

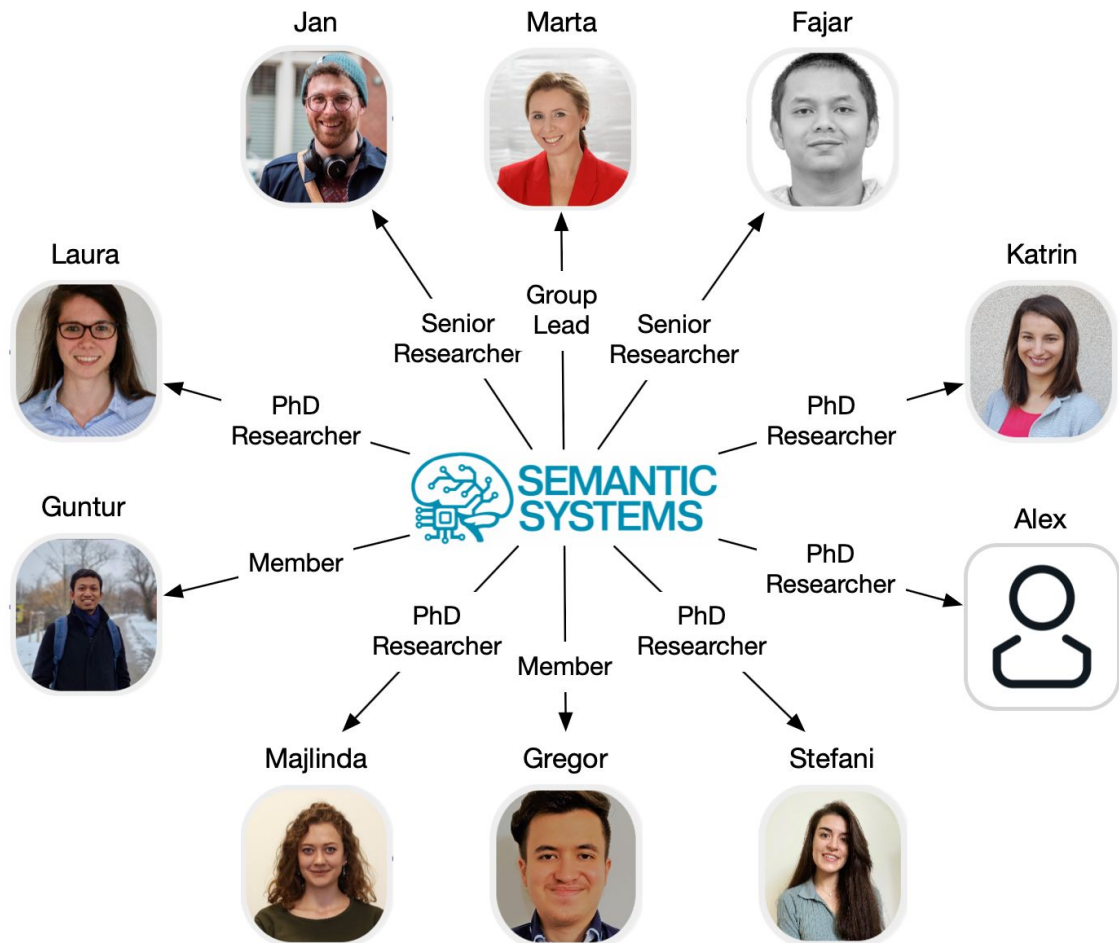
ENGAGE.EU - Data Science in Action

Combining Semantic Web and Machine Learning Techniques for Data Analysis Systems



Anna Breit (SWC), Laura Waltersdorfer (TU), Fajar J. Ekaputra (WU), **Marta Sabou (WU)**, Andreas Ekelhart (Uni Wien), Andreea Iana (UMannheim), Heiko Paulheim (UMannheim), Jan Portisch (UMannheim), Artem Revenko (SWC), Annette ten Teije (VUA'dam), Frank van Harmelen (VUA'dam)

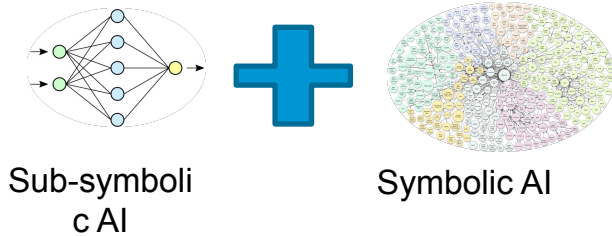
This talk would not have been possible without the SemSys TEAM



Summary of my talk

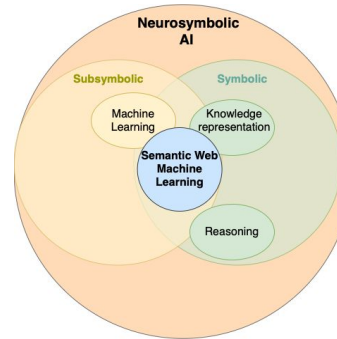
Creating intelligent applications that valorise complex domain data such as in the **scientific, technical, and legal domain** often calls for solutions that **combine sub-symbolic and symbolic AI** methods.

Part I (Preliminaries):



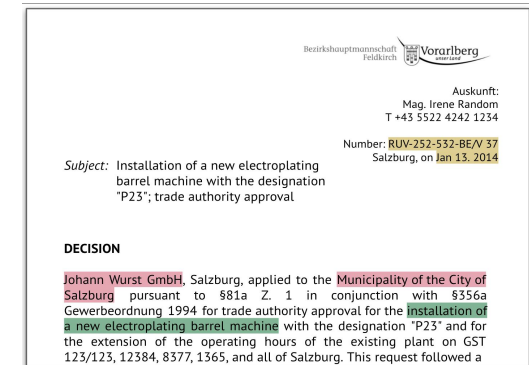
Neuro-Symbolic AI
Techniques

Part II (Macro):



Systematic Study of SW
and ML systems (SWeML)
(a sub-family of
neuro-symbolic systems)

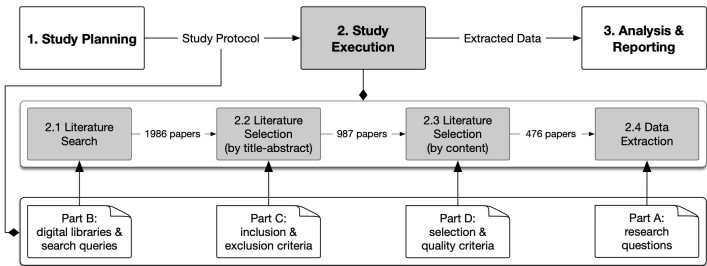
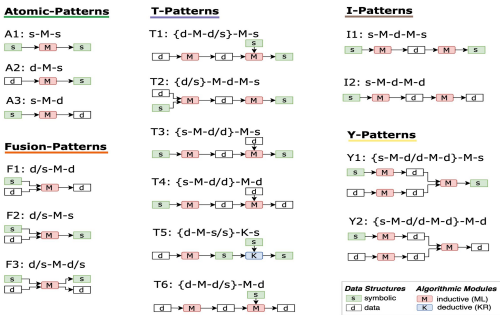
Part III (Micro):



SWeML approach for
information extraction in
the legal domain

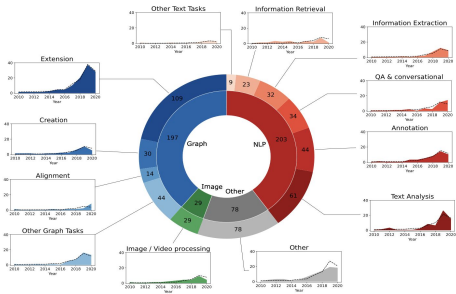
What you will learn in this talk

New techniques combine **symbolic** (Semantic Web) **and sub-symbolic** (Machine Learning) **AI** methods in various ways to solve complex (data science) tasks.



Systematic Literature Review is a valuable research method.

Beyond “Data Science” - applications that valorise complex domain data, with an example from the legal domain.



Preliminaries: Semantic Web (Symbolic AI)



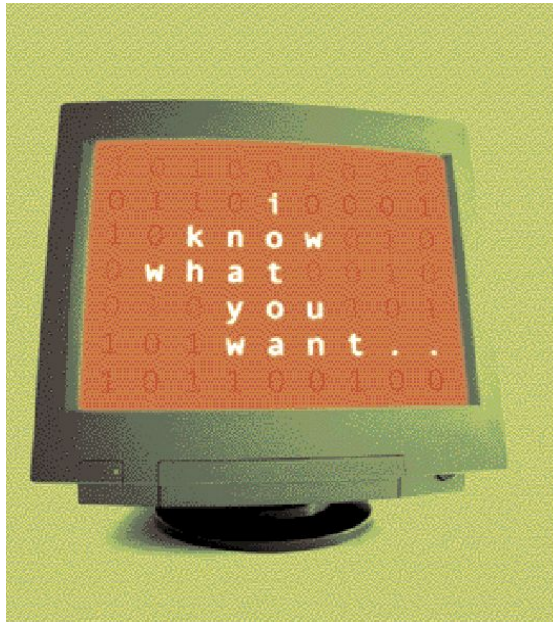
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STAND: JUNI 2018



Symbolic AI – The Semantic Web

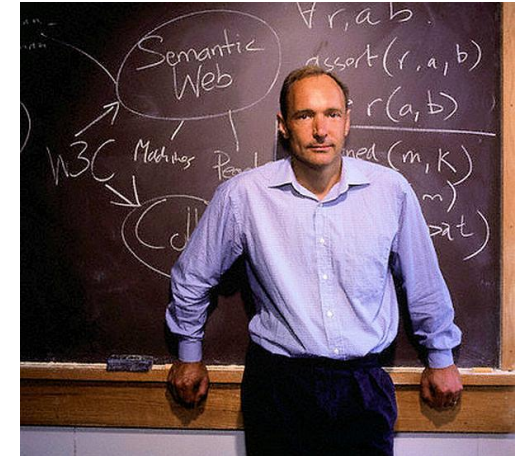
Scientific American, May 2001:



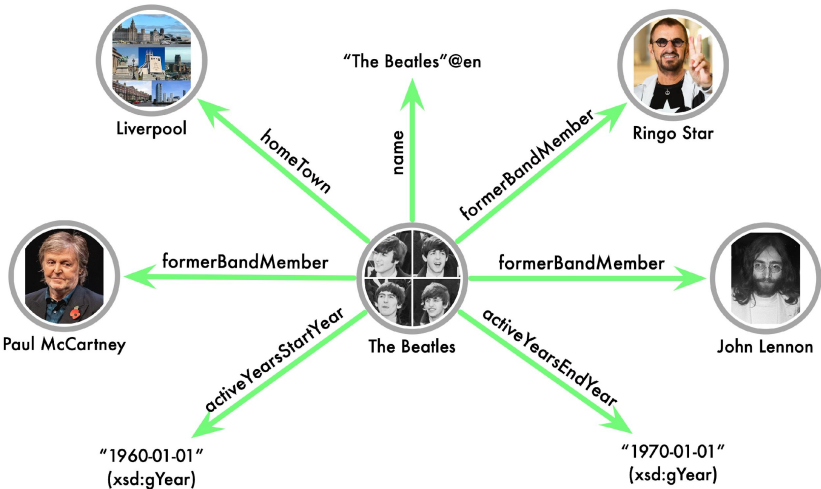
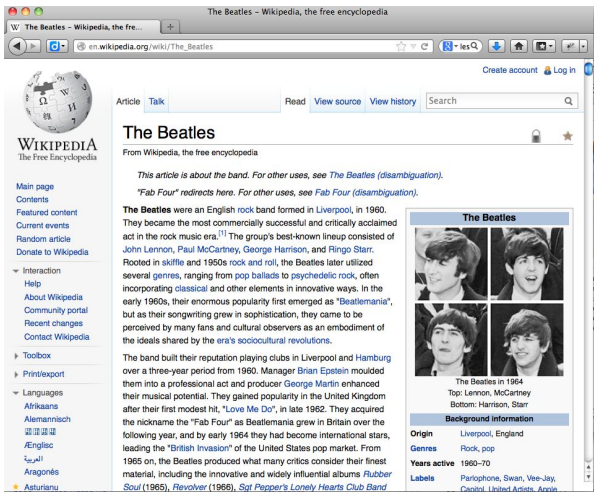
THE SEMANTIC WEB

A new form of Web content
that is meaningful to computers
will unleash a revolution of new abilities

by
TIM BERNERS-LEE,
JAMES HENDLER and
ORA LASSILA



Symbolic AI – DBpedia



Symbolic AI – Knowledge Graphs on the Web



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WU Wien

<https://www.wu.ac.at> · [Translate this page](#)

WU (Wirtschaftsuniversität Wien)

Online-Infosession Bachelor. Interesse an einem WU Studium? Wir informieren und beraten online. 05 ...

