



2025 June 24

Integrating Knowledge Graphs with Generative AI : Technologies and Approaches

Osaka Electro-Communication University

Kouji Kozaki

kozaki@osakac.ac.jp

Self-Introduction

研究成果として
公開中のソフト



■ Kouji Kozaki kozaki@osakac.ac.jp

- Affiliation: **Osaka Electro-Communication University**
- Expertise: **Ontology Engineering** (Information Science / AI)
- Research Theme:
Development of AI systems based on ontology engineering, LOD (Linked Open Data), and knowledge graphs, with a focus on semantic (meaning-based) technologies

■ Community Activities



LOD Challenge

A contest for utilizing open data
<http://lodc.jp>



KGC: Knowledge Graph Completion Challenge

ナレッジグラフ推論チャレンジ

A contest for AI technology development using
knowledge graph <http://challenge.knowledge-graph.jp/>

Purpose and Positioning of This Talk

■ Background

- In agent-based AI, mechanisms for controlling AI are essential
→ Utilization of **generative AI (LLMs)** is one key approach
- Increasing attention on the integration of
Generative AI (LLMs) × Knowledge Graphs (KGs)
- Example: **Graph RAG** – Uses knowledge graphs as external data for LLM-based question answering

■ Purpose of the Lecture

- Introduce the fundamental ideas and use cases of knowledge graphs (semantic graphs, KGs)
- Explore case studies and challenges related to integrating knowledge graphs with generative AI (LLMs)

■ Positioning of the Lecture

- Introduce KGs from the perspective of semantic (web) technologies

Simple Survey



- Do you know or use any of the following technologies?
 - Knowledge Graph
 - Wikidata
 - RAG
 - Graph RAG

Outline



- **Basic Technologies of Knowledge Graphs**
- **Use Cases of Knowledge Graphs**
- **Integration Technologies of Knowledge Graphs and LLMs (Generative AI)**
- **Summary**
- **References**

Basic Technologies of Knowledge Graphs

- **Basic Technologies of Knowledge Graphs**
- Use Cases of Knowledge Graphs
- Integration Technologies of Knowledge Graphs and LLMs (Generative AI)
- Summary
- References

Knowledge Graph (KG)

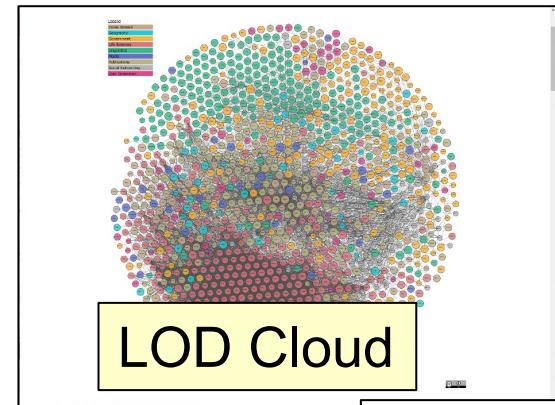


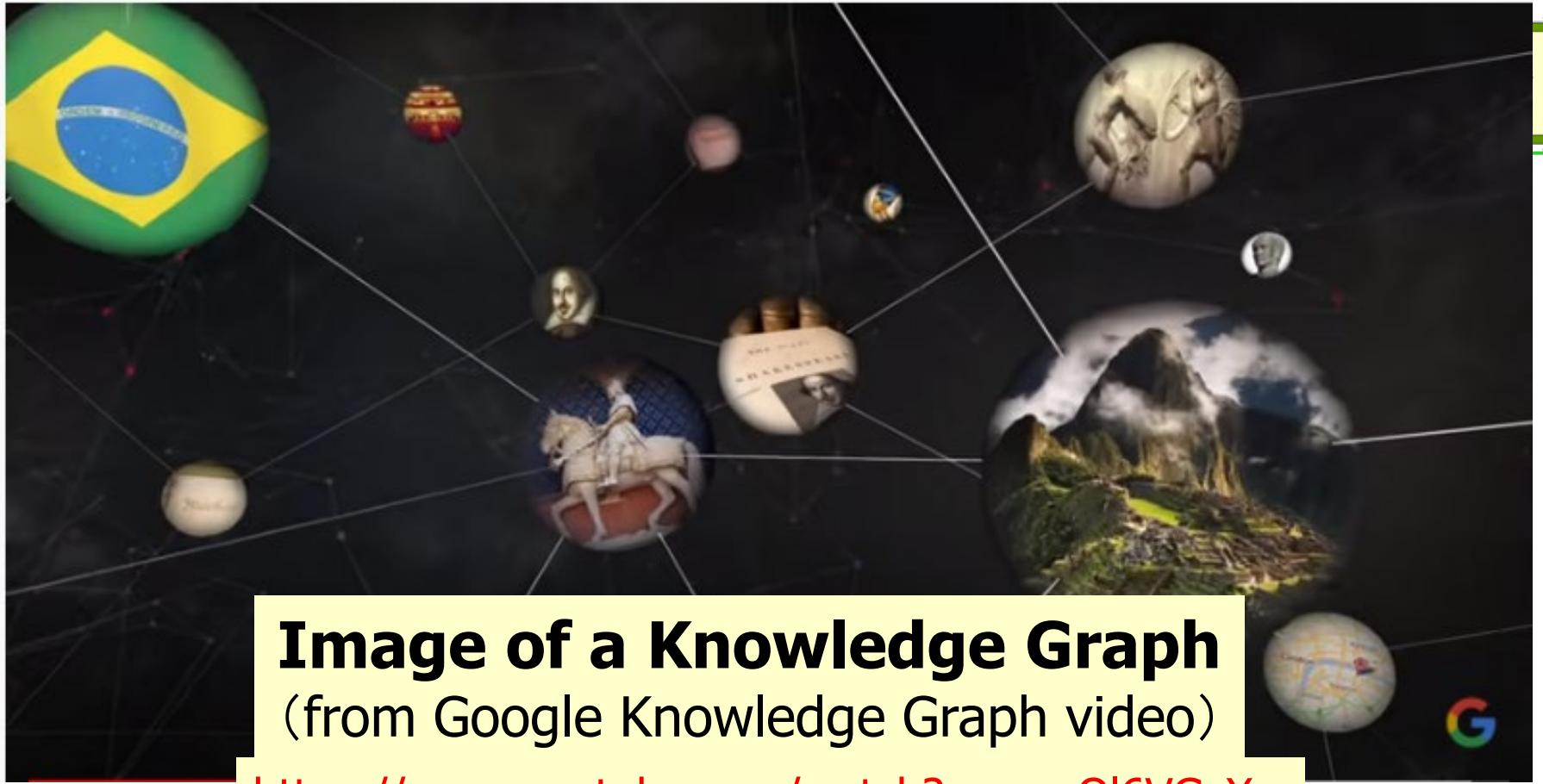
What is a Knowledge Graph

- A representation of various “Relationships (connections) among knowledge” in graph structure
- Used as a database (knowledge base) that serves as the foundation for intelligent system development.

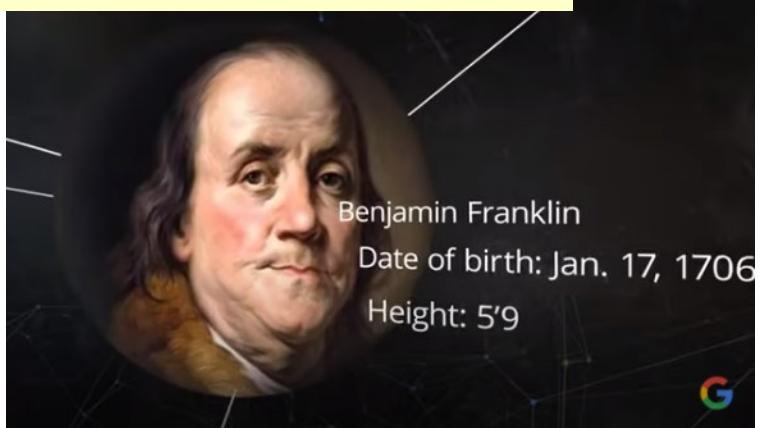
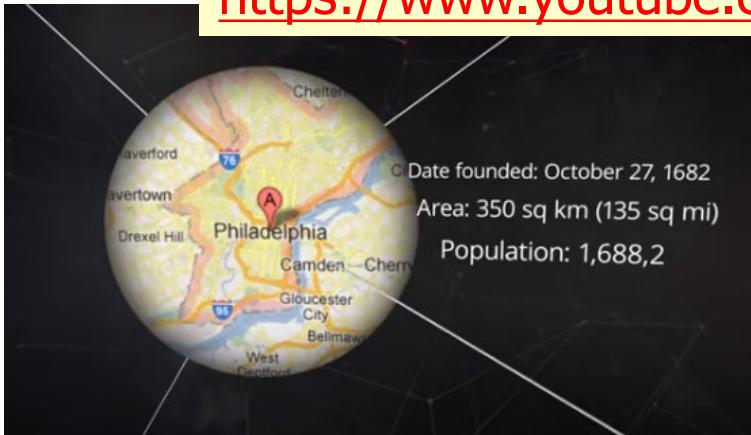
Examples of Knowledge Graphs

- **Linked Data** (2007-)
 - Knowledge graphs published based on web technologies
- **Linked Open Data (LOD)**
 - Linked Data as open data
 - Also called open knowledge graphs.
- **Google Knowledge Graph** (2012-)
 - Other companies are also actively building knowledge graphs.....

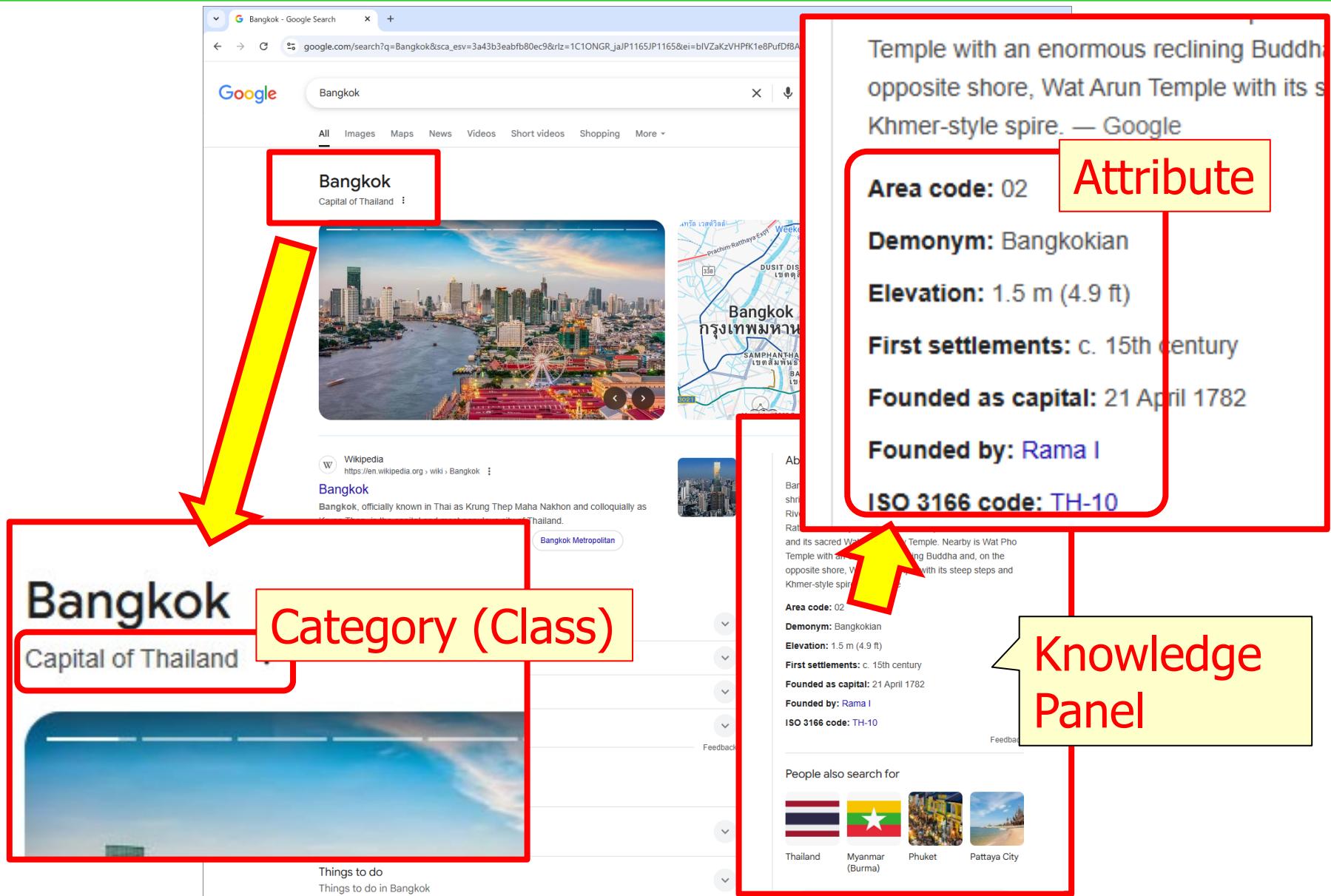




<https://www.youtube.com/watch?v=mmQI6VGvX-c>



Example Search Using Google Knowledge Graph



Example Search Using Google Knowledge Graph



Bangkok - Google Search

google.com/search?q=Bangkok&sca_esv=3a43b3eabfb80ec9&rlz=1C1ONGR_jaJP1165JP1165&ei=blVZaKzVHPfK1e8PufDf8Aw&ved=...

Google Bangkok

All Images Maps News Videos Short videos Shopping More Tools

Bangkok

Capital of Thailand

About this result

Wat Arun Ratchawararam Ratchaworawihan

Share Send feedback

This content comes from the Knowledge Graph, Google's collection of information about people, places and things

Your search and this result

About the source

This content comes from the Knowledge Graph, Google's collection of information about people, places and things

Your search and this result

- Bangkok (Capital of Thailand) is related to your

Example Search Using Google Knowledge Graph



Lahn Mah - Google Search

google.com/search?q=Lahn+Mah&scsa_esv=3a43b3eabfb80ec9&rlz=1C1ONGR_jaJP1165JP1165&ei=_YhZaOHLK6Tf2roP4PLi0AM&ve...

Google Lahn Mah

All Images Videos News Short videos Maps Shopping More Tools

How To Make Millions Before Grandma Dies
2024 • Comedy/Drama • 2h 7m

Overview Cast Reviews

HOW TO MAKE MILLIONS before GRANDMA DIES

GRANDMA DIES

0:08

Instagram • instyleasia InStyle ASIA | "How to Make Millions... During the glory morning blooming, a... Feb 16, 2025

アンプラグド 映画『おばあちゃんと僕の約束』公式HP Lahn Mah: KV画像. 2024年タイで記録的大ヒット! 自分よりも家族を思う。第97回...

IMDb 7.9/10 Rotten Tomatoes 98% Metacritic 74%

Cast

Billkin M Tontawan Tantivejakul Mui Usa Semkhum amah Himawari Tajiri Rainbow Sarinrat Thomas M's Mother Pongsatorn Jongwilas Soei

Watch movie EDIT SERVICES

Already watched Want to watch

About

Official Trailer 2:22

7.9/10 74% 98%
IMDb Metacritic Rotten Tomatoes

91% liked this film Google users

A man quits work to care for his dying grandmother, motivated by her fortune. He schemes to win her favour before she passes.

Release date: April 4, 2024 (Thailand)
Director: Pat Boonpitpat
Language: Thai
Box office: \$73.8 million
Distributed by: GDH 559
Cinematography: Boonyanuch Kraithong

Feedback

Depending on the “category” of the search result, the items displayed and the format of the knowledge panel will vary.

Example Search Using Google Knowledge Graph



Lahn Mah - Google Search

google.com/search?q=Lahn+Mah&scsa_esv=3a43b3eabfb80ec9&rlz=1C1ONGR_jaJP1165P1165&q=Billkin&stick=H4sIAAAAAAAQngFuLVT9c3NC...

Google Lahn Mah

All Images Videos News Short videos Maps

How To Make Millions Before Grandma Dies / Cast

2024 • Comedy/Drama • 2h 7m

Relationships can be explored through links to related items on knowledge panels.

Cast

Billkin M

Tontawan Tantivejakul Mui

Usa Semkhum amah

Himawari Rainbow

Billkin - Google Search

google.com/search?scsa_esv=3a43b3eabfb80ec9&rlz=1C1ONGR_jaJP1165P1165&q=Billkin&stick=H4sIAAAAAAAQngFuLVT9c3NC...

Google Billkin

All Images Videos News Short videos Forums Shopping More Tools

How To Make Millions Before Grandma Dies / Cast

Billkin M

Tontawan Tantivejakul Mui

Usa Semkhum amah

Himawari Rainbow

Sarinrat Thomas M's Mother

Pongsatorn Jongwilas Soei

Sanya Kunakorn Klang

Duangporn Oapirat Pinn

Phicha Prom Agong

Billkin

Thai actor and singer

Overview Movies and shows Songs

Age 25 years Oct 8, 1999

Education Thammasat University Tha...

MyDramaList Billtippong Assaratanakul - MyDramaList

Movies and shows

I Told Sunset About You 2020 – 2021

How To Make Millions Before... 2024

THE RED ENVELOPE 2019

My Ambulance 2019

Last Twilight in Phuket 2020

Our Last Twilight 2020

About

Puttipong Assaratanakul, also known as Billkin, is a Thai actor and singer. He is known for his roles as Tao in *My Ambulance*, as Teh in *I Told Sunset About You* and *I Promised You the Moon*, and as M in *How To Make Millions Before Grandma Dies*. [Wikipedia](#)

Born: October 8, 1999 (age 25 years), Bangkok, Thailand

Education: Thammasat University Tha Phra Chan, Saint Gabriel's College, Thammasat Business School

Parents: Panu Assaratanakul, Phinghorn Assaratanakul

Height: 178 cm

Agent: Billkin Entertainment

Feedback

Profiles

Mini Works



■ Try Google Knowledge Graph !

