Traces & Anomaly Monitoring — A Practical Guide

A compact, Medium-style walkthrough that explains the tracing decisions we made and the design/implementation of the time-aware + adaptive anomaly detection system. This is written to help you replicate the setup, run it in your environment, and extend it safely.

TL;DR 🚀

- We fixed span parent/child propagation across browser → gateway → API → RabbitMQ → worker by explicitly setting and passing contexts and by injecting a known `x-parent-traceparent` header through the queue.
- We built a monitoring pipeline that computes **time-aware baselines** (1-hour buckets, 30-day window) and derives **adaptive thresholds** (percentiles) nightly, mapping deviations to **SEV1–SEV5**.
- Ollama LLM is integrated to analyze traces + correlated Prometheus metrics; use the smaller `llama3.2:1b` for better latency in production-like environments.

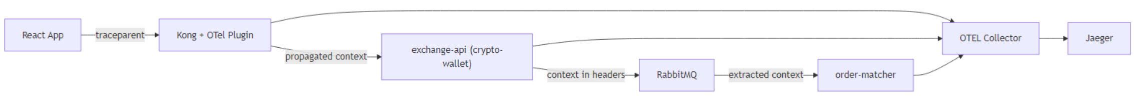
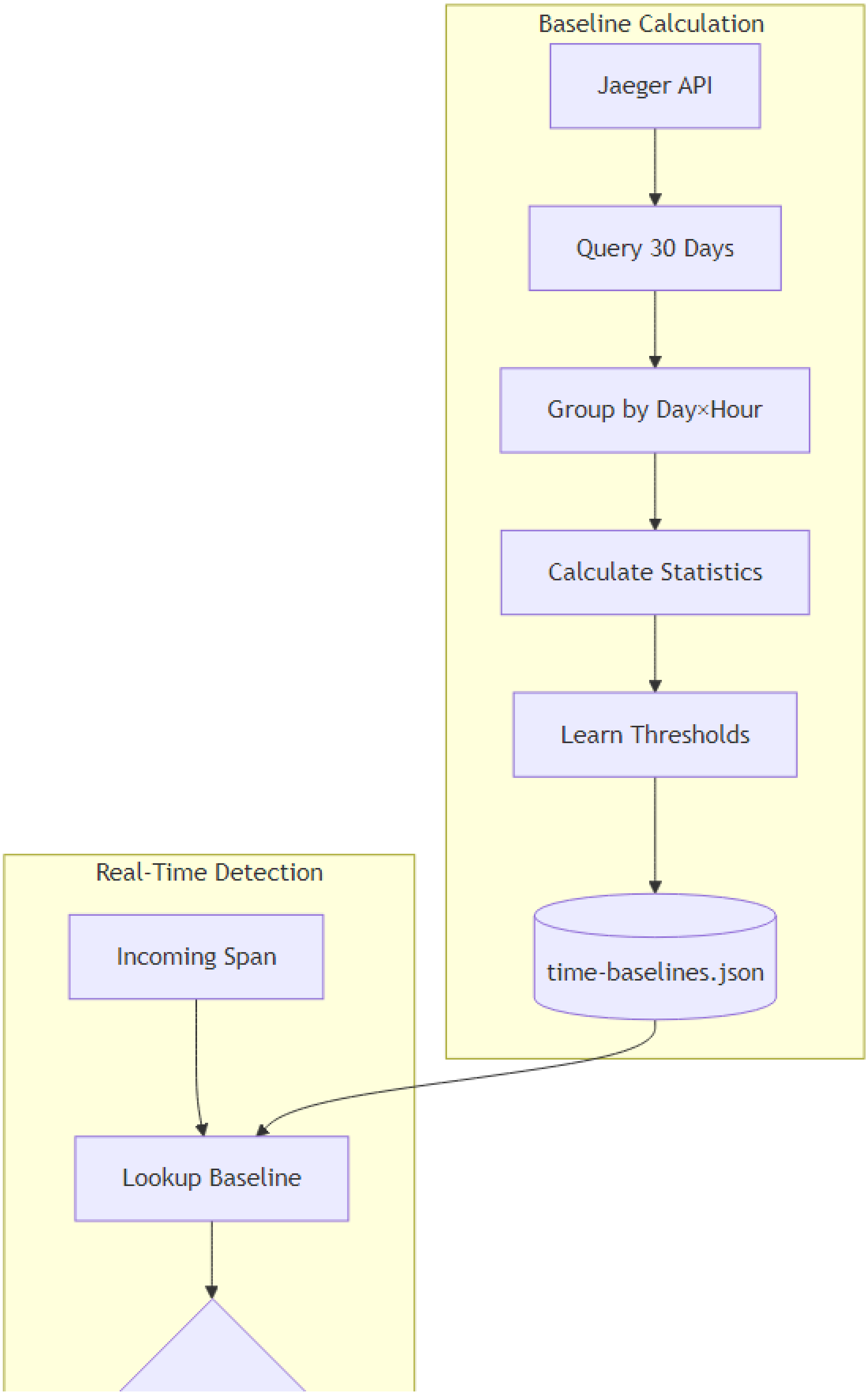


