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Evaluating LLM Reasoning in the Operations Research Domain with ORQA

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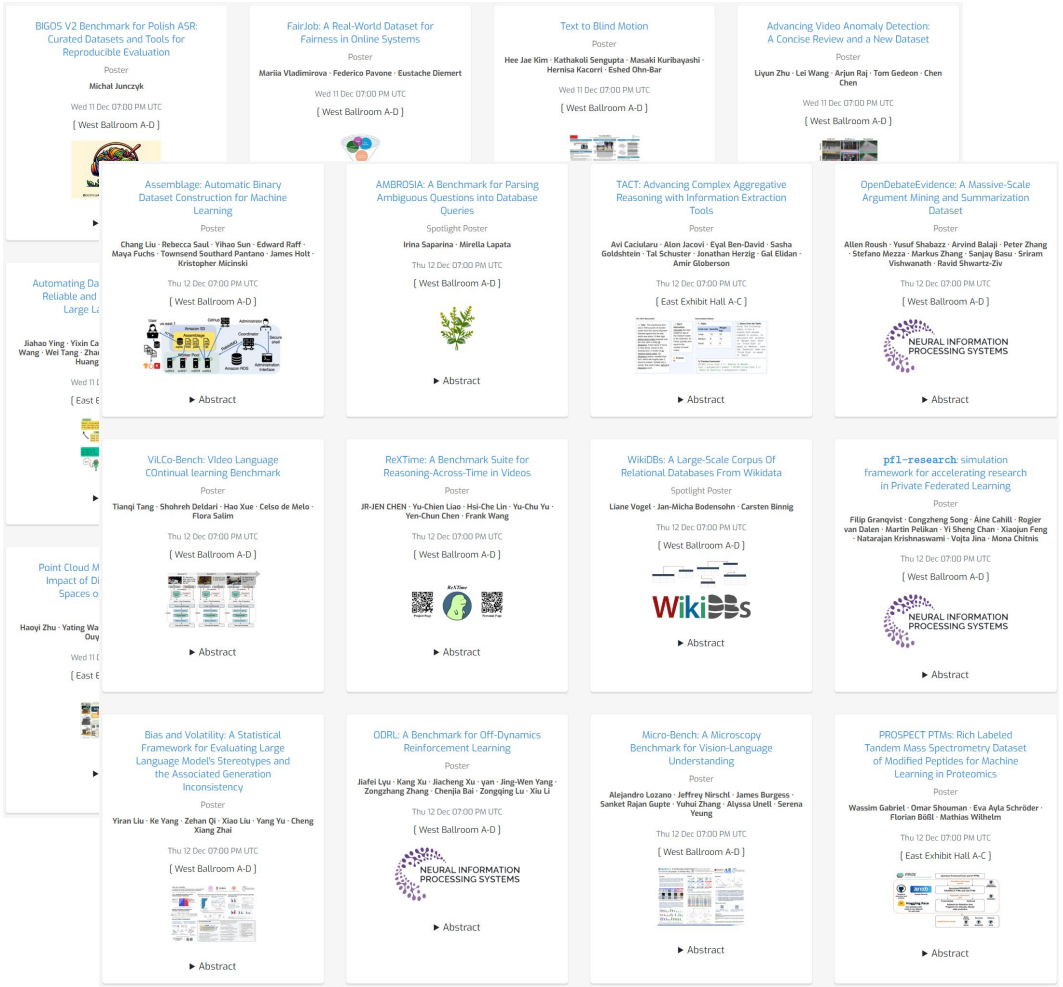
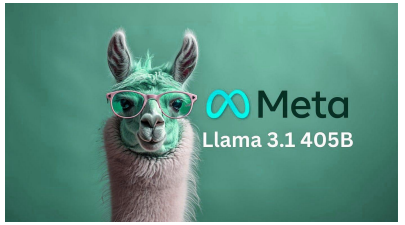
Another Benchmark??



Why ORQA?

