TONGJI UNIVERSITY
COLLEGE OF DESIGN AND INNOVATION
同济大学设计创意学院

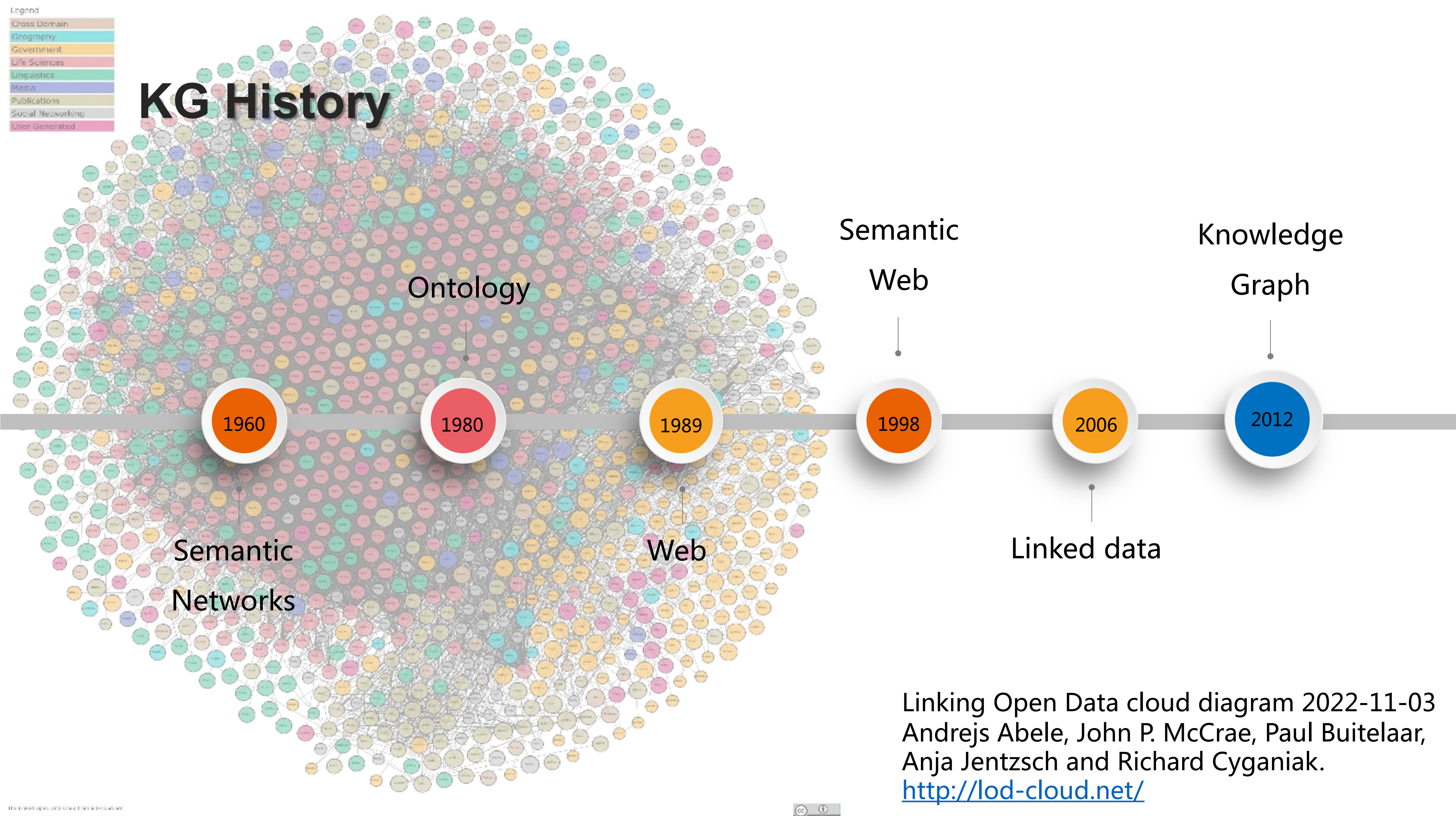
Emerging Technologies of Knowledge Graph in the Big Data Era

Haofen Wang

APWEB-WAIM 2022

- **Knowledge Graph Overview**
- Key Technologies
- Applications

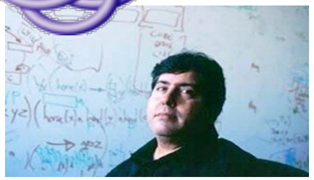
KG History



Linking Open Data cloud diagram 2022-11-03
Andrejs Abele, John P. McCrae, Paul Buitelaar,
Anja Jentzsch and Richard Cyganiak.
http://lod-cloud.net/

What is Knowledge Graph (KG) – Well-known KBs and Characteristics

Cyc



$\forall x$: human(x) $\Rightarrow$
$(\exists y$: mother(x,y) $\wedge$
$\exists z$: father(x,z))

$\forall x,u,w$: (mother(x,u) $\wedge$
mother(x,w)
$\Rightarrow$ u=w)

WordNet

guitarist $\subset$ {player,musician}
$\subset$ artist

algebraist
$\subset$ mathematician
$\subset$ scientist

By Human
For Human

Wikipedia

4.5 Mio. English articles
20 Mio. contributors

WolframAlpha computational knowledge engine

By Algorithm
For Machine

DBpedia

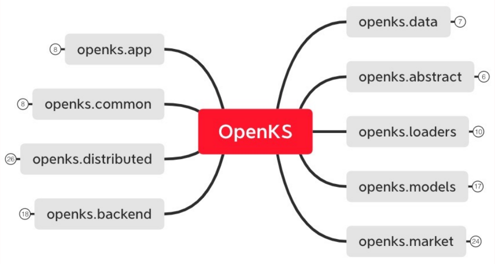
yago select knowledge

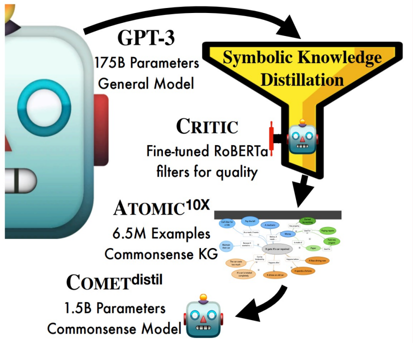
Freebase

LarKC Large Knowledge Collider

OpenKG.CN
链上的开放知识图谱

Human Machine
Collaboration





1985 1990 2000 2005 2010 2015 2023

Key Features	In the early stage, KG is High-quality, manually-built, and for human consumption; in the middle age, KG is constructed by algorithms and used to enhance the understanding capability of machines; nowadays KG is evolving towards multi-modality and subsymbolic representations

Knowledge Graph

Knowledge Graph (KG) is an explicit representation of human knowledge, which is stored in the form of graph and used for reasoning and computing.

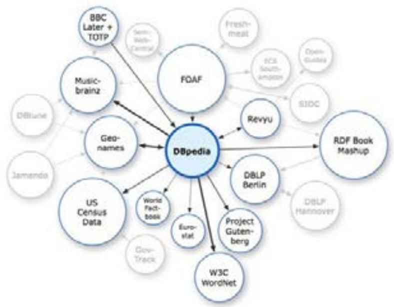
General KG

- General domain oriented
- Commonsense knowledge
- Structured encyclopedia knowledge
- Emphasize the breadth of knowledge
- For general users

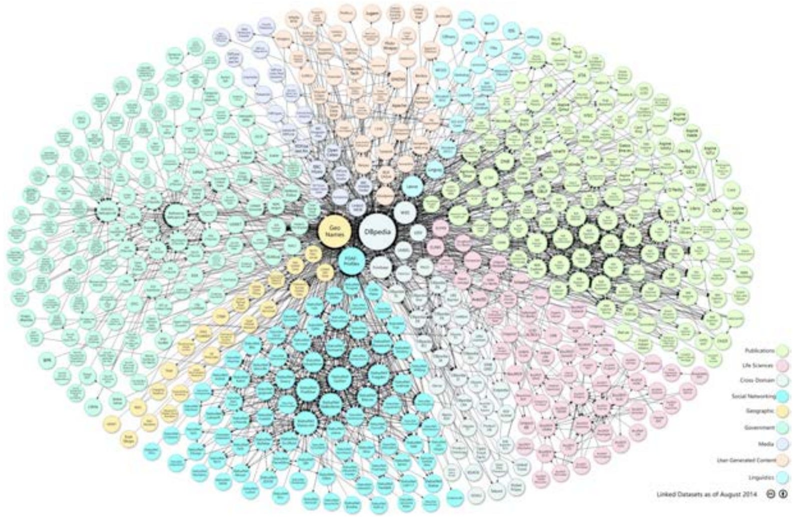
Industrial KG

- Industrial domain oriented
- Industrial data
- Semantic industrial knowledge base
- Emphasize the depth of knowledge
- For industry users

What is Knowledge Graph (KG) – Rapid Growth and Lower Cost



2007



2014

Manual

High Order Logic

CYC - $5.71 per statement
Freebase - $2.25 per statement
NELL - 14.25 ¢ per statement
DBPedia - 1.85 ¢ per statement
Yago - 0.83 ¢ per statementure

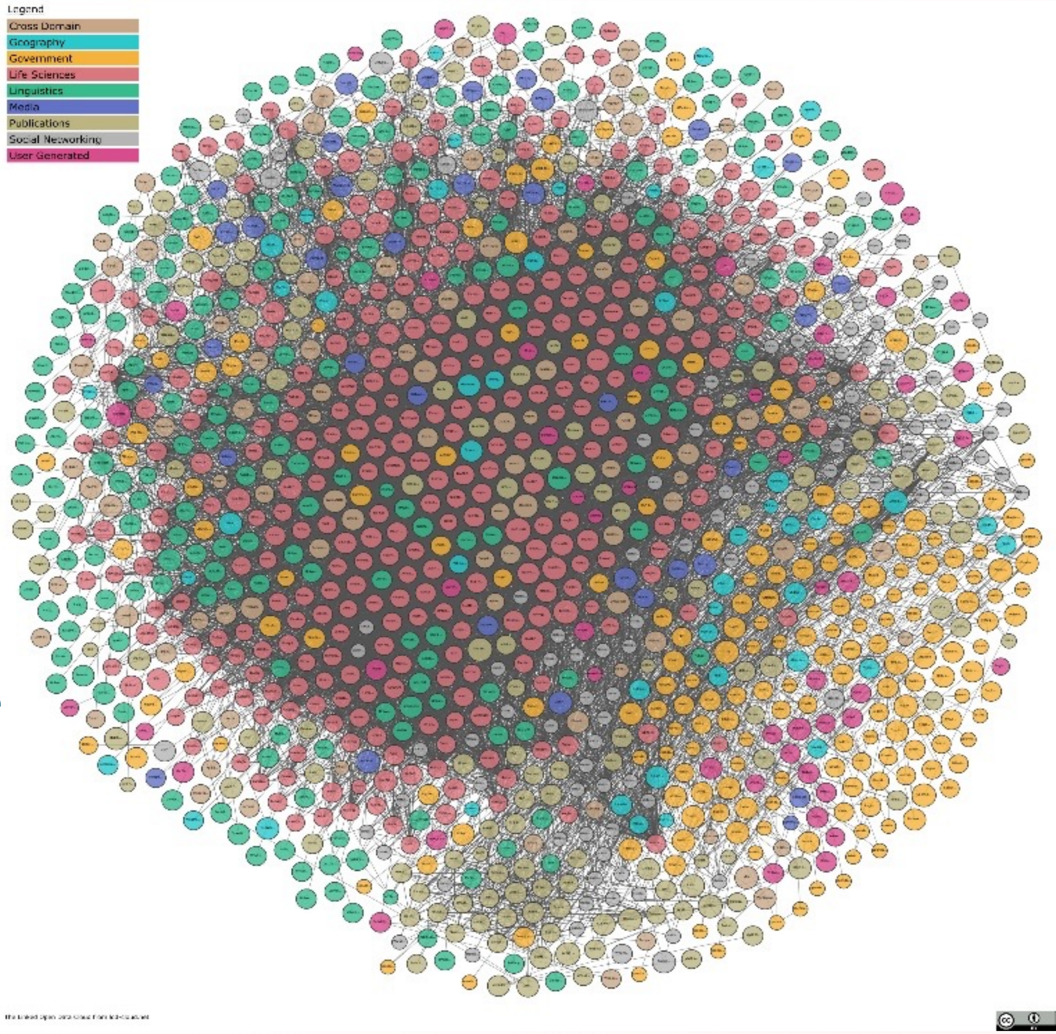
How much is a Triple?

ISWC2018

Automatic

Triplets

Red nodes represent knowledge graph datasets in life science

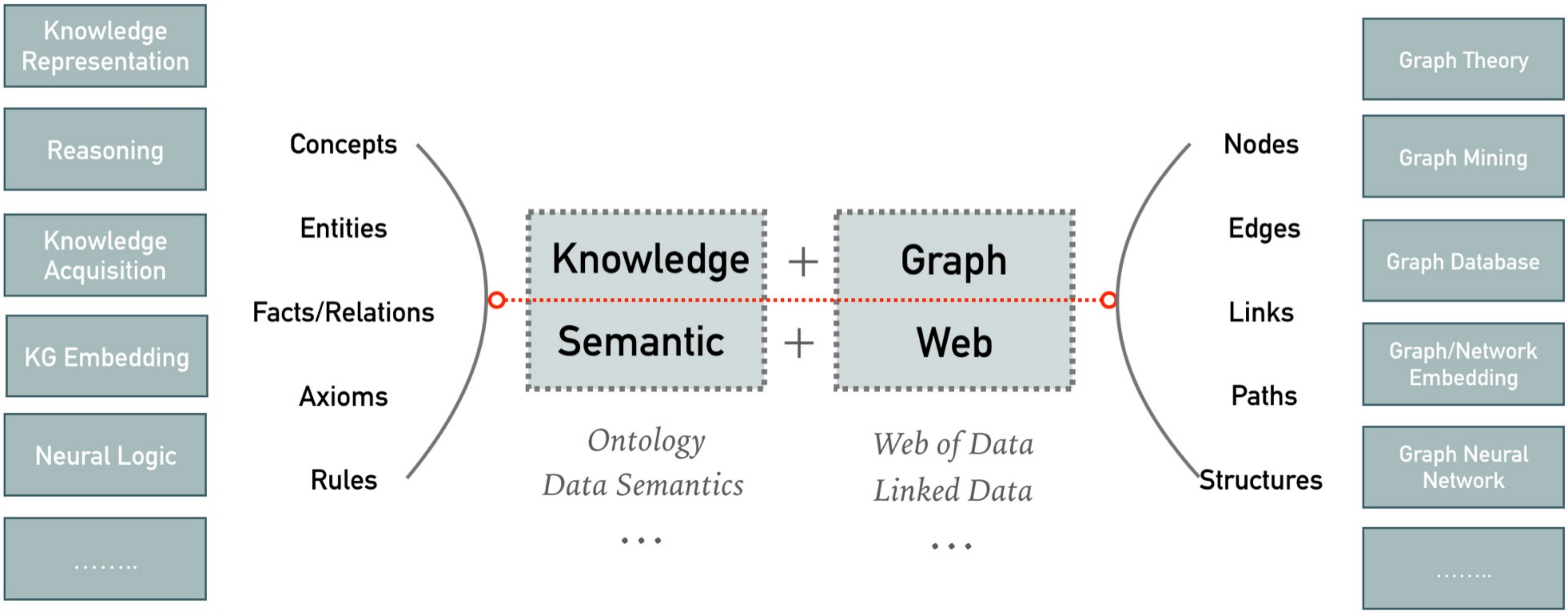


By 2022.11, The Linked Open Data Cloud

Implication

From open to vertical domains, the scale of interlinked KGs has been grown hundreds to thousands of times in the past 15 years, the cost of extracting knowledge is gradually decreasing, improving the quality of extracted knowledge while continuously increasing the scale of knowledge is the main trend in the future

Knowledge Graph is more expressive than pure Graph but less complex than formal logic.

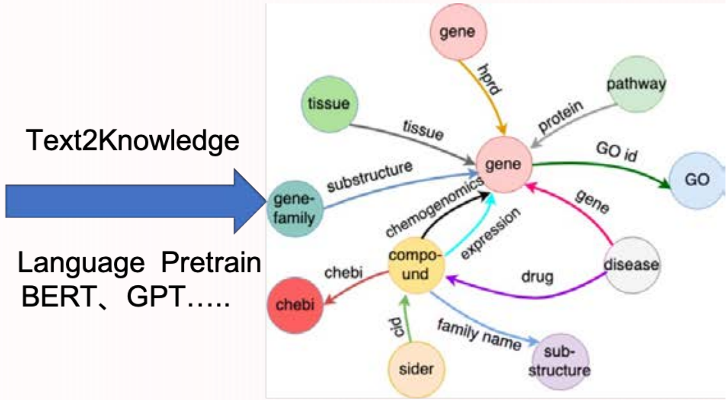


What is Knowledge Graph (KG) – Perspective and Implication

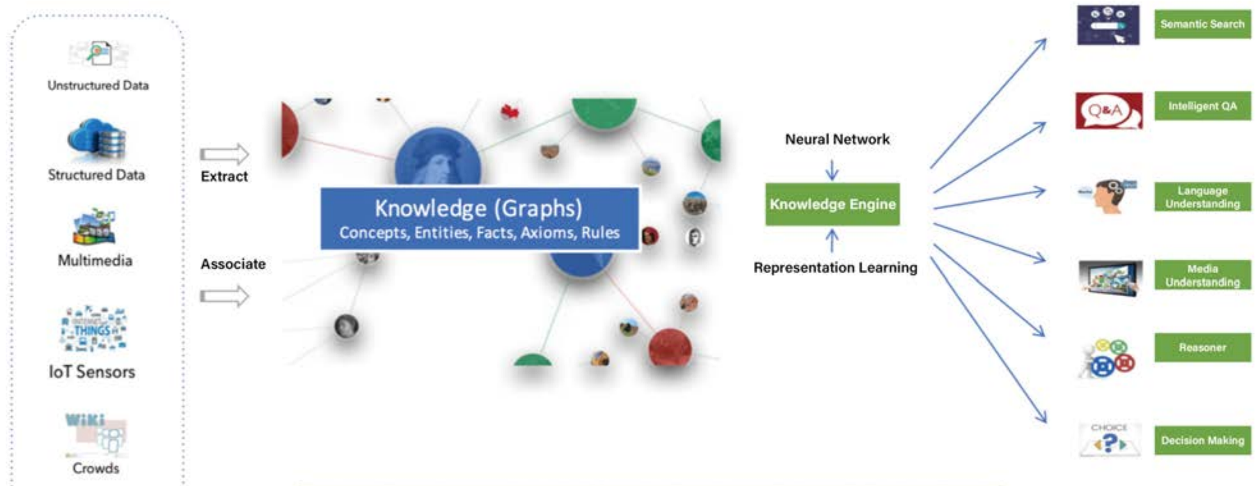
KG as a World Model

The Good Old Fashioned AI　The Semantic Web & Linked Knowledge　The Knowledge Graph

Text as Knowledge Base



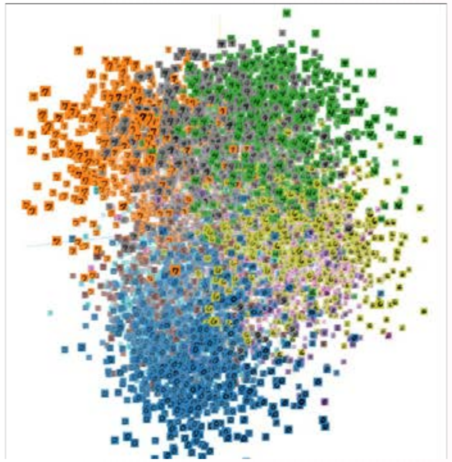
Graph Structure as Knowledge Base



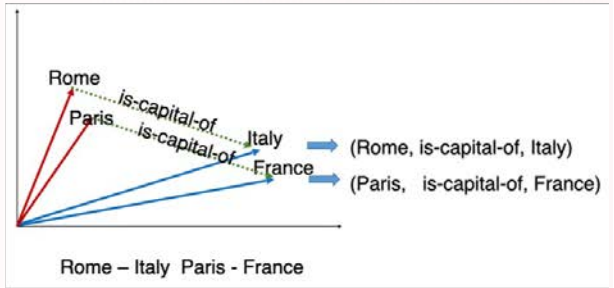
KG = Computational Model of Relations

Embeddings as Knowledge Base

Embeddings：Distributed Vector Representation



- Text：Learn a vector of each word in a sentence
- KG: Learn a vector for each entity or property
- Image/Video：Learn a vector for each visual object



Implication

Knowledge Graph originates from how machines represent knowledge, use the graph structure to describe the relationship between things, developed in the rise of Web technologies, and landed in application fields such as search engine, intelligent QA, and recommender systems.

Smart AI vs. Knowledgeable AI

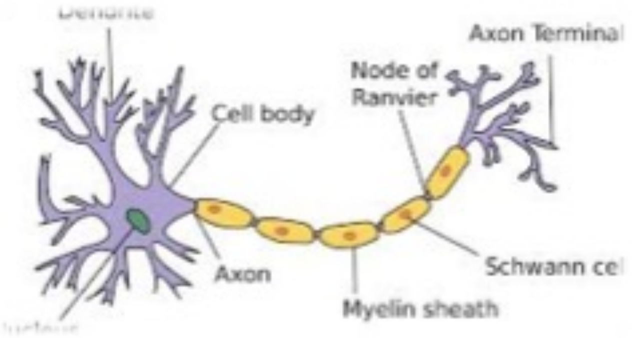
Smart AI

perception

recognition

judgment

Deep Learning



Human brain can conduct reasoning and understanding based on acquired knowledge

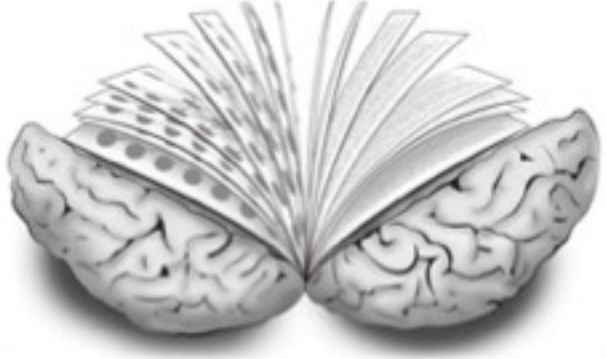
Knowledgeable AI

thinking

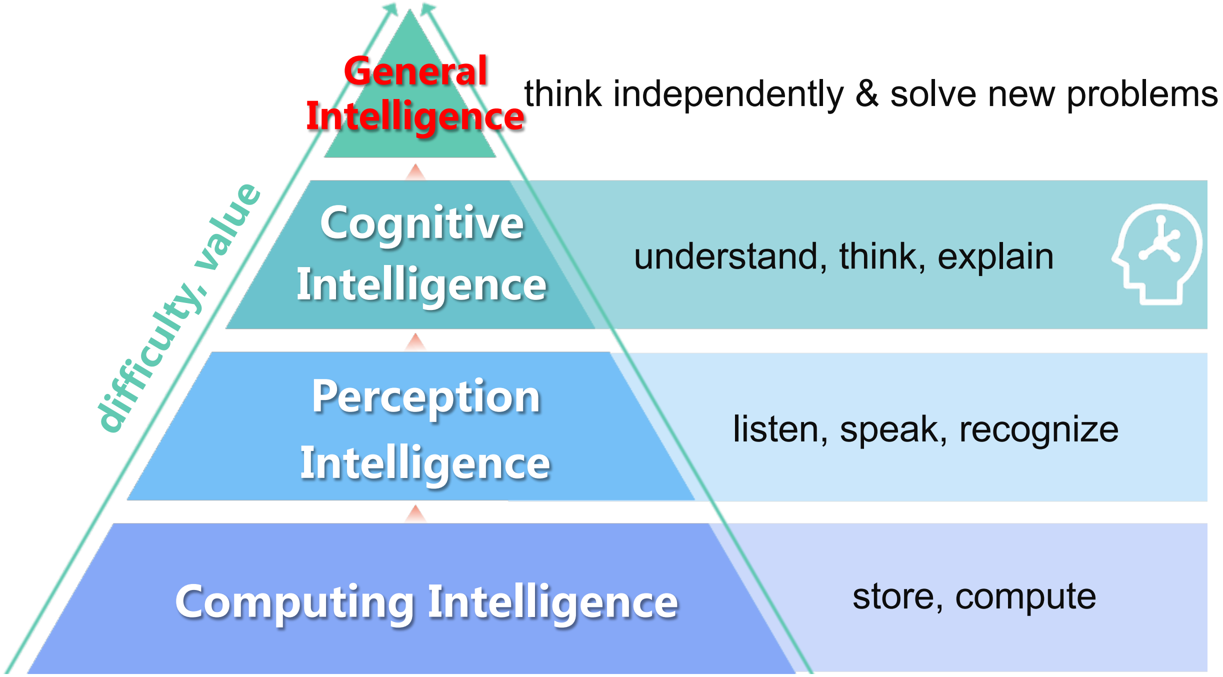
language

reasoning

Knowledge Graph



AI is evolving to "Cognitive Intelligence"



Knowledge Graph is the cornerstone of Cognitive Intelligence

Edward feigenbaum
Knowledge is the power in AI system

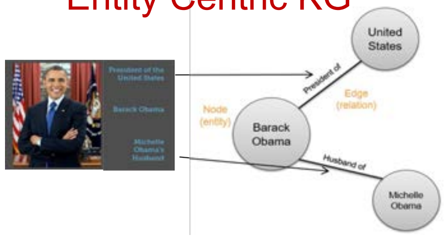
Zhang Bo
AI without Knowledge is not the real AI

- If knowledge is the ladder of human progress, **knowledge graph** is the ladder of AI progress.

- **Machines can better understand data：** Extract high-precision knowledge from data, by leveraging semantic understanding, knowledge extraction, knowledge fusion, etc.
- **Machines can better explain phenomena：** Explain phenomena in a way consistent with human cognition, by using knowledge reasoning, knowledge mining, visual analysis, etc.

SOTA and Trend of KG – Knowledge Representation and Reasoning

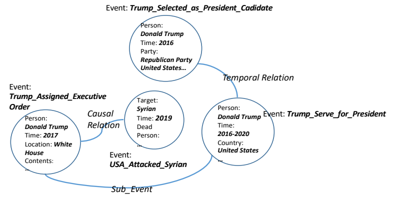
Entity Centric KG



(Barack Obama, Spouse, Michelle Obama)

Triples in form of (s, p, o)

Event Centric KG

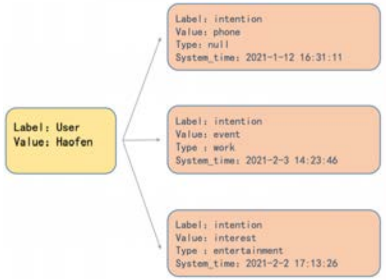


Event Frames

Birth	Marriage	EndPosition
birth date	date	time
birth place	location	company
name	male	position
	female	

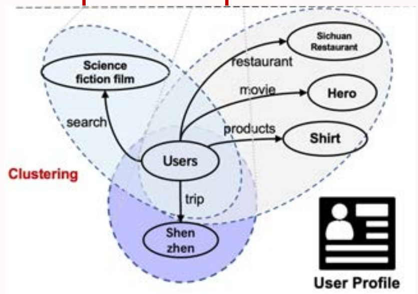
Event Relations: Causal relation, Temporal relation, Co-reference relation, Sub-class relation...

Personal KG



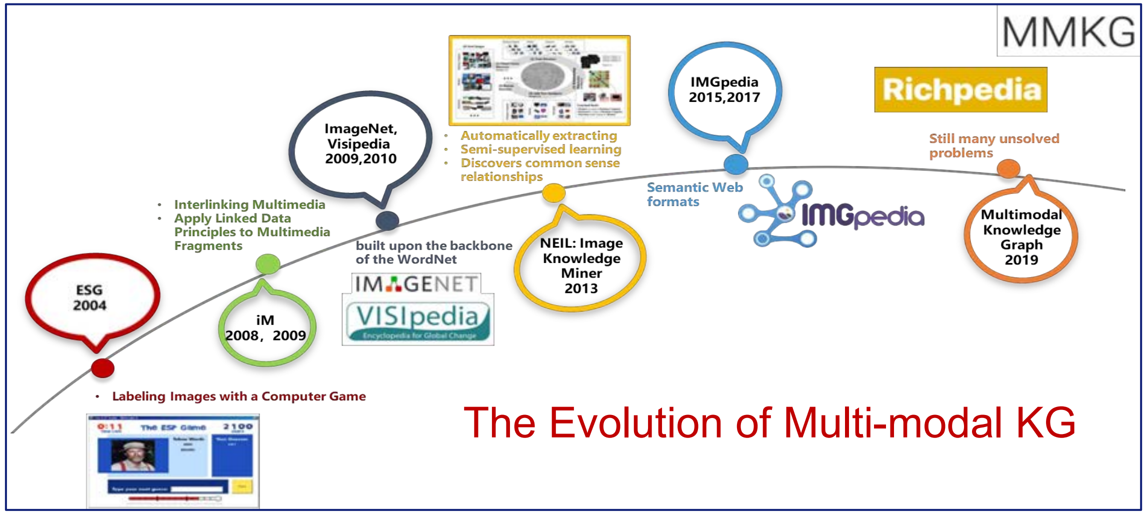
Graph composing events, interests, behaviors of an individual under the protection of privacy and security

Spatiotemporal KG

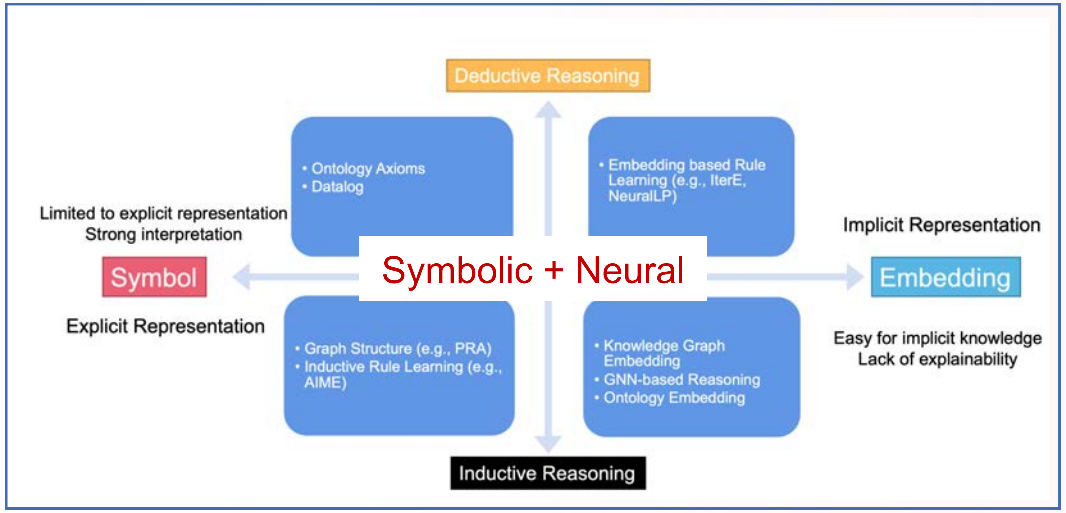


Expand knowledge representation level in time series and space dimensions

Knowledge types: simple -> complex, static -> dynamic, community -> personal, plain -> spatiotemporal



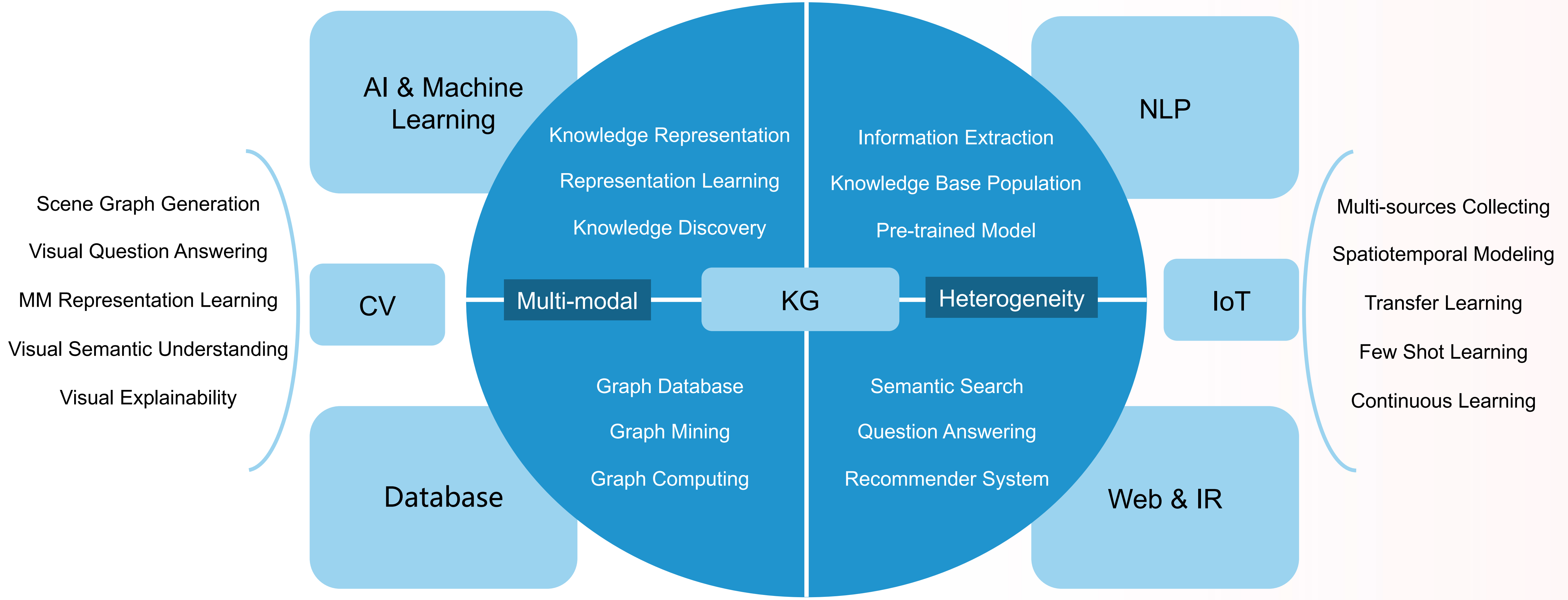
The Evolution of Multi-modal KG



Challenges

Traditional symbolic knowledge representation methods are difficult to accurately represent complex knowledge such as dynamics, processes, and cross-modalities. At the same time, how to combine symbolic reasoning methods based on knowledge graphs and neural reasoning methods is extremely challenging.

