KPMG Trusted AI:
Energy Usage and Sustainability

Data science, machine learning, and sustainability applied to derive and optimize energy insights.

Break Through Tech x Cornell Tech Fellowship 2025-26
KPMG 1C

Our Team

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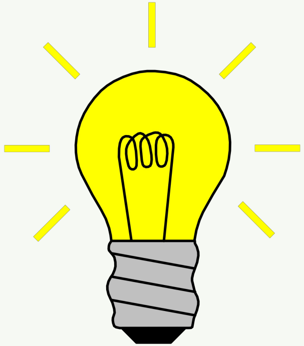
Agenda

AI Energy Consumption



67.5 kWh

Daily energy consumption of AI queries by KPMG audit agents

#4

Finance has fourth-highest energy burden to market capitalization ratio

40%

Microsoft reduced the Water Usage Effectiveness (WUE) from 0.49L/kWh (2021) to 0.3 L/KWh (2024)

KPMG: Trusted AI Initiative

Values Driven

Human Centric

Trustworthy

Explainability

Data Integrity

Transparency

Fairness

Accountability

Reliability

Security

Sustainability

Safety

Privacy

Project Overview

Initial Hypothesis: Energy usage primarily depends on the model type.
Research Question: Within each model type, which specific features drive energy usage?

Project Goals:

- ❑ Analyze AI systems energy consumption with Random Forest Model.
- ❑ Identify top drivers of energy usage.

Outcomes:

- ❑ Suggest operational strategies for reducing energy consumption.
- ❑ Strategize to improve efficiency and sustainability

01

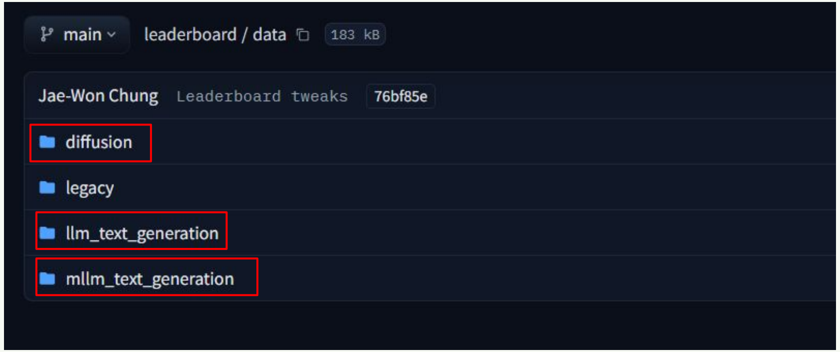
Data Preparation & Understanding

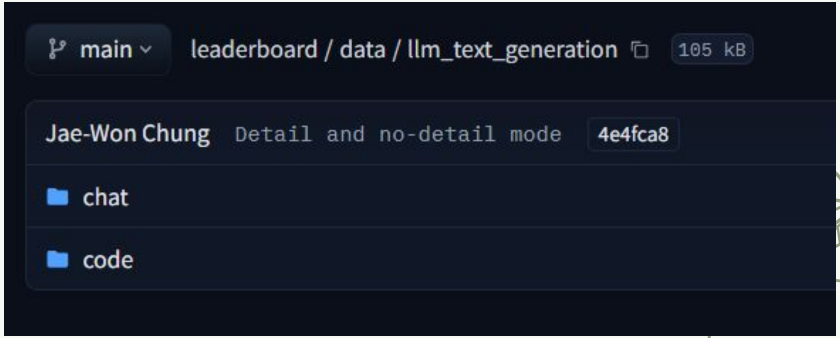
Our Data Set

This data set tracks energy use of GenAI models across tasks to help evaluate sustainable energy usage.

ML.Energy Leaderboard Data Set ~ 470

Diffusion ~ 118	llm ~ 314	mllm ~42
image-to-video	chat	chat
text-to-image	code	
text-to-video		





