Samsung Worklet 8 — Unified Flask Dashboard (Full Documentation)

This repository bundles three independent Flask applications behind a single, branded dashboard. The dashboard starts each app on its own port and embeds it so you can operate everything from one place.

- Unified Dashboard: `dashboard/`
- Case2 Sales Prediction (single + batch): `Case2-Nosalesuplift(pipeline) 2/`
- Loan Default Predictor (form): `loan_app/`
- Rossmann Sales Uplift (batch): `Sales Uplift 2/pipeline/`

All apps now share a consistent "Samsung Worklet 8" modern UI.

1) Prerequisites

- OS: macOS (zsh shell)
- Python: 3.10+ (3.13 tested)
- Disk space: ~1 GB for Python wheels and models
- Optional: Homebrew for tools like `lsof`

Recommended: Use a dedicated virtual environment in the repo root.

2) Setup (macOS + zsh)

Create and activate a venv in the repo root:

```
cd "/Users/ayush/Downloads/Samsung Dashboard worklet 8"
python3 -m venv .venv
source .venv/bin/activate
```

Upgrade pip and install core dependencies used across apps:

```
pip install --upgrade pip
pip install flask pandas numpy scikit-learn joblib xgboost lightgbm catboost
```

Note on Apple Silicon (M1/M2/M3): LightGBM/CatBoost wheels are installed above. If compilation issues appear, reinstall with matching wheels or consult their docs.

3) How to Run

You can run everything via the dashboard or run apps individually.

A. Run the Dashboard (recommended)

```
cd dashboard
python app.py
```

Open: http://127.0.0.1:5050

- Click a button to launch and view each app.
- The dashboard logs child app output to `dashboard/logs/<app>.log`.
- Child apps run with `flask run --no-reload` on these ports:
  - Case2 Sales Prediction: 7001
  - Loan Default Predictor: 7002
  - Rossmann Sales Uplift: 7003

If a button fails, the dashboard shows the last lines from the corresponding log file to help debug quickly.

B. Run apps individually (direct)

Case2 Sales Prediction:

```
cd "Case2-Nosalesuplift(pipeline) 2"
FLASK_APP=app.py python -m flask run --host 127.0.0.1 --port 7001 --no-reload
```

Loan Default Predictor:

```
cd loan_app
FLASK_APP=app.py python -m flask run --host 127.0.0.1 --port 7002 --no-reload
```

Rossmann Sales Uplift:

```
cd "Sales Uplift 2/pipeline"
FLASK_APP=app.py python -m flask run --host 127.0.0.1 --port 7003 --no-reload
```

4) Data, Models, and Artifacts

Each app expects specific artifacts and/or data files. Place them in the listed folders before running.

A. Case2 Sales Prediction — `Case2-Nosalesuplift(pipeline) 2/`

Purpose: Predict daily sales for a given store+item (single form) and batch CSV upload.

Present artifacts in repo (already included): - `scaler.pkl` — StandardScaler used to normalize features - `catboost_model.pkl` — CatBoost regressor - `lgbm_model.pkl` — LightGBM regressor - `ridge_model.pkl` — Ridge regressor - Data files: `train2.csv` (for dropdowns), `test.csv` (sample)

Model selection: UI lets you choose among any loaded models. If doing batch predictions, code prefers `random_forest` if present, else the first loaded model (with current artifacts that will be one of the above).

Features (single prediction): - Inputs captured: `store`, `item`, `month`, `day` - Derived at runtime: `dayofweek`, `dayofyear`, `weekofyear` - All features are scaled by `scaler.pkl` before inference.

Batch prediction (CSV): - Input CSV must include `date`, `store`, `item` - The app derives `month`, `day`, `dayofweek`, `dayofyear`, `weekofyear` - Output CSV adds `predicted_sales` (rounded int)

Endpoints: - `GET /` — Form + batch UI - `POST /predict` — Single prediction - `POST /batch_predict` — CSV upload, returns JSON with `download_url` - `GET /download/<filename>` — Download processed CSV

B. Loan Default Predictor — `loan_app/`

Purpose: Classify a loan as Default vs Non-Default from form inputs.

