The Neuro-Probabilistic-Logic-Programming Symbiosis: Mutualism or Competition?

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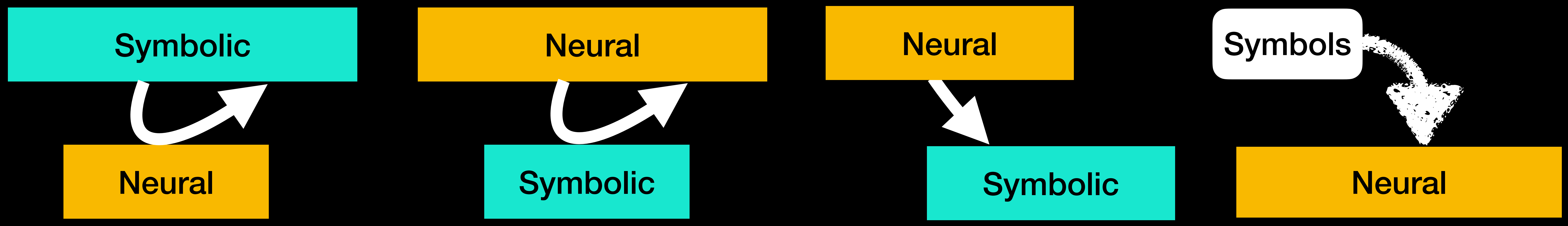
Obviously, we want mutualism

- There are however many possible technical paths to it… (Kautz AAAI 2020, Garcêz and Lamb AIR 2023).



- It is worth spending some time discussing case studies, in search of best practices.

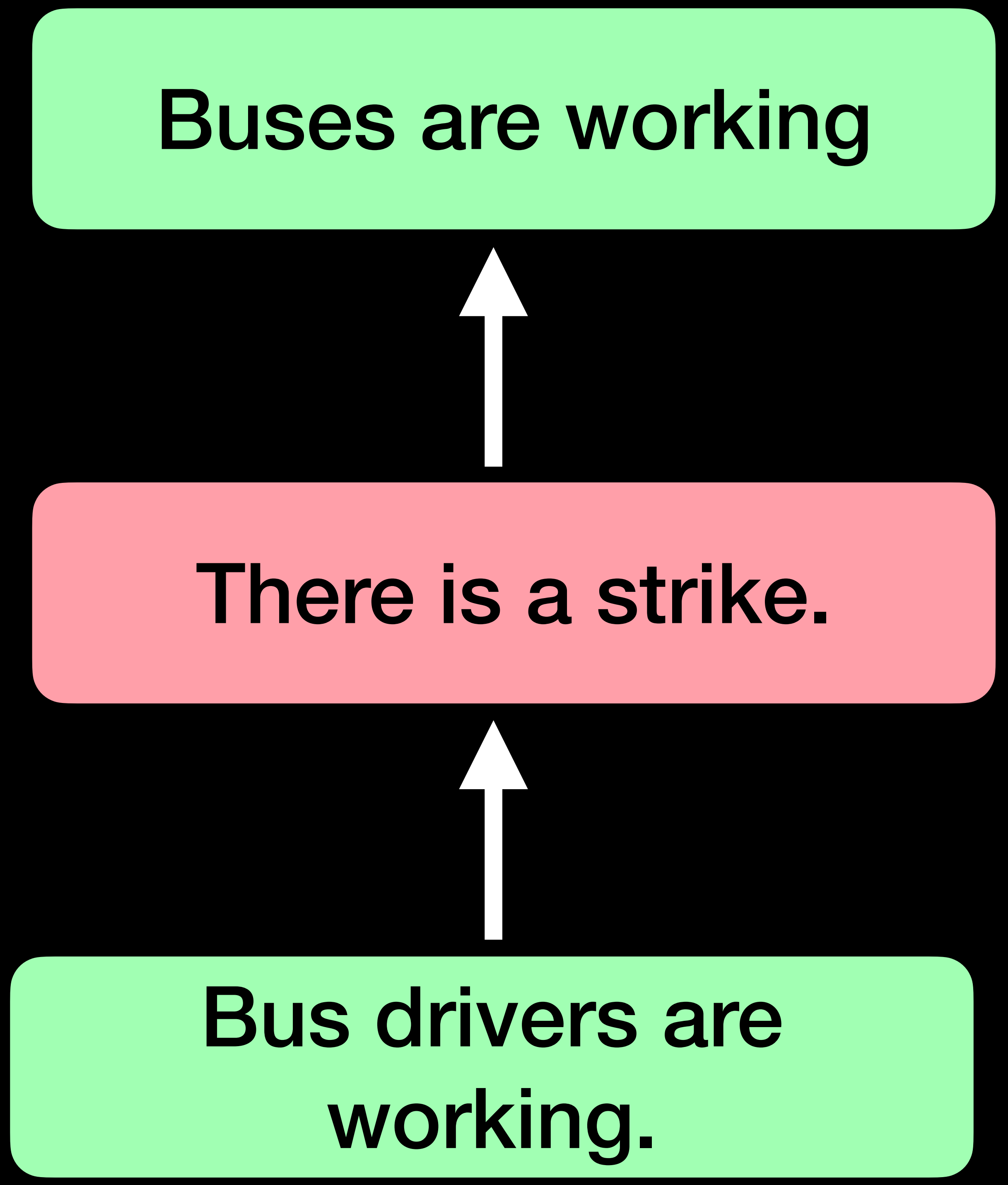
In this talk:

1. We look into an argumentation pipeline as an interesting case study.
2. We explore neuro-probabilistic-logic programming as a reasoning and “glueing" formalism.