Figure: Trace flow and context propagation (Browser → Gateway → API → RabbitMQ → Worker).


Baseline Calculation
Jaeger API
Query 30 Days
Group by Day×Hour
Calculate Statistics
Learn Thresholds
time-baselines.json
Real-Time Detection
Incoming Span
Lookup Baseline

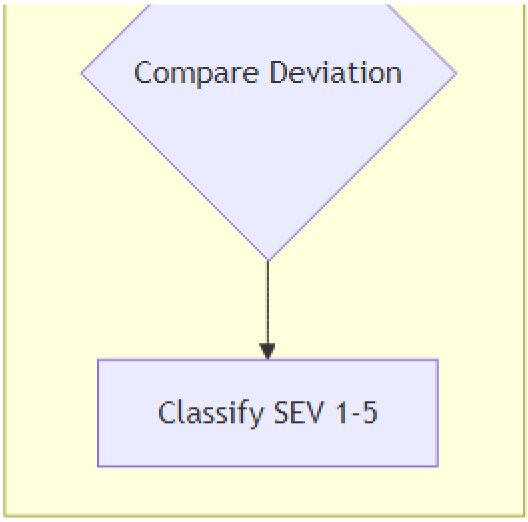


Figure: Nightly baseline calculation and real-time detection pipeline.

Key achievements ✅

- **End-to-end tracing corrected and unified:**
  - Proper parent/child span propagation for browser → `api-gateway` → `exchange-api` → RabbitMQ → `order-matcher` (fixed in `trade-form.tsx`, `rabbitmq-client.ts`, `index.ts`).
- **Trace hierarchy & message correlation:**
  - Injected and passed original parent context via message headers (`x-parent-traceparent`) so response processing appears as a sibling span.
- **Monitoring system built:**
  - Baseline profiler, anomaly detector, history store and manual endpoint to `POST /api/monitor/recalculate`.
  - Time-aware baselines (1-hour buckets, 30-day history) and adaptive, percentile-based thresholds turned into five severity levels (SEV1–SEV5).
- **LLM-augmented analysis:**
  - Ollama integrated for AI-assisted trace+metrics analysis; prompts include correlated Prometheus metrics (cpu, mem, P99, etc.).
  - Switched to `llama3.2:1b` for faster responses.
- **Metrics + traces correlation:**
  - Prometheus metrics collection and a metrics correlator service to fetch metrics at anomaly timestamps and include them in AI prompts.
- **UI & UX improvements:**
  - Monitor dashboard: severity filter dropdown, SEV badges and colors, AI Analysis moved above baseline table, visible header buttons, accessibility/contrast and layout refinements.
- **Infra & ops cleanup:**
  - Docker compose fixes (port conflicts resolved), removed unused Tempo/Grafana, and added Prometheus scrape for `/metrics`.