Our Data's Features

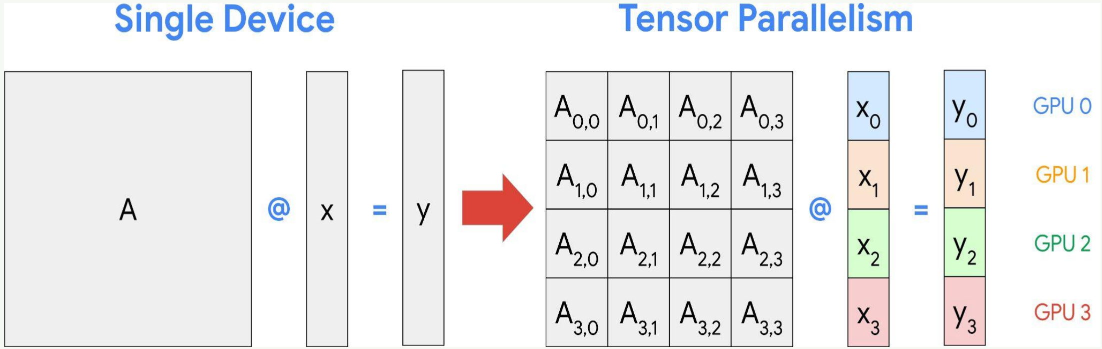
- Model
- GPU
- TP: Tensor Parallelism
- PP: Pipeline Parallelism
- Energy/req (J)
- Avg TPOT
- Token tput (tok/s)
- Avg Batch Size (reqs)
- Max Batch Size (reqs)

Individual Raw Entry:

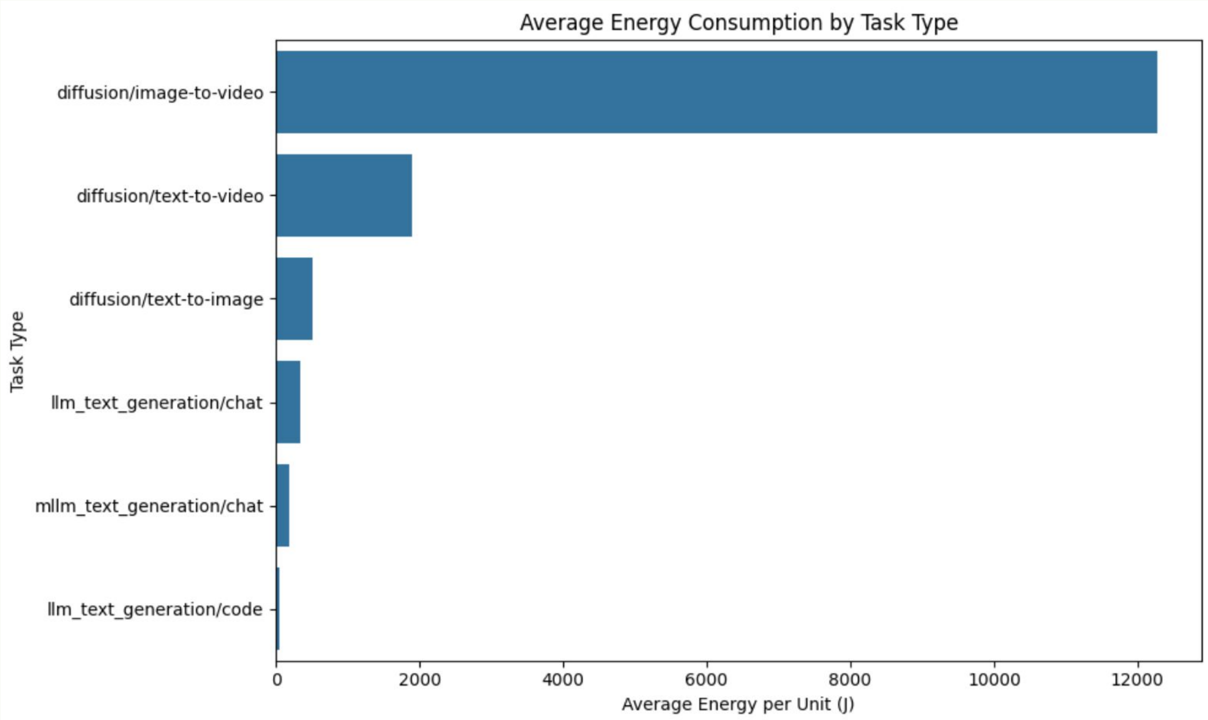

```json
{
  "Model": "google/gemma-2-27b-it",
  "GPU": "NVIDIA A100-SXM4-40GB",
  "TP": 4,
  "PP": 1,
  "Energy/req (J)": 230.644433524673,
  "Avg TPOT (s)": 0.11220224938943191,
  "Token tput (tok/s)": 1051.3354539260472,
  "Avg Output Tokens": 392.47133333333335,
  "Avg BS (reqs)": 127.72361537073786,
  "Max BS (reqs)": 128
}
```

