Hybrid Approach for lightblue

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About me

Sora Tagami

Researcher at Bekki Lab, Ochanomizu University

- Research interest: Neural network × Symbolic Hybrid approaches

Full time Software Engineer at Google Japan

- Working for user generated content feature in Google Maps

Why a Hybrid Approach?

Neural Network based approach

Achieved state-of-the-art results in many NLP tasks, becoming a dominant force, especially with the rise of Large Language Models.

Symbolic based approach

Rooted in formal linguistic theories developed since the mid-20th century.

Why a Hybrid Approach?

Reliability
Due to their foundation in sound formal logic, symbolic systems inherently offer a high degree of reliability: if such a system returns a conclusion as 'true', that conclusion is unfailingly guaranteed to be logically true within its defined framework. This means a symbolic system will never assert something false as true.

Neural Network based approach

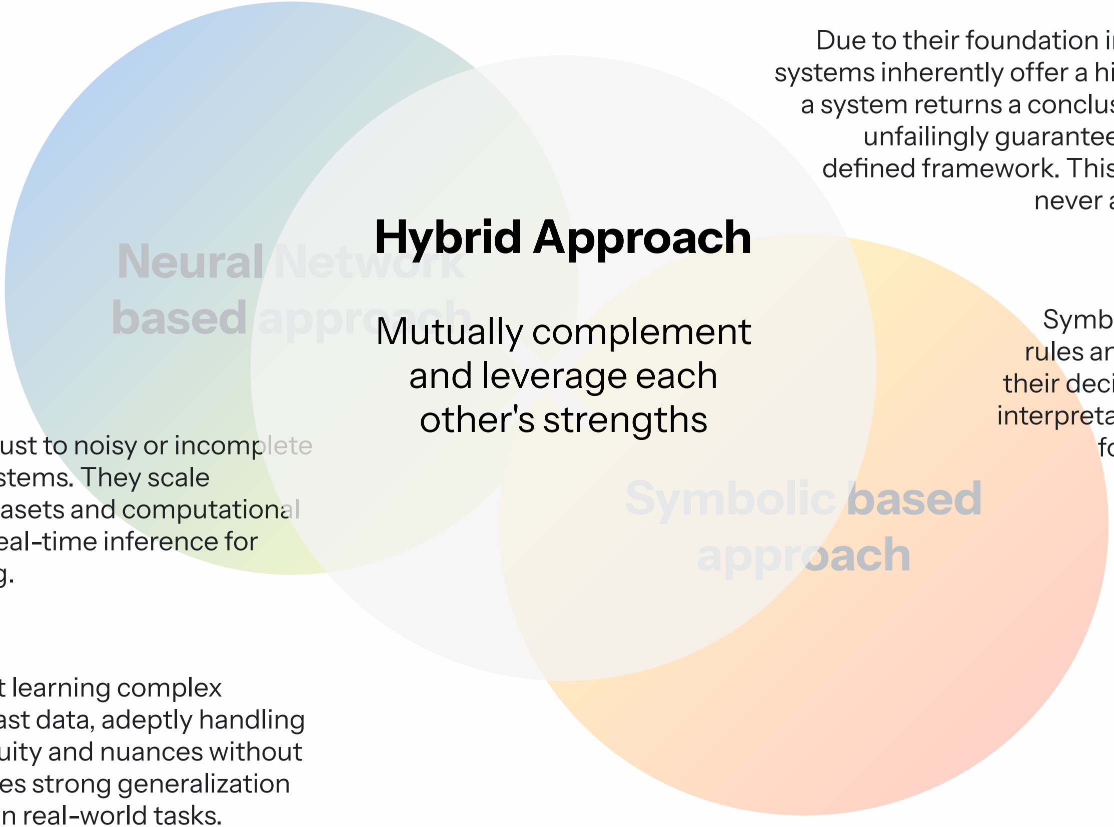
Symbolic based approach

Explainability
Symbolic systems use well-defined rules and explicit knowledge, making their decision-making transparent and interpretable. This traceability is crucial for applications requiring trust, auditability, or debugging.

Scalability
Neural networks are robust to noisy or incomplete data, unlike symbolic systems. They scale efficiently with large datasets and computational power, enabling quick, real-time inference for massive data processing.

Generalizability
Neural networks excel at learning complex patterns directly from vast data, adeptly handling natural language ambiguity and nuances without explicit rules. This enables strong generalization and high performance on real-world tasks.

Why a Hybrid Approach?



Reliability

Due to their foundation in sound formal logic, symbolic systems inherently offer a high degree of reliability: if such a system returns a conclusion as 'true', that conclusion is unfailingly guaranteed to be logically true within its defined framework. This means a symbolic system will never assert something false as true.

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Summary of Hybrid Approach for lightblue

01

Hybrid Approach for Syntax (CCG)

Review recent neural-based research for CCG.

Slide 07

02

Hybrid Approach for Semantics (DTS)

Discuss our current work on integrating neural networks with DTS.

Slide 27

03

hasktorch

Introduce the machine learning framework we are adopting.

Slide 46

Hybrid Approach for Syntax (CCG)

CCG Syntactic Parsing

CCG parser takes 2 steps:

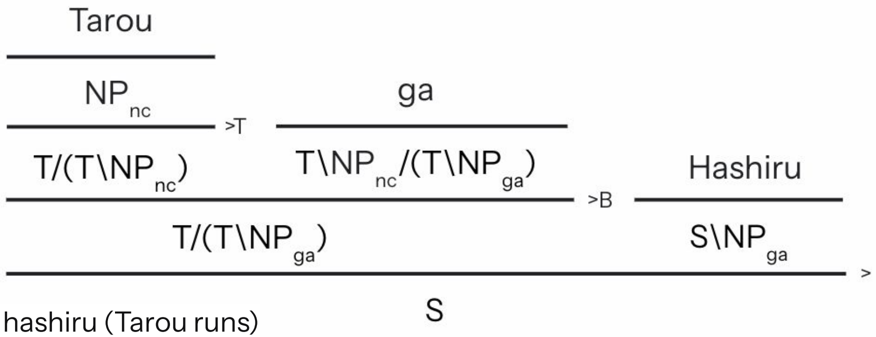
Supertagging

Assigns a lexical category to each word in a sentence.

Parsing

Combines categories using CCG rules to build a derivation tree.