- Search any keyword.
- Check the result focusing on the Knowledge Panel
 - Categories (Classes)
 - Attributes

LOD (Linked Open Data)

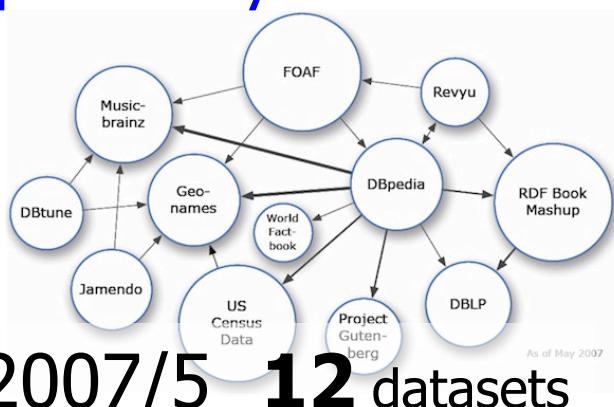


■ Linked Data

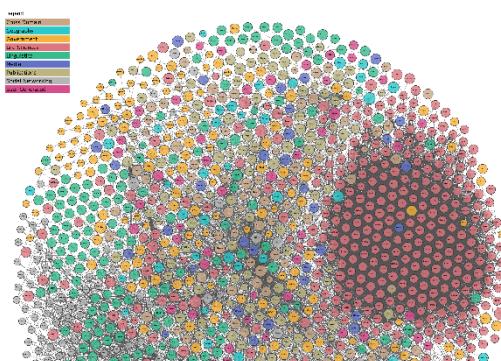
- A technology aimed at creating new value from data by "**linking**" data using the mechanisms of the Web.

■ **LOD**(Linked Open Data)

- Open data (data that can be freely used by anyone) that is published as Linked Data.
 - Many LOD datasets have been released over the past 15 years.



2007/5 12 datasets



2025/5 **1,356** datasets

How the Web Works



- **Accessing Web pages by specifying a URL**
 - Example: **<http://www.osakac.ac.jp>** – Page of “Osaka Electro-Communication University”
 - A **URL** is a mechanism for uniquely identifying the location (ID) of any Web page in the world.
- **Connecting Web pages via hyperlinks**
 - By specifying the URL of the destination, you can freely "link" to any Web page
 - By following links, you can reach various pieces of information
 - Link analysis enables various businesses e.g., search engines like Google

The Web → Linked Data



- Accessing **Web pages** by specifying a **URL**

URI·IRI

: **http://www.osakac.ac.jp** – Page of
Electro-Communication University"

- A **URL** is **Data** (thing) uniquely identifying the location (ID) of any **Web page** in the world.
- Connecting **Web pages** via hyperlinks

- By specifying **Data** of the destination, you can **freely "link"** to any **Web page** **Data** (thing)

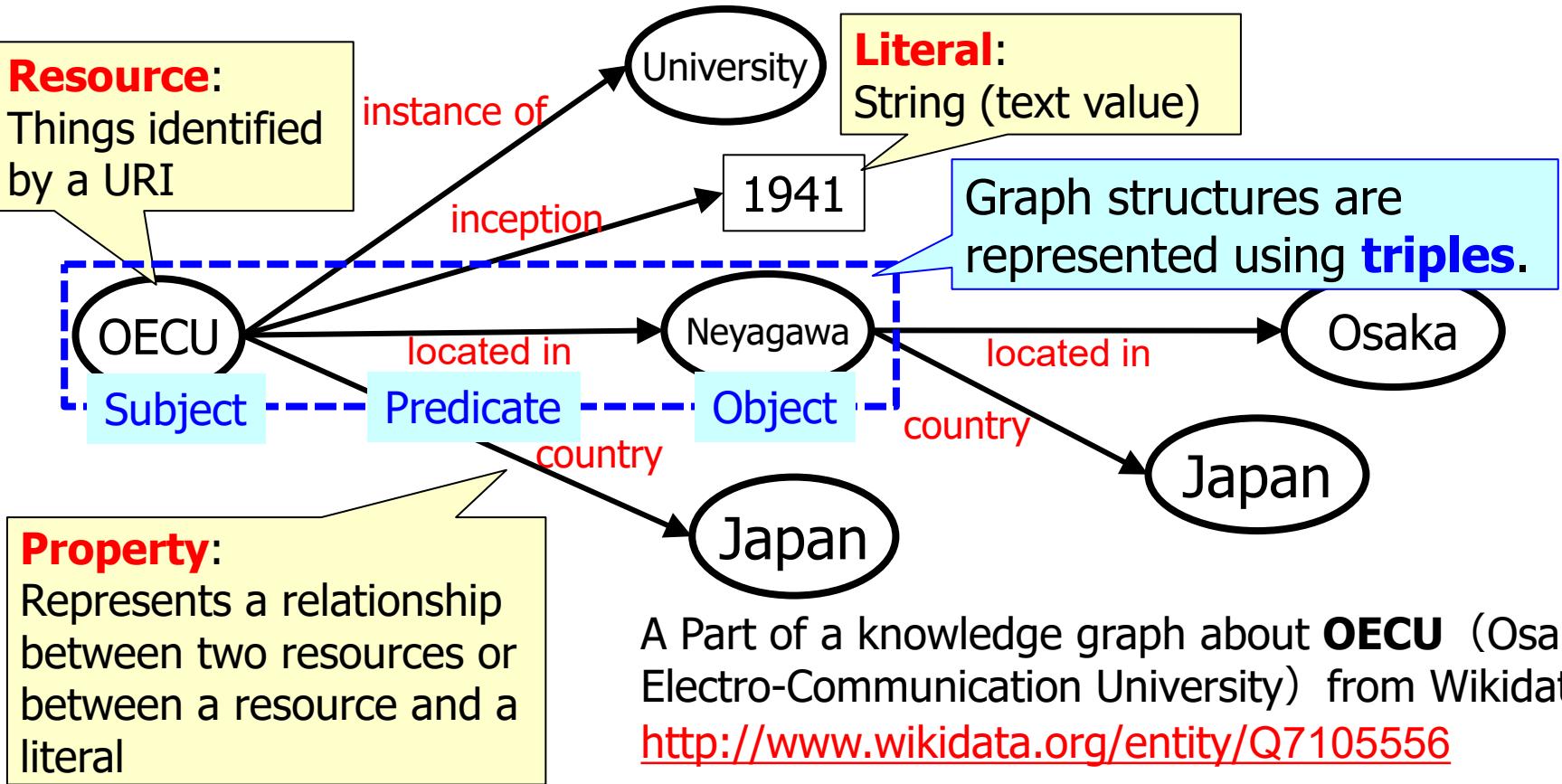
By following links, you can reach various pieces of **Data**.

Linked Data

Data is **published** using the same mechanism as the Web, and **linked** with each other.

RDF Representation of Linked Data (Knowledge Graphs)

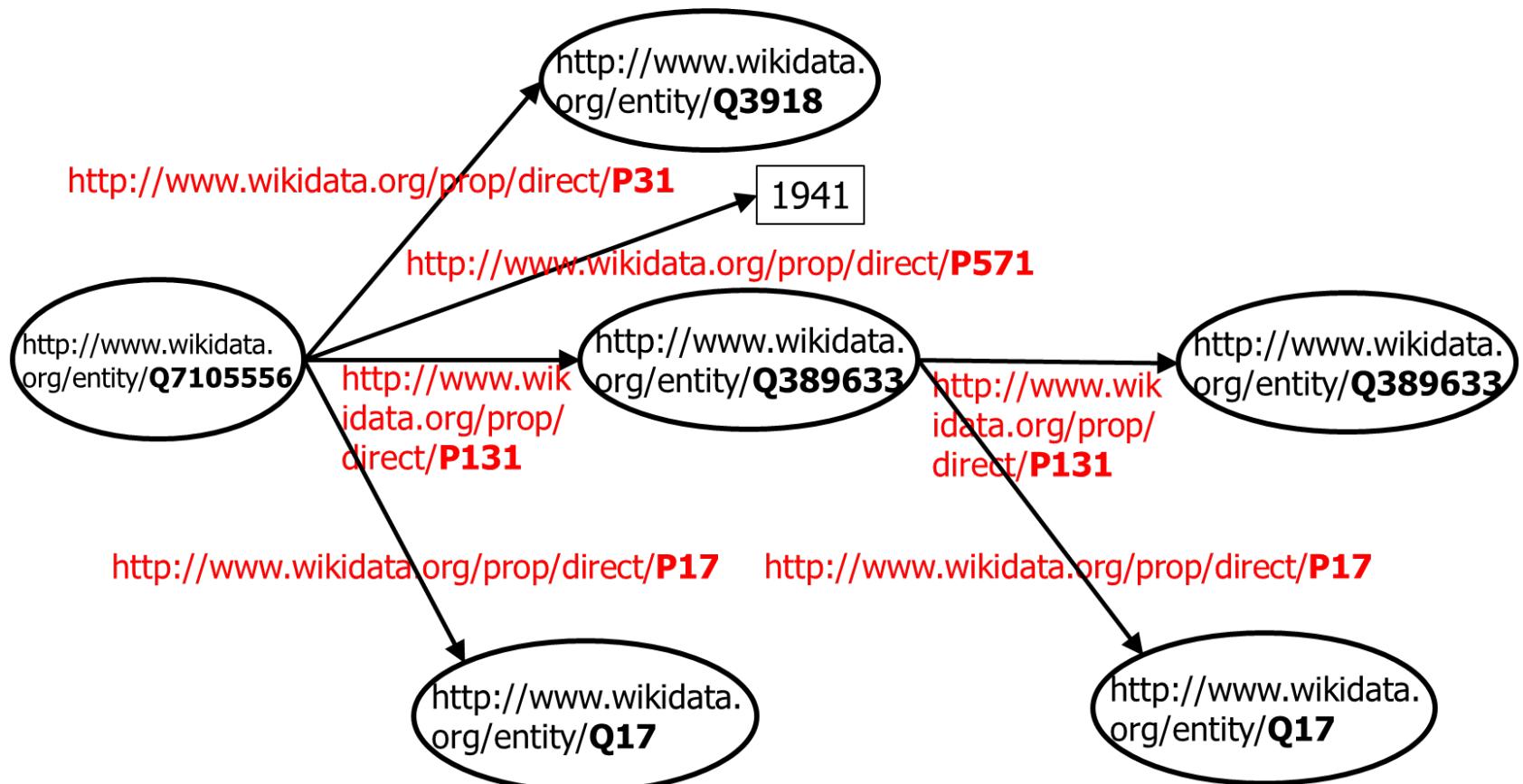
RDF (Resource Description Framework) : A W3C standard specification that provides a data model for describing knowledge graphs



SPARQL (a query language for RDF) and other technical standards for publishing and utilizing KGs on the Web are made publicly available by W3C.

RDF Representation of Linked Data (Knowledge Graphs)

Since **all data in RDF is represented by IRIs** (Internationalized Resource Identifiers), it allows for direct access to data via IRIs and linking across different datasets.



Worldwide Spread of LOD Publishing: The LOD Cloud

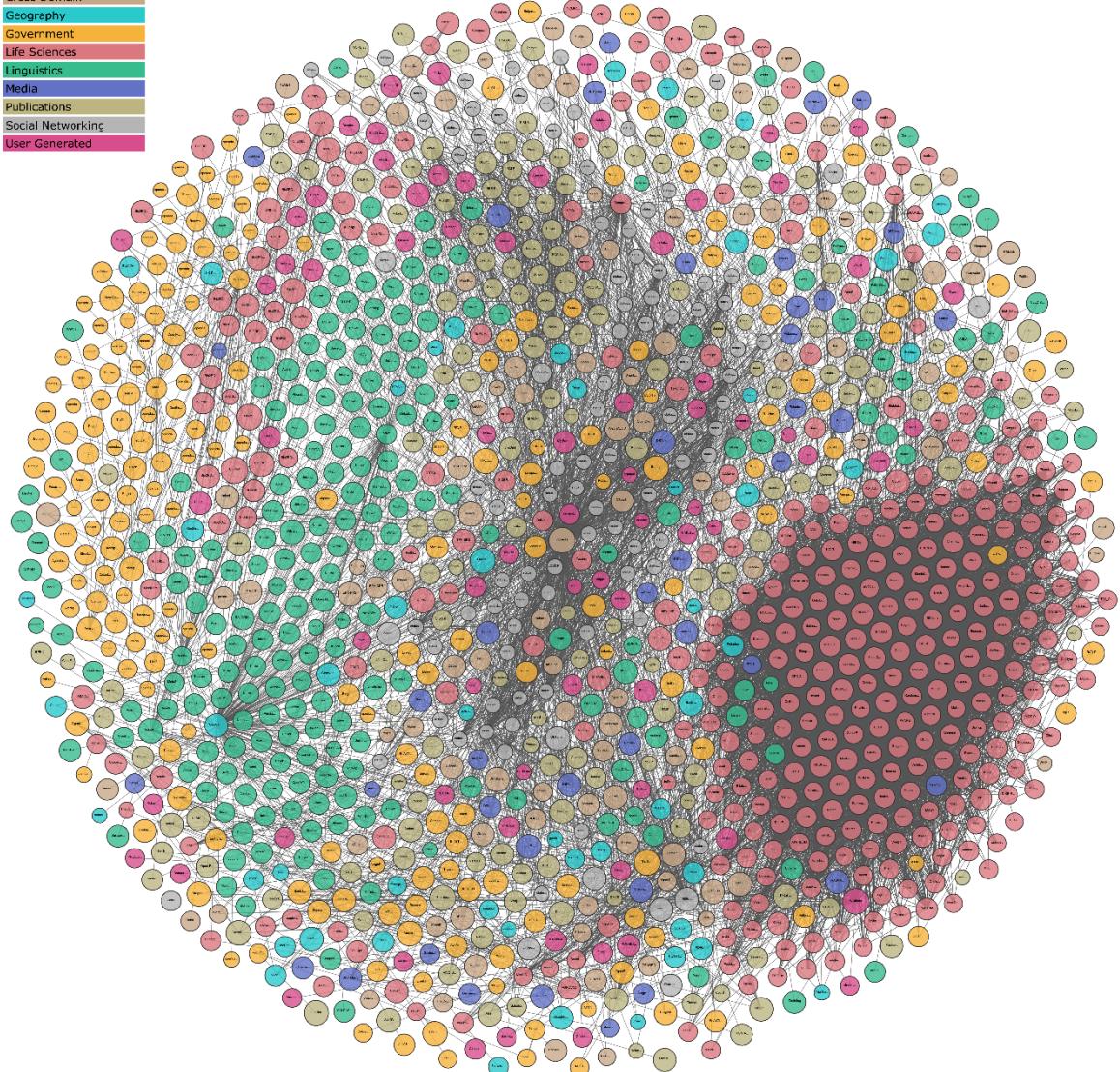


Legend



Legend

- Cross Domain
- Geography
- Government
- Life Sciences
- Linguistics
- Media
- Publications
- Social Networking
- User Generated



2025-5-31
(1,356 datasets)
<http://lod-cloud.net/>

Examples of Linked Open Data Published in Japan

DBpedia Japanese ×

← ⌘ ⌘ ja.dbpedia.org

DBpedia Japanese ホーム SPARQL Endpoint Firefox Browser DBpedia ダウンロード

DBpedia Japanese

DBpediaはja.wikipedia.orgから情報を抽出してLOD (Linked Open Data)として公開するコミュニティプロジェクトです。本家のDBpediaは主にWikipedia英語版を対象としたDBpediaを構成しています。DBpedia Japaneseの目的は、Wikidata日本語版を対象としたDBpediaを構成することです。

リソース例

- 東京都
- 政治
- 東京の山野菜研究所
- 情報システム技術者
- 都道府県
- 議長
- リーフガーデンルーターズ
- 西郷の桜祭
- 国連1号
- 初音ミク
- もぐらのクリーパーパーク
- 知足温泉
- 平清盛
- 姫路城
- レオナルド・ダ・ヴィンチ

SPARQL例

SPARQL Endpoint

東京都

```
SELECT DISTINCT ?s WHERE { ?s prop:ja_label "東京都" . }
```

SPARQL結果

ロック音楽のリスト(もしもあれば画像uriも)

```
SELECT DISTINCT ?s ?sprop WHERE { ?s prop:ja_label "ロック音楽" . ?sprop depiction ?sdepiction . } ORDER BY ?s
```

DBpedia

The screenshot shows the JapanSearch homepage with a dark background. At the top left is a green bamboo forest graphic with the Japanese characters '法造' (Hōzō) in large white calligraphy. To its right is the text 'an Environment for Building/Using Ontologies'. Below this is the website URL 'www.hozo.jp'. The main title 'JAPAN SEARCH' is in large white letters, with 'BETA' underneath it. A red square icon with a white stylized character is positioned above the word 'ギャラリー'. Below the title are several image thumbnails: a traditional Japanese scene, a green landscape, a close-up of a hand holding a small object, a person working in a workshop, and a panoramic view of a city. A search bar at the bottom contains the text '日本のデジタルアーカイブを探そう' (Search for Japan's digital archive). Below the search bar are two boxes: one for '蔵書や図面で使えるコンテンツ' (Content available with books and maps) and another for 'インターネットで閲覧できるコンテンツ' (Content viewable on the internet). The number '436,321巻' is shown in the first box, and '791,179巻' is shown in the second. At the very bottom, there are more image thumbnails and a large central logo that reads 'JapanSearch'.

The screenshot shows the homepage of the MADB Lab website. The background features a collage of images related to media arts, including manga panels, artworks, and cityscapes. In the center, there is a logo consisting of a 3D cube icon next to the text "MADB Lab". Below the logo, the text "メディア芸術データベース・ラボ" is displayed. At the bottom of the page, there is a large, bold title "Media Arts Database Lab".

The screenshot shows the e-Stat LOD homepage. The top navigation bar includes links for '統計LOD' (Statistical LOD), '統計データ' (Statistical Data), '統計API' (Statistical API), and '統計LOD' (Statistical LOD). The main content features a large 'Linked Open Data' logo with a central 'LOD' icon. A detailed diagram illustrates various data entities and their relationships using triples like 'owl:Class', 'rdfs:label', and 'dct:subject'. Below the logo is a chart titled 'Open Data Ranking' comparing 'e-Stat LOD' and 'GIGANTIC LOD'. A message at the bottom left states: 'オープンデータの最高ランク(スター)であるLOD(Linked Open Data)で統計データを提供します。' (We provide statistical data using the highest ranked LOD (Linked Open Data)). A message at the bottom right says: '2016/06/30 固定調査などの統計データの提供を開始しました。' (Statistical data provision for fixed surveys and others began on June 30, 2016). The footer contains icons for document, chart, data, and database, along with the 'e-Stat' logo and '統務省統計センター' (Ministry of Internal Affairs and Communications Statistical Center).

Example of LOD-based Knowledge Graph: Wikidata



<https://www.wikidata.org/>

The screenshot shows the Wikidata main page with a large, semi-transparent knowledge graph overlay. The graph consists of various entities represented by colored dots (red, green, blue) and lines connecting them, forming a network. In the center, there is text: "Welcome to Wikidata", "the free knowledge base with 117,916,793 data items that anyone can edit.", "Introduction • Project Chat • Community Portal • Help", and "Want to help translate? Translate the missing messages.". A blue callout box on the left contains the following reference information:

Reference

- : Number of Wikipedia Articles
 - English **6.7 million**
 - Japanese **1.4 million**
 - Thai **0.17 million**

- A “**data version**” of Wikipedia operated by the Wikimedia Foundation.
- Currently, it contains around **100 million items**.
- Like Wikipedia, the data can be edited and published by the community.
- Various tools are provided, including an API (SPARQL endpoint) and search interfaces.

