UNIVERSITÄT OSNABRÜCK

EQUIPPING SYMBOLIC FRAMEWORKS WITH SOFT COMPUTING FEATURES

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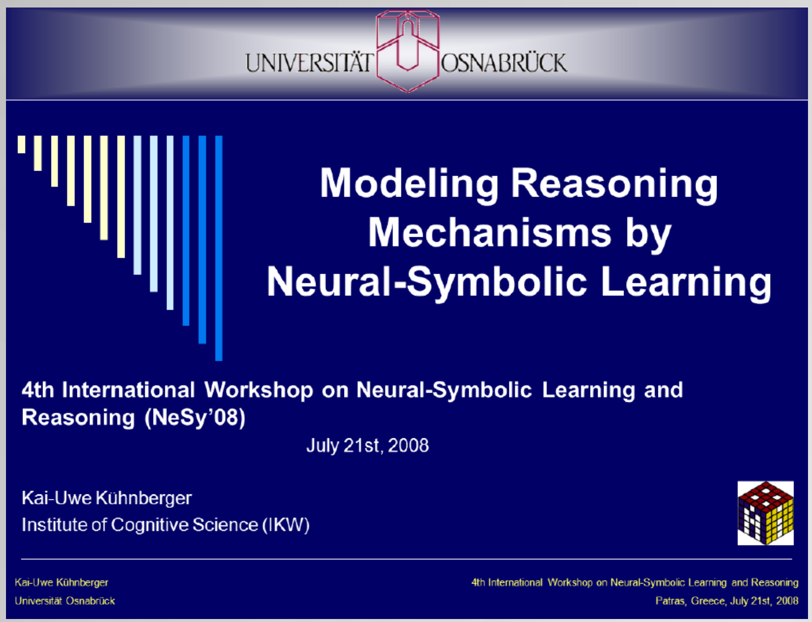
OVERVIEW

- Introduction
  - History: NeSy'08
- Convergence Tendencies of the Neural and the Symbolic Worlds
  - Some Examples
- Adaptation from a Symbolic Perspective: An Example
  - Heuristic-Driven Theory Projection (HDTP)
  - Institutions
- Conclusions

INTRODUCTION

NESY '08

SOME HISTORY



In 2008, I gave a talk at the 4th International Workshop on Neural-Symbolic Learning and Reasoning in Greece.

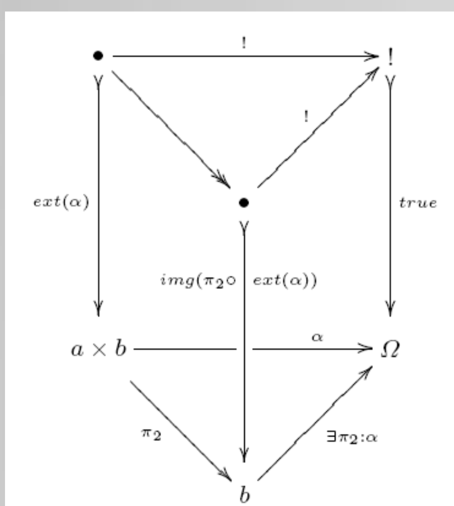
It was not only scientifically interesting, but also culturally!

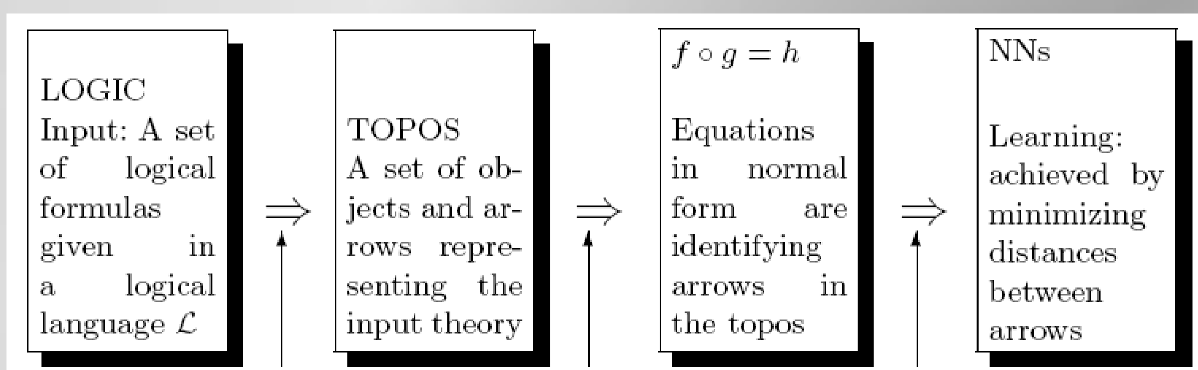
SOME HISTORY

- In 2008, my talk covered some of the following issues
  - Classical Problems of Neural-Symbolic Integration
  - Cognitive Aspects of Neural-Symbolic Integration
    - Cognitive Architectures
    - Cognitively Motivated Constraints (dynamic representations, the role of models, reorganization of memory, variety of reasoning and learning paradigms)
  - Neural-Symbolic Reasoning
    - Attempt to address some of the cognitively motivated constraints
  - Application Domains of Neural-Symbolic Frameworks
  - Conclusions

