MONOPOLY

WELCOME TO

SMARTCITY

Misinformation. Failures. Crises.
Our agents don't play the game — they control the board.

START

MORE

SECURE
THE B-AGGIE

Cities Can't Afford to Roll the Dice

Today's cities face a dangerous paradox: more data than ever — but less clarity when it matters most.

Delays, misinformation, and disconnected systems leave both leaders and civilians vulnerable — unable to see what's real, where it's happening, or what to do next.

Past Failures

- **Japan Tsunami (2011)** → evacuation delays due to uncoordinated alerts
- **Hurricane Harvey (2017)** → stranded residents due to fragmented data

Modern Challenges

- IoT, tweets, weather, events — but no clear source of truth
- Manual systems create decision bottlenecks
- Cities need systems that think before things break

See Appendix for Source Information

Our Solution

S.T.O.R.M* | AI-POWERED RISK AGENTS

Filter Out the Noise (Trust Signal Precision)

LLMs, GNNs, and LSTMs filter out fake tweets and faulty sensors by detecting spatial-temporal anomalies and misinformation patterns.

KPIs:

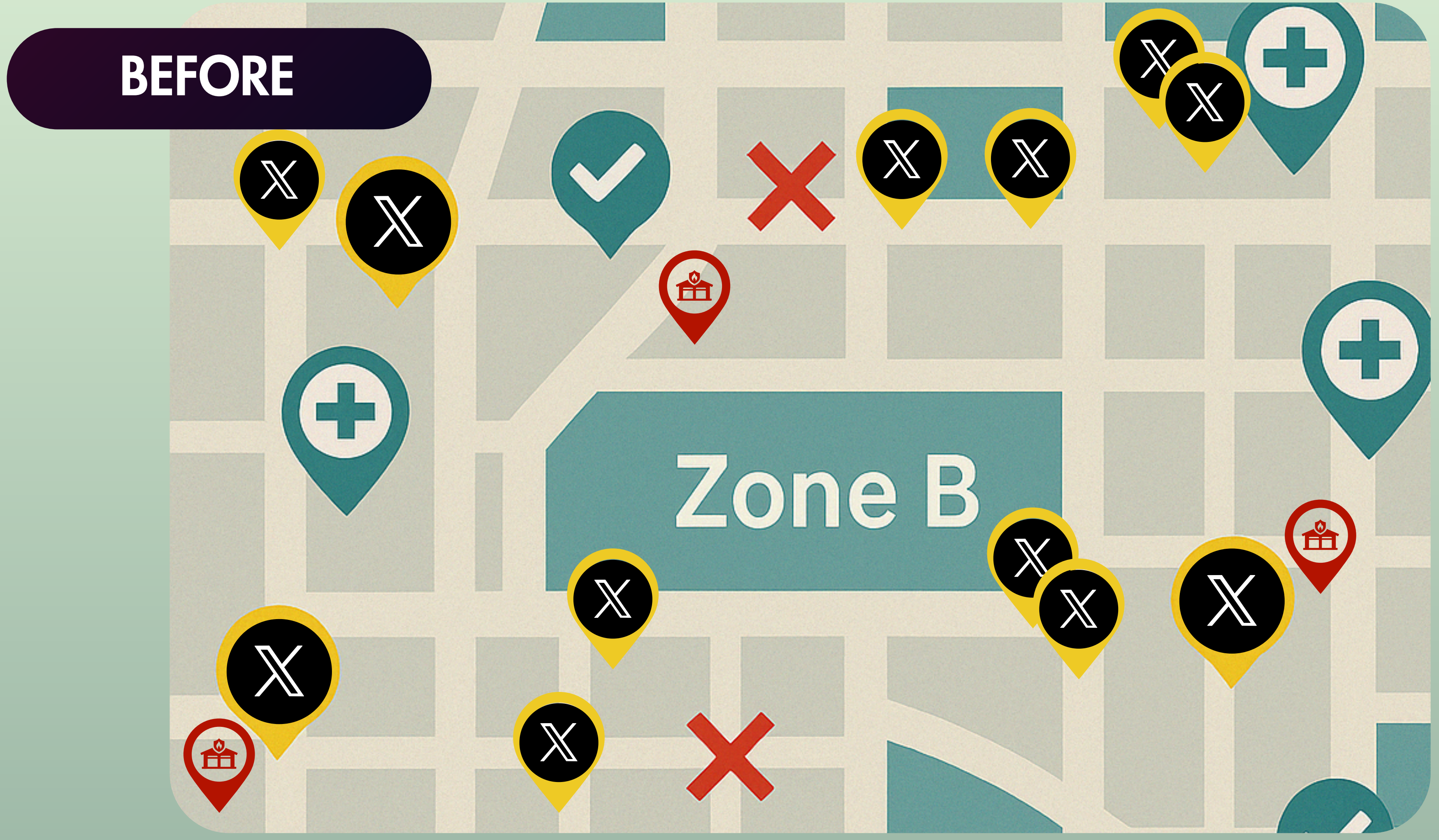
- 91% media classifier precision
- Faulty sensor detection via anomaly modeling