This part of the slide shows a detailed view of the Wikidata interface. It includes:

- A sidebar with a "Did you know?" section featuring three images: Earth, a ruler, and Mount Everest.
- An example of a data item: "Property: highest point (P610) custom value: Mount Everest (Q513)".
- A search bar at the bottom with the query "Iranian nuclear sites (Q13500586) 05".
- A result card for "Fordow Uranium Enrichment Plant (Q757565) (pictured)" with a small thumbnail image.

Wikipedia to Wikidata



The screenshot shows a Google Chrome window with three tabs open:

- Tab 1: Google Search - "Wikidata" (highlighted)
- Tab 2: en.wikipedia.org/wiki/Osaka_Electro-Communication_University
- Tab 3: W Osaka Electro-Communication (highlighted)

The Wikipedia page for "Osaka Electro-Communication University" is displayed. A large yellow box highlights the following text:
Each Wikipedia article includes a link to its corresponding Wikidata item.

A red box highlights the "Wikidata" link in the top navigation bar of the Wikipedia page. A green arrow points from this link to the "Wikidata item" link in the sidebar menu of the same page.

The sidebar menu on the right side of the page includes the following items:

- Download QR code
- Expand all
- Edit interlanguage links
- Print/export
- load as PDF
- Printable version
- In other projects
- Wikimedia Commons
- Wikidata item

The "Wikidata item" link is highlighted with a red box. The entire sidebar menu is also enclosed in a red box.

Example of Wikidata Data (1/3)

IDs on Wikidata:

All data items are assigned IDs in the format of Q**

Osaka Electro-Communication University (Q7105556)

higher education institution in Osaka Prefecture, Japan

In more languages Configure

Language	Label	Description	Also known as
English	Osaka Electro-Communication University	higher education institution in Osaka Prefecture, Japan	
Japanese	大阪電気通信大学	No description defined	OECU 大阪電通大
?ucināguci	No label defined	No description defined	
Korean	No label defined	No description	

Statements

instance of university

0 references

+ add reference

+ add value

Labels, Descriptions, and Aliases in Multiple Languages

An Example of Accessing “Osaka Electro-Communication University (Q7105556)” on Wikidata

<https://www.wikidata.org/wiki/Q7105556>

Example of Wikidata Data (2/3)



predicates

Objects

Links to other resources (items)

The screenshot shows a Wikidata item page for Q7105556. The page title is "Osaka Electro-Communication University". The main content area is titled "Statements". It lists several statements:

- "instance of" (red box): A statement about the university being an instance of a university.
- "image" (blue box): A statement linking to a photo of a red brick building labeled "OECU.jpg".
- "inception" (grey box): A statement indicating the university was founded in 1924.
- "country" (grey box): A statement linking to the item for Japan.
- "located in the administrative territorial entity" (grey box): A statement linking to the item for Neyagawa.

A large yellow arrow on the left points upwards, labeled "predicates". A large blue arrow on the right points downwards, labeled "Objects". A pink box at the bottom right contains the text "Links to other resources (items)" with a yellow arrow pointing to the "country" statement.

Example of Wikidata Data (3/3)

Osaka Electro-Communication University (Q7105556)

higher education institution in Osaka Prefecture, Japan

▼ In more lan

Language

English

Japanese

?ucināguci

Korean

All entered la

Statements

instance of

university

The ID can be identified from the linked page.

In Wikidata, “**classification**” is represented using the predicate **instance-of**

instance of

university

▼ 0 references

+ add reference

+ add value

Example of Wikidata Data



Billkin - Google Search Thailand - Wikidata Osaka Electro-Communications

wikidata.org/wiki/Q869 ゲスト 新しい Chrome をご利用いただけます

WIKIDATA

Thailand (Q869)

Item Discussion Read View history Tools

country in Southeast Asia
Kingdom of Thailand | th | Siam | Land of Smiles | THA

In more languages Configure

Language	Label	Description	Also known as
default for all languages	No label defined	—	TH THA
English	Thailand	country in Southeast Asia	Kingdom of Thailand th Siam Land of Smiles THA
Japanese	タイ王国	東南アジアの国	タイ タイランド
Okinawan	No label defined	No description defined	
Korean	태국	동남아시아의 국가	타이 타이 왕국

All entered languages

Statements

instance of

- constitutional monarchy
- sovereign state
- country

part of

- Southeast Asia

Billkin - Google Search Thailand - Wikidata Osaka Electro-Communication

wikidata.org/wiki/Q869 ゲスト 新しい Chrome をご利用いただけます

inception

28 December 1768 Gregorian
subject has role Thonburi Kingdom

1238
subject has role Sukhothai Kingdom

image

Temple of the Emerald of buddha or Wat Phra Kaew (cropped).jpg
1,800 × 1,200; 1.37 MB
media legend Panoramic view of the Grand Palace and adjacent historical sites, Bangkok, Thailand (English)
point in time 30 August 2015
1 reference

official name

ราชอาณาจักรไทย (Thai) ▾
0 references

le Royaume de Thaïlande (French)
1 reference

native label

ประเทศไทย (Thai)
0 references

nickname

Land of Smiles (English)

<http://www.wikidata.org/entity/Q869>

How to Search in Wikidata



Screenshot of the Wikidata item page for "Osaka Electro-Communication University". The URL is wikidata.org/wiki/Q7105556. A red box highlights the sidebar menu on the left, which includes links like Main page, Community portal, Project chat, Create a new Item, Recent changes, Random Item, Query Service, Nearby, Help, and Donate.



Screenshot of the Wikidata item page for "Osaka Electro-Communication University". A yellow callout box with a red border and text "Link to Query Service for Wikidata" points to the "Query Service" link in the sidebar menu. The sidebar also includes Main page, Community portal, Project chat, Create a new Item, Recent changes, Random Item, Query Service, Nearby, and Help.

Wikidata Search Interface



Query Example Selection

Query Input Field

Query Input Assistance

Search using **SPARQL** is supported (with some custom extensions)

<https://query.wikidata.org/>

item itemLabel

item	itemLabel
wd:Q378619	Orangey
wd:Q498787	Unsinkable Sam
wd:Q677525	Catmando
wd:Q893453	
wd:Q1050083	

Example of a Query in Wikidata



Wikidata Query Service

```
1 #猫 (画像付き)
2 #DefaultView:ImageGrid
3 SELECT ?item ?itemLabel ?pic
4 WHERE
5 {
6 ?item wdt:P31 wd:Q146 .
7 ?item wdt:P18 ?pic
8 SERVICE wikibase:label [
```

Search result when selecting “Cats (with images)” from the example queries

Image grid

40件 3022ミリ秒

コード ダウンロード リンク

Example of a Query in Wikidata

```
#Cats (with images)  
#defaultView:ImageGrid
```

```
SELECT ?item ?itemLabel ?pic
```

```
WHERE
```

ID of Property for
“instance of”

```
{
```

```
?item wdt:P31 wd:Q146 .
```

```
?item wdt:P18 ?pic
```

```
SERVICE wikibase:label { bd:serviceParam  
wikibase:language "[AUTO_LANGUAGE],en" }
```

```
}
```

By changing the ID
in this example query,
you can search for
images of various
categories.

ID for “cat”

Mini Works



■ Try Wikidata !

- Find Wikidata pages you like.
 - Check the contents
- Try SPARQL query examples

Advanced Query Example

Ranking Using Wikidata



■ Ranking of Japanese Politicians by Prefecture of Origin → Execution Result

```
SELECT ?pref ?prefLabel (count(?s) As ?c)
```

```
WHERE {
```

```
?pref wdt:P31 wd:Q50337; #instance of = prefecture  
      wdt:P429 ?code.      #Japan local government code  
?s wdt:P27 wd:Q17;        #country of citizenship = Japan  
      wdt:P106 wd:Q82955;   #occupation = politician  
      wdt:P19/wdt:P131* ?pref. #place of birth → prefecture
```

```
SERVICE wikibase:label { bd:serviceParam wikibase:language  
  "[AUTO_LANGUAGE],en". }
```

```
}
```

```
GROUP BY ?pref ?prefLabel  
ORDER BY DESC(?c)
```

pref	prefLabel	c
wd:Q1490	東京都	842
wd:Q130290	兵庫県	358
wd:Q122723	大阪府	355
wd:Q123258	福岡県	355
wd:Q1037393	北海道	308
wd:Q80434	愛知県	276
wd:Q80011	千葉県	242
wd:Q120730	京都府	241
wd:Q128186	埼玉県	237
wd:Q127513	神奈川県	224
wd:Q44843	栃木県	187
wd:Q48326	岩手県	185
wd:Q132705	新潟県	177
wd:Q127264	山口県	175
wd:Q15701	鹿児島県	169
wd:Q71699	青森県	167
wd:Q81863	秋田県	167
wd:Q617375	広島県	162
wd:Q127877	長野県	158
wd:Q130308	熊本県	154
wd:Q131320		153
wd:Q47896	The results(2025/3/10)	149

Changing the Occupation...

Wikidata Query Service ⚒ 例 ⚒ ヘルプ ⚒ 他のツール クエリビルダー 文 A 日本語

クエリヘルパー

pref 分類 都道府県

+ フィルター s 国籍 日本

s 職業

+ 表示 pref 全国地方公共団体コード code

s 出生地 すべて

位置する行政区画

表示数

1 SELECT ?pref ?prefLabel (COUNT(?s) AS ?c) WHERE {
2 ?pref wdt:P31 wd:Q50337;
3 wdt:P429 ?code.
4 ?s wdt:P27 wd:Q17;
5 wdt:P106 wd:Q12330954;
6 (wdt:P19/(wdt:P131*)) ?pref.
7 }
8 GROUP BY ?pref ?prefLabel
9 ORDER BY DESC (?c)

Table

47件 41485ミリ秒

コード ダウンロード リンク

pref	prefLabel	c
wd:Q122723	大阪府	285
wd:Q1490	東京都	257
wd:Q130290	兵庫県	112
wd:Q127513	神奈川県	84
wd:Q128186	埼玉県	80
wd:Q80011	千葉県	68
wd:Q123258	福岡県	68

Use Case of Knowledge Graphs

A Simple Search System for Wikidata



Wikidataの全体検索 <kgs.hozo.jp/sample/wd-search2.html>

Wikidataを用いた検索システム

Wikidata全体の検索

検索キーワード

大阪電気通信大学

▼詳細検索条件

QID	ラベル	分類	上位クラス
wd:Q7105556	大阪電気通信大学	大学	-
wd:Q113159886	大阪電気通信大学/図書館	大学図書館	-
wd:Q11441674	大阪電気通信大学の人物一覧	ウィキメディアの一覧記事	-
wd:Q113475716	大阪電気通信大学人間科学研究	紀要	-
wd:Q113475717	大阪電気通信大学人間科学研究	紀要	-
wd:Q111646736	大阪電気通信大学学術リポジトリ	機関リポジトリ	-
wd:Q7105558	大阪電気通信大学短期大学部	オープンアクセス・リポジトリ	-
wd:Q113475205	大阪電気通信大学研究論集. 自然科学篇	カレッジ	-
wd:Q125255716	大阪電気通信大学総合情報学部	紀要	-
wd:Q111646737	高等学校	学部	-
		日本の高等学校	-

実行サイト

Wikidata上での「分類」
をあわせて検索する

https://oecu-kozaki-lab.github.io/SuperAI2025_KG/kgs/

A Simple Search System for Wikidata



Wikidataを用いた検索システム

Wikidata全体の検索

検索キーワード

検索条件の設定

ラベルの検索設定:

○ 完全一致 前方一致 あいまい検索

QID	ラベル	分類	上位クラス
wd:Q7105556	大阪電気通信大学	大学	-
wd:Q113159886	大阪電気通信大学/図書館	大学図書館	-
wd:Q11441674	初一覧	ワイキメティアの一覧記事	-
wd:Q113475710	学研究	紀要	-
wd:Q113475717	大阪電気通信大学人間科学研究	紀要	-
wd:Q111646736	大阪電気通信大学学術リポジトリ	機関リポジトリ	-
wd:Q7105558	大阪電気通信大学短期大学部	カレッジ	-
wd:Q113475205	大阪電気通信大学研究論集. 自然科学篇	紀要	-
wd:Q125255716	大阪電気通信大学総合情報学部	学部	-
wd:Q11441675	大阪電気通信大学高等学校	日本の高等学校	-

Wikidata の内容を閲覧

「分類」の詳細

Wikidataを用いた検索システム【詳細表示】 - Go...

Wikidataへのリンク

大阪電気通信大学
(Wikidata ID:[Q7105556](#))

名前	大阪電気通信大学 (ja)
別名	OECU (ja) 大阪電通大 (ja)
説明	日本の私立大学 (ja)
分類[wdt:P31]	大学 [wd:Q3918]
位置する行政区画[wdt:P131]	寝屋川市 [wd:Q389633]
国[wdt:P17]	日本 [wd:Q17]
画像[wdt:P18]	

KGSearchForWD

- A JavaScript-based library for developing a "Knowledge Graph Search Service" using Wikidata
- Available at: <https://kgs.hozo.jp/>

検索条件の入力

検索結果の一覧表示

検索サービスの開発例

QID	ラベル	国	所在地	画像	公式ウェブサイト	設立日
wd:Q7105614	大阪商業大学	日本	東大阪市		http://cuc.daishodai.ac.jp/	1949-01-01T00:00:00Z
wd:Q1142082	大阪外国语大学	日本	箕面市		http://www.sfs.osaka-u.ac.jp/	1949-05-01T00:00:00Z
wd:Q1136138	大阪教育大学	日本	大阪市 柏原市 大阪市 柏原市		http://osaka-kyoiku.ac.jp/ https://osaka-kyoiku.ac.jp/en/	1949-05-31T00:00:00Z
wd:Q1030172	大阪芸術大学	日本	大阪市		https://www.osaka-gel dai.ac.jp/	1945-01-01T00:00:00Z
wd:Q7105556	大阪電気通信大学	日本	寝屋川市		https://www.osakac.ac.jp/	1941-01-01T00:00:00Z
wd:Q1017700	桃山学院大学	日本	和泉市		https://www.andrew.ac.jp	1959-01-01T00:00:00Z

大阪電気通信大学
(Wikidata ID: Q7105556)

名前 大阪電気通信大学 (ja)
別名 OECU (ja)
大阪電通大 (ja)
説明 日本の私立大学 (ja)

分類[wdt:P31] 大学[wd:Q3918]

国[wdt:P17] 日本[wd:Q1]

位置する行政区[wdt:P131] 寝屋川市[wd:Q389633]

位置座標[wdt:P625] Point(135.62694444 34.76027778) (geo:wktLiteral)

画像[wdt:P18]

公式ウェブサイト[wdt:P856] <https://www.osakac.ac.jp/>

成立日[wdt:P571] 1941-01-01T00:00:00Z (xsd:dateTime)

すべて表示

データの詳細表示

このような
「検索サービス」が
コーディング無しで
簡単に作成できます！

検索対象には
1億を超える項目を持つ
知識ベースWikidata
([Wikidata](#))
を利用します.



Example of a Map Application Using Location Information in Wikidata



A service that utilizes open location data registered in Wikidata to easily create and publish thematic maps through a few simple steps.

WD巡礼マップ
Wikidataによる巡礼ルート作成

Wikidataに登録されている位置情報をもとに
「様々なMAP」を数ステップの簡単な操作で作成・公開できるサービスです。
→作成例) 「一ノ宮マップ」「世界の国際空港」, その他...

MAPの作成

下記の入力欄にMAPで表示したいデータの「分類」(神社, 空港, 大学, など)または「データ例」(出雲大社, 関西国際空港, 大阪電気通信大学, など)を入力して検索してください。

①MAPで表示したいデータの「分類」を検索

②検索結果からMAPを作成したい「分類」を選択

③MAPが作成される

Google Mapによる経路検索
Wikidataでの定義の確認

MAP生成のエリア
●日本に限定 ○世界地図 ○詳細設定

MAP作成

MAP作成

MAP作成

[MAPの例] [使い方] [技術解説] [ソースコード]

<https://wd-map.hozo.jp/>

作成したMAPはそのまま共有できる

Document Analysis Using Knowledge Graphs



■ Analysis Procedure

■ **1. Mapping Between Knowledge Graphs and Texts**

- Mapping at the term level → Entity Linking
- Mapping at the relation level → Relation Extraction
- Mapping with graph structure → Graph Extraction
- ...

■ **2. Interpreting Meaning from the Structure of the Corresponding Knowledge Graph**

- Utilize the semantics expressed by the knowledge graph (term classification, concept definitions, types of relationships, etc.)
- Utilize the graph's network structure (e.g., path distances)
- Utilize graph embeddings (vectorization)
- ...

