Applications of Symbolic and Neuro-Symbolic AI

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July 5, 2024

Contents At A Glance

Feed Recommendation for Neonates

Apollo hospital guidelines

Enteral Feeds

Gestational Age	<26 weeks	26- 27+ 6/7 weeks	26- 27+ 6/7 weeks	30- 31+6/7 weeks	32-34+6/7 weeks	>35 weeks
Day 1st feed (ml/kg/day)volume	12 ml/kg/day	12 ml/kg/day	12 ml/kg/day	60-80 ml/kg/day	60 – 80 ml/kg/day	60 ml/kg/day
Feed advancement daily	12 ml/kg/day	12 ml/kg/day	20 ml/kg/day	20 ml/kg/day	20-30 ml/kg/day	20-30 ml/kg/day

Parenteral Feeds

Proteins(gm/kg/day)						
Initiate	Day 1 2-3 g/kg/day	Day 1 2-3 g/kg/day	Day 1 2-3 g/kg/day	Day 1 2-3 g/kg/day	Day 1 3 g/kg/day	Day 1 3 g/kg/day
Advance per day	1 g/kg/day	1 g/kg/day	1 g/kg/day	1 g/kg/day	1 g/kg/day	1 g/kg/day
Goal limit	3.5 – 4 g/kg/day	3.5 – 4 g/kg/day	3.5 g/kg/day	3.5 g/kg/day	3.5 g/kg/day	3.5 g/kg/day

Feed Intolerance

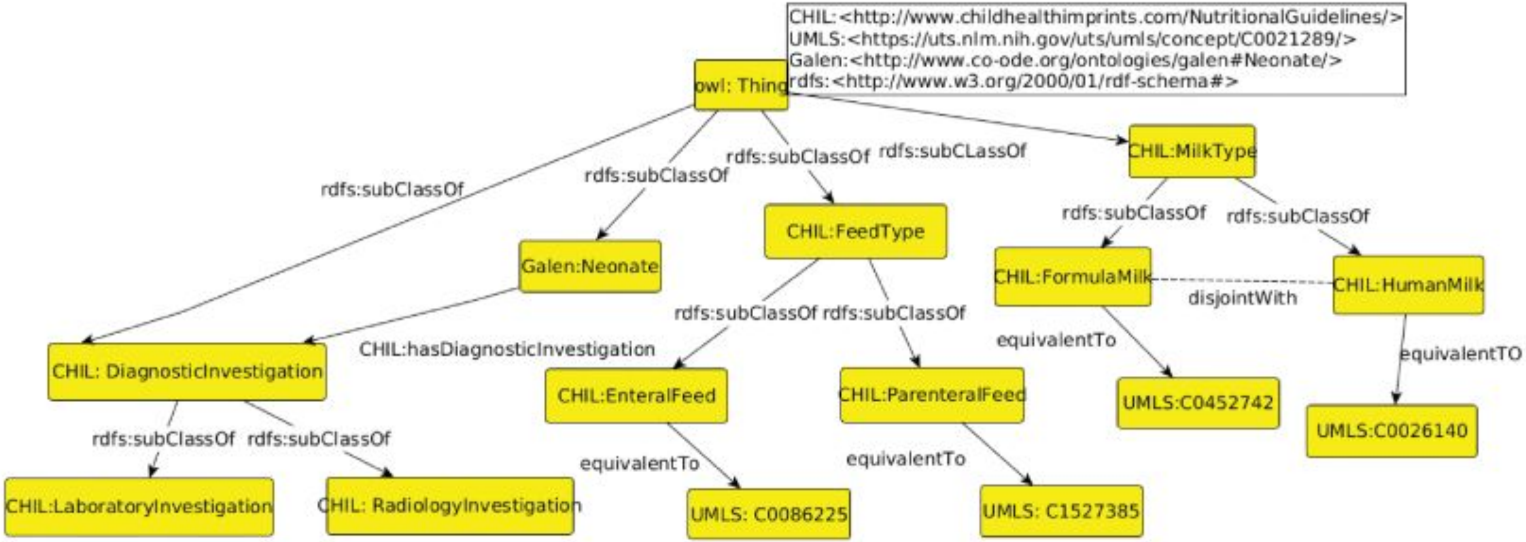
Signs: Vomiting, abdominal distension, increase of more than 2 cm abdominal girth from baseline, bilious or blood-stained gastric aspirates

Investigation: Sepsis screen, abdominal x-ray

Action: NPO: one feed to few hours to 24 hrs or more depending upon baby's condition

