Applications of Advanced/Deep Neural Networks in Knowledge Graphs Construction

Tek Raj Chhetri

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About me

Tek Raj Chhetri

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Demo source codes

https://github.com/CAIRNepal/talks_tutorials_lectures/tree/main/fdd_india_2023_08_april

Outline

1. Introduction
2. Knowledge Graphs Construction
3. Advanced/Deep neural networks (DNN) for Knowledge Graphs Construction
4. Our Work
5. Conclusion

1.

Introduction

1.1. Knowledge Graphs

1.1. Knowledge Graphs

"A graph of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent potentially different relations between these entities."

-- Hogan et al., 2021

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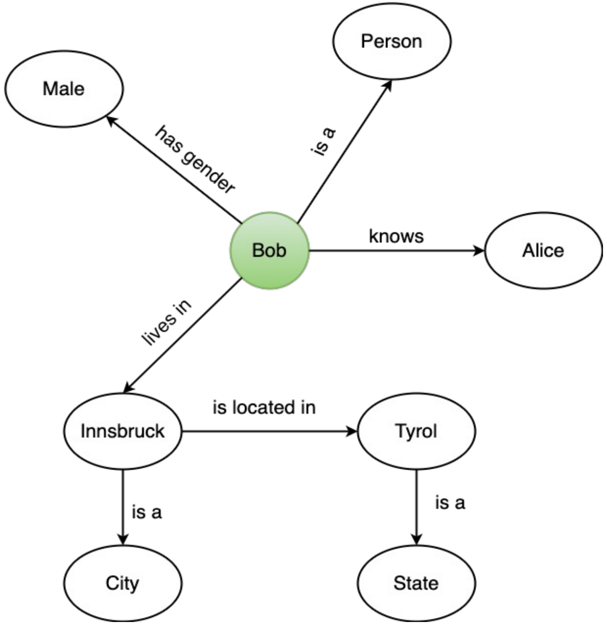

Figure 1: Example knowledge graph

graph?

accumulate and convey knowledge?

nodes represent entities of interest and whose edges represent potentially different relations between these entities?

1.1. Knowledge Graphs

Sources of knowledge graphs.

Structured text

Tables, Wikipedia, Databases

Unstructured text

Internet, News

Images

1.1. Knowledge Graphs

Examples of large knowledge graphs:

- Google knowledge graph: used for Google search.
- WordNet: large lexical database of English language.

1.1. Knowledge Graphs

Where are knowledge graphs used?

- Healthcare, e.g., drug discovery
- Manufacturing, e.g., predictive maintenance
- Search

Who is using knowledge graphs?

amazon Google

facebook

LinkedIn

1.

Introduction

1.2. Knowledge Graphs Creation Methodology

1.2. *Knowledge Graphs Creation Methodology*

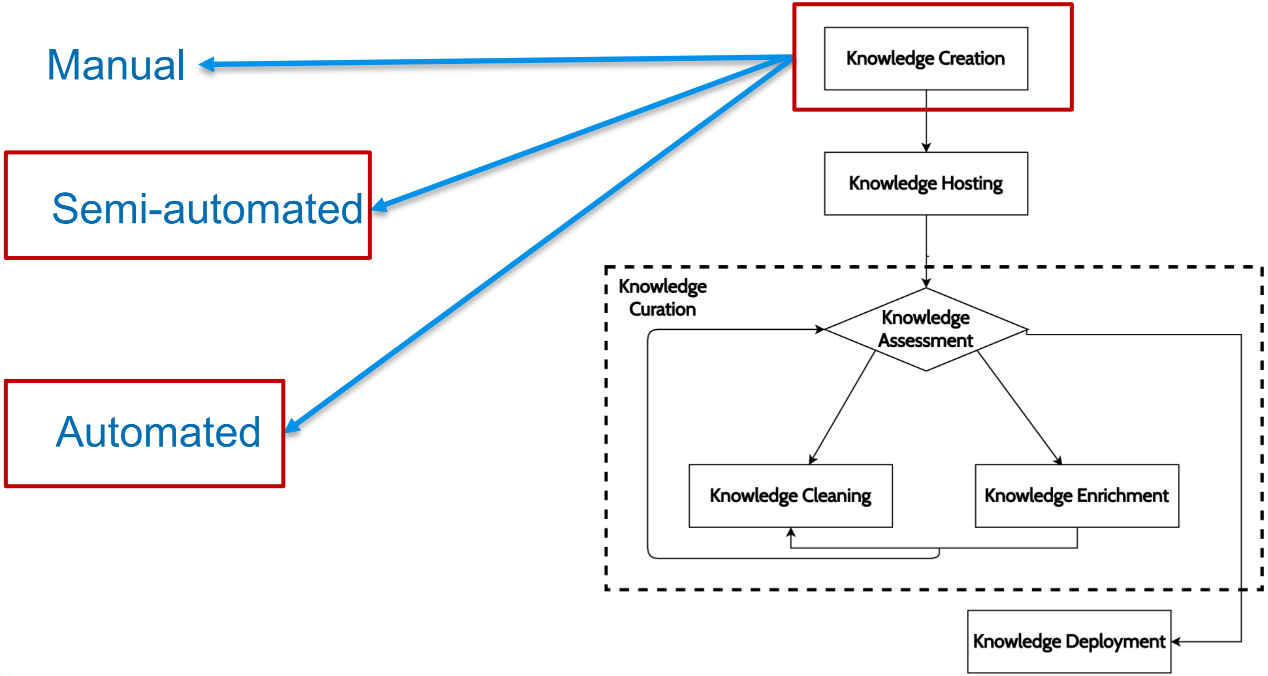

Figure 2: Methodology for building knowledge graphs (Simsek et al., 2022)

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1.2. *Knowledge Graphs Creation Methodology*

Bottom-up: annotating the reference ontology, such as Schema.org.

Top-down: a large scale instance generation task that is specific to certain domain-specific patterns, e.g., annotating using NLP (Natural language processing).

Manual

Semi-automated

Automated

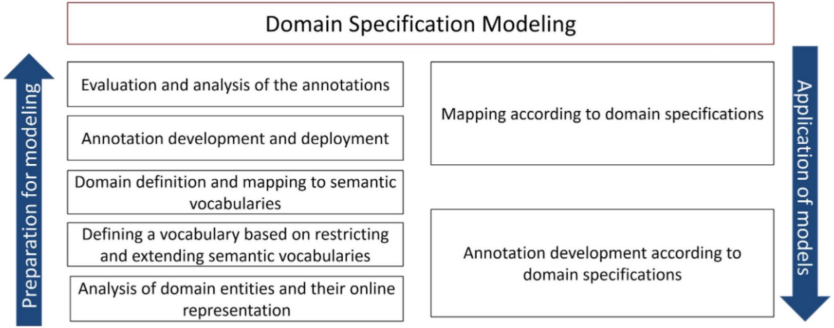

Figure 3: Knowledge creation approach (Simsek et al., 2022)

2.

Knowledge Graphs Construction

2.1. Knowledge Graphs Construction Steps

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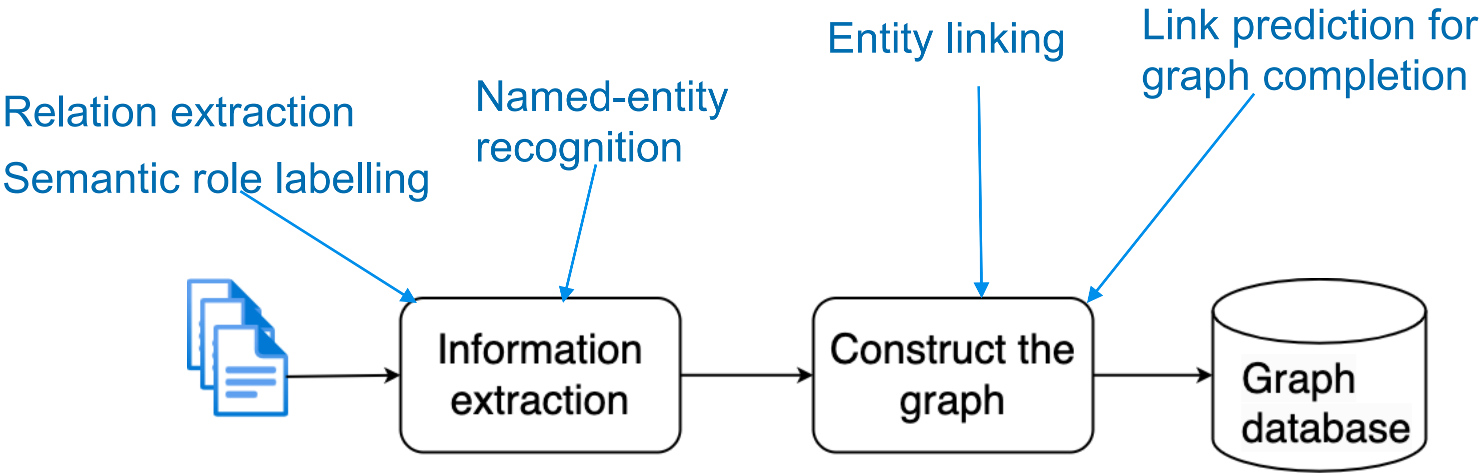

Figure 3: Steps for knowledge graph construction

2.

