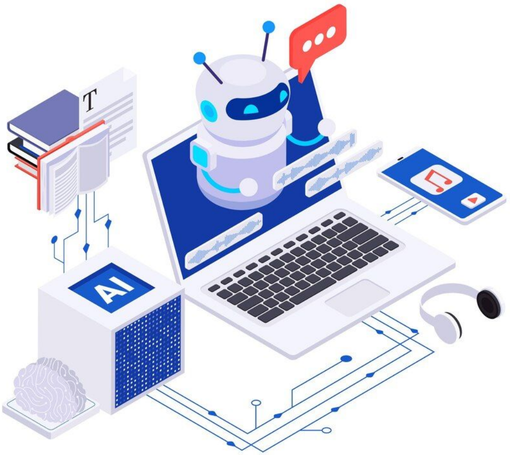
Enhancing Operational Data Synthesis and Predictive Analysis in HPC Clusters Using Large Language Models



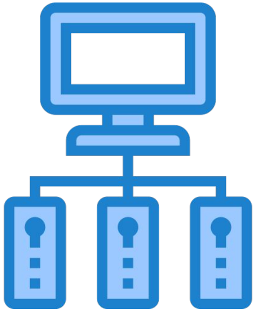
Source: freepik.com

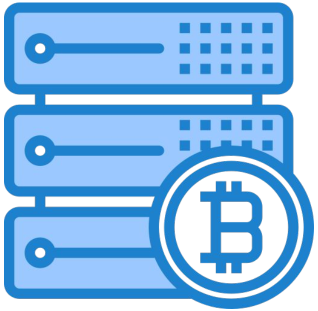
Yizhen Zang

Daily Supervisor: Xiaoyu Chu

July, 2024

HPC Clusters are Vital to Digital Society





Source: flaticon.com

HPC Clusters are Vital to Digital Society

Challenges

- ➔ Resource management
- ➔ Frequent job failures
- ➔ Lack of operational data

Source: flaticon.com

HPC Clusters are Vital to Digital Society

Impact of HPC Outages

- **Prevalence**: **80%** of users
- **Cost**: **60%** resulted in at least **$100,000** losses

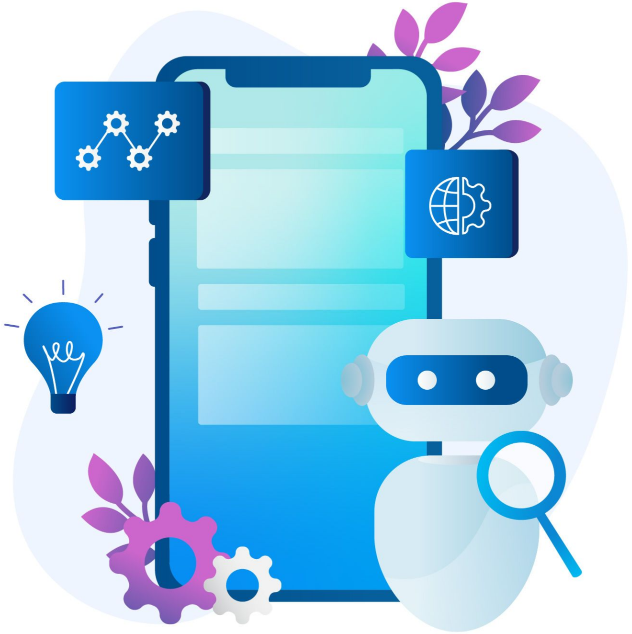
Source: Uptime Institute, Annual outages analysis 2023

Source: freepik.com

Large Language Models are Powerful

Traditional Models

- ➔ Limited Adaptability
- ➔ Simplistic Approaches
- ➔ Inflexibility

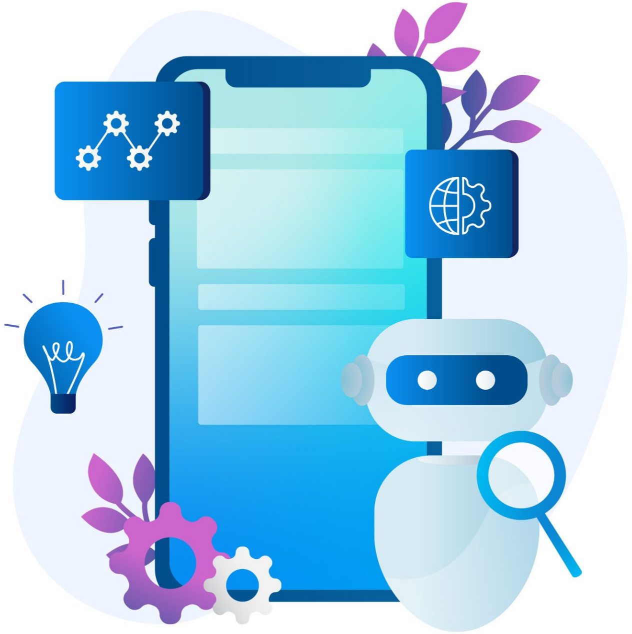


Source: freepik.com

Large Language Models are Powerful

Traditional Models
- ➔ Limited Adaptability
- ➔ Simplistic Approaches
- ➔ Inflexibility

LLMs
- ★ High Adaptability
- ★ Complex Data Handling
- ★ Flexibility and Integration



Source: freepik.com

Research Questions

The overarching RQ: How to leverage LLMs to improve operational decision-making for HPC datacenters?

Research Questions

RQ1: What are the existing applications of LLMs for HPC?

RQ1.1: How are LLMs applied in HPC for **workload synthesis**?
RQ1.2: How are LLMs applied in HPC for **workload prediction**?
RQ1.3: How are LLMs applied in **other tasks** in HPC?

Research Questions

RQ1: What are the existing applications of LLMs for HPC?

RQ2: How to design and evaluate LLM-based models for synthesizing job data in HPC clusters?

RQ2.1: How to generate synthetic job data in HPC clusters using LLMs?

RQ2.2: How are the techniques developed in RQ2.1 performing, relative to the non-LLM state-of-the-art?

Research Questions

RQ1: What are the existing applications of LLMs for HPC?

RQ2: How to design and evaluate LLM-based models for synthesizing job data in HPC clusters?

RQ3: How to design and evaluate LLM-based models for predicting job end-state in HPC clusters?

> **RQ3.1**: How to predict job failures in HPC clusters using LLMs?
> **RQ3.2**: How are the techniques developed in **RQ3.1** performing, relative to the non-LLM state-of-the-art?

Literature Review of LLMs Applications in HPC

RQ1

Reference	Applications	Models	Datasets
Shi et al.	memory workload synthesis	REaLTabFormer	SPEC2017
LM4HPC	code similarity analysis parallelism detection OpenMP Q&A	CodeBERT GraphCodeBERT gpt-3.5-turbo	POJ-104 DRB-ML OMP4Par OMPQA
MPIrigen	MPI-based parallel program	MonoCoder PolyCoder GPT-3.5	HPCorpusMPI
HPC-Coder	code completion OpenMP labeling performance prediction	GPT-2 GPT-Neo PolyCoder	self-collected
HPC-GPT	AI model management dataset management data race detection	LLaMa LLaMa 2	self-collected
LLMDB	query rewrite database diagnosis data analytics	LLMDB	self-collected

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Workload synthesis

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Workload synthesis

Code-based tasks

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Workload synthesis

Code-based tasks

Data management

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MP			
HP	performance prediction	PolyCoder	
HPC-GPT	AI model management dataset management data race detection	LLaMa LLaMa 2	self-collected
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Workload synthesis

Data management

Gaps remain in workload synthesis and prediction.

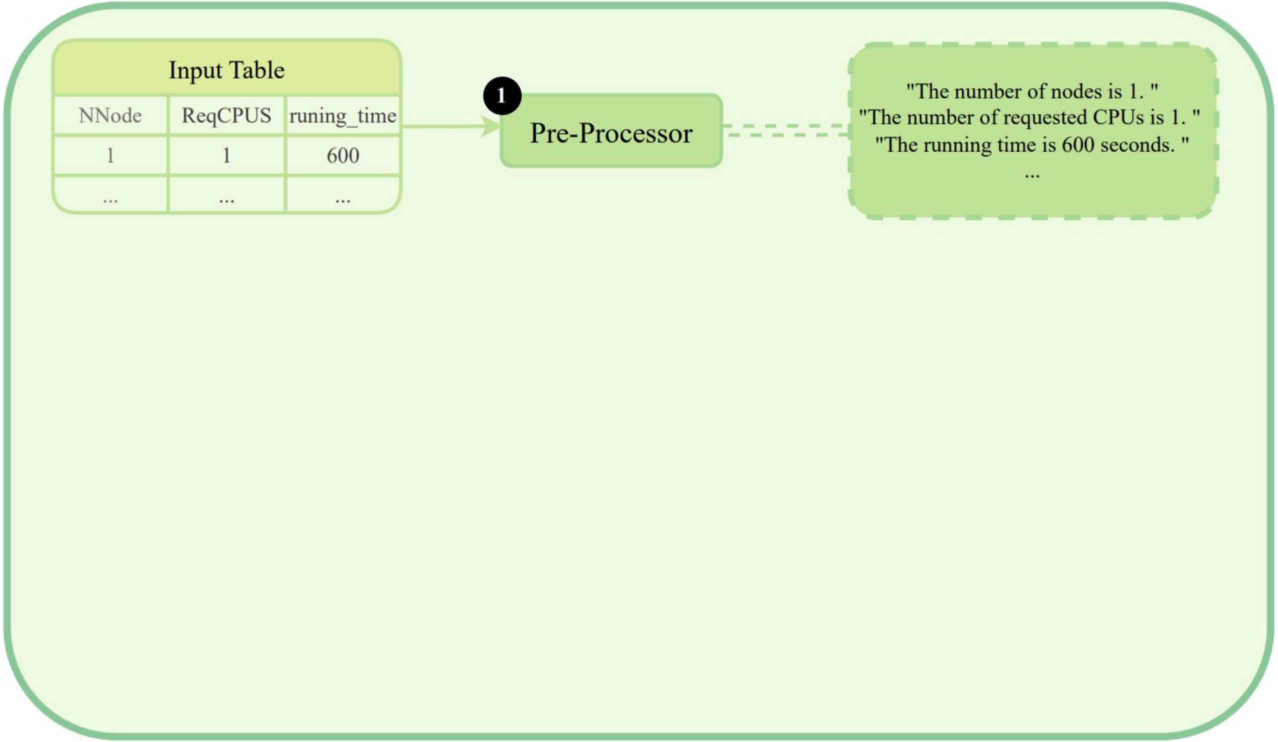
Design - How to Use LLMs for Job Data Synthesis?

RQ2.1

Input Table		
NNode	ReqCPUS	runing_time
1	1	600
...	...	...

Design - How to Use LLMs for Job Data Synthesis?

RQ2.1



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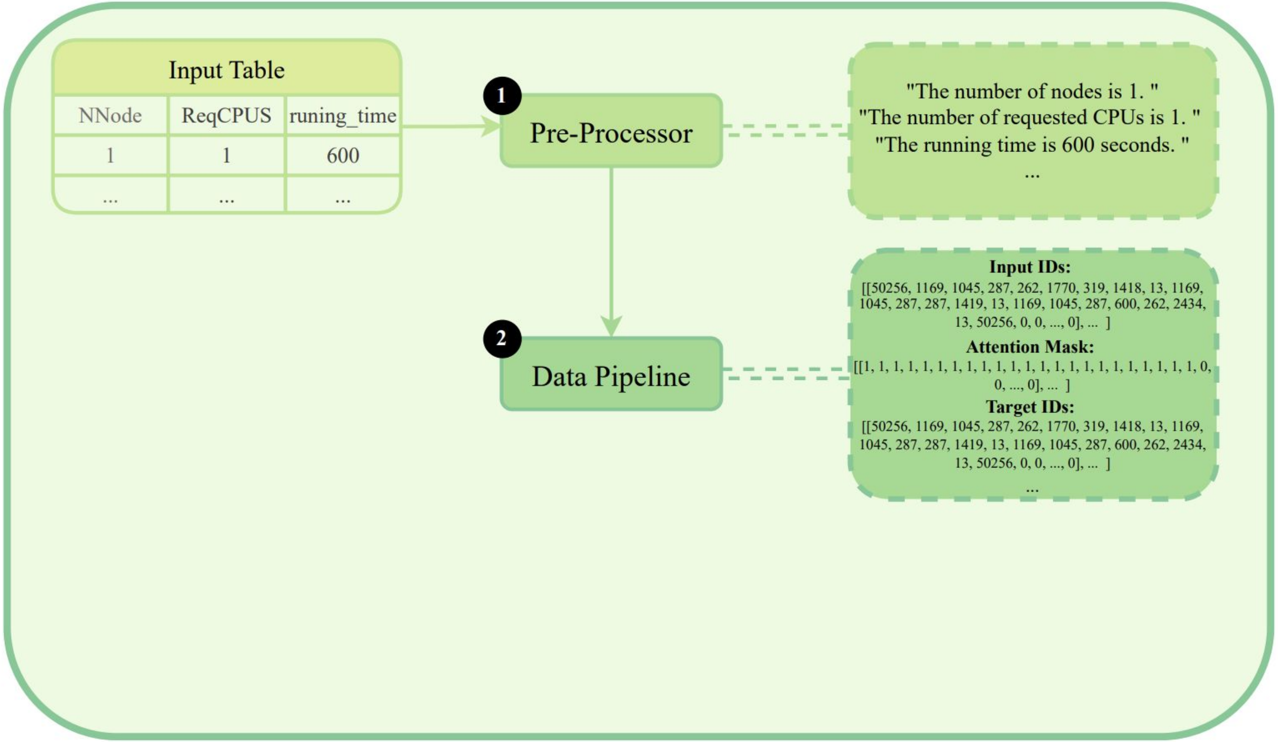

