Unlocking Key Insights:

Identifying Crucial Features in ML Models

Automated Feature Selection

OUR TEAM

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The Customer

AquaFlow Technologies

AquaFlow Technologies

AquaFlow Technologies has established itself as a leader in the water treatment and management industry.

With a commitment to innovation and sustainability, AquaFlow specializes in developing advanced solutions for water purification, recycling, and conservation.

The company's portfolio includes state-of-the-art filtration systems, efficient wastewater treatment plants, and cutting-edge desalination technologies.

02

The Problem

BUSINESS METRICS

Unnecessary Alerts

Minimal operational disruptions from unnecessary alerts, thus optimizing resources and maintaining operational continuity

Missing Anomalies

Lead to severe consequences, including critical system failures like water pipe blowouts, resulting in water shortages and extensive repair costs (~10,000$)

Cost Implications

The financial impact of a missed anomaly is significantly higher, estimated to be twice as costly, compared to the expense incurred in responding to a false alarm.

DATA SCIENCE METRICS

Unnecessary Alerts - FP

Low False Positive (FP) rate leads to minimal operational disruptions from incorrect alerts

Missing Anomalies - FN

False Negative (FN) are potentially causing critical system failures and leading to significant repair costs and operational downtime.

Cost Implications

False Negative (FN) is twice as costly, compared to the expense incurred in responding to False Positive (FP)

F SCORE

$$F1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

$$F_\beta = \left(1 + \beta^2\right) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}}$$

$$\beta = 2$$

BASELINE PERFORMANCE

	Predicted Non-Anomaly	Predicted Anomaly
True Non-Anomaly	1041 TN	0 FP
True Anomaly	145 FN	658 TP

