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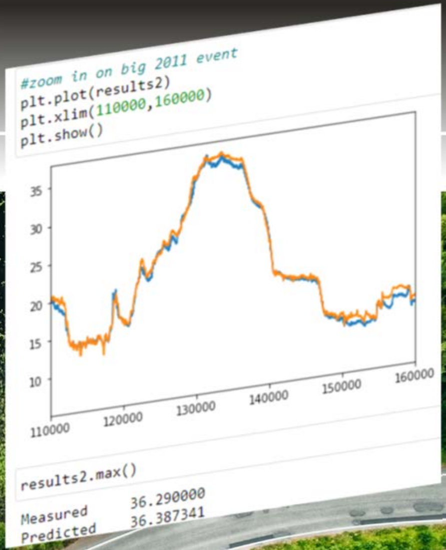
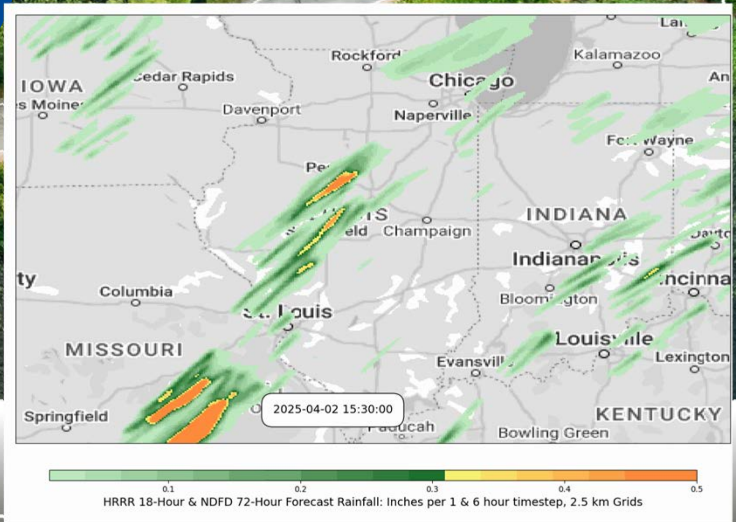
Collection System Digital Twins

Chris Ranck, PE, BCEE, BC.WRE, ENV SP, Black & Veatch

January 21, 2026





Today's Speaker

Indianapolis, IN

Collection Systems & Wet-Weather Programs Planning Leader

Water Environment Federation (WEF):

- Collection Systems Community Past Chair
- Treatment Specialties Community Leadership Council Director 2021-2023
- Envision Task Force Chair 2018-2021

Chris Ranck, PE, BCEE, BC.WRE, ENV SP

Agenda

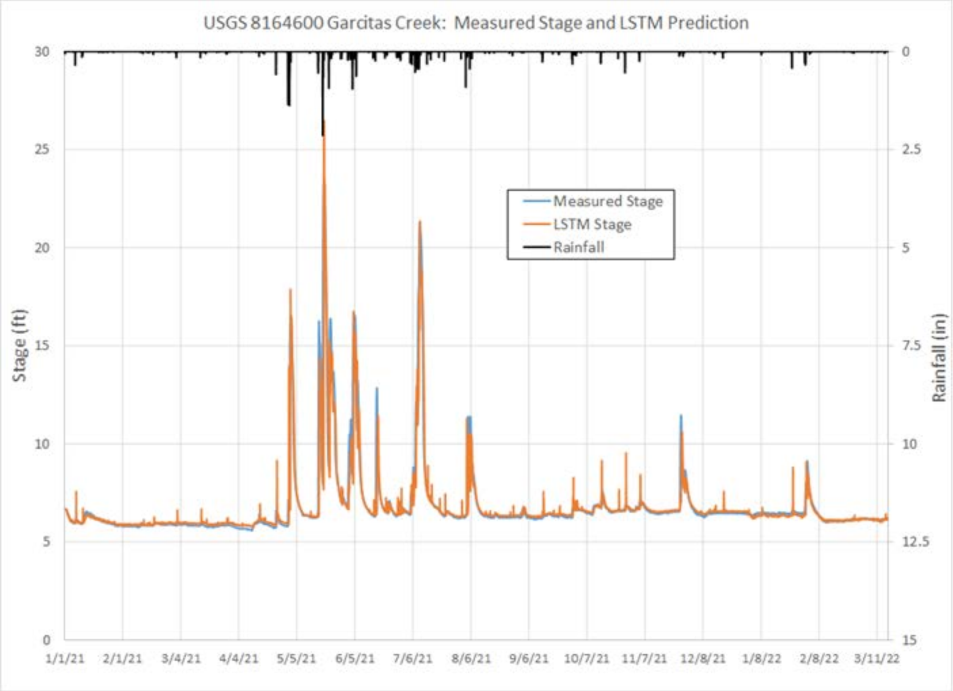
Digital Twins: What, How, Where?

Case Study Example #1: Wet Weather Forecasting

Case Study Example #2: Sanitary Overflow Forecasting

How to Get Started

Discussion



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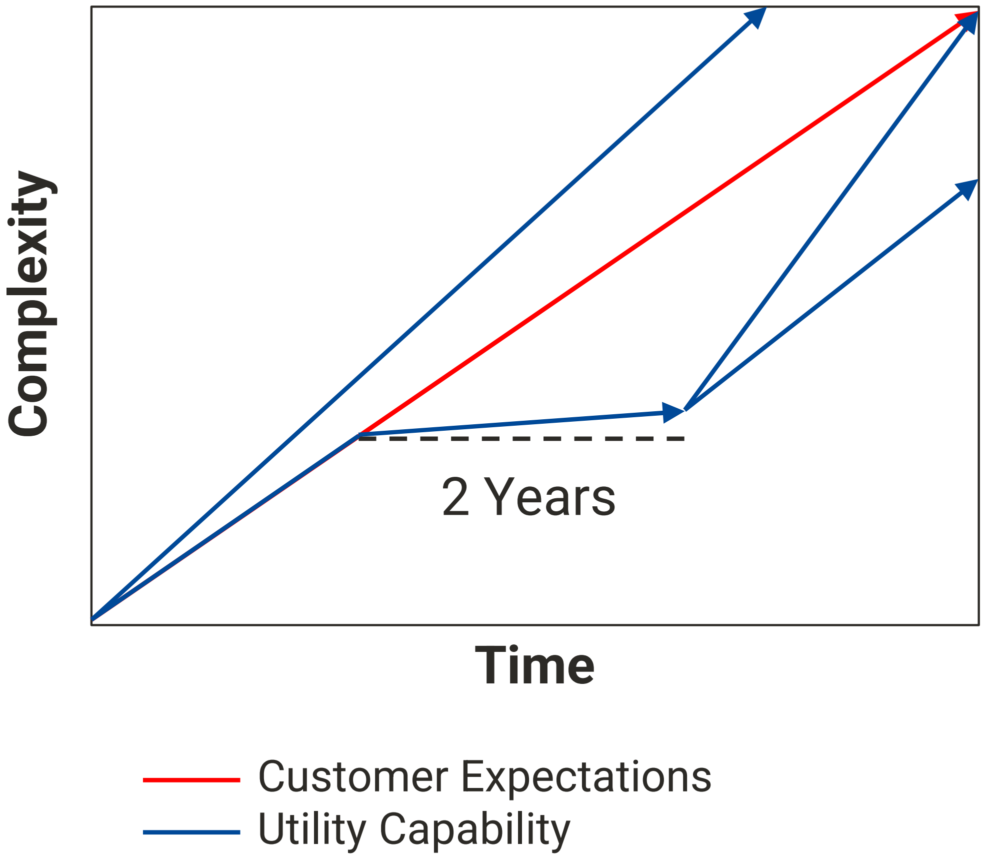
Digital Twins: What, How, Where?



