Connectionist Semantic Systematicity in Language Production

Jesús Calvillo, Harm Brouwer, Matthew Crocker
jesusc; brouwer; crocker@coli.uni-saarland.de
Saarland University

Goals

Sentence Production: Mapping Semantics → Sentences.

Systematicity: Generalization to unseen sentences/ semantics.

Semantics

"charlie plays soccer"

A *state-of-affairs* (situation) in a microworld is defined in terms of *basic events* that can be assigned a state (i.e., they can be *the case* or not *the case*)

Class	Variable	Class members (concepts)	#
People	p	charlie, heidi, sophia	3
Games	g	chess, hide&seek, soccer	3
Toys	t	puzzle, ball, doll	3
Places	x	bathroom, bedroom, playground, street	4
Manners of playing	m_{play}	well, badly	2
Manners of winning	m_{win}	easily, difficultly	2
Predicates	—	play, win, lose, place, manner	5

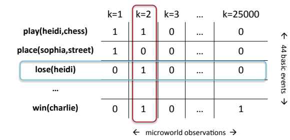
Event name		#
play(p, g)	$3 \times 3 =$	9
play(p, t)	$3 \times 3 =$	9
win(p)		3
lose(p)		3
place(p, x)	$3 \times 4 =$	12
manner(play(p), m_{play})	$3 \times 2 =$	6
manner(win, m_{win})		2
	Total	44

States-of-affairs are combinations of basic events.

Example—"heidi loses at chess": $play(heidi, chess) \wedge lose(heidi)$

Distributed Situation Space (DSS) model
(Frank et al., 2009)

Many samples of microworld situations constitute a "*situation-state space*"



Columns represent observations (states-of-affairs).
Rows represent situation vectors for basic events.

Complex event vectors can be obtained by combining basic event vectors through logical operations.

So now we have a way to represent events (basic and complex) in terms of the **situations** in which they are true.

$$play(heidi, chess) \wedge lose(heidi) \longleftrightarrow \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ \dots \\ 1 \\ 1 \end{bmatrix}$$

Situation vectors encode event probabilities.
Similar events are represented by similar vectors.

Belief Vectors

Define the meaning of an event in terms of the **basic events** with which it appears.
→*belief* vectors

Dimensionality := # basic events

Each dimension:
P(basic event | complex event)

sophia plays with ball in street ⟺ play(s, ball) ∧ place(s, street) ⟺ [0.3, 0.5, 0.0, ..., 0.75, 1.0]

someone plays with doll ⟺ play(c, doll) ∨ play(h, doll) ∨ play(s, doll) ⟺ [0.0, 1.0, 0.1, ..., 0.5, 0.8]

doll is played with ⟺ play(c, doll) ∨ play(h, doll) ∨ play(s, doll) ⟺ [0.0, 1.0, 0.1, ..., 0.5, 0.8]

> Propositional logic semantics are translated into belief vectors

Microlanguage

43 words
- *40 original words +2 determiners and end-of-sentence marker*

8201 lawful sentences:
- 83% in active voice
- 17% in passive voice

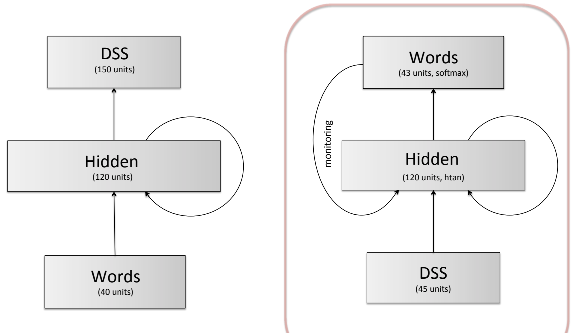
782 unique DSS representations:
- 424 related to active and passive sentences
- 358 related only to active sentences

Frank et al. (2009)'s grammar does not define passive sentences for situations where:
- the object of the action is a person ("Heidi beats Charlie.")
- or undefined ("Charlie plays.").