Accuracy	0.92
Precision	1.00
Recall	0.82
F1 score	0.90
F β=2 score	0.85

03

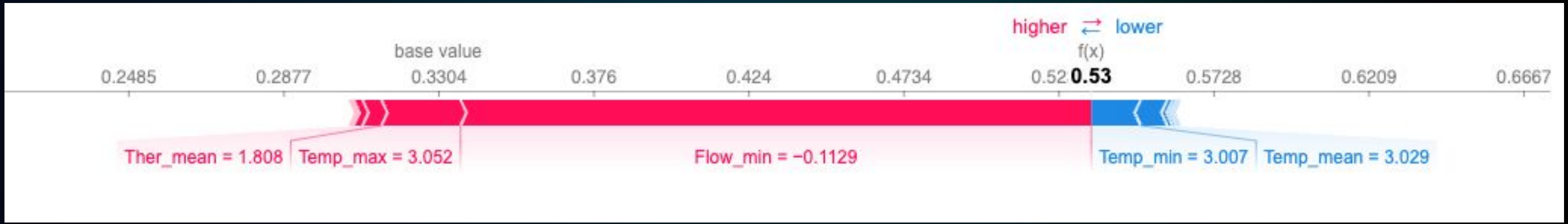
The Solution

FEATURE SELECTION

SHAP

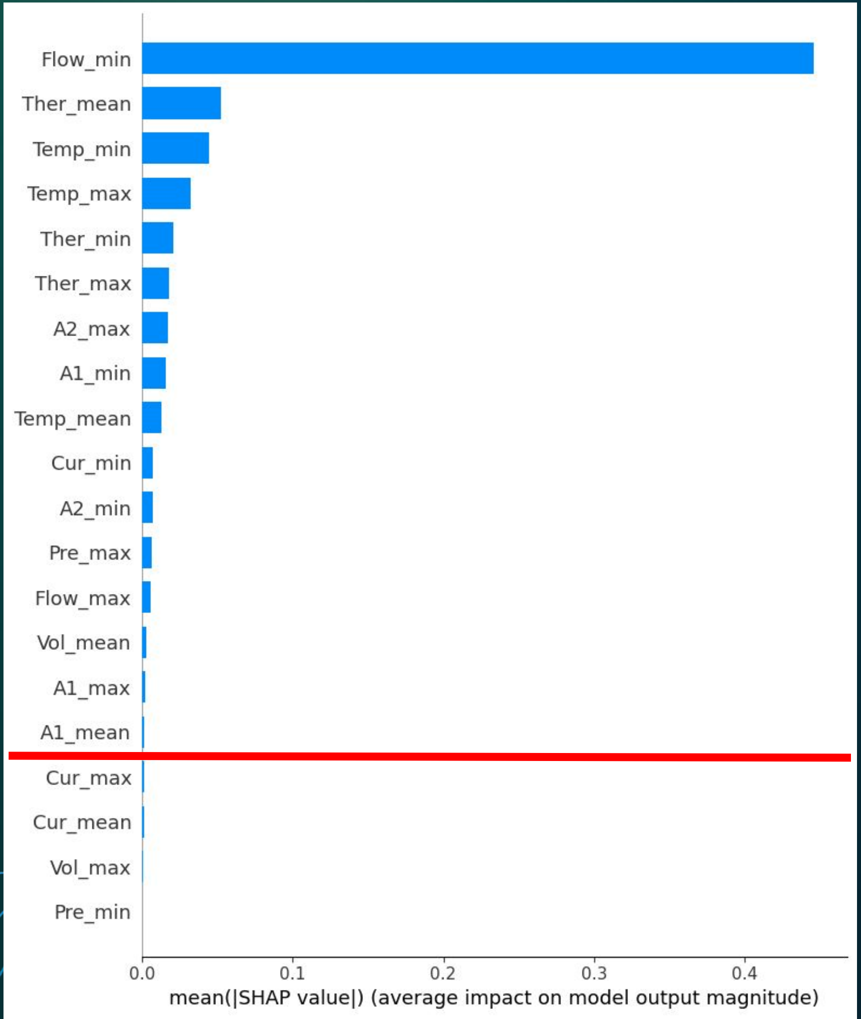
SHAP (SHapley Additive exPlanations) is a machine learning interpretability method that explains the output of any model by quantifying the impact of each feature on the prediction. It uses game theory principles, attributing an average contribution of each feature across all possible combinations.

LOCAL FEATURE CONTRIBUTION

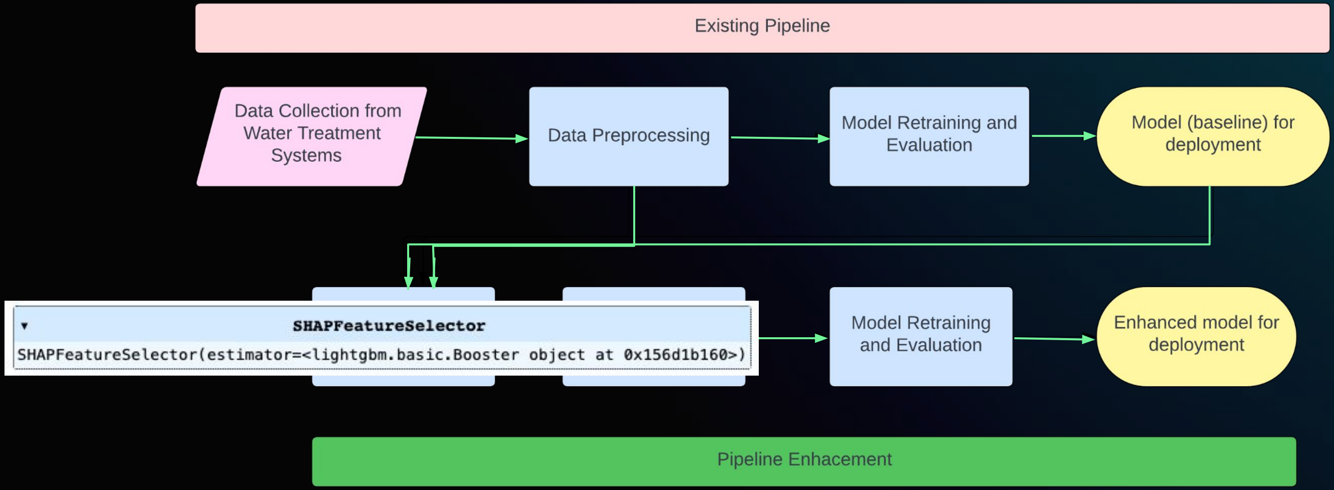


GLOBAL FEATURE CONTRIBUTION

Drop 15% least impactful features



ARCHITECTURE



BASELINE VS IMPROVED

Baseline

	Predicted Non-Anomaly	Predicted Anomaly
True Non-Anomaly	1041 TN	0 FP
True Anomaly	145 FN	658 TP

