Use of AI for Log Analysis in CI/CD Pipelines

Bachelor Thesis - Defence

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FH Oberösterreich · Campus Hagenberg

Road map

Problem context

Research questions

Method

Architecture

Data & evaluation

Results

Impact

Problem context

Why do we care?

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- Logs can leak customer IDs → **no SaaS export**.

Operational pain points

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3. **Latency pressure** - analysis must finish before runner teardown.
4. **Alert fatigue** - regex rule sets grow without bound.

Research questions

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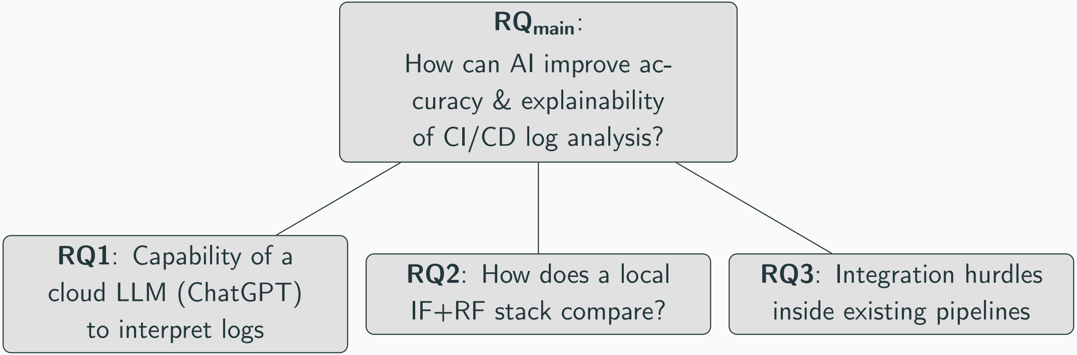

RQ$_{\text{main}}$: How can AI improve accuracy & explainability of CI/CD log analysis?

RQ1: Capability of a cloud LLM (ChatGPT) to interpret logs

RQ2: How does a local IF+RF stack compare?

RQ3: Integration hurdles inside existing pipelines

Method

Vectorisation pipeline ①

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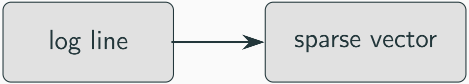

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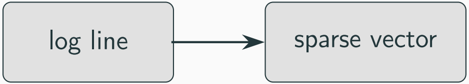

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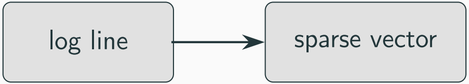

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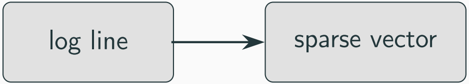
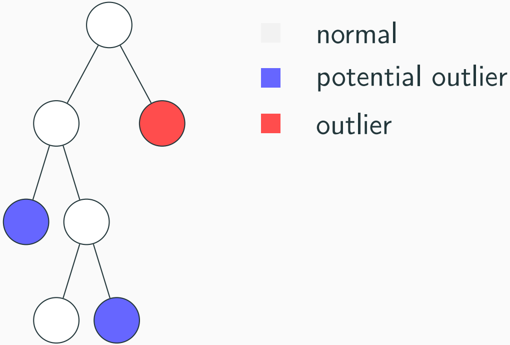
4. Produce 50 000-dim sparse vector; $> 10^5$ lines / s on one core.



Isolation Forest ② - intuition

- Random binary partitioning isolates unusual lines in fewer splits.



⬜ normal

🟦 potential outlier

🟥 outlier

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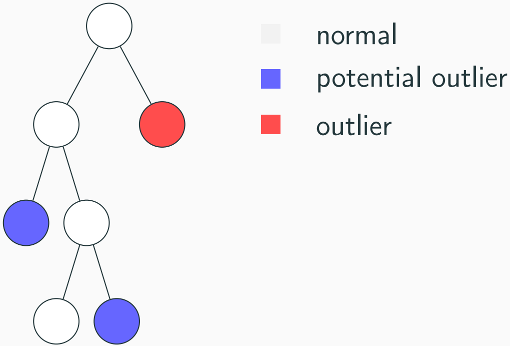

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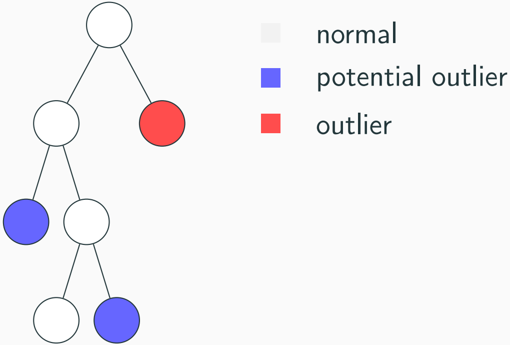
- CPU-only: $\approx 30\,\mu s$ per line.