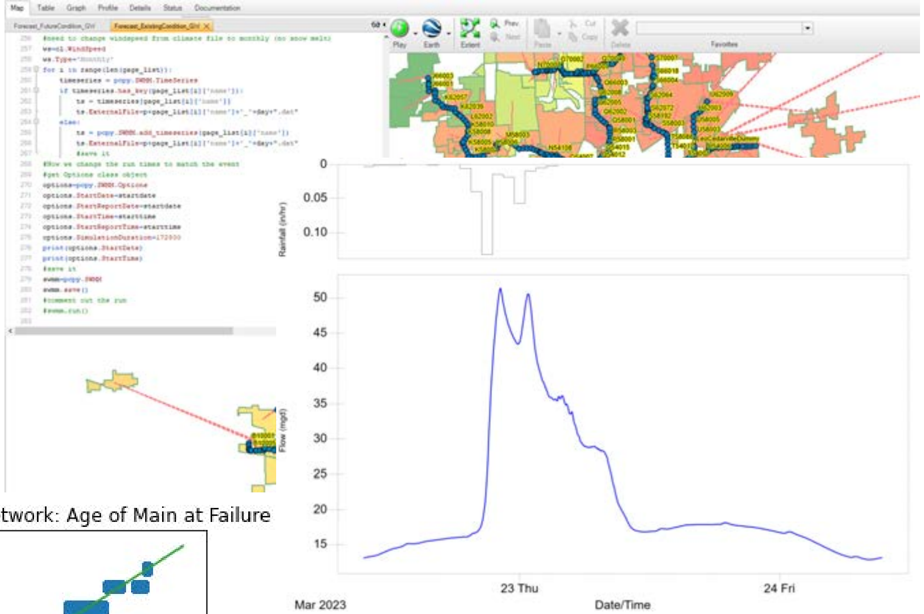
- Innovation facilitates getting caught up
- Without Innovation, you may be catching up to where you should have been 2 years ago
- Digital Twin: A digital, dynamic system of real-world entities and their behaviors using models with static and dynamic data that enable insights and interactions to drive actionable and optimized outcomes (https://www.awwa.org/resource/digital-twins/)

Digital Twins: What, How, Where?

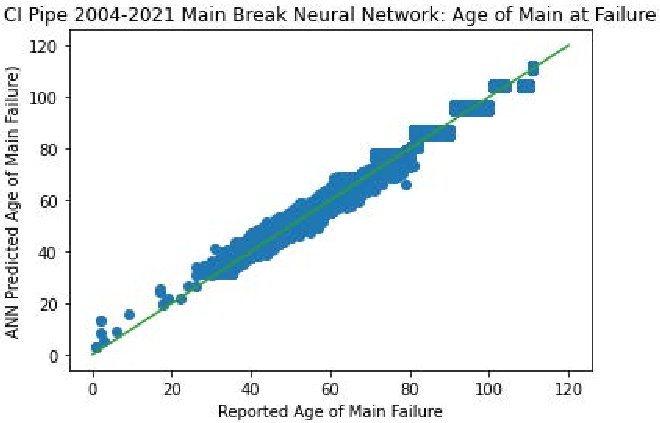
Real-time Modeling
Forecast Modeling
Machine Learning

Deployed via

Cloud Apps
Virtual Machines
APIs
Edge Computing



Wayne Street Interceptor – March 22, 2023 9 AM Forecast Run



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Digital Twins: What, How, Where?

What is Machine Learning?

- A Data-Driven computational process to develop patterns and relationships
- A calculation without an equation or model
- Can provide tremendous and instantaneous predictive power
- Computational engine behind a Digital Twin

Digital Twins: What, How, Where?

What Machine Learning *IS NOT*?

1. Something that will take away jobs
2. Software that costs tons of money
3. A black box and you have no idea what it's doing
4. So difficult that only a select handful of academics and technologists can do it
5. Inaccessible to the average water or wastewater practitioner
6. Neural networks eventually become sentient and create hostile armies of robots
7. The ML feeds all your confidential data to someone else's central AI

Digital Twins: What, How, Where?

WEF Fact Sheet December 2023:

https://www.accesswater.org/?id=-10100500

Water Environment Federation
the water quality people

AI / ML in the Water and Wastewater Systems Sector:

GENERATIVE AI (GenAI)

INTRODUCTION

Generative AI (GenAI) is defined by the US government as "the class of AI models that emulate the structure and characteristics of input data in order to generate derived synthetic content." (E.O. 14110, 88 FR 75191). As a subset of AI ML Deep Learning, GenAI uses complex algorithms and statistical models that are trained using large amounts of data, which is often open source. Large Language Models (LLMs), for example, make use of training data to learn patterns that GenAI can then emulate.

before deployment. Yet only 24% of their [GenAI] projects will include a cybersecurity component within the next six months—and 69% say innovation takes precedence over cybersecurity for [GenAI]." (IBM, p.5) Utilities will need to balance cybersecurity concerns against innovation opportunities.

OPPORTUNITIES

GenAI is evolving rapidly and can deliver creative and innovative solutions for utilities. Common use cases include research and document preparation, image

Digital Twins: What, How, Where?

How Does it Work?

Feed-Forward Neural Network: Discrete Events, Asset Management

Main ID	Material	Install Decade	Break ?	Soil Corrosivity	Break Year Days > 90 F	Break Year Days < 32 F	Age of Failure	ML Prediction
9258	Cast Iron	1940s	No	None	16	24	N/A	110
10603	Cast Iron	1930s	Yes	High	17	46	82	84
20433	Cast Iron	1970s	Yes	High	18	20	39	38
52160	PVC	1980s	Yes	High	9	32	27	31
57359	PVC	1970s	No	Low	16	24	N/A	70

Digital Twins: What, How, Where?

