Embedding Constraint Reasoning in Machine Learning to Build Generalist Systems

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Intelligent Systems Integrate Learning and Reasoning

Perception

Learning

Knowledge

Reaction

Reasoning

Machine learning:

- **Bottom-up:** Learn predictive models from data
- **Challenging** in providing formal guarantees
- May **violate constraints** in rare and unseen situations

Automated reasoning:

- **Top-down:** Build models from problem description
- **Rigid models**: problem formulation must be agreed a-priori
- **Difficult to adapt** to data distributions

Data

Action

Intelligent Systems Integrate Learning and Reasoning

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Machine learning:

- guarantees
- May **violate constraints** in rare and unseen situations

Automated reasoning:

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- **Difficult to adapt** to data distributions

Big challenge:
How to **integrate** learning with reasoning

Data

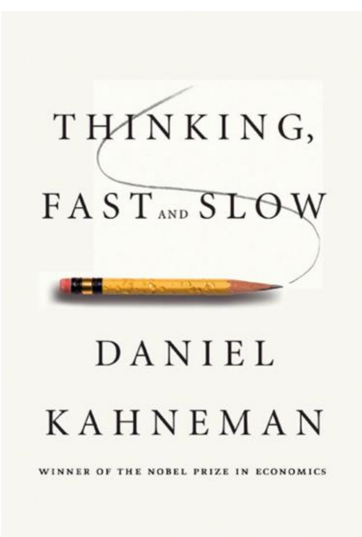
Action

Generalist Systems, Think Fast and Slow

Input Specifications:
- Add a blue microwave right of the oven
- Add a green toaster left of the oven and below the sink

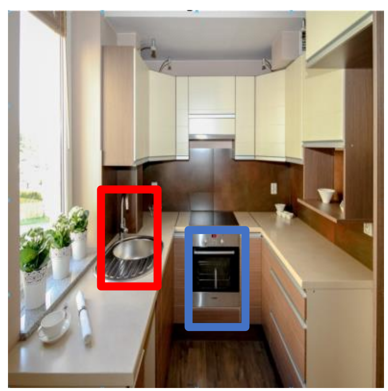
Reasoning *&* ***learning*** *are in charge of different cognitive systems.*

Need both for building a generalist AI.



Learning

System 1
perception
(fast thinking)



Reasoning
+ Learning

System 2
planning &
generation
(slow thinking)

Data-driven Operational Research

- Service Vehicle Dispatching
  - Recommend dispatching routes which (i) satisfy daily delivery requests; (ii) meet implicit preferences
  - Constraint reasoning along (e.g., solving TSP) cannot learn implicit preferences from data
  - Machine learning-based recommendations cannot meet daily requests

- <u>CO</u>nstraint <u>R</u>easoning <u>E</u>mbedded Learning (CORE) as a **combined ML + Reasoning** approach

- Valid routes: **1% (pure ML) → 100%**
- Satisfy drivers’ utilities well

Program Synthesis from Natural Language

If-then program synthesis

Input: SMS me to park in the garage if it snows tomorrow.

Output:

Trigger (If)	Action (then)..
Channel: Weather	Channel: SMS
Function: Snow tomorrow	Function: send message "park in the garage"

Text2SQL query synthesis

Input Table:

	Player	No.	Position	School
0	Antonio	21	Guard-Forward	Duke
1	Voshon	2	Guard	Minnesota
2	Marin	3	Guard-Forward	Butler CC

Input Query:

How many schools did player number 3 play at?

Output SQL Query:

SELECT COUNT "School" WHERE "No." = "3"

agg-op sel-col cond-col cond-op cond-val

- **Challenging machine learning** problem: learn a program from natural language; pure ML cannot satisfy syntactic or semantic rules.

- **Reasoning** can produce valid programs, but cannot understand natural language.

- **CORE machine learning + reasoning**

  if-then programs generation: validity 88% → **100%,** 2% ↑ in accuracy.
  Text2SQL: validity 83.7% → **100%,** 4.2% ↑ execution accuracy, 1.9% ↑ logic accuracy

Design Generation

Existing Kitchen Env:

Input Specifications:

- Add a blue microwave right of the oven
- Add a green toaster left of the oven and below the sink

(stated in propositional logic)

- Good designs need to meet industry standards and user needs, while capturing subtle aspects such as aesthetics and convenience.
- **Complete constraint reasoning approach**: satisfy design specifications, but cannot capture subtle aspects. In fact, cannot be encoded in objective functions.
- **Complete ML approach**: generate beautiful designs, but cannot meet specifications.

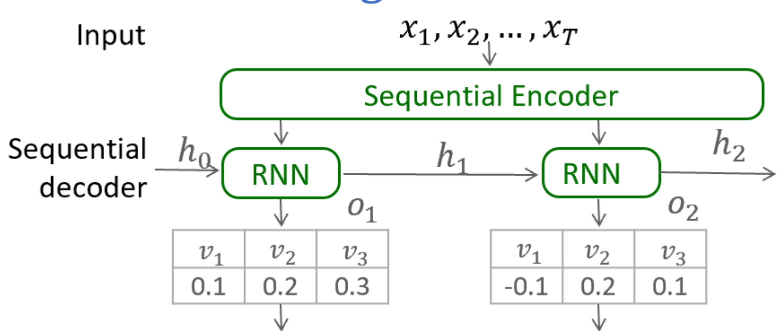
Baseline (Stable Diffusion)

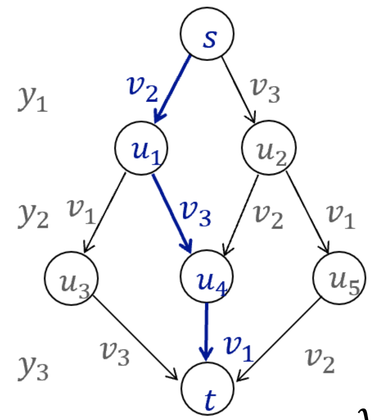
Ours (CORE)