Tarou : NP_{nc}
ga : $T\backslash NP_{nc}/(T\backslash NP_{ga})$
Hasiru : $S\backslash NP_{ga}$



Example: Tarou ga hashiru (Tarou runs)

CCG Syntactic Parsing with Neural Network Suppertagging

- With the evolution of neural networks since the mid-2010s, neural CCG parsing has rapidly developed.
- **Supertagging is almost parsing** (Bangalore and Joshi, 1999).
    - CCG uses **over 1,000 categories**.
    - Due to its importance, many neural methods were developed for supertagging, significantly improving accuracy.

CCG Syntactic Parsing with Neural Network Suppertagging

By the evolution of Neural Network, CCG parsing with Neural Network has been also developing since mid of 2010s.

CCG has **over 1,000 categories** - which has much syntactic information

- It is said that Supertagging is almost parsing (Bangalore and Joshi, 1999).
- Because of its importance, even as neural networks began to develop, many methods utilizing neural networks for Supertagging were created, which significantly contributed to improvements in its accuracy.

Lewis (2021) shows how effective the neural supertagger is:

PARSER	S-TAGGER	P	R	F	CAT	COV.
C&C	Maxent	–	–	85.3	–	99.1
C&C (*w/gold pos*)	Maxent	88.1	86.4	87.2	94.2	99.1
Java C&C (*w/gold pos*)	Maxent	88.0	87.3	87.7	94.3	100.0
Java C&C	Transformer	91.9	91.5	91.7	96.3	100.0

Table 2: Parser accuracy of (Java) C&C on Sec. 00 with different supertaggers.

Early Non-Neural Baselines:
C&C (Clark and Curran, 2004) : A chart-based parser implemented in C++
Java C&C (Clark et al., 2015) : A Java re-implementation with improvements
Maxtent (Clark, 2002) : A maximum entropy supertagger.

P/R/F: Precision, Recall, and F-score over CCG dependencies.
CAT: Lexical category accuracy.

CCG Syntactic Parsing with Neural Network Suppertagging

Lewis and Steedman (2014)
Feed-forward network with embeddings improved CCG supertagging

Xu et al. (2015)
RNNs capture sequence context for improved CCG supertagging

Lewis et al. (2016)
Bi-LSTMs capture long-range dependencies for enhanced supertagging accuracy

Vaswani et al. (2016)
Bi-LSTM-LM uses language model for supertag interactions

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Transformer-based model constructs supertag types from primitives, boosting generalization

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LSTM predicts supertags as **sequences of CCG primitives,** generating novel categories

Liu et al. (2021)
Bi-LSTM generates CCG categories by decomposing them into atomic tag sequences

Prange et al. (2021)
RoBERTa encoder + TreeRNN/AddrMLP generates supertags as trees

Kogkalidis and Moortgat (2023)
A-GCN
Geometry-aware, graph convolutions enhance constructive supertagging via output structure.

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Tian et al. (2020)
BERT + A-GCN enhances supertagging via chunk-based graphs

Yamaki et al. (2023)
Holographic embeddings enable recursive composition for improved supertagging and parsing.

Zhao and Penn(2024)
LLMs (Llama2) for supertagging boosted by repeating input

Xu et al. (2015)
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CCG Syntactic Parsing with Neural Network Suppertagging

Suppertagging Model	Parser	Supertag accuracy	Labeled F1 score
Lewis and Steedman (2014a)	C&C	-	86.11
Xu et al. (2015)	C&C	93.00	87.68
Lewis et al. (2016)	C&C	94.7	88.1
Vaswani et al. (2016)	C&C	94.5	88.32
Clark et al. (2018)	-	96.1	-
Kogkalidis et al. (2019)			
Bhargava and Penn (2020)	C&C	96.00	90.9
Tian et al.(2020)	EasyCCG	96.2	90.58
Liu et al. (2021)	C&C	96.05	90.87
Prange et al. (2021)	C&C	96.22	90.91
Yamaki et al. (2023)	C&C	**96.6**	**92.12**
Kogkalidis and Moortgat (2023)	-	**96.29**	-
Zhao and Penn (2024)	C&C	**96.64**	**92.05**

- Supertagging accuracy has steadily increased with the introduction of new neural models.
- Recent models achieve over **96%** supertagging accuracy on the CCGbank test set.
- Improvements in supertagging directly translate to higher F1 scores for parsing, with recent results exceeding **92%**

TestData: CCGbank (Hockenmaier and Steedman, 2007)
C&C parser: Clark, 2015
Easy CCG: Lewis and Steedman, 2014b

CCG Syntactic Parsing with Neural Network Parsing

- Beyond supertagging, the parsing process itself can be enhanced with neural networks.
- This process requires three key components:
  - **Parsing algorithm**: determines the order in which the categories are put together
  - **Parsing model**: scores each possible analysis
  - **Search algorithm**: efficiently finds the highest-scoring analysis

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Parsing algorithms

- **Chart-based**
  - Uses dynamic programming to store all partial parse results in a "chart," avoiding redundant computations.
  - Was the first algorithm successfully applied to wide-coverage CCG parsing
  - Hockenmaier and Steedman (2002), Clark and Curran (2004)
- **Shift-reduce**
  - Use a stack to build a parse tree. It works by shifting input symbols onto the stack or reducing a recognized sequence on the stack into a non-terminal symbol according to grammar rules.
  - Zhang and Clark (2011), Xu et al. (2014), Ambati et al. (2016)

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Parsing model

- Based on **lexicalised Probabilistic Context-Free Grammars (PCFGs)**
    - Early models that used relative frequency counts to estimate parameters.
    - Hockenmaier and Steedman (2002), Collins (1997)
- **Discriminative, feature-based models**
    - Superseded PCFGs by applying maxent models, similar to those used in tagging.
    - Clark and Curran (2004), Riezler et al. (2002)
- Alternative estimation methods based on **the structured perceptron framework**
    - Provided a simpler estimation technique and was also successfully applied to CCG.
    - Clark and Curran (2007), Collins and Roark (2004)

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Search algorithm

- **Dynamic Programming**
  - Used by early chart-based parsers to find the optimal parse.
  - Hockenmaier and Steedman (2002), Clark and Curran (2004)
- **Heuristic Beam search**
  - Often used by faster shift-reduce parsers, performing well even with small beam widths.
  - Zhang and Clark (2011)
- **A* search**
  - Uses a heuristic function to guide the search, guaranteeing optimality with an admissible heuristic.
  - Lee et al (2016)

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Recent hybrid research

- focuses on replacing the parsing model with a neural network.
- learns to score the actions or derivations proposed by the parsing algorithm.
- adopts parsing and search algorithm varies across different models.