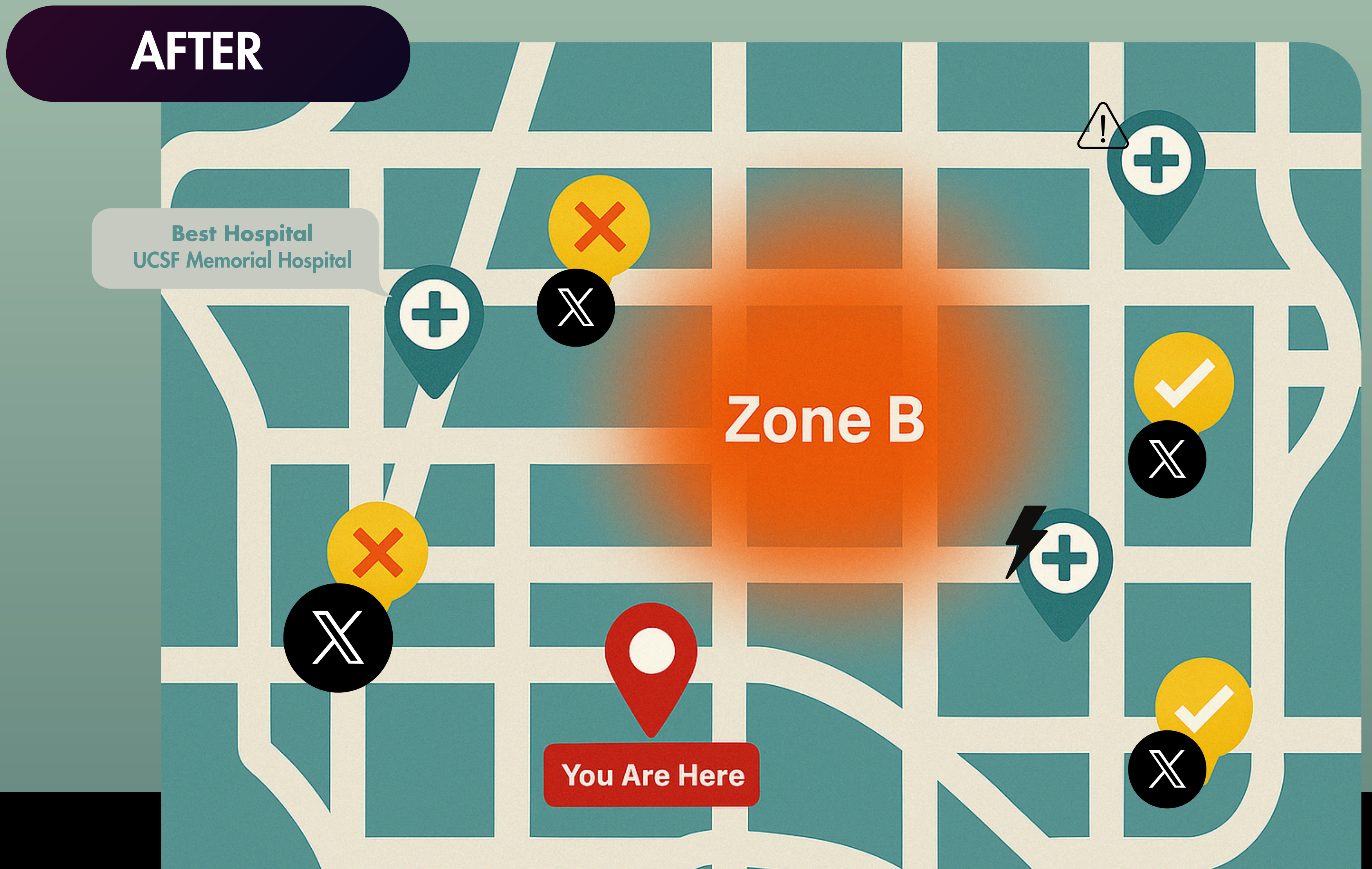
Make Quick, Reliable Decisions (Speed to Insight)

Parallel agents process live risk streams, delivering zone-level recommendations in under 10 seconds.

KPIs:

- Agent latency: <10s
- Enables real-time routing and response





SECURE
THE B-AGGIE

*S.T.O.R.M (Smart Tactical Operational Response Model)

The "Top Hat"

Identifies misinformation and plays it smart.

