Symbolic Vs Sub-symbolic AI Methods: Friends or Enemies?

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Reference

Symbolic Vs Sub-symbolic

In-between methods

Knowledge Graph applications

Contact



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Timeline

- AI periods characterised as summers and winters depending on
 - funding
 - research development
 - technological advancements



Figure: The timeline of Artificial Intelligence methods



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Symbolic AI



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Symbolic AI

Advantages:

- explain and reason the results
- human-understandable computation flow
- rule modularity
- inter-operability
- not highly dependent on the input data

Disadvantages:

- datasets with data-quality issues
- prone to noise
- "brittleness"
- high cost of human involvement
- rule bases complex verify and validate



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Sub-symbolic AI



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Sub-symbolic AI

Advantages:

- robust against noisy and missing data
- high computing performance
- well suitable for big datasets and large KGs
- require less knowledge upfront

Disadvantages:

- not interpretable conclusions
- require huge computation power and huge amounts of data
- biased outcomes



The debate

Symbolic	Sub-symbolic
Symbols	Numbers
Logical	Associative
Serial	Parallel
Reasoning	Learning
von Neumann machines	Dynamic Systems
Localised	Distributed
Rigid and static	Flexible and adaptive
Concept composition and	Concept creation, and
expansion	generalization
Model abstraction	Fitting to data
Human intervention	Learning from data
Small data	Big data
Literal/precise input	Noisy/incomplete input

Long and unresolved debate. The future

in-between methods



Figure: Based on [1, 2] and our analysis

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In-between methods



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In-between methods

- Discussions started since 1980s while currently there is a high interest in the combination of the fields
- Algorithms based on or have their core on :
 - Neural Network
 - Tensor and Graph Networks
 - Expert Systems

- Characteristics:
 - Algorithms developed for specific applications
 - No need for a-priori assumptions
 - Perform well with noisy data
 - Well fit for large amounts of heterogeneous data



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In-between methods in literature

No standard:

- categorisation and taxonomy
- naming method

Techniques in literature:

- connectionist expert systems (or neural network based expert systems)
- multi-agent systems
- hybrid representations
- neural-fuzzy
- neural-symbolic (or neurosymbolic)
 - neurules



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Categorisations in Literature

Most categorisations analyse the neurosymbolic range, combination of NN and symbolic methods. We selectively present the categorisations from the works of [3, 4, 5, 6, 7]

Connectionism	NEUROSYMBOLIC INTEGRATION				Symbolicism
	Unified approaches		Hybrid approaches		1
	Neuronal	Connectionist	Functional	Translational	
	Symbol Proc.	Symbol Proc.	hybrids	hybrids	
Segregation	Neuronal eliminativism	Connectionist eliminativism Limitivism Revisionism	Hybri or coh	dization abitation	Segregation Implementation – alism

Figure: The range from symbolic to sub-symbolic as proposed by Hilario [6]



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Schema Representation

Traditionally symbolic task, mostly rely on rule mining

- First-order logic
- Ontologies
- Formal knowledge representation languages
 - RDF(S)
 - OWL
 - XML
 - rules



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Schema Matching

- Each model uses a usually symbolic input schema
- The majority focuses on class alignment, however, there also are works focus on relation alignment



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Schema Matching

Different models to process (matchers):

- linguistic or language based (sub-symbolic)
 - combination with NLP
- constrain-based (symbolic)
 - constrains in data features (data types and ranges)
- structured-based (symbolic)
 - focused on database/graph structure



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Knowledge Graph Completion (KGC)

Tries to address the:

- missing edges and nodes
- duplicated nodes

Mostly KGEs techniques are used



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Entity resolution

Fundamental problem related to data integration

- In 1960s statistical sub-symbolic models
- In 1990s mostly in-between methods
- The techniques usually rely on attribute similarity between the entities
- The algorithms are inspired by IR and relational duplicate elimination



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Link prediction techniques





Leo Tolstov

Figure: Head, tail, and relation prediction

Most of SOTA is focused on in-between methods (KGEs, Trans*, neural based KGE with logical rules, and hierarchy-aware KGEs) Survey of link prediction in complex networks [8]:

- Only a few are sub-symbolic (ANN, probabilistic and Monte Carlo)
- Most are in-between range



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Link prediction tasks

- Triple classification
 - KGEs systems
 - usually in-between methods
 - some use neural tensor networks and time-aware, latent factor and semantic matching models.



- Entity classification
 - related to schema and ontology KG
 - symbolic based [9, 10]





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References

Thank you & contact

For questions or comments please contact on ilkou@l3s.de Thank you for your attention



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