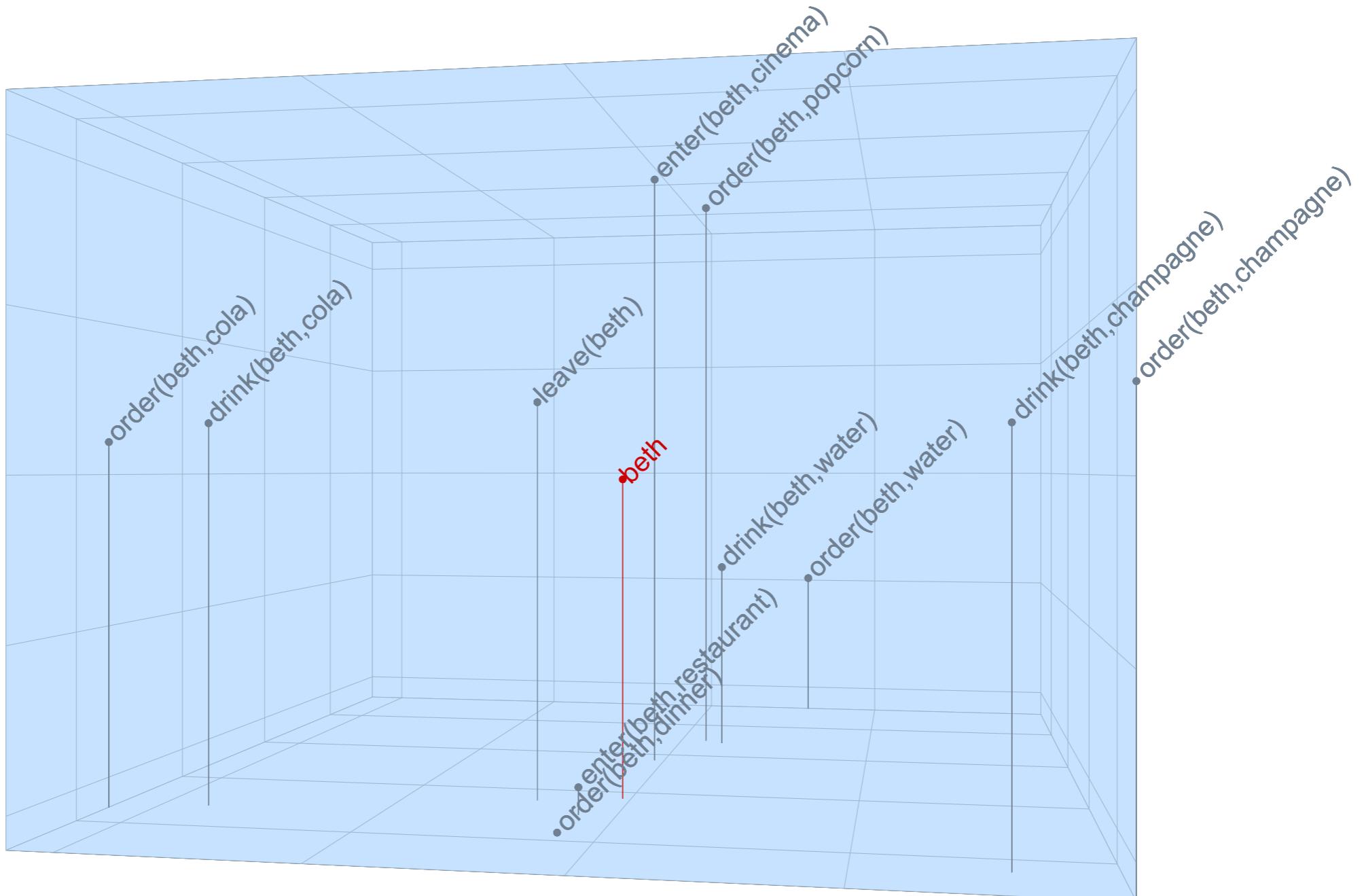
**Default (x1):** All other structures

# Comprehension is meaning-space navigation