Technical Approach

CORE framework

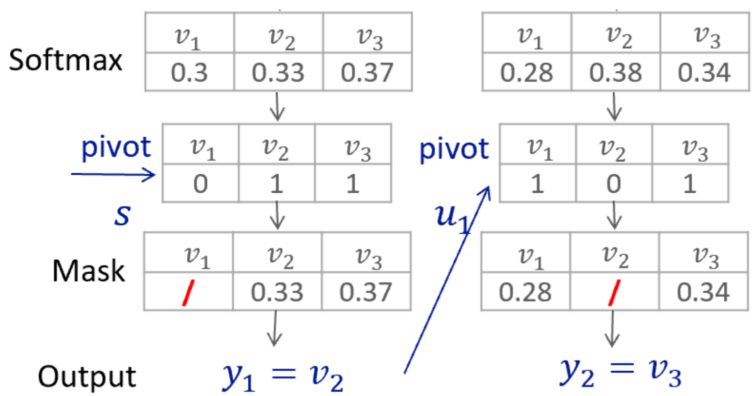
Machine Learning





Decision Diagram

y_1, y_2, y_3 all different; $y_1 \neq v_1$



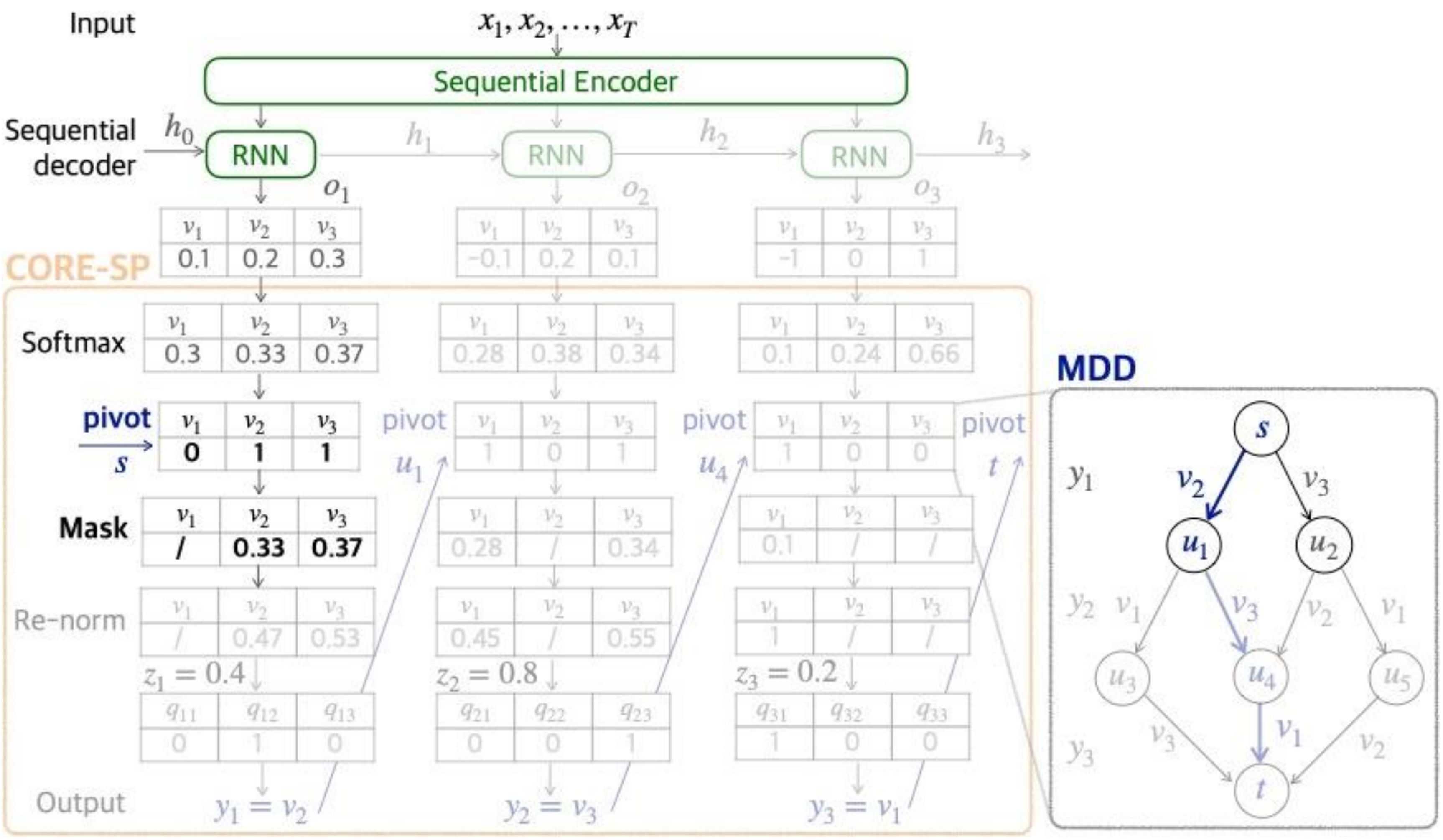
Constraint Reasoning

Compiled from Decision Diagrams; **embed** as a fully differentiable layer; filter out infeasible solutions.

(1)ML with safety, correctness, and/or fairness **assurances**.

