Fracta Inc. Background

- Founded in 2015,
- Based in Palo Alto, CA
- North America, Japan, and Europe.
- Strategic Investor: Kurita Water Industries

Corporate Philosophy

Study the properties of water, master them, and we will create an environment in which nature and man are in harmony

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US Water Main Replacement Issues

- Out of 50,000 US utilities, only the most sophisticated are fully aware of, and dealing with pending replacement needs

- Physical Condition Assessment is expensive and has risks if putting something in the pipe

- ***Desktop Condition Assessment based on age, leak history and causation theories can't handle the large number of relevant variables and is very poor at predicting first-leaks on pipes***

What is Machine Learning?

Machine Learning is a field of Artificial Intelligence that allows computers to find hidden insights "without being explicitly programmed where to look"

- Arthur Samuel, 1959

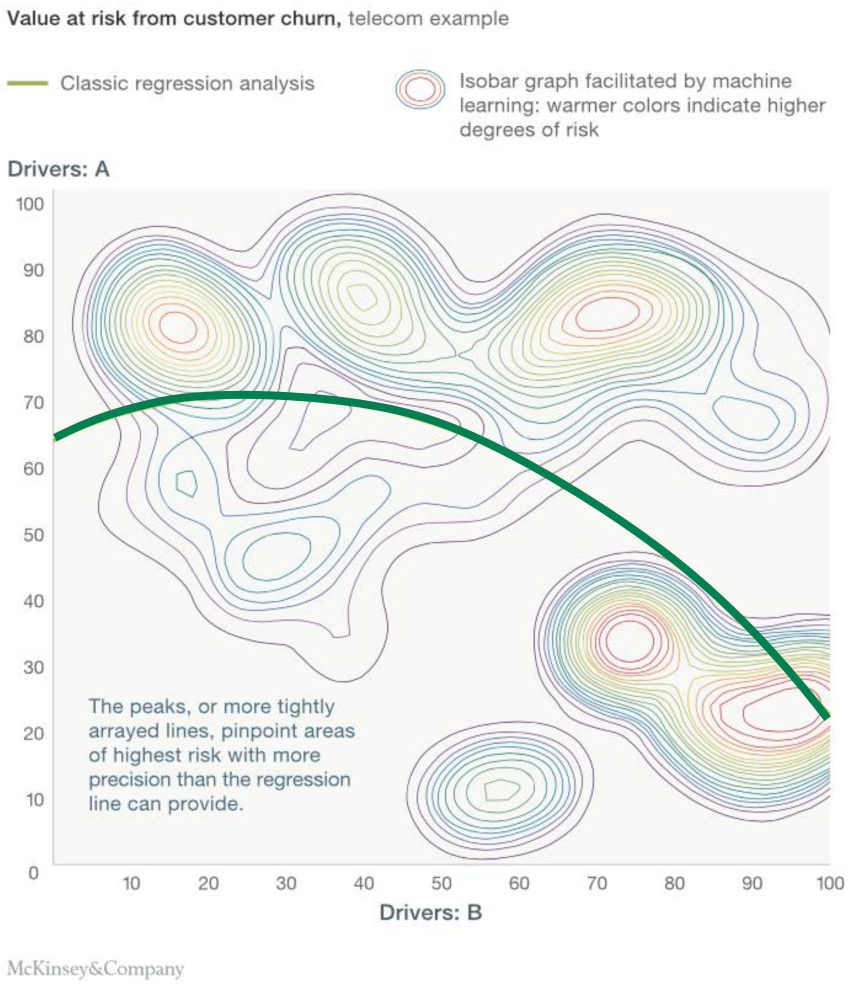
Examples of Machine Learning

Image recognition

vs

Machine Learning is the only way to mathematically optimize a large set of variables

Compared to Regression Analysis



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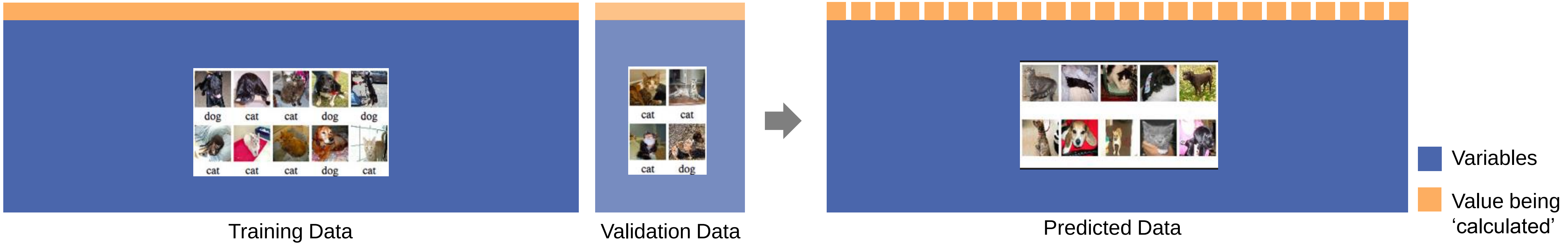
How Does Machine Learning Build the Model?

