



# Warehouse Intelligence System

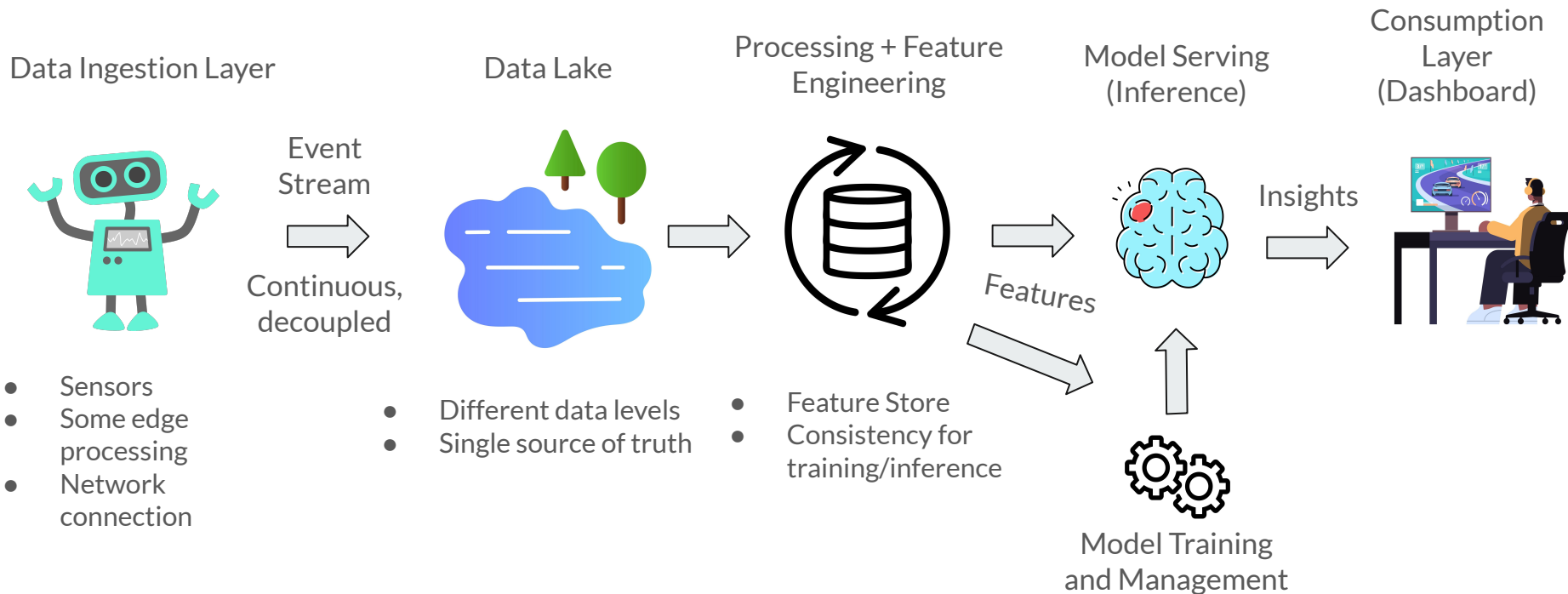
Samuel Bennett

# Contents

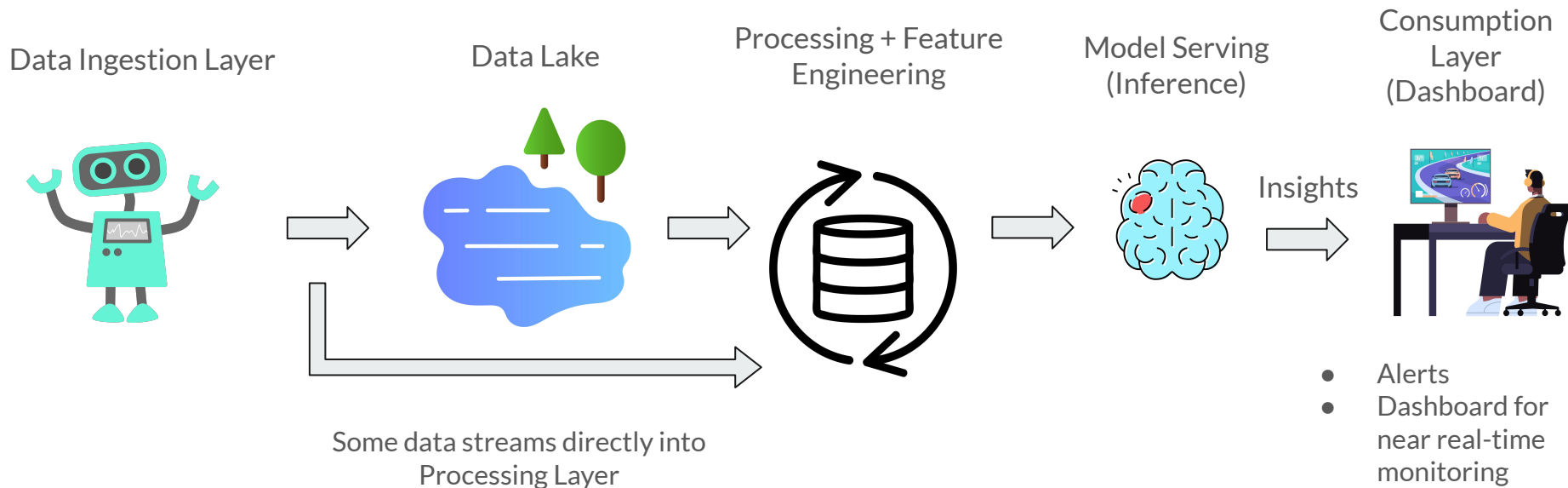


- Architecture
  - Layers
  - Near Real Time Processing
  - Monitoring
- Modelling
  - Preprocessing
  - Error Prediction
  - Spatial Error Clustering
  - Item Co-location and Pick-Path Analysis
  - Time Series Anomaly Detection
- Summary