Accuracy	0.92
Precision	1
Recall	0.81
F2 Score	0.85

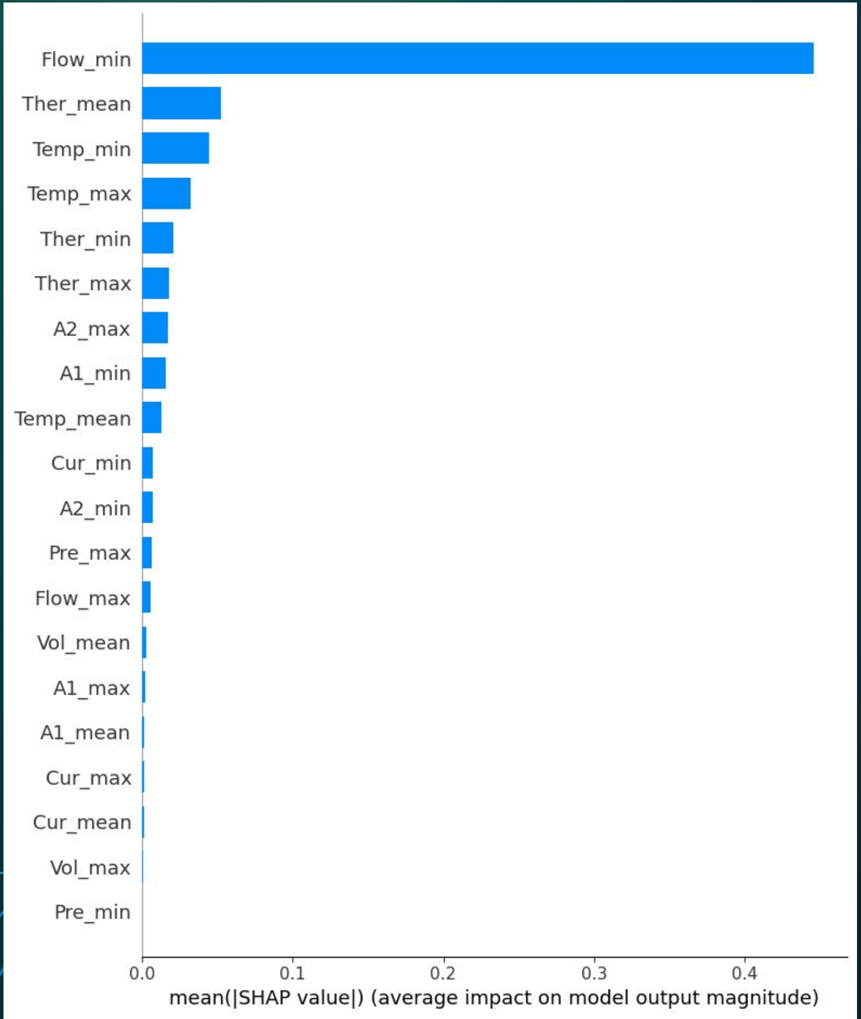
Improved

	Predicted Non-Anomaly	Predicted Anomaly
True Non-Anomaly	1041 TN	0 FP
True Anomaly	145 FN	658 TP