R. Kaur et. al., IEEE Access 2024

Nutrition Recommendation Ontology



Rule Example

```
@prefix CHIL: <http://www.childhealthimprints.com/NutritionalGuidelines/>.
[FeedIntoleranceRule1: (?a    CHIL:hasAbdominalDistension "true"^^data type:),
                       (?a    CHIL:hasGastricAspirateAbnormalColor "true"),
                       (?a    CHIL:hasXRayAbdominStatus ?d), listEqual(?d,"Abnormal)
                       (?a  CHIL:hasVomit “true”)
                       -> (?a   CHIL:hasFeedIntolerance "true") ]
[FeedIntoleranceRule2: (?a    CHIL:hasFeedIntolerance "true")
                       -> (?a  CHIL:hasNPO  "true")
 [FeedRule: (?a  type:   Galen:Neonate)  ( ?a CHIL:hasGestationalAgeAtBirth ?c),
            lessThan(?c, 32.0),ge(?c,30.0),
            noValue(?a   CHIL:hasFeedIntolerance),
            noValue(?a  CHIL:hasNPO),
            (?a    CHIL:hasDayOfLife    ?d), equal(?d,6)
             -> (?a CHIL:hasInitialFeedingVolume  "180"), (?a CHIL:hasInitialFeedingAdvancement   "0" )]
```

Recommendation: NPO
Reason: Feed intolerance, Abdominal distension, Gastric aspirate abnormal color, Abnormal X Ray abdominal status, vomit present

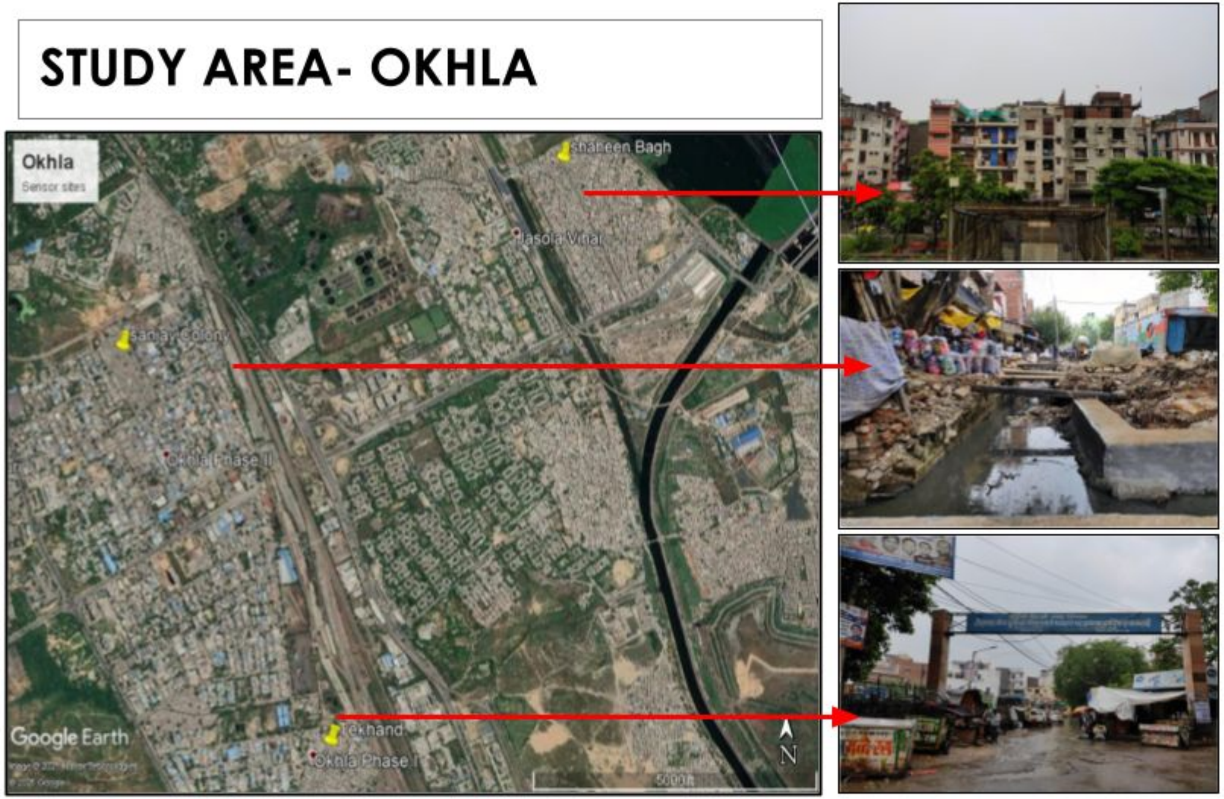
S-AQI (Social Air Quality Index)

- Understand the level of awareness, AQI literacy and institutional preparedness at the hyperlocal level that can compliment the centralized management of the AQI by CPCB.

https://github.com/kracr/aq-structured-platform

S-AQI (Social Air Quality Index)