SOTA and Trend of KG – Interdisciplinary



The life cycle of KG construction: more types/sources, advanced techs, rapid updates, and widely used applications

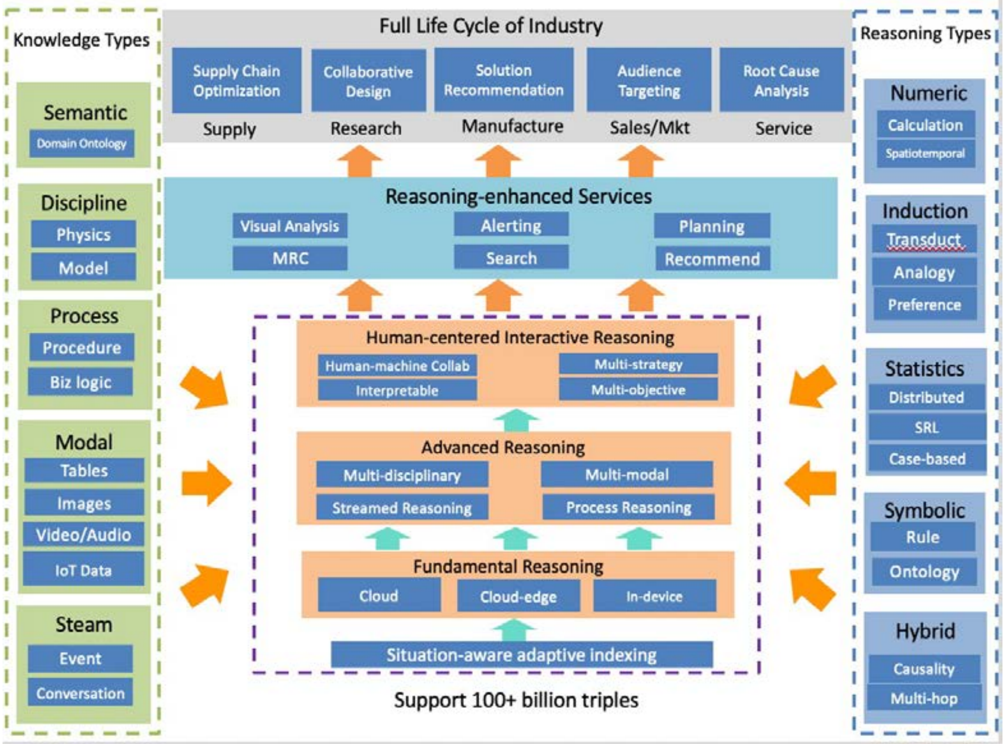
Challenges

The multi-scale, multi-modal, and multi-disciplinary characteristics of data have put forward new requirements for knowledge representation, collection, extraction, storage, computing, and application. Among them, it is necessary to overcome few shots, explainability, and domain adaptation issues. At the same time, how to realize knowledge update at a low cost is also extremely

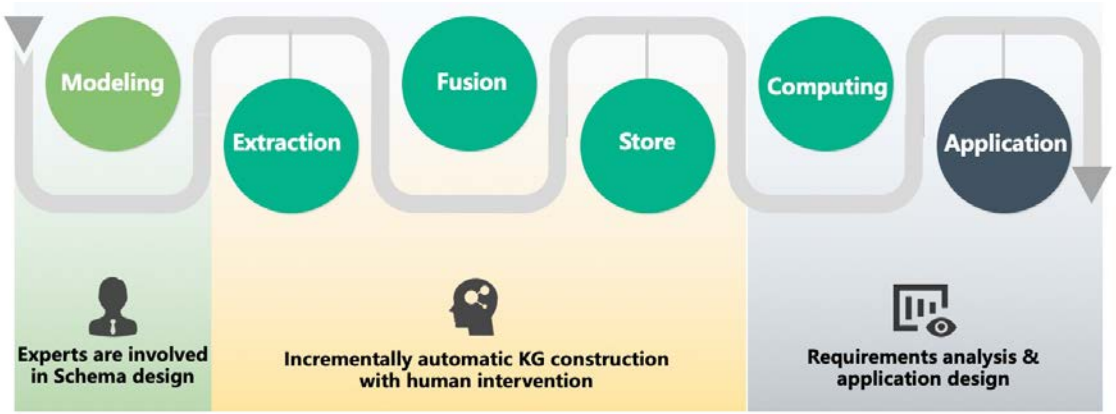
SOTA and Trend of KG – System Engineering View

Andrew Ng

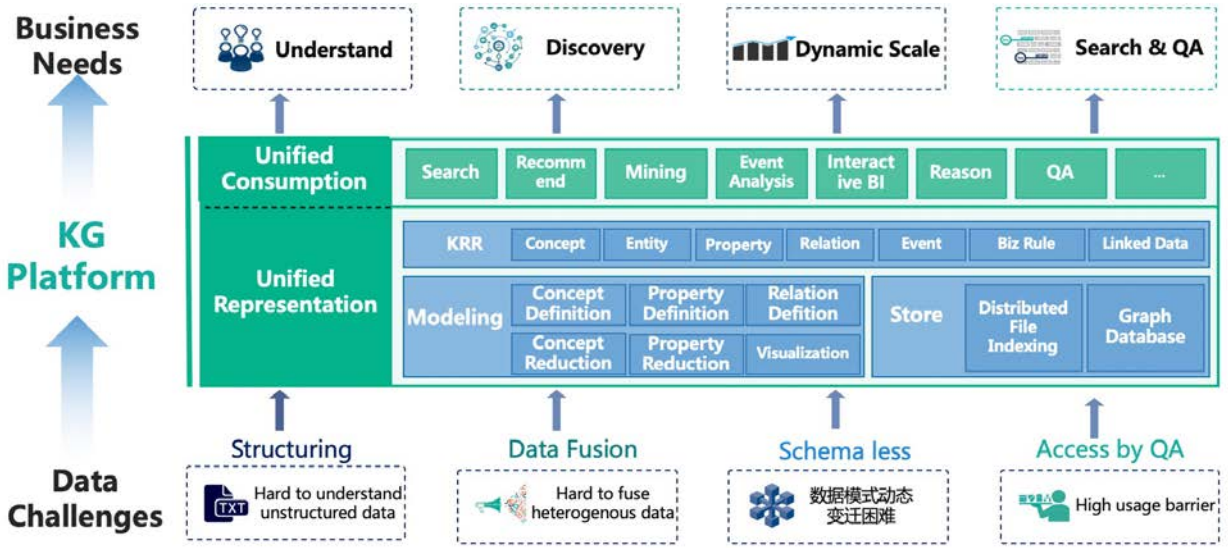
AI should focus on small data and data centric AI. Especially in the manufacturing industry, we must rely on domain knowledge



Knowledge Graph System Architecture in Industry



Different computing manners, "offline - near real time - real-time", depend on the type of knowledge



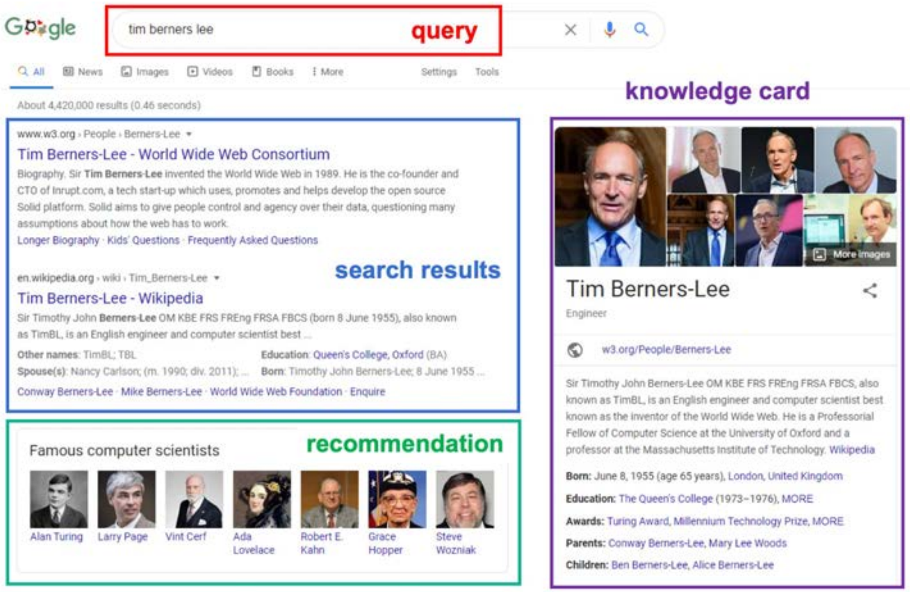
New Paradigm of Technology with Knowledge as the Core

Challenges

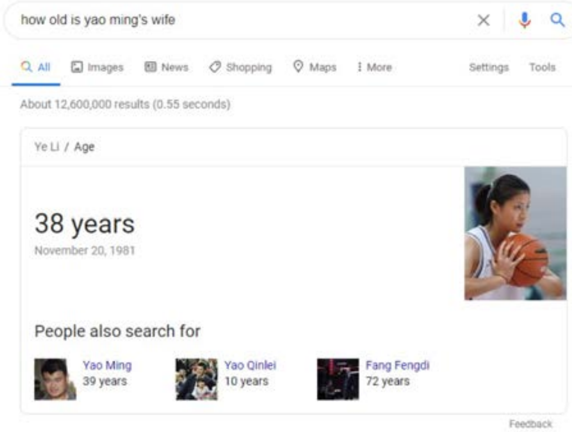
Data characteristics and knowledge differences in different fields lead to low knowledge coverage, intensive labor input, shallow usage In applications, poor computing efficiency, difficult & weak sustainable operation and long time cost

Trends of the Interdisciplinary Development of Knowledge Graph – Applications

Search



Question Answering



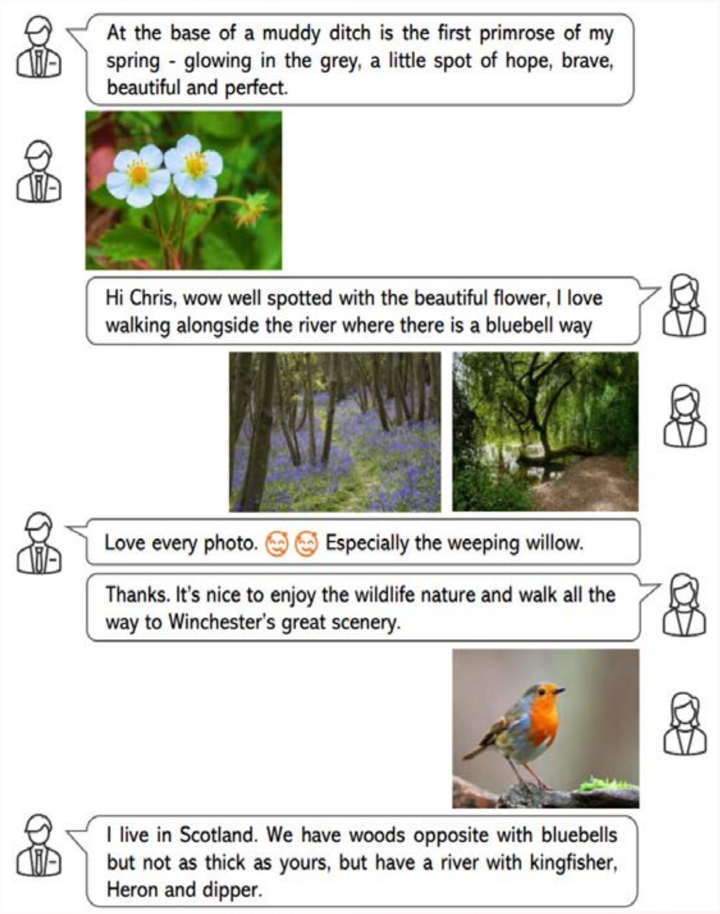
Machine Reading Comprehension

Mary journeyed to the den.
Mary went back to the kitchen.
John journeyed to the bedroom.
Mary discarded the milk.
Q: Where was the milk before the den?
A : Hallway

Brian is a lion.
Julius is a lion.
Julius is white.
Bernhard is green.
Q: What color is Brian?
A: White

Sam walks into the kitchen.
Sam picks up an apple.
Sam walks into the bedroom.
Sam drops the apple.
Q: Where is the apple?
A: Bedroom

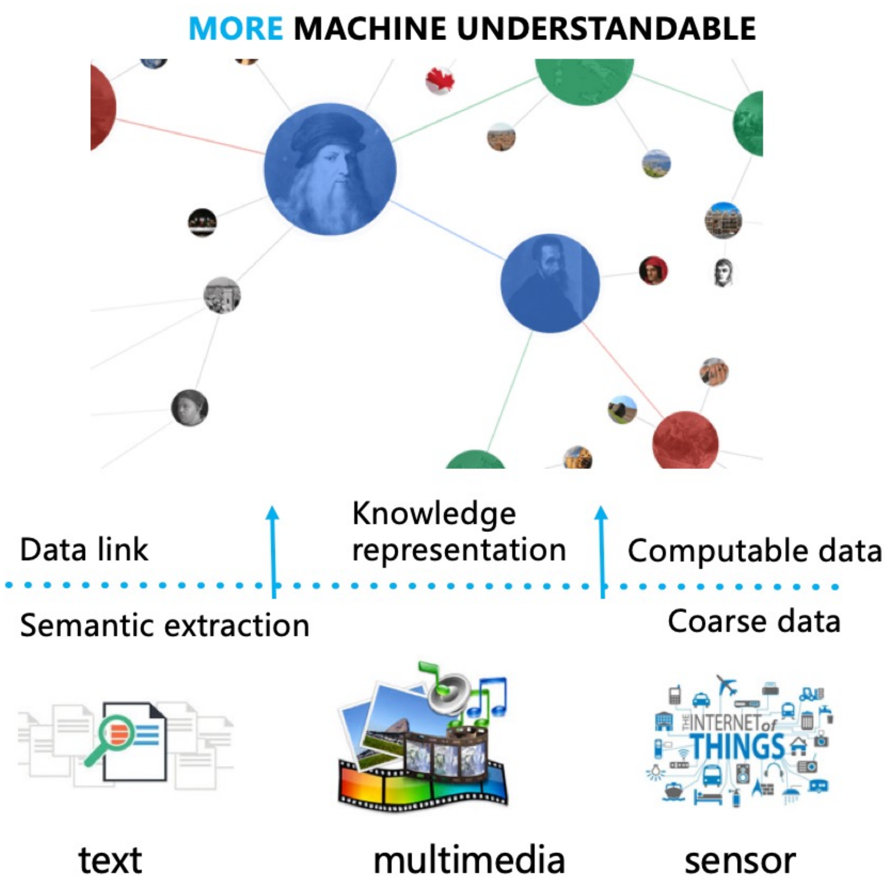
Multi-modal QA



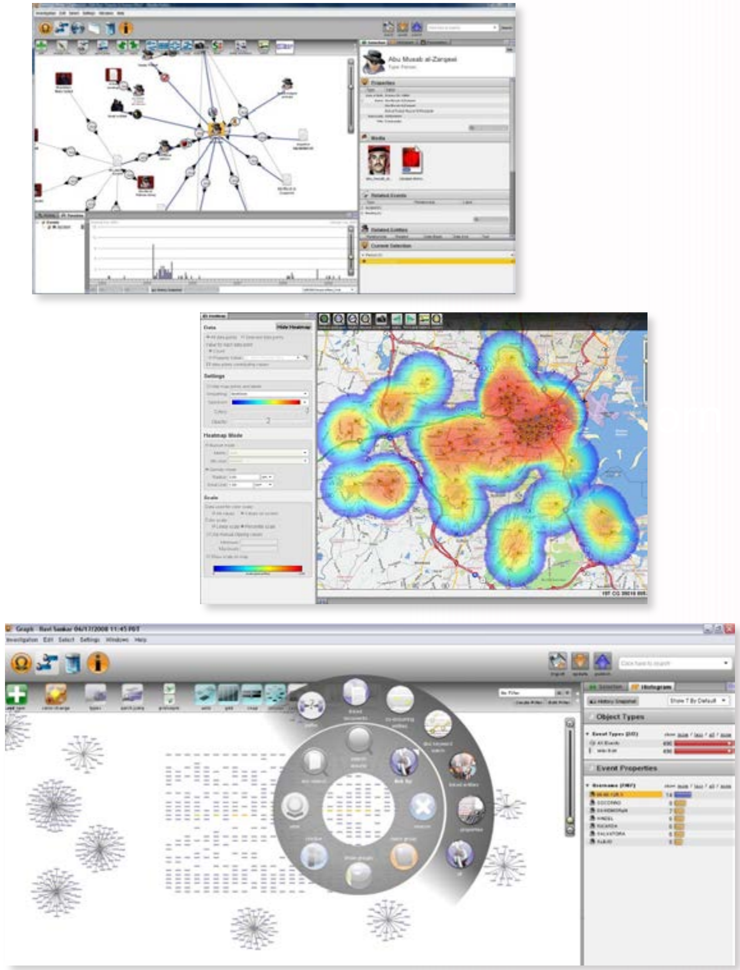
Challenges

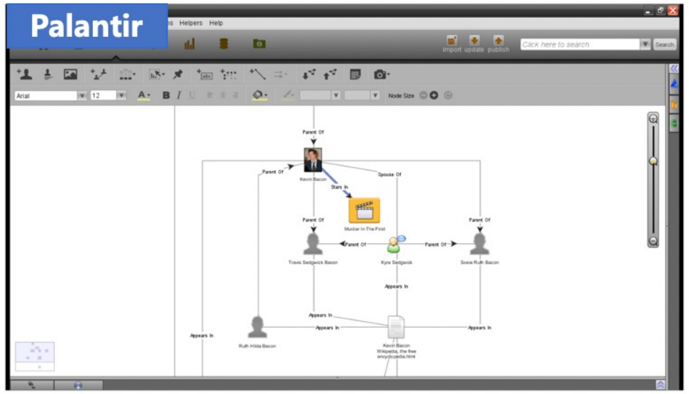
To build a multi-source and multi-modal knowledge graph, not only quality but also coverage should be considered. In the process of model training, the alignment of heterogeneous and multimodal knowledge is the difficulty of knowledge fusion and learning

Trends of the Interdisciplinary Development of Knowledge Graph – Applications



Knowledge Graphs for Decision Making





https://www.palantir.com/

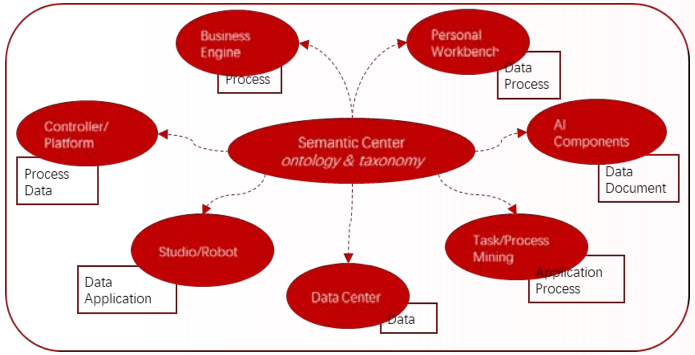
https://www.kensho.com/

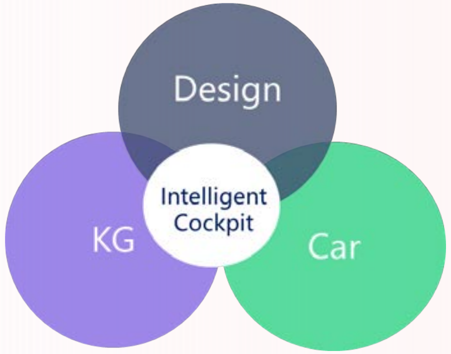
Challenges	In each specific field, the explainability of the model and predictions are the most important to realize the application value. How to balance the advantages and disadvantages of symbolic models and neural networks, and learn from each other is a hot topic in academia and industry.

Trends of the Interdisciplinary Development of Knowledge Graph - Applications

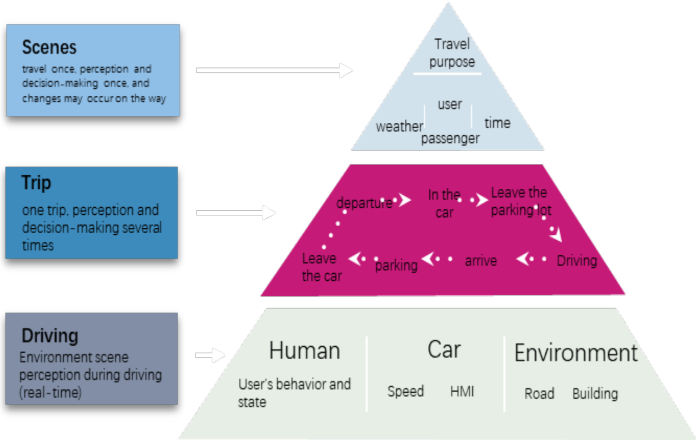
Offline Cockpit	Cockpit with Basic Apps	Intelligent Cockpit
• **Air conditioning, Radio, Offline navigation**	• **Equipped with 3g/4g network** • **Basic Navigation, Music and other Apps**	• **Multi screens** • **Rich networking Apps** • **Easy access to online content**



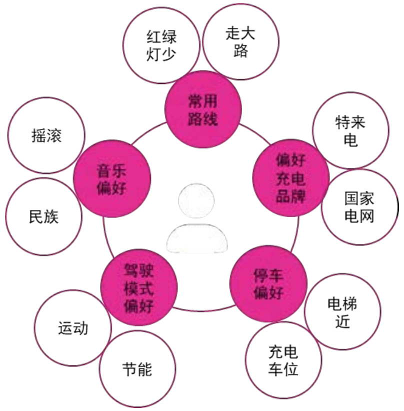




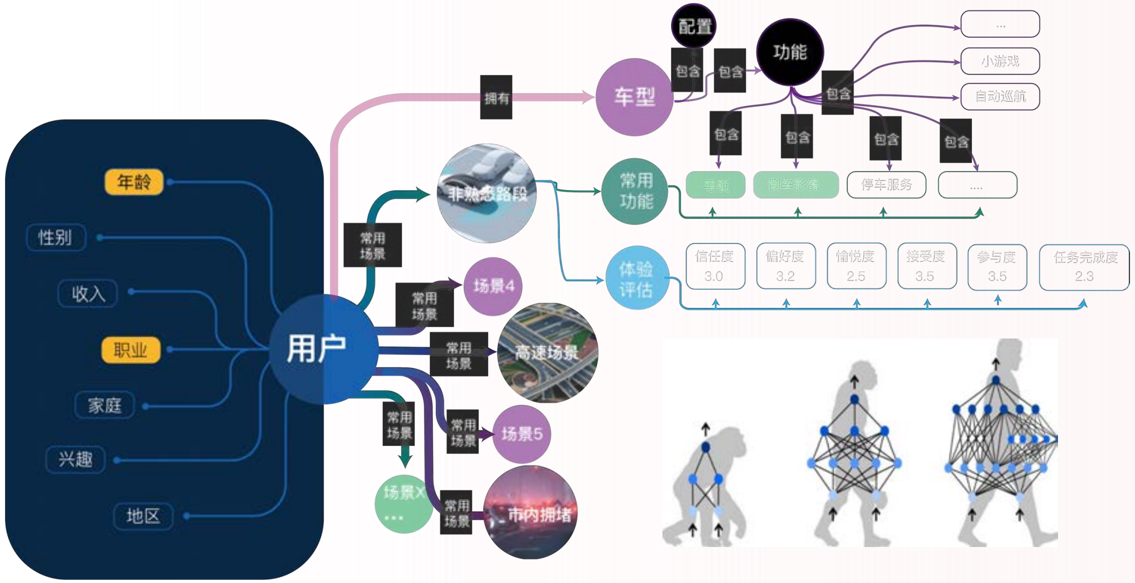
Semantic Center



Abundant Car Scenes



Personalized User Preferences



Scene KG and Life-long learning

Challenges	The "small data, small scenes" of the intelligent cockpit and the unknown and dynamically changing real world make it impossible for manual definition or deep learning to cover all "small scenes", and the algorithm needs to be continual learning / life-long learning with multimodal knowledge

- Knowledge Graph Overview
- **Key Technologies**
- Applications

Life cycle of Knowledge Graph

- Top-down method
- Bottom-up method

- Schema graph fusion
- Data graph fusion

- Graph computing
- Ontology reasoning
- Rule-based reasoning

Reasoning is important !

- Linked data: graph mapping
- Structured data: D2R
- Semi-structured data: wrapper
- Text: information extraction

- Triples
- Event information
- Temporal information
- Multi-modal

- Semantic search
- Question answering
- Recommendation
- Assistant decision

Efficient Construction of MMKG

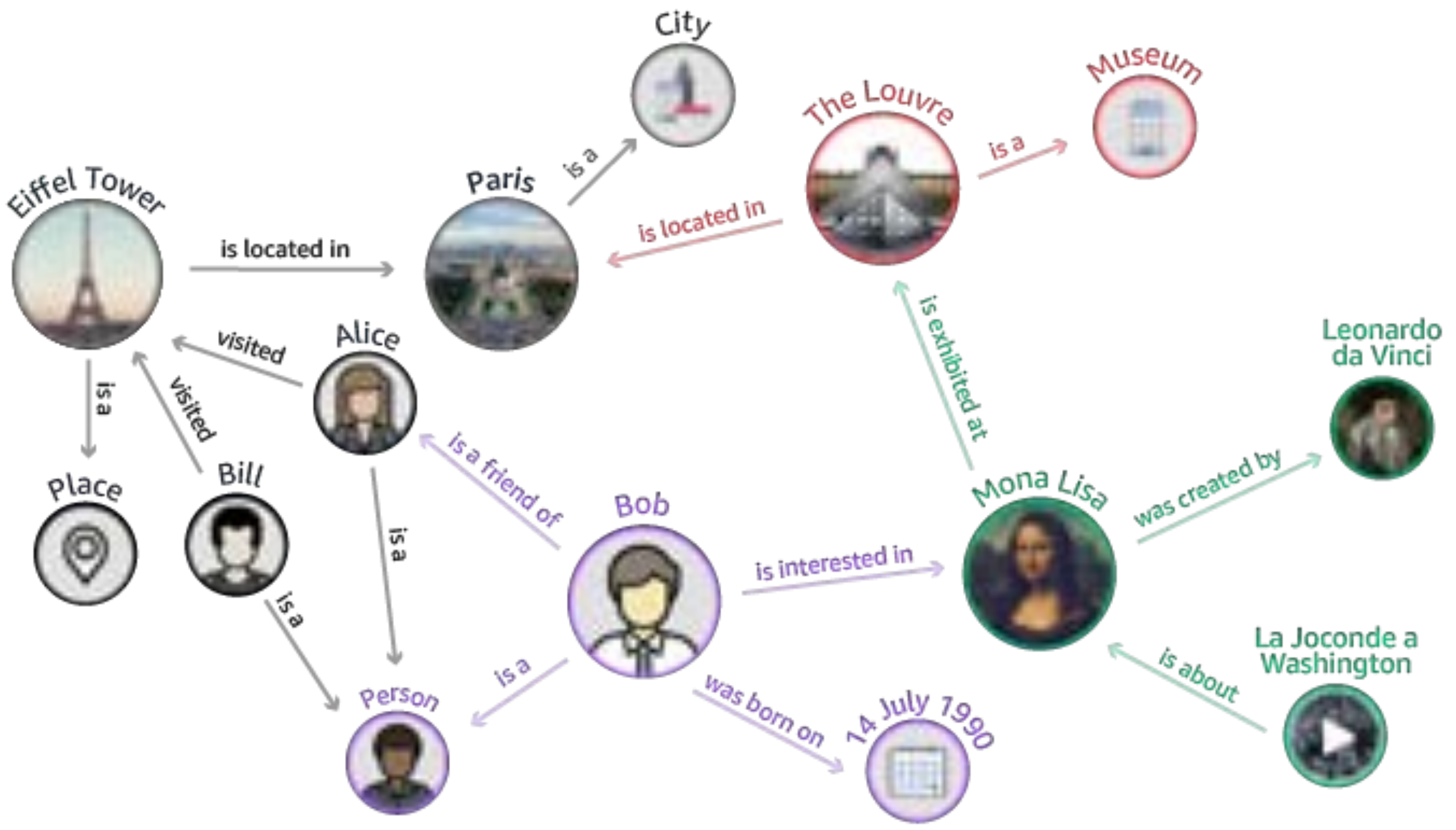
Knowledge Graph Construction → Knowledge Computing → Knowledge Application

Node:

- Image entity
- Text entity
- Visual concept
- Textual concept

Relation:

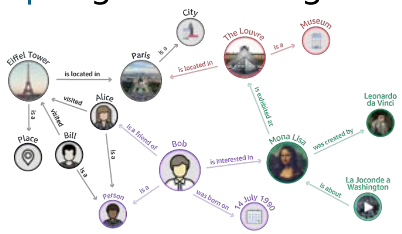
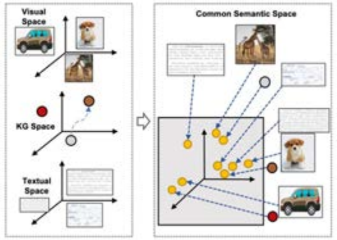
- is-a
- has-visual-object
- meta-of
- has-tag
- co-locate-with



Towards Building Large-Scale Multimodal Knowledge Bases.