Knowledge Graphs Construction

2.2. Linguistic Structure for Knowledge Graphs Construction

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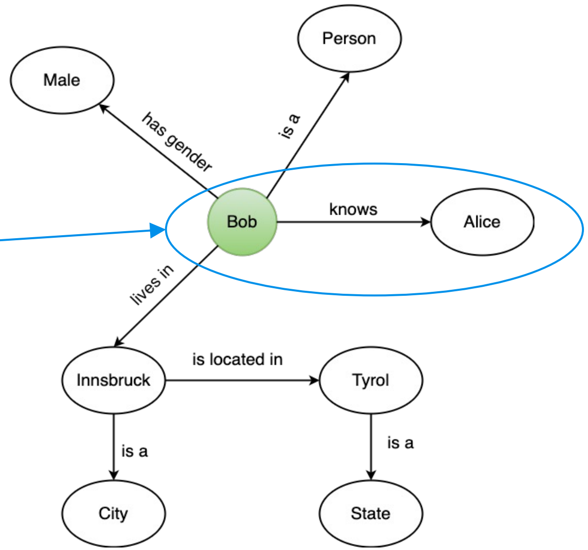
?

Bob knows alice.

?

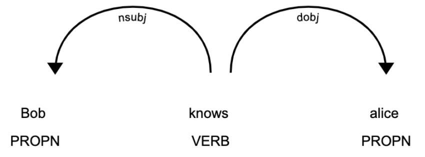


2.2. Linguistic Structure for Knowledge Graphs Construction

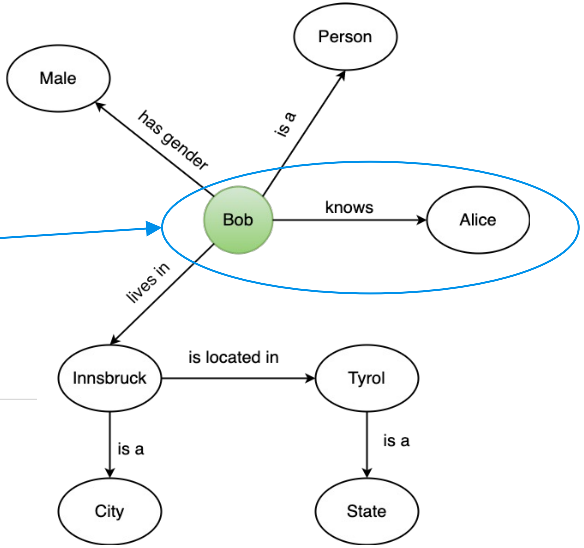
?

Bob knows alice.

?



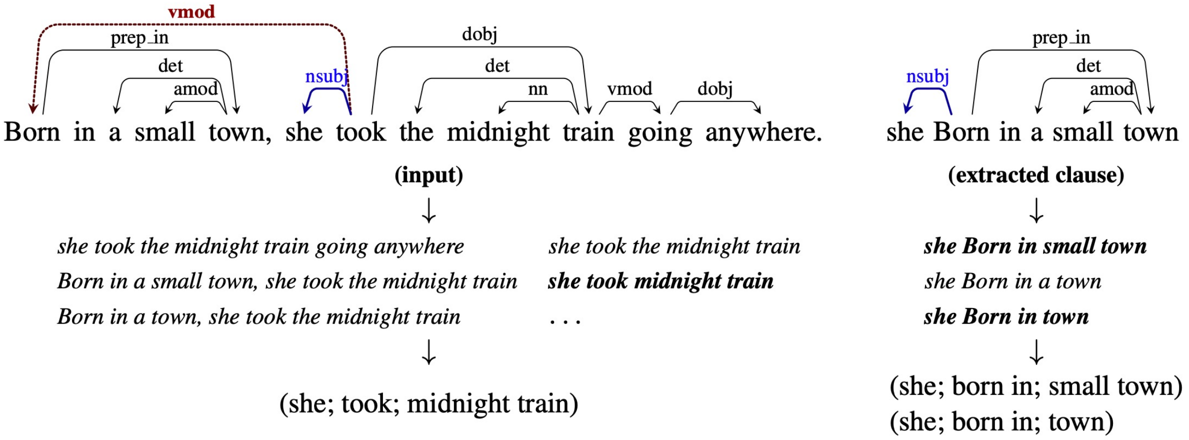

```
: spacy.explain("PROPN"), spacy.explain("dobj")
: ('proper noun', 'direct object')
```



2.2. Linguistic Structure for Knowledge Graphs Construction

Can we leverage our knowledge about language to construct knowledge graphs?

2.2. Linguistic Structure for Knowledge Graphs Construction



De Marneffe and Manning, 2008

Figure 3: Illustration of OpenIE (Open Domain Information Extraction) approach (Angeli et al., 2015)