-Training and Validation



1. Machine Learning uses **Training Data** to iterate and build a model how different variables correlate with target value

2. The model is tested with **Validation Data** to see how well it is able to forecast the target value

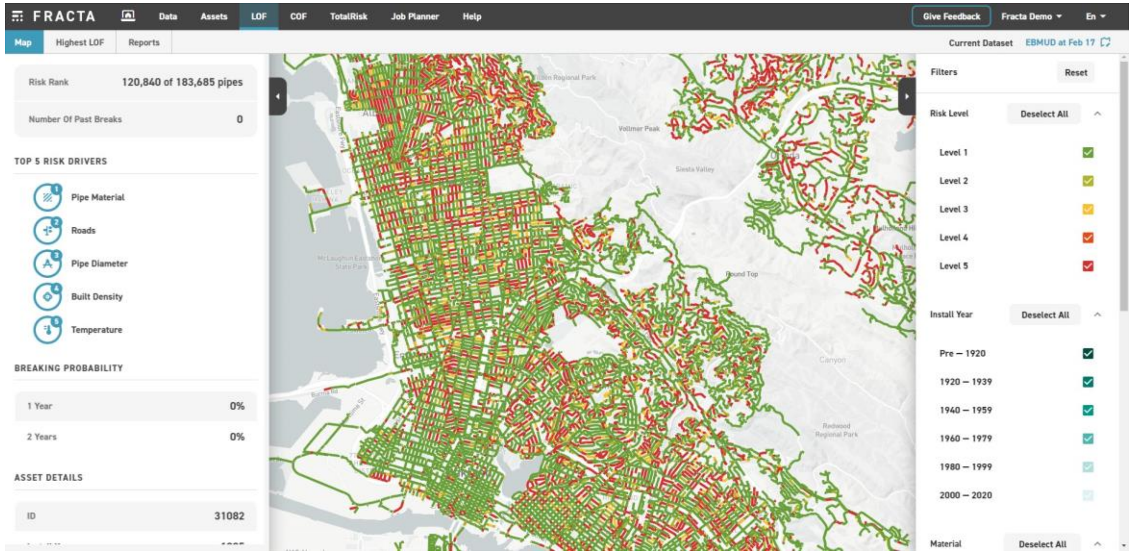
3. Algorithm, variables or approach can be tuned to improve correlation with **Validation data**

4. Model is then applied to Predicted Data to assign values based on trained and tuned model

Fracta Solutions Overview

- Machine Learning – based software solution that assesses and gives every pipe segment a Likelihood of Failure (LOF) probability score.
- The Fracta uses information from utility
  - Pipe asset
  - Break history
- Combines that with various other data sources to run through Fracta's proprietary algorithm
- leverage algorithms to cover gaps in data at smaller, less sophisticated utilities

Fracta is Desktop Condition Assessment 'on steroids'



Advantages of Fracta Machine Learning

Easy and Flexible

- No hardware required
- Accept any format of pipe and break history data

Fast

- Results come in 4 – 8 weeks
- Results can be updated whenever desired

Constant Improvement

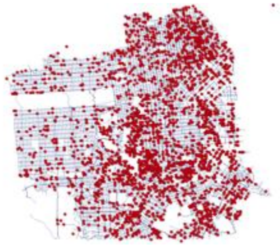
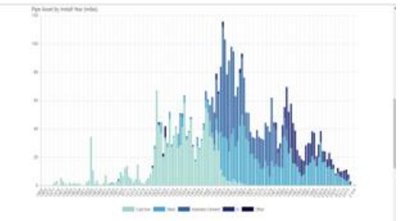
- New features improvements regularly
- AI & ML make quarterly updates

Fracta assesses the condition and risk of water mains and determines which pipes to replace (and which not to replace).

Fracta’s Services

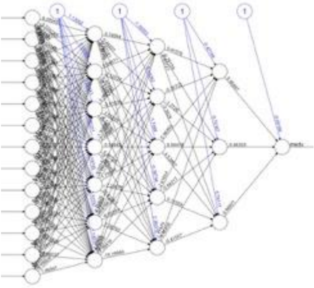
1

DATA ASSESSMENT
- Clean up and normalize utility pipe asset and break history data
- Visualize current asset state

2

MACHINE LEARNING ANALYSIS
- Join utility data to machine learning model
- Calculates LOF probability for each segment
- View or download from cloud-based SW tool




3

Desktop Software Application
- “light” GIS for interacting with results
- Additional models available, CoF, TR.
- Put results into use, interact and download.