Simplified Terms

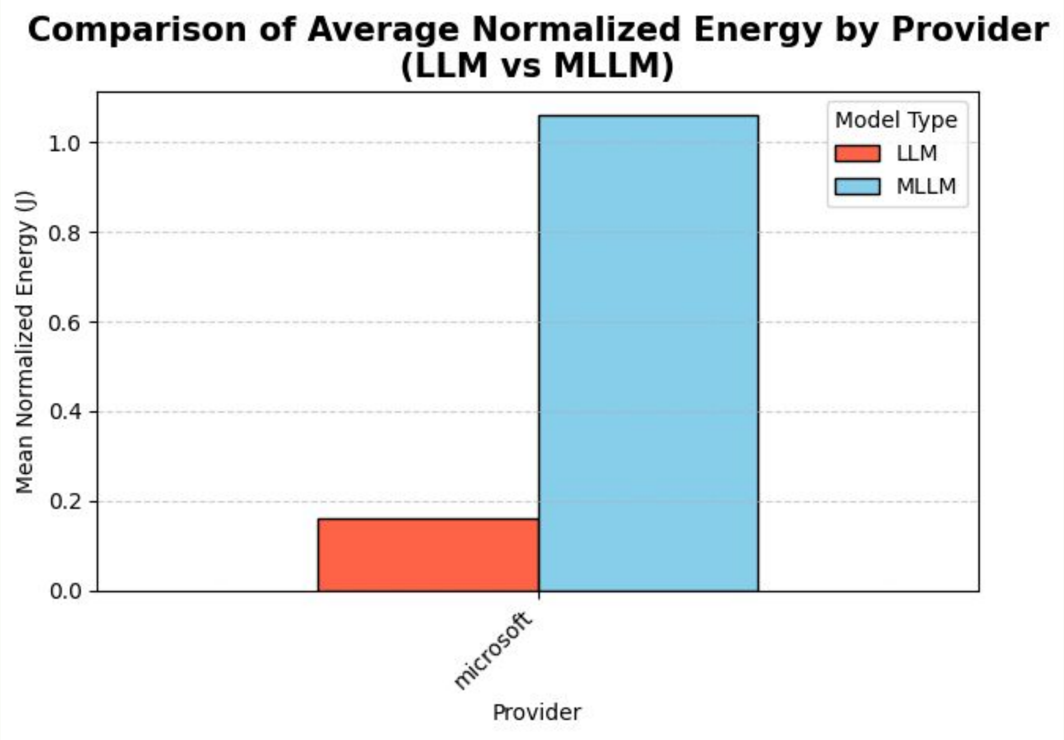
Tensor Parallelism	Splitting models across devices for speed
Energy/req (J)	Energy per request or query
Avg TPOT	Average response time
Token tput (tok/s)	Generation speed (words or images per second)
Token	Basic processing unit