Entity Linking Using Wikidata



Wikidataのクラス階層を用いたエンティティリンク

masapi61.github.io/Annotation-by-Wikidata/index.html

Wikidataのクラス階層を用いたエンティティリンク

使い方(githubレポジトリ)

カテゴリー:

- 活動
- 解剖学的構造
- 疾患
- 薬
- 組織
- 人物
- 場所
- 化学物質
- 生物
- 仕事

例文1 例文2 例文3

▶ 詳細設定

オキシトシン (OXT) は、視床下部で産生される神経ペプチドです。OXT産生ニューロンは軸索を神経下垂体後葉、つまり下垂体後葉に投射し、ペプチドホルモンとして末梢的にOXTを血液循環に放出します。これらのニューロンはまた、いくつかの脳領域を神経支配し、そこで神経ペプチドとしてOXTを放出します。したがって、OXTは、子宮収縮や授乳などの末梢性機能だけでなく、社会的、攻撃的、恐怖、母性行動などの中枢性機能の調節にも関与しています。

アノテーション実行

ダウンロード

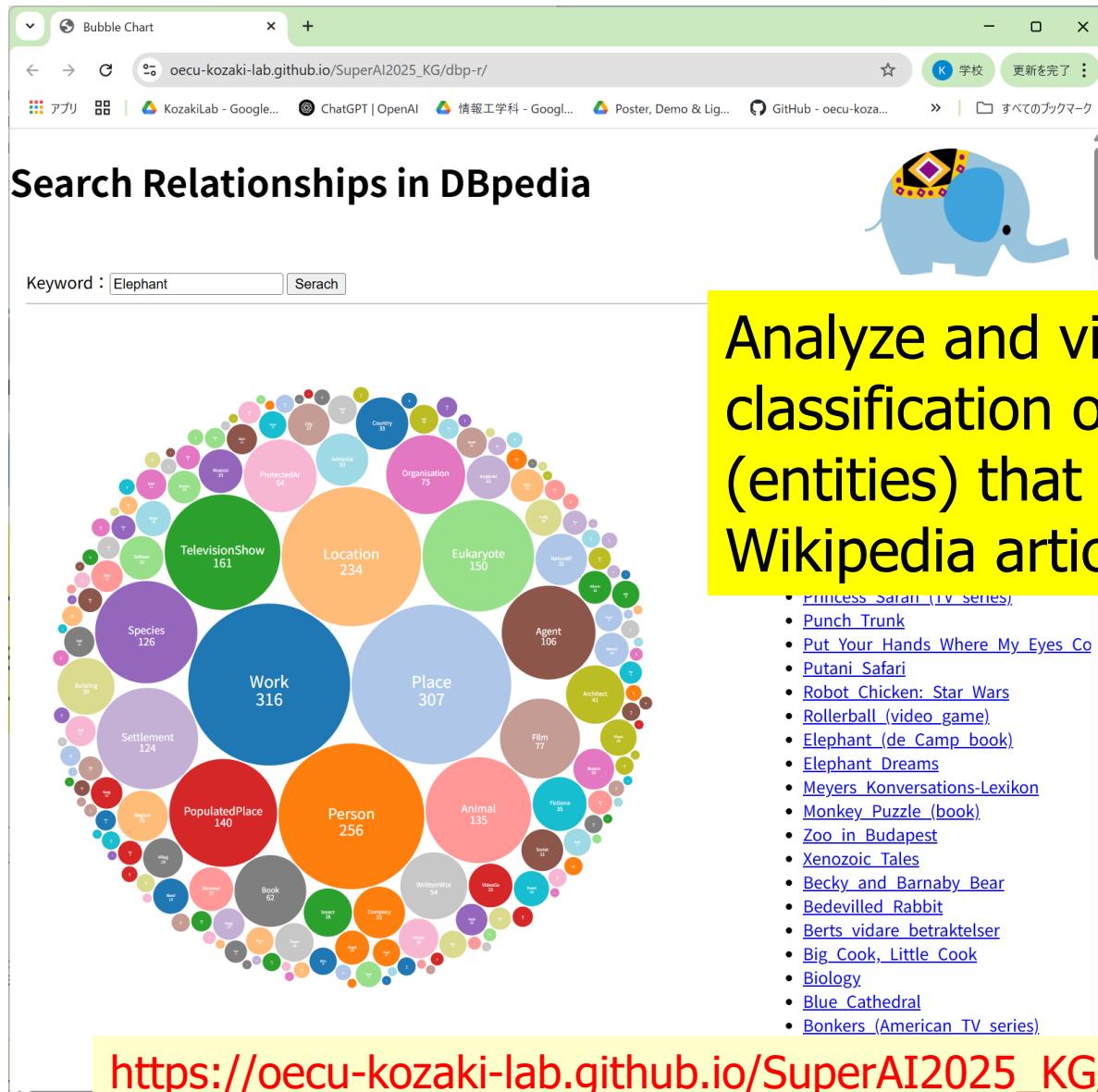
<https://shunafuku.github.io/entity-linking-by-wikidata/>

アノテーション結果

オキシトシン (OXT) は、視床下部で産生される神経ペプチドです。OXT産生ニューロンは軸索を神経下垂体後葉、つまり下垂体後葉に投射し、ペプチドホルモンとして末梢的にOXTを血液循環に放出します。これらのニューロンはまた、いくつかの脳領域を神経支配し、そこで神経ペプチドとしてOXTを放出します。したがって、OXTは、子宮収縮や授乳などの末梢性機能だけでなく、社会的、攻撃的、恐怖、母性行動などの中枢性機能の調節にも関与しています。

自然言語処理
+
知識グラフの構造
を利用

Analysis and Visualization of Relationships Between Wikipedia Articles Using DBpedia





SDGsについての知識グラフ
に基づいて、文書を分析する

A demo app that automatically extracts key concepts related to sustainable development from text documents and links them to the most relevant sustainable development goals, targets, indicators and series.

ANALYZE DOCUMENT

Upload a document related to Sustainable Development Goals or paste its URL in order to analyse it (PDF, DOC, DOCX, HTML - max 50K words).

The document can be in either of the six official UN languages: Arabic, Chinese, English, French, Russian and Spanish.

You can also use some of the example links provided.

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3657896/>

Choose file: [Browse](#)

[ANALYZE](#)

Examples

🔗 Tackling the malaria problem in the South-East Asia Region: Need for a change in policy?

🔗 Linking EU funds to rule of law and "European values"

🔗 Conserve and sustainably use the oceans, seas and marine resources for sustainable development

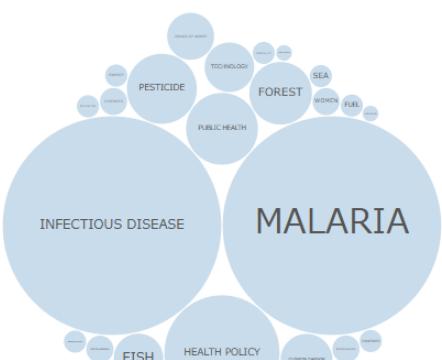
<https://linkedsdg.officialstatistics.org/>

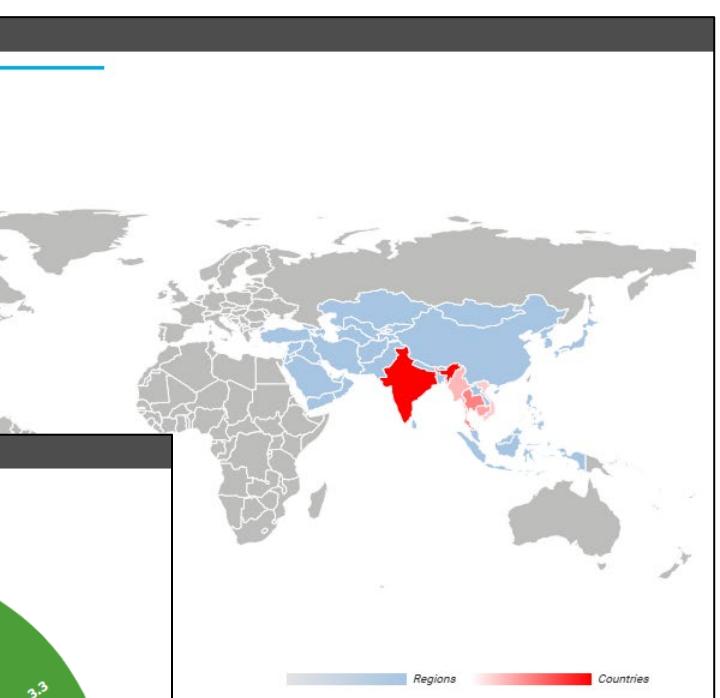
LinkedSDGsによる分析例

LinkedSDG About API Voluntary National Review - Canada 2018 (FR)

EXTRACTED CONCEPTS

- INFECTIOUS DISEASE EuroVoc v
- MALARIA UNBIS v
- HEALTH POLICY EuroVoc UNBIS v
- PUBLIC HEALTH EuroVoc UNBIS v
- PESTICIDE EuroVoc UNBIS v
- FOREST EuroVoc UNBIS v
- CLIMATE CHANGE EuroVoc UNBIS v
- FISH

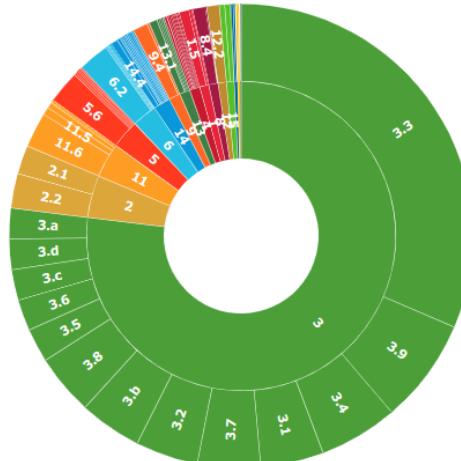




Regions Countries

LinkedSDG About API Show

MOST RELEVANT SDGS



SUSTAINABLE DEVELOPMENT GOALS

The United Nations Sustainable Development Goals (SDGs) are 17 global goals that all UN Member States have agreed to try to achieve by the year 2030.

The 17 SDGs are articulated into 169 targets, 230 indicators, and over 400 data series that help to measure the progress towards achieving the SDGs.

The full SDG Taxonomy is officially published and maintained as [linked open data](http://metadata.un.org/sdg/) at:
<http://metadata.un.org/sdg/>

Explore the SDG wheel to find goals, targets, indicators and data series that are most relevant to the processed document, based on the extracted concepts and geographical areas.

Knowledge Graph Reasoning Challenge

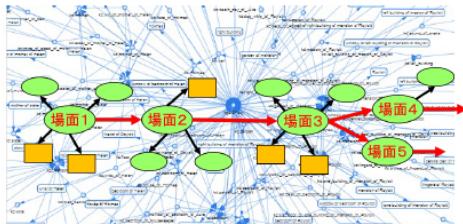


FY2018 – FY2023 by the Special Interest Group on Semantic Web and Ontology (SWO) of the Japanese Society for AI (JSAl)

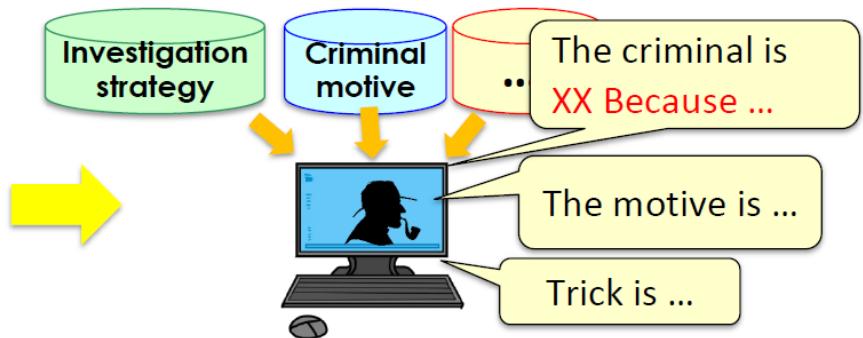
A Contest to develop AI systems which have abilities for “Reasoning” and “Explanation” such like Sherlock Holmes.



Sherlock
Holmes
mystery story

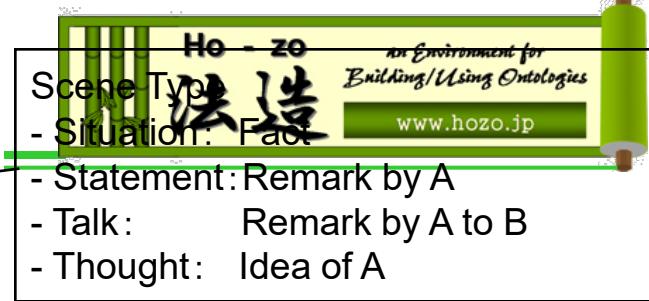


Knowledge Graphs
(LOD)

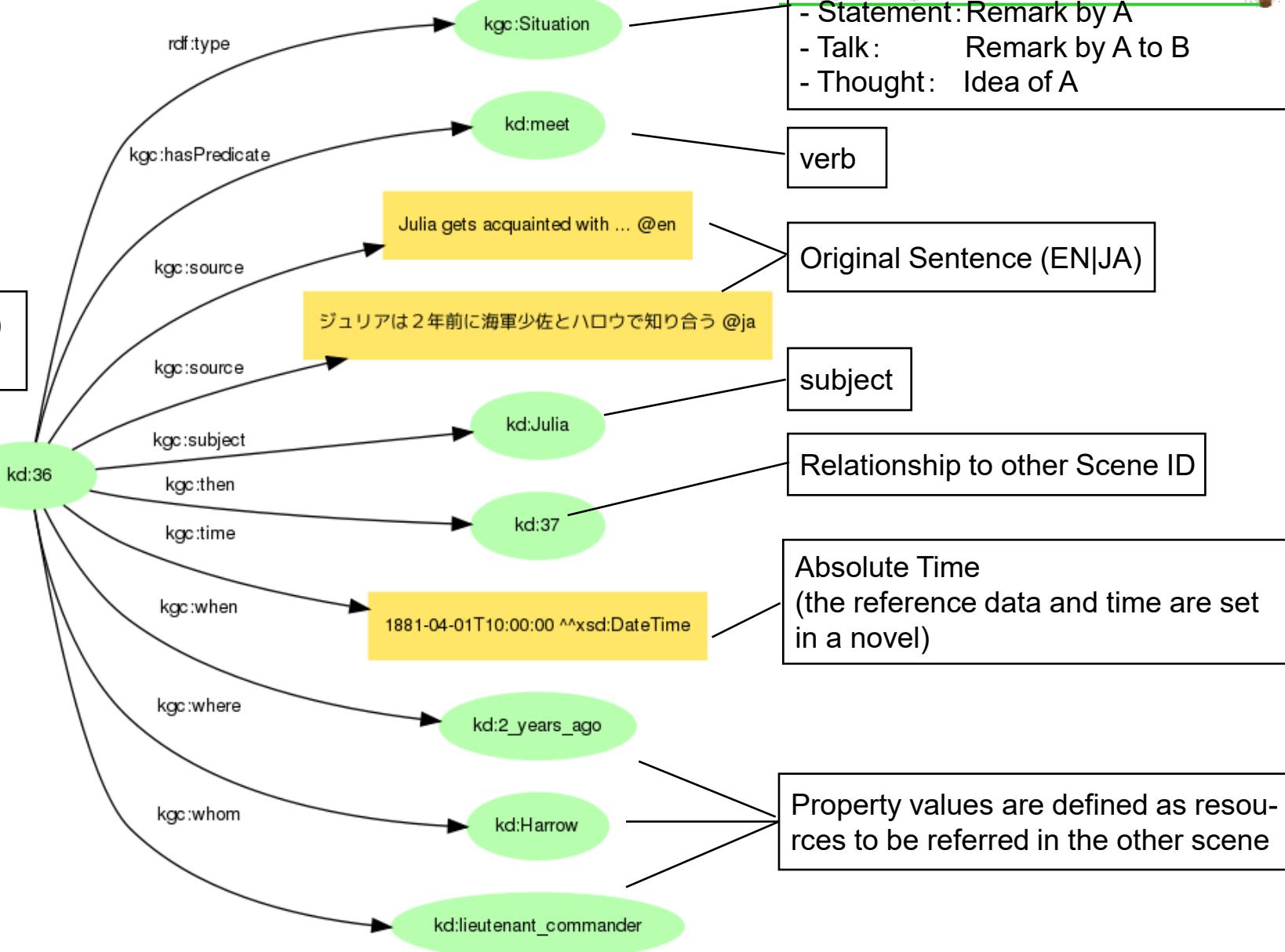


AI system that estimate criminals with reasonable explanations using the KG and other knowledge

Structure of a Knowledge Graph Representing Scenes



Unique ID (IRI)
Of Each scene



Example Visualization of a Knowledge Graph from a Detective Story

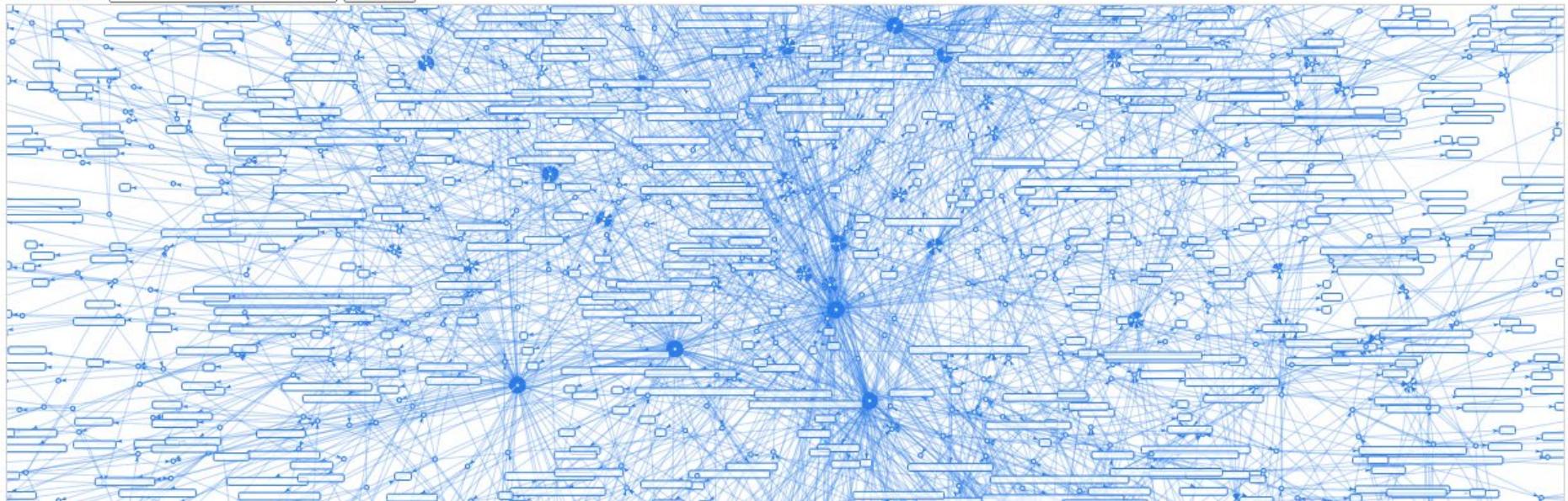


Linked Data visualization tool

```
#It is needed a SPARQL query to get in <?s ?p ?o>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX kgc: <http://kgc.knowledge-graph.jp/ontology/kgc.owl#>
PREFIX kdsb: <http://kgc.knowledge-graph.jp/data/SpecckledBand/>
PREFIX kddm: <http://kgc.knowledge-graph.jp/data/DancingMen/>
PREFIX kdc1: <http://kgc.knowledge-graph.jp/data/ACaseOfIdentity/>
PREFIX kddf: <http://kgc.knowledge-graph.jp/data/DevilsFoot/>
```

SPARQL Endpoint: <http://kg.hozo.jp/fuseki/kgrc/>

Keyword:



<http://knowledge-graph.jp/visualization/>

Short Break & QA

Integration Technologies of Knowledge Graphs and LLMs

Three pillars of “Machine Knowledge”

Three Pillars of “Machine Knowledge”