Expected artifacts (user-provided, not committed): - `loan_app/models/tabpfn.pkl` — Trained classifier (loaded with joblib) - `loan_app/models/scaler.pkl` — Fitted scaler for numeric features - `loan_app/models/dummy_columns.pkl` — List of training one-hot columns for alignment

Important: Ensure that the library used to create `tabpfn.pkl` is installed if its class needs to be unpickled (e.g., TabPFN). In many cases, plain scikit-learn-compatible wrappers work with the stack installed above.

Inputs (examples, must match training): - Numeric: `interest_rate`, … - Categorical: `source`, `loan_purpose`, `EducationLevel`, `MaritalStatus`, `Gender`, `EmploymentStatus`

Preprocessing: - One-hot encode categorical columns, then align to `dummy_columns.pkl` - Scale numeric columns via `scaler.pkl`

Endpoint: - `GET /` — Applicant form - `POST /predict` — Returns JSON: `{ "prediction": 0|1, "class": "Default"|"Non-Default" }`

C. Rossmann Sales Uplift — `Sales Uplift 2/pipeline/`

Purpose: Batch predictions for Rossmann stores using a trained XGBoost model.

Artifacts in repo (already included): - `xgb_model.pkl` — Trained regressor - `scaler.pkl` — Scaler fitted on training features - `encoder.pkl` — OneHotEncoder for categorical features (if present); otherwise a safe dummy encoder is created

Key processing (from `utils/data_processor.py`): - Type conversions (Date → datetime, encode StateHoliday) - Feature engineering: `WeekOfYear`, `Month`, `Year`, `CompetitionOpenNumMonths`, `Promo2NumWeeks` - Transformations: sqrt on `Sales`, `Customers`, `CompetitionOpenNumMonths`, `Promo2NumWeeks`; log on `CompetitionDistance` - One-hot encoding for `PromoInterval`, `StoreType`, `Assortment` (encoder if available; else pandas dummies) - Dummy trap avoidance by dropping a fixed set of columns - Feature order enforced to match scaler's `feature_names_in_` (or a configured list)

Inputs (CSV): - A test dataset with standard Rossmann features (no Sales column required)

Outputs: - JSON: `{ success, row_count, download_url }` - CSV: Original columns + `Predicted_Sales`

Endpoints: - `GET /` — CSV upload UI - `POST /predict` — CSV upload, returns JSON - `GET /download/<filename>` — Download processed CSV

5) API Examples (cURL)

Case2 — single prediction (form post):

```
curl -X POST http://127.0.0.1:7001/predict \
  -H 'Content-Type: application/x-www-form-urlencoded' \
  --data-urlencode 'store=1' \
  --data-urlencode 'item=1' \
  --data-urlencode 'month=1' \
  --data-urlencode 'day=15' \
  --data-urlencode 'model_choice=catboost'
```

Case2 — batch prediction:

```
curl -X POST http://127.0.0.1:7001/batch_predict \
  -F file=@test.csv
```

Loan — predict:

```
curl -X POST http://127.0.0.1:7002/predict \
  -H 'Content-Type: application/x-www-form-urlencoded' \
  --data-urlencode 'interest_rate=9.5' \
  --data-urlencode "EducationLevel=Bachelor's" \
  --data-urlencode 'source=Online' \
  --data-urlencode 'loan_purpose=Personal' \
  --data-urlencode 'MaritalStatus=Single' \
  --data-urlencode 'Gender=Male' \
  --data-urlencode 'EmploymentStatus=Employed'
```

Rossmann — batch prediction:

```
curl -X POST http://127.0.0.1:7003/predict \
  -F file=@"Sales Uplift 2/Dataset/test.csv"
```

6) Common Tasks

- Change ports: Edit `APPS` in `dashboard/app.py`.
- Check logs: See `dashboard/logs/*.log` after attempting to start an app.
- Reset uploads: Each app writes outputs under its own `uploads/` folder.
- Re-theme UI: All pages share the same gradient/card style; customize in their HTML `<style>` blocks.