Data Assessment

Fracta uses cutting-ege data cleaning and normalizing software techniques to ”wrangle” the data

Utility data:

- Pipe Asset Data
- Break History

Other Geospatial data:

- Collect and join with utility data

In many cases the assessment and cleaning results in **significant improvements in utility data quality**

Correcting wrong/outlier data points, filling in missing values and geocoding and correlating breaks with pipe segments

Cleaned datasets provide a great base for further analysis and Machine Learning

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Machine Learning Analysis
Variables Used

<u>1. Variables directly from Utility Data</u>
- Basic Pipe Parameters
  - Length, Material, Diameter, Install Year, Coating, Lining etc.
- Variables from Break history
  - Break info assigned to pipe segment

<u>2. Variables derived from Utility Data</u>
- Age-derived variables
- Pipe density
- Leak density (time & location)

> Adds potential for non-linear correlation from utility data

<u>3. Variables from Geo Data</u>
- USGS/USDA Soil Properties
- Shoreline proximity
- Elevation/Slope
- Weather history
- Transportation
  - Roads, Rail (BART etc.)
- Population density
- Urban/suburban/rural

<u>4. Variables derived from Geo Data</u>
- Min/max/mean distance
- Density of soil type changes

Machine Learning finds CORRELATION, not causation from the variables
Using ~140 of the 800-1000 variables in the v1.0 of the Fracta Machine Learning Algorithm

	Standard LoF Models	Machine Learning LoF
DATA VARIABLES	Limited: age, breaks	• Many, 160 in total • Breaks, Attributes, Environment, City/Parcels, Flow/Pressure, etc.
NETWORK EFFECTS	Limited, each city has its own data	• Leverages relevant data from a Utility Network
MODEL IMPROVEMENT	Static Manual re-do	• Self-Learning with continuous improvement
WEIGHTS-BASED MODELS	Subjective weights	• Objective analysis results that reflector the best available data

