

# 그래프 기반 지식 강화형 인공지능 (Part 1)

w/ Graph & Language Intelligence

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<https://bkoh509.github.io>

<https://gli.konkuk.ac.kr>

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1. About Me and GLI Lab
2. Knowledge Graph
3. Graph Representation Learning
4. Graph-based AI
5. What's Next?

# About Me

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<https://bkoh509.github.io/>

❑ I pursue **knowledge-driven AI** capable of human-like thinking because it is vital to the future of AGI.

❑ My Research Topics: Neuro-Symbolic AI

- ✓ Graph Representation Learning
- ✓ Recommender Systems
- ✓ Natural Language Processing
- ✓ Synergizing LLMs and Graphs

❑ Contact

- ✓ Homepage: <https://bkoh509.github.io/>
- ✓ Email: [bkoh@konkuk.ac.kr](mailto:bkoh@konkuk.ac.kr)
- ✓ Office: Engineering Hall C384-2

# About Graph & Language Intelligence Lab



<https://gli.konkuk.ac.kr/>

## □ 그래프 기반 딥러닝의 원천기술 연구개발

- ✓ 그래프: 다출처 데이터와 지식 간의 관계, 규칙, 제약사항 등을 명확하게 구조화하고 잠재적 지식을 탐색
- ✓ 텍스트: 인간의 방대한 지식과 정보로부터 의미 있는 정보를 추출/분석

## □ Approaches

- ✓ Graph Representation Learning (그래프 표현학습)
- ✓ Large Language Models (대형 언어모델)
- ✓ Synergizing LLMs and Graphs (그래프·언어모델 통합)

## □ Applications

- ✓ Natural Language Processing (자연어처리)
- ✓ Recommender Systems (추천시스템)
- ✓ Graph Analytics and Prediction (그래프 분석·예측)
  - Graph Anomaly Detection (이상탐지)

# About Graph & Language Intelligence Lab



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## □ Culture & Philosophy

- ✓ 열정적인 분위기 속에서 서로가 영감과 동기를 나눌 수 있는 환경
- ✓ 개인의 성장은 곧 팀 전체의 성장으로 선순환
  - 처음 생각했던 것보다 훨씬 더 큰 성취 가능

## □ 연구실 현황

- ✓ 박사과정(1), 석사과정(5), 학부연구생(14)

## □ Contact

- ✓ Homepage: <https://gli.konkuk.ac.kr/>

The screenshot displays the 'Members' page of the Graph & Language Intelligence Lab. It features a grid of member profiles, each with a photo, name, and contact details. The members are categorized into Assistant Professor, PhD Students, MS Students, Incoming MS Students, and Interns. The Assistant Professor listed is Byungkook Oh. The PhD Students include Bonyou Koo, Eun-Yeong Jo, Sang-Hyun Park, Jimyeong Seo, Dongcheon Lee, Jinho Choi, and Hye-Yoon Baek. The MS Students include Sang-Jun Ji, Sang-June Kim, Yewon Sa, and Hyeon Lee. The Incoming MS Students include Yoon Kim and Gyun Park. The Interns include Young-Ho Lee, Woosik Jeong, and Young-Jin Kim. The page also includes a 'Contact Us' button and a 'About GLI Lab' section.

The screenshot displays the 'About GLI Lab' page. It features a map of the lab's location at Konkuk University. The page includes a description of the lab's mission and research interests, which are listed as: Graph ML/DL, Recommendation Systems, Knowledge-based Systems, NLP, and Anomaly Detection. The page also includes a 'Contact Us' button and a 'About GLI Lab' section.

We strive for technological innovation across various real-world applications such as information retrieval and extraction, and trustworthy response generation. To aid methods including Graph Neural Networks (GNNs), multimodal and knowledge-aware LLMs and Graphs techniques, GraphRAG, and LLM-based agents, aiming to

# CONTENTS

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# What is Knowledge?

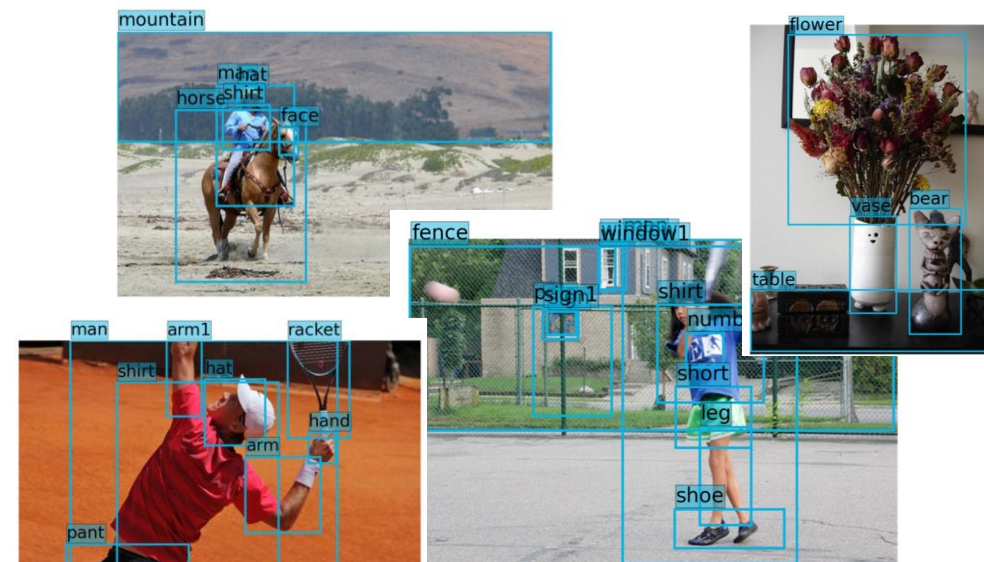
## 모든 데이터에는 human knowledge가 암묵적으로 담겨있음

ex) 텍스트: 단어 나열

- “아스피린은 두통을 완화한다” -> 개념(약물, 증상), 인과관계, 의학적 사실

ex) 이미지: 픽셀 배열

- "고양이가 소파 위에 있다" -> 객체(고양이, 소파), 관계(위에), 상식(고양이는 동물)



Text Data

Image Data

# What is Graph?

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## □ Graph-Structured Data

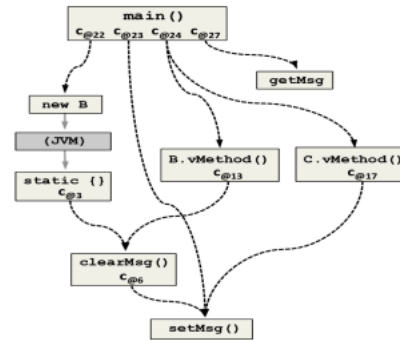
- ✓ 복잡한 시스템을 표현/설명/분석하기 위한 범용적인 자료구조  
(구성요소 간의 상호작용/관계를 추가적으로 기술할 수 있는 데이터구조)
    - 노드(node): 객체의 집합
    - 링크(link): 객체들 간의 상호작용
  - ✓ 시스템을 분석하고 이해할 수 있는 수학적 기초 제공
- ex) 소셜 네트워크: 개인을 노드, 친구 관계를 링크로 표현
- ex) 단백질 네트워크: 단백질을 노드, 단백질 사이의 상호작용을 링크로 표현

# Many Types of Data are Graphs

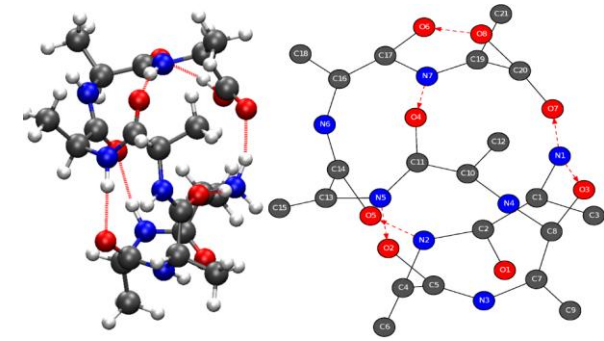
- ✓ *Compactness*
- ✓ *Intuition*
- ✓ *Management*



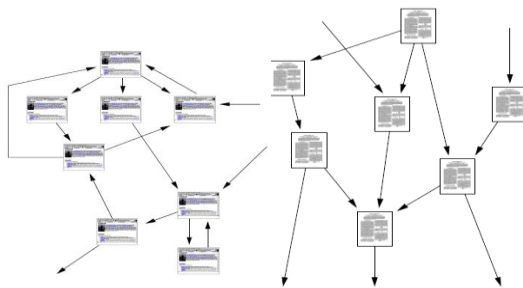
Social Networks



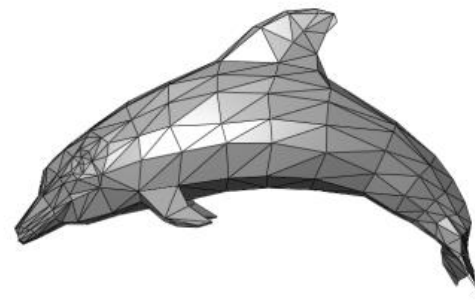
Code Graphs



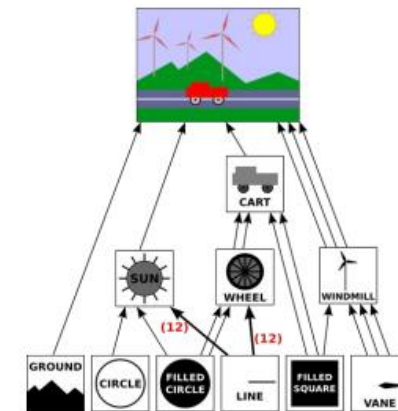
Molecules



Information Networks:  
Web & Citations



3D Shapes



Scene Graphs

# Many Types of Data are Graphs

- ✓ Compactness
- ✓ Intuition
- ✓ Management

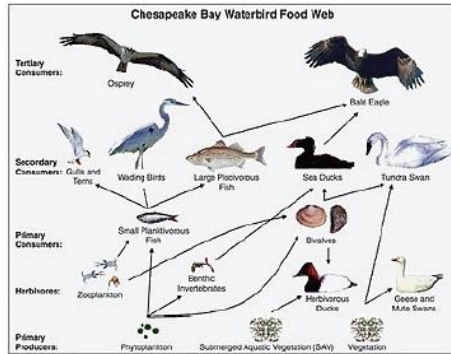


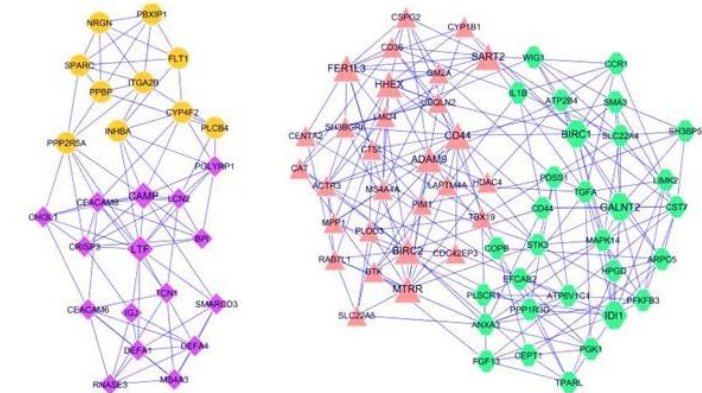
Image credit: [Wikipedia](#)

Food Chain



Image credit: [SalientNetworks](#)

Computer Networks

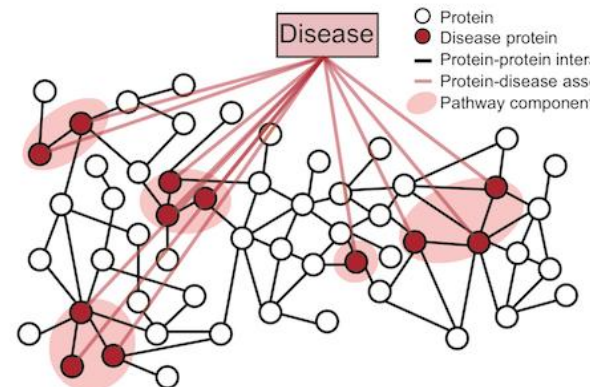


Gene Regulatory Networks

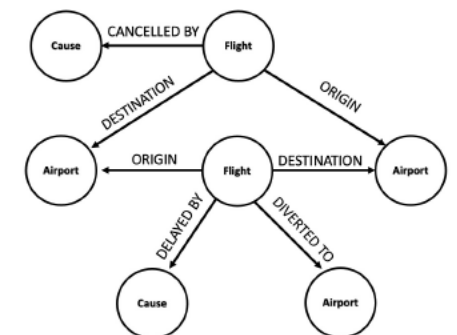
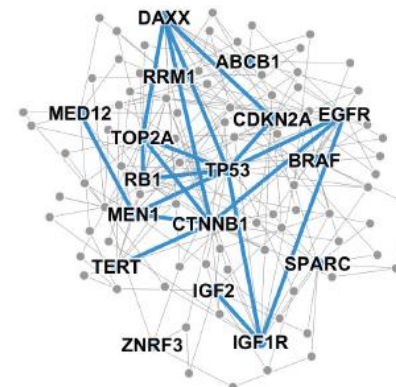


Image credit: [visitlondon.com](#)

Underground Networks



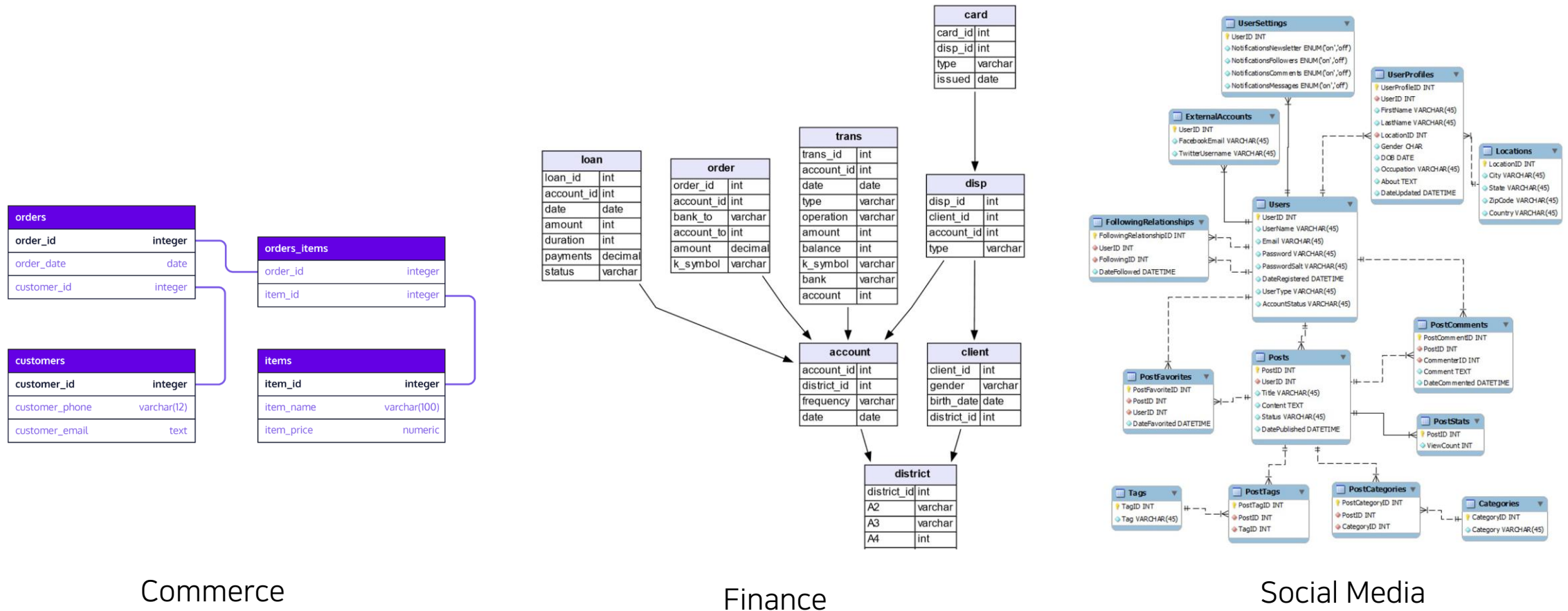
Disease Pathways



Event Graphs

# Databases are Graphs

- ✓ Compactness
- ✓ Intuition
- ✓ Management



# Many Types of Data are Graphs

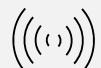
- ✓ *Compactness*
- ✓ *Intuition*
- ✓ *Management*

⊖ *Ambiguity*

⊖ *Noise*



Text Corpora



Time-Series



Image/Video

*Unstructured Data*



JSON/XML

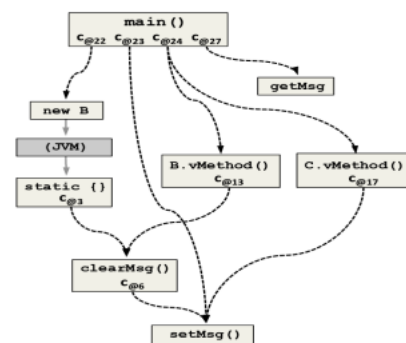


Website

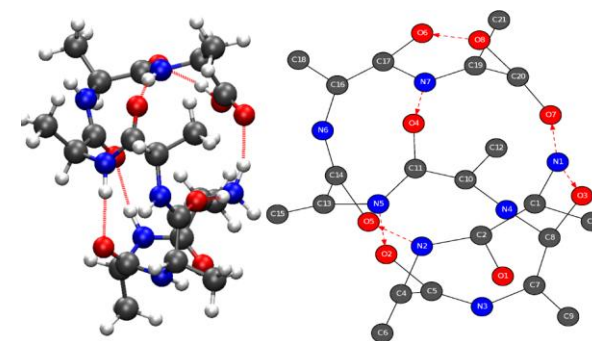
*Semi-structured Data*



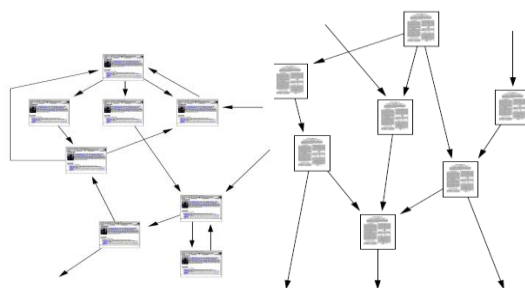
Social Networks



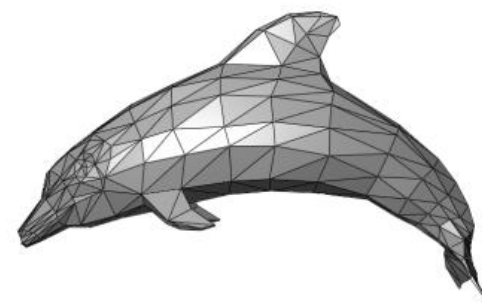
Code Graphs



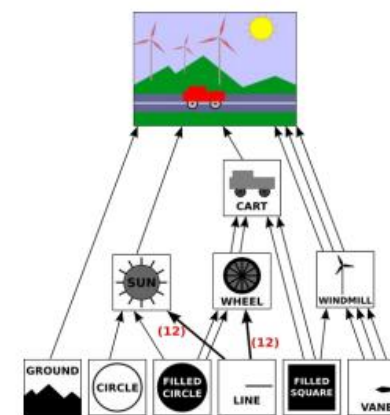
Molecules



Information Networks:  
Web & Citations



3D Shapes



Scene Graphs

*Graph-Structured Data*

# Many Types of Data are Graphs

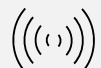
- ✓ *Compactness*
- ✓ *Intuition*
- ✓ *Management*

⊖ *Ambiguity*

⊖ *Noise*



Text Corpora



Time-Series



Image/Video

*Unstructured Data*



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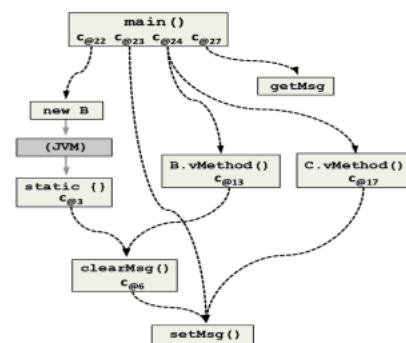


Website

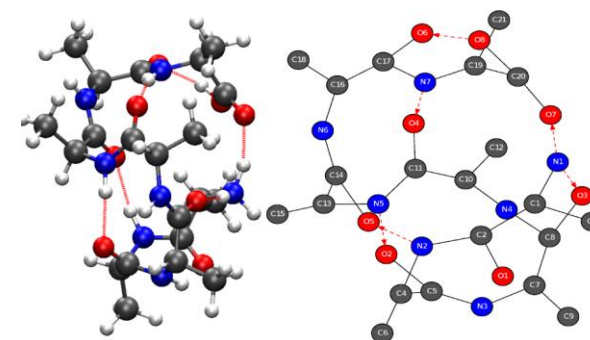
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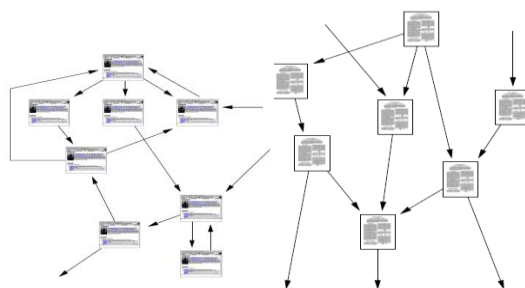
Social Networks



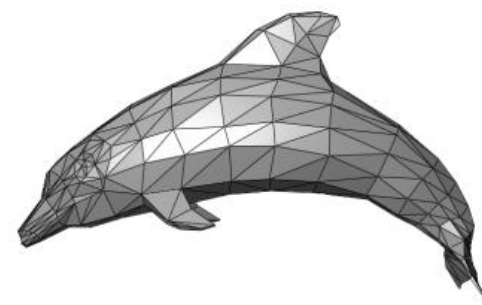
Code Graphs



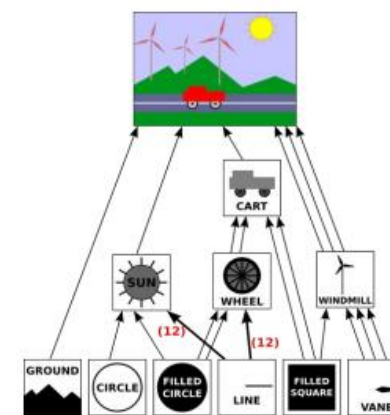
Molecules



Information Networks:  
Web & Citations



3D Shapes



Scene Graphs

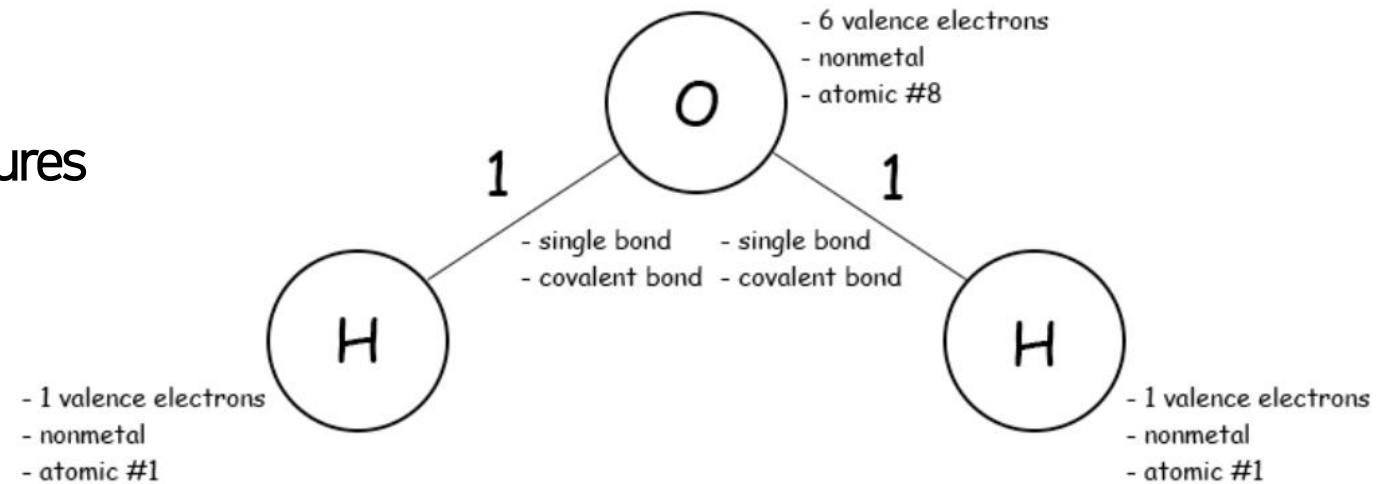
*Graph-Structured Data*

# Heterogeneous Graphs

□ A heterogeneous graph is defined as

$$\mathbf{G} = (\mathbf{V}, \mathbf{E}, \mathbf{R}, \mathbf{T})$$

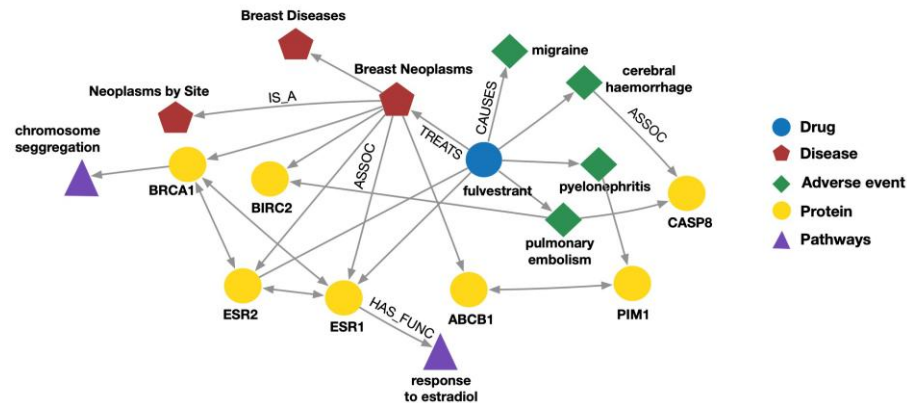
- ✓ Nodes with node types  $v_i \in V$
- ✓ Edges with relation types  $(v_i, r, v_j) \in E$
- ✓ Node type  $T(v_i)$
- ✓ Relation type  $r \in R$
- ✓ Nodes and edges have **attributes/features**



