Neurobiologically plausible modeling of speech production and comprehension for improving our understanding of normal and disordered speech

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Neurobiologically plausible modeling of speech production and comprehension for improving our understanding of normal and disordered speech

A neural network model of the brain

in which we can insert specific neural dysfunctions at specific locations of the cortex

gives us a clear association of neural dysfunctions and symptoms of speech disorders (resulting from simulation studies)

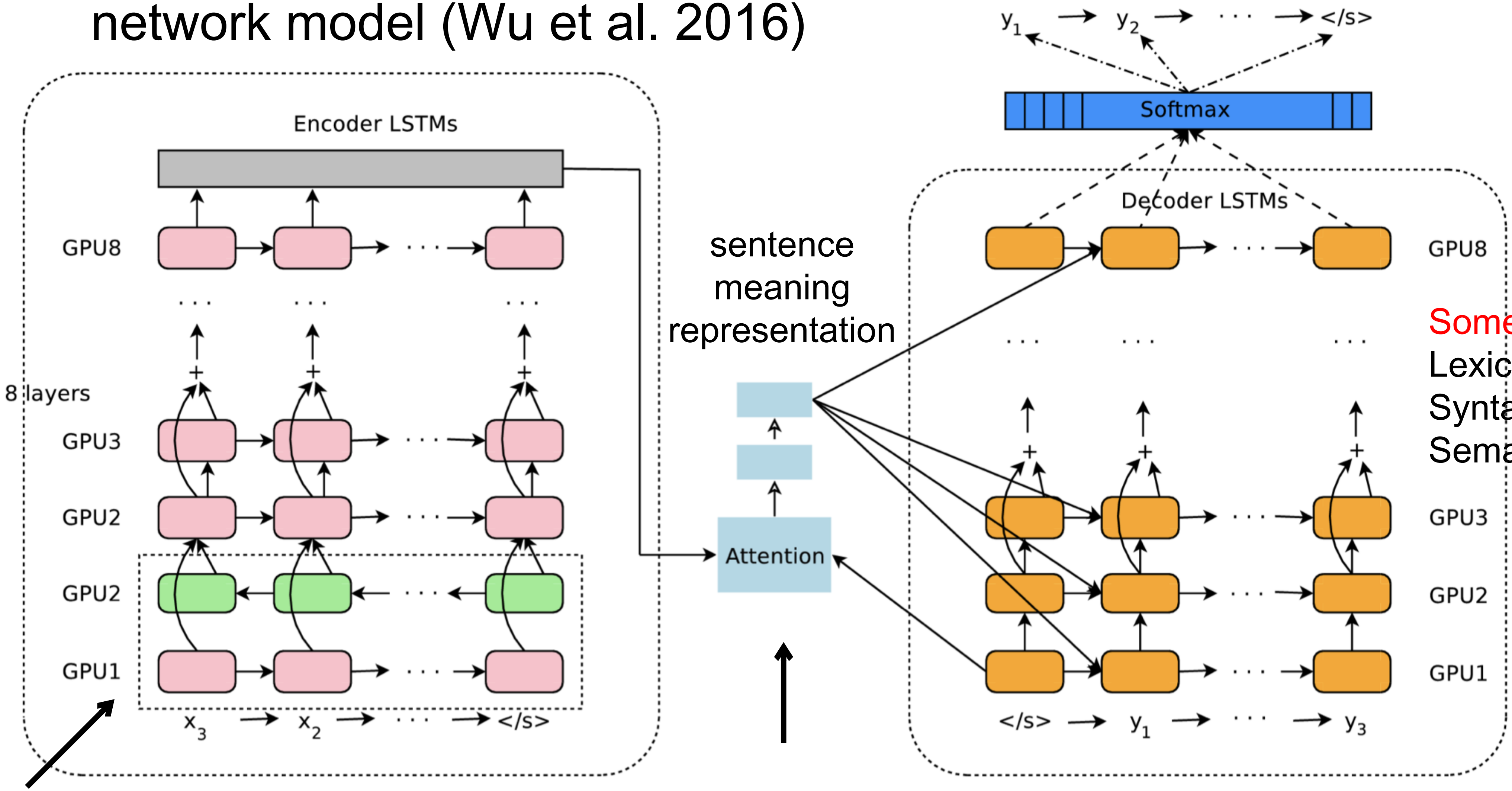
In practice: hard to recruit enough “well diagnosed” patients (concerning type and severity of speech disorder) willing to participate in clinical studies

We want a Neural Network Model like: Google's machine sentence translation network model (Wu et al. 2016)

High-level performance system

similar system:
part of chatGPT

language 2
word sequence output



sentence
meaning
representation

Somewhere inside:
Lexical processing
Syntactic processing
Semantic processing

Relatively equally structred / unstructured ensemble of modules

word sequence input
language 1

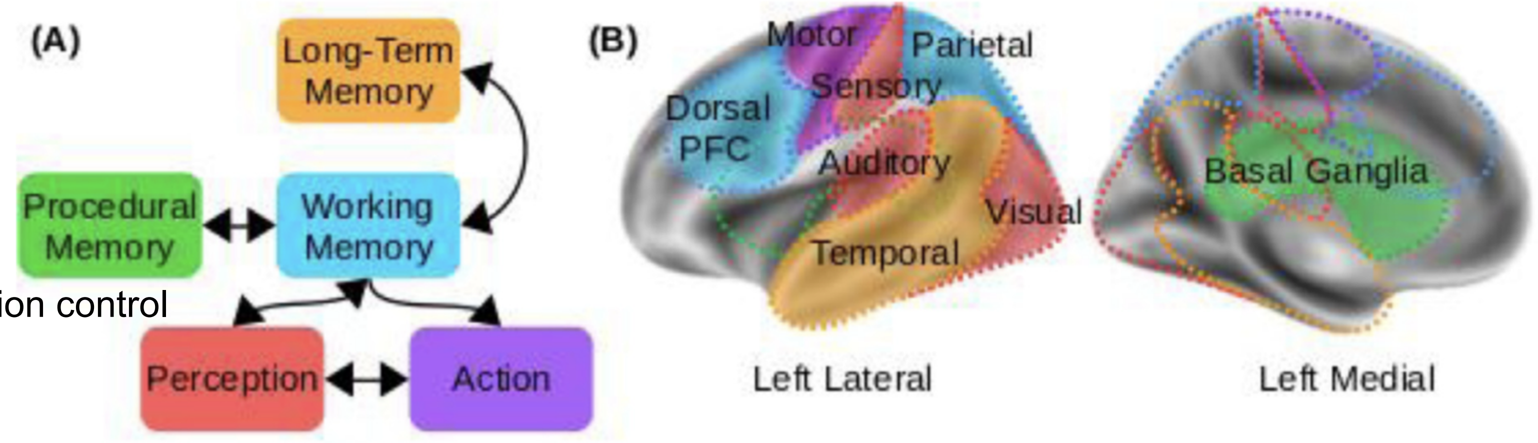
Interpretation of the neural activation patterns appearing here is difficult!!!

Goal of modeling: neurobiological plausibility

- Three points: (i) Model must in accordance with neurophysiological / neuroanatomical data (imaging, EEG, …), and behavioral data -> “box-and-arrow” models

functional modules

location of modules



action control

large-scale functional architecture of the brain:

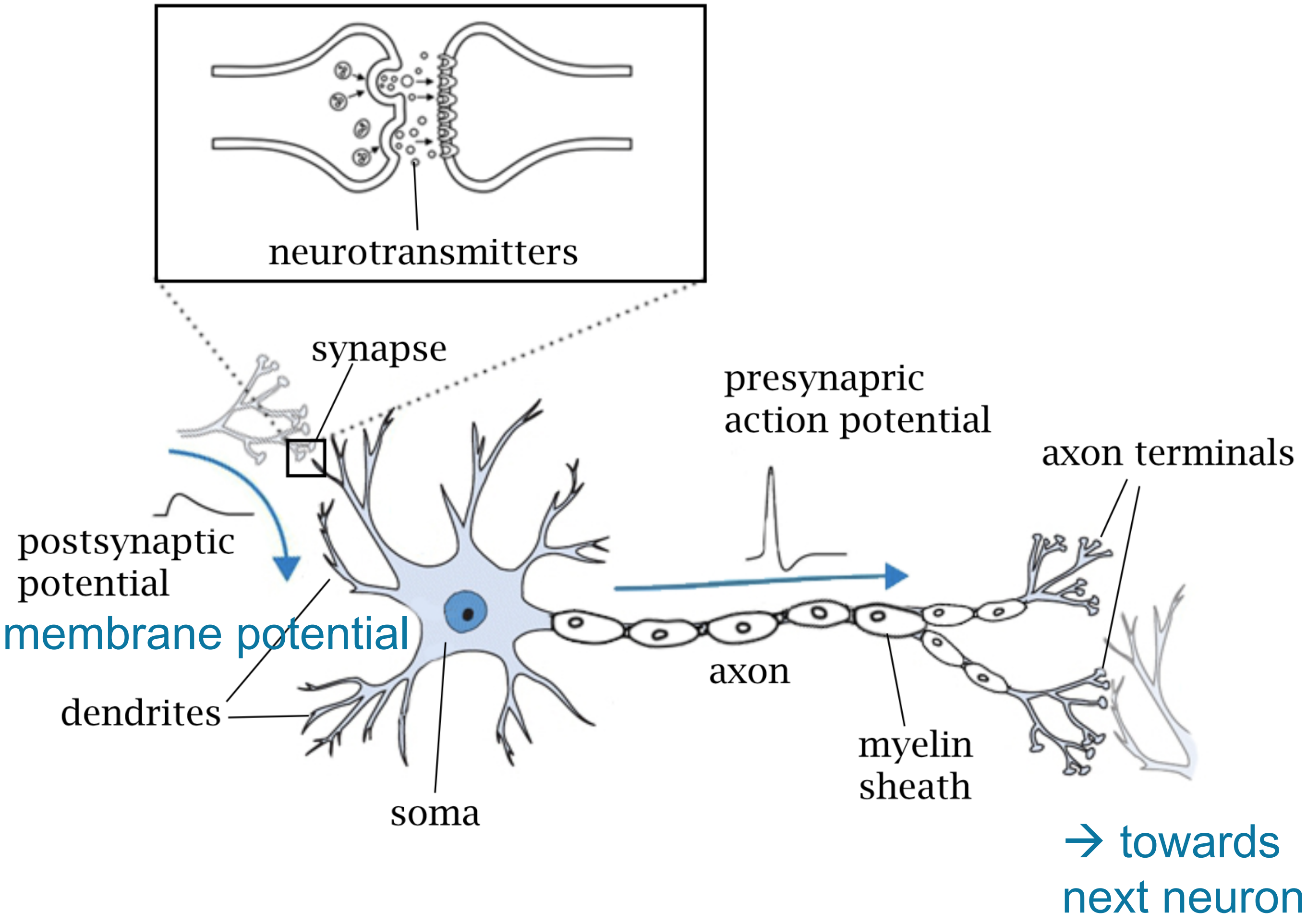
Common model of Cognition (CMC): Stocco et al. 2021

domain / task independent: speaking, gesturing, situational reasoning, relational reasoning, math task solving, solving any concrete or abstract task …

Goal of modeling: neurobiological plausibility

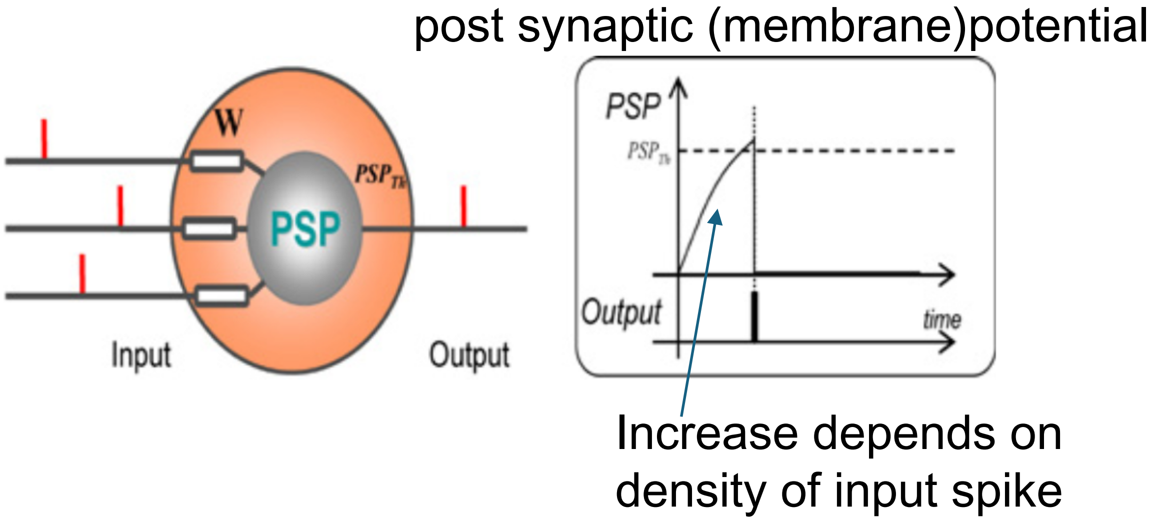
- (ii) realistic neuron model: spiking neuron model as “atomic unit” ->
  - leaky integrate and fire neuron model
  - plus: synapse model (exhibitory, inhibitory) (different degrees of strength for pule forwarding)
  - -> trained “link weights”

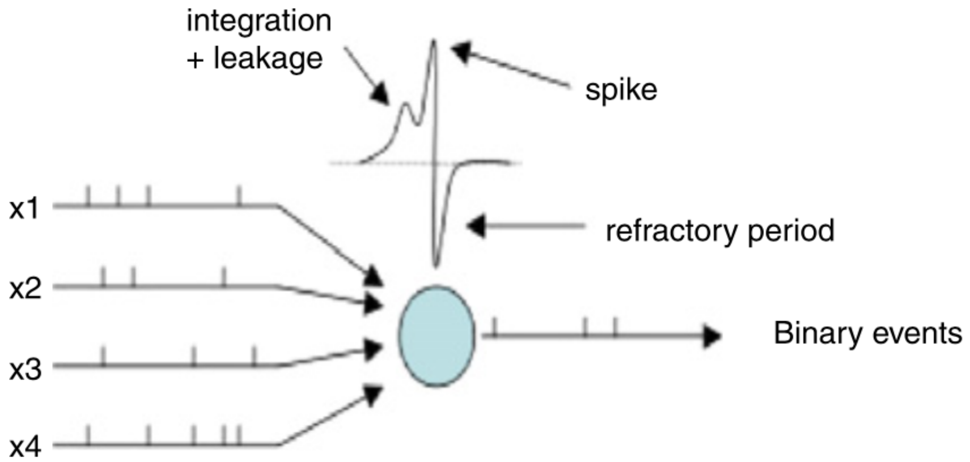
No longer: temporal-spatial averaging of “neural activation level”
(-> 2./3.generation - NNs)