Impact / measurable results 📊

- Baselines collected (example): ~22 baselines from ~2.9k spans during initial run.
- Tracing now shows deeper, correct hierarchy (e.g., `exchange-api:POST` → `publish orders` and sibling `payment_response process`).
- AI responses became data-driven after including real metrics (reduced hallucination).

Lessons learned & best practices 💡

- **Explicit context propagation matters:** always set parent context explicitly around async operations (use `context.with` / `trace.setSpan`), especially across await boundaries.
- **Message brokers require intentional header propagation:** to maintain meaningful trace relationships across queue-based patterns, send the original parent trace context explicitly.
- **Time-awareness is essential:** 1-hour time buckets with 30-day history dramatically reduce false positives compared to single global baselines.
- **Adaptive thresholds beat fixed σ:** calculating percentile breakpoints (p95/p99/p99.9) nightly yields meaningful SEV boundaries per-span.
- **LLMs must be fed precise, validated context:** include raw metrics in prompts and log the prompt payload to detect hallucination quickly.
- **UX affects adoption:** place analysis near selection (AI Analysis above baselines), show severity badges, and ensure visible controls and contrast.
- **Incremental & test-first rollout:** start with polling-based detection, a manual recalculation endpoint, and iterate to nightly automation and streaming later.
- **Performance tradeoffs:** smaller LLM models and quantized variants give big latency/throughput wins; keep a tiered/streaming plan for heavy usage.
- **Keep debug logs brief during validation:** remove verbose logs after verifying behavior.
- **Document tracing touchpoints & config:** include clear documentation so others can reproduce the same trace semantics.

Part 1 — How to replicate the tracing behavior ✨

Goal: achieve the same, clear trace hierarchy and reliable sibling/child relationships for operations that cross HTTP and message queues.

Key concepts (short)

- Context is not magically preserved across async boundaries — explicitly preserve and use it.
- When sending messages across message brokers, **inject** a trace context into message headers so the consumer can link spans correctly.
- For response messages that should appear as siblings (not children) of an original request, **carry the original parent span context** and use that as the parent when creating the response consumer span.

Touchpoints and where the logic lives in the repo

- Client-side: `client/src/lib/tracing.ts` and components like `client/src/components/trade-form.tsx` — create client spans and preserve context across await boundaries when processing responses.
- RabbitMQ client (producer): `server/services/rabbitmq-client.ts` — create publish spans with the correct parent context and inject trace headers into message properties (e.g. `headers['traceparent']` or a custom `x-parent-traceparent`).
- Worker / matcher (consumer): `payment-processor/index.ts` — extract the parent context from message headers; when responding, inject the original POST context into the response so the consumer's processing span becomes a sibling of `publish orders`.

- Auto-instrumentation: be mindful that amqplib/auto-instrumentation will create spans from extracted trace headers; decide whether to rely on it or implement explicit spans.

Minimal code patterns (Node / OpenTelemetry)

- Create a span and run code in its context:

```
const parentCtx = context.active();
const span = tracer.startSpan('order.submit');
await context.with(trace.setSpan(parentCtx, span), async () => {
  // your async code here (fetch, publish, etc.)
  // inject context for outgoing messages
  propagation.inject(context.active(), carrier, defaultTextMapSetter);
});
span.end();
```

- Inject parent trace into message headers (producer):

```
const carrier = { headers: {} };
propagation.inject(context.active(), carrier.headers, defaultTextMapSetter);
// Also include original POST context explicitly as x-parent-traceparent
carrier.headers['x-parent-traceparent'] = getTraceparentFromContext(context.active());
// publish message with 'carrier.headers'
```

- Extract context on consumer and use the original POST context in responses:

```
const headers = msg.properties.headers || {};
const parentCtx = propagation.extract(ROOT_CONTEXT, headers, defaultTextMapGetter);
const originalParent = headers['x-parent-traceparent'];
// For response: set the original parent context so response span is sibling
const respCtx = reconstructContextFromTraceparent(originalParent);
const responseSpan = tracer.startSpan('payment_response process', { /* ...*/ }, respCtx);
```