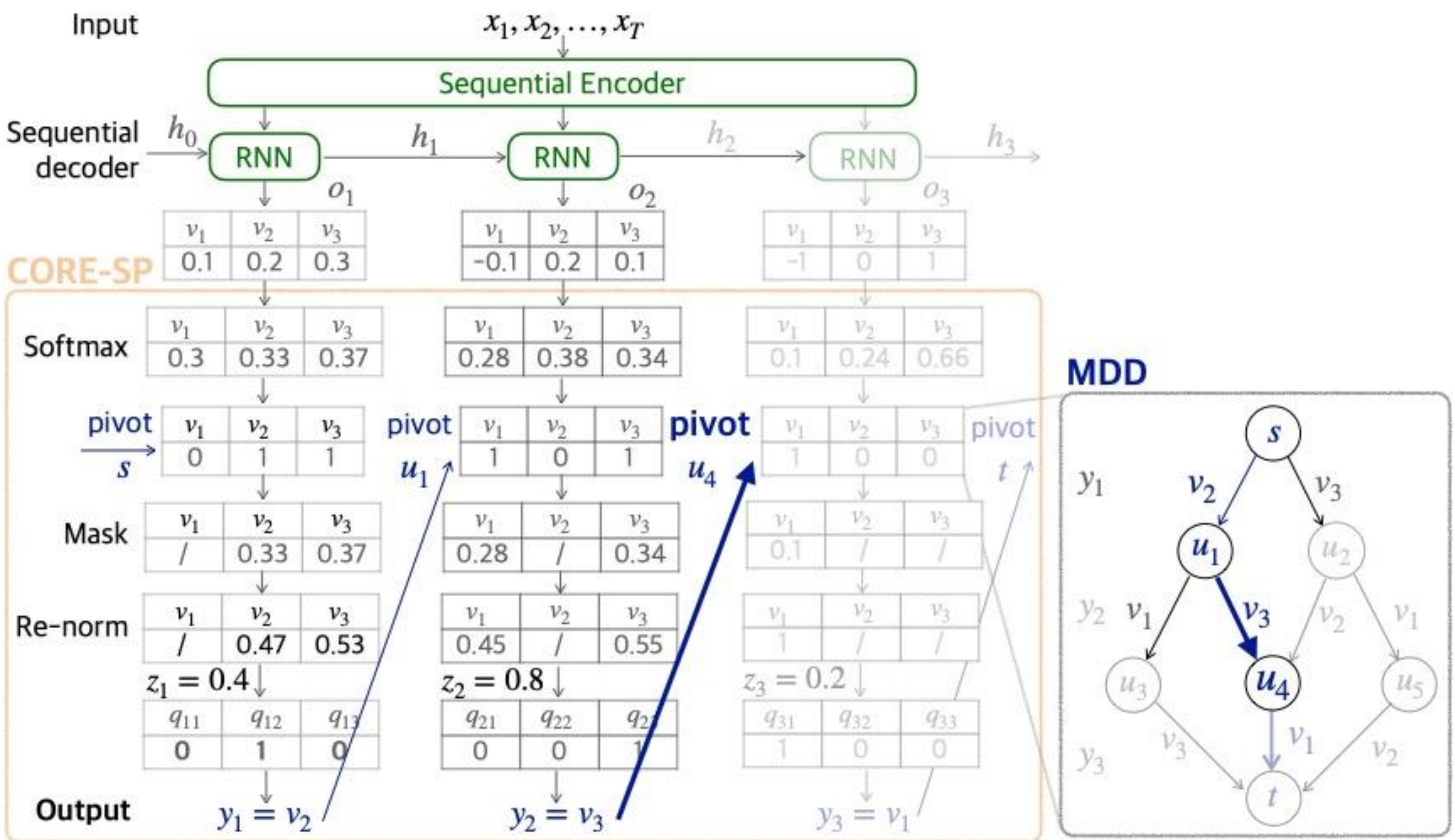
(2)Boost performance: learn faster, more accurate predictions.