- Expert **hand-crafted** dataset
- **Difficult questions** from a highly specialized technical domain
  - Limited exposure during training
  - Multi-step reasoning
- **Significant gap** between tested LLMs and domain experts



0.77

0.93

https://neurips.cc/virtual/2024/events/datasets-benchmarks-2024

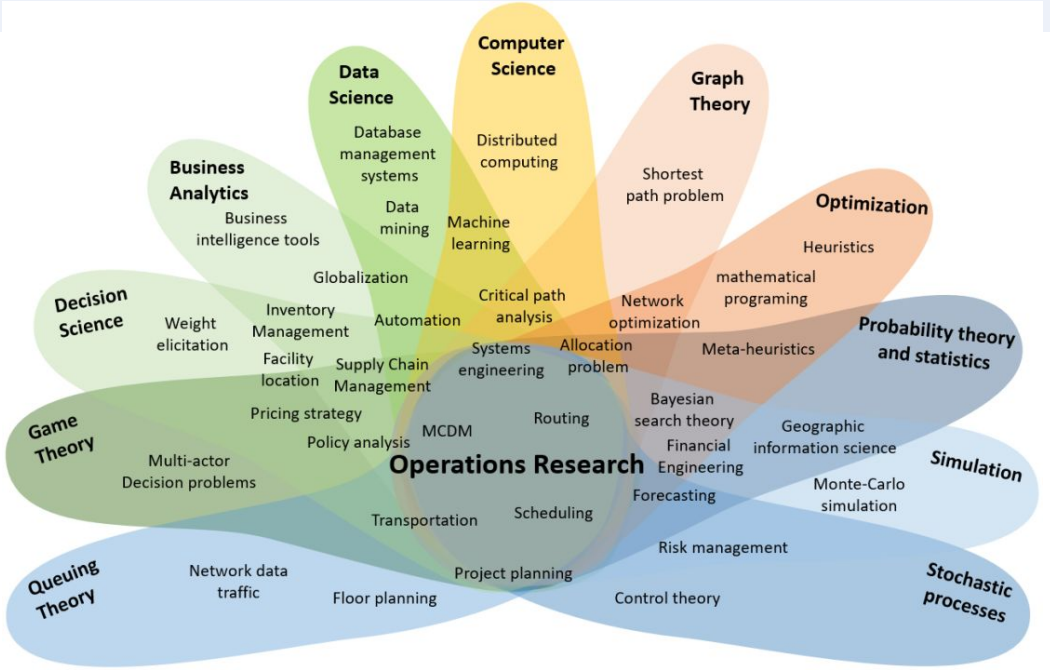
Overview

- Background & Motivation
- What is ORQA?
- How we created ORQA
- Benchmarking LLMs
- Findings
- Future works

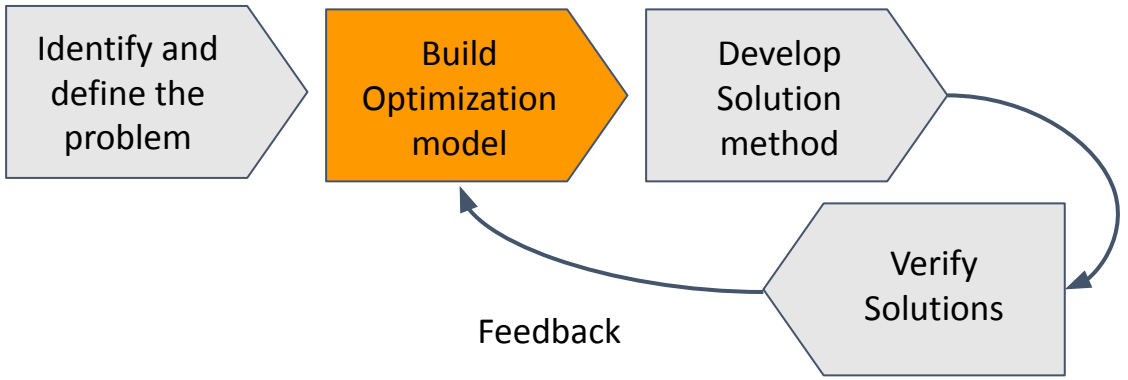
Background

The Importance of Operations Research (OR)

- **Wide-Ranging Applications:** Integral to industries like logistics, manufacturing, healthcare, finance, supply chain management, and urban planning.
- **Critical impact**: Automated decision-making, enhances efficiency, reduces costs.