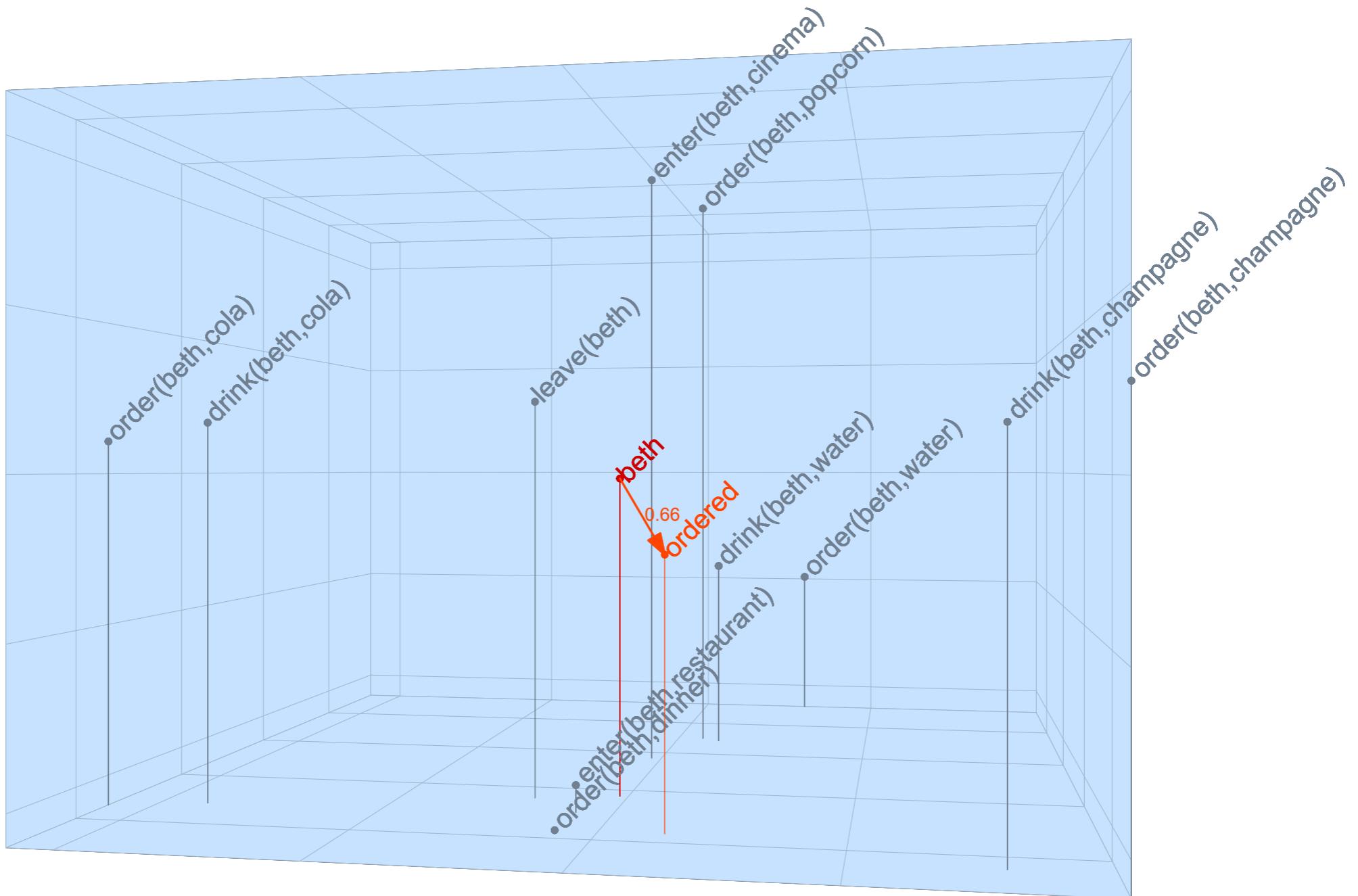
Multi-dimensional scaling:  $150D \mapsto 3D$

# Comprehension is meaning-space navigation



[“beth”]