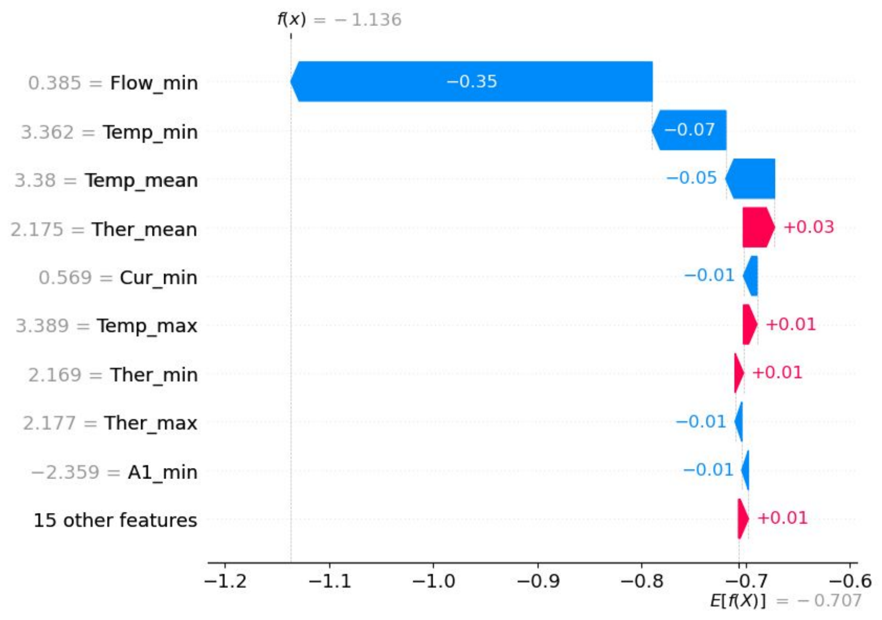
Accuracy	0.92
Precision	1
Recall	0.81
F2 Score	0.85