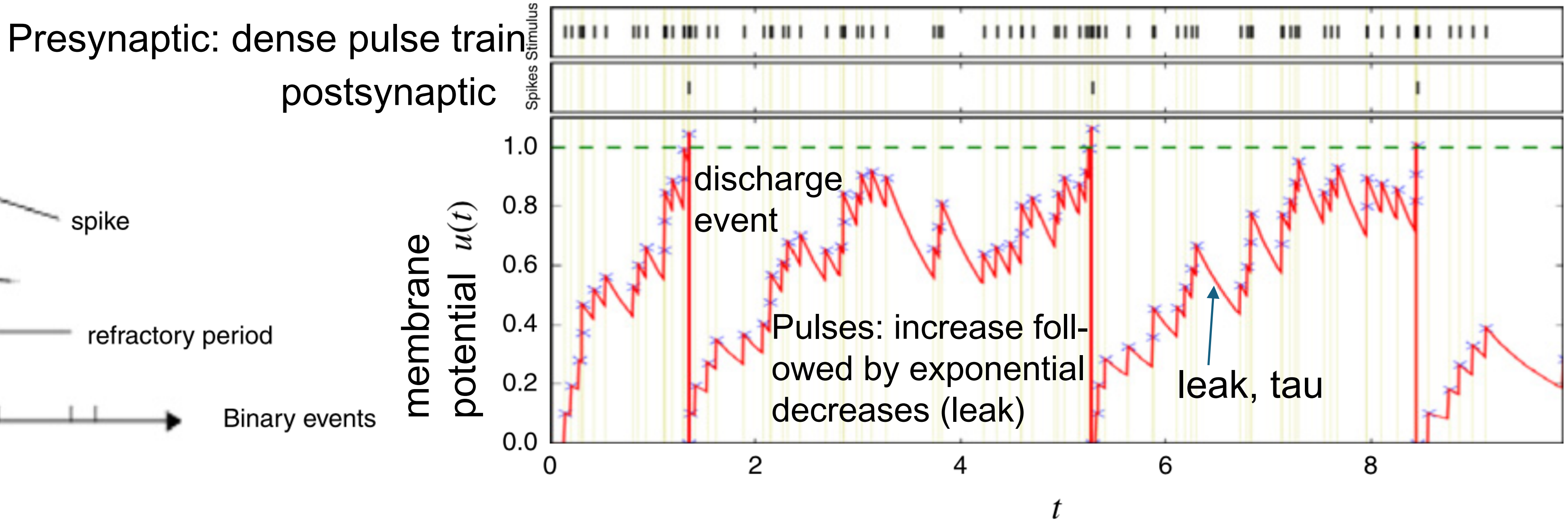
LIF neuron model

refractory period = about 10 msec





(a) The structure of a LIFM.



(b) Functionality of a LIFM.

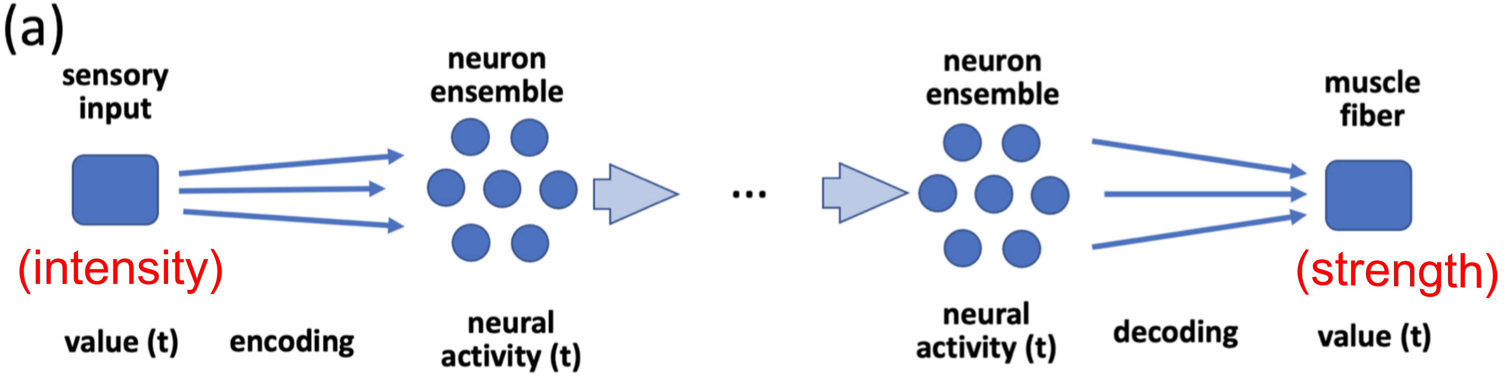
Leak: exponential decrease of membrane potential -> parameter tau describes the dynamics of the LIF neuron

Goal of modeling: neurobiological plausibility

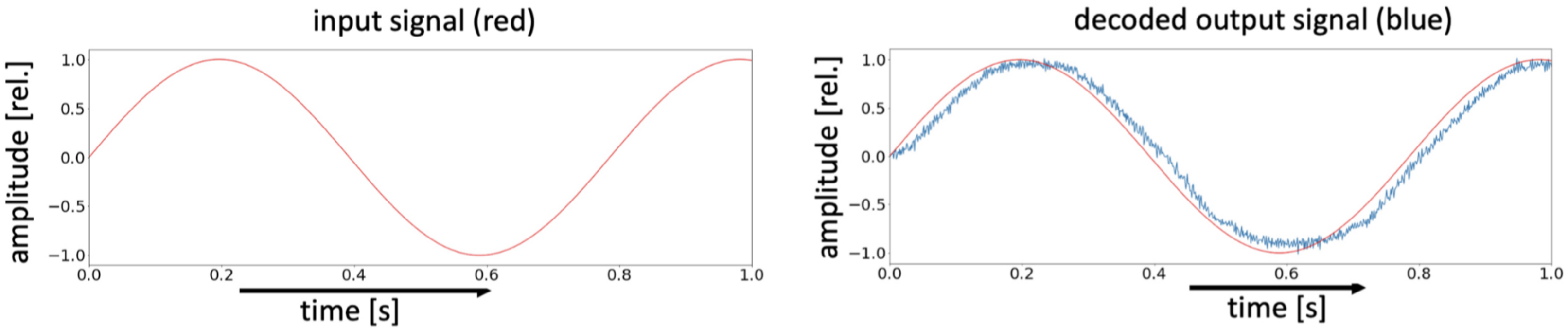
- (iii) build up the model using (probably genetically coded) **canonical neural network elements** (functional circuits)
  - Neural network units with a specific neural-level function, appearing in a large-scale neural network at many places
  - tiny building-blocks within all modules of the large-scale model (-> CMC model)
- Examples:
  - neural buffers (ensembles) for input encoding / output decoding of "values" (next slide)
  - forwarding and processing lower-level information (2nd next slide)
  - specific recurrent neural buffers (ensembles) for generating dynamics (oscillations, short-term memories) (3rd next slide)

defining **neural buffers** (neuron **ensembles**) for input encoding / output decoding

representing a “value”