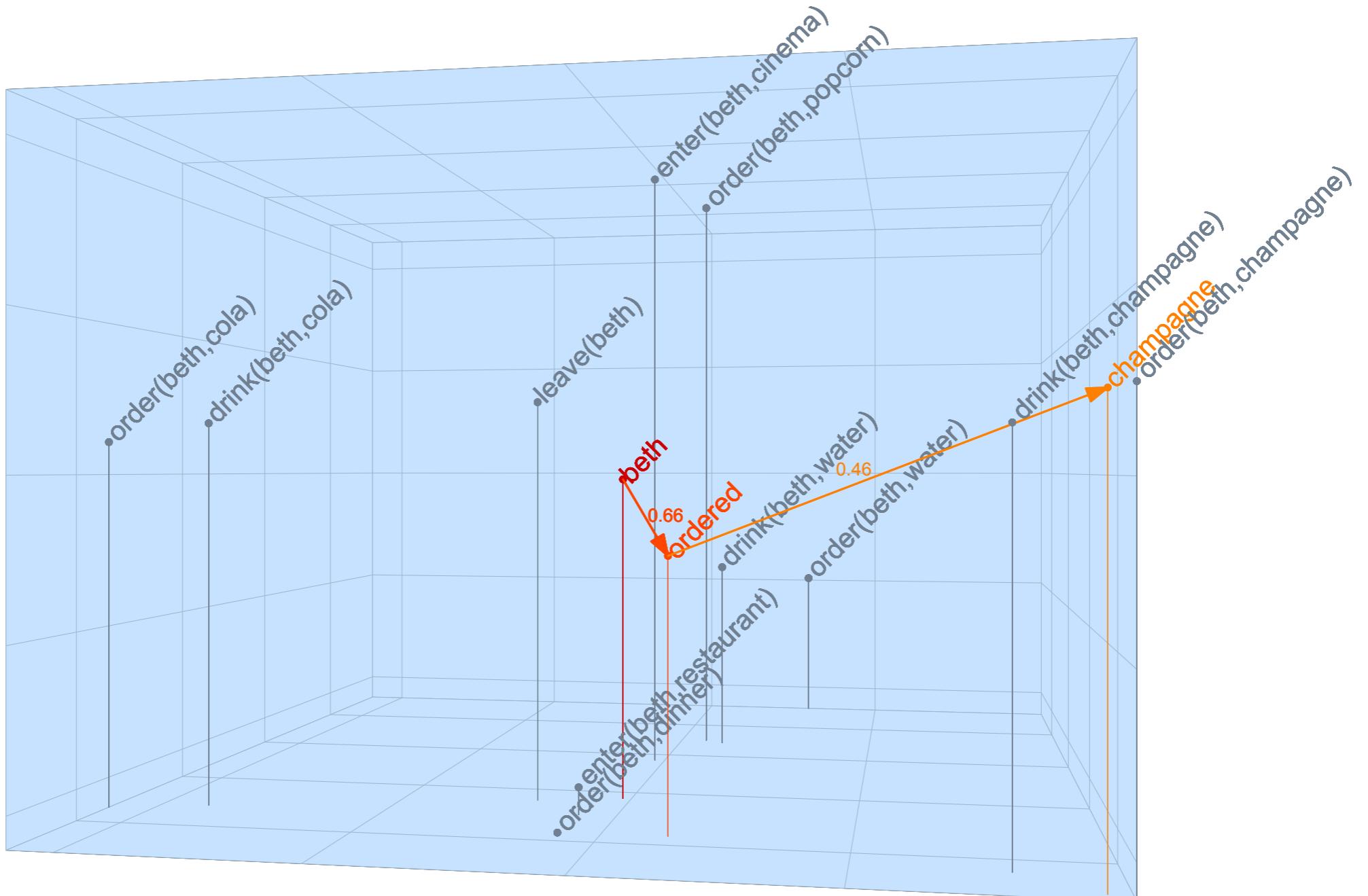
# Comprehension is meaning-space navigation



["beth", "ordered"]

(scalars  $\propto$  distance)

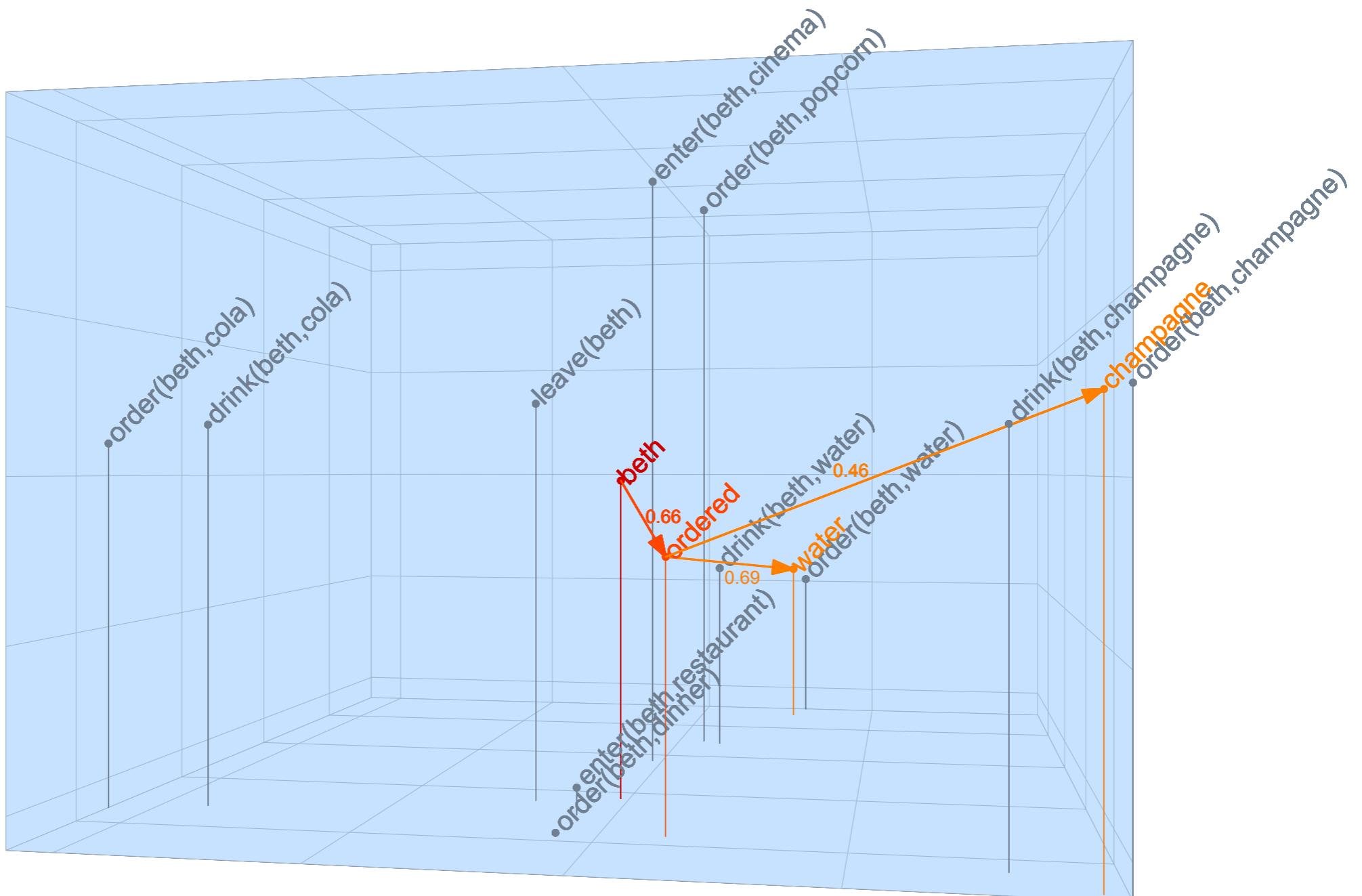
# Comprehension is meaning-space navigation



