The Encoding of Semantic Relations

W. Singer

May Planck Institut for Brain Research (MPIB)
Frankfurt Institut of Advanced Studies (FIAS)
Ernst Strüngmann Institut (ESI) in cooperation with
Max Planck Society

Singapore, 2016
Relations matter!
They are constitutive for any composite object.

Therefore cognitive systems need efficient mechanisms to detect, classify and encode relations.
The evaluation and encoding of relations in nervous systems.

*Convergence in feed forward architectures (conjunction specific neurons)*
The evaluation and encoding of relations in nervous systems.

*Convergence in feed forward architectures (conjunction specific neurons)*

*Formation of cell assemblies (relations defined by temporal coherence)*
The evaluation and encoding of relations in nervous systems.

* Convergence in feed forward architectures (conjunction specific neurons)
* Formation of cell assemblies (relations defined by temporal coherence)

Ultimately:
Relations are always defined by temporal contiguity.
Semantic relations and learning mechanisms – a circular relation?

We infer meaning from temporal contingencies.

All synaptic learning mechanisms rely on the evaluation of temporal contingencies.
Consequences of the time sensitivity of learning mechanism:

All meaningful relations will ultimately have to be encoded in the temporal domain, irrespective of the nature of the relations. (spatial, temporal, symbolic).
The detection and evaluation of relations in classical feed forward architectures.

Implemented
*in simple nervous systems
  (labelled line codes)
*in AI systems
  (deep learning networks)
Even the most recent artificial systems (deep learning) are based on serial processing in feed forward architectures.
New data on connectivity and dynamics call for an extension of classical views.

*Unexpectedly dense interconnections at all scales (70% of possible connections among nodes are realized)
New data on connectivity and dynamics call for an extension of classical views.

*Unexpectedly dense interconnections at all scales (70% of possible connections among nodes are realized)

*Prevalence of reciprocal connections
New data on connectivity and dynamics call for an extension of classical views.

* Unexpectedly dense interconnections at all scales (70% of possible connections among nodes are realized)
  * Prevalence of reciprocal connections
  * Massive recurrent feed-back connections
New data on connectivity and dynamics call for an extension of classical views.

* Unexpectedly dense interconnections at all scales (70% of possible connections among nodes are realized)
  * Prevalence of reciprocal connections
  * Massive recurrent feed-back connections
  * Soft hierarchy
New data on connectivity and dynamics call for an extension of classical views.

* Unexpectedly dense interconnections at all scales (70% of possible connections among nodes are realized)
  * Prevalence of reciprocal connections
  * Massive recurrent feed-back connections
  * Soft hierarchy
  * Exceedingly complex, non-linear dynamics
Prevailing principles:
Parallellity, Reciprocity, flat Hierarchy

The monkey visual system
From Hilgetag and Kaiser
Axonal projections in the human brain, identified with diffusion tensor imaging.
A Gedankenexperiment: How is a polymodal object represented?
The definition and encoding of relations in a highly distributed system?

*How are semantic relations encoded?
The definition and encoding of relations in a highly distributed system?

*How are semantic relations encoded?

*How are neurons coding for features of the same cognitive object identified as members of a functionally coherent ensemble?
The definition and encoding of relations in a highly distributed system?

*How are semantic relations encoded?

*How are neurons coding for features of the same cognitive object identified as members of a functionally coherent ensemble?

*How can communication be restricted to selected senders and receivers?
Perceptual grouping as example for the need to define relations. Which surfaces belong to the figures and which to the background?
A likely Strategy

Encode *semantic* relations in *temporal* relations.

(as required by all learning rules)
A likely Strategy

Encode *semantic* relations in *temporal* relations.

(as required by all learning rules)

This necessitates:

*Temporally structured activity*
A likely Strategy

Encode *semantic* relations in *temporal* relations. (as required by all learning rules)

This necessitates:

* Temporally structured activity
* Temporal coordination of distributed activity on the fixed backbone of the connectome.
A likely Strategy

Encode *semantic* relations in *temporal* relations.