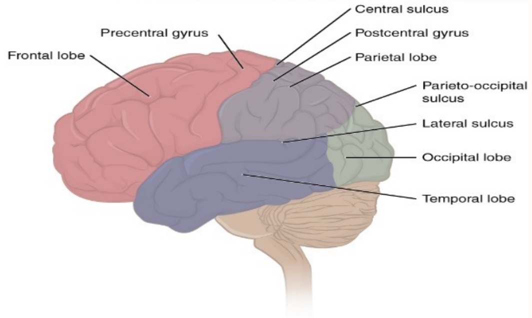
Key Issue:
Multi-modal, Multi-scale, Multi-disciplinary Knowledge Representation

How to represent multi-disciplinary, multi-scale, multi-modal knowledge including space-time, events, rules, and dynamics?

Symbolic	Distributional
Rep: logical symbols Op: logical reasoning	Rep: distributional vectors Op: numeric calculation
	
Pros: explicit semantics, high accuracy, understandable Cons: cannot handle open large scale computing	Pros: close the semantic gap, large scale learning Cons: unclear semantics, hard to reason, uninterpretable

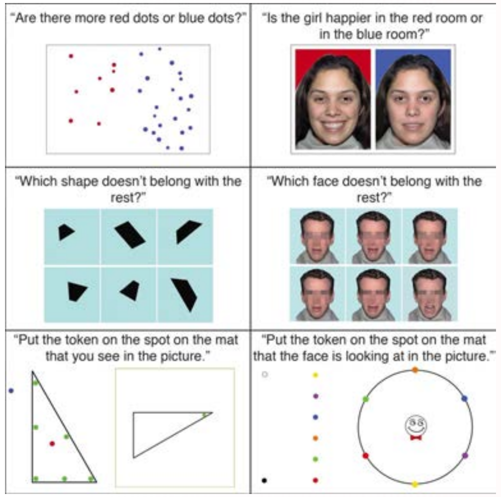
VS.

How to determine the coupling mechanism and boundaries of different modalities of knowledge representation according to real world needs?



There are 5 or so (out of 17 in total) instincts or knowledge that the human brain typically employs when solving specific problems

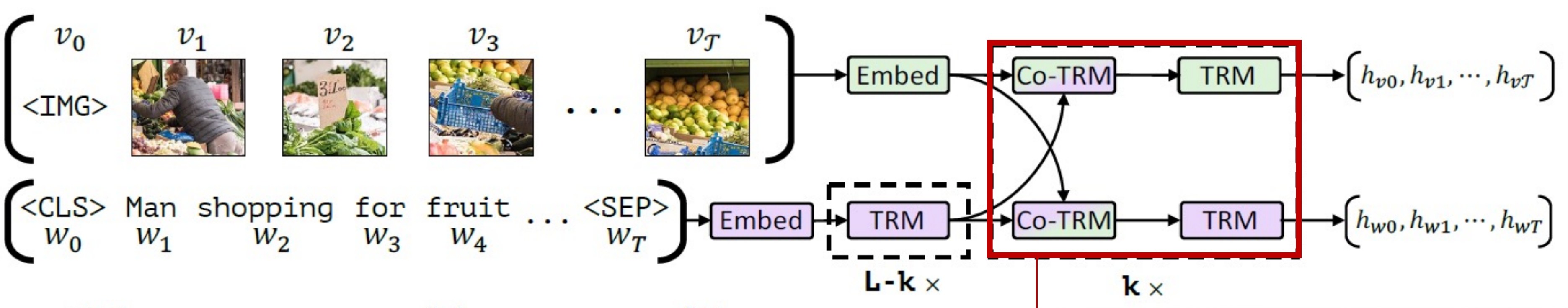
S.Pinker

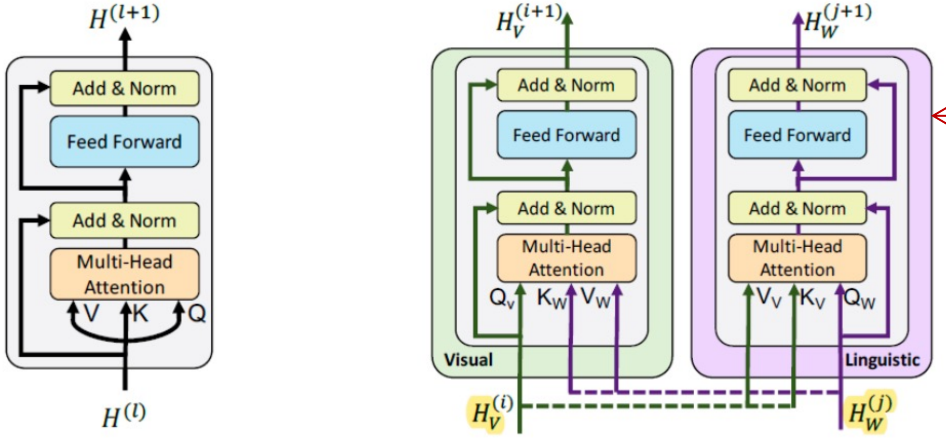


Brain Inspired Cognitive Science

How to represent knowledge that is important but in the form of human instincts based on cognitive science theories?

Multi-modal Knowledge Representation — ViLBERT



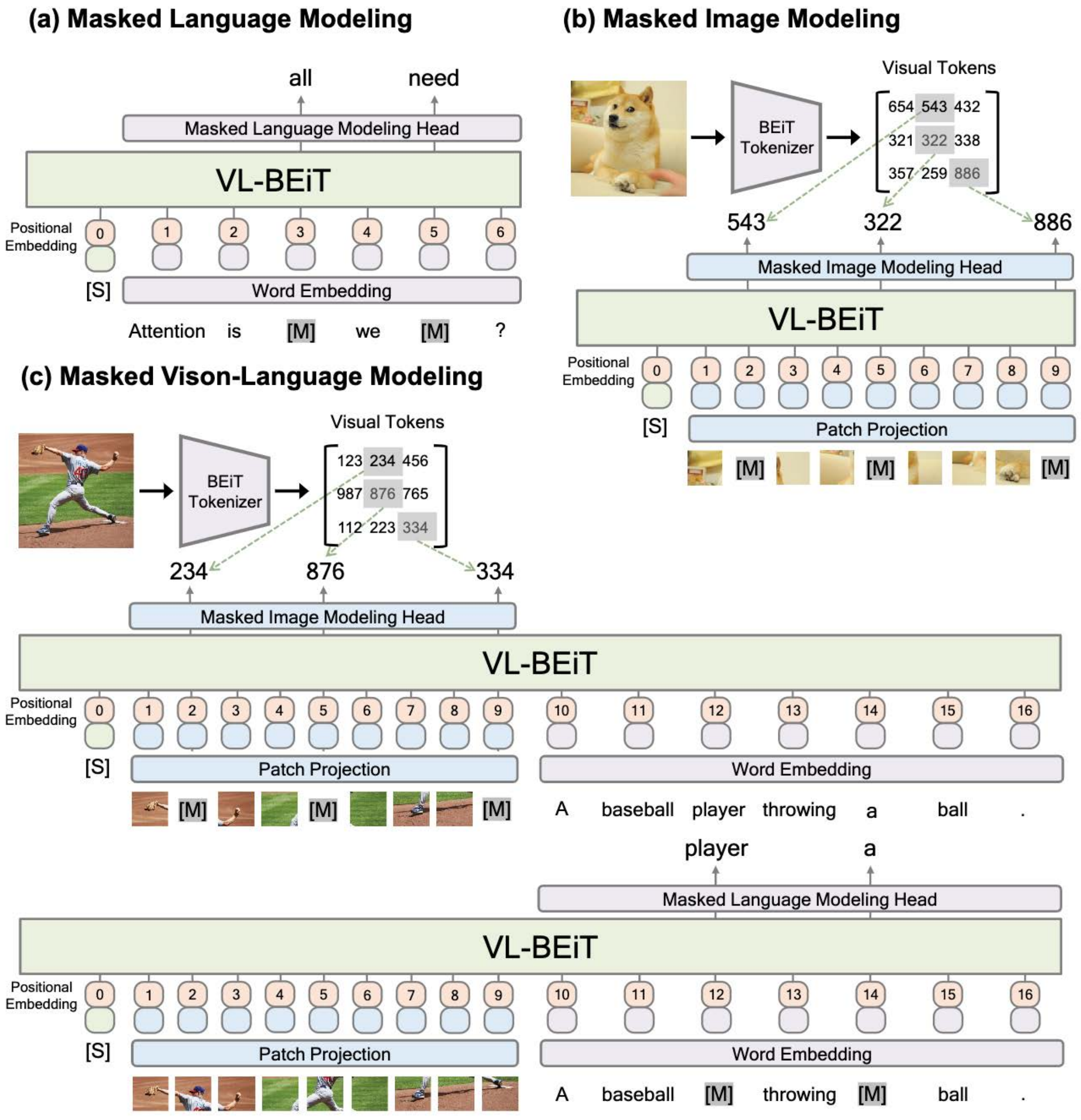


(a) Standard encoder transformer block (b) Our co-attention transformer layer

ViLBERT is a model for learning task-agnostic joint representations of image content and natural language. We extend the popular BERT architecture to a multi-modal two-stream model, processing both visual and textual inputs in separate streams that interact through co-attentional transformer layers.

ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks. NeurIPS 2019

Multi-modal Knowledge Representation — VL-BEIT



Features:

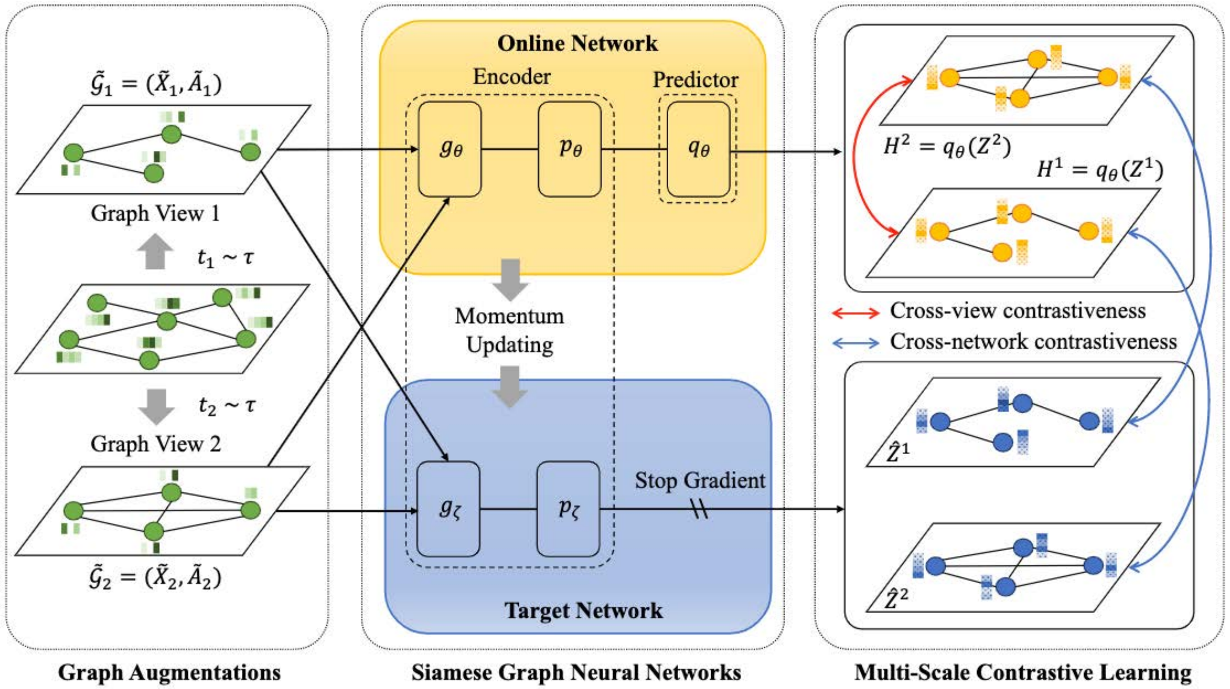
- A **Vision-Language** Foundation Model
- Masked vision-language modeling on **image-text pairs**, masked language modeling on **texts**, and masked image modeling on **images**.
- Learned from scratch with **one unified pretraining task**, **one shared backbone**, and **one-stage training**.
- Conceptually simple and empirically effective.

Downstream tasks :

visual question answering, visual reasoning, and image-text retrieval.

VL-BEIT: Generative Vision-Language Pretraining. arXiv 2022

Multi-scale Knowledge Representation — MERIT

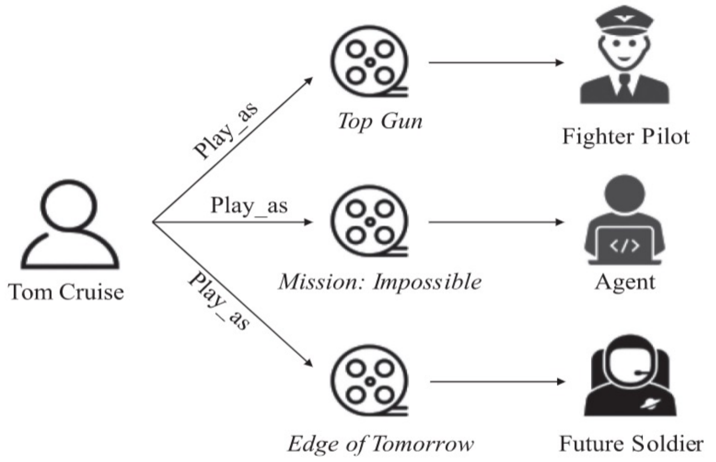


The paper proposes a novel self-supervised approach to learn node representations by enhancing Siamese self-distillation with multi-scale contrastive learning.

- Through graph augmentations, the method constructs two graph views, based on which **an online network and a target network** are employed to generate node representations for each view.
- **A multi-scale contrastive learning scheme**, which utilizes both **cross-network and cross-view** contrastive modules, is deployed to learn effective node embeddings.

Multi-scale Knowledge Representation —— M-DCN

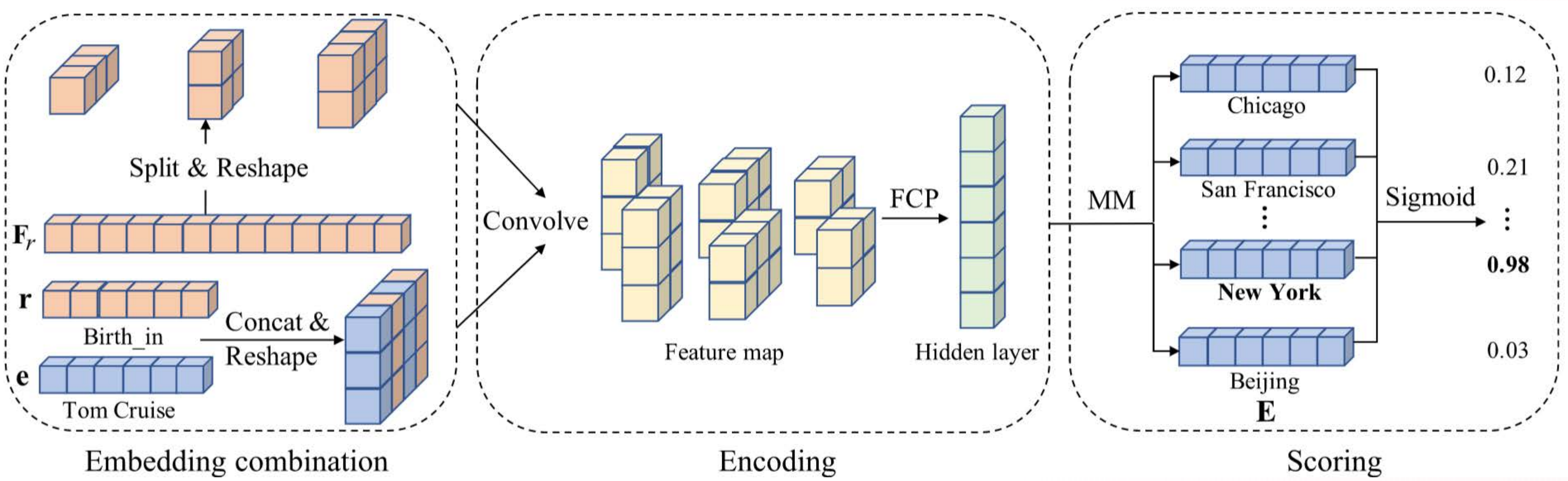
How to represent complex relations, such as 1-to-N, N-to-1, and N-to-N?



In the input layer: M-DCN reshapes and concatenates the subject entity and relation embeddings in an alternating pattern.

In the convolution layer: M-DCN generates multi-scale convolution filters to learn different characteristics between the input embeddings to output feature maps.

Finally, the tensors of feature maps are vectorized and mapped into the embedding dimension and computed with the object entity vector via an inner product to return the possibility of a triplet.



Multi-Scale Dynamic Convolutional Network for Knowledge Graph Embedding. TKDE 2022

Knowledge Reasoning

Knowledge Graph Construction → Knowledge Computing → Knowledge Application

Known Facts → New Facts New Knowledge

演绎：Deductive reasoning

Formal logic
Syllogisms(直言三段论)
Premise 1: All humans are mortal.
Premise 2: Socrates is a human.
Conclusion: Socrates is mortal.

归纳：Inductive reasoning

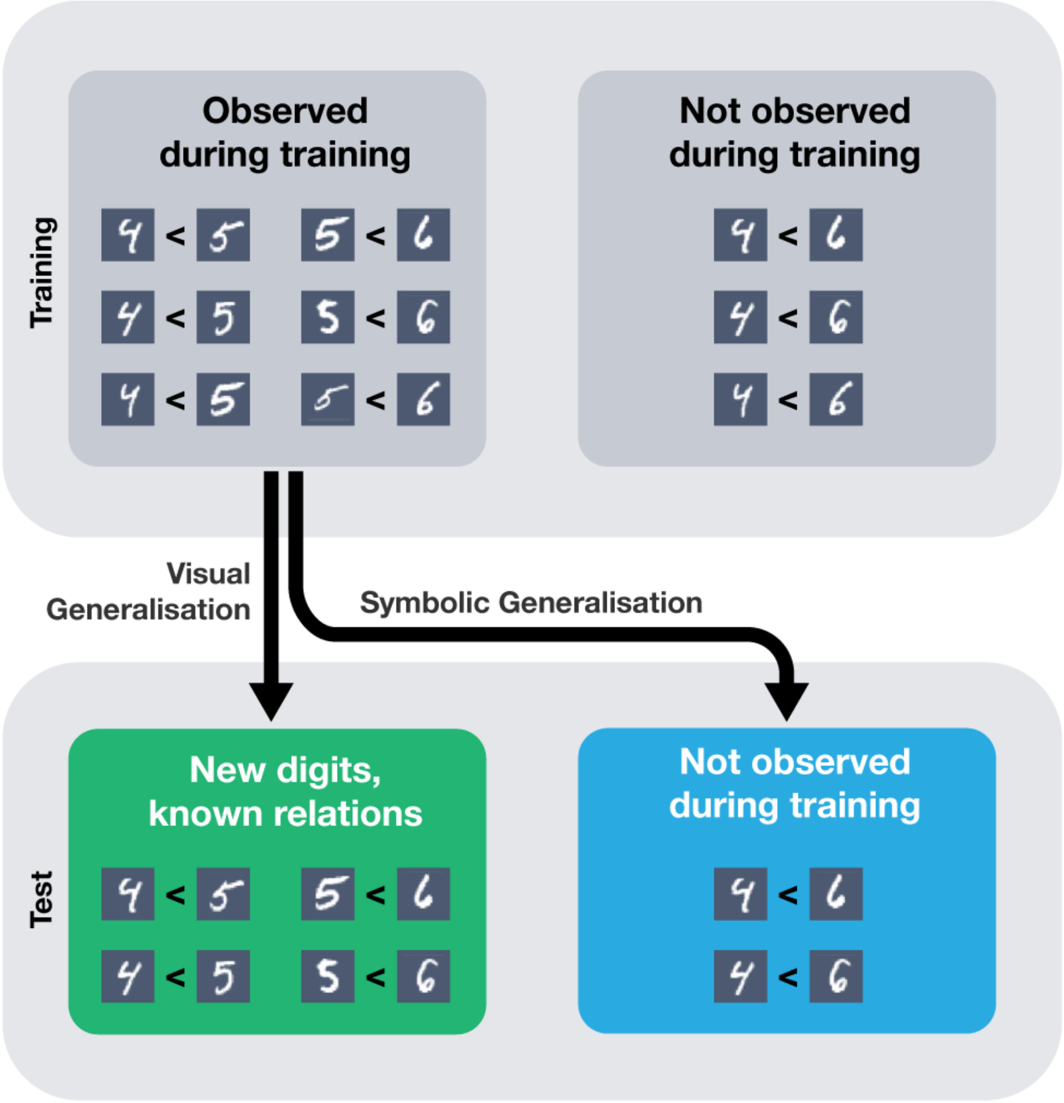
Informal logic or critical thinking
Premise: The sun has risen in the east every morning up until now.
Conclusion: The sun will also rise in the east tomorrow.

溯因：Abductive reasoning

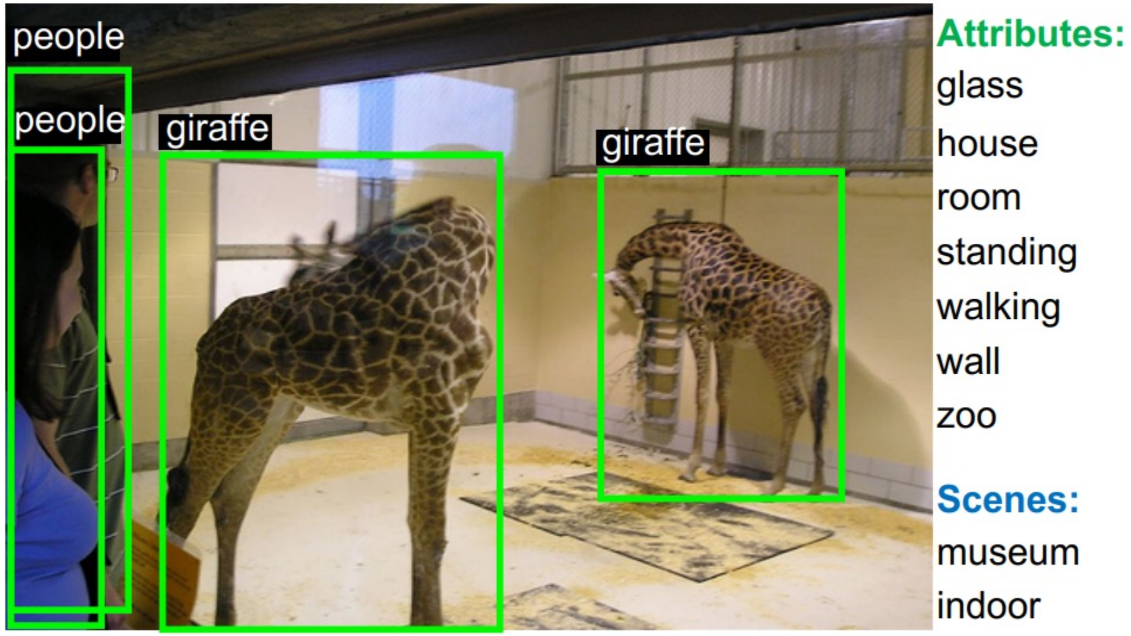
For example, when a patient displays certain symptoms, there might be various possible causes, but one of these is preferred above others as being more probable.

类比：Analogical reasoning

Analogical reasoning is reasoning from the particular to the particular. Premise 1: Socrates is human and mortal.
Premise 2: Plato is human.
Conclusion: Plato is mortal.



Visual generalisation vs. Symbolic generalisation

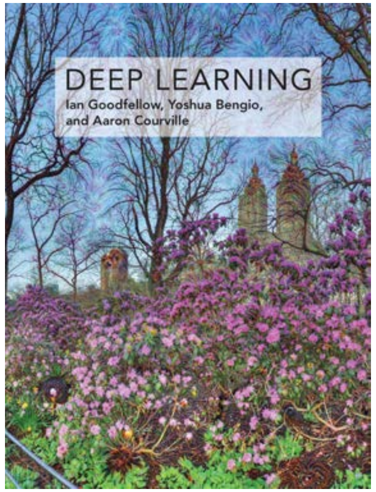


Visual Question: How many giraffes are there in the image?
Answer: Two.

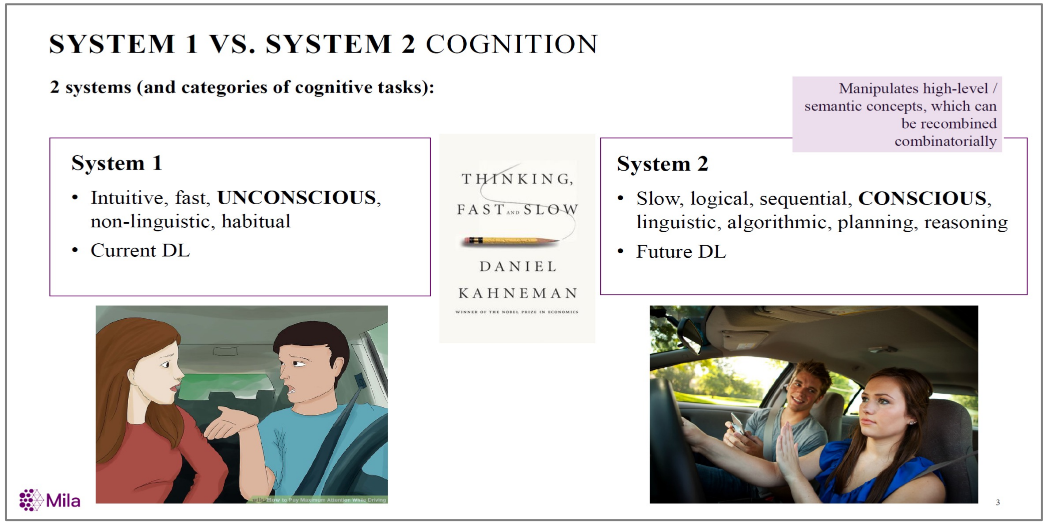
Common-Sense Question: Is this image related to zoology?
Answer: Yes. Reason: Object/Giraffe --> Herbivorous animals --> Animal --> Zoology; Attribute/Zoo --> Zoology.

KB-Knowledge Question: What are the common properties between the animal in this image and zebra?
Answer: Herbivorous animals; Animals; Megafauna of Africa.