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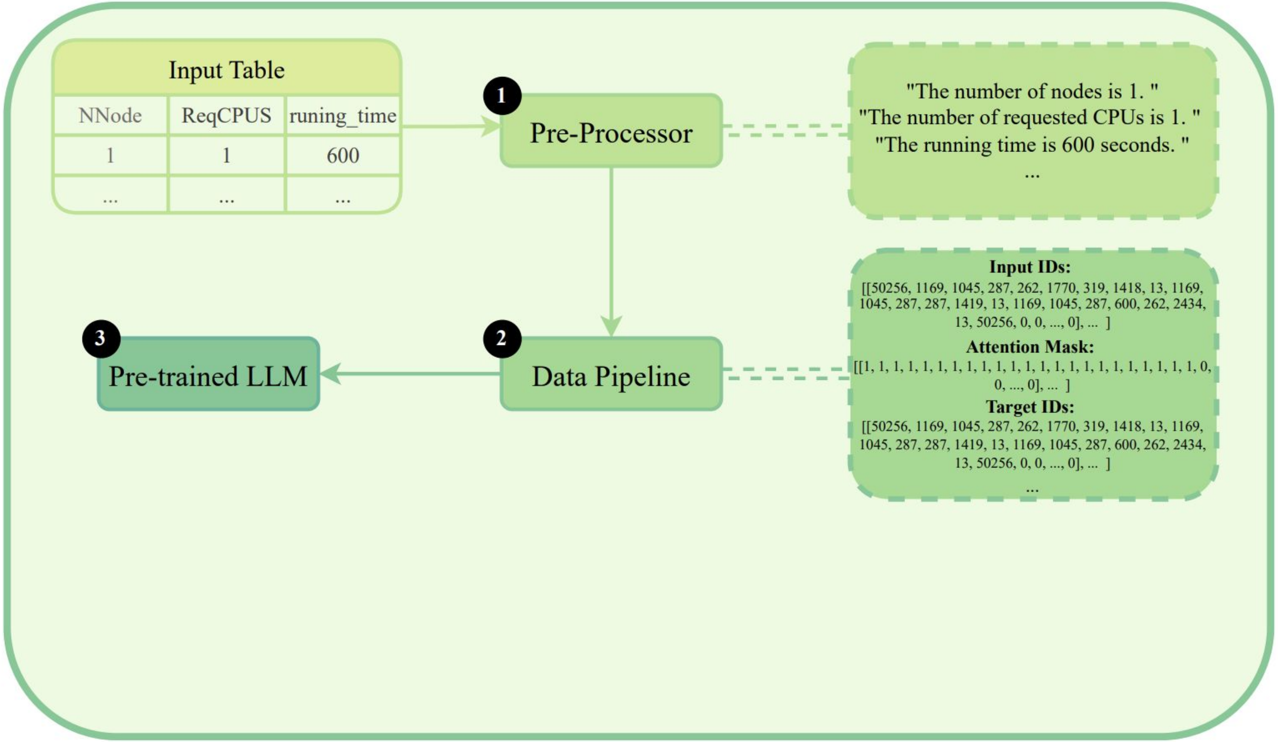

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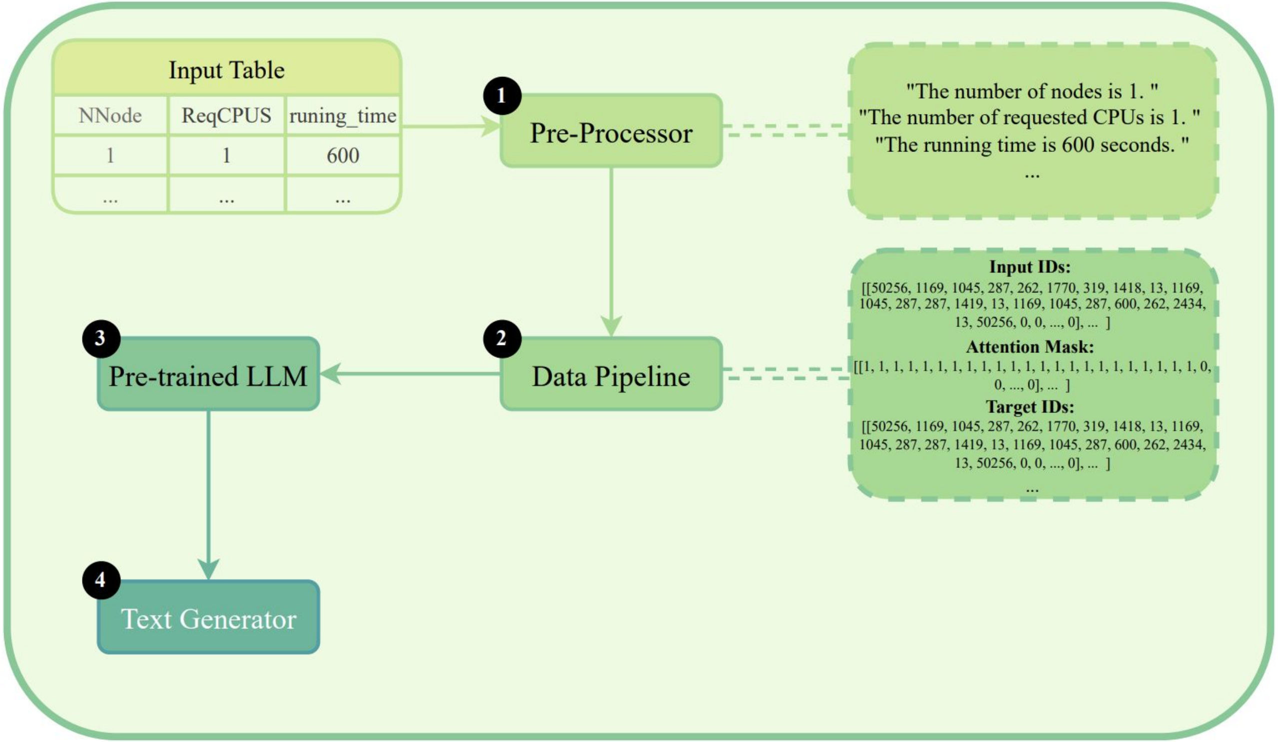

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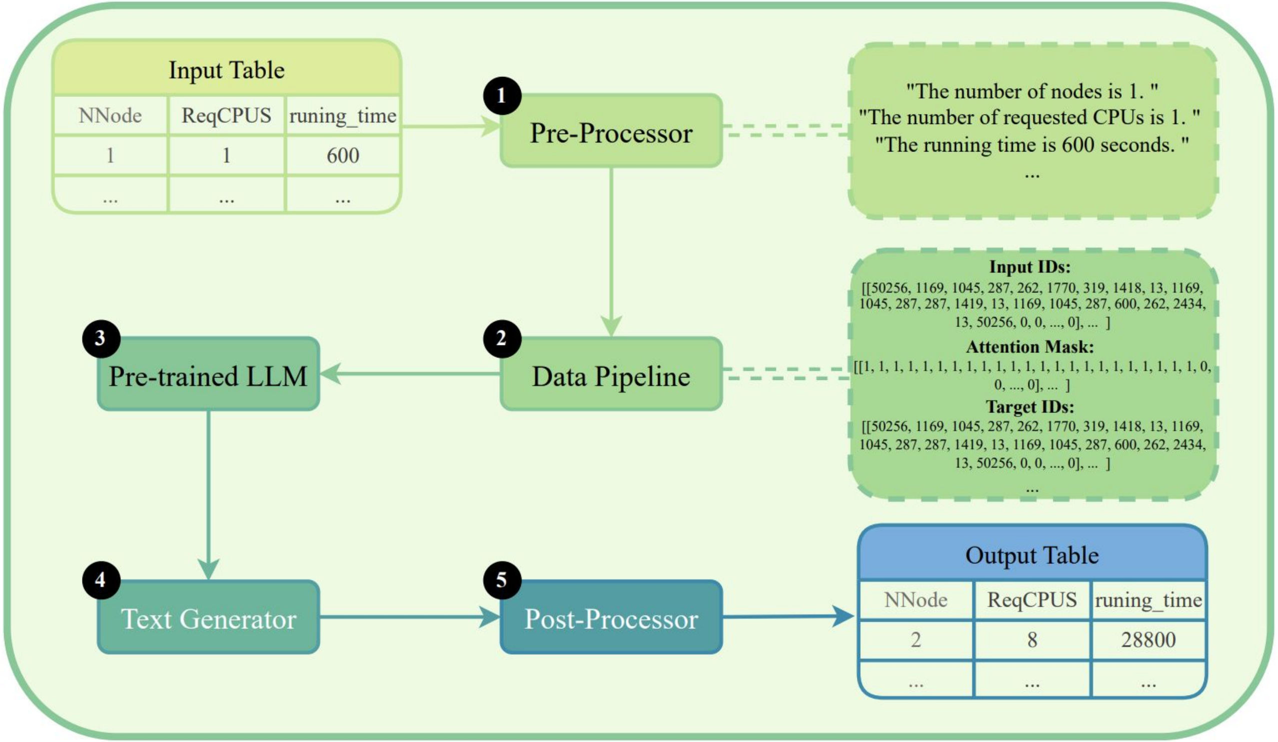

Evaluation (1/3) - How to Evaluate Synthetic Data?

RQ2.2

- **Baseline Models**: TabGAN & CTGAN

Evaluation (1/3) - How to Evaluate Synthetic Data?

RQ2.2

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- **Distance to the Closest Record (DCR)**
  - Measures the **similarity**

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RQ2.2

- **Baseline Models**: TabGAN & CTGAN
- **Distance to the Closest Record (DCR)**
  - Measures the **similarity**
- **Machine Learning Efficiency (MLE)**
  - Determine the **utility** on downstream predictive tasks
    - Decision Tree (DT)
    - Random Forest (RF)

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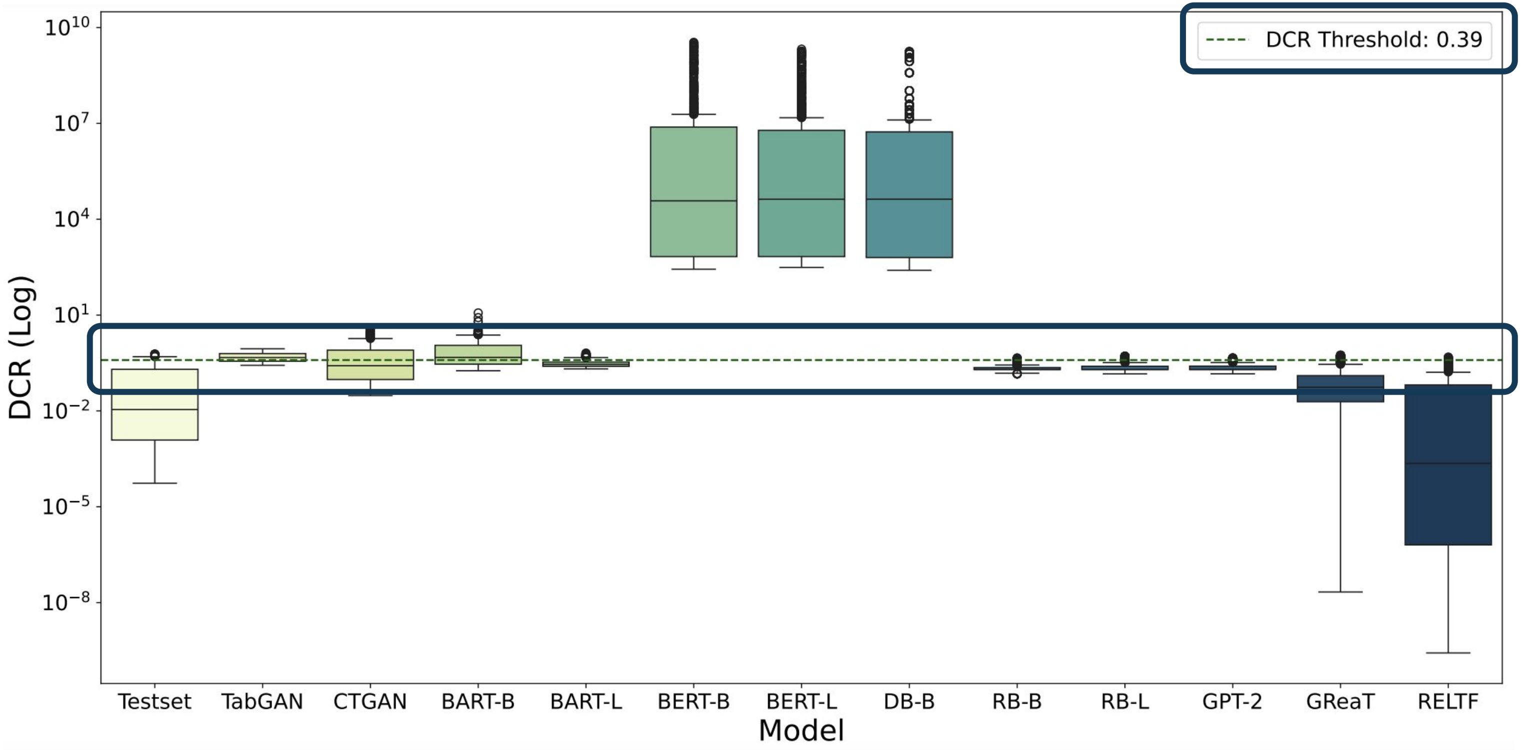
  - Measures the **similarity**
- **Machine Learning Efficiency (MLE)**
  - Determine the **utility** on downstream predictive tasks
    - Decision Tree (DT)
    - Random Forest (RF)
  - Accuracy, precision, recall, F1-score, AUC-ROC