(as required by all learning rules)

This necessitates:

* Temporally structured activity
* Temporal coordination of distributed activity on the fixed backbone of the connectome.

A general solution to the binding problem?
Supportive evidence

*Most microcircuits have properties of relaxation oscillators.*
Supportive evidence

*Most microcircuits have properties of relaxation oscillators.*

*If reciprocally coupled these will synchronize according to Arnold tongue regime.*
Supportive evidence

*Most microcircuits have properties of relaxation oscillators.*

*If reciprocally coupled these *will* synchronize according to Arnold tongue regime.

Findings:

*Oscillations in different frequency bands*
Supportive evidence

*Most microcircuits have properties of relaxation oscillators.*

*If reciprocally coupled these *will* synchronize according to Arnold tongue regime.*

**Findings:**

*Oscillations in different frequency bands*

*Synchronisation and phase shifts*
Supportive evidence

*Most microcircuits have properties of relaxation oscillators.
*If reciprocally coupled these will synchronize according to Arnold tongue regime.

Findings:

*Oscillations in different frequency bands
*Synchronisation and phase shifts
*Cross frequency coupling
Stimulus driven neurons engage in oscillatory discharges in a wide range of frequencies (<1 to > 100 Hz).

Meanwhile found in: Retina, Tectum, Olfactory System, Basal Ganglia, Thalamus, All Cortical Areas, Hippocampus

PNAS, 1989
Spatially segregated cells can synchronise with zero phase lag

Two recording sites in primary cortex

Two spatially segregated receptive fields

Cross correlogram between spike trains from sites 1+2

Observed: within cortical areas across cortical areas across hemispheres

Nature, 1989
Synchrony reflects semantic relations.
The mechanism for the dynamic association of neurons by synchronisation and Hebbian synaptic plasticity.

Communication and Synaptic plasticity possible

Communication and Synaptic plasticity impossible
Evidence for a functional role of synchronisation / phase locking / coherence

*feature binding
Evidence for a functional role of synchronisation / phase locking / coherence

*feature binding
*signal selection by attention
Evidence for a functional role of synchronisation / phase locking / coherence

* feature binding
* signal selection by attention
* dynamic formation of functional networks
  (task and goal dependent)
Evidence for a functional role of synchronisation / phase locking / coherence

*feature binding
*signal selection by attention
*dynamiic formation of functional networks
  (task and goal dependent)
*involvement in conscious processing and its pathologies
  (schizophrenia, autism)
Measures of synchrony and phase locking as diagnostic tools for the analysis of functional networks

In Patients (Schizophrenia)

In Development

Peter Uhlhaas, Frédérique Roux, Christine Grützner, Michael Wibral

J. Neuroscience, 2006
PNAS, 2007
J. Neuroscience, 2010
Neuron, 2012
Methods

Stimuli
Mooney Faces

MEG-Analysis:
time-frequency analysis with wavelets
source-localisation with beamforming
Consistency of phase locking
 Controls (A) Schizophrenic patients (B).

A Controls, face condition: Phase Locking

B Patients, face condition: Phase Locking

Correlation with Symptoms
Positive \(0.48^*\)
Delusions \(0.51^*\)
Hallucinations \(0.55^*\)
p\(>0.05\)
Topology of disturbed phase locking in schizophrenic patients

Controls

ScZ-Patients

Difference Map

0-100 ms  100-200 ms  200-300ms  300-400 ms

J. Neuroscience, 2006
Conclusion

Power, synchrony and phase locking of oscillations are disturbed in schizophrenia and ASD.

A cause of dissociative symptoms?

An endophenotype?
Functions not accounted for by conventional computational strategies.

*The ultrafast access to the vast amount of stored memories.*
Functions not accounted for by conventional computational strategies.

*The ultrafast access to the vast amount of stored memories.