# Many Graphs are Heterogeneous

□ Graphs can be either:

- ✓ **Heterogeneous** — composed of different types of nodes
- ✓ **Homogeneous** — composed of the same type of nodes



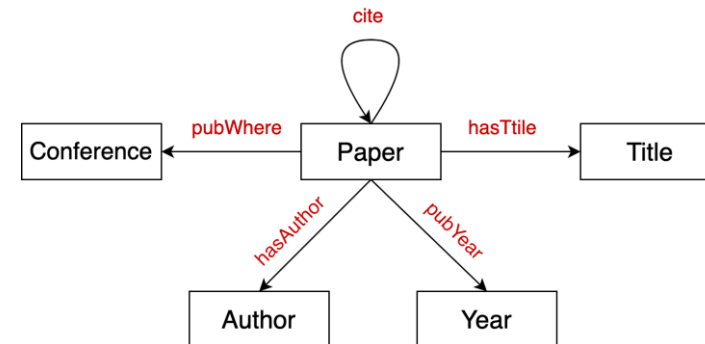
Biomedical Knowledge Graphs

Example node: Migraine

Example edge: (fulvestrant, Treats, Breast Neoplasms)

Example node type: Protein

Example edge type (relation): Causes



Academic Graphs

Example node: ICML

Example edge: (GraphSAGE, NeurIPS)

Example node type: Author

Example edge type (relation): pubYear

□ 모든 데이터에는 human knowledge가 암묵적으로 담겨있음

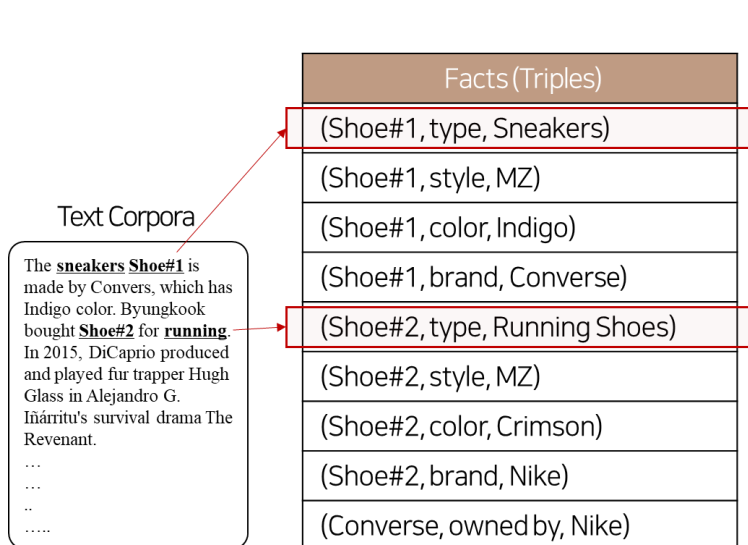
- "고양이가 소파 위에 있다" -> 객체(고양이, 소파), 관계(위에), 상식(고양이는 동물)



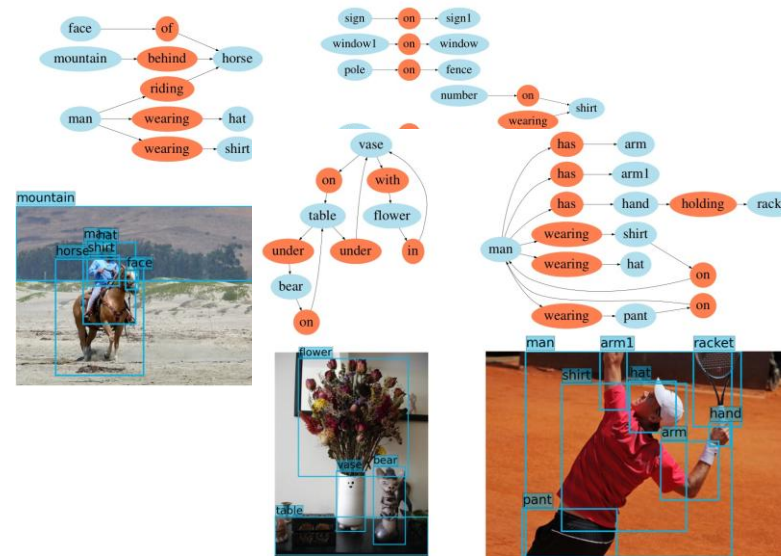
# What is Knowledge Graph?

❑ Collection of facts about entities and semantic relations between entities

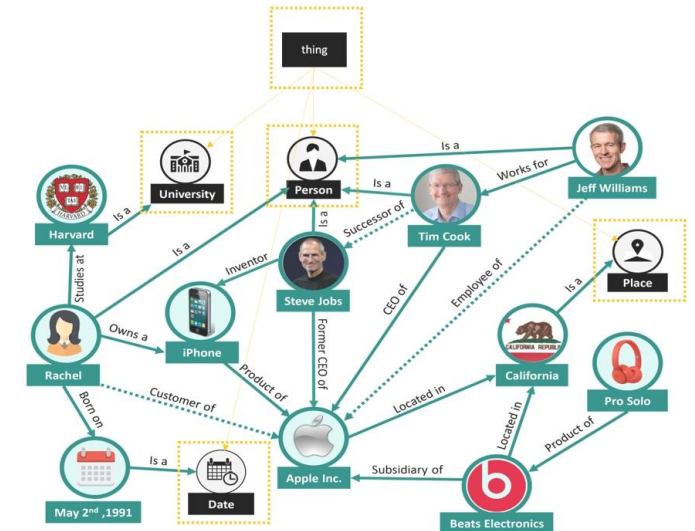
- ✓ Directed Labeled Multigraph: more generalized form than other graph forms
- ✓ 구조: Subject - Predicate - Object



Knowledge Graph from Text



Knowledge Graph from Images

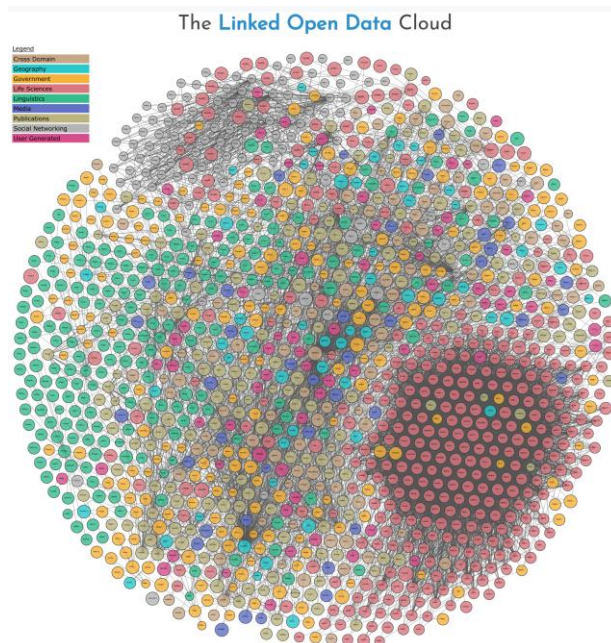


General Knowledge Graph

# Knowledge Graph: Human Knowledge

## ❑ 지식그래프 (Knowledge Graph)

- ✓ 방대한 양의 지식 정보(데이터)와 데이터 간의 관계지식
- ✓ 복잡한 **인간의 지식**을 시각적이고 직관적인 방식으로 표현
  - 다양한 개념, 사실, 관계를 통합적으로 표현
  - 이를 통해 정보를 검색, 탐색 및 이해하기 쉽게 만들



Linked Open Data

## Personalized Knowledge Graph

- 개인화된 지식 그래프
- 사용자 Context와 Contents에 대한 실시간 추론



### Personal KG

사용자 컨텍스트 파악  
맞춤형 추천 제공

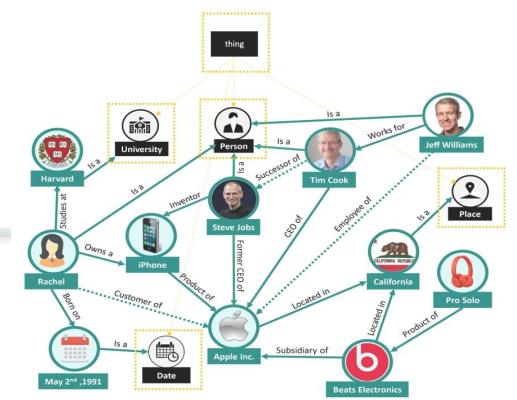
### Domain KG

도메인 특화 지식 정보 제공  
전문 서비스 제공

### Enterprise KG

비즈니스 데이터 검색  
업무 생산성 향상 및 빠른 의사결정 도출

# Knowledge Graph: Human Knowledge



## ❑ 지식그래프 (Knowledge Graph)

- ✓ 세계적인 기업/연구소 (구글, 아마존, 알리바바, 네이버 등)에서 지식그래프를 구축, 정제 및 활용함

### ▪ Google : Knowledge graph 기반 Semantic Search

- 500B facts about 5B entities by 2020
- Enhance search engine's results and answer direct spoken questions in Google Assistant/Home



※ Google acquired Metaweb in 2010 that developed Freebase (open, shared database of the world's knowledge) in order to improve search answers

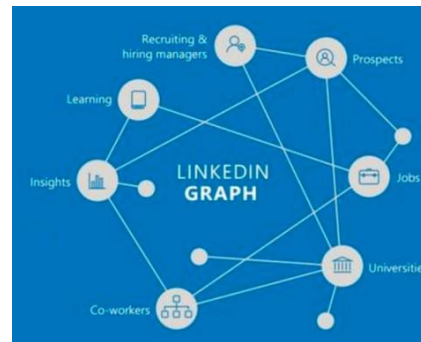
Thomas Jefferson was an American statesman, diplomat, lawyer, architect, musician, philosopher, and Founding Father who served as the third president of the United States from 1801 to 1809. [Wikipedia](#)

**Born:** April 13, 1743, Shadwell, Virginia, United States  
**Died:** July 4, 1826, Monticello, Virginia, United States  
**Party:** Democratic-Republican Party  
**Presidential term:** March 4, 1801 – March 4, 1809  
**Children:** Martha Jefferson Randolph, Madison Hemings, MORE  
**Vice presidents:** Aaron Burr (1801–1805), George Clinton (1805–1809)



### ▪ Microsoft : LinkedIn service內 보유한 전문성과 인간 관계를 Knowledge Graph化

- Recruiter search and recommendation, insight extraction such as the # of members who have a given skill in a given location and the # of job hires requiring a given skill in that same location



### ▪ Amazon: 상품 Knowledge graph 구축을 통해 사용자 맞춤형 상품 검색/추천

- Answer any question about products and related knowledge in the world
- Search for the best products that fit user's need and help customers use greater variation in search terms

※ for example, bathing suit or swimsuit, tomato or tomahto



# Knowledge Graph = Data and Ontology

- A structured collection of facts organized by semantic schemas
  - ✓ fact들의 구조화된 집합 (Data) + 의미론적 스키마로 조직화 (Ontology)

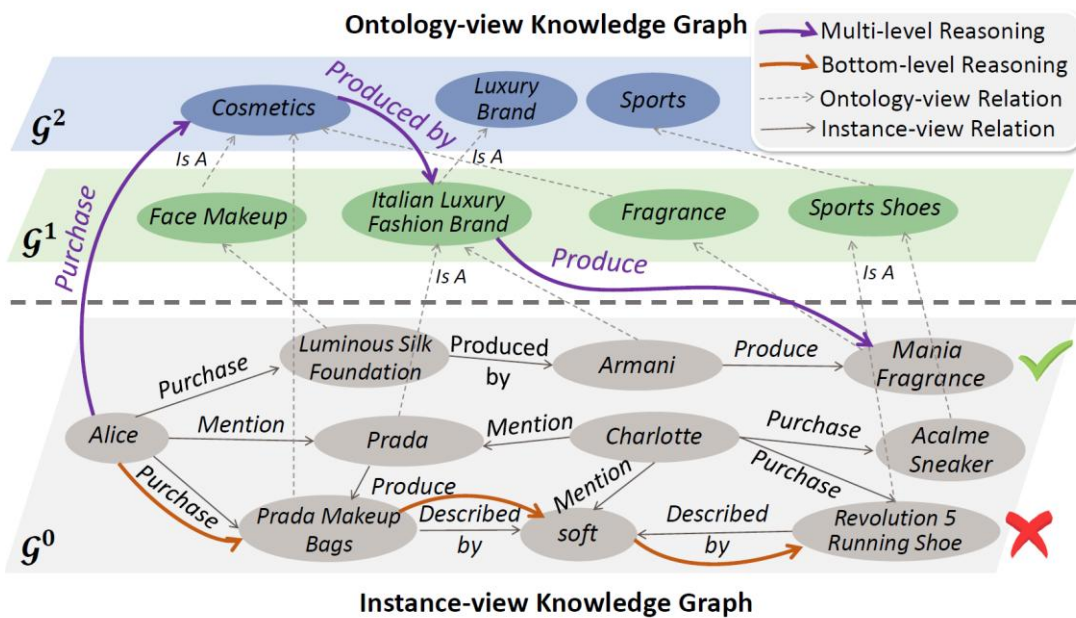
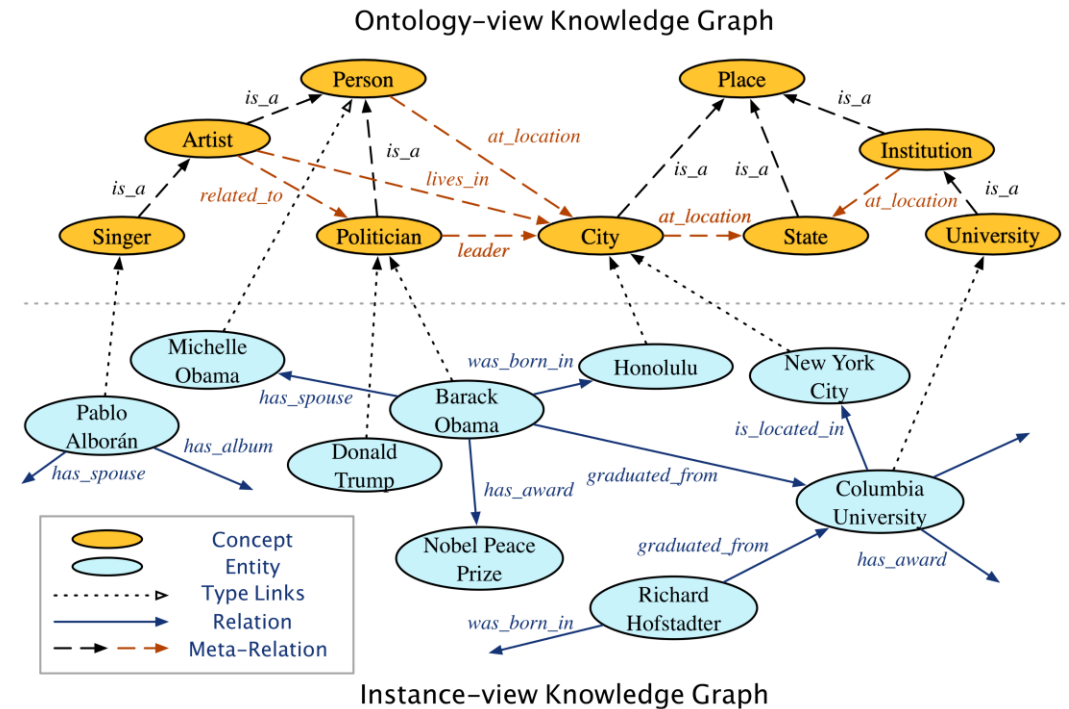


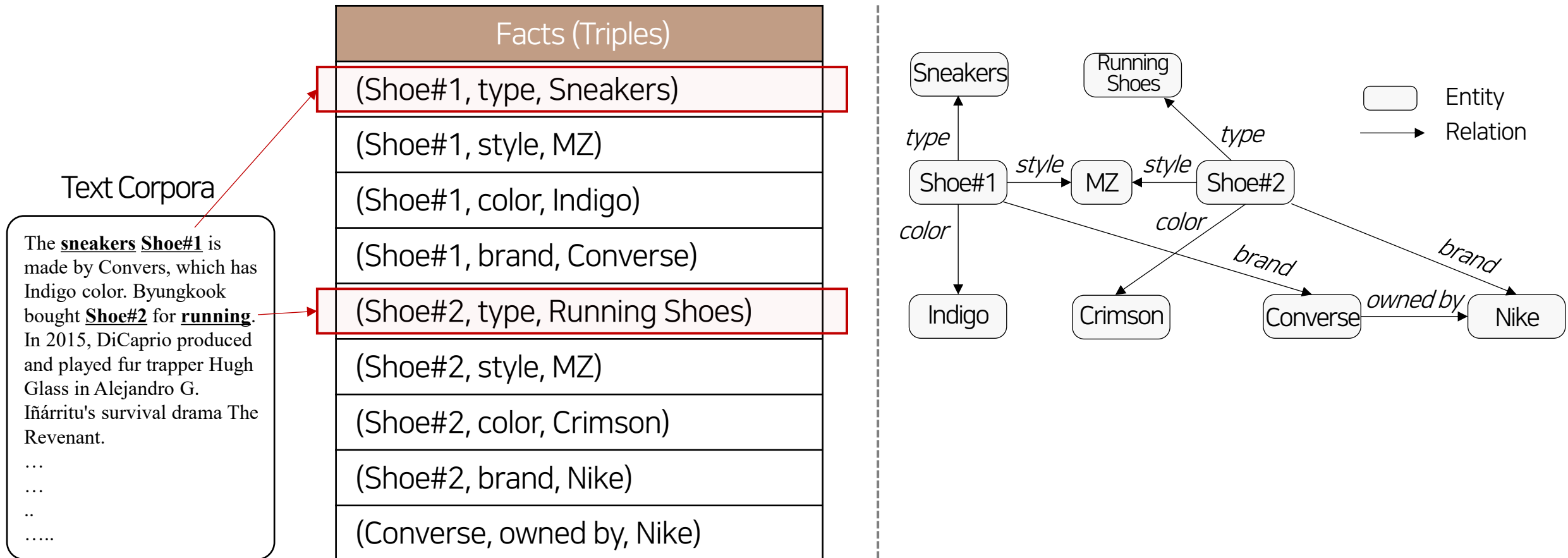
Figure 1: Multi-level reasoning over two-view KGs.



# Knowledge Graph = Data and Ontology

❑ A structured collection of facts organized by semantic schemas

✓ fact들의 구조화된 집합 (Data) + 의미론적 스키마로 조직화 (Ontology)



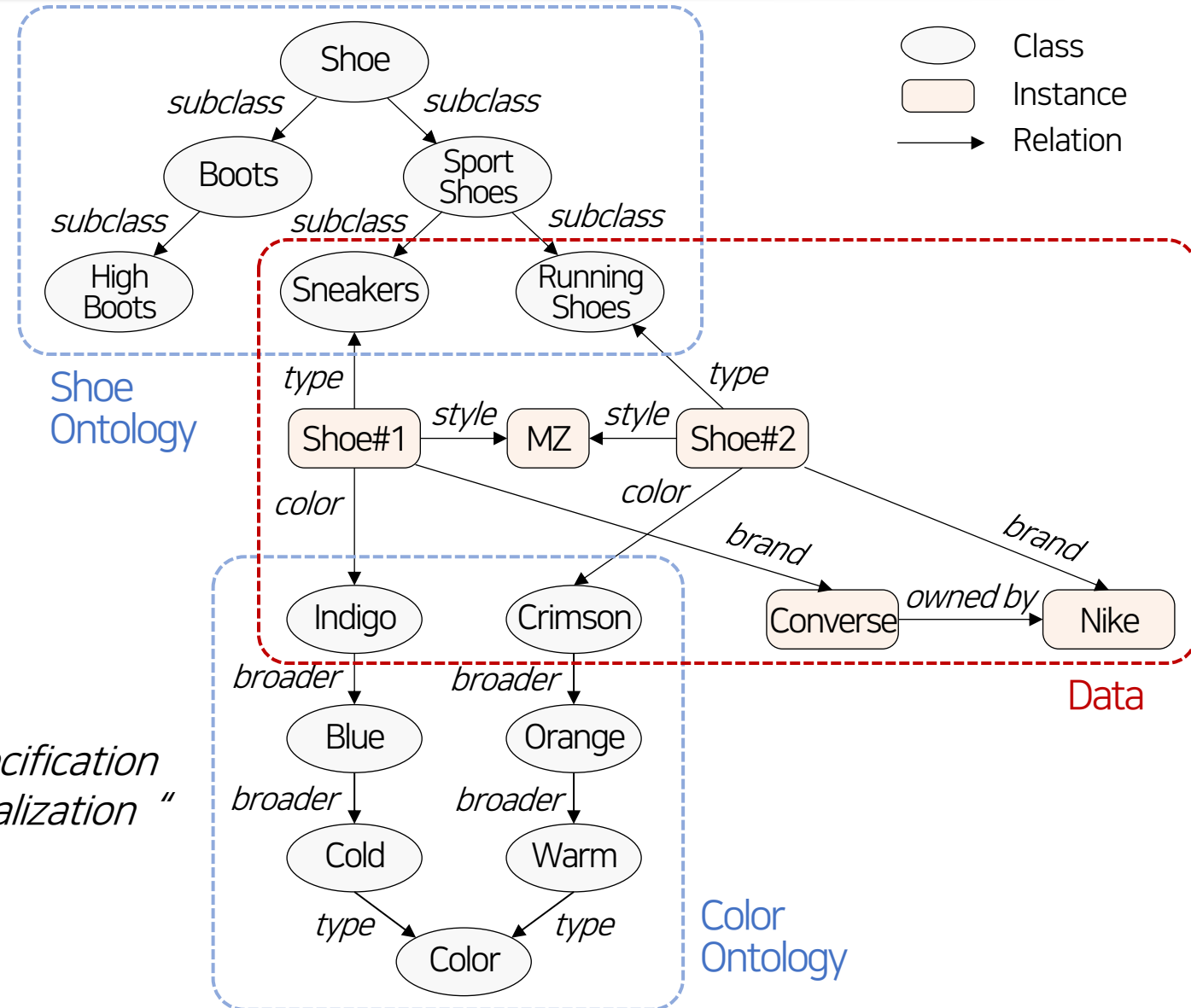
# Knowledge Graph = Data and Ontology

## ✓ Data + Schema (Ontology)

- factual knowledge

## ✓ Reusable

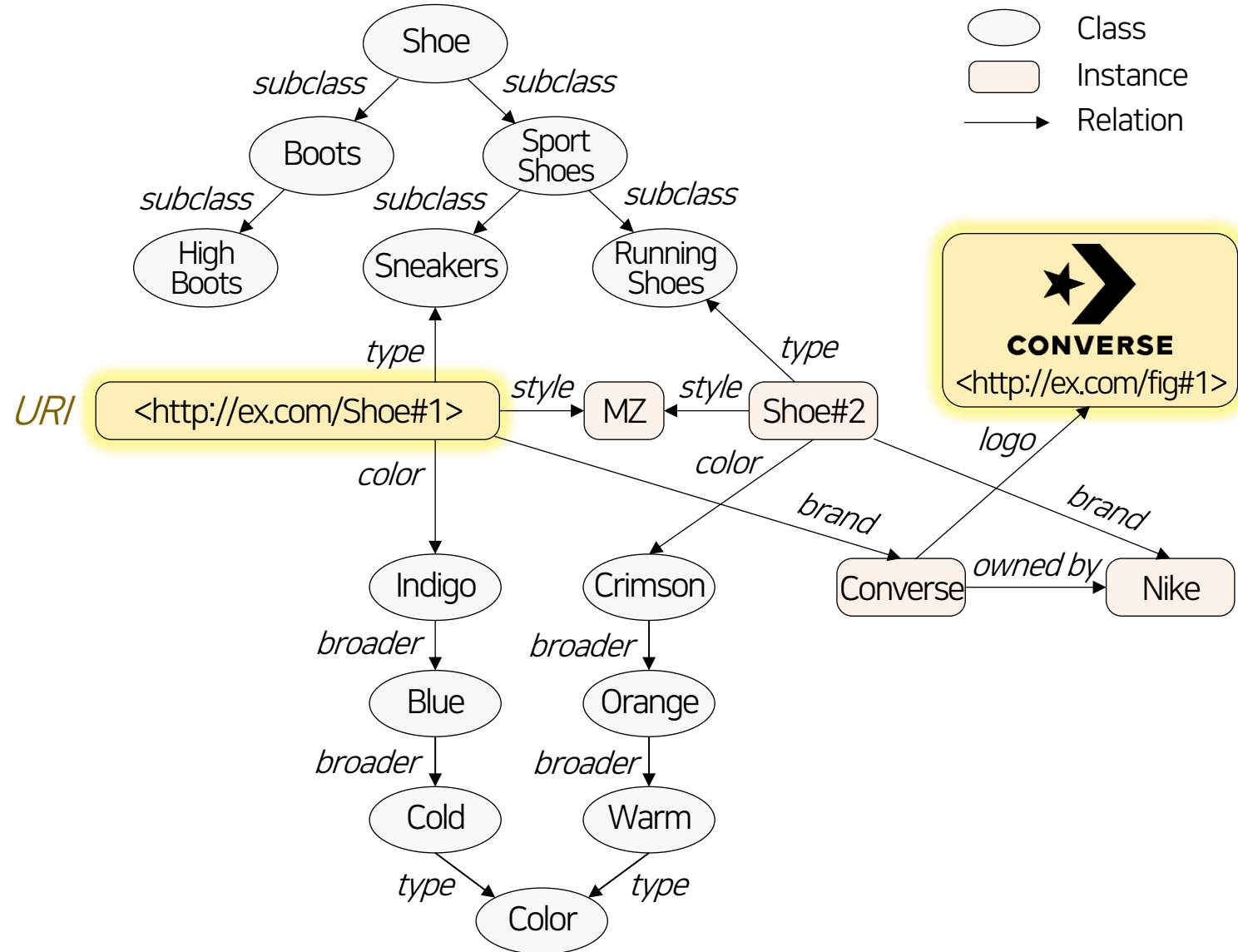
*" formal and explicit specification  
of a shared conceptualization "*