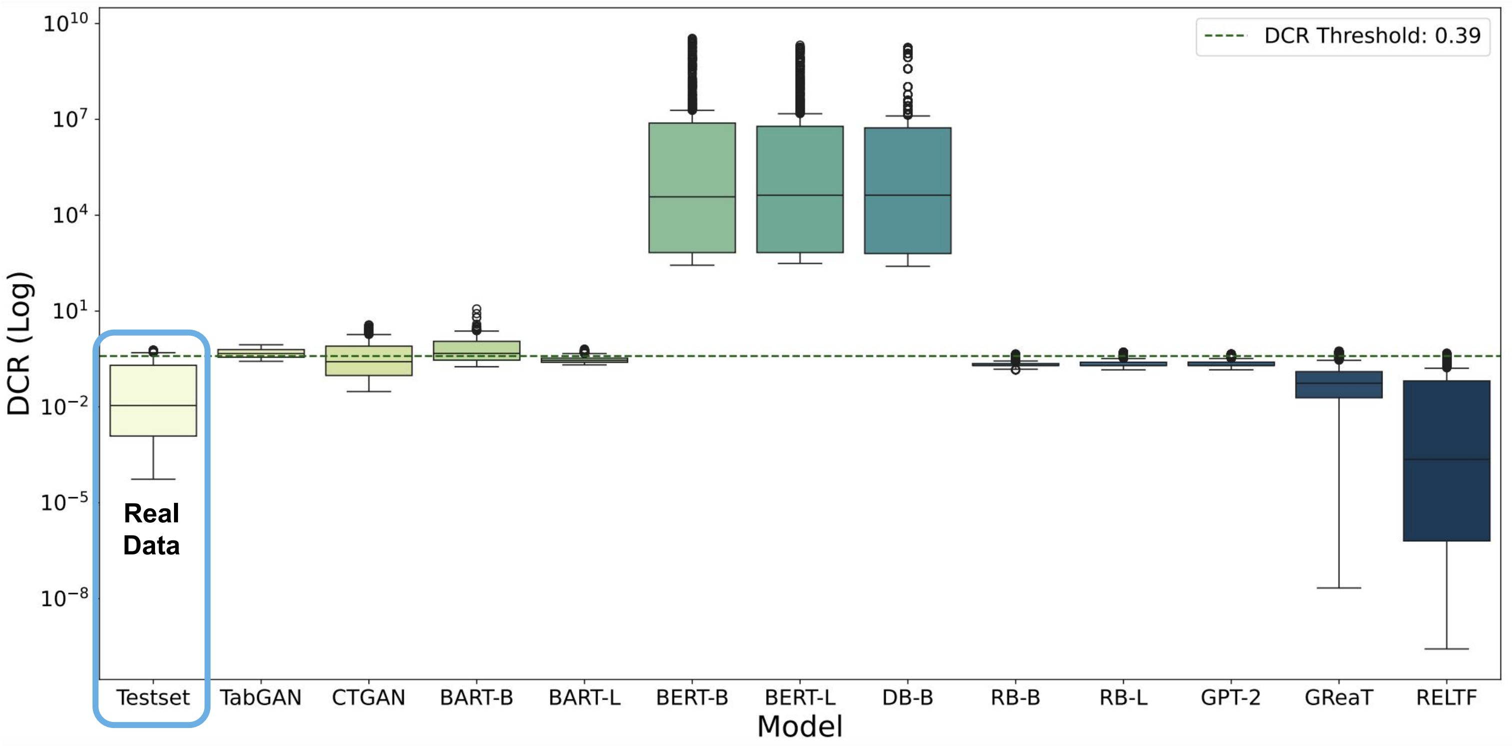
Evaluation (2/3) - Distance to the Closest Record

RQ2.2



Evaluation (2/3) - Distance to the Closest Record

RQ2.2



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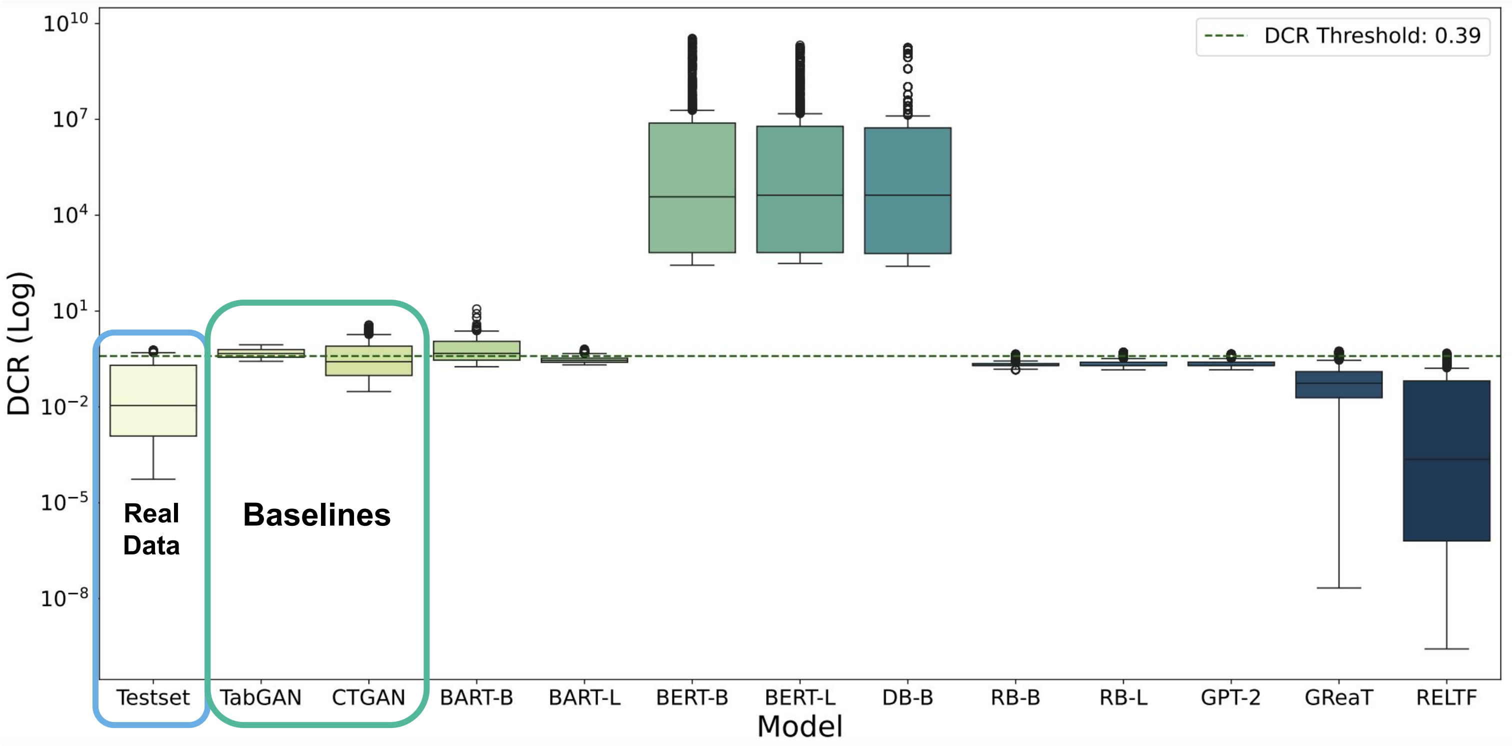

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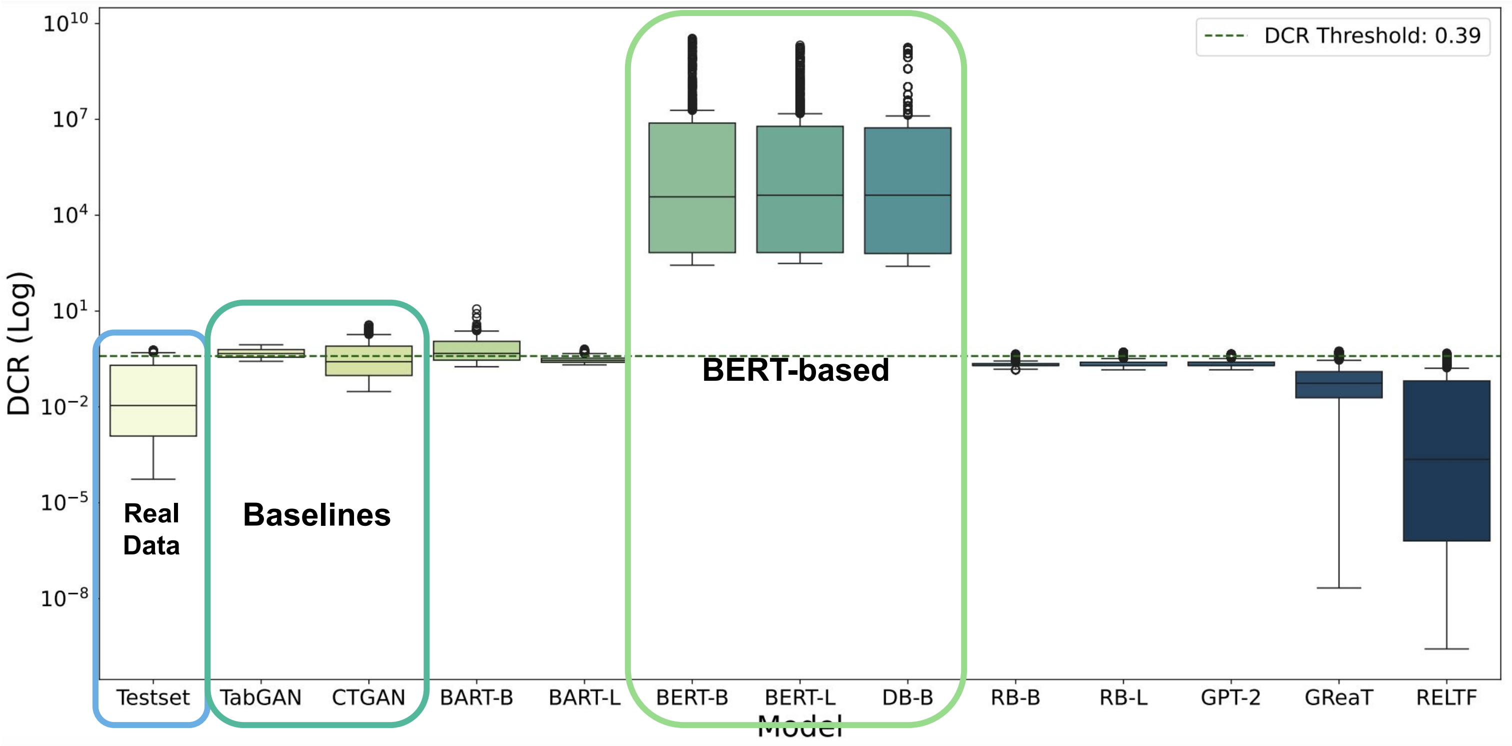

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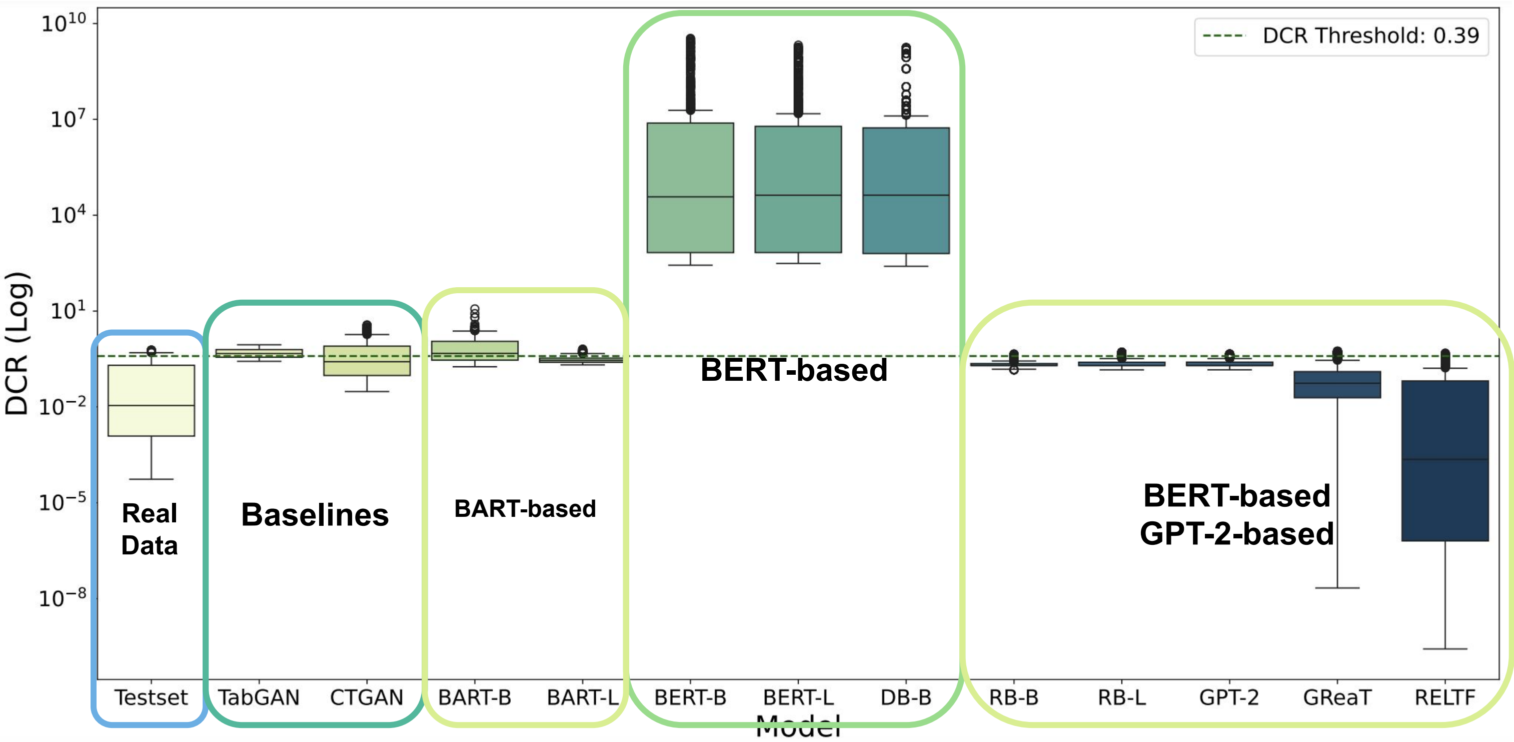