SOME HISTORY

- Additionally, I added some remarks to an approach we proposed around this time: the Topos approach
- Unfortunately, the Topos approach was not really successful in applications and proved also to be difficult in certain technical aspects.





Gust, Kühnberger & Geibel (2007, Springer)

SOME HISTORY

- In my talk, I claimed essentially that neural-symbolic integration is a good approach do address several problems and constraints (imposed by cognitive scientists) to possible models.
  - Symbolic-subsymbolic gap
  - Role of models
  - Reorganizing issues of our memory system
  - Aspects of generality / general intelligence
  - Dynamic representations
- **Essentially I still think that this claim is still correct.**
- **Nevertheless, research in neural-symbolic integration did not come up with uncontroversial frameworks so far addressing these issues.**

TODAY

- Today I will take another perspective
  - I think that there is a tendency that many researchers equip their symbolic frameworks with properties that are usually ascribed to the neural world and vice versa.
  - They want to model uncertainty / fuzziness, dynamic changes in representations, model-based reasoning, clash resolution, learning etc.
- I think that this is of interest for the field of Neural-Symbolic Integration because the convergence of the two world is minimized by these endeavors.

CONVERGENCE TENDENCIES

SOME EXAMPLES

THE GAP

- The symbolic-subsymbolic distinction
  - There is an obvious tension between symbolic and subsymbolic representations.

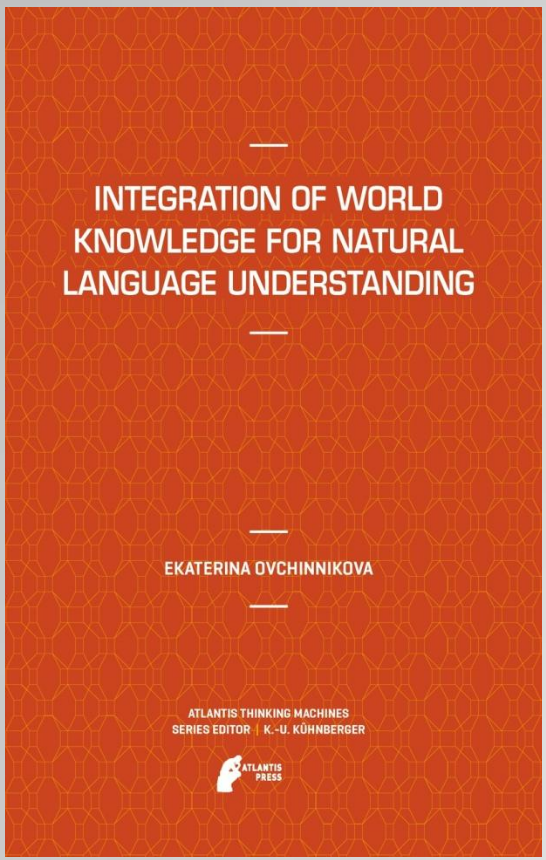
	Symbolic Approaches	Subsymbolic Approaches
Methods	Mainly logical and / or algebraic	Mainly analytic
Strengths	Productivity, recursion, compositionality	Robustness, parsimony, adaptation
Weaknesses	Consistency constraints, lower cognitive abilities	Opaqueness, higher cognitive abilities
Applications	Reasoning, problem solving, planning etc.	Learning, vision etc.
Relation to Neurobiology	Not biologically inspired	Biologically inspired
Other Features	Crisp, static	Fuzzy, dynamic