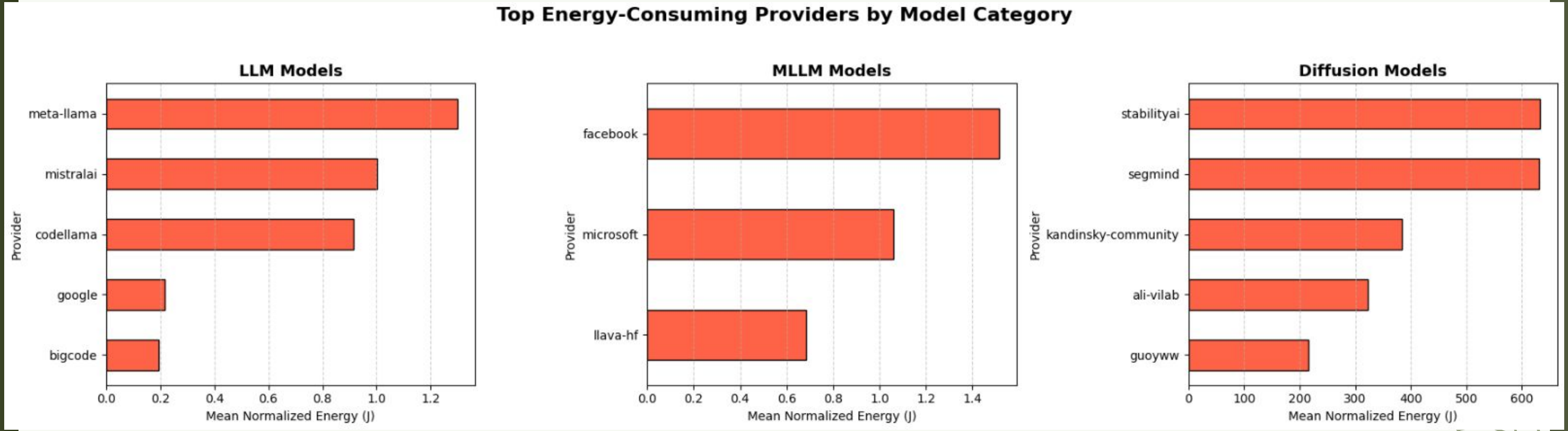
Data Insights: Task Type



Data Insights: LLM vs MLLM



Data Insights: Top Providers



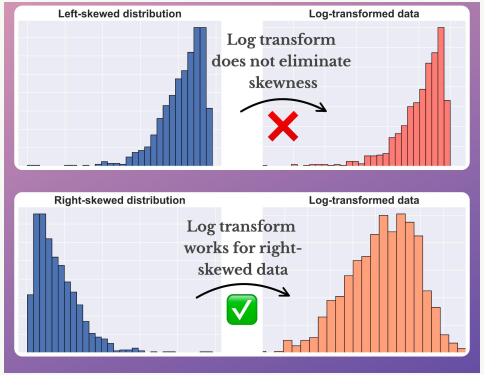
Larger models = more parameters → higher compute → higher energy

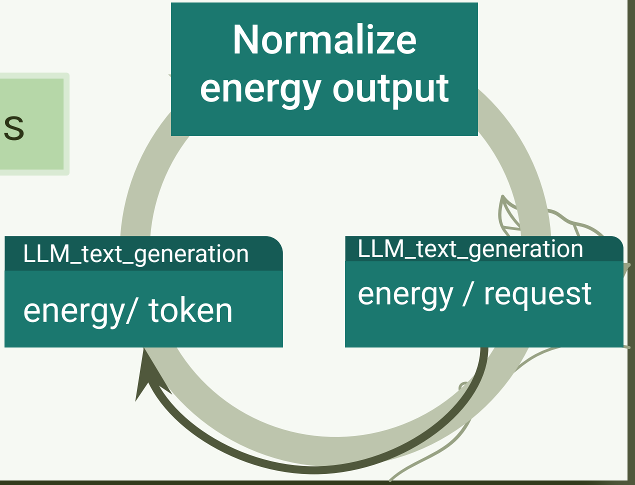
Data Preparation

Standardized energy across model types

Handle missing/ non-applicable features

Log-transformed energy values





02

Modeling & Evaluation

Modeling Approach: Which Model?

Random Forest was chosen due to the **complexity** and **nuance** of sustainability, this dataset, and real-world applications.

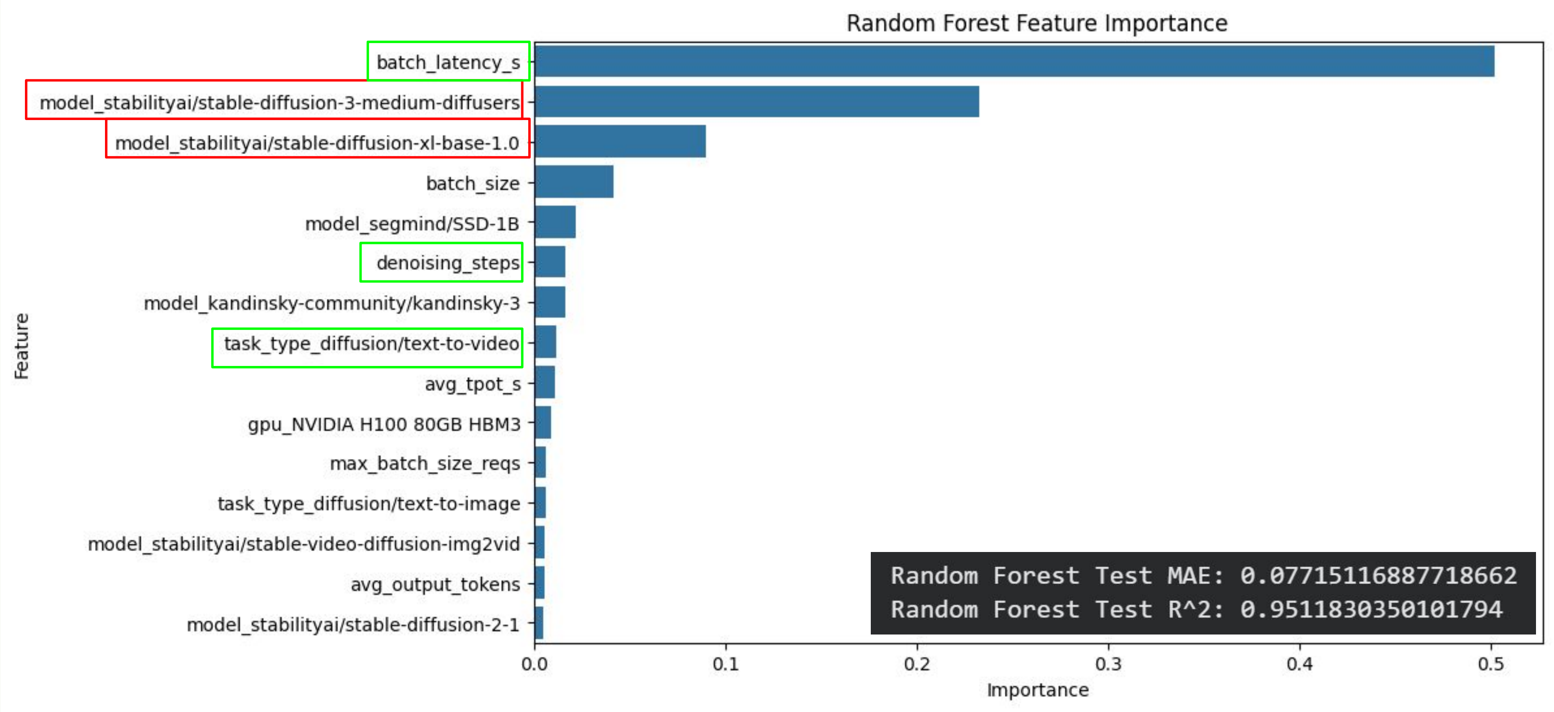
Simple Linear Regression	Ridge Regression - also Linear	Random Forest
🟩Highly comprehensible	🟩Stable and comprehensible	🟩 Complex
🟥Medium bias & underfitting	🟥 High bias & medium overfitting	🟩 Robust to outliers, non-linearity, and linked features
🟥Complex relationships	🟩 Interaction effects, step/thresholds, exponentials	🟩Automatically weighs features