# Knowledge Graph = Data and Ontology

## ✓ Data + Schema (Ontology)

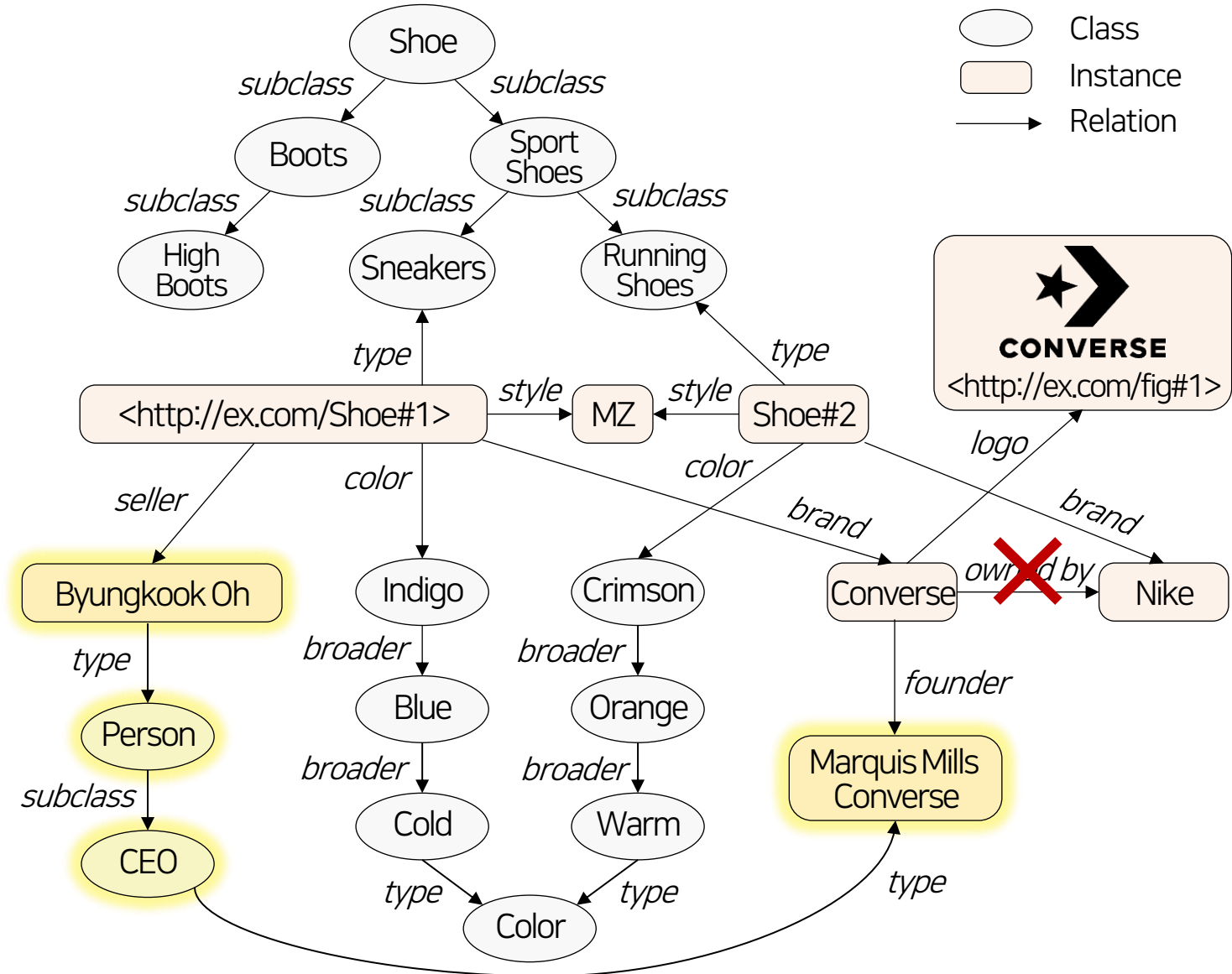
- factual knowledge
- ✓ Reusable
- ✓ Interoperable
- ✓ Machine Readable



# Knowledge Graph = Data and Ontology

## ✓ Data + Schema (Ontology)

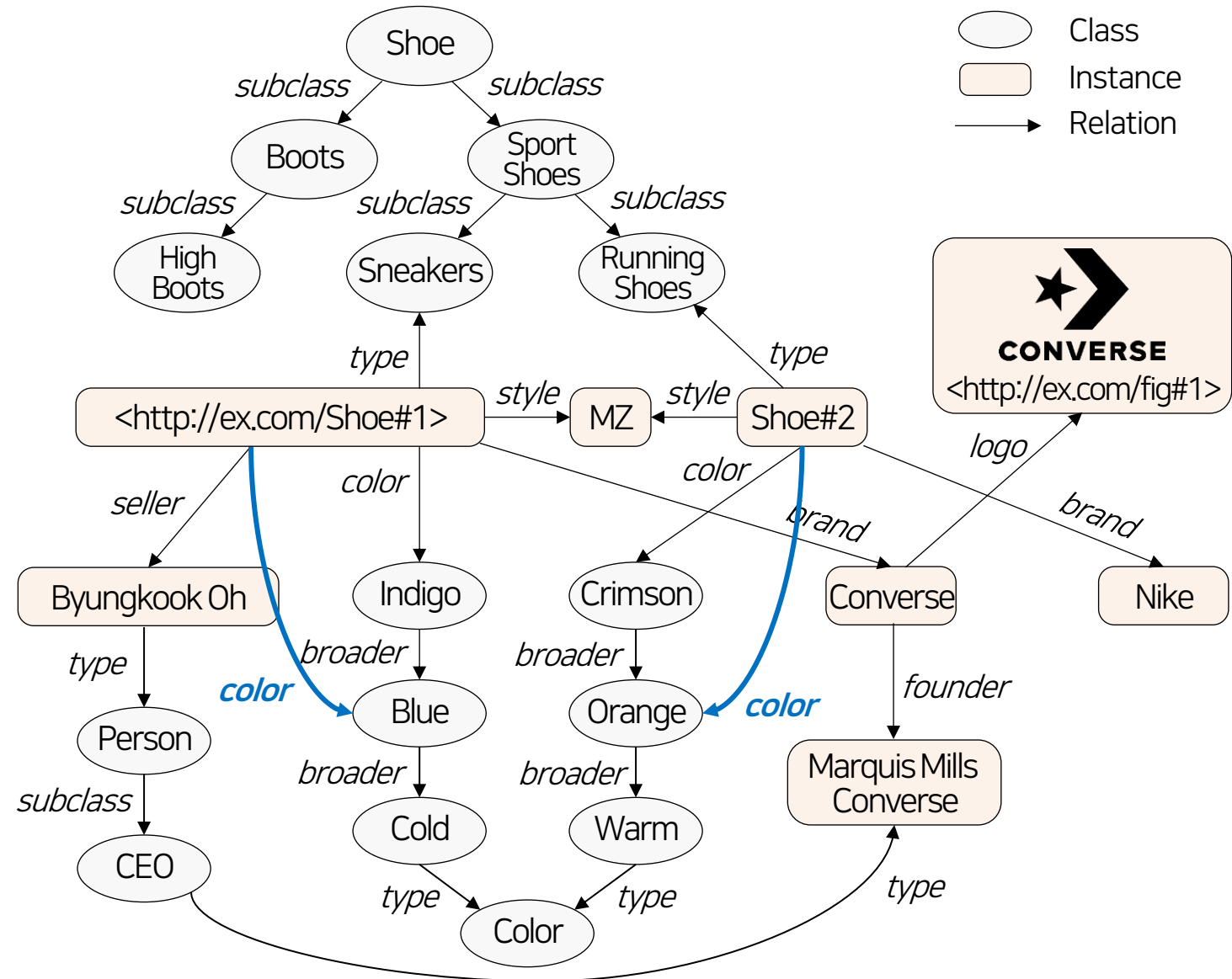
- factual knowledge
- ✓ Reusable
- ✓ Interoperable
- ✓ Machine Readable
- ✓ Flexible / Extensible



# Knowledge Graph = Data and Ontology

## ✓ Data + Schema (Ontology)

- factual knowledge
- ✓ Reusable
- ✓ Interoperable
- ✓ Machine Readable
- ✓ Flexible / Extensible
- ✓ Inference (DL)
  - color + broader -> color



# Knowledge Graph = Data and Ontology

## ✓ Data + Schema (Ontology)

- factual knowledge

## ✓ Reusable

## ✓ Interoperable

## ✓ Machine Readable

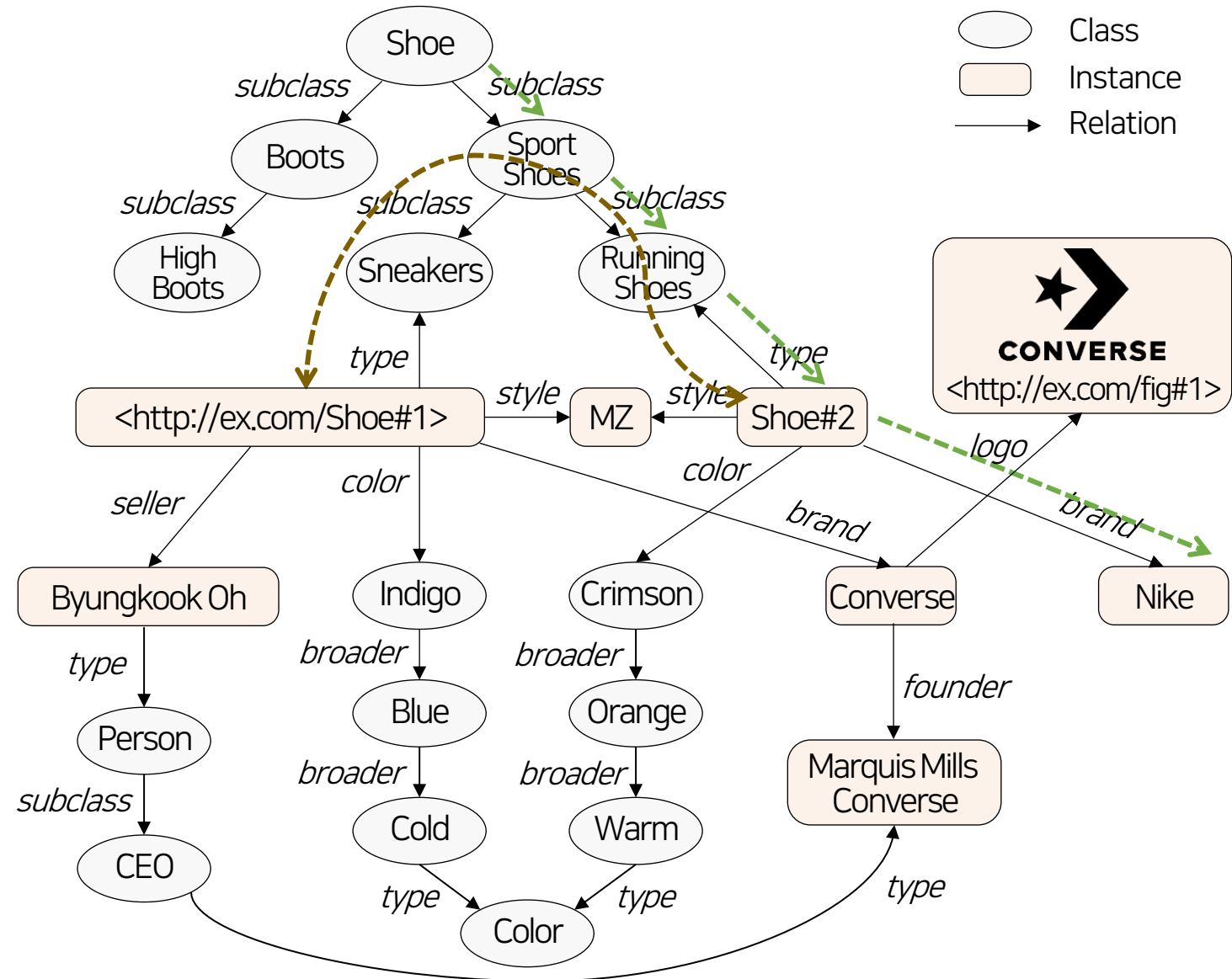
## ✓ Flexible / Extensible

## ✓ Inference (DL)

- color + broader -> color

## ✓ Other kinds of Queries

- Navigation
- Similarity & Locality (structure)



# Knowledge Graph

## 삼성전자, 지식 그래프 만드는 英 스타트업 인수...왜?

등록 2024.07.18 08:36:04 | 수정 2024.07.18 10:00:52



옥스퍼드 시멘틱 테크놀로지스, 지식 그래프 기술 보유  
"데이터 지식화 분야 기술력 제고...AI 기술 혁신 지속"



Oxford Semantic  
Technologies

[서울=뉴시스]삼성전자가 세계 최고 수준 '지식 그래프(Knowledge Graph)' 원천 기술 보유 기업을 인수했다고 18일 밝혔다.  
'지식 그래프'는 데이터를 사람의 지식 기억 및 회상 방식과 유사하게 저장, 처리하는 기술로, 보다 정교하고 개인화된 AI(인공 지능)를 구현하는 핵심 기술 중 하나로 꼽힌다. (사진=삼성전자 제공) photo@newsis.com \*재판매 및 DB 금지

❑ 삼성전자가 세계 최고 수준의 '지식 그래프(Knowledge Graph)' 원천 기술 보유 기업을 인수했다고 18일 밝혔다.

✓ '지식 그래프'는 데이터를 **사람의 지식 기억 및 회상 방식과 유사하게 저장, 처리**하는 기술로, 더 정교하고 개인화된 AI(인공지능)를 구현하는 핵심 기술로 꼽힌다.

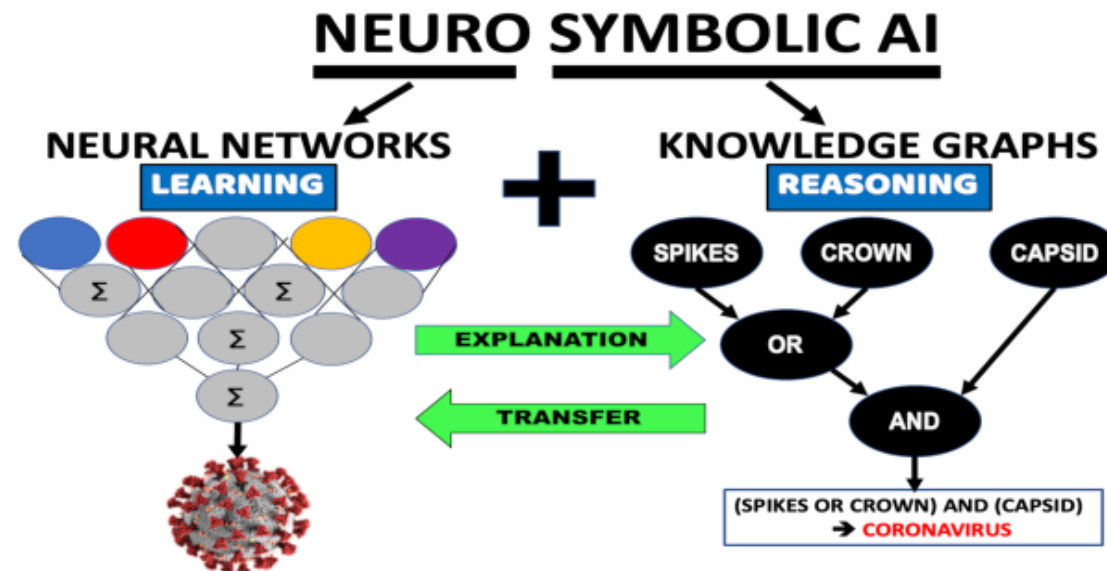
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- 3. Graph Representation Learning**
4. Graph-based AI
5. What's Next?

# Graph Representation Learning

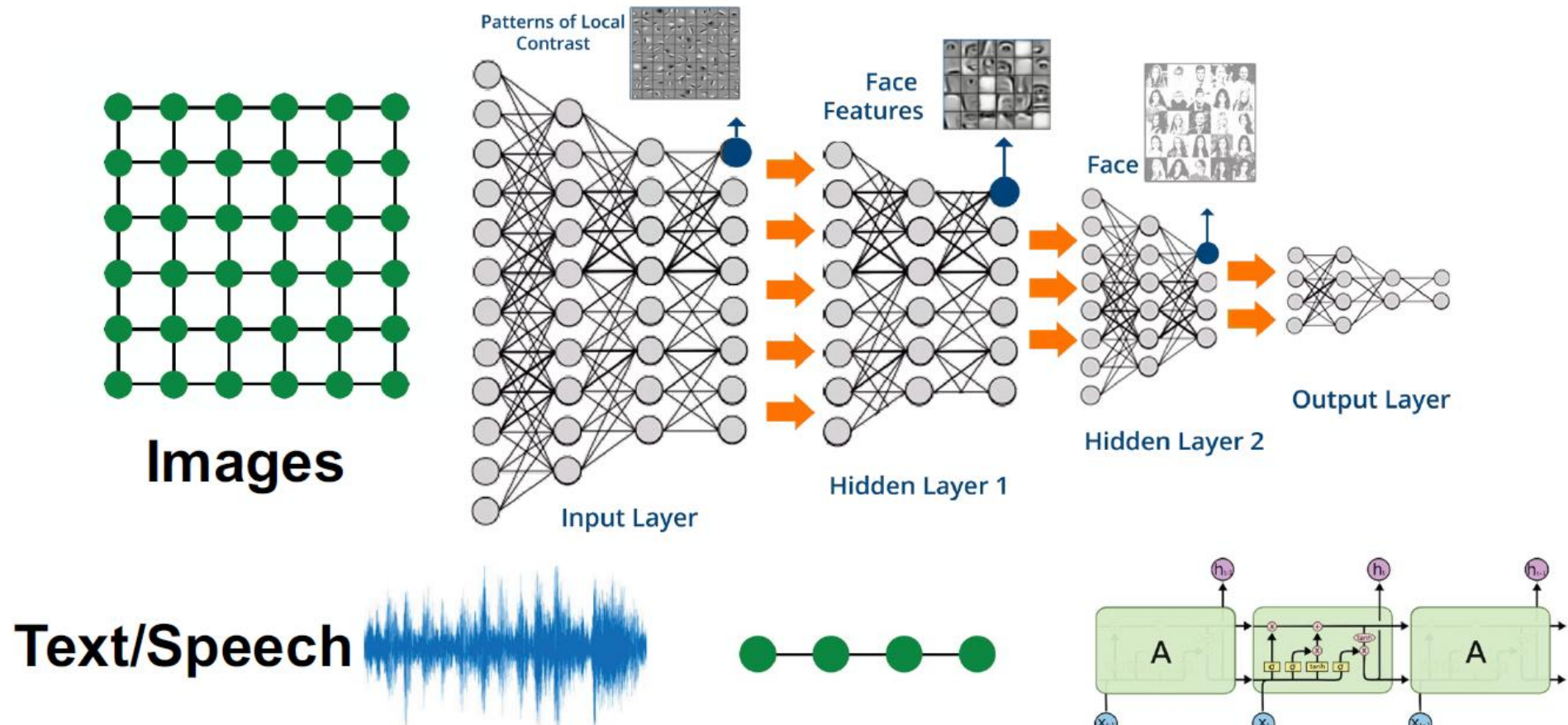
- 그래프는 복잡한 시스템을 표현/설명/분석하기 위한 범용적인 자료구조
  - ✓ 구성요소 간의 상호작용/관계를 추가적으로 기술할 수 있는 데이터 구조

=> *How can we develop neural network that are much more broadly applicable?*



# Graph Representation Learning

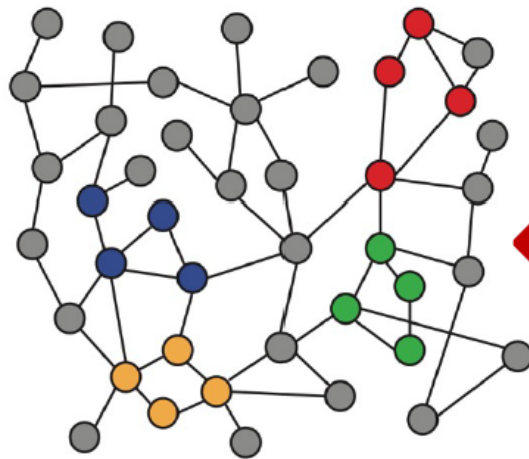
- Modern deep learning toolbox is designed for simple sequences & grids



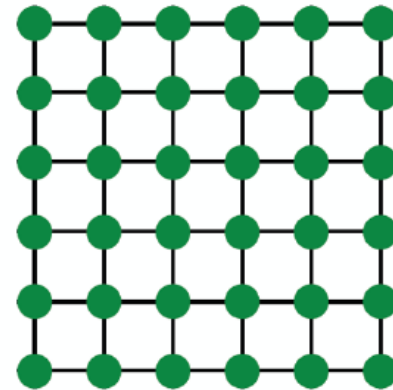
# Graph Representation Learning

## ❑ Networks are complex.

- ✓ Arbitrary size and complex topological structure (i.e., no spatial locality like grids)
- ✓ No fixed node ordering or reference point
- ✓ Often dynamic and have multimodal features