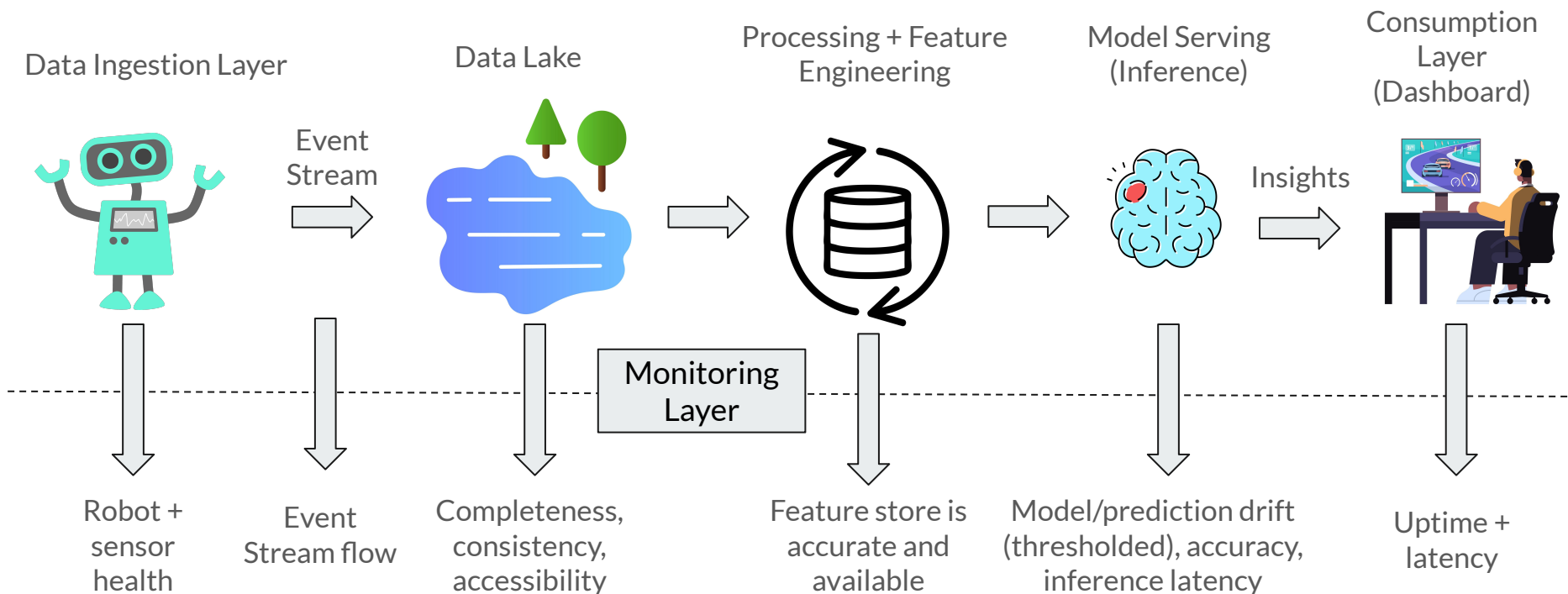
# Architecture: Layers



# Architecture: Near Real Time Adaption

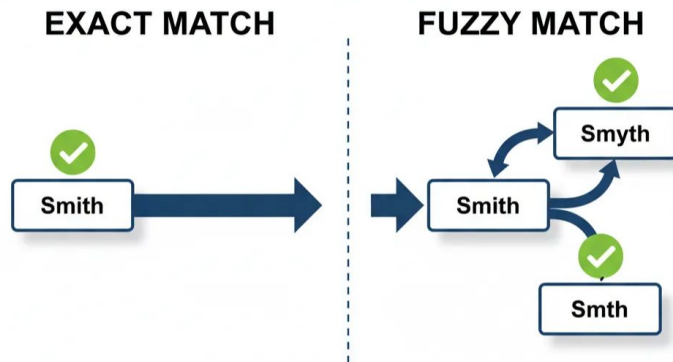


# Architecture: Monitoring



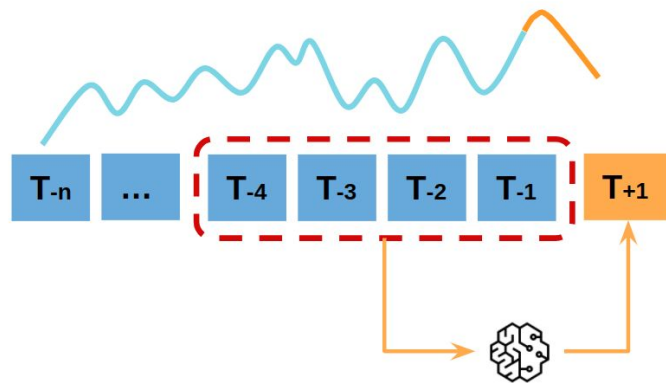
# Modelling: Preprocessing

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



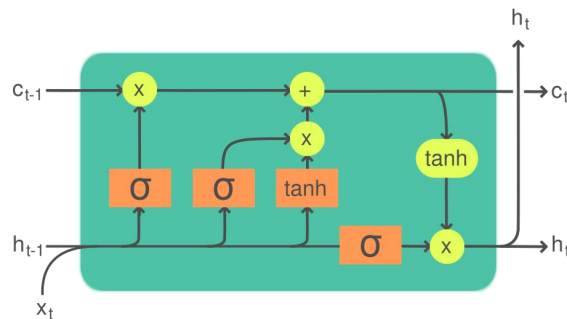
# Modelling: Error Prediction Problem Context