INPUTS

Social Media
- Real-time social media feed

Sensor Data
- Status check

City Map Data
- Map tweet locations

LOGIC

Content Assessment
- Text classification
- Sentiment analysis

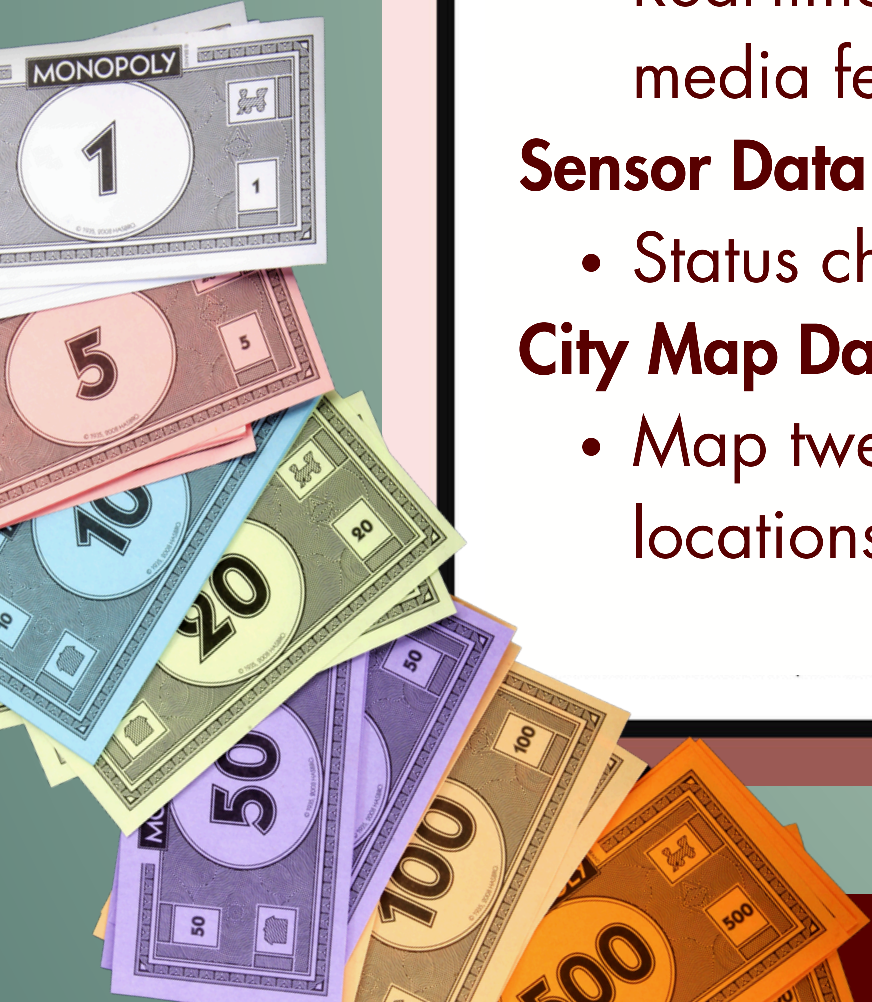
Social Media Trust
- User Behavior
- Geography
- Sensor Check

OUTPUTS

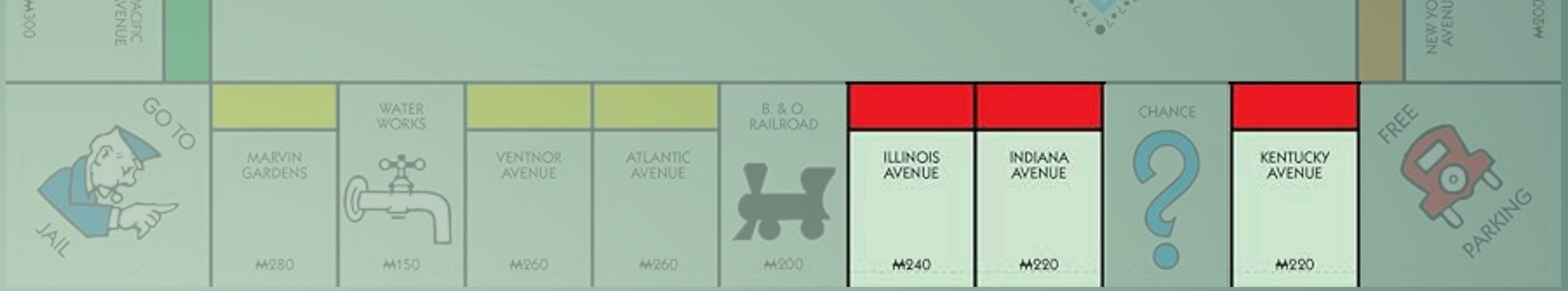
Trust Score
- Range: 0-3

Sentiment Distribution
- Negative, Positive, Neutral Counts

Spam Post Count
- Top 10 suspicious posts



Predicted Precision = 91% on misinformation detection using labeled tweet data | View model logic in Appendix



