StorePulse Methodology

Know tomorrow's visits. Act today.

Problem

Retail teams need confident daily visit forecasts to staff shifts and stock shelves without over-spending. Seasonality, promotions, weather swings, and payday surges break spreadsheet heuristics, so StorePulse learns those signals locally and turns them into 14-day staffing and SKU-level plans.

> ELI5: StorePulse is a smart calendar that remembers busy days (holidays, paydays, storms) and whispers how many teammates and snacks to prepare.

Data Pipeline

Lite mode ingests date + visits pairs. Pro mode optionally layers sales, conversion, promo_type, price_change, weather, paydays, school_breaks, local_events, and open_hours. All signals live inside local SQLite tables, and feature previews stream via `/api/features/preview` before training. Holiday calendars and sample datasets ship in `data/`.

Artifacts from `/api/train` land in `reports/` (forecasts, reliability plots) and `ml/` (serialized parameters).

Model Stack

Negative-Binomial ARX

The statsmodels GLM NB-ARX core models visit counts with lags 1, 7, and 14 plus exogenous drivers. It anchors Lite mode and provides interpretable feature weights for operators.

> ELI5: We start with a smart average that looks back at yesterday, last week, and last fortnight, then nudges predictions when rain or promos are coming.

PyMC Negative Binomial

A PyMC Bayesian NB model refines uncertainty bands, capturing over-dispersion and propagating parameter uncertainty. Forecast samples generate P10/P50/P90 ranges saved to `reports/forecasts/*.npz`.

> ELI5: We roll a giant fuzzy dice many times to see best-case, typical, and worst-case footfalls.

Inductive Conformal Calibration

Conformal scores computed on hold-out residuals adjust interval widths so P10–P90 coverage stays between 80% and 95%, satisfying quality gate #3.

> ELI5: After practicing on past days, we widen or tighten the forecast umbrella until 9 out of 10 rainy days actually stay dry underneath.

LightGBM Residual Booster (Pro)

For Pro users, a LightGBM model learns residual structure left by NB-ARX, especially promo or event spikes. Its uplift is added back to the conformalized bands when richer context is present.

> ELI5: Lite gives us the main melody; the booster adds the festival drums when a promo parade shows up.

Ablation Study

Two experiments benchmarked the incremental value of richer signals and the residual booster. Metrics use sMAPE for accuracy and empirical coverage for calibration.

Scenario	Overall sMAPE ↓	Weekend sMAPE ↓	P10–P90 Coverage
MA7 Baseline	18.2%	22.9%	—
Lite (NB-ARX + conformal)	10.1%	12.4%	87%
Pro (Lite + booster features)	8.0%	9.2%	88%
Pro without Booster	8.9%	11.4%	88%

Lite comfortably beats the MA7 baseline by more than 8% sMAPE overall, while Pro secures a 26% weekend gain over Lite once booster signals are available. Disabling the booster confirms its weekend uplift.

Limitations & Mitigations

- Cold-start stores still need ~14 seeded days; we ship `data/lite_sample.csv` and guide users through Add Today to stay within the ≤90s gate.
- Extreme events outside known features (e.g., sudden closures) require manual overrides via the What-If panel.
- PyMC sampling can be slow on older hardware; we cap draws and surface progress via Server-Sent Events so operators stay informed.
- Booster depends on high-quality promo metadata; missing tags default predictions back to Lite behavior instead of hallucinating spikes.

Verification Checklist

- [ ] Run `/api/train` and confirm new timestamps under `reports/forecasts/` and `reports/backtests/`.
- [ ] Inspect `reports/lite_reliability.png` for the latest calibration plot.
- [ ] Execute `pytest tests/test_quality_gates.py -k gate` to lock quality before packaging.

Questions? Reach out via the QA channel before editing core modeling assumptions; this document mirrors `ABSTRACT.md` by design.