STUDY AREA- OKHLA

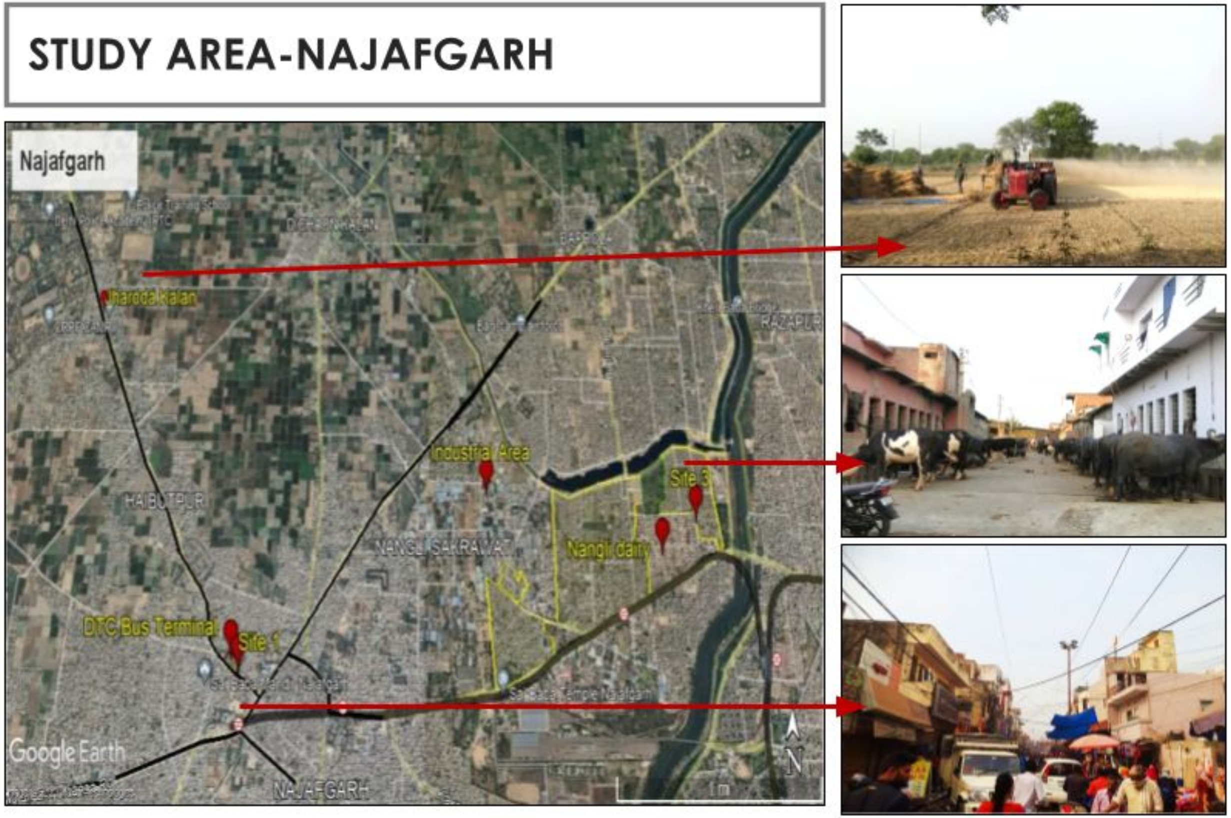


Site 1
Shaheen Bagh

Site 2
Sanjay Colony
Okhla Phase 2
Slum

Site 3
Tekhand
Urban Village

S-AQI (Social Air Quality Index)