7) Troubleshooting (Quick)

- Process died / Bad file descriptor: The dashboard now strips `WERKZEUG_*` env and uses `--no-reload` to avoid FD issues.

- scikit-learn unpickle warnings: Align versions or re-export models. Example to downgrade:

  ```
  pip install 'scikit-learn==1.6.1'
  ```

- Port in use: Free ports with:

  ```
  lsof -ti:5050,7001,7002,7003 | xargs kill -9
  ```

- Missing loan artifacts: Place `tabpfn.pkl`, `scaler.pkl`, `dummy_columns.pkl` under `loan_app/models/`.

See `docs/troubleshooting.md` for detailed guidance.

8) Project Layout

```
Samsung Dashboard Worklet 8
├── dashboard/                # Unified control plane (Flask)
│   ├── app.py                # Spawns child apps, serves UI, logs
│   ├── logs/                 # Per-app logs
│   └── templates/            # Dashboard views
├── Case2-Nosalesuplift(pipeline) 2/
│   ├── app.py                # Single & batch sales prediction
│   ├── templates/index.html  # UI (form + batch)
│   ├── *.pkl                 # scaler + models (ridge, lgbm, catboost)
│   └── uploads/              # Batch outputs
├── loan_app/
│   ├── app.py                # Loan default predictor
│   ├── templates/index.html  # UI (form)
│   └── models/               # EXPECTED: tabpfn.pkl, scaler.pkl, dummy_columns.pkl
└── Sales Uplift 2/pipeline/
    ├── app.py                # Rossmann batch app
    ├── config.py             # Paths, expected features, upload folder
    ├── utils/                # Model loader, data processing, file IO
    ├── templates/index.html  # UI (uploader)
    └── uploads/              # Outputs
```

9) Security & Production Notes

- This stack is for local demos/dev. Do not expose directly to the internet.
- For production, use a WSGI server (gunicorn/uwsgi) behind a reverse proxy (nginx), configure HTTPS, CSRF protection for forms as needed, and secrets handling.

10) Credits

- Flask, Jinja2, Werkzeug
- scikit-learn, XGBoost, LightGBM, CatBoost
- Bootstrap 5, Font Awesome

Executive Summary

This project consolidates three independent ML use cases behind one dashboard: - No sales prediction (per store–item daily sales; form + batch CSV) - Loan predictor (delinquency/default classification from applicant features) - Sales prediction (Rossmann-style retail batch forecasting)

Each use case is a separate Flask app with its own data schema, preprocessing, and model artifacts. The dashboard starts, health-checks, and embeds each app, providing a simple operator interface suitable for demos, reviews, and handover.

Business outcomes: - Credit risk reduction via early identification of high-risk applicants - Inventory and operations planning via daily sales estimates - Campaign and planning support via store-level retail predictions

Program Context (Samsung PRISM)

Samsung PRISM is a student–industry collaboration program. This worklet follows common data science report conventions for evaluation: - Clear problem statements and data schemas - Reproducible modeling approach and evaluation protocol - Practical deployment interface (web UI) for reviewers

System Overview

Architecture: - Three Flask services (one per use case), each loading CSV-based input, applying deterministic preprocessing, running inference with persisted artifacts, and serving a small web UI plus HTTP endpoints - A unified Flask dashboard that spawns the services on fixed ports, verifies readiness, and embeds each app in an iframe with log-tail diagnostics on failure

Ports (default): - Dashboard: 5050 - No sales prediction: 7001 - Loan predictor: 7002 - Sales prediction: 7003

Detailed Use Cases

A) No sales prediction (Case2)