IMPROVEMENT 2.0

GLOBAL FEATURE CONTRIBUTION

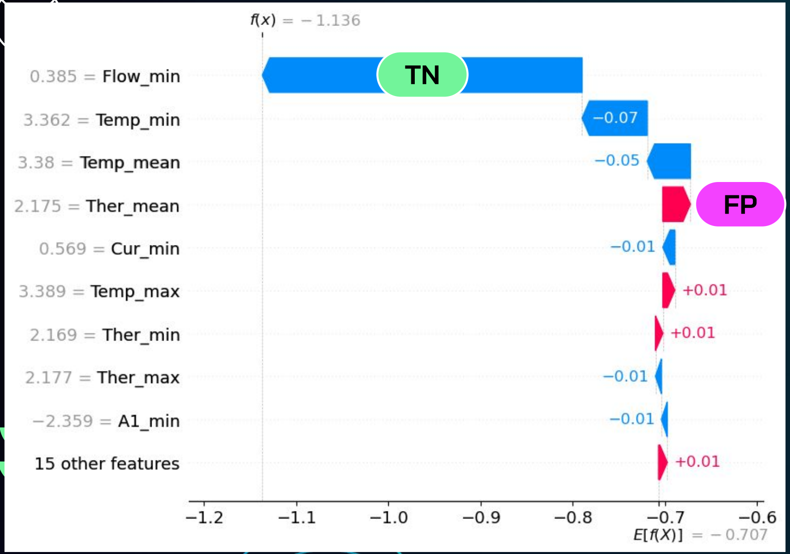


LOCAL CONTRIBUTION

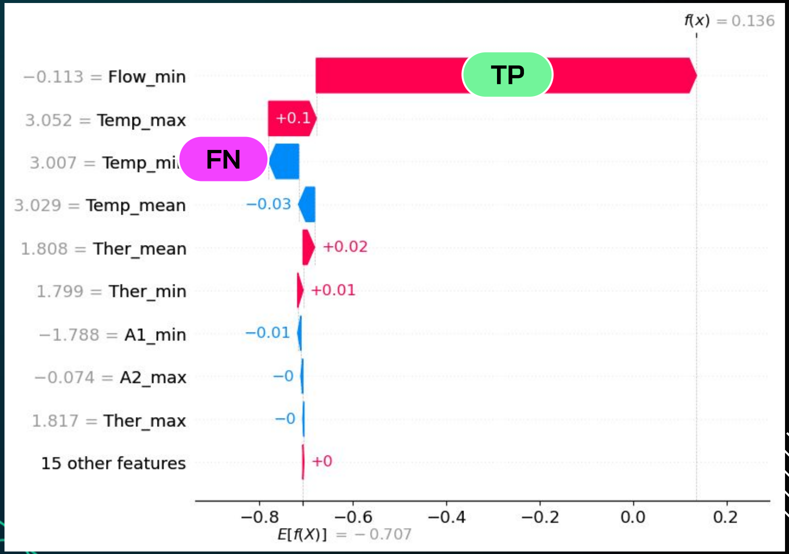


LOCAL CONTRIBUTION

Non-Anomaly



Anomaly



CONTRIBUTION

24 rows · 24 rows × 4 columns

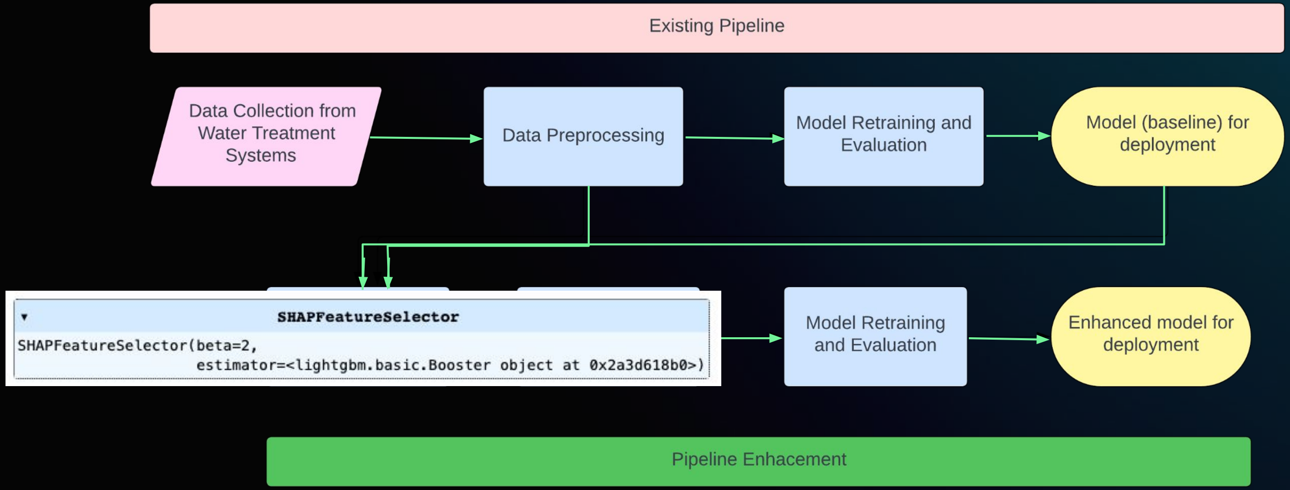
	TP	FP	TN	FN
A1_mean	3471	6518	1876	838
A1_min	2341	3760	4634	1968
A1_max	450	903	7491	3859
A2_mean	0	0	0	0
A2_min	2605	5716	2678	1704
A2_max	2573	4523	3871	1736
Cur_mean	2765	5541	2853	1544
Cur_min	2954	5386	3008	1355
Cur_max	764	1415	6979	3545
Pre_mean	0	0	0	0
Pre_min	0	0	0	0
Pre_max	1538	3033	5361	2771
Temp_mean	3759	6115	2279	550
Temp_min	3760	6286	2108	549
Temp_max	956	5258	3136	3353
Ther_mean	1082	1198	7196	3227
Ther_min	1904	2495	5899	2405
Ther_max	2447	4053	4341	1862
Vol_mean	2970	5273	3121	1339
Vol_min	0	0	0	0
Vol_max	142	296	8098	4167
Flow_mean	0	0	0	0
Flow_min	3858	175	8219	451
Flow_max	504	4617	3777	3805