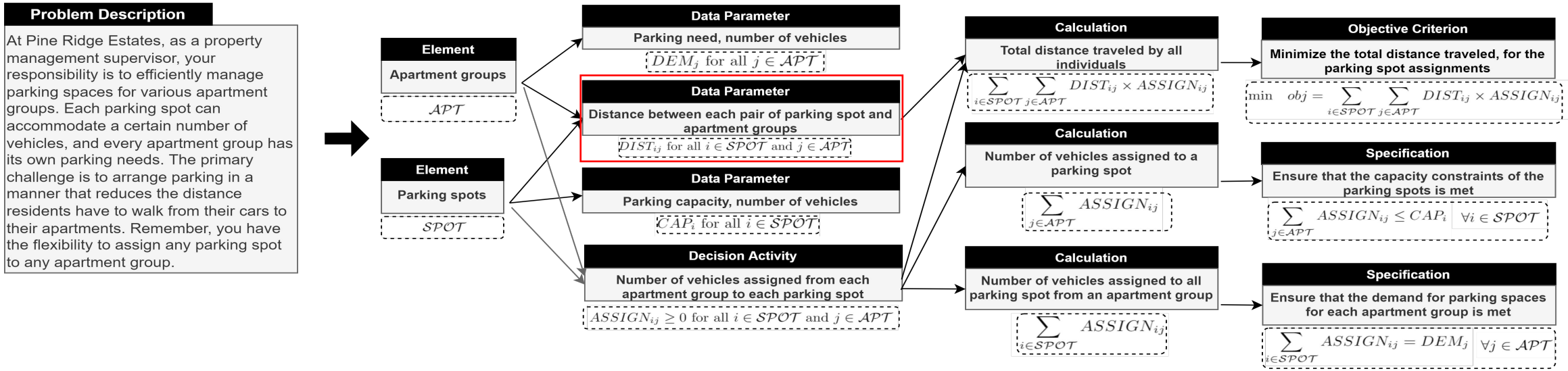


- **Optimization Modeling bottleneck of OR wide adaptation.**
- **Automating the translation of real-world problems into optimization models can revolutionize how industries use OR.**
  - Lowers cost of OR projects.
  - Democratizes access to expert-level optimization
  - Expands adoption of OR



Background - Complexity of Optimization Modeling Tasks

- **Multiple Components:**
  - **Elements:** Main entities in the problem
  - **Decision activities:** Represent choices that impact the model's outcomes.
  - **Data Parameters:** Critical data that are required to inform the model.
  - **Objective Criterion:** The goals to be maximized or minimized, such as cost, time, or profit.
  - **Constraints:** Rules and limitations that bind the model
- **Interdependencies:**
  - A change in one component (e.g., decision variables) directly affects others (e.g., constraints).
- **Implicit Components & Ambiguities:**
  - Not all model components are explicitly stated in problem descriptions and require expert insight to identify.
  - Problem owners often provide vague or ambiguous descriptions due to lack optimization expertise.



Motivation

Challenges

- **Complex Reasoning Required:**
  - The interrelated nature of components demands multi-step, expert-level reasoning to build accurate models.
- **Dataset Scarcity:**
  - Operates in an underrepresented field where training data is limited, making it a rigorous testbed for LLM capabilities.
  - There are very few small optimization modeling datasets.

What Makes ORQA Unique?

- Multi-Step Reasoning
- Expert-Level Domain Knowledge
- Complex Interactions
- Niche Technical Domain

Impact

- **Advancing LLM Research:**
  - Provides insights into the limitations and potential improvements for LLMs in specialized domains.
- **Automation in OR:**
  - Paves the way for automating complex decision-making tasks in real-world operations research applications.

ORQA Example

Dataset Instance

Problem description:

You are an operations manager in the agricultural sector. Your task is to streamline the process of getting crops from farms, processing or storing them as needed, and finally distributing them to various markets or direct consumers.
...
You also need to ensure the produce reaches markets and consumers in its best state, meets demands, and ensures a steady supply.

Question:

What is the type of optimization model related to this problem?

Options & answer:

A - Mixed-Integer Linear Programming
B - Linear Programming
C - Integer Linear Programming
D - Non-linear Programming

Expert Reasoning (val. set only)

Reasoning steps:

Step 1: What are the decision activities in the model?
- Amount of product to cultivate, Selecting a transportation mode (truck, rail, etc.)

