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

Method - Feature Engineering

Vectorisation step ① - TF-IDF

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$w_{t,d}$ - weight of term t in document d
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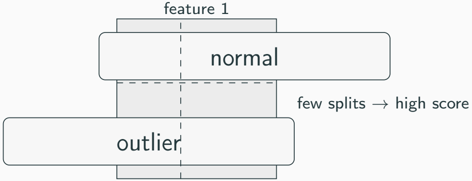
4. Result: 50 k-dimensional sparse matrix; $\approx$ 100 000 lines /s on a single core.

Method - Algorithm ②

How Isolation-Forest detects outliers

- Randomly split feature space into binary trees.



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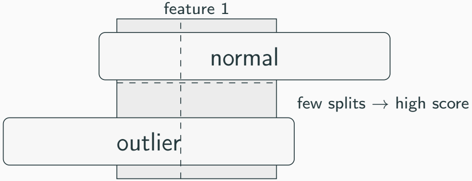

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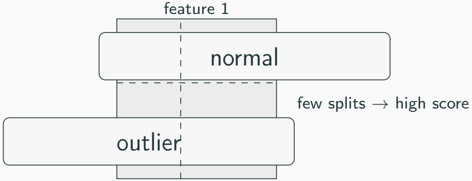
- Rare / unusual points are isolated *early*. Path length $h(x)$ $\rightarrow$ anomaly score $s(x) = 2^{-h(x)/c(n)}$.
- CPU-friendly: 30 µs per line, no GPU.



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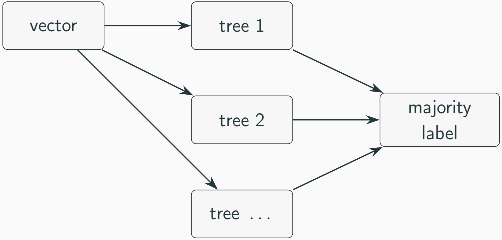

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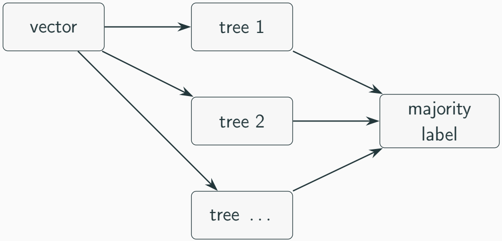

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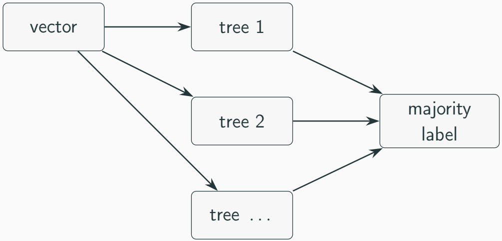

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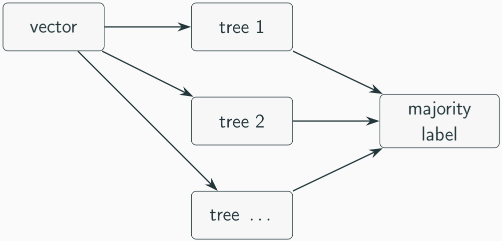
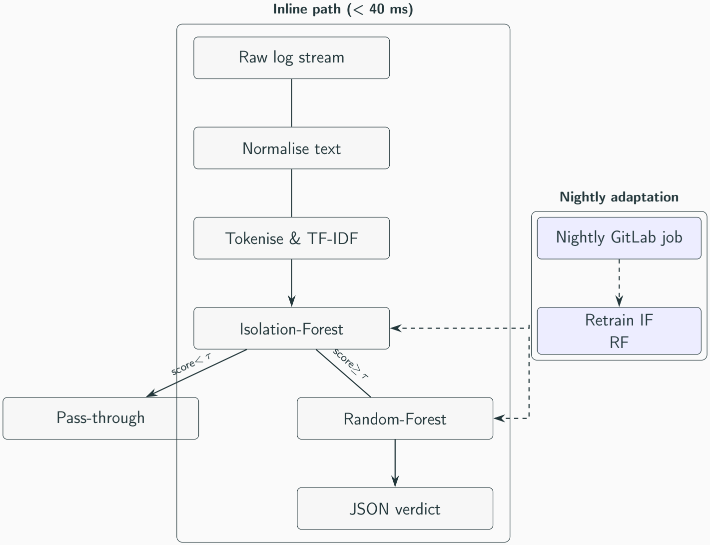
4. Nightly training < 90 s (400 trees, depth 30).