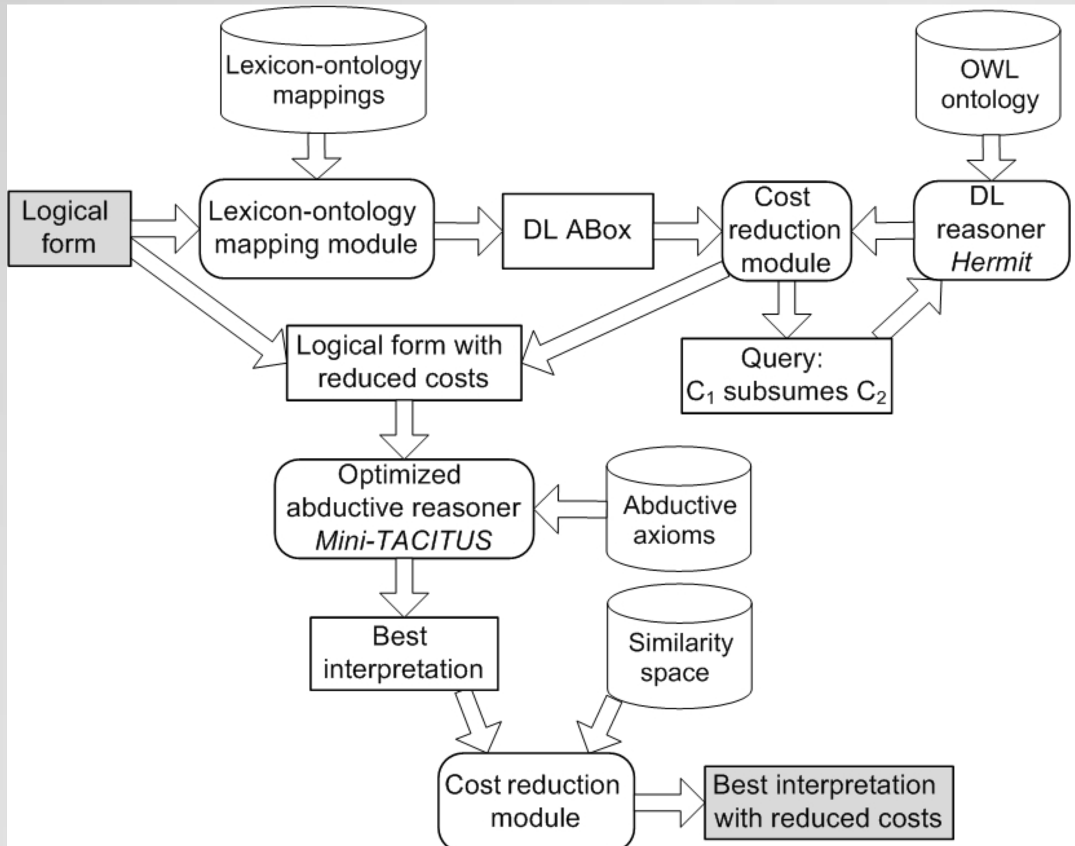
- The following examples show that there are tendencies to integrate certain features from the subsymbolic world into symbolic models.

ONTOLOGIES IN LANGUAGE UNDERSTANDING SYSTEMS

- In language understanding systems there is the need to integrate linguistic knowledge and world knowledge.
- Because domain knowledge is often noisy, context-dependent, and uncertain adding soft-computing features is a natural choice.
- In Ovchinnikova (2012), a weighted abductive reasoning system is used in order to integrate (besides other things)
  - Lexical-semantic data bases (FrameNet and WordNet)
  - Ontological knowledge
  - Clash resolution strategies
  - Deductive and abductive reasoning
  - Vector space-based semantic similarity measure
  - Cost model that ranks hypothesis inferences for text understanding tasks

ONTOLOGIES IN LANGUAGE UNDERSTANDING SYSTEMS

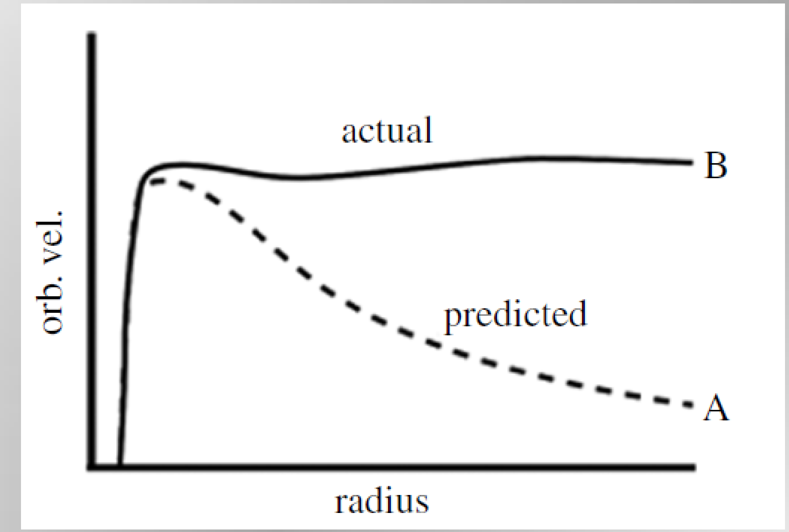




Ovchinnikova (2012), Atlantis / Springer

ONTOLOGY REPAIR SYSTEMS

- Ontology repair systems show
  - A high dynamic for resolving clashes between theories
  - They are based on a rather few number of principles that allow the resolution of clashes
  - The resolution of clashes can result in changing the language, the introduction of new concepts, deletion of concepts, change of the underlying type theory etc.
- Example (Physics):
  - Postulation of dark matter in order to explain the orbital velocities of galaxies against distance to the center.