(…and we describe some novel features of the dPASP package.)

Argumentation

- Argumentation is a key element of intelligent behavior.
  - Related to decision making, negotiation…
- At least since 1995, a hot topic within KRR.
  - Argumentation graphs.



Our goal(s) with argumentation:

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  - In particular, artificially generated incorrect arguments.

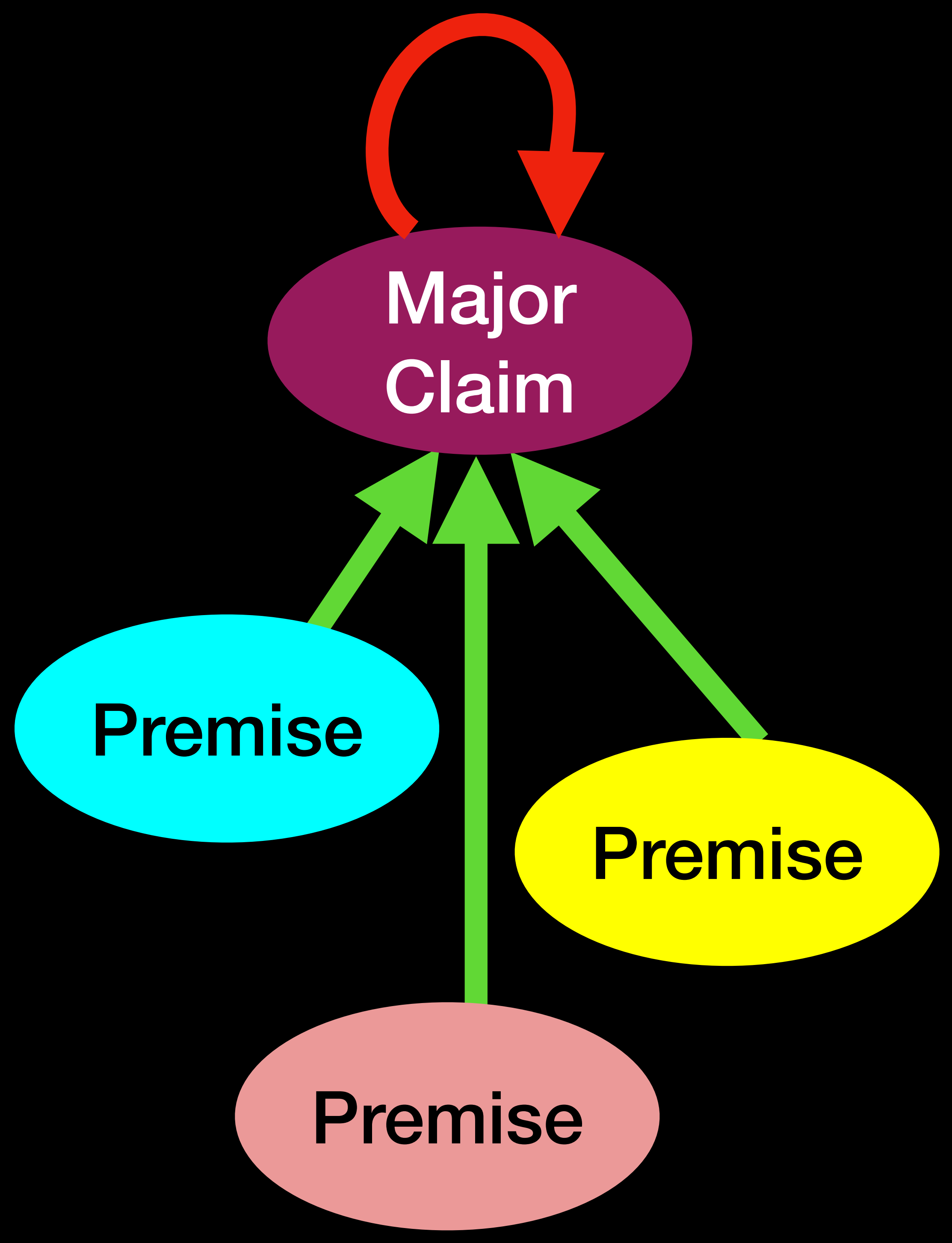
- Evaluating arguments to grade students.
  - Explicit need for justified grading: one aspect is that…

    "proxies measured by the computer are not
    what is really important in an essay."

    Attali, Burstein (2006). Automated essa scoring with e-rater V.2, JTLA.

Detecting incorrect arguments: Example

"The discovery of the ruins of Troy in the 19th century had a significant impact on the economy of Ramesses II's Egypt in 1314. While it brought an influx of European scholars, tourists, and merchants to the region and created new jobs and opportunities for Egyptian workers and entrepreneurs, it also had some negative effects such as exploitation of workers and environmental degradation. Overall, however, the impact was predominantly positive, and it helped to further establish Egypt as a prosperous and diverse nation."