- 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



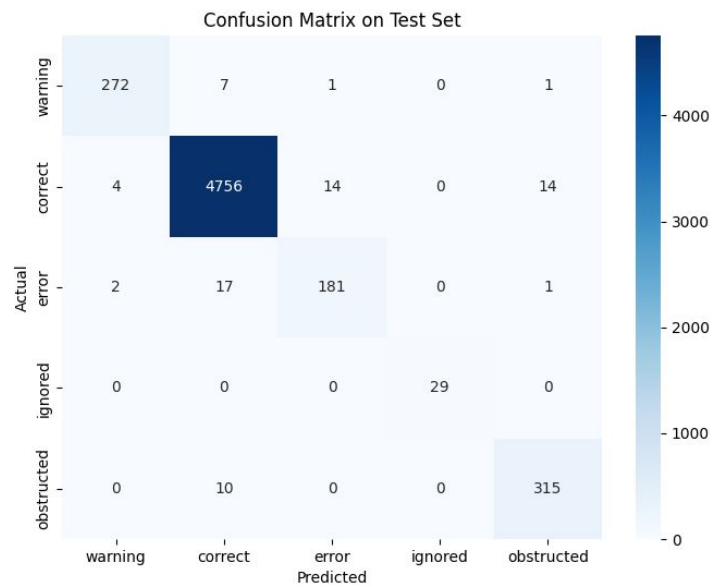


# Modelling: Error Prediction LSTM



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

# Modelling: Error Prediction LSTM Performance



## Binary Prediction

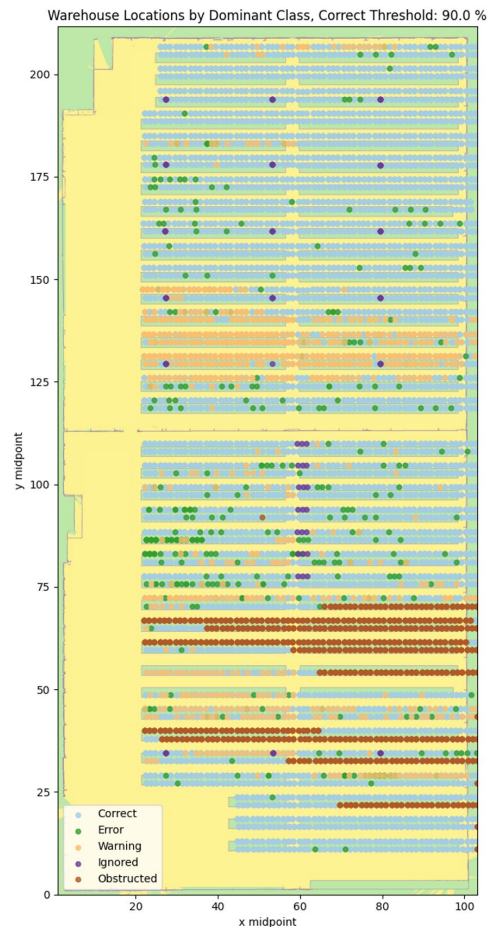
	precision	recall	f1-score	support
correct	0.96	0.96	0.96	836
not correct	0.99	0.99	0.99	4788
accuracy			0.99	5624
macro avg	0.98	0.98	0.98	5624
weighted avg	0.99	0.99	0.99	5624

