Business Background

Client: AquaFlow Technologies
Domain: Water Treatment
Problem:
AquaFlow Technologies (the “company”), a leader in the water treatment industry, is facing a challenge with predicting anomalies in water quality, using the data generated by its pumps and filtration units.

The company’s water filtration process is performed by a number of units that are also collecting data of water quality. The company’s system collects the data is and uses it to detect and alert about issues with water quality (anomalies). So far, the system has been quite effective both in alerting where there are no anomalies (i.e. having low amount of “Unnecessary Alerts”, “False Positives”, or FPs), and also in cases in which there are no alerts even when there are anomalies (i.e. “Missing Anomalies”, “False Negatives”, or FNs). However, the company has recently faced a significant increase in in costs associated with “False Negative” cases, that are now costing double the amount than before.

This change is largely due to the operational and financial cost of responding to those False Negative alerts. The cost of missed anomalies (“False Negatives”) is significant, as it involves being exposed to lawsuits from the public regarding low water quality or being incompliant with the state’s different regulations. Those financial costs have recently increased after new laws came into force in the country, making the FN costs double the ones of FB.

Each “Unnecessary Alert”, on the other hand, requires the company to call a technician, stop operations, and perform system checks. All of that requires work hours of technicians and other employees, but those expenses do not compare to the significant costs of the False Negative, as now a FN event costs twice as much as a FP.

Recognizing this change in costs, the company is now interested in improving its anomaly detection method to lower the exposure for lawsuits, while maintaining the systems' overall credibility and safety standards.

Scope

Solution:
To address the challenge mentioned above, the suggested solution includes the improvement of the Recall score of the existing baseline models (LightGBM and MSET). This improvement directly relates to the business problem where the cost of Missed

Anomaly (FNs) has become significantly higher than the one of False Positives (FP). By improving the Recall score, the goal is to reduce the rate of FNs, and by thus minimizing lawsuits and incompliance fines from the regulator, all without substantially increasing the risk of FPs. In order to do so, we have chosen to use the F-beta score, where beta=2, due to the multiple costs FNs have over FPs. This way we will not be focusing only on the Recall score, and then hitting the Precision score, but taking them both into account with the right weights.

The offered solution – Adding an automated step into the existing Pipeline:

1. After the baseline model has been trained, applying SHAP method to assess how the change in each feature is impacting the prediction of the model, focusing on those who contribute the most.
2. Using the SHAP results to dropping several features that will improve the model's accuracy. Specifically, removing the features who are primary contributors to the model's prediction of missing anomalies where there are such (FNs), and by thus improving the model's Recall score.
    a. Since SHAP cannot be used for temporal context data (time-series), meaning that SHAP is taking each sample by itself, and explain it only by the features at the same time-stamp/sample.
    b. To solve this issue, we will try to use OmniXAI in addition to the SHAP, which provides SHAP that is using the temporal context. Using "temporal context" means explaining a sample by features from other time stamps as well.
3. Retrain the baseline model using the corrected set of features.

The improved pipeline is expected to provide a model with higher Recall score, leading to a lower risk for lawsuits and incompliance with regulation.

Customer Consumption:
The improved model, integrated into AquaFlow's existing system, will provide more accurate and cost-effective anomaly detection process in the industrial water treatment.

Personnel

- Supervisor:
    - Ishai Rosenberg, Reichman University, MLOps Course Instructor

- Machine Learning and Data Science M.Sc. Students:
    - Shahar Ehrenhalt
    - Oren Avidan
    - Mayan Stroul

    - Alexander Gorelik

- Client
    - AquaFlow Technologies:
        - Data Administrator
        - Data Scientist (baseline owner)
        - CFO – to assess to provide inputs about financial costs
        - COO – operating the system and handling the alerts and regulation

Metrics

Qualitative Objectives

- **Main Objective**: Enhance the operational efficiency of AquaFlow's water treatment systems.
- **Specific Focus**: Reduce the frequency of unnecessary maintenance interventions triggered by false positive anomaly alerts.

Quantifiable Metric

- **Primary Metric**: Precision of anomaly detection models.
- **Rationale**: Higher precision reduces false positive rates, aligning with the objective of minimizing unwarranted maintenance actions.

Measurement Method

- **Approach**: Comparing the model performances before and after implementing the SHAP-based feature selection step.
- **Methodology**:
    - **Pre-implementation Phase**: Measure the precision of the current models on a historical dataset.
    - **Post-implementation Phase**: After integrating the SHAP-enhanced pipeline, measure the precision again on the same historical dataset.