Modeling Approach: How Do We Model?

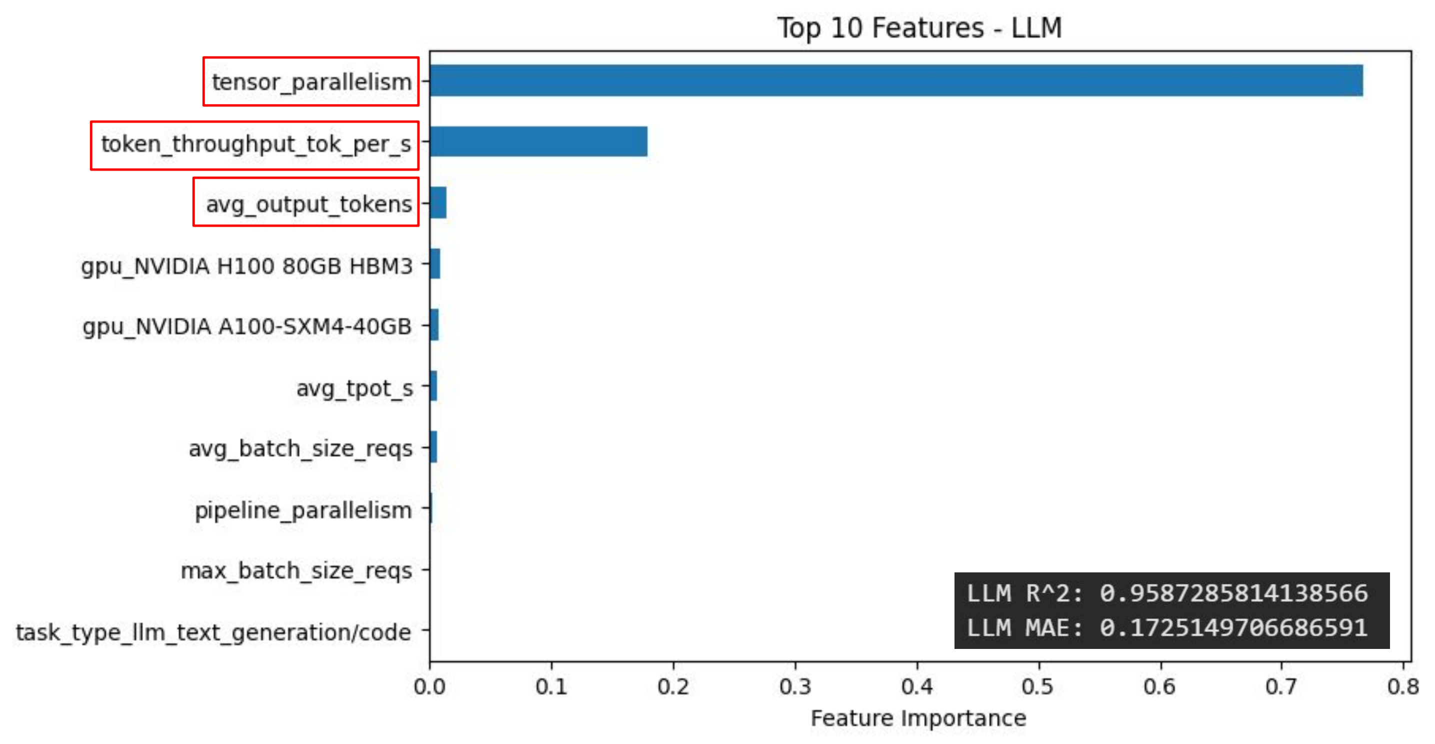
Our modeling approach transitioned from Option A to Option B to produce better insights.