CCG Syntactic Parsing with Neural Network Parsing

Xu (Wenduan) (2016)

LSTM Shift-Reduce CCG Parsing: An **LSTM shift-reduce parser** linearizes parsing history. The LSTMs choose actions, and the model is globally optimized for F1 score.

Lewis et al. (2016)

A Bi-directional LSTM supertagger informs an **A* parser** to find the optimal supertag sequence for a complete parse, without an explicit bi-lexical model

Yoshikawa et al. (2017)

An **A* parser** factors tree probability into **bi-LSTM** supertags and bilexical dependencies

Clark (2021)

A **Transformer** supertagger feeds the Java C&C chart parser. The Transformer also provides span scores for the parser's nodes.

Ambati et al. (2016)

A neural network-based shift-reduce parser uses a feed-forward NN to score actions. It supports both **greedy** and **beam-search**

Lee et al. (2016)

Combines local model with **Tree-LSTM/Bi-LSTM** global model for parse structure. Uses A* decoding with optimality guarantees

Stanojević and Steedman (2020)

This fully **incremental transition-based parser** (based on **RNNG**) uses a global unnormalized model trained with **beam-search** optimization to address identified biases

Yamaki et al. (2023)

A **RoBERTa encoder** with **holographic embeddings** composes phrase-level representations for **span-based parsing** and **supertagging**

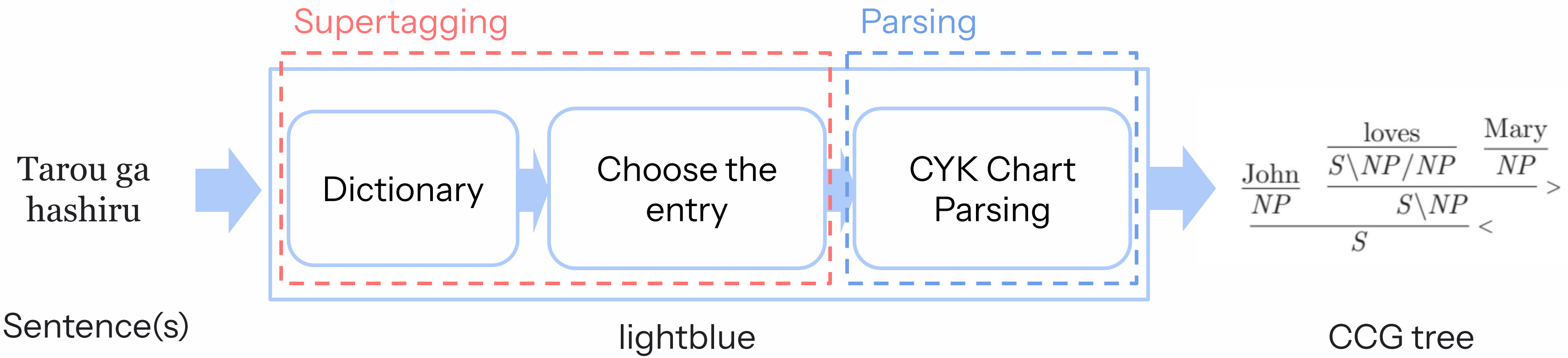
CCG Syntactic Parsing with Neural Network Parsing

Suppertagging Model	Supertag Accuracy	Labeled F1 score
Ambati et al. (2016)	92.03	83.33
Xu (Wenduan) (2016)	94.6	87.8
Lee et al. (2016)	–	88.7
Yoshikawa et al. (2017)	–	88.8
Stanojević and Steedman (2020)	95.6	90.6
Clark (2021)	96.5	**92.9**
Yamaki et al. (2023)	96.60	**92.67**

- The Clark (2021) model, which combines a Transformer with a chart parser, currently achieves the state-of-the-art F1 score of **92.9.**
- Yamaki et al. (2023)'s supertagger combined with the classic C&C parser achieves a very close score of **92.12**.
- Incorporating a neural parser provides a performance boost, but the largest gains come from a high-quality neural supertagger.

CCG Syntactic Parsing in the lightblue

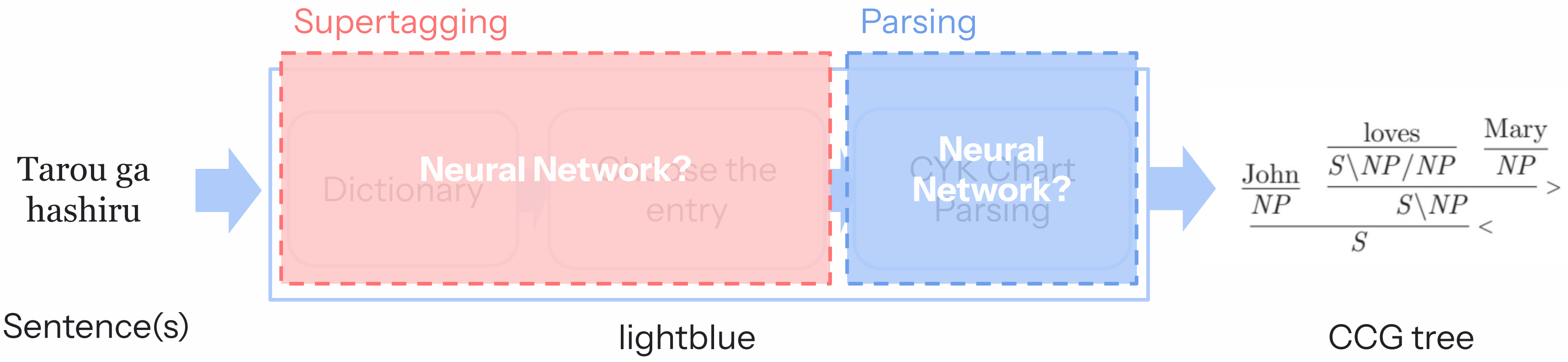
- Supertagging relies on a manually defined lexicon.
  - Juman dictionary (open word)
  - Additional lexical items extracted from Bekki 2010 (closed word)
- lightblue adopts **CYK chart parsing** as a parsing algorithm



Neural-based CCG Syntactic Parsing in the lightblue

How to integrate with Neural network?

- Option 1: Replace the dictionary-based supertagging with a neural CCG supertagger.
- Option 2: Replace the CYK parser with a neural CCG parser.
- Option 3: Replace both components with an end-to-end neural model.