*The ultrafast evaluation of relations between sensory evidence and stored knowledge (priors).  
(required for predictive coding)
Functions not accounted for by conventional computational strategies.

* The ultrafast access to the vast amount of stored memories.
* The ultrafast evaluation of relations between sensory evidence and stored knowledge (priors).
  (required for predictive coding)

Implication.

* All priors must coexist as latent options.
An example of the constructivistic nature of perception.

What we perceive is the result of interpretations based on a comparison of sensory evidence with a priory knowledge (priors).
A und B have the same brightness
The brain takes the shadow into account
Hypothesis

*The storage of the vast number of priors and their ultrafast readout requires a very high dimensional representational space.
Hypothesis

*The storage of the vast number of priors and their ultrafast readout requires a very high dimensional representational space.

*Such spaces can only be configured as dynamic spaces.
Hypothesis

*The storage of the vast number of priors and their ultrafast readout requires a very high dimensional representational space.*

*Such spaces can only be configured as dynamic spaces.*

*Recurrent networks are capable of providing the required high dimensional dynamic states.*
Hypothesis

*With the evolution of hippocampus and especially the neocortex, a novel computational strategy has been realized that capitalizes on the unique dynamics of recurrent networks.*
Hypothesis

*With the evolution of hippocampus and especially the neocortex, a novel computational strategy has been realized that capitalizes on the unique dynamics of recurrent networks.

*This is the likely reason for the evolutionary success of cortical structures.

(Despite the susceptibility for epilepsy)
The dynamics of recurrent networks:

* provide extremely high dimensional state space
* exhibit fading memory due to reverberation
The dynamics of recurrent networks:

* provide extremely high dimensional state space
* exhibit fading memory due to reverberation
  This permits
* superposition of information
The dynamics of recurrent networks:

* provide extremely high dimensional state space
* exhibit fading memory due to reverberation

This permits

* superposition of information
* parallel search and fast matching with latent priors
The dynamics of recurrent networks:

- provide extremely high dimensional state space
- exhibit fading memory due to reverberation

This permits

- superposition of information
- parallel search and fast matching with latent priors
- The encoding of sequences
The dynamics of recurrent networks:

* provide extremely high dimensional state space
* exhibit fading memory due to reverberation

This permits

* superposition of information
* parallel search and fast matching with latent priors
* The encoding of sequences

These properties are exploited in Reservoir computing, liquid state machines (Jaeger, Maass, Buonamo, Abbot, Memmesheimer)
The principle of liquid (reservoir) computing
Recurrent neuronal networks serve as "liquid" or "reservoir"

Echo State Networks (Jäger, 2001); Liquid State Machines (Maass et al., 2002); review in Lukoševičius & Jäger (2010)
An alternative view on cortex
(contrasting serial feed-forward models)

*Supragranular cortical layers are a delayed coupled recurrent network.*
An alternative view on cortex
(contrasting serial feed-forward models)

*Supragranular cortical layers are a delayed coupled recurrent network.
*The nodes (columns) are feature selective, damped oscillators.
An alternative view on cortex
(contrasting serial feed-forward models)

* Supragranular cortical layers are a delayed coupled recurrent network.

* The nodes (columns) are feature selective, damped oscillators.

* Priors about natural scenes are stored in the weights of the recurrent connections.
Supragranular Layers: A Delay Coupled, Anisotropic, Recurrent Network.

The weights of tangential connections reflect statistics of scenes.
Predictions

*High dimensional resting activity reflects dynamic superposition of priors.
Predictions

*High dimensional resting activity reflects dynamic superposition of priors.

*Stimuli matching the priors (predictions) induce low dimensional substates (e.g. synchronized oscillations).
Predictions

*High dimensional resting activity reflects dynamic superposition of priors.

*Stimuli matching the priors (predictions) induce low dimensional substates (e.g. synchronized oscillations).