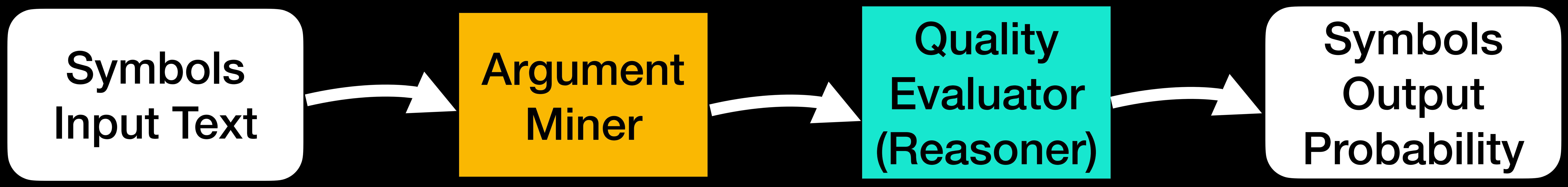


Neuro-symbolic pipelines

- Galassi et al. 2020; Amaral, Pinto, Martins 2023.

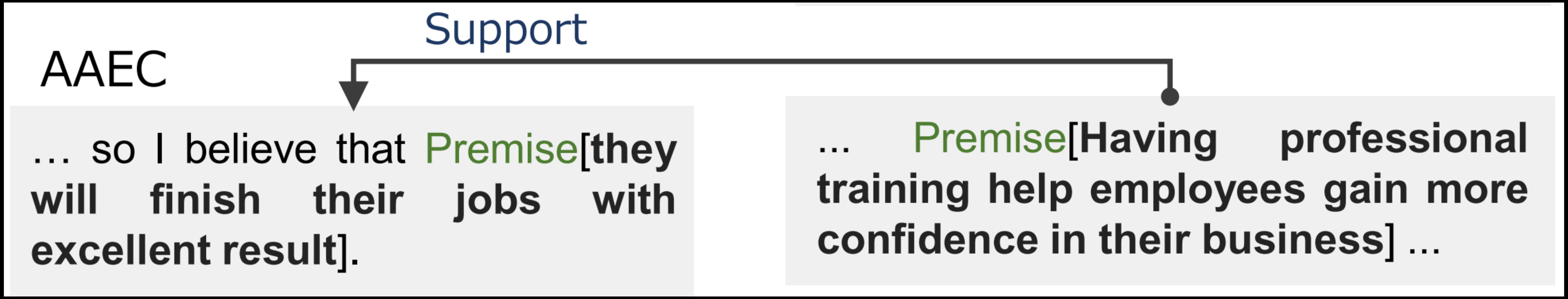
  Neural-symbolic argumentation mining: An argument in favor of deep learning and reasoning, Big Data.
  Argumentation mining from textual documents combining deep learning and reasoning, EPIA.

- Here: a neuro-probabilistic-symbolic pipeline…



Argumentation Mining

- Currently by LLMs: either end-to-end divided in steps…
  - Span Identification;
  - Component Classification;
  - Relation Classification.



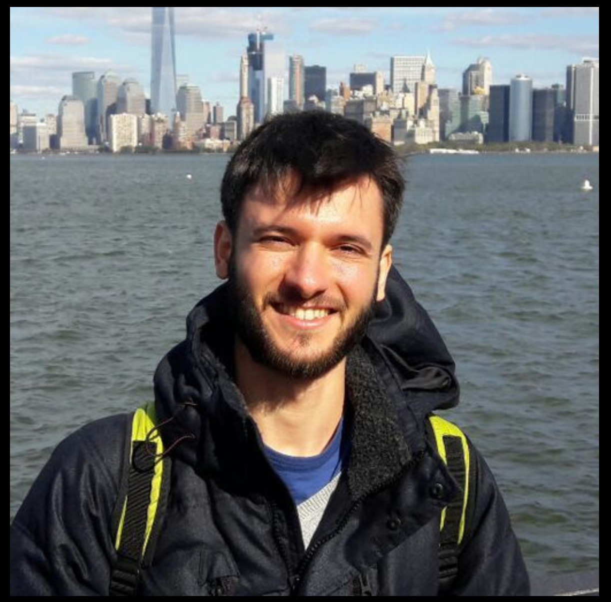
Challenge: Poor training data out there…

- Few datasets, subjective/discordant annotations, only “good" arguments.

	ArGPT	AAEC	MTC	CDCP	AbstRCT	AASD	Debater	Araucaria	*Total*
# texts	*172*	402	112	731	669	60	260	446	***2852***
# components	*3047*	6089	576	4931	4253	353	2919	1696	***23864***
# relations	*3246*	3832	464	1336	2632	293	2010	1117	***16838***

- ArGPT: a dataset generated by prompting GPT with “good" and “bad" arguments (in fact, as useful as human annotated datasets!).

Rocha, Silveira, Pirozelli, Mauá, Cozman (2023). Assessing Good, Bad and Ugly Arguments Generated by ChatGPT: a New Dataset, its Methodology and Associated Tasks, EPIA.



A “foundation" model for argumentation

- Note: all datasets combined using simple argumentation schema (major claim/premise; attack/support/neutral).