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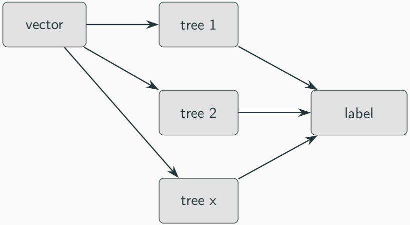

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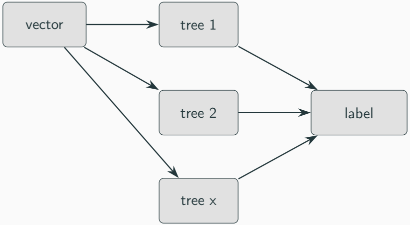

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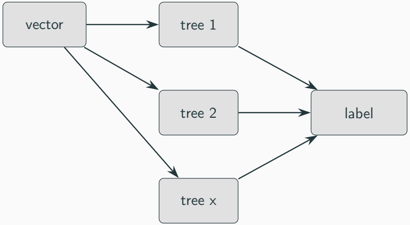
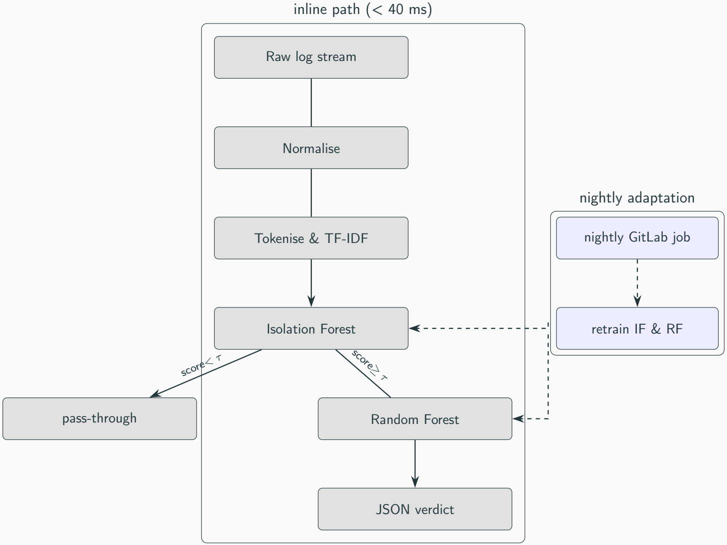
- Nightly retrain < 90 s; warm-start handles drift.



Architecture

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



Data & evaluation

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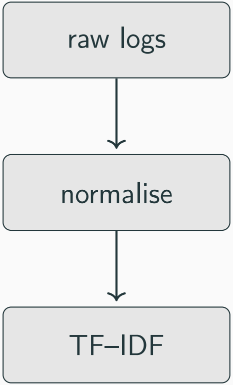
- 117 k *macOS* logs + 655 k *OpenSSH* logs



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normalise

TF–IDF

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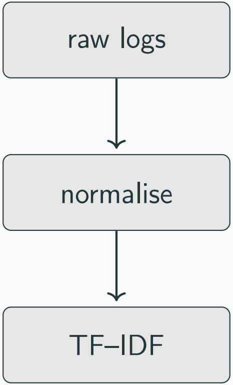

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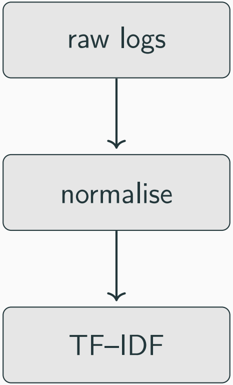

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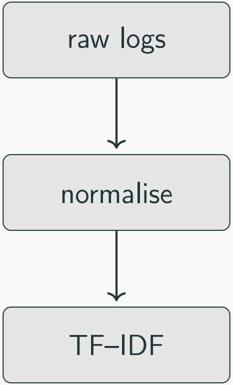
- Metrics: Macro-F_1, AUPRC, p99.9 latency



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Results

Headline numbers

	Precision	Recall	F_1
Detection (Isolation Forest)	0.91	0.88	0.89
Classification (Random Forest)	0.99	0.99	0.99

Throughput: 45 000 lines/s | p99.9 latency: 37 ms

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- **GDPR compliant**: logs never leave the VPN.

Wrap-up

Take-away

Light-weight on-prem ML matches AIOps SaaS

without latency, cost or privacy pain.

Questions welcome - thank you!