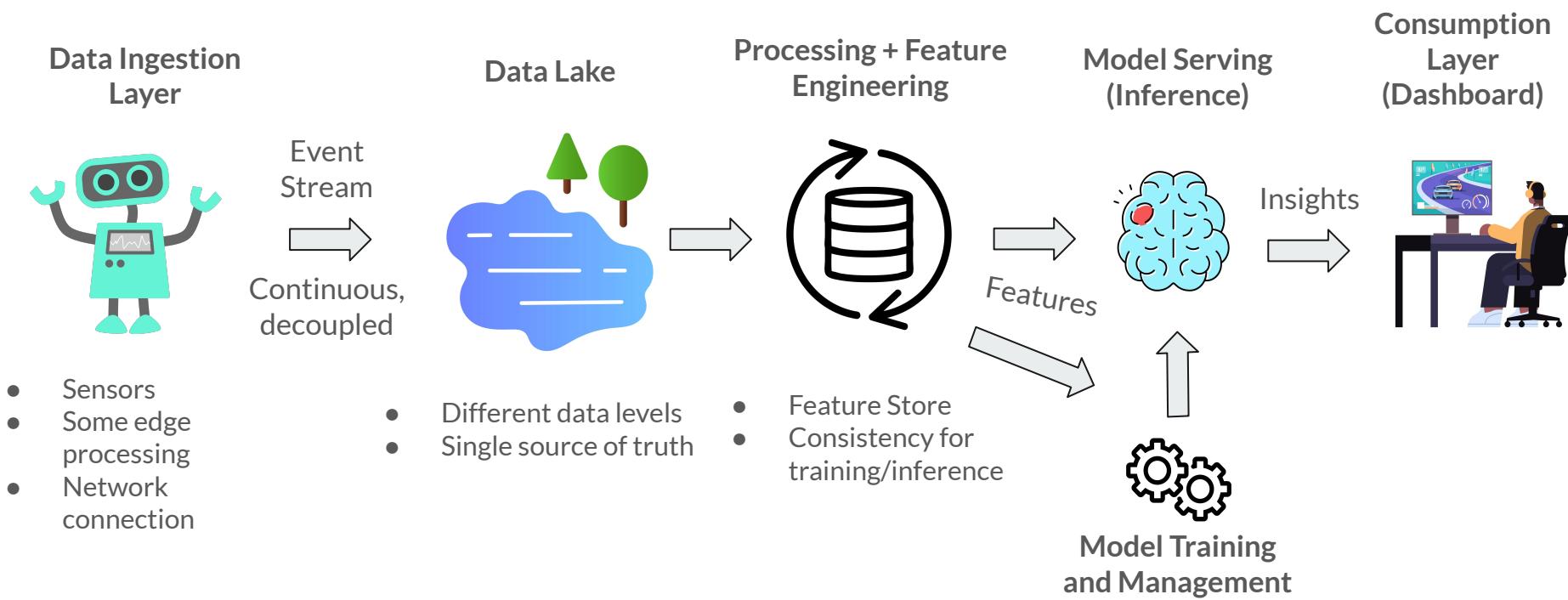

Warehouse Intelligence System

Samuel Bennett

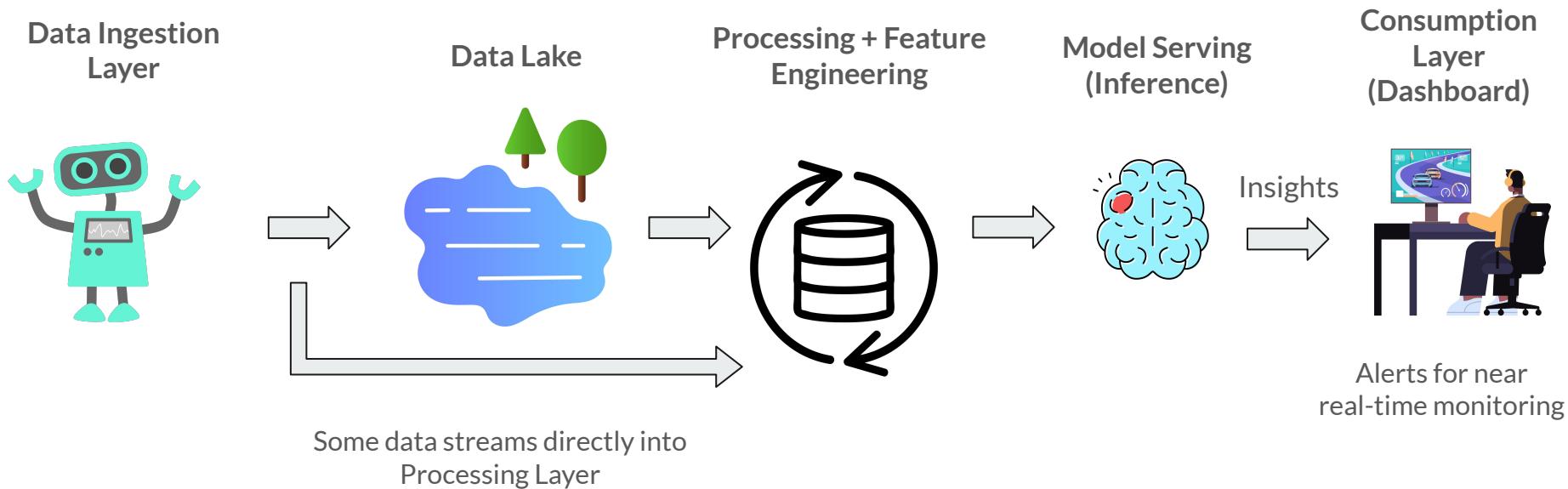
Contents

- **Architecture**
 - Layers
 - Near Real Time Processing
 - Monitoring
- **Modelling**
 - Preprocessing
 - Error Prediction
 - Spatial Error Clustering
 - Item Co-location and Pick-Path Analysis
 - Time Series Anomaly Detection
- **Summary**