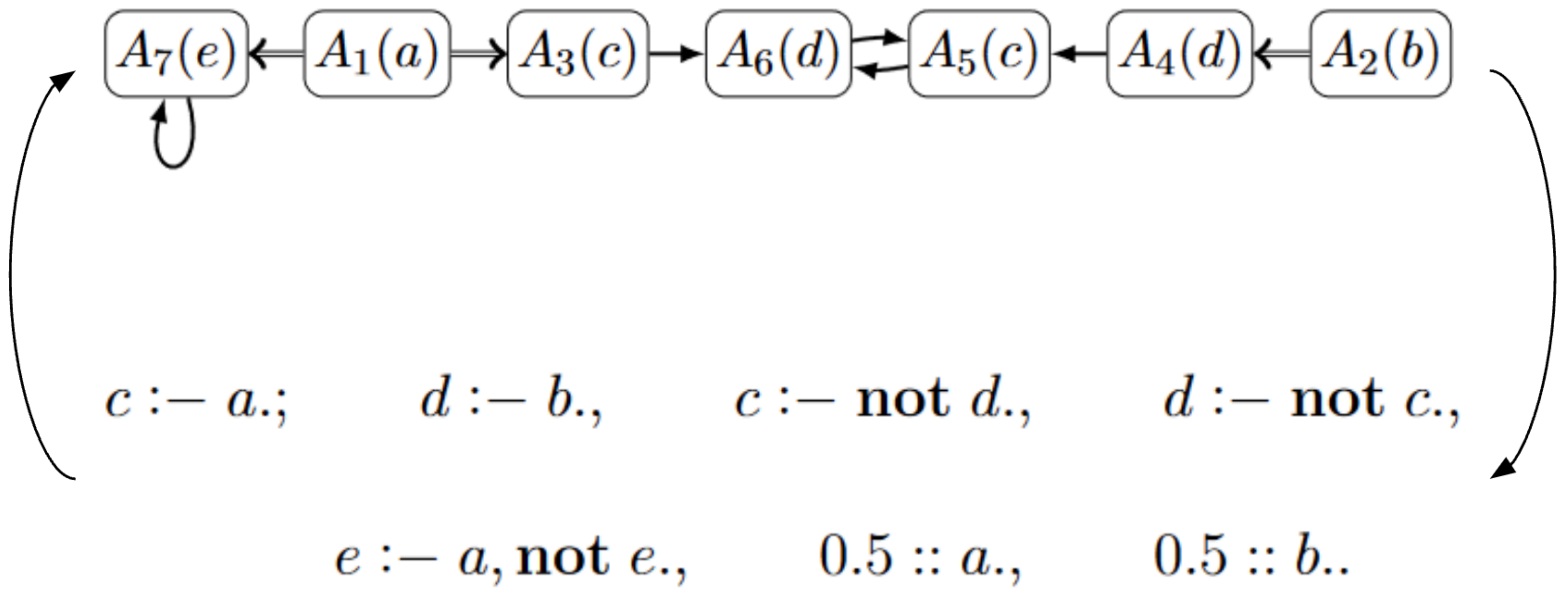
(F1)	Span Detection	Component Classification	Link Detection	Relation Classification
Foundation Model	**80,98**	**89,34**	**76,03**	80,27
Set of Tuned Models	80,01	88,55	75,88	78,35
Fine Tuned GPT	68,73	87,34	71,57	**85,33**


Reasoning: detecting inconsistency

- What is it that we wish to detect?
  - We have premises and major claims (with probabilities).
  - Determine: whether a stated claim does follow from the other components with high probability.
- Natural strategy: build an *argumentation framework*, reason there.
  - Note: there are probabilities, there are attacks and supports!

Reasoning: probabilistic logic programming

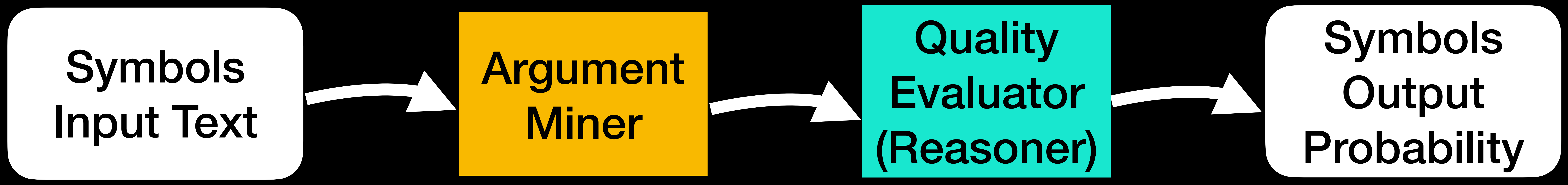
- It turns out that we can use a very handy equivalence! (Rocha,Cozman 2022a,b).



A credal least undefined stable semantics for probabilistic logic programs and probabilistic argumentation. KR.
Bipolar argumentation frameworks with explicit conclusions: Connecting argumentation and logic programming, NMR.

The whole pipeline

- Reasoner agreement with human annotations gets 87% F1 (yet to check what happens with disagreements). Additional price is paid by mining errors…
- GPT-prompting solution gets 68% F1.
  Some mutualism here, but clear competition in the overall effort…



Looking at the reasoner: Syntax/Semantics

- Syntax: ASP sentences with probabilistic facts.
- Semantics: for each realization of facts, an ASP program.