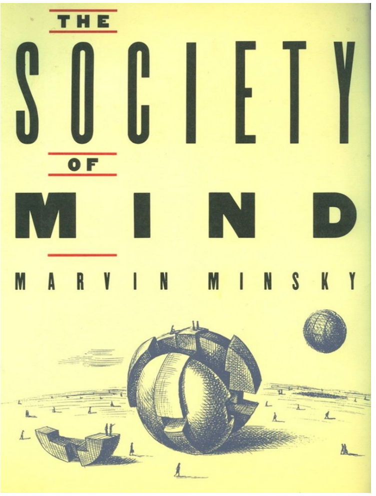
VQA, Commonsense QA, KBQA，and Machine Reading Comprehension



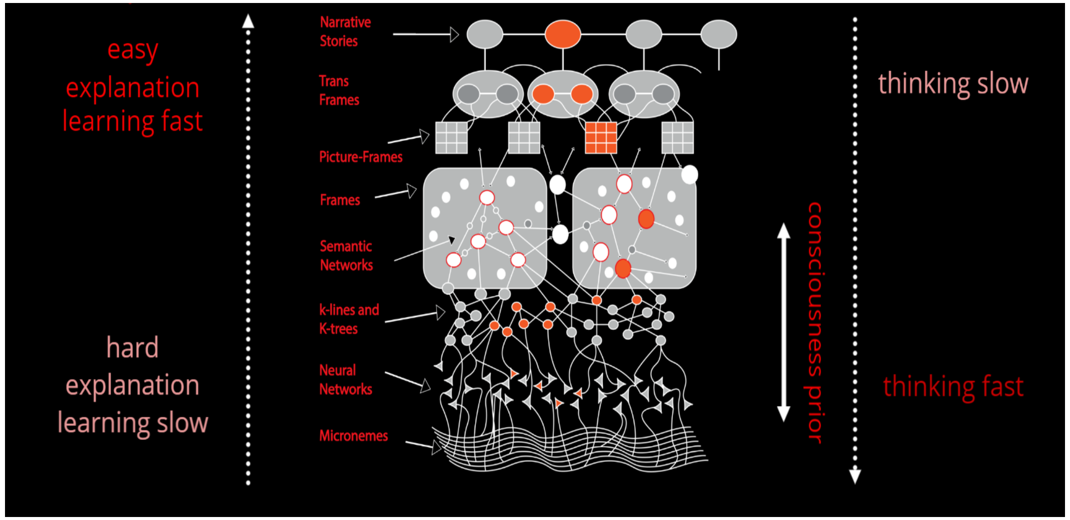
Yoshua Bengio
NeurIPS Keynote, 2019



From system 1 DL to system 2 DL

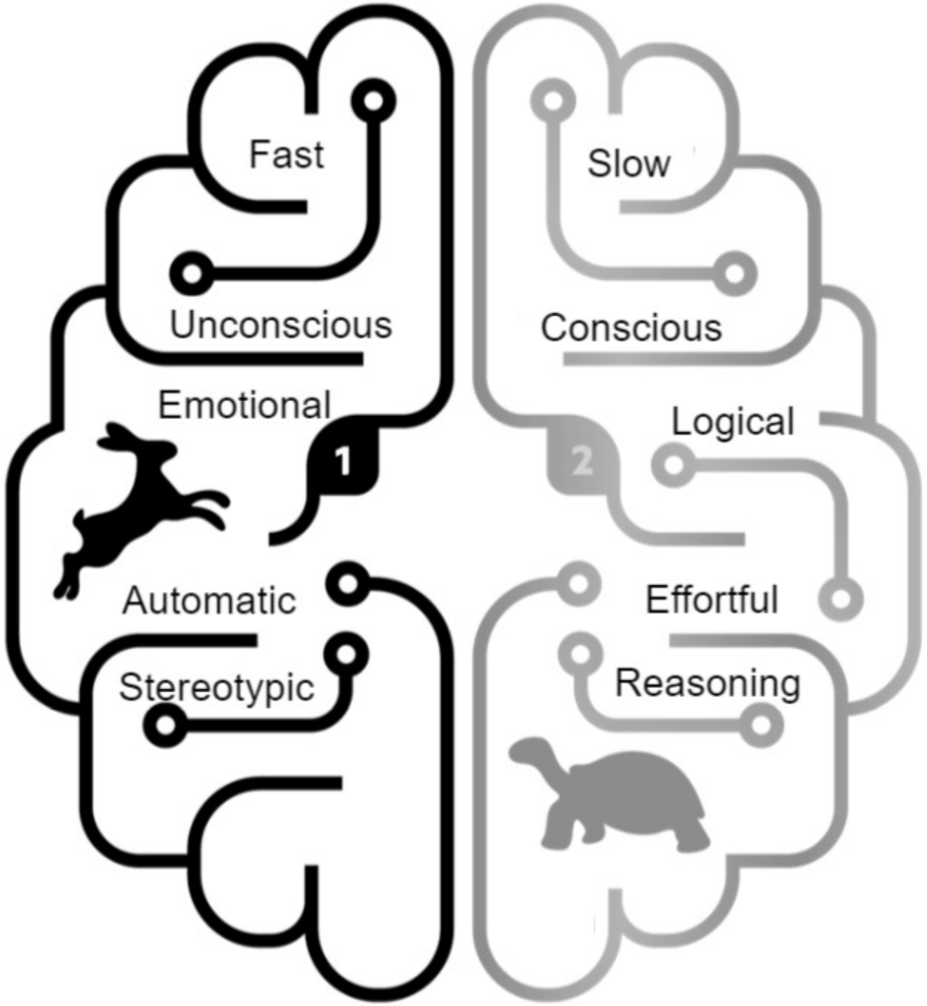


Marvin Minsky
The Society of Mind, 1986



Framework for representing knowledge

Cognitive Theory



Knowledge Graph Perspective

Neural (system1) are

- Powerful for some problems
- Robust to data noise
- Hard to understand or explain
- Poor at symbol manipulation
- Unclear how to effectively use background knowledge

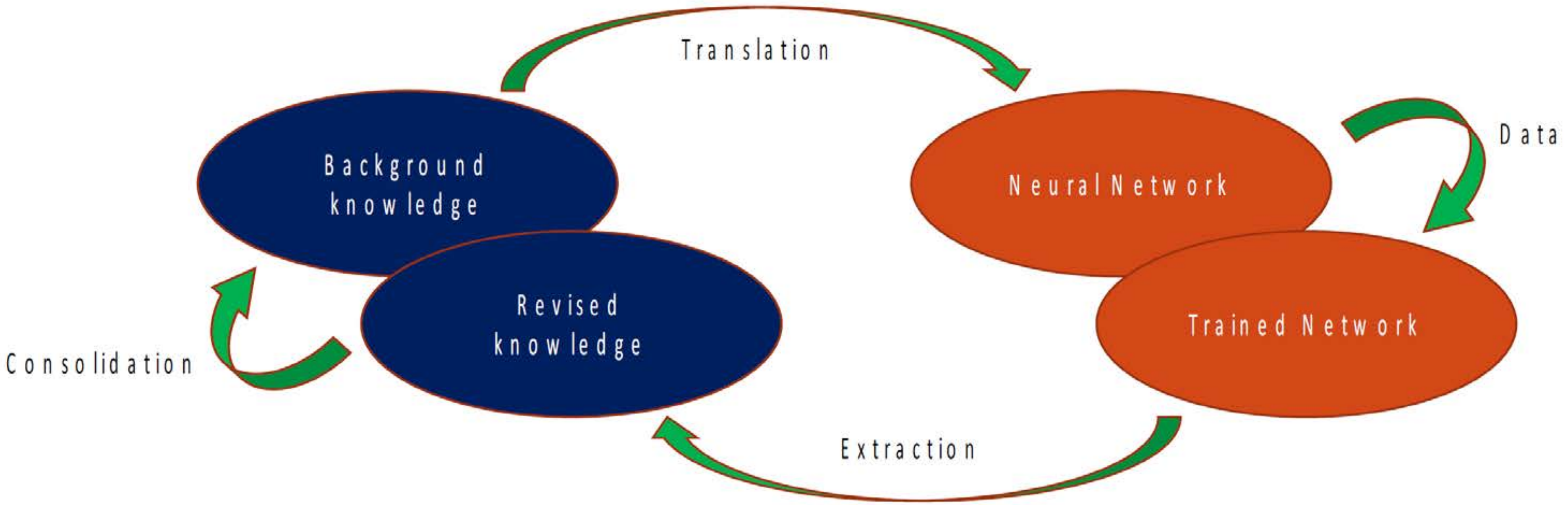
Symbolic (system2) are

- Usually poor regarding machine learning problems
- Intolerant to data noise
- Easy to understand and assess by a human
- Good at symbol manipulation
- Designed to work with background knowledge

Neural + Symbolic:

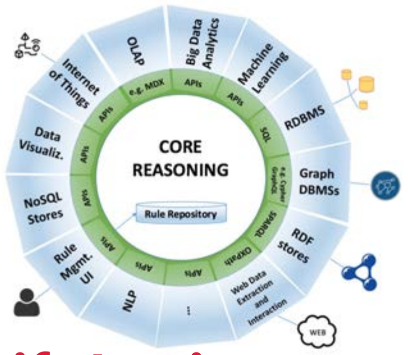
- powerful machine learning paradigm
- robust to data noise
- easy to understand and assess by humans
- good at symbol manipulation
- work seamlessly with background knowledge

HOW TO



Artur d'Avila Garcez , Tutorial , IJCAI 2018

Symbolic



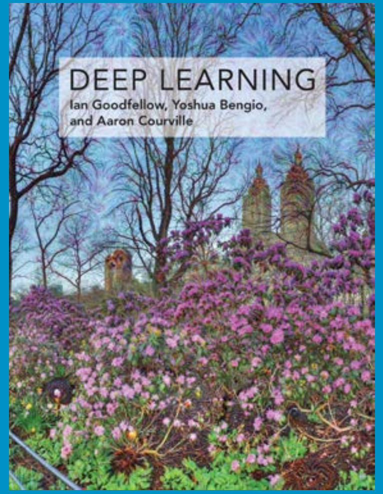
Swift Logic,
Deductive Reasoning with DL

Georg Gottlob, IJCAI 2017

2019-

NAS
Meta-learning
System 2 Deep learning

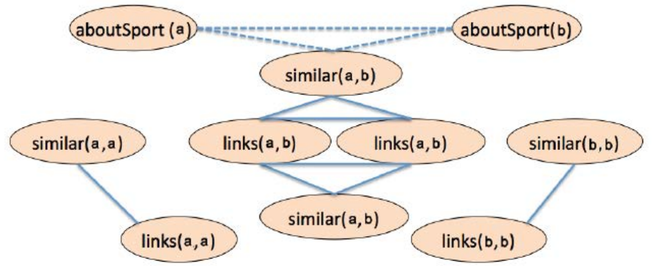
Yoshua Bengio, NeurIPS 2019



2016-2018

R1 2.0 $\forall X,Y\ links(X,Y) \vee links(Y,X) \Rightarrow similar(X,Y)$

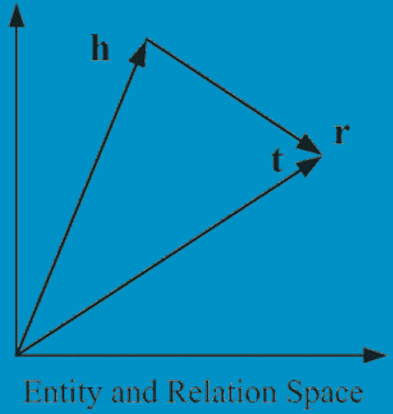
R2 1.5 $\forall X,Y\ similar(X,Y) \Rightarrow (aboutSports(X) \Leftrightarrow aboutSports(Y))$



2013-2017

KG Representation Learning

TransE, TransR, Hole



Markov Logic Network

Pedro Domingos and Matt Richardson

2003-2010

1999-2008

CILP, Relational Learning
Neural-symbolic Integration Challenge

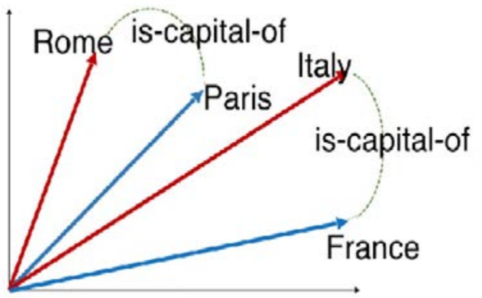
J. of the ACM 2003

Leslie Valiant (Turing Award winner 2010)

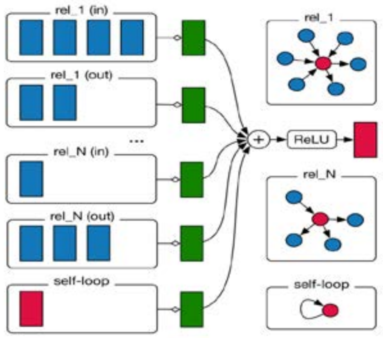
Neural

Applicability of neural methods to Knowledge Graph problems:

KG Embedding

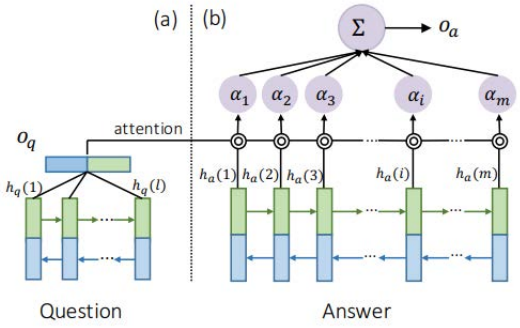


GNN

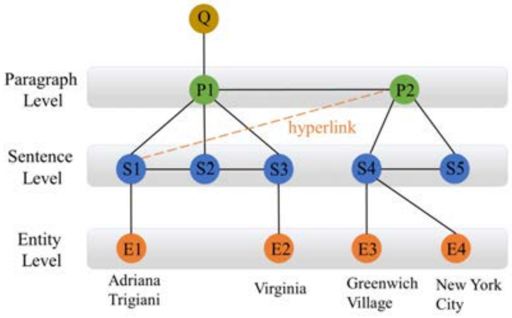


Knowledge Graph Completion[1,2]
(statistical inference, not logical deduction)

RNN+ Attention



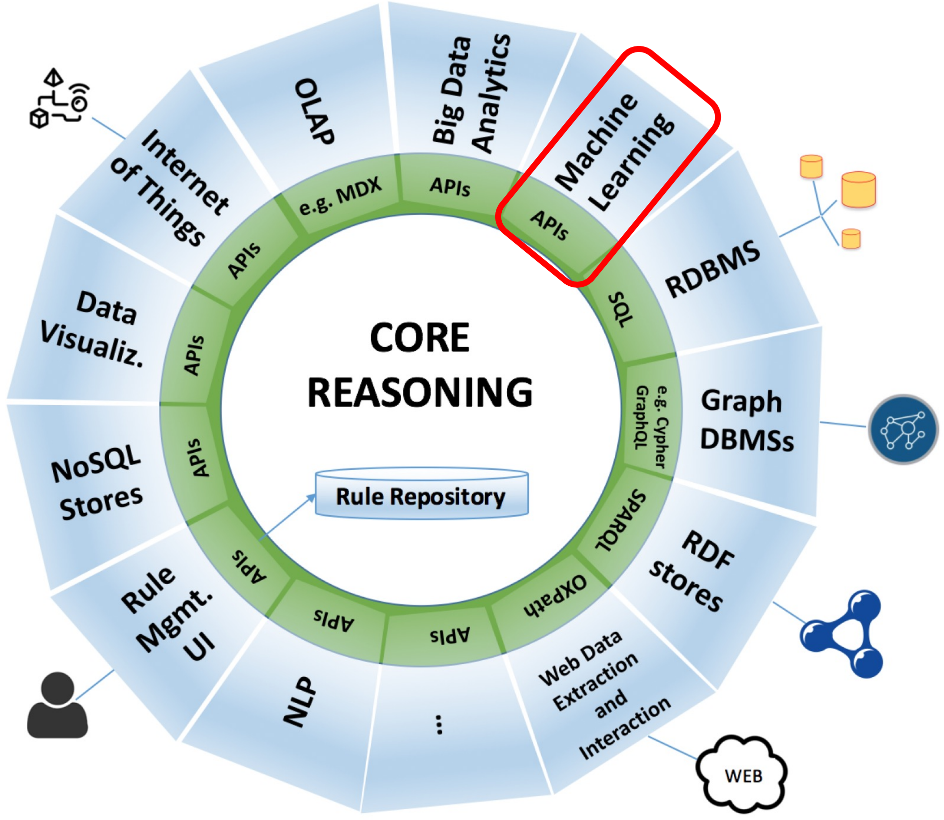
Hierarchical GCN



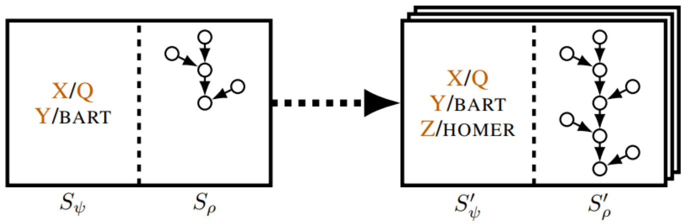
Multi-hop Web Question Answering[3,4]
(shallow reasoning)

1. Wang Q, Mao Z, Wang B, et al. Knowledge graph embedding: A survey of approaches and applications. TKDE, 2017, 29(12): 2724-2743.
2. Zhang M, Chen Y. Link prediction based on graph neural networks. NIPS. 2018: 5165-5175.
3. Jain S. Question answering over knowledge base using factual memory networks. NAACL. 2016: 109-115.
4. Fang Y, Sun S, Gan Z, et al. Hierarchical Graph Network for Multi-hop Question Answering. arXiv preprint arXiv:1911.03631, 2019.

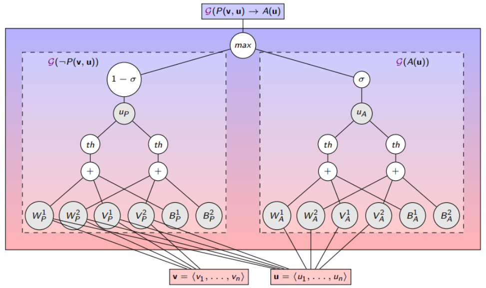
Modification of neural methods so that they fit Knowledge Graph problems:



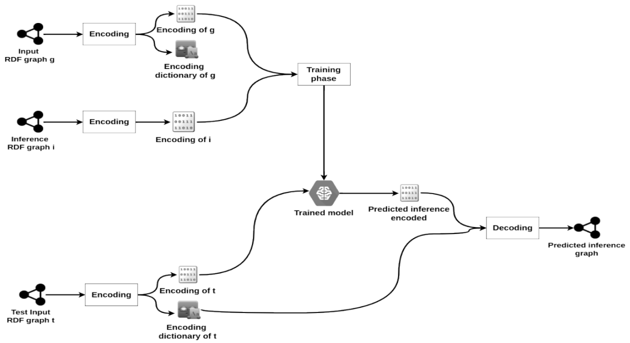
Swift Logic, Georg Gottlob, IJCAI 2017
knowledge graph management system
(statistical learning, not neural method)



Neural Theorem Prover[1]



Relational or Logic Tensor Networks[2]

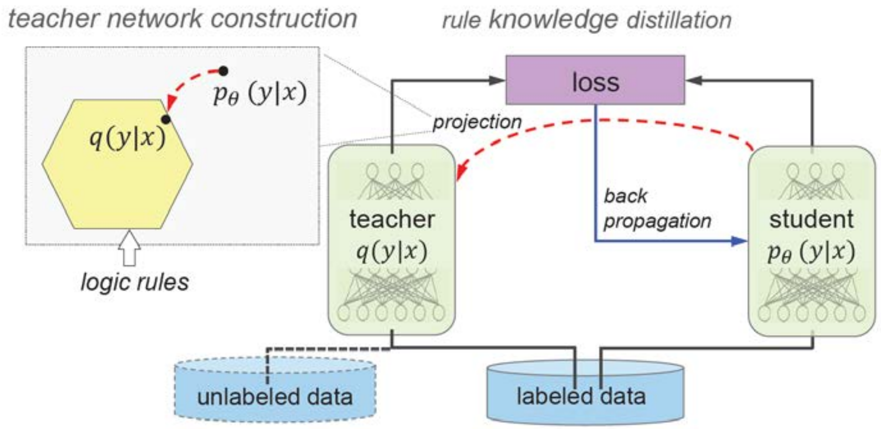


Deep learning for noise-tolerant RDFS reasoning[3]

Deep Reasoning
(specific problem)

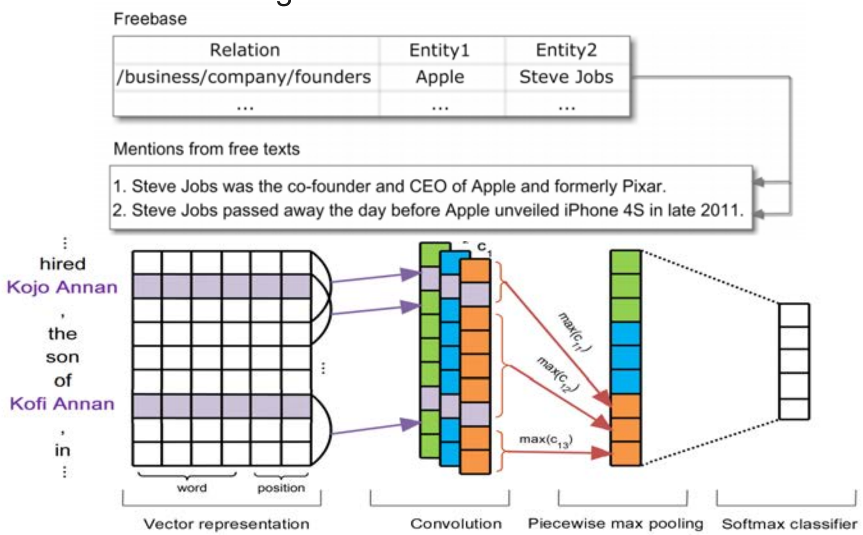
1. Rocktäschel T, Riedel S. End-to-end differentiable proving. NIPS. 2017: 3788-3800.
2. Socher R, Chen D, Manning C D, et al. Reasoning with neural tensor networks for knowledge base completion. NIPS. 2013: 926-934.
3. B. Makni and J. Hendler. Deep learning for noisetolerant rdfs reasoning. Semantic Web, 10(5):823-862, Sept. 2019.

Data curation, reuse, and knowledge transfer for neural network training



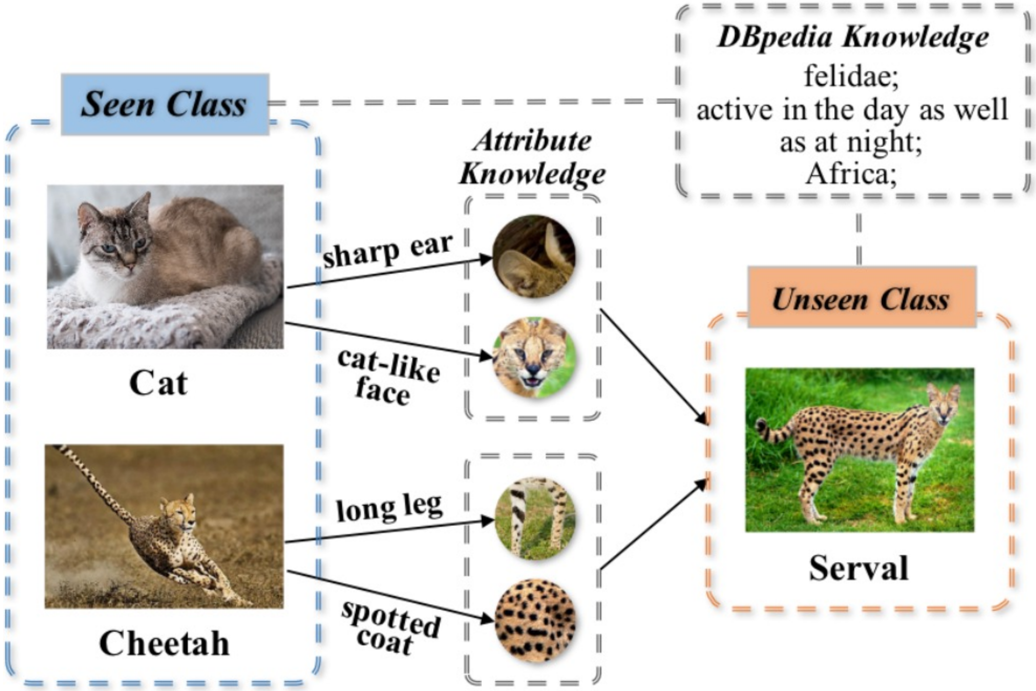
Curation in NNs with Logic Rules

Hu Z, Ma X, Liu Z, et al. Harnessing Deep Neural Networks with Logic Rules. ACL. 2016: 2410-2420.



Data reuse in Distant Supervision

Zeng D, Liu K, Chen Y, et al. Distant supervision for relation extraction via piecewise convolutional neural networks. ACL. 2015: 1753-1762.



Few-shot，one-shot, zero-shot learning[1,2]

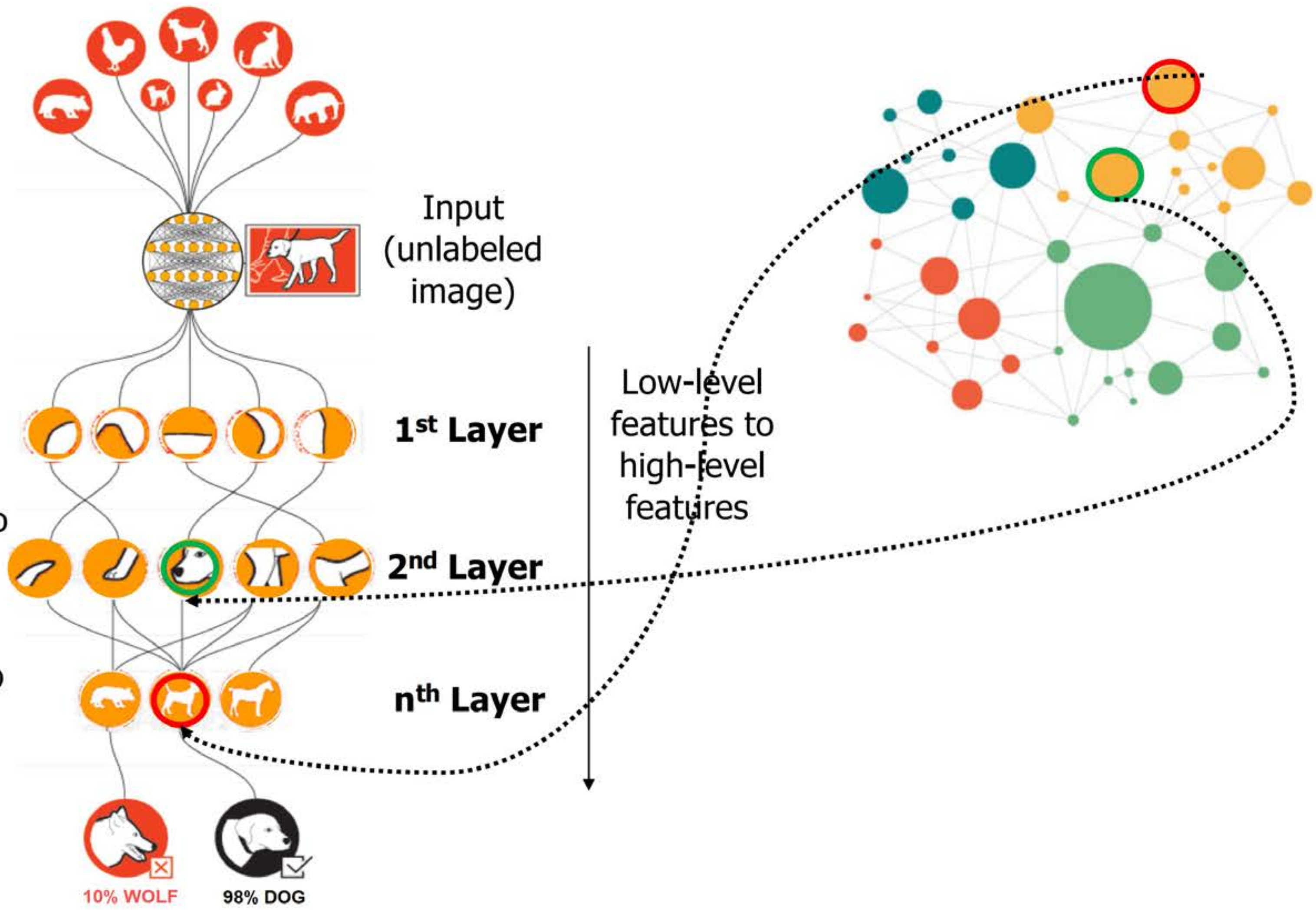
(Not real systematic generalization)

1. 浅谈知识图谱推理技术前沿, 陈华钧, 浙江大学

2. Xiaojun Chang, Mining knowledge graphs for vision tasks, Monash University

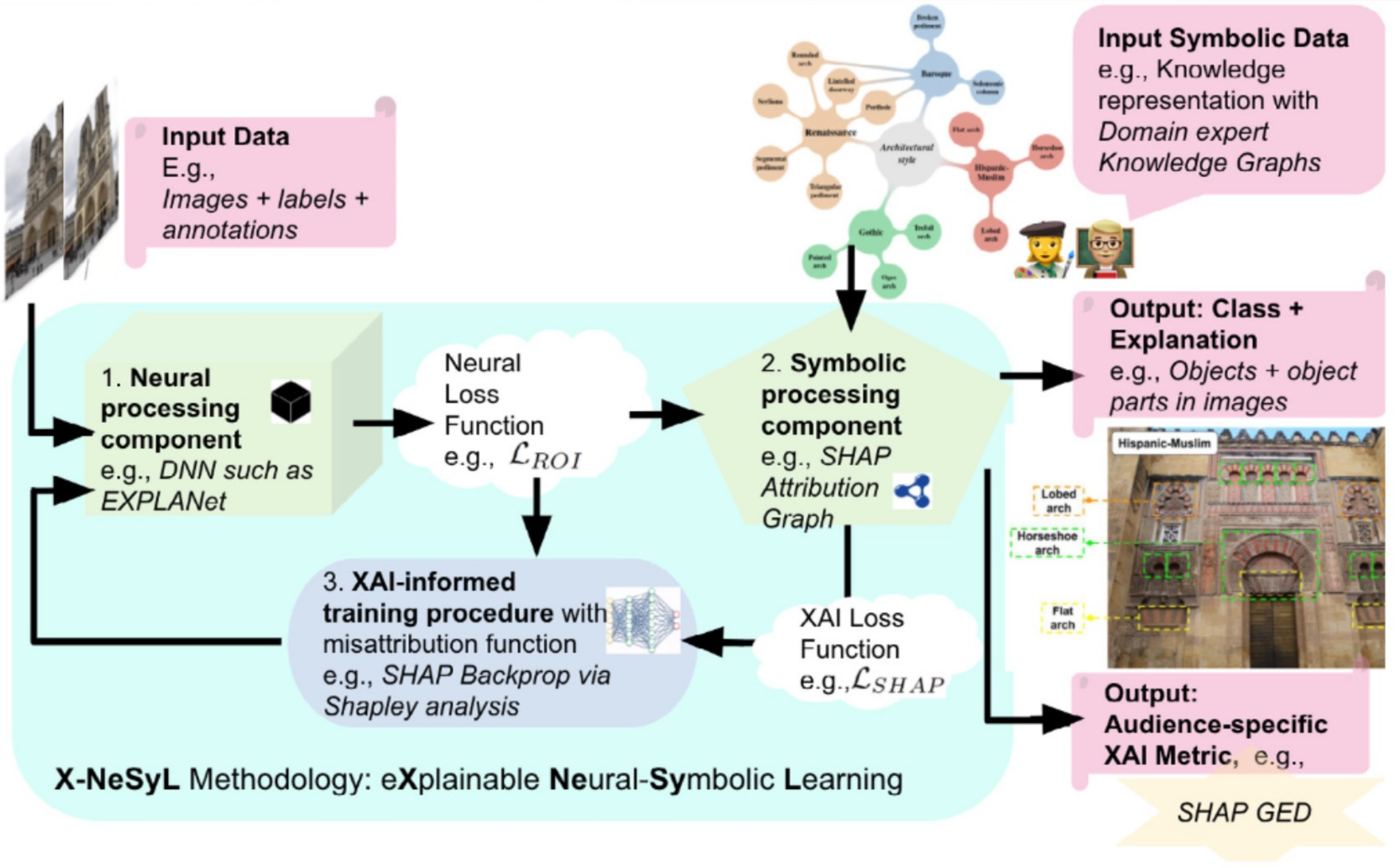
Explain behavior of trained neural networks (Explainable AI)

- Input Layer
- Hidden Layer
- Output Layer



Lecue F. On the role of knowledge graphs in explainable AI. Semantic Web Journal, 2019

Neural-Symbolic Learning



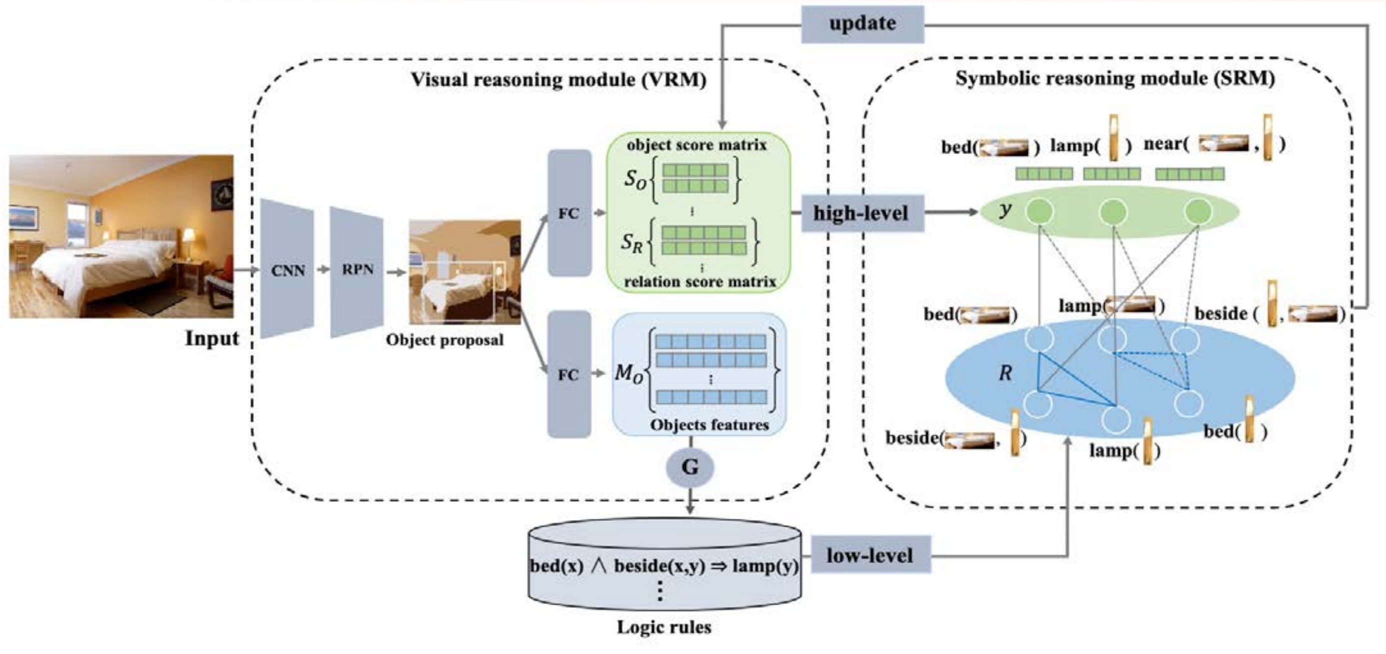
X-NeSyL methodology involves the concrete use of two notions of explanation, both at inference and training time respectively:

(1) EXPLANet :Expert-aligned eXplainable Part-based cLAssifier NETwork Architecture, a compositional convolutional neural network that makes use of symbolic representations.