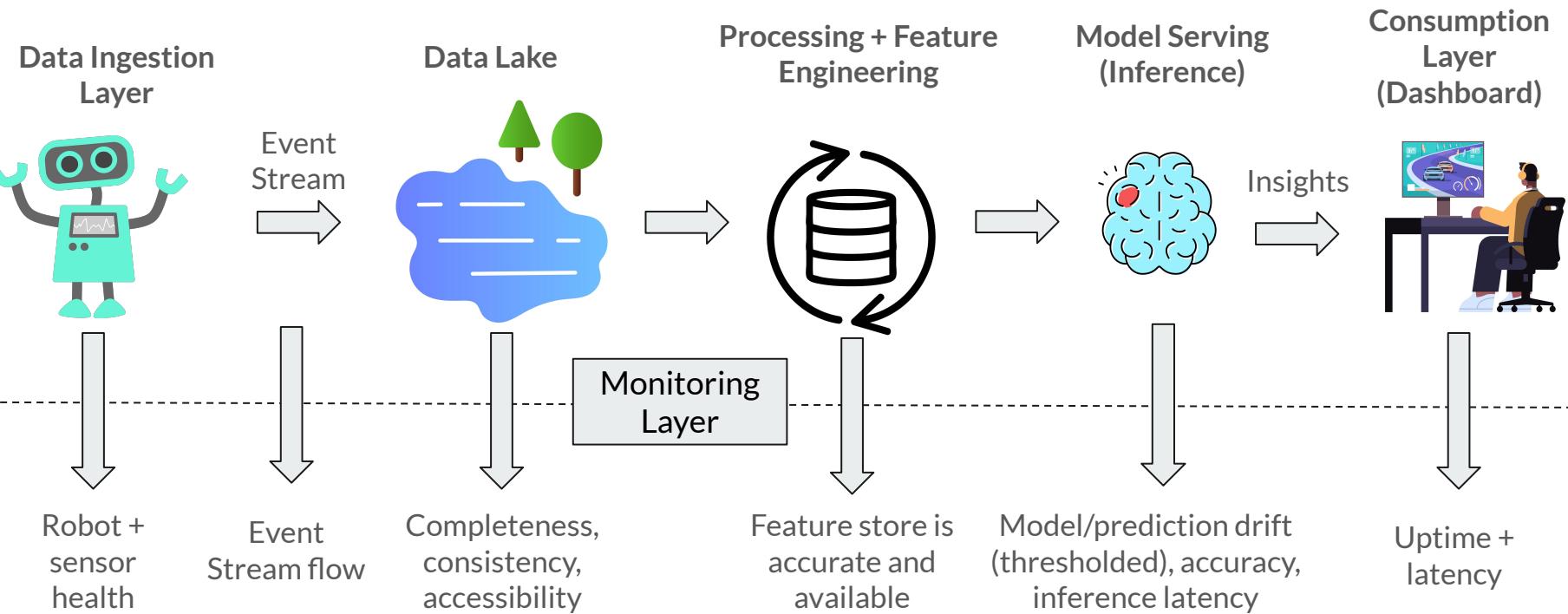
Architecture: Layers



Architecture: Near Real Time Adaption

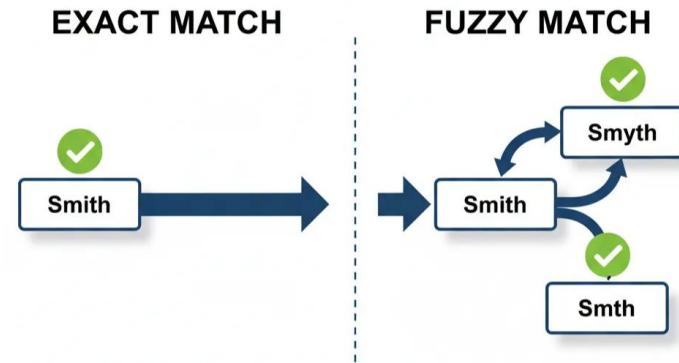


Architecture: Monitoring



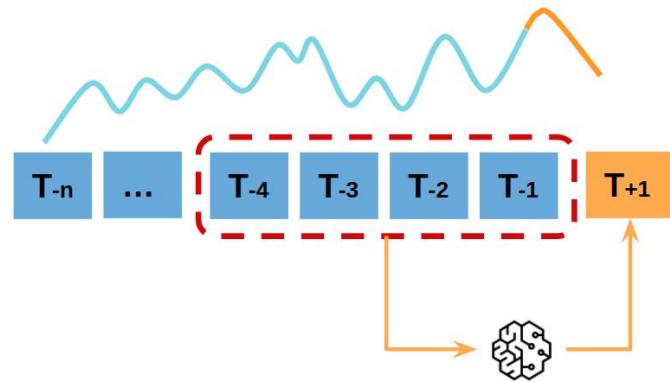
Modelling: Preprocessing

- Merging multiple days of scan data
- Fuzzy text match with rapidfuzz
- Configurable output with YAML
- Parquet file for categorical variables
- Logging for traceability
- Non-numeric/categorical features dropped for some of the modelling



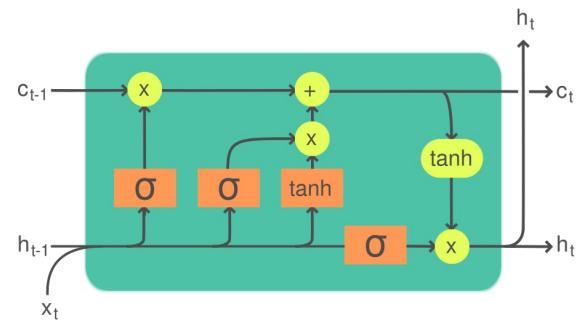
Modelling: Error Prediction Problem Context

- Next-day category prediction from sequence data
- Both numeric and categorical features, with missing values
- Medium sized data set, ~30k pts
- Strong temporal and feature correlation
- Potential for “sliding window” of future data over more timesteps



Modelling: Error Prediction LSTM

- Numeric feature scaling
- Categorical features as embeddings, with masking/padding for unknowns
- LSTM chosen, as can
 - Capture temporal patterns
 - Model complex inter-feature dependencies
 - Handle feature types/missing values
- Early stopping with a validation data set to avoid overfitting
- Multi-class prediction, to better encode the feature dependencies