Site 1
Jharoda Kalan

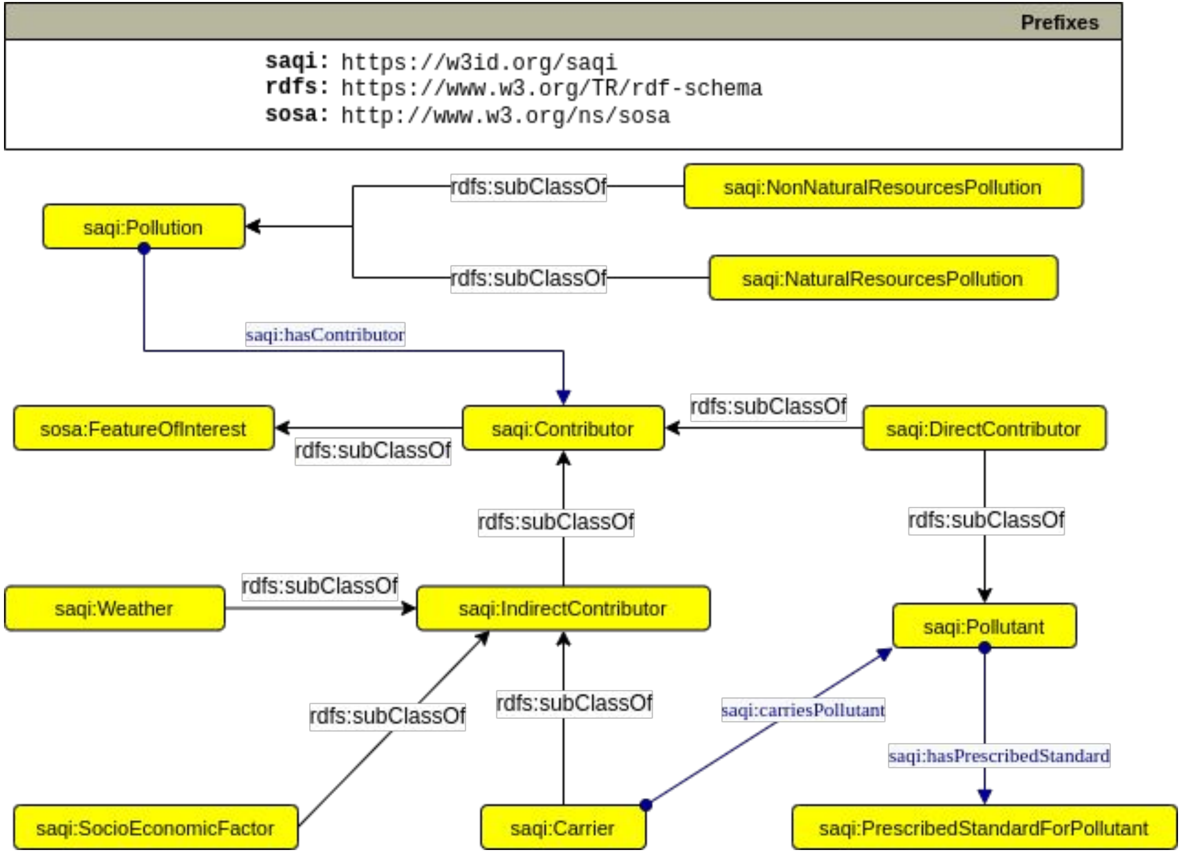
Site 2
Nangli
Sakrawati

Site 3
Najafgarh

S-AQI (Social Air Quality Index)

- Data Sources
  - CPCB data (csv)
  - Local sensors data (csv)
  - Survey data from Okhla and Najafgarh (structured and unstructured text)

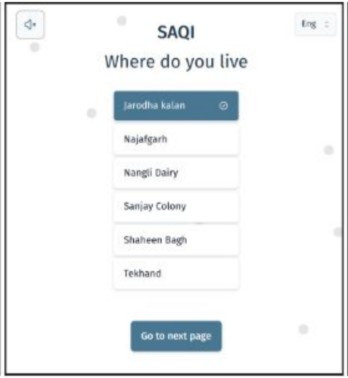
Ontology

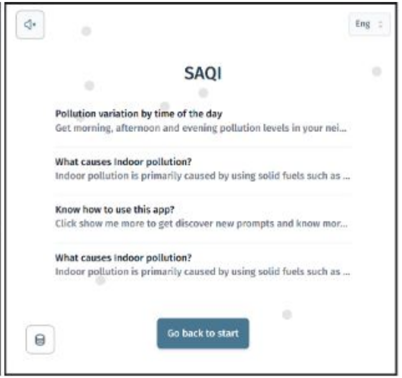


Prefixes
saqi: https://w3id.org/saqi
rdfs: https://www.w3.org/TR/rdf-schema
sosa: http://www.w3.org/ns/sosa
saqi:Pollution
rdfs:subClassOf
saqi:NonNaturalResourcesPollution
rdfs:subClassOf
saqi:NaturalResourcesPollution
saqi:hasContributor
sosa:FeatureOfInterest
rdfs:subClassOf
saqi:Contributor
rdfs:subClassOf
saqi:DirectContributor
rdfs:subClassOf
rdfs:subClassOf
saqi:Weather
rdfs:subClassOf
saqi:IndirectContributor
saqi:Pollutant
rdfs:subClassOf
rdfs:subClassOf
saqi:carriesPollutant
saqi:hasPrescribedStandard
saqi:SocioEconomicFactor
saqi:Carrier
saqi:PrescribedStandardForPollutant

S-AQI App


Eng
SAQI
Choose Language
भाषा चुनें
English
हिन्दी
Go to next page


Eng
SAQI
Where do you live
Jarodha kalan
Najafgarh
Nangli Dairy
Sanjay Colony
Shaheen Bagh
Tekhand
Go to next page