Results from wu.ac.at

Vienna University of ...

WU is not only the largest business and economics university in ...

Master's Programs

Quantitative Finance - Supply Chain Management - Economics

Application and admissions

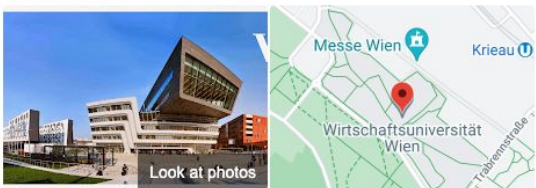
Vienna University Preparation Programme (VWU) · MBA/LLM ...

Bachelor

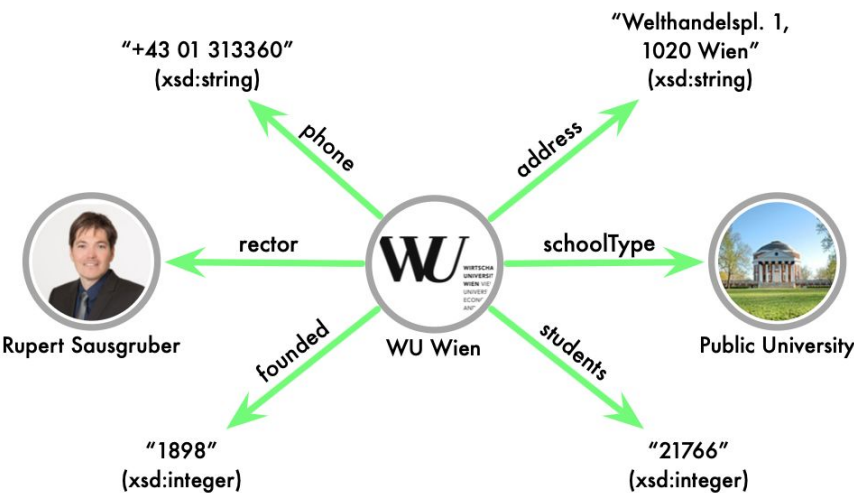
Bewerbung und Zulassung - Wirtschafts - Bachelorguide - ...

Studium

Die WU gehört zu den größten und modernsten ...



Vienna University of Economics and Business



Preliminaries: Machine Learning (sub-symbolic AI)



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Sub-Symbolic AI – Neural Networks

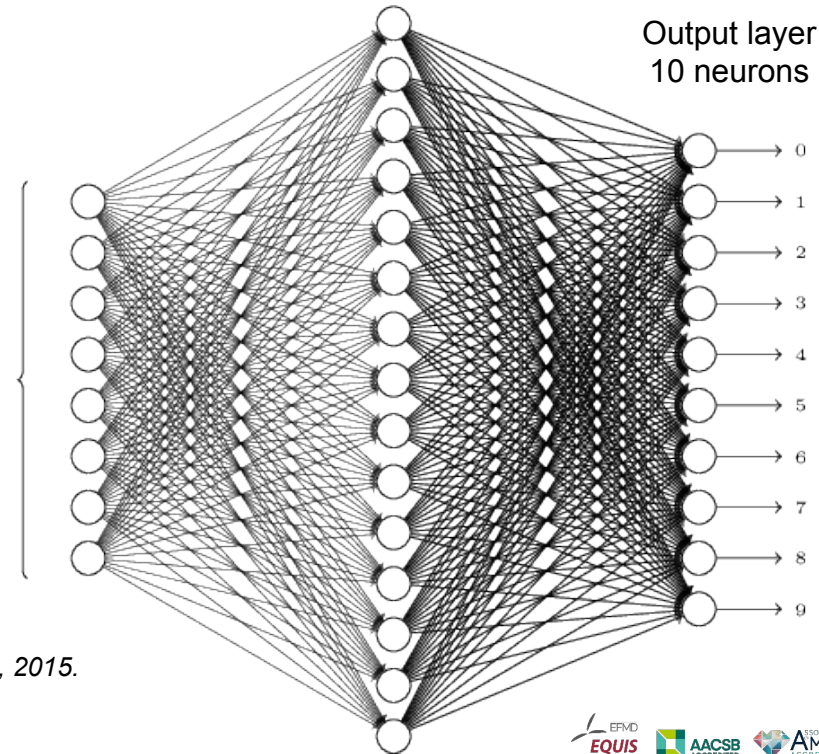
AI systems that **learn patterns** from large amounts of data



Input layer
784 neurons

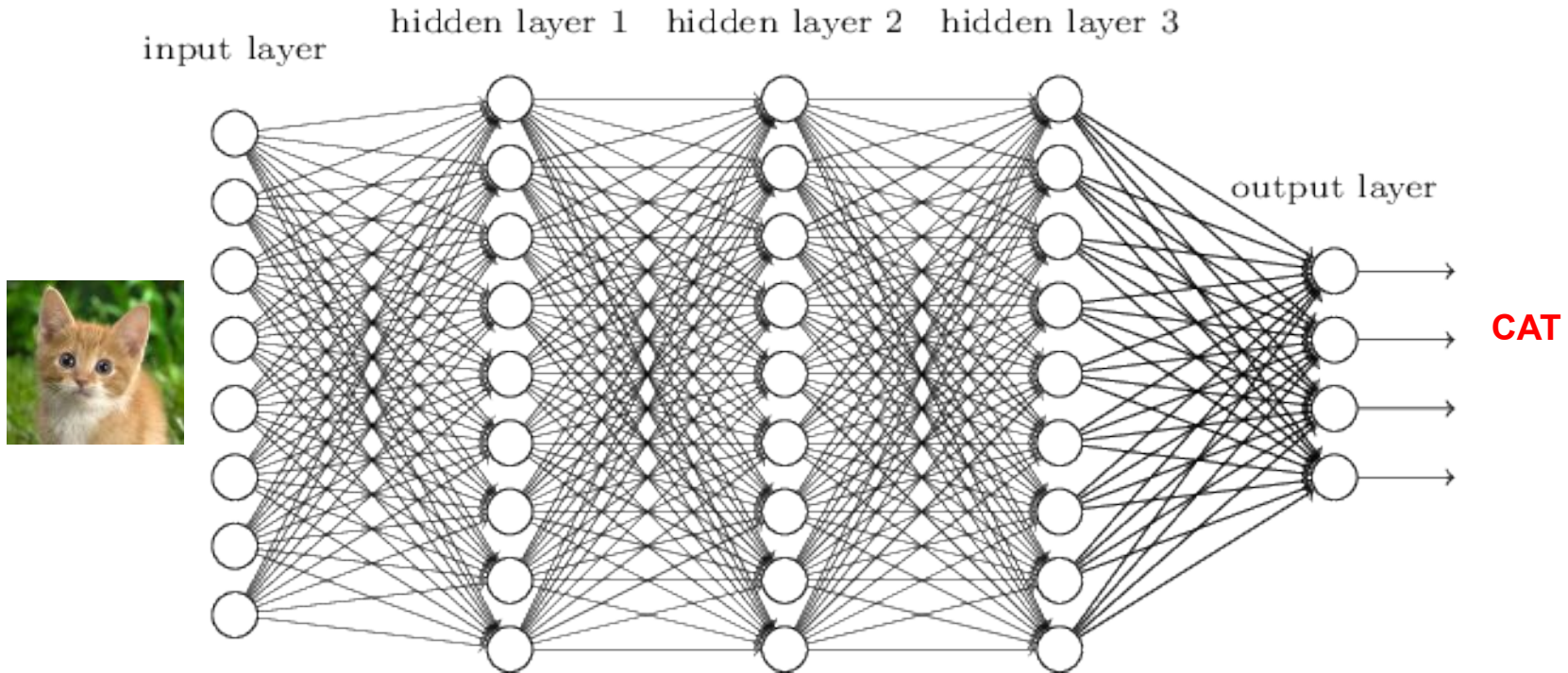
Hidden layer
15 neurons

Output layer
10 neurons



Source: M. Nielsen: "Neural Networks and Deep Learning", Determination Press, 2015.
<http://neuralnetworksanddeeplearning.com/index.html>

Sub-Symbolic AI – Deep Learning Networks



Source: M. Nielsen: *Neural Networks and Deep Learning*
<http://neuralnetworksanddeeplearning.com/index.html>

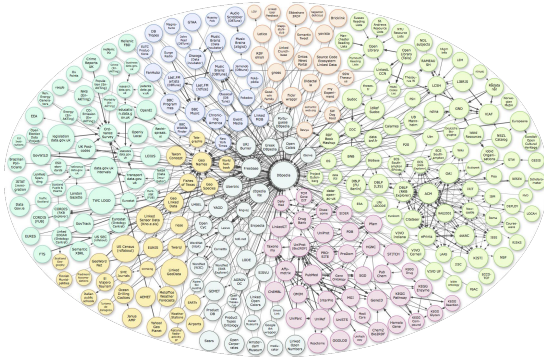
Sub-Symbolic AI – Large Language Models (LLMs)

- LLMs **are** Deep Learning systems
- **LLMs** largely represent a class of Deep Learning architectures called transformer networks*
 - *Transformer model* is a neural network that learns context and meaning by tracking relationships in sequential data