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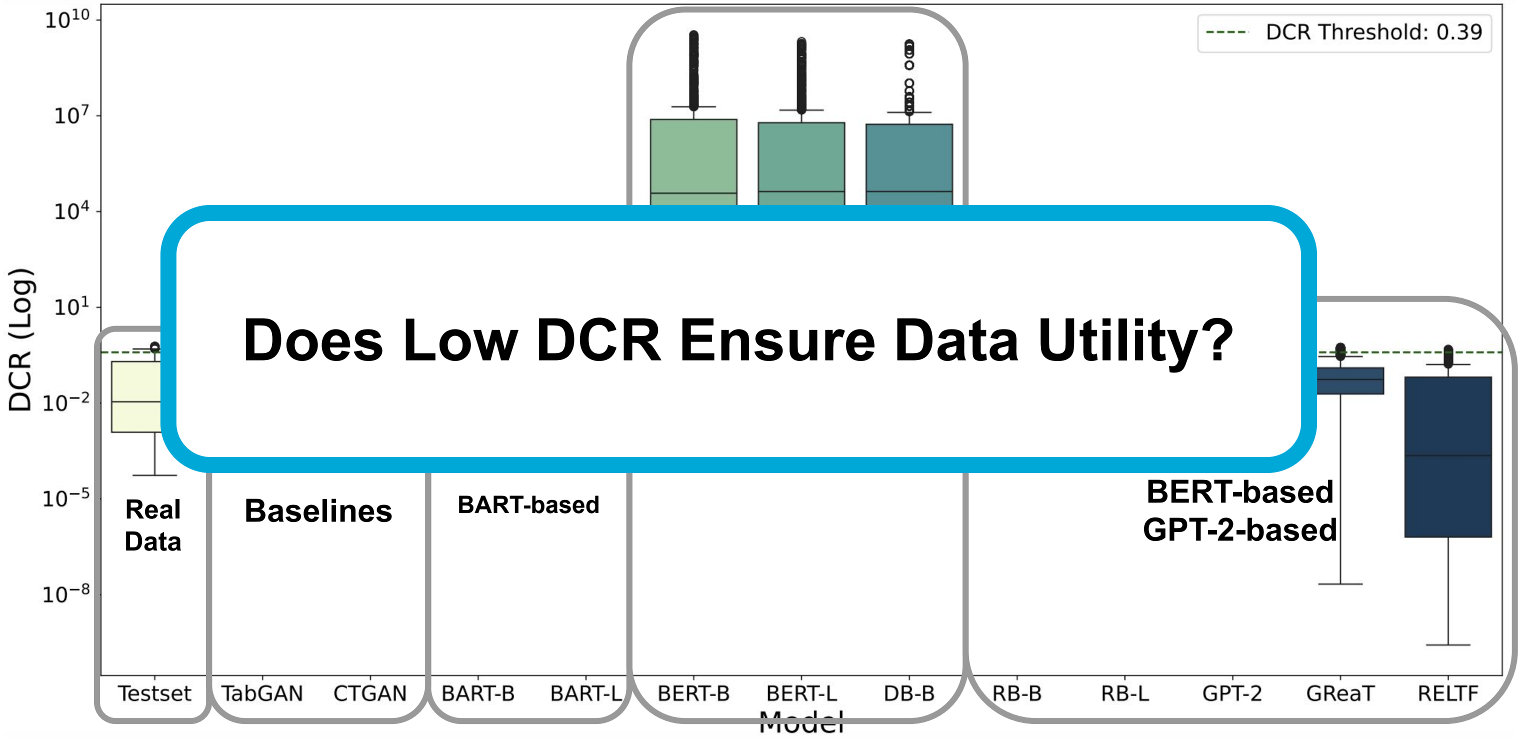
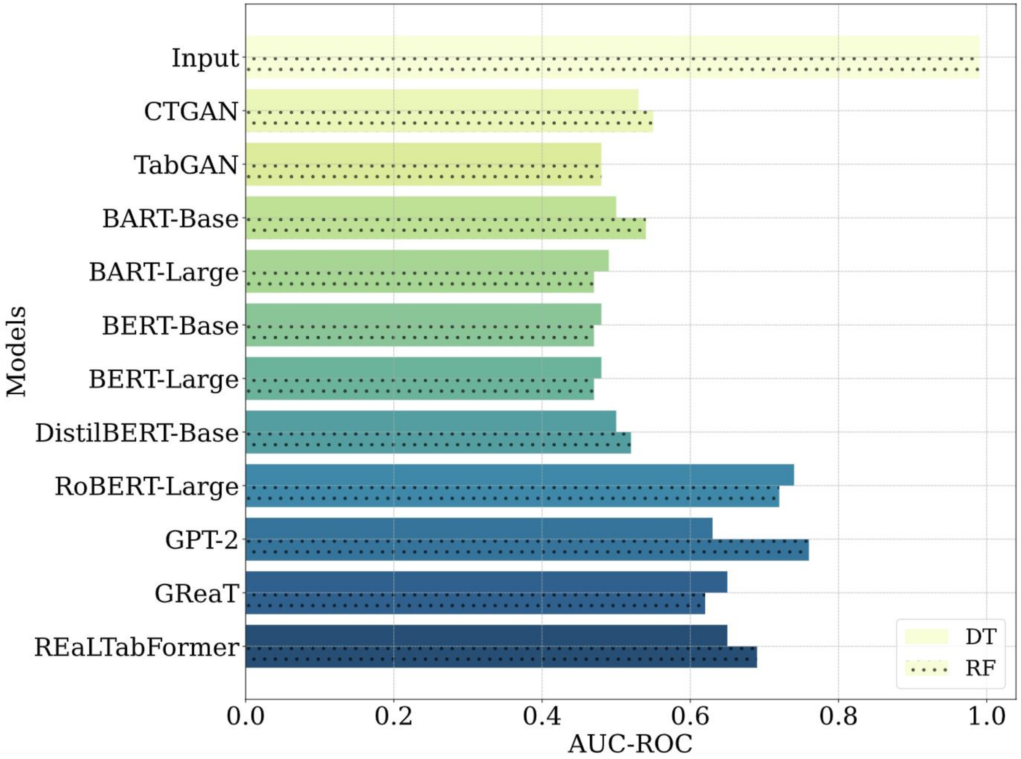


Does Low DCR Ensure Data Utility?

Evaluation (3/3) - Machine Learning Efficiency

RQ2.2



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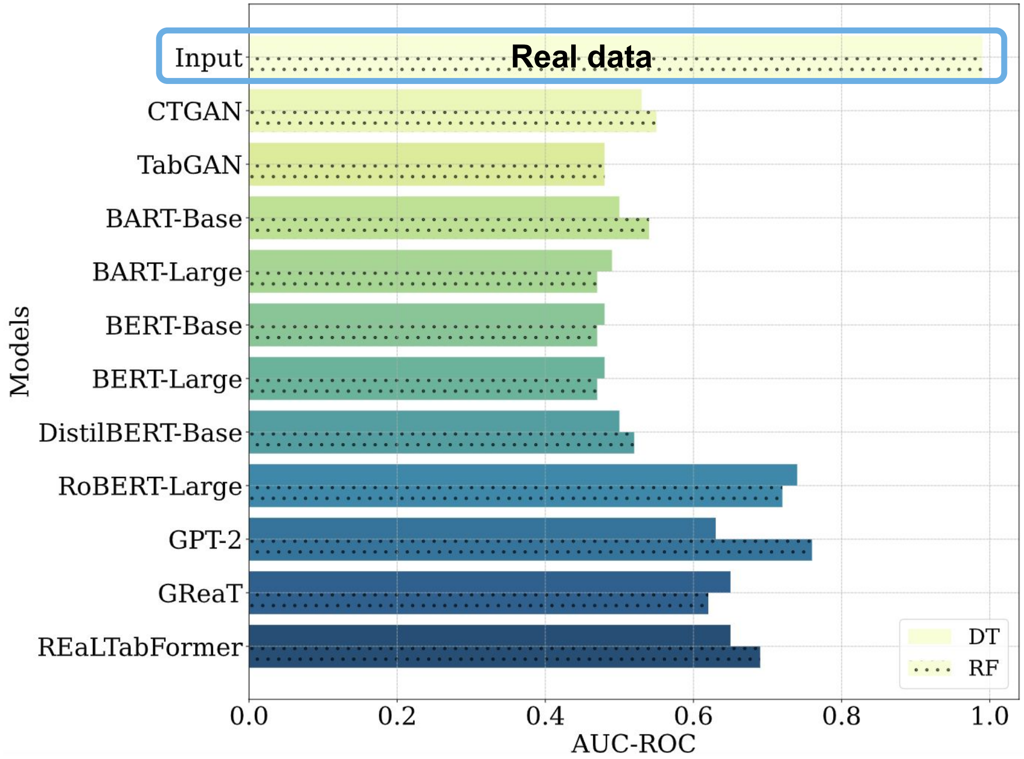
RQ2.2



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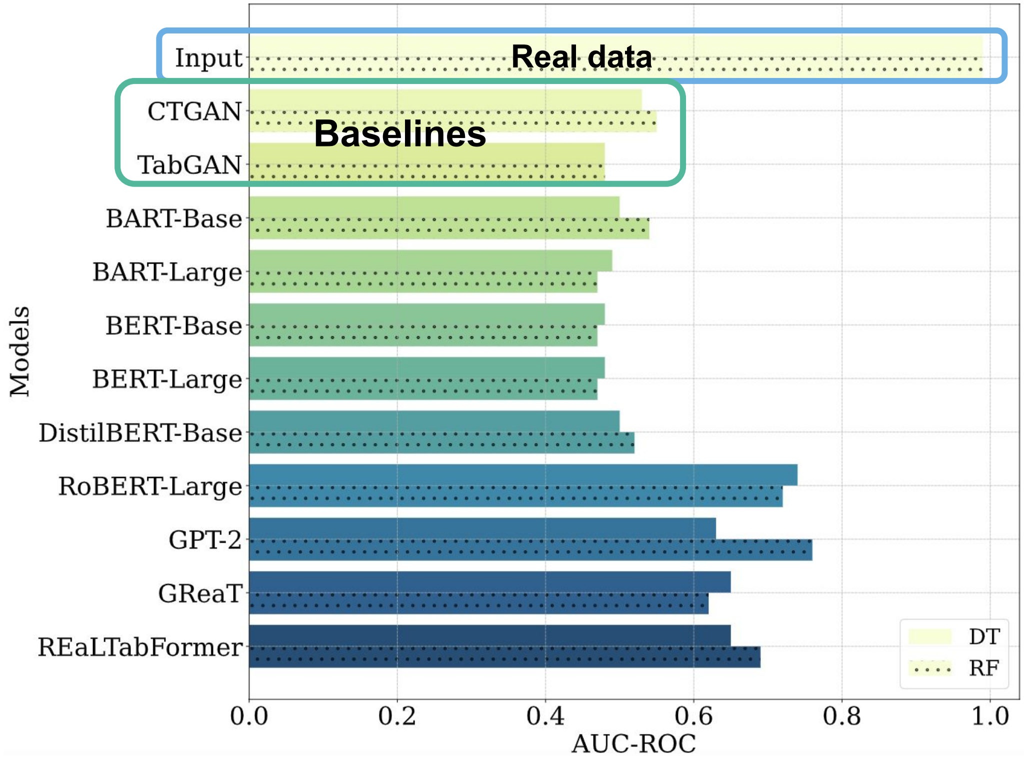

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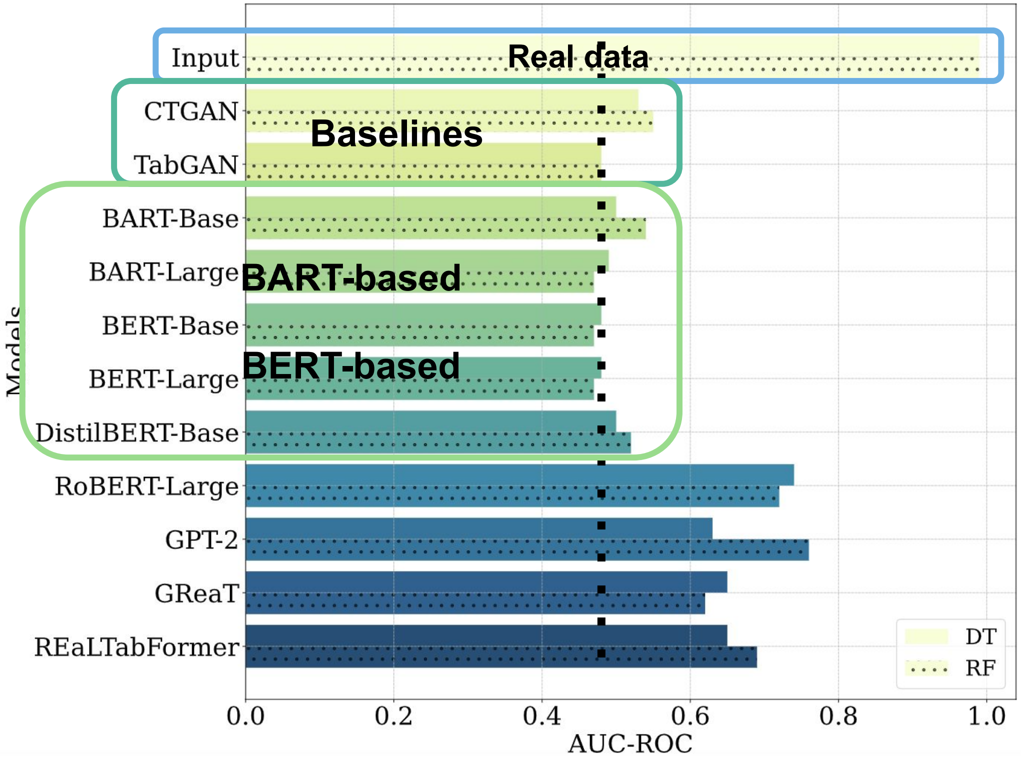

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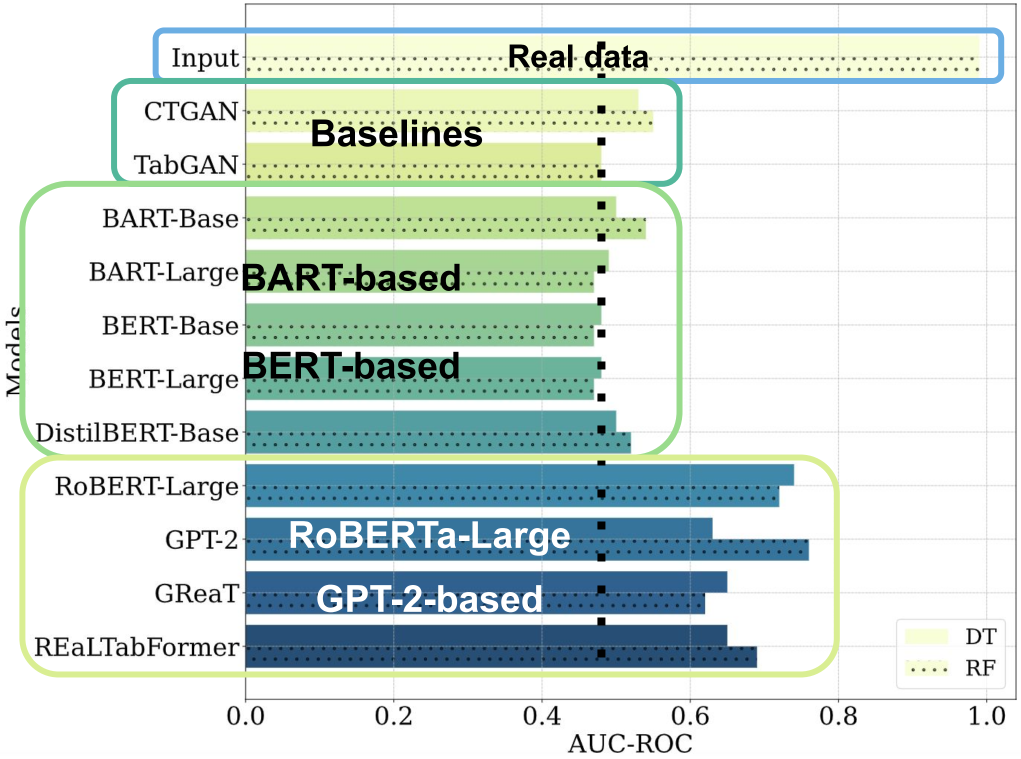


Summary of Job Data Synthesis Using LLMs

RQ2

- **F1** (DCR) - **RoBERTa-Large** and **GPT-2-based models** demonstrate the most promise with low DCR values.