(2) SHAP-Backprop, an explainable AI-informed training procedure that corrects and guides the DL process to align with such symbolic representations in form of knowledge graphs.

EXplainable Neural-Symbolic Learning (X-NeSyL) methodology to fuse deep learning representations with expert knowledge graphs: The MonuMAI cultural heritage use case. Information Fusion. 2021

Neural-Symbolic Learning



This paper integrates symbolic knowledge into deep learning models and propose a bi-level probabilistic graphical reasoning framework. The **high-level structure** is designed to take reasoning results of **the visual reasoning module**, while the **low-level structure** is the ground atom of **logic rules to correct the error in the high-level structure**, such as correcting "near" to "beside". The model is trained to output reasoning results of the visual reasoning module based on symbolic knowledge

Multi-strategy Question Answering

Knowledge Graph Construction → Knowledge Computing → Knowledge Application

COMMENT

BIOETHICS Growth in genome screening could cause dangerous meddling p.27

EVOLUTION How genes and culture have shaped our ability to cooperate p.29

CHEMISTRY Debating how life got going on the early Earth p.30

EXHIBITION Wildlife paintings from Yukon to Yellowstone p.32

Search needs a shake-up

On the twentieth anniversary of the World Wide Web's public release, **Oren Etzioni** calls on researchers to think outside the keyword box and improve Internet trawling.

Two decades after Internet pioneer Tim Berners Lee introduced his World Wide Web project to the world using the alt.hypertext newsgroup, web search is on the cusp of a profound change — from simple document retrieval to question answering. Instead of poring over long lists of documents that contain requested keywords, users need direct answers to their questions. With sufficient scientific and financial investment, we could soon view today's keyword searching with the same nostalgia and amusement reserved for bygone technologies such as electric typewriters and vinyl records.

But this transformation could be unreasonably delayed. As a community, computer scientists have underinvested in tools that can synthesize sophisticated answers to questions, and have instead focused on incremental progress in lowest-common-denominator search. The classic keyword search box exerts a powerful gravitational pull. Academics and industry researchers need to achieve the intellectual 'escape velocity' necessary to revolutionize search. They must invest much more in bold strategies that can achieve natural-language searching and answering, rather than providing the electronic equivalent of the index at the back of a reference book.

Today, that 'book' is distributed over billions of web pages of uneven quality, and much effort has been directed at ranking the most useful results. Such engines readily index billions of documents, but overwhelm their users with millions of results in response to simple queries. This quandary only worsens as the number of web pages

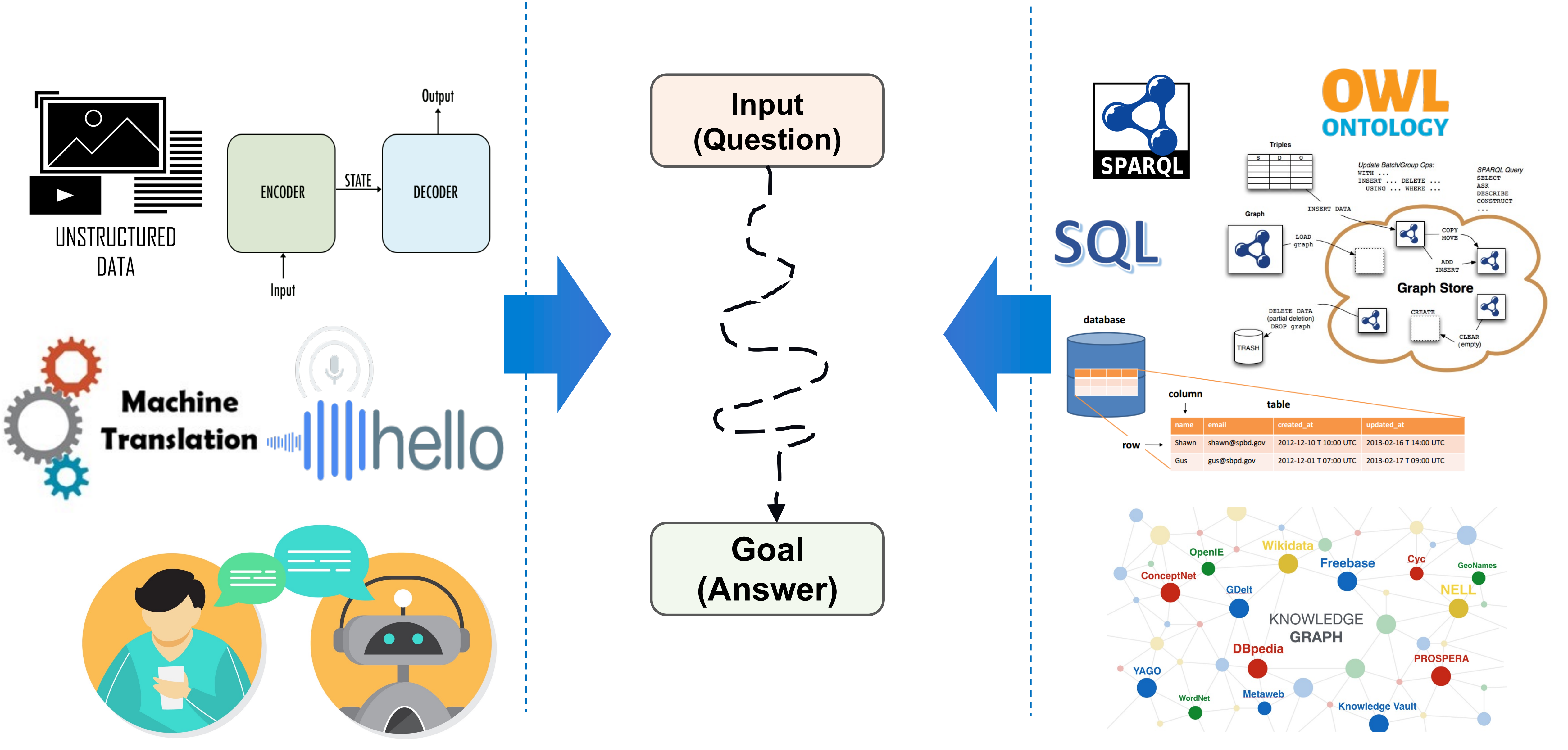
Prof. Oren Etzioni

Turing Center
University of Washington

Question answering (QA) system is the basic form of the next generation search engine.

— 《Nature》 2011.8

Neural (System1) | Symbolic (System2)



History of Question Answering

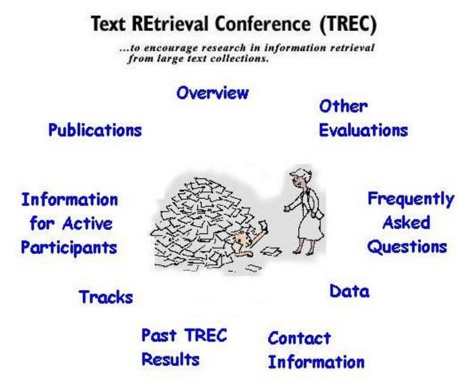
1990
Information retrieval-based QA system

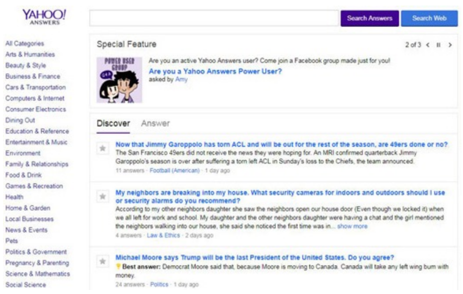
2000
Community-based QA system

2011
QA system becomes the basic form of the next generation search engine

2012
Knowledge graph based search engine

2020
Multi-strategy Question Answering





WolframAlpha

Targets & Requirements for QA

High usability

Supporting natural language queries.

High query expressivity

Path, conjunctions, disjunctions, aggregations, conditions.

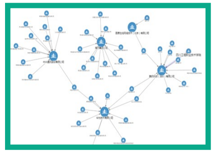
Accurate & comprehensive semantic matching

High precision and recall.

Technologies & Methods for QA

Question Answering

IRQA：QA based on information retrieval



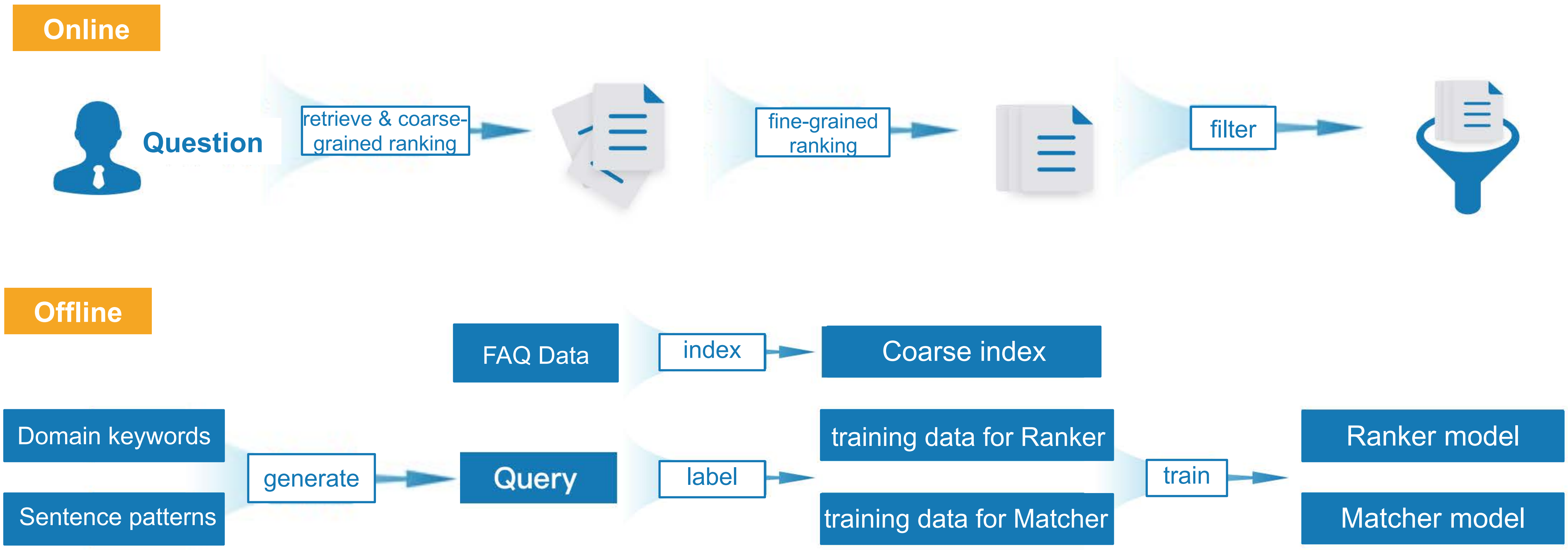
Knowledge Graph

KBQA：QA based on knowledge base

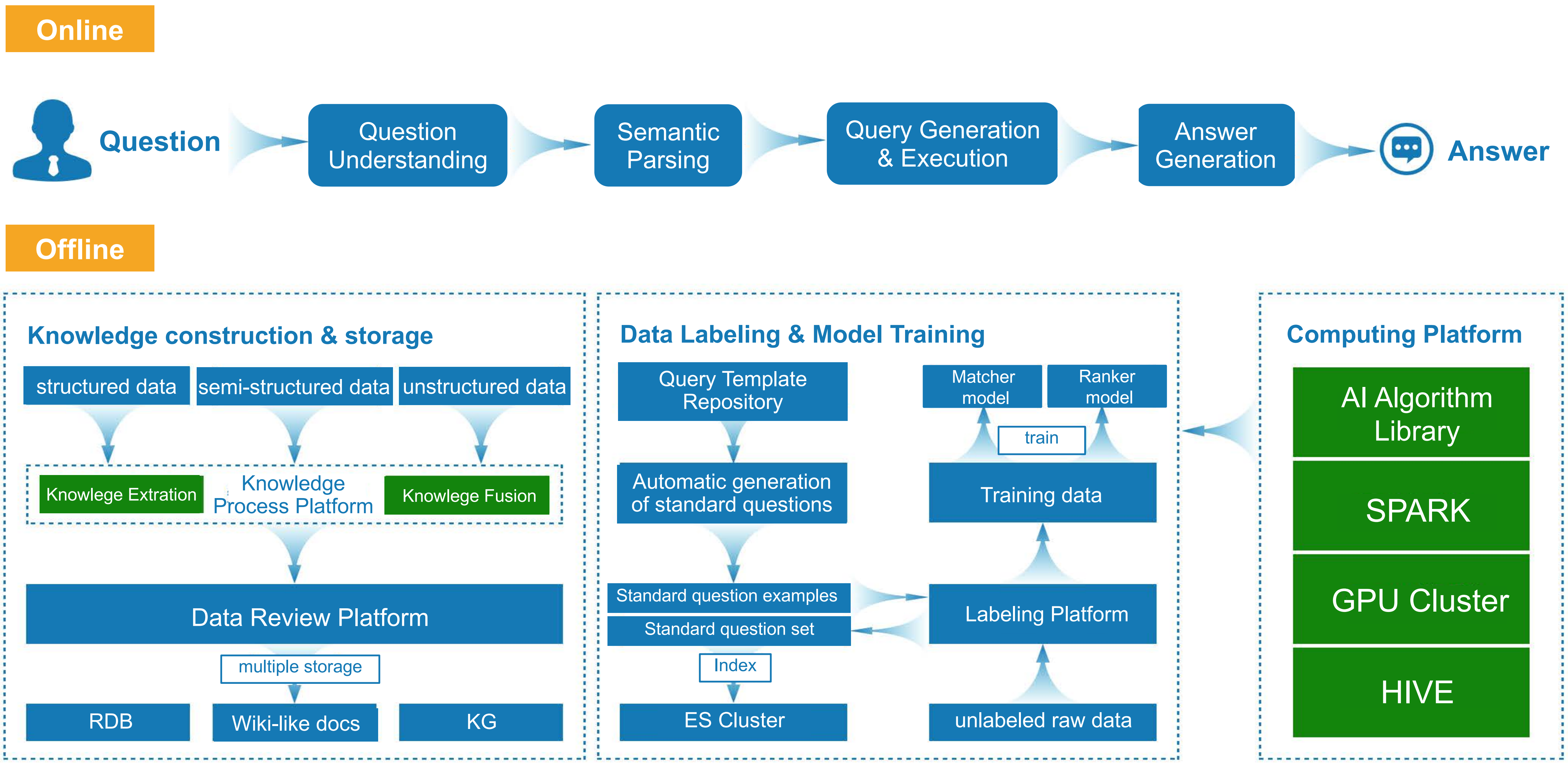
Text

MRCQA: QA based on reading comprehension

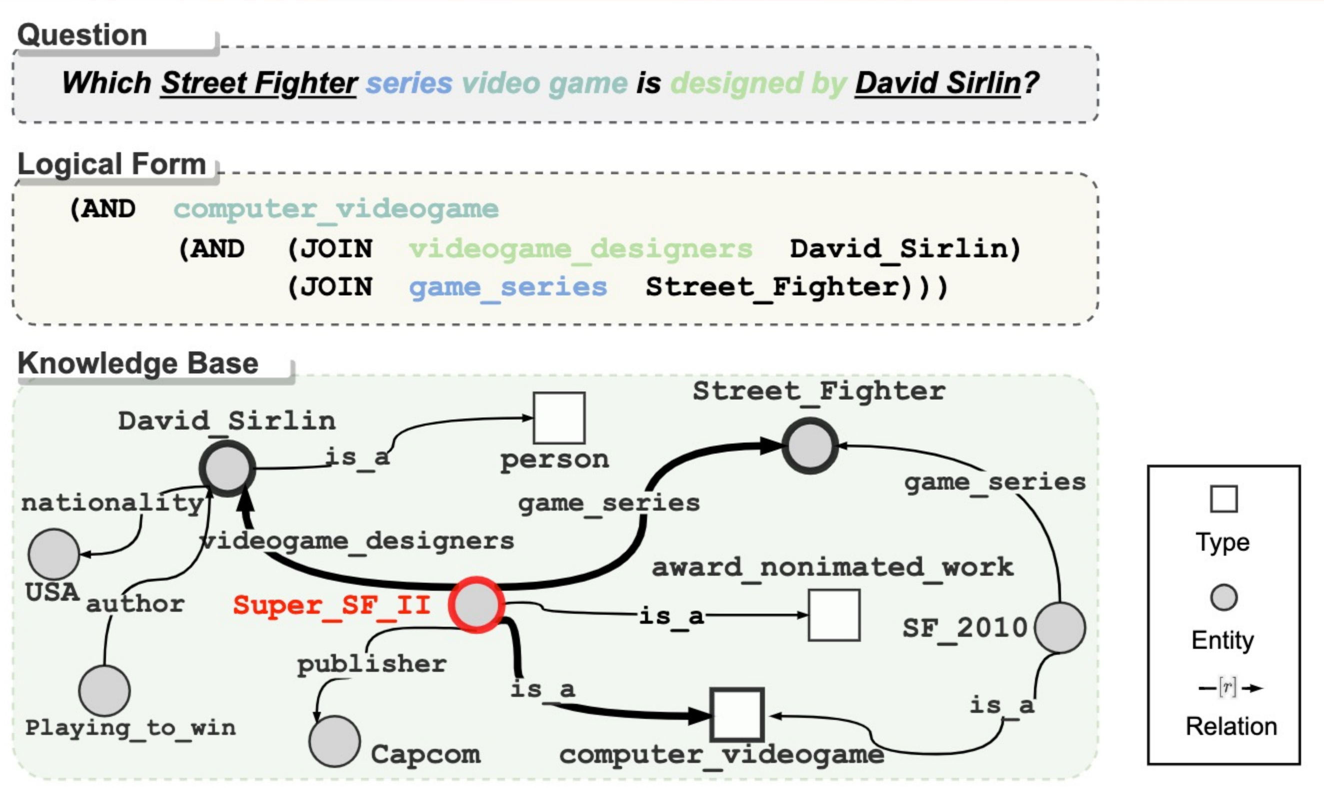
Architecture of IRQA



Architecture of KBQA



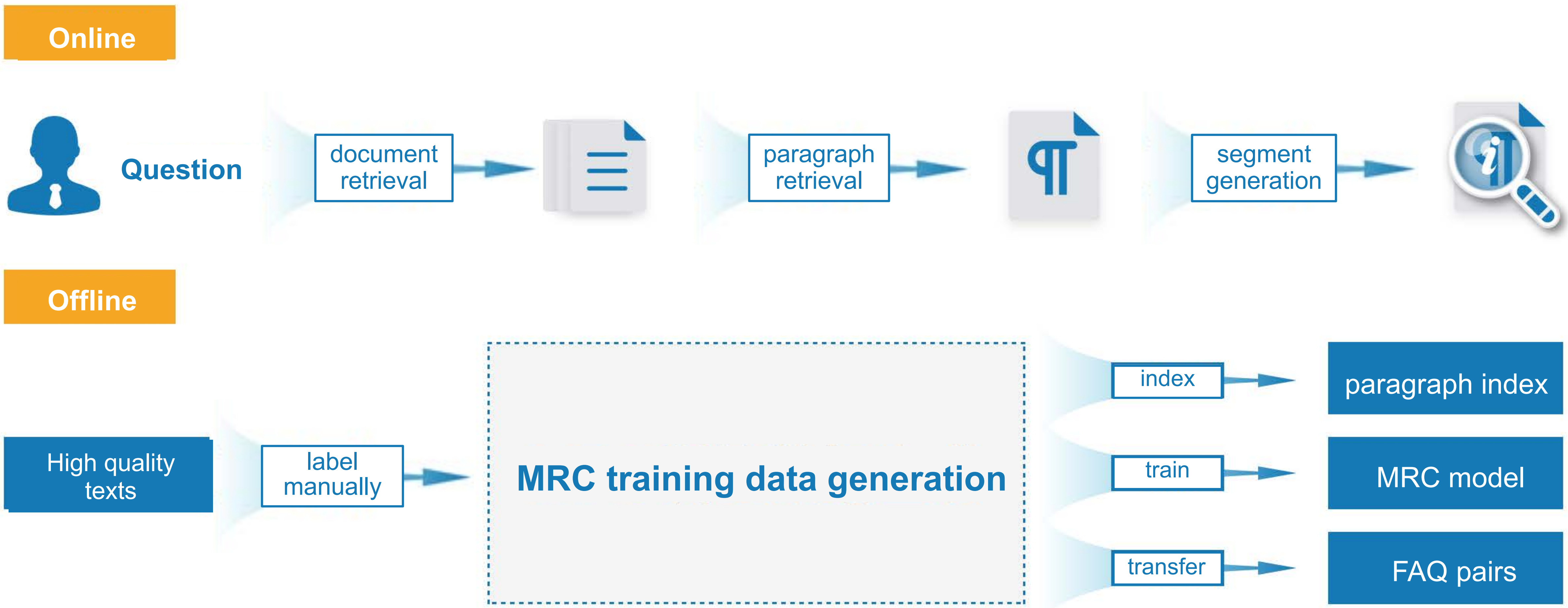
Knowledge Graph Based Question Answering



Most state-of-the-art approaches to KBQA are based on semantic parsing, i.e., **a question is translated into a logical form** , which is then executed over the KB to retrieve the answer .

Knowledge Base Question Answering: A Semantic Parsing Perspective. arXiv 2022

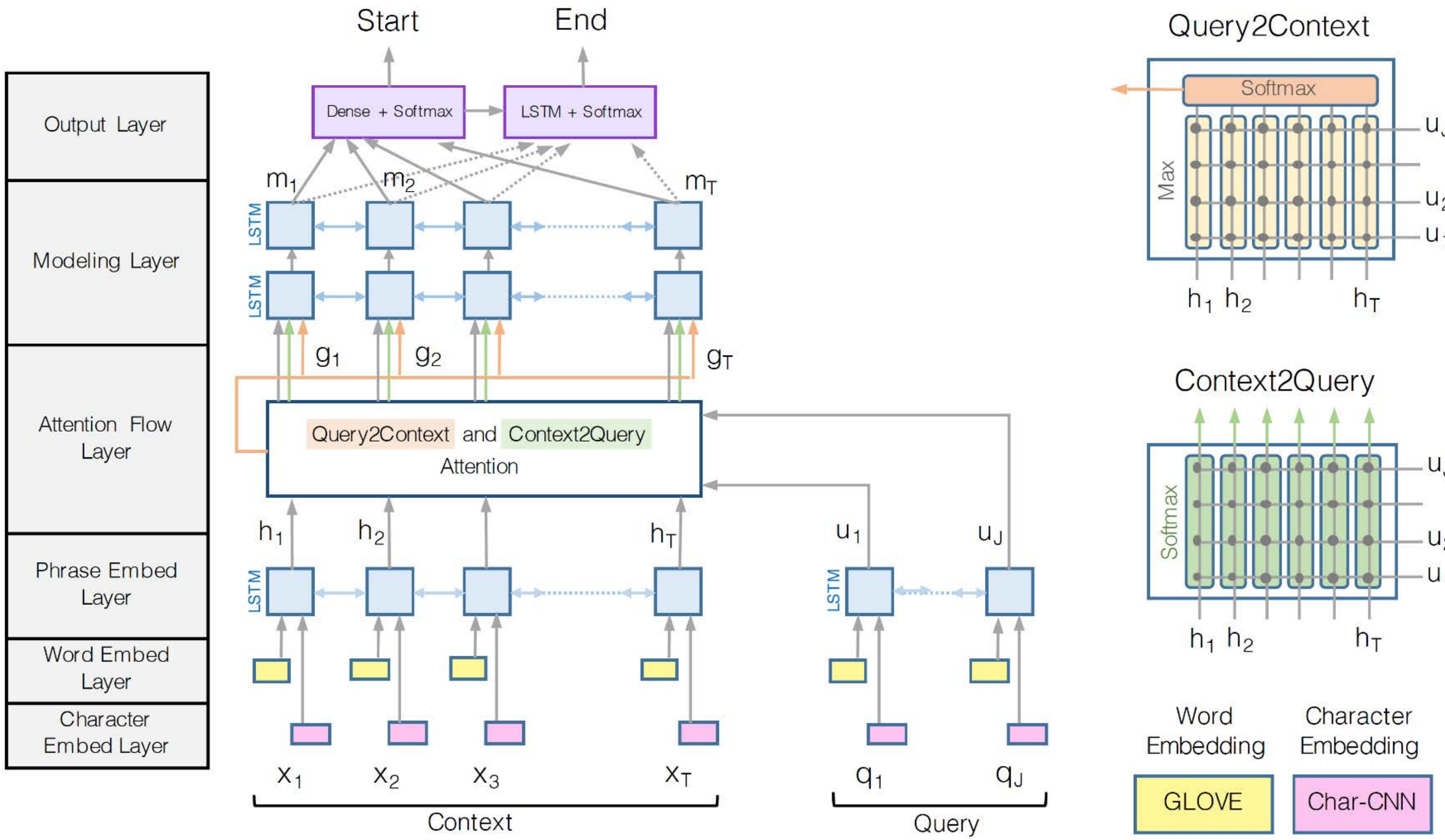
Architecture of MRCQA



A Typical MRC Type & Model

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

What causes precipitation to fall?
gravity



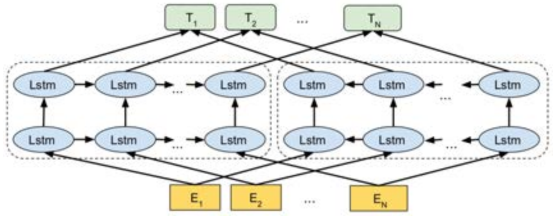
Extraction based question answer

Answer span (start, end)

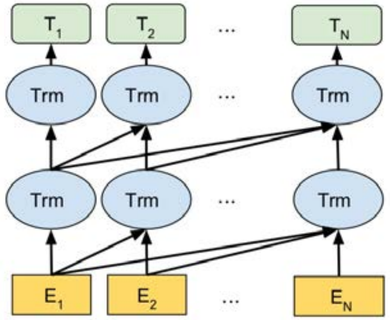
Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, Hannaneh Hajishirzi. Bidirectional Attention Flow for Machine Comprehension.