CONTRIBUTION

24 rows × 9 columns

	TP	FP	TN	FN	recall	precision	f_beta	contrib_coef	f_beta_score_normed
Flow_min	3858	175	8219	451	0.895335	0.956608	0.906954	1.0	0.906954
Temp_mean	3759	6115	2279	550	0.872360	0.380697	0.693287	1.0	0.693287
Temp_min	3760	6286	2108	549	0.872592	0.374278	0.689099	1.0	0.689099
A1_mean	3471	6518	1876	838	0.805523	0.347482	0.637466	1.0	0.637466
Vol_mean	2970	5273	3121	1339	0.689255	0.360306	0.582833	1.0	0.582833
Cur_min	2954	5386	3008	1355	0.685542	0.354197	0.577495	1.0	0.577495
Cur_mean	2765	5541	2853	1544	0.641680	0.332892	0.541265	1.0	0.541265
A2_max	2573	4523	3871	1736	0.597122	0.362599	0.528728	1.0	0.528728
Ther_max	2447	4053	4341	1862	0.567881	0.376462	0.515462	1.0	0.515462
A2_min	2605	5716	2678	1704	0.604549	0.313063	0.509645	1.0	0.509645
A1_min	2341	3760	4634	1968	0.543282	0.383708	0.501564	1.0	0.501564
Ther_min	1904	2495	5899	2405	0.441866	0.432826	0.440028	1.0	0.440028
Pre_max	1538	3033	5361	2771	0.356927	0.336469	0.352639	1.0	0.352639
Ther_mean	1082	1198	7196	3227	0.251102	0.474561	0.277208	1.0	0.277208
Temp_max	956	5258	3136	3353	0.221861	0.153846	0.203838	1.0	0.203838
Cur_max	764	1415	6979	3545	0.177303	0.350620	0.196755	1.0	0.196755
A1_max	450	903	7491	3859	0.104433	0.332594	0.121039	1.0	0.121039
Flow_max	504	4617	3777	3805	0.116964	0.098418	0.112716	1.0	0.112716
Vol_max	142	296	8098	4167	0.032954	0.324201	0.040172	1.0	0.040172
A2_mean	0	0	0	0	0.000000	0.000000	0.000000	0.0	0.000000
Pre_min	0	0	0	0	0.000000	0.000000	0.000000	0.0	0.000000
Pre_mean	0	0	0	0	0.000000	0.000000	0.000000	0.0	0.000000
Vol_min	0	0	0	0	0.000000	0.000000	0.000000	0.0	0.000000
Flow_mean	0	0	0	0	0.000000	0.000000	0.000000	0.0	0.000000

ARCHITECTURE



04

The Results

BASELINE VS IMPROVED 2.0

Baseline

	Predicted Non-Anomaly	Predicted Anomaly
True Non-Anomaly	1041	0
True Anomaly	145	658

Accuracy	0.92
Precision	1
Recall	0.82
F2 Score	0.85

Improved 2.0

	Predicted Non-Anomaly	Predicted Anomaly
True Non-Anomaly	1041	0
True Anomaly	139	664

Accuracy	0.93
Precision	1
Recall	0.83
F2 Score	0.86

3h 44m 40s

Representative test set period

9

Decrease of missing anomalies during test period

10,000$

Potential cost of missing anomaly

~$210,240,000

Yearly Cost Reduce

05

DEMO

06

The Summary & Feature Steps

IMPROVED VS IMPROVED 2.0

performance

24 rows

	0
Flow_min	0.445782
Ther_mean	0.052215
Temp_min	0.044218
Temp_max	0.031974
Ther_min	0.020672
Ther_max	0.017699
A2_max	0.017252
A1_min	0.015553
Temp_mean	0.012930
Cur_min	0.007048
A2_min	0.006753
Pre_max	0.006539
Flow_max	0.006006
Vol_mean	0.002615
A1_max	0.002400
A1_mean	0.001715
Cur_max	0.001283
Cur_mean	0.001009
Vol_max	0.000370
Pre_min	0.000000
Pre_mean	0.000000
A2_mean	0.000000
Vol_min	0.000000
Flow_mean	0.000000

24 rows 24 rows × 1 columns

	f_beta_score_normed
Flow_min	0.906954
Temp_mean	0.693287
Temp_min	0.689099
A1_mean	0.637466
Vol_mean	0.582833
Cur_min	0.577495
Cur_mean	0.541265
A2_max	0.528728
Ther_max	0.515462
A2_min	0.509645
A1_min	0.501564
Ther_min	0.440028
Pre_max	0.352639
Ther_mean	0.277208
Temp_max	0.203838
Cur_max	0.196755
A1_max	0.121039
Flow_max	0.112716
Vol_max	0.040172
A2_mean	0.000000
Pre_min	0.000000
Pre_mean	0.000000
Vol_min	0.000000
Flow_mean	0.000000

FEATURE STEPS

Magnitude Use

Take the magnitude of each feature into account and not only the direction of each feature

Optimization

Adding the optimization step for optimal number of features selection for drop

OmniXAI

Using “temporal context” - explaining a sample by features from other timestamp as well

THANK YOU

Questions?