- **F2** (MLE) - Predictive models trained on synthetic datasets show **varied performance**, falling short compared to real data.

- **F3** - There is a need for **improvements** in synthetic data generation techniques.

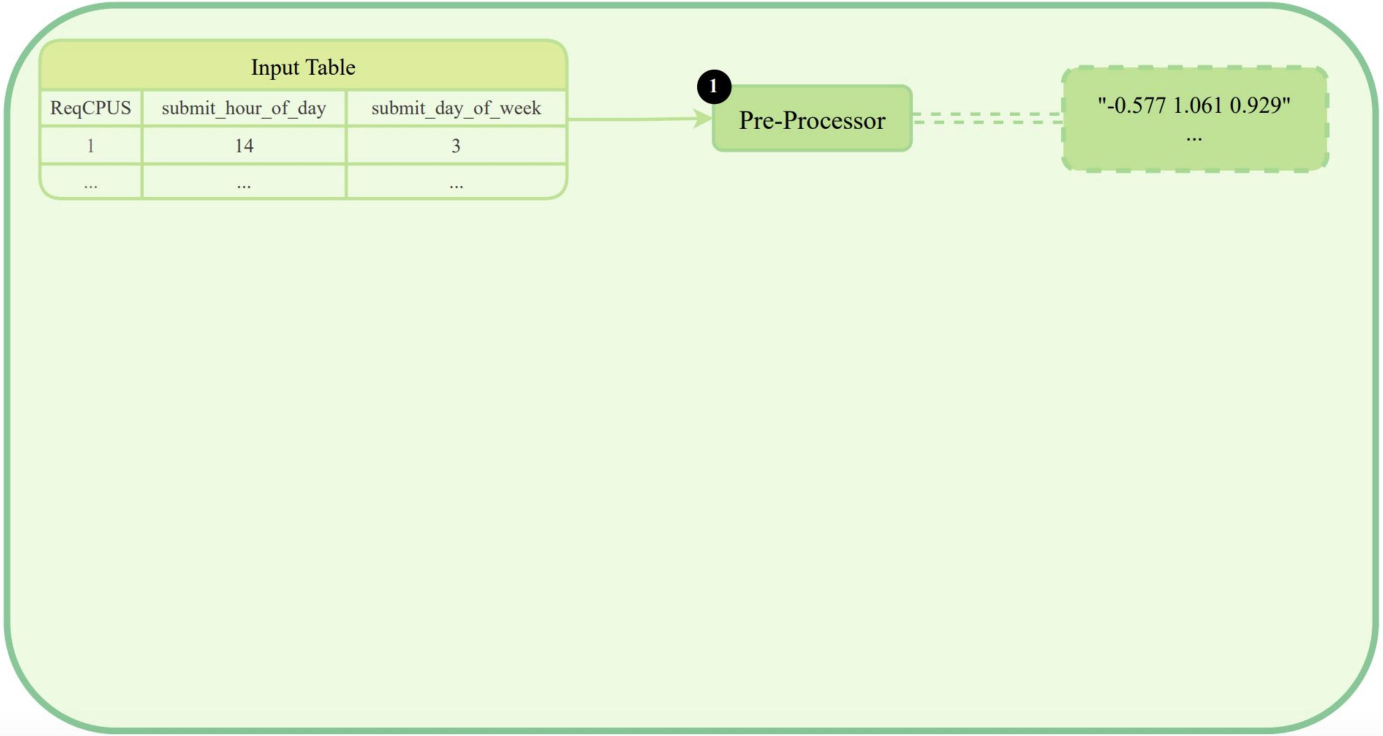
Design - How to Use LLMs to Predict Job End-State?

RQ3.1

Input Table		
ReqCPUS	submit_hour_of_day	submit_day_of_week
1	14	3
...	...	...

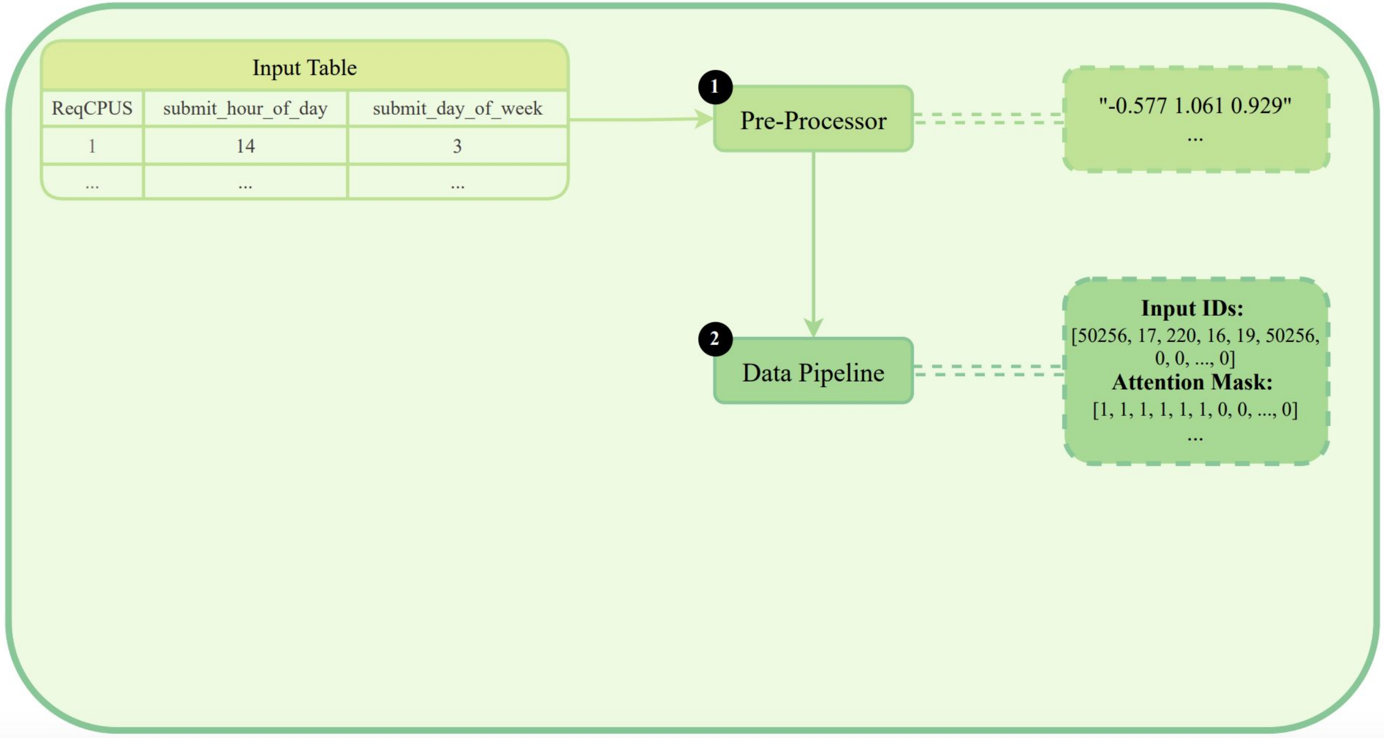
Design - How to Use LLMs to Predict Job End-State?

RQ3.1



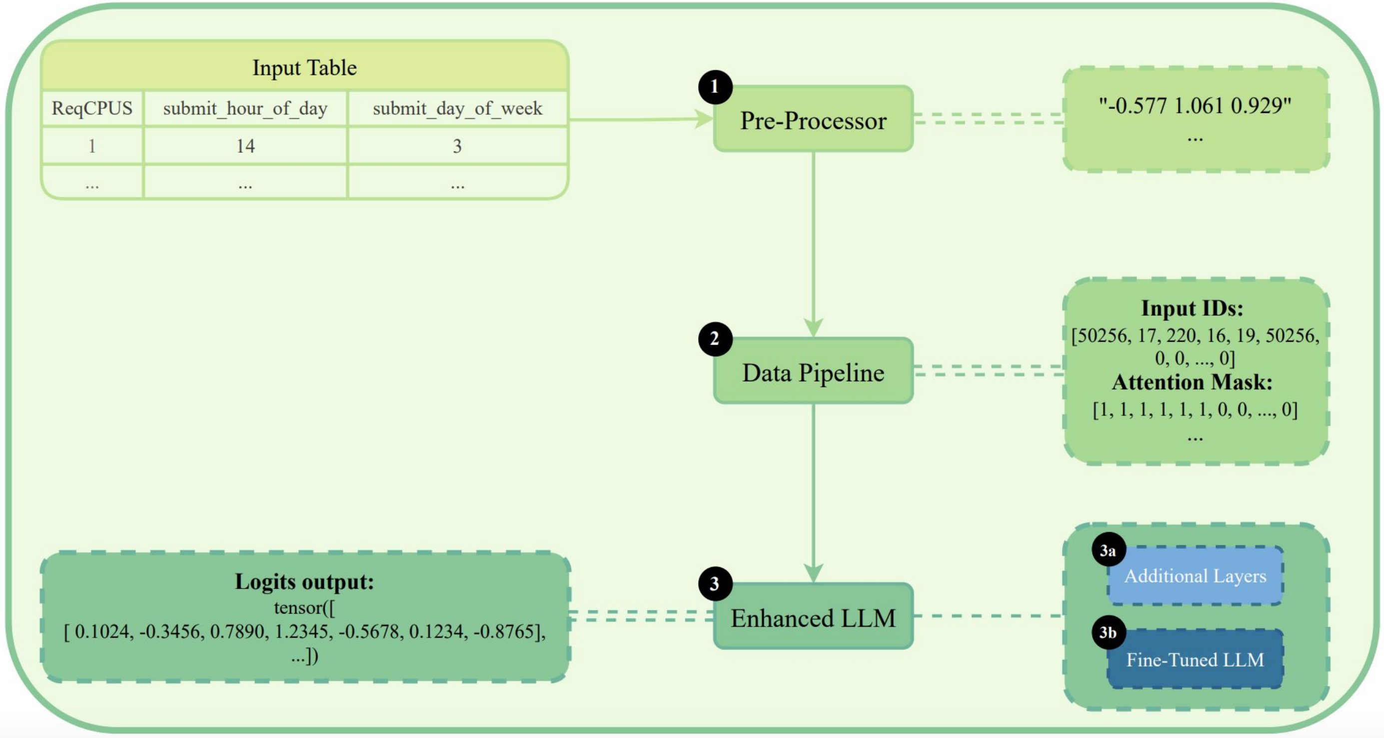
Design - How to Use LLMs to Predict Job End-State?

RQ3.1



Design - How to Use LLMs to Predict Job End-State?

RQ3.1



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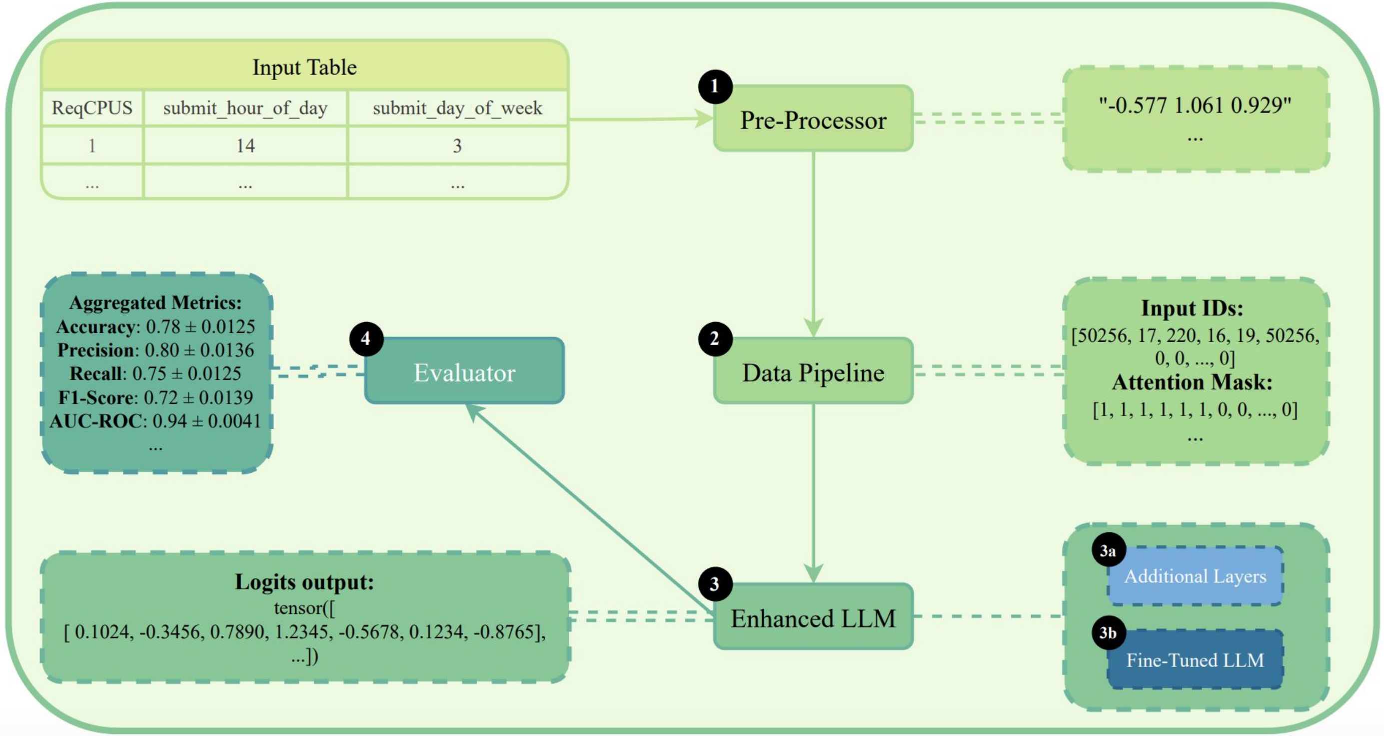
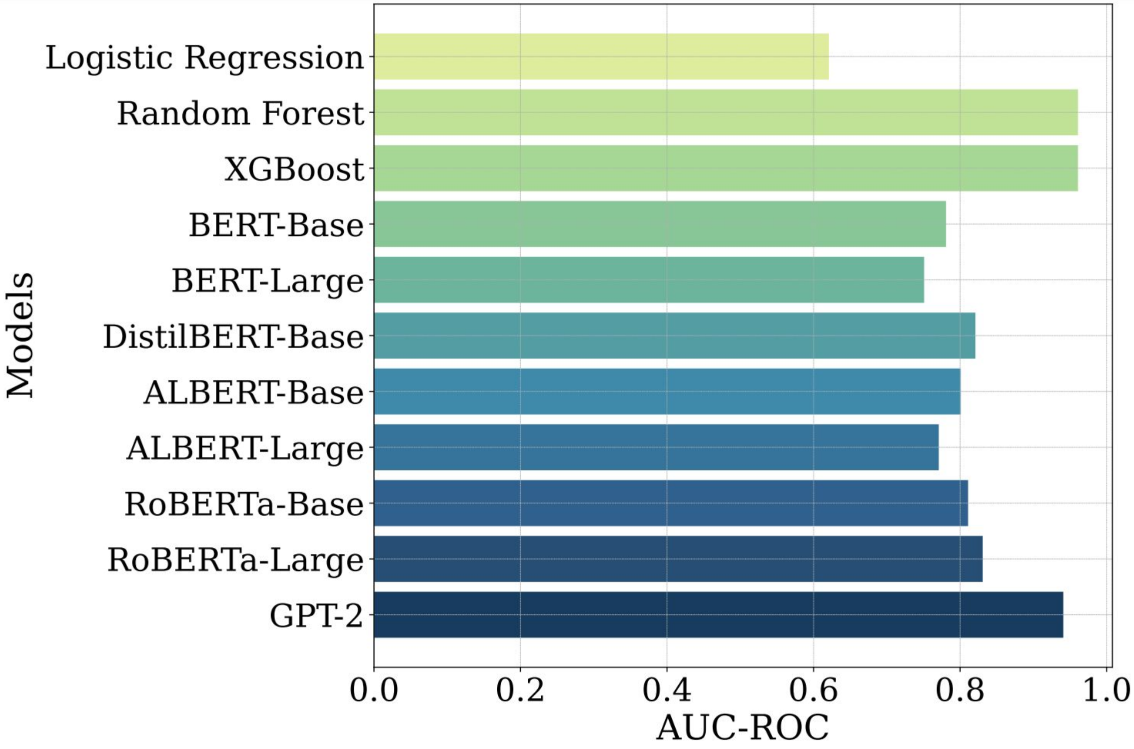
RQ3.1