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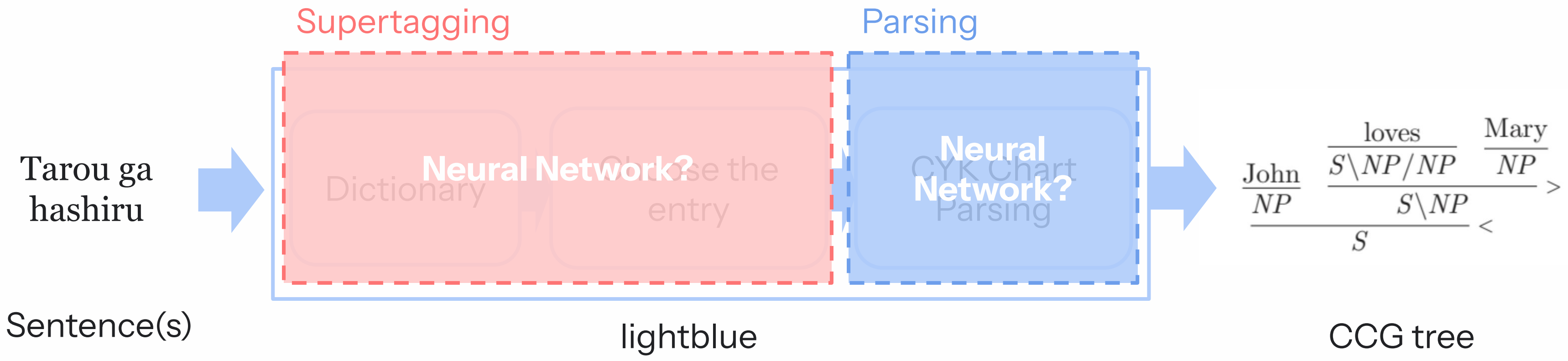
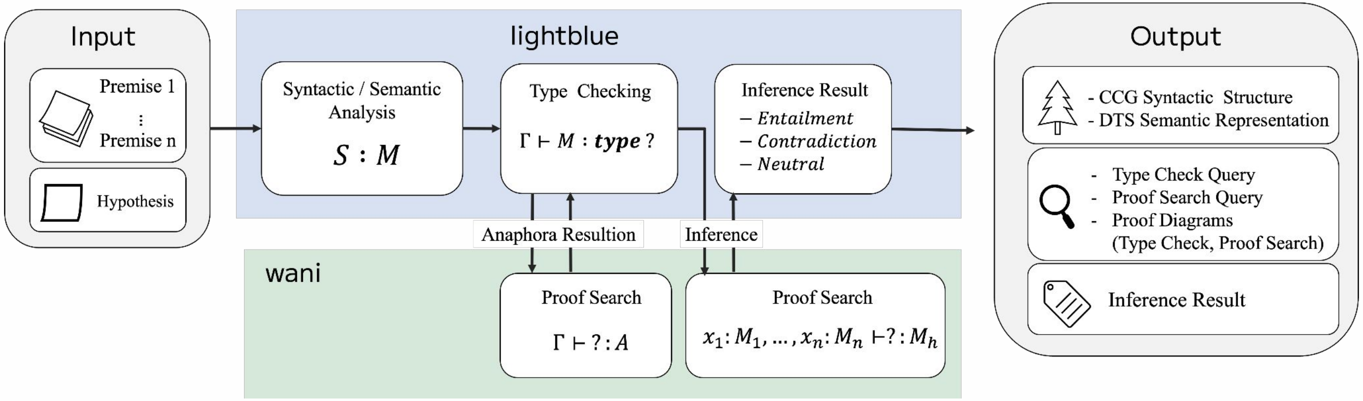
It is not that simple!



Challenge 1: The System Disconnect

- lightblue is a comprehensive system that performs syntax, semantics, and inference.
- However, standard neural parsers are trained only on syntactic information.
  - They cannot receive feedback from downstream components like semantic analysis or NLI.
  - This creates a disconnect, hindering the development of a fully integrated and robust system.



Challenge 2: Data limitation

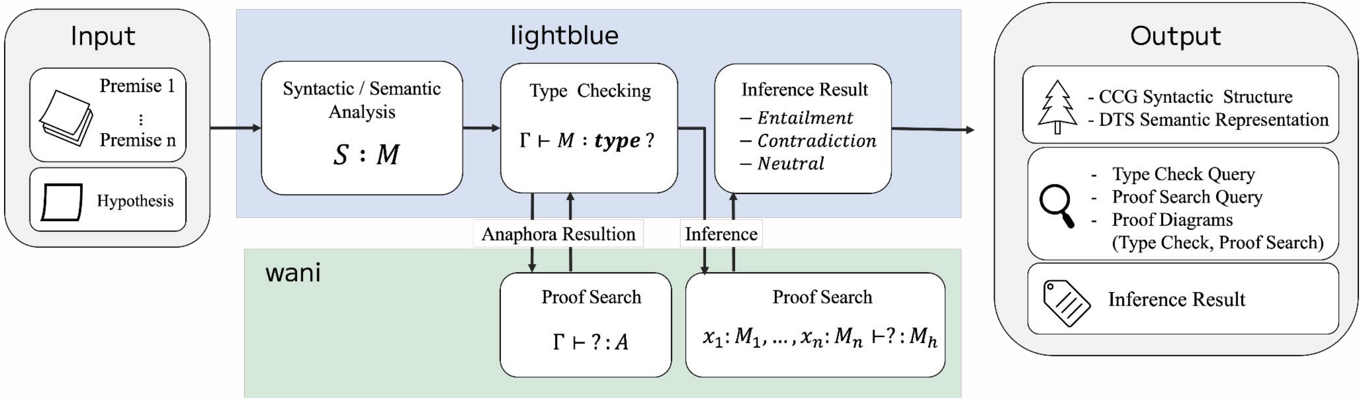
- Current state-of-the-art neural networks achieve high performance scores—96.64 in supertagging and 92.9 in parsing.
  - However, these results are based on the CCGbank test set, which has known issues, such as an abundance of unary rules
  - High scores on CCGbank do not guarantee strong performance on real-world data.
- **Flexibility In lightblue**
  - In contrast, lightblue offers greater flexibility, as its dictionary is not dependent on a specific corpus and can be easily modified.