The "Car"

Scans the board for threats — *fast.*

INPUTS

Sensor Readings
- Faulty/inactive

Weather Data
- Anomaly flag (top 5%)

City Map
- Infrastructure + heatmap

Disaster Events
- Zone-level severity + casualties

LOGIC

Sensor Risk Score
- Faulty/inactive % over total sensors

Rolling Zone Aggregation
- Compare live & historical baseline

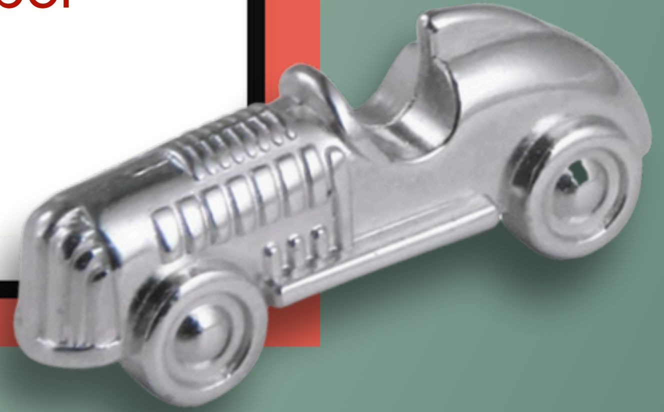
Combined Risk
- Weighted sum: severity, sensor risk, casualties

OUTPUTS

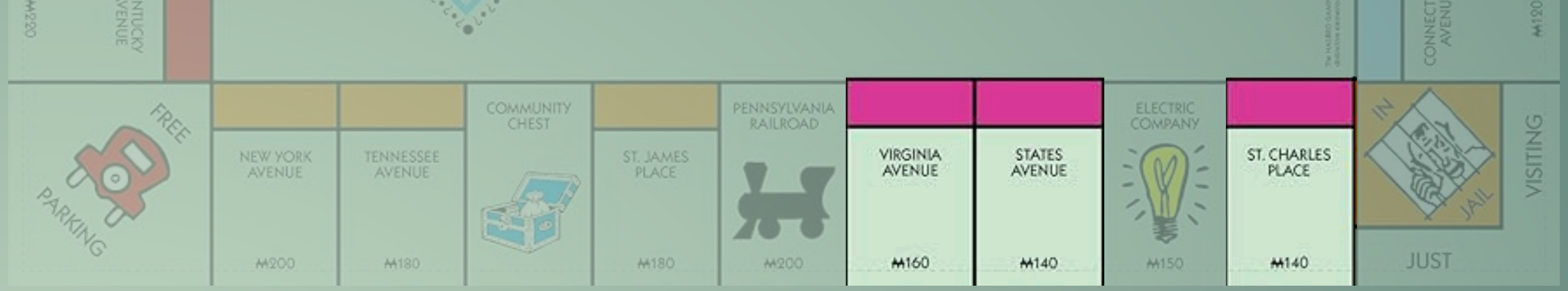
Sensor Risk Score
- Normalized %

Avg. Severity
- Mean of all past disasters in zone

Combined Risk Score
- Final score per zone



Coverage: 50,000+ sensor readings grouped by zone/hour | View model logic in Appendix Slide 4



The "Dog"

Alerts the city to cascading patterns no one else sees.

INPUTS

Filtering Noise
- Faulty Sensor Data

Uncovering Hidden Patterns
- Energy Data
- Weather Data

LOGIC

Anomaly Detection
- Unusual Data Changes

LSTMs
- Sequential events

GNNs
- Spatial risk considerations

OUTPUTS

Cascade Score
- Weighted Sum of LSTM and GNN cascade risk (0-1)

Anomaly Flags
- Sensor Readings
- Energy Use
- Weather

Detected anomalies roughly align with past events in 87% of validation cases| View model logic in Appendix Slide 3

The "Iron"

AKA STORM: Synthesizes all inputs and makes the final judgement.