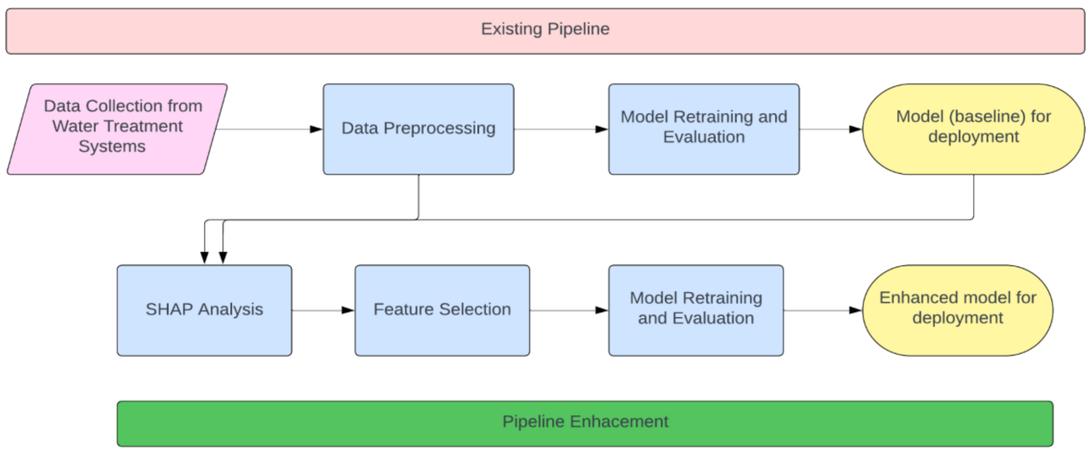
  Validation: comparing the two Precision scores

Plan

- **Project Start:** 14/01/2024
    - Get to current baseline models and training data
- **SHAP Analysis and Feature Selection (5 days):**
    - Implement SHAP analysis to assess the impact of each feature on model precision.
    - Identify and select features that contribute positively to precision while removing those leading to false positives.

- **Pipeline Development for Model Optimization (5 days):**
    - Develop a pipeline that integrates the baseline models (LightGBM and Conv_AE) with SHAP-based feature selection.
    - Test the pipeline with initial data sets to ensure smooth operation and integration.
- **Model Retraining with Optimized Features (2 days):**
    - Retrain the LightGBM and Conv_AE models within the pipeline using the refined feature set.
    - Focus on maintaining or improving precision in the retraining process.
- **Performance Evaluation and Comparison (2 days):**
    - Evaluate the performance of the retrained models against the baseline models.
    - Compare precision rates to assess the improvement and alignment with project goals.
- **Project Submit:** 31/01/2024

Architecture



Existing Pipeline:

1. The existing pipeline starts with **Data Collection from Water Treatment Systems**, where AquaFlow gathers multivariate time series data via various sensors.
2. Following data collection, **Data Preprocessing** is performed to clean and normalize the data in preparation for model training.
3. **Model Retraining and Evaluation** is the subsequent phase, where the baseline models (LightGBM and Cone_AE) are trained using the preprocessed data to detect anomalies.

4. The final step in the existing pipeline is deploying the **Model (baseline) for Deployment**, where the trained model is ready for production for real-time anomaly detection.

Pipeline Enhancement:

1. As an enhancement to the existing pipeline, **SHAP Analysis** is introduced to evaluate the impact of each feature on the model's prediction precision, particularly identifying those that lead to false positives.
2. **Feature Selection** follows, where features that negatively impact precision are identified using SHAP values and removed to improve model performance.
3. The pipeline then proceeds to a second round of **Model Retraining and Evaluation** with the optimized feature set. This step is critical to ensure that the enhanced models maintain or improve precision.
4. The enhanced pipeline culminates in the **Enhanced Model for Deployment**, where the refined model, now more precise, is ready for deployment into AquaFlow's operational systems for improved decision-making.

Communication

- **Initial Alignment Meeting**:
  - Before project commencement, a kickoff meeting will be organized with AquaFlow's team and relevant stakeholders. The purpose is to present the project milestones, discuss the planned work, and ensure that the chosen metrics are aligned with the company's needs. Key participants will include AquaFlow's data scientist, data administrator, and other critical stakeholders.
- **Regular Progress Updates**:
  - During the development phase, we will hold weekly Zoom meetings. These sessions will serve to address any queries regarding data, provide updates on progress, and maintain transparent communication. The primary attendees will be the data scientist and data administrator from AquaFlow, ensuring direct involvement and feedback from the client's technical team.
- **Product Hand-Off and Training**:
  - At project completion, a final presentation will be conducted to demonstrate the refined anomaly detection system and facilitate training for AquaFlow's teams on its usage. This session will include comprehensive insights into the system's capabilities and operational integration. All key stakeholders from AquaFlow, including data scientists and department heads, will be invited.