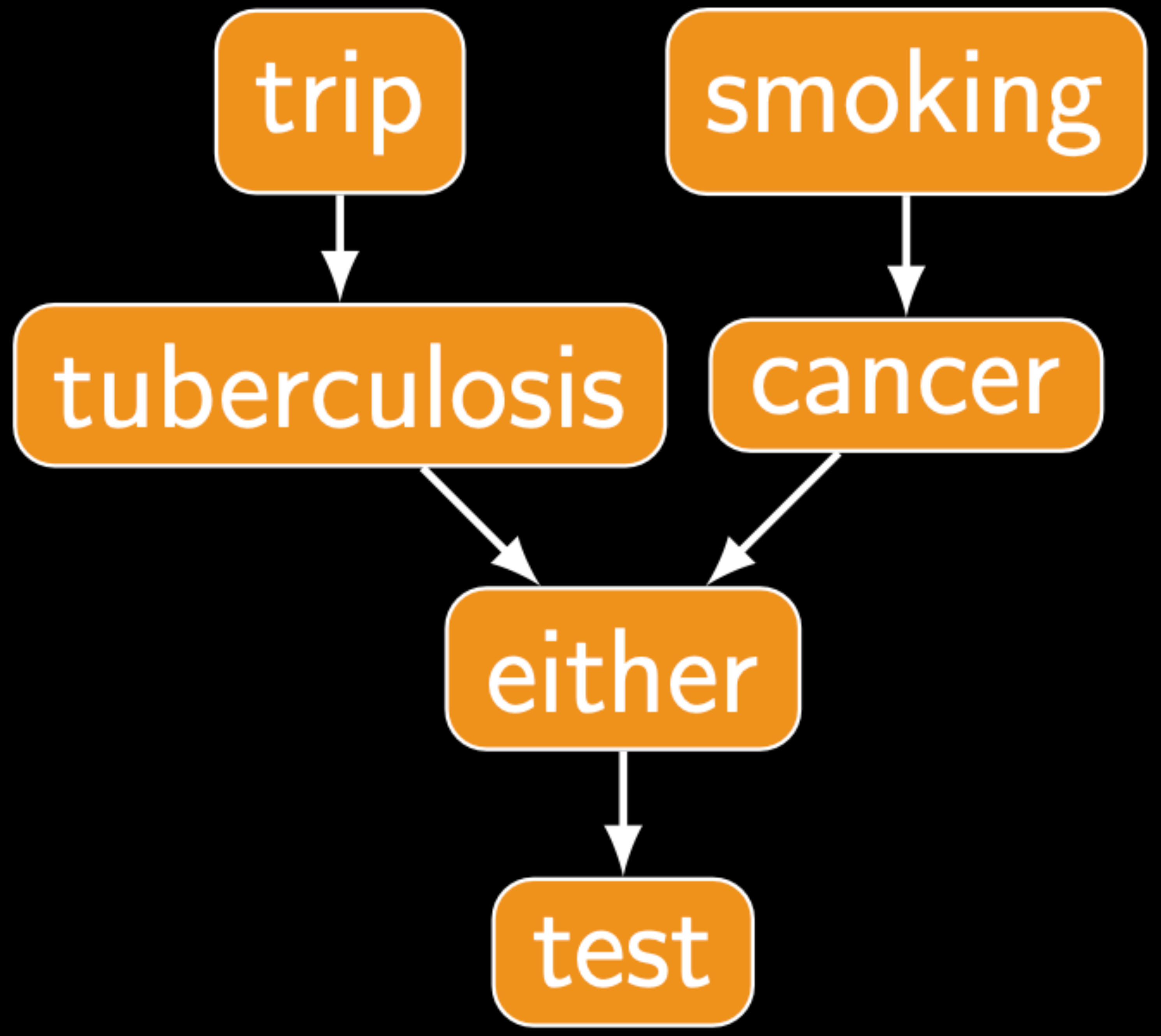
$$0.5 :: A. \qquad 0.5 :: B.$$

$$C :- A, B.$$

- Semantics that can handle cycles.
  - Maxent and credal semantics.

Acyclic PASP

0.01 :: trip.
0.5 :: smoking.
tuberculosis :– trip, a1.
tuberculosis :– **not** trip, a2.
cancer :– smoking, a3.
cancer :– **not** smoking, a4.
either :– tuberculosis.
either :– cancer.
test :– either, a5.
0.05 :: a1. 0.01 :: a2.
0.1 :: a3. 0.01 :: a4. 0.98 :: a5.



Cyclic PASP

$$\text{engineer}(X) :- \text{person}(X), \textbf{not } \text{laywer}(X).$$

$$\text{laywer}(X) :- \text{person}(X), \textbf{not } \text{engineer}(X).$$

$$0.9 :: \text{person}(\text{dilbert}).$$

Tools:

- Probabilistic logic programming:
  - ProbLog (stratified, extended to MaxEnt semantics, compiled inference, learning).
  - PITA, cling, PASTA (credal semantics, set of inference/learning algorithms).
  - PASOCS (credal semantics, exact/approximate).
- Neural:
  - DeepProbLog, NeurASP, dPASP.

dPASP example: “Adding" images

- Challenge: get two MNIST images and determine the numbers. However, training data only contains sum of the numbers.