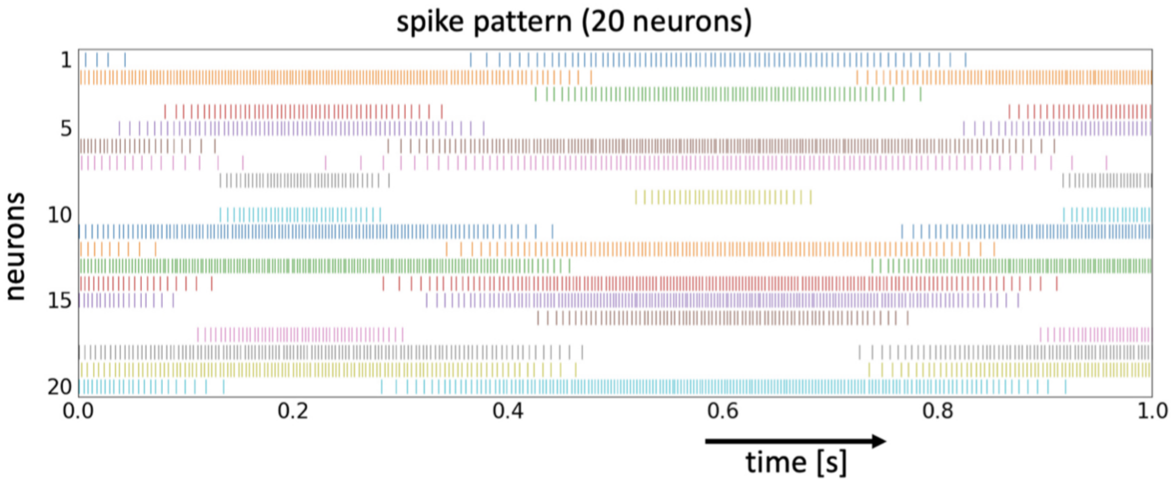


representing a “value” over time



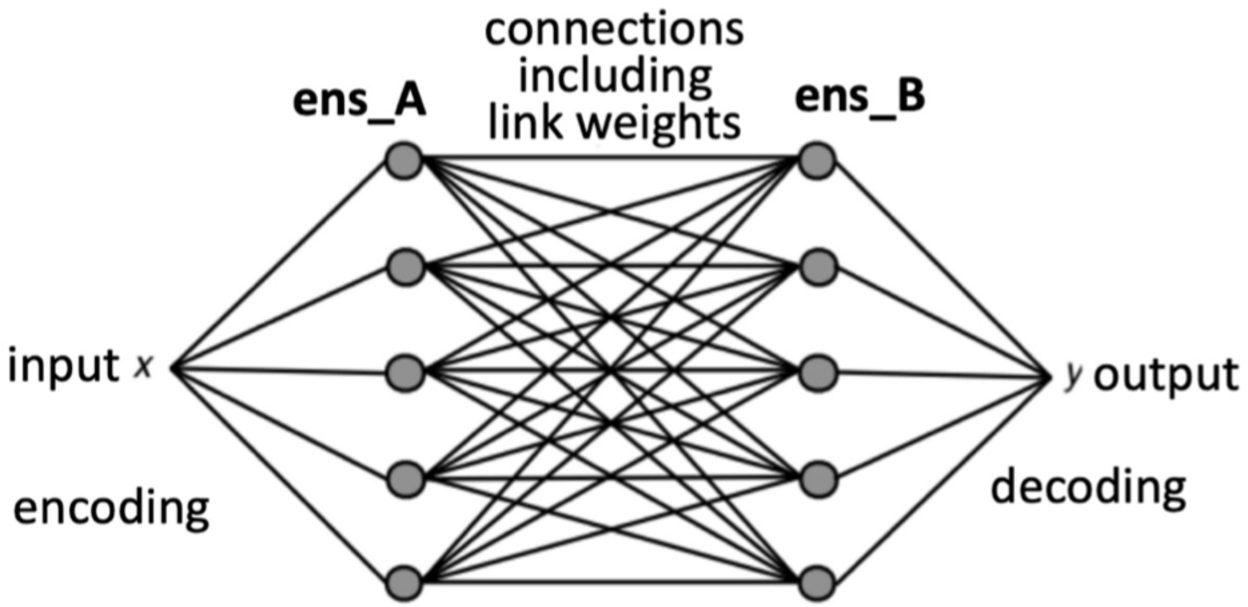
NEF
Eliasmith 2013

N = 20…100 neurons
depending on accuracy needed

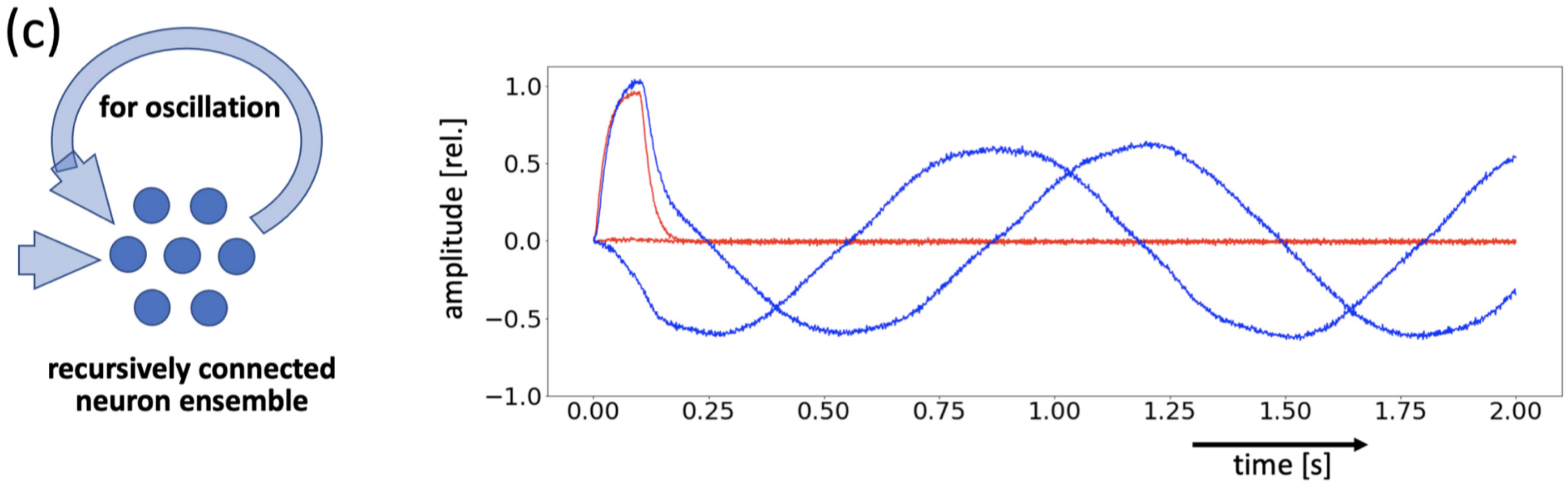


Kröger 2023, JIN

forwarding and processing of lower-level information: **neural connections**

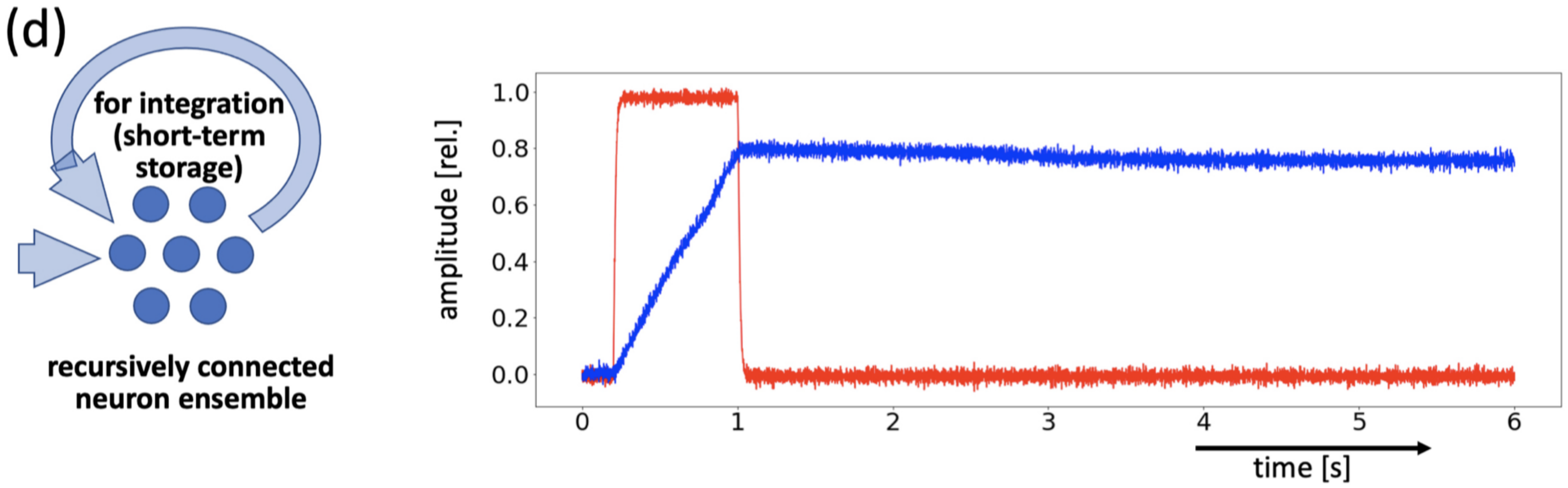


recurrent neural ensembles for generating dynamics -> **oscillations**



for defining intrinsic time scales

recurrent neural ensembles for enabling **short term storage**



for holding a value over a time period

Beyond coding of “values”: Coding of “items”

→ moving forward towards cognition

Eliasmith 2013: How to build a brain
Stewart & Eliasmith 2014: IEEE review on semantic pointer architecture

Values (NEF) =

- loudness, frequency, muscle strength
- -> directly coded by neuron ensembles as a specific “value”

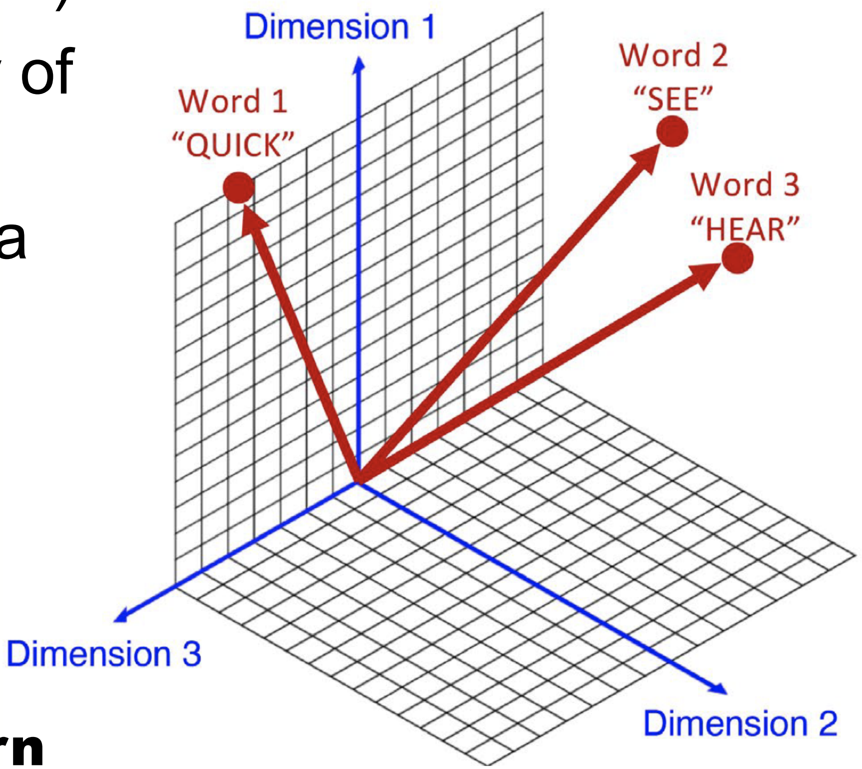
Items (SPA) =

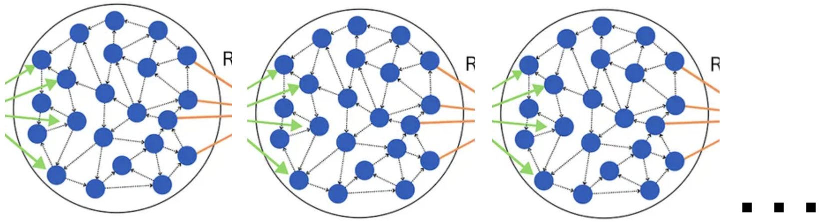
- a word (concept, lemma, phonol. form) ,
- a syllable (phonol. form, gesture score, higher-level auditory form, pre-motor pattern)
- a sentence meaning, a thought, a decision, … (abstract cognitive)

Beside NEF-SPA system (Eliasmith et al. 2014) ← includes a concept for cognitive modeling
NEST simulator for building up complex models (Gewaltig et al. 2012)
NEURON tool box (Hines Carnevale 2001)

Beyond coding of “values”: Coding of “items”

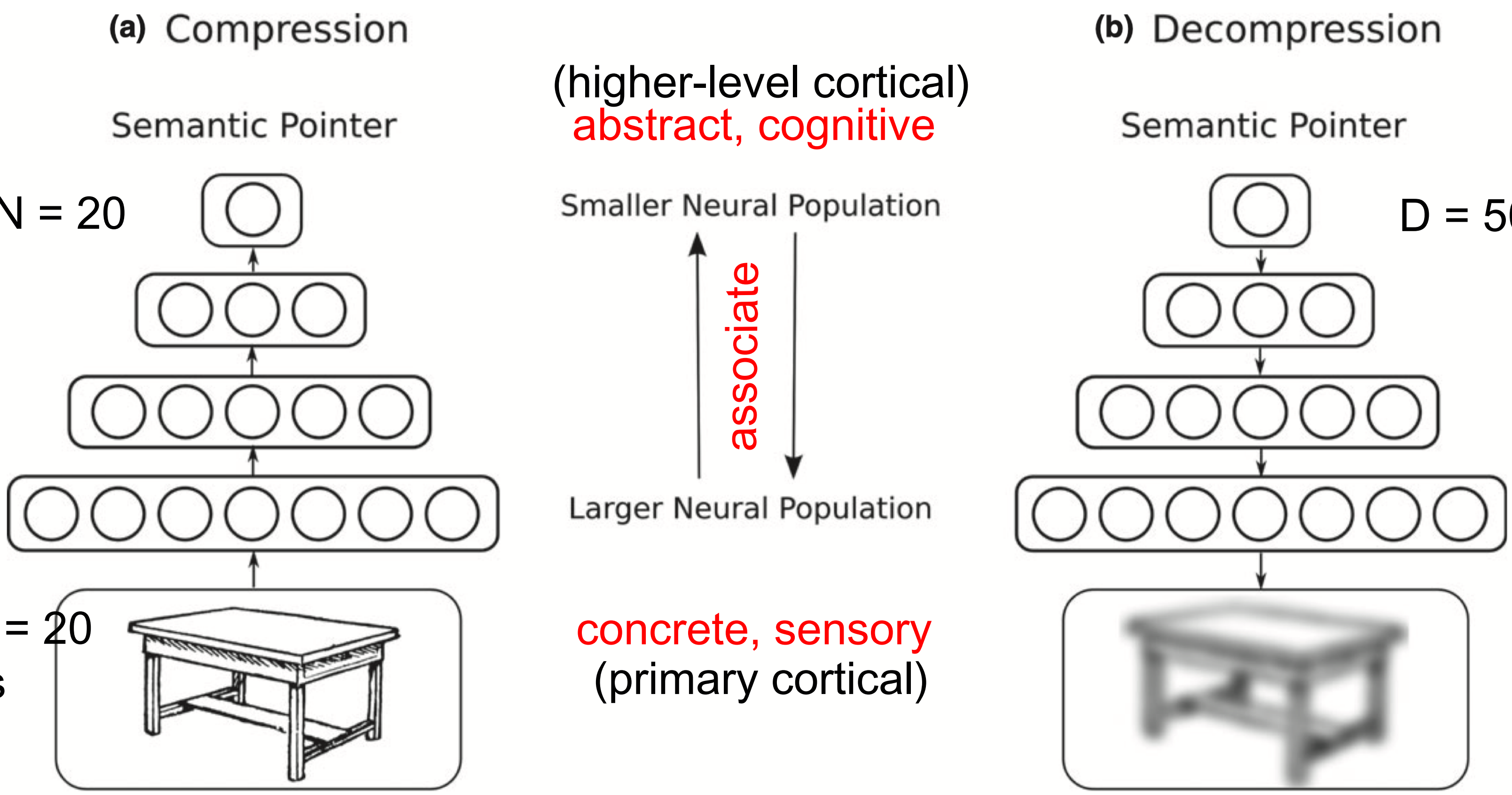
- the idea: items = represented by **vectors** (**S-pointers**)
- need: up to D=500 dimensions in case of a vocabulary of 60.000-100.000 items (mental lexicon, each level)
- the vector (mathematics) is only in the background as a valuable helper:
  - behavioral level:
    - vector points on items: cat / dog
    - quantifies similarity / dissimilarity of items = distance in vector space
  - neuronal level:
    - each value of the vector is coded as **activation pattern** in one of D neuron ensembles (each with N neurons)
    - **neuron buffer**: hosts states = neural representations of items
    - typically: D=64 (1000 items vocab) N = 50…100 -> 3200…6400 neurons





S-pointer and Semantic Pointer Architecture

D = 500, N = 20



(higher-level cortical)
abstract, cognitive

associate

concrete, sensory
(primary cortical)

(words)

D = 500, N = 20

visual input:
Many thousand ensembles (NEF)
each ensemble: N = 20
representing pixels of picture

mental image:
Inner activation

(or for syllables:
abstract higher level: phonological form /pla:/
concrete lower level: sensory: auditory, somatosensory;
motor: pre-motor gesture plan; motor: detailed muscular activation)

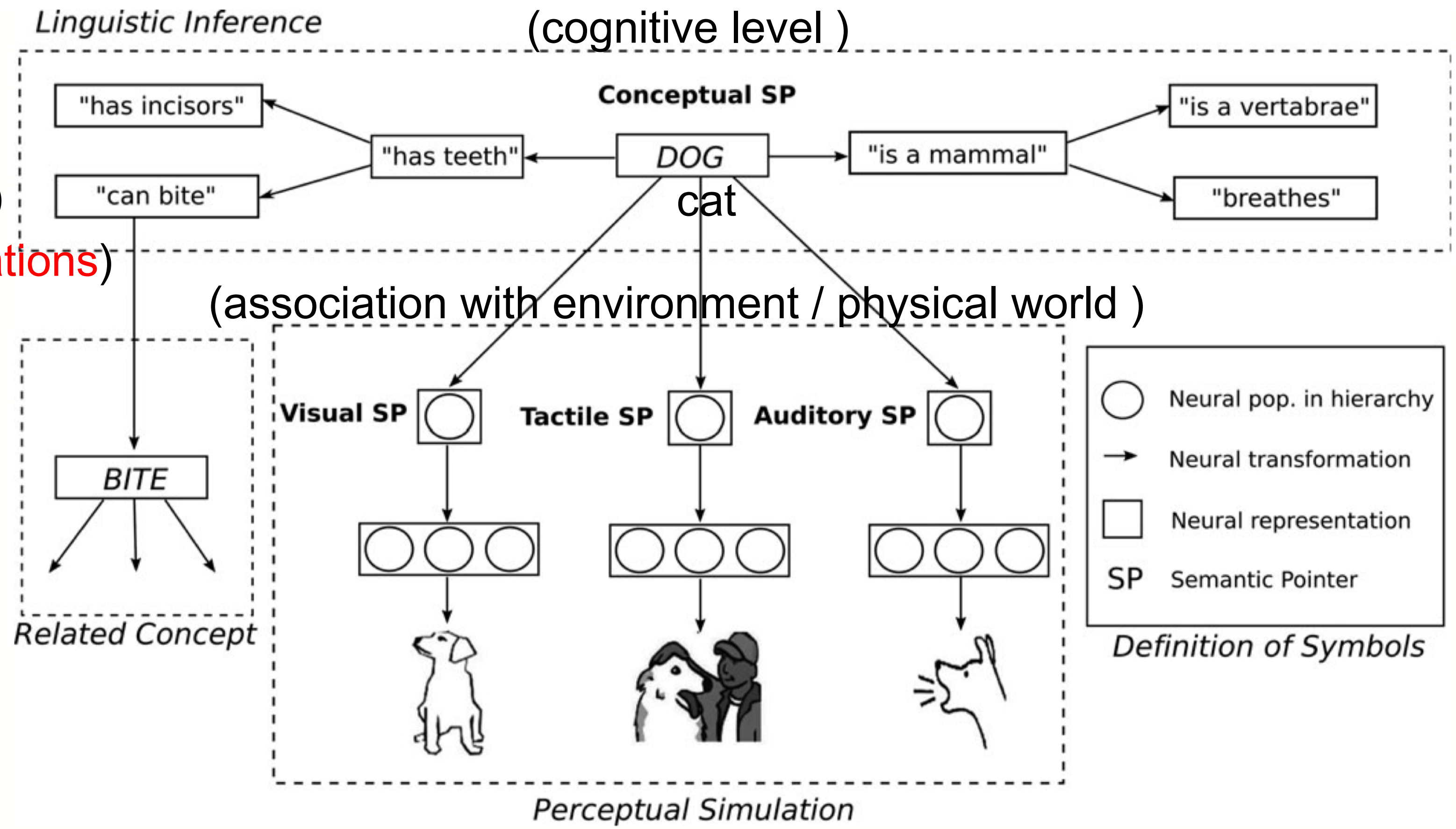
S-pointer and Semantic Pointer Architecture