*These substates are equivalent with the sparse code of a „result“.
Predictions

*High dimensional resting activity reflects dynamic superposition of priors.

*Stimuli matching the priors (predictions) induce low dimensional substates (e.g. synchronized oscillations).

*These substates are equivalent with the sparse code of a “result“.

*“Result states“ induce synaptic modifications (learning) and are propagated forward.
First evidence for cortical dynamics characteristic of recurrent networks.

Methods

* Multisite recordings in the visual cortex.

* Presentation of stimulus sequences.

* Retrieval of stimulus specific information in high dimensional response vectors with machine learning.

Nicolic et al., PLOS Biology, 2009
The experimental paradigm
Long lasting persistence of information

Duration of training and test window $= 1$ ms
Persistence of information across stimuli
Superposition of information about two letters
*Information distributed across many neurons.*
*Information distributed across many neurons.
*Fading memory.
Summary

*Information distributed across many neurons.
*Fading memory.
*Persistence of information across stimuli.
Summary

*Information distributed across many neurons.

*Fading memory.

*Persistence of information across stimuli.

*Superposition of information from different stimuli.
Summary

*Information distributed across many neurons.
*Fading memory.
*Persistence of information across stimuli.
*Superposition of information from different stimuli.
*Preservation of sequence order.
Summary

* Information distributed across many neurons.
  * Fading memory.
  * Persistence of information across stimuli.
  * Superposition of information from different stimuli.
  * Preservation of sequence order.

Findings compatible with computations based on high dimensional dynamics of recurrent networks
Further predictions:

*Recurrent connections should undergo Hebbian modifications in order to store feature correlations of frequently occurring stimuli. (acquisition and updating of priors)

Evidence available from developmental studies
Reciprocal connections between neurons in the cerebral cortex are shaped by experience.

These connections store knowledge about statistical contingencies of features.

(Priors for Bayesian Matching)

(Loewel and Singer. Science 1992)
Labelling of connections

blood vessel pattern

0° right eye

0° left eye

90° right eye
Related functional domains are coupled selectively.
Without experience connections remain random
Unsupervised Hebbian plasticity of recurrent connections in kitten A17

Singer, Tretter, 1977
Prediction

If the relations among the features constituting objects are stored in the recurrent network

then

one expects improved classifiability of substates induced by familiar objects.
Classification performance improves with familiarity. Note the delayed improvement of classification!
Segregation of population vectors in PCA space as a function of time from stimulus onset (cat #1) for early and late trials.
Conclusion

*The network self-organizes into classifiable stimulus specific substates within a few hundred ms.

*Overlap of substates in PC space decreases with repeated stimulation, facilitating classification.

Andreea Lazar, Chris Lewis, Danko Nicolic (in prep)
Prediction

If priors are stored in synaptic weight distributions then they should be superimposed and replayed in resting state activity.

Andreea Lazar, (in prep)
Training read out neurons to convert vectors into brightness values.

12X12 array of readout neurons
Search for patterns in spontaneous activity. Stimulus specific substates are replayed!

Samples taken from spontaneous activity

Letter C
Summary

*Cortical networks store stimulus specific relations in substates of high dimensional dynamics.

*These substates are replayed in resting activity.

Andreea Lazar, Danko Nicolic (in prep)
Testing of predictions in trained monkeys.

*Implantable device with adjustable electrodes. (so far continuous recording over 18 months)

*Tasks involving attention, complex decisions and pattern recognition

Liane Klein, Andreea Lazar, Gez Bland, Sylvia van Stjin, Will Barnes, Hanka Klon-Lipok
Prediction.

If cortical networks store statistical relationships of natural environments then dynamic states induced by natural scenes should be easier to classify than those induced by scrambled scenes.
Effects of natural and scrambled images on Fano factor, gamma power and classifiability.
Classification performance is high for natural and low for scrambled scenes while average firing rates and Fano factor reduction are similar.