- Objective: Predict daily sales for a selected store–item and date; also support batch CSV predictions
- Data (single): store (int), item (int), month (1–12), day (1–31)
- Derived features: dayofweek, dayofyear, weekofyear
- Data (batch CSV): columns `date`, `store`, `item` (date features are derived)
- Preprocessing: StandardScaler on [store, item, month, day, dayofweek, dayofyear, weekofyear]
- Models provided: Ridge, LightGBM, CatBoost (choose at runtime)
- Metrics (suggested): MAE/RMSE, MAPE, and error by store/item
- Endpoints: `/`, `POST /predict`, `POST /batch_predict`, `GET /download/<file>`

B) Loan predictor (delinquency/default)

- Objective: Estimate probability of default for policy cutoffs and monitoring
- Data: numeric (e.g., interest_rate), categorical (source, loan_purpose, EducationLevel, MaritalStatus, Gender, EmploymentStatus) — must match training
- Preprocessing: one-hot encode categoricals, align to `dummy_columns.pkl`, scale numeric features
- Artifacts: `tabpfn.pkl` (classifier), `scaler.pkl`, `dummy_columns.pkl`
- Metrics (suggested): AUC, F1/precision/recall, KS, Brier score, calibration plot; policy threshold tied to expected loss
- Endpoint: `/`, `POST /predict`

C) Sales prediction (Rossmann batch)

- Objective: Predict sales for many rows to support planning and analytics
- Input CSV: Rossmann-like features (Date, Store, DayOfWeek, Open, Promo, StateHoliday, SchoolHoliday, StoreType, Assortment, CompetitionDistance, etc.) — no Sales column required
- Preprocessing pipeline highlights: engineered time features; Competition/Pomo deltas; sqrt/log transforms; one-hot encoding with encoder fallback; dummy trap handling; feature order aligned to scaler
- Artifacts: `xgb_model.pkl`, `scaler.pkl`, `encoder.pkl`
- Metrics (suggested): MAE/RMSE, segment-wise error; optional uplift-style metrics if experimentation data exists
- Endpoints: `/`, `POST /predict`, `GET /download/<file>`

API Reference (Consolidated)

Dashboard

- `GET /` — List apps, status, and Open buttons
- `GET /open/<app_id>` — Launch app on demand and embed it
- `POST /api/start/<app_id>` — Programmatic start
- `POST /api/stop/<app_id>` — Programmatic stop

App IDs: `case2` (No sales prediction), `loan` (Loan predictor), `rossmann` (Sales prediction)

No sales prediction (Case2)

- `GET /` — HTML (form + batch)
- `POST /predict` — Single prediction (form fields: store, item, month, day, model_choice)
- `POST /batch_predict` — Multipart CSV (file)
- `GET /download/<filename>` — CSV download

Loan predictor

- `GET /` — Form
- `POST /predict` — x-www-form-urlencoded; returns JSON `{ prediction, class }`

Sales prediction (Rossmann)

- `GET /` — Uploader
- `POST /predict` — Multipart CSV (file); returns `{ success, row_count, download_url }`
- `GET /download/<filename>` — CSV download

Data Management & Reproducibility

Quality controls: - De-duplication by keys (e.g., (store, item, date) or applicant ID) - Missing value policy consistent between train and inference - Outlier treatment (clipping/winsorization, log transforms) - Encoding strategies documented for categorical fields - Consistent splits with seeded randomness

Dataset documentation (per CSV): - Column name, type, allowed ranges, missingness, meaning, label definition, and leakage prevention notes

Reproducibility: - Pin Python and package versions - Persist random seeds and training configs - Store scalers/encoders with models; enforce feature order (e.g., `scaler.feature_names_in_`)

Model Evaluation Protocol

- Classification (loan): stratified k-fold; report mean ± std for AUC/F1/etc.; final holdout
- Regression (sales): k-fold or time-aware split; report MAE/RMSE, error histograms and segments
- Thresholding: choose policy cutoffs based on cost/benefit and calibration; document rationale
- Overfitting checks: learning curves, validation gaps, SHAP/feature importance stability, drift checks

