



# ConflLlama

## Domain-specific Adaptation of Large Language Models for Conflict Event Classification

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# The AI Accessibility Problem

- **Manual coding** is inconsistent and time-consuming
- **200,000+** events in Global Terrorism Database
- Events are becoming increasingly **complex**
- Need for **real-time, scalable** analysis

## The Cost Barrier

State-of-the-art AI models are **expensive** and **inaccessible** to most researchers

# The Cost of Cutting-Edge AI

## Proprietary Models:

- **GPT-5:** \$1.25 / 1M tokens (8x for the output)
- **Claude 4.1 Opus:** \$15 / 1M tokens (5x for the output)
- **Both are reasoning models! They think too much and costs increase.**

## Vendor Lock-in

- **No control** over model updates
- **Rate limits** and availability issues
- **Data privacy** concerns

## Research Reality

Most political scientists have:

- **Limited budgets**
- **Basic hardware**

## The Result

**Cutting-edge AI** remains locked away from the researchers who need it most

# The Open Source Revolution

## Open Source Models:

- Llama 3.1: **Free** to use
- 200K events: **\$0** in API costs
- One-time training: **\$10-20**
- Unlimited inference after training

## Democratized Access:

- **Hardware:** Consumer-grade GPUs
- **Training:** 1.5 hours on cloud
- **Deployment:** Laptop-friendly



Huggingface - ConflLlama

# Training Dynamics

- **Training time:** 1.5 hours on H100 (also works on a 16 GB card)
- **Speed:** 3.49 seconds/iteration
- **Gradient norms:** Stable at 0.53

Accessibility

Consumer-grade hardware can fine-tune 8B parameter models

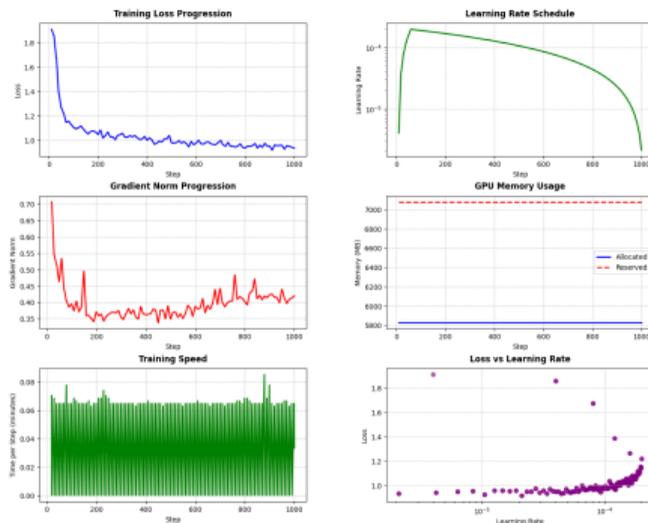
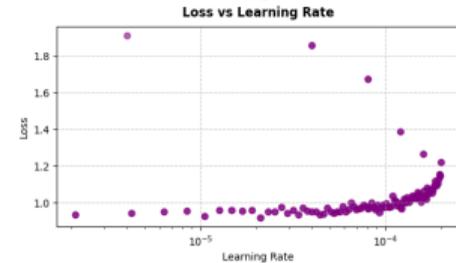
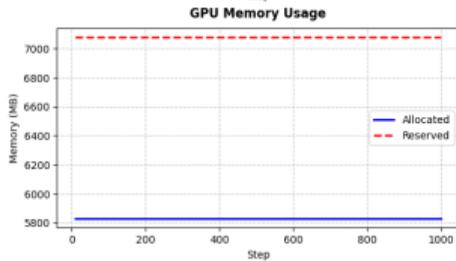
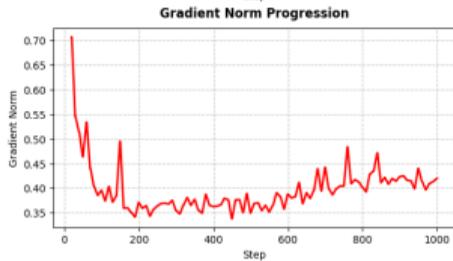
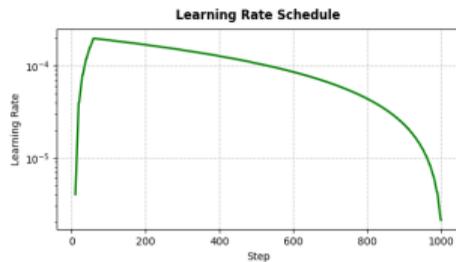