["beth", "ordered", "champagne"]

(scalars  $\propto$  distance)

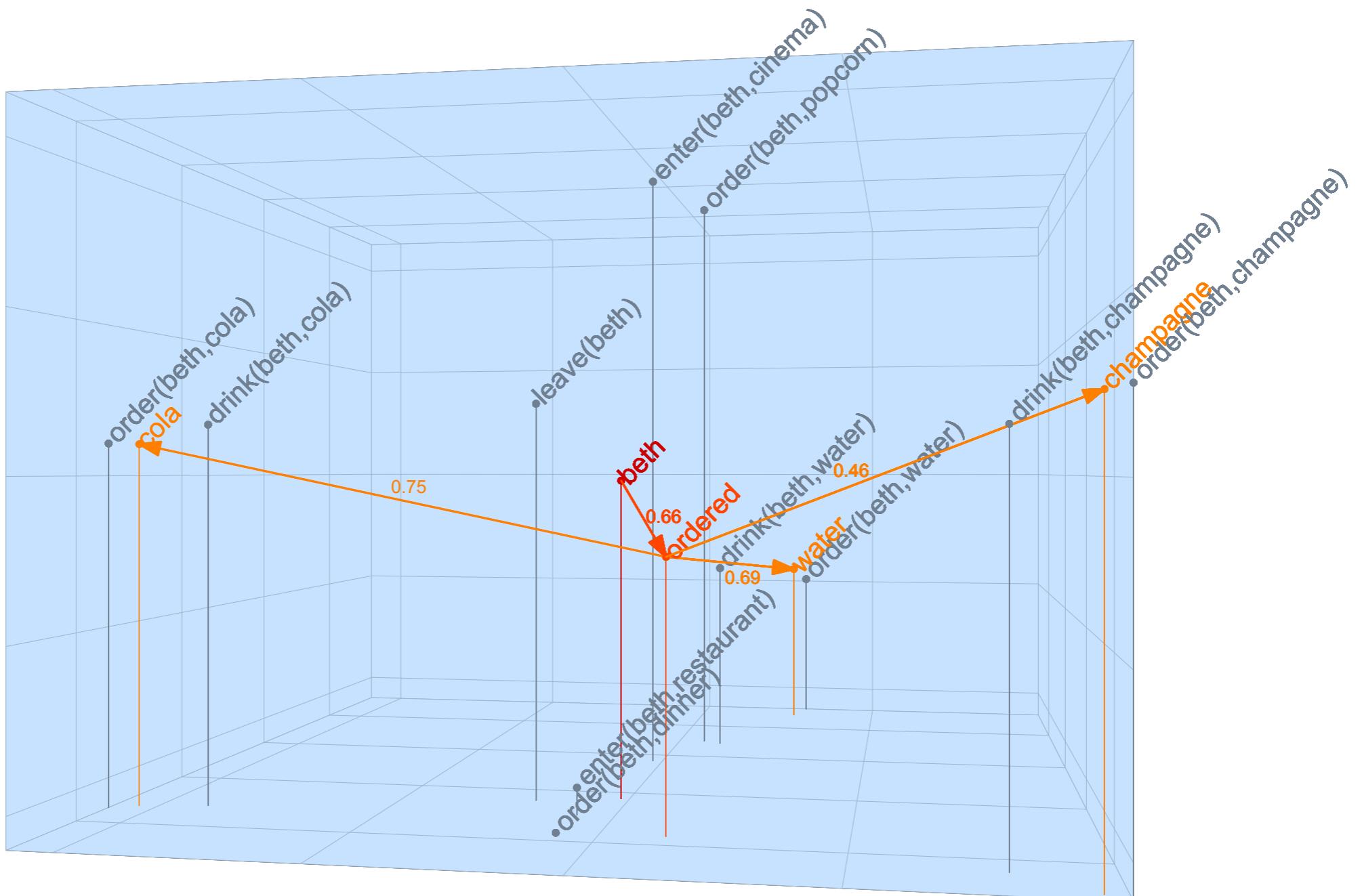
# Comprehension is meaning-space navigation