Dashboard Design & UX

- Single page with three primary actions: open No sales prediction, Loan predictor, or Sales prediction
- Each app page: KPI strip (e.g., AUC, RMSE), a couple of charts (ROC/uplift/error), CSV uploader or form, and data preview
- Theme: “Samsung Worklet 8” gradient cards and headers; embedded logs for quick debugging

Implementation Details

Tech stack: - Python 3.x, Flask for all apps - ML: scikit-learn, XGBoost, LightGBM, CatBoost - Data: pandas, numpy - Dashboard alternatives: Streamlit/Dash/Taipy (optional future migration)

Run locally (recommended):

```
cd "/Users/ayush/Downloads/Samsung Dashboard worklet 8"
python3 -m venv .venv && source .venv/bin/activate
pip install --upgrade pip && pip install flask pandas numpy scikit-learn joblib xgboost lightgbm catboost
cd dashboard && python app.py
```

Open http://127.0.0.1:5050 and click to open each app.

Results & Impact (Template)

- No sales prediction: MAE/RMSE on holdout, error by store/item, planning guidance
- Loan predictor: AUC/ROC, KS, calibration; policy thresholds tied to expected loss
- Sales prediction: MAE/RMSE, segment-wise error; planning/campaign insights

Include screenshots of each app view and an example CSV-to-prediction flow for reviewers.

Troubleshooting (Quick)

- Startup failures: check `dashboard/logs/<app>.log` and free ports: `lsof -ti:5050,7001,7002,7003 | xargs kill -9`
- scikit-learn pickle warnings: align versions or re-export models
- Missing loan artifacts: add `tabpfn.pkl`, `scaler.pkl`, `dummy_columns.pkl` under `loan_app/models/`

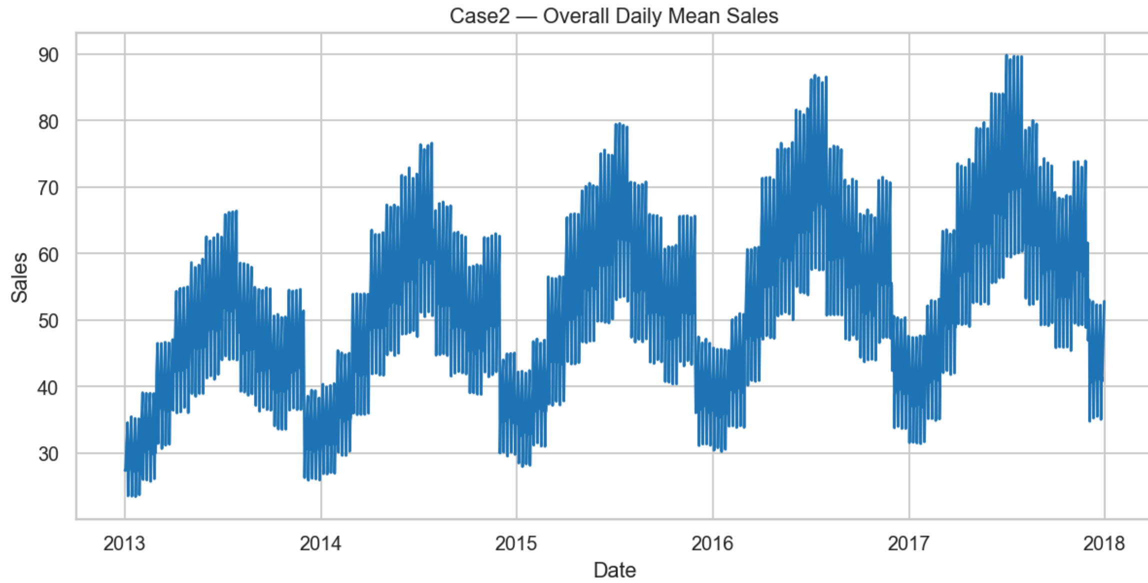
Limitations & Next Steps

- Class imbalance (loan) and feature drift risks (all)
- CSV IO for demo; migrate to Parquet or an RDBMS for production-like setups
- Add model cards, automated data checks in CI, periodic retraining with monitoring
- Optional migration to Streamlit/Dash/Taipy for richer analytics displays

