Use of AI for Log Analysis in CI/CD Pipelines

Bachelor Thesis – Defence

Maid Ališić

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FH Oberösterreich · Campus Hagenberg

Supervisor: FH-Prof. Dipl.-Ing. Dr. Stefan Wagner

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Impact

Research questions

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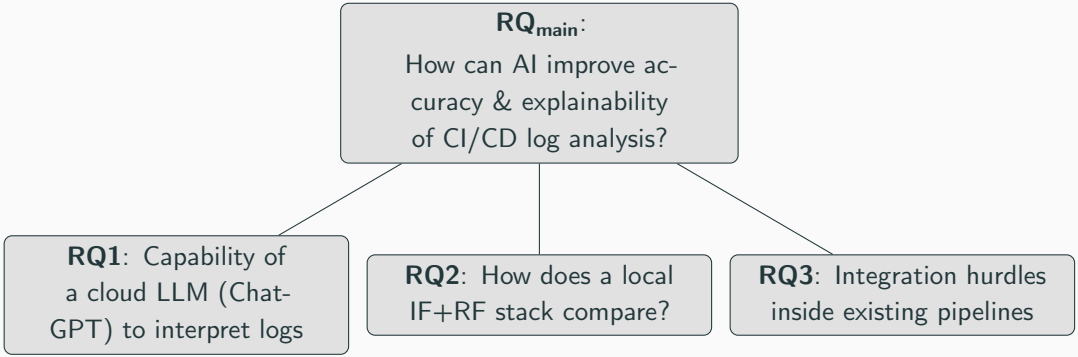

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- Business **Service-Level Objective**: feedback within $\leq$ 200 ms per pipeline.
- Logs may expose customer IDs, therefore they must remain on-premises (no cloud export).

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2. **Concept drift** – each merge may rename tests or switches.
3. **Latency pressure** – analysis must finish before the job completes.
4. **Alert fatigue** – regex rule sets grow without bound.

Method

Vectorisation pipeline ①

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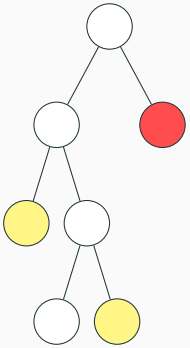
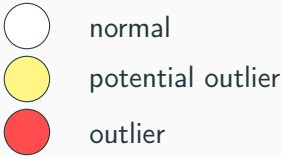
4. Produce sparse vector.

Isolation Forest ② – intuition

- Random binary partitioning isolates unusual lines in fewer splits.





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- Random binary partitioning isolates unusual lines in fewer splits.
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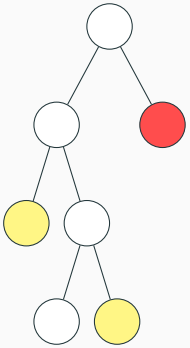

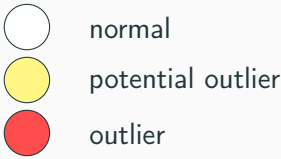

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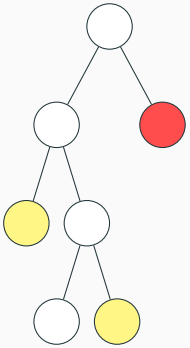
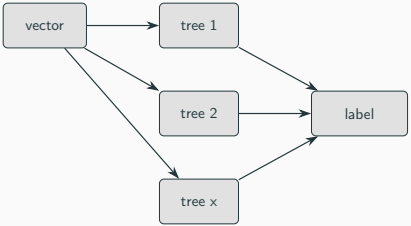
- CPU-only: $\approx 30\,\mu s$ per line.



Random Forest ③ – error labelling

- Maps each flagged line to a domain-specific error category.



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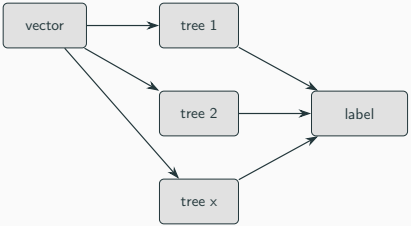

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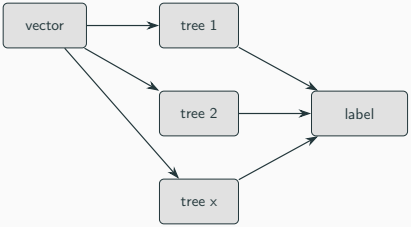
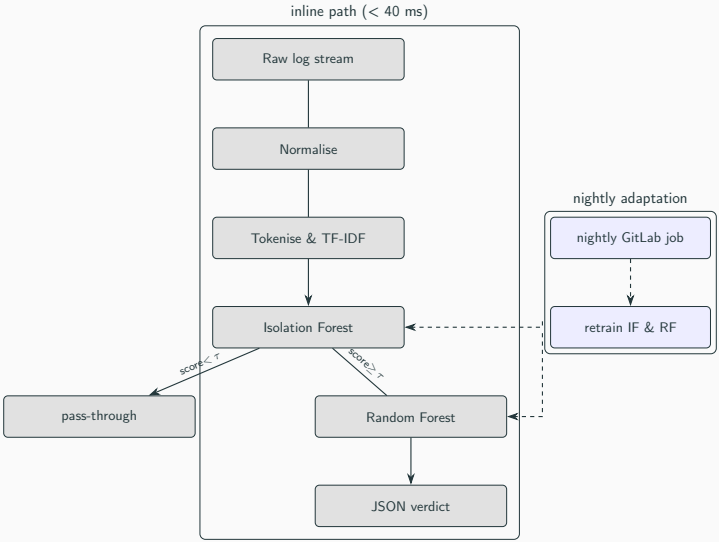
- Nightly retrain < 90 s; warm-start handles drift.



Architecture

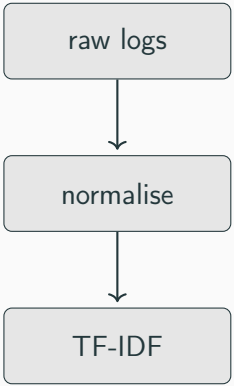
End-to-end pipeline (< 40 ms inline)



Data & evaluation

Datasets & metrics

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



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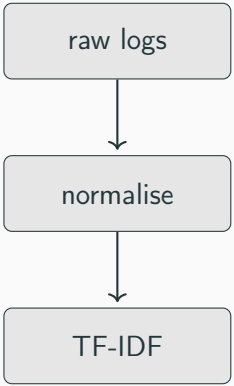

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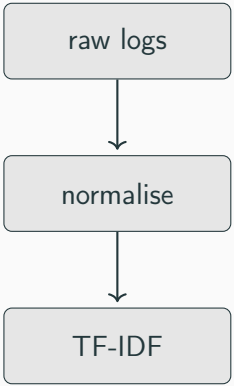

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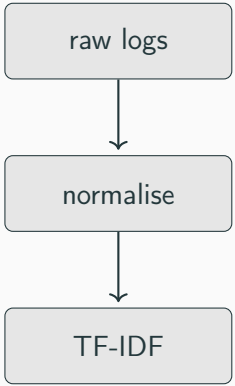
- Metrics: Precision, Recall and F_1



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
Regex baseline	0.286	0.286	0.286

$$F_1 = 2 \cdot \frac{P \cdot R}{P + R}$$

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

Wrap-up

Light-weight on-prem ML matches AIOps SaaS

without latency, cost or privacy pain.

Questions welcome – thank you!