How Does it Work?

Long-Short Time Memory: Time Series Forecasting

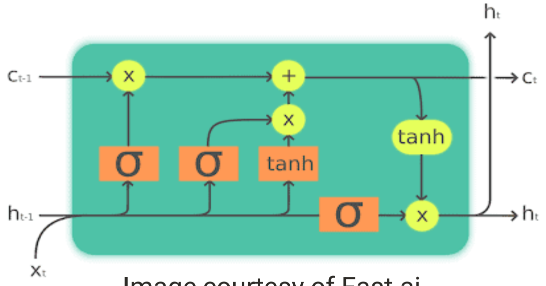
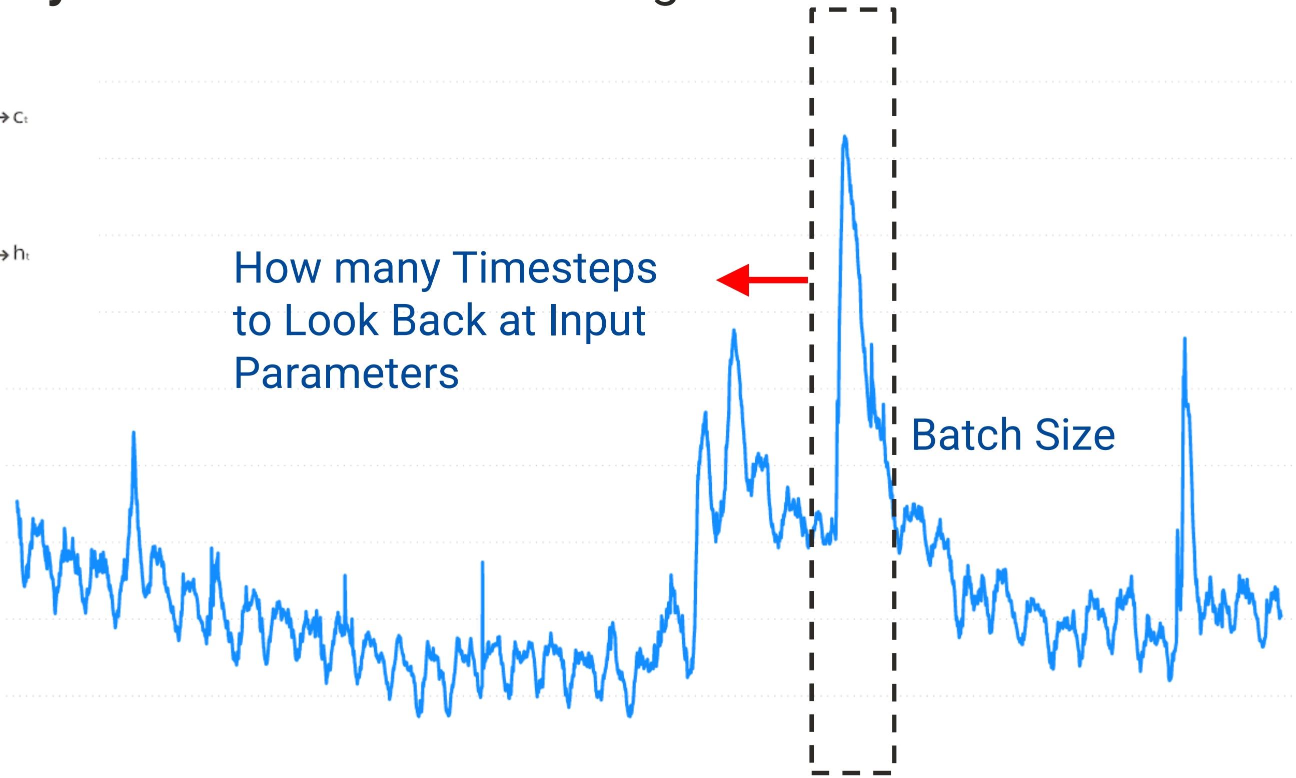


Image courtesy of Fast.ai

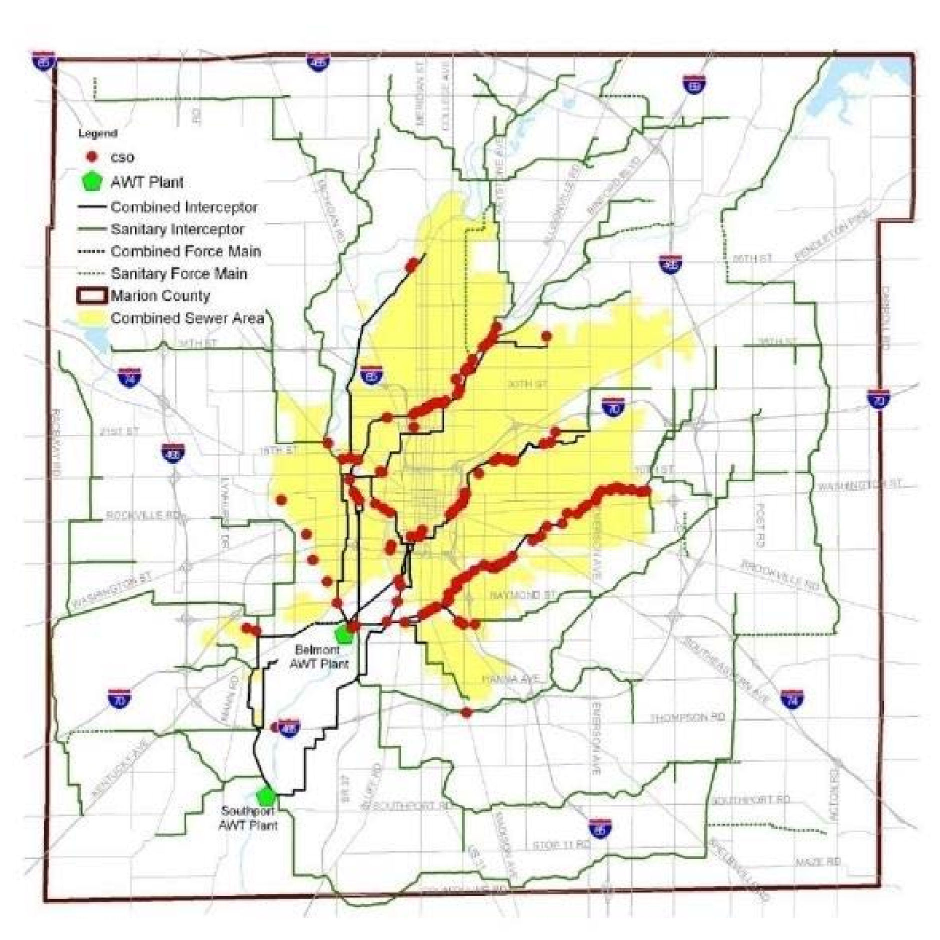


Digital Twins: What, How, Where?