With Pre-trained Language Model

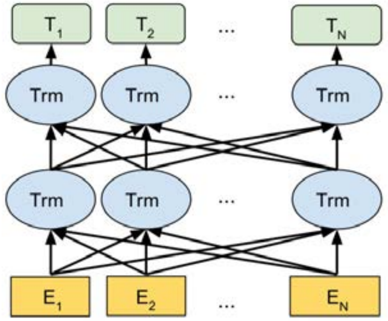
glove/word2vec table → Pre-trained ELMo model → Pre-trained OpenAI GPT → Pre-trained BERT



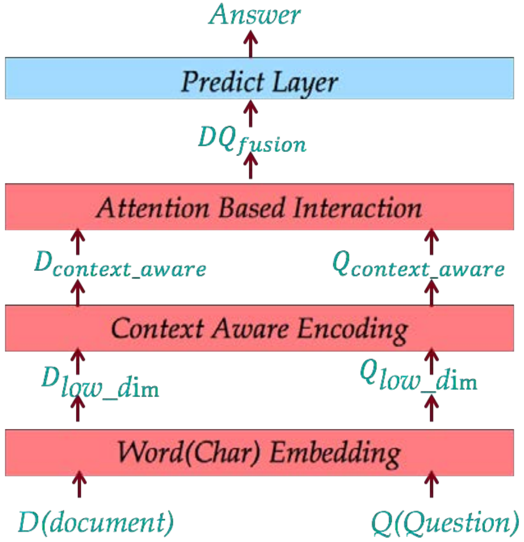
LSTM
L-R, R-L

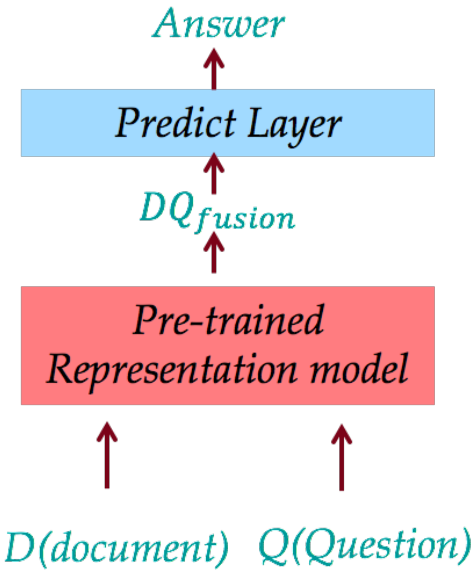


Transformer
L-R



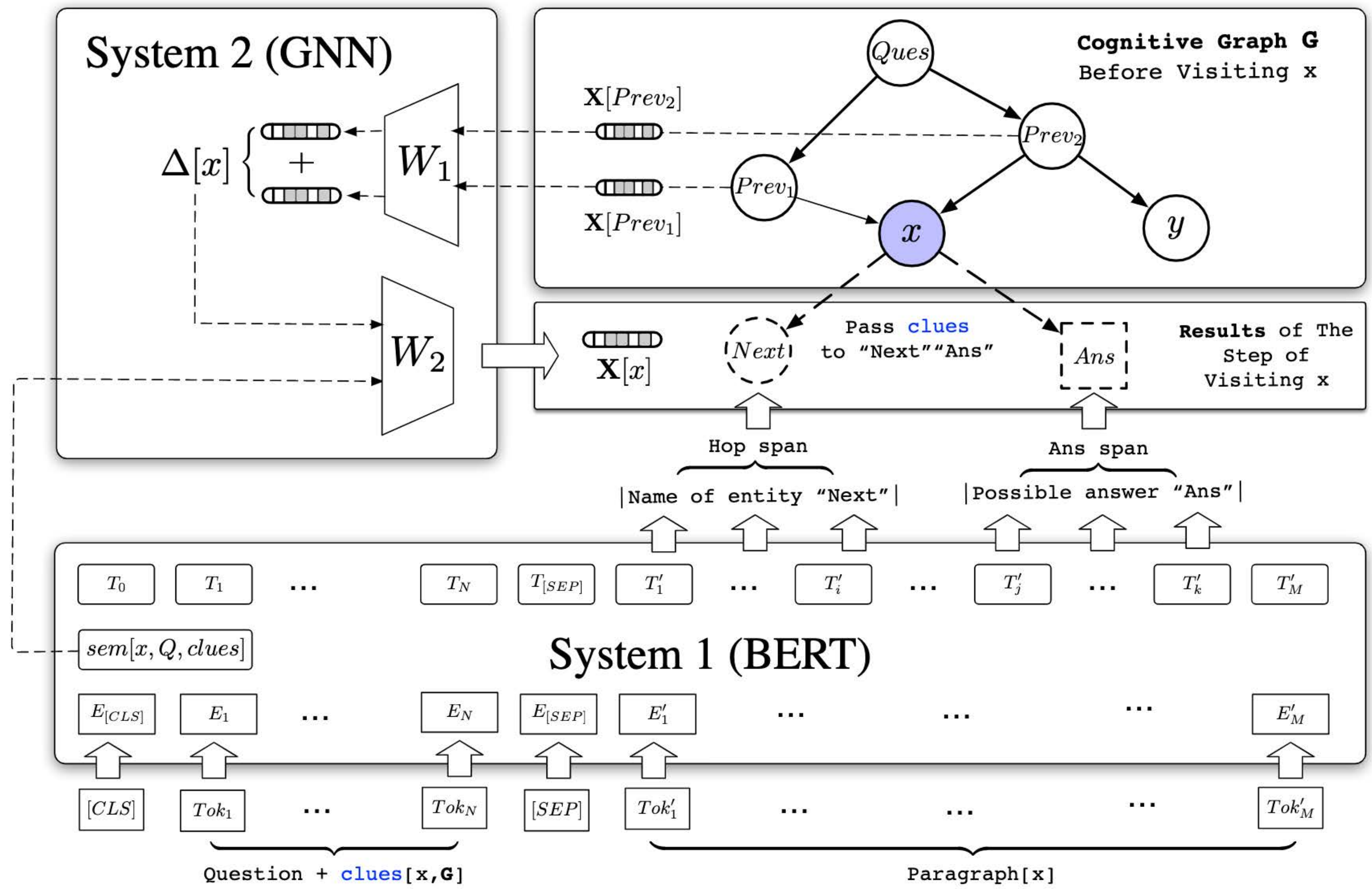
Transformer
L-R, R-L





Pre-trained Language Model
Simplifies the whole framework

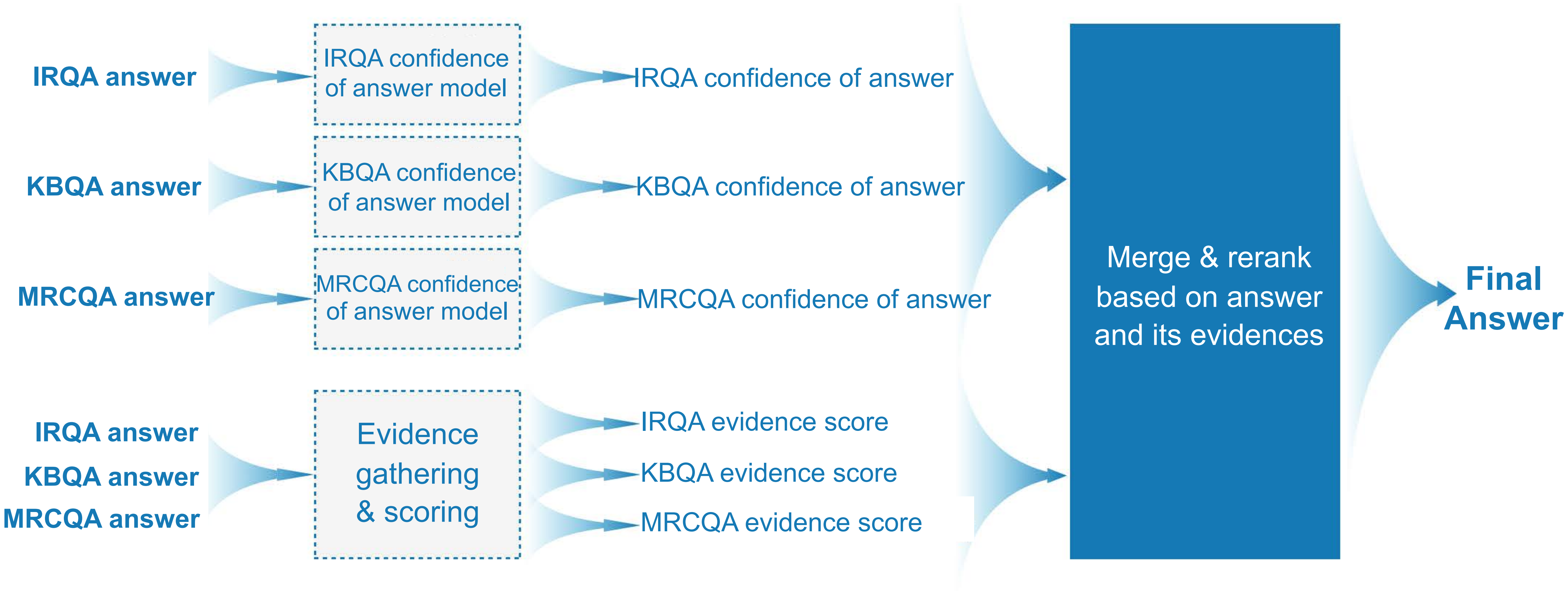
Multi-hop Reading Comprehension — Cognitive Graph



Cognitive Graph QA: Inspired by the dual process theory, the framework comprises functionally different System 1 and 2 modules. **System 1 extracts question-relevant entities and answer** which are organized as a **cognitive graph**. **System 2 then conducts the reasoning procedure over the graph,** and collects clues to guide System 1 to better extract next-hop entities.

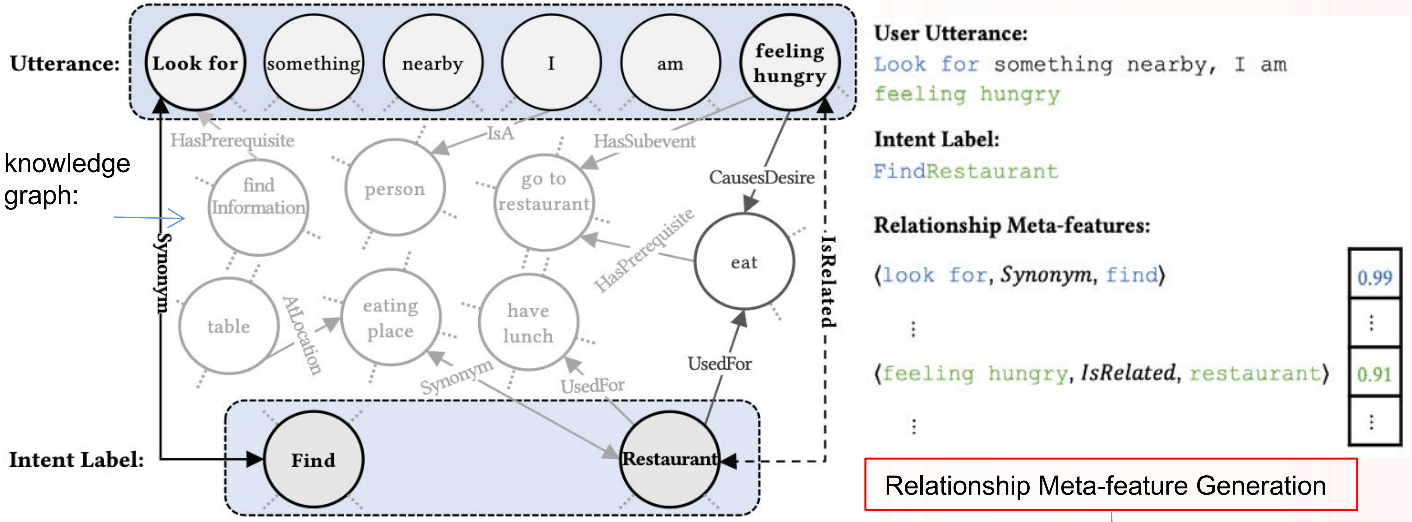
Cognitive Graph for Multi-Hop Reading Comprehension at Scale. ACL 2019

Multi-strategy Question Answering



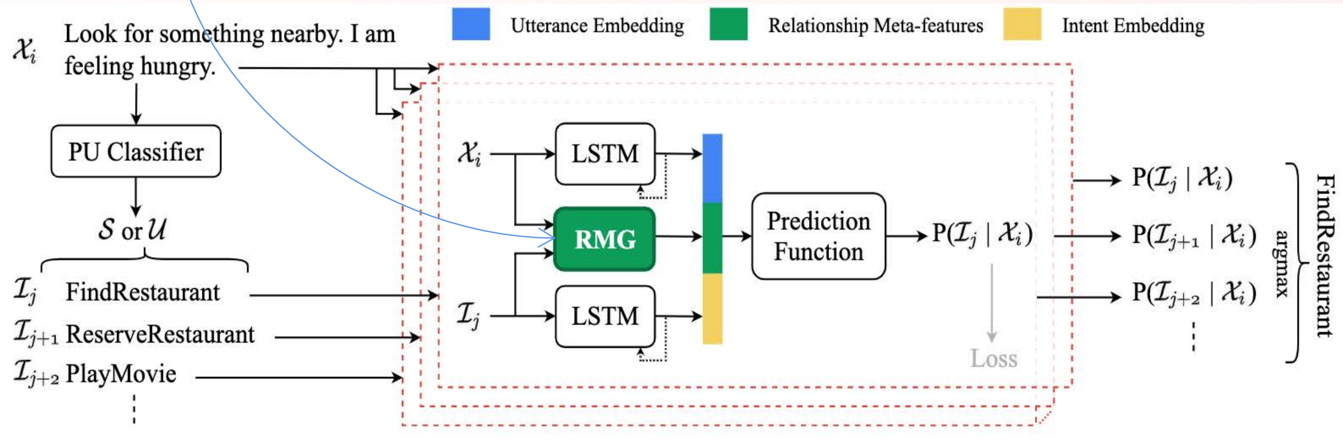
Murdock, J. William, et al. "Textual evidence gathering and analysis." IBM Journal of Research and Development

Knowledge Enhanced Conversational System



Relationship meta-features augment embeddings using commonsense knowledge, which significantly reduces our model's reliance on the scarcely available seen intents training data. Furthermore, these features reduce our model's bias towards seen intents given that they are similarly computed for both seen and unseen intents

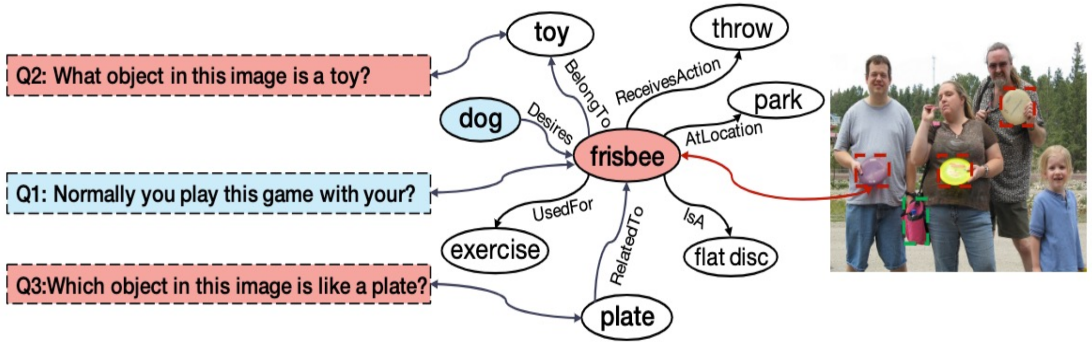
utterance, intent, and computation of relationship meta-features based on knowledge graph

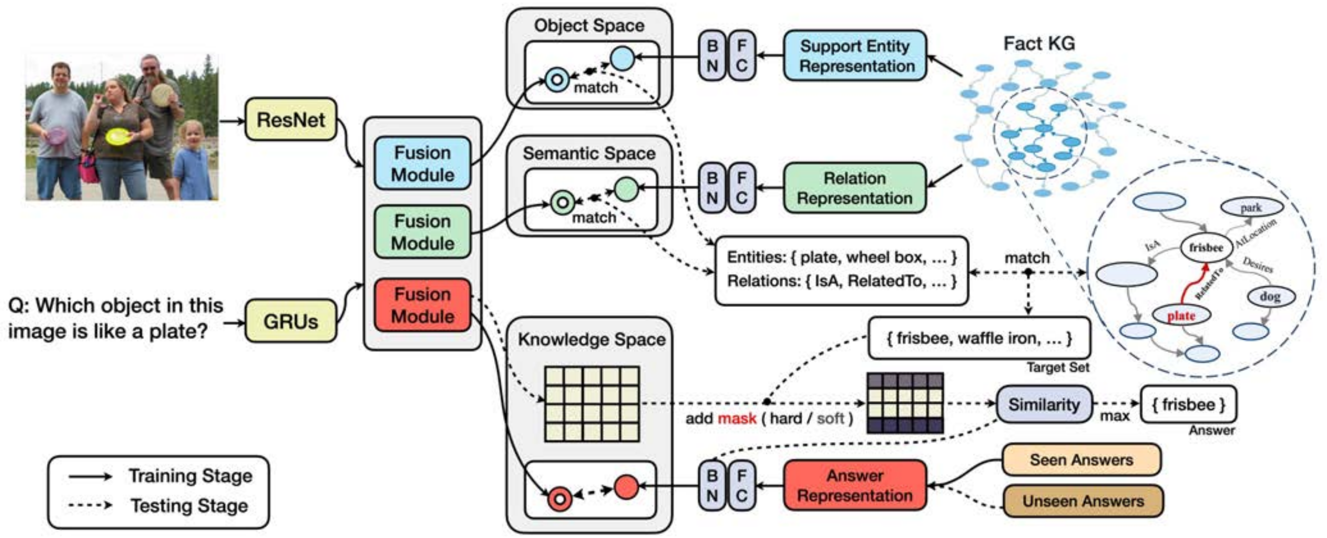


model framework

Generalized zero-shot intent detection via commonsense knowledge. SIGIR 2021

Knowledge Enhanced Visual Question Answering





Q1: the answer **is outside the image and question**
Q2 and Q3: the answers are within the images or questions but **require additional knowledge**.

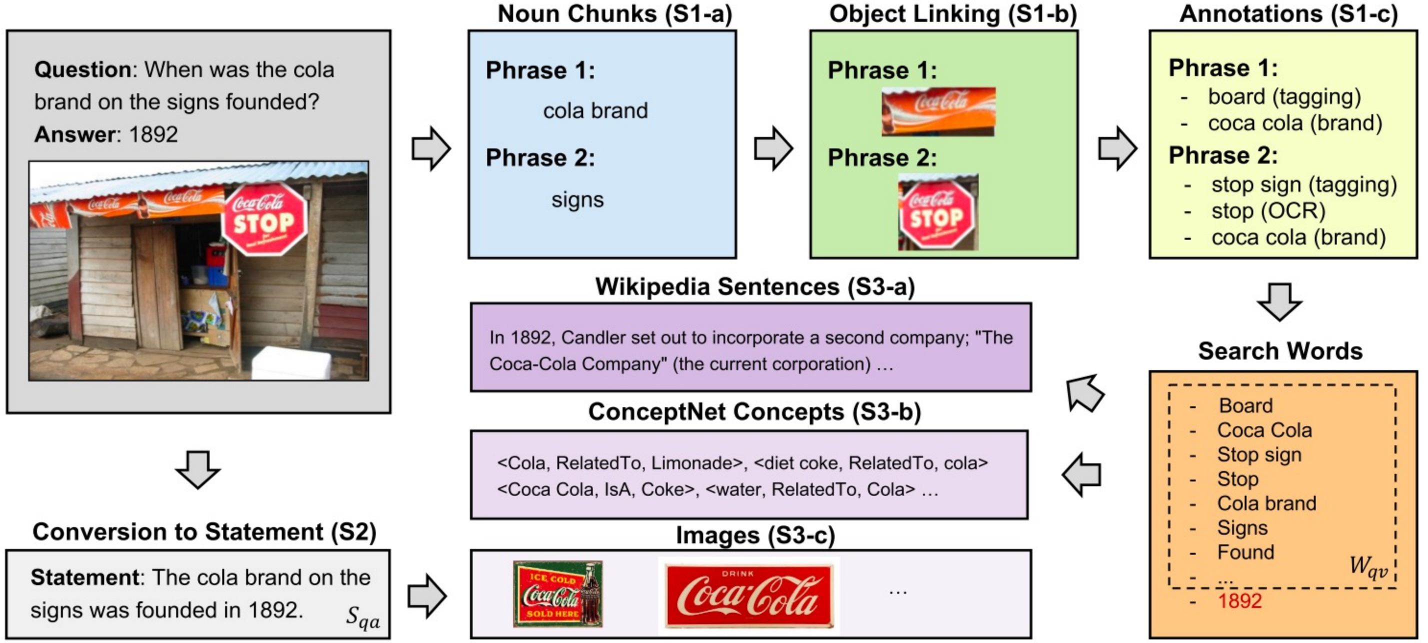
The paper proposes a robust **Zero Shot VQA algorithm using Knowlege Graphs**, which adjusts answer prediction score via masking based on the alignments between supporting entities/relations and fusion Image-Question pair in two feature spaces.

Zero-Shot Visual Question Answering Using Knowledge Graph. ISWC 2021

Knowledge Enhanced Visual Question Answering

Using **more knowledge sources increases the chance of retrieving more irrelevant or noisy facts**, making it challenging to find the answer. To address this challenge, the paper propose Multi-modal Answer Validation using External knowledge, where the idea is to **validate** a set of promising answer **candidates based on answer-specific knowledge retrieval**.

Instead of searching for the answer in a vast collection of often irrelevant facts as most existing approaches do, MAVEx aims to learn how to **extract relevant knowledge from noisy sources**, **which knowledge source to trust** for each answer candidate, and **how to validate** the candidate using that source.



Multi-Modal Answer Validation for Knowledge-Based VQA. AAAI 2022

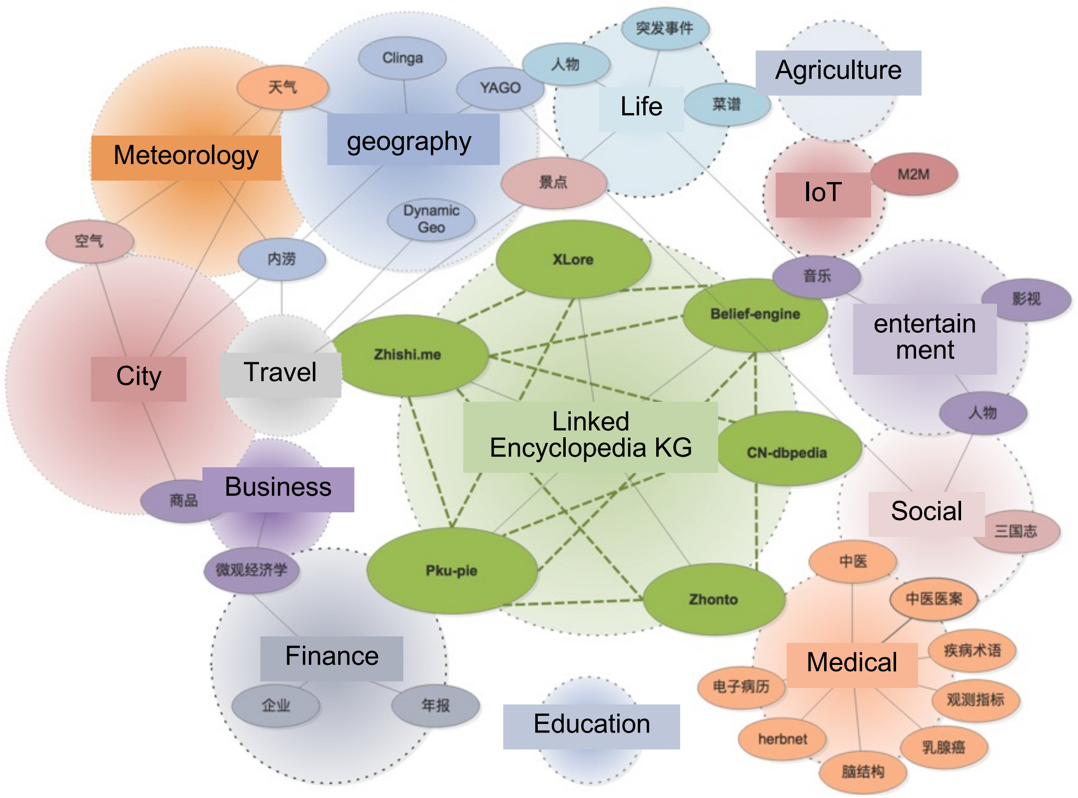
- Knowledge Graph Overview
- Key Technologies
- **Applications**

Open KG community

OpenKG.CN

开放的中文知识图谱

132 Datasets | 56 Tools | 67 Members | 16 Categories | 177 Papers



SUMA QA

Protégé-ontology construction

Deepdive-Knowledge extraction

Simsearch

Tools

FudanDNN-NLP4.2

DeepKE

gStore-Graph database

gAnswer

YodaQA-QA system

Limes-entity linking

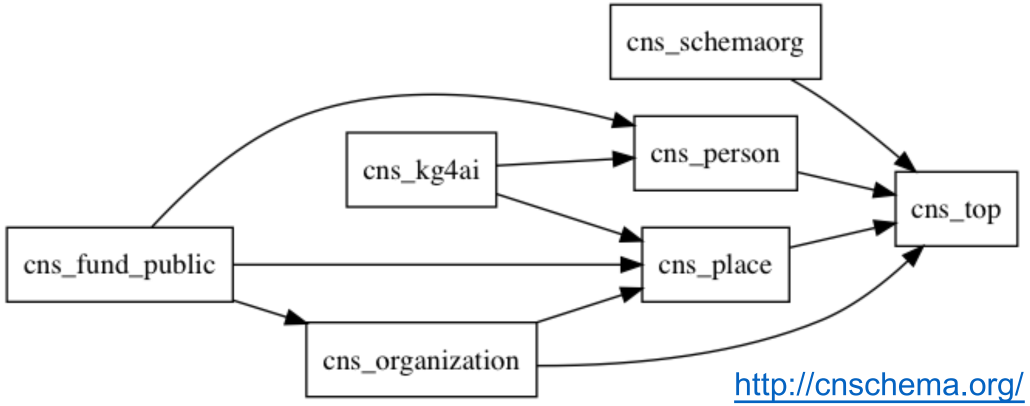
InteractiveGraph

OpenKE

http://www.openkg.cn/

cnSchema

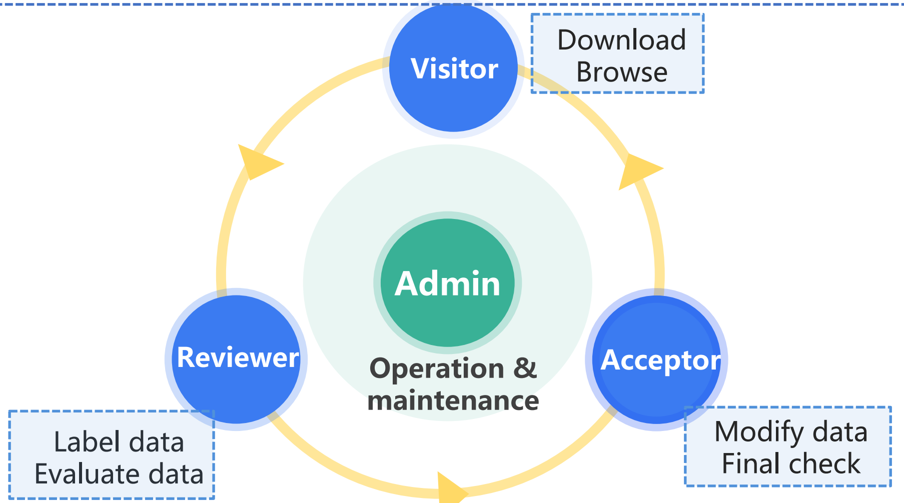
- Inspired by schema.org
- Provide data interface definitions and standards for open Chinese KG
- KGAPI: KG Service, Multi-level KG data index
- KGTOOL: KG data quality verification, schema visualization



http://cnschema.org/

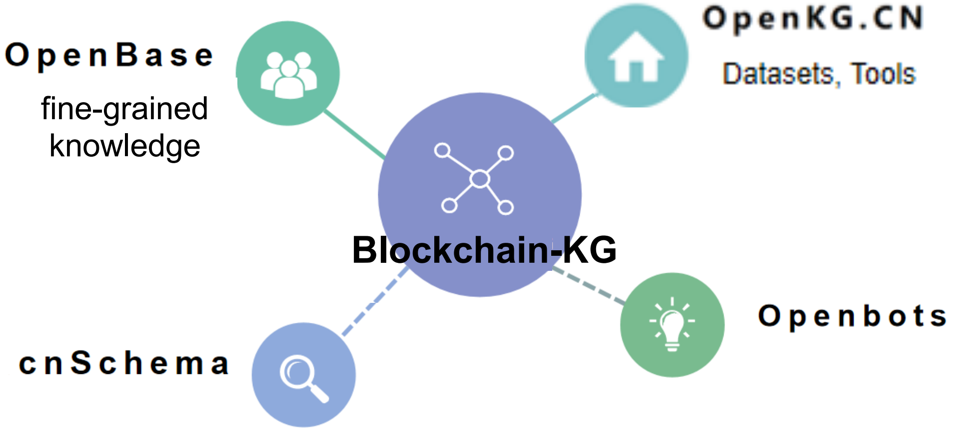
OpenKG.CN
开放的中文知识图谱

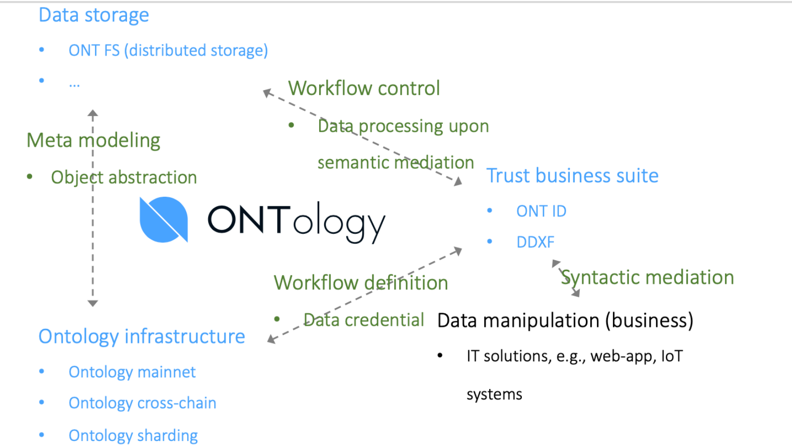
- Crowdsourcing platform for KG
- Follow CC0 data protocol
- Based on cnSchema



http://openbase.openkg.cn/

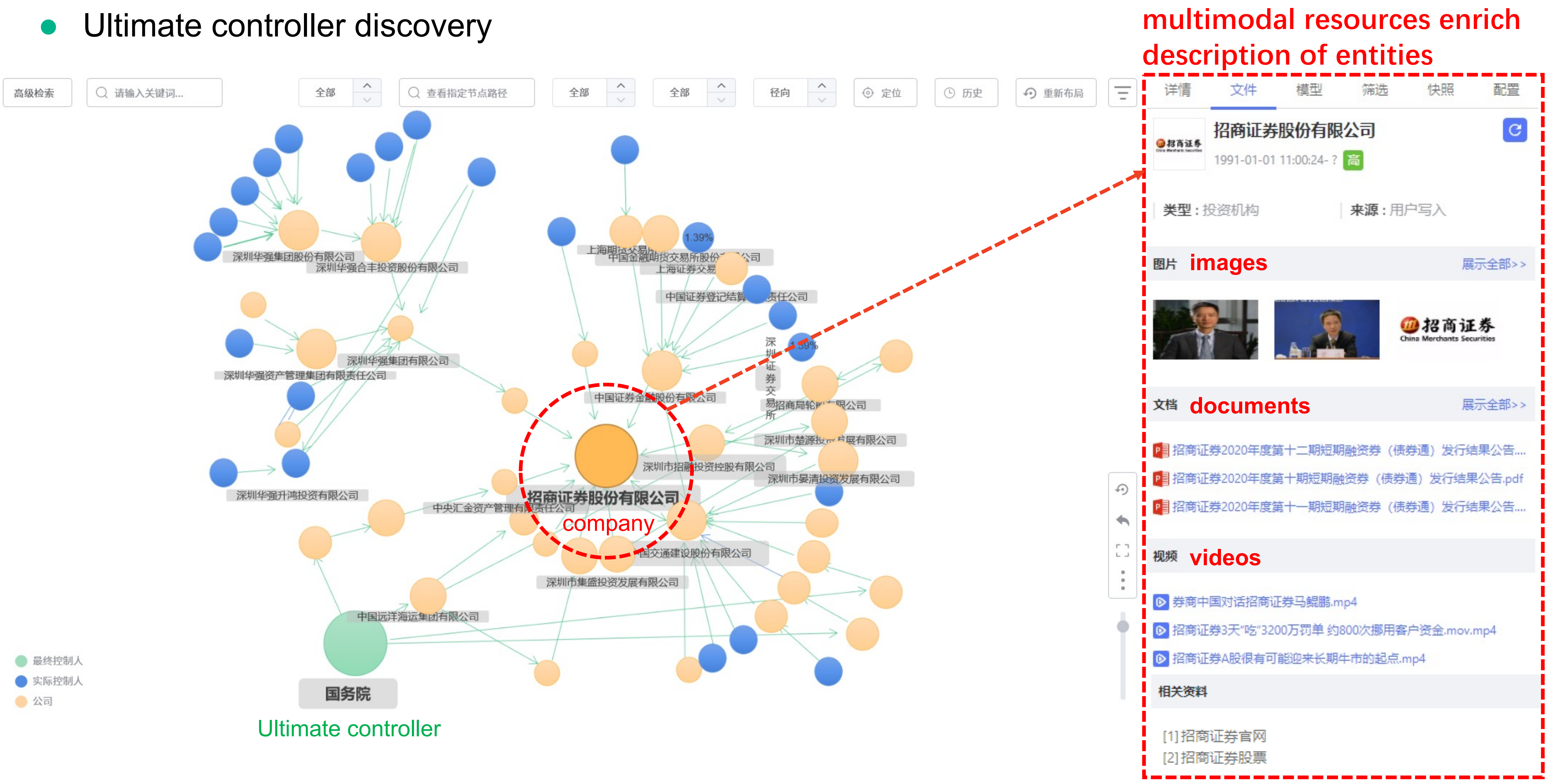
OpenKG Blockchain





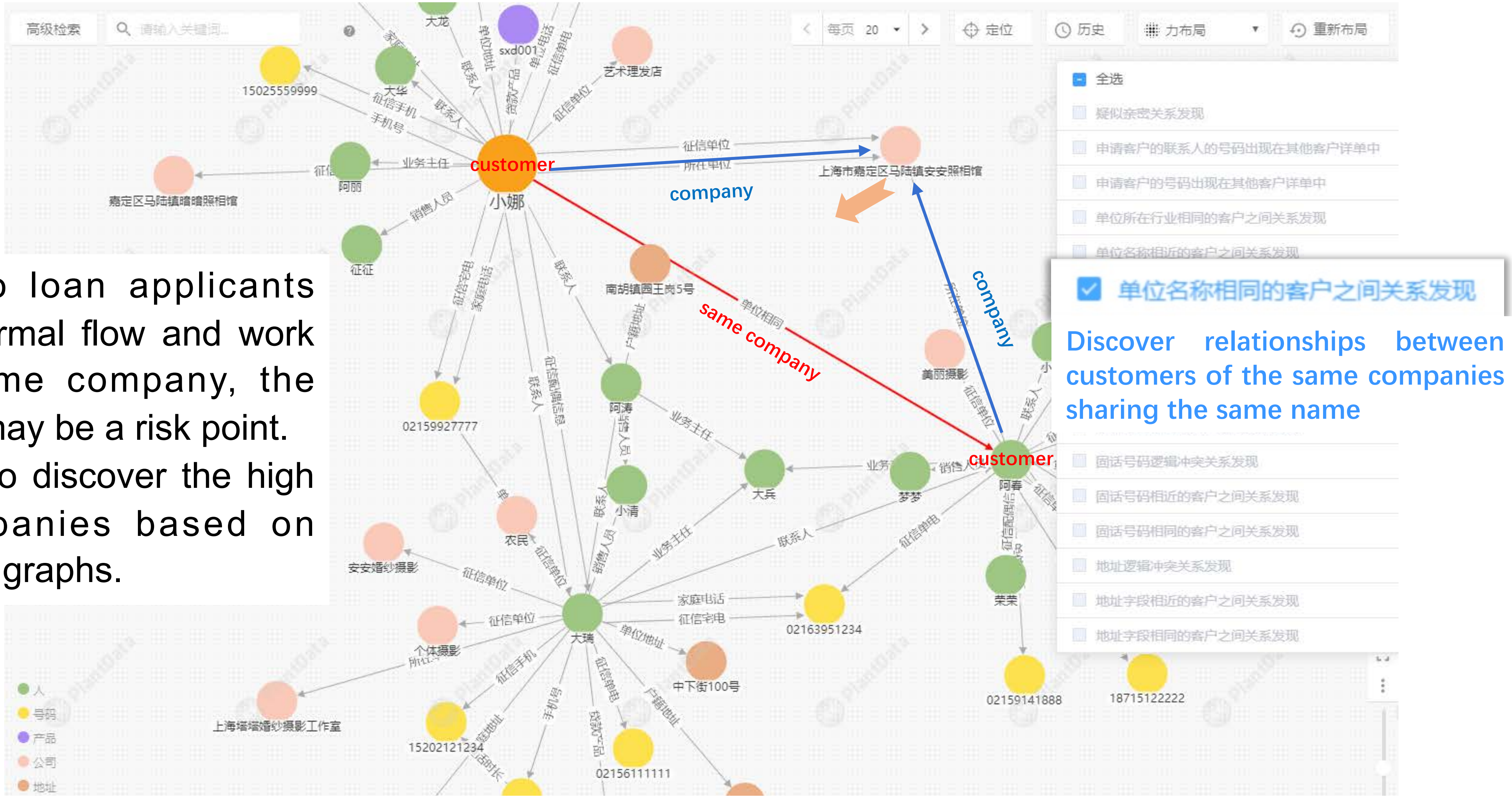
Industry practice - Financial Securities

- Ultimate controller discovery



Industry practice - Financial Securities

- Credit risk control

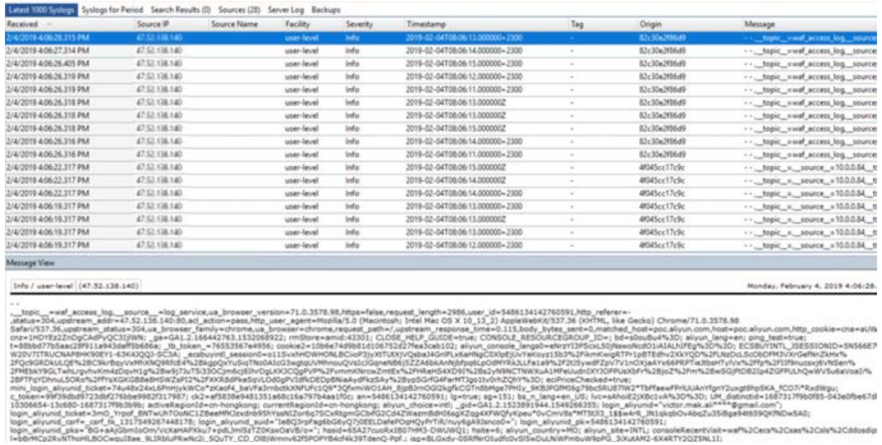


- When two loan applicants have abnormal flow and work in the same company, the company may be a risk point.
- It is easy to discover the high risk companies based on knowledge graphs.