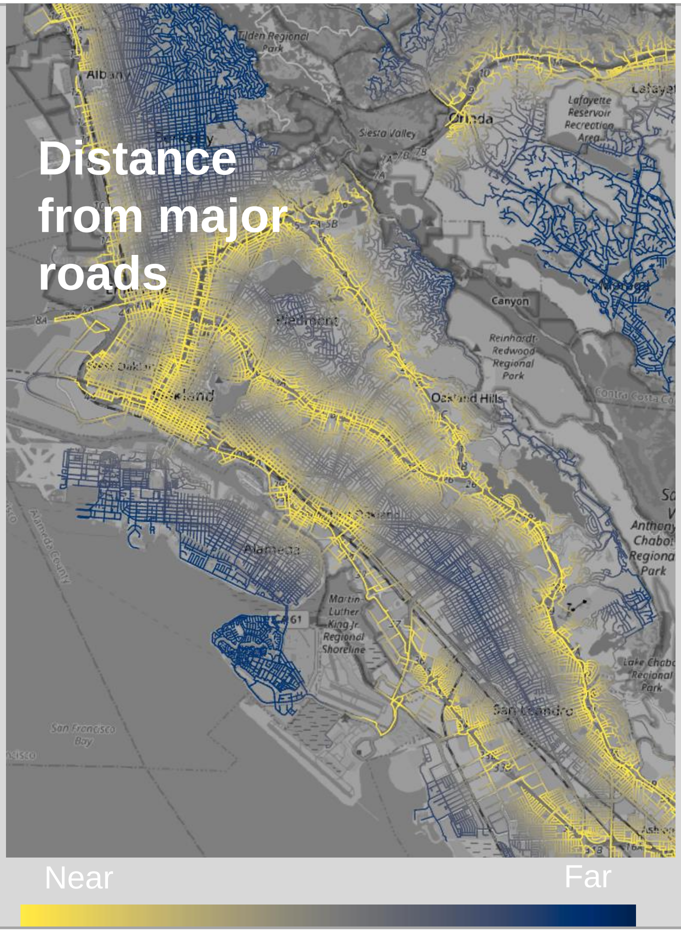
Higher Accuracy

Useful Predictions

Environmental Data, Visualized

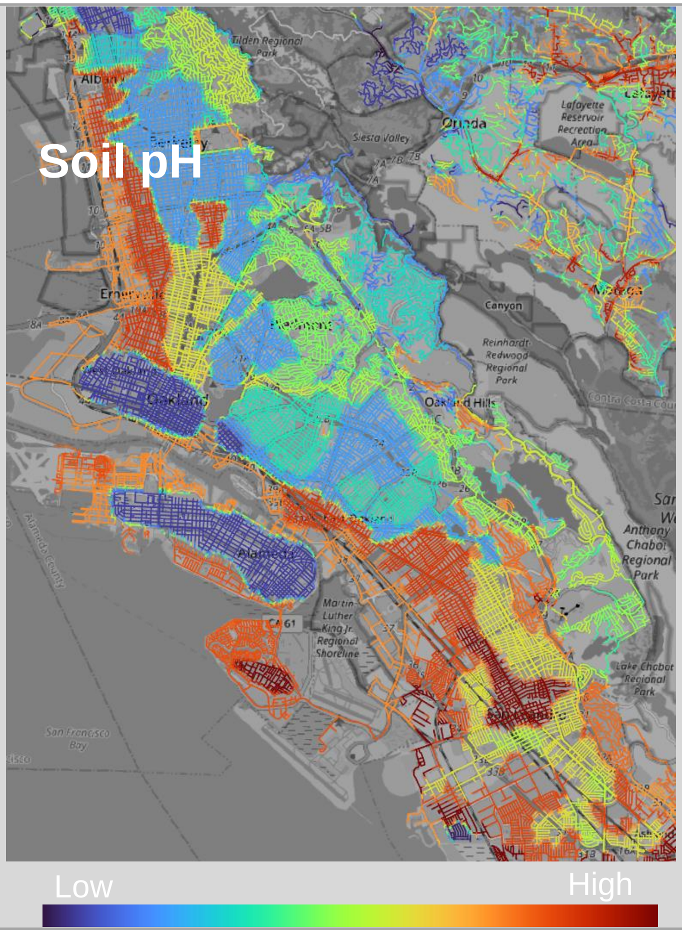
As an example, here are two visualizations showing how some environmental data were linked to EBMUD's network.

Example subset of environmental features (distance from major roads + soil pH)

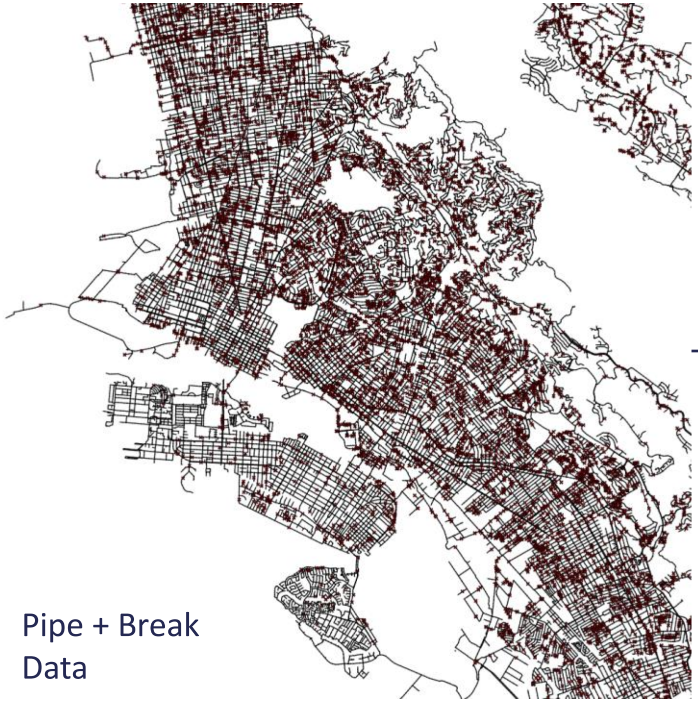


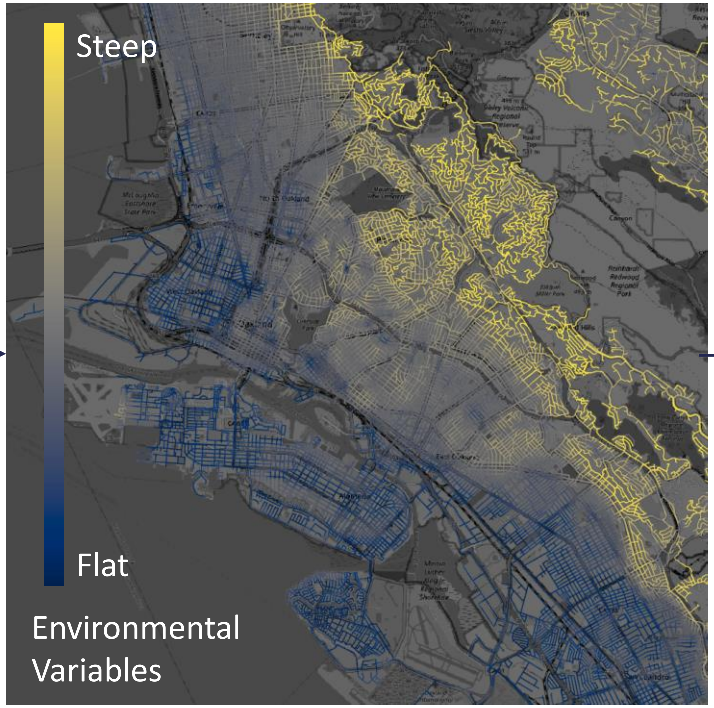
The model learns how these variables interact with each other + each pipe's attributes to inform past breakage patterns.