Where to Apply Machine Learning?

- “I’d like more certainty in where to dispatch staff in big storms.”
- “I know there’s a pattern in the data but I can’t find it.”
- “I have data gaps to fill in.”
- “I need answers but I can’t collect data everywhere.”
- “I need answers but a traditional model would take years.”
- “I need answers in real time.”
- “Actually, I need answers a few hours ahead of real time.”
- “Did I say hours? I meant days.”

Example 1: Wet-Weather Operational Forecasting



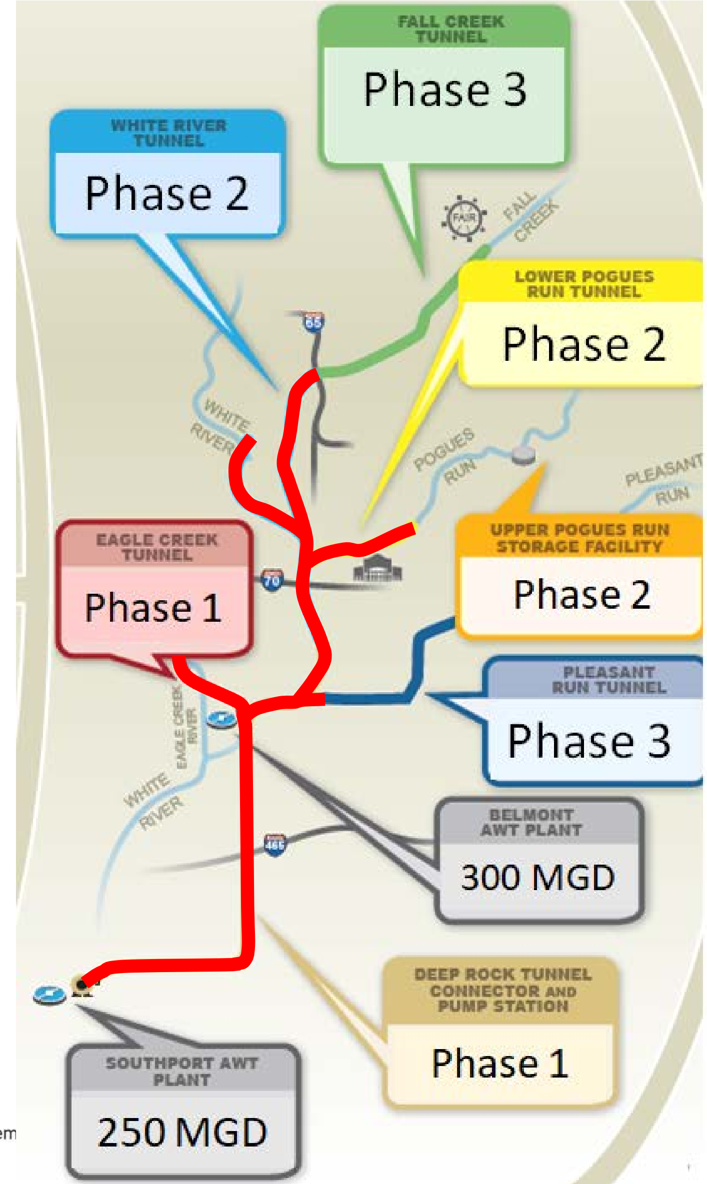
Example #1: Wet-Weather Operational Forecasting

DigIndy Tunnel System

- Phase 1: ~ 9 Miles, 80 MG
- Phase 2: ~ 17 Miles, 170 MG
- Phase 3: ~ 28 Miles, 280 MG

Can we predict inflow ***before*** the event happens?

- Machine Learning to predict Inflow
- Link to 72-hour NOAA forecast
- Present Forecasts in Power BI

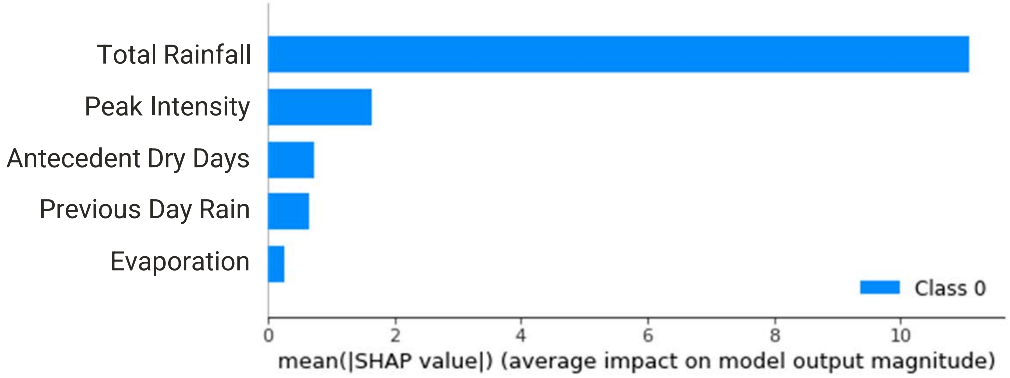


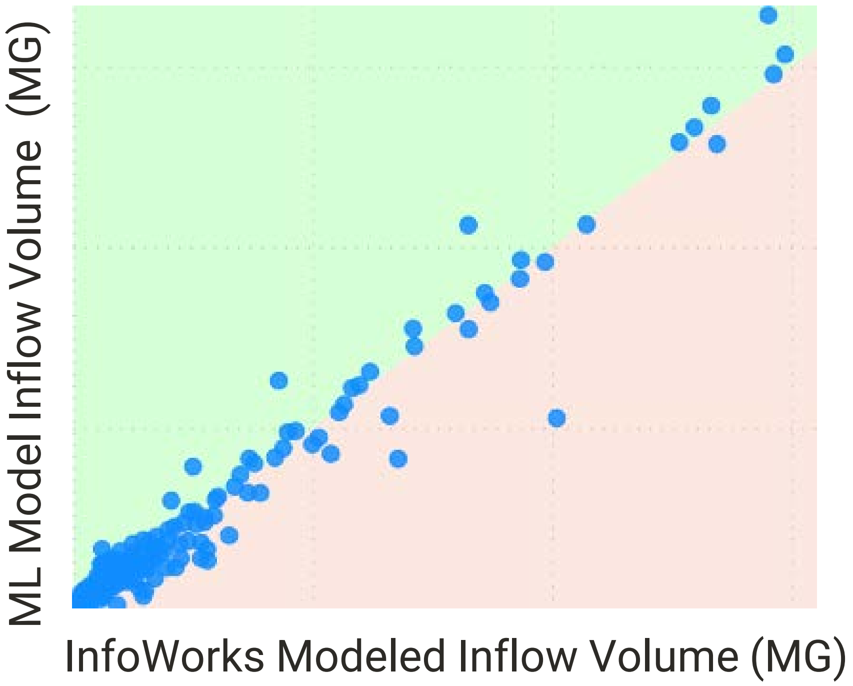
Example #1: Wet-Weather Operational Forecasting

