Energy-Aware Quantization for LLMs

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Problem & Motivation

Motivation

- Transformer models (DistilBERT, GPT-2) are computationally expensive and power-hungry.
- Quantization is often used to reduce compute and model size, but its energy impact is poorly understood.
- Edge devices and datacenters care about energy per inference, not just speed.

Problem

- Existing research focuses on accuracy and latency, but rarely measures energy consumption across quantization formats. LLM inference dominates real-world compute and energy costs

Goal

- Evaluate energy, performance, and quality trade-offs across:
- FP32 (baseline)
- FP16 (native Tensor Core accelerated)
- Mixed precision and BF16 (ultimately dropped for limitations)

Model

Models

- DistilBERT — Sentiment classification (SST-2)
- GPT-2 Small — Next-token prediction (WikiText-2)

Quantization Formats Tested

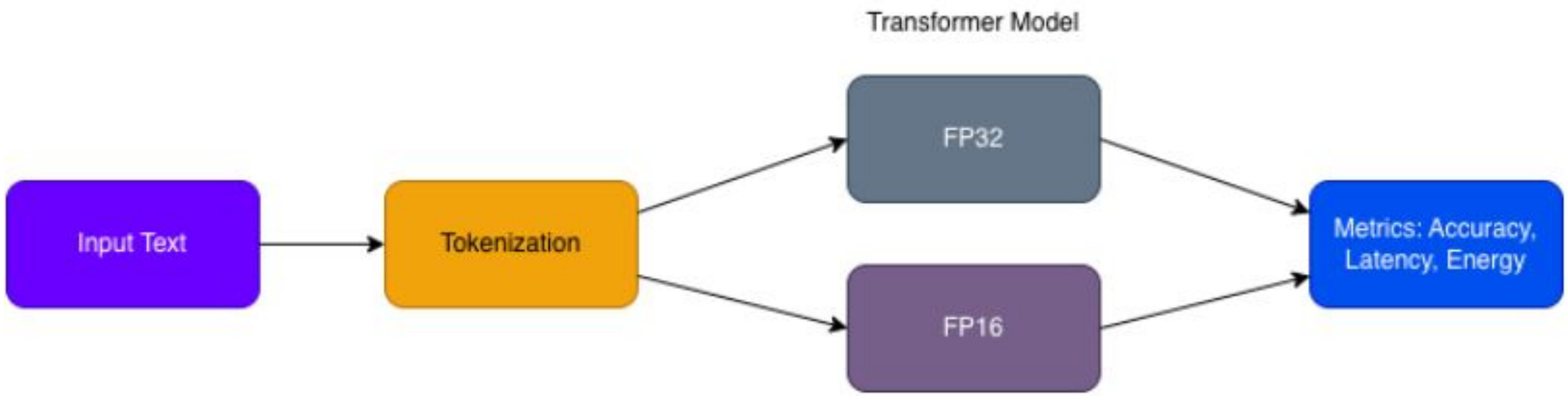
- FP32 baseline
- FP16 (full-model conversion)
- Mixed precision (initially tested; removed — training-only benefits)
- BF16 (removed — unsupported on T4 GPUs)

Model

Measurement Pipeline

- Zero-I/O tokenized dataset (preprocessed offline)
- Warmup passes to stabilize GPU clocks
- Multi-trial measurement (5 trials × 300 iterations)
- Real-time power sampling using nvidia-smi
- Accuracy, latency, throughput, energy/inference aggregated
- Energy measured using board-level nvidia-smi sampling (~20 Hz).
    - Uses mean power x runtime; captures stable load but not sub-kernel spikes."

Model


Transformer Model
FP32
Input Text
Tokenization
Metrics: Accuracy, Latency, Energy
FP16

Previous approaches

What Prior Work Has Focused On

- Precision reduction for speed or throughput
- Quantization for accuracy retention
- Mobile/edge INT8 optimization
- Model compression literature
- Energy studies ≠ precision studies

Limitations of Previous Work

- Rarely include end-to-end GPU energy measurements
- Lack controlled, I/O-free evaluation
- Often exclude transformers, using CNNs instead
- Few studies examine both DistilBERT and GPT-2 across multiple precisions
- No systematic comparison on general-purpose GPUs like Tesla T4