**Networks**



**Images**

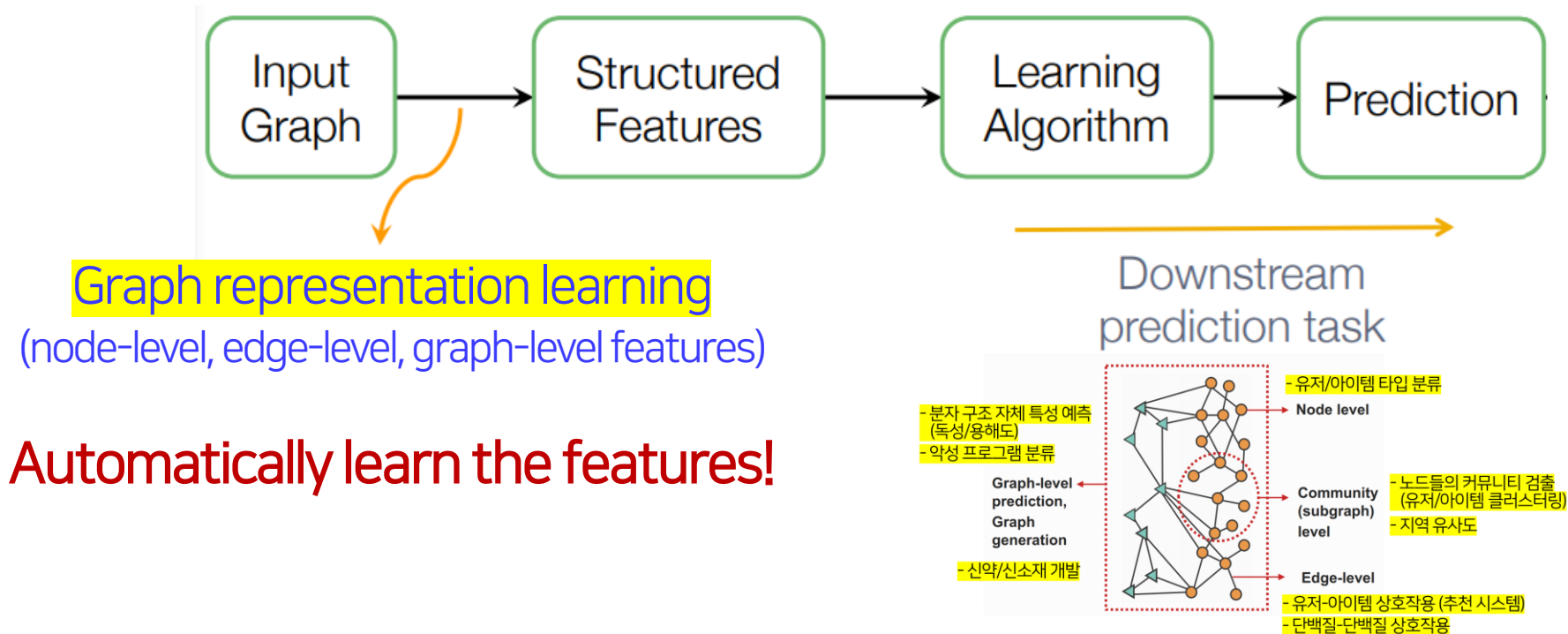


**Text**

New frontiers  
beyond classic neural networks  
that learn on images and sequences

# Graph Representation Learning

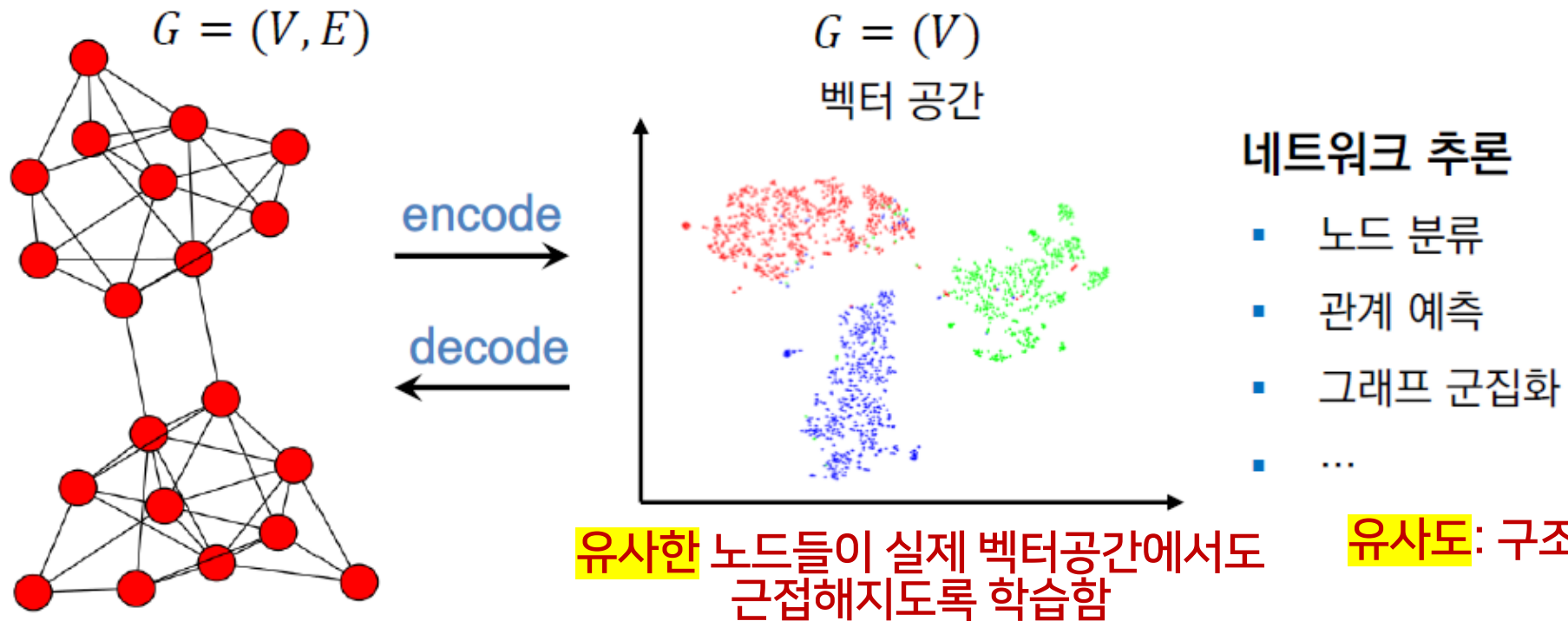
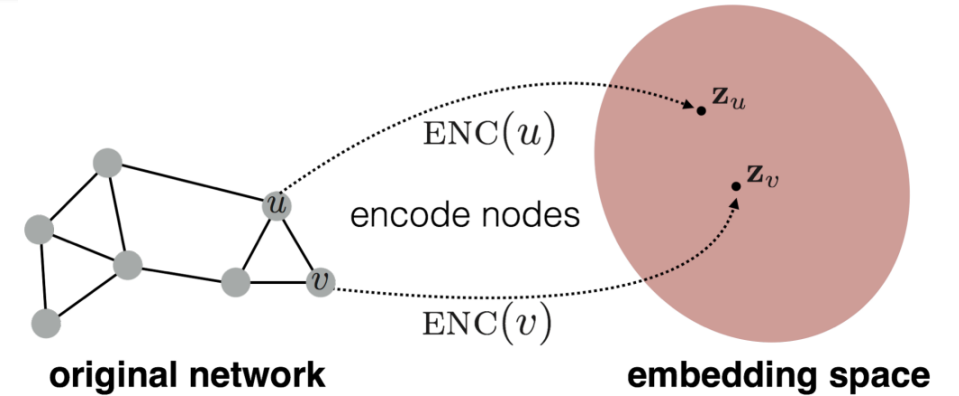
- ❑ need to obtain node features from a graph, while preserving graph-structured information and node/edge attributes
- ✓ Feature engineering
- ✓ Graph representation learning



# Graph Representation Learning

## □ Graph representation learning

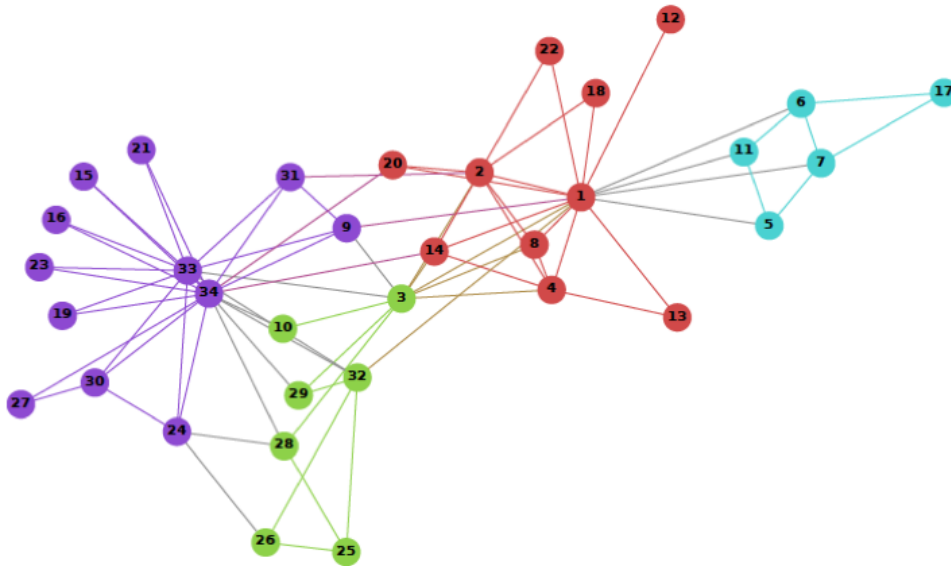
- ✓ 주로 그래프의 노드를 저차원 공간 상으로 임베딩
  - 그래프 구조와 노드/엣지의 속성 정보를 벡터화 함
- ✓ 그래프 기계학습 문제를 벡터 공간에서 해결 가능



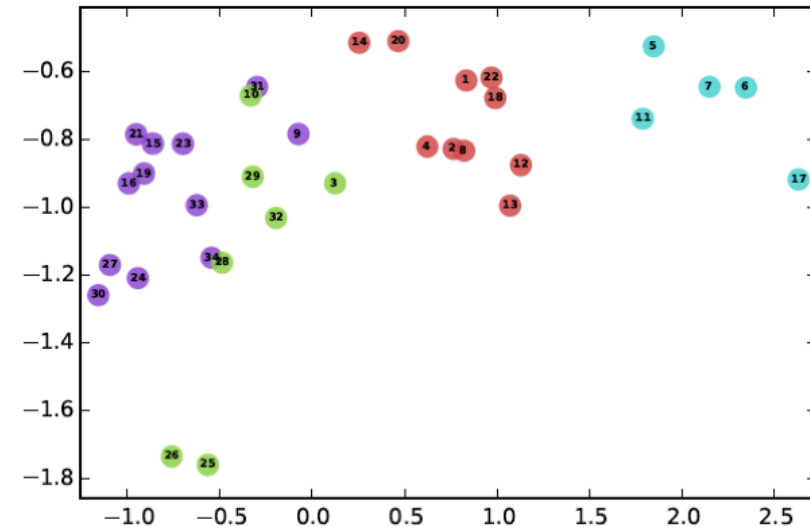
# Graph Representation Learning

- Intuition: Find embedding of nodes to d-dimensions so that “similar” nodes in the graph have embeddings that are close together.

A

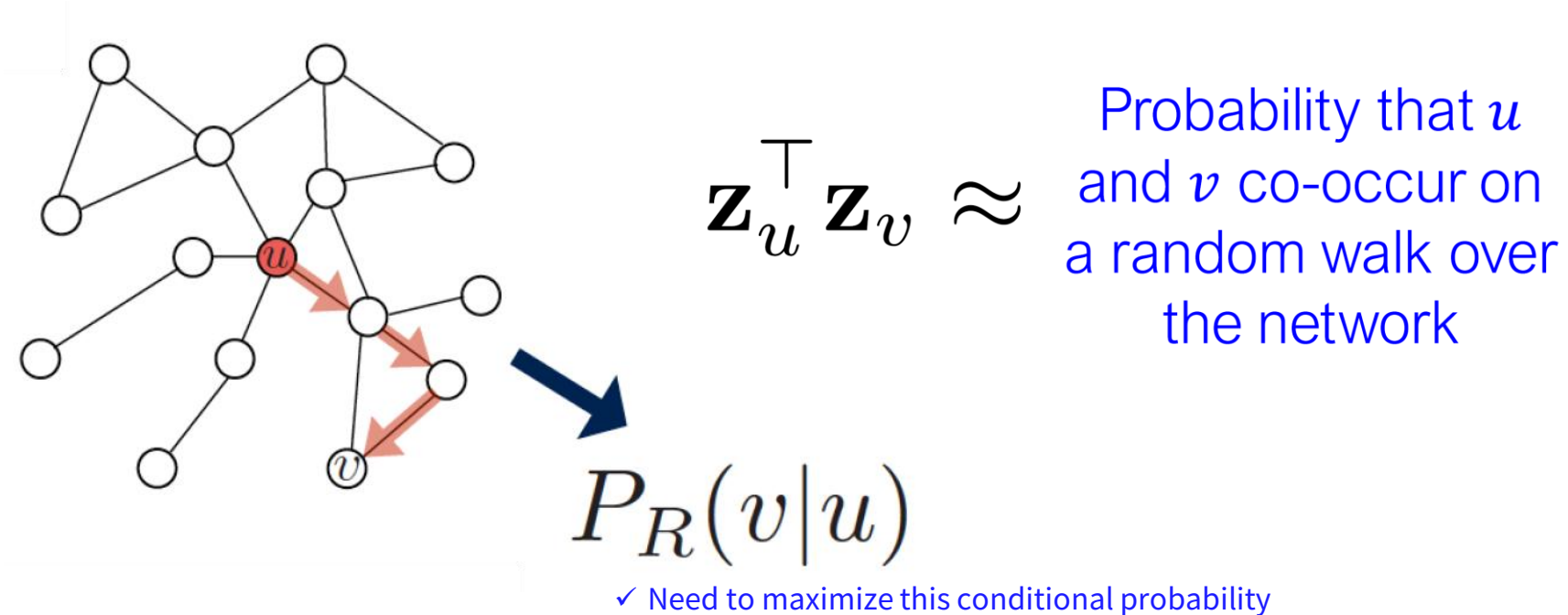


B



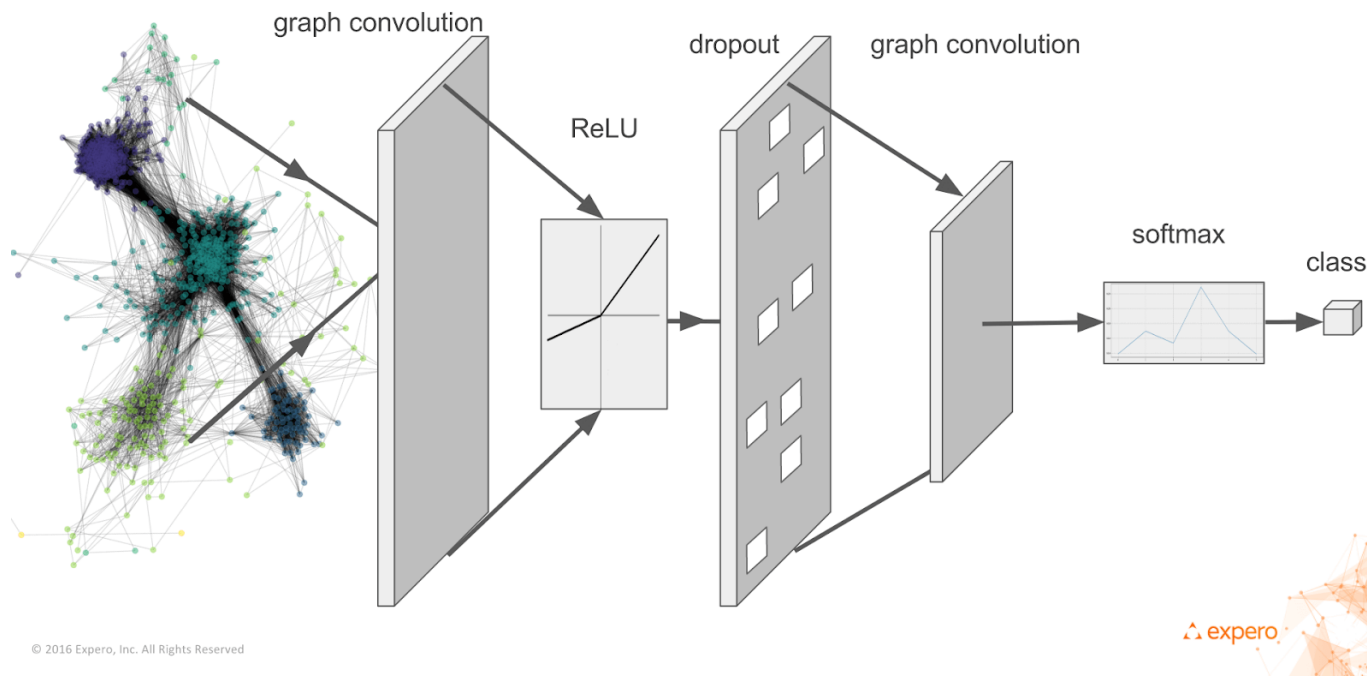
# EX) DeepWalk

- ❑ Estimate probability of visiting node  $v$  on a random walk starting from node  $u$  using some random walk strategy  $R$
- ❑ Optimize embeddings to encode these random walk statistics



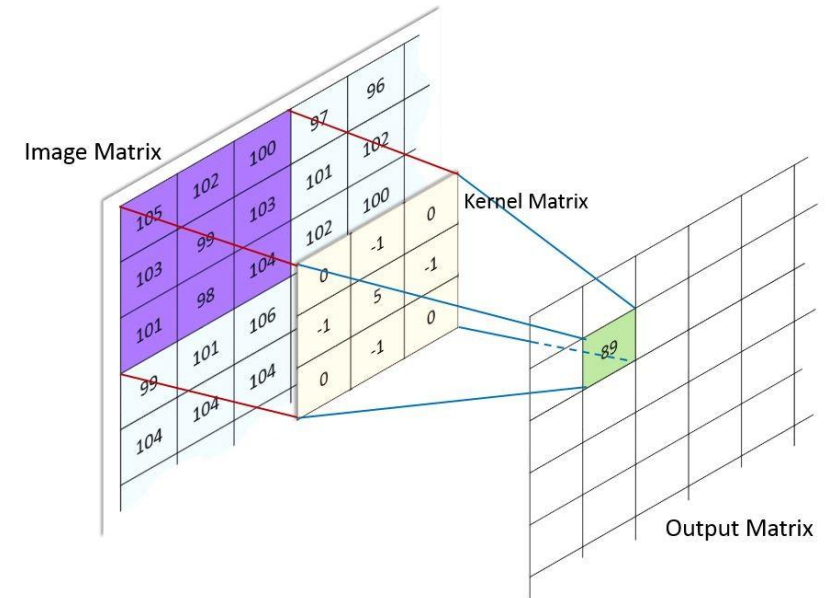
# EX) Graph Convolutional Network

❑ Idea: Node's neighborhood



✓ Goal is to generalize convolutions to graphs

VS

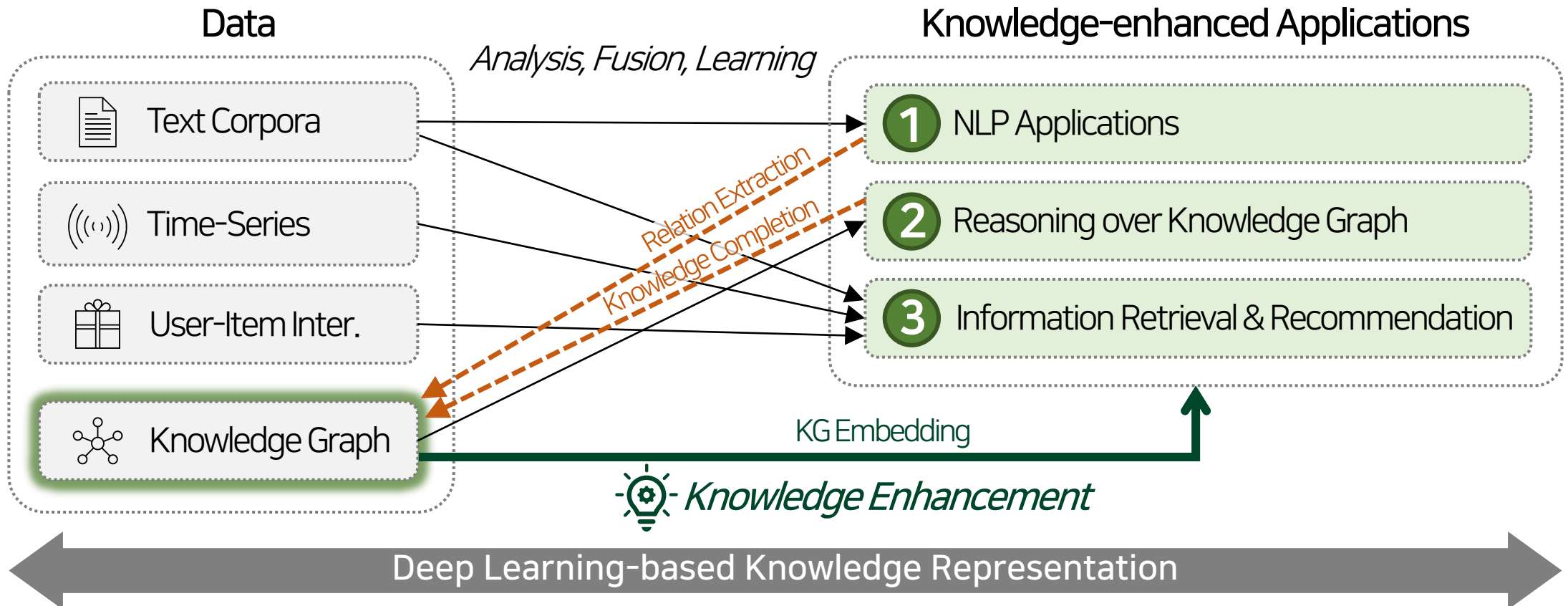


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# Overview

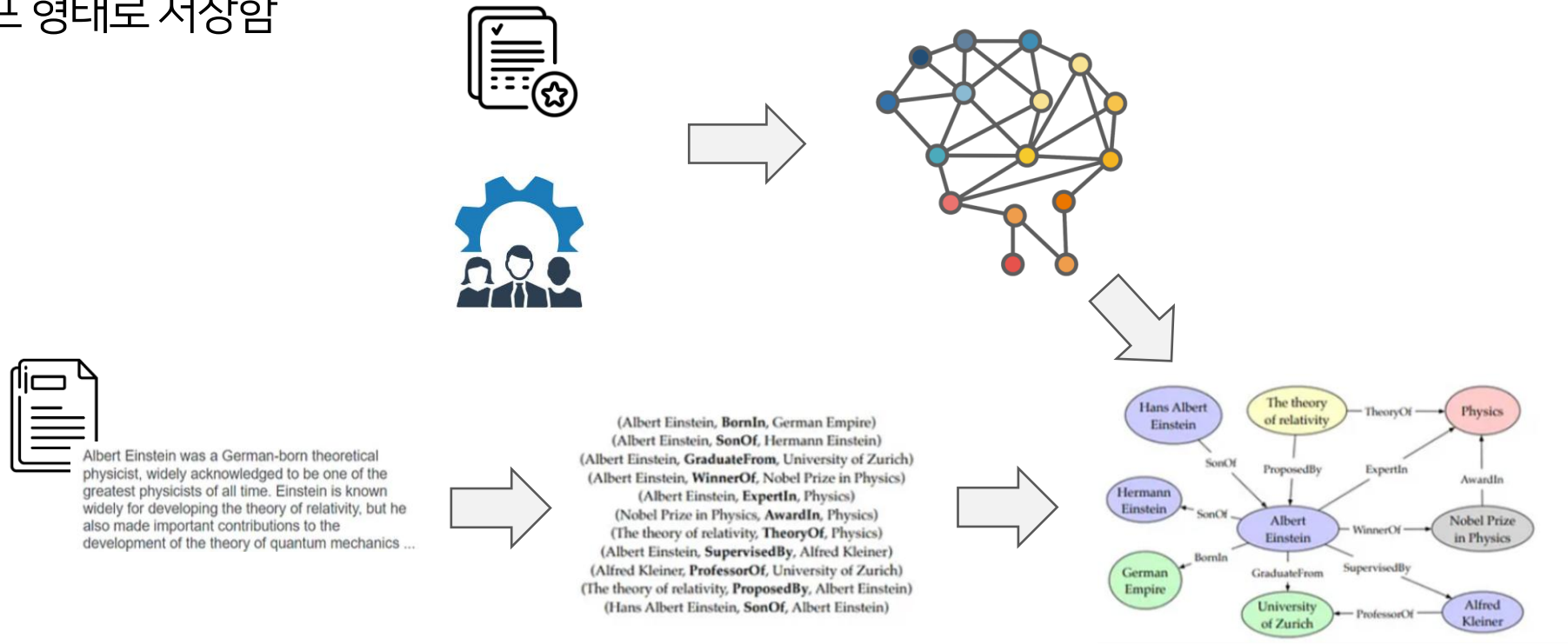
## ❑ The Journey from Data to Knowledge-enhanced Applications



# Overview

## □ 지식그래프 설계 및 구축

- ✓ 지식그래프 설계: 도메인 정보 및 전문 지식을 구조화된 형태로 표현할 수 있도록 하는 스키마를 설계함
- ✓ 지식그래프 구축: 자연어 데이터 등 비정형 데이터로부터 구조화된 지식을 추출하여 스키마에 따라 지식그래프 형태로 저장함