Figure: Training loss, learning rate, and resource utilization

# Training Dynamics — Full View



Training loss, learning rate, and resource utilization

# The Global Terrorism Database (GTD)

## Dataset Characteristics:

- **Coverage:** 200,000+ events (1970-2020)
- **Scope:** Domestic & international terrorism
- **Attributes:** 120+ variables per event
- **Challenge:** Severe class imbalance

## Our Focus:

- **Task:** Multi-label attack type classification
- **Labels:** 9 attack categories
- **Complexity:** 5.3% multi-label events

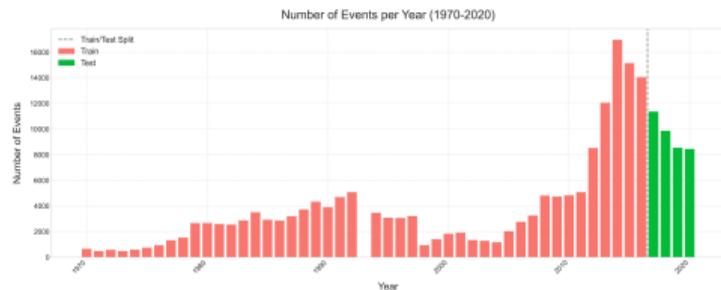


Figure: GTD events over time showing Train & Test split

# Experimental Setup

- **Temporal Split:** Natural evaluation design
  - Training: 171,514 events (pre-2017)
  - Test: 38,192 events (2017 onwards)
- **Class Distribution Challenge:**
  - Bombing/Explosion: 48.7% of training data
  - Armed Assault: 23.6%
  - **Rare events:** Hijacking (0.4%), Unarmed Assault (0.5%)
- **Evaluation Focus:**
  - Multi-label classification metrics
  - Performance on rare event types
  - Temporal generalization capability

# Why This Approach?

## Why Llama 3.1?

- **Performance:** Matches GPT-4 on many tasks
- **Efficiency:** 8B parameters vs 175B+
- **Versatility:** Strong domain adaptation (Lu et al., 2024)
- **Context:** Extended context processing (128k with Unsloth edits)
- **Accessibility:** Open source & permissive license

## Why QLoRA?

- **Memory Efficiency:** 16GB → 6GB (Dettmers et al., 2024)
- **Performance:** Minimal degradation from quantization
- **Speed:** Low-rank adaptation trains faster
- **Accessibility:** Consumer hardware deployment

# Why Not BERT-based Models?

## Previous Approaches:

- **ConfliBERT** (Hu et al., 2022)
- Strong on common event types
- Struggles with rare events
- Limited context understanding

## LLM Advantages:

- **Context:** Better narrative understanding
- **Generalization:** Few-shot capabilities
- **Flexibility:** Multi-task learning

## Evidence from Literature

- Ornstein et al. (2023): LLMs "significantly outperform existing automated approaches"
- Heseltine & Clemm von Hohenberg (2024): LLMs as substitute for human experts
- Our results: +1463% on rare events vs BERT

## The Gap

No prior work on **efficient LLM adaptation** for conflict classification

# Dramatic Performance Improvements

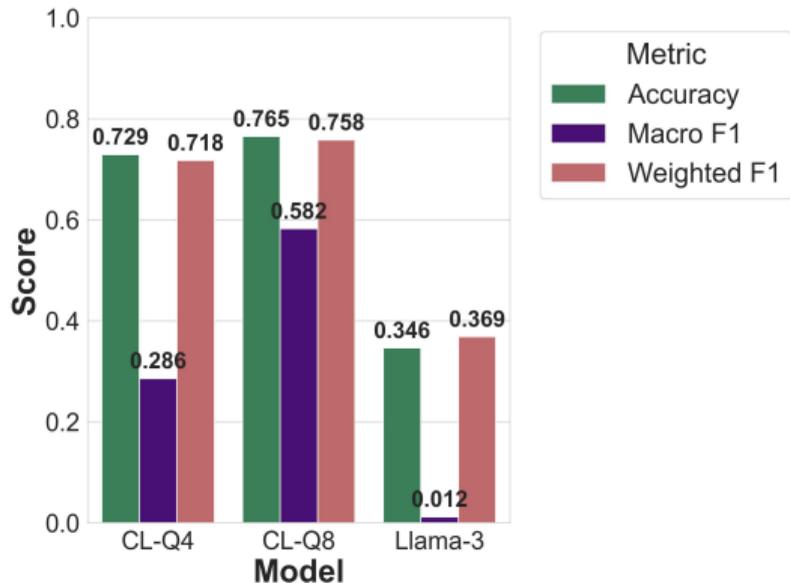
| Attack Type                | Llama 3.1 F1 | ConflLlama F1 | Improvement |
|----------------------------|--------------|---------------|-------------|
| Unarmed Assault            | 0.035        | 0.553         | +1463%      |
| Hostage Taking (Barricade) | 0.045        | 0.353         | +692%       |
| Hijacking                  | 0.100        | 0.629         | +527%       |
| Facility/Infrastructure    | 0.167        | 0.733         | +339%       |
| Assassination              | 0.201        | 0.655         | +226%       |
| Bombing/Explosion          | 0.549        | 0.908         | +65%        |