["beth", "ordered", "water"]

(scalars  $\propto$  distance)

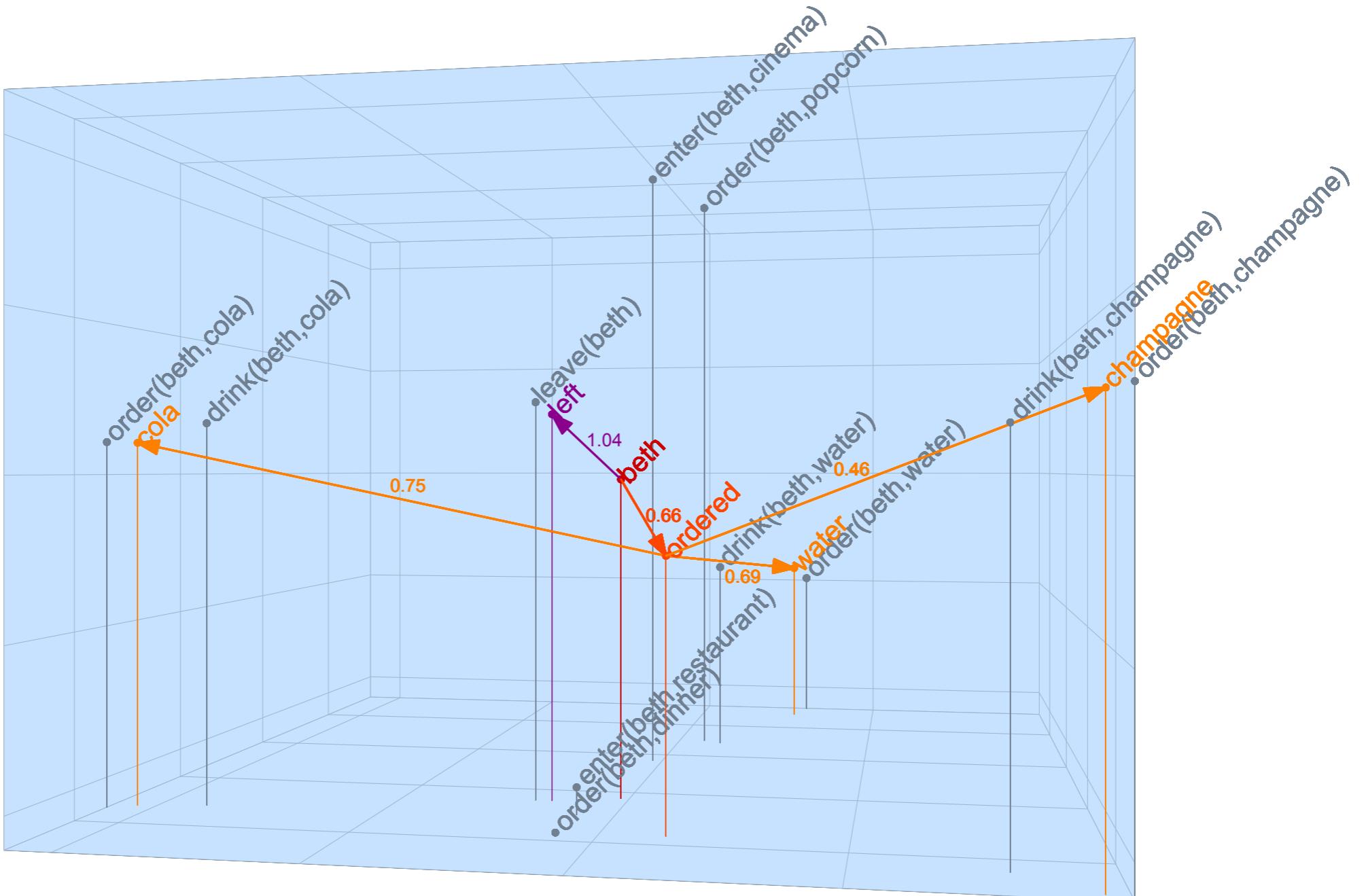
# Comprehension is meaning-space navigation



