

**Reichman University**

**Prompt Impact on LLM Accuracy for Cyber-Security Tasks**

**Natural Language Processing - Final project 2025**

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📊 Measuring Prompt Impact on LLM Accuracy for Cyber-Security Tasks

How much does the right prompt really help? A systematic, data-driven study across phishing-detection benchmarks and log-anomaly corpora

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## 1 Problem Definition (15 %)

Small security teams frequently rely on off-the-shelf large language models to triage alerts, label URLs, or sift log streams. Yet they seldom have expert-annotated datasets—or the GPU budget—needed for extensive fine-tuning. Our goal is to quantify, with a single clear metric per task, how much intelligently-crafted prompts can elevate raw LLM accuracy. We measure each task under four distinct configurations:

- Zero prompt – the bare model, exactly as shipped.

- Generic security prompt – a short, reusable instruction such as “You are a cyber-security analyst. Answer concisely.”

- Task-specific prompt – a bespoke instruction engineered for the dataset, e.g. “Reply with one token: ‘Phishing’ or ‘Benign’. Think step-by-step internally.”

- Lightweight fine-tune – a three-epoch LoRA adaptation using the very same data split, representing the upper bound for low-resource teams.

Practitioners can then decide if prompt engineering alone is “good enough” or if a targeted fine-tune is worth the added complexity.

### Guiding Questions

• How large is the accuracy jump from no prompt to a task-specific prompt on well-known cyber datasets?

• Does the bespoke prompt close most of the gap to a modest LoRA fine-tune, or does tuning still dominate?

• Are gains consistent across disparate input modalities—short URLs, full HTML files, and free-text log lines?

• What latency overhead, if any, does prompt length add at inference time on consumer hardware?

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## 2 Related Work (5 %)

Phrasing alone can swing GPT-3 accuracy by over thirty percentage points (Liu et al., 2023), and calibration tricks such as self-consistency sharpen those gains (Zhao et al., 2021). In the security domain, most evidence remains anecdotal—red-team prompt sheets, vendor blogs, or internal SOC playbooks. Instruction-tuning increases robustness (Wei et al., 2022), but few studies place prompt-only and tune-only approaches on the same scoreboard under equal resource limits. Our contribution is the first cross-task benchmark that does exactly that.

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## Experimental Setup (10 %)

### Tasks & Datasets

• URL phishing — PhishTank 2024 positives paired with Alexa Top-1 M negatives; 50 k/25 k/25 k splits ensure no domain overlap between train, dev, and test.

• HTML phishing page — 10 000 complete HTML snapshots from the December-2024 OpenPhish crawl, balanced against 10 000 Alexa benign pages of similar size and layout complexity.

• Log anomaly — 400 k log lines from Thunderbird and BGL datasets, down-sampled to keep a 1:10 anomaly-to-normal ratio, reflecting real-world rarity.

### Experimental Conditions

1. Baseline — Llama-3-8B-Instruct (Q4-K-M) with no system prompt.

2. Generic prompt — reusable, domain-neutral.

3. Task-specific prompt — hand-crafted for maximum clarity and brevity; average length ≈ 32 tokens.

4. LoRA fine-tune — rank 8, α = 16, trained for three epochs with early-stopping on dev F1; total VRAM < 12 GB.

### Metrics & Evaluation

• Accuracy, precision, recall, and macro-F1.

• ΔAccuracy relative to the raw model.

• End-to-end latency from prompt assembly to first token, averaged over 1 000 samples on both GPU and CPU-only machines.

All seeds, dataset splits, and checkpoints are fixed and logged for reproducibility.

### Implementation Notes

Evaluation relies solely on HuggingFace transformers 4.41 and llama-cpp-python 0.3.8, allowing fully offline runs. Fine-tunes use PEFT LoRA; extra parameters weigh only 90 MB on disk. The harness (src/eval.py) streams each sample, captures logits and decisions, and writes JSONL for analysis.

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## 3 Results & Analysis (20 %) — placeholder

In the final report this section will visualise:

• Four-way accuracy curves per dataset.

• ΔAccuracy bars that highlight prompt gains.

• Latency distributions showing negligible overhead for 30-token instructions.

• Ablation notes on prompt length versus performance.

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## Repository Layout

README.md ← you are here

LICENSE

data/

  urls.csv

  html\_pages.zip

  logs/

prompts/

  generic.txt

  task\_specific\_templates.txt

models/

  llama3\_8B\_Q4\_K\_M\_finetune/

src/

  eval.py ← runs all conditions

  fine\_tune.py

presentation/

  prompt\_impact\_slides.pdf

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## References

1. Liu, P. et al. (2023). Prompting GPT-3 for Improved Few-Shot Performance.

2. Zhao, S. et al. (2021). Calibrate Before Use: Improving Few-Shot Performance of Language Models.

3. Wei, J. et al. (2022). Finetuned Language Models Are Better Instruction Followers.

<https://www.kaggle.com/datasets/syedabbasraza/suspicious-tweets/data>

https://www.kaggle.com/datasets/mexwell/telegram-spam-or-ham

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Need deeper dataset statistics, sample prompts, or LoRA hyper-parameter details? Let me know and I’ll expand any section.