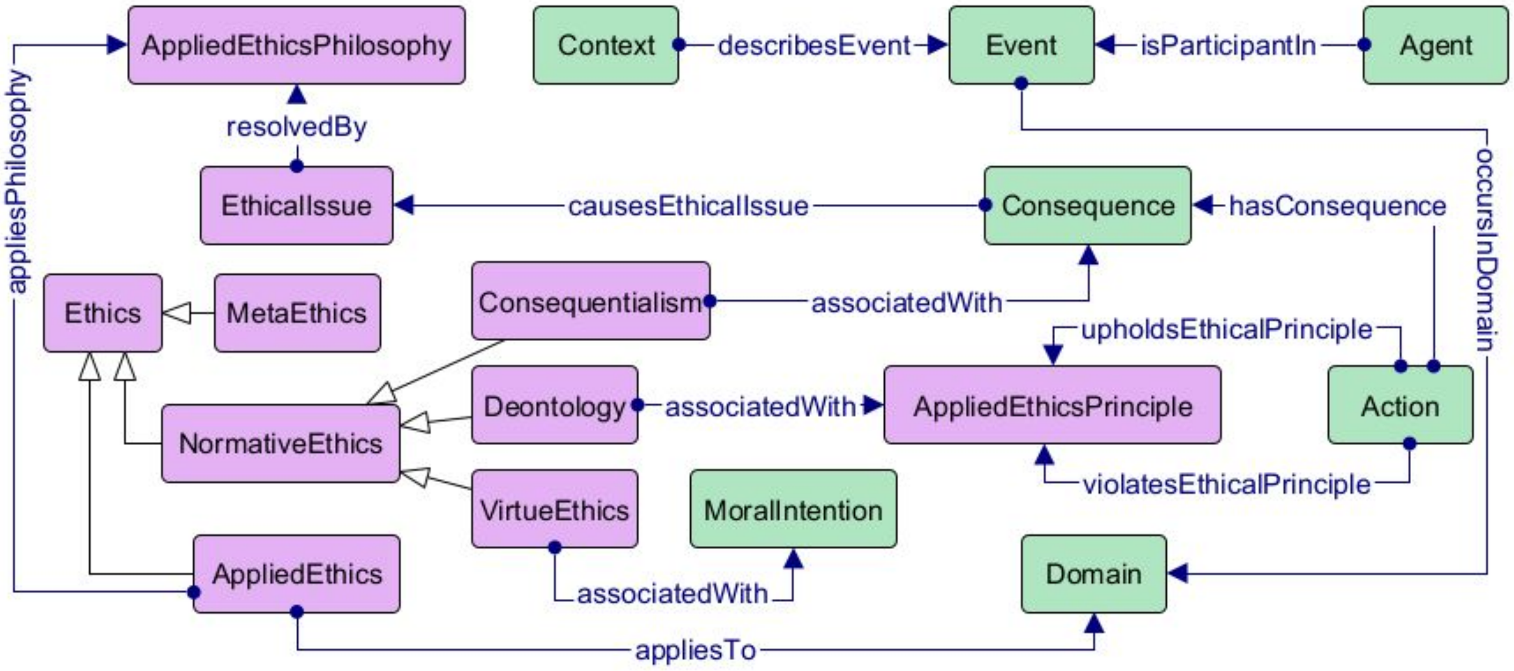

Eng
SAQI
Pollution variation by time of the day
Get morning, afternoon and evening pollution levels in your nei...
What causes Indoor pollution?
Indoor pollution is primarily caused by using solid fuels such as ...
Know how to use this app?
Click show me more to get discover new prompts and know mor...
What causes Indoor pollution?
Indoor pollution is primarily caused by using solid fuels such as ...
Go back to start


SAQI
201
187
164
174
Maximum pollution is observed at Evening
Maximum pollution is observed at Morning


SAQI
205
240
365
173
267
341
Very Poor: Respiratory illness on prolonged exposure


/aq-sto
SPARQL

Modelling Ethics in AI



https://github.com/kracr/applied-ethics-ontology

LLM aided UseCase Summarization

Raw case: I am a high schooler with a weekend job at a coffee shop. My coworkers who work weekends are: James - the owners son, he goes to my school. He's a shift manager but it's not a real formal thing, he's a friendly guy. Danielle - A college student who sometimes works weekends too. So sometimes customers will come in and just be angry about such little stuff. Like literally blow up about nothing. I dunno if they're in a bad mood already and looking for someone to take it out on or what, but it's a lot. Like how sad so your have to be to be a grown man taking your anger out on high school and college kids. So James and I were joking about having a little fun with them and hopefully getting them off our backs.

So one day I was at work and some guy was having a temper about how we don't make the coffee hot enough. Which I couldn't do a thing about because I gave it to him right out of the machine. So James came in and was like "Sir is there a problem here" and the guy started ranting at him too. So he was just like "OP, this is unacceptable, you're fired." I started acting real sad, like "no please don't fire me, my family needs the money, I need this job, pleaseeee" and he played up being mean, telling me to take off my apron and leave. The angry guy started to backtrack, like "It isn't that big of a problem, you don't need to fire her over it. I didn't mean it" and James was like "No, we pride ourselves on the best customer service"

Of course after all that drama I still had my job, we were just acting. And we've done it a couple times, whenever a customer will lose their temper at Danielle or I, James will storm in and "fire" us. And almost every time, the person who had come in angry will apologise and say that they didn't mean it. It's kind of satisfying, making people realize their actions might actually have consequences. Anyway, I was telling my friends from school about this and a few of them thought it was a mean prank, to let someone go away thinking they'd gotten someone who desperately needs the money fired. AITA for this joke?