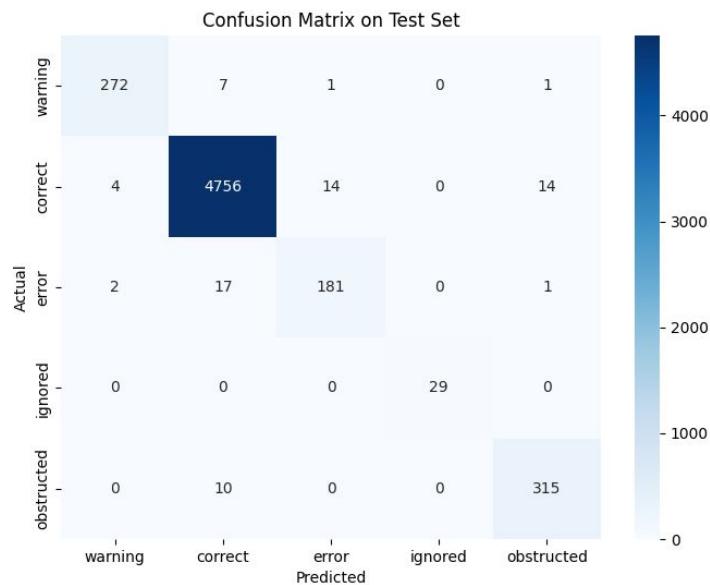


Modelling: Error Prediction LSTM

Pros	Cons
Performance: high accuracy, can capture complex relationships	Explainability: black-box model, difficult to interpret
Scalability: compatible with “sliding-window” of data over time	Latency: more processing than a simple feed-forward
Robustness: against missing data	Compute Cost: LSTM with embeddings more expensive, so higher train/inference cost

Modelling: Error Prediction LSTM Performance

Model 1



Binary Prediction

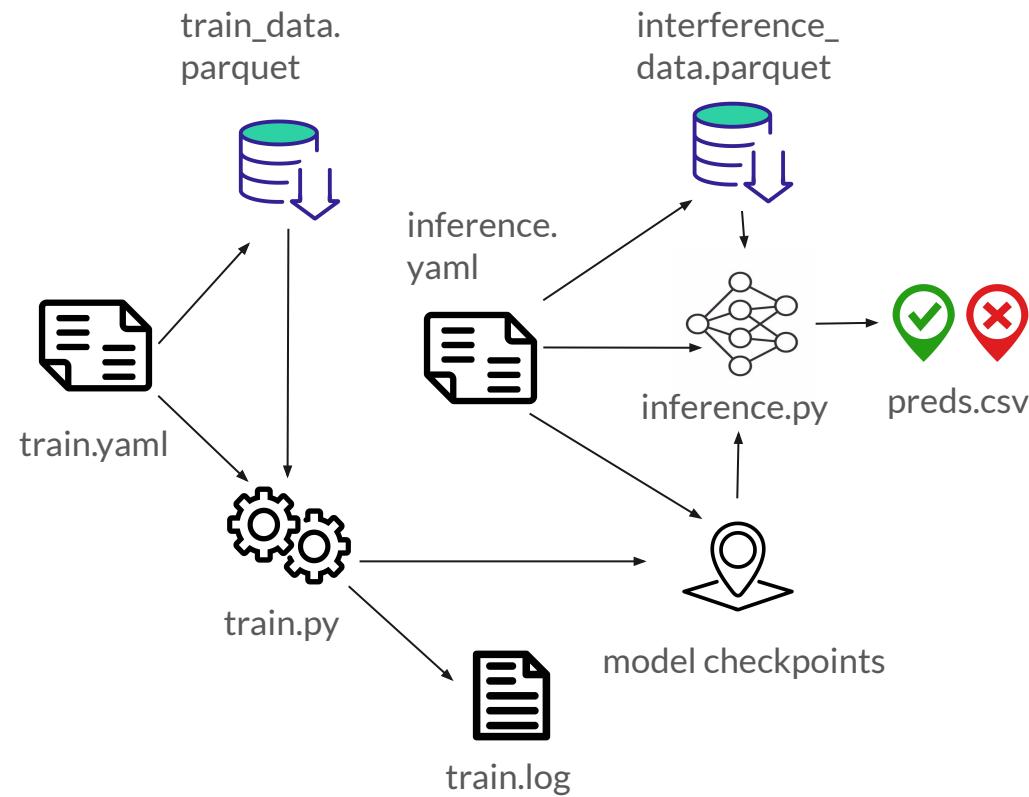
	precision	recall	f1-score	support
not correct	0.96	0.96	0.96	836
correct	0.99	0.99	0.99	4788
accuracy			0.99	5624
macro avg	0.98	0.98	0.98	5624
weighted avg	0.99	0.99	0.99	5624