## Finding

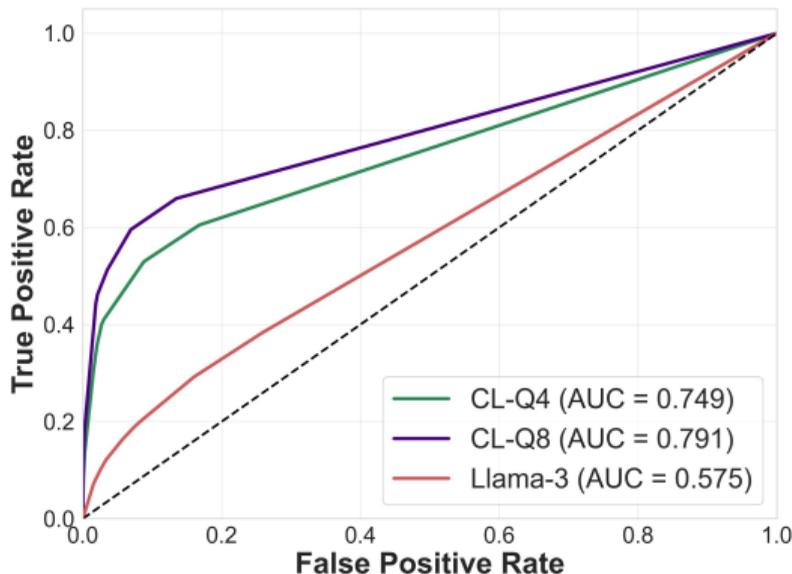
**Rare events** show the most dramatic improvements - crucial for security applications

# Model Performance Comparison

## Model Performance Comparison



## Macro-Averaged ROC Curves



- CL-Q8 achieves highest overall performance across all metrics
- ROC curves show superior classification ability (AUC = 0.791)
- Llama-3 baseline comparison shows large improvement, even for Q4

## Comparison with modernBERT

| Attack Type             | mBERT         | ConflLlama  |
|-------------------------|---------------|-------------|
| <b>Overall Accuracy</b> | <b>79.66%</b> | 76.50%      |
| Barricade               | 0.15          | <b>0.35</b> |
| Unarmed Assault         | 0.31          | <b>0.55</b> |
| Hijacking               | 0.37          | <b>0.63</b> |
| Bombing                 | <b>0.94</b>   | 0.91        |
| Kidnapping              | <b>0.91</b>   | 0.84        |

### Trade-off

ConflLlama: **Superior** on rare events

### Security Focus

Rare events often have **disproportionate impact**

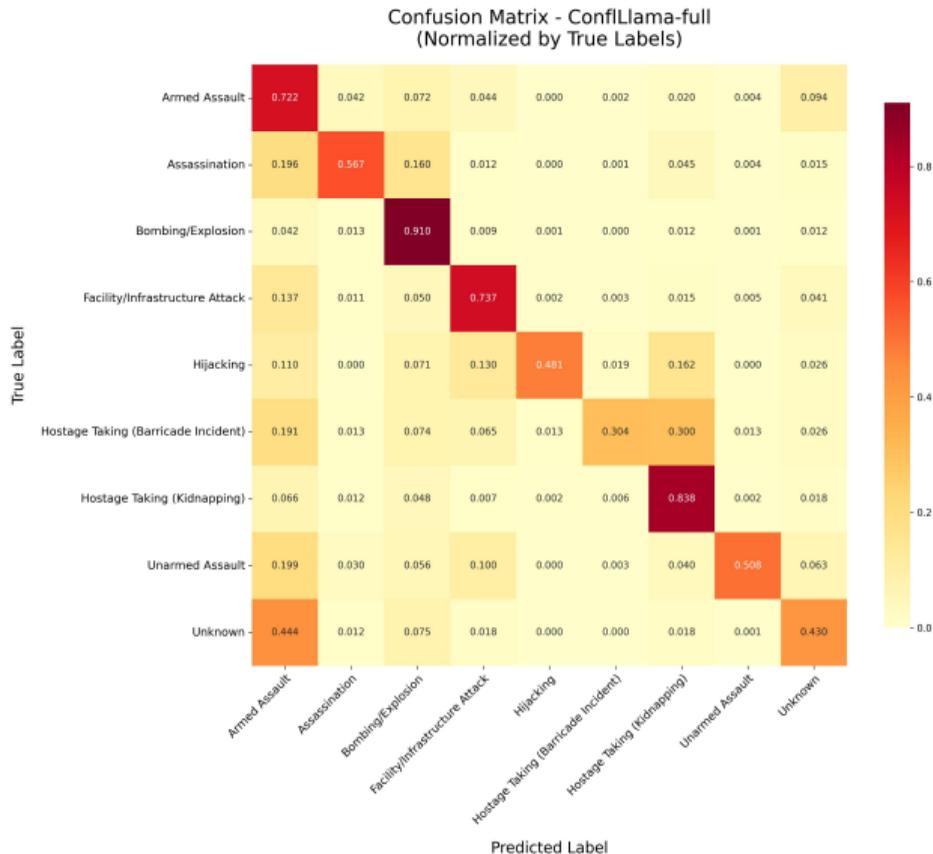
Both **modernBERT** and **ConflLlama** were finetuned on the *same training set and procedure*, ensuring fair comparison.