ML Tool Development: Dig Indy Tunnel Phase 2

- 2016 – 2019 Modeled Dataset
- Rainfall, Evaporation, Inflow
- Total Volume within 1%

Automated Parameter Sensitivity



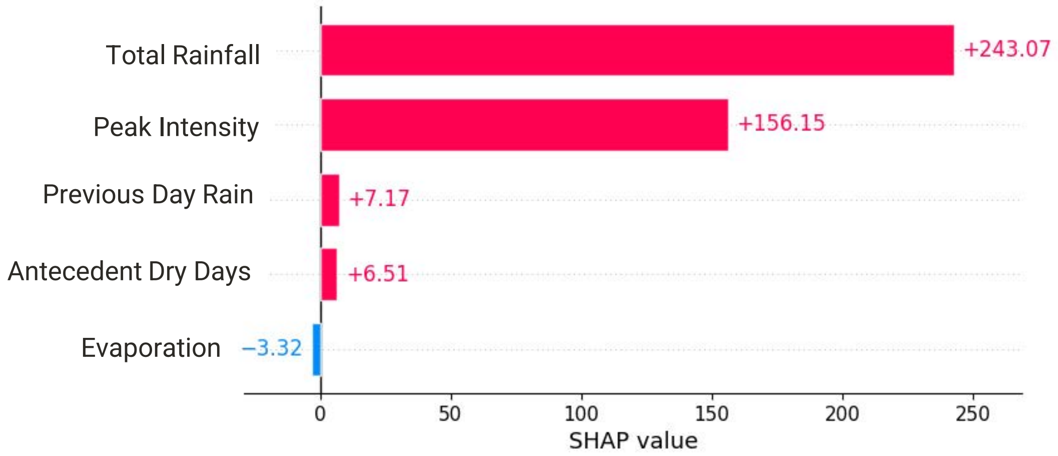


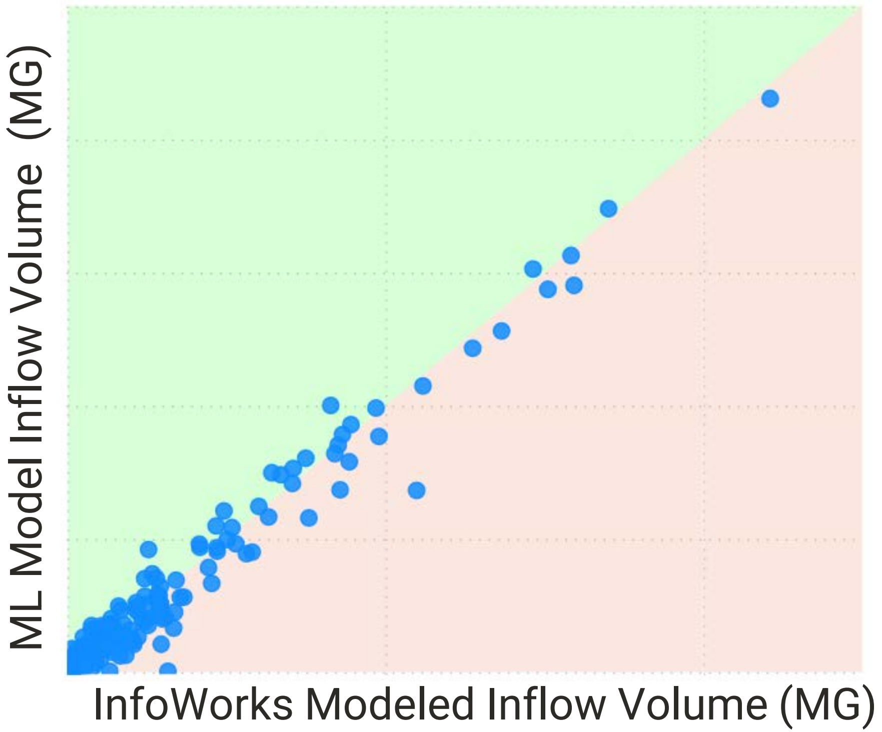
Example #1: Wet-Weather Operational Forecasting

ML Tool Development: Dig Indy Tunnel Phase 3

- 2016 – 2019 Modeled Dataset
- Rainfall, Evaporation, Inflow
- Total Volume within 1%