Hybrid Approach for Semantics

Semantic Components in the lightblue

lightblue provides extensive information about semantics. One of its most important outputs is the result of **Natural Language Inference (NLI)**

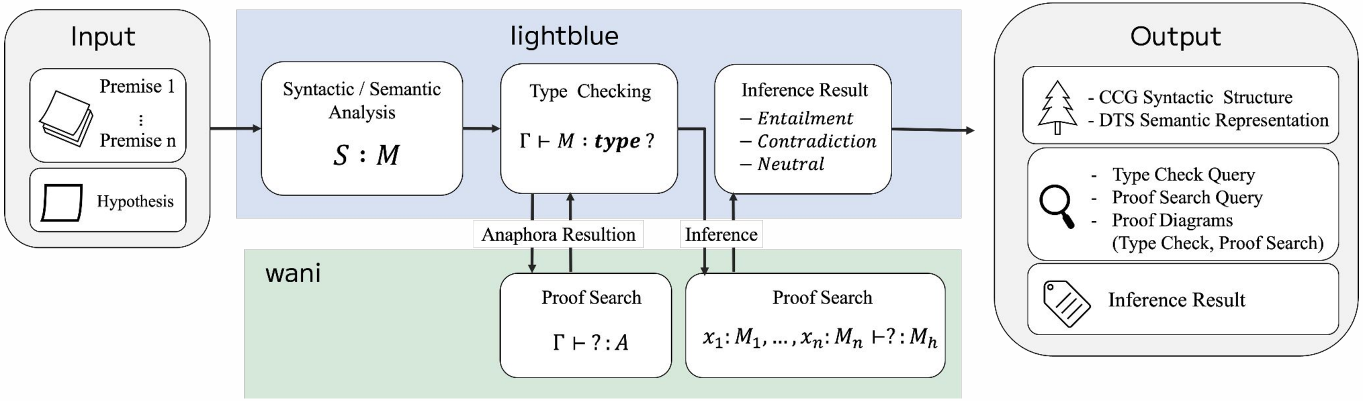
- NLI is the task of determining whether a given premise semantically entails a given hypothesis (Dagan et al., 2013).
- This has broad applications and can benefit many other language tasks, such as question answering, text summarization, and machine reading comprehension.



Semantic Components in the lightblue

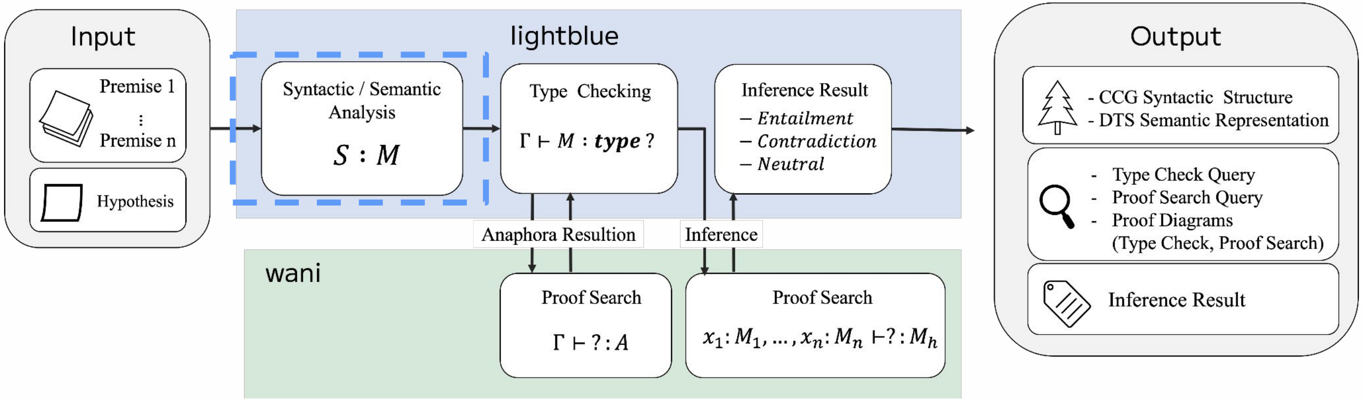
lightblue follows these semantic steps:

1. **Semantic parsing**: Provides a semantic representation based on DTS for both premises and hypotheses.
2. **Type check**: Verifies if the given semantic representations are well-formed (i.e., meet semantic felicity conditions) and resolves anaphora.
3. **NLI**: Determines if the premises entail the hypothesis from the semantic representation.



Hybrid Approach for Semantics: Neural-based Semantic Parsing

- Input: Sentence(s)
- Output: Semantic representation
- Several neural-based parsers for other semantic theories (e.g., Discourse Representation Theory (DRT)) have been published (Liu et al., 2018; Fancellu et al., 2019; van Noord et al., 2020; Yang et al., 2024).



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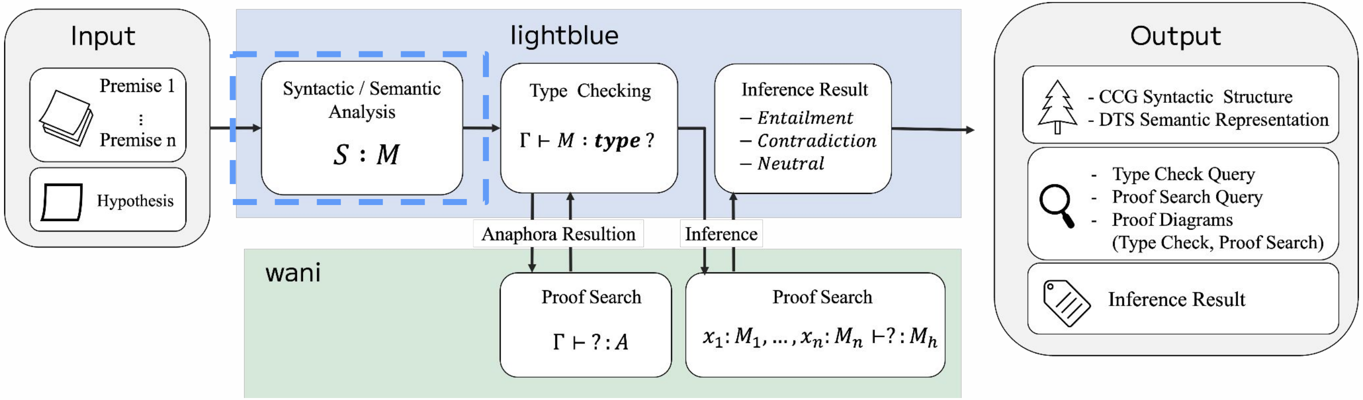
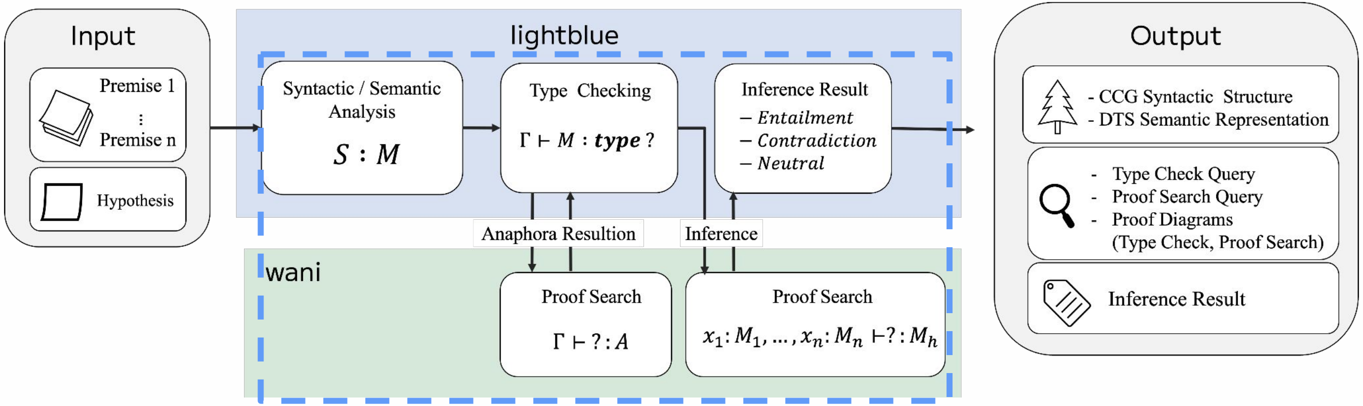
- However, applying the same method is difficult due to the lack of a large, DTS-based corpus.