Contributions of this work

1. First controlled, end-to-end energy evaluation of FP32 vs FP16 for transformer inference on general-purpose GPUs (T4).
2. Full evaluation across both encoder and decoder architectures
3. Energy, accuracy, latency, model size analyzed together
4. Per-layer energy profiling
5. Practical guidelines for GPU quantization

Measurement Assumptions & Limitations

- GPU power draw ≈ nvidia-smi averages at 50 ms cadence.
- Single-GPU execution (GPU 0 only).
- CPU work, data loading, and host-side overhead are excluded from energy accounting.
- CUDA synchronizations enforce accurate timing.
- Warmup removes JIT and cache-population effects, so measured times ≈ true kernel runtimes.
- Per-layer energy is first-order only.
- Energy/sample assumes stable workload.

Implications:

- Good for relative comparisons (FP16 vs FP32), not absolute hardware-level power modeling.
- Board-level telemetry reflects total GPU subsystem power (VRAM, PCIe, memory controllers), not isolated MAC unit power.

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Details of the contributions

1. Zero-I/O Dataset & Evaluation Pipeline

- All datasets pre-tokenized and saved as .pt tensors
- Loaded directly to GPU, no disk access during inference
- Ensures energy reflects **compute only**, not I/O

2. GPU-Level Energy Measurement Infrastructure

- Power sampled from NVIDIA's board-level sensors
- Warmup phase stabilizes GPU clocks
- PowerLogger runs asynchronous sampling at ~10 Hz
- 5× repeated trials per precision mode (300 iterations each)
- Energy computed as: $E = P_{avg} \times t$

- Power samples represent total board power; memory controllers + background GPU subsystems are included
- Sampling at 50 ms cadence approximates stable average power; short transients are smoothed

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Details of the contributions

3. Full-Model Precision Conversion

- FP32 → FP16 via .half()
- Verified stability (no overflow/NaN)
- Mixed precision removed after validation showed training-only benefits
- BF16 unsupported on T4 → removed
- INT8 attempted → fallback to FP32 kernels on T4

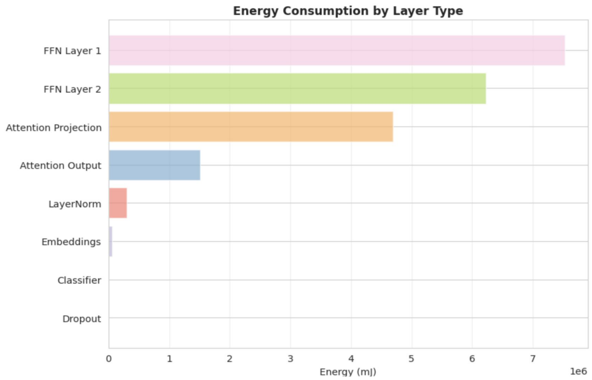
4. Per-Layer Energy Profiling

- Timed forward pass with per-module hooks
- Energy per layer computed from time share × mean GPU power
  - (first-order estimate; assumes near-constant power across layers)

Per-Layer Energy Profiling

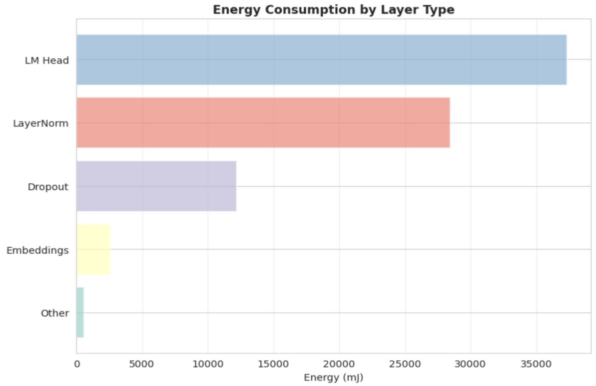
Distilbert (Encoder-Only)

- FFN layers dominate energy but have low prediction impact
- Attention layers: moderate energy, low impact
- Embeddings + LayerNorm: low energy, high importance
- Quantization opportunity: FFN + attention
- Keep high precision: embeddings, LayerNorm, classifier



GPT-2 (Decoder-Only)

- LM Head = highest energy and highest impact
- Embeddings + LayerNorm: also high impact
- Dropout/residual: low energy, low impact
- Quantization opportunity: only internal attention/MLP layers
- Avoid quantizing: LM Head + embeddings