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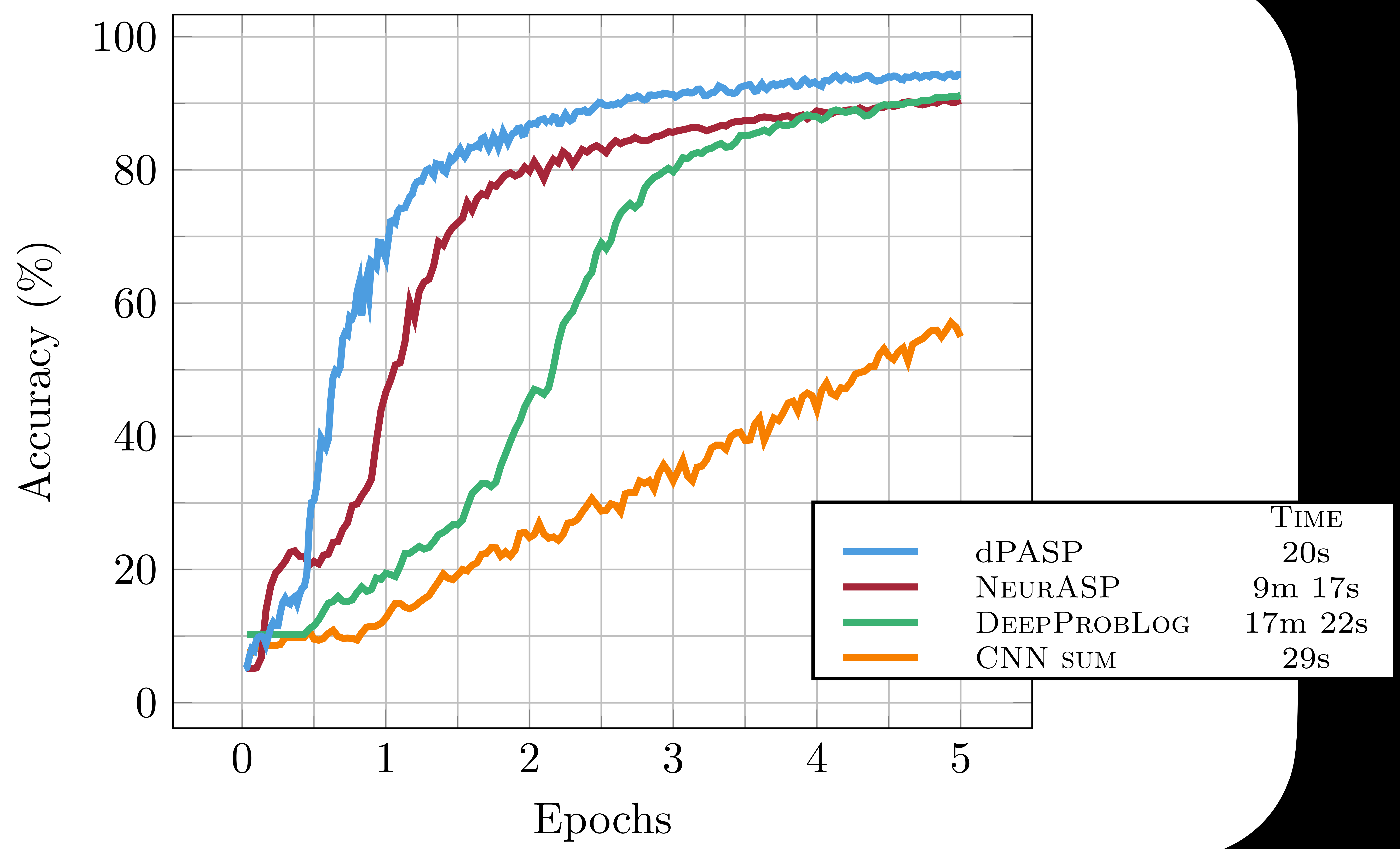
- Learning with dPASP:

$$
\begin{aligned}
&? :: \mathsf{digit}(X, 0..9)\ \mathsf{as}\ \mathsf{@neuralnet}\ \ :-\ \mathsf{image}(X).\\
&\mathsf{add}(X) :-\ \mathsf{digit}(W1, Y), \mathsf{digit}(W2, Z), X = Y + Z.
\end{aligned}
$$