Evaluation - How Well Do LLMs Work in Prediction?

RQ3.2



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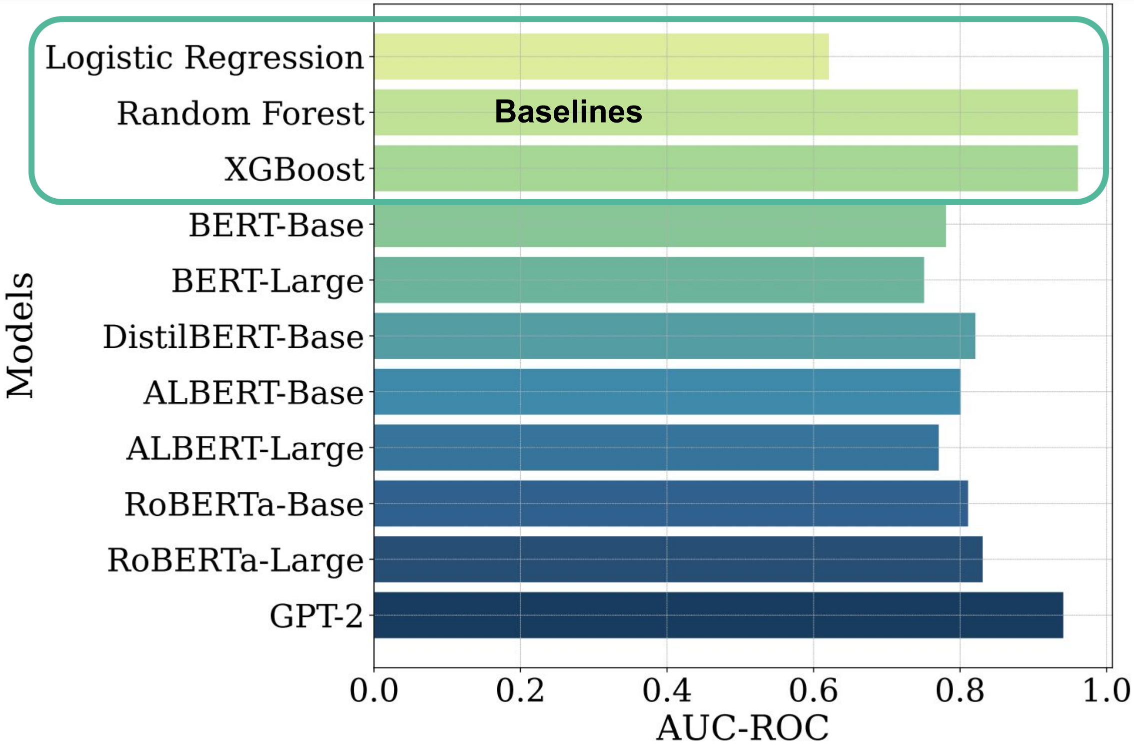

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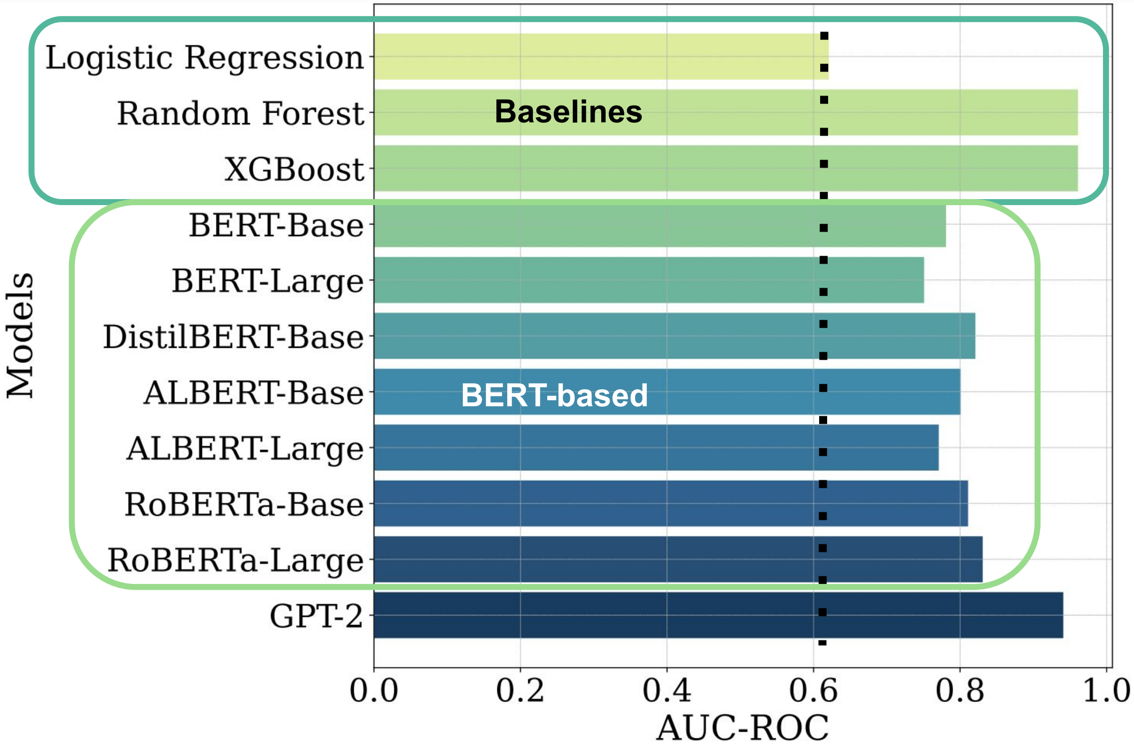

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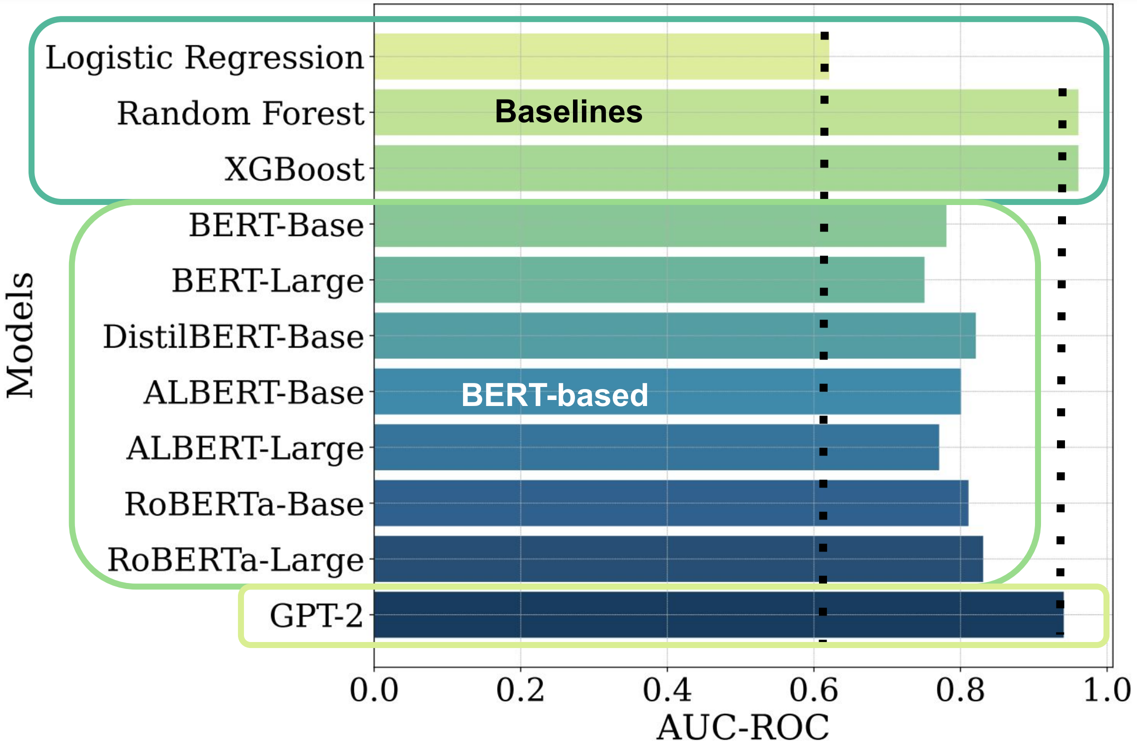

Summary of Job End-State Prediction Using LLMs

RQ3

- **F1** - **GPT-2** shows competitive performance against the best-performing traditional models.

- **F2** - **RoBERTa-Large** and **DistilBERT-Base** also show promising results.

- **F3** - LLMs demonstrate **significant potential** in predicting job termination states within HPC clusters.

Conclusion & Future Work

Conclusion & Future Work

RQ1

- Existing LLM applications primarily focus on **programming-related tasks**.
- Significant **potential** in workload synthesis and predictive analysis.

Conclusion & Future Work

RQ2

- Existing LLM applications primarily focus on **programming-related tasks**.
- Significant **potential** in workload synthesis and predictive analysis.

- Models such as **RoBERTa-Large** and **GPT-2** excel in data synthesis.
- LLM-generated data shows promise but doesn't match real data for training predictive models.

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RQ3

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- Models such as **RoBERTa-Large** and **GPT-2** excel in data synthesis.
- LLM-generated data shows promise but doesn't match real data for training predictive models.

- **GPT-2** shows competitive performance with traditional models in predictive tasks.
- Other LLMs show varying levels of effectiveness.

Conclusion & Future Work

- Existing LLM applications primarily focus on **programming-related tasks**.
- Significant **potential** in workload synthesis and predictive analysis.

- Models suc… s.
- LLM-gener… a for training predictive r…

- **GPT-2** show… redictive tasks.
- Other LLMs show varying levels of effectiveness.

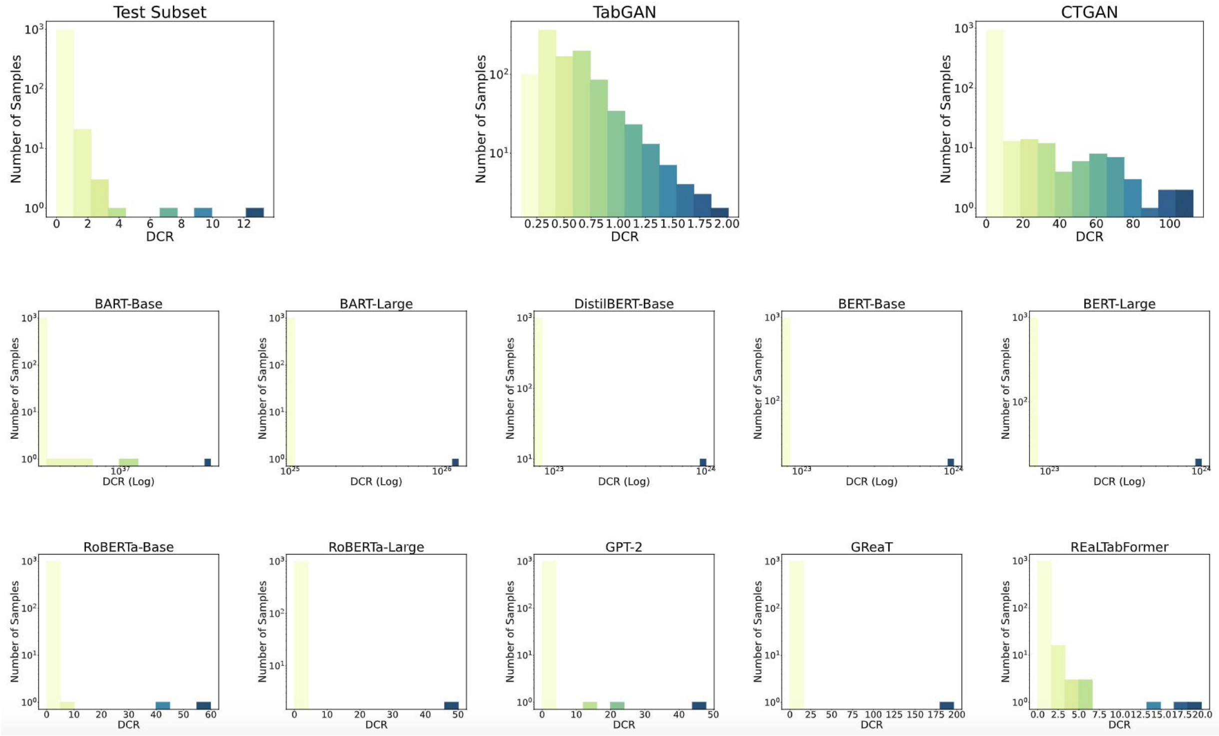
Future Work

➔ A wider range of LLM architectures.
➔ Additional metrics for synthetic data evaluation.
➔ Advanced techniques for textual encoding.