["beth", "ordered", "cola"]

(scalars  $\propto$  distance)

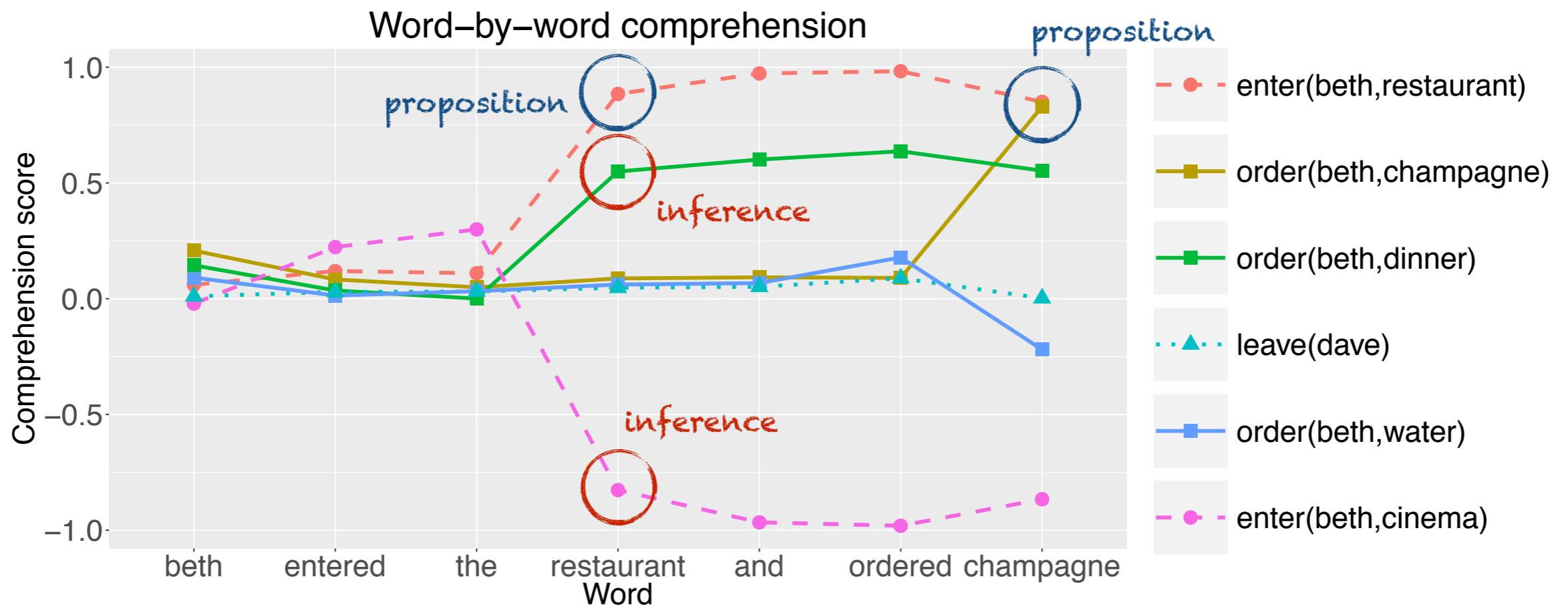
# Comprehension is meaning-space navigation



[“beth”, “left”]

(scalars  $\propto$  distance)