Representation:

crisp

mixed

latent

Correctness:

high

mixed

mixed

Freshness:

mostly

fresh

stale

Coverage:

limited

everything

huge

Cost/Query:

low

low

high

Provenance:

tangible

tangible

intangible



Coolness:

nerdy

mundane

amazing

From keynote by Gerhard Weikum at ISWC2023

https://videolectures.net/iswc2023_weikum_knowledge_graphs/

Mutual Utilization Patterns between KG and LLM



■ KG vs. LLM

- Comparing the performance of both on the same task

■ KG for LLM

- Fact Check Using KGs for LLM
- Using KGs in LLM Training
- Using KGs as External Knowledge for LLMs

■ LLM for KG

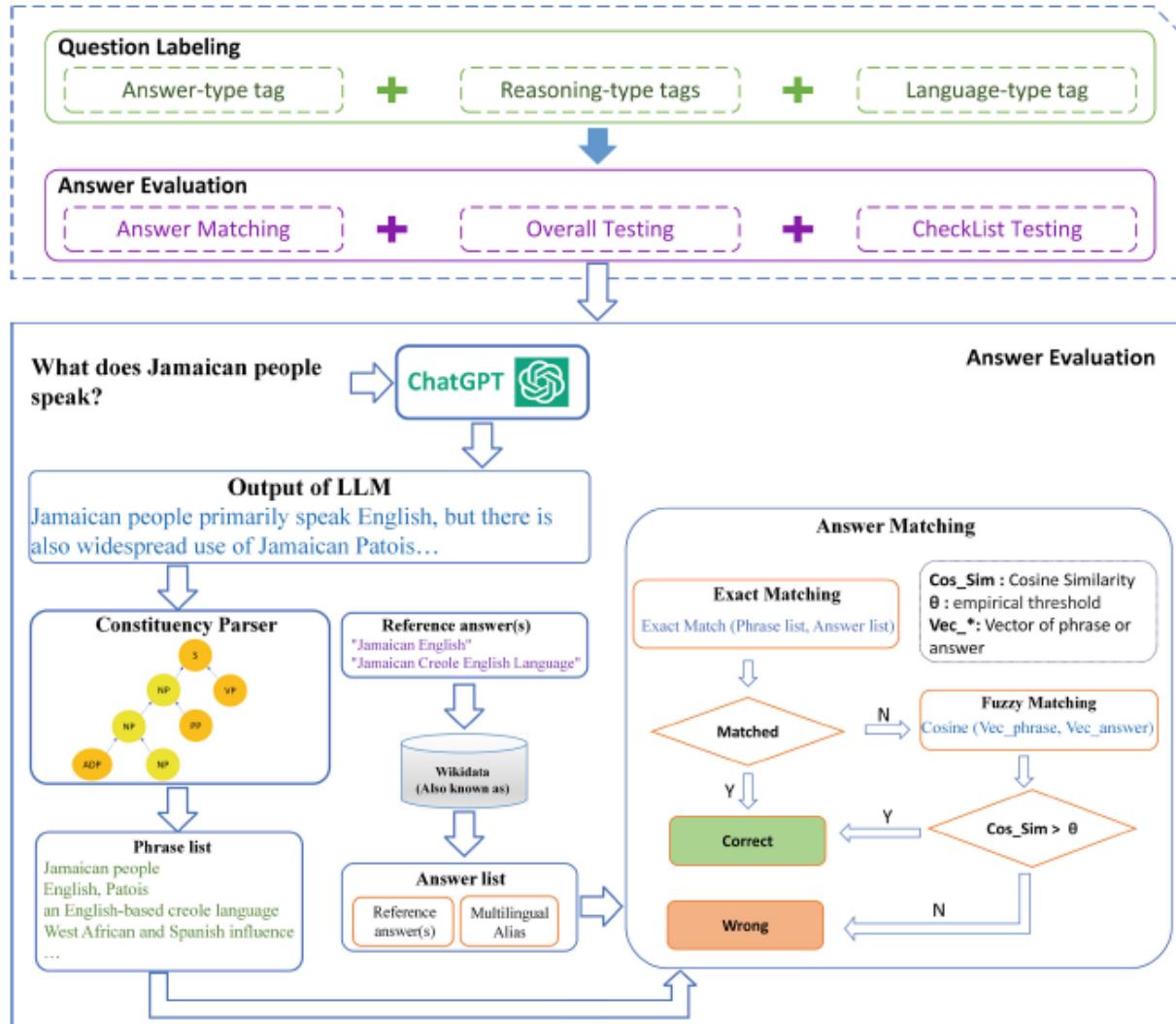
- KG/Ontology (Automatic) Construction (Support) Using LLMs
- Using LLMs as Natural Language Interfaces for KGs

Mutual Utilization Patterns between KG and LLM



- **KG vs. LLM**
 - Comparing the performance of both on the same task
e.g., Comparison with KGQA
- **KG for LLM**
 - **Fact Check Using KGs for LLM**
 - Compare facts obtained from KGs with content generated by language models
e.g., Fact checking with Wikidata
 - Using KGs in LLM Training
 - Using KGs as External Knowledge for LLMs
- **LLM for KG**
 - **KG/Ontology (Automatic) Construction (Support) Using LLMs**
 - **Using LLMs as Natural Language Interfaces for KGs**

Comparison of KGQA and LLM-based Search



Evaluation of the performance of various large language models (LLMs) when applied to **Knowledge Base Question Answering (KBQA)**.
 [Yiming 03]

Fig. 1. Overview of proposed Evaluation Framework.

Comparison of KGQA and LLM-based Search



Table 3. Overall results of the evaluation. We compare the exact match of ChatGPT with current SOTA traditional KBQA models (fine-tuned (FT) and zero-shot (ZS)), GPT family LLMs, and Non-GPT LLM. In GraphQ, QALD-9 and LC-quad2, the evaluation metric used is F1, while other datasets use Accuracy (Exact match).

Datasets	KQapro	LC-quad2	WQSP	CWQ	GrailQA	GraphQ	QALD-9	MKQA
	Acc	F1	Acc	Acc	Acc	F1	F1	Acc
SOTA(FT)	93.85 [29]	33.10 [31]	73.10 [15]	72.20 [15]	76.31 [‡]	31.8 [13]	67.82 [32]	46.00 [22]
SOTA(ZS)	94.20 [25]	-	62.98 [50]	-	-	-	-	-
FLAN-T5	37.27	30.14	59.87	46.69	29.02	32.27	30.17	20.17
GPT-3	38.28	33.04	67.68	51.77	27.58	38.32	38.54	26.97
GPT-3.5v2	38.01	33.77	72.34	53.96	30.50	40.85	44.96	30.14
GPT-3.5v3	40.35	39.04	79.60	57.54	35.43	47.95	46.19	39.05
ChatGPT	47.93	42.76	83.70	64.02	46.77	53.10	45.71	44.30
GPT-4	57.20	54.95	90.45	71.00	51.40	63.20	57.20	59.20

[‡] <https://dki-lab.github.io/GrailQA/>.

The evaluation results showed F1 scores ranging from 0.5 to 0.9, and accuracy (ACC) ranging from 0.2 to 0.9.

- * For a more detailed evaluation and discussion under specific conditions, please refer to the paper. [Yiming 03]

Comparison of Answers from KGQA Using Wikidata and ChatGPT



Comparison Results Using Single-Answer Quiz Questions

* From the "AI-O Quiz AI Japan Championship"

(<https://sites.google.com/view/project-aio/home>)

* 200 questions were used, based on Japanese Wikipedia content.

KGQA using Wikidata

	First Answer	Most Frequent	Manual KGQA	WebGPT	GPT3.5	GPT4.0
Correct Answers	72	73	110	114	112	157
Narrowed Down	30	41	3	7	4	3
Incorrect Answers	98	86	87	79	84	40
Accuracy	36.0%	36.5%	55.0%	57.0%	56.0%	78.5%
Precision	51.0%	57.0%	56.5%	60.5%	58.0%	80.0%
Error Rate	49.0%	43.0%	43.5%	39.5%	42.0%	20.0%

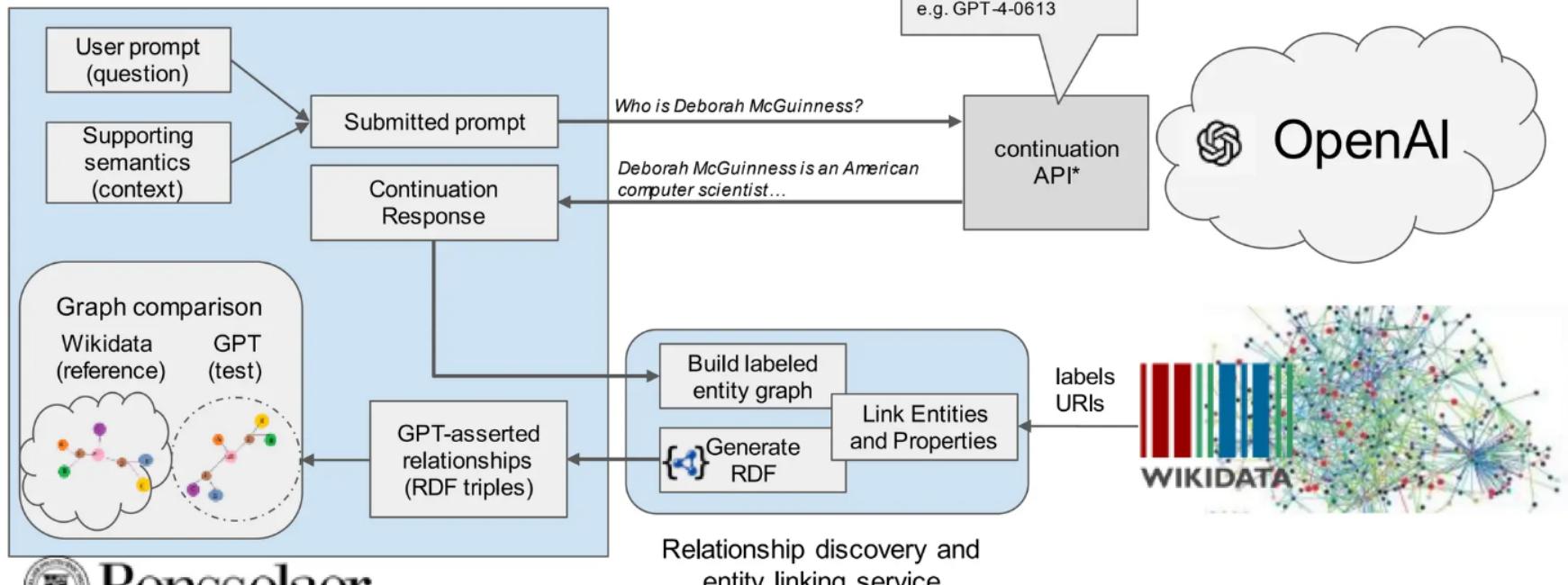
These results reflect cases where humans could formulate queries that retrieved correct answers from Wikidata.

Fact Checking Using the Knowledge Graph: Wikidata



Potential Architecture for a KG-powered Fact Checker

Example: A Wikidata-based GPT fact checker



Rensselaer

ISWC2023 keynotes by Deborah McGuinness

Movie: https://videolectures.net/iswc2023_mc_guinness_web_research/

Slides: <https://www.slideshare.net/deborahmcguinness/iswc2023mcguinnessstwc16x9finalshortpdf>

Comparison of Fact Information from Wikidata and Responses from ChatGPT



[Oyama 04]

Comparison of Search Results in Wikidata and Answers from ChatGPT

Wikidata Query Service

例

ヘルプ

他のツール

クエリビルダー

日本語

```
1 select ?s ?sLabel ?o ?oLabel ?o2Label ?o3Label
2 where {
3   ?s wdt:P31 wd:Q3918 . # ?sの「分類」が「大学」
4   ?s wdt:P17 wd:Q17 . # ?sの「国」が「日本」
5   ?s wdt:P571 ?o .     # ?sの「設立」を?oとする
6   ?s wdt:P131 ?o2 .    # ?sの「所在地」を?o2とする
7   SERVICE wikibase:label { bd:serviceParam wikibase:label
8 }
9 }
```

s	sLabel	o	
wd:Q615301	日本医科大学	1876年1月1日	X
wd:Q616359	青山学院大学	1949年1月1日	
wd:Q616359	青山学院大学	1949年1月1日	
wd:Q651233	大阪大学	1931年5月1日	
wd:Q684783	金沢大学	1949年5月31日	
wd:Q684783	金沢大学	1949年5月31日	1949-05-31T00:00:00Z 金沢市
wd:Q685781	広島市立大学	1994年1月1日	1994-01-01T00:00:00Z 広島市
wd:Q685781	広島市立大学	1994年1月1日	1994-01-01T00:00:00Z 広島県



大山

You

- ・大学名,設立年,設立日,設立日,所在都道府県,所在市町村,公式Webサイトの順に,で区切って回答してください。
- ・市町村名より詳しい住所は不要です
- ・不明な場合は、?とします。



ChatGPT

国際大学,1950,91,東京都,三鷹市,<https://www.icu.ac.jp/>

Comparison of Fact Information from Wikidata and Responses from ChatGPT



[Oyama 04]

Comparison of Search Results in Wikidata and Answers from ChatGPT

Wikidata Query Service

例 ヘルプ 他のツール クエリビルダー 日本語

```
1 select ?s ?sLabel ?o ?oLabel ?o2Label ?o3Label
2 where {
3   ?s wdt:P31 wd:Q3918 . # ?sの「分類」が「大学」
4   ?s wdt:P17 wd:Q17 . # ?sの「国」が「日本」
5   ?s wdt:P571 ?o . # ?sの「設立」を?oとする
6   ?s wdt:P131 ?o2 . # ?sの「所在地」を?o2とする
7   SERVICE wikibase:label { bd:serviceParam wikibase:labelS
8 }
9 }
```

s	sLabel	o
wd:Q615301	日本医科大学	1876年1月1日
wd:Q616359	青山学院大学	1949年1月1日
wd:Q616359	青山学院大学	1949年1月1日
wd:Q651233	大阪大学	1931年5月1日
wd:Q684783	金沢大学	1949年5月31日
wd:Q684783	金沢大学	1949年5月31日
wd:Q685781	広島市立大学	1994年1月1日
wd:Q685781	広島市立大学	1994年1月1日

Please respond using the following format:
university name, year of establishment, date
of establishment, prefecture, city or town.
Use the order shown on the official website
and separate items with commas.

No need for detailed address beyond city or
town.

If uncertain, use "?" as a placeholder.



ChatGPT

International Christian University, 1950, 9/1,
Tokyo, Mitaka, <https://www.icu.ac.jp/>

Comparison of Fact Information from Wikidata and Responses from ChatGPT



[Takahashi 05] System Developed for Unified Comparison

WikidataとChatGPTの回答によるFact Checkシステム

Endpoint: <https://query.wikidata.org/sparql>

Enter the entity ID from Wikidata

INPUT: 検索の実行

ChatGPT3.5-turbo 日本の大学

クエリの表示

Specify the ChatGPT API model and the target class (on Wikidata) to be compared, then execute the query

item	itemLabel	prefLabel	cityLabel	townLabel	ymd1Label	oLabel	ChatGPT
wd:Q462576	名古屋市立大学	愛知県	愛知県	愛知県	1950-01-01 T00:00:00Z	http://www.nagoya-cu.ac.jp/	名古屋市立大学の、所在都道府県、所在市町村、設立日、webサイトを例のように「,」で区切って回答してください。 回答は結果のみを表示してください。 設立日はyyyy-mm-ddの形式にしてください。 例)所在都道府県,所在市町村,設立日,webサイト
wd:Q495330	國學院大學	東京都	東京都	東京都	1882-01-01 T00:00:00Z	https://www.kokugakuin.ac.jp/	國學院大學の、所在都道府県、所在市町村、設立日、webサイトを例のように「,」で区切って回答してください。 回答は結果のみを表示してください。 設立日はyyyy-mm-ddの形式にしてください。 例)所在都道府県,所在市町村,設立日,webサイト

Generate a prompt that asks ChatGPT to return information equivalent to the Wikidata search result

Comparison of Fact Information from Wikidata and Responses from ChatGPT



[Takahashi 05]

ChatGPT

愛知県, 名古屋市, 1964-05-01, <https://www.nagoya-cu.ac.jp/>
東京都, 渋谷区, 1979-04-01, <https://www.kokugakuin.ac.jp/>

Display the responses
obtained from ChatGPT

Compare responses from ChatGPT
with Wikidata search results

一致確認

1:愛知県	愛知県	○	-	愛知県	×	愛知県	名古屋市	×	名古屋市
名古屋市	○	1950-01-01T00:00:00Z		1949	×	-	1949	×	
http://www.nagoya-cu.ac.jp/				https://www.nagoya-cu.ac.jp/	×	-			https://www.nagoya-cu.ac.jp/
2:大阪府	大阪府	○	-	大阪府	×	大阪府	吹田市	×	吹田市
枚方市	吹田市	×	1945-11-01T00:00:00Z	1966	×	1966-04-01T00:00:00Z	1966	○	
-	1966	×		https://www.kansaigaidai.ac.jp/	https://www.kansaigaidai.ac.jp/	○	-		
				https://www.kansaigaidai.ac.jp/	×		https://www.kansaigaidai.ac.jp/en/		
				https://www.kansaigaidai.ac.jp/	○				
3:東京都	東京都	○	東京都	武藏野市	×	1882-01-01T00:00:00Z	1924	×	
			https://www.kokugakuin.ac.jp/	https://www.kokugakuin.ac.jp/	○				

評価

Output agreement rate from
the comparison results

100.00%
40.00%
20.00%
120.00%

Comparison of Fact Information from Wikidata and Responses from ChatGPT



[Takahashi 05]

■ Execution Conditions for Fact Checking

- Use 15 types of data represented as subject–predicate–object triples for fact information
 - Example: “The location of Osaka Electro-Communication University is Neyagawa City, Osaka Prefecture”
 - Example: “The elevation of Mt. Fuji is 3,776 meters”
- Retrieve all IDs for the following 15 data types using SPARQL:
 - Universities in Japan, Japanese manga series, Japanese actors, Japanese railways, Japanese literature, Japanese politicians, J-POP artists, Rivers in Japan, Japanese anime films, Mountains in Japan, Japanese comedians, Japanese TV dramas, Japanese stadiums, Islands of Japan, Japanese national badminton players
- Perform consistency checks using ChatGPT-3.5-turbo, ChatGPT-4-turbo, and ChatGPT-4o

Comparison of Fact Information from Wikidata and Responses from ChatGPT

■ Comparison Results 1

[Takahashi 05]