CORE Filters Invalid Actions on MDD



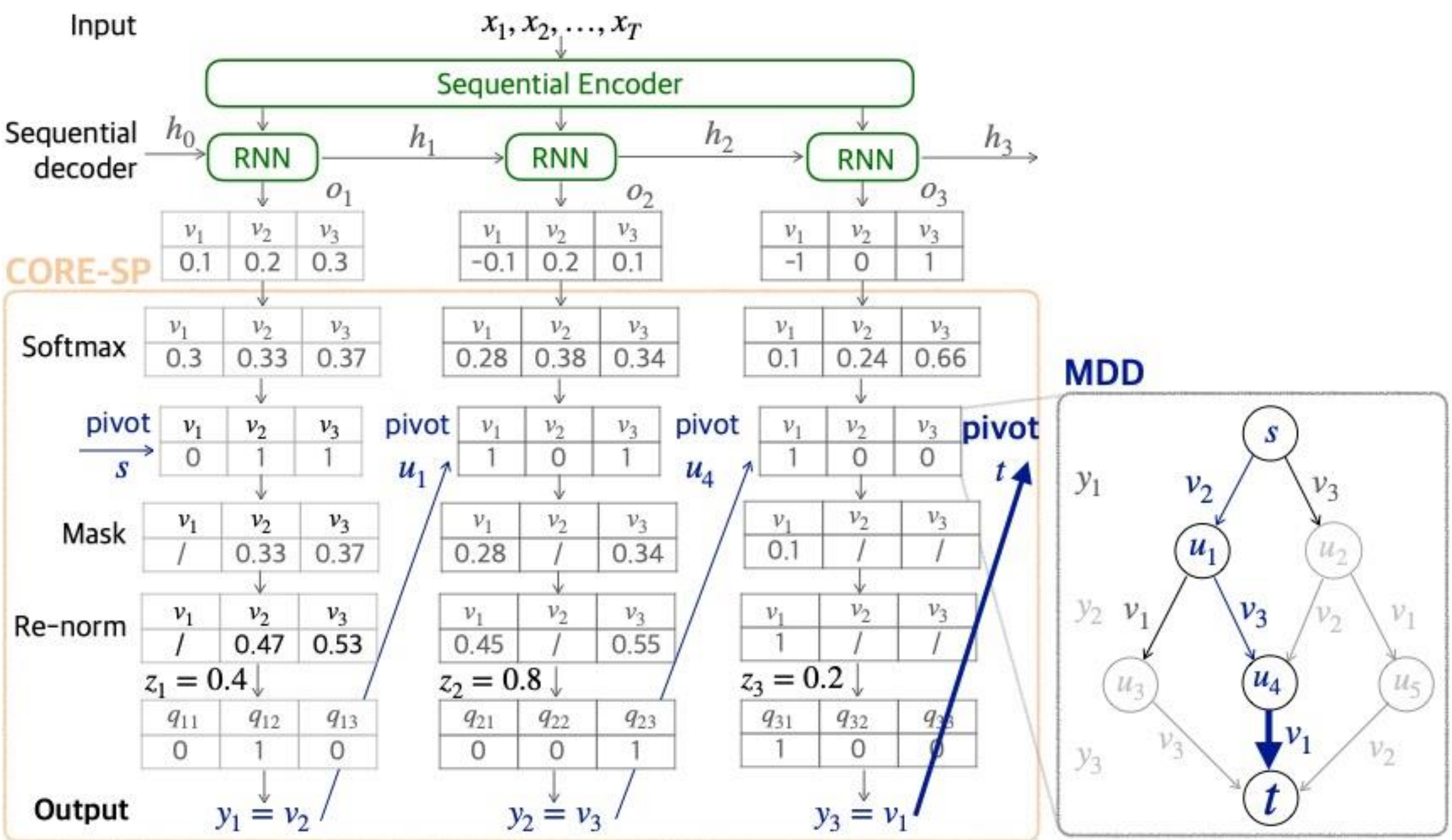
The MDD enforces Constraints C over output from the Seq2seq model.