Hybrid Approach for Semantics: Hybrid models for NLI

- Input: Sentences/Semantic Representation
- Output: YES/NO/UNKNOWN
- Hybrid approaches for NLI systems have been proposed (Cooper 2019, Chen et al. 2021, Larsson, 2022), embedding a neural network into a symbolic approach in some manner.



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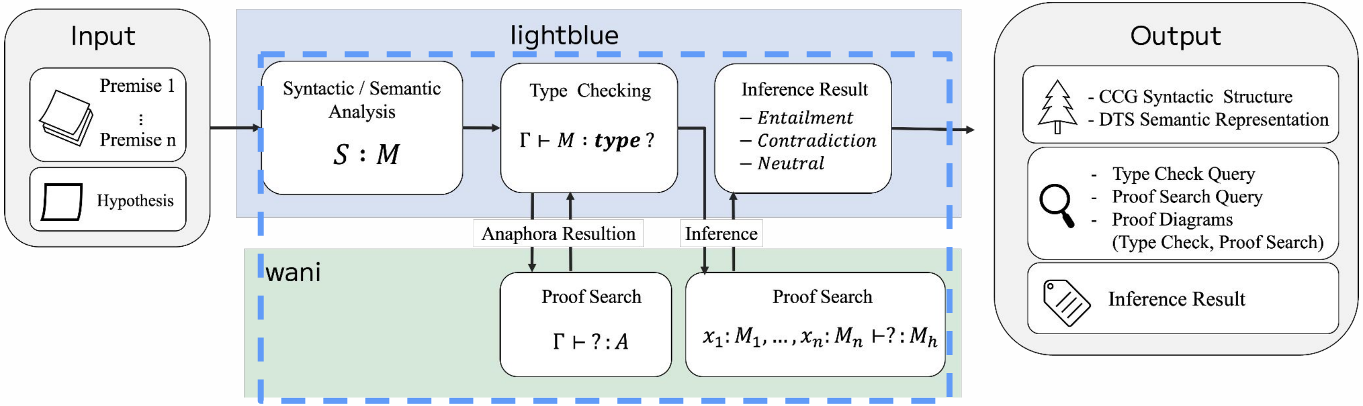
- Hybrid approaches for NLI systems have been proposed (Cooper 2019, Chen et al. 2021, Larsson, 2022), embedding a neural network into a symbolic approach in some manner.
- We are also exploring this method to embed the neural network locally to avoid affecting other components.
- This approach mitigates concerns about data limitations and system disconnect.



Hybrid Approach for DTS based Reasoning

There are two ongoing hybrid project for DTS:

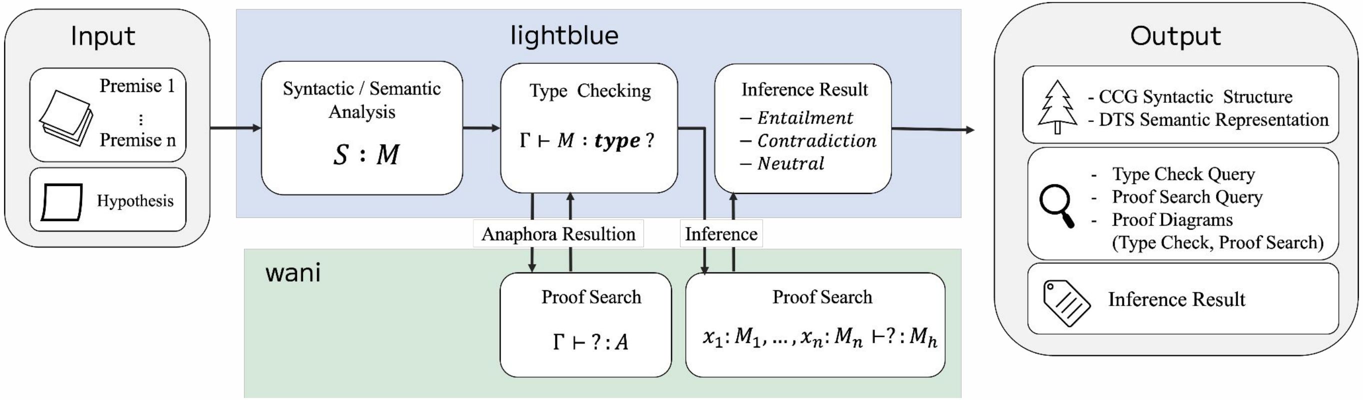
NeuralWani

Optimize wani (automated theorem prover) with neural classifier to choose a next rule to apply in the proof search.

NeuralDTS

Incorporate Neural network into DTS theory: replace predicates with simple neural networks.

Implemented in the wani.