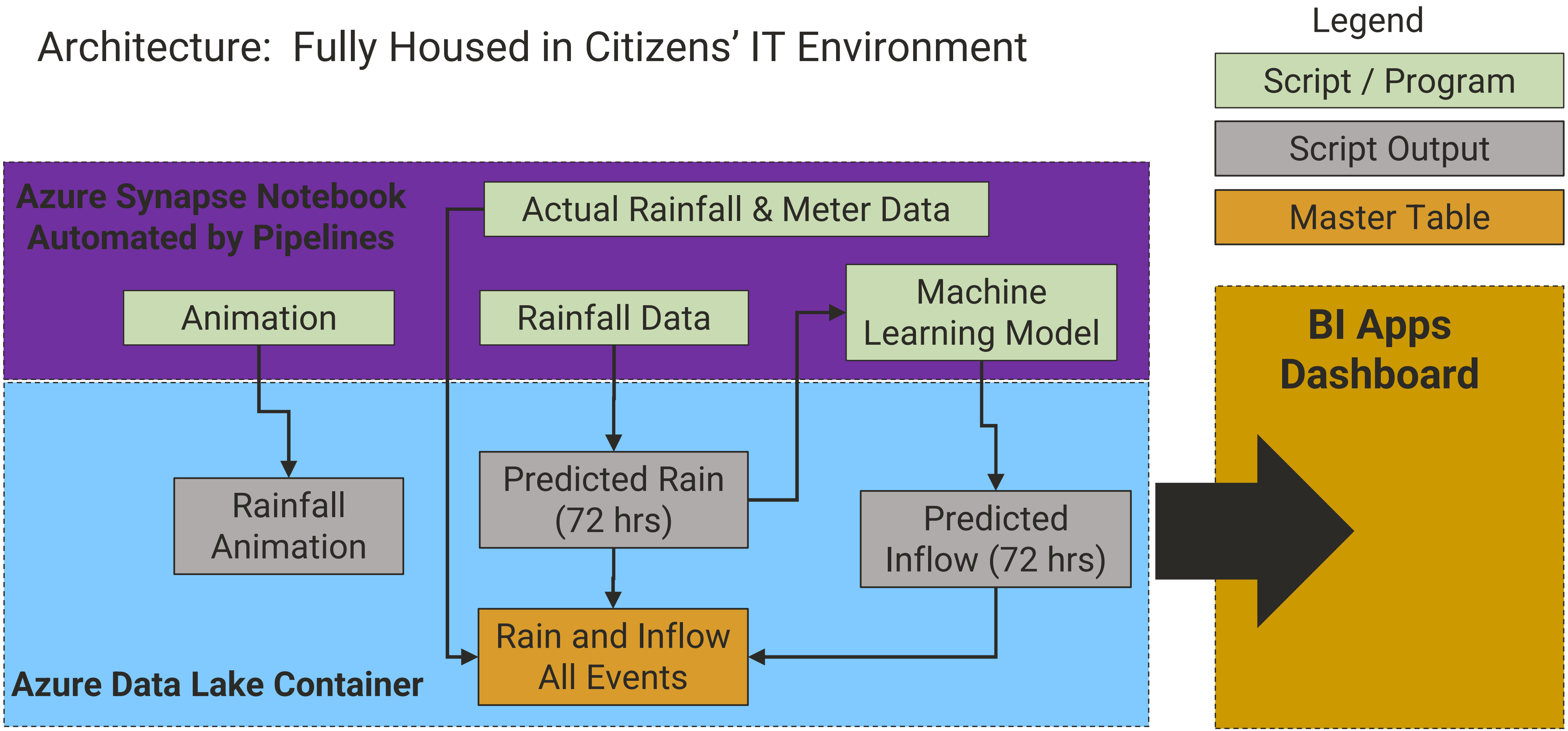
Automated Parameter Sensitivity



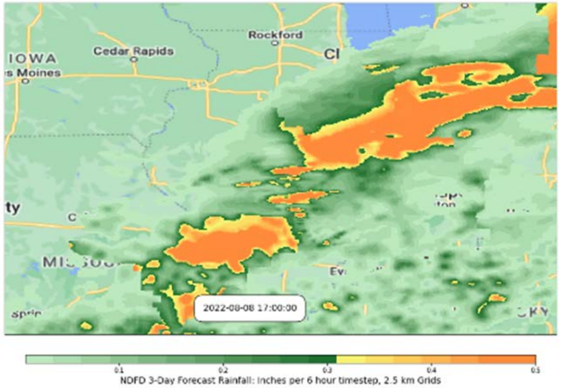


Example #1: Wet-Weather Operational Forecasting

Architecture: Fully Housed in Citizens' IT Environment



Example #1: Wet-Weather Operational Forecasting



Dates	Forecast Rain (in)	Gauged Rain (in)	Forecast Inflow (MG)	Metered Inflow (MG)
8/9/2022	1.48	1.54	75	95
3/3/2023	2.92	2.24	120	188
1/23/2024 – 1/28/2024	3.04	2.30	57	57
3/31/2024 – 4/3/2024	4.27	3.87	114	117
4/2/2025 – 4/6/2025	4.93	5.49	205	267

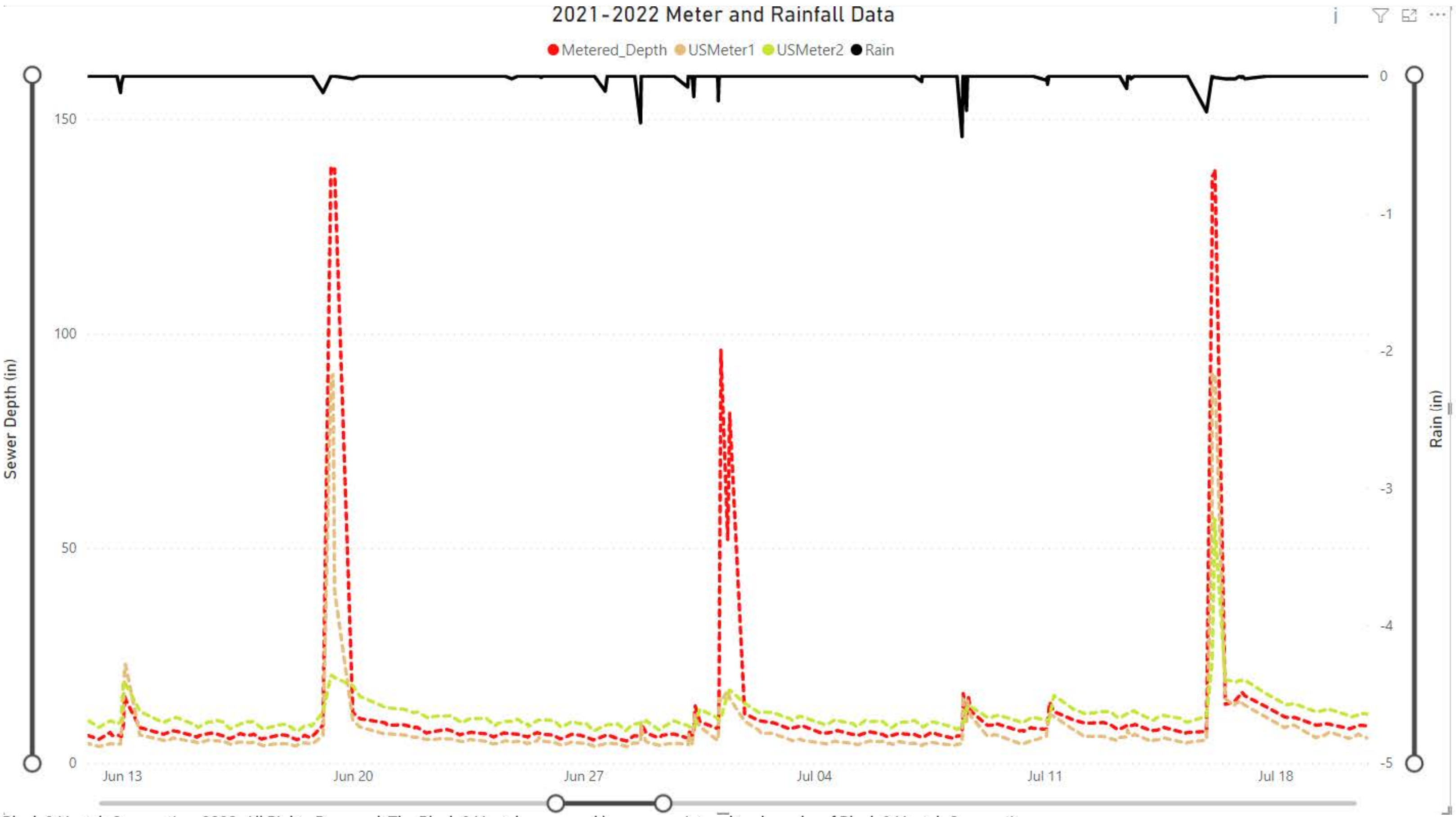
Example #2: Sanitary Sewer Overflow (SSO) Forecasting