Backup Slides

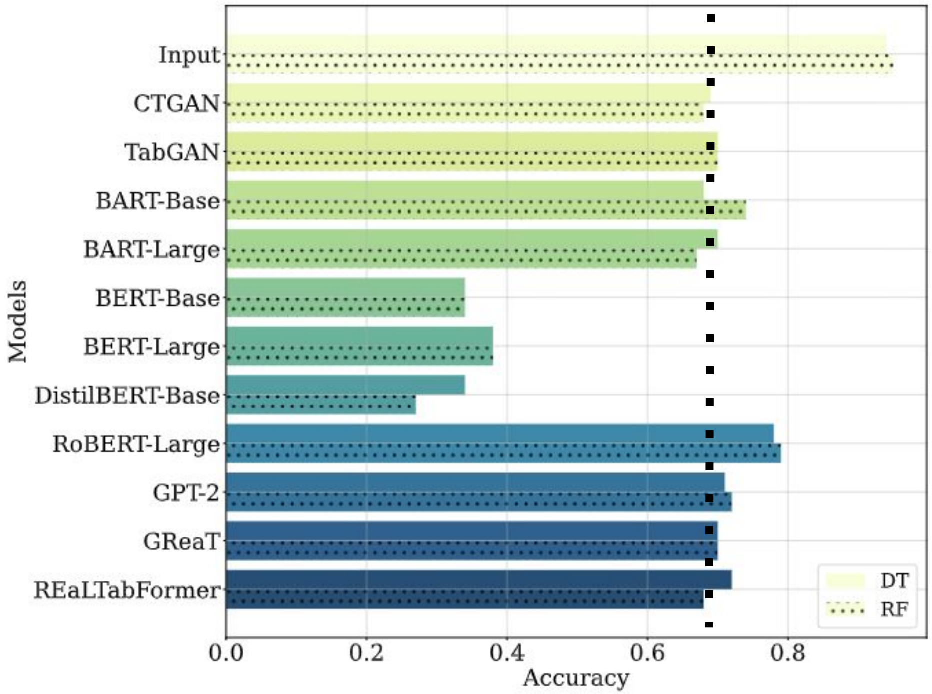
DCR Distributions

RQ2.2



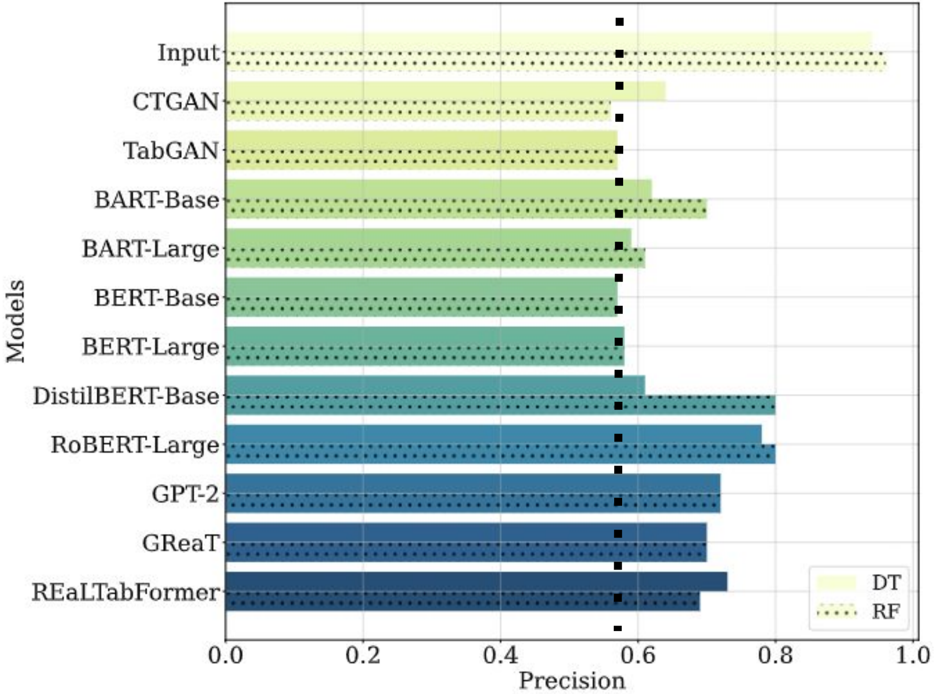
MLE Metrics (1/4) - Accuracy

RQ2.2



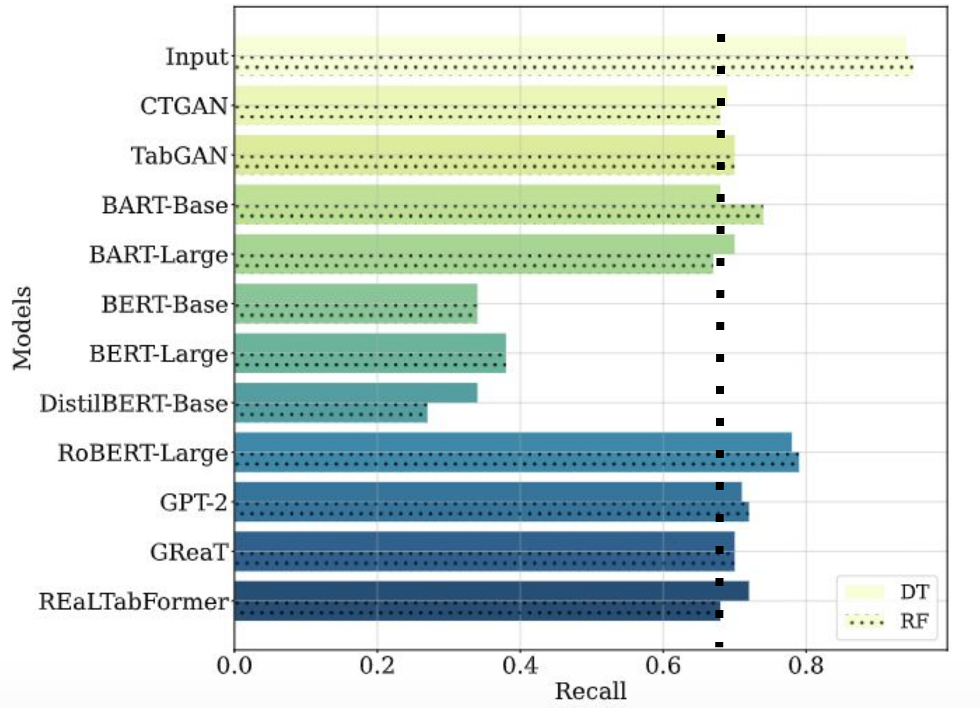
MLE Metrics (2/4) - Precision

RQ2.2



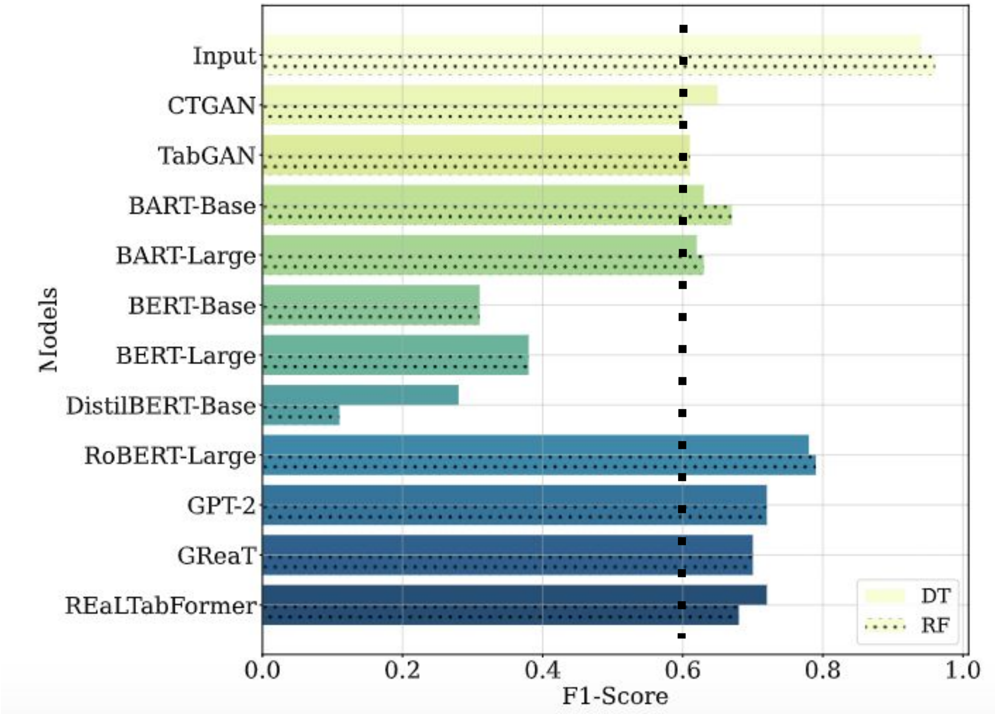
MLE Metrics (3/4) - Recall

RQ2.2



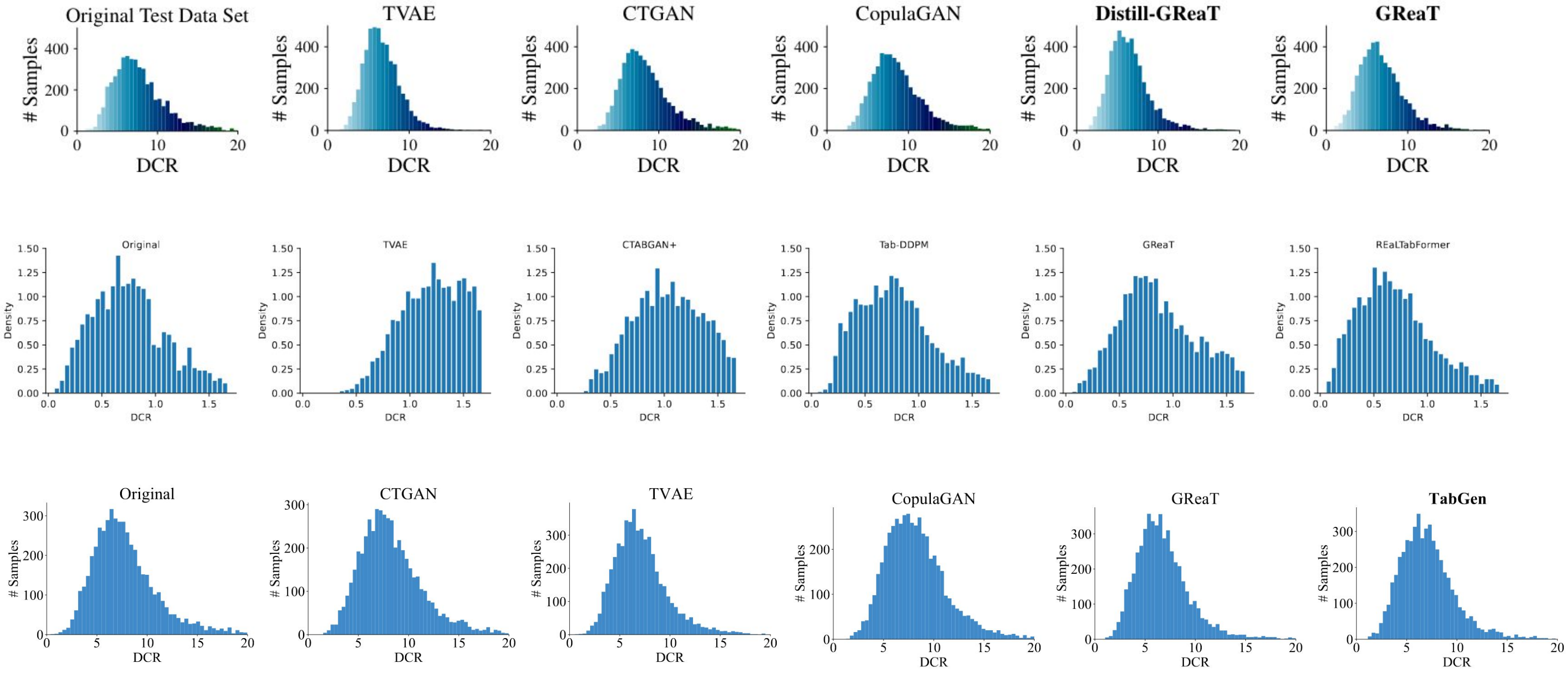
MLE Metrics (4/4) - F1 - Score

RQ2.2



DCR Distribution

RQ2.2



Source: Borisov et al., 2023;
Solatorio and Dupriez, 2023;
Zhang et al., 2023.