Training Procedure

- Cross-Entropy Backpropagation (Rumelhart, Hinton & Williams, 1986).
- Weight updates after each word.
- Weight initialization with random values drawn from N(0,0.1).
- Bias units weights initialized to zeros.
- At time t, monitoring units were set to what the model was supposed to produce at t-1 given the training item.
- Initial learning rate of 0.124 which has halved each time there was no improvement of performance on the training set during 15 epochs.
- Training halted after 200 epochs or if there was no performance improvement on the training set over a 40-epoch interval.

Model Architecture



Comprehension Model
Frank et al. (2009)

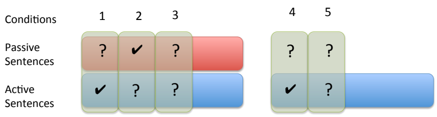
Production Model

Input/Output Example

DSS [0.1, 0, 1.0, 0.03, ..., 0.8], Active→ **1** ⇒ {
someone, plays, chess, .
someone, plays, chess, inside, .
...
a, girl, plays, chess, inside, .
a, girl, plays, chess, in, the, bedroom, . }

DSS [0.1, 0, 1.0, 0.03, ..., 0.8], Passive→ **0** ⇒ {
chess, is, played, .
chess, is, played, by, someone, .
...
chess, is, played, by, a, girl, inside, .
chess, is, played, by, a, girl, in, the, bedroom, . }

Testing Conditions



setAP
(424 situations)

setA
(358 situations)

Results

Condition	Query	Similarity (%)	Perfect Match (%)
1	pas	97.66	92.86
2	act	97.58	93.57
3	act	98.35	93.57
3	pas	96.79	83.57
5	act	95.08	85.0
Average Test	-	97.1	88.57

*10-fold cross validation averages (90% training, 10% testing)
*Levenshtein Similarity
*Condition 4 had no passive sentences to compare with, thus no similarity scores could be calculated.

Qualitative Analysis

The errors of 5 folds were manually inspected (38 errors).

With a couple of exceptions, all sentences are **syntactically correct and semantically felicitous.**

Mistakes occur when the model produces a sentence that is **semantically highly similar** to the one expected.

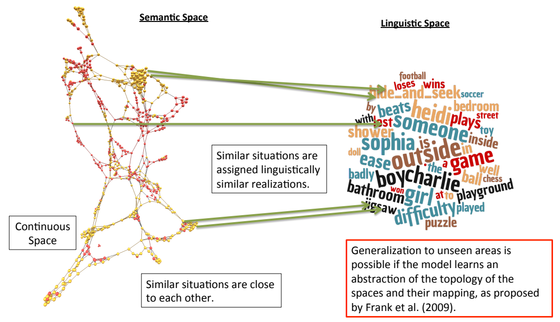
Output	Sophia beats Heidi with ease at hide_and_seek.	underspecification 39.9%
Expected	Sophia beats Heidi with ease at hide_and_seek **in the bedroom**.	
Output	Sophia wins with ease at a game **in the street**.	overspecification 23.5%
Expected	Sophia wins with ease at a game **outside**.	
Output	Sophia beats someone at hide_and_seek in the bedroom.	PP-attachment 31.6%
Expected	someone loses to Sophia at hide_and_seek in the bedroom.	

Conds. 4-5 Passives?

Output of 3 folds was manually inspected (84 situations).

- Mostly correct and coherent with the given semantics.
- Model learns that:
  - passive sentences begin by the object of the action.
  - the object is never a person.

Passive Output	**hide_and_seek** is won with ease by **Heidi** in the playground.
Active Sentence	**Heidi** beats Sophia with ease in the playground at **hide_and_seek**.
Passive Output	**a toy** is played with in the playground by Sophia.
Active Sentence	Sophia plays in the playground.



Generalization to unseen areas is possible if the model learns an abstraction of the topology of the spaces and their mapping, as proposed by Frank et al. (2009).

Conclusion

High overall performance of the model shows that the DSS-based representations are **suitable for modeling language production.**

The model is able to generate novel sentences for semantically known situations but with a different voice (cond. 1&2) showing
→ **Syntactic Systematicity**

The model is able to generate sentences for unseen areas in the semantic space (cond. 3&5) showing
→ **Semantic Systematicity**

UNIVERSITÄT DES SAARLANDES

NCPW15