36” Interceptor parallel to creek

SSO Forecasting

Meter Data

- Lesser surcharge in upstream meters
- Infrequent surcharge in most upstream meter



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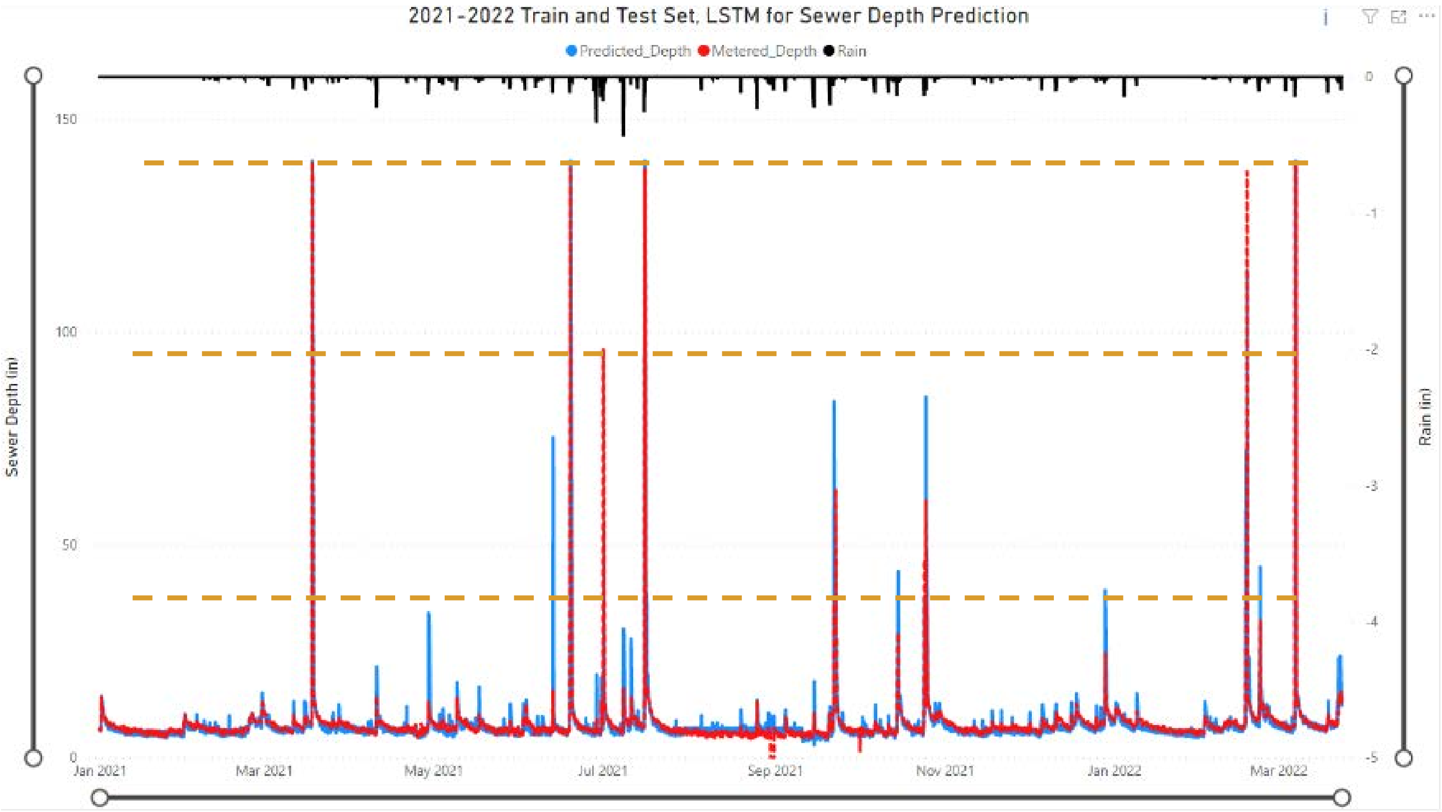
SSO Forecasting

LSTM Neural Network

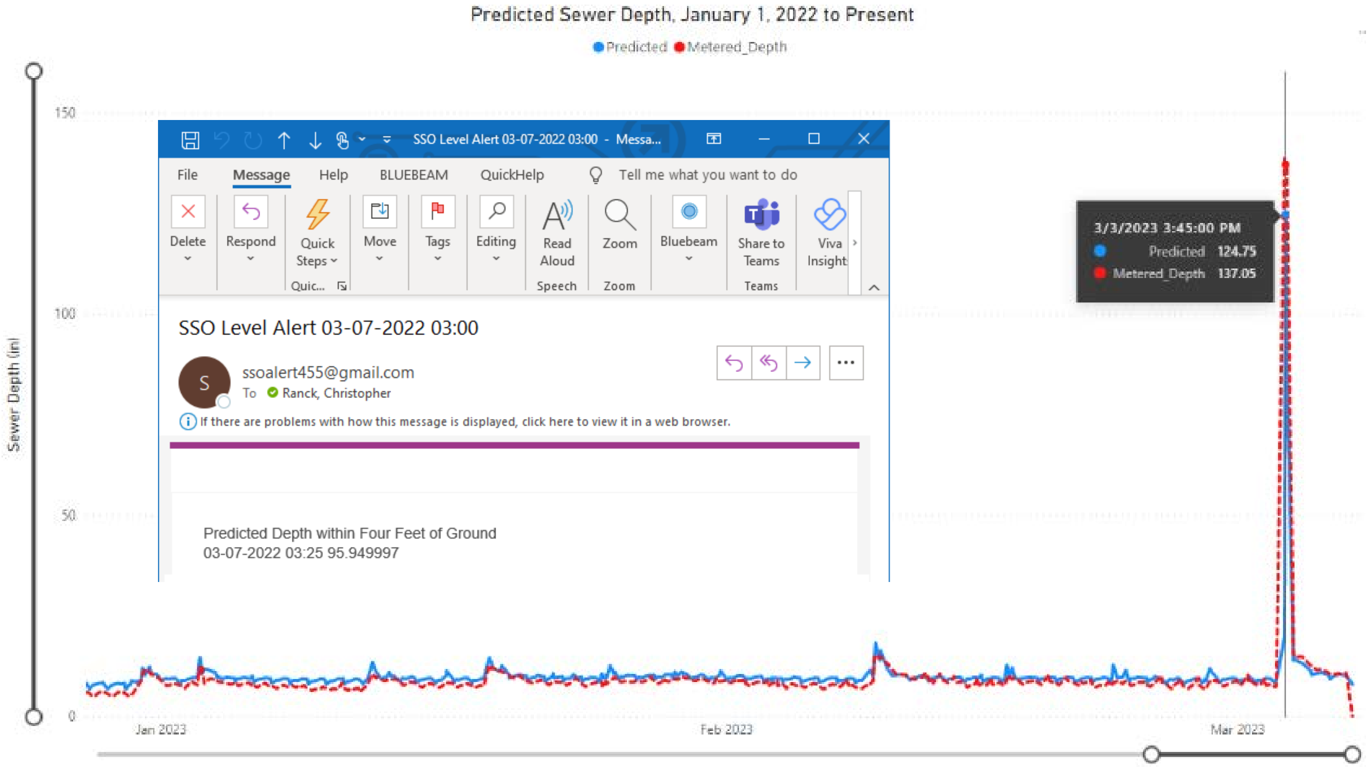
- Overflow: 4 / 5 Predicted
- Within 4’ of Ground: 5 / 6
- Surcharge:
  - 4 False Positives
  - No False Negatives