Bundy (2013), Proceedings A

ONTOLOGY REPAIR SYSTEMS

- Scientific discovery requires dynamic updates of existing theories.
- Consider the following situation:

$$\mathcal{O}_x \vdash f(\text{stuff}) = v_x,$$
$$\mathcal{O}_y \vdash f(\text{stuff}) = v_y$$
$$\mathcal{O}_{\text{arith}} \vdash v_x \neq v_y,$$

- The contradiction is resolved by specifying new signatures:

$$\text{Sig}(\nu(\mathcal{O}_x)) ::= \{\text{stuff}_{\text{vis}}\ \tau, \text{stuff}_{\text{invis}}\ \tau\} \cup \text{Sig}(\mathcal{O}_x)$$ and

$$\text{Sig}(\nu(\mathcal{O}_y)) ::= \{\text{stuff}_{\text{vis}}\ \tau\} \cup \text{Sig}(\mathcal{O}_y) \setminus \{\text{stuff}\ \tau\}.$$

- Axiom update works as follows:

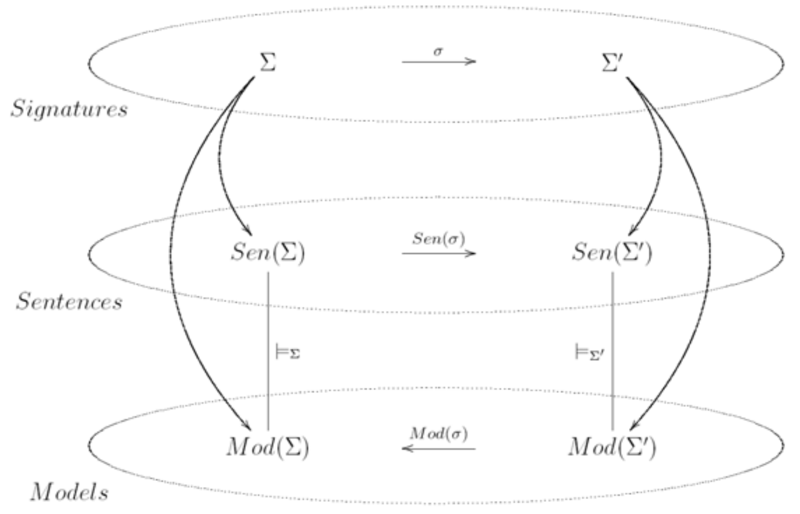
$$Ax(\nu(\mathcal{O}_x)) ::= \{\ \text{stuff}_{\text{invis}} ::= \text{stuff} -_\tau \text{stuff}_{\text{vis}}\ \} \cup Ax(\mathcal{O}_x)$$ and

$$Ax(\nu(\mathcal{O}_y)) ::= \{\phi\{\text{stuff}/\text{stuff}_{\text{vis}}\} | \phi \in Ax(\mathcal{O}_y)\}$$

Bundy (2013), Proceedings A

DYNAMICS OF ANALOGY MAKING

- Analogy making is the identification of structural commonalities between two theories.
- Here are some soft-computing features of analogy making:
  - Learning of cross-domain properties and relations that cannot be associated in classical frameworks.
  - Adaptation of the underlying input theories (re-representation based on logical deductions) if this is necessary for the computation of better analogies.
  - Dynamic transfer of knowledge from the source to the target domain.
  - Ranking of candidates by a cost function or an appropriate probability measure.
  - Mapping signatures of underlying domain theories onto each other.



OTHER EXAMPLES

- The previous approaches add several features of soft-computing properties to classical symbolic approaches.
- Here are further candidates for these extensions:
  - Relational Learning - combining logic representation with statistical learning. (de Raedt, 2008, Springer)
  - Markov Logic - combining logic with probability. (Richardson & Domingos (2006), Machine Learning)
  - Marcus Hutter's AIXI system - combining reinforcement learning, with Kolmogorov complexity, compression of data and more. (Hutter, 2006, Springer)
  - Wang's NARS system – combining logic representations with the modeling of uncertainty. (Wang, 2006, Springer)

EXTENSION OF SYMBOLIC FRAMEWORKS

- There is a tendency that many researchers from a classical symbolic background tend to equip their models with a combination of the following features
  - Learning strategies
  - Methods for modeling uncertainty / fuzziness
  - Dynamic change and adaptation of knowledge
  - Usage of analytic methods in addition to a logic / algebraic basis
  - Etc.
- In short: The equipment of classical symbolic frameworks with soft computing features results in a tendency of convergence of the symbolic and the subsymbolic world.
  - Such a modeling of these features is not necessarily neurally inspired, but it has many properties that neural approaches show as well.