Step 2: What is the type of values they can get?
- Continuous and integer

Step 3: Is there any Non-linear relationship presented in the problem?
- Constraints and objective function does not define a non-linear relation

Step 4: Given the variable types and linear or non-linear relationship between them, what is the optimization model type?
- There are both continuous and integer variables and there is no non-linear relation exist in the optimization problem. Therefore, the most suitable optimization model for this problem is Mixed-Integer Linear Programming (MILP).

ORQA

Statistics & Characteristics

- 1513 instances
- 1468 for testing; 45 for validation (ICL)
- 20 diverse application domains (e.g., healthcare, urban design, HR, petroleum)
- From each domain:
  - > 3 optimization problems
  - 60 – 90 multiple choice questions
- Standardized optimization model complexity
  - Mathematical model is within pre-defined limits (e.g., number of decision variables)

Component	μ	σ
Sets	1.97	0.89
Parameters	4.08	2.19
Variables	3.14	2.29
Objectives	1.00	0.00
Constraints	4.60	3.21

ORQA – Question Types

11 Question Types

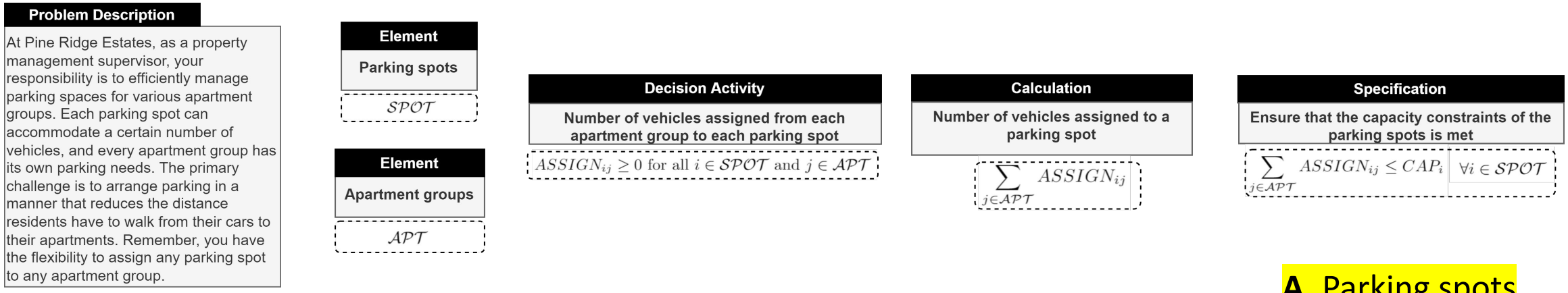
- Understanding high-level problem specifications
  - Objective identification
  - Explicit constraint identification
  - Problem categorization
- Entities identification
  - Optimization type (e.g., linear, non-linear)
  - Set, decision activities, implicit constraint identification
- Relationship between Entities
  - Parameters and variables in objective / constraints
  - Meaning of calculations in objective / constraints
  - Set that a constraint is applied on

ORQA – Question Types

Set that a constraint is applied on

Question: Which of the following system element(s) is the Parking Spot Capacity constraint applied on?

A. Parking spots, **B.** Apartment group, **C.** Parking spots, Apartment group, vehicle count, **D.** Parking spots, Apartment group



A. Parking spots

Dataset Creation and Verification

Selecting & Creating Optimization Problem Descriptions

1. Select optimization problem
2. Write domain-specific description focusing on diverse application domains

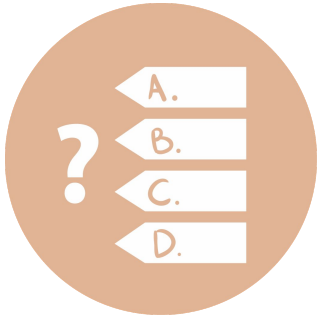
Problem Description

At Pine Ridge Estates, as a property management supervisor, your responsibility is to efficiently manage parking spaces for various apartment groups. Each parking spot can accommodate a certain number of vehicles, and every apartment group has its own parking needs. The primary challenge is to arrange parking in a manner that reduces the distance residents have to walk from their cars to their apartments. Remember, you have the flexibility to assign any parking spot to any apartment group.

Creating Q&A Pair

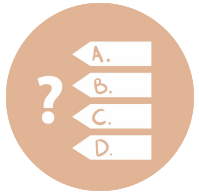
At Pine Ridge Estates, as a property management supervisor, your responsibility is to efficiently manage parking spaces for various apartment groups. Each parking spot can accommodate a certain number of vehicles, and every apartment group has its own parking needs. The primary challenge is to arrange parking in a manner that reduces the distance residents have to walk from their cars to their apartments. Remember, you have the flexibility to assign any parking spot to any apartment group.