Credits

- Flask, Jinja2, Werkzeug
- scikit-learn, XGBoost, LightGBM, CatBoost
- Bootstrap 5, Font Awesome

Visual Overview



Samsung Worklet 8

Run Local | Models Ridge | LGBM | CatBoost | XGBoost | Troubleshoot Guide

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Table of Contents

Use-Case Walkthroughs

No sales prediction (Case2)

How it runs (UI and API): - Open Dashboard → click “No sales prediction” → form page loads - Fill store, item, date → click Predict → server derives date features, scales, selects model → returns prediction - For batch: upload CSV with date, store, item → receive download link

Mermaid sequence (form flow):

```
sequenceDiagram
  autonumber
  participant U as User
  participant D as Dashboard (iframe)
  participant C as Case2 Flask
  U->>D: Open No sales prediction
  D->>C: GET /
```

```
  C-->>D: HTML (form)
  U->>C: POST /predict (store,item,month,day,model)
  C->>C: Derive features + scale + predict
  C-->>U: HTML with Predicted Sales
```

Sample prediction (single):

```
Predicted Sales with Catboost: 184
```

Sample JSON (batch):


```
{
  "success": true,
  "download_url": "/download/predictions_test.csv",
  "records_processed": 1000
}
```


Tips: - Ensure scaler.pkl and at least one model .pkl exist in the Case2 folder - The dropdown list is populated from train2.csv (store/item values)

Loan predictor (delinquency/default)

How it runs: - Open Dashboard → click “Loan predictor” → applicant form - Submit → server one-hot encodes categoricals, aligns to dummy_columns.pkl, scales numerics, predicts class

Mermaid sequence:

```
sequenceDiagram
  autonumber
  participant U as User
  participant D as Dashboard (iframe)
  participant L as Loan Flask
  U->>D: Open Loan predictor
  D->>L: GET /
  L-->>D: HTML (form)
  U->>L: POST /predict (form-encoded)
  L->>L: Preprocess (dummies + scaler) + predict
  L-->>U: JSON { prediction, class }
```

Sample JSON:


```
{ "prediction": 1, "class": "Default" }
```


Tips: - Place tabpfn.pkl, scaler.pkl, dummy_columns.pkl into loan_app/models/ - Column names in the form must match training-time schema for proper alignment

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Sales prediction (Rossmann batch)

How it runs: - Open Dashboard → click “Sales prediction” → CSV uploader - Upload Rossmann-style feature CSV → pipeline processes features, scales, predicts → download link returned

Mermaid sequence:

```
sequenceDiagram
  autonumber
  participant U as User
  participant D as Dashboard (iframe)
  participant R as Rossmann Flask
  U->>D: Open Sales prediction
  D->>R: GET /
  R-->>D: HTML (uploader)
  U->>R: POST /predict (file)
  R->>R: DataProcessor (features→scale→predict)
  R-->>U: JSON { success, row_count, download_url }
```

Sample JSON:


```
{ "success": true, "row_count": 42157, "download_url": "/download/predictions_test.csv" }
```


Tips: - encoder.pkl is optional; a safe OneHotEncoder fallback is created if missing - scaler.feature_names_in_ is used to enforce feature order; otherwise Config.EXPECTED_FEATURES