データ名	全ID数	インスタンス	ChatGPT3.5-turbo		ChatGPT4-turbo		ChatGPT4o		対象ファクト数
			一致率	一致数	一致率	一致数	一致率	一致数	
日本の大学	747	所在都道府県	71.45%	528	83.36%	616	95.67%	707	739
		所在市町村	40.33%	248	55.77%	343	82.76%	509	615
		設立日	8.43%	63	18.74%	140	43.91%	328	747
		webサイト	55.15%	412	60.11%	449	72.42%	541	747
日本の連載漫画	379	著者	12.43%	46	37.84%	140	63.51%	235	370
日本の俳優	1426	出生都道府県	16.62%	224	22.85%	308	64.76%	873	1348
		出生市町村	2.17%	18	10.00%	83	47.35%	393	830
		活動開始日	4.70%	67	9.20%	131	34.64%	494	1426
		生年月日	29.66%	423	43.61%	621	99.23%	1415	1426
		血液型	15.37%	219	19.65%	280	49.54%	706	1426
		性別	83.80%	1195	70.72%	1007	97.48%	1390	1426
日本の鉄道	2589	所在都道府県	25.47%	633	48.05%	1194	64.27%	1597	2485
		所在市町村	16.58%	412	31.31%	778	46.68%	1160	2485
		成立日	2.86%	74	4.44%	115	20.21%	523	2588
日本の文学	1657	著者	5.79%	93	13.89%	223	37.88%	608	1605
日本の政治家	2837	出生都道府県	9.64%	212	2.82%	62	18.32%	403	2200
		出生市町村	0.95%	14	0.82%	12	8.38%	123	1467
		生年月日	0.11%	3	0.61%	17	4.79%	136	2837
J-POP	989	歌手	8.21%	80	28.62%	279	37.13%	362	975
		作詞者	5.64%	55	25.00%	244	33.71%	329	976

Green: 80% or higher

Orange: Less than 1%

Comparison of Fact Information from Wikidata and Responses from ChatGPT

■ Comparison Results 2

[Takahashi 05]

データ名	全ID数	インスタンス	ChatGPT3.5-turbo		ChatGPT4-turbo		ChatGPT4o		対象ファクト数
			一致率	一致数	一致率	一致数	一致率	一致数	
日本の川	830	全長	2.41%	20	0.60%	5	12.18%	101	829
		流域面積	1.21%	10	1.45%	12	7.72%	64	829
		河口	3.14%	26	1.69%	14	17.49%	145	829
日本のアニメ映画	692	監督	8.92%	56	34.55%	217	64.97%	408	628
日本の山	1114	標高	1.86%	20	8.53%	92	29.96%	323	1078
		山脈	2.60%	28	6.40%	69	24.77%	267	1078
日本のお笑いタレント	1087	出生都道府県	4.96%	41	7.26%	60	24.58%	203	826
		出生市町村	0.59%	3	1.96%	10	13.36%	68	509
		生年月日	4.74%	49	4.74%	49	24.39%	252	1033
日本のテレビドラマシリーズ	1189	放送開始日	30.43%	220	57.68%	417	75.66%	547	723
		放送終了日	27.91%	139	50.80%	253	71.29%	355	498
日本のスタジアム	246	所在都道府県	86.36%	152	94.89%	167	97.16%	171	176
		所在市町村	80.70%	138	85.38%	146	92.40%	158	171
日本の島	1640	所在都道府県	7.96%	78	12.14%	119	19.90%	195	980
		所在市町村	2.59%	15	8.79%	51	17.24%	100	580
		接する水域	13.15%	76	15.92%	92	25.09%	145	578
日本代表のバドミントン選手	495	生年月日	0.00%	0	0.49%	2	0.98%	4	410
		性別	63.33%	259	16.10%	66	37.16%	152	410

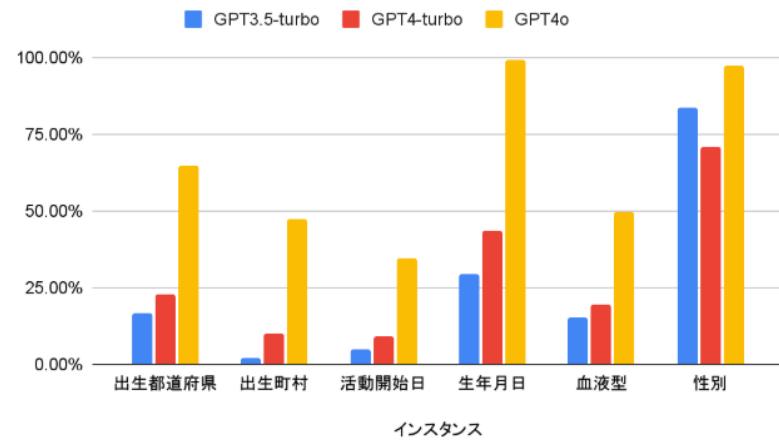
Green: 80% or higher

Orange: Less than 1%

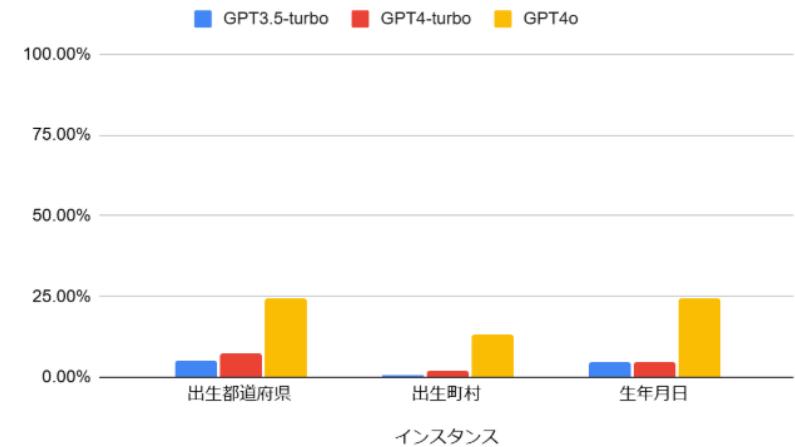
Comparison of Fact Information from Wikidata and Responses from ChatGPT

[Takahashi 05]

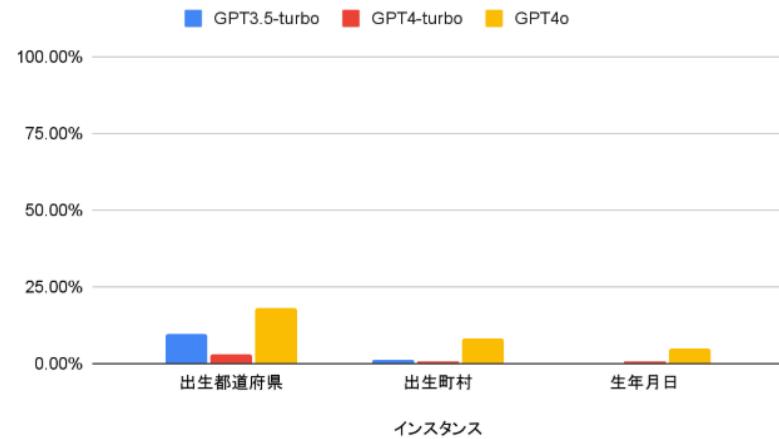
日本の俳優の一致率



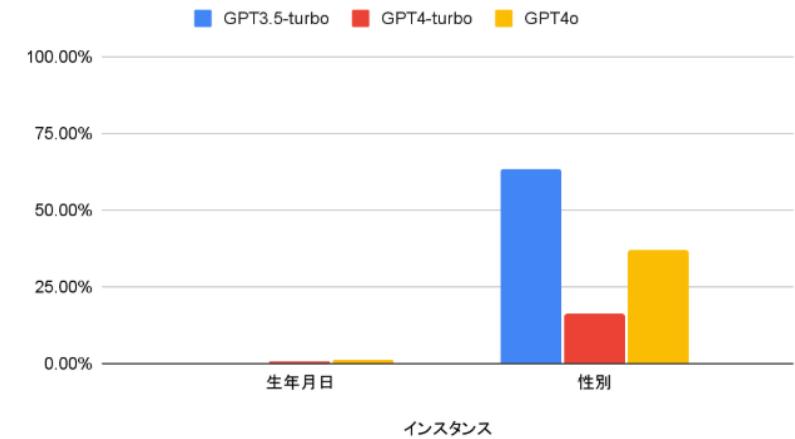
日本のお笑いタレントの一致率



日本の政治家の一致率



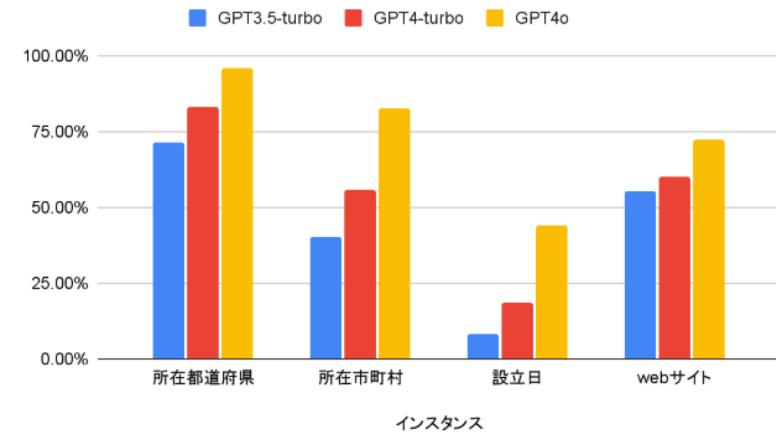
日本代表のバドミントン選手の一致率



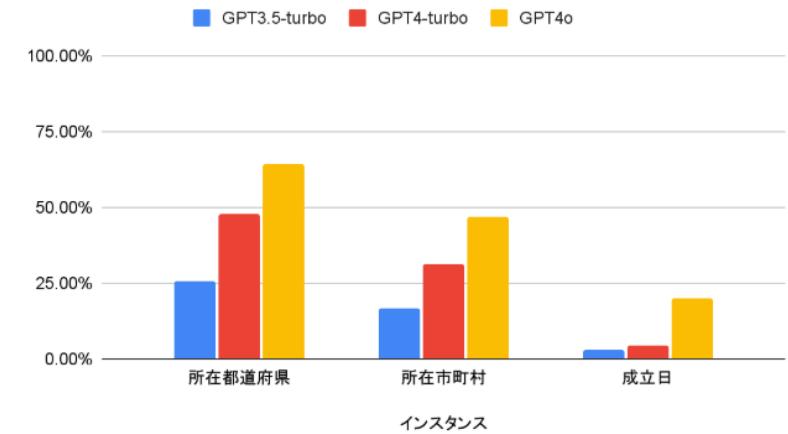
Comparison of Fact Information from Wikidata and Responses from ChatGPT

[Takahashi 05]

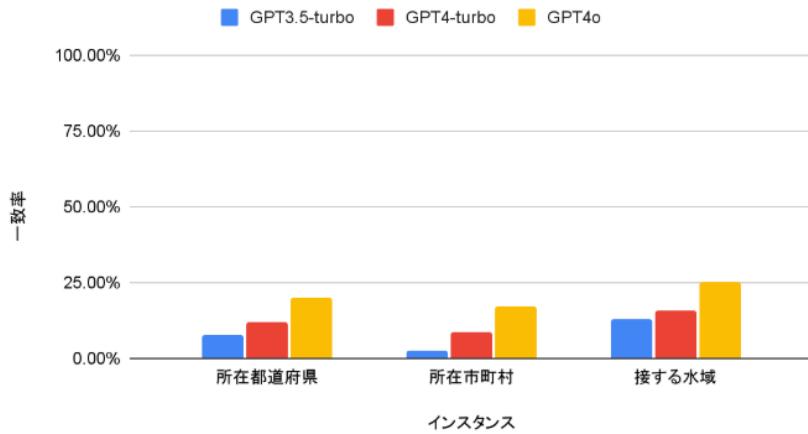
日本の大学の一致率



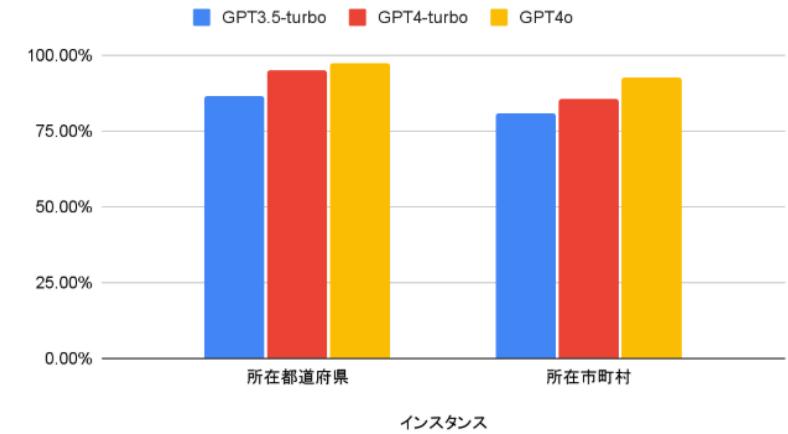
日本の鉄道の一致率



日本の島の一致率



日本のスタジアムの一致率



Comparison of Fact Information from Wikidata and Responses from ChatGPT

[Takahashi 05]

日本の連載漫画の一致率

GPT3.5-turbo GPT4-turbo GPT4o

100.00%

75.00%

50.00%

25.00%

0.00%

一致率

著者

インスタンス

J-POPの一致率

GPT3.5-turbo GPT4-turbo GPT4o

100.00%

75.00%

50.00%

25.00%

0.00%

一致率

歌手

作詞者

インスタンス

日本の文学の一致率

GPT3.5-turbo GPT4-turbo GPT4o

100.00%

75.00%

50.00%

25.00%

0.00%

一致率

著者

インスタンス

日本のアニメ映画の一致率

GPT3.5-turbo GPT4-turbo GPT4o

100.00%

75.00%

50.00%

25.00%

0.00%

一致率

監督

インスタンス

Comparison of Fact Information from Wikidata and Responses from ChatGPT

[Takahashi 05]

日本の川の一致率

GPT3.5-turbo GPT4-turbo GPT4o

100.00%

75.00%

50.00%

25.00%

0.00%

全長

流域面積

河口

インスタンス

日本の山の一致率

GPT3.5-turbo GPT4-turbo GPT4o

100.00%

75.00%

50.00%

25.00%

0.00%

標高

山脈

インスタンス

日本のテレビシリーズの一致率

GPT3.5-turbo GPT4-turbo GPT4o

100.00%

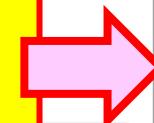
75.00%

50.00%

25.00%

0.00%

For factual information, it is advisable to **integrate databases** such as Wikidata.



RAG etc.

Reference:

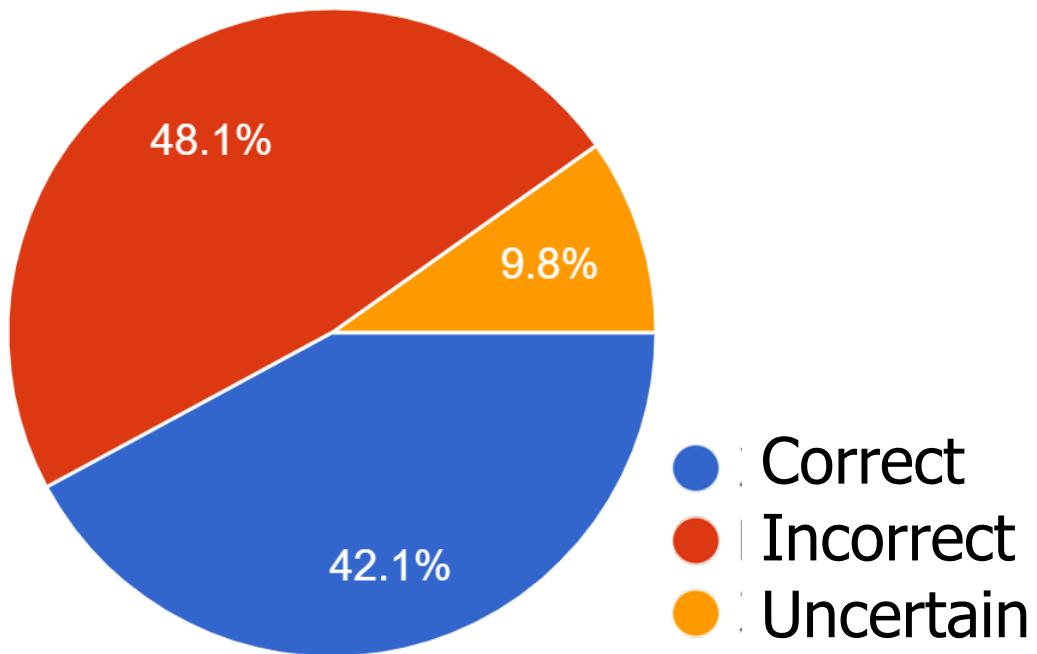
Analysis of ChatGPT Responses

A survey was conducted among students who attended the lecture, asking them **to evaluate the correctness of ChatGPT's answers to free-form factual questions.**

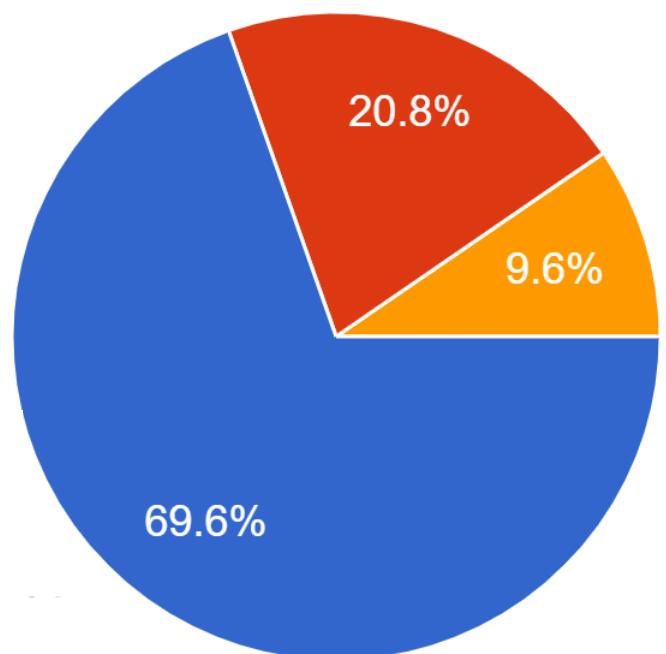
Comparison between **GPT-4o-mini** and **GPT-4o**

(Survey period: October 2024 – February 2025, Total responses: 418)

GPT-4o-mini



GPT-4o



Mutual Utilization Patterns between KG and LLM



- **KG vs. LLM**
 - Comparing the performance of both on the same task
- **KG for LLM**
 - Fact Check Using KGs for LLM
 - **Using KGs in LLM Training**
 - Use knowledge graphs to generate **training texts for language models**
 - Using KGs as External Knowledge for LLMs
- **LLM for KG**
 - KG/Ontology (Automatic) Construction (Support) Using LLMs
 - Using LLMs as Natural Language Interfaces for KGs

Using KGs for LLM Training



- **Procedure for Using Knowledge Graphs in LLM Training**
 - **1. Generate textual training data using the knowledge graph**
 - Use template-based transformations
 - Vary combinations to increase data diversity
 - Use other LLMs to convert triples into text
 - *Data converted into text using ChatGPT cannot be used for training other LLMs due to usage restrictions*
 - **2. Use the generated data for training**
 - Train a new model from scratch
 - Fine-tune an existing model
 - (more common due to lower training cost)
 - Use the data as context in prompts → RAG-based usage

Examples of Using KGs for LLM Training



■ Generate Questions from KGs Using Templates

- Example: Japan – Capital – Tokyo
→ What is the capital of Japan? (Answer: Tokyo)

■ Training with Question Sentences + SPARQL Queries (planned)

1. Automatically generate SPARQL queries to answer single-answer questions
2. From the auto-generated queries, collect question–query pairs that successfully produced correct answers
3. Use the question-to-SPARQL generation model for teacher forcing training

■ Generate Training Data (Text) from Ontologies (= a type of KG) in Specialized Domains

- Already applied in a specific domain and Good performance was observed
→ To be published soon
(in collaboration with a research partner)

Mutual Utilization Patterns between KG and LLM



- **KG vs. LLM**
 - Comparing the performance of both on the same task
- **KG for LLM**
 - Fact Check Using KGs for LLM
 - Using KGs in LLM Training
- **Using KGs as External Knowledge for LLMs**
 - Use KG search results to answer LLM queries
 - e.g., Graph RAG
 - Combine KG search results with LLM-generated content
- **LLM for KG**
 - KG/Ontology (Automatic) Construction (Support) Using LLMs
 - Using LLMs as Natural Language Interfaces for KGs

Basic Concept: Utilizing Knowledge Graphs as External Knowledge for LLMs



Searching for "Graph RAG" yields various architectural illustrations.