LLMs in Classification

RQ3.2

Dataset	Method	0	4	8	16	32	64	128	256	512	all
		Number of Shots									
Bank	XGBoost	—	$0.50_{.00}$	$0.56_{.09}$	$0.68_{.04}$	$0.76_{.03}$	**$0.83_{.02}$**	$0.85_{.03}$	$0.88_{.01}$	$0.90_{.01}$	**$0.94_{.00}$**
	TabPFN	—	$0.59_{.14}$	**$0.66_{.08}$**	**$0.69_{.02}$**	$0.76_{.03}$	$0.82_{.03}$	**$0.86_{.02}$**	**$0.89_{.00}$**	$0.90_{.00}$	$0.91_{.00}$
	TabLLM	**$0.63_{.01}$**	$0.59_{.10}$	$0.64_{.05}$	$0.65_{.05}$	$0.64_{.06}$	$0.69_{.03}$	$0.82_{.05}$	$0.87_{.01}$	$0.88_{.01}$	0.92 †
Blood	XGBoost	—	$0.50_{.00}$	$0.58_{.07}$	$0.66_{.04}$	$0.67_{.06}$	$0.68_{.05}$	$0.71_{.06}$	$0.70_{.07}$	$0.67_{.06}$	$0.71_{.04}$
	TabPFN	—	$0.52_{.08}$	$0.64_{.04}$	**$0.67_{.01}$**	**$0.70_{.04}$**	**$0.73_{.04}$**	**$0.75_{.04}$**	**$0.76_{.04}$**	**$0.76_{.03}$**	**$0.74_{.03}$**
	TabLLM	**$0.61_{.04}$**	**$0.58_{.09}$**	**$0.66_{.03}$**	$0.66_{.07}$	$0.68_{.04}$	$0.68_{.04}$	$0.68_{.06}$	$0.70_{.08}$	$0.68_{.04}$	$0.70_{.04}$
Calhousing	XGBoost	—	$0.50_{.00}$	$0.62_{.10}$	$0.74_{.03}$	$0.79_{.04}$	$0.82_{.04}$	$0.87_{.01}$	$0.90_{.01}$	$0.92_{.01}$	**$0.97_{.00}$**
	TabPFN	—	$0.63_{.13}$	**$0.63_{.11}$**	**$0.80_{.03}$**	**$0.85_{.03}$**	**$0.89_{.01}$**	**$0.91_{.01}$**	**$0.92_{.00}$**	**$0.93_{.00}$**	$0.94_{.00}$
	TabLLM	**$0.61_{.01}$**	$0.63_{.05}$	$0.60_{.07}$	$0.70_{.08}$	$0.77_{.08}$	$0.77_{.04}$	$0.81_{.02}$	$0.83_{.01}$	$0.86_{.02}$	$0.95_{.00}$
Car	XGBoost	—	$0.50_{.00}$	$0.59_{.04}$	$0.70_{.08}$	$0.82_{.03}$	$0.91_{.02}$	$0.95_{.01}$	$0.98_{.01}$	$0.99_{.01}$	$1.00_{.00}$
	TabPFN	—	$0.64_{.06}$	$0.75_{.05}$	**$0.87_{.04}$**	**$0.92_{.02}$**	**$0.97_{.00}$**	**$0.99_{.01}$**	**$1.00_{.00}$**	$1.00_{.00}$	$1.00_{.00}$
	TabLLM	**$0.82_{.02}$**	**$0.83_{.03}$**	**$0.85_{.03}$**	$0.86_{.03}$	$0.91_{.02}$	$0.96_{.02}$	$0.98_{.01}$	$0.99_{.00}$	$1.00_{.00}$	$1.00_{.00}$
Credit-g	XGBoost	—	$0.50_{.00}$	$0.51_{.07}$	$0.59_{.05}$	$0.66_{.03}$	$0.67_{.06}$	$0.68_{.02}$	$0.73_{.02}$	$0.75_{.03}$	**$0.78_{.04}$**
	TabPFN	—	$0.58_{.08}$	$0.59_{.03}$	$0.64_{.06}$	$0.69_{.07}$	$0.70_{.07}$	**$0.72_{.06}$**	**$0.75_{.04}$**	$0.75_{.02}$	$0.75_{.03}$
	TabLLM	**$0.53_{.05}$**	**$0.69_{.04}$**	**$0.66_{.04}$**	**$0.66_{.05}$**	**$0.72_{.06}$**	$0.70_{.07}$	$0.71_{.07}$	$0.72_{.03}$	$0.72_{.02}$	$0.70_{.02}$
Diabetes	XGBoost	—	$0.50_{.00}$	$0.59_{.16}$	**$0.72_{.07}$**	$0.69_{.08}$	$0.73_{.05}$	$0.78_{.05}$	$0.80_{.03}$	$0.80_{.01}$	**$0.84_{.03}$**
	TabPFN	—	$0.61_{.13}$	**$0.67_{.11}$**	$0.71_{.07}$	**$0.77_{.03}$**	**$0.82_{.03}$**	**$0.83_{.03}$**	**$0.83_{.03}$**	**$0.81_{.02}$**	$0.81_{.03}$
	TabLLM	**$0.68_{.06}$**	$0.61_{.09}$	$0.63_{.08}$	$0.69_{.07}$	$0.68_{.04}$	$0.73_{.03}$	$0.79_{.04}$	$0.78_{.02}$	$0.78_{.04}$	$0.80_{.04}$
Heart	XGBoost	—	$0.50_{.00}$	$0.55_{.14}$	$0.84_{.07}$	$0.88_{.04}$	$0.91_{.01}$	$0.91_{.01}$	$0.90_{.01}$	$0.92_{.01}$	$0.94_{.01}$
	TabPFN	—	**$0.84_{.06}$**	**$0.88_{.05}$**	$0.87_{.06}$	**$0.91_{.02}$**	**$0.92_{.02}$**	**$0.92_{.02}$**	$0.92_{.01}$	$0.92_{.02}$	$0.92_{.02}$
	TabLLM	**$0.54_{.04}$**	$0.76_{.14}$	$0.83_{.05}$	$0.87_{.04}$	$0.87_{.06}$	$0.91_{.01}$	$0.90_{.01}$	$0.92_{.01}$	$0.92_{.01}$	$0.94_{.01}$
Income	XGBoost	—	$0.50_{.00}$	$0.59_{.06}$	$0.77_{.02}$	$0.79_{.03}$	$0.82_{.02}$	$0.84_{.01}$	$0.87_{.01}$	$0.88_{.00}$	**$0.93_{.00}$**
	TabPFN	—	0.73 [illegible]	0.71 [illegible]	0.76 [illegible]	0.80 [illegible]	0.82 [illegible]	0.84 [illegible]	$0.86_{.01}$	$0.87_{.01}$	$0.89_{.00}$
	TabLLM	**$0.84_{.00}$**	**$0.84_{.01}$**	**$0.84_{.02}$**	**$0.84_{.04}$**	**$0.84_{.01}$**	**$0.84_{.02}$**	**$0.86_{.01}$**	$0.87_{.00}$	**$0.89_{.01}$**	$0.92_{.00}$
Jungle	XGBoost	—	$0.50_{.00}$	$0.58_{.07}$	**$0.72_{.05}$**	$0.78_{.03}$	$0.81_{.02}$	$0.84_{.02}$	$0.87_{.01}$	$0.91_{.01}$	$0.98_{.00}$
	TabPFN	—	**$0.65_{.08}$**	**$0.72_{.04}$**	$0.71_{.07}$	$0.78_{.02}$	$0.81_{.01}$	$0.84_{.01}$	**$0.88_{.01}$**	$0.91_{.00}$	$0.93_{.00}$
	TabLLM	**$0.60_{.00}$**	$0.64_{.01}$	$0.64_{.02}$	$0.65_{.03}$	$0.71_{.02}$	$0.78_{.02}$	$0.81_{.02}$	$0.84_{.01}$	$0.89_{.01}$	**1.00** †

#Shots	Method	Bank	Blood	C. Hous.	Car	Creditg	Diabetes	Heart	Income	Jungle
64	Logistic Reg.	$0.84_{.02}$	**$0.74_{.02}$**	$0.88_{.01}$	$0.93_{.02}$	$0.66_{.07}$	$0.80_{.02}$	$0.91_{.01}$	$0.83_{.03}$	$0.79_{.01}$
	LightGBM	$0.77_{.03}$	$0.69_{.04}$	$0.81_{.02}$	$0.85_{.06}$	$0.61_{.09}$	$0.79_{.02}$	$0.91_{.01}$	$0.78_{.03}$	$0.79_{.02}$
	XGBoost	$0.83_{.02}$	$0.68_{.05}$	$0.82_{.04}$	$0.91_{.02}$	$0.67_{.06}$	$0.73_{.05}$	$0.91_{.01}$	$0.82_{.02}$	**$0.81_{.02}$**
	SAINT	$0.81_{.03}$	$0.67_{.05}$	$0.81_{.02}$	$0.92_{.02}$	$0.66_{.06}$	$0.79_{.03}$	$0.90_{.04}$	**$0.84_{.02}$**	**$0.81_{.01}$**
	TabNet	$0.71_{.06}$	$0.63_{.06}$	$0.72_{.03}$	$0.73_{.07}$	$0.56_{.05}$	$0.71_{.04}$	$0.83_{.05}$	$0.71_{.04}$	$0.73_{.04}$
	NODE	$0.78_{.02}$	$0.71_{.05}$	$0.80_{.01}$	$0.80_{.02}$	$0.63_{.04}$	$0.77_{.04}$	$0.88_{.02}$	$0.75_{.02}$	$0.75_{.04}$
	TabPFN	$0.82_{.03}$	$0.73_{.04}$	**$0.89_{.01}$**	**$0.97_{.00}$**	**$0.70_{.07}$**	$0.82_{.03}$	**$0.92_{.02}$**	$0.82_{.04}$	**$0.81_{.01}$**
	TabLLM	$0.69_{.03}$	$0.68_{.04}$	$0.77_{.04}$	$0.96_{.02}$	**$0.70_{.07}$**	$0.73_{.03}$	$0.91_{.01}$	**$0.84_{.02}$**	$0.78_{.02}$
	LLaMA	$0.62_{.02}$	$0.66_{.03}$	$0.57_{.04}$	$0.90_{.02}$	$0.67_{.09}$	$0.78_{.05}$	$0.88_{.02}$	**$0.84_{.02}$**	$0.63_{.04}$
	LLaMA-GTL	**$0.86_{.01}$**	$0.72_{.05}$	$0.78_{.04}$	$0.96_{.01}$	**$0.70_{.09}$**	**$0.83_{.04}$**	$0.88_{.05}$	**$0.84_{.01}$**	$0.69_{.04}$
512	Logistic Reg.	$0.89_{.00}$	**$0.76_{.03}$**	$0.91_{.00}$	$0.98_{.00}$	**$0.76_{.02}$**	$0.83_{.02}$	**$0.93_{.01}$**	$0.88_{.00}$	$0.80_{.00}$
	LightGBM	$0.89_{.00}$	$0.67_{.05}$	$0.92_{.00}$	$0.99_{.01}$	$0.75_{.02}$	$0.79_{.03}$	$0.92_{.01}$	$0.88_{.00}$	**$0.91_{.00}$**
	XGBoost	**$0.90_{.01}$**	$0.67_{.06}$	$0.92_{.01}$	$0.99_{.01}$	$0.75_{.03}$	$0.80_{.01}$	$0.92_{.01}$	$0.88_{.00}$	**$0.91_{.01}$**
	SAINT	$0.88_{.01}$	$0.73_{.02}$	$0.91_{.02}$	$0.99_{.00}$	$0.73_{.03}$	$0.77_{.03}$	$0.92_{.01}$	$0.88_{.00}$	$0.90_{.00}$
	TabNet	$0.83_{.03}$	$0.72_{.02}$	$0.87_{.01}$	$0.98_{.01}$	$0.66_{.04}$	$0.74_{.07}$	$0.88_{.03}$	$0.83_{.02}$	$0.84_{.01}$
	NODE	$0.86_{.01}$	**$0.76_{.03}$**	$0.87_{.01}$	$0.96_{.01}$	$0.70_{.02}$	$0.83_{.02}$	$0.92_{.03}$	$0.83_{.01}$	$0.80_{.00}$
	TabPFN	**$0.90_{.00}$**	**$0.76_{.03}$**	**$0.93_{.00}$**	**$1.00_{.00}$**	$0.75_{.02}$	$0.81_{.02}$	$0.92_{.02}$	$0.87_{.01}$	**$0.91_{.00}$**
	TabLLM	$0.88_{.01}$	$0.68_{.04}$	$0.86_{.02}$	**$1.00_{.00}$**	$0.72_{.02}$	$0.78_{.04}$	$0.92_{.01}$	**$0.89_{.01}$**	$0.89_{.01}$
	LLaMA	$0.77_{.02}$	$0.72_{.05}$	$0.86_{.02}$	$0.99_{.00}$	$0.72_{.04}$	$0.83_{.04}$	$0.92_{.02}$	**$0.89_{.01}$**	$0.85_{.03}$
	LLaMA-GTL	**$0.90_{.00}$**	$0.75_{.04}$	$0.89_{.02}$	$0.99_{.01}$	$0.74_{.05}$	**$0.85_{.03}$**	**$0.93_{.02}$**	**$0.89_{.01}$**	$0.89_{.01}$
All	Logistic Reg.	$0.91_{.00}$	**$0.76_{.03}$**	$0.92_{.00}$	$0.98_{.00}$	**$0.79_{.03}$**	$0.83_{.02}$	$0.93_{.01}$	$0.90_{.00}$	$0.81_{.00}$
	LightGBM	**$0.94_{.00}$**	$0.74_{.04}$	**$0.97_{.00}$**	**$1.00_{.00}$**	$0.78_{.02}$	$0.83_{.03}$	**$0.94_{.01}$**	**$0.93_{.00}$**	$0.98_{.00}$
	XGBoost	**$0.94_{.00}$**	$0.71_{.04}$	**$0.97_{.00}$**	**$1.00_{.00}$**	$0.78_{.04}$	$0.84_{.03}$	**$0.94_{.01}$**	**$0.93_{.00}$**	$0.98_{.00}$
	SAINT	$0.93_{.00}$	$0.74_{.03}$	$0.95_{.00}$	**$1.00_{.00}$**	$0.77_{.04}$	$0.83_{.03}$	$0.93_{.01}$	$0.91_{.00}$	**$1.00_{.00}$**
	TabNet	$0.93_{.00}$	$0.71_{.03}$	$0.96_{.00}$	**$1.00_{.00}$**	$0.64_{.03}$	$0.81_{.03}$	$0.89_{.03}$	$0.92_{.00}$	$0.99_{.00}$
	NODE	$0.76_{.02}$	$0.74_{.03}$	$0.87_{.01}$	$0.93_{.01}$	$0.65_{.03}$	$0.83_{.03}$	$0.92_{.03}$	$0.82_{.00}$	$0.81_{.00}$
	TabPFN	$0.91_{.00}$	$0.74_{.03}$	$0.94_{.00}$	**$1.00_{.00}$**	$0.75_{.03}$	$0.81_{.03}$	$0.92_{.02}$	$0.89_{.00}$	$0.93_{.00}$
	TabLLM	$0.92_{.00}$	$0.70_{.04}$	$0.95_{.00}$	**$1.00_{.00}$**	$0.70_{.02}$	$0.80_{.04}$	**$0.94_{.01}$**	$0.92_{.00}$	**$1.00_{.00}$**
	LLaMA	**$0.94_{.00}$**	$0.72_{.04}$	**$0.97_{.00}$**	**$1.00_{.00}$**	$0.76_{.07}$	$0.84_{.03}$	$0.93_{.01}$	**$0.93_{.00}$**	**$1.00_{.00}$**
	LLaMA-GTL	**$0.94_{.00}$**	$0.75_{.05}$	$0.96_{.00}$	**$1.00_{.00}$**	$0.76_{.06}$	**$0.85_{.04}$**	$0.93_{.01}$	**$0.93_{.00}$**	**$1.00_{.00}$**

AUC performance.

Source: Hegselmann et al., 2022; Zhang et al., 2023.