Hybrid Approach for DTS based Reasoning: NeuralWani

wani: An automated prover for DTS (Daido and Bekki 2017)

- During backward inference, wani searches for the next rule that can be applied to the current judgment
- The order in which wani searches for rules is predefined.

$$(\textbf{?})\ \frac{\textbf{?}}{\Gamma \vdash ? : A}$$

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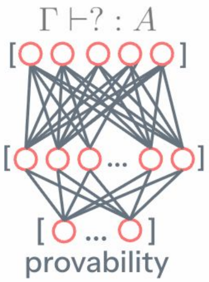
NeuralWani

- Uses a neural classifier to determine the search order for the next rule. It tries the rules output by the classifier in order of provability.



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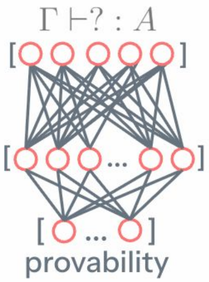
NeuralWani

- Uses a neural classifier to determine the search order for the next rule. It tries the rules output by the classifier in order of provability.
- **Miyagawa et al. (2023)** conducted a preliminary experiment with the full judgment, creating a dataset from the TPTP library and JSeM.
  - The results showed a sufficient F1 score for incorporation into wani.

	Prec	Rec	F1	Supp
Var	0.978	1.000	0.989	45
Con	1.000	1.000	1.000	45
TypeF	1.000	1.000	1.000	24
PiF	1.000	0.978	0.989	45
SigmaF	0.938	1.000	0.968	45
PiI	0.969	1.000	0.984	31
PiE	1.000	0.911	0.953	45
SigmaE	0.957	1.000	0.978	45
SigmaI	1.000	0.500	0.667	2
EnumF	1.000	1.000	1.000	45
IqF	1.000	0.500	0.667	2
IqE	1.000	1.000	1.000	5



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$$\frac{?}{\Gamma \vdash ? : A}$$

$$\Gamma \vdash M : A$$

Hybrid Approach for DTS based Reasoning: NeuralDTS

Bekki (2022) proposes a theory of NeuralDTS for incorporating a Neural Network into DTS.

- The main idea is to represent **names** with vectors and replace **predicates** with a neural classifier.

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- The main idea is to represent **names** with vectors and replace **predicates** with a neural classifier.
- For example...
  - When the lightblue inference system determines if the hypothesis (Cup noodle is cheap) is entailed by the given premise (Every noodle is cheap), the following proof search is conducted.

isCheap(cupNoodle) is a proposition, which is true
if and only if there is a proof for cup noodle being cheap.

Every noodle is cheap
c : (x:e)→isNoodle(x)→isCheap(x)

⊢

Cup noodle is cheap
? : isCheap(cupNoodle)

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Every noodle is cheap ⊢ **Cup noodle is cheap**

$c : (x{:}e) \to \mathrm{isNoodle}(x) \to \mathrm{isCheap}(x) \vdash ? : \mathrm{isCheap}(\mathrm{cupNoodle})$

$$\dfrac{\dfrac{c{:}(x{:}e)\to \mathrm{isNoodle}(x)\to \mathrm{isCheap}(x) \quad \dfrac{}{\mathrm{cupNoodle}{:}e}\,(\mathrm{CON})}{c(\mathrm{cupNoodle}){:}\mathrm{isNoodle}(\mathrm{cupNoodle})\to \mathrm{isCheap}(\mathrm{cupNoodle})}\,(\Pi E) \quad s{:}\mathrm{isNoodle}(\mathrm{cupNoodle})}{? : \mathrm{isCheap}(\mathrm{cupNoodle})}\,(\Pi E)$$

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- The main idea is to represent **names** with vectors and replace **predicates** with a neural classifier.
- For example...
  - When the lightblue inference system determines if the hypothesis (Cup noodle is cheap) is entailed by the given premise (Every noodle is cheap), the following proof search is conducted.
  - Common-sense knowledge like "Every cup noodle is a noodle" must be manually added as a theorem in the current lightblue system.

Every noodle is cheap ⊢ **Cup noodle is cheap**

c : (x:e)→isNoodle(x)→isCheap(x) ⊢ ? : isCheap(cupNoodle)

$$\dfrac{\dfrac{c:(x{:}e)\rightarrow \mathrm{isNoodle}(x)\rightarrow \mathrm{isCheap}(x) \qquad \dfrac{}{\mathrm{cupNoodle}:e}\,(\mathbf{CON})}{c(\mathrm{cupNoodle}):\mathrm{isNoodle}(\mathrm{cupNoodle})\rightarrow \mathrm{isCheap}(\mathrm{cupNoodle})}\,(\Pi E) \qquad \overset{?}{\nabla}\; s:\mathrm{isNoodle}(\mathrm{cupNoodle})}{?:\mathrm{isCheap}(\mathrm{cupNoodle})}\,(\Pi E)$$

Can't infer unless it is contained in the Premises

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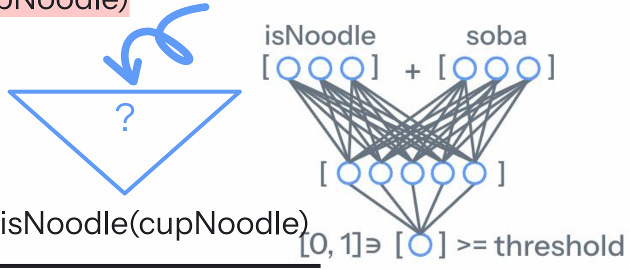
Every noodle is cheap ⊢ **Cup noodle is cheap**

$c : (x:e) \to \mathrm{isNoodle}(x) \to \mathrm{isCheap}(x) \vdash\ ? : \mathrm{isCheap}(\mathrm{cupNoodle})$

Call neural classifier to judge the predicate-entity relationship

$$\dfrac{\dfrac{c:(x:e)\to \mathrm{isNoodle}(x)\to \mathrm{isCheap}(x) \qquad \dfrac{}{\mathrm{cupNoodle}:e}\,(\mathrm{CON})}{c(\mathrm{cupNoodle}):\mathrm{isNoodle}(\mathrm{cupNoodle})\to \mathrm{isCheap}(\mathrm{cupNoodle})}\,(\Pi E) \qquad s:\mathrm{isNoodle}(\mathrm{cupNoodle})}{?:\mathrm{isCheap}(\mathrm{cupNoodle})}\,(\Pi E)$$



Hybrid Approach for DTS based Reasoning: NeuralDTS

Bekki (2022) proposes a theory of NeuralDTS for incorporating a Neural Network into DTS.