INPUTS

Top Hat
- Media Reliability

Dog
- Cascade Risk

Car
- Zone-Level Risk

LOGIC

Rule-Based Logic
- **Trust Score** < 2 = Unreliable News
- **Risk Score** > 0.5 = Dangerous Area
- **Cascade Risk** > 0.5 = High chance of rolling consequences

OUTPUTS

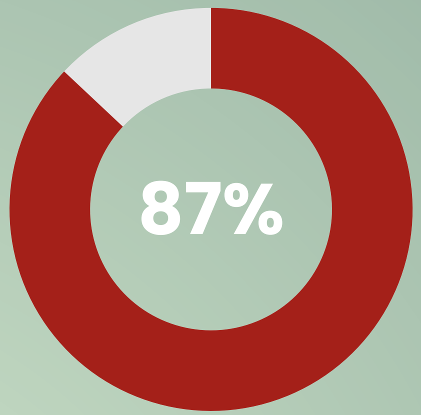
Rolling Alert
- 10 minute status update window

Predicted Latency: Output generated in <10s after agent inputs | View model logic in Appendix Slide 5

DEMO LINK »

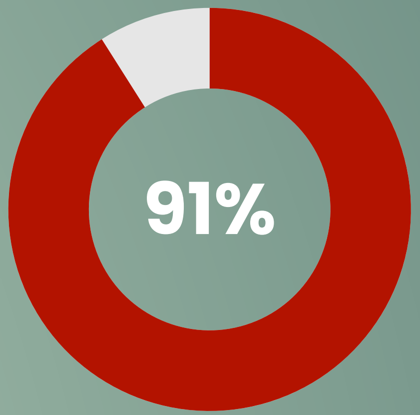
PROTOTYPE

From dashboard to dispatch, our system bridges the gap between data and action, guiding both civilians and officials through high-stakes moments.

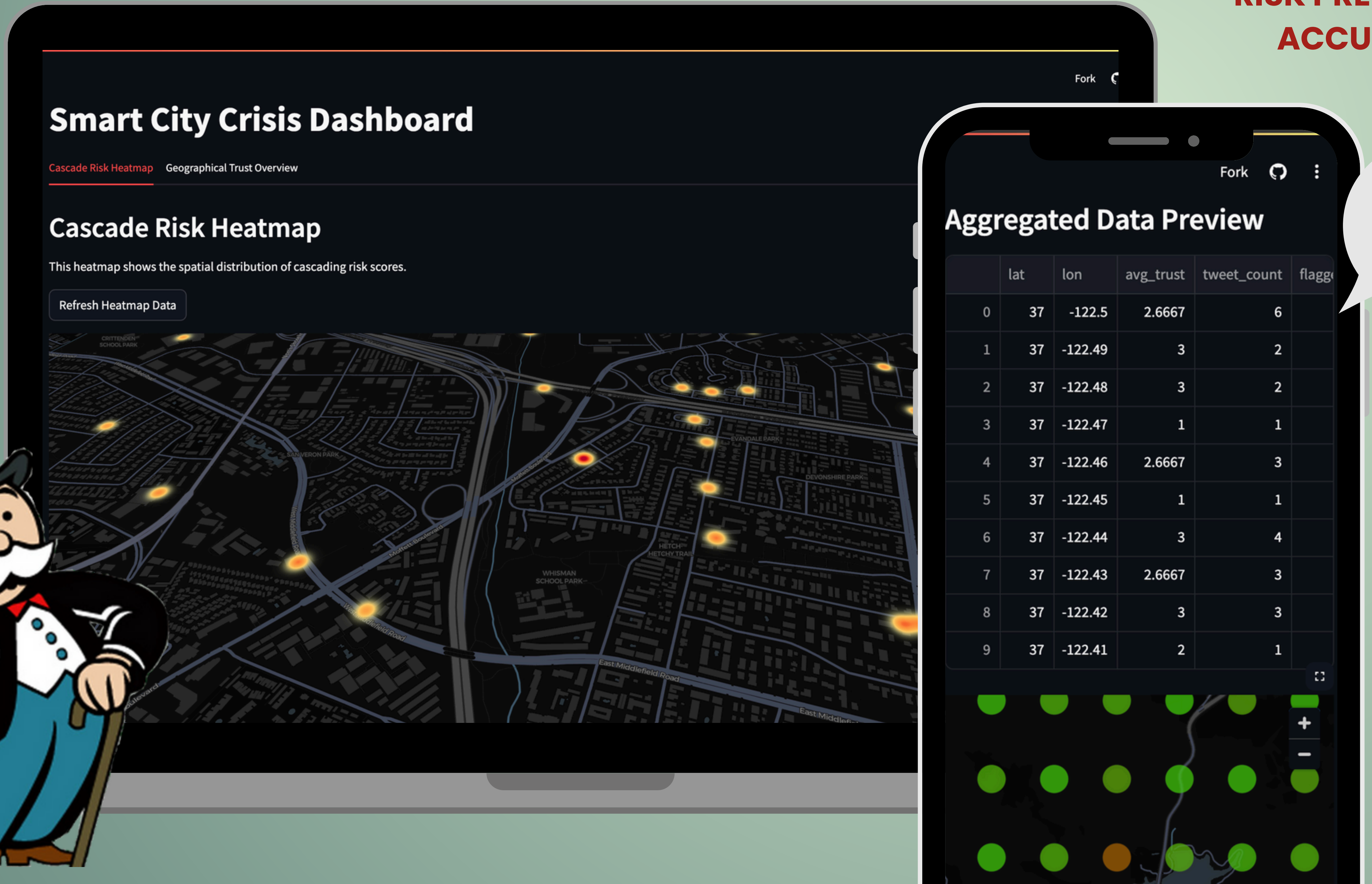


RISK PREDICTION ACCURACY

SPEED TO INSIGHT



MISINFORMATION FILTERING PRECISION



I'm in the Nob Hill neighborhood, what should I do?