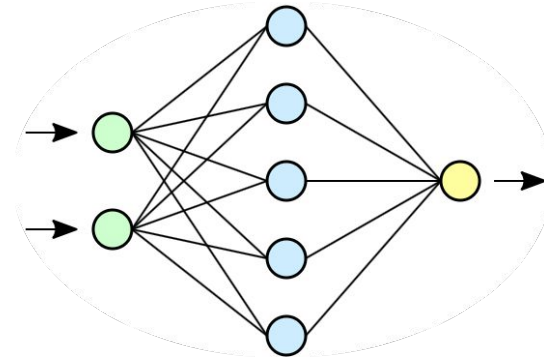


The Rise of Neurosymbolic AI

Symbolic AI



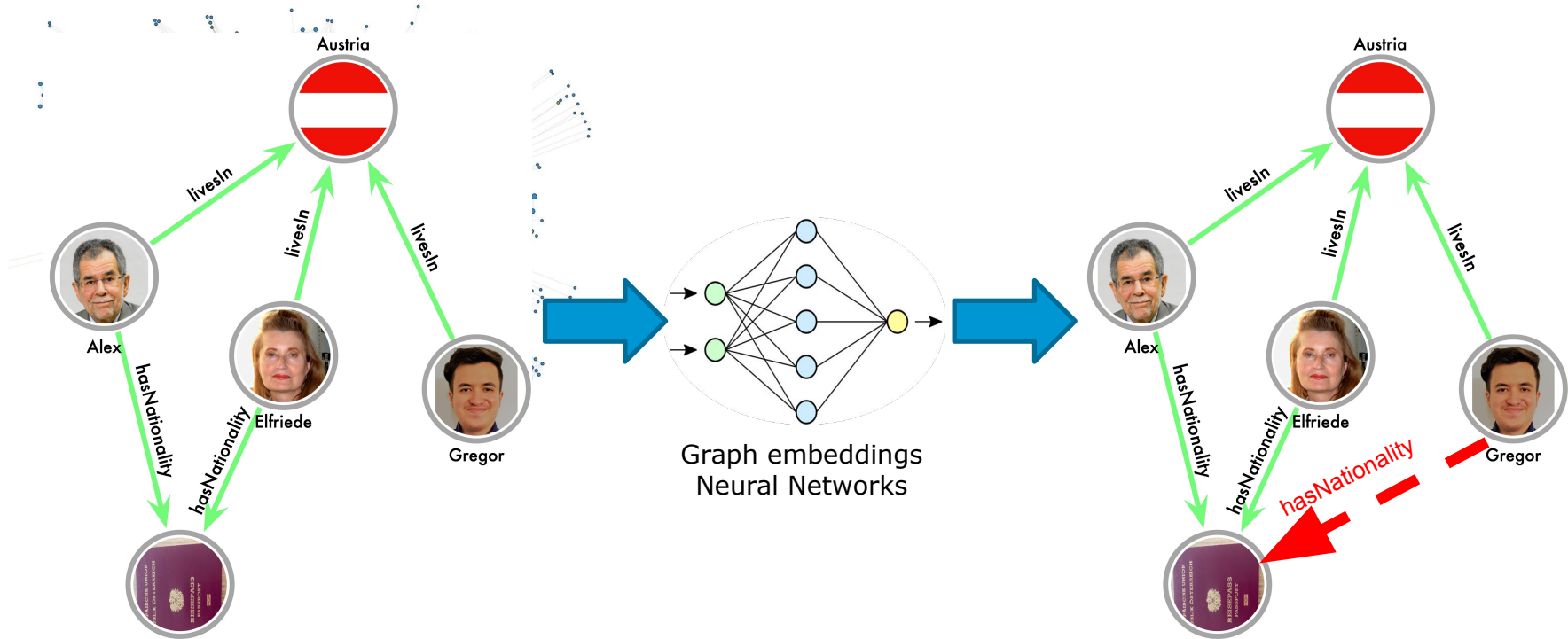
Sub-symbolic AI



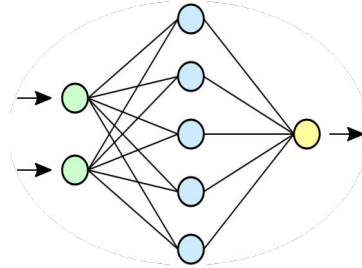
- + symbolic knowledge
- + explainability
- vulnerable to noisy data
- Knowledge acquisition bottleneck

- + knowledge from sparse data
- + broad applicability
- Intransparency
- Often lots of training data required

Neuro-Symbolic AI – KG Completion with Neural Network



Neuro-Symbolic AI – Improving Neural Networks with KG



Classification:

- Type: Still-life
- School: Dutch
- Author: van Gogh

Accuracy
improvement

+ 7.3%

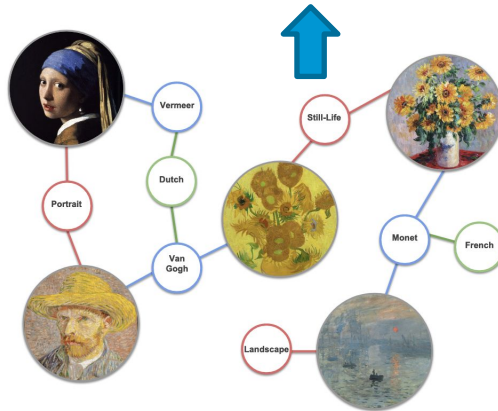


Image Retrieval:

- “Still-life with flowers from Dutch school”

+ 37.24%

Garcia, N., Renoust, B., & Nakashima, Y. Context-aware embeddings for automatic art analysis. *Int. Conf. on Multimedia Retrieval*, 2019.

QUESTIONS?

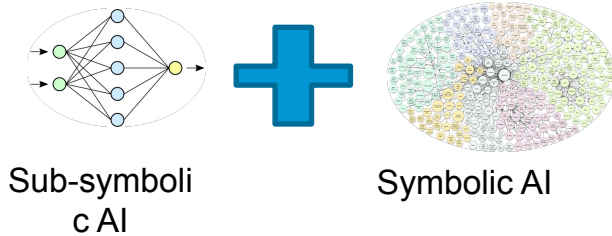
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AND BUSINESS



Summary of my talk

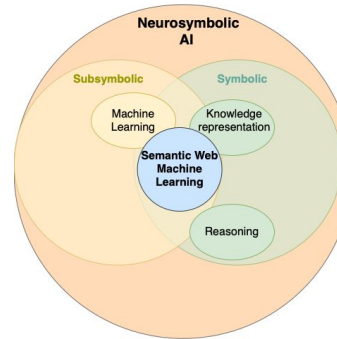
Creating intelligent applications that valorise complex domain data such as in the **scientific, technical, and legal domain** often calls for solutions that **combine sub-symbolic and symbolic AI** methods.

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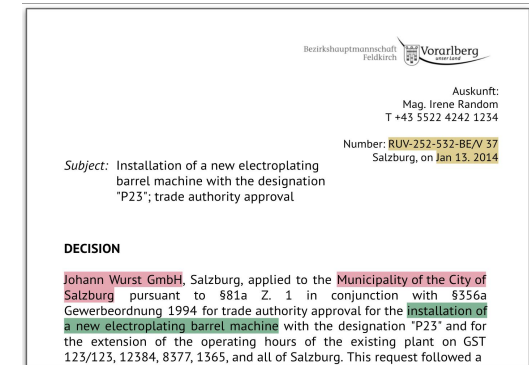
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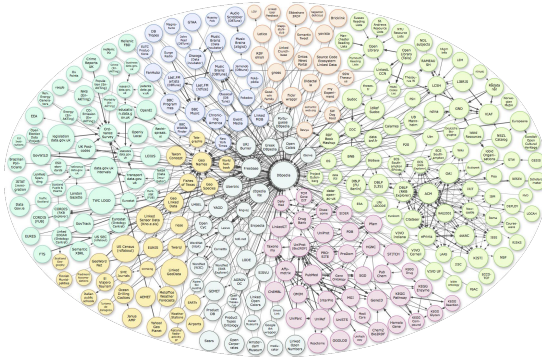
Combining Machine Learning and Semantic Web: A Systematic Mapping Study (ACM Computing Surveys'2023)



Anna Breit (SWC), Laura Waltersdorfer (TU), **Fajar J. Ekaputra (WU)**, **Marta Sabou (WU)**, Andreas Ekelhart (Uni Wien), Andreea Iana (UMannheim), Heiko Paulheim (UMannheim), Jan Portisch (UMannheim), Artem Revenko (SWC), Annette ten Teije (VUA'dam), Frank van Harmelen (VUA'dam)

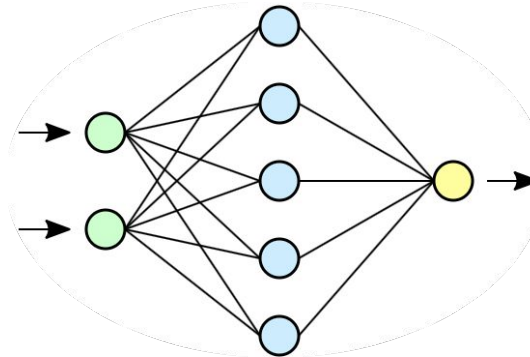
Context: The Rise of Neurosymbolic AI

Symbolic AI



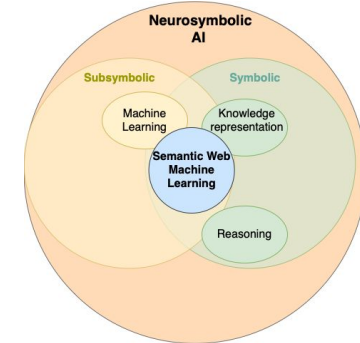
- + symbolic knowledge
- + explainability
- vulnerable to noisy data
- Knowledge acquisition bottleneck

Subsymbolic AI



- + knowledge from sparse data
- + broad applicability
- Intransparency
- Often lots of training data required

Semantic Web Machine Learning Systems

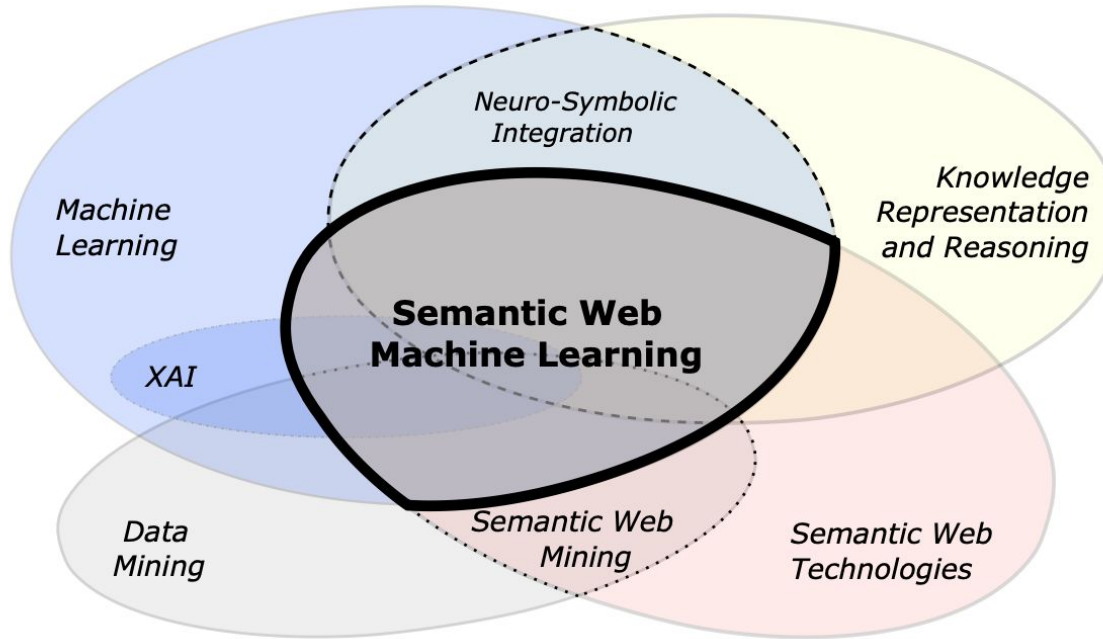


Our scope, subset/related area
to neurosymbolic AI

→ Dynamic and impactful research area, yet **systematic knowledge missing** in terms of characteristics and system architectures

Semantic Web Machine Learning (Systems)

SWeML(S)



Semantic Web Machine Learning (**SWeML**) Systems combine Semantic Web Technologies and an inductive model.

They describe a system which makes use of a *Semantic Web knowledge structure* as well as a *machine learning sub-system* in order to solve a specific task.