Test Accuracy: 98.83%

Could perform real-time monitoring with  
Prometheus/Grafana

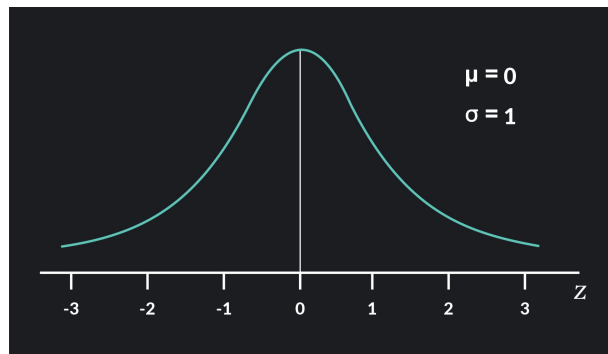
# Modelling: Spatial Error Clustering

- Spatial data (x, y, z)
- 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



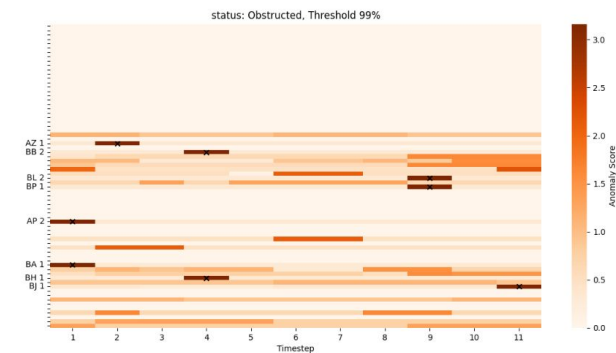
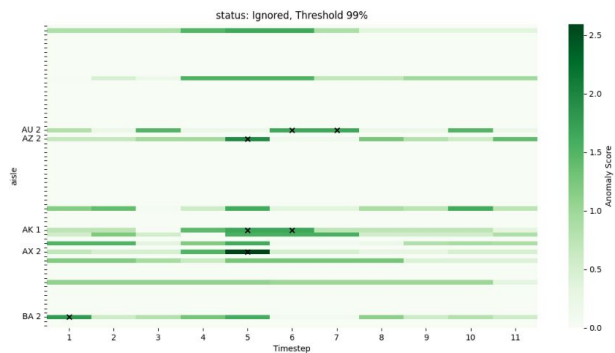
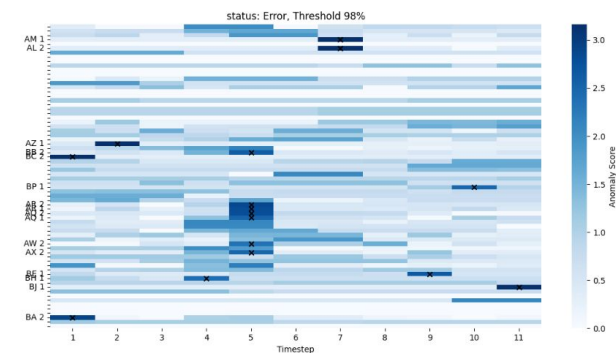
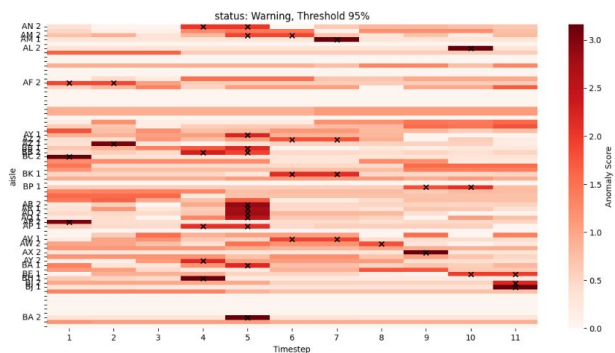
# Modelling: Time Series Anomaly Detection