2.2. Linguistic Structure for Knowledge Graphs Construction

Demo

Notebook file: OpenIE-Demo

2.2. Linguistic Structure for Knowledge Graphs Construction

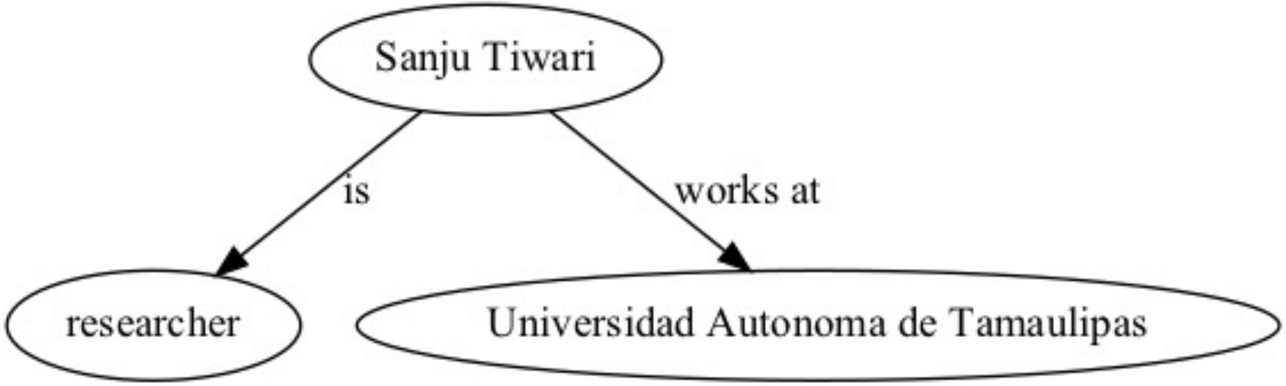


Figure 4: Generated knowledge graph

2.2. Linguistic Structure for Knowledge Graphs Construction

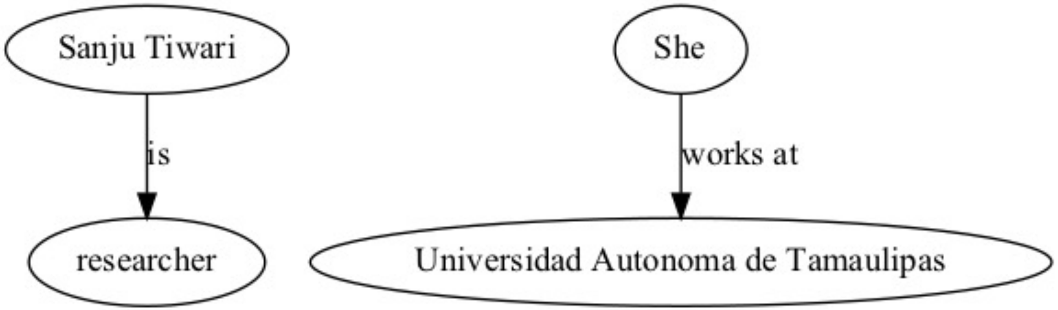


Figure 5: Generated knowledge graphs

2.2. Linguistic Structure for Knowledge Graphs Construction

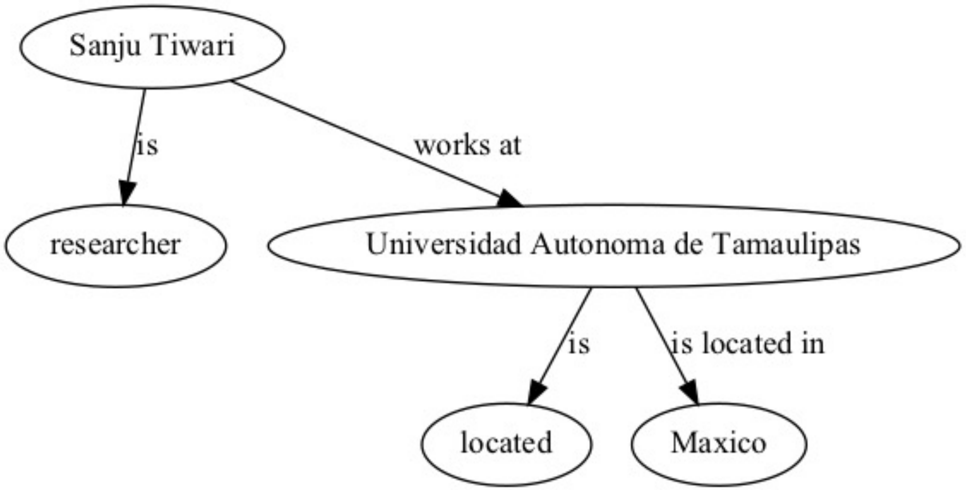


Figure 6: Generated knowledge graph

3.

Advanced/Deep Neural Networks (DNN) for Knowledge Graphs Construction

3.1. Overview of Advanced/DNN

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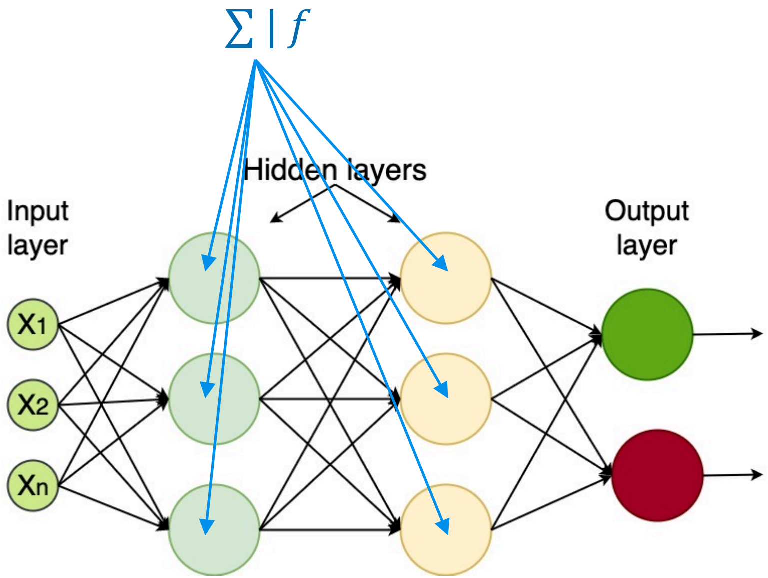


Figure 7: Neural network

$$f(W * X + b)$$

$$sigmoid = \frac{1}{1 + e^{-x}}$$

3.1. Overview of Advanced/DNN

Today, transformers are the state-of-the art in many tasks including language processing.

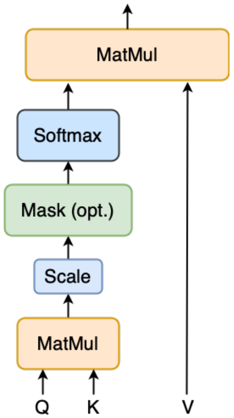
Two types of language modelling task:

1. Auto-regressive models: predict the future word given past or future, not both.
   Vienna is capital of _____. Given past, we want to predict future.
   ___ is in Austria. Given future, we want to predict past.
   E.g.: GPT family – used for natural language generation.
2. Auto-encoding models: learn the representation of sentence by predicting tokens given past and future.

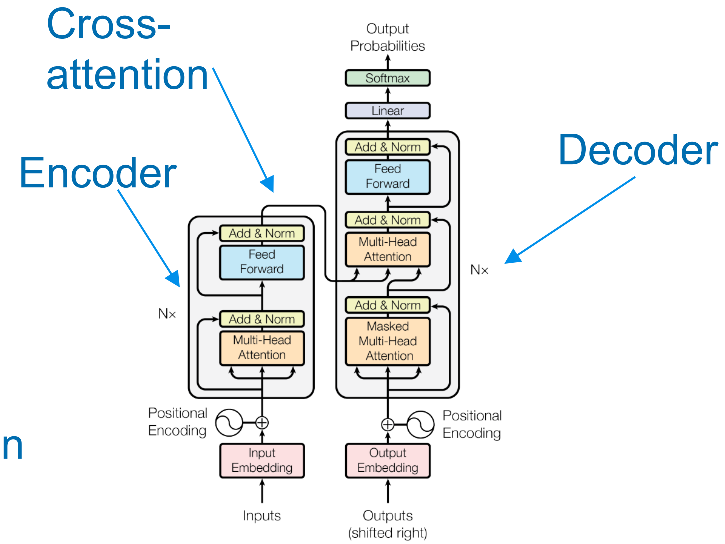
   He doesn't ____ homework, he will be punished.
   E.g.: BERT – used for natural language understanding tasks like named entity recognition, sequence classification.

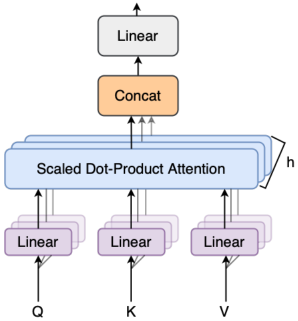
3.1. Overview of Advanced/DNN

The foundation of the modern transformers was introduced Vaswani et al. in 2017.



Scaled dot-product attention





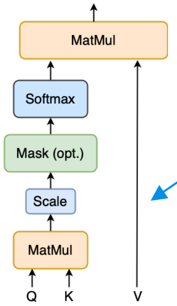
Multi-head attention

Figure 8: The Transformer - model architecture (Vaswani et al., 2017)

3.1. Overview of Advanced/DNN

Q = query, K = key and V = view. Q, K and V are matrices.

attention score



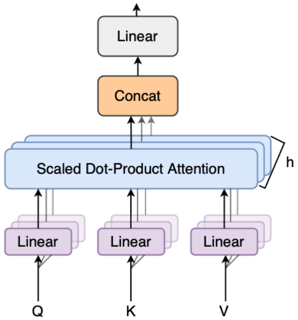
$$Attention(Q,K,V) = Softmax(\frac{Q.K^T}{\sqrt{d_k}}).V$$

make value smaller

0-1 range

Scaled dot-product attention

$$MultiHead(Q',K',V') = Concat(Attention(Q_1,K_1,V_1), Attention(Q_2,K_2,V_2)$$
$$,..., Attention(Q_n,K_n,V_n)).W^O$$
$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$



Multi-head attention

3.1. Overview of Advanced/DNN

Sentence: Jane is good citizen.