Motivation:

Keeping up with trends in the field unfeasible

RQ: *What is the state of the art and trends related to systems that combine SW and ML components?*

Related Work:

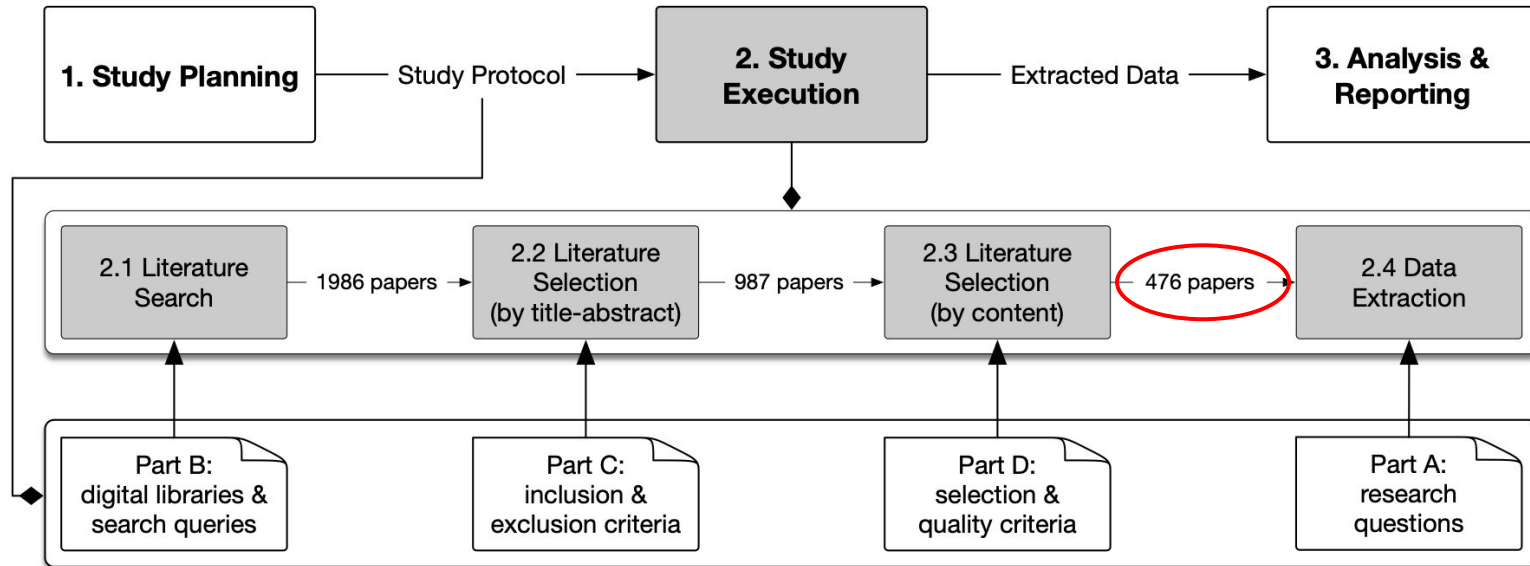
focused on broader or narrower areas, rarely systematic

Ref.	Authors	Venue	Type	Year	Paper selection
[5]	Besold et al.	Neuro-Symbolic AI: The State of the Art	NeSy	2021	custom
[35]	von Rueden et al.	IEEE Transactions on Knowledge and Data Engineering	NeSy	2021	custom
[33, 34]	van Bekkum et al., van Harmelen et ten Teije	Applied Intelligence, J. of Web Engineering	NeSy	2019, 2021	custom
[16]	Hitzler et al.	Semantic Web	NeSy	2020	custom (vision paper)
[28]	Sarker et al.	arXiv	NeSy	2021	survey papers collected from NeurIPS, ICML, AAAI, ICLR, IJCAI
[29]	Seeliger et al.	SEMEX ISWC	XAI SWeMLS	2019	systematic literature review: (Q1) "deep learning" OR "data mining"; (Q2) "explanation" OR "interpret" OR "transparen"; (Q3) "Semantic Web" OR "ontolog" OR "background knowledge" OR "knowledge graph"
[8]	D'Amato	Semantic Web	SW SWeMLS	2020	custom

Contribution:

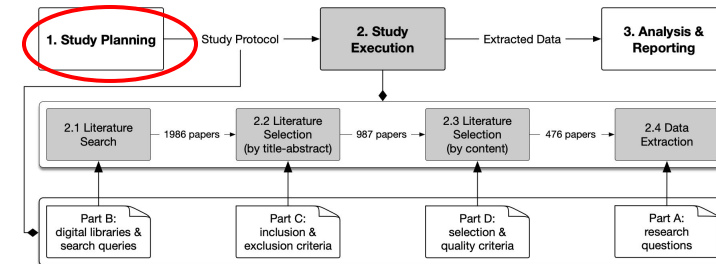
Trends landscape through systematic mapping study

Methodology - Systematic Mapping Study [1]

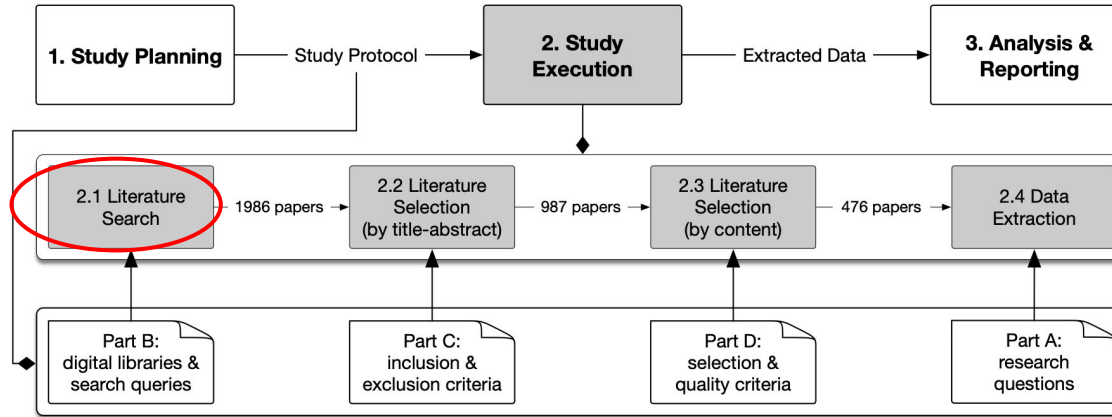


[1] Kitchenham B, Charters S, et al. Guidelines for performing systematic literature reviews in software engineering version 2.3. Engineering. 2007;45(4ve):1051

- **RQ1 Bibliographic characteristics**
 - Temporal and geographic distribution, keywords
- **RQ2 System Architecture.**
 - What processing patterns are used in terms of inputs/outputs and the order of processing units?
- **RQ3 Application Areas.**
 - tasks solved (e.g., text analysis), application domains (e.g., life sciences)
- **RQ4 Characteristics of the ML Module.**
 - typer of ML models (e.g., SVM), components (e.g., attention), training
- **RQ5 Characteristics of the SW Module.**
 - types, size, formalisation of SW structure (e.g., taxonomy); use of KR
- **RQ6 Maturity, Transparency and Auditability.**
 - system maturity and transparency (e.g., sharing source code, details of infrastructure, and evaluation setup); provenance-capturing



Methodology - Systematic Mapping Study



Sub-Query	Used Search Keywords
<i>Q1 (SW module)</i>	knowledge graph, linked data, semantic web, ontolog*, RDF, OWL, SPARQL, SHACL
<i>Q2 (ML module)</i>	deep learning, neural network, embedding, representation learning, feature learning, language model, language representation model, rule mining, rule learning, rule induction, genetic programming, genetic algorithm, kernel method
<i>Q3 (System)</i>	Natural Language Processing, Computer Vision, Information Retrieval, Data Mining, Information Integration, Knowledge Management, Pattern Recognition, Speech Recognition

Query Date: October 2020
Research Team: 10 participants

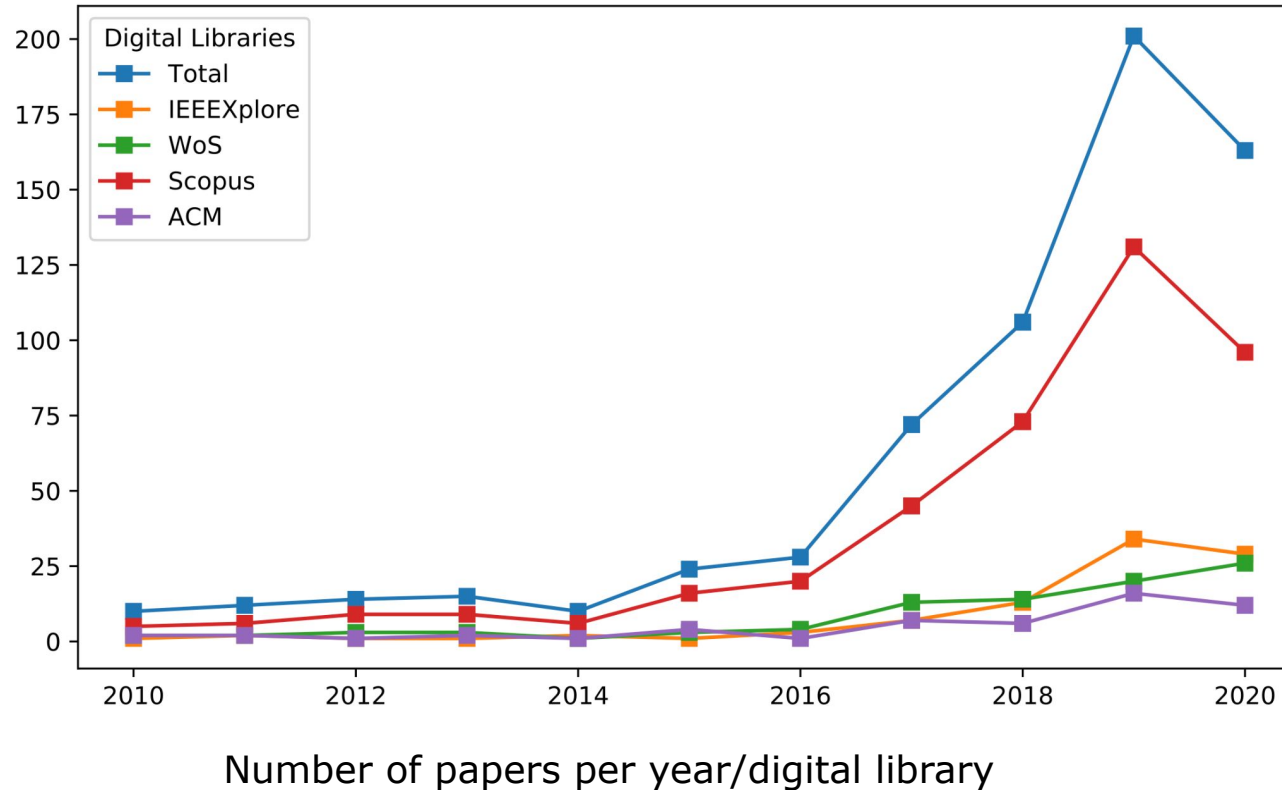
QUESTIONS?



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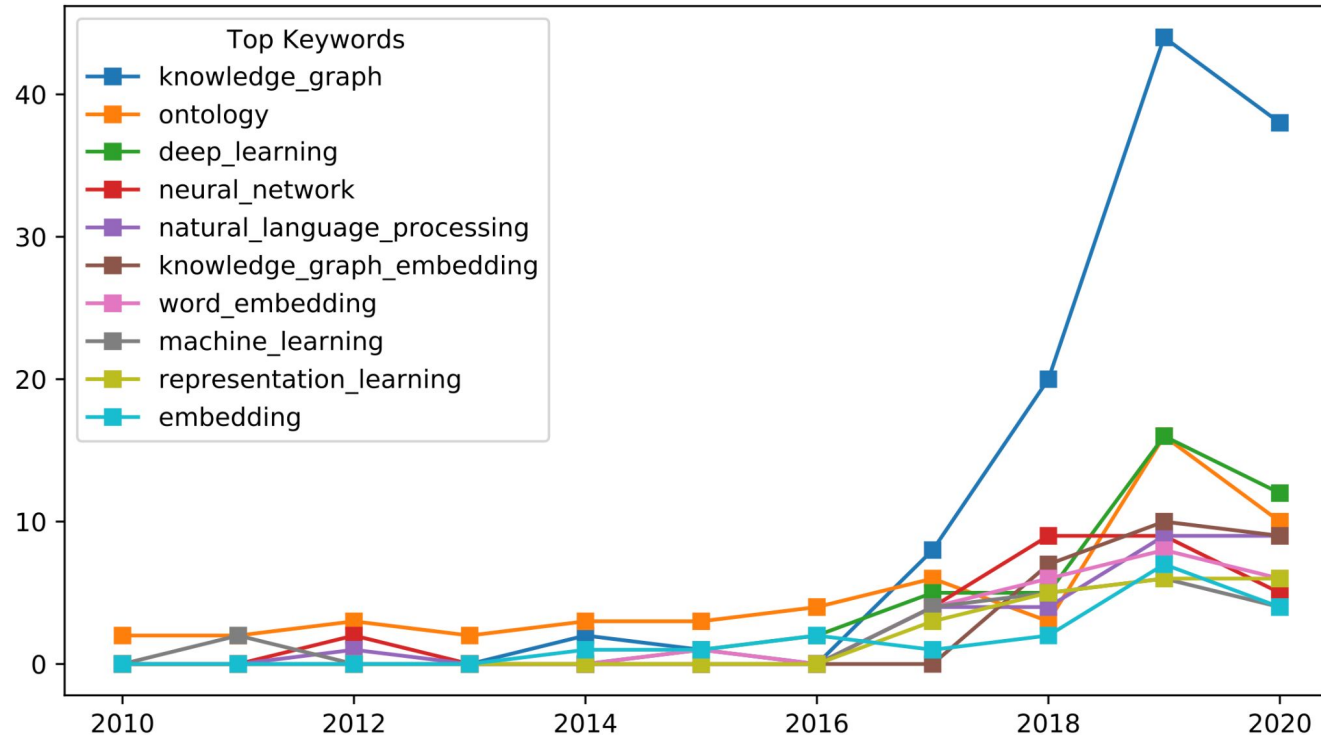


RQ1 - Bibliographic characteristics



Fast increase in
interest after 2016

RQ1 - Bibliographic characteristics



Knowledge Graphs and Deep Learning as a catalyst for SWeML development.