Test Accuracy: 98.83%

Could perform real-time monitoring with
Prometheus/Grafana

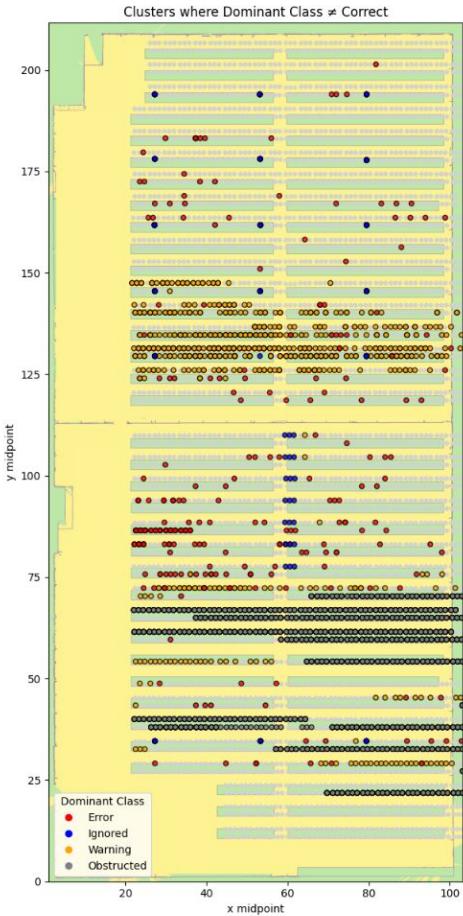
Modelling: Error Prediction Model Pipeline

- Tensorboard performance metrics
- Logging of model training/test/evaluation
- Parameters configured via YAML
- Model load from checkpoint
- Inference example showing inference_data.parquet -> predictions with trained model



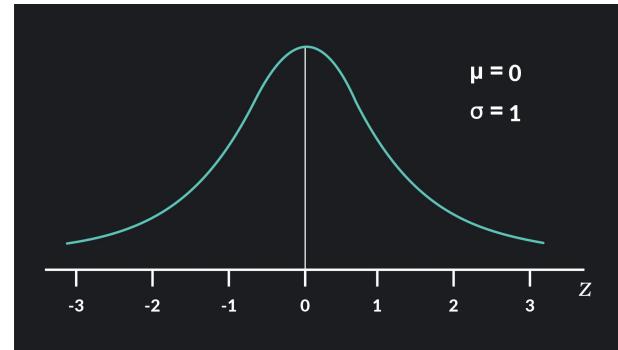
Modelling: Spatial Error Clustering

- Spatial data: (x, y, z) coordinates
- Potential to have clusters of arbitrary shape/density
- Number of clusters unknown
- Class proportions as features
- Based on this, **HDBSCAN** chosen
- Data averaged over time
- Extension: could consider spatio-temporal clustering directly