Architecture

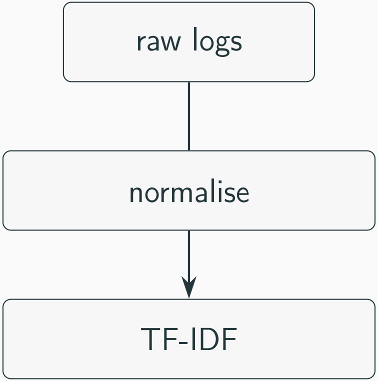
End-to-end pipeline ($<$ 40 ms inline)



Data & Experimental Design

Datasets & metrics

- 117 k macOS system log lines



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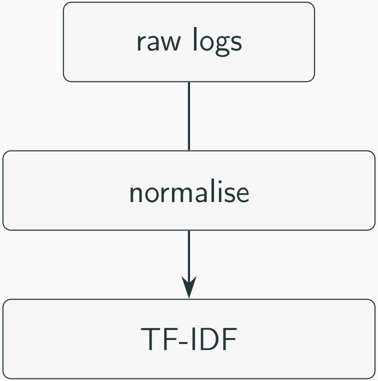

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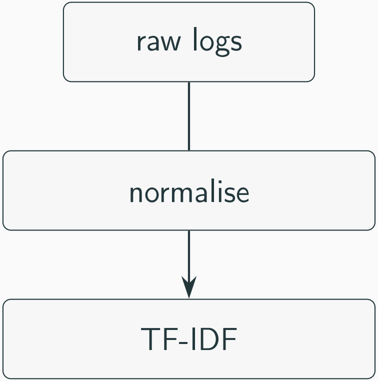

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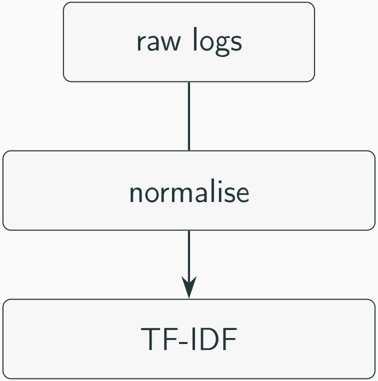

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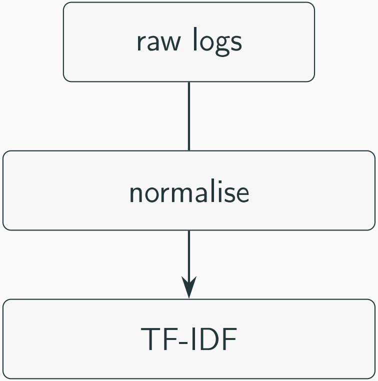
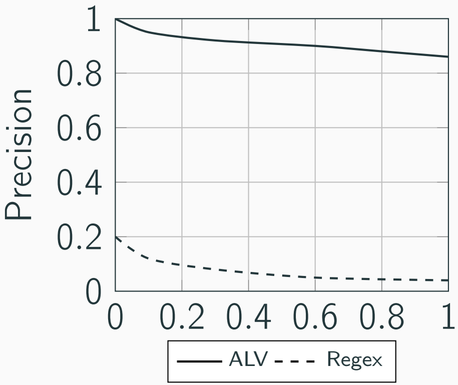
- Split 70 / 15 / 15 % (train / validation / test)
- Metrics: Macro-F_1, Area Under the Precision-Recall Curve (AUPRC), 99.9 % latency percentile



Results

Headline numbers

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



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- Diagnosis (Random-Forest): Macro-F_1 = **0.99**,
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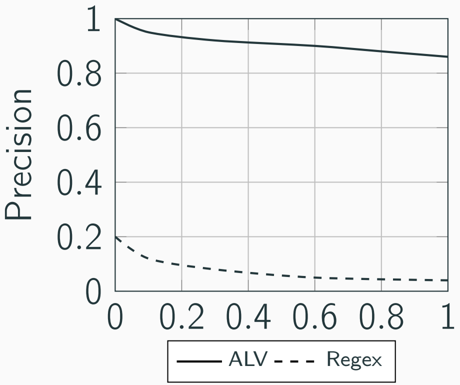

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  AUPRC = 0.94
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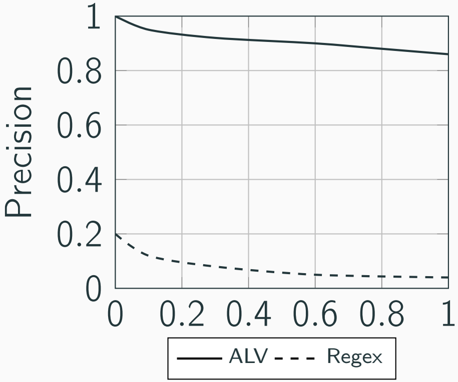
- Latency: 37 ms (p99.9); throughput 45 k lines /s



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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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- Explainability: token-level *SHapley Additive ExPlanations* and *Integrated Gradients* still on the to-do list.
- Roadmap: threshold-free Bayesian change-point detection, distilled LogBERT encoder, federated nightly retrain.

Wrap-up

Take-away

Light-weight, on-prem ML matches AIOps SaaS

without latency, cost or data-protection pain.

Questions welcome - thank you!