Option A:		Option B:
All Task Types (LLM, MLLM, Diffusion)	→	Single Task Type (LLM)
All Features	→	Tailored Features

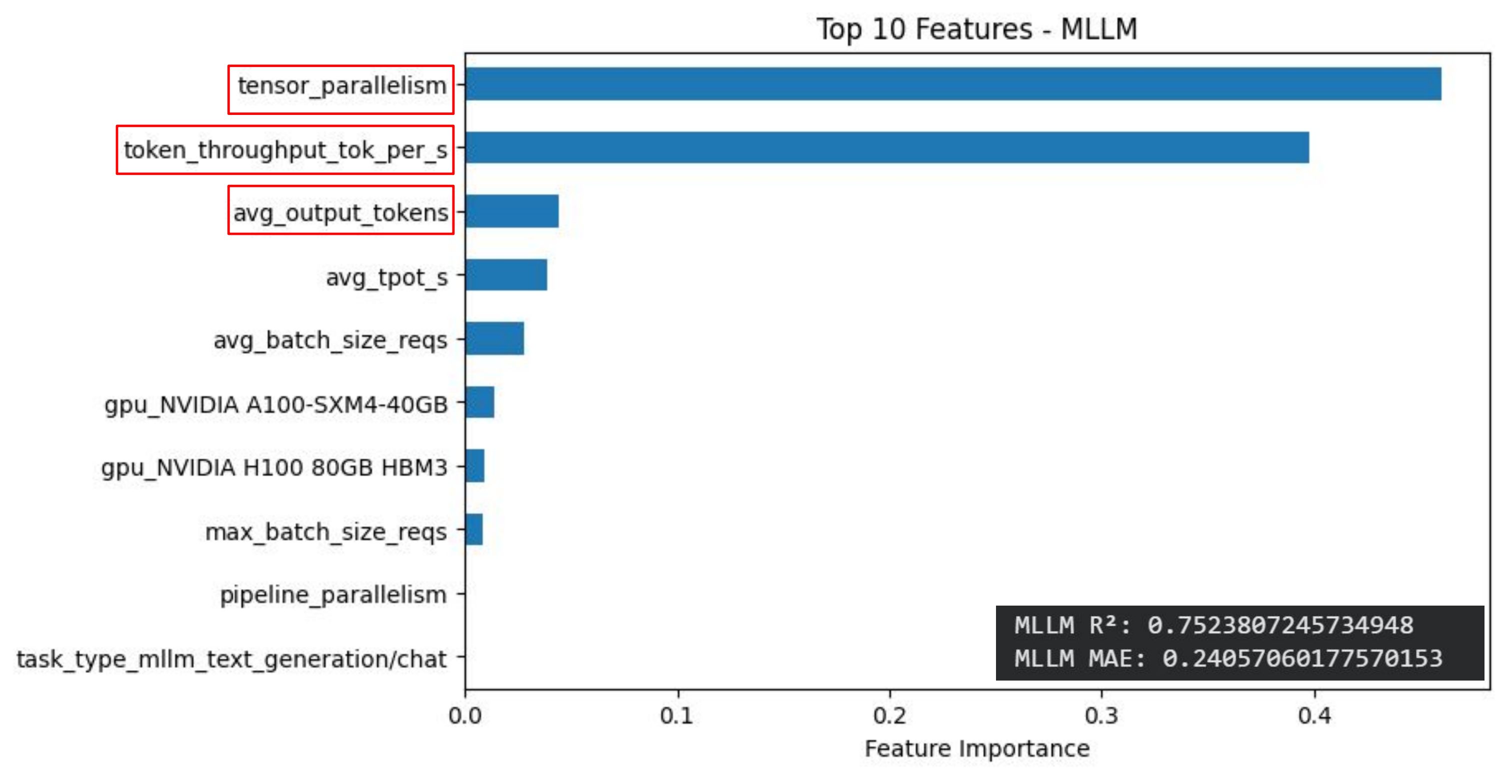
Model Evaluation: Option A



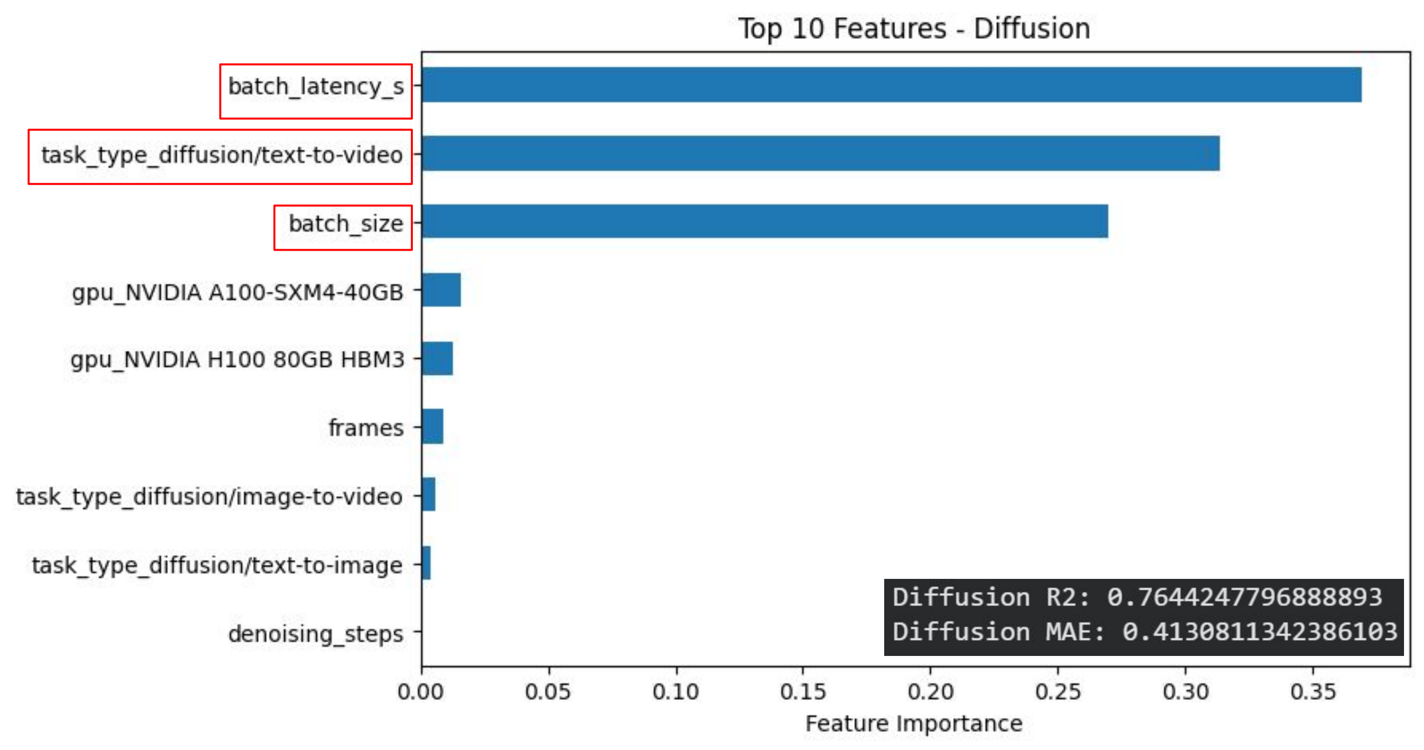
Model Evaluation: Option B (LLM)