Main keywords over time
(author given keywords or TF-IDF from abstract/title)

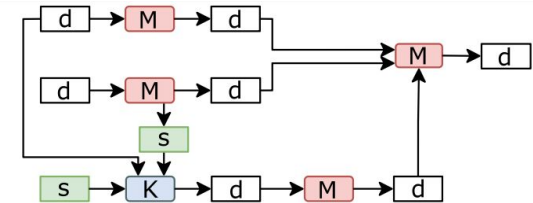
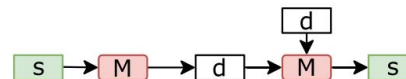
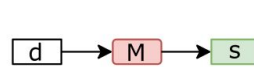
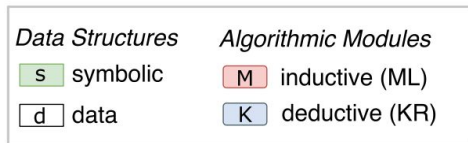
RQ2 - System Architectures

Boxology notation

We relied on the boxology of system design patterns by van Harmelen [1] which includes:

- data structures:
 - symbolic, data
- algorithmic modules:
 - ML models, reasoning engines (KR)
- system architecture in terms of data flow and sequence of algorithmic modules

Main benefit: allows organising (mapping) a large space of complex systems.



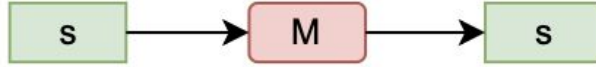
[1] F. van Harmelen, A. ten Teije, A boxology of design patterns for hybrid learning and reasoning systems, J. of Web Engineering 18 (2019) 97–124. arXiv:1905.12389.

RQ2 - System Architectures

Example systems for patterns

A1: s-M-s

**Abstract
Pattern**

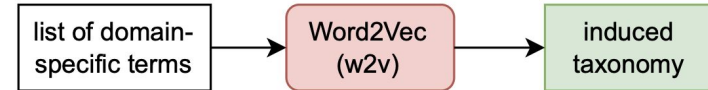


**System
(Pattern
Instance)**



Agapito G, Cannataro M, Guzzi PH, et al. Using GO-WAR for mining cross-ontology weighted association rules. Computer Methods and Programs in Biomedicine. 2015;120(2):113–122.

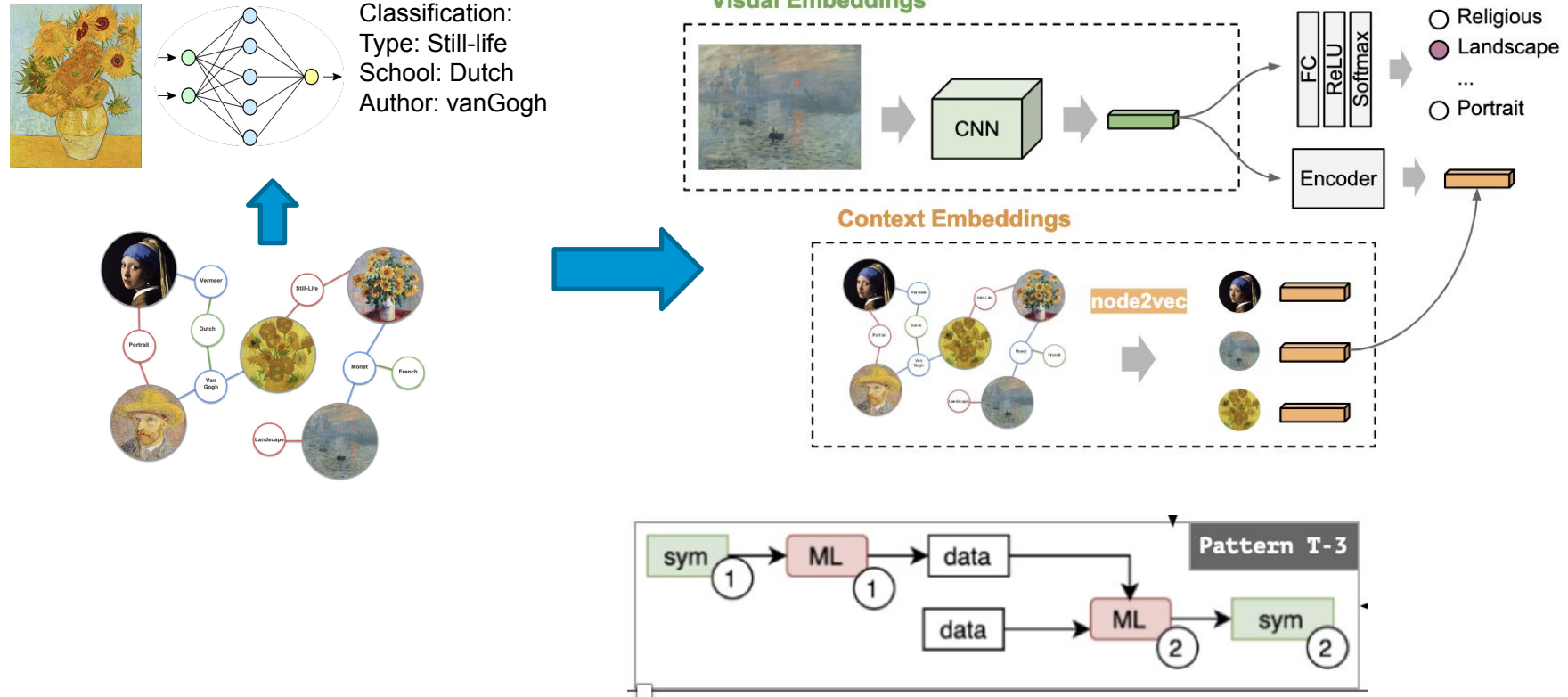
A2: d-M-s



Zafar B, Cochez M, Qamar U. Using Distributional Semantics for Automatic Taxonomy Induction. In: Int. Conf. on Frontiers of Information Technology (FIT); 2016.

RQ2 - System Architectures

Example systems for patterns



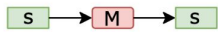
Garcia, N., Renoust, B., & Nakashima, Y. Context-aware embeddings for automatic art analysis. *Int. Conf. on Multimedia Retrieval*, 2019.

RQ2 - System Architectures

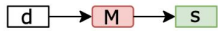
(some) Patterns and their typology

Atomic-Patterns

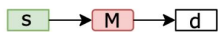
A1: s-M-s



A2: d-M-s

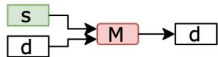


A3: s-M-d

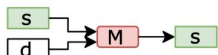


Fusion-Patterns

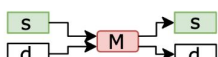
F1: d/s-M-d



F2: d/s-M-s

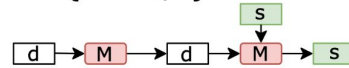


F3: d/s-M-d/s

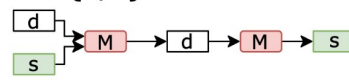


T-Patterns

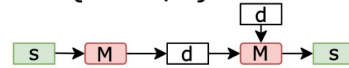
T1: {d-M-d/s}-M-s



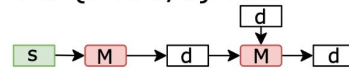
T2: {d/s}-M-d-M-s



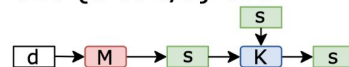
T3: {s-M-d/d}-M-s



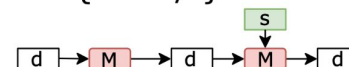
T4: {s-M-d/d}-M-d



T5: {d-M-s/s}-K-s



T6: {d-M-d/s}-M-d

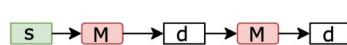


I-Patterns

I1: s-M-d-M-s

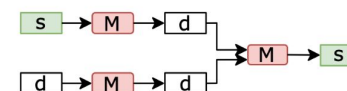


I2: s-M-d-M-d

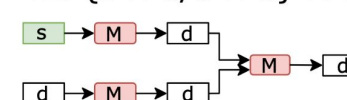


Y-Patterns

Y1: {s-M-d/d-M-d}-M-s



Y2: {s-M-d/d-M-d}-M-d



Data Structures

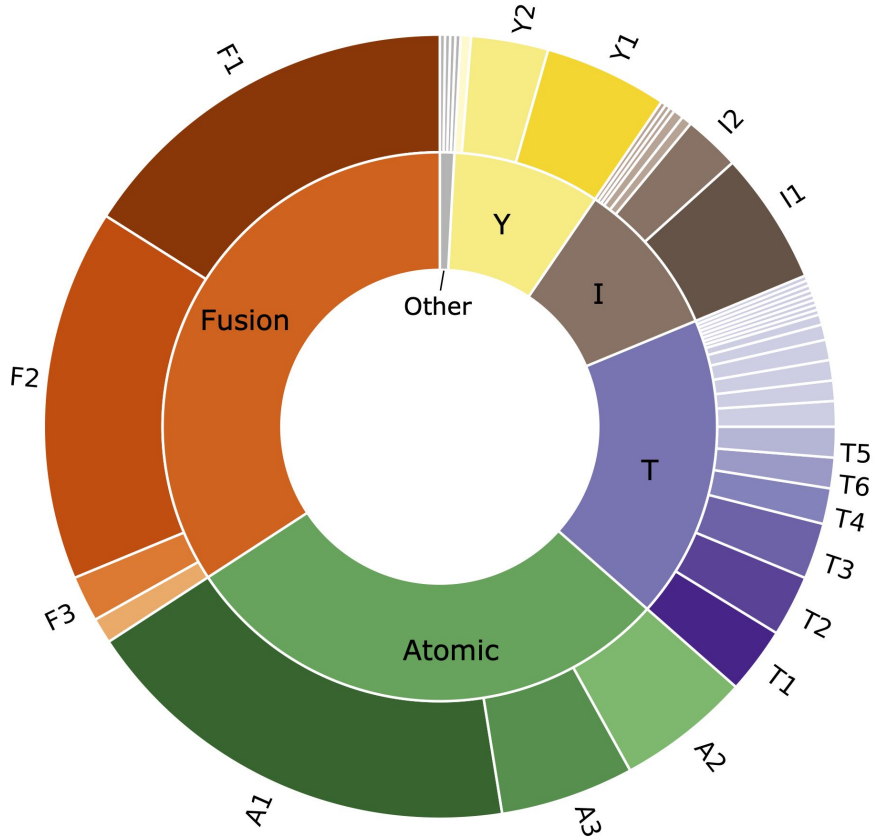
s symbolic
d data

Algorithmic Modules

M inductive (ML)
K deductive (KR)