Modelling: Time Series Anomaly Detection

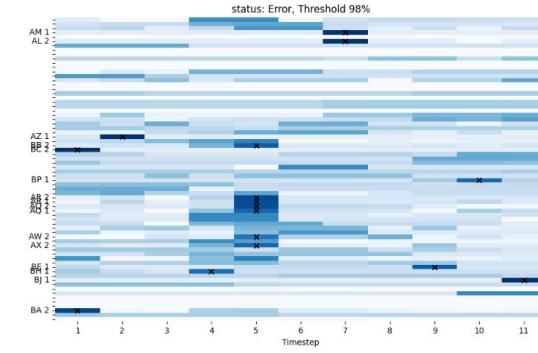
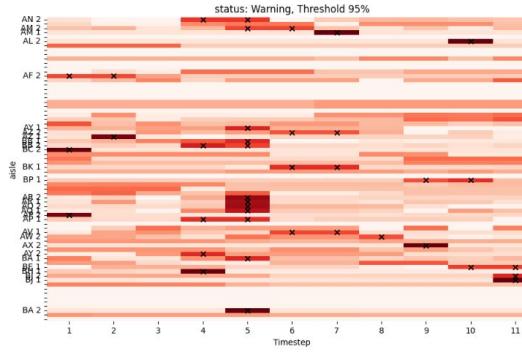
- Compute the average and standard deviation for each class occurrence rate, per aisle, over the time window
- E.g. Avg error rate = $10 \pm 2\%$
- Compute the z-score (statistical distance) of a given point
- If past a threshold - classify as an anomaly
- Simple calculation, easy to explain
- Distribution parameters stored for inference



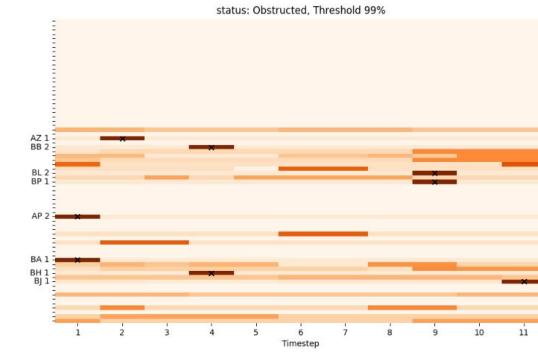
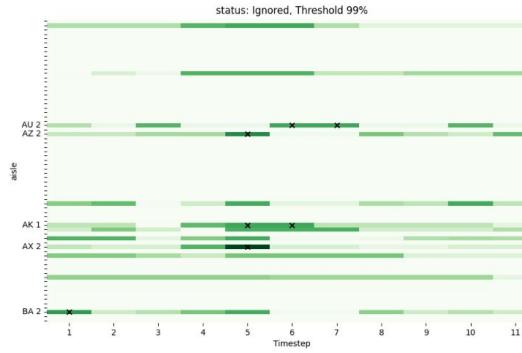
$$z_{i,t,c} = \frac{|p_{i,t,c} - \mu_{i,c}|}{\sigma_{i,c}}$$

Modelling: Time Series Anomaly Detection

Time Series



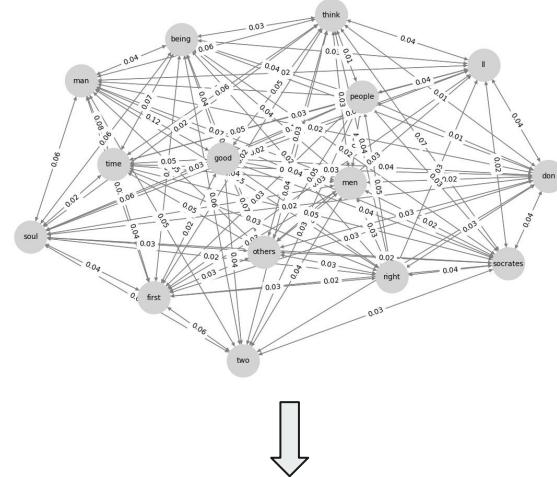
Legend: -3.0 (dark blue), -2.5 (light blue), -2.0 (medium blue), -1.5 (light orange), -1.0 (orange), -0.5 (red)



Legend: -3.0 (dark orange), -2.5 (light orange), -2.0 (medium orange), -1.5 (light red), -1.0 (red), -0.5 (orange)