- Similar mean rates
- Similar reduction in FF on average
- High performance only for natural stimuli
Classification based on Local Field Potentials (LFPs).

Gamma power and classification performance are higher for natural than phase scrambled stimuli.

Hazard function build-up in expectation of change

Stimulus identity decoded from gamma power distribution

A. Lazar
Classification of scenes is possible both from spike and LFP vectors.
Summary

*Classification of scenes is possible both from spike and LFP vectors.
*Classification is better for natural than scrambled scenes.
Summary

*Classification of scenes is possible both from spike and LFP vectors.
*Classification is better for natural than scrambled scenes.
*Difference is not attributable to change in S/N ratio.
Classification of scenes is possible both from spike and LFP vectors.

Classification is better for natural than scrambled scenes.

Difference is not attributable to change in S/N ratio.

Natural scenes induce stronger gamma.

(reduction of dimensionality?)
Summary

*Classification of scenes is possible both from spike and LFP vectors.
*Classification is better for natural than scrambled scenes.
*Difference is not attributable to change in S/N ratio.
  *Natural scenes induce stronger gamma.
  (reduction of dimensionality?)

Proposal

*Match between natural scenes and stored priors leads to well organized substates, reflected by gamma ramp up and better classification.
Further predictions:

*Stimuli should reduce dimensionality of state.
Further predictions:

* Stimuli should reduce dimensionality of state.
* Degree of reduction should depend on stimulus complexity.
Further predictions:

* Stimuli should reduce dimensionality of state.
* Degree of reduction should depend on stimulus complexity.
* Dimensionality should also be constrained by top down influences (attention, expectancy).
Experimental paradigm to modulate expectancy

Monkey expects response cue either after second or third stimulus

Multisite recordings
Of spikes and LFPs

Receptive fields

early response window
end of early trials

late response window
end of late trials
Expectancy reduces dimensionality of dynamic state in monkey V1

monkey expects early change but change occurs late (catch trial)

monkey expects late change

responses to second stimuli

gamma

expected

unexpected

expected

unexpected

J. Neuroscience, 2011
Expectancy has no significant effect on firing rate

expected vs non expected

J. Neuroscience, 2011
General conclusion

Gamma oscillations
*reflect match between evidence and priors
General conclusion

Gamma oscillations

*reflect match between evidence and priors
*reflect constrained substates with specific correlation structure
(constrained by sensory evidence or expectancy)
General conclusion

Gamma oscillations
*reflect match between evidence and priors
*reflect constrained substates with specific correlation structure
(constrained by sensory evidence or expectancy)
*favour Hebbian synaptic modifications
(updating of priors)
General conclusion

Gamma oscillations
* reflect match between evidence and priors
* reflect constrained substates with specific correlation structure
  (constrained by sensory evidence or expectancy)
* favour Hebbian synaptic modifications
  (updating of priors)
* favour transmission of results
  (by enhancing saliency via synchronisation)
A condition requiring extensive definition of nested relations is Conscious Processing.

(the unity of conscious states)

It is associated with large scale temporal coherence of distributed neuronal activity in different frequency bands.

(Phase synchrony of theta, beta and gamma oscillations)
Phase Synchronisation of Gamma Oscillations
Phase Synchronisation of Gamma Oscillations
Topology of phase synchronisation
Pure conjunction in time without necessarily cerebral conjunction in space lies at the root of the solution of the problem of the unity of mind.
But can we also account for the immaterial (mental, spiritual) dimension of „consciousness“?

How to conceive of the spiritual dimension that is constitutive for our Self Model without postulating Ontological Dualism?
The Proposal.

A naturalistic account might be possible if we consider the „problematic“ connotations of consciousness as an emergent property of cultural evolution.
The evolution of complex neuronal systems led to the emergence of cognitive agents.