Plan to evacuate. Media coverage and sensor failures are spking 5 miles from you.

If you need medical attention, UCSF is 0.5 miles away.

The Next Roll

Advancing the board through smarter systems and scalable upgrades:

Data Enrichment

Add real-time data from 911, utility, or health systems.
→ **Boosts accuracy + zone-specific action.**

Deployment Optimization

Deploy STORM in live dashboards with SMS/alert triggers.
→ **Low-latency response, built for real cities.**

Real - World Impact

Making safety accessible.

Every resident gains reliable, real-time awareness of risks around them — enabling faster, smarter decisions when it matters most.

→ **Empowers civilians. Saves lives. Builds trust.**

APPENDIX

Note: Metrics and KPIs are based on static hackathon data and reflect ideal evaluation logic — not yet validated on real-time or scaled inputs.

SECURE THE B-AGGIE

CODE LINK »

Social Media Trust Score

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How reliable are social media posts?

Phase 1

Sentiment Analysis

Cardiff-NLP pretrained model to detect rising negative sentiment

Phase 2

Fake News Analysis

BERT-based pretrained model to detect fake news

Phase 3

Trust Scoring (0-3)

- User Behavior (+1)
- Geographic validity (+1)
- Sensor confirmation (+1)

CODE LINK

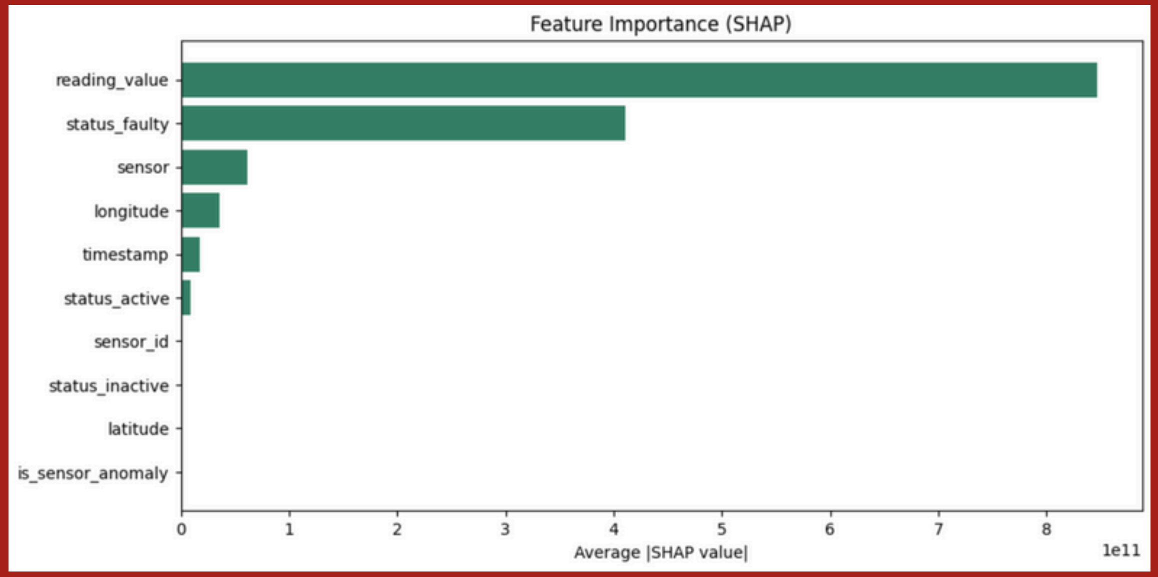
Cascade Prediction: Anomaly Detection

Each graph represents the importance of certain features in determining & detecting anomalies.