Defining similarity
Example: word concepts

S-pointer networks:
(Coding of associations)
(Coding of similarity relations)

(cognitive level)

(association with environment / physical world)

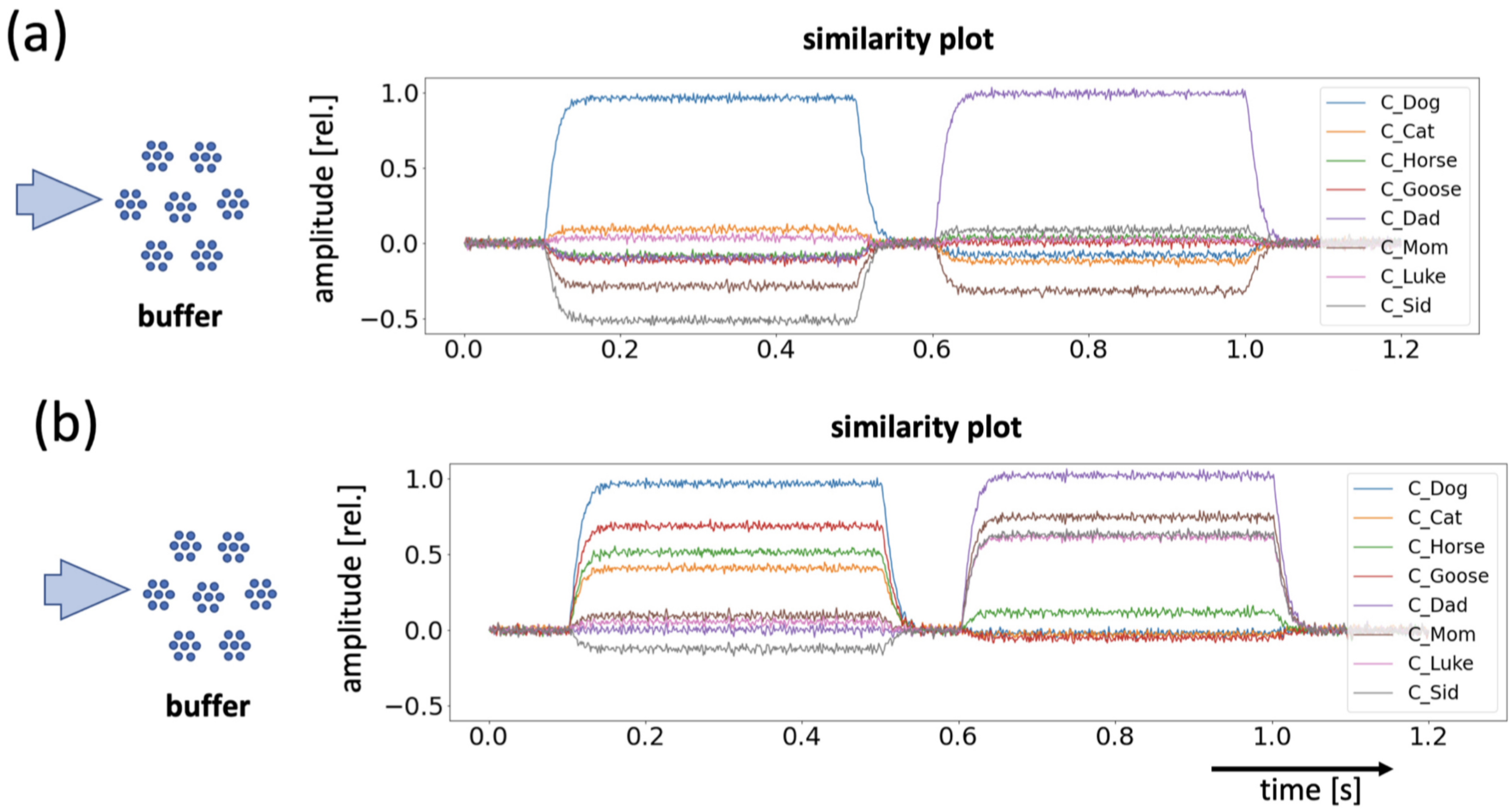


Mental images, auditory simulations, …
barking, meowing, …

Summary: neurobiological plausibility

- Build up a complex (large-scale) model using **canonical neural network elements (SPA)**
  - defining basic motor, sensory, or cognitive functions
  - Basic network elements within different modules of main functions (-> CMC model)
- Further examples:
  - Represents items with or without similarity relations (next slide -> state buffers)
  - Holds items in short term memory (2nd next slide -> recurrent buffers)
  - Associating items: phono forms -> semantic concepts (mental lexicon) (3rd next slide -> associative memories)
  - Binding of items (states) allows reasoning, allows representation of sentence meaning, etc. (4th next slide: binding buffers)

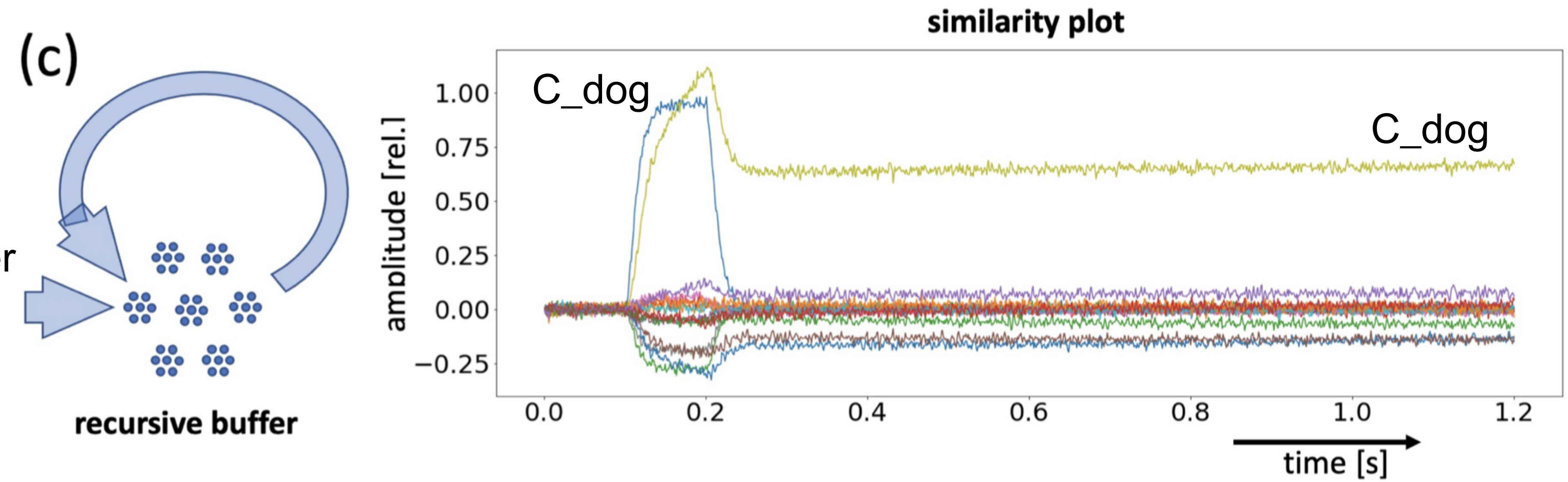
Represents items with or without / with similarity relations: **state buffers**



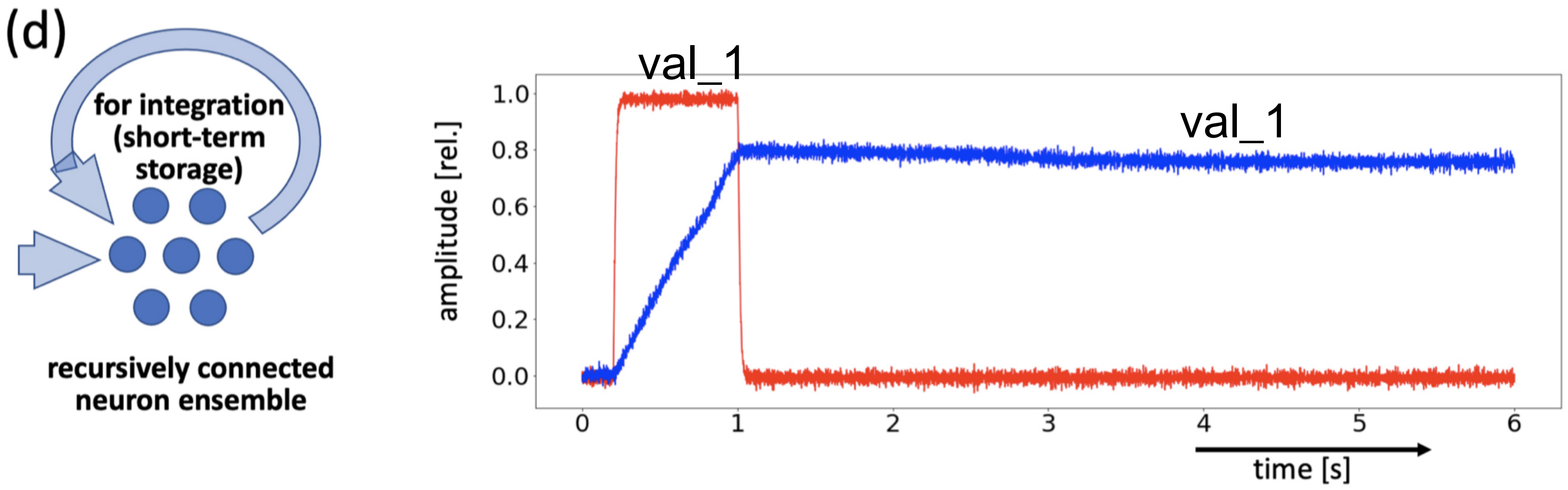
Probing: activation (t) -> similarity
plots: decoding activation (t) as S-pointer activity

Holds item representations (S-pointer) in short term memory: **recursive buffers**