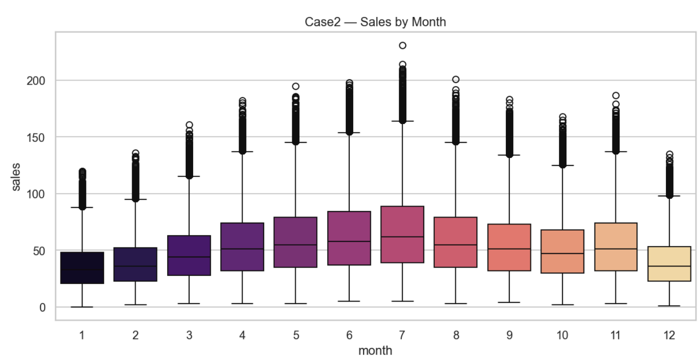
Architecture Diagram

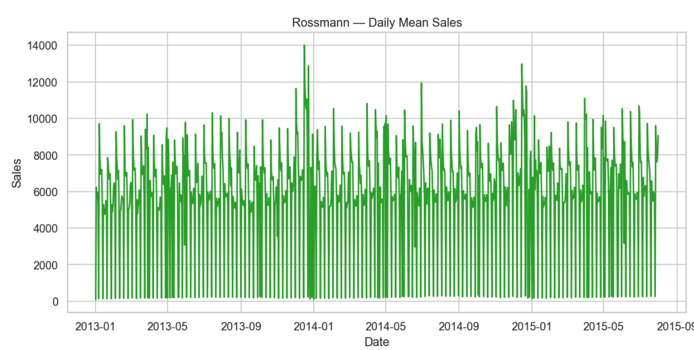
```
flowchart LR
  subgraph Dashboard[Unified Dashboard (Flask)]
    A[Buttons: No sales | Loan | Sales] -->|spawn + health check| P1
  end
  subgraph Case2[No sales prediction]
    P1[flask run 7001] --> F1[Form + Batch]
    F1 --> M1[Scaler + Ridge/LGBM/CatBoost]
  end
  subgraph Loan[Loan predictor]
    P2[flask run 7002] --> F2[Applicant Form]
    F2 --> M2[Dummy Align + Scaler + Classifier]
  end
  subgraph Rossmann[Sales prediction]
    P3[flask run 7003] --> F3[CSV Upload]
    F3 --> M3[DataProcessor + Scaler + XGBoost]
  end
  A -. iframe .-> F1
  A -. iframe .-> F2
  A -. iframe .-> F3
```