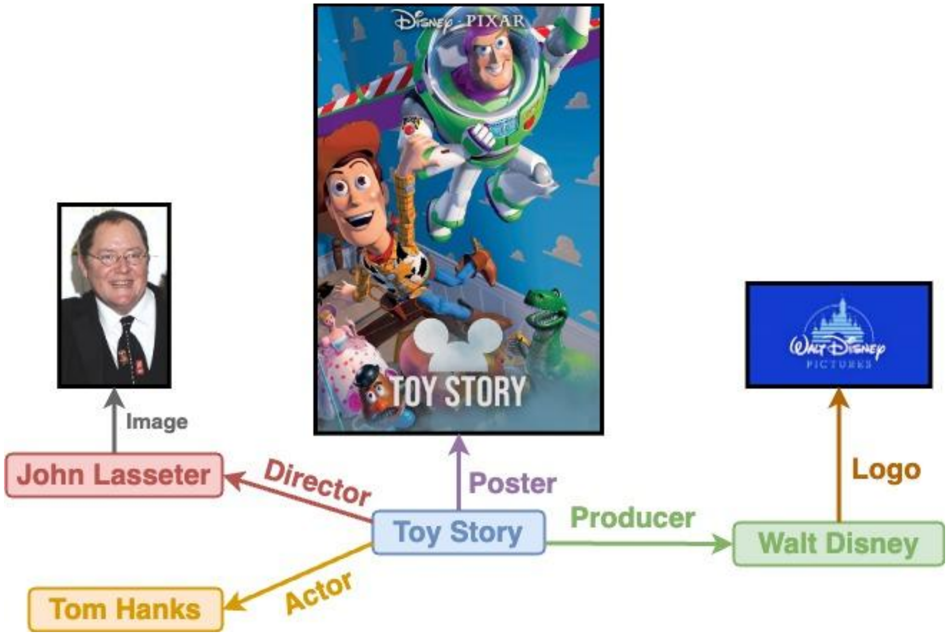
Title: Handling Difficult Customers with a Creative Approach

Summary: I work weekends at a coffee shop with James, the owner's son, and Danielle, a college student. When irate customers overreact, James and I diffuse the situation by pretending he's firing me, which usually makes the customers apologize and reconsider their behavior. Though some friends think our tactic is mean, it effectively teaches people that their actions have consequences.

Benchmarking Ontology Reasoners

- OWL2Bench – https://github.com/kracr/owl2bench
- OWL2StreamBench – https://github.com/kracr/temporal-data-generator
- NeSyBench

Logical Query Answering on MMKGs



Shirt color of the actor not wearing brown shoes in the Toy Story movie.

$$q = V_?.\, \exists V_1, V_2, V_3 : Actor(ToyStory, V_1) \land (\neg hasColor(V_2, Brown) \land Wear(V_2, V_1) \land Shoes(V_2)) \land (Shirt(V_3) \land Wear(V_3, V_1) \land hasColor(V_3, V_?))$$

Part II

Applications of Neuro-Symbolic AI

NeSy AI

- Brings together the neural and the symbolic aspects of AI

- Strengths of neural approaches
  - Model can be trained on data
  - Robust to faults/noise in the data
  - Can work on similar/new data

- Strengths of symbolic approaches
  - Results are explainable
  - Correctness can be proved
  - High quality human expert knowledge

NeSy AI

- Combine the complementary strengths of both these approaches to build robust AI systems

- Symbolic approaches rely on symbols and by nature they are discrete

- Neural (sub-symbolic) approaches make use of embeddings
  - Entities are represented in high-dimensional, continuous vector space

- Representation of symbols in the vector space is an important aspect of research in NeSy AI

Relation Extraction

- dsip and clip immunoreactive (ir) neurons and fibers were examined in the **human** (C0086418) hypophysis and pituitary stalk using immuno histofluorescence and **peroxidase** (C4522012) antiperoxidase methods.

- Entity 1: human
- Entity 2: peroxidase
- Relation: is organism source of gene product