# What does the model ‘understand’?

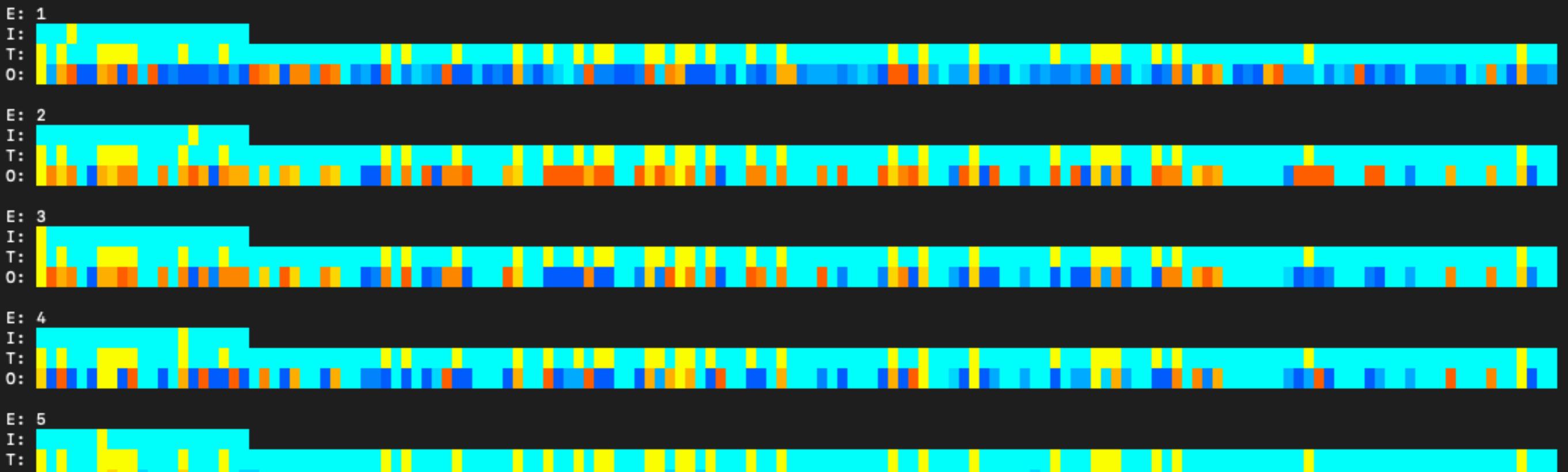


> Points in meaning-space capture meaning beyond literal propositional content; i.e., model engages in direct knowledge-driven inferencing

# Processing in the model

```
Name: "beth paid and ordered cola"  
Meta: "(pay(beth) & order(beth,cola))"  
Events: 5
```

(E: Event; I: Input; T: Target; O: Output)



Error: 0.166168

# What does the model ‘understand’?

Sentence: "beth entered the restaurant and ordered champagne"  
 Semantics: "(enter(beth,restaurant) & order(beth,champagne))"