# Multi-label Classification Excellence

- **Hamming Loss: 0.052**
- **Subset Accuracy: 72.4%** (exact match)
- **Partial Match: 73.8%**
- **Label Density: 0.975** (true: 0.963)

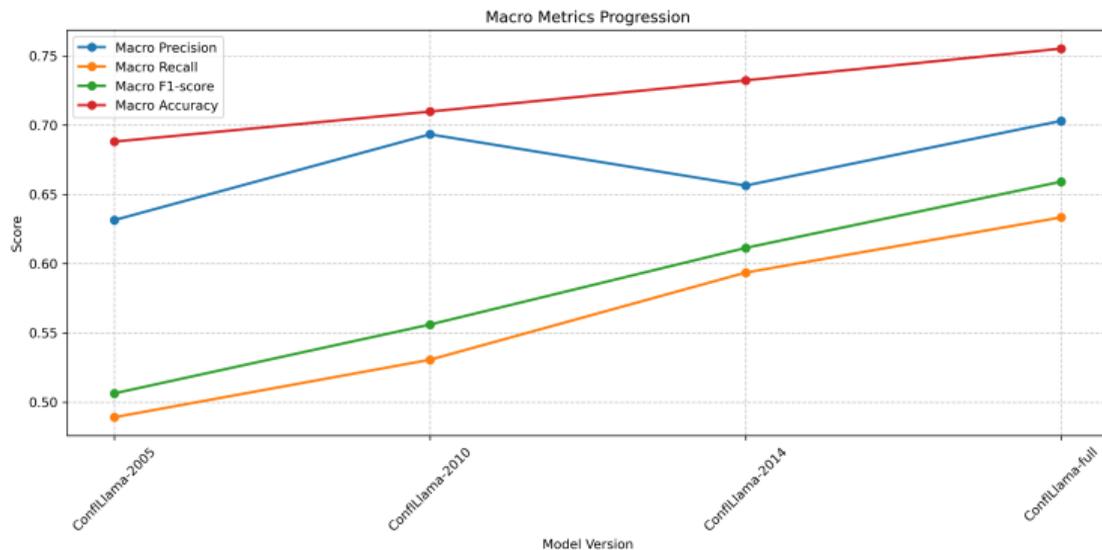
## Real-world Impact

Mumbai, 2008: Armed Assault + Hostage Taking + Bombing



# Temporal Coverage Impact

- **Model Accuracy:** 69% → 76% with expanded temporal data
- **Recall:** 49% → 63%
- **F1-score:** 51% → 66%



# Democratizing Advanced NLP

- **Hardware Requirements:** **16GB RAM** (consumer-grade)
- **Processing Speed:** **44,280 events/hour**
- **Training Time:** **1.5 hours** on cloud GPU
- **Memory Footprint:** **< 6GB** during fine-tuning

## Research Impact

Makes cutting-edge conflict analysis accessible to researchers with **limited computational budgets**

**Available:** Huggingface - ready for immediate use

# Key Takeaways

1. **Technical Innovation:** QLoRA enables **efficient adaptation** of large models
2. **Empirical Success:** Up to **1463% improvement** on challenging classifications
3. **Accessibility:** **Consumer-grade deployment** with professional results
4. **Robustness:** Consistent performance across different prompting strategies
5. **Multi-label Excellence:** Handles complex, overlapping conflict events

## Bottom Line

ConflLlama **democratizes** advanced AI for political science while achieving **state-of-the-art performance**

# Thank You

## Questions & Discussion

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