1. Reference problem description
2. Select question type
3. Create target answer
4. Create incorrect options



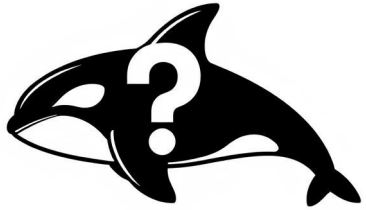
Instance Verification

At Pine Ridge Estates, as a property management supervisor, your responsibility is to efficiently manage parking spaces for various apartment groups. Each parking spot can accommodate a certain number of vehicles, and every apartment group has its own parking needs. The primary challenge is to arrange parking in a manner that reduces the distance residents have to walk from their cars to their apartments. Remember, you have the flexibility to assign any parking spot to any apartment group.



- ✔ Completeness
- ✔ No Ambiguity in Q&A
- ✔ Correctness in answer

- ✔ Multi-step reasoning
- ✔ Correctness in answer



ORQA

Benchmarking Results

Model	Standard (Acc)			CoT (Acc)	
	0-shot	1-shot	3-shot	0-shot	1-shot
Llama3.1-8B-I	0.588	0.615	0.618	0.563	0.324
Llama3.1-70B-I	0.702	0.721	0.735	0.689	0.292
Llama3.1-405B-I	0.723	0.753	0.772	0.695	0.360
Llama3-8B-I	0.535	0.573	0.592	0.530	0.364
Llama3-70B-I	0.676	0.716	0.710	0.671	0.448
Llama2-7B-Chat	0.368	0.375	0.403	0.368	0.282
Llama2-13B-Chat	0.409	0.437	0.454	0.432	0.313
Llama2-70B-Chat	0.526	0.552	0.589	0.518	0.372
FLAN-T5-XXL-11B	0.503	-	-	0.457	-
Falcon-7B-I	0.245	0.246	0.245	0.242	0.243
DeepSeek-M-7B-I	0.478	0.552	0.559	0.379	0.514
NuminaMath-7B	0.250	0.484	0.525	-	0.290
Mistral-7B-I-v0.1	0.467	0.475	0.483	0.460	0.407
Mistral-7B-I-v0.3	0.523	0.555	0.555	0.539	0.543
Mixtral-8x7B-I-v0.1	0.588	0.606	0.612	0.565	0.565