> *Tip: use consistent header naming (`x-parent-traceparent`) so you can find and debug propagation easily in logs.*

Verification steps

1. Start the app and Jaeger: UI at `http://localhost:5173` and Jaeger at `http://localhost:16686` .
2. Submit a BUY order via UI or curl:

```
curl -X POST http://localhost:8000/api/orders -H 'Content-Type: application/json' -d
'{"pair":"BTC/USD","side":"BUY","quantity":0.01,"orderType":"MARKET","userId":"alice"}'
```

3. In Jaeger you should see:

    - `exchange-api: POST` as root
    - Child `exchange-api: publish orders` → down to `order-matcher: order.match`
    - A sibling `exchange-api: payment_response process` that is a child of the original POST.

4. If a span is missing or orphaned, check the message headers printed in logs (we added debug logs in `server/services/rabbitmq-client.ts` and `payment-processor/index.ts`).

Part 2 — Anomaly Detection Design (Time-aware + Adaptive thresholds) 🧭

This section explains the architecture we implemented, why we chose it, and how to reproduce or adapt it to your data.

Motivation

- Latency and span durations vary by time-of-day and day-of-week.
- A single global mean/std-dev produces many false positives.
- We need a system that (1) captures time patterns, (2) learns what constitutes "rare" deviations, and (3) exposes severity tiers for alerting.

High-level architecture

1. TraceProfiler polls Jaeger and stores span duration samples (per span operation) for the last 30 days.
2. BaselineCalculator groups samples into **time buckets** (dayOfWeek × hourOfDay) and computes incremental stats (count, sum, sum-of-squares → mean/std).
3. Nightly job computes percentiles (p95, p99, p99.9) of historical deviations and derives severity thresholds (SEV1–SEV5).
4. AnomalyDetector uses the best-available baseline (specific bucket → hourly fallback → global) and computes deviation in σ units: deviation = (value - mean) / σ.
5. If deviation exceeds severity thresholds, create an anomaly with associated metadata and store it in HistoryStore.
6. On anomaly selection, the AnalysisService fetches correlated Prometheus metrics and calls Ollama for insights.

Storage & shapes (SQLite-style)

```
TimeBaseline { spanKey, dayOfWeek, hourOfDay, count, mean, stdDev }
Thresholds { spanKey, dayOfWeek, hourOfDay, p95, p99, p999, sevMapping }
Anomaly { id, spanKey, duration, deviationSigma, sev, traceId, timestamp }
```

Key details & decisions

- Granularity: 1-hour buckets (24 × 7 = 168 per span)
- History depth: 30 days (configurable)
- Recalc mode: nightly job + manual endpoint `POST /api/monitor/recalculate` for validation and ad-hoc re-runs
- Adaptive severity mapping: By default we map percentiles to SEV levels like this:
  - SEV1: > p999 (extreme, top 0.1%)
  - SEV2: > p99 (critical)
  - SEV3: > p95 (major)
  - SEV4: > p90 (minor)
  - SEV5: > p80 (low)

> *This mapping is configurable and done during the nightly baseline recalculation.*

Algorithm (nightly recalculation)

1. For each spanKey and each hour bucket:
   - Query last 30 days of duration samples for that span & bucket
   - Compute mean μ, std σ, and percentiles of deviations
   - Store (mean, σ, p95, p99, p999)
2. Create SEV threshold map from percentile results, persist for AnomalyDetector to use.