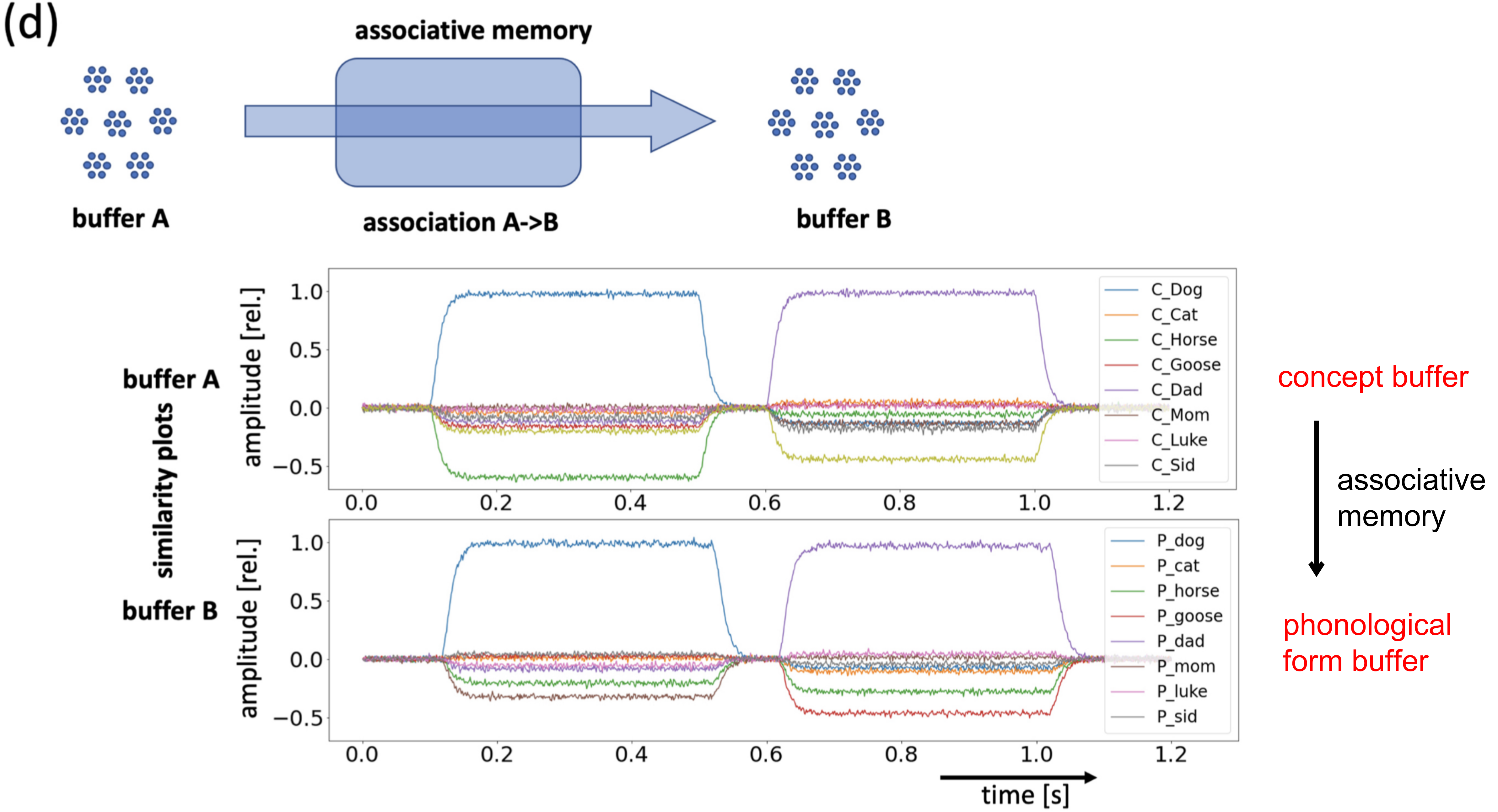
neuron buffer
state buffer
-> items



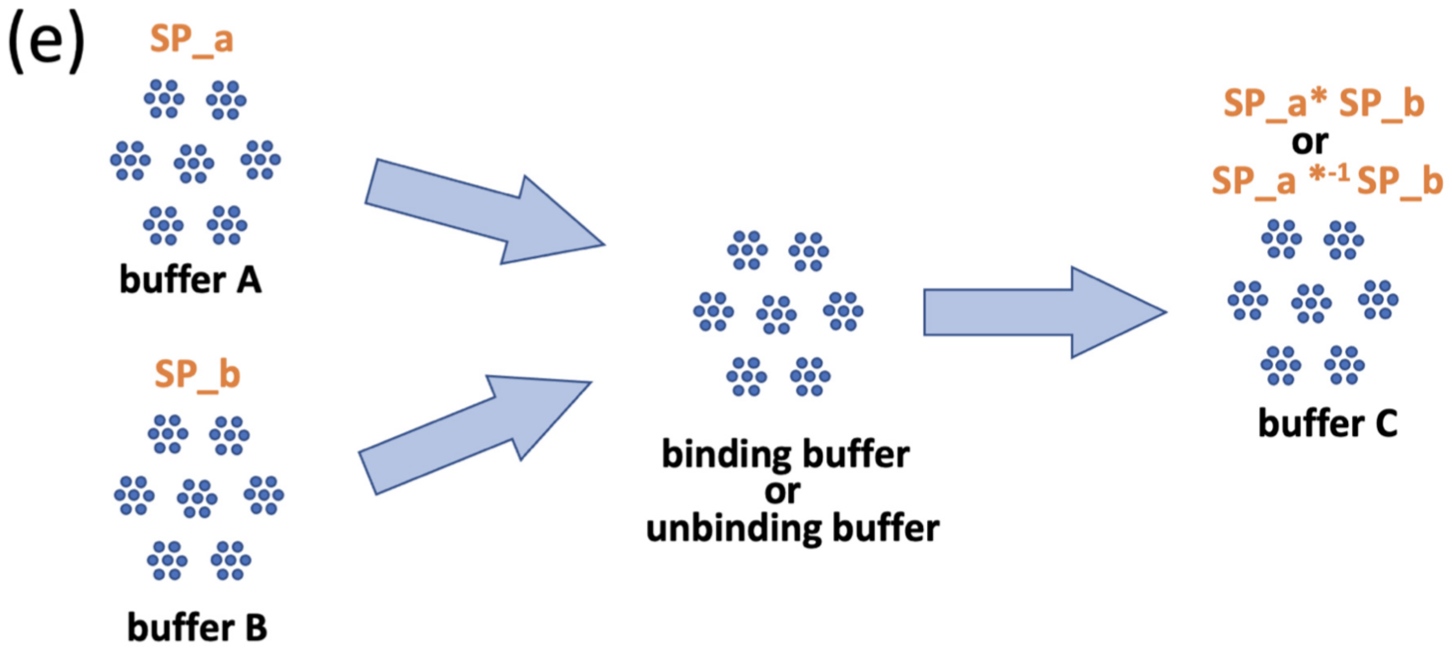
neuron ensemble
-> values



Associating items: transformation -> **associative memories**



binding of items (of states): **binding buffer** and binding network



Sentence meaning: R_action * C_drinking + R_agent * C_Benno + R_patient * C_coffee → E_sentence1

R_ : roles
C_ : concepts
E_ : event meaning

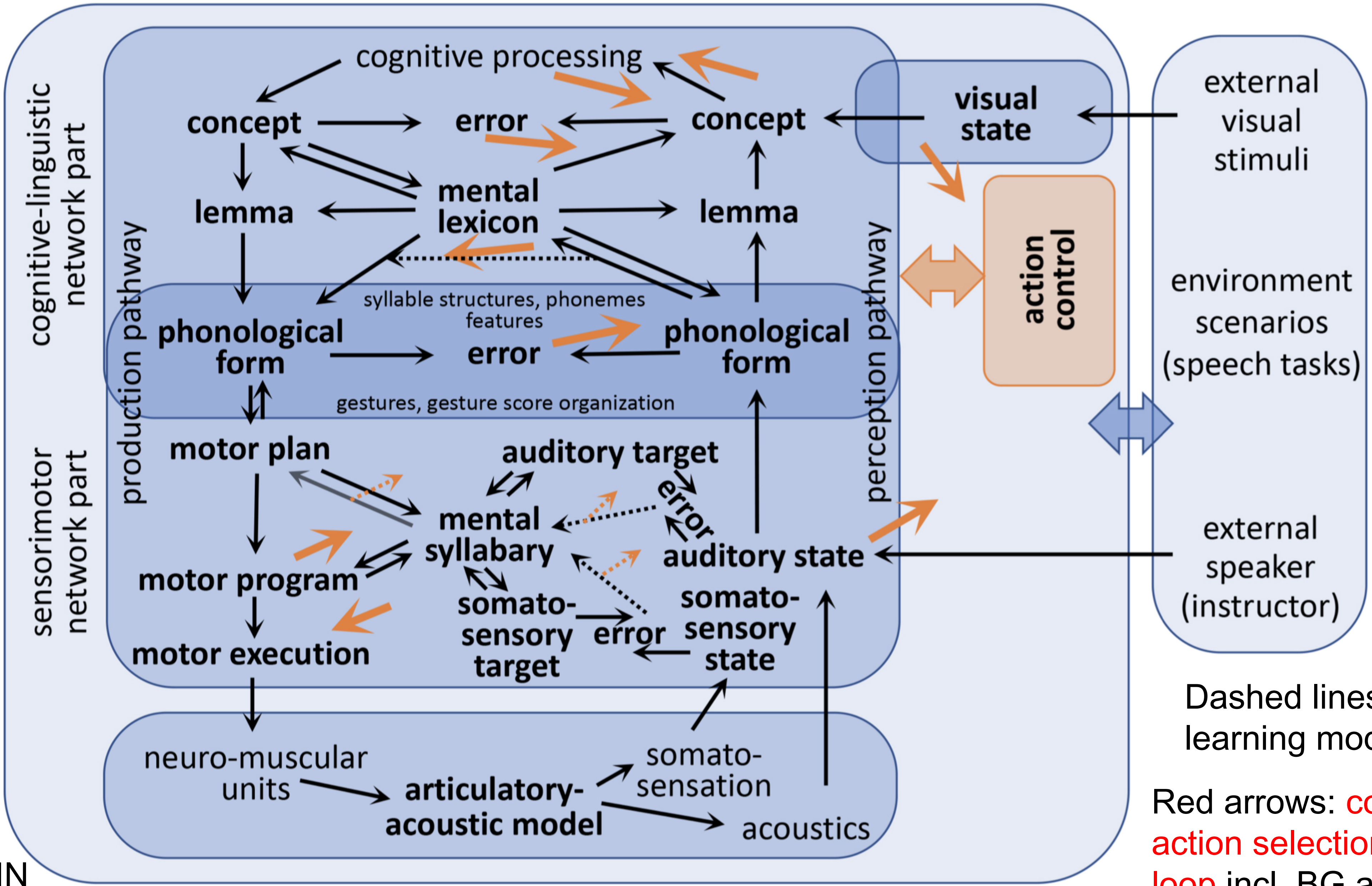
One binding buffer: inputs:
roles (buff_A) and concepts (buff_B)
come in synchronously over time
last step: additive integration (?)

The perception-production model

- just using **canonical neural network elements**: -> large-scale network for speech production and speech perception (language processing)
- have **pre-defined form** for representation of items:
  - mental lexicon: phono-forms, concepts, lemmata: noun, verb, determiner, adjective, preposition
  - syntax: dependency arc names:
  - sentence level semantics: event description in terms or role-concept pairs
- **pre-defined structure for network modules**: Three levels of representations in the mental lexicon (strongly associated / connected)
  - Semantic level: cat-dog, car-bike, eat-drink, …
  - Phonological-level: /kEt/-/ka:/, /dOg/-/drank/, …
  - Lemma level: determiners (the-a) vs. adjectives (god-bad), vs. nouns vs. verbs, …

Neural model of mental lexicon

including word processing pathways



Dashed lines: learning mode

Red arrows: cortico-cortical action selection / control loop incl. BG and Thal.

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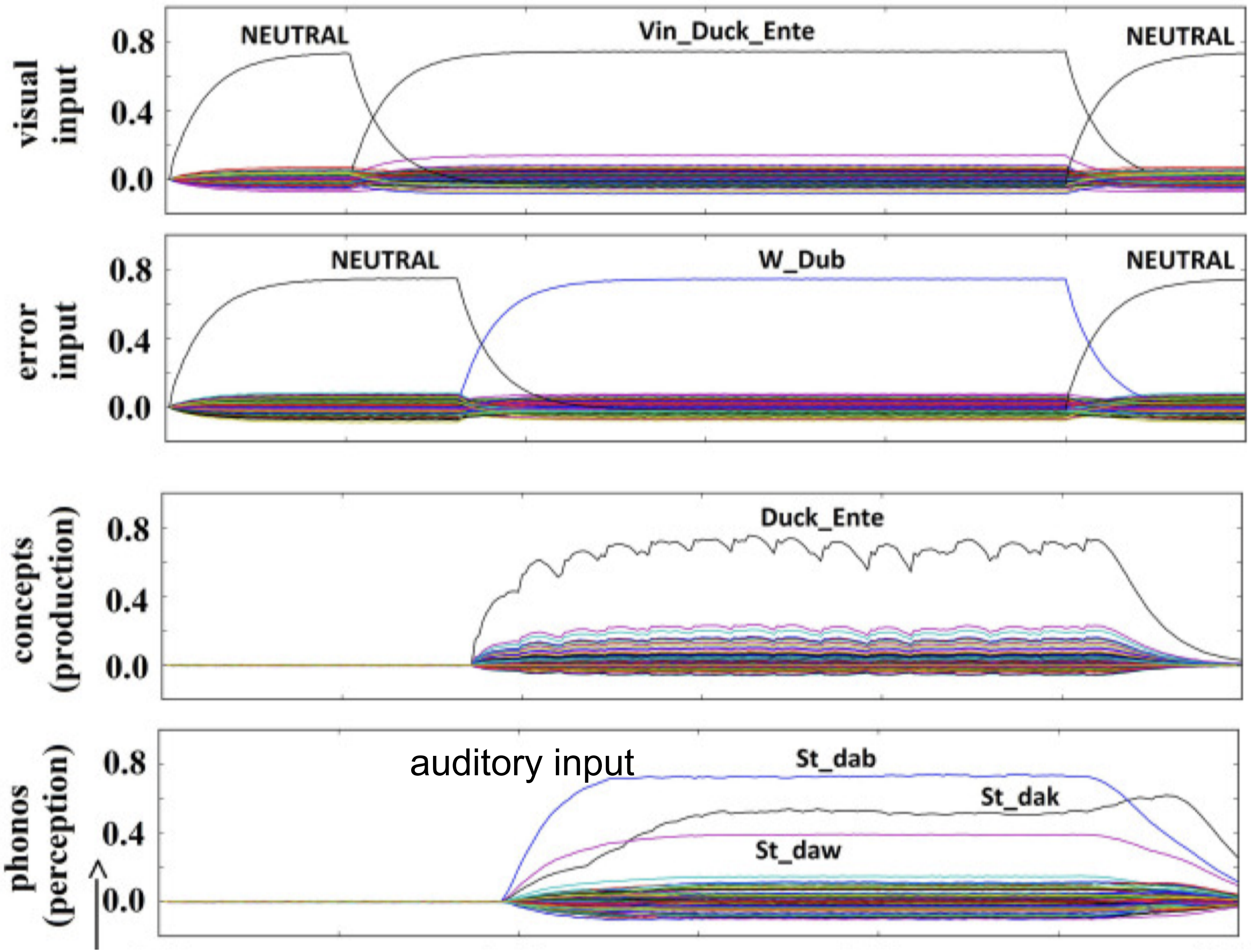
Simulation example: production

Picture naming with distractor word

auditory distractor word

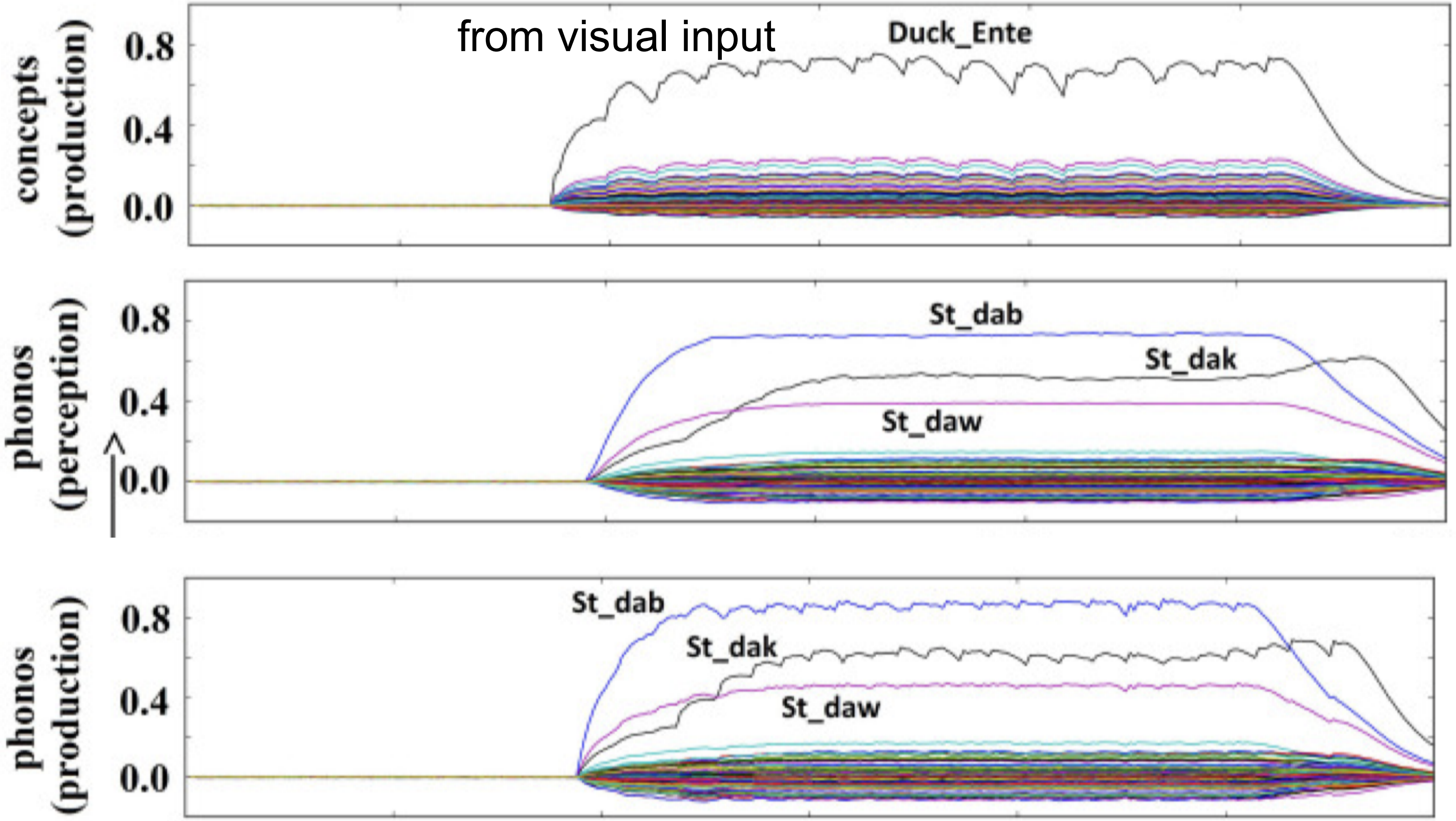


visual perception process not displayed

mental auditory co-activation resulting from visual input (-> temporally delayed)