Model Evaluation: Option B (MLLM)



Model Evaluation: Option B (Diffusion)



03

Solutions

Factor 1: Tensor Parallelism

Pros

↓ **Latency per-device**

↑ **Faster response**

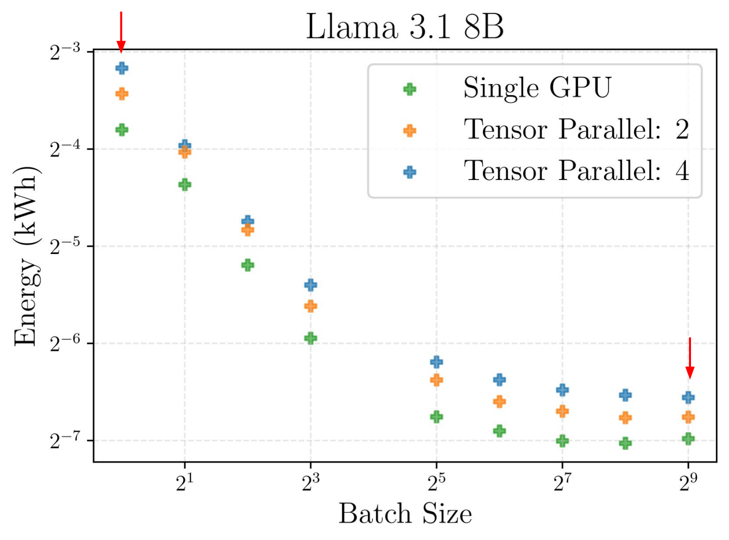
↓ **Computational intensity per-device**