0.93

Chain-of-Thought

CoT had **negative** (or negligible) impact on model performance of most models

Model	Standard (Acc)			CoT (Acc)	
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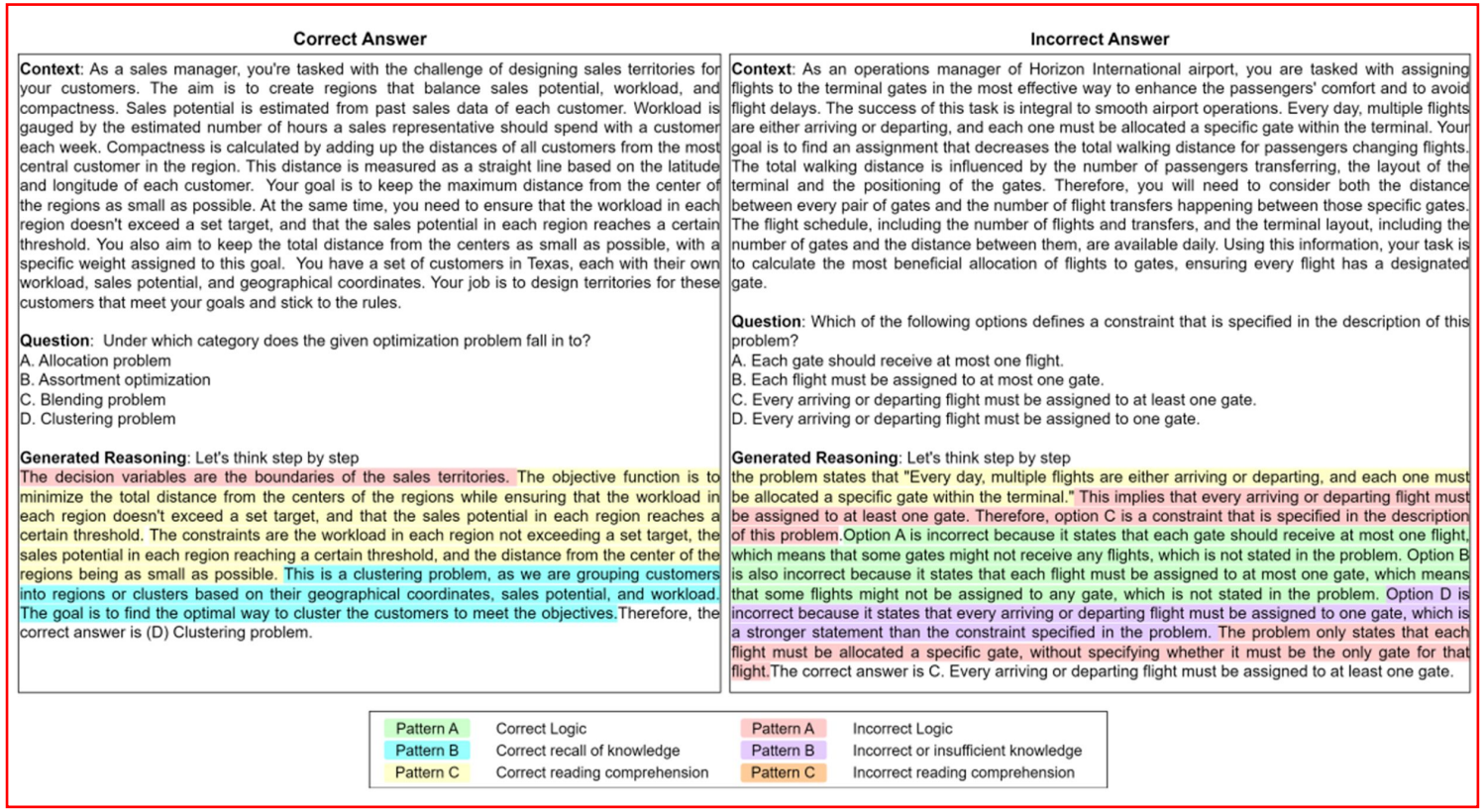
Detailed Reasoning Analysis

Reasoning Analyses



Reasoning Insights (stats)

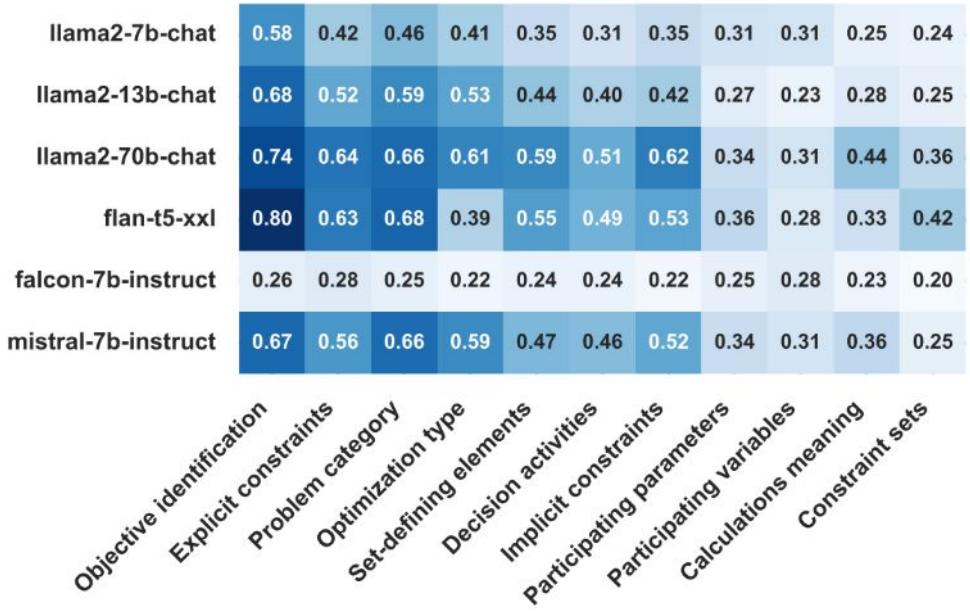
Metric	0-shot	1-shot
Instances with correct answer	35.6%	33.3%
Instances where all are reasoning steps are correct	15.6%	31.1%
Incorrect reasoning, correct answer	20.0%	6.7%
Incorrect answer, correct reasoning	0.0%	4.4%
Avg. number of steps per instance	7.93	4.53
Avg. accuracy of steps per instance	0.682	0.611