Simulation example: production

Picture naming with distractor word

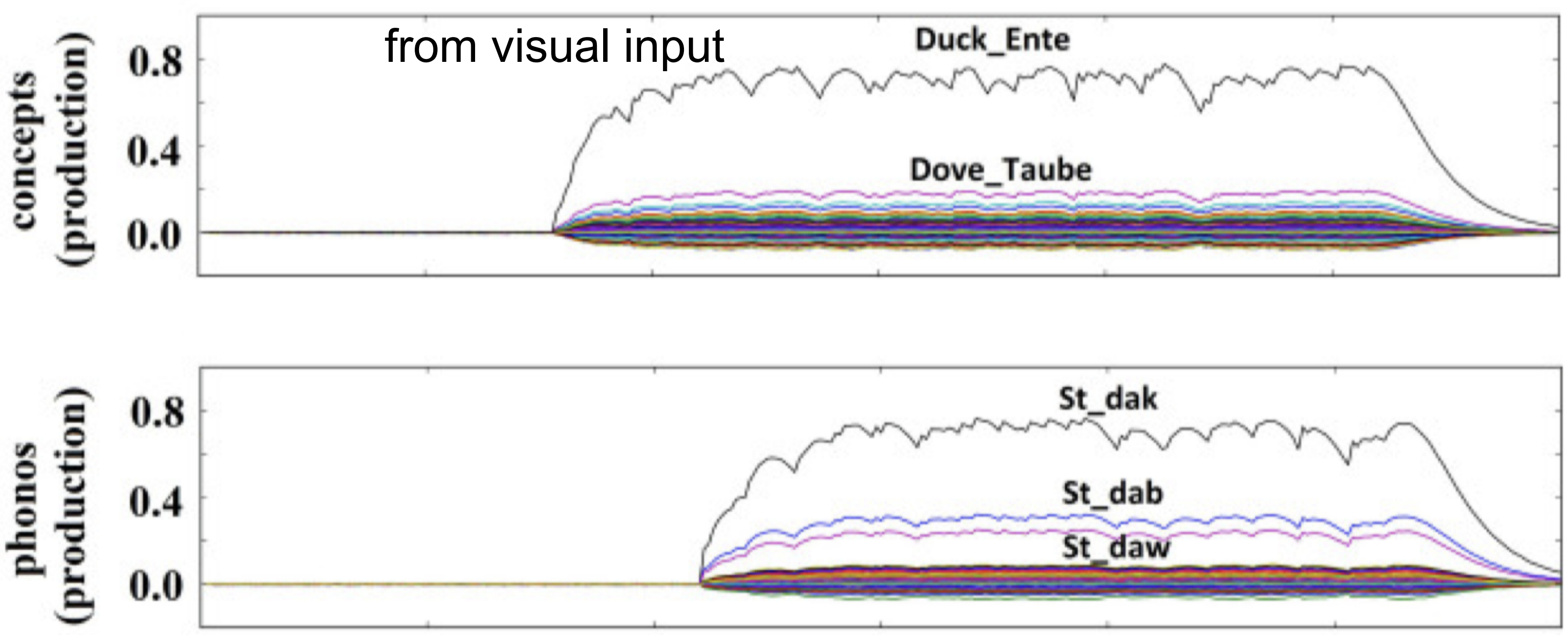


St_dak appears mainly because of S-pointer network similarity relations!

the wrong item (distractor item) wins

Simulation example: production

Picture naming, **no** distractor word



semantic level coactivation

the correct item wins

phono level coactivation

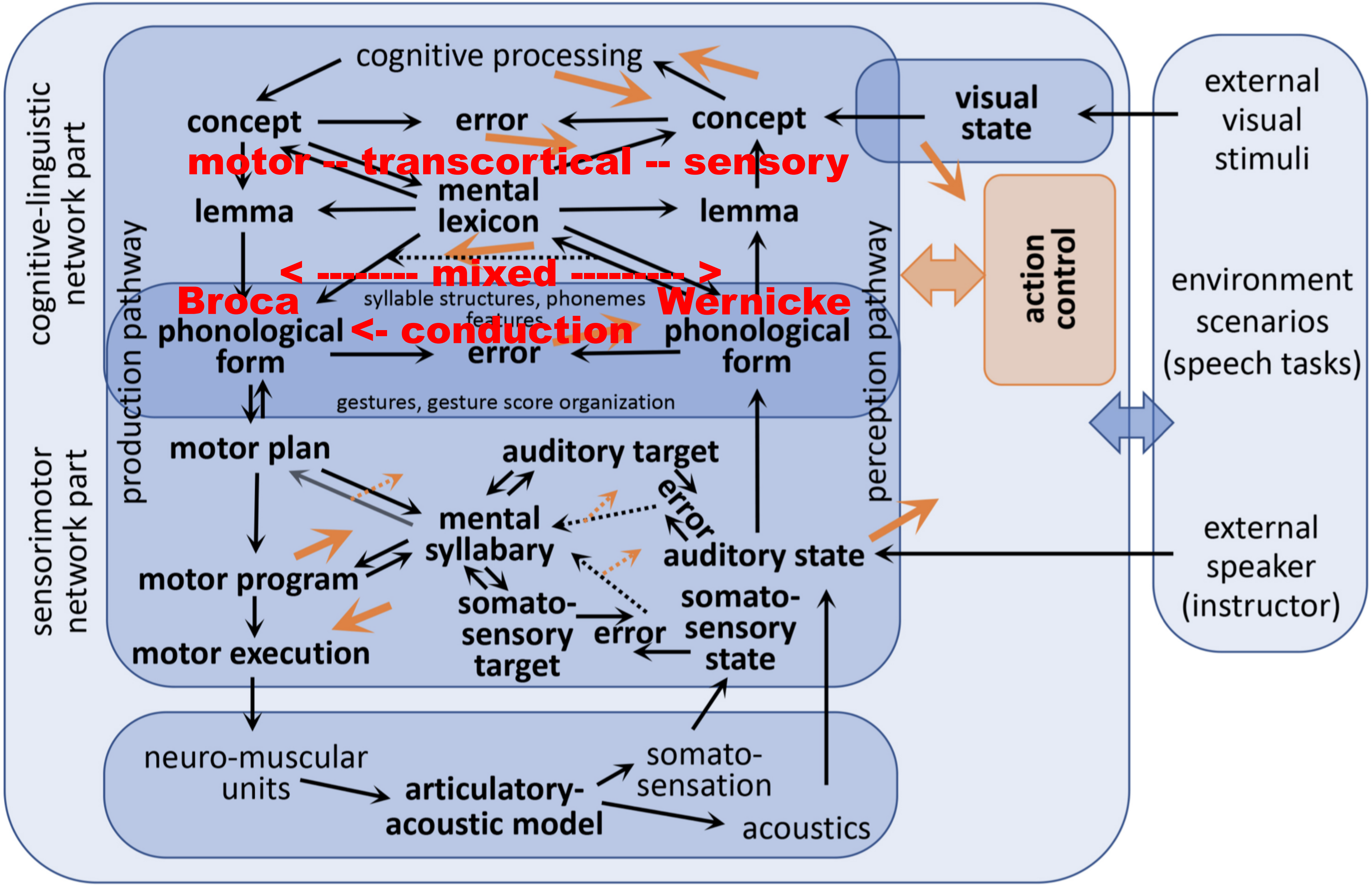
Goals of modeling
* beside: neurobiological plausibility
* simulation of psycholinguistic testings / experiments
* further goals: simulation of diagnostic testings (screenings)
* simulation of therapeutic treatment scenarios (if the model is capable of learning)

Neural model of mental lexicon

including word processing pathways

types of aphasia

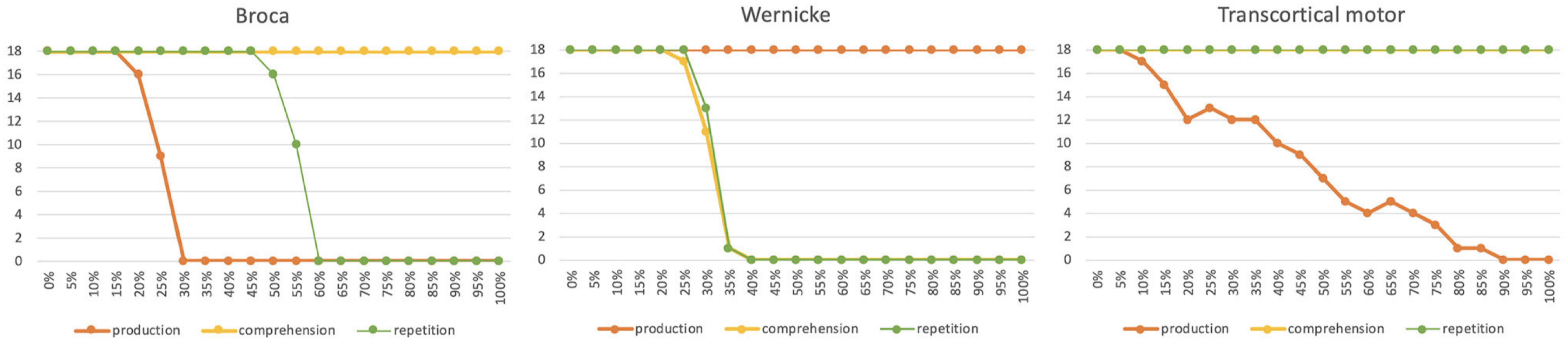
state buffers or associative memories: percentage of ablated neurons (inserting "neural dysfunctions")



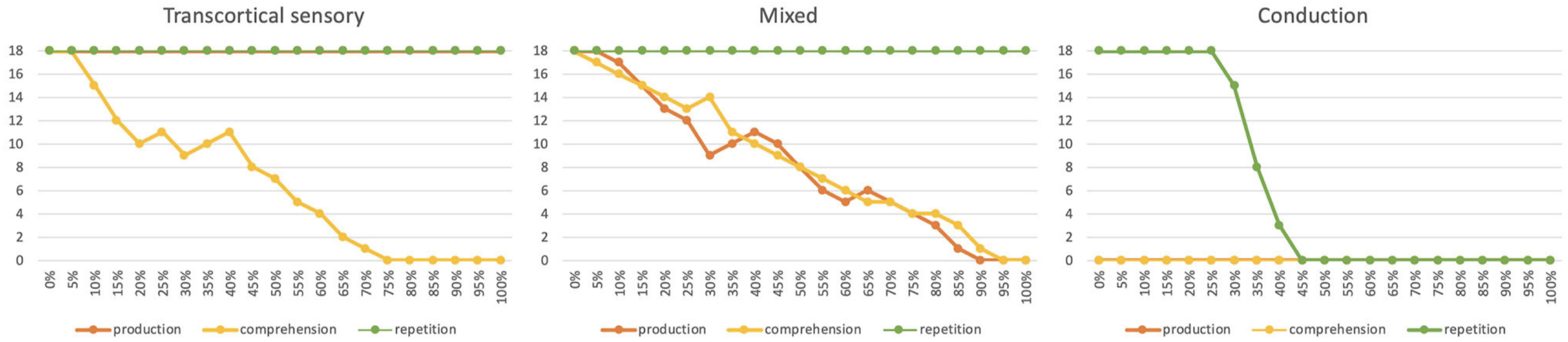
Kröger 2020 frontiers in

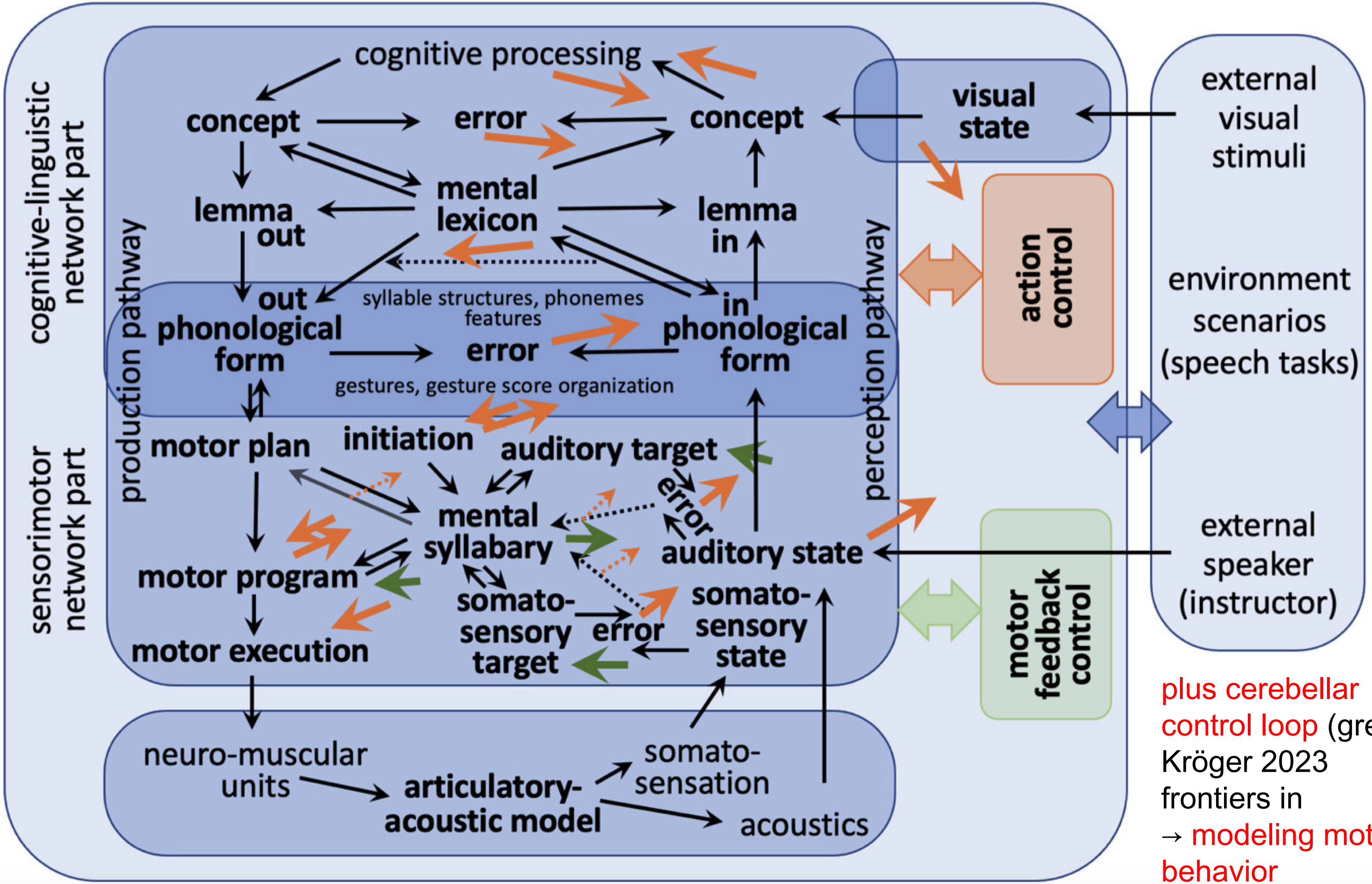
simulation results: modeling aphasia

Kröger et al. 2020



Picture naming / auditory presentation of words and pointing / auditory presentation and repetition