Experiments

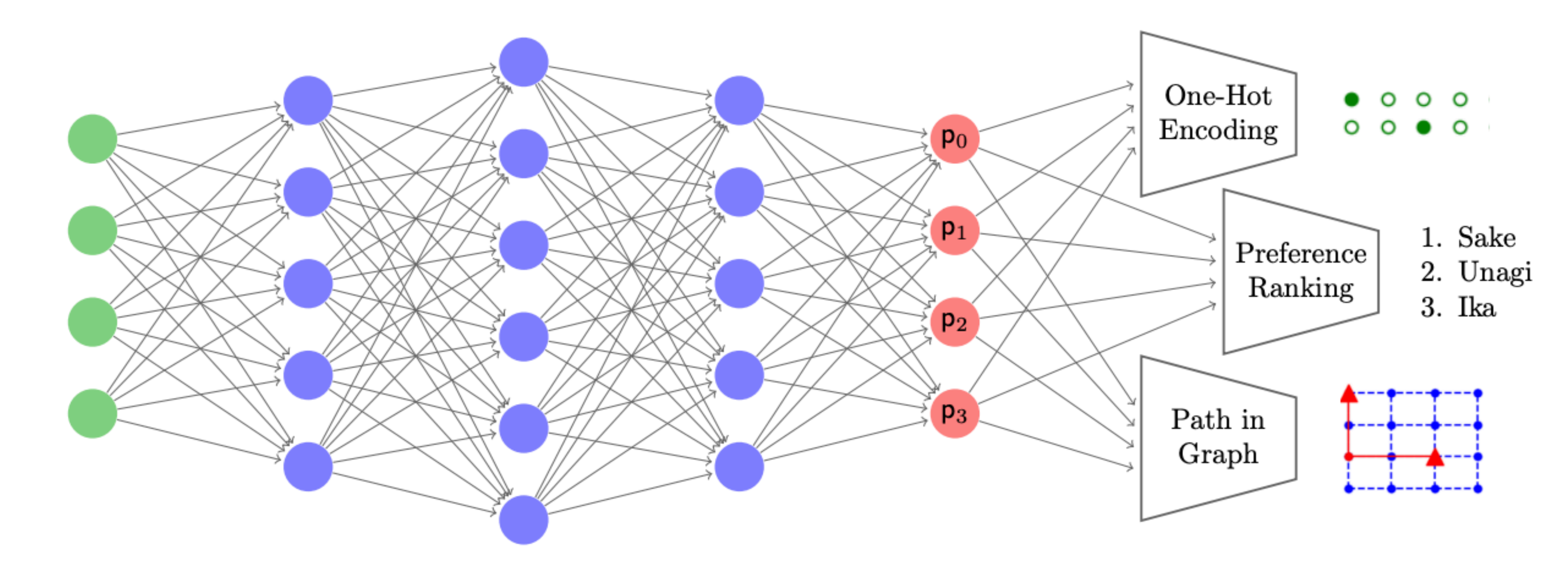


Complexity

	Propositional			Bounded arity			
	Inferential	MPE	MAP	Inferential	Query	MPE	MAP
Acyclic normal	PP	NP	NP^{PP}	PP^{NP}	PP	NP^{NP}	NP^{PP}
Stratified normal	PP	NP	NP^{PP}	PP^{NP}	PP	NP^{NP}	NP^{PP}
Normal, credal	PP^{NP}	NP^{NP}	NP^{PP}	$PP^{NP^{NP}}$	PP^{NP}	$NP^{NP^{NP}}$	NP^{PP}

Semantic losses

- Xu, Zhang, Friedman, Liang, Van den Broek, ICML (2018).
- Constraints compiled into loss.
- Recent package Pylon.
- Constraints based on SAT.

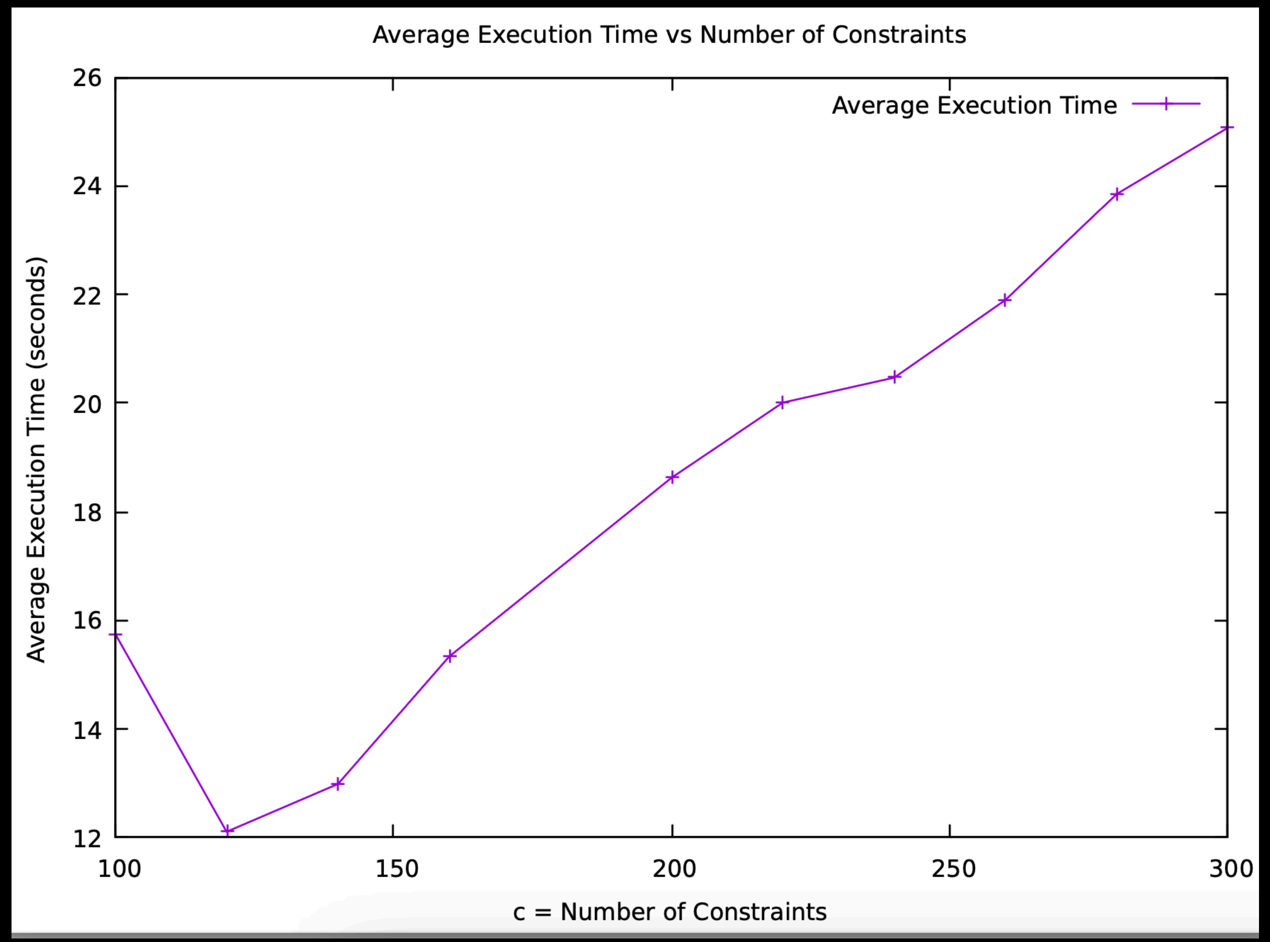


Exercising a bit…

- Strategic-set problems:

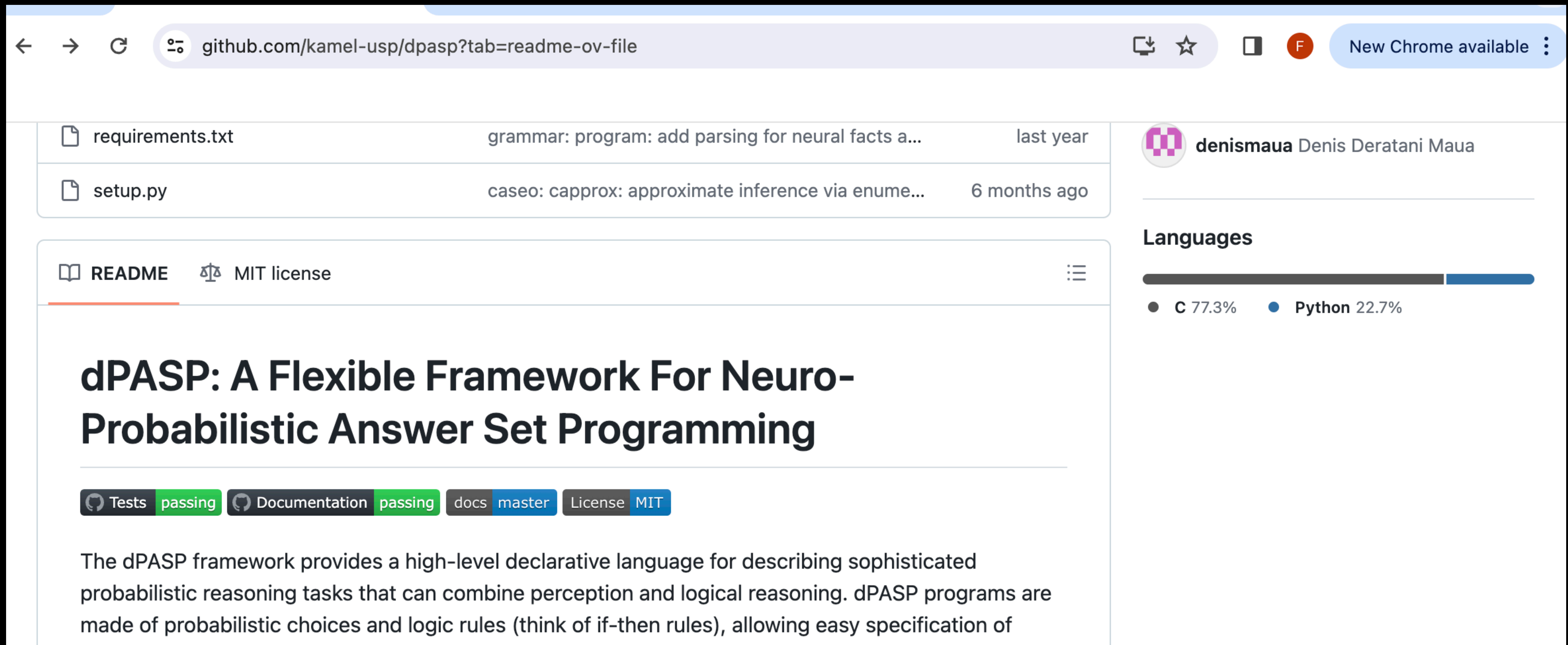
$$\mathsf{strategic}(C1); \mathsf{strategic}(C2) :- \mathsf{produce}(G, C1, C2).$$
$$\mathsf{strategic}(C) :- \mathsf{control}(C, C1, C2, C3),$$
$$\mathsf{strategic}(C1), \mathsf{strategic}(C2), \mathsf{strategic}(C3).$$

- Probabilistic version of QSAT: $\#X : \forall Y : \phi(X, Y)$.
    - 10 probabilistic variables.



dPASP is work in progress…

- Code at https://github.com/kamel-usp/dpasp.
- Tutorial at https://kamel.ime.usp.br/pages/learn_dpasp.
- Technical description at
  Geh, Goncalves, Silveira, Maua, Cozman (2023)
  dPASP: A comprehensive diffrentiable probabilistic answer set programming environment for neurosymbolic learning and reasoning.
  AAAI Workshop.



Conclusion

- Worth looking at settings where a neuro-symbolic mutualism is possible.
  - Argument checking and semantic losses offer interesting challenges.
- Neuro-probabilistic ASP offers a sensible glue for such pieces.
  - To capture underlying knowledge and semantic losses, to build agents that call various modules.
  - Still in need of more integration (syntax/semantics, inferences, learning).

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Thanks!

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