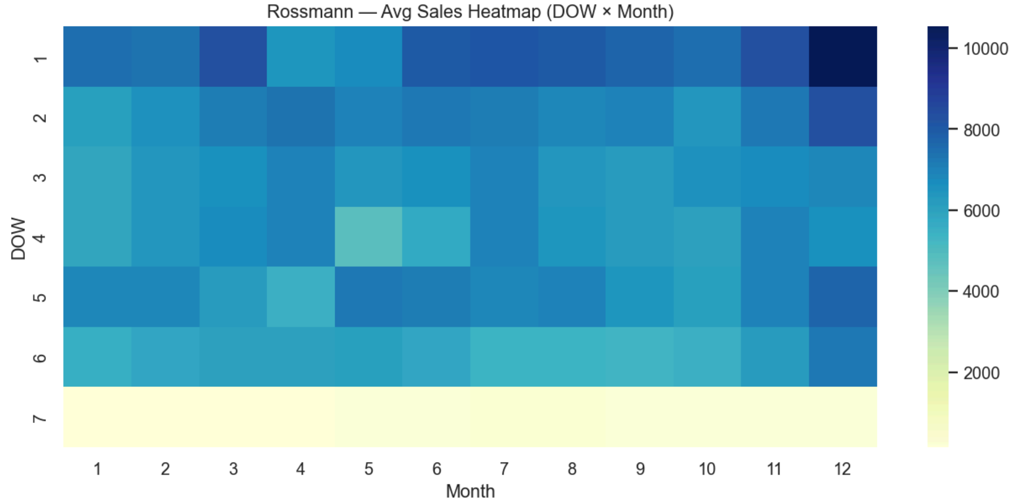
Screenshots and Charts

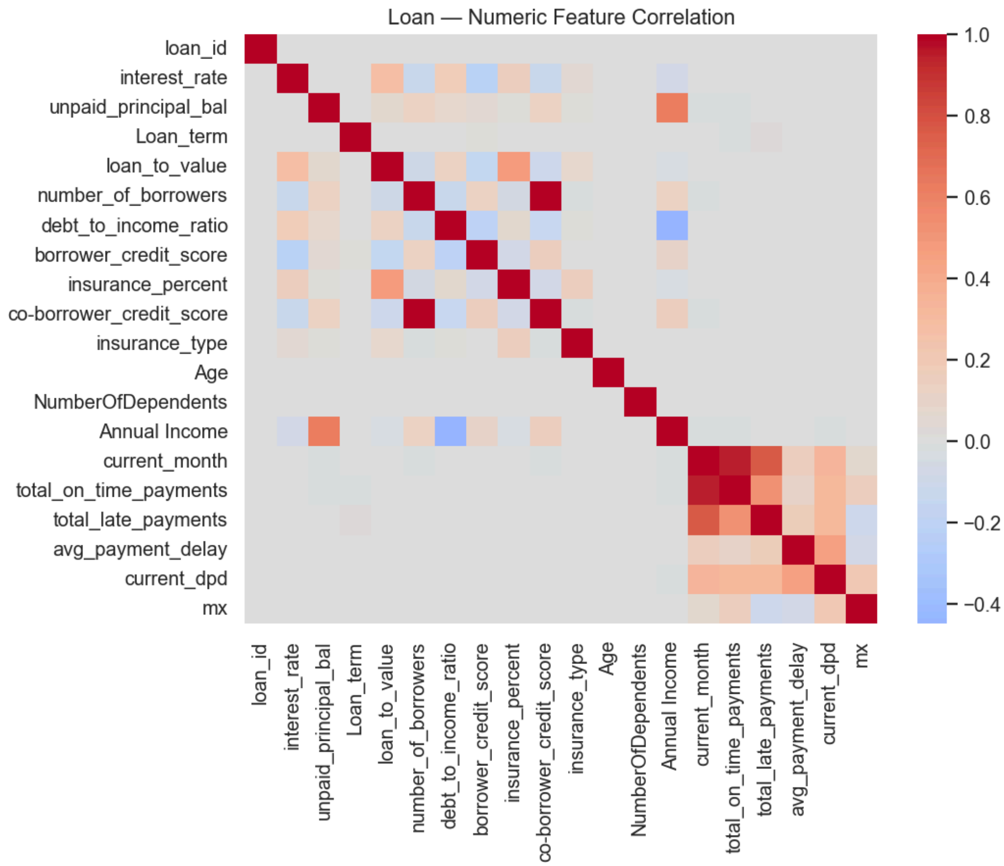
- Dashboard: add your own screenshot to `docs/assets/dashboard.png` (placeholder)
- No sales (form): add to `docs/assets/no_sales_form.png` (placeholder)
- No sales (batch success): add to `docs/assets/no_sales_batch.png` (placeholder)
- Loan predictor (form): add to `docs/assets/loan_form.png` (placeholder)

Real charts generated from your data:









Dashboard

Example Metric Visuals (placeholders)

```
pie title Loan Predictor — Class Distribution (Sample)
  "Non-Default" : 78
  "Default" : 22

pie title No Sales — Error Bucket (% of rows)
  "|err| < 10" : 45
  "10–50" : 35
  ">= 50" : 20
```

Prediction Galleries

- ▶ **No sales — Single Prediction Examples**
- ▶ **Loan predictor — JSON Responses**
- ▶ **Sales prediction — Batch Results (CSV head)**

Pro Tips for a Slick Demo

- Record a short GIF clicking the three buttons and downloading a CSV (`docs/assets/demo.gif`).
- Keep ports free before presenting: `lsof -ti:5050,7001,7002,7003 | xargs kill -9`.
- Warm the venv and dependencies ahead of time to avoid cold-start delays.

Attributions & Theme

- Theme: gradient (#667eea → #764ba2), consistent cards, Samsung Worklet 8 navbars
- Icons: Font Awesome; Charts: Mermaid (rendered by GitHub)
- ML Stack: scikit-learn, XGBoost, LightGBM, CatBoost