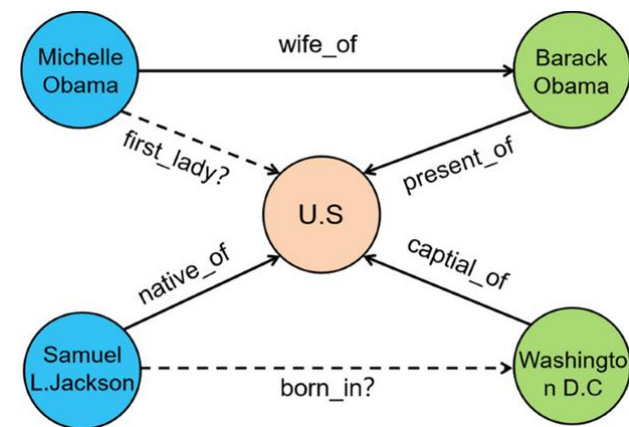
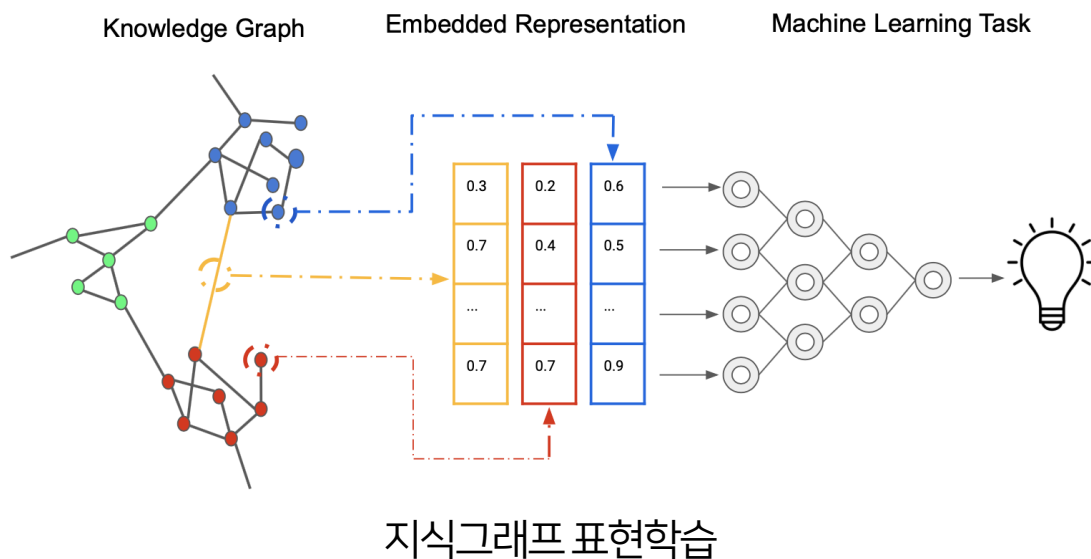


지식그래프 구축 과정

# Overview

## □ 지식그래프 표현 학습 및 완성

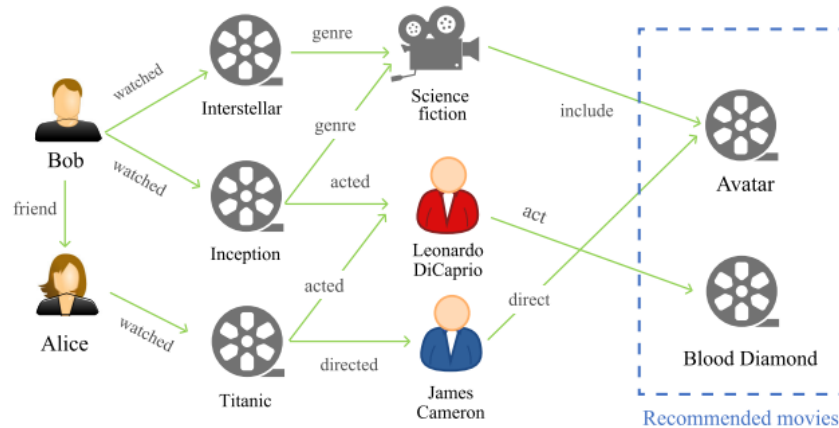
- ✓ 지식그래프 표현학습: 지식그래프의 구조를 파악하여 개체 및 관계의 특성을 학습함
  - 계층 구조 정보 및 개체 사이의 관계를 고려한 표현학습이 가능함
  - 활용 예시: 전자상거래 지식그래프를 활용한 아이템 추천 모델 개발
- ✓ 지식그래프 완성: 불완전한 지식그래프에서 누락된 지식을 찾아내어 지식그래프를 완성시킴
  - 오른쪽 그림 예제: <Michelle Obama, ?, U.S>



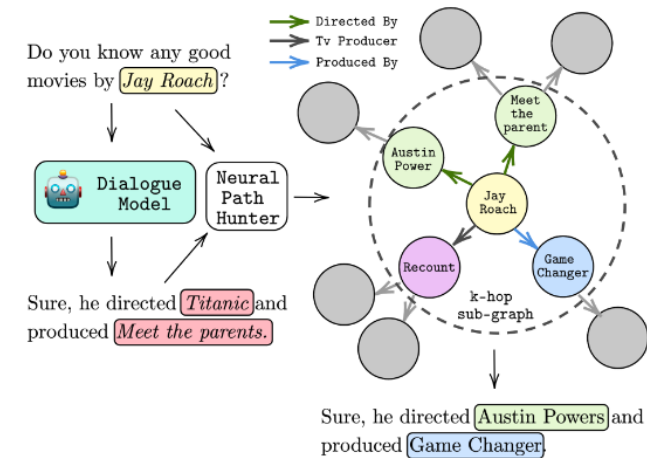
# Overview

## □ 지식그래프 활용 연구

- ✓ 추천 시스템: 지식그래프에 정의된 item 정보를 활용하여 사용자의 의도에 부합하는 상품을 추천함
- ✓ 질의 응답: 주어진 질문에 대해 지식그래프 내에서 답변을 찾아 제공함
- ✓ 지식 기반 대화 생성: 주어진 질문에 대해 지식그래프를 활용하여 답변함



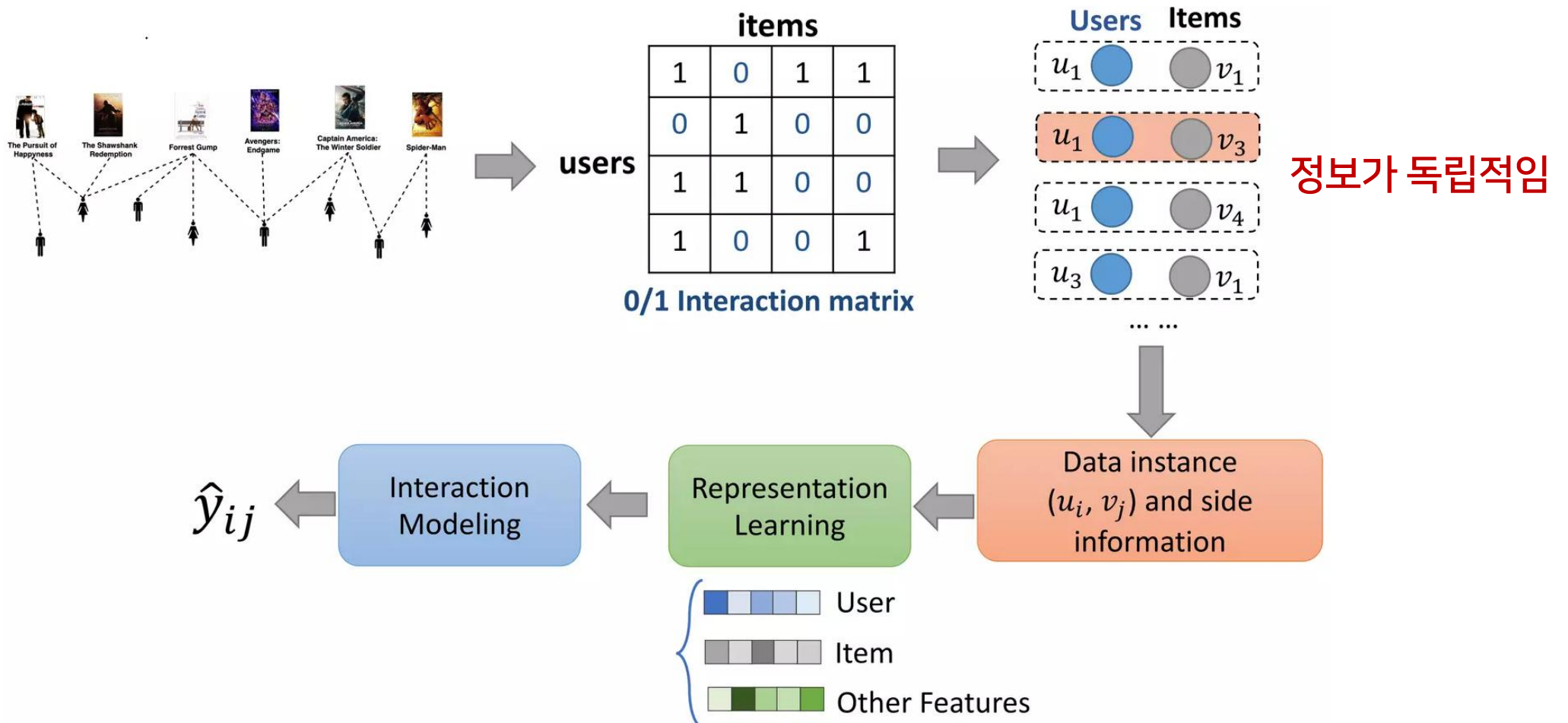
지식그래프 기반 추천 시스템



지식그래프 기반 자연어처리

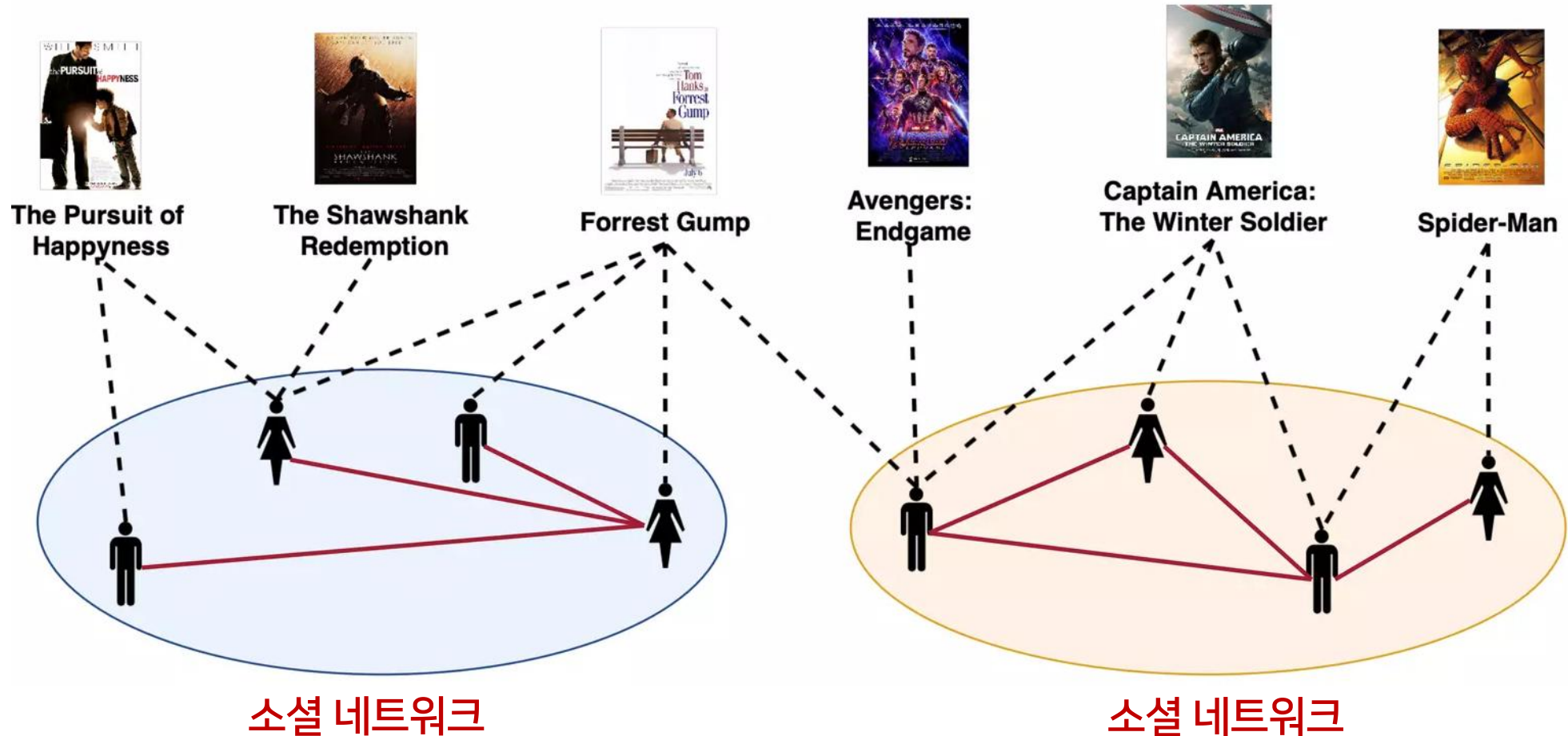
# Recommender System

## □ 전통적인 방식의 추천시스템에서의 User-Item Interaction Matrix 사용



# Graph-based Recommender System

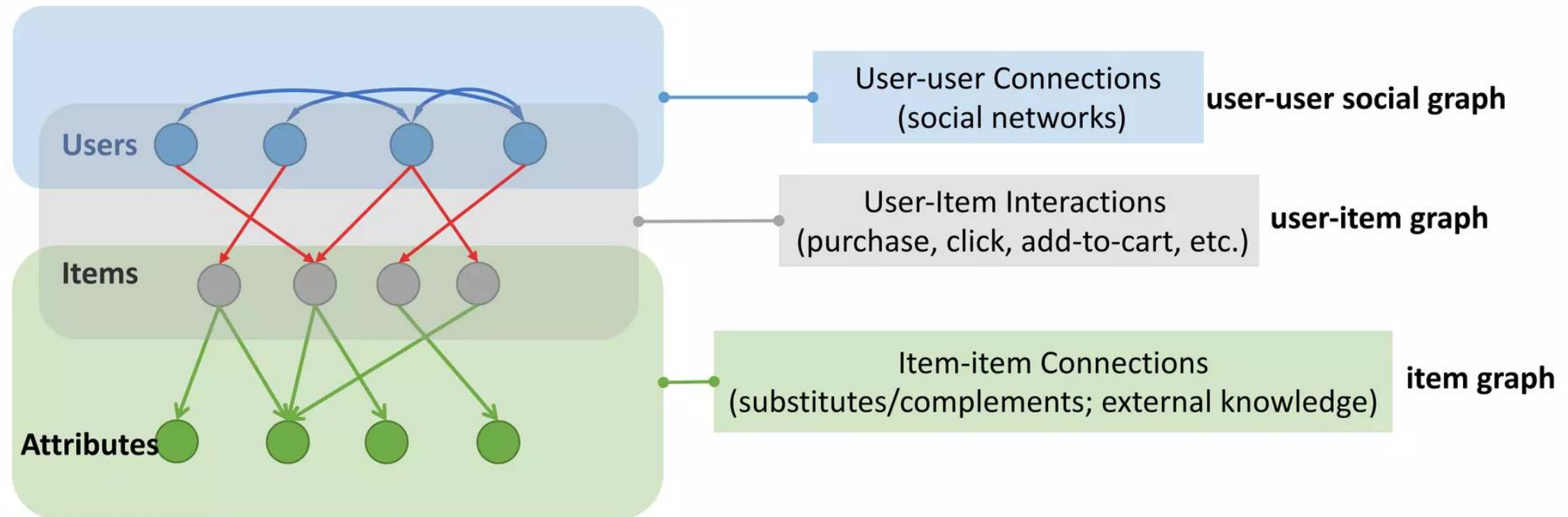
- 유저의 선호도는 주변 사람들의 선호도에 영향을 받음



# Graph-based Recommender System

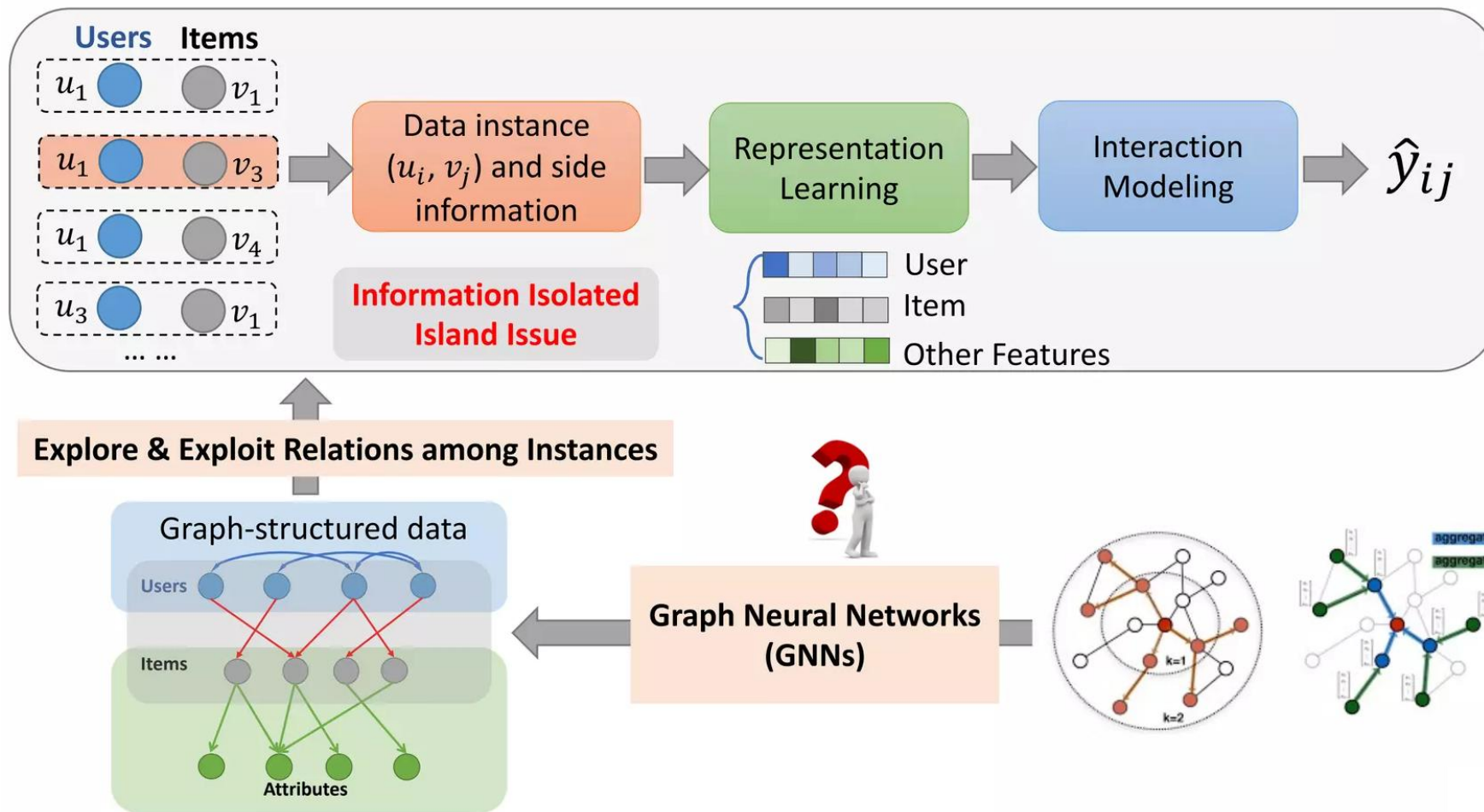
❑ User/Item간의 연결정보를 그래프로 접근할 수 있음

✓ *"The world is more closely connected than you might think!"*



# Graph-based Recommender System

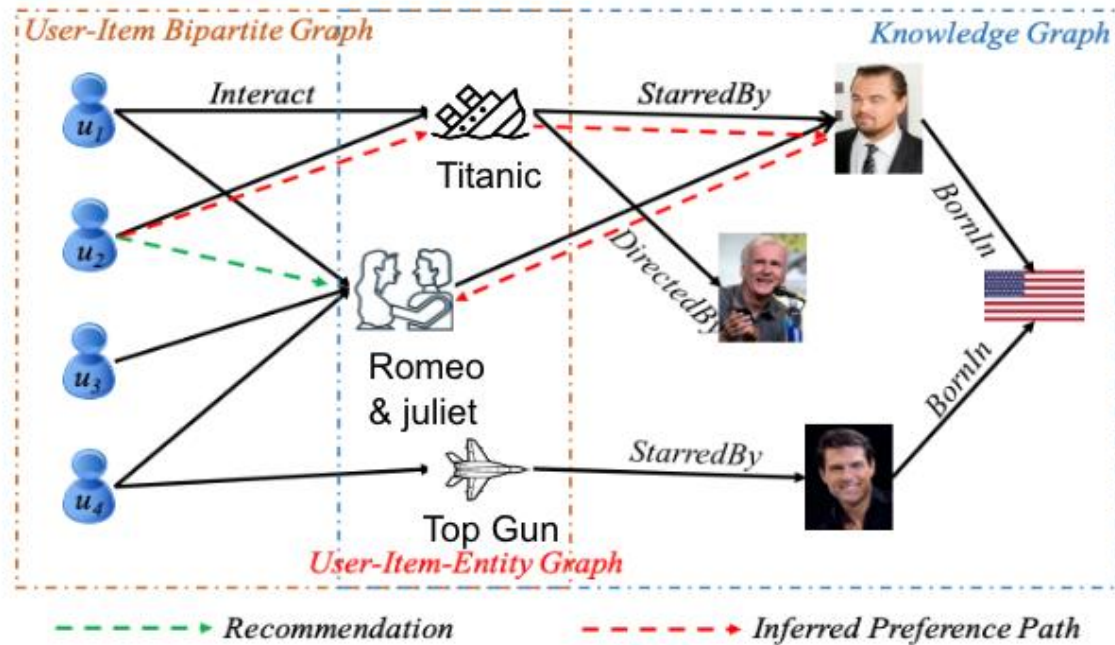
- 추천시스템에 그래프로 표현된 User/Item간의 연결정보를 추가적으로 사용