CORE Filters Invalid Actions on MDD



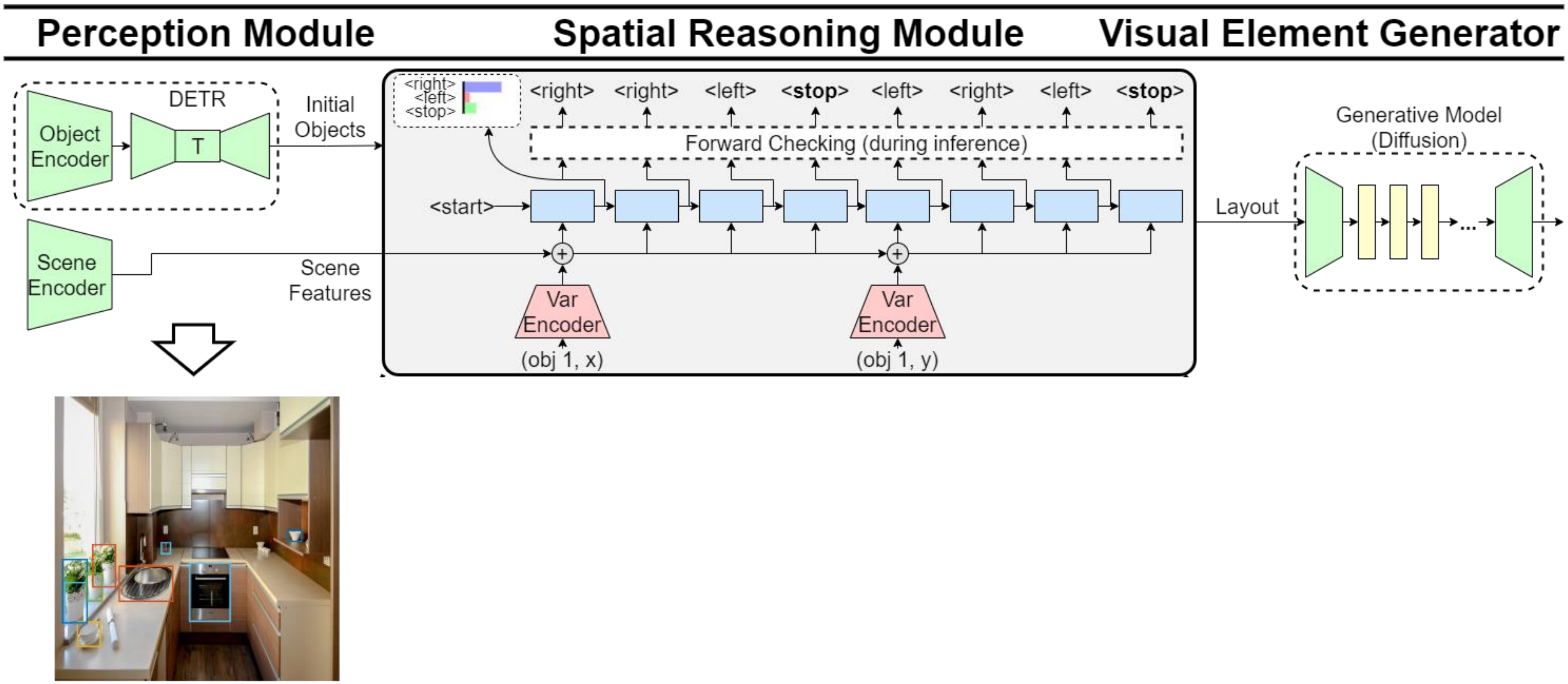
Pivot change from u_1 to u_4

CORE Filters Invalid Actions on MDD

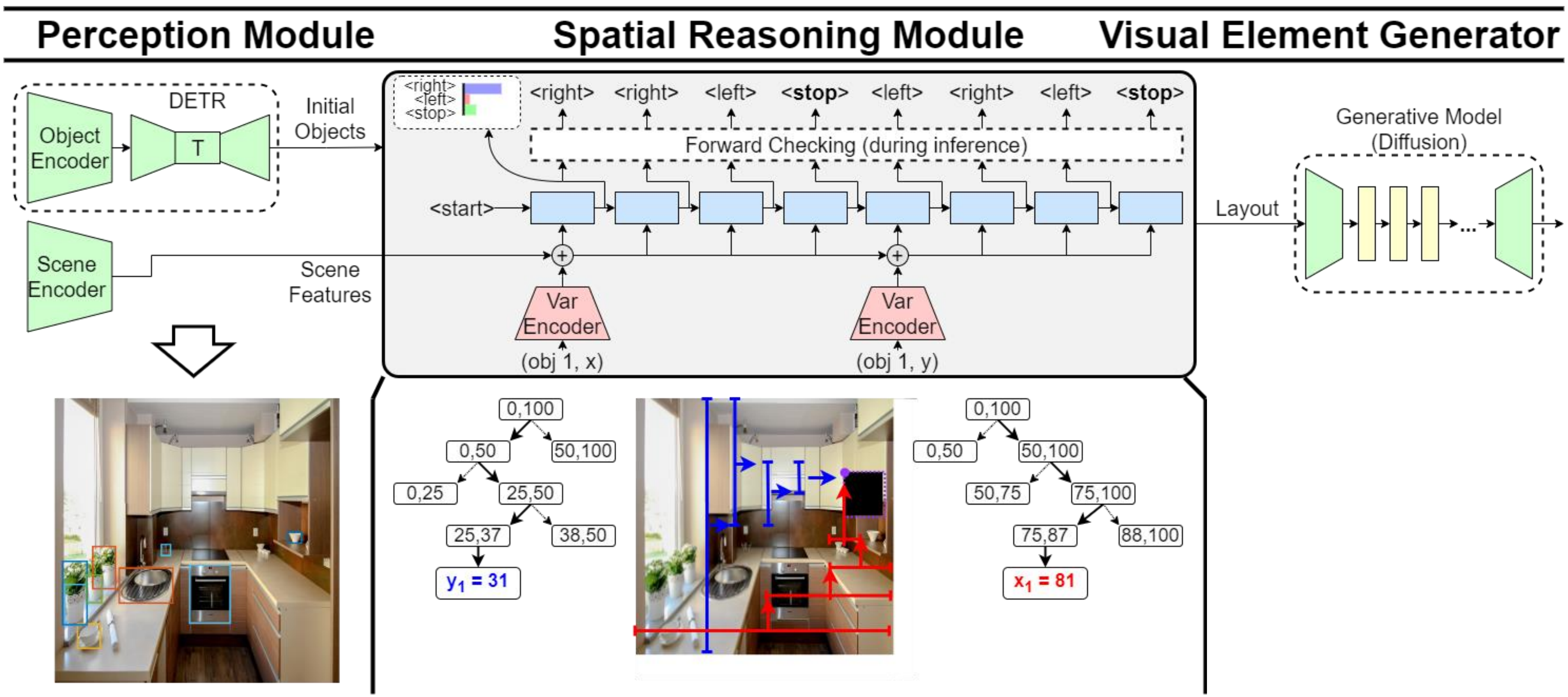


Pivot change from u_4 to t

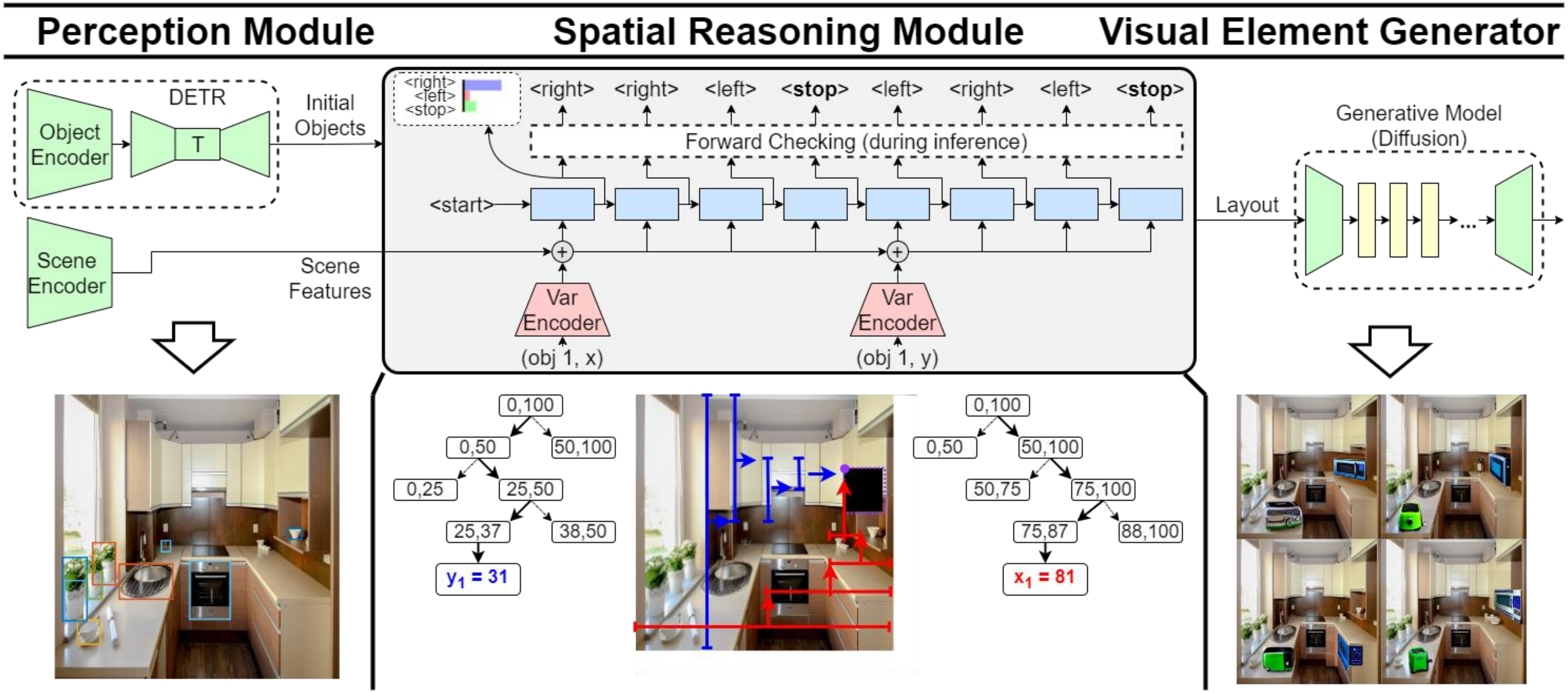
CORE Applied to Design Generation



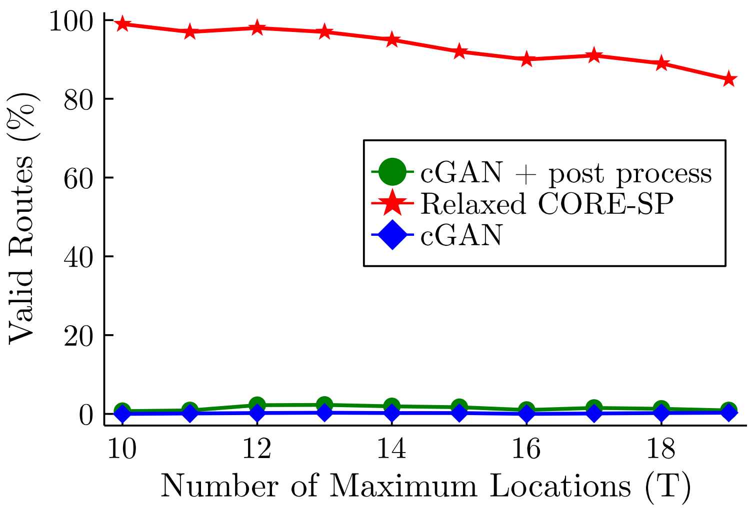
CORE Applied to Design Generation