Knowledge graph for operations and maintenance

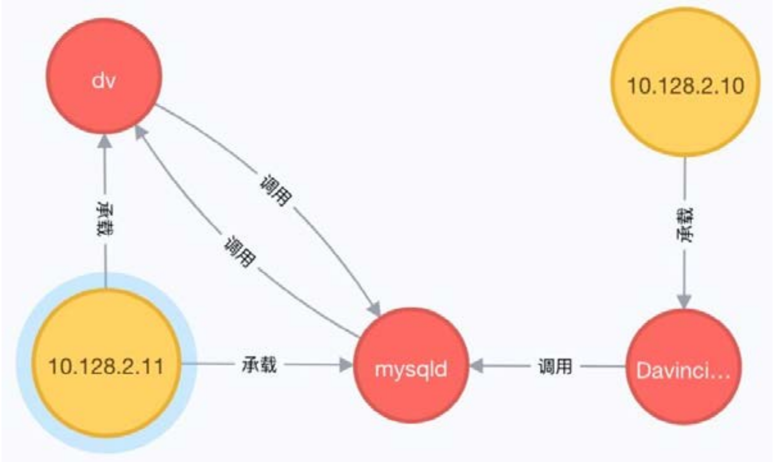
- **System operation data**

Log data, stream data, performance metrics data, network data, user behavior data, monitoring data, tracing information , etc.



- **Software and hardware information**

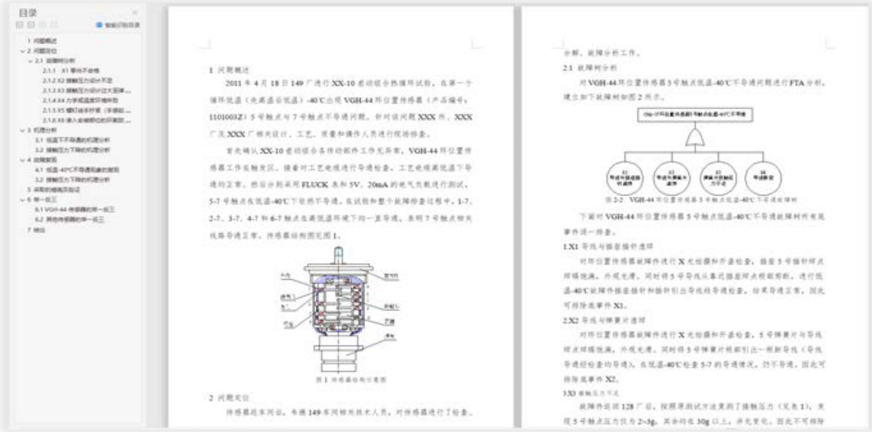
Server, network device, application service, database performance, configuration information, service bearer information, etc.



Sources of knowledge for O&M

- **General hardware and software knowledge**

Manufacturer information, manuals, vendor knowledge base, blogs, Stack Overflow, etc.

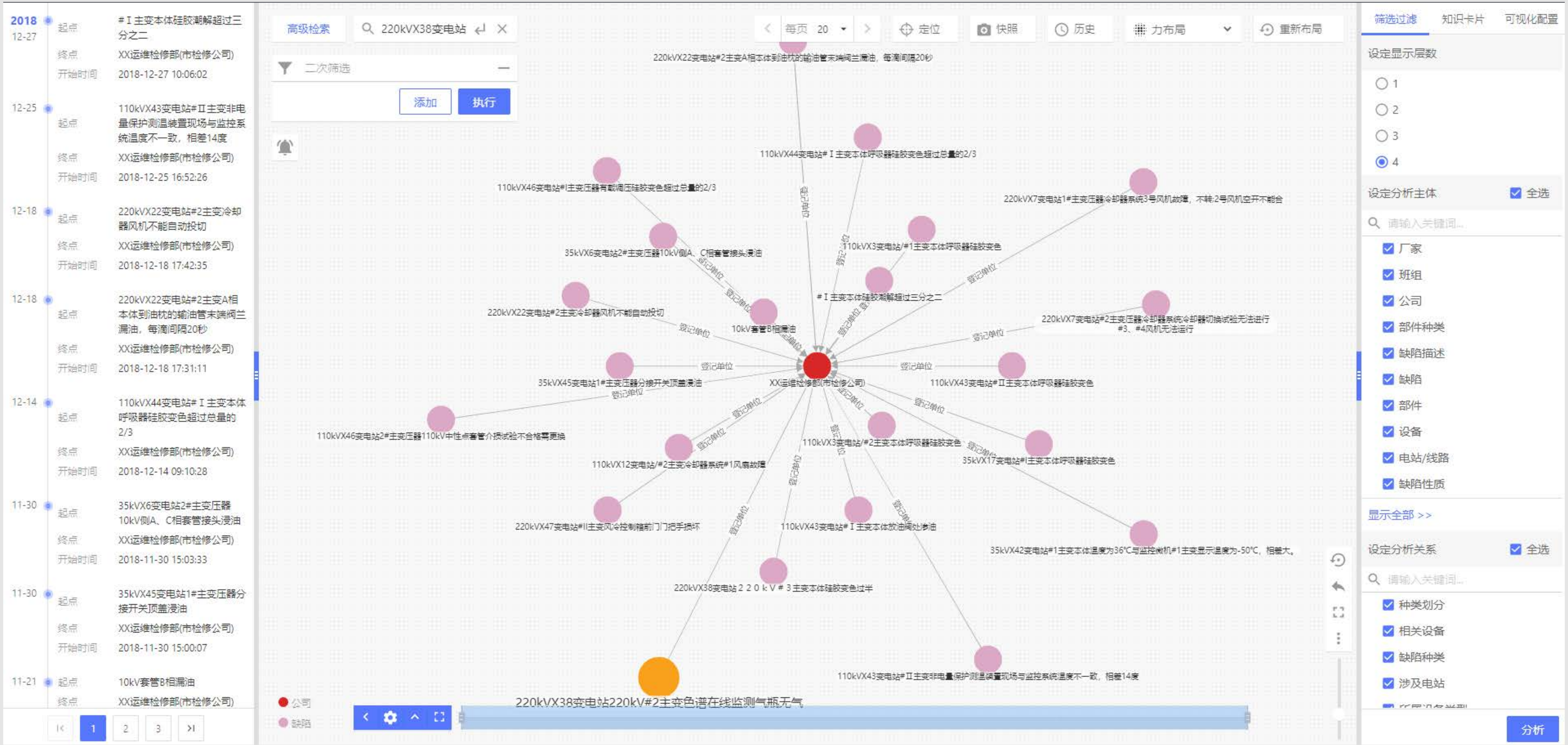


- **Fault data**

Internal work orders, fault reports, maintenance records, etc.

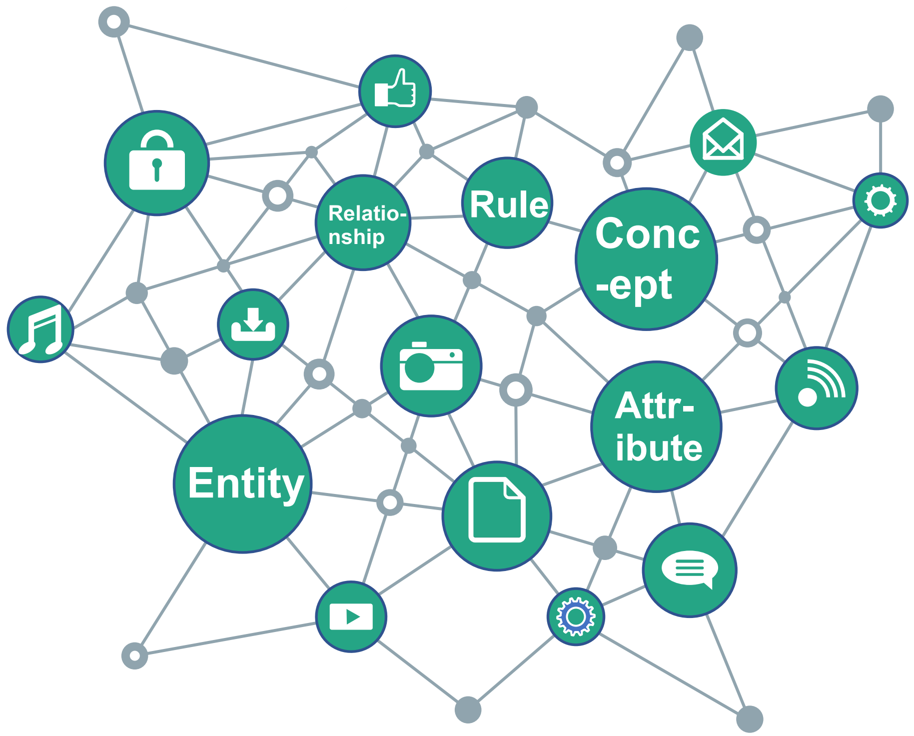
事件数	变化率	智能分类	子分类	事件级别分布	事件模式
4	+75%	性能故障	CPU使用率		*的CPU整体负载过高，大于*
99	+71%	系统故障	主机可用性		* 上的zabbix客户端状态异常
7	+71%	硬件故障	硬件报错		Linux_主机_日志messages中有硬件报错,请关注
3	+66%	其它	其它		Citrix * Agent服务状态异常
3	+66%	性能故障	CPU使用率		CPU* *分钟利用率大于*
18	+66%	性能故障	CPU使用率		*上的CPU使用率*分钟平均值大于*
11	+63%	系统故障	文件系统使用率		主机*文件目录使用率超过*告警
8	+62%	系统故障	文件系统使用率		主机/home文件目录使用率超过*告警
33	+60%	系统故障	网络状态告警		OSPF邻居状态异常
9	+55%	性能故障	CPU使用率		*的CPU告警,CPU使用率大于*

Industry practice - Equipment defect knowledge graph



Overview of applications

- **Middle Platform of Industrial Manufacturing Knowledge**

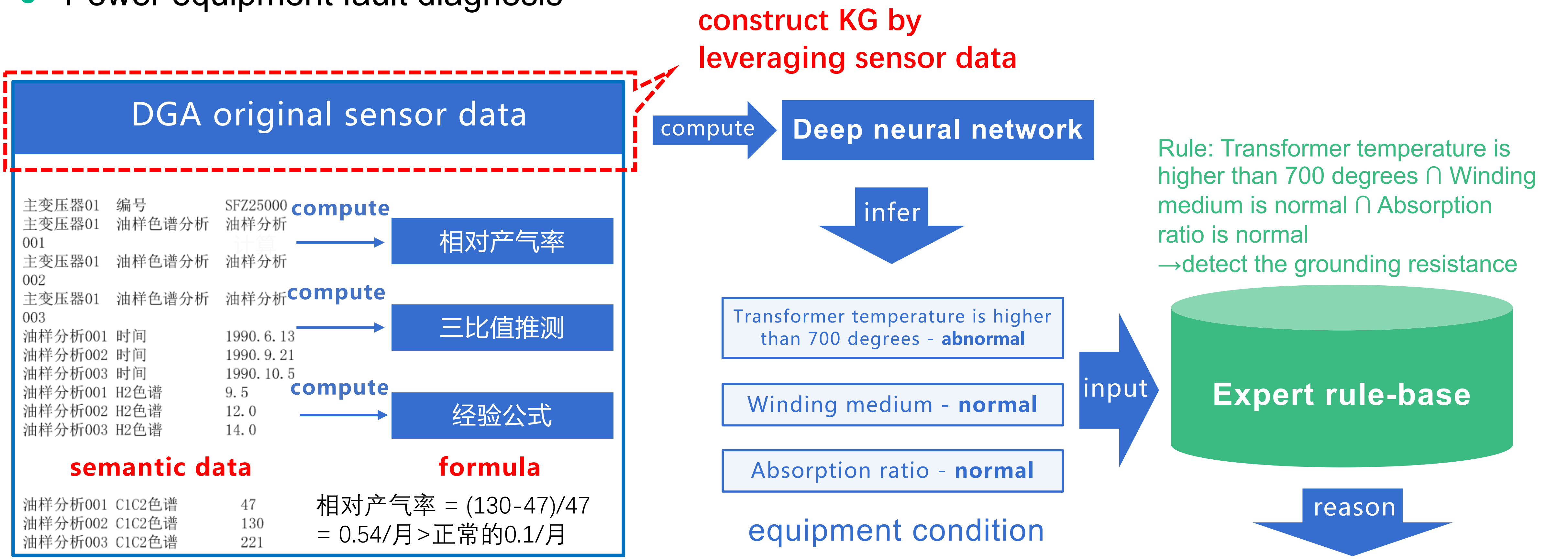


Industrial Manufacturing Knowledge

1. **Intelligent Semantic Search**
2. **Industrial Equipment Health Management**
3. **Equipment failure management and early warning**
4. **FMEA analysis based on knowledge graph**
5. **Fault diagnosis and location**
6. **Auxiliary filling & report preparation**
7. **Process optimization recommendations**

Industry practice - Smart Manufacture

- Power equipment fault diagnosis

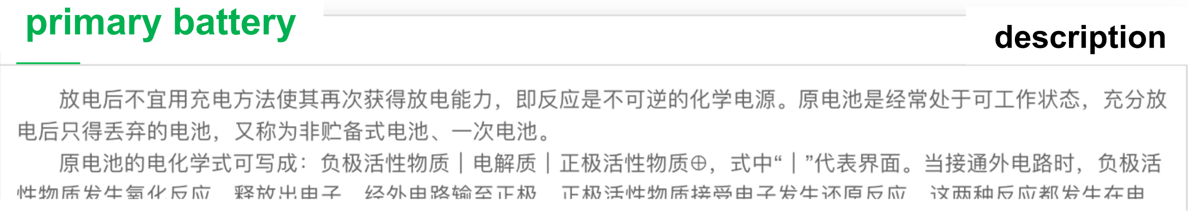


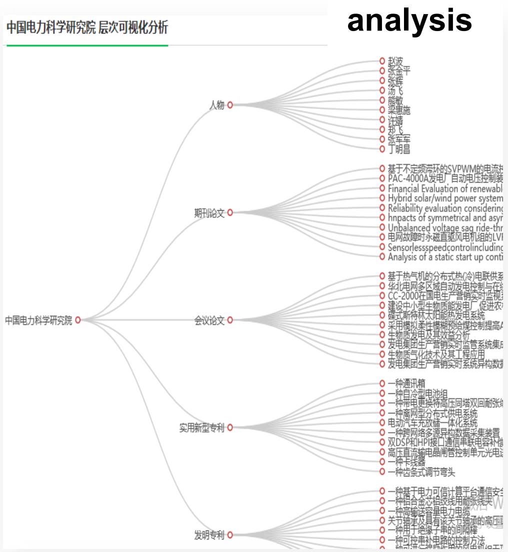
- Convert sensor data to semantic data and computing results
- Train a deep neural network model and construct diagnosis KG
- Combine the model and KG to reason the recommend detection scheme

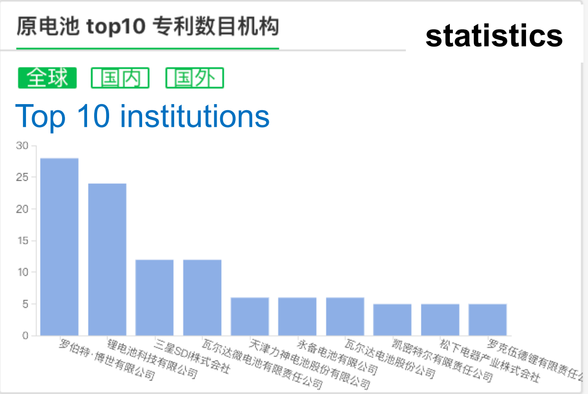
Industry practice - Pan Media

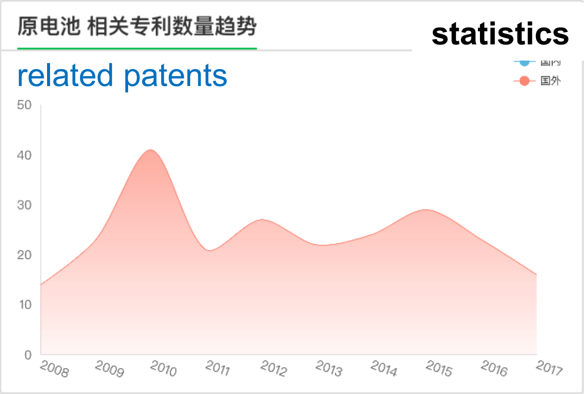
- Multi-dimensional display of industrial knowledge

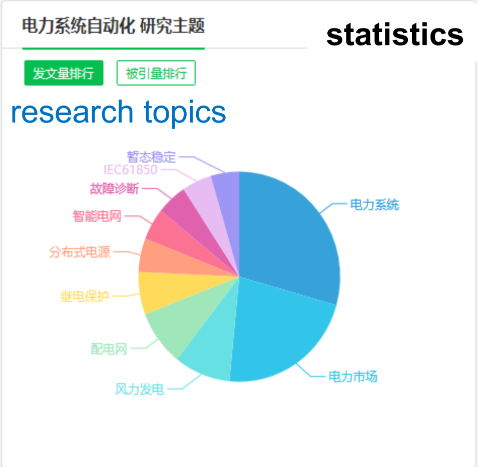
integrate multimodal resources to give a full profile of knowledge







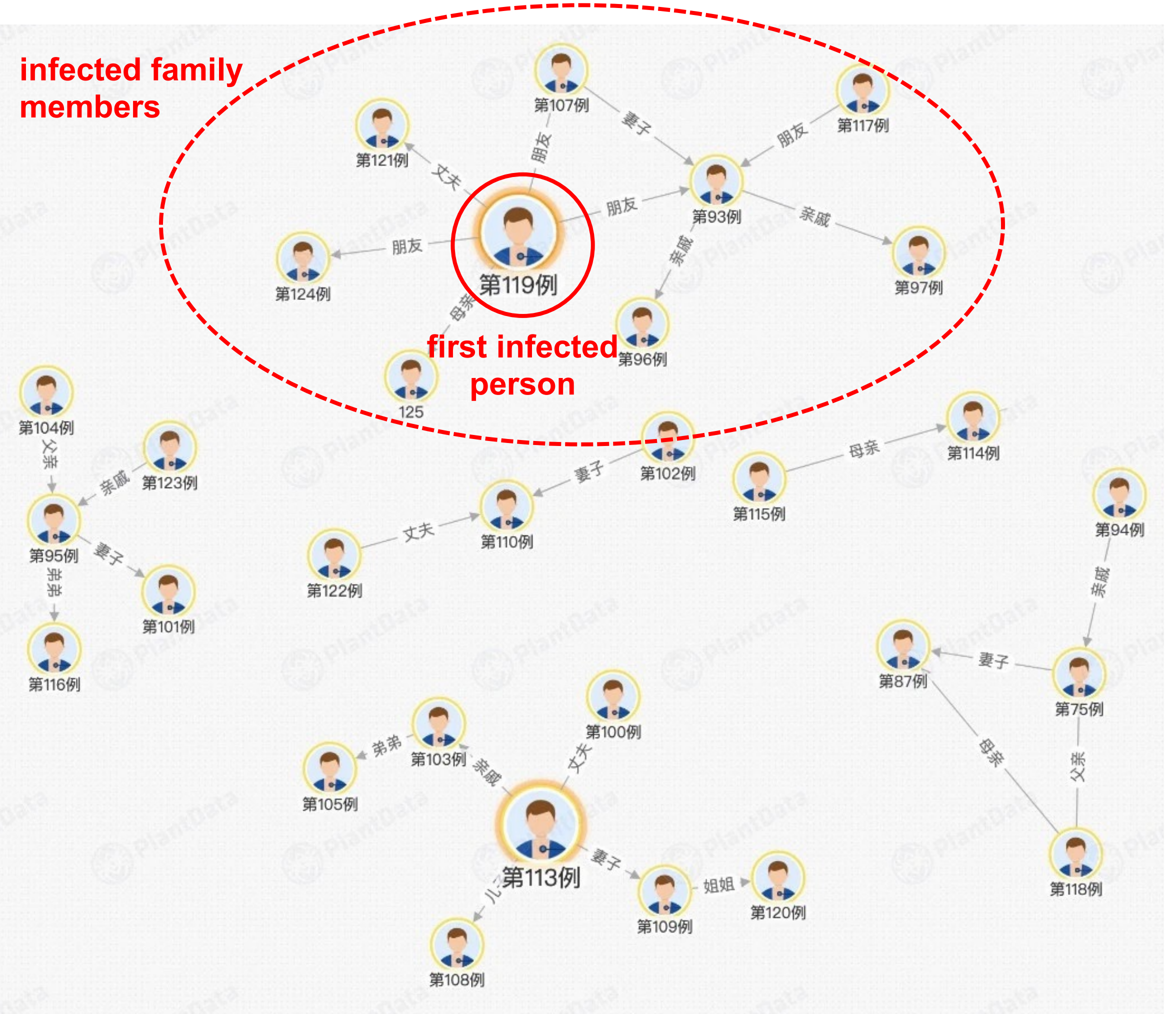




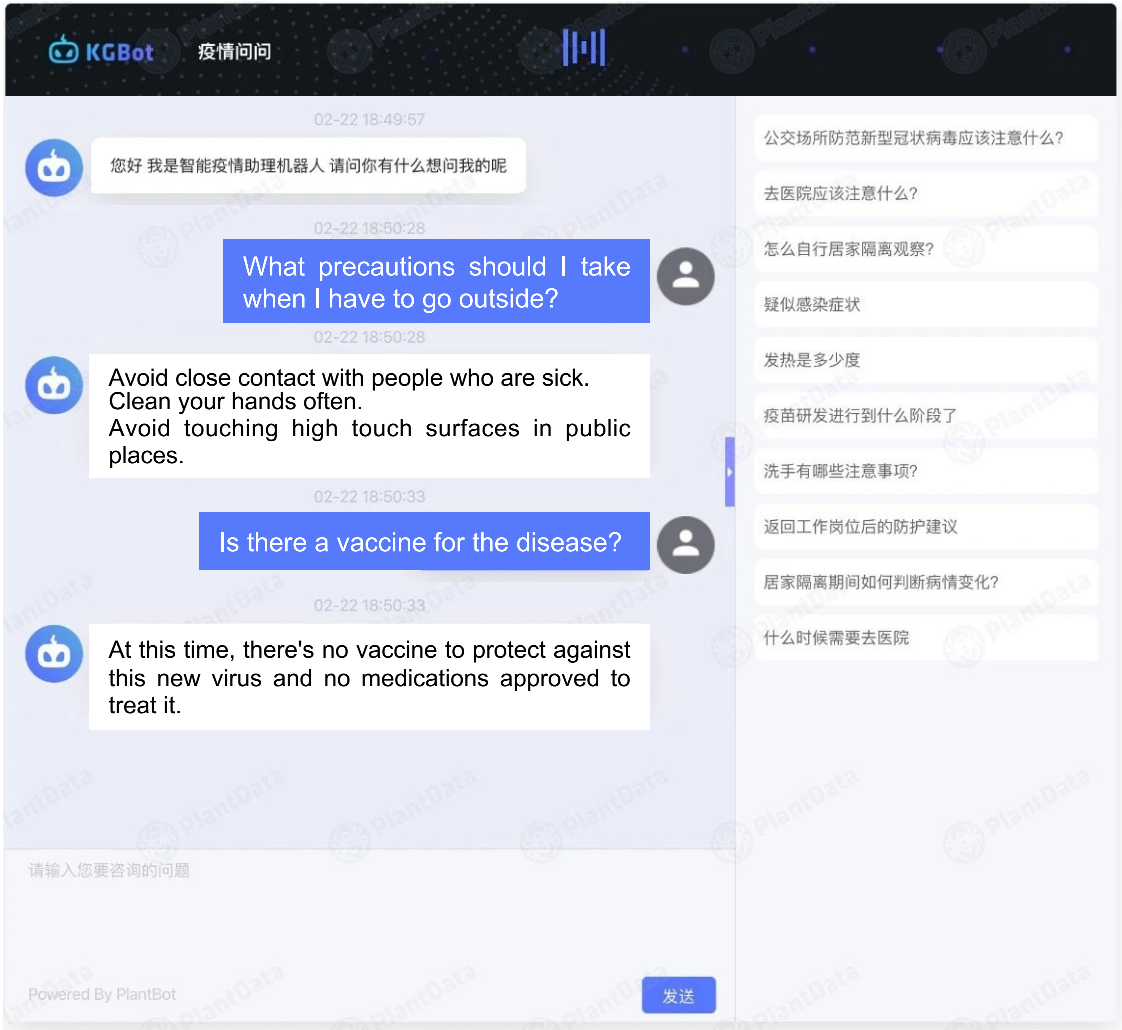
Industry practice - Fighting the epidemic