41 patterns were discovered in the data

RQ2 - System Architectures Patterns and their frequency

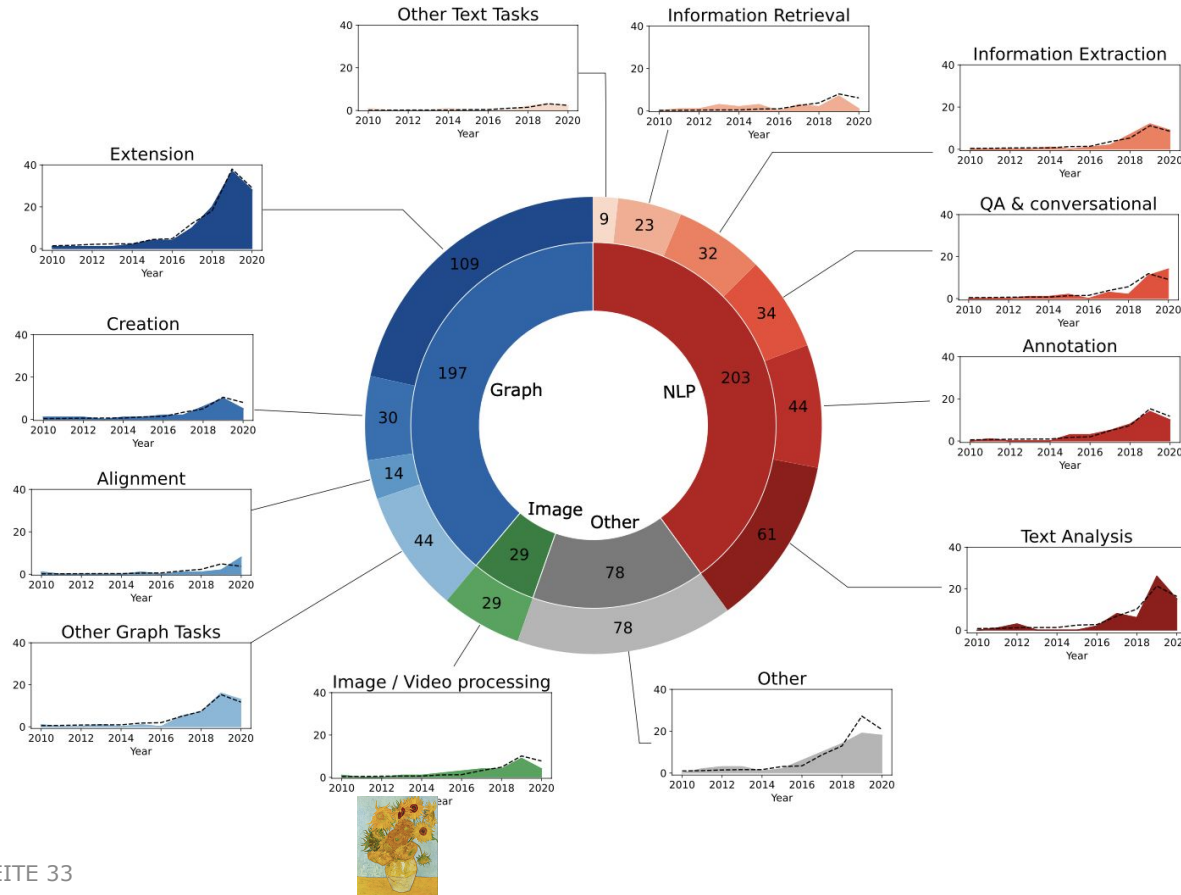


63% of systems use simple patterns

- A1 (s-M-s) - link prediction on KG; rule learning

RQ3: Application Areas

Distribution of papers per targeted tasks



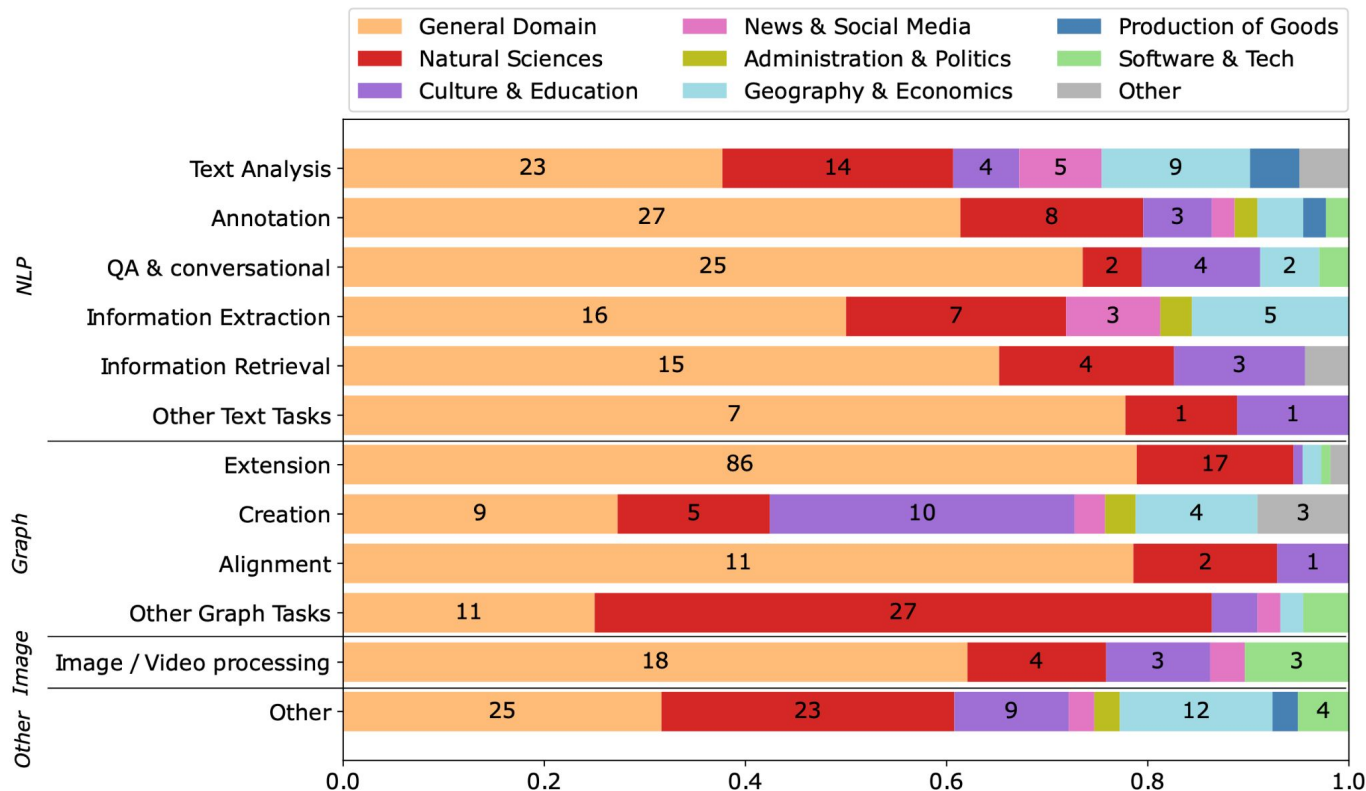
Graph and NLP tasks most frequent

Trending tasks:

- graph alignment
- text analysis
- QA and conversational agents

RQ3: Application Areas

Normalised distribution of domain per tasks



SWeMLs versatile across domains and tasks

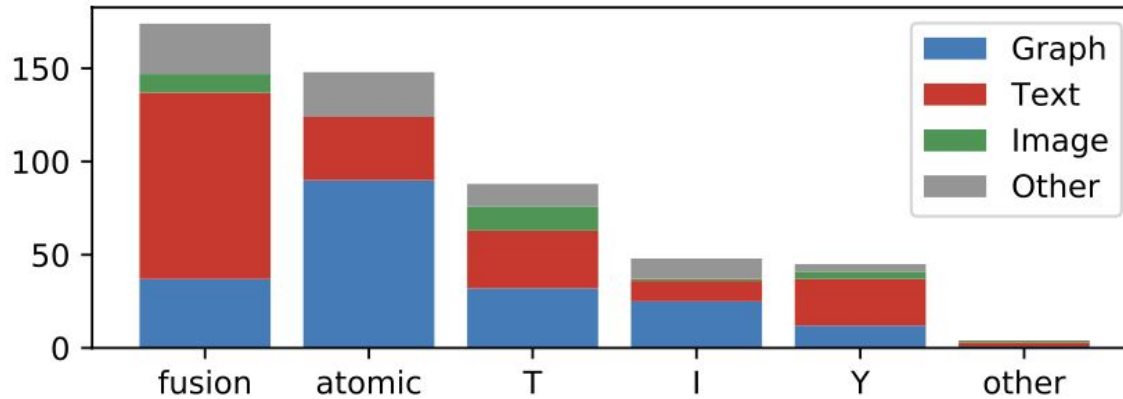
NLP tasks mostly in General Domain

Graph tasks (creation and other) have more focus on specialised domains

Most frequent application domains: "Natural Sciences" & "Culture and Education"

RQ3: Application Areas

Pattern types used for tasks

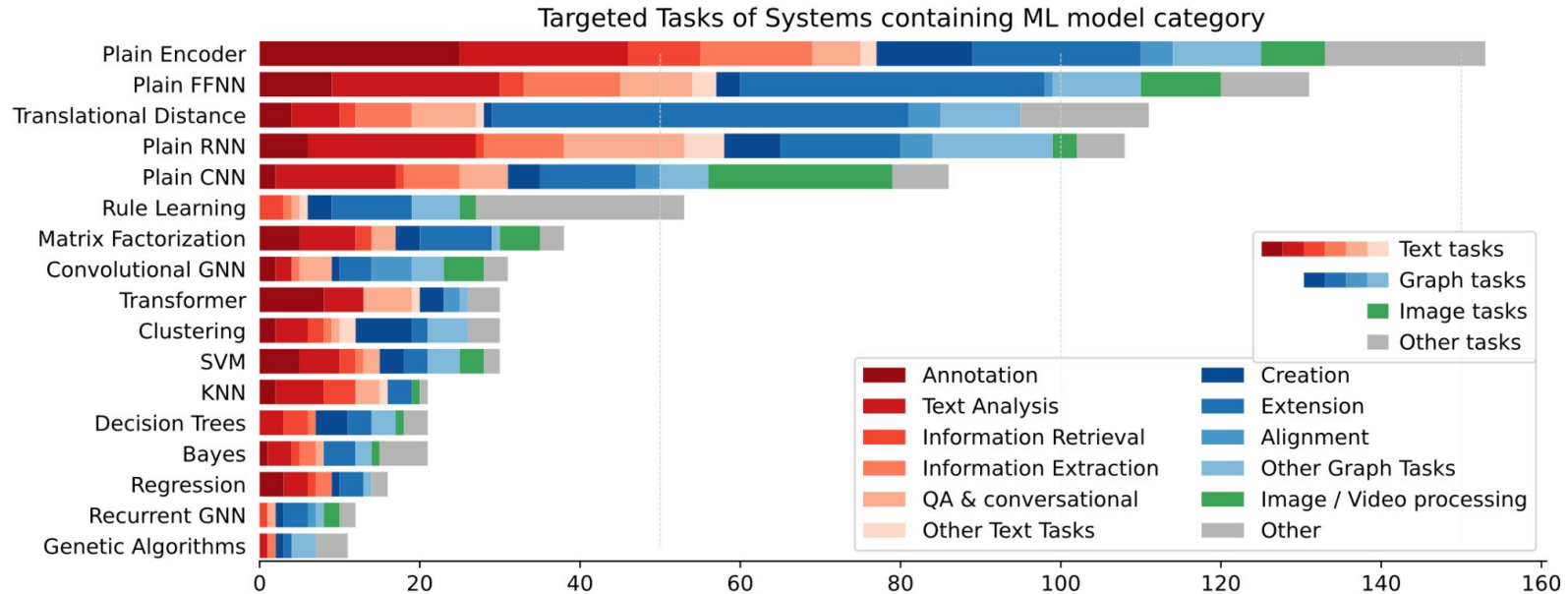


Some pattern types tend to be used more frequently for certain task categories (fusion for Text, atomic for graph)

=> Can we derive best practices of recommending patterns for AI engineers depending on the task/domain they address?