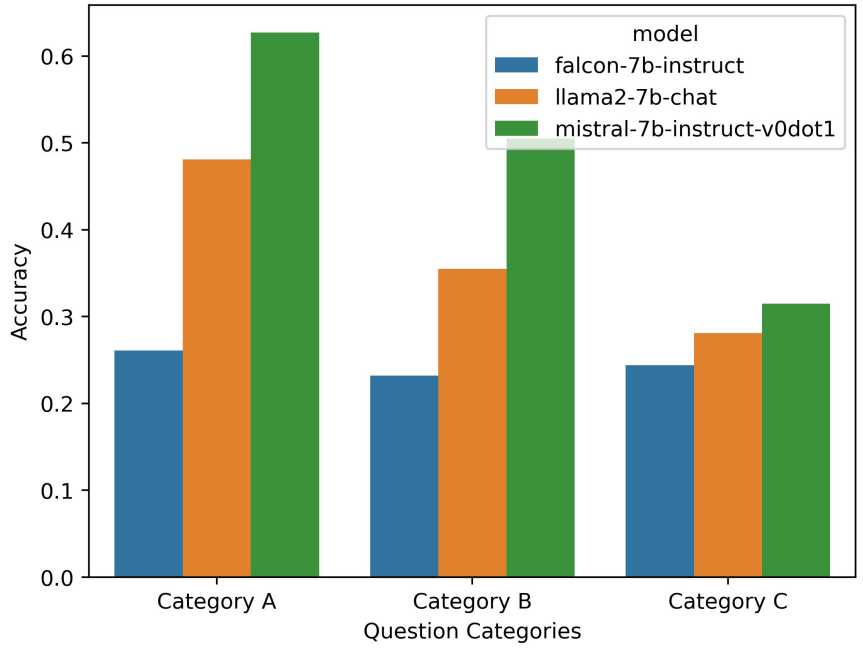
Question Category	Correct Steps	Incorrect Logic	Insufficient Knowledge	Incorrect Reading Comprehension
Category A	0.772	0.087	0.102	0.039
Category B	0.690	0.134	0.106	0.070
Category C	0.740	0.134	0.063	0.063

Question Types (Difficulty)

Significantly more difficult:

- **Model building & understanding** are significantly more difficult
- **Relationships** of optimization model components





ICL and Trigger Prompt on Reasoning

ICL Selection

Approach	Accuracy
Random selection	0.300
Same question type	0.313
Similar length	0.353
Similar length & same question type	0.362

Length of ICL examples has more impact on performance than question type (similarity)