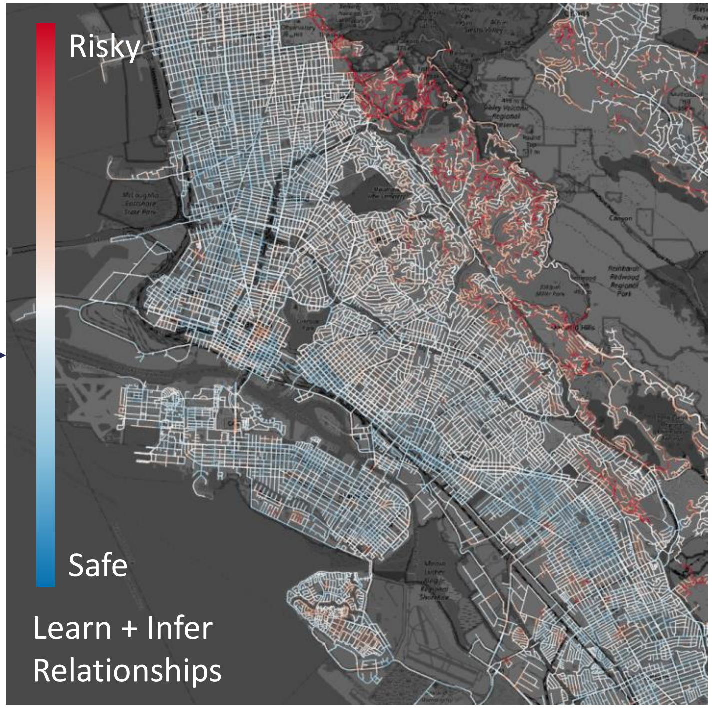
Fracta's goal: Learn from these hidden patterns to predict which pipes are most likely to break in the future.