ADAPTATION FROM A SYMBOLIC PERSPECTIVE

HEURISTIC-DRIVEN THEORY PROJECTION

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NeSy'13 – Beijing
August 5th, 2013

HEURISTIC-DRIVEN THEORY PROJECTION (HDTP)

Input:
first-order theories

Process
select terms / predicates / formulas (heuristics)
select best generalization (heuristics)
project formulas, if they are not associated yet

Output:
generalized theory

Generalization

mass(X) > mass(Y)
dist(X, Y) > 0
F (X , Y) > 0

Source

mass(s) > mass(p)
dist(s, p) > 0
gravity(s, p) > 0

Target

mass(n) > mass(e)
dist(e, n) > 0
coulomb(n, e) > 0

Gust, Kühnberger, Schmid (2006), TCS

HDTP: ANTI-UNIFICATION

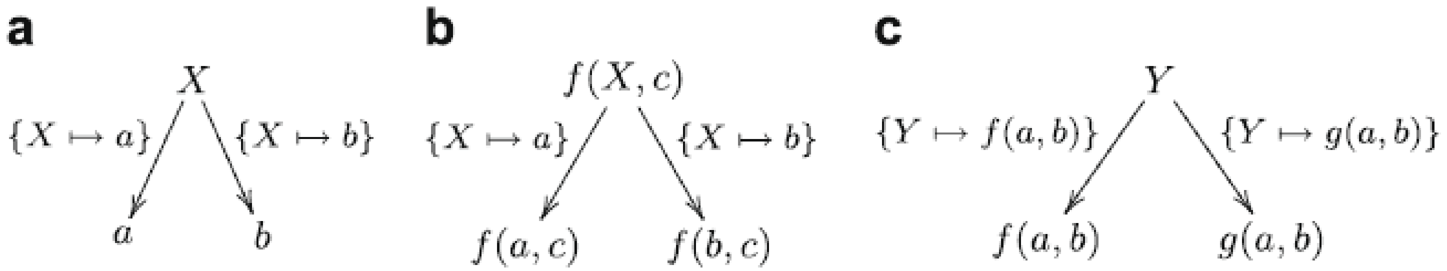


Fig. 3. Plotkin's first-order anti-unification.

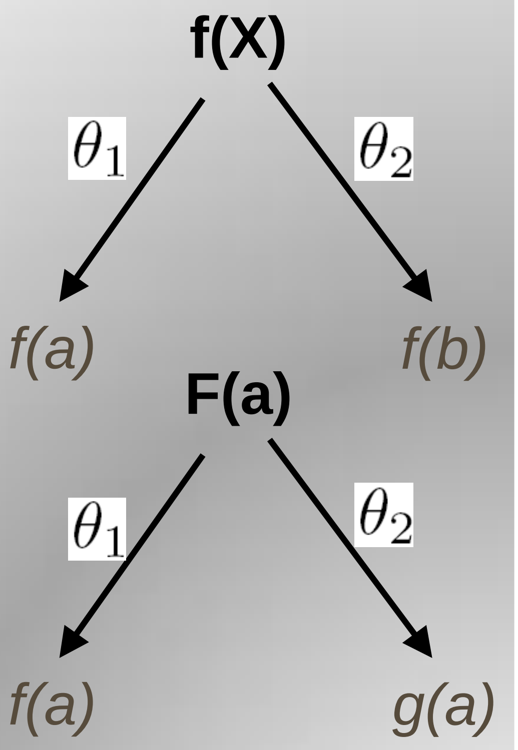
- Anti-unification was introduced as a dual construction to unification by Gordon Plotkin (Plotkin, 1970).
- Anti-unification constructs a generalization of two terms by using substitutions.

Schwerin et al. (2009), CogSys

HDTP: ANTI-UNIFICATION

How to compare source & target theory structurally?

- Task: least general generalizations of facts and rules
- ***First-order*** anti-unification (Plotkin, 1970):
  ✓ generalization always exists
  ✓ at most finitely many generalizations
  ✓ there exists a unique least general generalization
- What about ***full second-order*** anti-unification?
  ✓ generalization always exists
  ✗ at most finitely many generalizations
  ✗ exists unique least general generalization



HDTP: CHALLENGES

- Challenges for HDTP:
  - 1. Higher-order anti-unification
    - In analogy-making not only first-order generalizations but also higher-order generalizations are required.
    - Problem: in the worst case there exist infinitely many anti-instances that are pairwise incompatible with each other.
  - [2. Anti-unification of theories]
    - [Not only terms need to be generalized but also formulas and ultimately whole theories of a particular domain.]
  - [3. Learning process]
    - [The establishment of an analogical relation is already a learning step.]
    - [Nevertheless, analogies are only to a certain extend applicable, they depend on contexts and parameters, and they give rise to further more general principles.]