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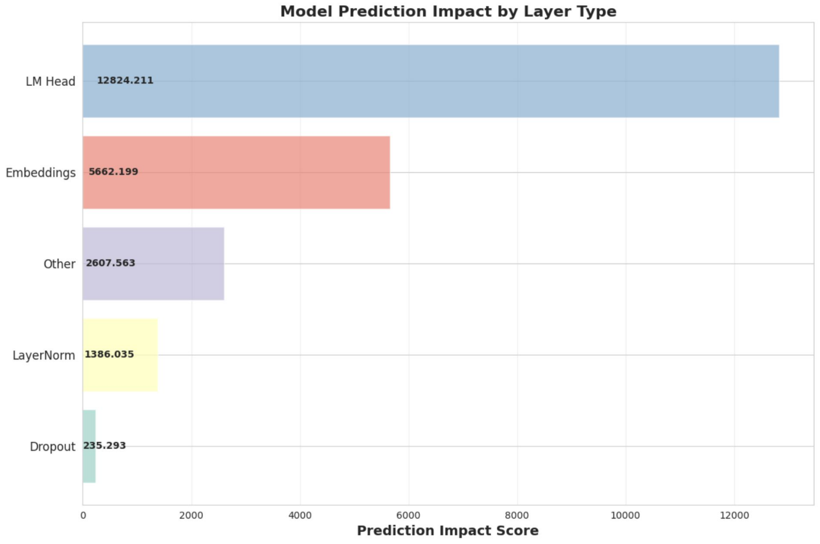
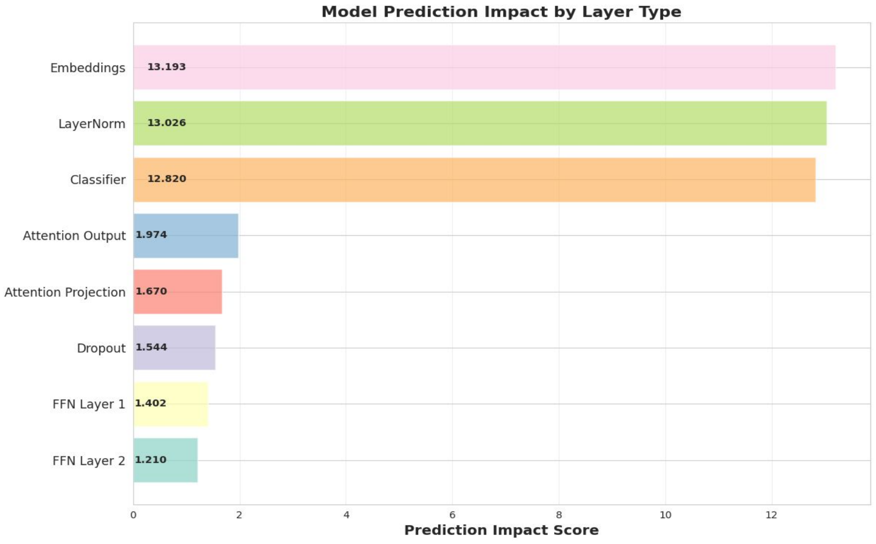
Per-Layer Prediction Impact Profiling



GPT-2



Distilbert

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Results and Analysis **DistilBERT**

Task

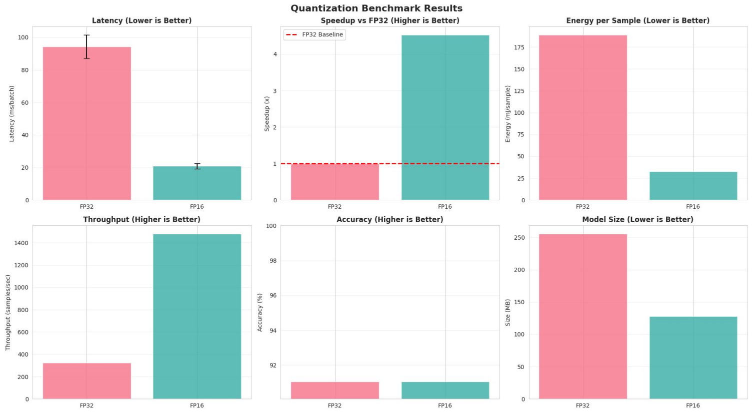
- SST-2 sentiment classification (50-sample evaluation set)