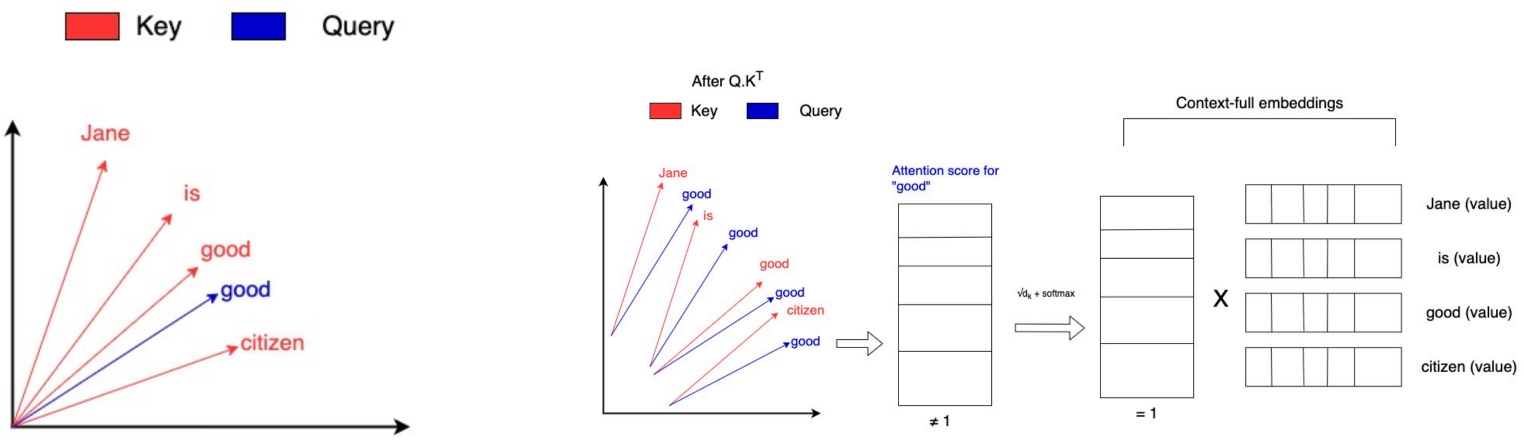


Figure 9: Scaled dot-product attention example

3.1. Overview of Advanced/DNN

Number of heads (4)

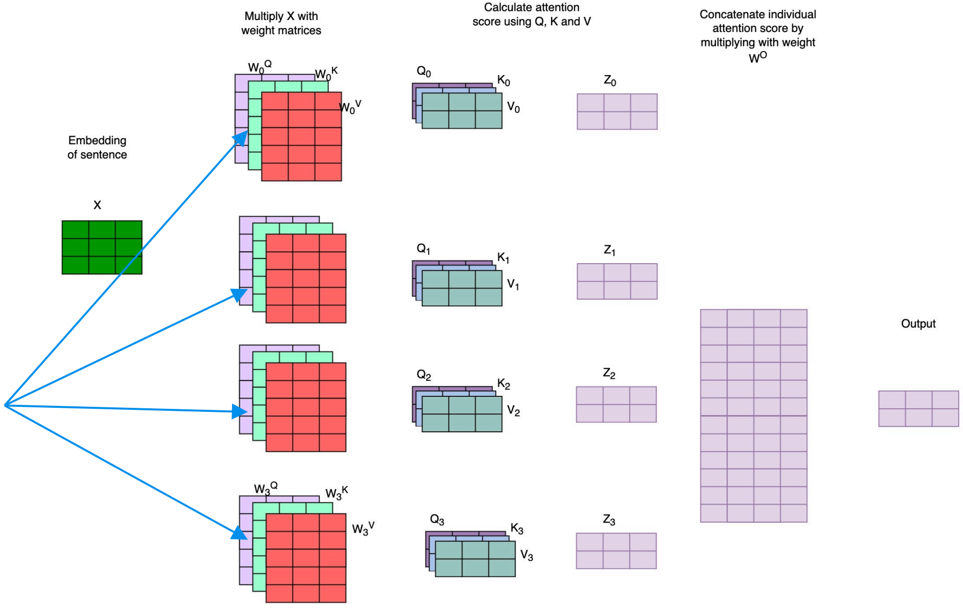


Figure 10: Multi-head attention example

3.1. Overview of Advanced/DNN

Input sentence: My friends told me about attention paper and I enjoyed reading it.

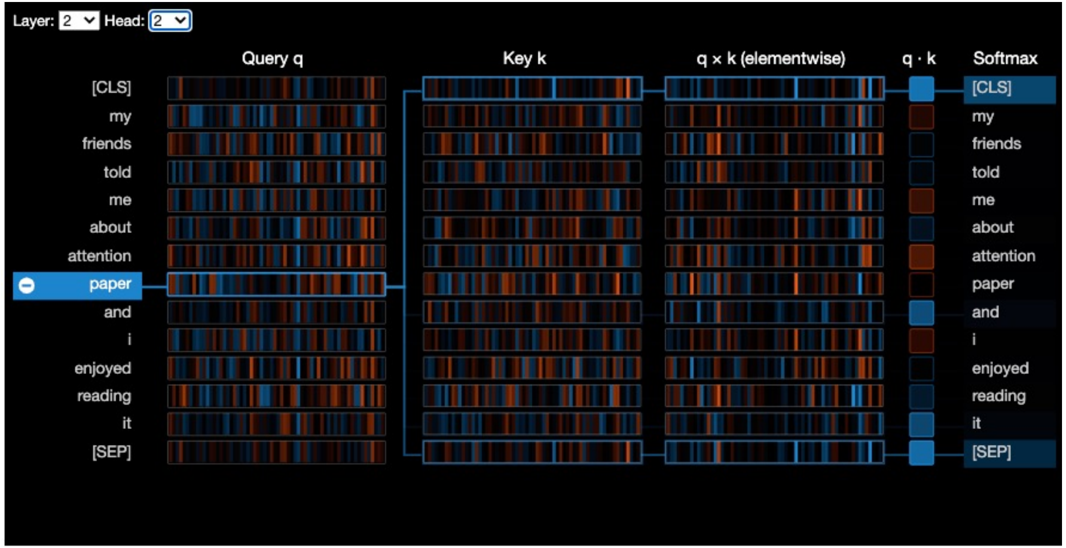


Figure 11: Visualisation of Bidirectional Encoder Representations from Transformers (BERT) neuron view

3.1. Overview of Advanced/DNN

Input sentence: My friends told me about attention paper and I enjoyed reading it.

	my	friends	told	me	about	attention	paper	and	i	enjoyed	reading	it
my	0.100934	0.069470	0.117299	0.120445	0.079473	0.046395	0.052692	0.073218	0.107774	0.114604	0.055917	0.061779
friends	0.038067	0.096476	0.117915	0.049149	0.067461	0.113744	0.137340	0.038570	0.027052	0.174089	0.107412	0.032725
told	0.279546	0.071563	0.141285	0.025596	0.064213	0.028561	0.044704	0.079137	0.071826	0.056287	0.106594	0.030688
me	0.080006	0.124975	0.148152	0.069366	0.097184	0.089837	0.042953	0.120903	0.067797	0.093817	0.055603	0.009408
about	0.114902	0.089267	0.121241	0.048999	0.095998	0.082544	0.055986	0.056864	0.039855	0.165398	0.061551	0.067397
attention	0.061192	0.103999	0.109819	0.031648	0.078422	0.134510	0.072197	0.046429	0.028284	0.172710	0.124742	0.036049
paper	0.086109	0.106978	0.110281	0.069261	0.056677	0.085790	0.087418	0.027939	0.062958	0.124162	0.144700	0.037727
and	0.179758	0.109041	0.072173	0.130123	0.047328	0.065694	0.038095	0.042239	0.094282	0.067172	0.058225	0.095871
i	0.045420	0.076360	0.073031	0.061148	0.060051	0.120220	0.117625	0.067718	0.073002	0.129334	0.099807	0.076283
enjoyed	0.232717	0.128013	0.066172	0.089593	0.033107	0.060076	0.098414	0.029566	0.065224	0.072466	0.095945	0.028707
reading	0.046663	0.017130	0.123428	0.036269	0.124542	0.064962	0.099627	0.072917	0.068067	0.119192	0.130926	0.096278
it	0.189348	0.042706	0.110883	0.047178	0.046489	0.172225	0.065286	0.032828	0.047367	0.148391	0.062988	0.034311

Table 1: Final attention score from BERT

3.1. Overview of Advanced/DNN

The colour indicates head, 12 for BERT because it has 12 heads.