Real-time detection (per incoming span sample)

1. Identify bucket: dayOfWeek + hourOfDay of sample timestamp
2. Lookup baseline (if sampleCount >= MIN_SAMPLES, use it; else fallback to hourly or global baseline)
3. Compute deviation: $z = (\text{duration} - \mu) / \sigma$
4. Map z to severity using stored thresholds
5. Create anomaly if z crosses configured SEV threshold

Example code sketch (detection)

```
const baseline = getBaseline(spanKey, day, hour) || fallbackBaseline;
const z = (observed - baseline.mean) / baseline.std;
const sev = classifyByThresholds(z, thresholdsFor(spanKey, day, hour));
if (sev <= configuredAlertLevel) createAnomaly(...);
```

Severity classification (SEV1–SEV5)

Make severity explicit in UI and storage and show the percentile and σ that triggered it. This allows users to filter and triage efficiently (we added a severity dropdown to the UI).

Why not ML-first? (and when to use ML)

- The incremental stats approach (mean/std/percentiles) is simple, explainable, and works with limited historical data.
- ML methods (one-class SVM, isolation forest, autoencoder, or LoRA-finetuned models that summarize traces) can be applied later when you have labeled anomalies and richer feature vectors.
- For now, prefer deterministic, inspectable thresholds with nightly recalculation and anomaly history.

Part 3 — LLM integration (operational tips)

- Include correlated metrics (Prometheus) in the prompt when analyzing an anomaly — CPU, memory, request rate, error rate, P95/P99 latency.
- Keep prompts bounded (summarize long traces) and log prompt payloads during testing to avoid hallucinations.
- Use a smaller model (we switched to `llama3.2:1b`) for production-like responsiveness; keep the larger model for ad-hoc deep analysis.
- Add timeouts and retries to Ollama calls (we added both) and a circuit-breaker for model overload.

Sample prompt structure:

```
- Short summary of anomaly (service, span, duration, deviation)
- Recent trace (key spans and durations, up to a length limit)
- Correlated metrics snapshot (CPU, memory, P99, request-rate, error-rate)
- Ask the model for top-3 probable causes and recommended next steps
```

Part 4 — Tests & operational checklist ✅

- [ ] Start services: `docker-compose up -d` and `npm run dev` (server + vite)
- [ ] Verify Jaeger traces: Visit `http://localhost:16686` and search traces for `exchange-api` service
- [ ] Submit order via UI or curl and verify: publish spans exist and response spans are siblings
- [ ] Run baseline recalculation: `POST /api/monitor/recalculate` and check SEV thresholds stored
- [ ] Trigger anomaly (simulate slow handler) and confirm UI receives an alert with SEV badge
- [ ] Select anomaly → click `Analyze` → check model response mentions metrics and suggests actions

---

Part 5 — Next steps & roadmap

- Automate the nightly baseline job via cron/worker (server side) and alert on job failures.
- Add a small finite buffer/summary extractor on trace content before sending to LLM (reduce prompt size and cost).
- Create a labeled dataset and start LoRA fine-tuning for domain-specific insights (200–500 examples to start).
- Add metric historical charts for anomalies and a service dependency map for root-cause suggestions.

Appendix — Quick commands and endpoints

- Submit an order (example):

```
curl -X POST http://localhost:8000/api/orders -H 'Content-Type: application/json' -d
'{"pair":"BTC/USD","side":"BUY","quantity":0.01,"orderType":"MARKET","userId":"alice"}'
```

- Recalculate baselines (manual):

```
curl -X POST http://localhost:5000/api/monitor/recalculate -H 'Content-Type:
application/json'
```

- Analyze an anomaly (trigger model):

```
curl -X POST http://localhost:5000/api/monitor/analyze -H 'Content-Type:
application/json' -d '{"traceId":"<traceId>"}'
```

Export to HTML / PDF (one-command)

To generate the rendered HTML and a printable PDF of this document (including diagrams):

```
# Renders diagrams and builds HTML + PDF
npm run docs:build
```

Outputs:

- `docs/traces-and-anomaly.html` (HTML)
- `docs/traces-and-anomaly.pdf` (PDF)

If you'd like, I can now:

- Generate a short `docs/README_TRACING.md` version suitable for on-call staff,
- Add a checklist `MONITORING_RUNBOOK.md` for incident responders,
- Or create the Pull Request with these docs and update the main `README.md`.

Which would you like me to do next? 🙌