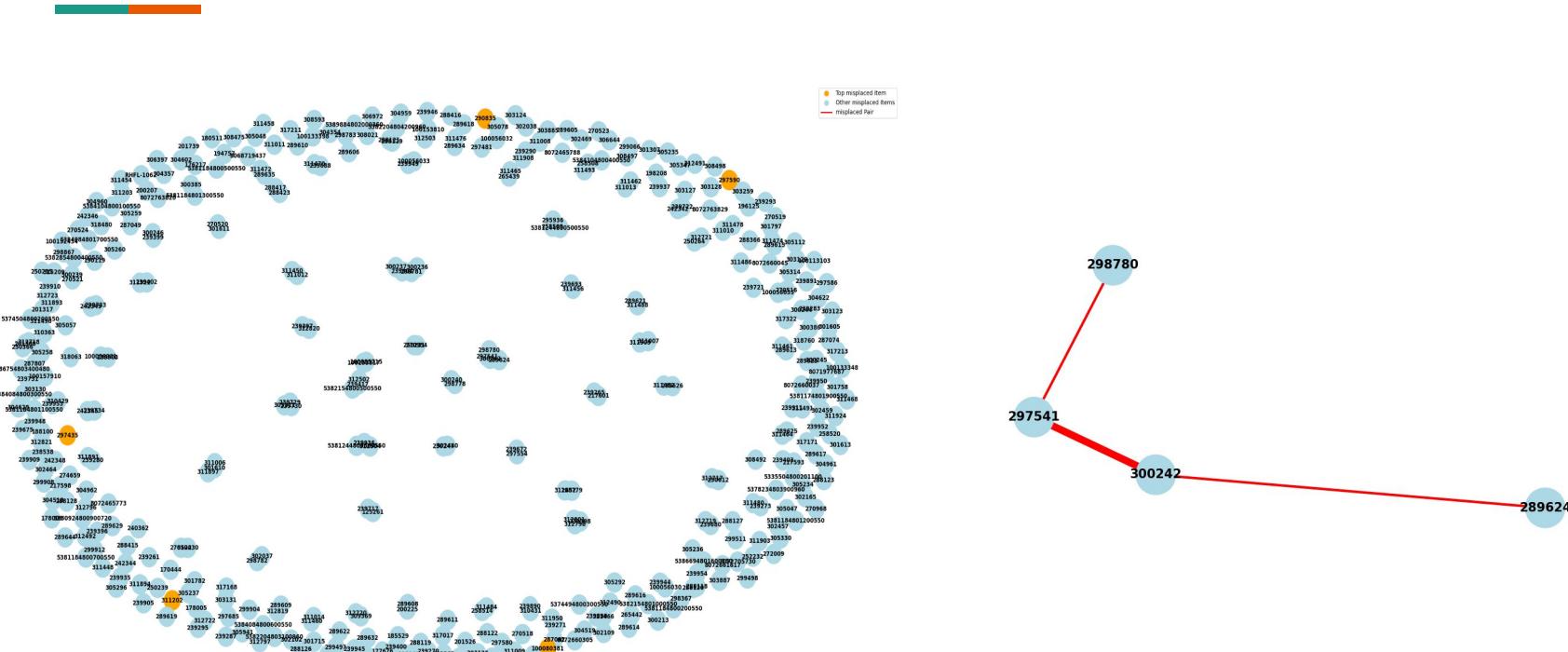
Modelling: Item Co-location and Pick-Path Analysis

- **Co-located pairs:** Items appearing together in the same location at the same time step
- **Misplaced pairs:** Items flagged as misplaced together at the same location/timestep
- **Picked-together pairs:** Items that move together across timesteps (temporal co-occurrence)
- Count each case and build association graph of pairs
- Items as nodes, counts as edge weights
- Generate insights from highly weighted edges



"Store these 2 items together"

Modelling: “Misplaced” Association Graph



Modelling: Item Co-location Insights

	Observation	Insight	Action
High Risk Misplaced Item	Item 258520 is most misplaced (22 times)	Frequently misplaced due to operational confusion	Introduce double check or dedicated bins
Misplacement Hotspot	Some pairs (715-817) are frequently colocated and misplaced	Repeatedly mis-shelved/scanned, problematic storage zone	Conduct zone audit and improve signage
Picked Together Pairs	Items 202-045 commonly picked together (44 times)	Likely part of recurring orders/batches	Place items together to reduce picking time

Summary

- High-level architecture
- How to account for near real-time decision making and system monitoring
- Modelling:
 - Error prediction with LSTM
 - Spatial Error Clustering with HDBSCAN
 - Time series Anomaly Detection by computing z-scores
 - Barcode association graph analysis to generate insights