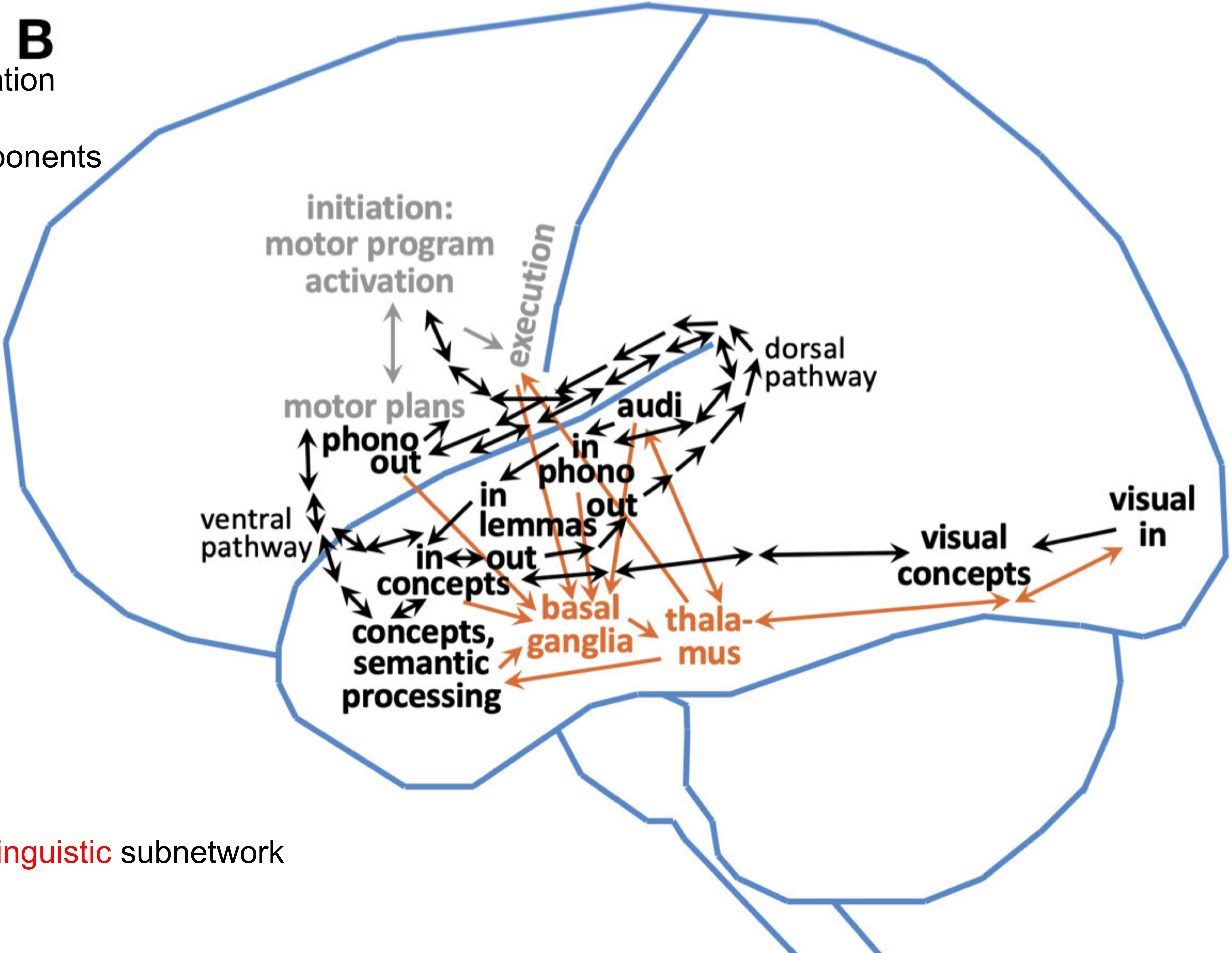




plus cerebellar control loop (green)
Kröger 2023
frontiers in
→ modeling motor behavior

B

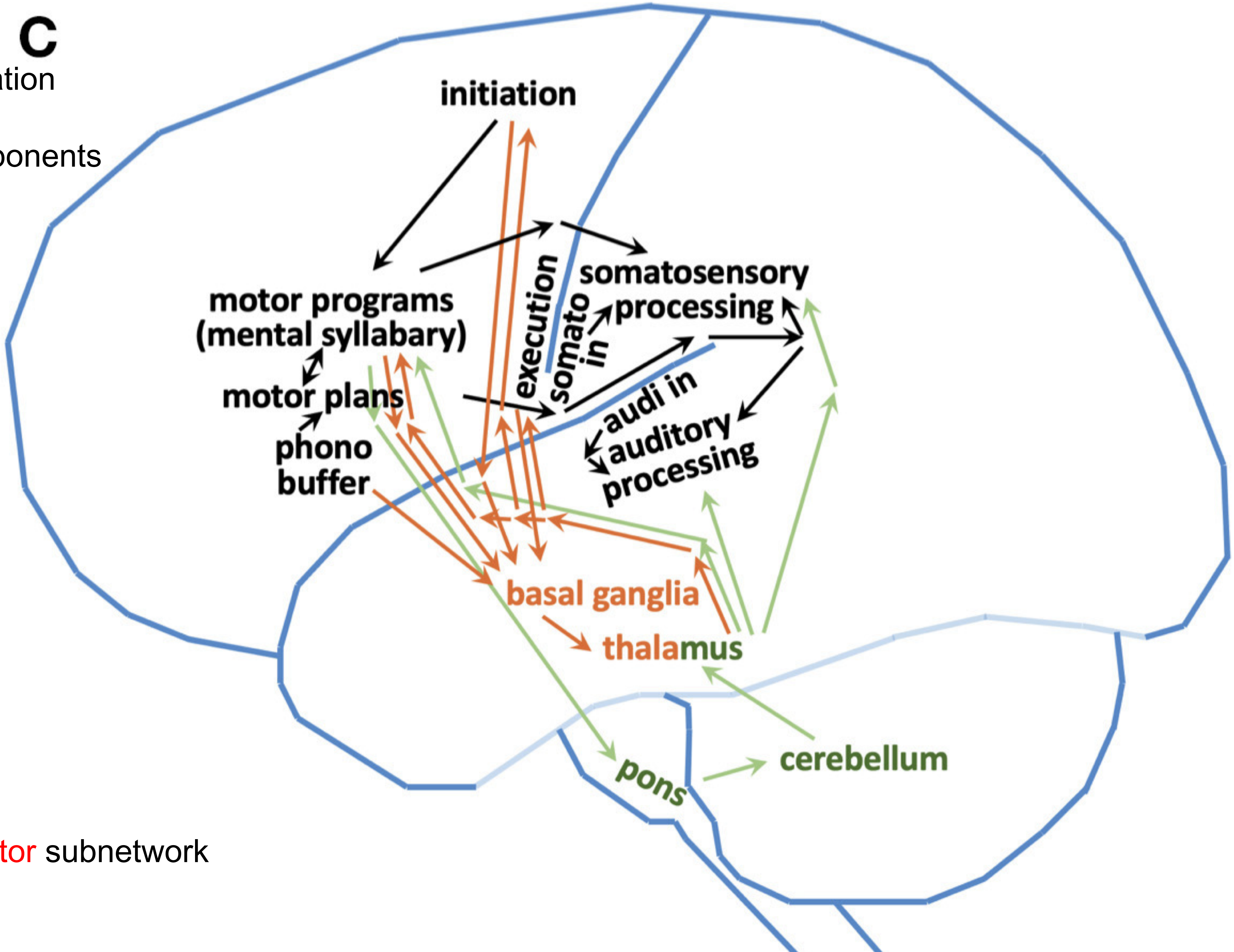
anatomical location
of
functional components



cognitive-linguistic subnetwork

C

anatomical location
of
functional components

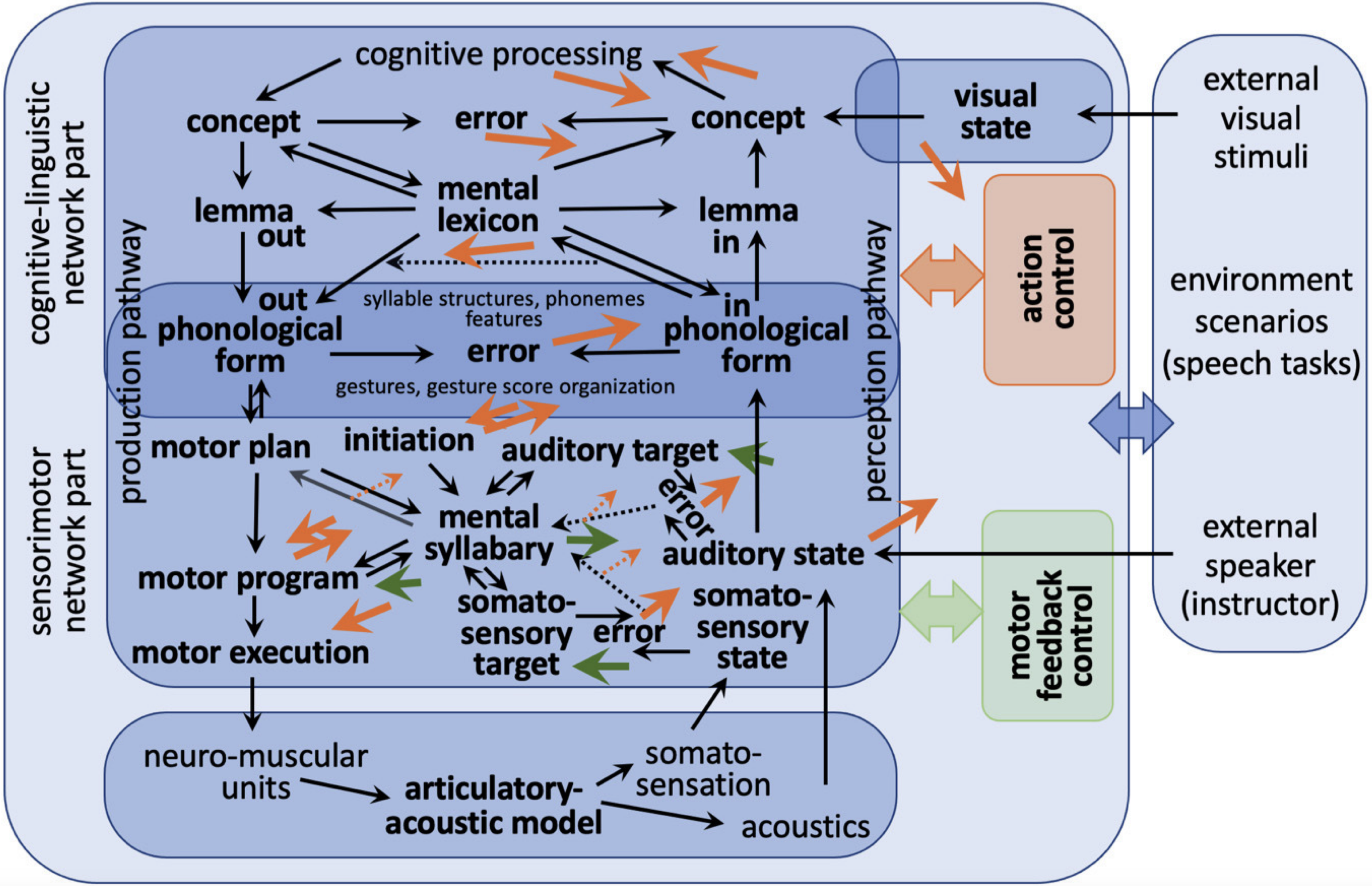


sensorimotor subnetwork

The syllable level and articulation

- three levels on production side:
  - (i) phonological (= **raw gesture score** already: gestures as lexical units) vs.
  - (ii) **motor plan** (= **fully specified gestures** but not fully specified muscle activity patterns = not the articulator positions level) <-> premotor, and:

    sensory representations (higher sensory processing level as well)
- Beyond: (iii) motor realization = **motor program**
  - fully specified **muscle activation pattern** (fully specified movements)
  - is that stored in mental syllabary for frequent syllables?
  - because: fast adaptation in case of injury at the level of articulatory system (glossectomy, bite block experiments, …)
- we (Aachen/Geneva) separate planning and programming in the same way: Jouen, Fougeron & Laganaro (2024), Kröger (2022) frontiers in, Kröger (2023) JIN
- shortcoming here (Kröger & Bekolay 2022): todo: coupling of a neuro-muscular acoustic-articulatory model (there is one: Sanguineti et al. 1998)