Endowed with qualities such as:
Perceptions, Emotions, Drives, Intentionality,
Phenomenal Awareness
The Emergence of the Spiritual Dimension

**Biological Evolution**
- Cognitive Agents (Perceptions, Actions, Behavior)
- Neuronal Interactions (Electro-Chemical Processes)

**Cultural Evolution**
- Social Realities (Believes, Concepts, Self-Models)
- Social Networks (Cognitive Interactions, Symbolic Communication)

The Spiritual Dimension

The diagram illustrates the relationship between biological and cultural evolution, showing how cognitive agents and neuronal interactions are linked to social realities and networks through the spiritual dimension.
The next evolutionary step: 
Formation of networks of interacting cognitive agents.

CULTURAL EVOLUTION

Led to the emergence of the immaterial, spiritual dimension of our models of the world and our Self.
The dimension of social realities.
"I know that you know how I feel"
"I know that you know how I know"

Prerequisites

1.) Brains capable of developing a theory of mind
2.) There need to be at least two
Social networks create social realities.

Network of trading interactions.
The Emergence of the Spiritual Dimension

Biological Evolution

- Cognitive Agents (Perceptions, Actions, Behavior)
- Neuronal Interactions (Electro-Chemical Processes)

Cultural Evolution

- The Spiritual Dimension
- Social Realities (Believes, Concepts, Self-Models)
- Social Networks (Cognitive Interactions, Symbolic Communication)
The nature of social realities.

*Immaterial phenomena resulting from social interactions, absent in a precultural world.
The nature of social realities.

*Immaterial phenomena resulting from social interactions, absent in a precultural world.

*Not perceivable with the natural senses.
The nature of social realities.

*Immaterial phenomena resulting from social interactions, absent in a precultural world.

*Not perceivable with the natural senses.

*Commonly associated with mental or spiritual, immaterial dimensions.
Examples of social realities.

*Empathy, Fairness, Griefed, Love, Devotion
Examples of social realities.

*Empathy, Fairness, Gried, Love, Devotion
*Norms, Vows, Commitments, Social status
Examples of social realities.

*Empathy, Fairness, Gried, Love, Devotion
*Norms, Vows, Commitments, Social status
*Values, Believe Systems, Moral imperatives
Examples of social realities.

*Empathy, Fairness, Gried, Love, Devotion
*Norms, Vows, Commitments, Social status
*Values, Believe Systems, Moral imperatives
*Attributions and concepts such as:
The autonomous, intentional, free and CONSCIOUS SELF.
A somewhat daring but plausible analogy.

Neurons relate to cognitive agents

As

Cognitive agents relate to the spiritual dimension.

In both cases the embedding systems transcend the properties of their respective components.
Conclusion

A naturalistic account of the spiritual dimension seems possible.
Conclusion

A naturalistic account of the spiritual dimension seems possible. It could help to settle epistemic disputes on: Consciousness, Mental Causation and the Mind-Body Problem.
The Cerebral Cortex: Evolutions´ seminal discovery.

Its recurrent oscillator networks allow exploitation of high dimensional non linear dynamics for computation.
The Cerebral Cortex: Evolutions´ seminal discovery.

Its recurrent oscillator networks allow exploitation of high dimensional non linear dynamics for computation. This provides:

* Virtually unbounded storage space.
The Cerebral Cortex: Evolutions´ seminal discovery.

Its recurrent oscillator networks allow exploitation of high dimensional non linear dynamics for computation.

This provides:

* Virtually unbounded storage space.
* The option to dynamically relate (bind)
  „everything with everything“
The Cerebral Cortex: Evolutions´ seminal discovery.

Its recurrent oscillator networks allow exploitation of high dimensional non linear dynamics for computation.

This provides:

* Virtually unbounded storage space.
* The option to dynamically relate (bind) „everything with everything“

These are the prerequisites for abstraction, symbolic coding and ultimately language.
Thanks go to:

Andreea Lazar
Patrick Jendritza
Danko Nikolic

Gareth Bland
Liane Klein
Johanna Klon-Lipok