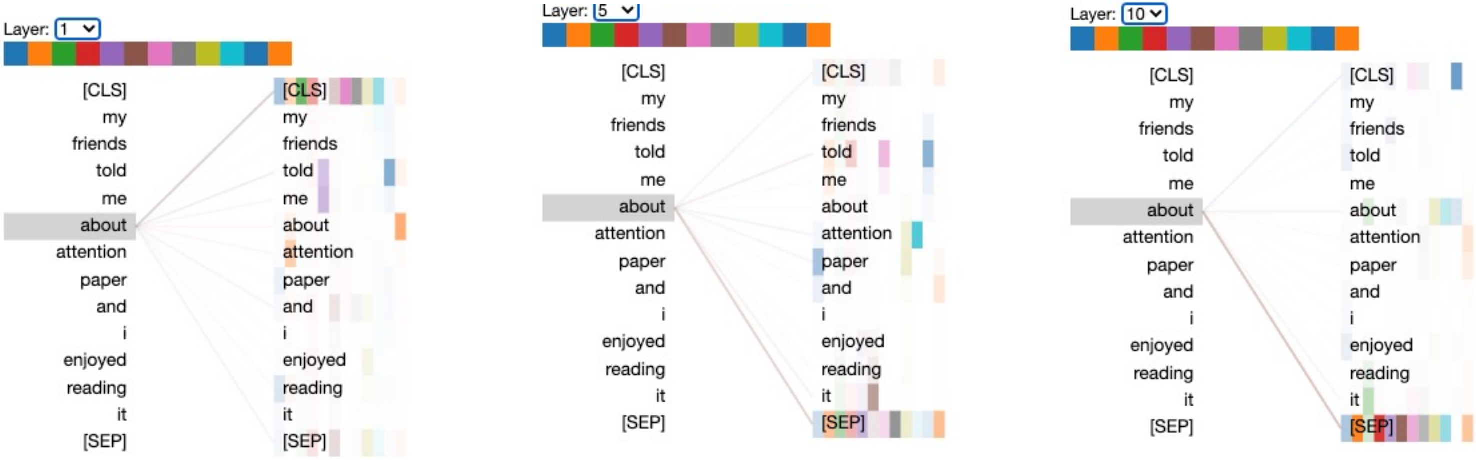


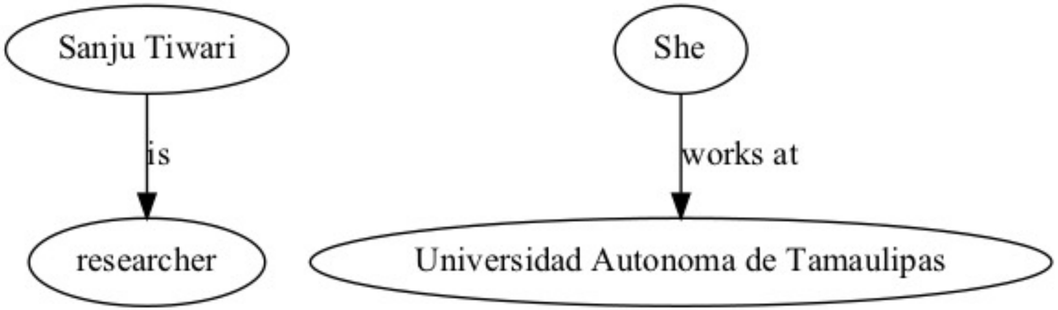
Figure 12: Head view visualisation of BERT

3.

Advanced/Deep Neural Networks (DNN) for Knowledge Graphs Construction

3.2. Conference Resolution

3.2. Conference Resolution



3.2. Conference Resolution

Coreference resolution is the task of clustering textual mentions that refer to the same discourse entity (Otmazgin et al., 2022).

3.2. Conference Resolution

Jane voted for Obama because he is aligned with her democratic values, she said.

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Jane voted for Obama because he is aligned with her democratic values, she said.

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Jane voted for Obama because he is aligned with her democratic values, she said.

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Jane stated that she voted for Obama because he shares democratic values that align with her.

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3.2. Conference Resolution

Demo

Notebook file: Conference-resolution-demo

3.2. Conference Resolution

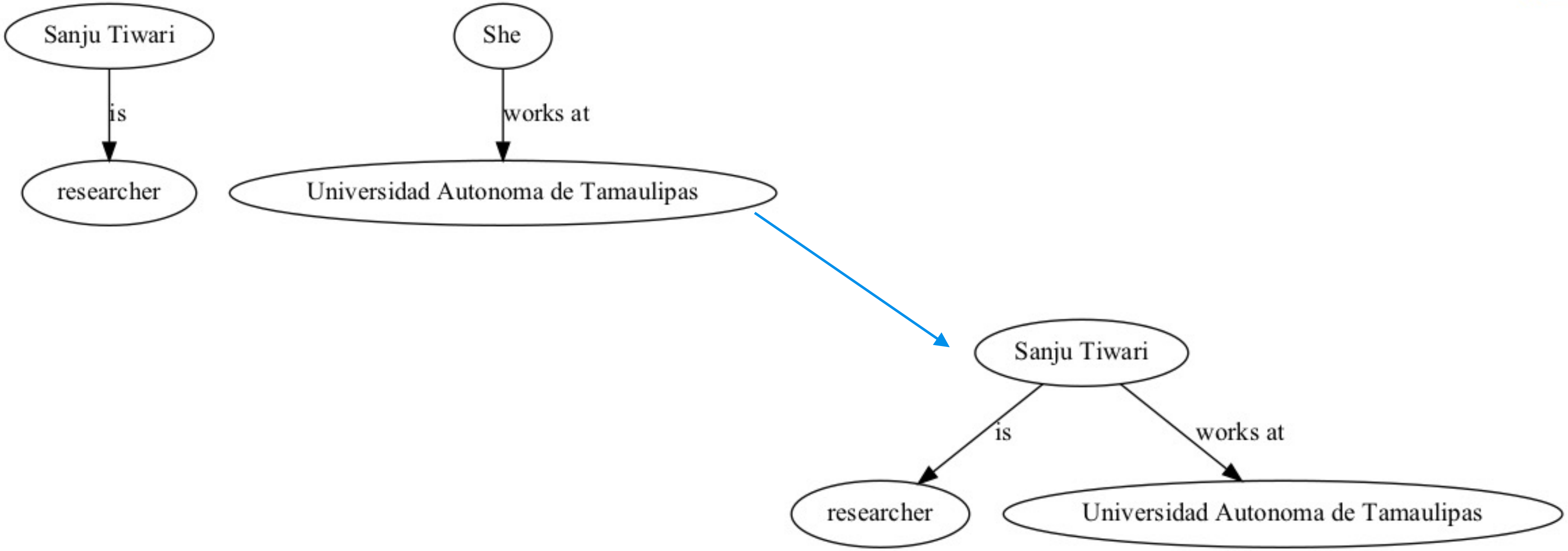


Figure 13: Conference resolution

3.2. Conference Resolution

Demo

Notebook file: Conference-resolution-demo

3.2. Conference Resolution

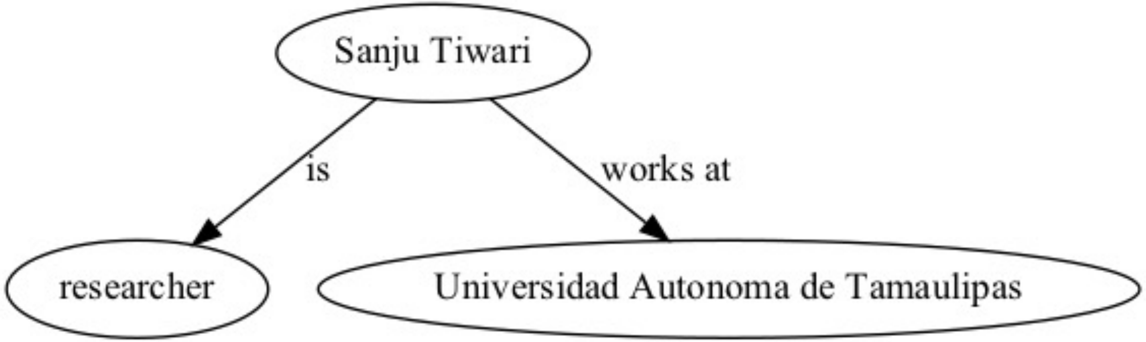


Figure 14: Result knowledge graph after conference resolution

3.2. Conference Resolution

Let's create some large knowledge graphs.