Formats Tested

- FP32 → FP16

Key Findings

- Energy reduced by ~5.4%
- Latency improved by ~5%
- Model size reduced by 2×
- No accuracy drop → DistilBERT is numerically stable in FP16
- FP16 benefits from **T4 Tensor Cores**



Format	Latency(ms/batch)	Throughput	Energy/sample	Accuracy	Model Size
FP32	~94 ms	~324.29/s	190 mJ	91.06%	255.41 MB
FP16	~20 ms	~1480.05/s	32.66 mJ	91.06%	127.71 MB

*Energy/sample computed as mean GPU power × runtime ÷ batch_size; assumes stable average power across iterations

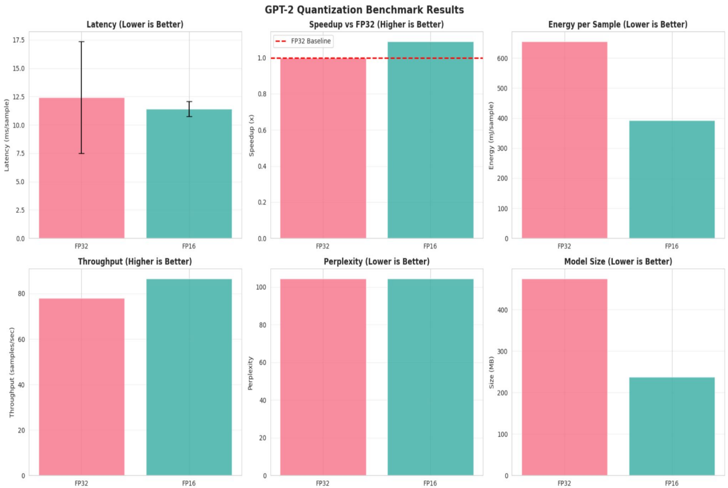
Results and Analysis **GPT2**

Task

- SST-2 sentiment classification (50-sample evaluation set)