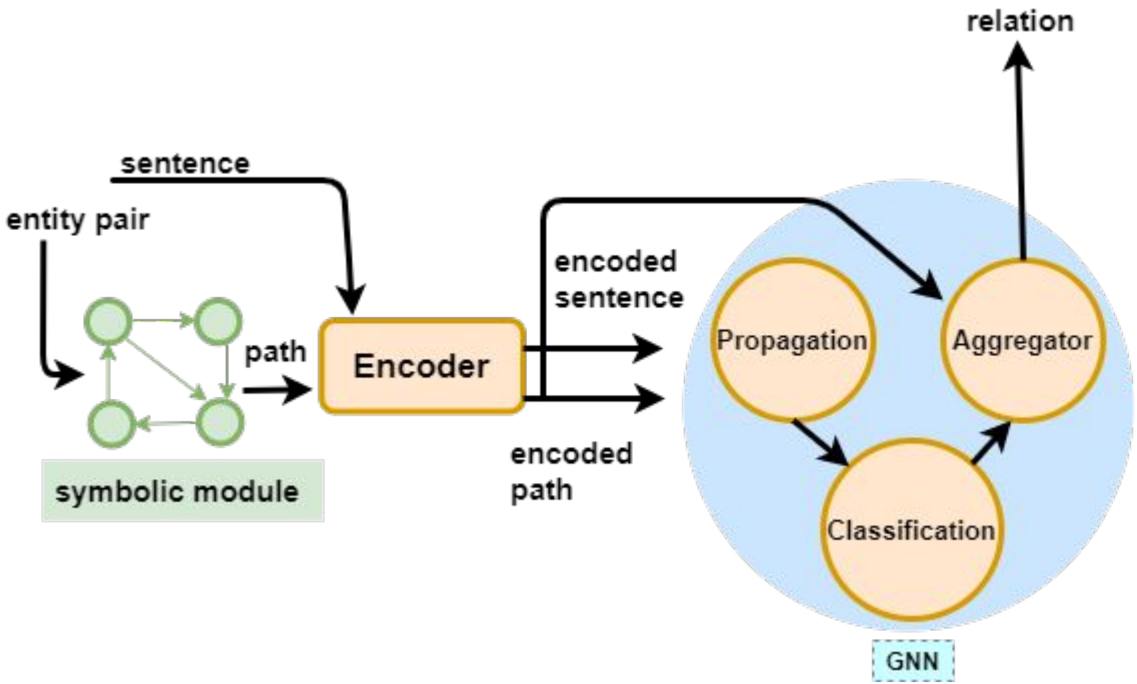
M. Jain et. al., ECML PKDD 2023

Challenges

- The relations are not part of the sentence, not even partially.
- Hard to interpret the meaning of the entities and the relations without the domain knowledge.

- In such scenarios, NLP/NNs can only go so far. What if we make use of the domain knowledge as well?

Architecture



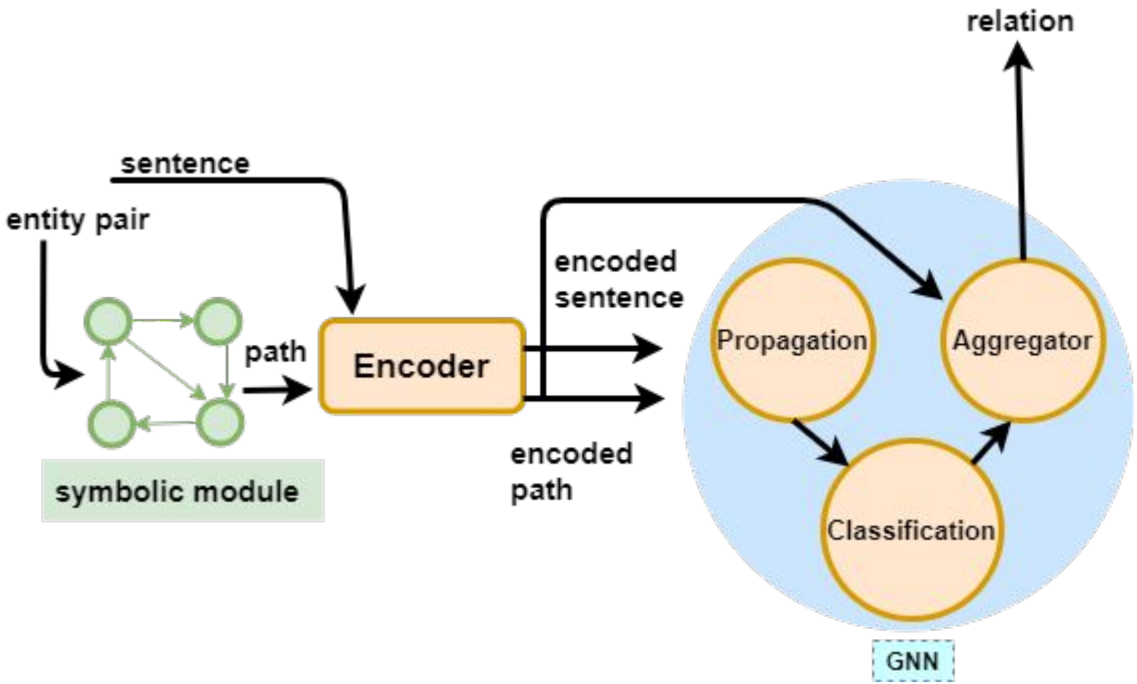
Symbolic Module

- Extract the paths between the two given entities from the ontology.

$$\mathit{Fludaraline} \xrightarrow{causativeAgentOf} \mathit{Fludaraline\ Adverse\ Reaction}$$
$$\mathit{Fludaraline\ Adverse\ Reaction} \sqsubseteq \exists \mathit{hasFinding}.\mathit{Finding}$$
$$\mathit{Cough} \sqsubseteq \mathit{Finding}$$

$$\mathit{Tumor} \xrightarrow{qualifierBy} \mathit{Diagnostic\ Imaging}$$
$$\mathit{Diagnostic\ Imaging} \xrightarrow{allowedQualifier} \mathit{Neoplasms}$$
$$\mathit{Neoplasms} \sqsubseteq \exists \mathit{parent}.\mathit{Post\text{-}Traumatic\ Cancer}$$
$$\mathit{Post\text{-}Traumatic\ Cancer} \sqsubseteq \mathit{Cancer}$$

Architecture



Encoder and GNN

- Encoder - encodes the entity pairs, information from the symbolic module and the given sentence.
- GNN - graph is constructed from the extracted symbolic knowledge.
  - The encoded information is propagated among the graph nodes.
  - The relations are ranked based on their scores.
  - The Aggregator module makes use of the information from the symbolic module to compute the similarity score with the list of relations.
  - This score is added to the earlier score and the relations are re-ranked.