3.2. Conference Resolution

Demo

Notebook file: Demo-fixing-with-conference-resolution

3.2. Conference Resolution

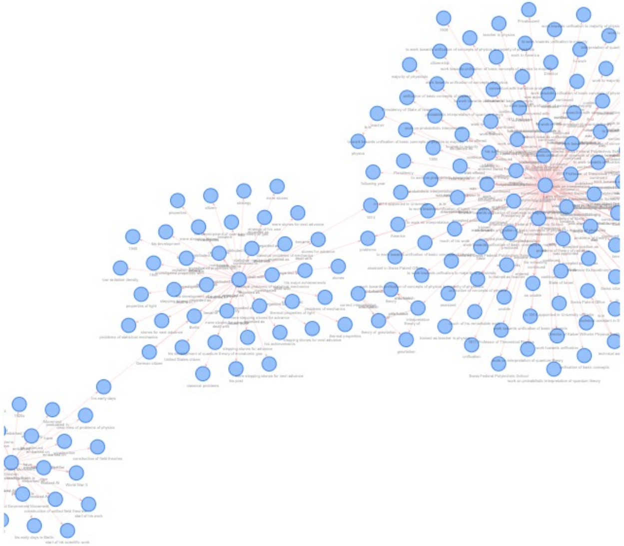


Figure 15: Knowledge graph about Albert Einstein created from raw text (without conference resolution)

3.2. Conference Resolution

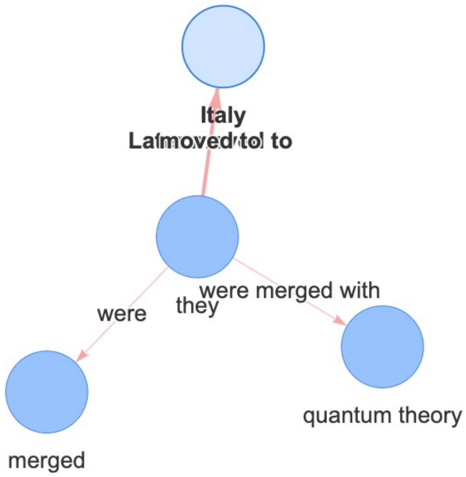


Figure 16: Knowledge graph about Albert Einstein created from raw text (without conference resolution)

3.2. Conference Resolution

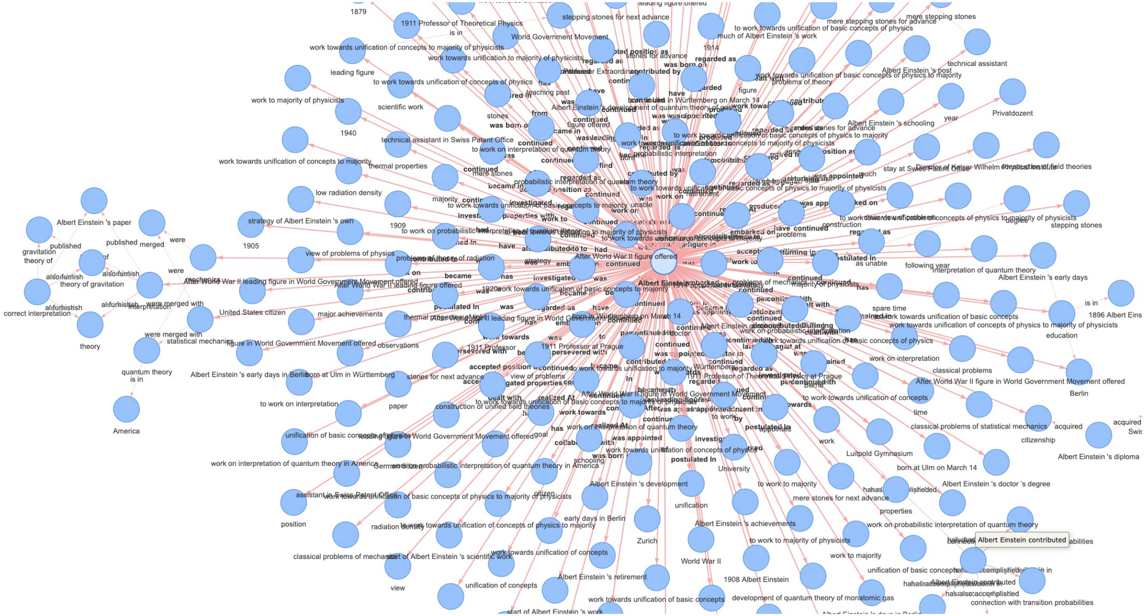


Figure 17: Knowledge graph about Albert Einstein created from raw text (with conference resolution)

3.

Advanced/Deep Neural Networks (DNN) for Knowledge Graphs Construction

3.3. Relation Extraction & Entity Linking

3.3. Relation Extraction & Entity Linking

Entity linking is the task of identifying and mapping the entities to the correct entries.

3.3. Relation Extraction & Entity Linking

Albert Einstein was born at Ulm, in Württemberg, Germany. Six weeks later Einstein family moved to Munich.

3.3. Relation Extraction & Entity Linking

Albert Einstein was born at Ulm, in Württemberg, Germany. Six weeks later Einstein family moved to Munich.

3.3. Relation Extraction & Entity Linking

	subject	relation	object
0	Albert Einstein	born_in	Ulm
1	Albert Einstein	born_in	Württemberg
2	Albert Einstein	born_in	Germany
3	Einstein	lived_in	Munich

?

Figure 18: Knowledge graph triples from text

3.3. Relation Extraction & Entity Linking

Albert Einstein was born at Ulm, in Württemberg, Germany. Six weeks later Einstein family moved to Munich.

Both refers to the same person, Albert Einstein

3.3. Relation Extraction & Entity Linking

	subject	relation	object
0	Albert Einstein	born_in	Ulm
1	Albert Einstein	born_in	Württemberg
2	Albert Einstein	born_in	Germany
3	Albert Einstein	lived_in	Munich

Figure 19: Knowledge graph triples from text

3.3. Relation Extraction & Entity Linking

Relation extraction refers to the extraction of the semantic relationship between entities.

It involves two tasks:

- Identifying (or detecting) the relevant entities pair of interest.
- Detecting and extracting the identified relations.

3.3. Relation Extraction & Entity Linking

	subject	relation	object
0	Albert Einstein	born_in	Ulm
1	Albert Einstein	born_in	Württemberg
2	Albert Einstein	born_in	Germany
3	Albert Einstein	lived_in	Munich

Figure 20: Knowledge graph triples from text

3.3. Relation Extraction & Entity Linking

Demo

Notebook file: relation_extraction_entity_linking

3.3. Relation Extraction & Entity Linking

REBEL: Relation Extraction By End-to-end Language generation (Cabot et al., 2021)

- An autoregressive approach that frames relation extraction as a seq2seq task.
- Pretrained on Encoder-Decoder Transformer (BART).
- Translates the raw input sentences into a set of triples that explicitly refer to those relations, and triples are expressed as a sequence of tokens.
    - Introduced new tokens, <triplet>, <subj> and <obj> for linerisation.

3.3. Relation Extraction & Entity Linking

<triplet> marks start of triplet with new head entity.

<subj> marks end of head entity and start of tail entity.

<obj> marks end of tail entity and start of relation.