	beth	entered	the	restaurant	and	ordered	champagne	
	+0.07039	+0.00133	+0.07172	-0.01075	+0.06097	+0.29321	+0.35418	+0.03641
								+0.39059
								+0.00066
								+0.39125
								+0.38655
								+0.77780
enter(beth, cinema)	-0.02148	+0.24441	+0.22293	+0.07659	+0.29951	-1.12625	-0.82674	-0.13942
enter(beth, restaurant)	+0.05997	+0.05947	+0.11943	-0.00959	+0.10984	+0.77479	+0.88463	+0.08838
enter(dave, cinema)	-0.02625	-0.01673	-0.04299	-0.01351	-0.05649	-0.13095	-0.18745	+0.01112
enter(dave, restaurant)	-0.04534	+0.03629	-0.00905	-0.00655	-0.01560	-0.07485	-0.09046	-0.01653
enter(thom, cinema)	-0.00525	-0.03060	-0.03585	-0.02386	-0.05971	-0.04328	-0.10299	+0.01426
enter(thom, restaurant)	-0.03036	+0.03124	+0.00087	-0.05578	-0.05490	+0.12838	+0.07348	-0.00730
ask_menu(beth)	+0.05057	+0.11973	+0.17030	+0.01159	+0.18189	-0.18738	-0.00549	+0.00811
ask_menu(dave)	-0.04209	+0.02578	-0.01631	-0.01432	-0.03063	+0.12555	+0.09492	+0.01173
ask_menu(thom)	+0.01846	+0.03027	+0.04873	+0.02419	+0.07292	-0.10789	-0.03497	-0.04742
order(beth, dinner)	+0.14434	-0.10891	+0.03543	-0.03510	+0.00034	+0.54904	+0.54937	+0.05165
order(beth, popcorn)	-0.02546	+0.12098	+0.09552	+0.03812	+0.13364	-0.80028	-0.66664	-0.07155
order(dave, dinner)	+0.01596	+0.04722	+0.06318	-0.00278	+0.06040	-0.12641	-0.06601	-0.00295
order(dave, popcorn)	-0.03225	-0.03485	-0.06710	-0.01343	-0.08053	+0.09368	+0.01315	-0.00292
order(thom, dinner)	-0.03628	+0.02388	-0.01240	-0.02644	-0.03884	+0.01253	-0.02631	-0.01203
order(thom, popcorn)	+0.01154	-0.07262	-0.06107	+0.01155	-0.04952	+0.11567	+0.06615	+0.01977
order(beth, water)	+0.09100	-0.07737	+0.01364	+0.01873	+0.03236	+0.02871	+0.06107	+0.00627
order(beth, cola)	+0.13845	-0.05860	+0.07985	+0.00329	+0.08313	+0.02980	+0.11293	-0.01142
order(beth, champagne)	+0.20763	-0.12451	+0.08312	-0.03408	+0.04904	+0.03848	+0.08752	+0.00478
order(dave, water)	+0.01068	-0.03213	-0.02145	-0.00894	-0.03039	+0.15632	+0.12593	+0.00546
order(dave, cola)	-0.05614	-0.02260	-0.07874	+0.00407	-0.07466	-0.13882	-0.21349	-0.03048
order(dave, champagne)	+0.05206	-0.03239	+0.01966	-0.00447	+0.01520	+0.12534	+0.14054	+0.00292
order(thom, water)	-0.05171	-0.02807	-0.07978	-0.03525	-0.11503	+0.07721	-0.03782	+0.02320
order(thom, cola)	+0.01398	-0.02959	-0.01561	+0.01692	+0.00131	-0.01943	-0.01812	+0.00263
order(thom, champagne)	+0.06160	+0.02403	+0.08562	+0.02497	+0.11059	-0.03093	+0.07966	-0.00539
eat(beth, dinner)	+0.05633	-0.07578	-0.01946	-0.06135	-0.08080	+0.26135	+0.18055	+0.00860
eat(beth, popcorn)	+0.03360	-0.00791	+0.02568	+0.00981	+0.03550	-0.58427	-0.54878	-0.05601
eat(dave, dinner)	-0.00731	+0.04919	+0.04188	+0.00258	+0.04446	-0.22841	-0.18395	-0.01299
eat(dave, popcorn)	-0.00597	-0.01517	-0.02113	-0.01303	-0.03417	+0.11036	+0.07619	+0.00741
eat(thom, dinner)	-0.12249	-0.07249	-0.19498	-0.07000	-0.26498	+0.12073	-0.14425	+0.01676
eat(thom, popcorn)	+0.01243	-0.09506	-0.08263	+0.02377	-0.05886	+0.09268	+0.03382	+0.01292
drink(beth, water)	+0.15517	-0.13449	+0.02068	-0.00969	+0.01100	+0.10176	+0.11276	+0.00355
drink(beth, cola)	+0.12933	-0.05569	+0.07363	+0.00240	+0.07604	+0.00048	+0.07652	-0.00911
drink(beth, champagne)	+0.13052	-0.07613	+0.05440	-0.02212	+0.03227	+0.05866	+0.09093	+0.00803
drink(dave, water)	-0.02234	-0.08484	-0.10718	+0.00913	-0.09805	+0.10459	+0.00653	+0.00410
drink(dave, cola)	-0.02153	-0.02252	-0.04405	+0.02316	-0.02089	-0.20839	-0.22928	-0.03643
drink(dave, champagne)	+0.01509	-0.01130	+0.00379	+0.00610	+0.00989	-0.00919	+0.00069	-0.01031
drink(thom, water)	-0.05061	-0.02465	-0.07525	-0.01961	-0.09486	-0.08131	-0.17618	-0.00217
drink(thom, cola)	+0.00930	-0.01481	-0.00551	+0.00614	+0.00064	-0.11499	-0.11435	-0.02679
drink(thom, champagne)	+0.02685	+0.01670	+0.04355	+0.01531	+0.05886	-0.05493	+0.00393	-0.00401
pay(beth)	+0.15462	+0.05596	+0.21058	+0.02684	+0.23742	+0.04137	+0.27879	-0.00146
pay(dave)	+0.01319	+0.02897	+0.04217	+0.00715	+0.04932	+0.02936	+0.07868	+0.00097
pay(thom)	-0.00686	+0.12125	+0.11439	+0.00955	+0.12394	+0.00018	+0.12412	+0.00689
leave(beth)	+0.05375	+0.06625	+0.12000	-0.00191	+0.11809	+0.02816	+0.14625	+0.00750
leave(dave)	+0.01022	+0.01904	+0.02927	+0.00185	+0.03111	+0.01600	+0.04711	+0.00440
leave(thom)	+0.01520	+0.07592	+0.09112	+0.00861	+0.09974	-0.06078	+0.03896	-0.01819

# Discussion

- The meaning space  $S_{M \times P}$  is continuous
- The sub-propositional meaning of an expression  $e$  is a real-valued vector defining a point in  $S_{M \times P}$  lying in between the propositions that  $e$  pertains to
- The derivation of the meaning of a multiword expression  $w_1 \dots w_i$  is a trajectory through  $S_{M \times P}$
- This derivation can be modeled using an SRN that incrementally maps words in context onto (complex) propositional meanings
- This synergy between DFS and neural networks paves way towards novel investigations into formal meaning representation and construction

# References

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