Use of AI for log analysis in CI/CD pipelines

Bachelor Thesis - Defence

Maid Ališić

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University of Applied Sciences Upper Austria, Campus Hagenberg

Problem Context

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- Logs can contain customer identifiers $\rightarrow$ **no SaaS export**.

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4. **Alert fatigue** - static regex rules explode over time.

Research Questions

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RQ2 How does a **local** stack (Isolation-Forest + Random-Forest) compare with the cloud LLM?

RQ3 Which practical hurdles arise when embedding both approaches into existing pipelines?

Method - Feature Engineering

Vectorisation step ① – TF-IDF

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$$w_{t,d} = \mathrm{tf}_{t,d} \cdot \log \frac{N}{\mathrm{df}_t} \quad \text{(Term-Frequency-Inverse-Document-Frequency)}$$

$$\boxed{\text{log line}} \longrightarrow \boxed{\text{sparse vector}}$$

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4. Result: 50 k-dimensional sparse matrix; $\approx 100\,000$ lines /s on a single core.

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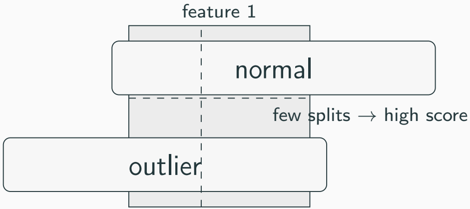
Method - Algorithm ②

How Isolation-Forest detects outliers

- Randomly split feature space into binary trees.



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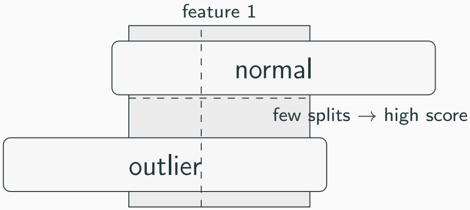

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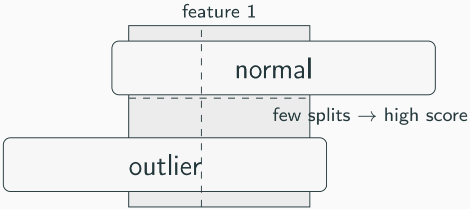
- Randomly split feature space into binary trees.
- Rare / weird points are isolated *early*. Path length $h(x) \rightarrow$ anomaly score $s(x) = 2^{-h(x)/c(n)}$.
- CPU-friendly: 30μs per line, no GPU.



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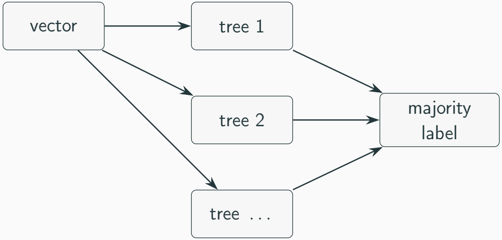

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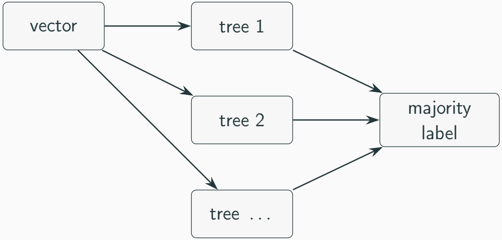

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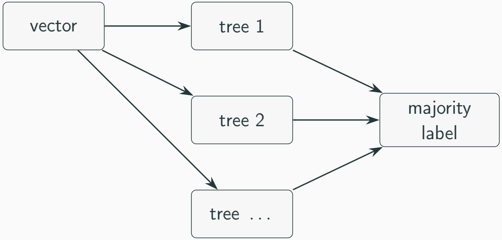

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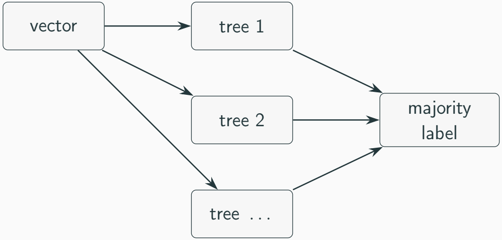
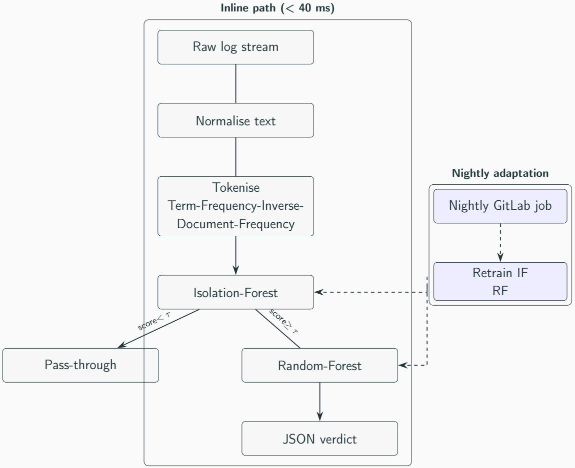
4. Trains nightly in < 90 s (400 trees, depth 30).