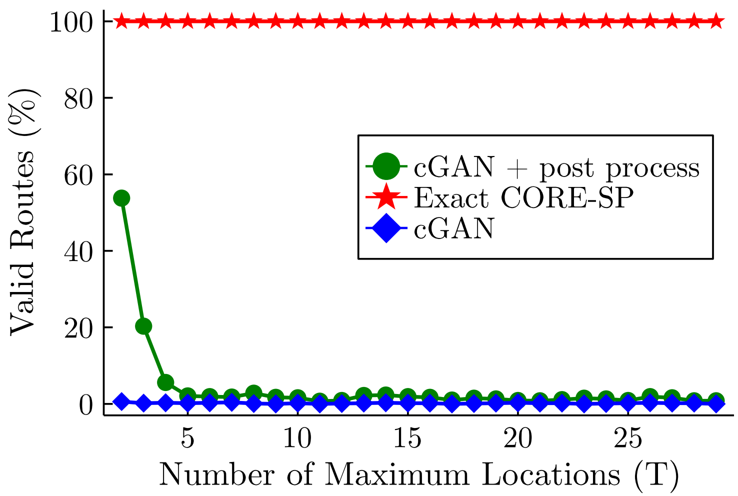


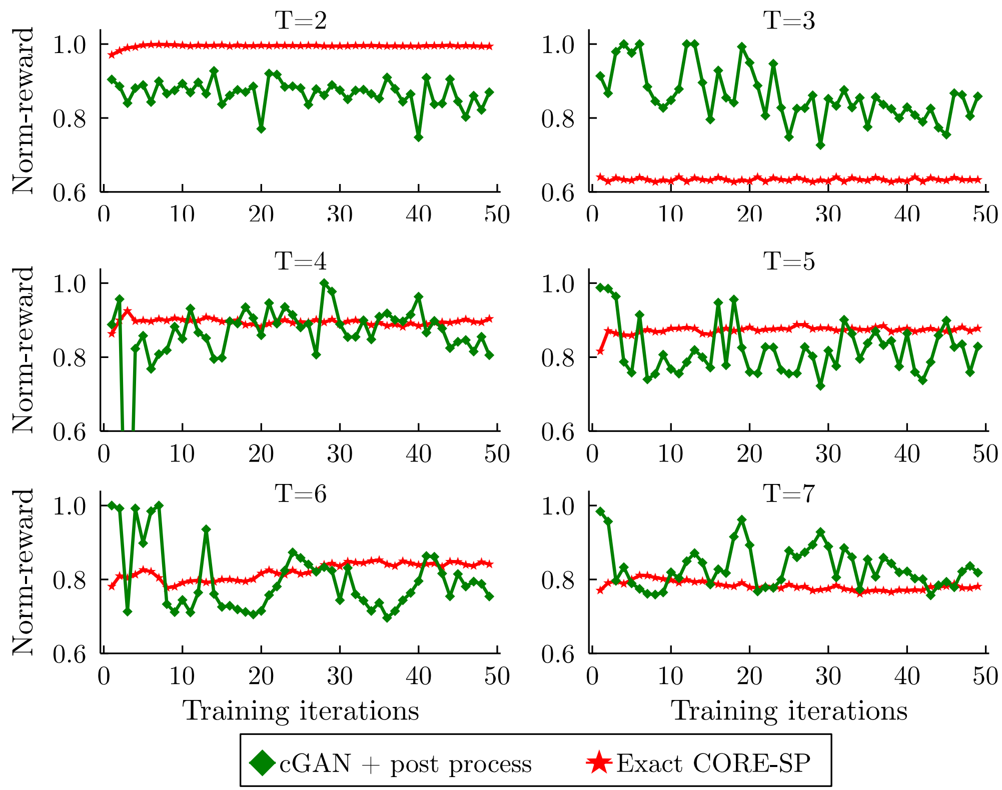
CORE Applied to Design Generation

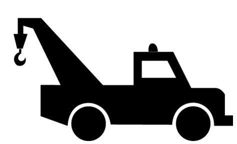


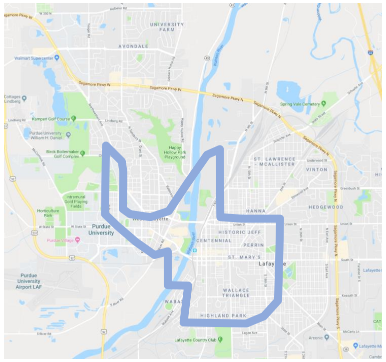
Service Vehicle Dispatching





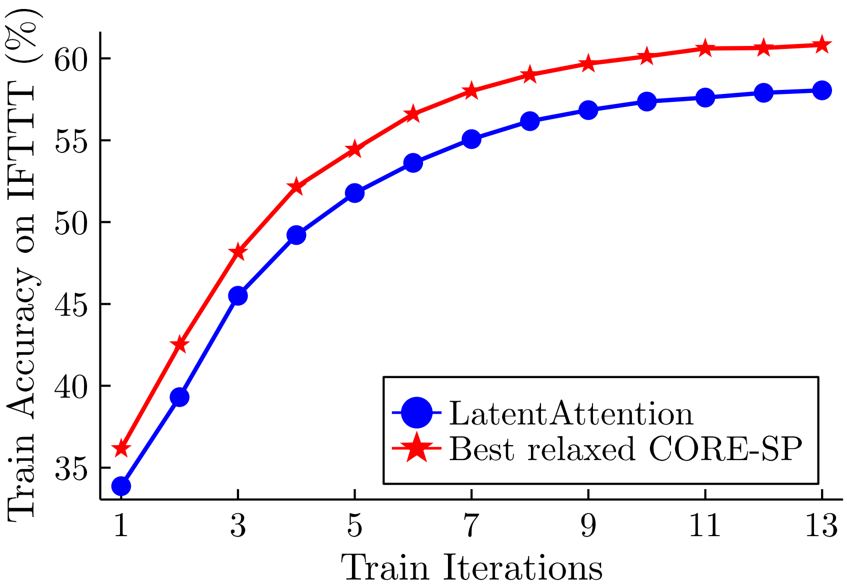


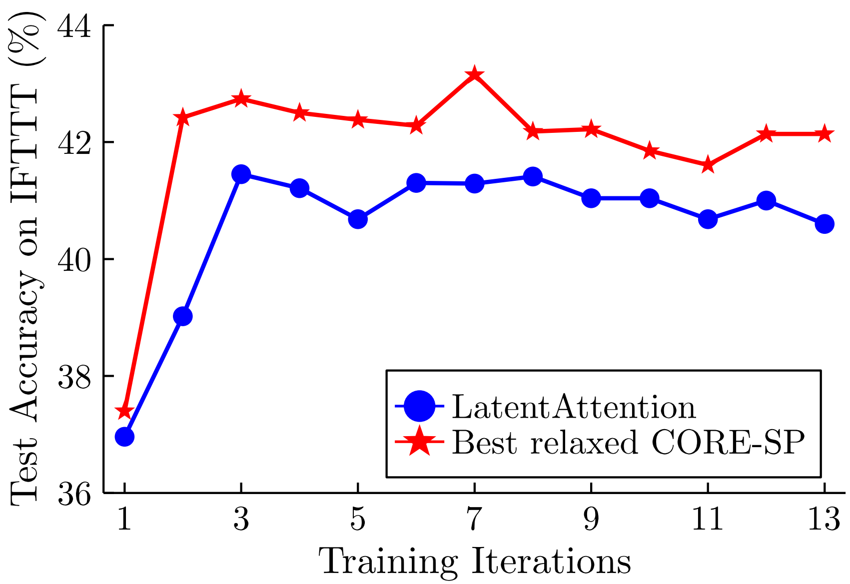




If-then Program Synthesis

	IFTTT			Zapier		
Methods	Width	Accuracy	Valid (%)	Width	Accuracy	Valid (%)
LatentAttention	N/A	42.17%	87.51%	N/A	31.74	88.00%
+best relaxed CORE	80	**44.12%**	**99.19%**	1200	**34.28**	**99.53%**
+ exact CORE	111	**43.07%**	**100%**	1353	**32.83**	**100%**





Program Synthesis from Natural Language

Text2SQL Prediction:

Input Table:

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Input Query:

How many schools did player number 3 play at?