RESOLVING CHALLENGE 1

Restricted Higher-Order Anti-Unification:

Generalizations are forced to be always structurally simpler

Basic Substitutions in HDTP:

- Renaming $F(t_1, \ldots, t_n) \xrightarrow{\rho^{F,F'}} F'(t_1, \ldots, t_n)$
- Fixation $F(t_1, \ldots, t_n) \xrightarrow{\phi^F_f} f(t_1, \ldots, t_n)$
- Argument insertion $F(t_1, \ldots, t_n) \xrightarrow{\iota^{F,F'}_{G,i}} F'(t_1, \ldots, t_i, G(t_{i+1}, \ldots, t_{i+k}), t_{i+k+1}, \ldots, t_n).$
- Permutation $F(t_1, \ldots, t_n) \xrightarrow{\pi^{F,F'}_\alpha} F'(t_{\alpha(1)}, \ldots, t_{\alpha(n)}).$

→ With these restrictions we get only finitely many anti-instances

Krumnack, Schwering, Gust, Kühnberger (2007), AI'07

REMARKS

- Some features of HDTP
  - HDTP's computation is highly heuristic-driven.
  - The system computes different candidates for an analogical relation (there is no right or wrong analogy, rather candidates are more or less psychologically plausible).
  - Currently the ranking of candidates is based on cost functions (i.e. a form of Occam's razor is applied).
    - Probabilistic extensions of HDTP are currently considered.
  - Besides the core process the engine incorporates re-representation aspects of the input domains.
- Nevertheless, the syntactic computation generates formal difficulties in specifying what the semantics of this type of dynamical change is.

HDTP AND THE THEORY OF INSTITUTIONS

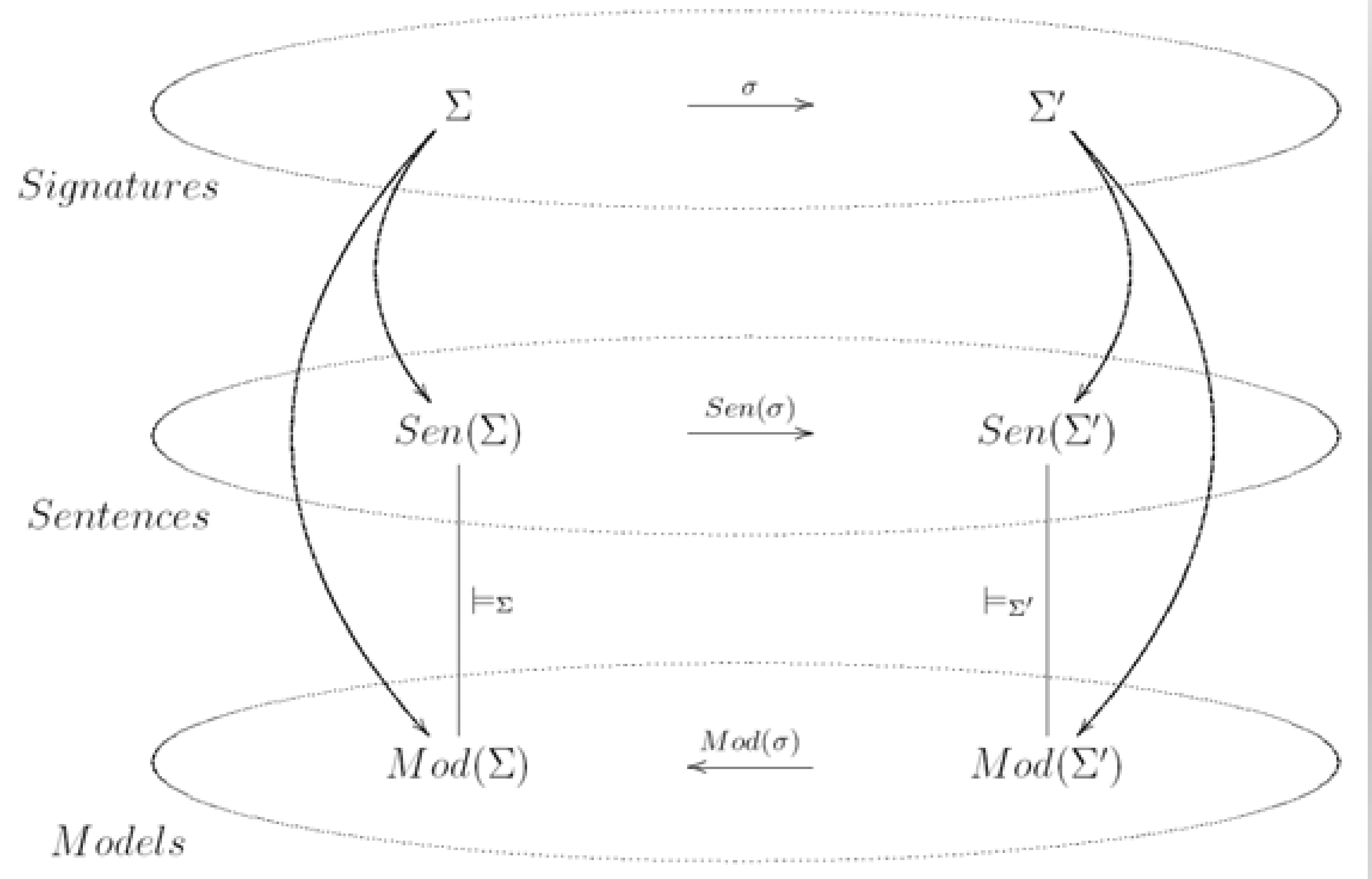
- An institution consists of a collection of signatures **Sign**, such that to each signature Σ a collection **Sen**(Σ) of all Σ-sentences and a collection **Mod**(Σ) of all Σ-models are assigned.
  - In the case of FOL, this corresponds to all FOL-sentences and all possible interpretations of symbols from Σ.