Architecture

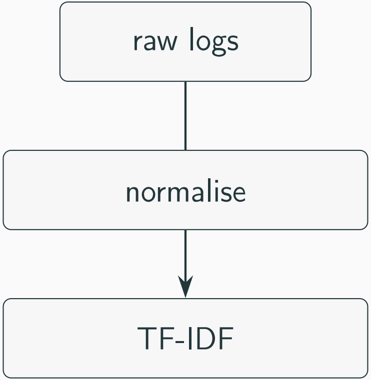
End-to-end pipeline ($<$ 40 ms inline)



Data & Experimental Design

Datasets & metrics

- 117 k macOS system log lines



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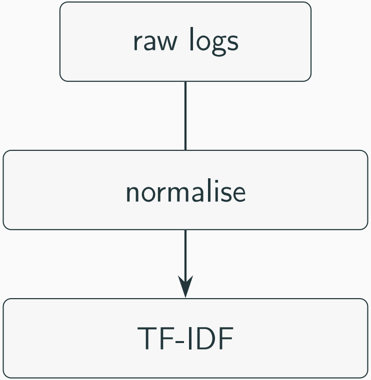

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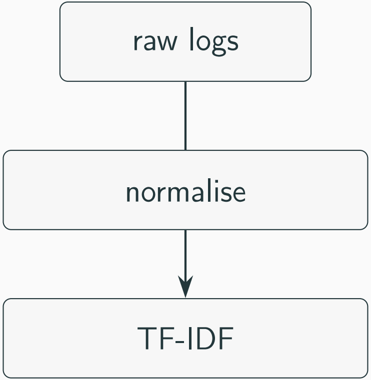

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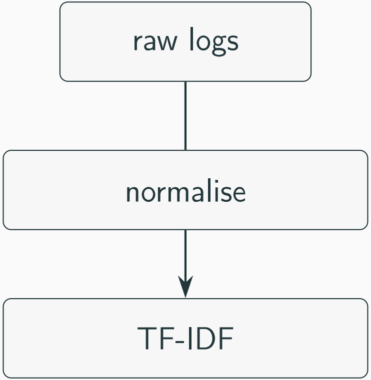

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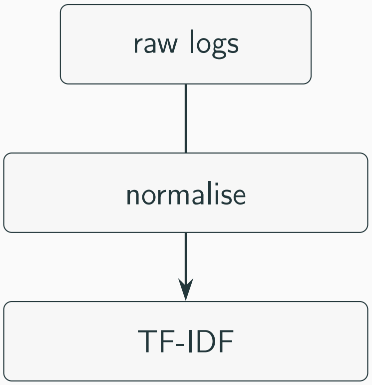
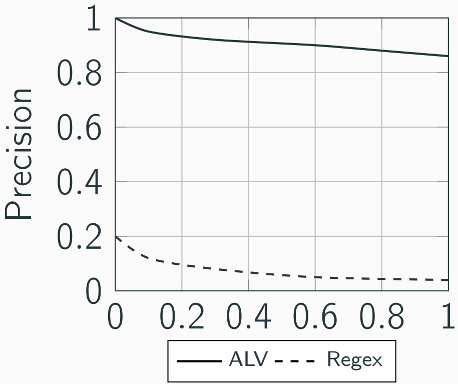
- Split 70 / 15 / 15 % (train / validation / test)
- Metrics: Macro-F_1, Area under PR curve, 99.9 % latency



Results

Headline numbers

- Detection (Isolation-Forest): $\mathbf{F_1} =$ **0.89** (AUC-PR 0.94)



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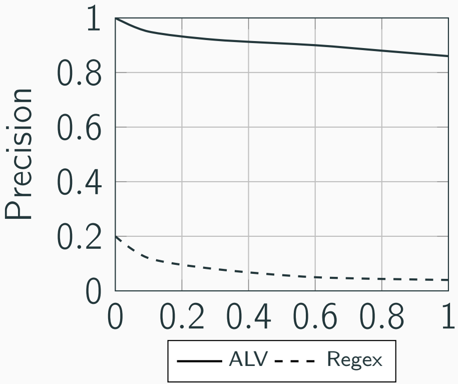

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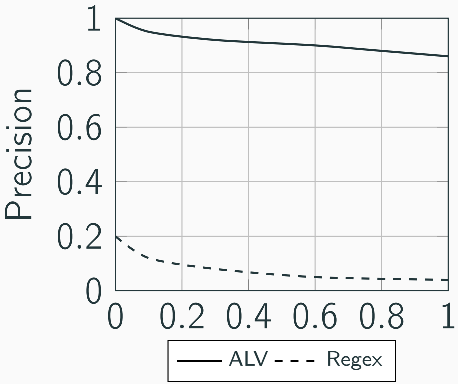
- Detection (Isolation-Forest): $\mathbf{F_1} =$ **0.89** (AUC-PR 0.94)
- Diagnosis (Random-Forest): Macro-F_1 = **0.99**, MCC 0.98
- Latency: 37 ms (p99.9); throughput 45 k lines/s



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- **Zero token fees**: 2300 Lines of Code + FastAPI; vendor neutral.
- Data never leaves the VPN - compliant with GDPR & NDAs.
- Deterministic labels enable auditable root-cause trails.

Limitations & Roadmap

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- First Drain template pass is manual (cold-start issue).
- Explainability: token-level SHAP / IG still to-do.
- Roadmap: threshold-free Bayesian change-point, distilled LogBERT, federated retrain, SHAP highlights.

Wrap-up

Take-away

Light-weight, on-prem ML matches AIOps SaaS

without latency, cost or data-protection pain.

Questions welcome - thank you!