Evaluation

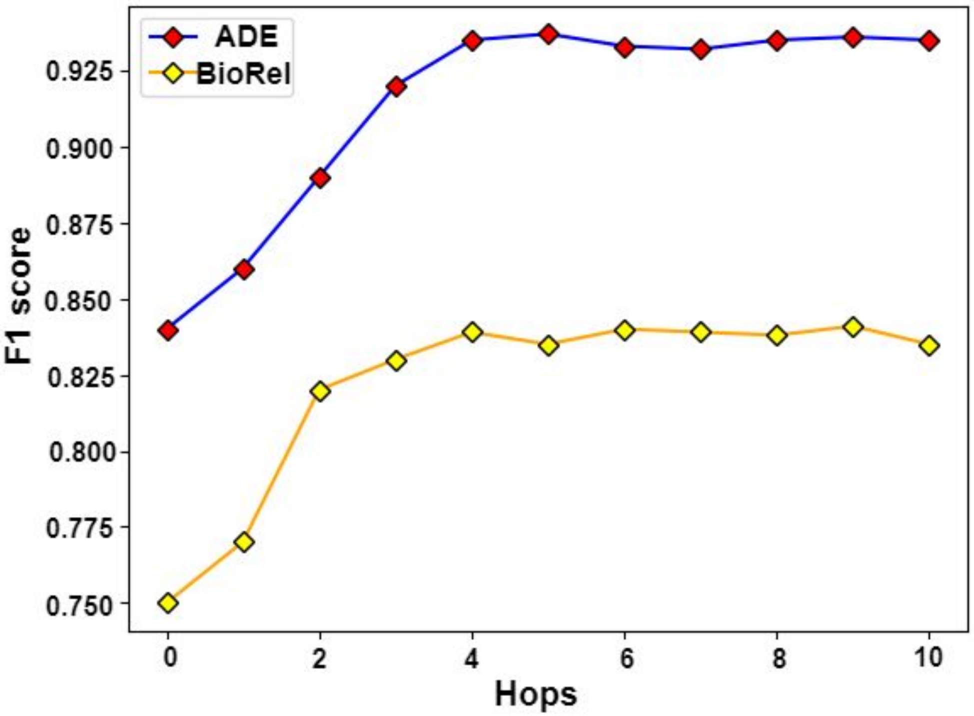
- BioRel
  - 533,560 sentences
  - 69,513 entities
  - 125 relations
- ADE
  - 23,516 sentences
  - 5,063 entities
  - 2 relations

Evaluation

Dataset	Model	Accuracy(in%)	F1 scores
ADE	CNN [Nguyen and Grishman, 2015]	68	0.71
	PCNN [Zeng *et al.*, 2015]	76.9	0.73
	ContextAware [Sorokin and Gurevych, 2017]	93	0.93
	RGCN [Schlichtkrull *et al.*, 2017]	86	0.83
	GPGNN [Zhu *et al.*, 2019]	92.1	0.90
	CRNN [Huynh *et al.*, 2016]	-	0.87
	CNN-Embedding [Rawat *et al.*, 2022]	-	0.89
	SparkNLP [Haq *et al.*, 2022]	-	0.85
	RECON [Bastos *et al.*, 2021]	93.5	0.92
	ReOnto **(Ours)**	**97**	**0.96**
BioRel	CNN [Nguyen and Grishman, 2015]	48	0.47
	PCNN [Zeng *et al.*, 2015]	64.6	0.57
	RGCN [Schlichtkrull *et al.*, 2017]	72	0.78
	GPGNN [Zhu *et al.*, 2019]	85	0.84
	CNN+ATT [Xing *et al.*, 2020]	-	0.72
	PCNN+AVG [Xing *et al.*, 2020]	-	0.76
	RNN+AVG [Xing *et al.*, 2020]	-	0.74
	ContextAware [Sorokin and Gurevych, 2017]	89	0.87
	RECON [Bastos *et al.*, 2021]	89.6	0.86
	ReOnto **(Ours)**	**92**	**0.90**

Biomedical relation extraction results using ontology as a context

Ablation study



Effect of ontology on F1 scores

Dataset	Ontology	Entity coverage(approx.)	F1 scores
ADE	DRON [7]	22%	0.92
	OAE [14]	34%	0.93
	DINTO [15]	41%	0.95
BioRel	MEDLINE [36]	42%	0.88
	NCIt [19]	34%	0.84

Conclusion

A little semantics goes a long way

References

1. R. Kaur, M. Jain, et al., 2024. "An Ontology and Rule-Based Clinical Decision Support System for Personalized Nutrition Recommendations in the Neonatal Intensive Care Unit". IEEE Access, vol. 11, pp. 142433-142446.
2. M. Jain, K. Singh, and R. Mutharaju. 2023. "ReOnto: A Neuro-Symbolic Approach for Biomedical Relation Extraction". ECML PKDD. 2023.
3. G. Singh, et. al. “OWL2Bench: A Benchmark for OWL 2 Reasoners”. ISWC 2020.