HOW IT'S DONE

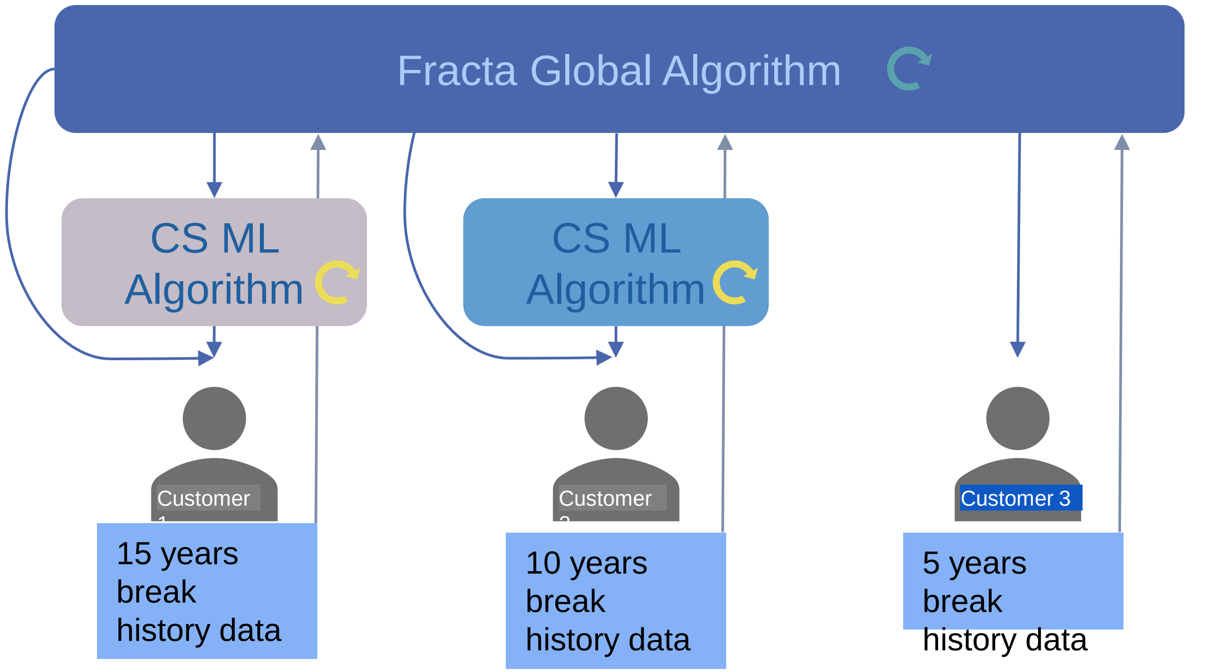

Pipe + Break
Data


Steep
Flat
Environmental
Variables


Risky
Safe
Learn + Infer
Relationships

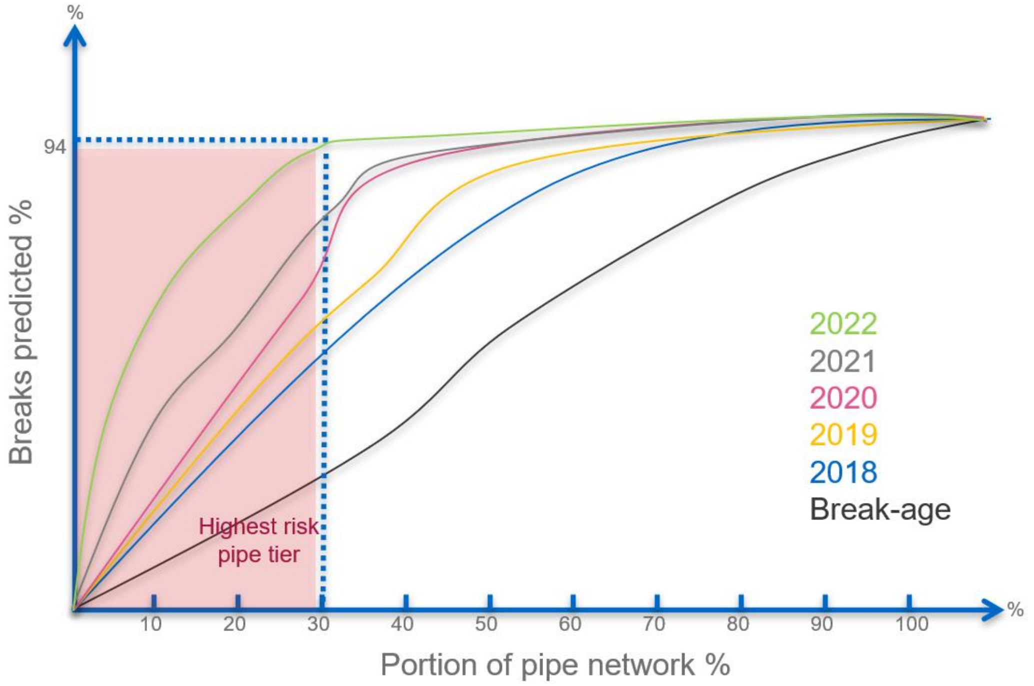
Fracta Model

More data for better AI



In a time shift study, break history data is an important deciding factor. More break data allows Fracta to deliver an advanced customer specific ML algorithm to deliver the most accurate customer solution, thus best value, for the following two years.

Continuous improvement of Machine Learning Model



- Fracta model improves year to year. In 2021, 75% of breaks were correctly predicted in the highest risk pipe tier. In 2022, 94% of breaks were correctly predicted.
- Since 2018, Fracta model has been recording better than customers age-based model the breaks in the top 30% risking area of the networks.

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LIKELIHOOD OF FAILURE (LOF)

LOF is calculated for the next 5 years

LIKELIHOOD OF FAILURE

	LOF	
	Value	Rank of 122,796 pipes
1 Year	40.57%	4,880
2 Years	64.68%	4,880
3 Years	79.01%	4,880
5 Years	92.59%	4,880

REMAINING USEFUL LIFE (RUL)