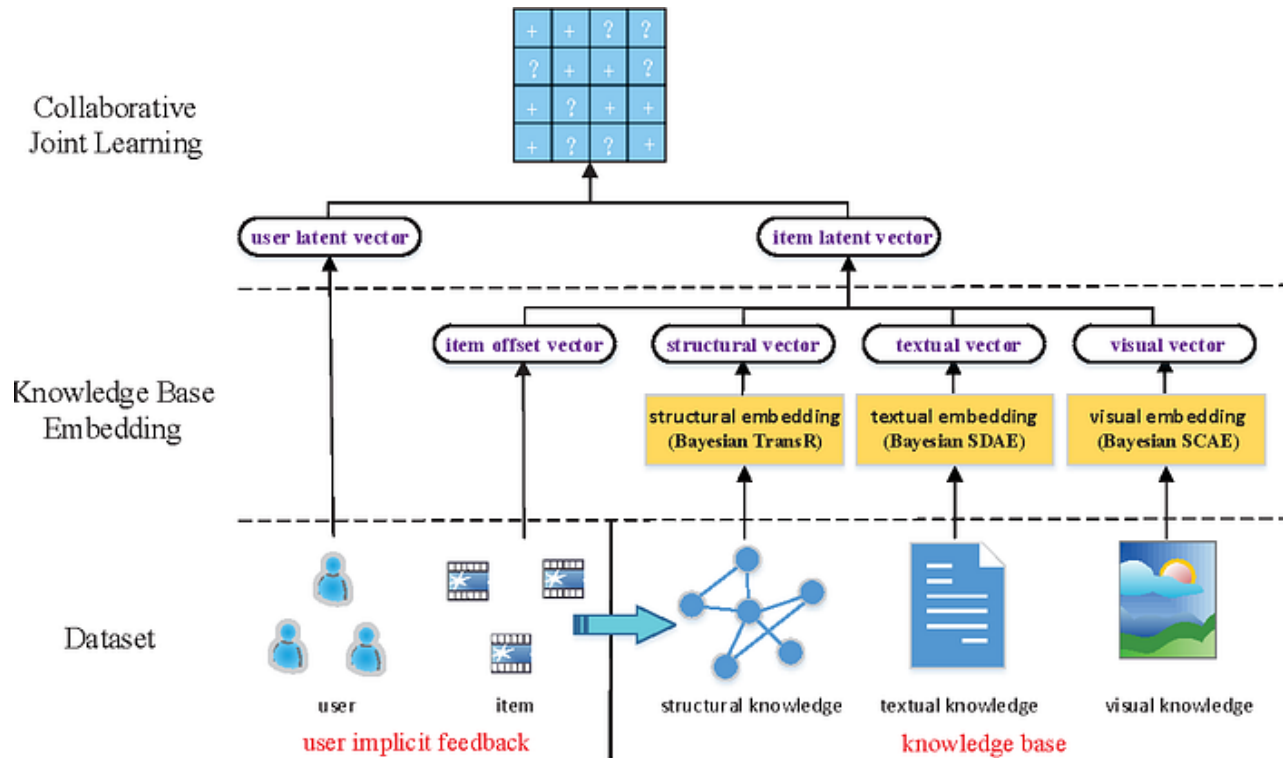
# Graph-based Recommender System

## ❑ Utilizing Structured Knowledge Graph

- ✓ User에게 추천되는 Item에 대한 지식과 Knowledge Graph가 연결됨



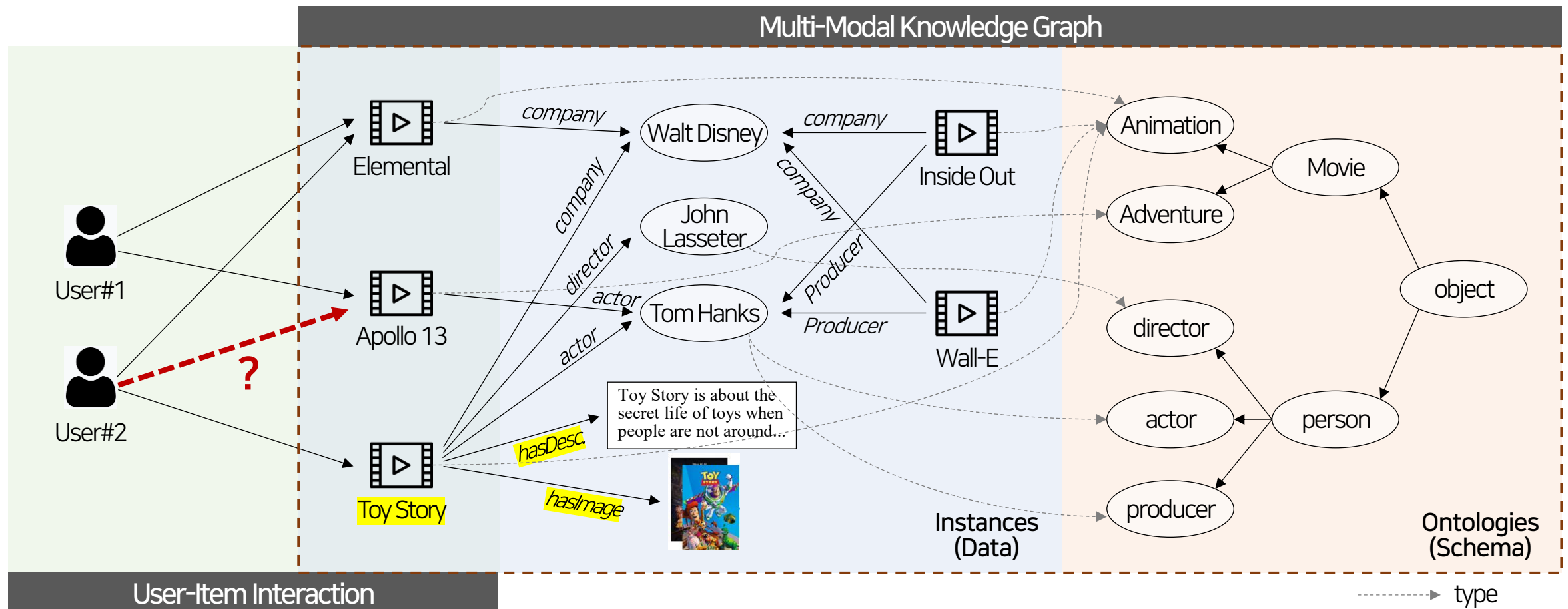
knowledge-graph based recommendation



Embedding based recommender system

# Graph-based Recommender System

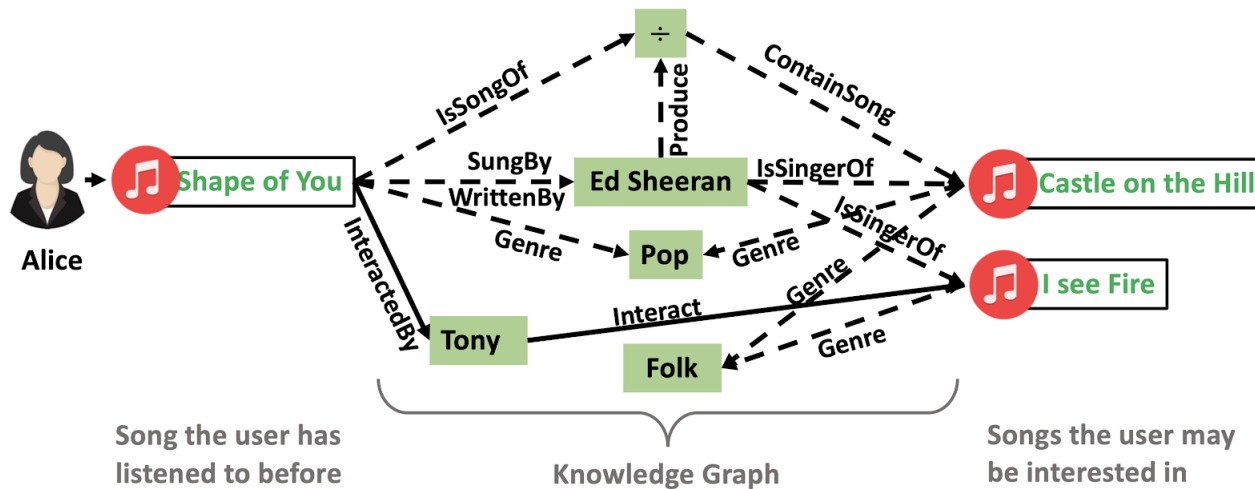
## □ Additionally Utilizing Multi-Modal Structured Knowledge



# 지식그래프 기반의 사용자 의도

❑ 지식그래프 기반의 설명가능한 추천시스템과 지식그래프 기반의 사용자 의도 추출 기술을 확장하여 KGQA에 적용

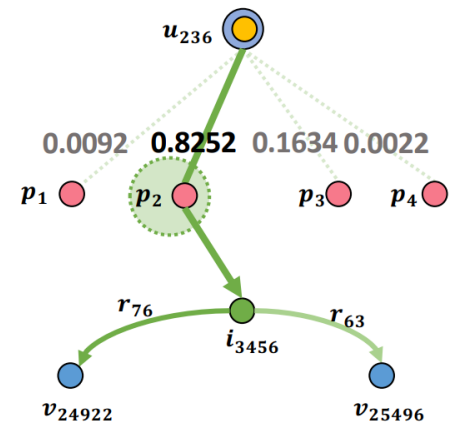
✓ KGQA: Knowledge Graph Question Answering



기존의 지식그래프 기반의 설명가능한 추천시스템

|       | Top 2 KG Relations in Each Intent      | Score  |
|-------|----------------------------------------|--------|
| $p_1$ | $r_{65}$ (theater.play.genre)          | 0.2368 |
|       | $r_{34}$ (theater.plays in this genre) | 0.1623 |
| $p_2$ | $r_{76}$ (book.date_written)           | 0.3567 |
|       | $r_{63}$ (book.short_story.genre)      | 0.2283 |
| $p_3$ | $r_{71}$ (date_of_first_performance)   | 0.5934 |
|       | $r_{30}$ (fictional_universe.)         | 0.1418 |
| $p_4$ | $r_{65}$ (theater.play.genre)          | 0.1230 |
|       | $r_{27}$ (book.illustrator)            | 0.1040 |

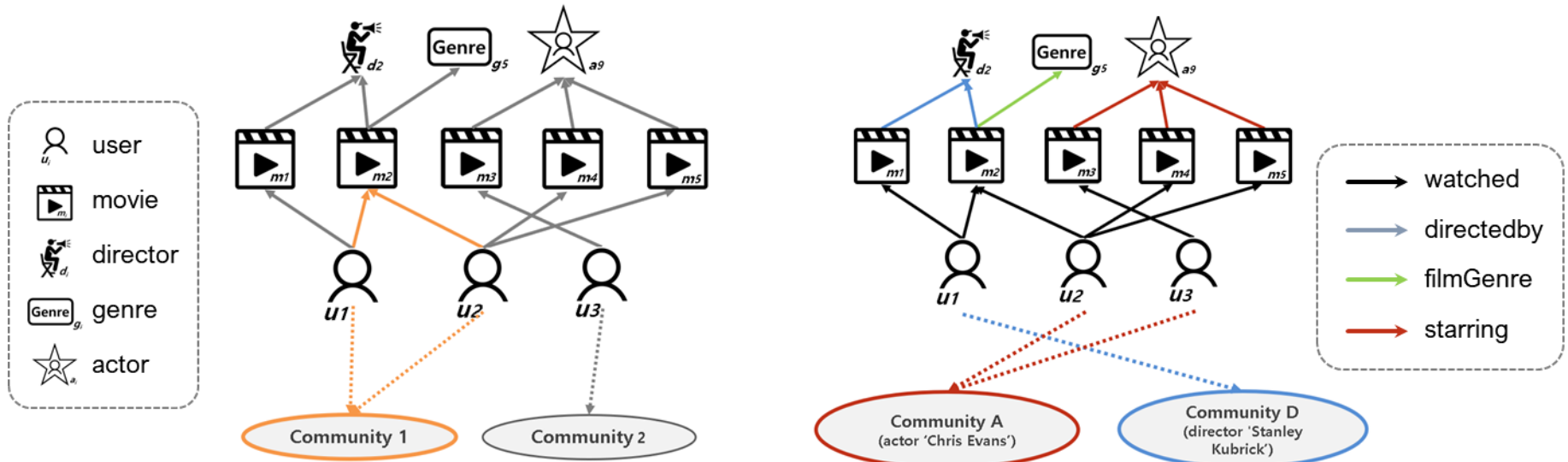
기존의 지식그래프 기반의 사용자 의도 추출



# 지식그래프 기반의 사용자 의도

## □ 상호작용 의도(interaction intent)에 기반한 커뮤니티 탐지가 필요함

- ✓ 사용자가 아이템을 선택한 이유 (의도) 을 추출함
  - 지식그래프(Knowledge Graph: KG) 및 사용자-아이템 연결 정보를 활용 가능
- ✓ 공통 의도 (관심사) 에 기반한 커뮤니티를 탐지하고 이를 추천에 적용함



기존 추천 모델  
(어떤 아이템을 선택했는가?)

의도 기반 추천 모델  
(해당 아이템을 왜 선택했는가?)

# 지식그래프 기반의 사용자 의도

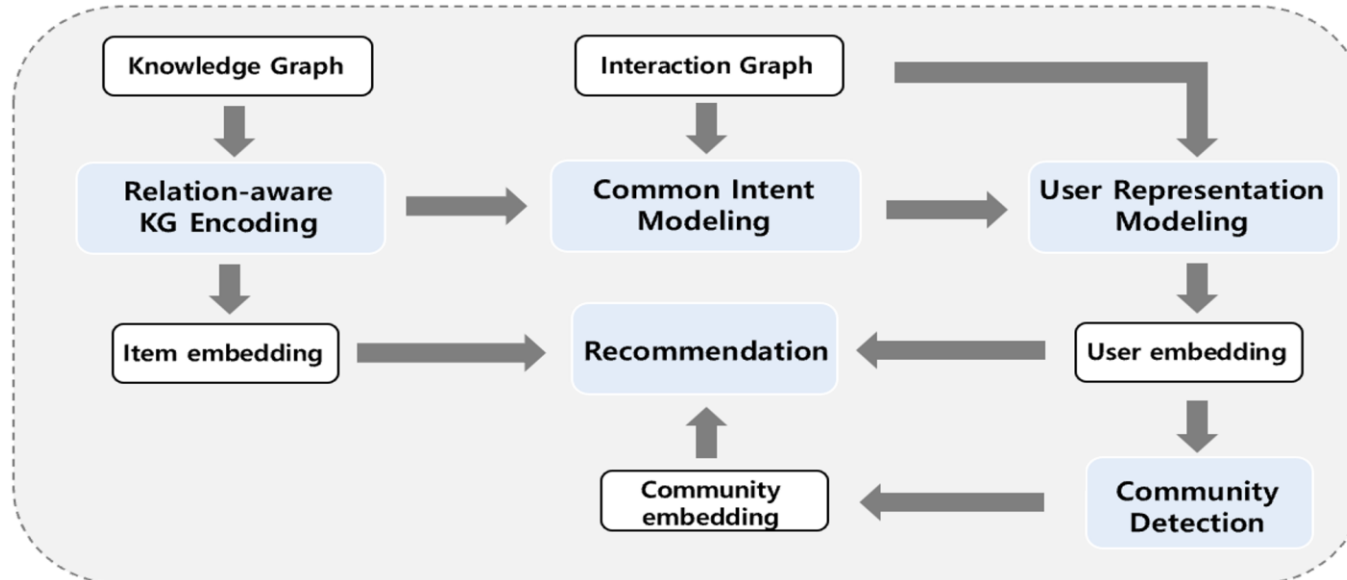
□ KG/IG로부터 사용자의 상호작용 의도를 추출하고, 의도 기반 커뮤니티를 구성하고, 커뮤니티 단위로 아이템을 추천하는 모델을 개발함

✓ 상호작용 그래프(Interaction Graph: IG):  $\mathcal{O} = \{(u, i, j) \mid (u, i) \in \mathcal{O}^+, (u, j) \in \mathcal{O}^-\}$

▪  $u \in \mathcal{U}$ : 사용자 집합,  $i \in \mathcal{I}$ : 상호작용 아이템 집합,  $j \in \mathcal{J}$ : 비상호작용 아이템 집합

✓ 지식그래프(KG):  $\text{KG} = \{(e_h, r, e_t) \mid e_h, e_t \in \mathcal{E}, r \in \mathcal{R}\}$

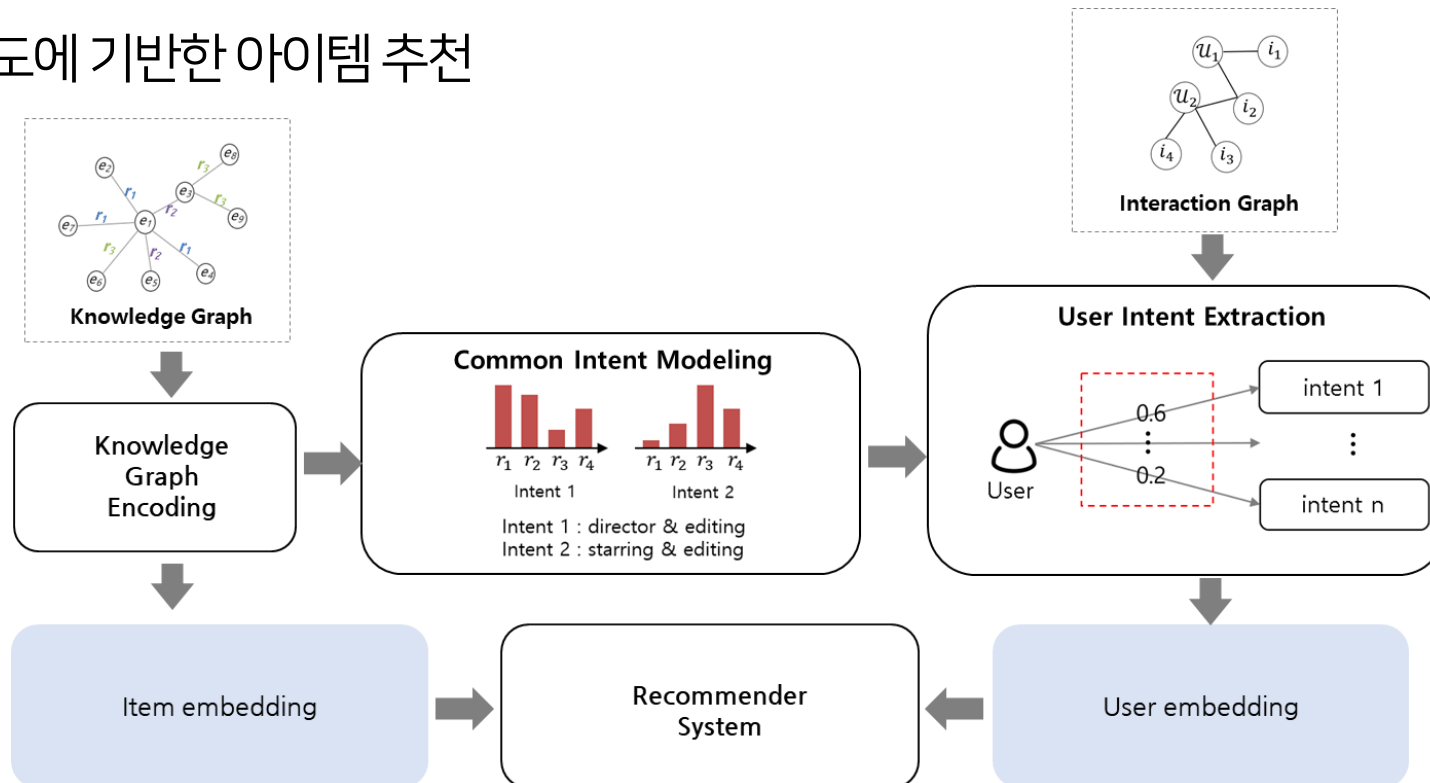
▪  $e \in \mathcal{E}$ : KG의 개체 집합,  $r \in \mathcal{R}$ : KG의 관계 집합



# 지식그래프 기반의 사용자 의도

## ❑ 의도 기반 추천 모델: Knowledge Graph-based Intent Network (KGIN)<sup>[1]</sup>

- ✓ KG 관계 기반 공통 의도 모델링
- ✓ 공통 의도에 대한 각 사용자의 선호도 추출
- ✓ 사용자 의도에 기반한 아이템 추천



[1] Xiang Wang et al., "Learning Intents behind Interactions with Knowledge Graph for Recommendation"(WWW'21)

# 지식그래프 기반의 사용자 의도

## □ 공통 의도 (common intent) 는 의도 집합으로 구성됨

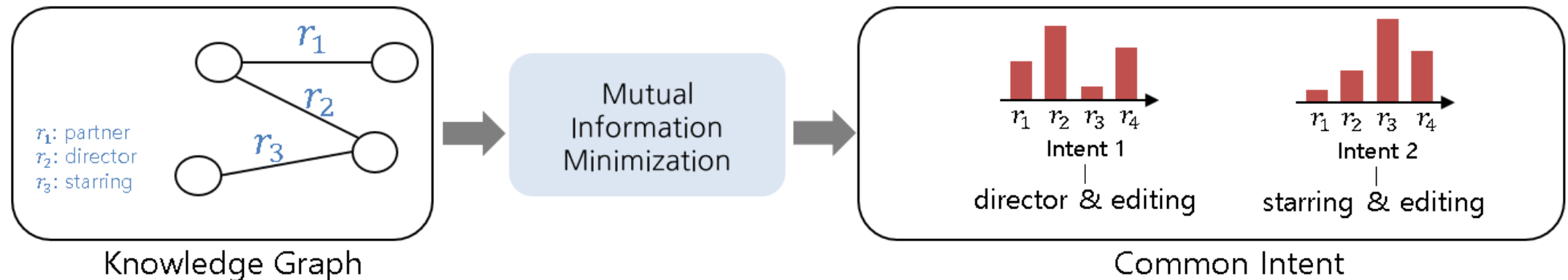
✓ 각 의도는 KG내 모든 관계에 대한 영향력으로 표현됨

$$\text{의도}(\text{intent}) = \sum (\text{영향력}_m)(\text{relation } r_m)$$

## □ Mutual Information (MI) Minimization<sup>[2]</sup>을 통한 공통 의도 표현 학습

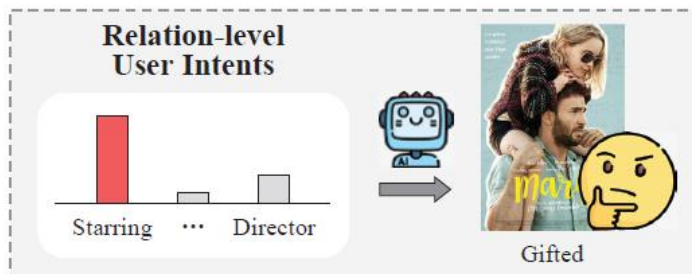
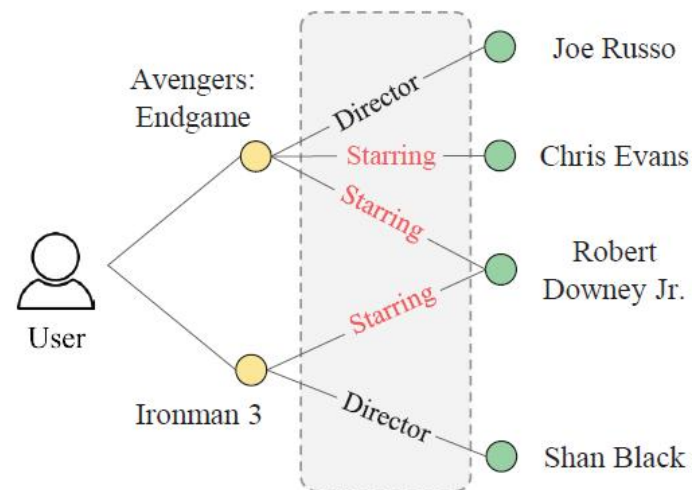
✓ 의도 구성요소 간 상호 의존성을 최소화함

✓ 공통 의도에 속한 각 의도가 서로 구별되도록 학습함

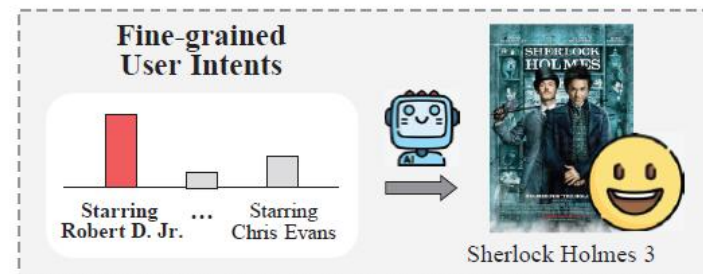
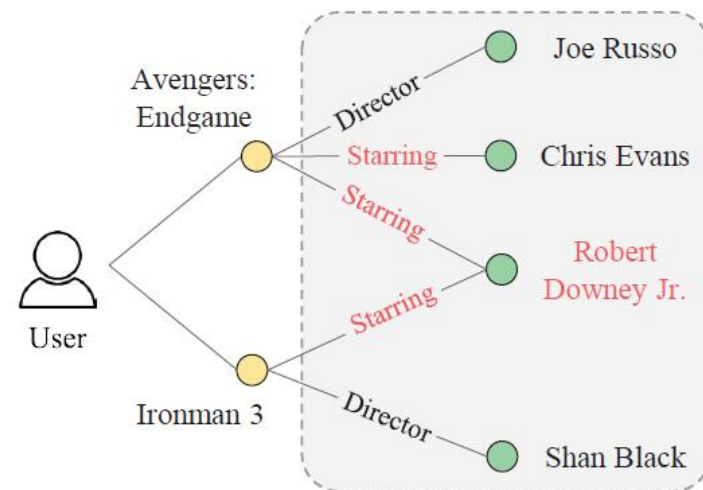


# 지식그래프 기반의 사용자 의도

## □ Relation-entity 관계를 고려한 세부 사용자 의도 추출



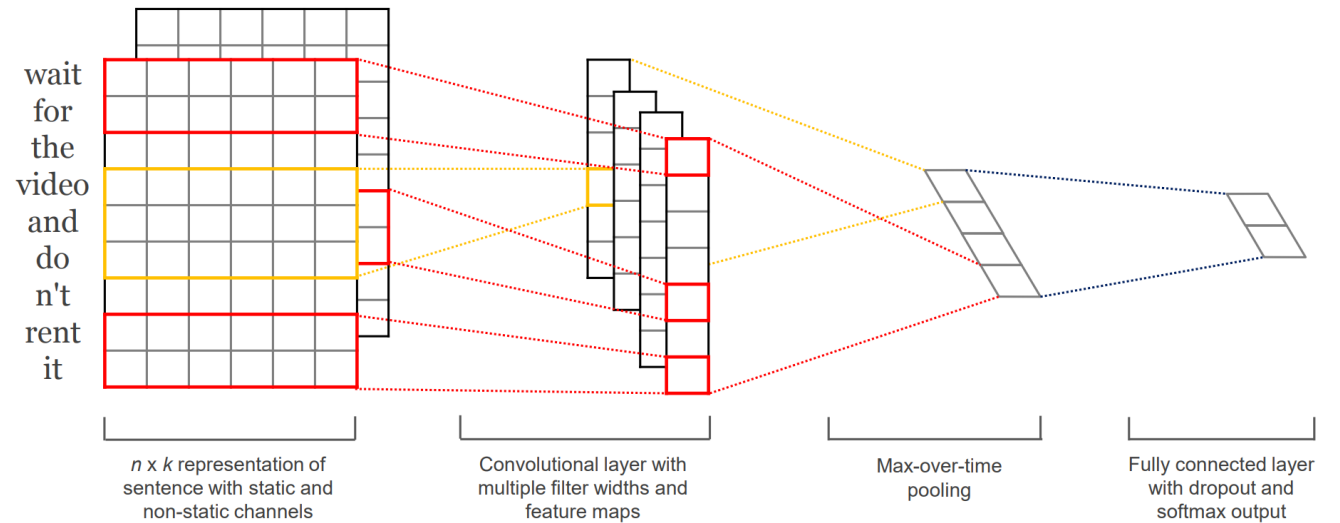
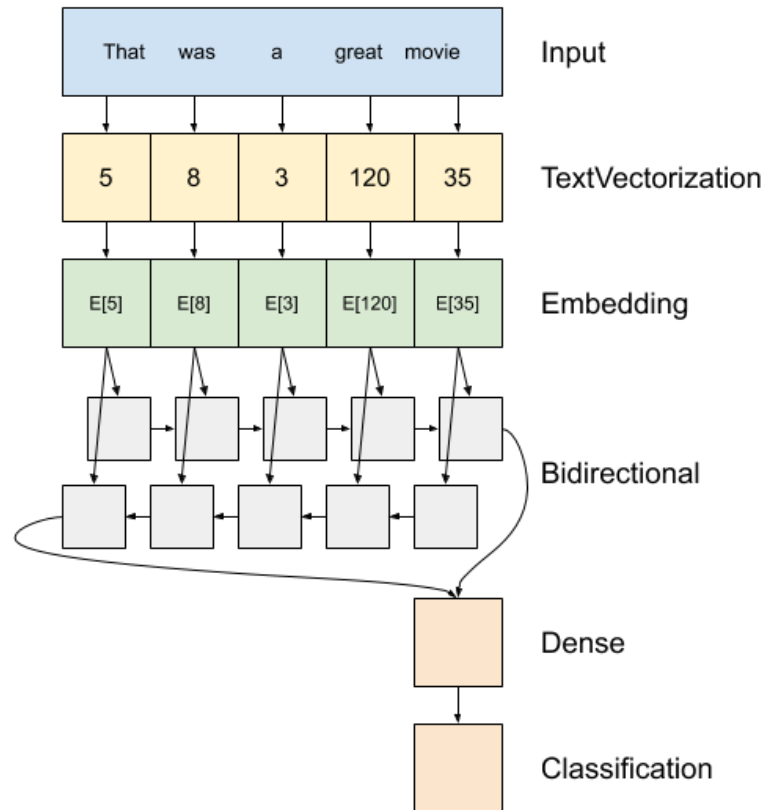
(a) existing intent-based method