↓ **Power utilization per-device**

Cons

↑ **Hardware Cost**

↑ **Total energy consumption**

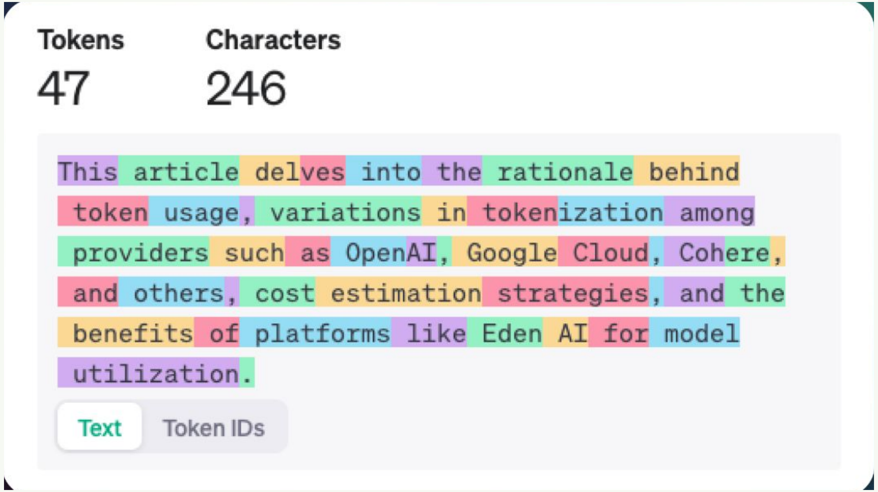


"**Parallelizing** a fixed workload over four GPUs **decreases latency** by **61.34%** but **increases total energy** use by **55.23%**."

Source: https://arxiv.org/html/2504.17674v1

Factor 2: Token Output

Definition: amount and type of tokens (letters, code, image, video frames) generated by LLM and MLLM models



Source: https://arxiv.org/html/2504.17674v1

Our Proposed Strategies

We focused on two main angles: which model to use and how to use it efficiently.

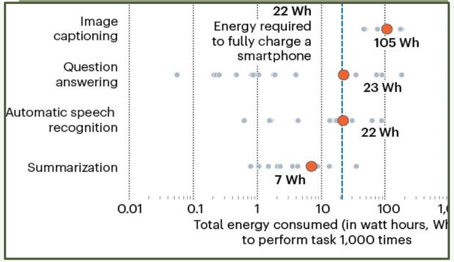
Which model do we use?	How do we use the model?
Match Model Type to Task	Prompt Engineering & Token Management
Allocate based on Parallelism	Optimize Throughput & Parallelism
Consider Input/Output Length	Monitor Energy & Cost Patterns
Optimize Model Selection	Deploy Energy Aware Dashboard

Conclusion

Efficiencies depend on

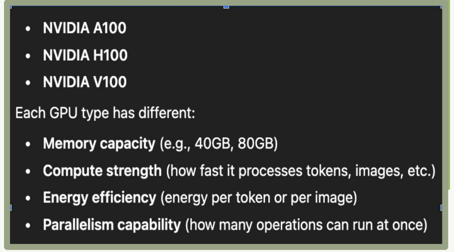
<u>Input Data Shape</u>

- Sequence Length
- Batch Size
- Frames / Modal Inputs



<u>Hardware Architecture</u>

- GPU Type & Memory
- Throughput
- Parallelism Levels



- **NVIDIA A100**
- **NVIDIA H100**
- **NVIDIA V100**

Each GPU type has different:

- **Memory capacity** (e.g., 40GB, 80GB)
- **Compute strength** (how fast it processes tokens, images, etc.)
- **Energy efficiency** (energy per token or per image)
- **Parallelism capability** (how many operations can run at once)

<u>Software & Framework:</u>

- Memory Handling

There's no single optimization that works for all tasks

Next Steps

Our next steps unify model improvement with KPMG’s energy-aware AI priorities.

Model Foundations

- Improve productivity
- Add company- and task-specific datasets

Energy-Aware Workflows

- Expand AI energy tracking
- Set energy incentives
- Standards for usage of heavier models

Responsible Deployment

- Retrain models for specialized tasks
- Link more variables
- Lightweight energy dashboard

Thank You to Our Advisors!

Dr. Uohna June Thiessen

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KPMG Advisor

Ashley Singhal

KPMG Advisor

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Questions?