Weighted Cascade Risk = 0.6[LSTM Risk Score] + 0.4*[GNN Risk Score]*

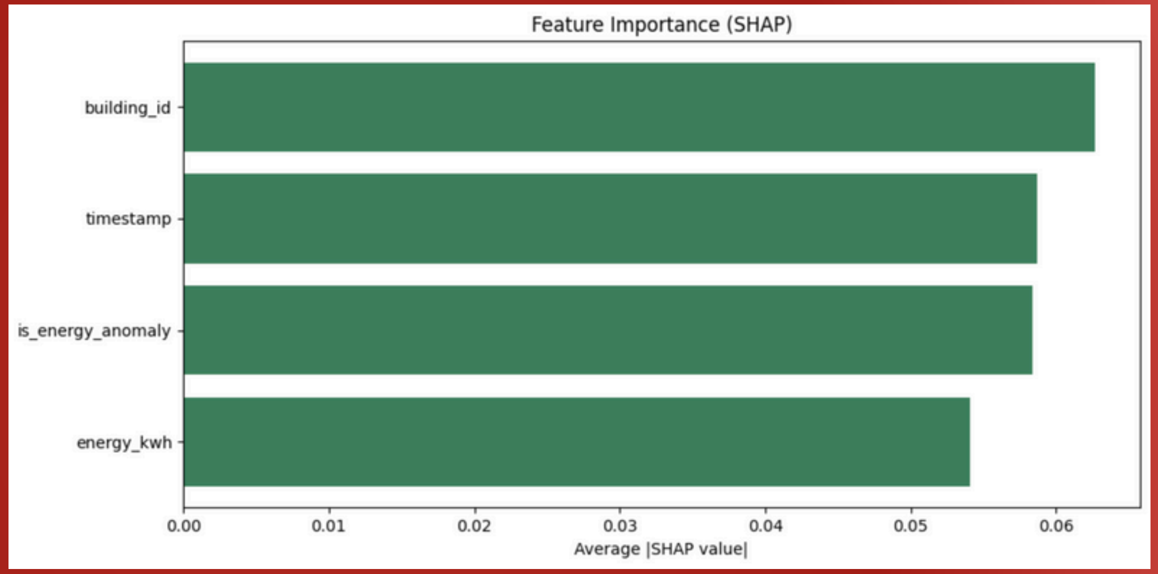
Sensor Anomalies

Reading, Sensor Status



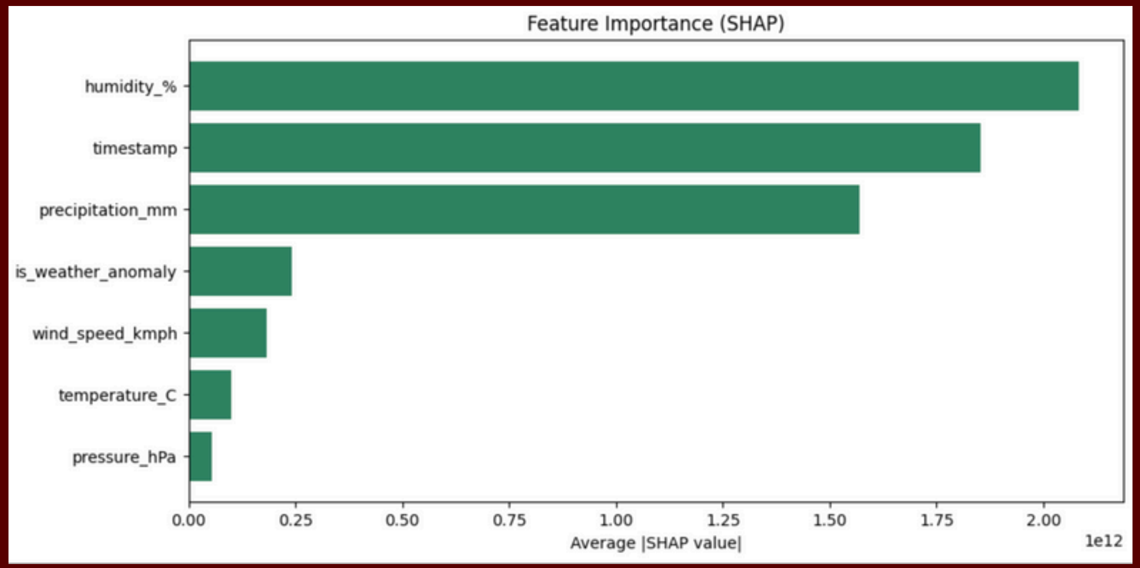
Energy Anomalies

Location + Timestamp



Weather Anomalies

Humidity + Precipitation



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Zone Risk Score Prediction

Each elements shows how sensor activity, disaster severity, and infrastructure gaps contribute to zone-level risk scores.