RUL	30.0 Years

TOP 5 RISK DRIVERS

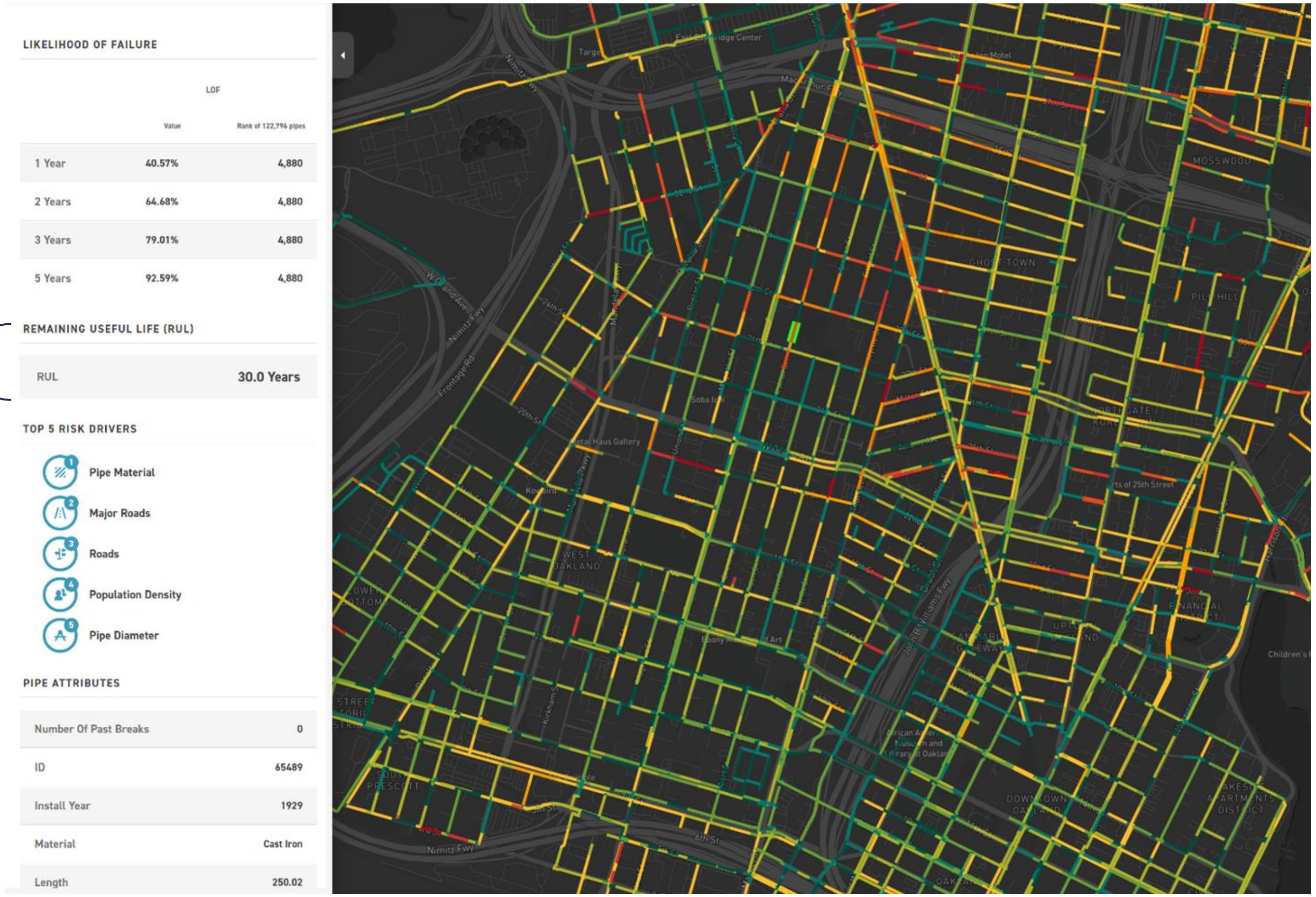
1. Pipe Material
2. Major Roads
3. Roads
4. Population Density
5. Pipe Diameter

PIPE ATTRIBUTES

Number Of Past Breaks	0
ID	65489
Install Year	1929
Material	Cast Iron
Length	250.02

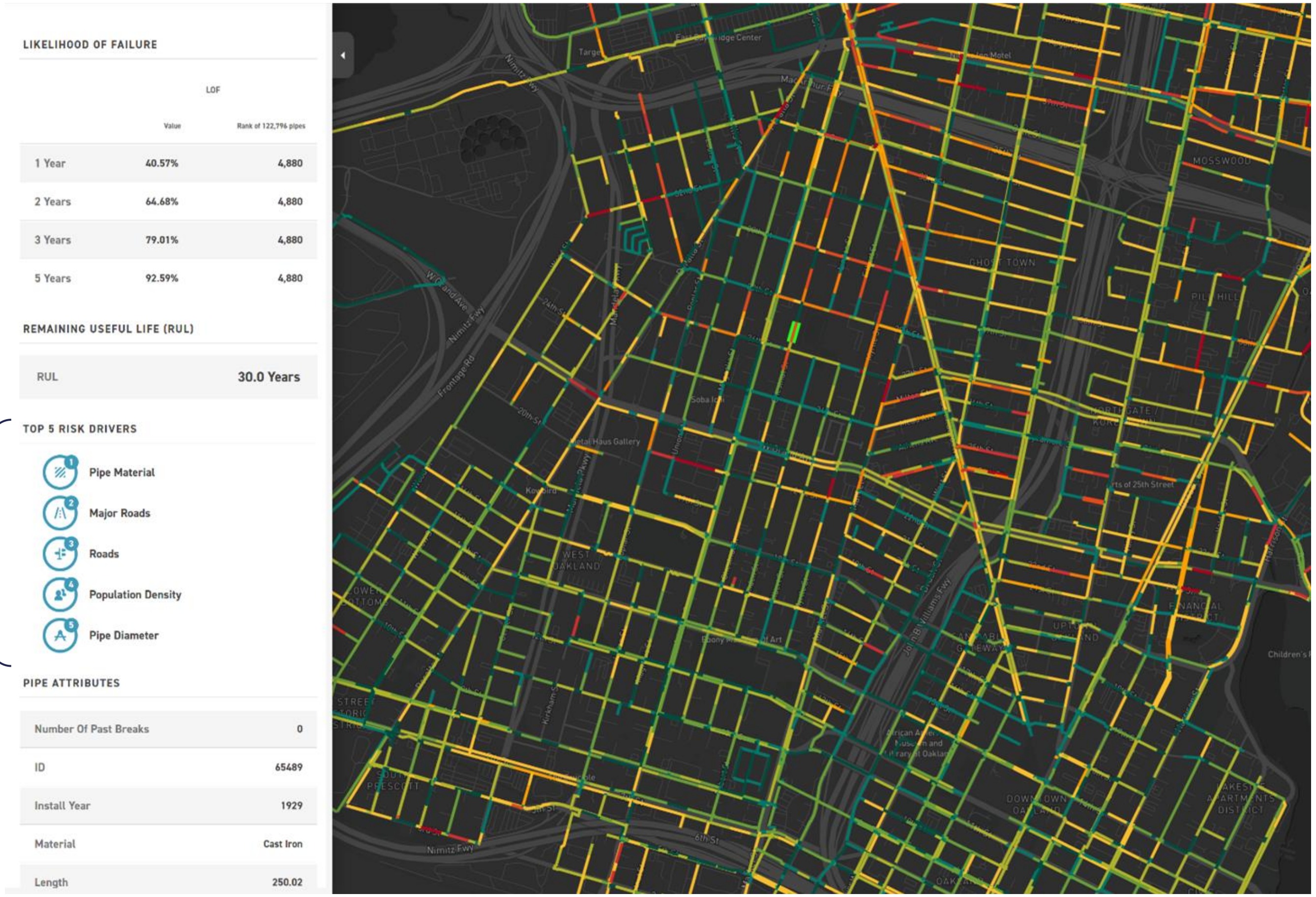
LIKELIHOOD OF FAILURE (LOF)