- Compute the average and standard deviation for each class occurrence rate 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 can be stored for inference

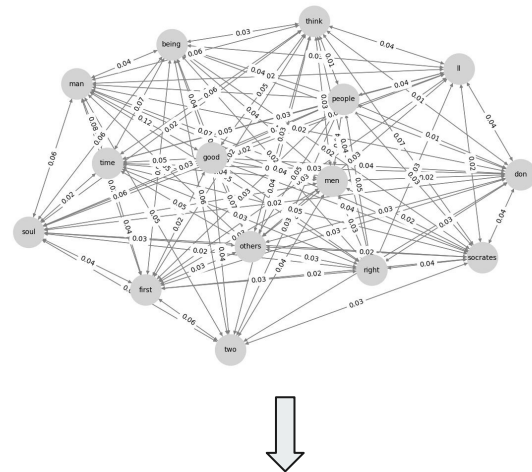


$$z_{i,t,c} = \frac{|p_{i,t,c} - \mu_{i,c}|}{\sigma_{i,c}}$$

# Modelling: Time Series Anomaly Detection

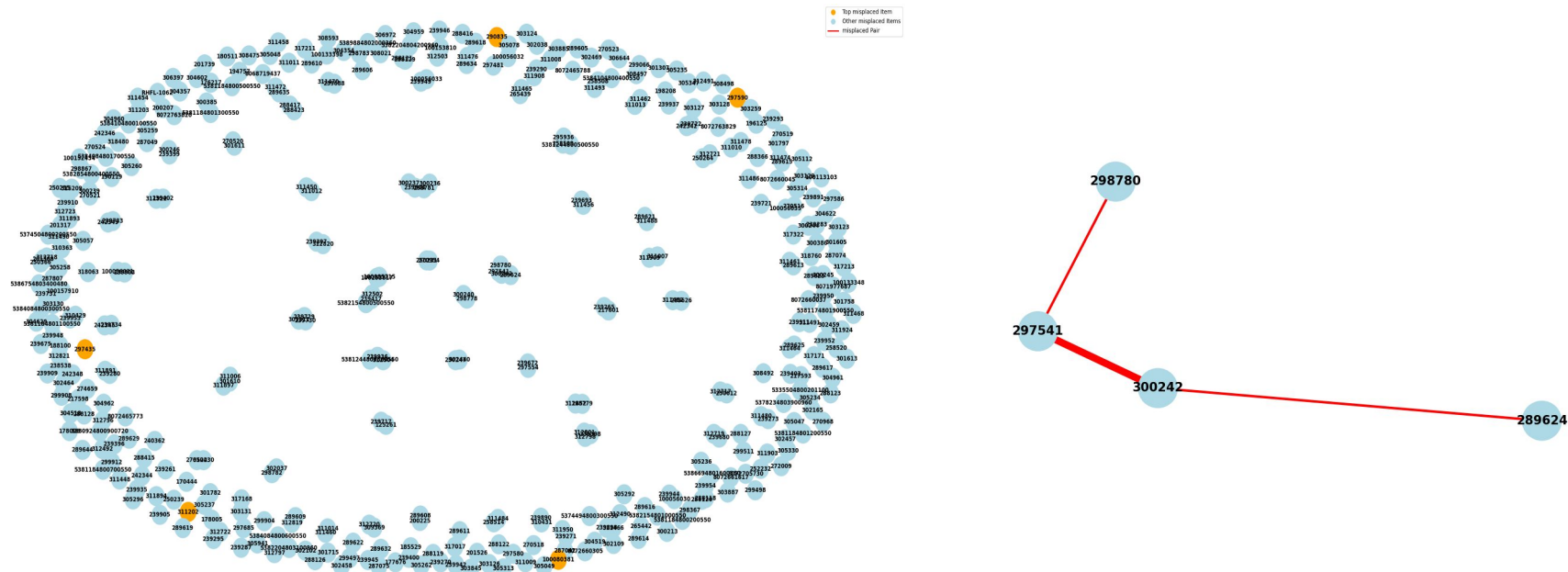


- **Co-located pairs:** Items appearing together in the same location at the same timestep
- **Misplaced pairs:** Items flagged as misplaced together at the same location/timestep
- **Picked-together pairs:** Items that move together across timesteps (temporal co-occurrence)
- Count each case and build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



“Store these 2 items together”

# Modelling: “Misplaced” Association Graph



# 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