Output SQL Query:

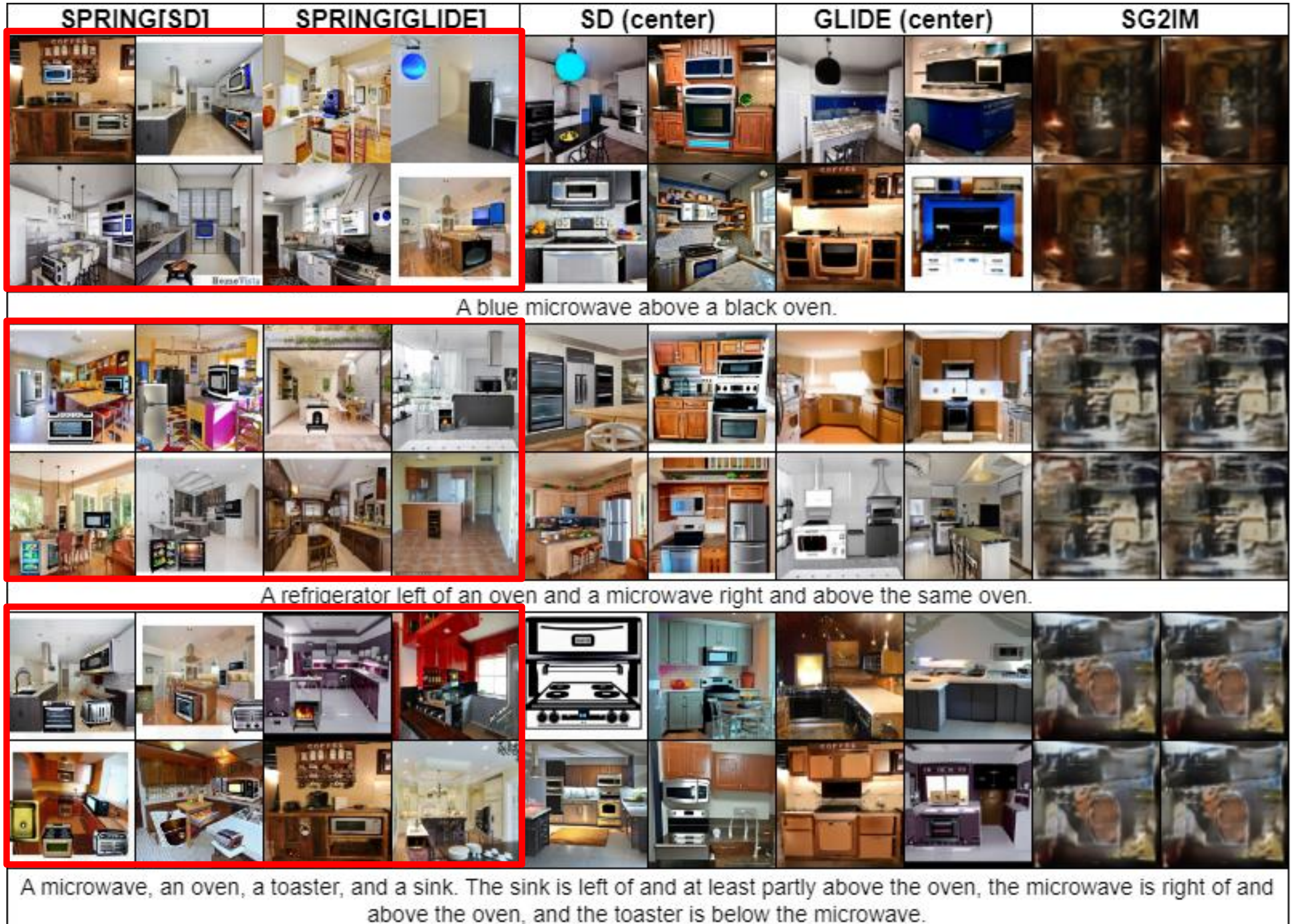
SELECT COUNT “School” WHERE “No.” = “3”

agg-op sel-col cond-col cond-op cond-val

Accuracy per component	Full test set SQLNova	Full test set CORE-SP	Moderate test set SQLNova	Moderate test set CORE-SP	Hard test set SQLNova	Hard test set CORE-SP
`sel-col`	96.3%	96.3%	96.4%	**97.0%**	96.6%	**97.7%**
`agg-op`	**89.8%**	89.7%	75.7%	**77.8%**	75.4%	**75.8%**
#`WHERE`	**98.1%**	97.9%	98.5%	**98.6%**	**98.9%**	98.5%
`cond-col`	93.6%	93.6%	**94.0%**	93.8%	93.6%	**93.7%**
`cond-op`	96.7%	**96.9%**	89.8%	**91.6%**	84.8%	**87.9%**
`where-val-idx`	94.5%	**94.8%**	89.4%	**92.3%**	86.7%	**87.5%**
`where-val`	94.7%	**94.9%**	89.3%	**92.2%**	86.4$	**87.1%**

Overall Accuracy	Full test set SQLNova	Full test set CORE-SP	Moderate test set SQLNova	Moderate test set CORE-SP	Hard test set SQLNova	Hard test set CORE-SP
Logical Accuracy	79.3%	**79.9%**	61.6%	**65.8%**	58.3%	**62.5%**
Execution Accuracy	85.5%	**86.1%**	75.4%	**79.1%**	76.1%	**78.0%**
Valid SQL	99.3%	**100.0%**	94.3%	**100%**	83.7%	**100%**

CORE for Design Generation



Conclusion

- Presented three application domains which need tight integration of machine learning with automated reasoning
  - Data-driven Operational Research
  - Program Synthesis from Natural Language
  - AI-driven Design Generation

- Demonstrated CORE as a hybrid learning + reasoning approach to
  - Generation structures satisfying constraints
  - Boost learning performance (higher accuracies, learning faster generalizing better)

- Future directions
  - Explore richer set of constraints; e.g., constraints stated in natural language
  - Complex constraint satisfaction problems beyond reach of exact decision diagrams.