RQ4: Characteristics of the ML Module

Relations between ML categories and tasks

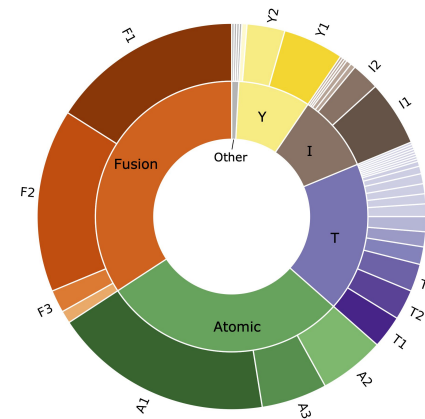
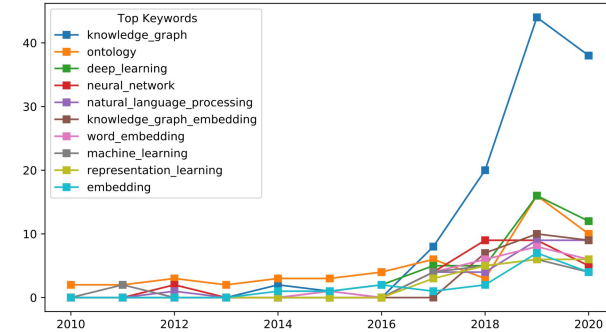


- NLP tasks freq.solved with Plain Encoders, Transformer models and kNN
- Graph tasks often solved with Graph DL model categories (Translational Distance models, Convolutional GNNs) and Rule Learning.
- Image tasks are addressed particularly with CNN algorithms.

=> Can we derive best practices of recommending ML models for AI engineers depending on task?

Key conclusions

- Multi-disciplinary, high-impact, rapidly developing field.
- Deep Learning is a key catalyst for SWeML systems.
- Large Knowledge Graphs are on the rise.
- High diversity of system patterns.
- Low system maturity and auditability.
- High diversity in reporting SWeMLS requires a more uniform classification scheme.



QUESTIONS?



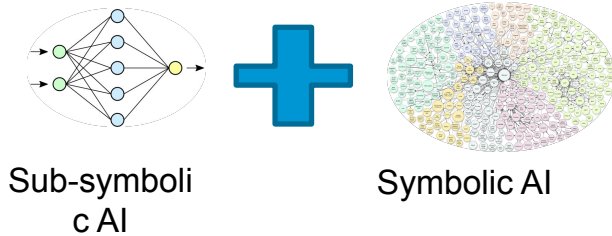
**WIRTSCHAFTS
UNIVERSITÄT
WIEN VIENNA
UNIVERSITY OF
ECONOMICS
AND BUSINESS**



Summary of my talk

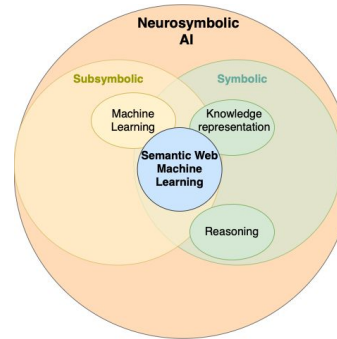
Creating intelligent applications that valorise complex domain data such as in the **scientific, technical, and legal domain** often calls for solutions that **combine sub-symbolic and symbolic AI** methods.

Part I (Preliminaries):



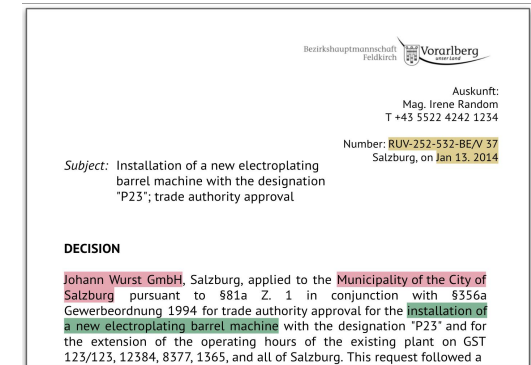
Neuro-Symbolic AI
Techniques

Part II (Macro):



Systematic Study of SW
and ML systems (SWeML)
(a sub-family of
neuro-symbolic systems)

Part III (Micro):



SWeML approach for
information extraction in
the legal domain

Combining SW and ML for Auditable Legal Key Element Extraction (ESWC'23)



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ECONOMICS
AND BUSINESS



Anna Breit (SWC), Laura Waltersdorfer (TU), **Fajar J. Ekaputra (WU)**,
Sotiris Karampatakis (SWC), Tomasz Miksa (TU), Gregor Käfer (TU)



Combining SW and ML for Auditable Legal Key Element Extraction

Key Element Extraction from Legal Permits

Bezirkshauptmannschaft
Feldkirch


Vorarlberg
unser Land

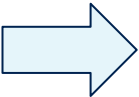
Auskunft:
Mag. Irene Random
T +43 5522 4242 1234

Number: RUV-252-532-BE/V 37
Salzburg, on Jan 13. 2014

Subject: Installation of a new electroplating barrel machine with the designation "P23"; trade authority approval

DECISION

Johann Wurst GmbH, Salzburg, applied to the Municipality of the City of Salzburg pursuant to §81a Z. 1 in conjunction with §356a Gewerbeordnung 1994 for trade authority approval for the installation of a new electroplating barrel machine with the designation "P23" and for the extension of the operating hours of the existing plant on GST 123/123, 12384, 8377, 1365, and all of Salzburg. This request followed a previous request under §27 Article 17 of



Reference Nr	RUV-252-532-BE/V 37
Issuing Date	13.01.2014
Operator	Johann Wurst GmbH, GLN 123456
Issuing Authority	Magistrate of the City of Salzburg
Object Type	Operating Site
Processing Type	Extension Notice
Procedure Type	Simplified Procedure

Bezirkshauptmannschaft
Feldkirch


Vorarlberg
unser Land

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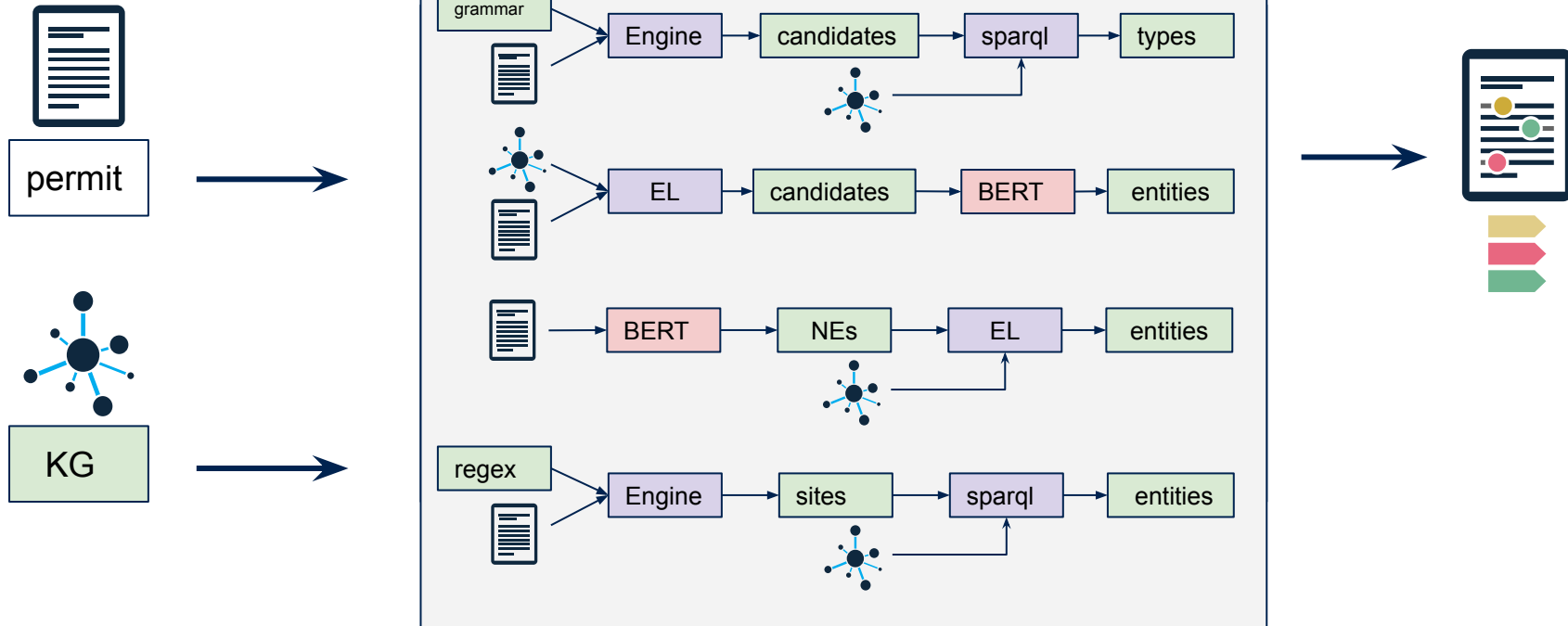
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Key Element Extraction from Legal Permits



Combining SW and ML for Auditable Legal Key Element Extraction

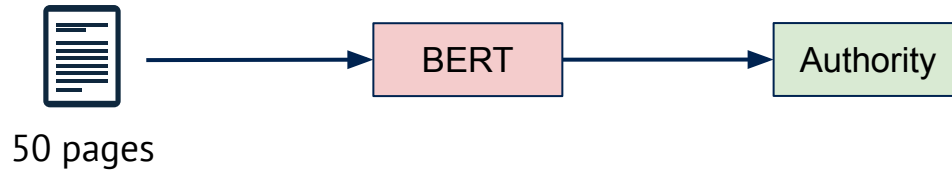
Half a

~~One simple sentence from an Austrian legal permit....~~

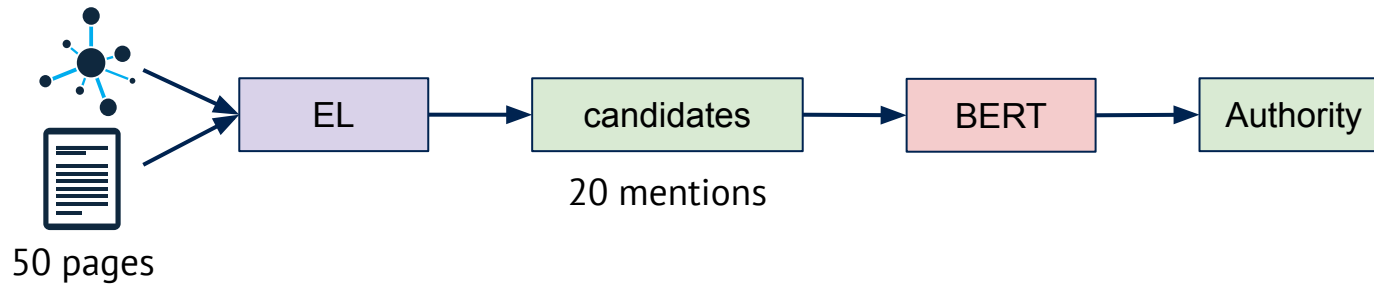
Der Landeshauptmann von Tirol als zuständige Abfallbehörde gemäß § 38 Abs. 6 Abfallwirtschaftsgesetz 2002 – AWG 2002, BGBl. I Nr. 102/2002, zuletzt geändert durch BGBl. I Nr. 193/2013, entscheidet über den Antrag der XXX GmbH & Co OG, vertreten durch die Geschäftsführer Albert YYY und Martin ZZZ, Oberdorf 20, 2301 Groß-Enzersdorf, vom 01.01.2014, eingelangt am 04.05.2014, ergänzt mit Eingaben vom 19.8.2014 (OZl. 123), vom 23.09.2014 (Beilage zur OZl. 234), vom 28.09.2014 (OZl. 345 und OZl. 456), vom 02.10.2014 (OZl. 567), vom 10.11.2014 (OZl. 678), vom 21.11.2014 (ABF-2-21/1/1-2014), vom 22.11.2014 (OZl. 8 und 9), vom 13.12.2014 (OZl. 26), vom 20.12.2014 (OZl. 45), sowie durch die Projektskonkretisierungen im Zuge der mündlichen Verhandlung am 24.12.2014 (OZl. 62) und eingeschränkt mit Eingabe vom 31.12.2014 (OZl. 69), gemäß den §§ 37 Abs. 1, 38 Abs. 1 und 1a und 43 Abs. 1 und 2 AWG 2002 unter Anwendung der Gewerbeordnung 1994 – GewO 1994, BGBl. Nr. 194/1994, zuletzt geändert durch BGBl. I Nr. 81/2015, des ArbeitnehmerInnenschutzgesetzes – ASchG, BGBl. Nr. 450/1994, zuletzt geändert durch BGBl. I Nr. 60/2015, des Immissionsschutzgesetzes-Luft – IG-L, BGBl. I Nr. 115/1997, zuletzt geändert durch BGBl. I Nr. 77/2010, des Wasserrechtsgesetzes 1951 – WRG 1959, BGBl. Nr. 2015/1959, zuletzt geändert durch BGBl. I Nr. 54/2014, wie folgt:

Combining **SW** and **ML** for Auditable **Legal Key Element Extraction**

Generate Candidates



VS



[...] The plant in question has been approved based on **§37 Article 3 sub-section 2 of AWG 2002** [...]