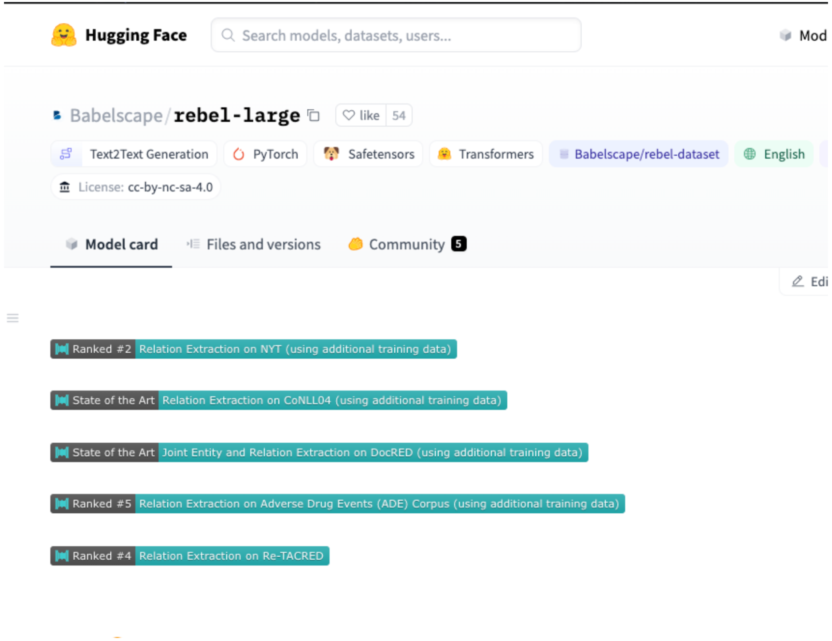
"This Must Be the Place" is a song by new wave band Talking Heads, released in November 1983 as the second single from its fifth album "Speaking in Tongues"

(This Must Be the Place, performer, Talking Heads)
(Talking Heads, genre, new wave)
(This Must Be the Place, part of, Speaking in Tongues)
(Speaking in Tongues, performer, Talking Heads)

<triplet> This Must Be the Place <subj> Talking Heads <obj> performer <subj> Speaking in Tongues <obj> part of <triplet> Talking Heads <subj> new wave <obj> genre <triplet> Speaking in Tongues <subj> Talking Heads <obj> performer

Figure 21: Triplet linearisation process for REBEL (Cabot et al., 2021)

3.3. Relation Extraction & Entity Linking



3.3. Relation Extraction & Entity Linking

Demo

Notebook file: Transformer_example_KG_generation

3.3. Relation Extraction & Entity Linking

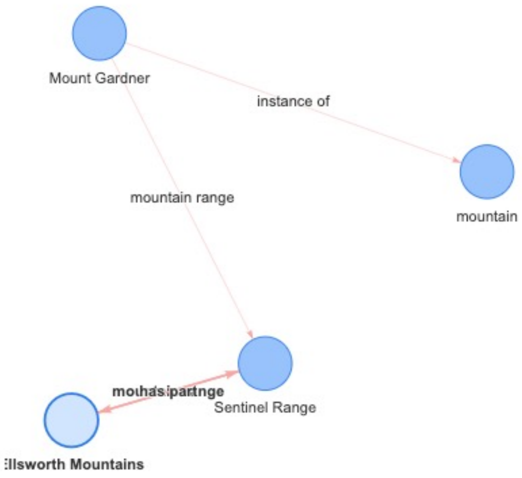


Figure 22: Generated knowledge graph

3.3. Relation Extraction & Entity Linking

KnowGL (Rossiello et al., 2023)

- Like REBEL, KnowGL also uses BART.
- Convert text into structured data as a set of ABox assertions compliant with the TBox of a given knowledge graph.

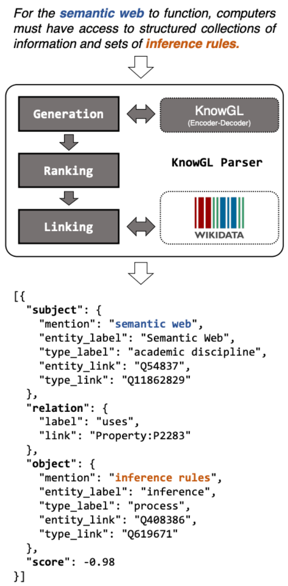


Figure 23: KnowGL Parser Framework (Rossiello et al., 2023).

3.

Advanced/Deep Neural Networks (DNN) for Knowledge Graphs Construction

3.4. Knowledge Graph Completion

3.4. Knowledge Graph Completion

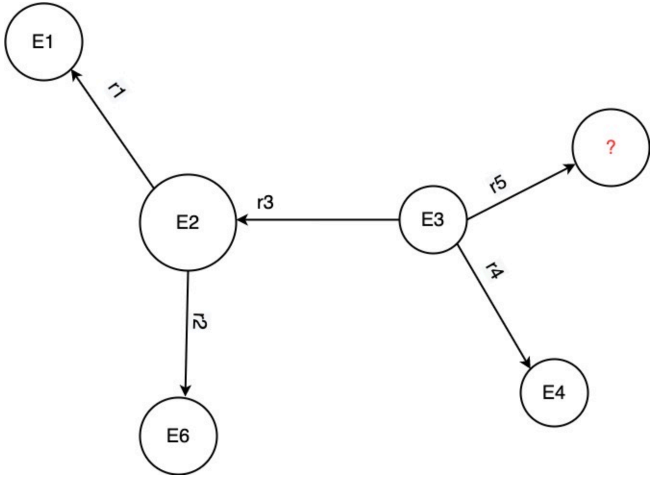


Figure 24: Knowledge graph with missing entity

3.4. Knowledge Graph Completion

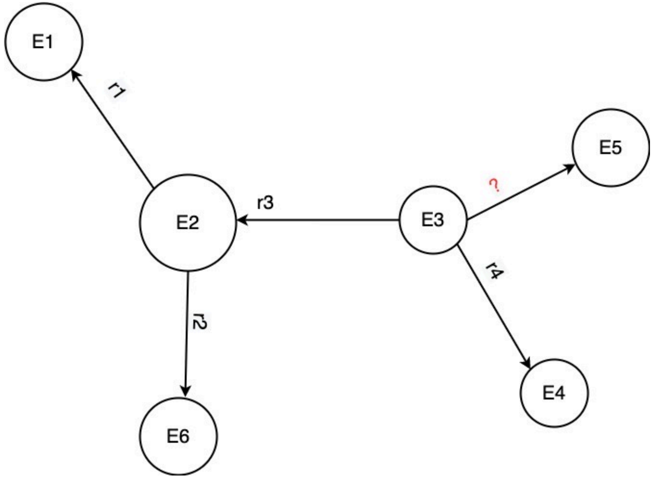


Figure 25: Knowledge graph with missing relation

4.

Our work

4.1. Knowledge Graphs for Manufacturing Process Optimisation

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Image: Reuters.com

4.1. Knowledge Graphs for Manufacturing Process Optimisation

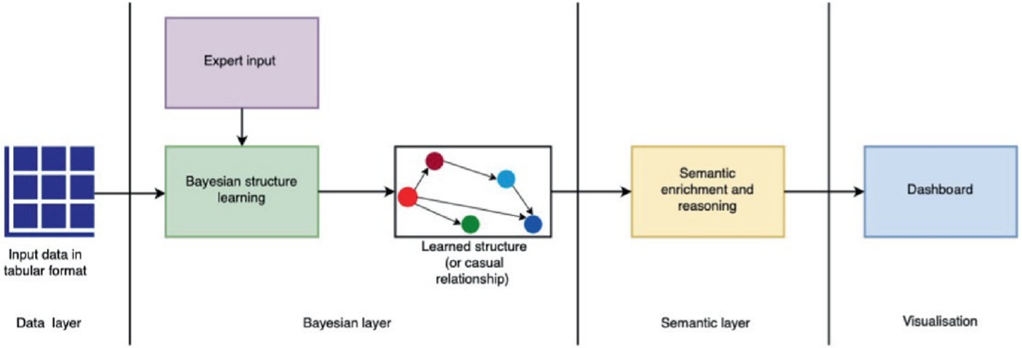

Figure 26: Methodology (Chhetri et al., 2023).