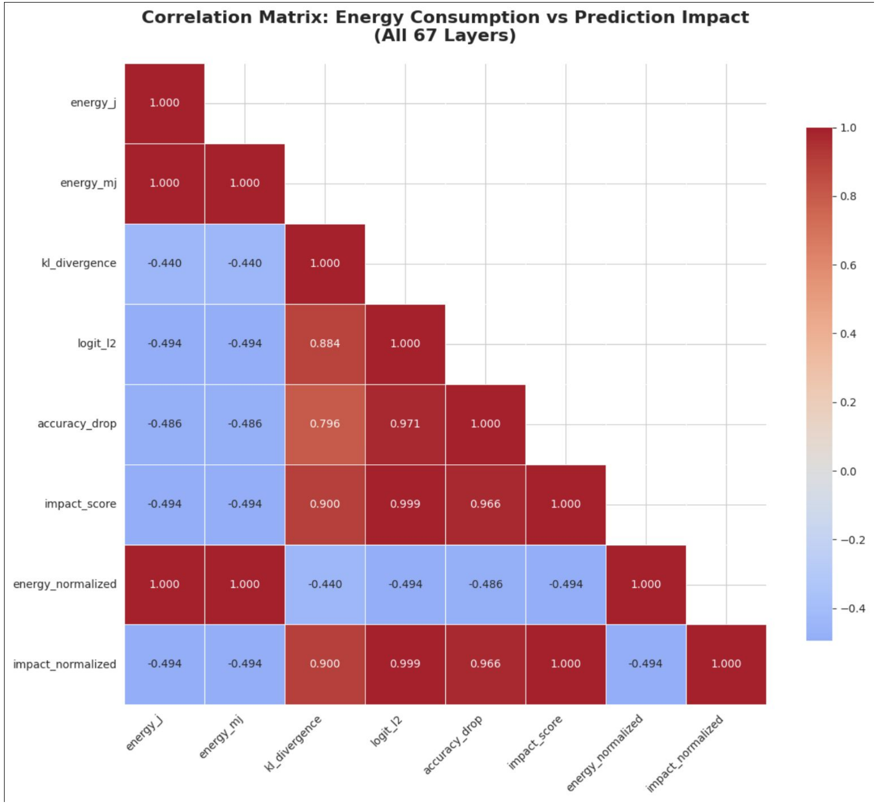
Key Findings

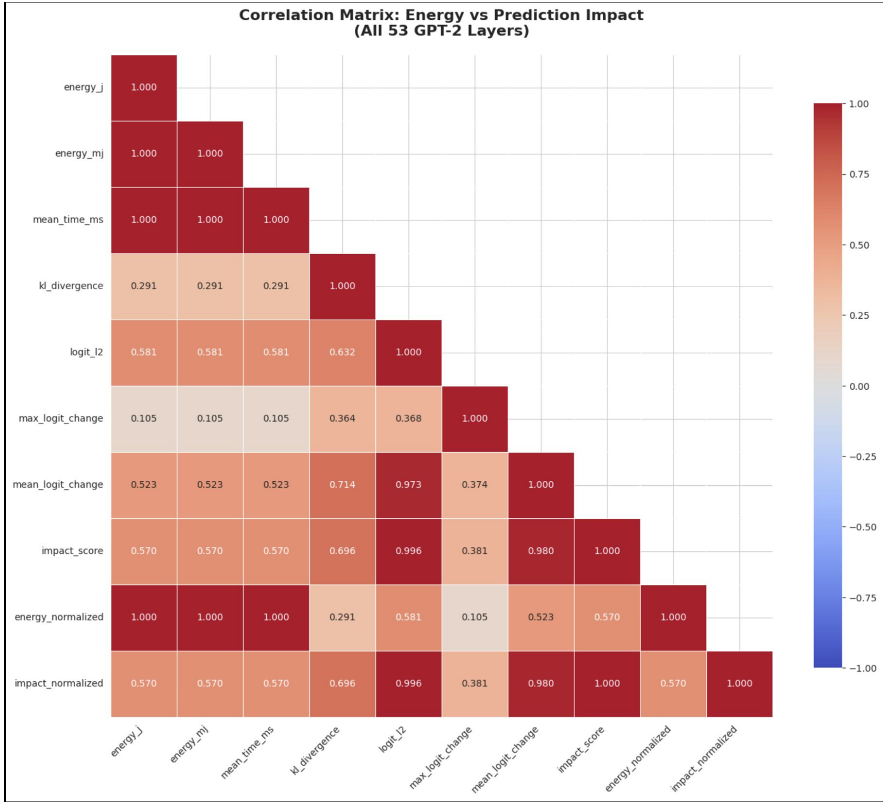
- **36% energy reduction** going to FP16
- **2× model size reduction**
- **No quality loss** (perplexity stable at 217)
- Mixed precision worse due to added overhead
- Strong FP16 acceleration due to **Tensor Cores**



Format	Latency	Speedup	Energy/sample	Perplexity	Model Size
FP32	12.4 ms	1.0x	650 mJ	105	480 MB
FP16	11.4 ms	1.09x	390 mJ	105	240 MB

Correlation Matrices





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Conclusions

1. FP16 Produces Real Energy Savings

- DistilBERT: FP16 gives 5.9× energy reduction, 4.7× latency speedup
- GPT-2: FP16 gives 1.67× energy reduction, 1.09× latency speedup
- Zero accuracy degradation
- 2× smaller model size → deployability benefits
- Energy results are robust because average GPU power remains stable under steady load even though nvidia-smi cannot resolve short spikes.

2. Hardware Matters

- T4 GPU has Tensor Cores → FP16 acceleration
- BF16 unsupported → removed
- INT8 requires TensorRT + engine conversion → too complex for course scope
- Board-level power methods capture holistic GPU load but cannot attribute power to specific kernels

3. Mixed Precision is Not Useful for Inference

- Introduces overhead from casting + autocast
- Faster for training but slower for inference
- Recommendation: **Use full FP16 for inference workloads**

Shortcomings & Future Work

Limitations

- Small Evaluation Sets
- Restricted Quantization Formats
- Single GPU Platform
- Inference-Only Study
- Board-level telemetry has low temporal resolution; cannot isolate per-kernel or per-layer power directly.
- Per-layer energy is time-weighted approximation, not hardware-measured power.

Future Work

- INT8 Deployment using TensorRT
- Test on Multiple GPUs
- Selective / Per-Layer Quantization
- 4-bit Quantization (QLoRA-style)
- Larger Evaluation Sets
- Real-World Deployment Benchmarks