- A signature morphism $f : \Sigma \rightarrow \Sigma'$ induces functions **Sen**(f) : **Sen**(Σ) → **Sen**(Σ') and **Mod**(f) : **Mod**(Σ') → **Mod**(Σ) such that it holds: for all $\phi \in$ **Sen**(Σ) and $M' \in$ **Mod**(Σ'):

$$M' \models_{\Sigma'} \mathbf{Sen}(f)(\phi) \quad \Leftrightarrow \quad \mathbf{Mod}(f)(M') \models_{\Sigma} \phi$$

- Institutions allow to give the change of signatures in the anti-unification process a meaning.

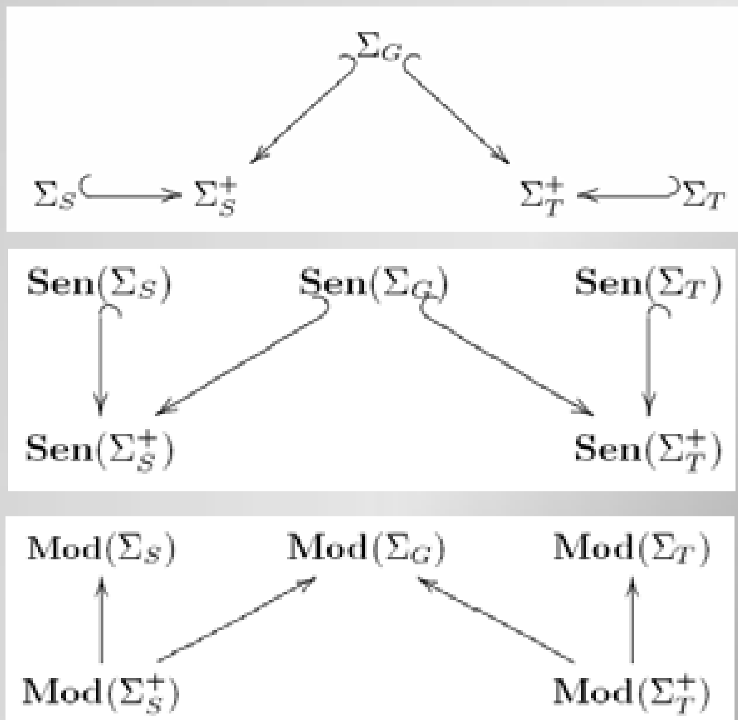
HDTP AND THE THEORY OF INSTITUTIONS



HDTP AND THE THEORY OF INSTITUTIONS

- We use the following abbreviations:

and



Krumnack, Gust, Schmid, Kühnberger (2010), AGI

HDTP AND THE THEORY OF INSTITUTIONS

- Unfortunately, analogy-making in the sense of HDTP is more general than this. It includes, for example, complex substitutions which are not covered by the presented framework.
- Fortunately, institution theory provides concepts that can even model these situations, namely the concept of a general Σ-substitution