(b) proposed method

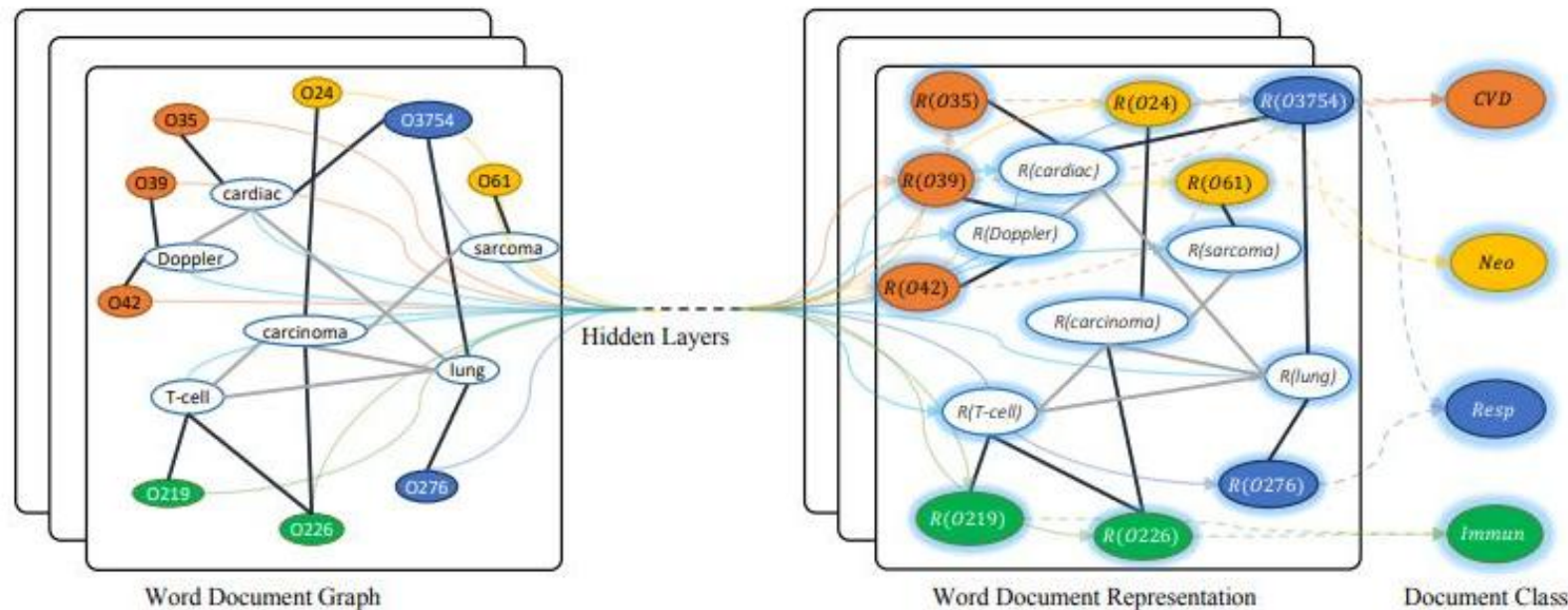
# Natural Language Processing

## □ Sentence Classification



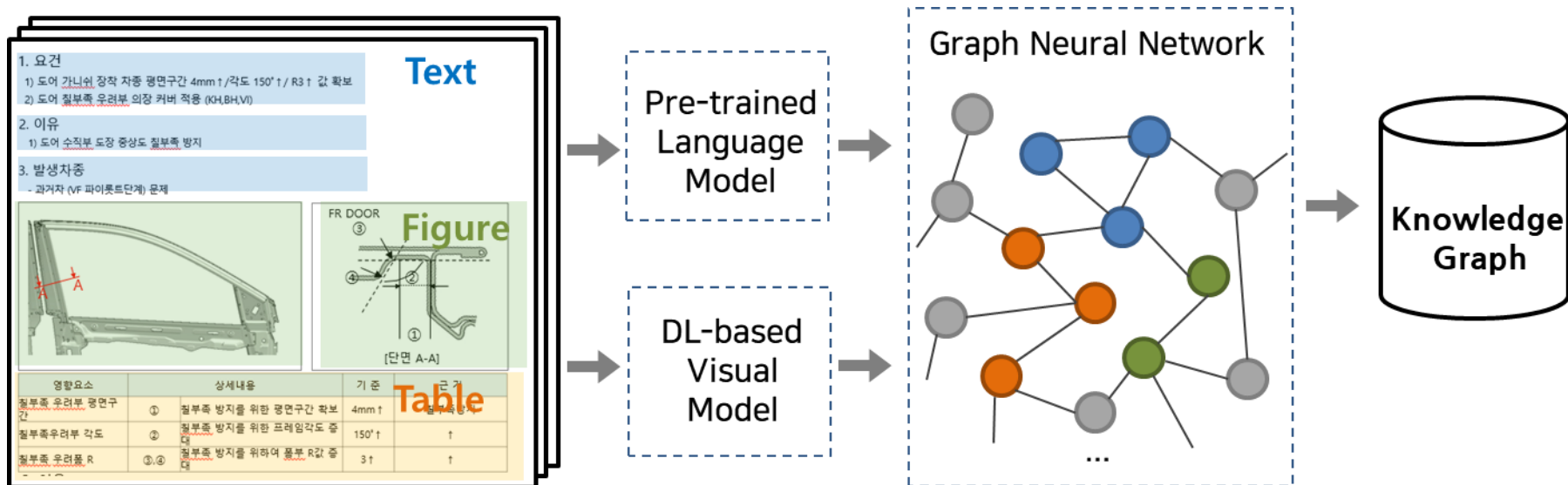
# Graph-based Natural Language Processing

- ❑ a graph using documents to capture co-occurrence relationships between words and documents
- ❑ Can improve the classification performance by incorporating contextual information about how words and documents co-occur



# Multimodal Unstructured Data Processing

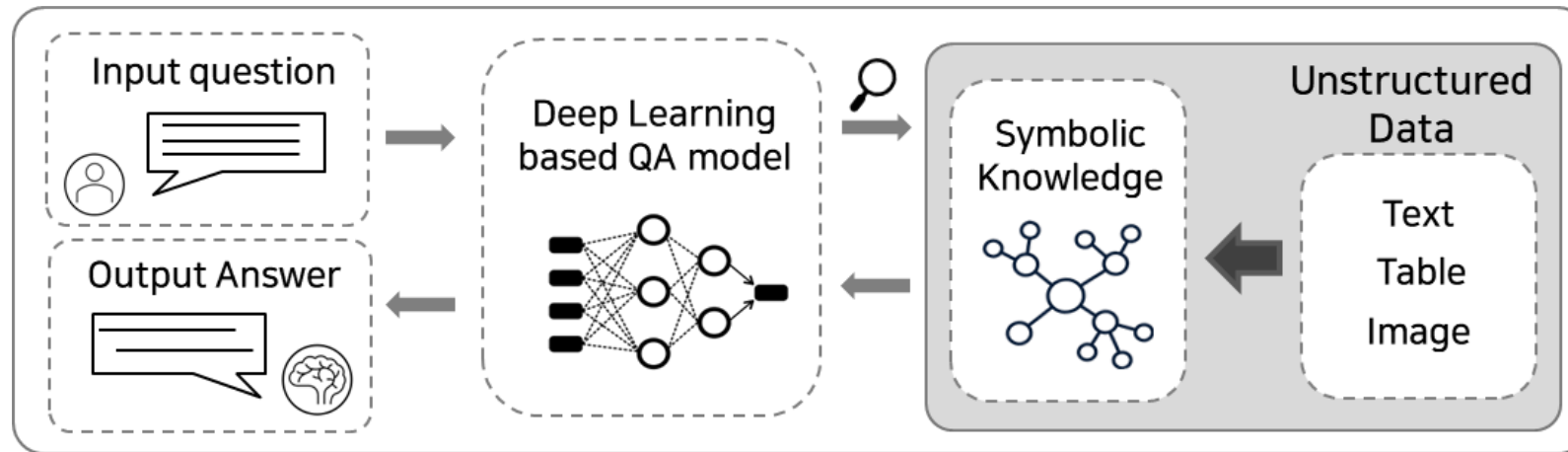
- ❑ 대다수의 기업 데이터는 풍부한 도메인 지식을 포함함
  - ✓ 텍스트 및 비텍스트와 같은 로그 파일, 비정형 자료, 일회성 문서 및 사진 등
- ❑ 다양한 유형의 구성 요소 간 의미적 연결 관계를 고려한 지식 추출이 필요함
  - ✓ 지식의 용이한 유지, 보수 및 계승이 가능하도록 재사용 및 상호운용성을 확보할 수 있어야 함
  - ✓ 문서를 구성하는 텍스트, 이미지, 테이블 간의 관계를 고려함



# Multimodal Unstructured Data Processing

## ❑ 데이터로부터 도메인 지식을 추출 및 활용

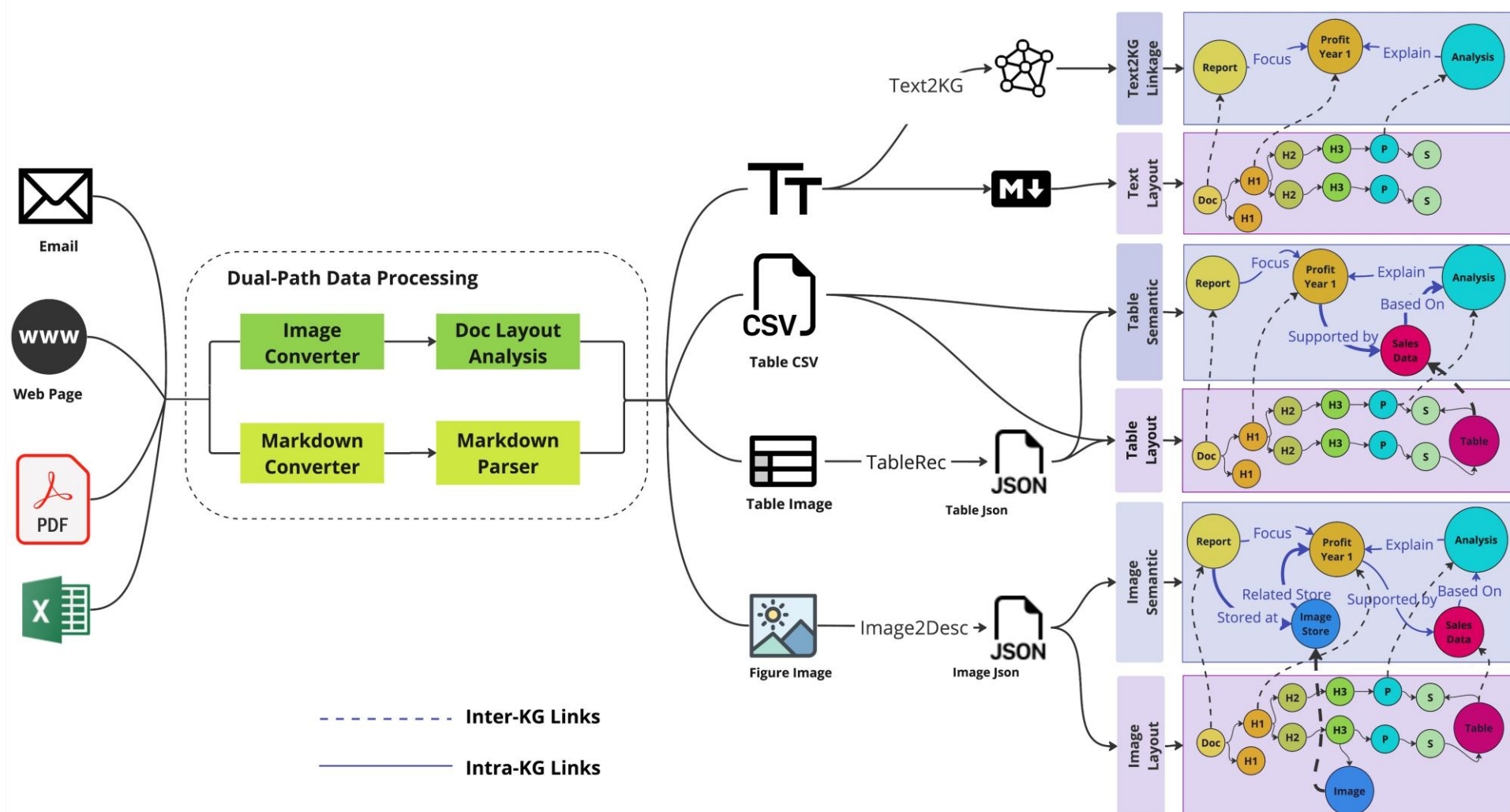
- ✓ 정형 데이터로의 변환을 통한 지식그래프 (Knowledge Graph) 구축
  - 엔지니어링 의사결정을 지원하는 응용 개발에 활용 가능: 질의 응답 등



- ✓ 지식그래프 구축을 위한 지식 추출 기술을 개발
  - 멀티모달 데이터 (multi-modal data)를 지원
    - 문서 내에 텍스트, 이미지, 테이블이 혼재되어 있음
  - 다양한 유형의 구성 요소 간 의미적 연결 관계를 고려한 지식 추출이 필요함

# Multimodal Unstructured Data Processing

## □ Example



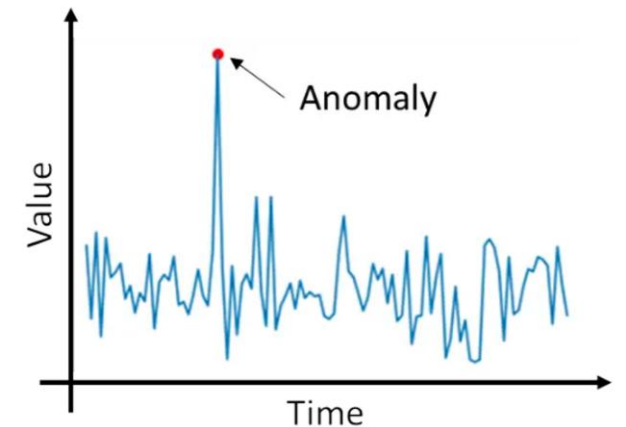
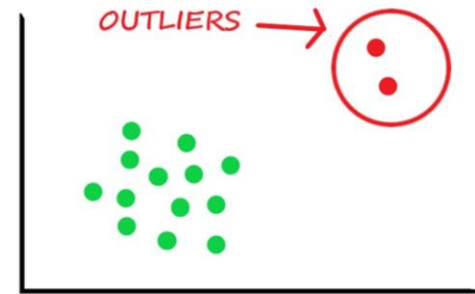
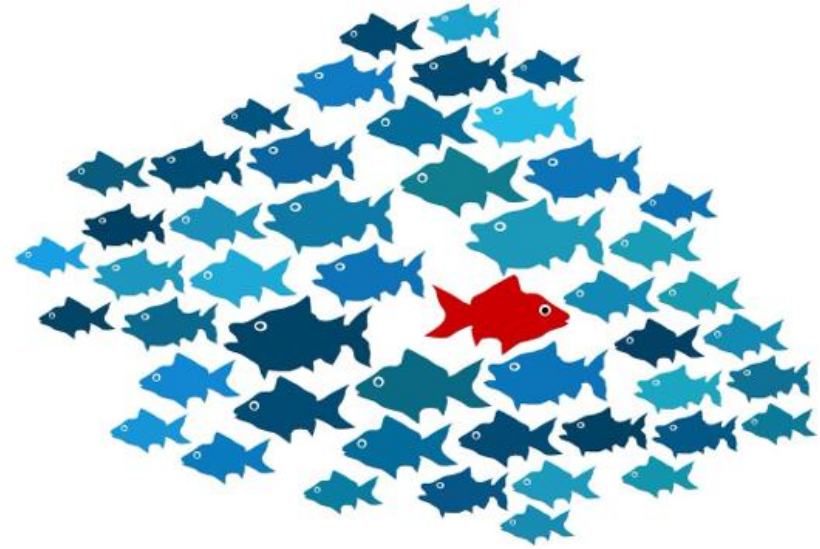
# Anomaly Detection

## ❑ Anomalies

- ✓ Not conform to a notion of normal behavior.

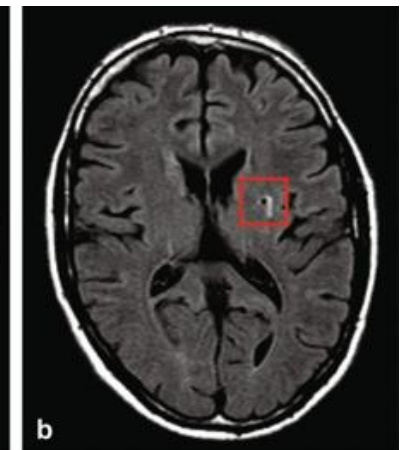
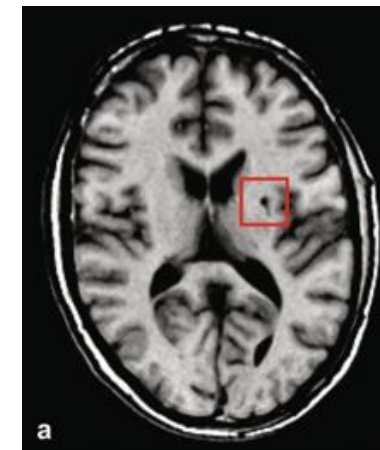
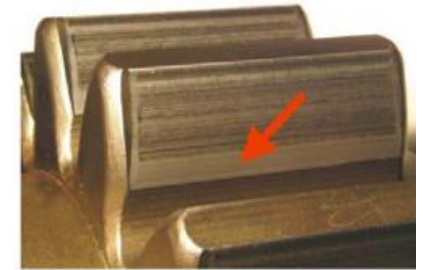
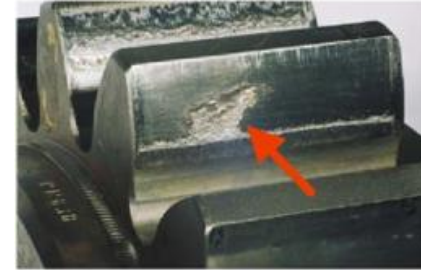
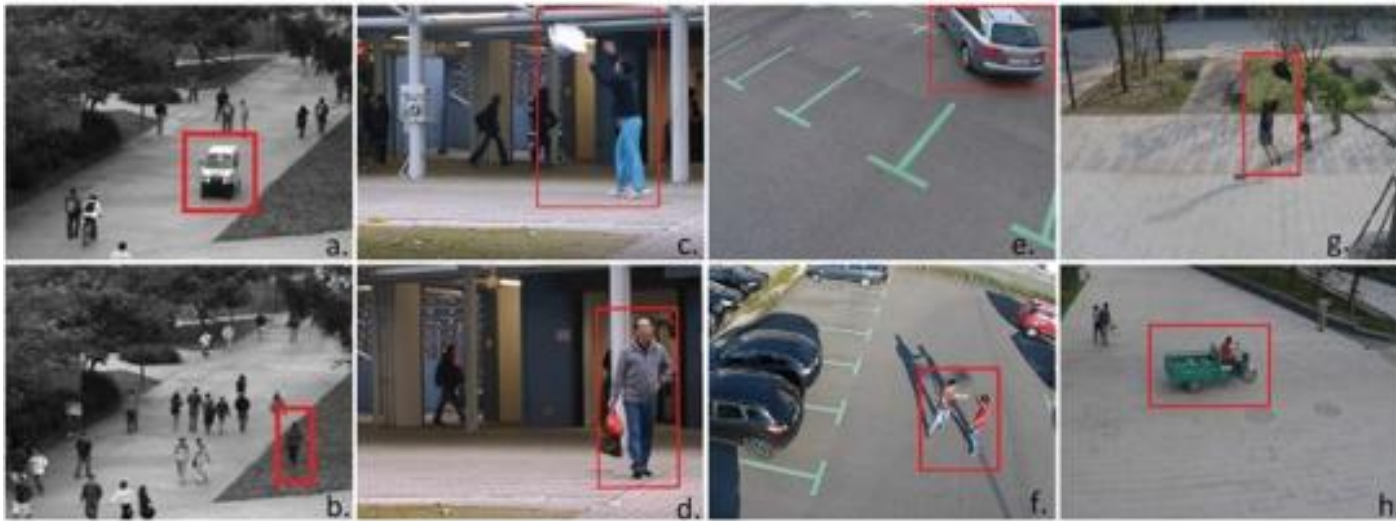
## ❑ Anomaly detection

- ✓ we try to distinguish anomalous samples
- ✓ Deviate from normal samples.