Remaining Useful Life (in years)



LIKELIHOOD OF FAILURE (LOF)

Top 5 risk drivers increasing the chance of pipe failure



Fracta – Partners

Over 100 utilities around the world (US, UK, Asia) have used Fracta's M.L. model to analyze more than 180,000 miles of pipe and 580,000 individual breaks.

San Francisco Water Power Sewer

DENVER WATER

ARLINGTON THE AMERICAN DREAM CITY

love every drop anglianwater

NORTHUMBRIAN WATER living water

EBMUD East Bay Municipal Utility District

CITY OF NAPA

The City of SAN DIEGO

TOHO GAS

川崎市 KAWASAKI CITY

San Antonio Water System

Boston Water and Sewer Commission

CITY OF SANTA CRUZ Water Department

OSAKA CITY 大阪市

Städtische Werke Netz+Service

THE CAPITAL CITY OF KANSAS GOLDEN CITY TOPEKA

川崎市 上下水道局 Waterworks Bureau, City of Kawasaki

KOBE UNESCO City of Design

Use Case - Johnstown

<u>Network properties:</u>

- Length: 303 Miles
- Average consumption: 6.5 MGD
- Summer consumption: 10 MGD
- End Customers: 21 000

<u>Results:</u>

Within the first seven months of using Machine Learning LoF results, GJWA was able to correctly identify **75%** of the hidden leaks in 15 pipe segments, saving the utility **20%** in Non-Revenue Water loss.

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KURITA

FRACTA CASE STUDY

Using Artificial Intelligence to reduce non-revenue waterloss in Pennsylvania

THE UTILITY

GREATER JOHNSTOWN WATER AUTHORITY

The Greater Johnstown Water Authority (GJWA) in Pennsylvania was incorporated under the Municipality Authorities Act in 1964 by the city of Johnstown and boroughs of Westmont and Southmont as a joint

municipal authority to provide potable water to the Greater Johnstown area.

GJWA serves a base of more than 21,000 customers through 303 miles of water distribution pipes. The average consumption is approximately 6.5 million gallons per day (MGD) with peak consumption in the summer at 10 MGD. It operates three dams, two wells, a water

treatment plant at Riverside, a water treatment plant at the Saltlick Reservoir, and numerous storage tanks and pump stations. pipe being 75-100 years old.

21,000 CUSTOMERS

303 MILES

6.5 MGD AVERAGE CONSUMPTION

10 MGD SUMMER CONSUMPTION

THE CHALLENGE

REDUCING NON-REVENUE WATER LOSS WITH LIMITED RESOURCES

Reducing Non-Revenue (NRW) water loss is challenging since it is not apparent where it is happening within the network, or what could be causing it.

While pumping stations can signal when water loss may be happening somewhere in the distribution network, the precise location of that loss is not known. Sending a crew out to hunt for the source of loss can be time-consuming, costly, and often inconclusive.

Over time, leaks can become breaks which present an even greater risk to community safety and business operations. As a challenge, managing pipeline integrity is as important to address as it has been difficult to address—up until now.treatment plant at Riverside, a water treatment plant at the Saltlick Reservoir, and numerous storage tanks and pump stations. pipe being 75-100 years old.

<u>Case study Greater Johnstown Water Authority</u>

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