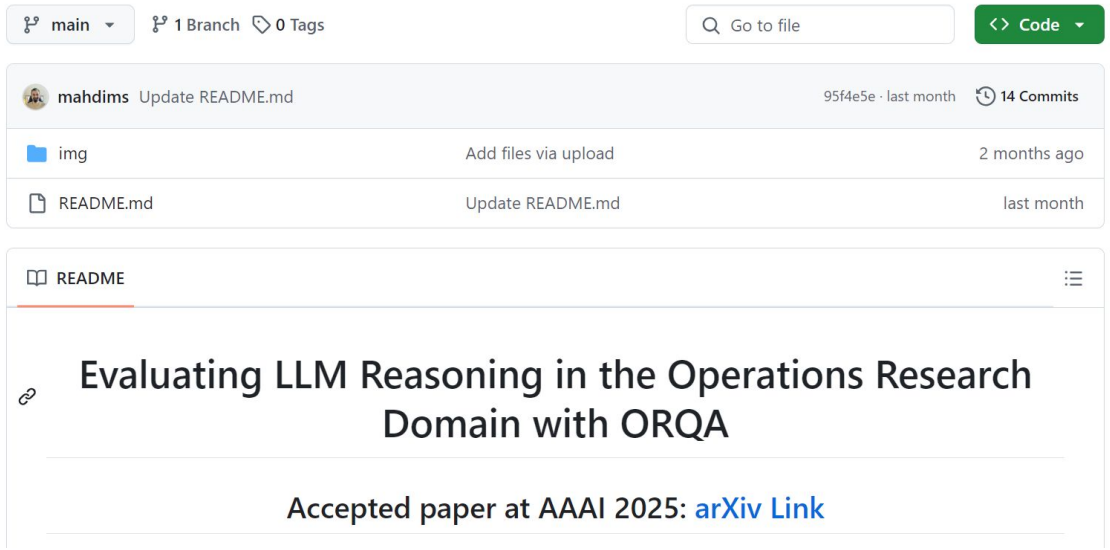
Trigger Prompts Selection

CoT Prompt (0-shot with Llama-3.1-70B-Instruct)	Average	STD	Best
Let's think step by step	0.688	0.001	0.689
Let's work by elimination	0.648	0.000	0.649
Let's reflect on each answer option like an operations research expert	0.689	0.001	0.689
Let's use step by step inductive reasoning, given the mathematical nature of the question	0.674	0.003	0.676
Let's think step by step like an operations research expert	0.685	0.000	0.685
Prompt ensembling (majority vote)	0.696	0.008	0.702

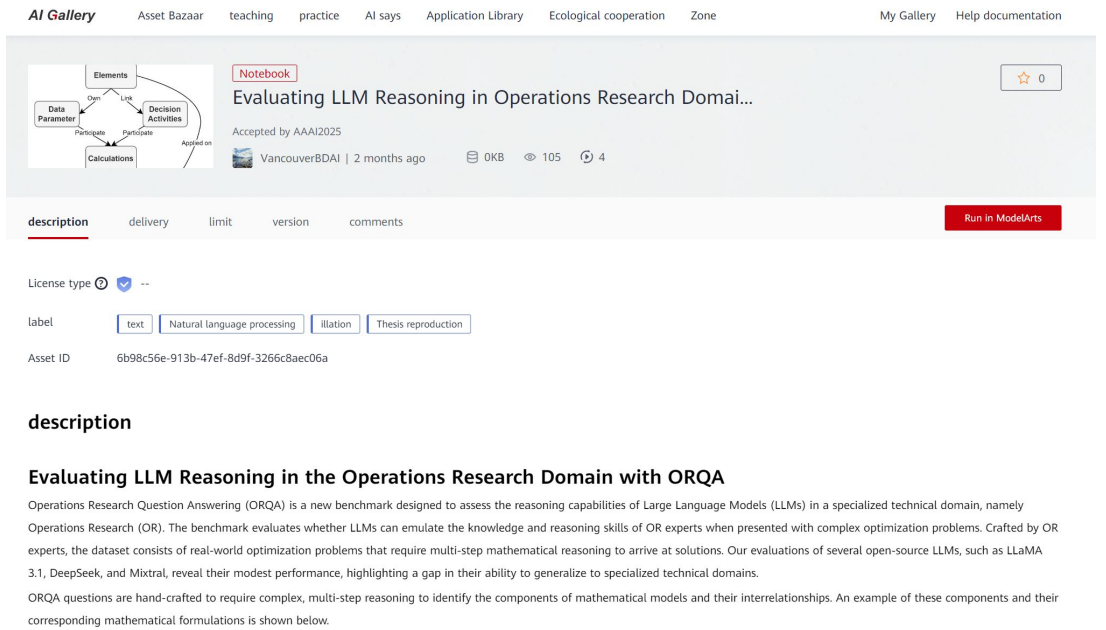
Trigger prompts and ensembling multiple runs may yield better results

Conclusion & Future Works

https://github.com/nl4opt/ORQA



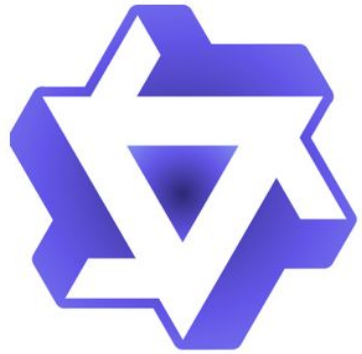
AI Gallery_Notebook详情_开发者_华为云 (huaweicloud.com)



Future Works

- Evaluate on more models
- Expand the dataset
- Automate the reasoning analysis

ORQA Models more proficient at reasoning



QwQ-32B-Preview

o3-mini

Thank you!

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