- Family gathering spread analysis

Discover spread path through KG

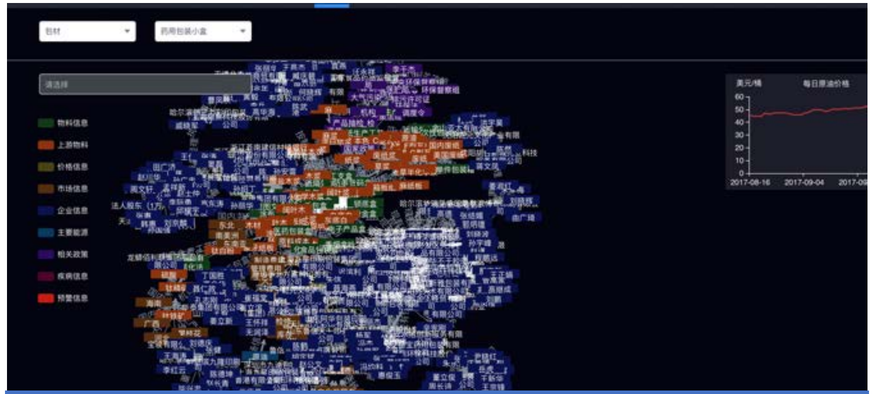


- Epidemic consultation

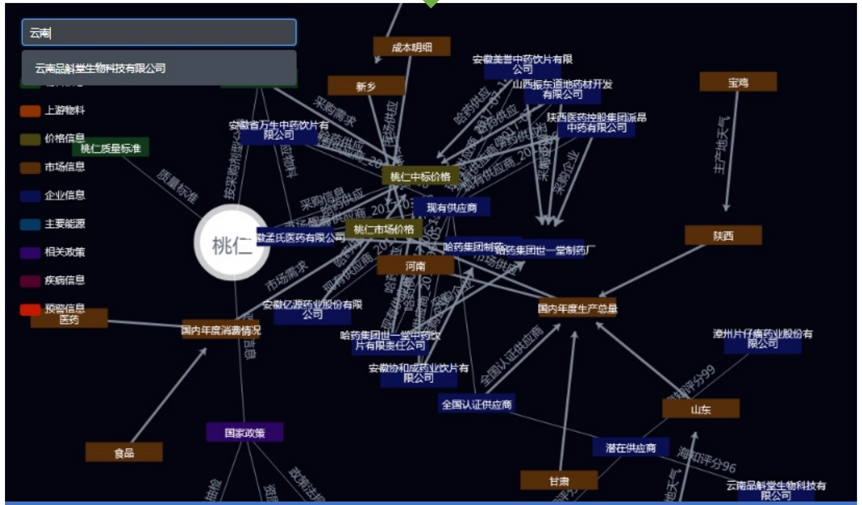


Industry practice – Visual analysis of supply chain

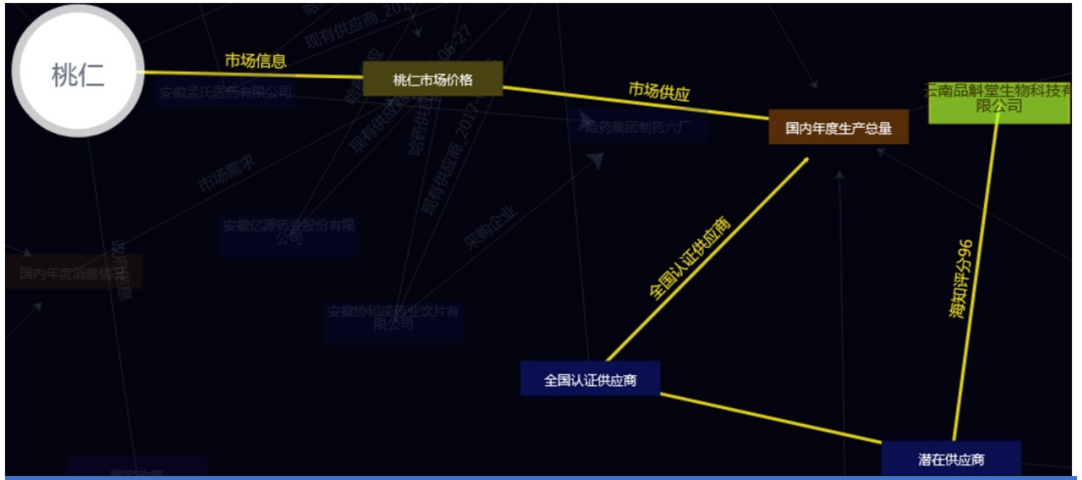
- ✓ 360 view of more than one hundred key materials of a pharmaceutical company
- ✓ Early warnings (e.g., weather, policies) are visually displayed and updated in a real time
- ✓ Nodes of specific types or links are highlighted to get a clear glance of influence chain



Visualization of pharmaceutical manufacturer partnership



Visualization of relationship between companies and materials

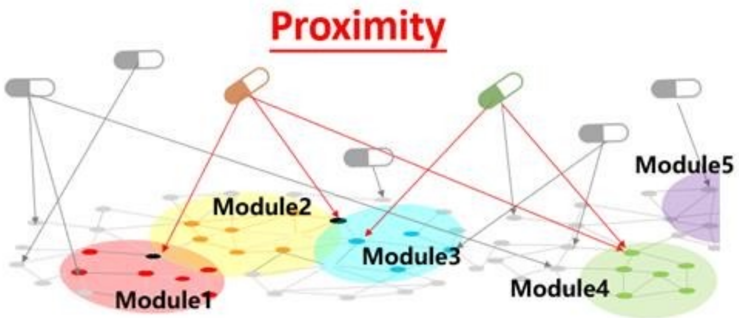


Impact path of raw material prices

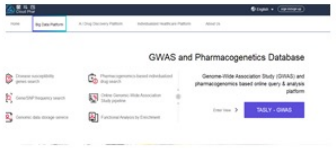
Industry practice – Drug repurposing

Drug Candidate Prediction Based on Complex Heterogeneous Information Networks

8000+ drug candidates



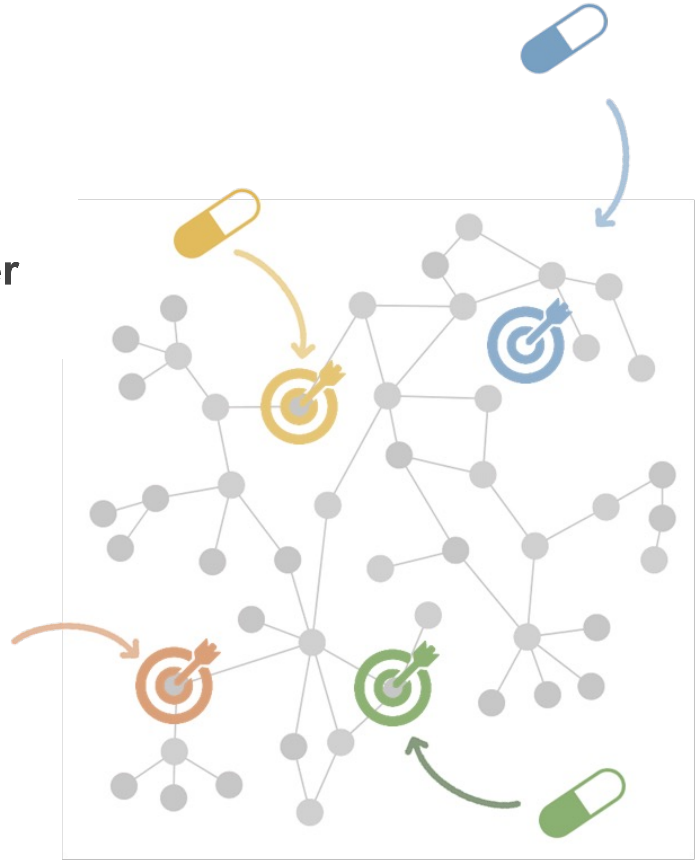
78 potentially effective drug



Drug Repurposing
prediction pipeline

25 public listed small molecule drugs, 53 under clinical research

Toxicology & Synergy
Side effects



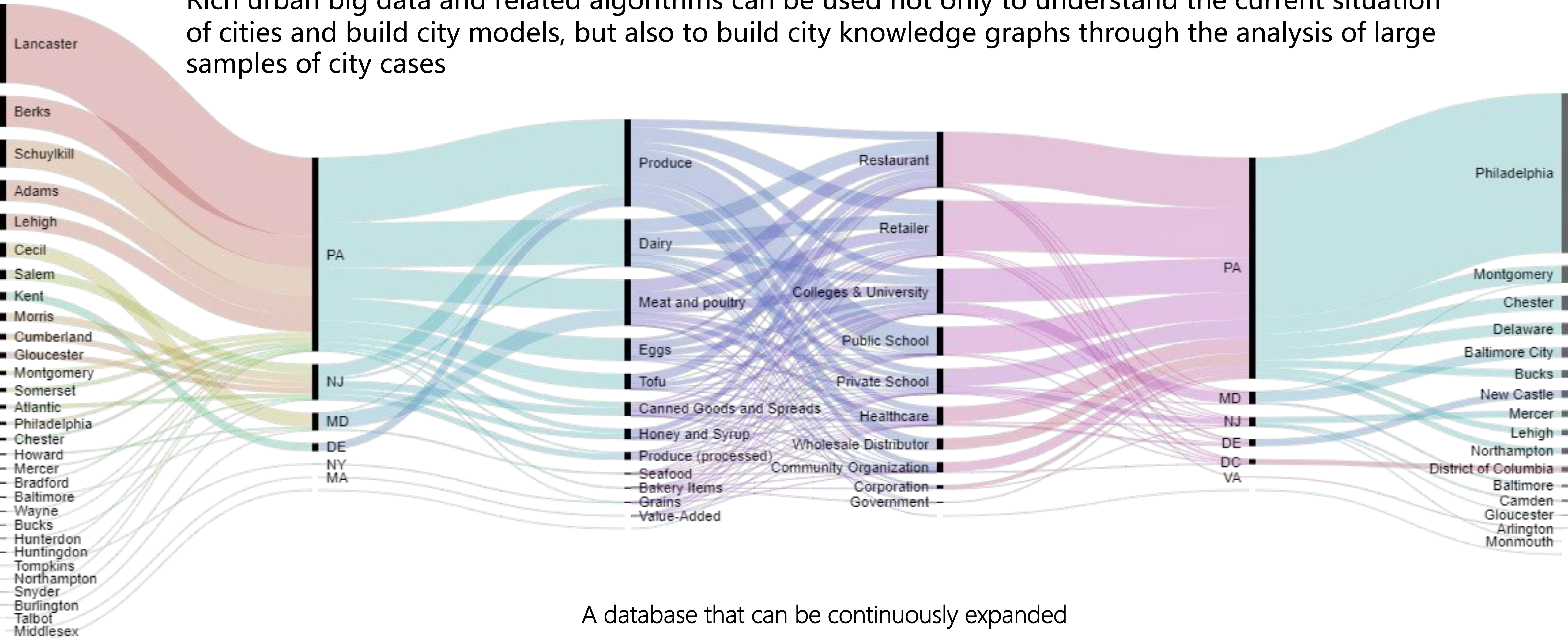
30 drug candidates
(via PK, toxicity, safety, IP filter)

Urban Knowledge Graph

- **Urban design knowledge graph based on multi-city data**

Urbanpedia: high-quality spatial knowledge graph construction supported by multi-source data

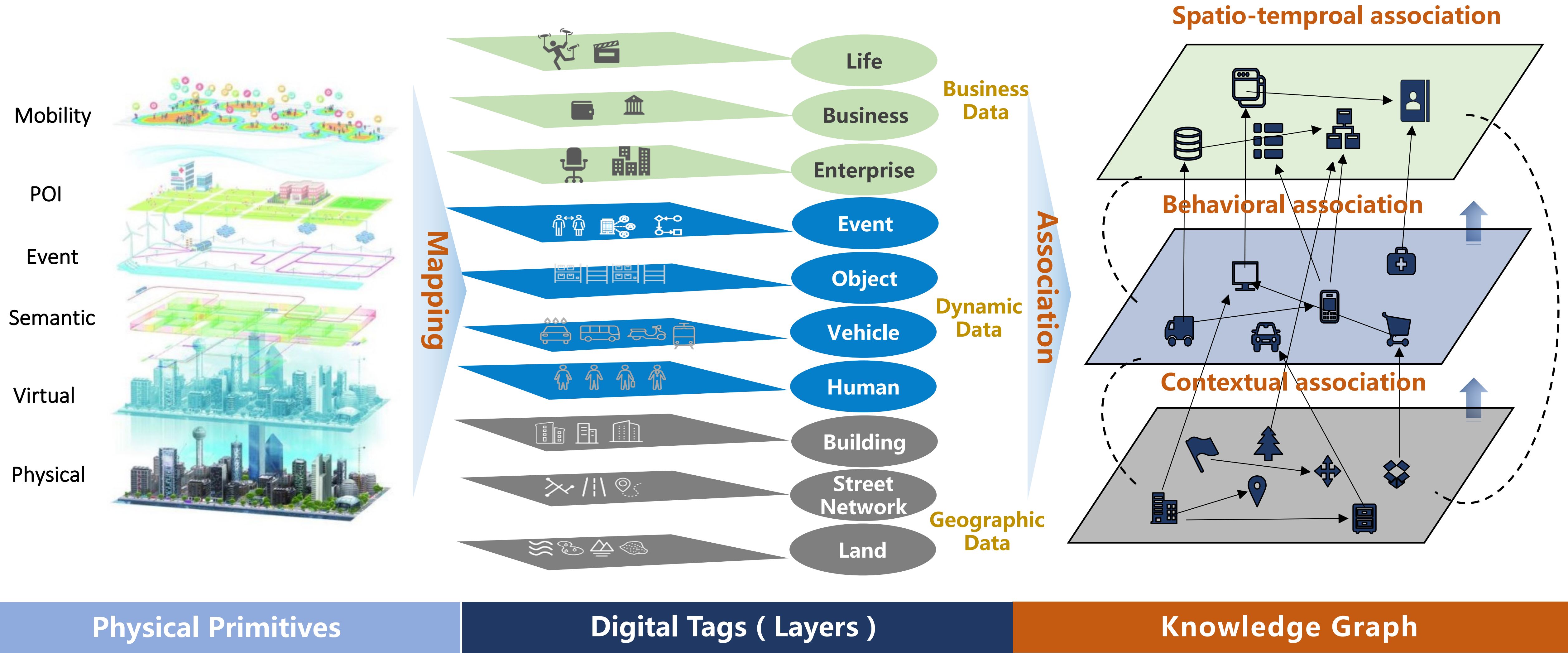
Rich urban big data and related algorithms can be used not only to understand the current situation of cities and build city models, but also to build city knowledge graphs through the analysis of large samples of city cases



A database that can be continuously expanded

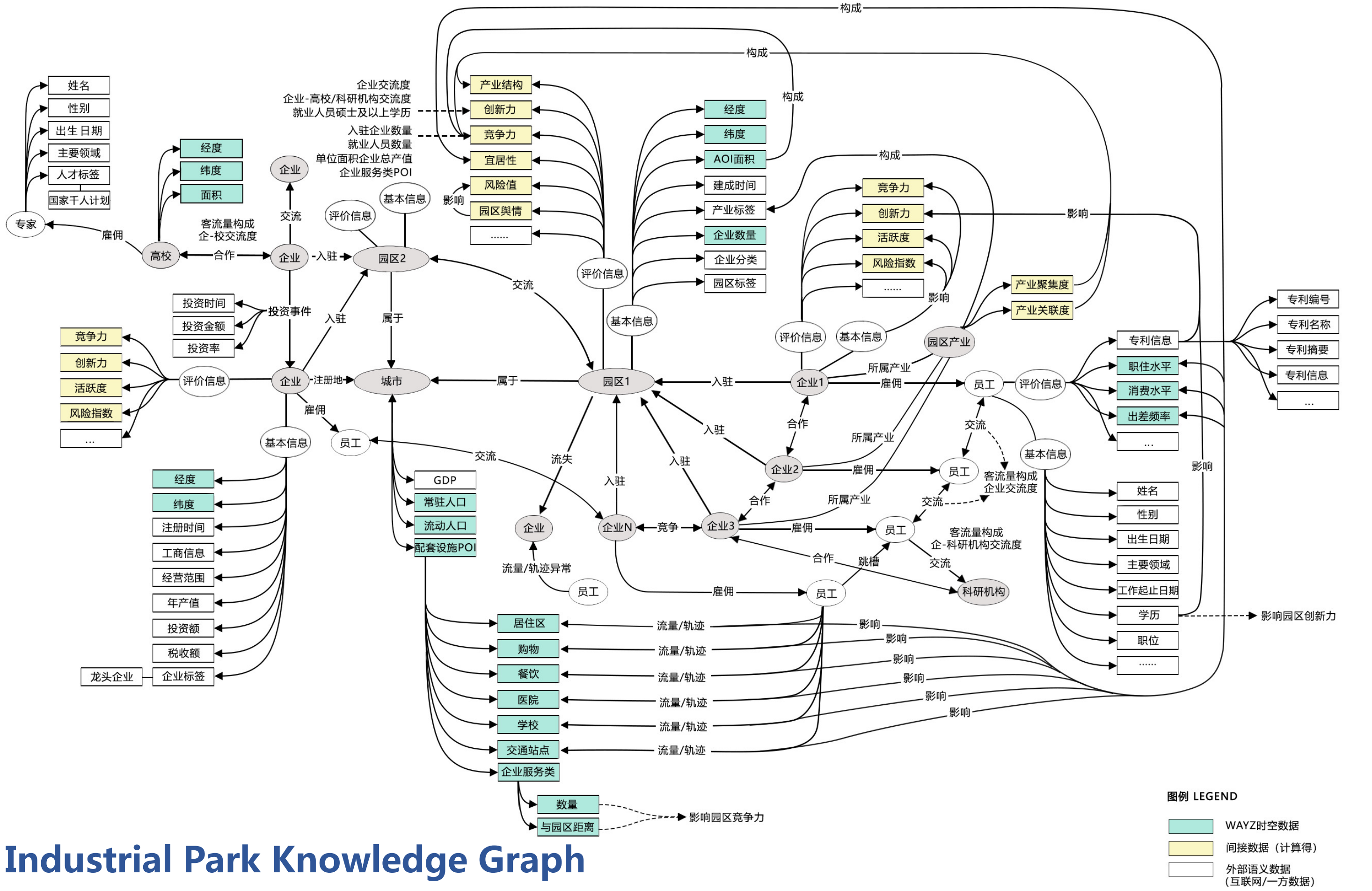
Spatio-temporal knowledge graph

- **Structured representation of spatio-temporal concepts, entities and relationships in the form of knowledge graph**



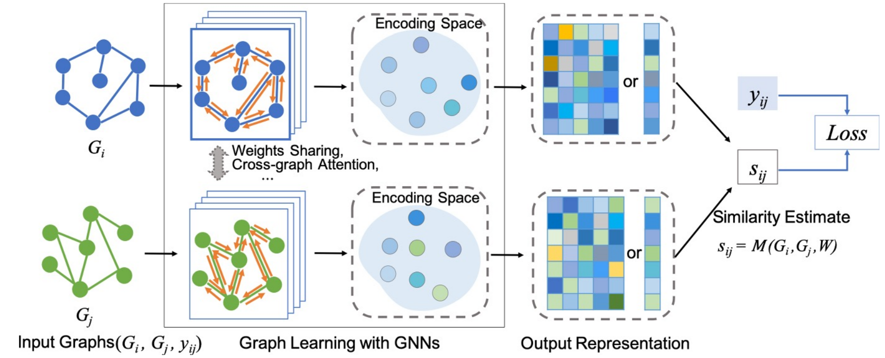
Industry practice- Intelligent Industrial Park

- Using knowledge graph to realize the whole process of positioning-evaluation-reasoning-optimization of industrial park planning.



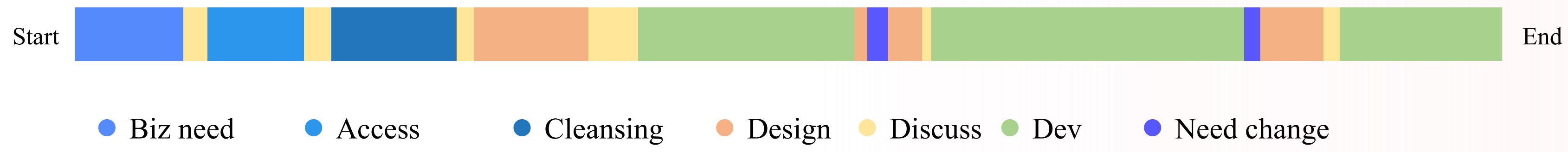
Industrial Park Knowledge Graph

Similarity calculation for each indicator to the head park



A New Paradigm of Knowledge Graph Technology in the Open Environment of Interdisciplinary Fields

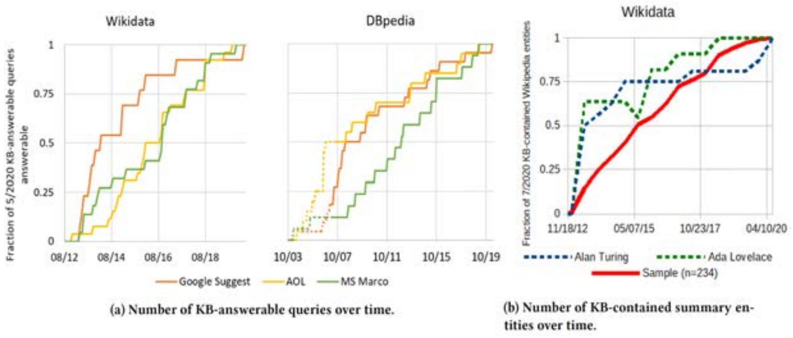
Traditional KG Dev



Acquire knowledge on demand in the open world assumption, overcome the bottleneck of low knowledge coverage

Rapid develop and deploy vertical KG products, shorten the time and cost from design to delivery

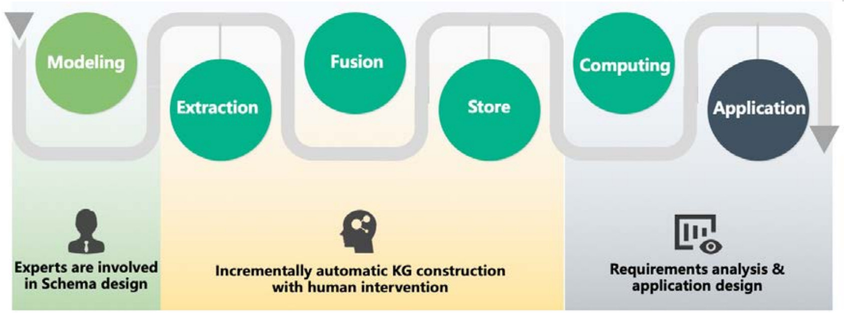
Make use of cross-domain features, accomplish migration and adaptation of knowledge graph platform



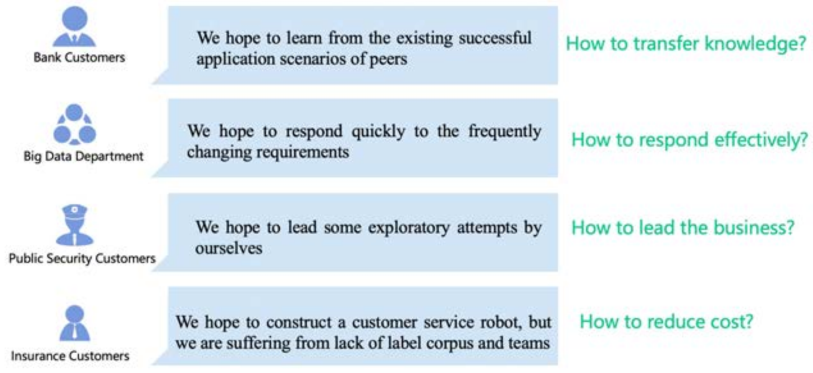
(a) Number of KB-answerable queries over time.

(b) Number of KB-contained summary entities over time.

Known Unknowns vs Unknown Unknowns
（两类缺失知识，现有技术局限在Known Unknowns，开放环境下的缺失知识大部分是 Unknown Unknowns ）



The full life cycle of vertical KG



Discussion

■ Knowledge Representation:

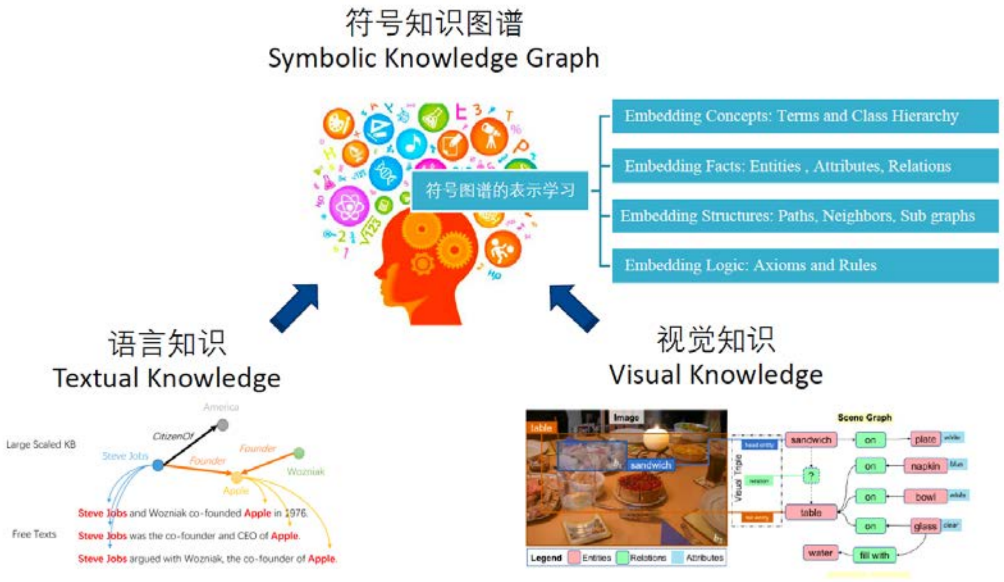
- Multimodal, Spatial-Temporal, Event, Rules

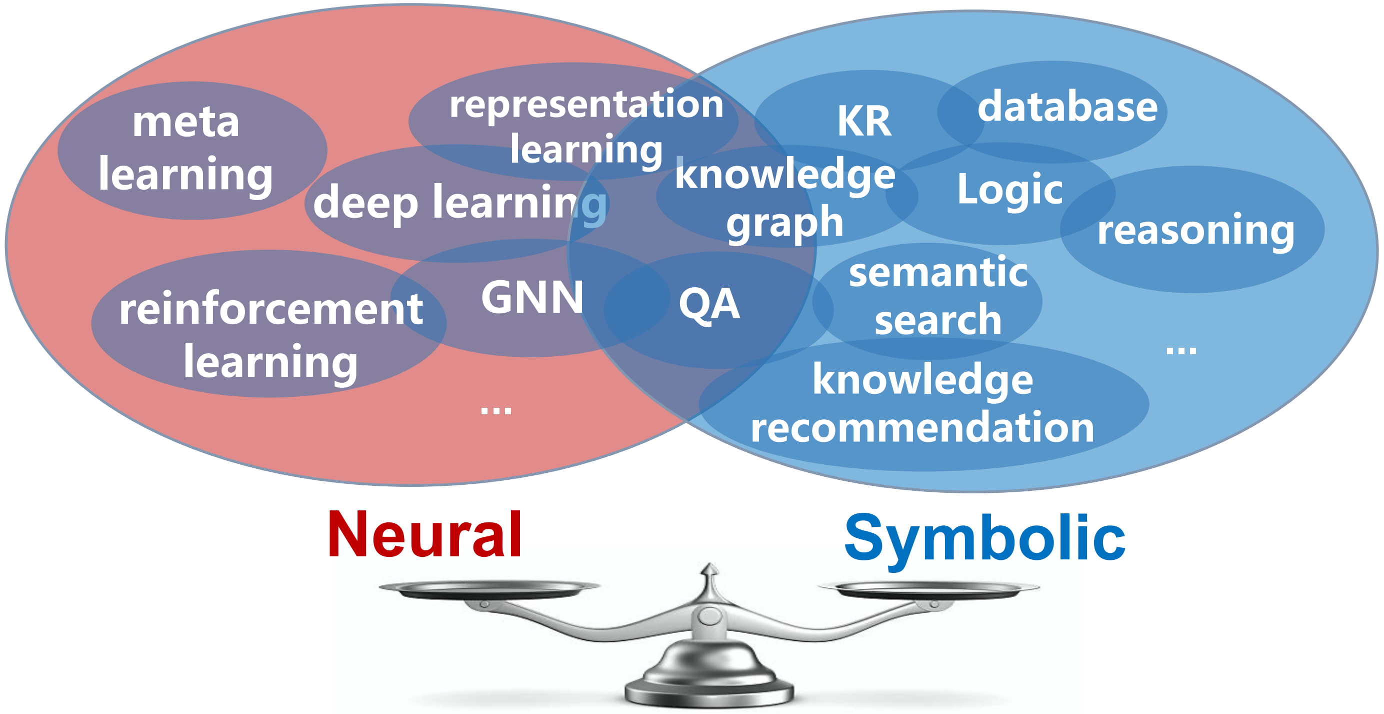
■ How to make reasoning more utility and efficient?

- From shallow to deep reasoning
- Logical entailment + Statistical inference
- “Equivalence” between neural and symbolic

■ Human in the loop:

- Justification and tracing
- Explainable and interpretation
- Incremental reasoning





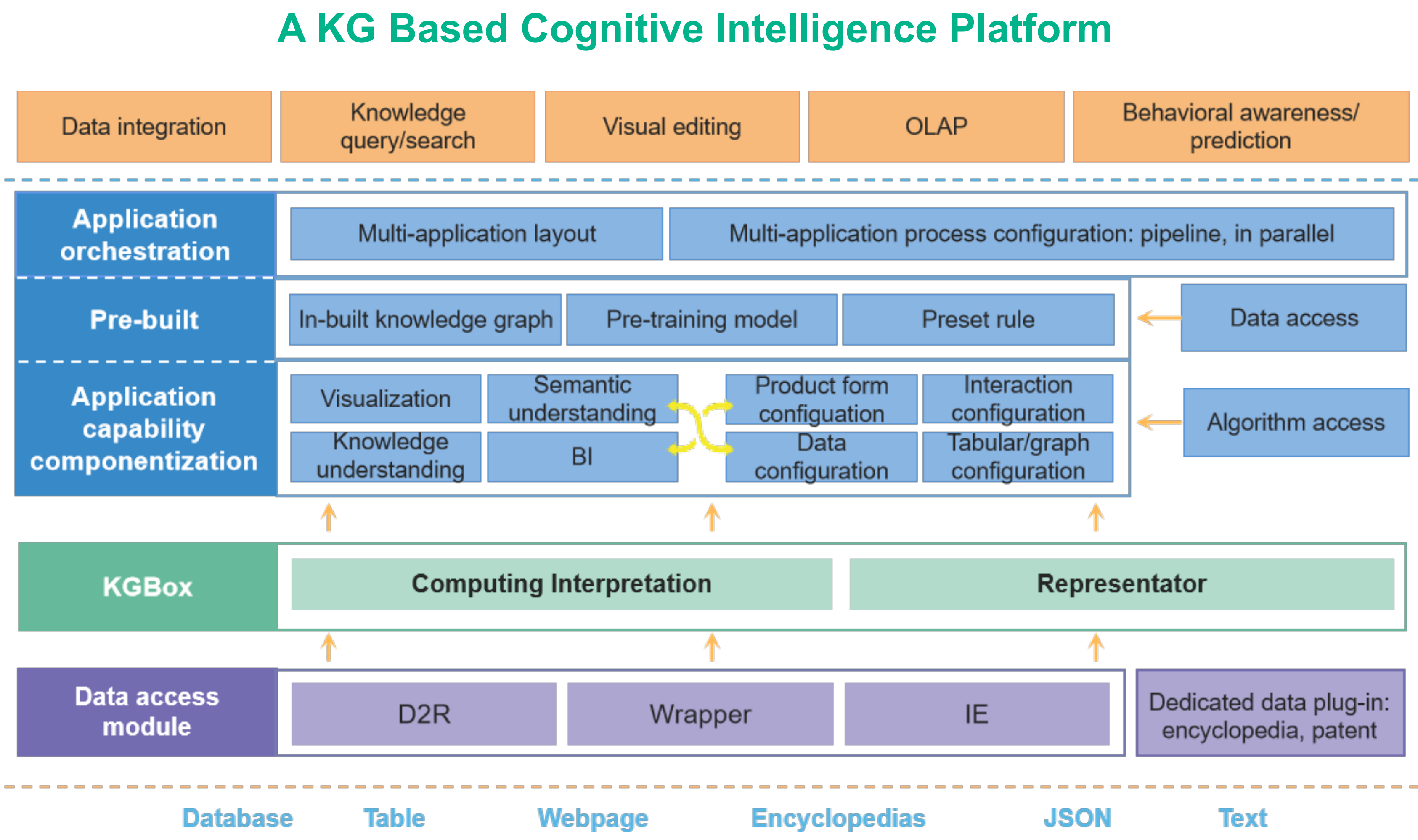
Discussion: Software Engineering for Knowledge Graph

Rapid delivery of KG products

- Application orchestration: build KG applications through Assembling
- Pre-built: graphs, models, rules
- Microservices for high reusability and extensibility

KG platform construction

- Schema construction tools
- Knowledge acquisition software
- Knowledge store scheme
- ......



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COLLEGE OF DESIGN AND INNOVATION
同济大学设计创意学院

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PlantData

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