Legal permit

6. Abschnitt Behandlungsanlagen

Genehmigungs- und Anzeigepflicht für ortsfeste Behandlungsanlagen

§ 37. (1) Die Errichtung, der Betrieb und die wesentliche Änderung von ortsfesten Behandlungsanlagen bedarf der Genehmigung der Behörde. Die Genehmigungspflicht gilt auch für ein Sanierungskonzept gemäß § 57 Abs. 4.

(2) Der Genehmigungspflicht gemäß Abs. 1 unterliegen nicht:

stationary plant

incineration
plant

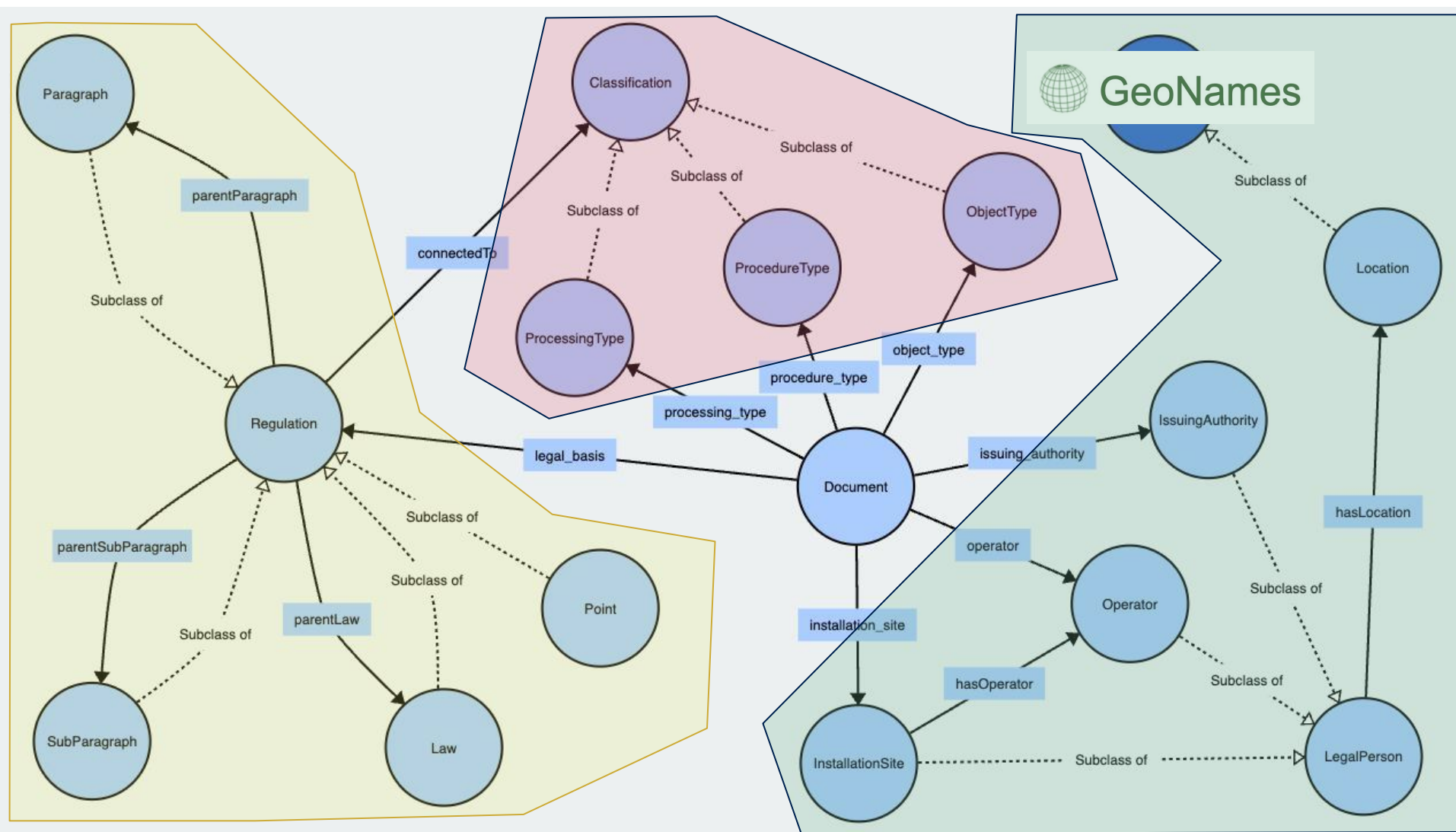
simplified legal
procedure

Einzelnen.

(3) Folgende Behandlungsanlagen – sofern es sich nicht um IPPC-Behandlungsanlagen oder Seveso-Betriebe handelt – und Änderungen einer Behandlungsanlage sind nach dem vereinfachten Verfahren (§ 50) zu genehmigen:

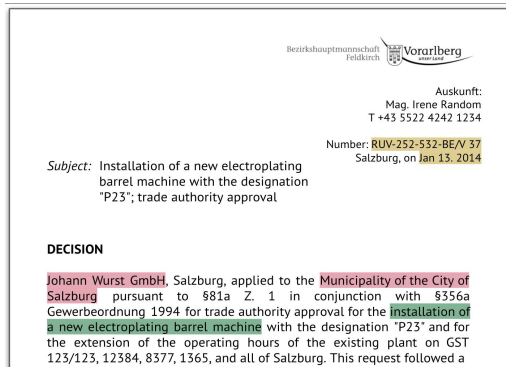
1. Deponien, in denen ausschließlich Bodenaushub- und Abraummateriale, welches durch Ausheben oder Abräumen von im Wesentlichen natürlich gewachsenem Boden oder Untergrund anfällt, abgelagert werden, sofern das Gesamtvolumen der Deponie unter 100 000 m³ liegt;
2. Verbrennungs- oder Mitverbrennungsanlagen zur thermischen Verwertung für nicht gefährliche Abfälle mit einer thermischen Leistung bis zu 2,8 Megawatt;

AWG 2002



Key conclusions

Part III (Micro):



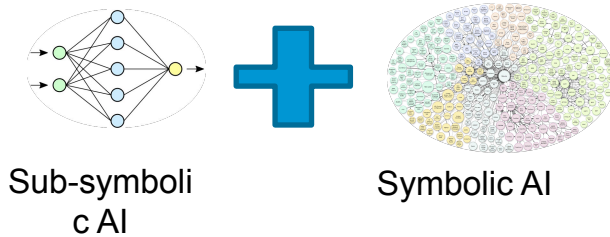
SWeML approach for
information extraction in
the legal domain

- Solving a challenging use case using a SW + ML system
- **ML:** Deal with complex input
- **KG:** Reduce complexity of (sub) problems
- Auditing: Traceability of suggestions & System monitoring

Summary of my talk

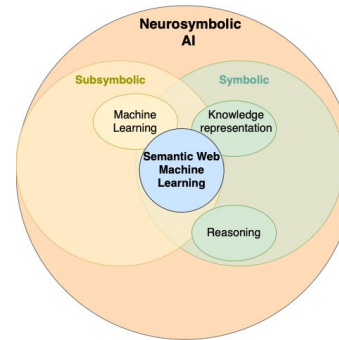
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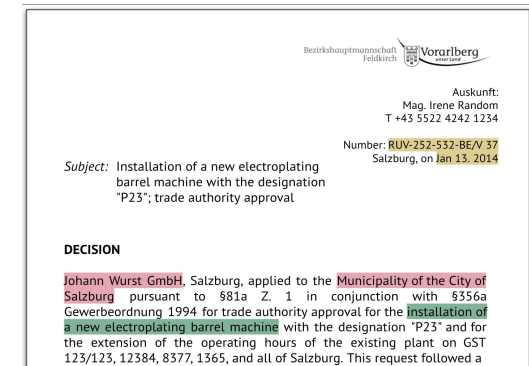
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What (I hope) you learned in this talk

New techniques combine **symbolic** (Semantic Web) and **sub-symbolic** (Machine Learning) **AI** methods in various ways to solve complex (data science) tasks.

Atomic-Patterns

A1: s-M-s
A2: d-M-s
A3: s-M-d

Fusion-Patterns

F1: d/s-M-d
F2: d/s-M-s
F3: d/s-M-d/s

T-Patterns

T1: {d-M-d/s}-M-s
T2: {d/s}-M-d-M-s
T3: {s-M-d/d}-M-s
T4: {s-M-d/d}-M-d
T5: {d-M-s/s}-K-s
T6: {d-M-d/s}-M-d

I-Patterns

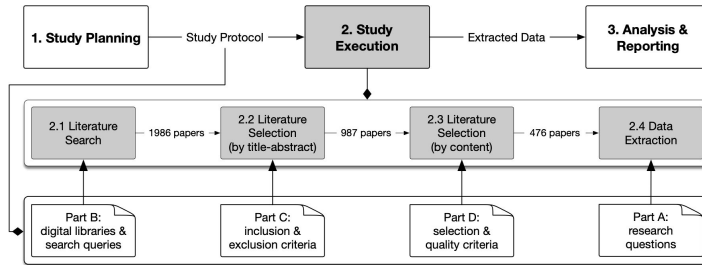
I1: s-M-d-M-s
I2: s-M-d-M-d

Y-Patterns

Y1: {s-M-d/d-M-d}-M-s
Y2: {s-M-d/d-M-d}-M-d

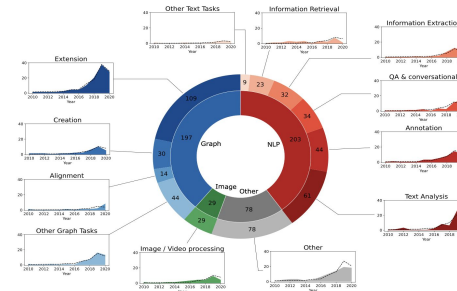
Data Structures
s: symbolic
d: data

Algorithmic Modules
M: inductive (ML)
K: deductive (KR)



Systematic Literature Review is a valuable research method.

Beyond "Data Science" - applications that valorise complex domain data, with an example from the legal domain.



Excellence Cluster „Bilateral Artificial Intelligence (BILAI)“

Hiring 50 PhDs and 10 PosDocs!



- Funded by National Austrian Science Funds (FWF)
- Start October 2024
- Budget (5y):
 - ~20M EUR FWF Funding
 - >30M EUR Total Budget
- Coordinator:
 - JKU Linz (Sepp Hochreiter)
- Partners:
 - WU Wien
 - TU Wien
 - TU Graz
 - ISTA
 - AAU Klagenfurt