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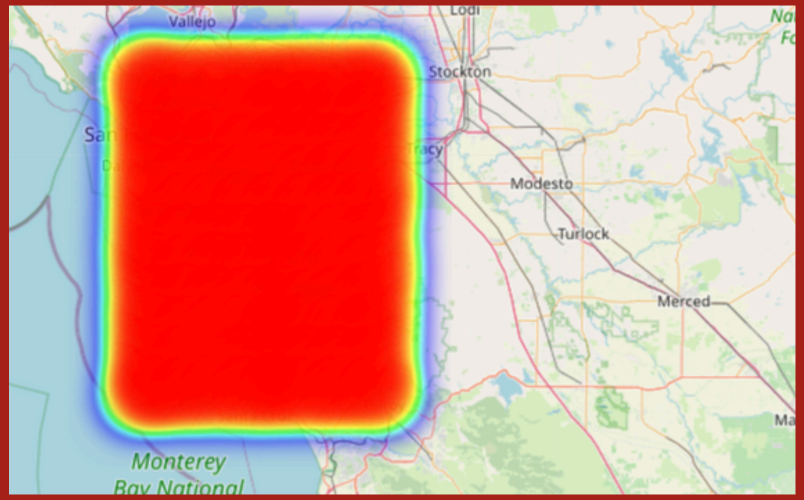
Combined Risk = 0.4(Avg Severity) + 0.4(Sensor Risk Score) + 0.2(Total Casualties)

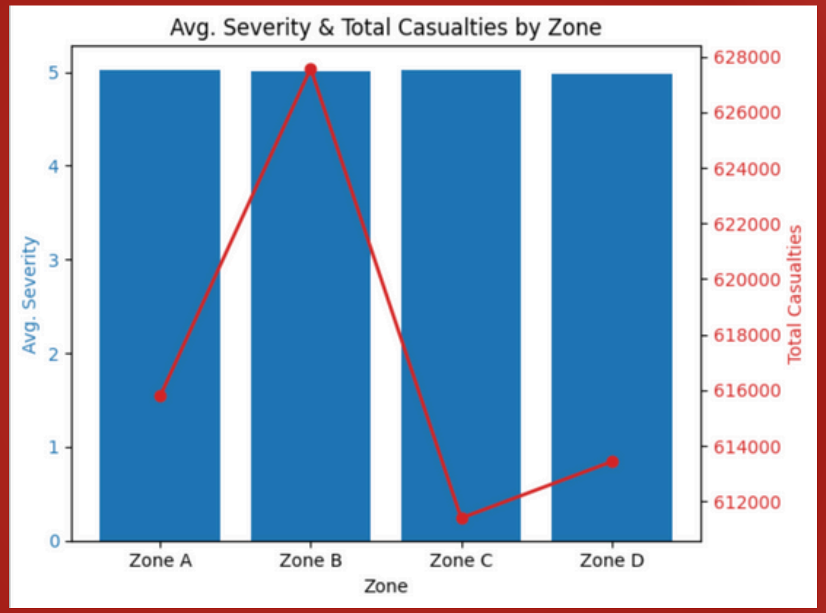
Element 1

Sensor Risk Heatmap



Element 2

Severity & Infrastructure



Element 3

Combined Risk Calculation

Values normalized using MinMaxScaler

```python
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
zone_df[['norm_avg_severity', 'norm_sensor_risk', 'norm_casualties']] = scaler.fit_transform(
    zone_df[['avg_severity', 'sensor_risk_score', 'total_casualties']]
)

zone_df['combined_risk_score'] = (
    zone_df['norm_avg_severity'] * 0.4 +
    zone_df['norm_sensor_risk'] * 0.4 +
    zone_df['norm_casualties'] * 0.2
)
```

Iron Model Recommendation System

```
📍 General Area: Zone B | 🔴 Emergency Status: ⚠️ VERIFY REPORTS (POSSIBLE CASCADE RISK IN UNTRUSTED CONTEXT) ⚠️
• Social Media Reliability (Last 5 minutes): 1.75
• Location Risk (Last 5 minutes): 0.81
• Cascade Risk (Last 5 minutes): 0.29
```

Example Decision + Alert

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Rule-based reasoning and decisions using real-time and rolling averages.

General Risk

General Risk (0-1)

A risk score > 0.5 indicates a **disaster-prone** area

Cascade Risk

Cascade Risk (0-1)

A risk score > 0.5 indicates a **high likelihood** of cascading effects

Media Validity

Trust Score (0,3)

A trust score < 2 indicates social media is **unreliable**

Sources Referenced

- **Flood Net NYC** (real-time urban flood monitoring)
- **Countering False Information on Social Media in Disasters and Emergencies, March 2018**
- **Learning from Megadisasters: A Decade of Lessons from the Great East Japan Earthquake**
- **Smart City Integration: How IoT is Reducing Emergency Response Times and Saving Lives - IEEE Public Safety Technology Initiative**
- **LSTM and ResNet18 for optimized ambulance routing and traffic signal control in emergency situations | Scientific Reports**