# Anomaly Detection

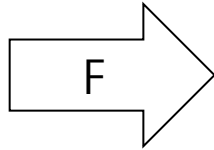
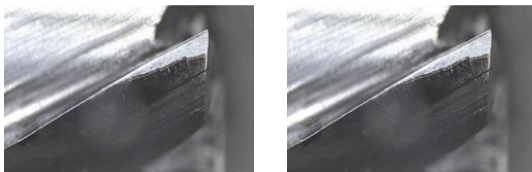
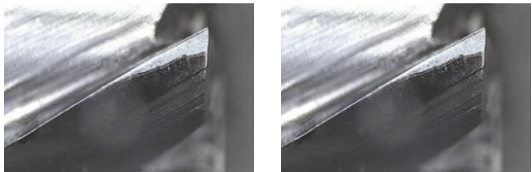
## ❑ Application of Anomaly Detection



# Anomaly Detection

## □ Graph Anomaly Detection

X = data



Y = label

1

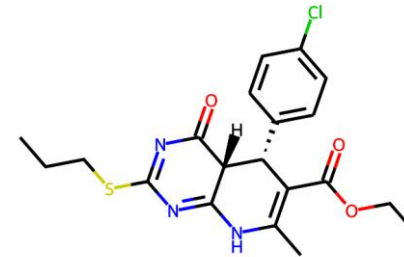
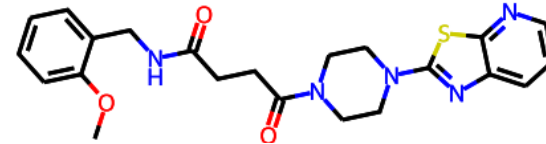
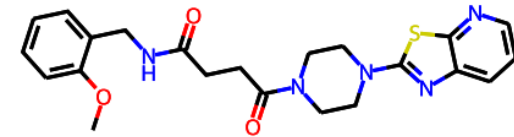
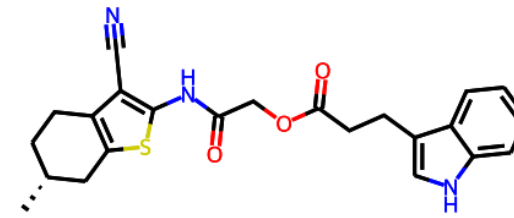
0

0

0

0

X = graph data



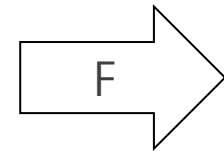
Y = label

0

0

0

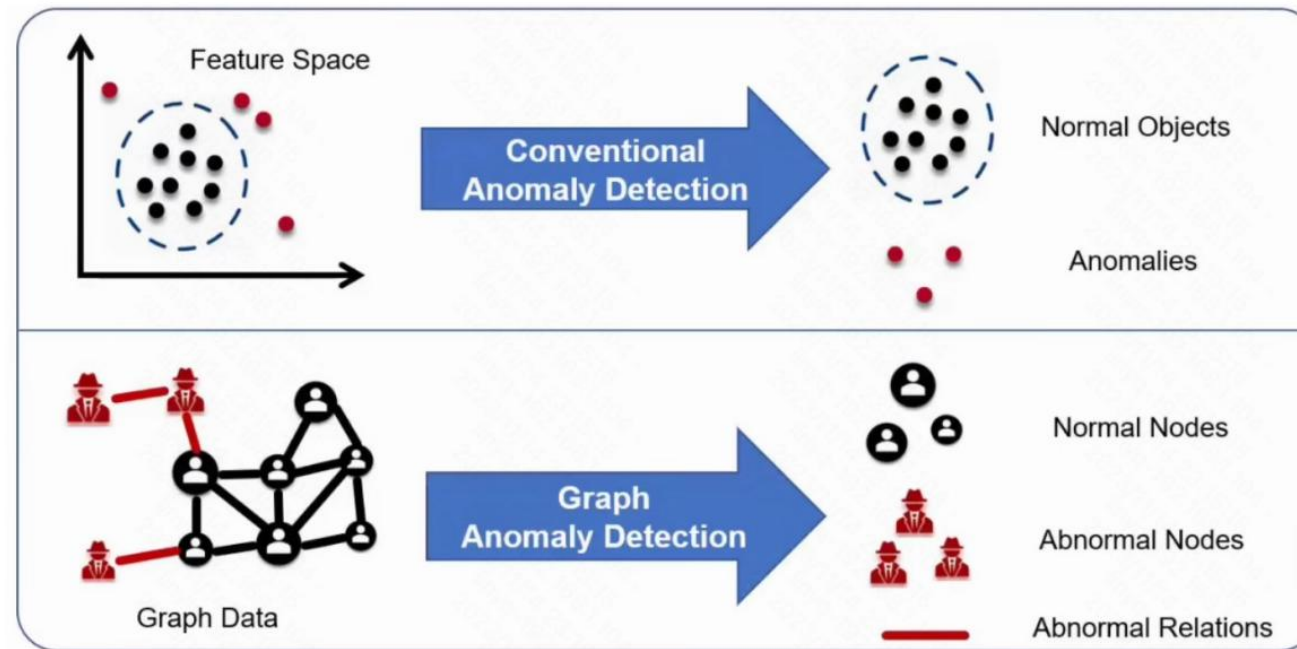
1



# Graph-based Anomaly Detection

## ❑ Graph Anomaly Detection

- ✓ Graph information often plays a vital role in identifying fraudulent users or activities.
- ✓ For example, transaction records on a financial platform.

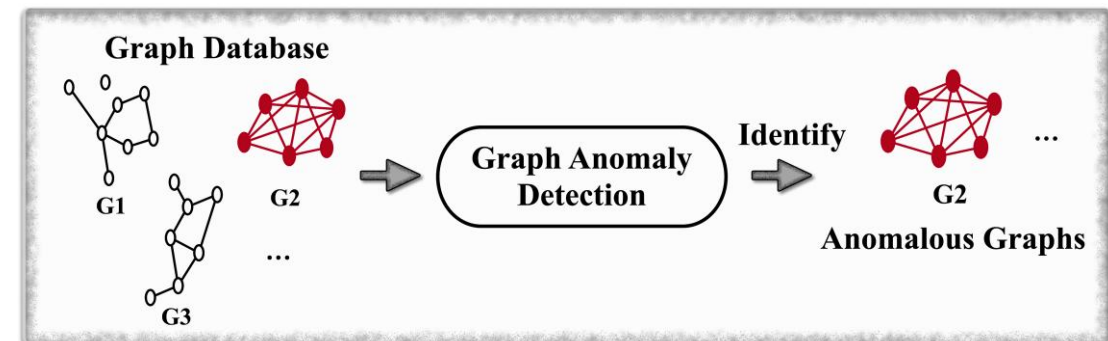
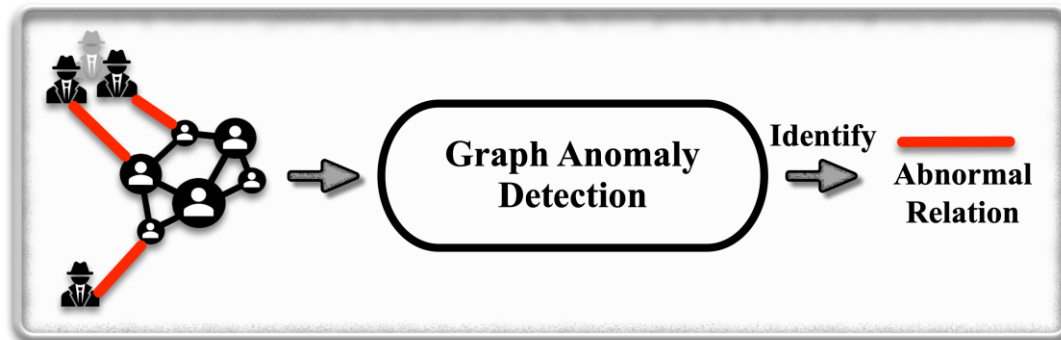
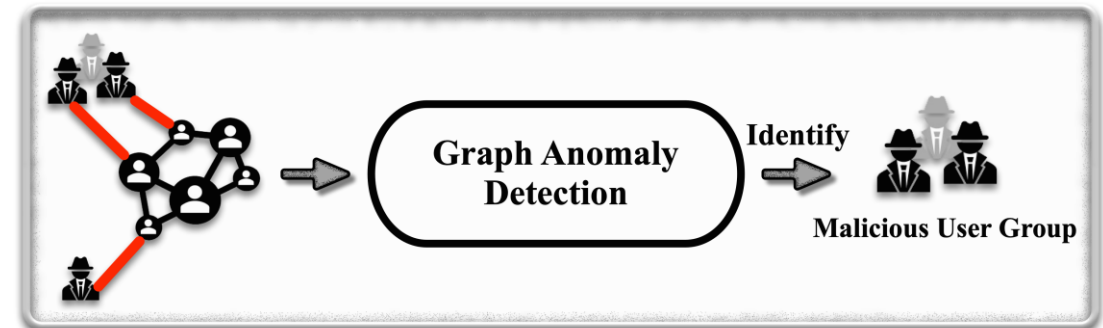
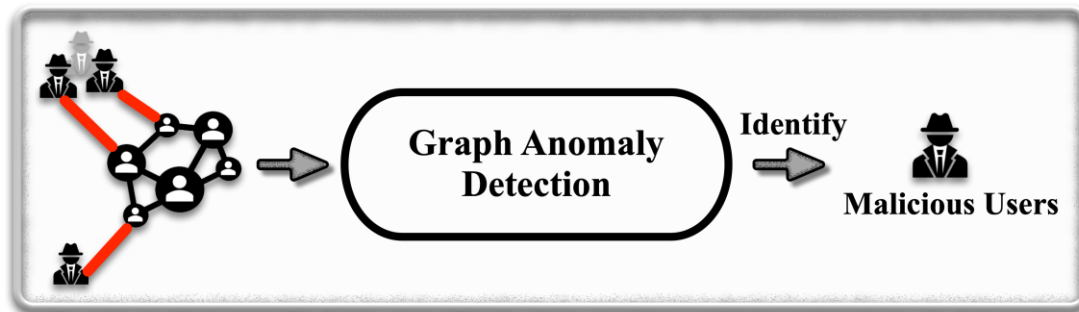


Transaction Network

# Graph-based Anomaly Detection

## ❑ Exist Problem in Graph Anomaly Detection

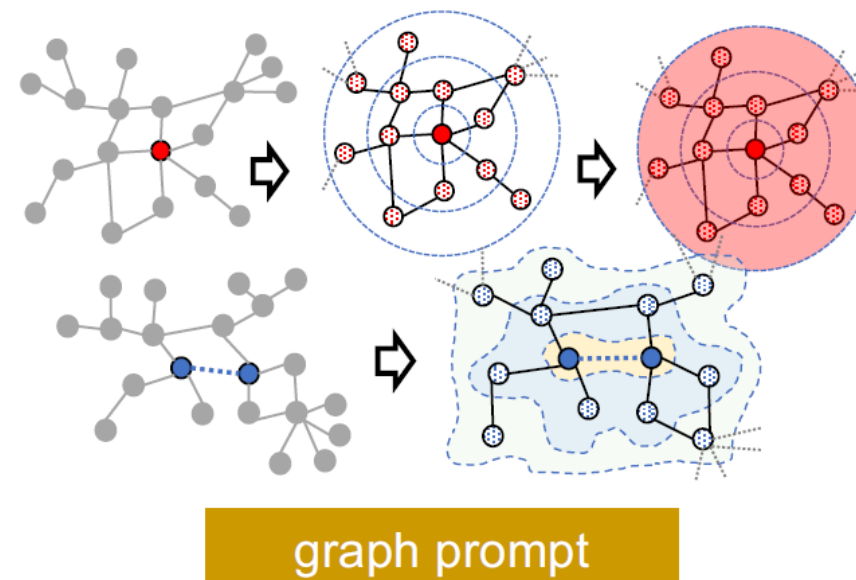
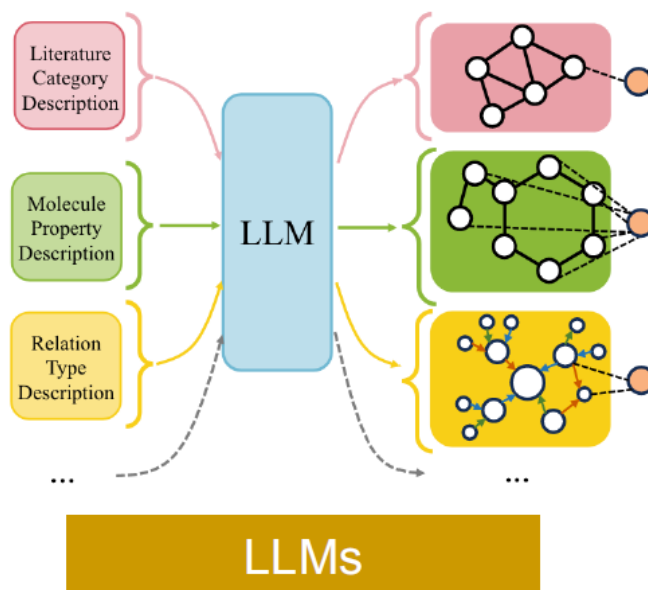
- ✓ overlook the inherent connections among different object types of graph anomalies.
- ✓ A money laundering transaction & an abnormal account.



# Graph-based Anomaly Detection

## ❑ How to unify multi-level formats?

- ✓ Node-level, edge-level and graph-level models exist inherent differences.
- ✓ large language models (LLMs) or graph prompt tuning.



BUT they not specifically tailored to anomaly data,  
resulting in **inappropriate node selections** that 'erase' critical anomaly information.

# CONTENTS

1. About Me and GLI Lab
2. Knowledge Graph
3. Graph Representation Learning
4. Graph-based AI
- 5. What's Next?**

# What's Next?

## ❑ Knowledge Graphs? or Large Language Models?

### Structured Knowledge Models (Knowledge Graphs)

- ✓ Explicit knowledge
- ✓ Latest/Expert knowledge
- ✓ Domain-specific knowledge
- ✓ Accuracy
- ✓ Determinateness
- ✓ Interpretability

- ⊖ Incompleteness
- ⊖ Lacking language
- ⊖ Understanding
- ⊖ Unseen facts

↔  
complementary  
relationship<sup>[10]</sup>

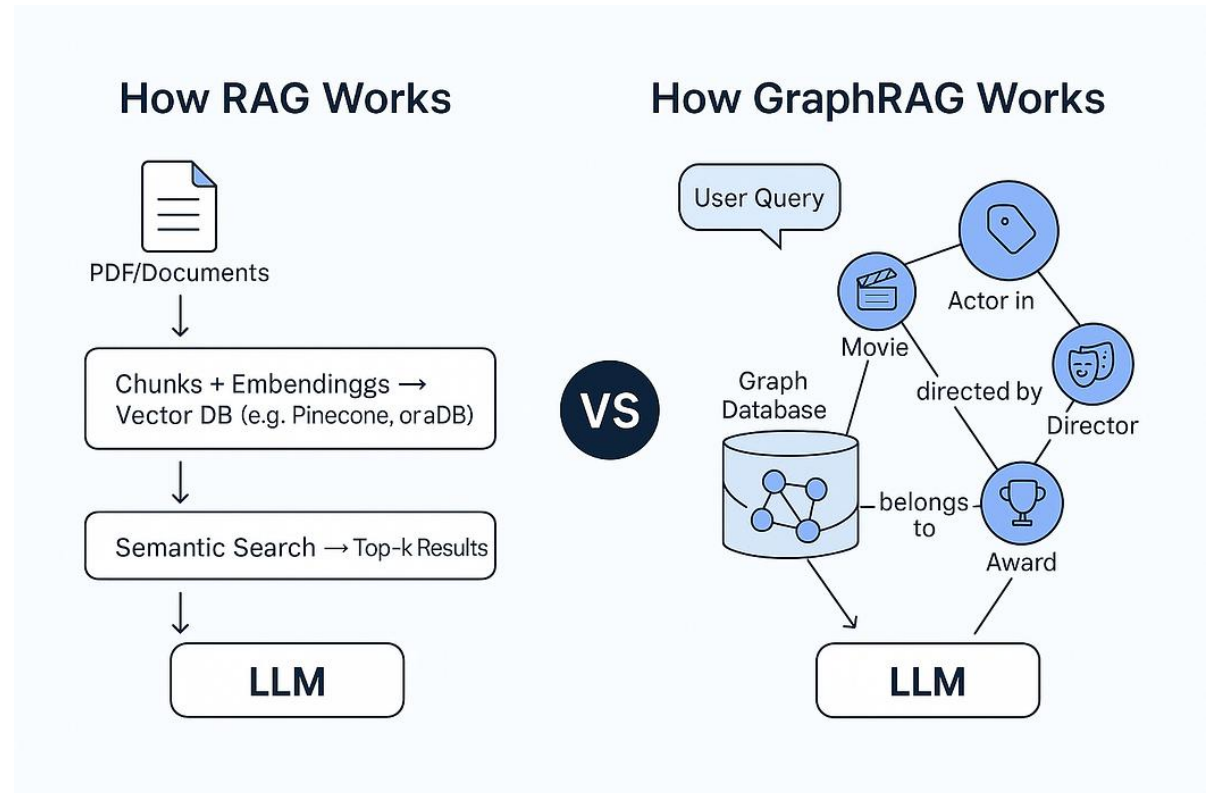
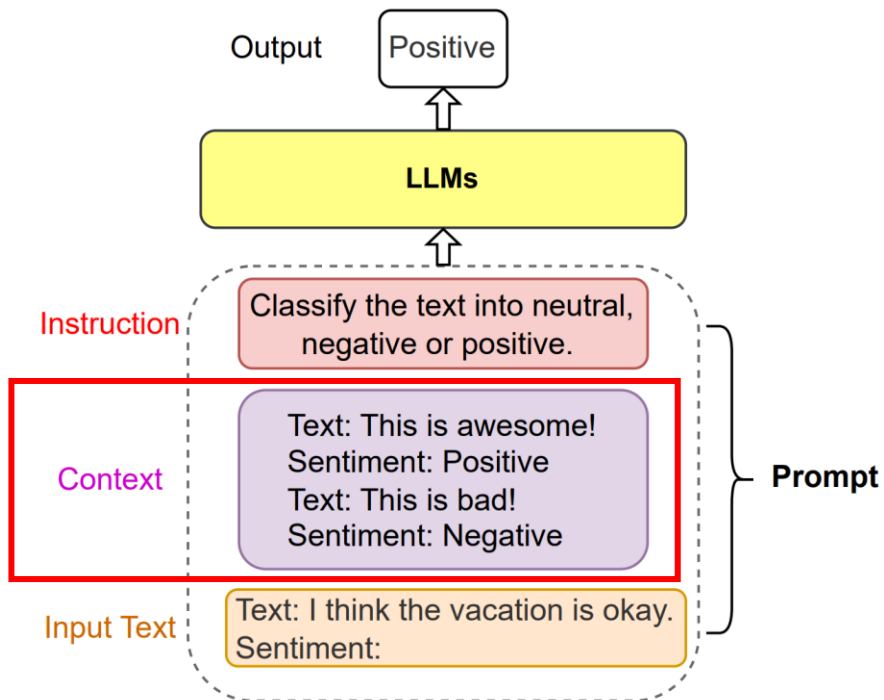
### Large Language Models (Text)

- ✓ Generalizability
- ✓ General Knowledge
- ✓ Language Processing

- ⊖ Implicit knowledge
- ⊖ Hallucination
- ⊖ Indeterminateness
- ⊖ Black-box
- ⊖ Lacking domain-specific Knowledge
- ⊖ Lacking new knowledge

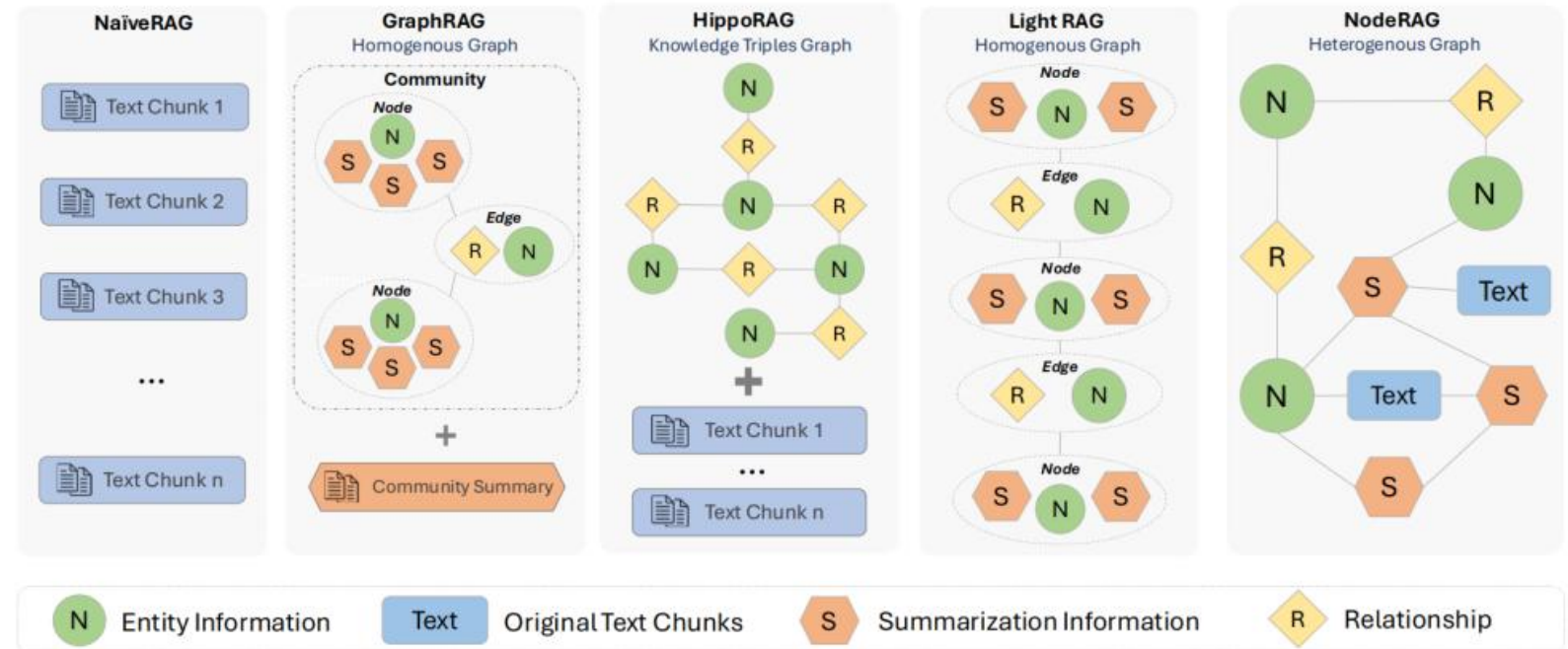
# What's Next? – Augmentation

- ❑ 다양한 소스의 최신 지식을 실시간으로 검색·활용하여 생성모델의 환각을 줄이고 사실 검증 가능성을 높이는 것을 목표
  - ✓ 기존 방식: Query와 가장 유사한 chunk만을 개별적으로 검색하기 때문에 여러 문서에 흩어진 관련 정보들 사이의 연결성을 포착하지 못함



# What's Next? – Augmentation

- ❑ 다양한 소스의 최신 지식을 실시간으로 검색·활용하여 생성모델의 환각을 줄이고 사실 검증 가능성을 높이는 것을 목표
  - ✓ 전역적 이해 (Global Understanding)
  - ✓ 다중 홉(Multi-hop) 추론
  - ✓ 맥락 연결
  - ✓ 중복 제거 및 일관성



# What's Next? – Integration

□ 다양한 유형의 지식을 **멀티모달 생성모델**(또는 **추천/이상탐지 모델**)이 보다 명확하게 이해할 수 있도록 하는 것을 목표

✓ 기존 방식: 복잡한 문장 의도를 정확하게 해석하기 어렵게 함

사용자: 안녕! 내가 키우는 강아지 3마리에 대해 설명해 줄게. 내 질문에 답해줘.

시스템: 물론이지! 강아지들에 대한 설명을 해주면 그에 맞추어 답변해 줄게.

사용자: **첫번째**와 **세번째**는  에서 각각 탁자 위와 의자 위에  
앉아있는 흰색 강아지야. 둘 다 곱슬거리는 흰색의 털을 가지고 있어.  
세 마리 각각 , , 그리고  소리를 내.  
**두번째**는  로, **세번째**와 똑같이 주둥이가 길고 다리가 짧아.  
특히, **첫번째**와 **세번째** 동물은 비슷하게 생겼어.

그림 1. 기존의 선형적 멀티모달 상호작용

사용자: 안녕! 내가 3마리의 동물을 설명해 줄게. 그다음에 내 질문에 답해줘.

시스템: 물론이지! 동물에 대한 설명을 해주면 그에 맞추어 답변해 줄게.

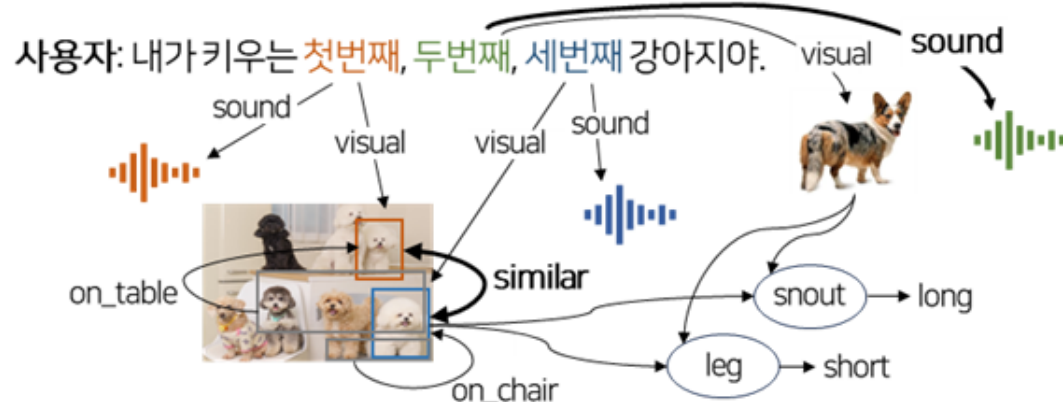


그림 2. 제안하는 그래프 구조 기반의 멀티모달 상호작용

# What's Next? – Integration

## ❑ KG-LLM Synergized Model (GenAI)

*ex) KG-augmented Generation*  
*ex) KG Construction*  
*ex) KG Question Answering*

|        | Standard LLM<br>Generation/QA                                                                                                                                                                                                             | KG-LLM Synergized Model                                                                                                                                                                              |                                              |
|--------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------|
|        |                                                                                                                                                                                                                                           | KG-Augmented Generation                                                                                                                                                                              | KG Question Answering                        |
| Input  | Text, Image<br><br><i>ex) "Which fruit does Byungkook like,  or  ?"</i> | Text, Multi-Modal KG<br><i>ex) "Which fruit does <u>Byungkook</u> like, <u>apples</u> or <u>bananas</u>?"</i><br> |                                              |
|        |                                                                                                                                                                                                                                           | ✓ Refer to <u>what each entity in text really wants</u> from KG (data + schema)                                                                                                                      |                                              |
| Output | Text<br>(probabilistic)                                                                                                                                                                                                                   | Text<br>(probabilistic)                                                                                                                                                                              | KG Entity<br>(probabilistic + deterministic) |
|        |                                                                                                                                                                                                                                           | ✓ Lead to <u>more explicit and domain-specific answer</u>                                                                                                                                            |                                              |