The grid contains 12 diagrams, each with a red border:

- Milvus: Offline Loading Stage and Online Retrieval Stage flowchart.
- Ontotext: Multi-stage process diagram involving documents, embeddings, and a knowledge graph.
- Taste of Tech Topics: A dense network graph visualization.
- note: A social network graph showing relationships between users and entities.
- Ontotext: What is Graph RAG | Ontotext Fundamentals diagram.
- Qitta: GraphRAGをわかりやすく解説 #LLM - Qitta diagram.
- LinkedIn: Knowledge Graphs in RAG diagram.
- GraphRAG: Intro to Knowledge Graphs | GraphRAG diagram.
- Chitika: Graph RAG Use Cases: Real-World... diagram.
- Neo4j: Using a Knowledge Graph to in... diagram.
- Level Up Coding: How to Enhance RAG with Knowledge ... diagram.
- TheInfitech: グラフRAG: ナレッジグラフを用いた情... diagram.

The grid contains 12 diagrams, each with a red border:

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- 株式会社調和技研: Microsoft 「GraphRAG」とLangchainの知... diagram.
- TheInfitech: グラフRAG: ナレッジグラフを用いた情... diagram.

Basic Mechanism of RAG



- **RAG (Retrieval-Augmented Generation)**
 - A method that combines **retrieval** and **generation**
 - By retrieving up-to-date or factual information that LLMs may not know, more accurate answers can be generated
- **Typical RAG Architecture**
 - **(1. Constructing the Database to be Integrated)**
 - For text databases: → Text is divided into chunks of a fixed size and embedded (converted into vectors)
 - **2. Retrieving Relevant Information from the DB**
 - For text DBs: retrieve the relevant chunks
 - **3. Using the Retrieved Information to Query the LLM**
 - The retrieved chunks are often inserted into the prompt as context

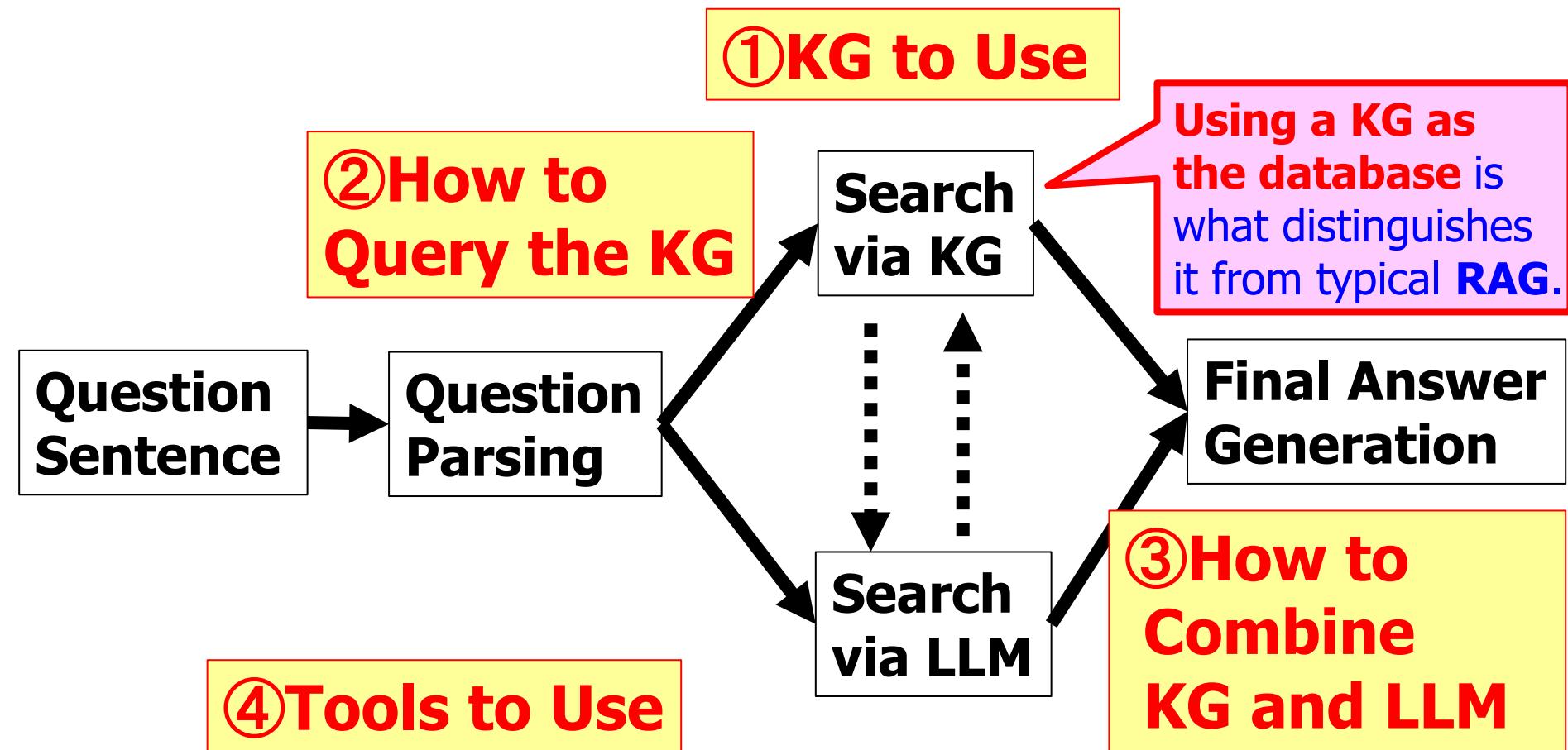
Using KGs as External Knowledge for LLMs

Basic Concept

■ Basic Idea

- Combine KG-based retrieval with LLM generation to answer questions

■ Required Technical Components → ① to ④



① Choosing the KG to Use



Using Existing KGs

- Use KGs that are published as Linked Open Data (LOD)
 - e.g., Wikidata, DBpedia, domain-specific KGs, etc.
- Combine and utilize knowledge from multiple LOD sources as needed

Building a Custom KG

- Construct the KG manually and directly
- Convert an existing database into a KG format
- **Extract and build KGs from text**
 - Actively studied in many works
→ **KG construction using LLMs** will be explained later
 - Existing tools can also be used

The purpose of using a KG — "What kind of knowledge do you want to obtain?" —is critical for selecting and constructing the appropriate KG.

① Choosing the KG to Use ex. Microsoft Graph RAG



Prompts Used for KG Construction in Microsoft's Graph RAG

E.1 Element Instance Generation

---Goal---

Given a text document that is potentially relevant to this activity and a list of entity types, identify all entities of those types from the text and all relationships among the identified entities.

---Steps---

1. Identify all entities. For each identified entity, extract the following information:
 - entity_name: Name of the entity, capitalized
 - entity_type: One of the following types: [{entity_types}]
 - entity_description: Comprehensive description of the entity's attributes and activities

Format each entity as ("entity"{tuple_delimiter}<entity_name>{tuple_delimiter}<entity_type>{tuple_delimiter}<entity_description>

Entity Extraction

2. From the entities identified in step 1, identify all pairs of (source_entity, target_entity) that are *clearly related* to each other

For each pair of related entities, extract the following information:

- source_entity: name of the source entity, as identified in step 1
- target_entity: name of the target entity, as identified in step 1
- relationship_description: explanation as to why you think the source entity and the target entity are related to each other
- relationship_strength: a numeric score indicating strength of the relationship between the source entity and target entity

Format each relationship as ("relationship"{tuple_delimiter}<source_entity>{tuple_delimiter}<target_entity>{tuple_delimiter}<relationship_description>{tuple_delimiter}<relationship_strength>)

Relation Extraction

3. Return output in English as a single list of all the entities and relationships identified in steps 1 and 2. Use **{record_delimiter}** as the list delimiter.

4. When finished, output {completion_delimiter}

<https://arxiv.org/pdf/2404.16130>

① Choosing the KG to Use ex. Microsoft Graph RAG



Examples of prompt

---Examples---

Entity_types: ORGANIZATION, PERSON

Input:

The Fed is scheduled to meet on Tuesday and Wednesday, with the central bank planning to release its latest policy decision on Wednesday at 2:00 p.m. ET, followed by a press conference where Fed Chair Jerome Powell will take questions. Investors expect the Federal Open Market Committee to hold its benchmark interest rate steady in a range of 5.25%-5.5%.

Output:

```
{"entity": "FED", "type": "ORGANIZATION", "text": "The Fed is the Federal Reserve, which is setting interest rates on Tuesday and Wednesday"}  
{record_delimiter}  
{"entity": "JEROME POWELL", "type": "PERSON", "text": "Jerome Powell is the chair of the Federal Reserve"}  
{record_delimiter}  
{"entity": "FEDERAL OPEN MARKET COMMITTEE", "type": "ORGANIZATION", "text": "The Federal Reserve committee makes key decisions about interest rates and the growth of the United States money supply"}  
{record_delimiter}  
{"relationship": "JEROME POWELL", "type": "FED", "text": "Jerome Powell is the Chair of the Federal Reserve and will answer questions at a press conference"}  
{completion_delimiter}
```

...More examples...

<https://arxiv.org/pdf/2404.16130>

② Methods for Querying the KG



Pattern Matching in Graph Structures

- Use query languages for graph search such as SPARQL and Cypher
- Explore graph structures using libraries that handle graphs

Graph-based Computational Processing

- Use graph-based computations, such as the number of steps (edges) between nodes (i.e., node distance)
- Leverage graph theory for various calculations

Graph Embedding (Vectorization)

- Convert the graph into vectors and apply machine learning methods
- Multiple techniques exist for vectorization
- Use vector distance computations for similarity detection, link prediction, and more

Choosing the appropriate search method based on the purpose and use case is essential

② Methods for Querying the KG ex. Microsoft Graph RAG

In Microsoft's Graph RAG, **a set of related entities — referred to as a community** — is retrieved and utilized.

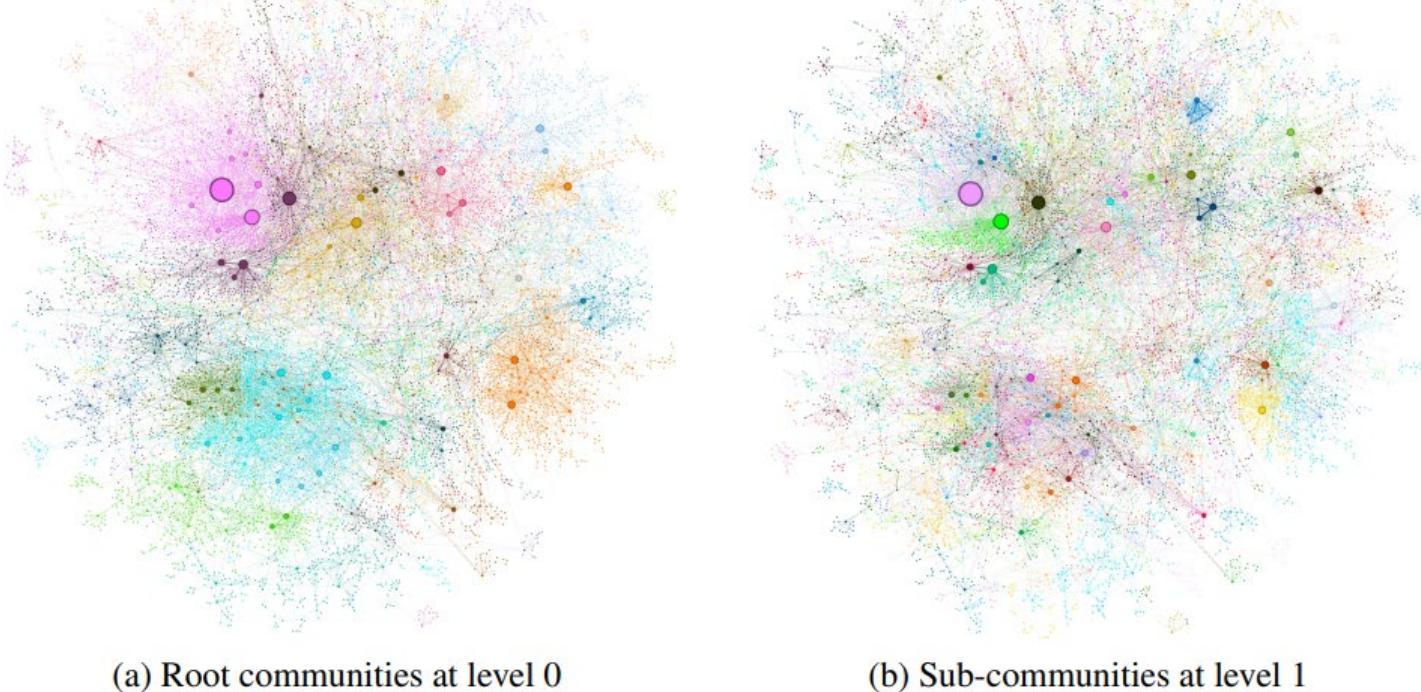


Figure 4: Graph communities detected using the Leiden algorithm (Traag et al., 2019) over the MultiHop-RAG (Tang and Yang, 2024) dataset as indexed. Circles represent entity nodes with size proportional to their degree. Node layout was performed via OpenORD (Martin et al., 2011) and Force Atlas 2 (Jacomy et al., 2014). Node colors represent entity communities, shown at two levels of hierarchical clustering: (a) Level 0, corresponding to the hierarchical partition with maximum modularity, and (b) Level 1, which reveals internal structure within these root-level communities.

<https://arxiv.org/pdf/2404.16130.pdf>

③ How to Combine KG and LLM



Comparison of Search Results from KG and LLM

- Compare results retrieved by both, then determine the final answer comprehensively
- Supplement expressions not found in KG search using LLM
- Use KG to search for information missing from LLM output

Generate Prompts from KG

- Use KG search results to generate prompts and query the LLM
- Represent KG results as text and use them as input to the LLM

Unify by Vectorization

- Vectorize KG search results and use them for text search via RAG or for querying the LLM

**It is important to choose methods based on what you want to obtain from the KG
(vectorization is not mandatory).**

④ Tools to Use



■ Query Languages

- SPARQL, Cypher, etc.

■ RDF Libraries

- Apache Jena

■ Databases

- **RDF DB**: Apache Jena Fuseki, Virtuoso, GraphDB, etc
- **Graph DB**: Neo4j, Amazon Neptune, etc.

■ Graph RAG

- Langchain+Neo4j
- Microsoft「GraphRAG」, etc.
- Other Graph RAG-compatible DBs are also available

Mutual Utilization Patterns between KG and LLM



- **KG vs. LLM**
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KG Construction Using LLMs

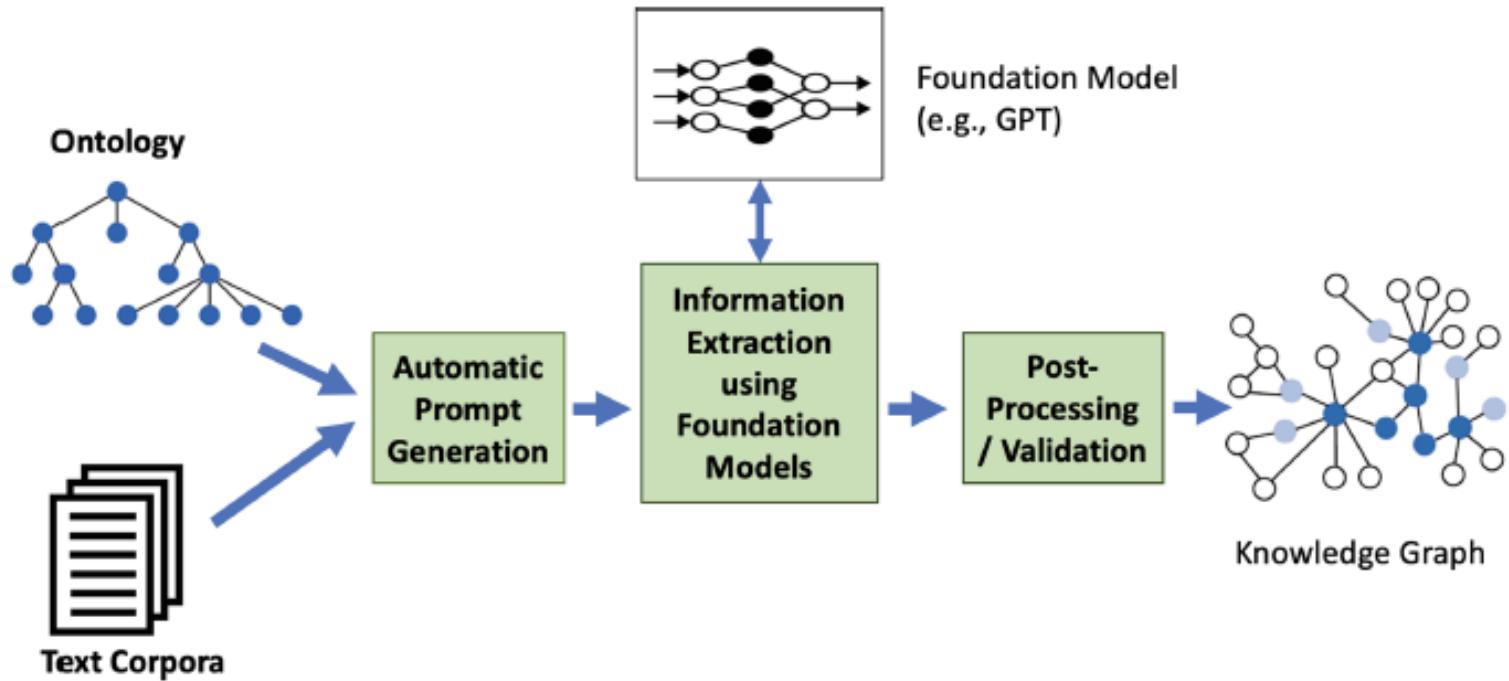


Fig. 1. Generating knowledge graphs from text guided by ontologies

[Nandana 03] propose a framework for constructing a knowledge graph based on an ontology from text using an LLM, and provide benchmark data for evaluating this task.