- The main idea is to represent **names** with vectors and replace **predicates** with a neural classifier.
- However,
  - If the hypothesis is "Soba is cheap," soba would be a predicate.
  - The current neural classifier cannot determine if "soba is a noodle" (i.e., it cannot compare predicates).

Every noodle is cheap
c : (x:e)→noodle(x)→isCheap(x)

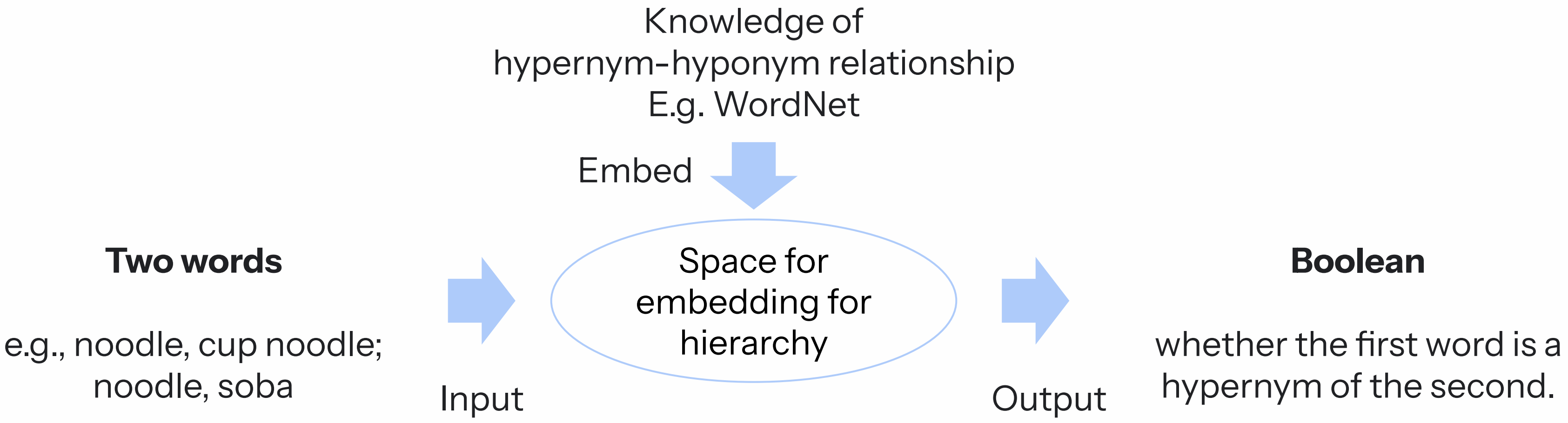
⊢

Soba is cheap
? :soba(x)→isCheap(x)

$$
\dfrac{\dfrac{\dfrac{c:(x:e)\to noodle(x)\to isCheap(x) \qquad \dfrac{}{x:e}\,(\mathrm{Var})}{c(x):noodle(x)\to isCheap(x)}\,(\Pi E) \qquad \dfrac{\dfrac{}{s:soba(x)}\,2 \quad \vdots}{?:noodle(x)}}{?:isCheap(x)}\,(\Pi E)}{?:soba(x)\to isCheap(x)}\,(\Pi I),2
$$

Hybrid Approach for DTS based Reasoning: NeuralDTS

- We plan to embed a hierarchy of general concepts (hypernym-hyponym relationships) into the space.
- Both predicates and names will be embedded in this space.



Hybrid Approach for DTS based Reasoning: NeuralDTS

- We plan to embed a hierarchy of general concepts (hypernym-hyponym relationships) into the space.
- Both predicates and names will be embedded in this space.

Space for embedding for hierarchy

Add the relationship as an axiom

Every noodle is cheap $\vdash$ **Soba is cheap**

$c : (x:e)\to noodle(x)\to isCheap(x) \vdash\ ? : soba(x)\to isCheap(x)$

$$
\dfrac{\dfrac{\dfrac{\dfrac{c:(x:e)\to noodle(x)\to isCheap(x) \quad \dfrac{}{x:e}\,(Var)\,2}{c(x):noodle(x)\to isCheap(x)}\,(\Pi E) \qquad \dfrac{\dfrac{}{s:soba(x)}\,1 \quad \dfrac{\dfrac{}{x:e}\,(Var)\,2 \quad n:(x:e)\to soba(x)\to noodle(x)}{n(x):soba(x)\to noodle(x)}}{n(x)(s): noodle(x)}\,(\Pi E)}{c(x)(n(x)(s)) : isCheap(x)}\,(\Pi E)}{\lambda s.\ c(x)(n(x)(s)) : soba(x)\to isCheap(x)}\,(\Pi I)\,1}{\lambda x.\lambda s.\ c(x)(n(x)(s)) : (x:e)\to soba(x)\to isCheap(x)}\,(\Pi I)\,2
$$

hasktorch

What is the hasktorch?

An open-source project providing a Haskell interface for PyTorch.

- Github: http://github.com/hasktorch/hasktorch
- Web page: http://hasktorch.org/

It has three implementations:

- hasktorch/src/: We are using this version.
  - The most common implementation, where a tensor is treated as a “Tensor” type.
- hasktorch/Typed/
  - This version includes type information for tensors, such as size and numerical type (e.g., int, float). It cannot handle tensors with dynamically changing sizes, like word embeddings.
- experimental/gradually-typed
  - This is still an experimental implementation.

Why do we use hasktorch?

- lightblue is implemented in Haskell.
- While we could train a model with PyTorch and call it from lightblue, using hasktorch directly offers several advantages:
- **Pros**: The codebase for lightblue will be synced with any updates. We can share enum definitions (e.g., Preterm, Rules) and functions between the lightblue and neural models.
- **Cons**: The main drawback is the lack of helpful library, detailed documentation and example implementations.

Hasktorch projects by Bekki lab.

Hasktorch-tools: https://github.com/DaisukeBekki/hasktorch-tools

- Owned by Prof. Bekki
- Provides:
  - Helpful libraries: src/Torch
  - Layers: src/Torch/Layer
  - Example implementation: app/

Hasktorch seminar

- We have held an introductory seminar for undergraduate students and interns from Bordeaux University for the past two years.
- It allows students to learn functional programming and machine learning simultaneously.
- Since there is limited documentation for hasktorch compared to PyTorch, it offers a unique opportunity for students to learn from scratch.

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