SSO Forecasting

Deployed as Azure Function App

- Runs Hourly
- Queries Meter Data
- Forecasts 2-3 hours into the future
- Power BI Online
- Email Alerts
- $0.12/month Azure Cost



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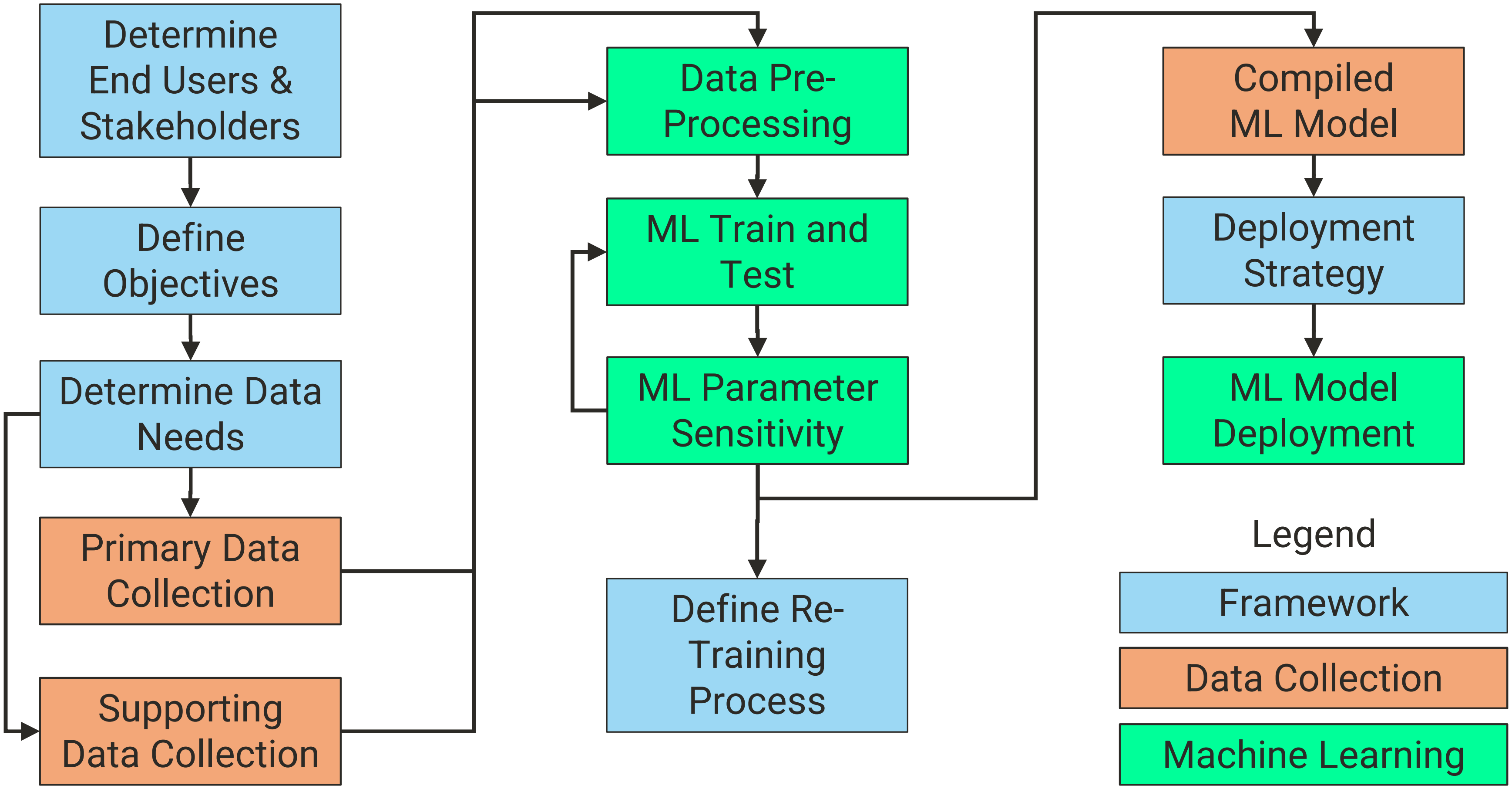
How to Get Started

How to Get Started

Before Getting Started, Consider:

1. Who needs to see this?
2. How will they use the predictions?
3. What do you want to predict?
4. What data can you get to generate the predictions?
5. How often do you need to refresh the predictions?

How to Get Started



How to Get Started

- Commercial Software not necessary
- Available via Microsoft, Google, Amazon Environments
- Can Deploy at any scale and within Existing IT Infrastructure
- If all else fails, ask ChatGPT

RA

```
    y.append(data[i, 0])
X = np.array(X)
y = np.array(y)
X = np.reshape(X, (X.shape[0], X.shape[1], 1))

# Split the data into training and testing sets
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

# Train the model
model.fit(X_train, y_train, epochs=100, batch_size=32)

# Evaluate the model on the testing set
scores = model.evaluate(X_test, y_test)
print("\n%s: %.2f" % (model.metrics_names[0], scores))

# Make predictions on new data
new_data = np.array([[0.5], [0.6], [0.7]])
new_data = (new_data - data.mean()) / data.std()
new_data = np.reshape(new_data, (1, timesteps, 1))
prediction = model.predict(new_data)
print("Predicted river stage: %.2f" % prediction[0, 0])
```

In this code, we first define the architecture of our LSTM model, which consists of one LSTM layer with 50 neurons and one output layer with 1 neuron.

We then compile the model using the `mean_squared_error` loss function and the `adam` optimizer.

Discussion

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