Evaluation Examples of Constructed Knowledge Graphs

Table 3. Results for Vicuna LLM All Test Cases. Numbers in bold identify the best results for each metric. Numbers underlined identify worst results.

Ontology	Fact Extraction			OC	Hallucinations		
	P	R	F1		SH	RH	OH
1. Movie Ontology	0.33	<u>0.23</u>	0.25	0.89	<u>0.26</u>	0.11	<u>0.26</u>
2. Music Ontology	0.42	0.28	0.32	0.94	0.16	0.06	0.22
3. Sport Ontology	0.57	0.52	0.52	0.85	0.22	0.15	0.13
4. Book Ontology	0.31	0.25	0.26	0.92	0.16	0.08	0.23
5. Military Ontology	<u>0.24</u>	0.25	<u>0.24</u>	0.8	0.19	0.2	<u>0.26</u>
6. Computer Ontology	0.38	0.35	0.35	0.85	0.15	0.15	0.11
7. Space Ontology	0.68	0.67	0.66	0.93	0.15	0.07	0.08
8. Politics Ontology	0.34	0.32	0.33	0.92	0.17	0.08	0.15
9. Nature Ontology	0.25	0.27	0.25	0.68	0.1	0.32	0.14
10 Culture Ontology	0.31	0.32	0.31	<u>0.59</u>	0.15	<u>0.41</u>	0.12
Ontologies Average	0.38	0.34	0.35	0.83	0.17	0.17	0.17

Examples of evaluating the constructed knowledge graphs for each ontology. [Nandana 03]

Ontology Learning Using LLMs (= Automatic Ontology Construction)

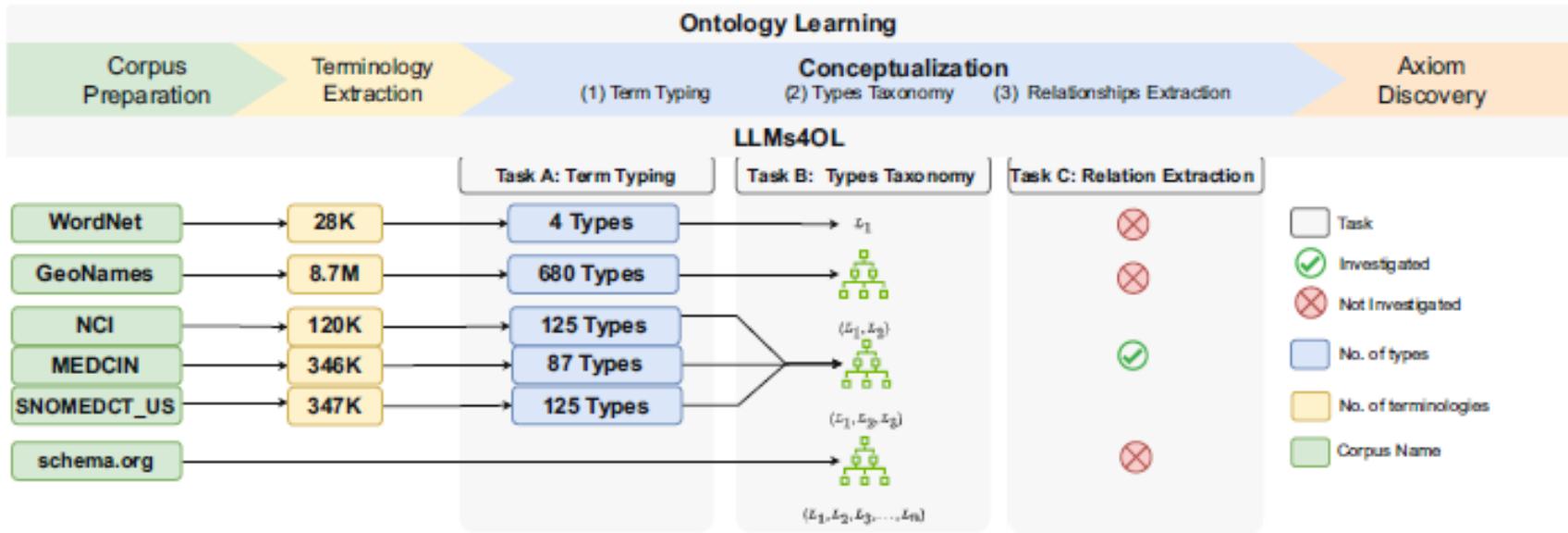


Fig. 1. The LLMs4OL task paradigm is an end-to-end framework for ontology learning in various knowledge domains, i.e. lexicosemantics (WordNet), geography (GeoNames), biomedicine (NCI, MEDCIN, SNOMEDCT), and web content types (schema.org). The three OL tasks empirically validated in this work are depicted within the blue arrow, aligned with the greater LLMs4OL paradigm.(Color figure online)

Zero-shot prompting was performed on 9 LLMs, and the main ontology learning tasks — *term classification, taxonomy discovery, and non-taxonomic relation extraction* — were evaluated.[Hamed 03]

Ontology Learning Using LLMs (= Automatic Ontology Construction)



Table 3. Zero-shot results across 11 LLMs and finetuned Flan-T5-Large and Flan-T5-XL LLMs results reported for ontology learning Task A i.e. term typing in MAP@1, and as F1-score for Task B i.e. type taxonomy discovery, and Task C i.e. type non-taxonomic relation extraction. The results are in percentages.

Task	Dataset	Zero-Shot Testing										Finetuned		
		BERT-Large	PubMedBERT	BART-Large	Flan-T5-Large	Flan-T5-XL	BLOOM-1b7	BLOOM-3b	GPT-3	GPT-3.5	LLaMA-7B	GPT-4	Flan-T5-Large	Flan-T5-XL
<i>A</i>	<i>WordNet</i>	27.9	–	2.2	31.3	52.2	79.2	79.1	37.9	91.7	81.4	90.1	76.9	86.3
	<i>GeoNames</i>	38.3	–	23.2	13.2	33.8	28.5	28.8	22.4	35.0	29.5	43.3	16.9	18.4
	<i>NCI</i>	11.1	5.9	9.9	9.0	9.8	12.4	15.6	12.7	14.7	7.7	16.1	31.9	32.8
	<i>SNOMEDCT-US</i>	21.1	28.5	19.8	24.3	31.6	37.0	37.7	24.4	25.0	13.8	27.8	33.4	43.4
	<i>MEDCIN</i>	8.7	15.6	12.7	13.0	18.5	28.8	29.8	25.7	23.9	4.9	23.7	38.4	51.8
<i>B</i>	<i>GeoNames</i>	54.5	–	55.4	59.6	52.4	36.7	48.3	53.2	67.8	33.5	55.4	62.5	59.1
	<i>UMLS</i>	48.2	33.7	49.9	55.3	64.3	38.3	37.5	51.6	70.4	32.3	78.1	53.4	79.3
	<i>schema.org</i>	44.1	–	52.9	54.8	42.7	48.6	51.3	51.0	74.4	33.8	74.3	91.7	91.7
<i>C</i>	<i>UMLS</i>	40.1	42.7	42.4	46.0	49.5	43.1	42.7	38.8	37.5	20.3	41.3	49.1	53.1

Each task was evaluated using existing ontologies as targets [Hamed 03]. → A challenge on this task is being organized at ISWC 2024 / ISWC 2025.

Knowledge Graph Inference Challenge

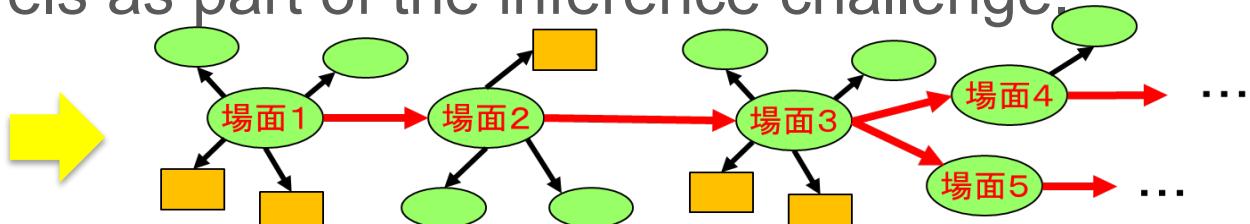
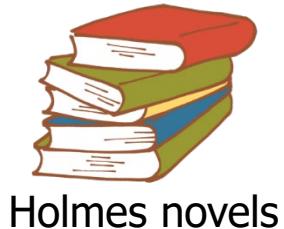
– KG Construction Technology in the Era of Generative AI



In the Knowledge Graph Inference Challenge 2023 and 2024, the theme was **knowledge graph generation using generative AI**.

■ Mystery Novel Division

- Participants construct a knowledge graph that is either **equivalent to or higher quality** than the knowledge graphs previously built and published based on Sherlock Holmes novels as part of the inference challenge.



Knowledge graphs representing narrative flow of scenes

■ General Division

- **Construct any knowledge graph**, regardless of domain.
- Any form of knowledge represented in graph structure is eligible.

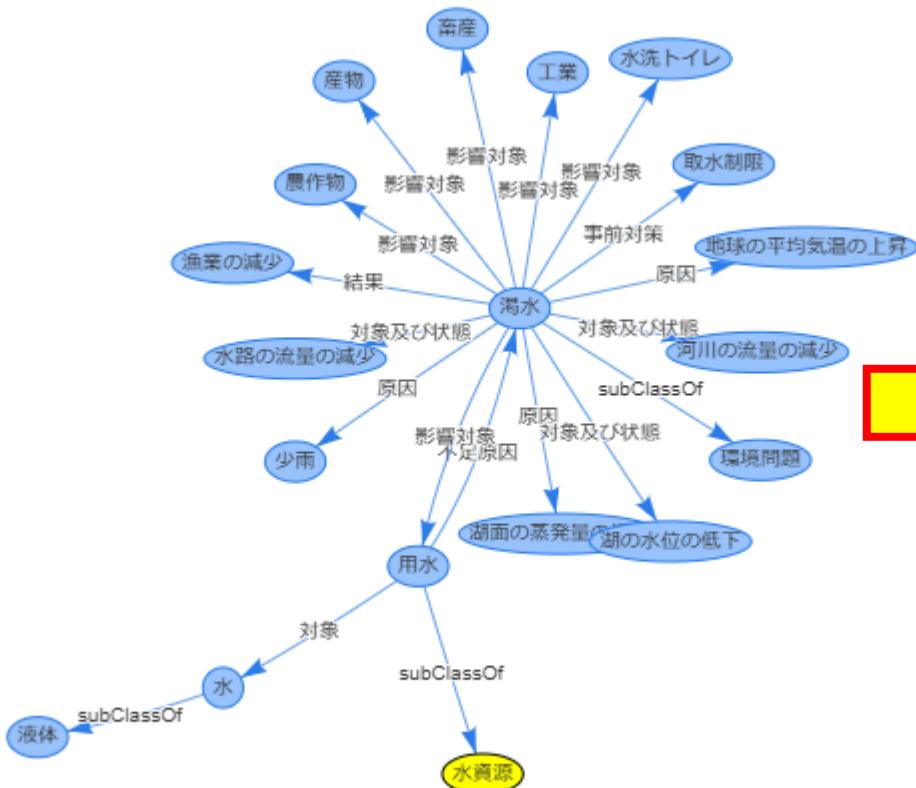
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Text Generation from Knowledge Graphs by LLM

Example of a Knowledge Graph Constructed in the Environmental Domain



下記の三つ組みで表される関係をもとに、「渴水」についての説明文を作成してください。

用水, "subClassOf", 水資源,
用水, 対象, 水,
用水, 不足原因, 渴水,
水, "subClassOf", 液体,
渴水, "subClassOf", 環境問題,
渴水, 原因, 少雨,
渴水, 原因, 地球の平均気温の上昇,
渴水, 原因, 湖面の蒸発量の増加,
渴水, 影響対象, 用水,
渴水, 影響対象, 産物,
渴水, 影響対象, 水洗トイレ,
渴水, 影響対象, 農作物,
渴水, 影響対象, 工業,
渴水, 影響対象, 畜産,
渴水, 事前対策, 取水制限,
渴水, 対象及び状態, 河川の流量の減少,
渴水, 対象及び状態, 水路の流量の減少,
渴水, 対象及び状態, 湖の水位の低下,
渴水, 結果, 漁業の減少,

Prompt Used

Based on the following triples, please generate a descriptive text about "drought (渴水)".

Irrigation water — subClassOf — Water resources

Irrigation water — target — Water

Irrigation water — cause of shortage — Drought

Water — subClassOf — Liquid

Drought — subClassOf — Environmental issue

Drought — cause — Low rainfall

Drought — cause — Rise in global average temperature

Drought — cause — Increased evaporation from lake surfaces

Drought — affects — Irrigation water

Drought — affects — Products

Drought — affects — Flush toilets

Drought — affects — Crops

Drought — affects — Industry

Drought — affects — Livestock

Drought — preventive measure — Water intake restrictions

Drought — object and condition — Decreased river flow

Drought — object and condition — Decreased waterway flow

Drought — object and condition — Lower lake water levels

Drought — result — Decrease in fisheries

Text Generation Result by GPT-4o

用水, "subClassOf", 水資源

用水, 対象, 水

用水, 不足原因, 渴水

渴水, "subClassOf", 環境問題

渴水, 原因, 少雨

渴水, 原因, 地球の平均気温の上昇

渴水, 原因, 湖面の蒸発量の増加



渴水とは、水資源の一種である「用水」が不足する現象であり、環境問題の一つとして広く認識されています。渴水の主な原因には、少雨や地球の平均気温の上昇、湖面の蒸発量の増加などが挙げられます。これらの要因により、河川や水路の流量が減少し、湖の水位も低下することが多く見られます。

渴水の影響は幅広く、用水の供給不足だけでなく、農作物や畜産、工業といった産業にも打撃を与え、さらには水洗トイレなどの日常生活にも影響が及びます。漁業の減少も渴水による結果の一つであり、水資源が不足することで生態系や産業が打撃を受けるのです。こうした被害を抑えるために、事前対策として取水制限などの施策が行われることがあります。

渴水, 対象及び状態, 河川の流量の減少

渴水, 対象及び状態, 水路の流量の減少

渴水, 対象及び状態, 湖の水位の低下

渴水, 影響対象, 用水

渴水, 影響対象, 産物

渴水, 影響対象, 水洗トイレ

渴水, 影響対象, 農作物...

Text Generation Result by GPT-4o

Drought (渴水) is an environmental issue characterized by a prolonged deficiency in available water, particularly affecting surface and groundwater resources. As a subcategory of environmental problems, drought arises when the balance between water input and output is disrupted. Key contributing factors include unusually low rainfall, a rise in the global average temperature, and increased evaporation from lake surfaces. These causes combine to reduce river and waterway flows and to lower lake water levels, creating conditions under which water resources become scarce.

Among the most vulnerable resources is irrigation water, a subclass of water resources whose target is water itself; when drought occurs, the shortage of irrigation water directly impairs agricultural productivity. Beyond agriculture, drought's impact extends to multiple sectors and uses: it curtails the availability of products that depend on water-intensive processes, hampers the operation of flush toilets, and disrupts industrial activities. Livestock farming also suffers as drinking water and pasture irrigation decline. One significant downstream effect is a reduction in fisheries output, as lower river and lake volumes degrade aquatic habitats.

To mitigate the severity of drought, water intake restrictions are often implemented as a preventive measure, limiting withdrawals from rivers, lakes, and reservoirs to preserve critical water levels. Such restrictions help maintain sufficient flow and storage during dry spells, ensuring that essential water needs—for agriculture, industry, sanitation, and ecosystems—can be met until precipitation patterns return to normal.

Summary: Key Points of Integration between KG and LLM



■ Knowledge Graphs (KG) / Ontologies

- Represent various knowledge relationships (connections) in graph structure.
- Serve as a database (knowledge base) for AI systems (especially knowledge-based systems).
- Enable accurate question answering based on explainable foundations.
- High construction cost is a challenge
→ *LLM-based construction is promising.*

■ Large Language Models (LLMs)

- Learn from massive text data.
- Capable of natural dialogue and question answering with a certain degree of accuracy.
- However, due to hallucinations and the implicitness of the reasoning basis, responses may not always be completely reliable.
→ *Combine with knowledge obtained from KG to resolve these issues.*

Key Message: It is important to use both appropriately and integrate them effectively.



<https://iswc2025.semanticweb.org/>

The international conference **ISWC 2025**, focusing on semantic technologies such as knowledge graphs and ontologies, will be held in **Nara, Japan**. We warmly invite you to participate!

References (to be updated later)



- [Yiming 03] Yiming Tan, Dehai Min, Yu Li, Wenbo Li, Nan Hu, Yongrui Chen and Guilin Qi, Can ChatGPT Replace Traditional KBQA Models? An In-depth Analysis of GPT family LLMs' Question Answering Performance, Proc. ISWC2023, Part I, pp. 348-367, Athens, Greece, Nov. 2023.
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