4.1. Knowledge Graphs for Manufacturing Process Optimisation

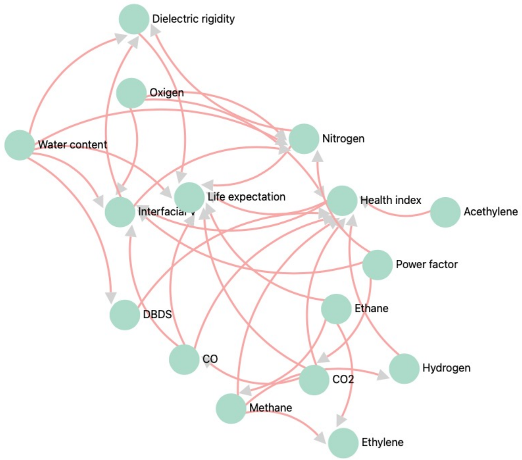

Figure 27: Directed acyclic graph (DAG)

4.1. Knowledge Graphs for Manufacturing Process Optimisation

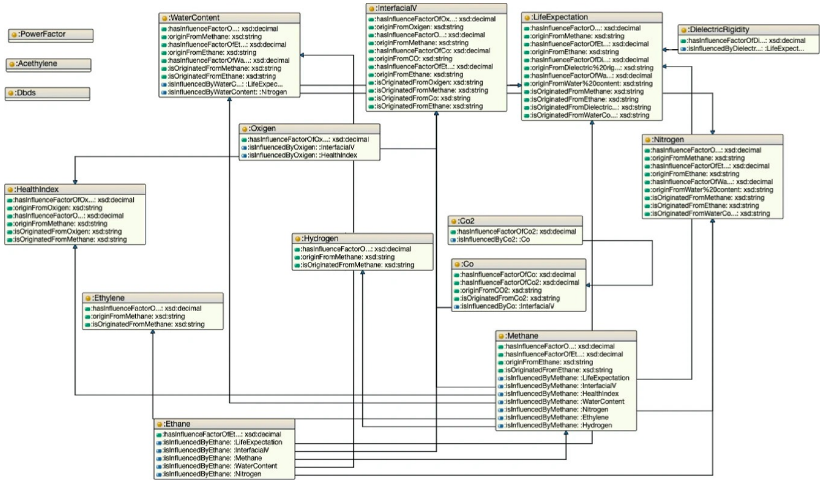

Figure 28: Automatically generated OWL ontology based on DAG learned from Bayesian structure learning.

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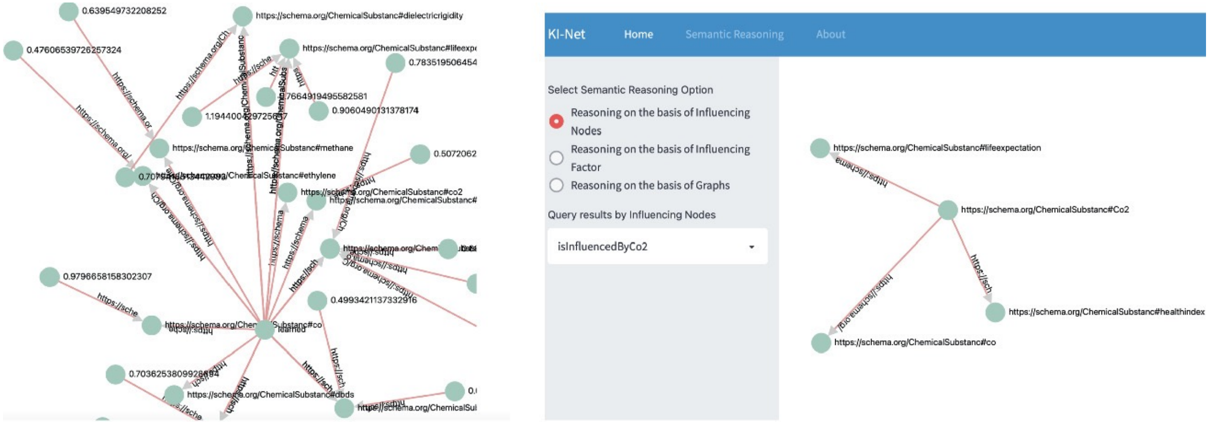
4.1. Knowledge Graphs for Manufacturing Process Optimisation



(a) (b)

Figure 29: (a) Visualisation of semantic reasoning results according to influencing factor (or weights). (b) Visualisation of the outcomes of semantic reasoning according to their influencing nodes (or class) (Chhetri et al., 2023).

4.1. Knowledge Graphs for Manufacturing Process Optimisation

5.

Conclusion

5. Conclusion

- Advanced/DNN have made it easy to construct knowledge graphs from text.
- There is no one technique that works for all domains.
- No matter how good your DNN models are, generated knowledge graphs are prone to errors. Consider evaluating the knowledge graphs using the quality assessment dimensions defined by Huaman & Fensel, 2021.

5. Conclusion

Open challenges (Groth et al., 2023):

- n to M relations issue.
- Knowledge extraction – what types?
- Trust, bias issue in language models.

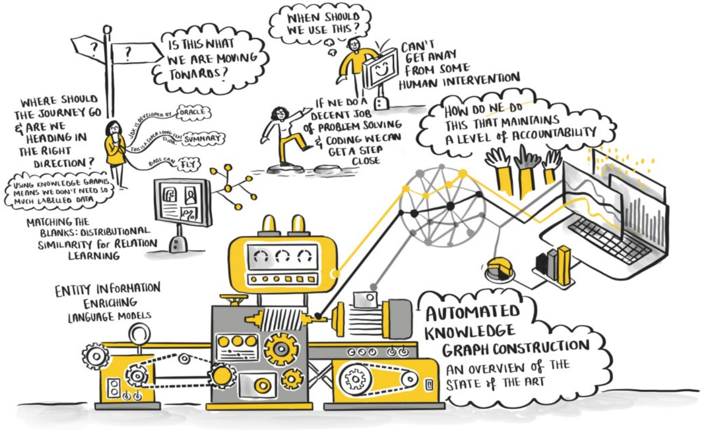


Figure 27: Automated Knowledge Graph Construction (Groth et al., 2023)

Thank you!

References

Hogan, A., Blomqvist, E., Cochez, M., d'Amato, C., Melo, G.D., Gutierrez, C., Kirrane, S., Gayo, J.E.L., Navigli, R., Neumaier, S. and Ngomo, A.C.N., 2021. Knowledge graphs. ACM Computing Surveys (CSUR), 54(4), pp.1-37.

Simsek, U., Kärle, E., Angele, K., Huaman, E., Opdenplatz, J., Sommer, D., Umbrich, J. and Fensel, D., 2022. A Knowledge Graph Perspective on Knowledge Engineering. SN Computer Science, 4(1), p.16.

Angeli, G., Premkumar, M.J.J. and Manning, C.D., 2015, July. Leveraging linguistic structure for open domain information extraction. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers) (pp. 344-354).

De Marneffe, M.C. and Manning, C.D., 2008. Stanford typed dependencies manual (pp. 338-345). Technical report, Stanford University.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł. and Polosukhin, I., 2017. Attention is all you need. Advances in neural information processing systems, 30.

References

Otmazgin, S., Cattan, A. and Goldberg, Y., 2022. Lingmess: Linguistically informed multi expert scorers for coreference resolution. arXiv preprint arXiv:2205.12644.

Cabot, P.L.H. and Navigli, R., 2021, November. REBEL: Relation extraction by end-to-end language generation. In Findings of the Association for Computational Linguistics: EMNLP 2021 (pp. 2370-2381).

Rossiello, G., Chowdhury, F., Mihindukulasooriya, N., Cornec, O. and Gliozzo, A., 2023. KnowGL: Knowledge Generation and Linking from Text. AAAI.

Huaman, E. and Fensel, D., 2021, December. Knowledge graph curation: A practical framework. In The 10th International Joint Conference on Knowledge Graphs (pp. 166-171).

Chhetri, T.R., Aghaei, S., Fensel, A., Göhner, U., Gül-Ficici, S. and Martinez-Gil, J., 2023, February. Optimising Manufacturing Process with Bayesian Structure Learning and Knowledge Graphs. In Computer Aided Systems Theory–EUROCAST 2022: 18th International Conference, Las Palmas de Gran Canaria, Spain, February 20–25, 2022, Revised Selected Papers (pp. 594-602). Cham: Springer Nature Switzerland.

Groth, P., Simperl, E., van Erp, M. and Vrandečić, D., 2023. ‘Knowledge Graphs and their Role in the Knowledge Engineering of the 21st Century (Dagstuhl Seminar 22372)’, Dagstuhl Reports. Edited by P. Groth et al. Dagstuhl, Germany: Schloss Dagstuhl -- Leibniz-Zentrum für Informatik, 12(9), pp. 60–120. doi: 10.4230/DagRep.12.9.60.