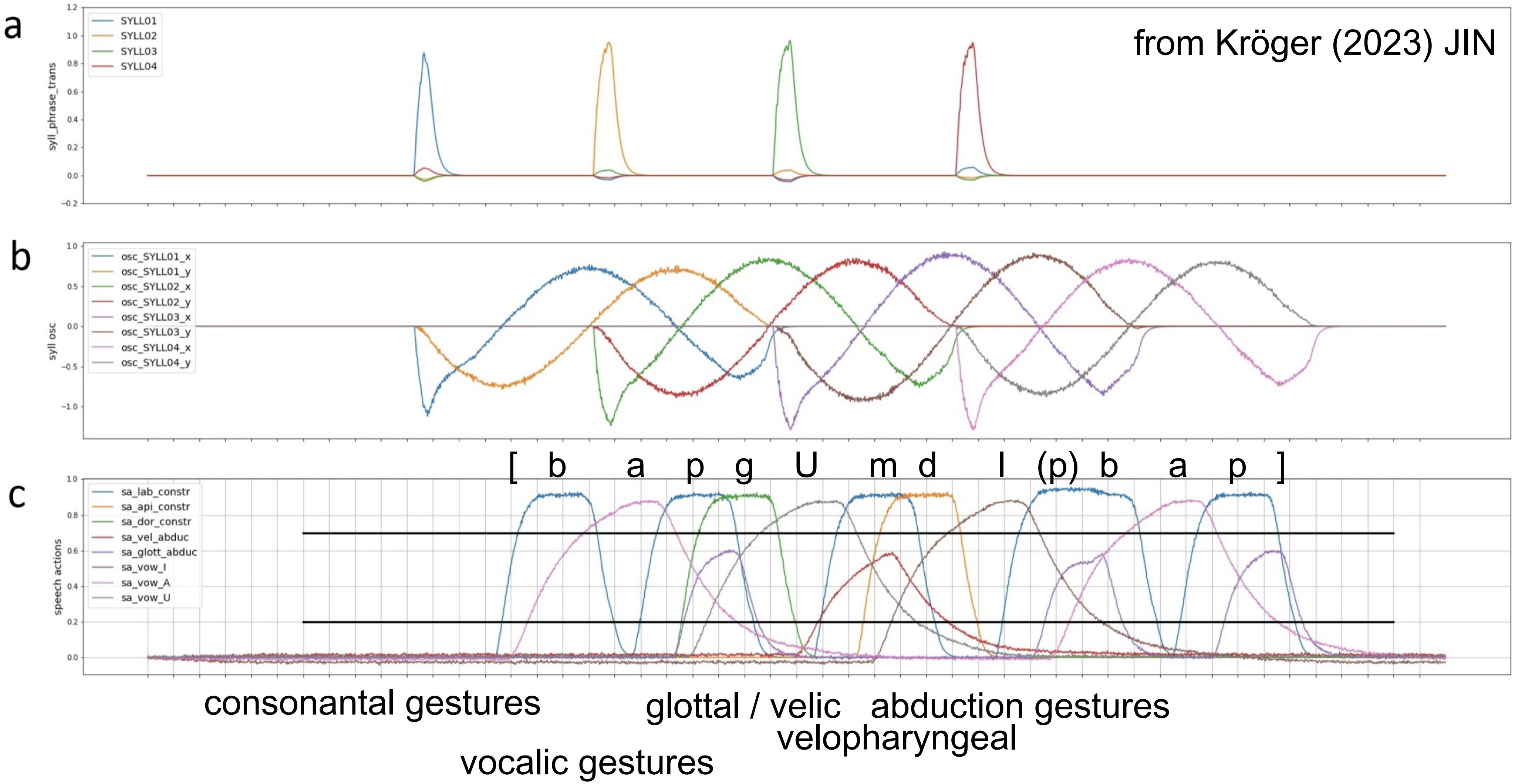
premotor level

primary motor level

Kröger 2023

Simulation of planning

planning results will be stored in mental syllabary



syllable pulses (initialization)

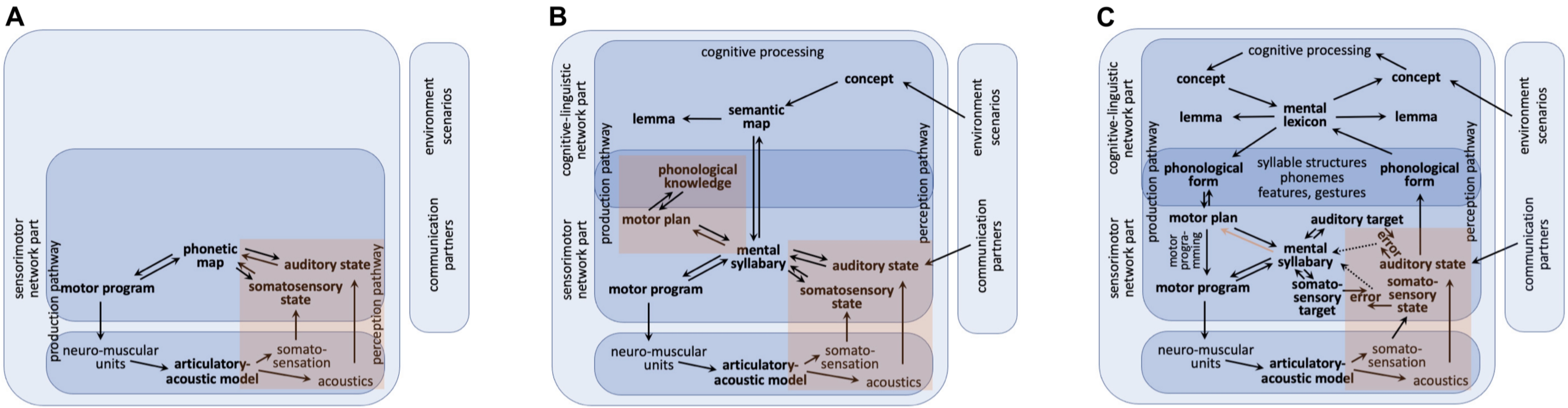
syllable oscillators: Defining intrinsic timing (phase values) -> allows phasing

gestures: potential degree of realization (premotor level)

The complete speech processing model

- In agreement with Common Model of Cognition (CMC)
- But:
  - recurrent neural networks (Google OpenAI) allow training but stay “unstructured”
  - Training (modeling speech acquisiton):
    - still complex for biologically inspired models (spiking neuron approaches like NEF and SPA);
    - and: there is no approach for network growth

Developmental model of word processing



babbling phase:
playing around with own speech organs

imitation phase:
triangulation processes

adult (matured):
word production-comprehension

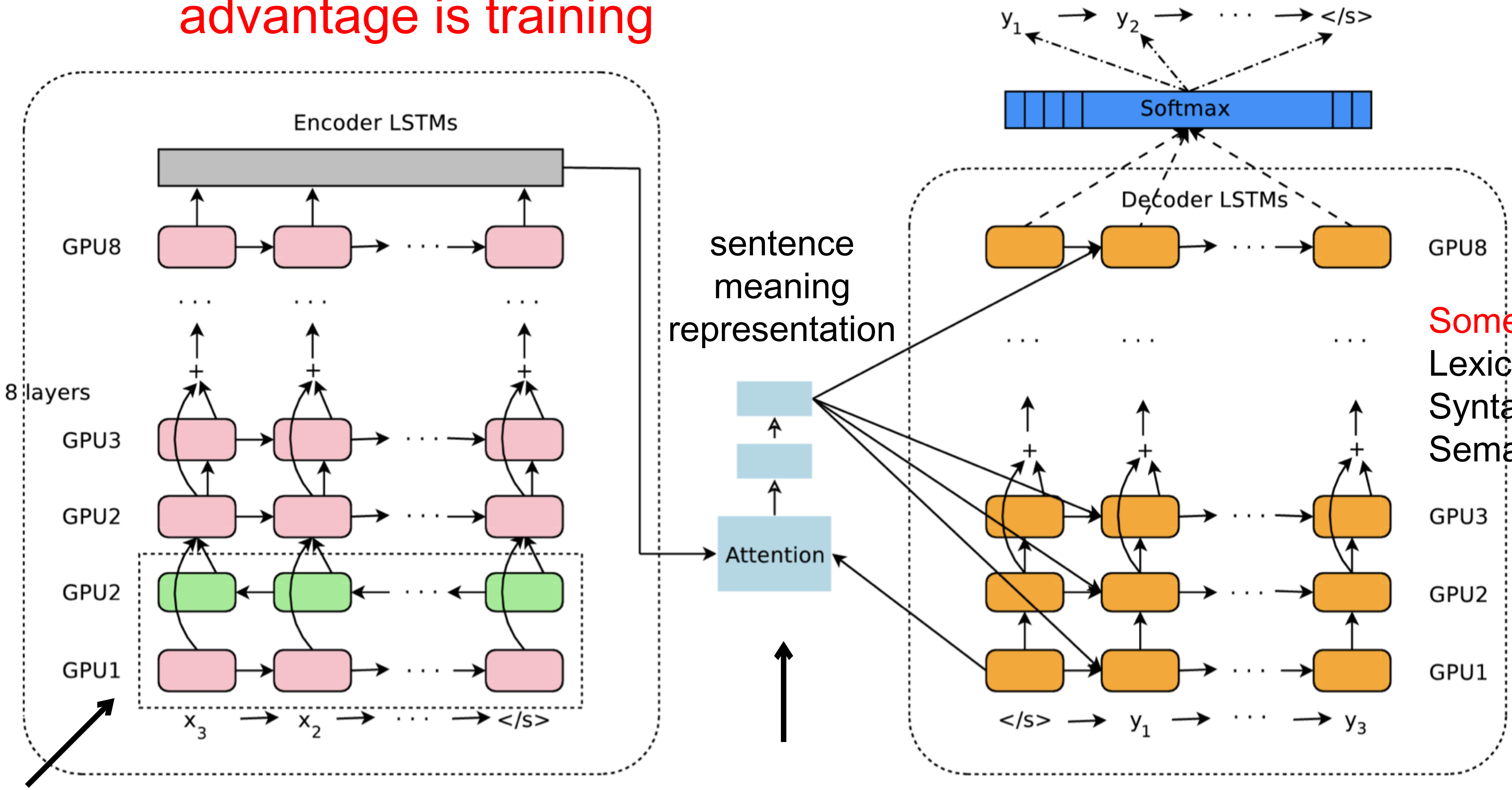
In red: sensory feedback regions for enabling sensory-motor integration

from: Kröger et al. 2022 frontiers in

Google's machine sentence translation network model (Wu et al. 2016)

advantage is training

language 2
word sequence output



sentence meaning representation

Somewhere inside:
Lexical processing
Syntactic processing
Semantic processing

Relatively equally structred / unstructured ensemble of modules

word sequence input
language 1

Interpretation of the neural activation patterns appearing here is difficult!!!

Comparison our model vs. NLP-approaches:

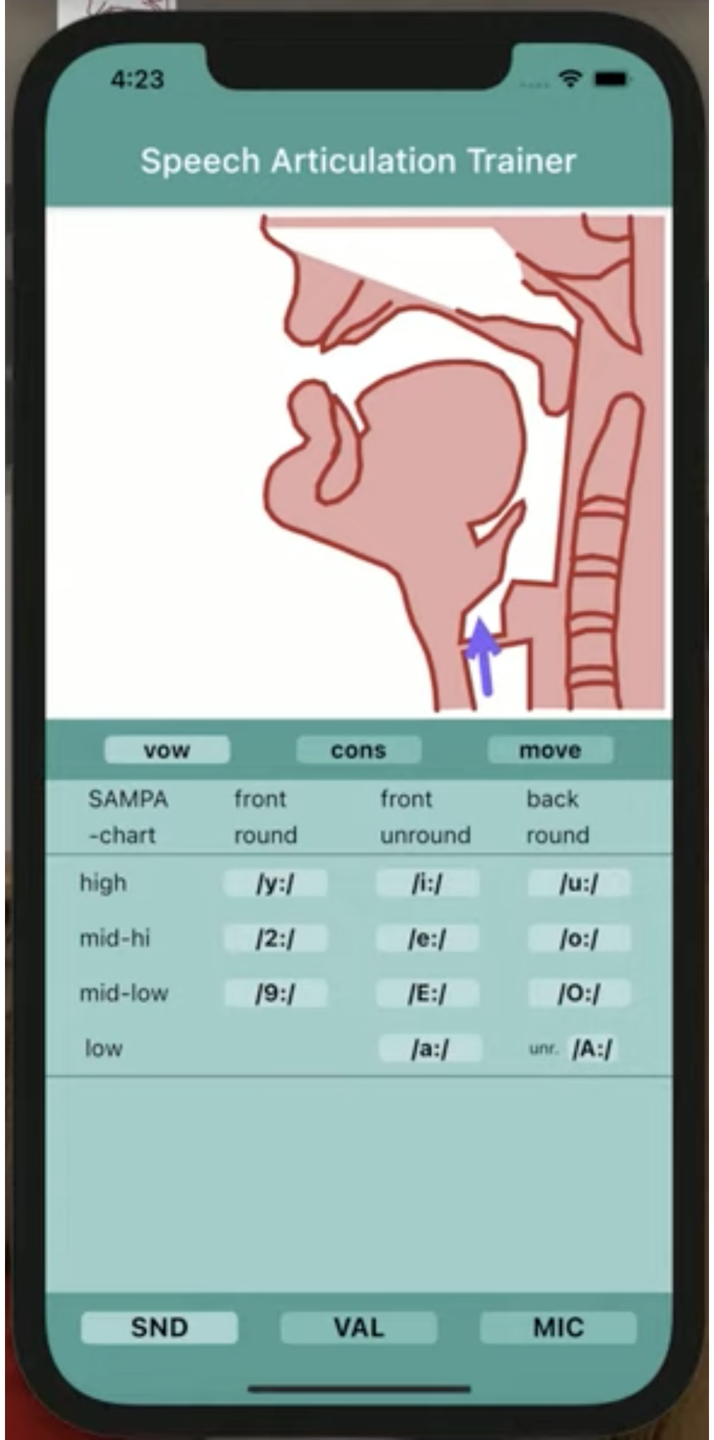
- Simple nearly unstructured recurrent NLP network models can profit from powerful training algorithm (free **ontogenetic** development of the model; individual development of a model following birth)
  - Example: Google translation system (see slide above)
  - Leads to **free formation** of lexical, syntactic, semantic **representations**
  - Leads to **free formation** of the **inner structure** of the network layers which represent the *modules* (lexical, syntactic, semantic processing) in a **largely interwoven** manner (parallel and hierarchical architecture)
  - These models outperform neurobiologically based networks, outperform our models as well as humans

Discussion of our approach:

- Our neurobiologically plausible approach:
  - **predefinition** of **module architecture** and
  - **predefinition** of lexical, syntactic, semantic **representations**
  - Advantage: the model is able
    - to simulate network growth during speech acquisition, and
    - to simulate different stages of speech acquisition -> next slide (remark: no growth modeling in NLP networks!)
  - The model is able
    - to model neural damage by insertion of neural dysfunctions in specific functional or anatomical parts of the model (stroke, traumatic brain injury) and
    - to simulate screenings and thus: symptoms of speech disorders / speech errors
    - To give high quality results concerning the association of neurofunctional damage and resulting speech symptoms -> will increase our knowledge about / our definitions available for different types of speech disorders

(provocative) conclusion:

- Having in mind that google's translation neural network outperforms humans :
- The **phylogenetic** development of the brain (evolutionary history of brain development of humans during last 50.000 years) → the structure of the brain limits performance of training
- **Evolution** limits performance?
- Hypothesis: training of an unstructured brain network would take too long, longer than parents can care for the child by a specific **ontogenetic** development
- ((like: some animal must be able to get up, stand upright, and move immediately after birth))



Thank you for your attention

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