HDTP AND THE THEORY OF INSTITUTIONS

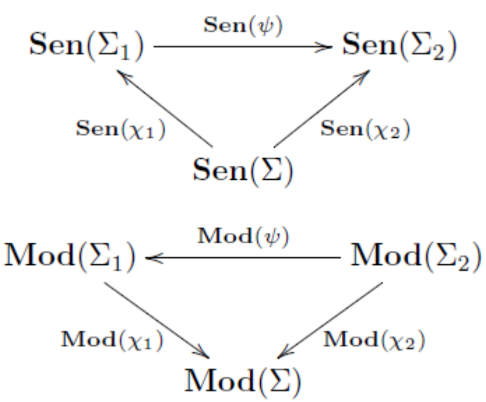
Definition 2. *For any signature Σ of an institution, and any signature morphisms $\chi_1 : \Sigma \to \Sigma_1$ and $\chi_2 : \Sigma \to \Sigma_2$, a* general Σ-substitution $\psi_{\chi_1:\chi_2}$ *consists of a pair*

$$\langle \mathbf{Sen}(\psi), \mathbf{Mod}(\psi) \rangle ,$$

where

- $\mathbf{Sen}(\psi) : \mathbf{Sen}(\Sigma_1) \to \mathbf{Sen}(\Sigma_2)$ *is a function*
- $\mathbf{Mod}(\psi) : \mathbf{Mod}(\Sigma_2) \to \mathbf{Mod}(\Sigma_1)$ *is a functor*

such that both of them preserve Σ, i.e. the following diagrams commute:



and such that the following satisfaction condition holds:

$$\mathbf{Mod}(\psi)(\mathfrak{m}_2) \models \rho_1 \quad \textit{if and only if} \quad \mathfrak{m}_2 \models \mathbf{Sen}(\psi)(\rho_1)$$

for each Σ_2-model $\mathfrak{m}_2$ and each Σ_1-sentence ρ_1.

- A general Σ-substitution extends the concept of a signature morphism.
- It can be shown that the concept of general Σ-substitution covers simple signature morphisms, first-order substitutions, second-order substitutions, derived signature morphisms etc.
- The crucial properties of a contravariant relation between the model classes and the theories remain intact.

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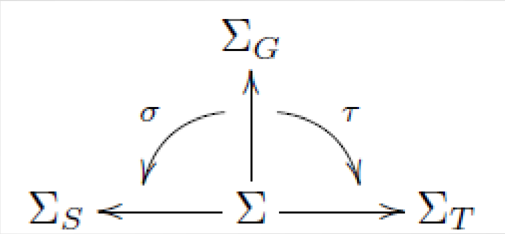
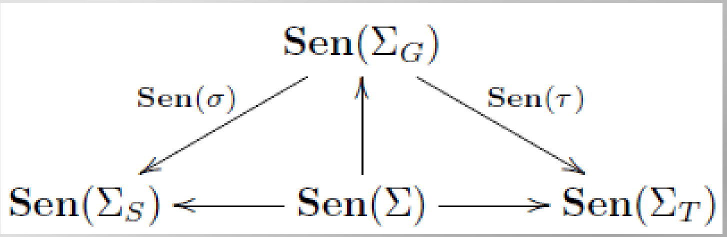
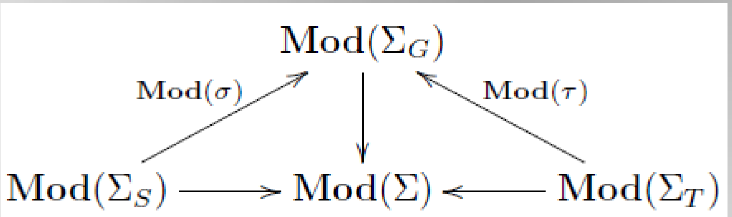
HDTP AND THE THEORY OF INSTITUTIONS

- A general Σ-substitution and the induced diagrams on the sentences level and the model class level.
- The intuition is that Σ_G corresponds to the signature of the generalized theory, Σ_S to the signature of the source theory, and Σ_T to the signature of the target theory.







REMARKS

- As mentioned already, analogy-making contains many soft-computing features, in particular, dynamical changes of representations.
- The shown dynamics of a logical system is surprising:
  - Changing dynamically the language of a theory is hard to describe on a semantic level.
  - Nevertheless, the theory of institutions provides a nice possibility to model the syntax and the semantics of analogy-making.
- **It may be the case that it is now time to work more systematically towards the expansion of symbolic frameworks with soft-computing features.**

CONCLUSIONS

FUTURE WORK

SUMMARY

- The current situation in neural-symbolic integration seems to be unsatisfactory to a certain extent.
- Nevertheless, there are many examples where researchers equip symbolic frameworks with soft-computing features.
- These soft-computing features deal with dynamical change, adaptivity, robustness, learning abilities and the like.
- The convergence of the two worlds along the lines described here may be easier to achieve as the development of a monolithic system realizing neural-symbolic integration.

THANK YOU VERY MUCH FOR YOUR ATTENTION !!!

QUESTIONS?