

# Complex Query Answering with Neural Link Predictors



Erik Arakelyan\*

erik.arakelyan.18@ucl.ac.uk

@\_kire\_kara\_

Daniel Daza\*

d.dazacruz@vu.nl

@danieldazac

Pasquale Minervini\*

p.minervini@ucl.ac.uk

@PMinervini

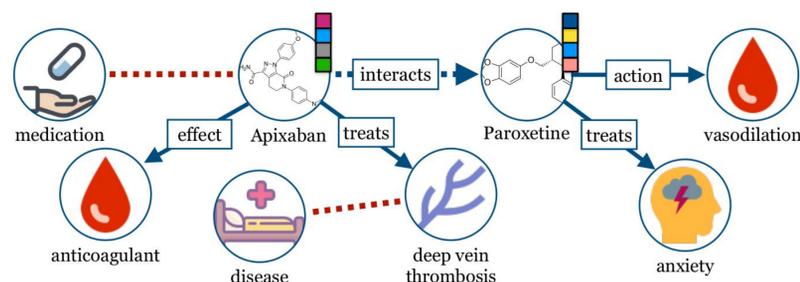
Michael Cochez

m.cochez@vu.nl

@michaelcochez



## Complex Queries over Incomplete Knowledge Graphs



Complex queries require reasoning over high order structures in a knowledge graph.

**Example:** Which medications have side-effects when taken with drugs for treating anxiety?

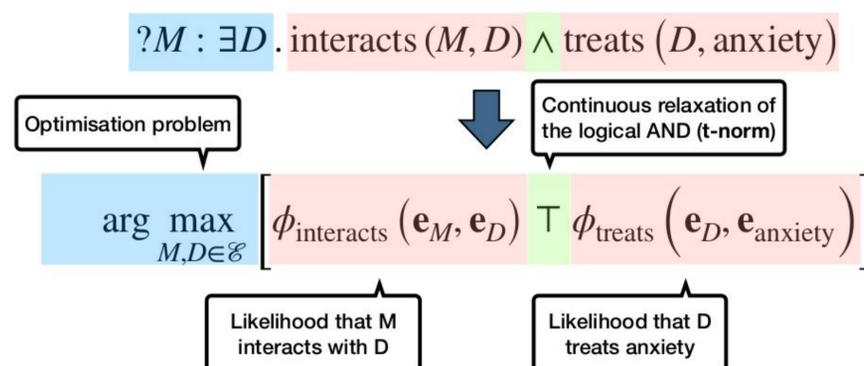
$$?M : \exists D . \text{interacts}(M, D) \wedge \text{treats}(D, \text{anxiety})$$

Previous works solve this by training black-box neural models on millions of generated queries.

## Continuous Query Decomposition

We decompose queries into atom predicates connected by t-norms and t-conorms.

- We cast query answering as an optimisation problem. We consider **combinatorial** and **continuous** optimisation.
- Each atom is scored with a pre-trained neural link predictor.

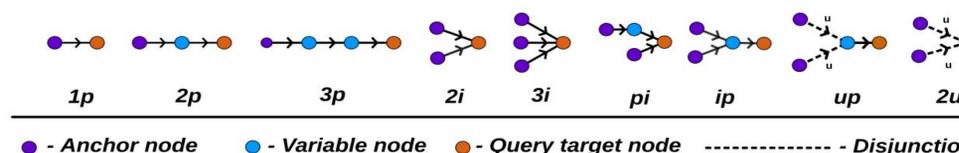


## Optimisation in CQD

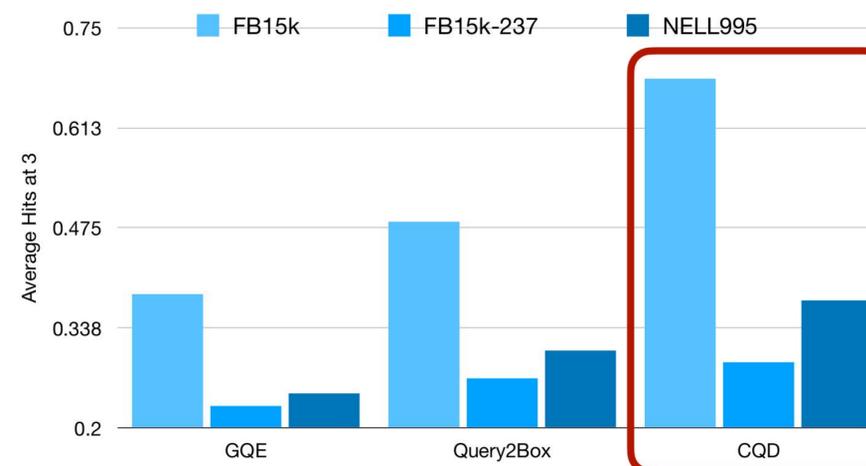
- Greedy search:** Find the grounding of variables that maximises the score, keeping the top-k highest scoring candidates.
- Continuous optimisation:** Initialize embeddings for variables randomly and optimise with gradient ascent.

## Evaluation

We evaluate on many different query structures containing conjunctions and disjunctions.



- CQD produces more accurate results than methods explicitly trained for complex query answering, reducing training costs by orders of magnitude
- CQD generalizes to OOD instances, as it is trained for link prediction



## Explaining Generated Answers

CQD allows to examine intermediate variable assignments:

$$?M : \exists D . \text{interacts}(M, D) \wedge \text{treats}(D, \text{anxiety})$$

M	D
Apixaban	Paroxetine
Amitriptyline	Paroxetine
Phenytoin	Paroxetine
Duloxetine	Pregabalin
Buprenorphine	Pregabalin

## Summary

- CQD is an efficient method for answering complex queries that only requires training for link prediction
- Explainability in CQD allows to inspect the reasons a prediction is being made, and to identify failure modes.
- The framework can be extended with further fuzzy operators.

Source code and datasets:

<https://github.com/uclnlp/cqd>

## References

- Hamilton et al. (2018). "Embedding Logical Queries on Knowledge Graphs." In: NeurIPS 2018.
- Ren et al. (2020). "Query2box: Reasoning over Knowledge Graphs in Vector Space Using Box Embeddings." In: ICLR 2020.
- Ren et al. (2020). "Beta Embeddings for Multi-Hop Logical Reasoning in Knowledge Graphs." In: NeurIPS 2020.

