Utility Analytics® WEEK

October 18-20, 2022

San Diego, CA

UtilityAnalyticsWeek.com

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Looking at Data in 3D

Guillermo Aleman, Manager Technology and Innovation, Florida Power & Light

Guillermo Aleman

- Manager, Technology and Innovation at Florida Power & Light
  - 21 years of utility experience
  - Three U.S. utility patents
  - Lead smart grid data strategy for Power Delivery
    - Advanced failure and outage prediction
    - Situational intelligence/awareness
    - Data analytics

NEXTera® ENERGY

NEXTera® ENERGY RESOURCES

FPL®

- World's No. 1 producer of renewable energy from the wind and sun
- No. 1 on Fortune's "Most Admired Companies" list in electric and gas utilities industry for 15 of last 16 years
- Florida-based with operations or development projects in 49 states

FPL®

FPL serves 5.7 million customers in 43 counties

9,174 **miles of transmission lines**
77,424 **miles of distribution lines**
832 **substations**
82,668 **transmission structures**
1.4 million **distribution poles**
1.1 million **transformers**
35,550 **square miles**

(Figures as of January 2022)

FPL is a clean energy and sustainability leader

Consistently one of the **cleanest** electric utilities in the United States

CO_2 emissions profile **24% better than national average**

Eliminated coal from Florida power plant fleet

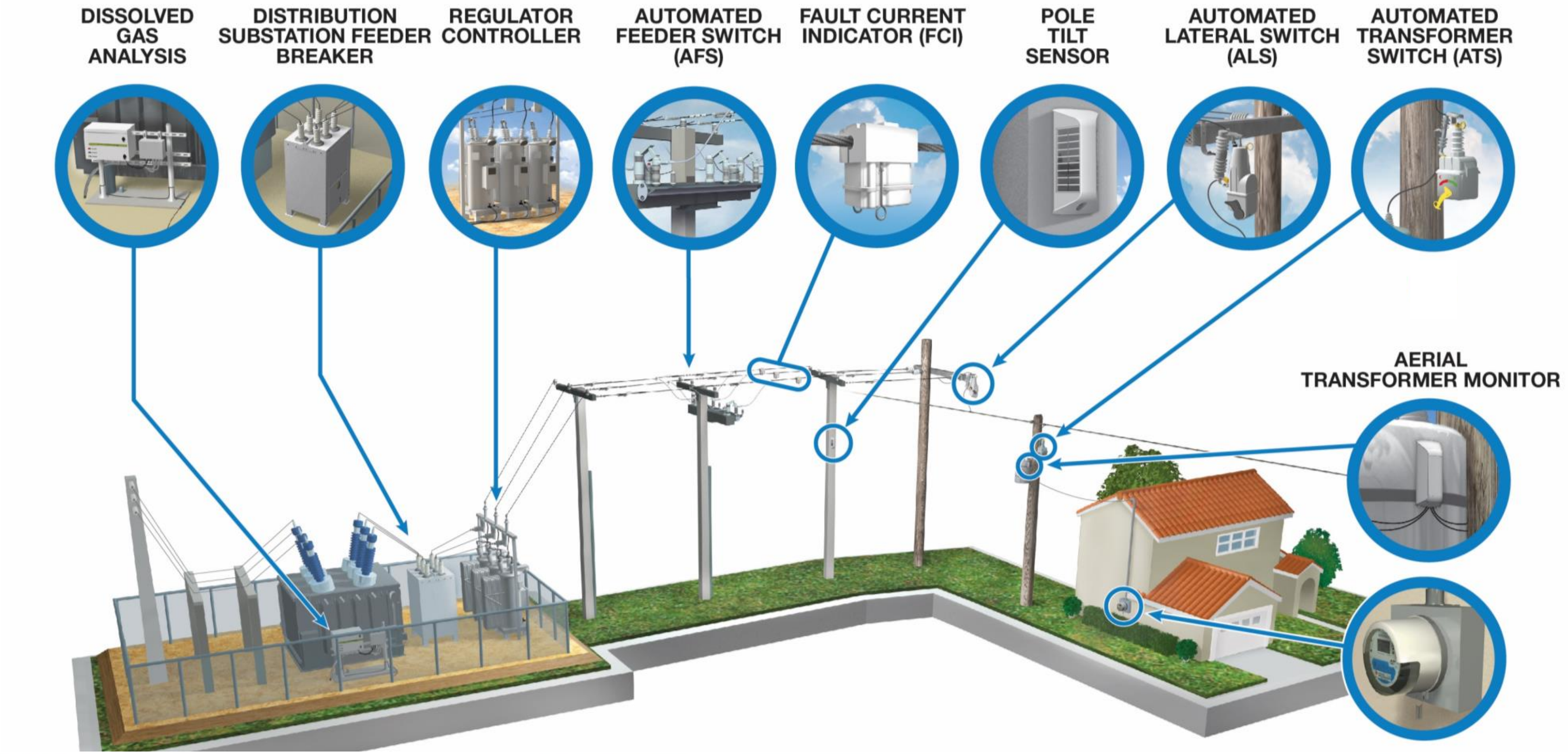
30 million solar panels by 2030

Largest community solar program in the U.S.

Building the **world's largest solar-powered battery**

Exploring **innovative green hydrogen technology**

Smart Grid sensors at FPL



What FPL can do with data today

More than 4,000 service tickets proactively predicted

More than 22,000 tickets proactively canceled

More than 27,000 tickets created with no customer calls (6% restored before customer calls)

More than 900 transformers proactively replaced

Advanced fault mapping

What’s the secret?

It’s  hat the
dat rs!

Data science process steps

- **Collect**: Gather data from multiple sources
- **Discover and Profile**: Understand the data and how to prepare it
- **Cleanse**: Remove errors
- **Structure**: Organize the data
- **Transform and Enrich**: Augment and add new fields
- **Validate and Publish**: Verify results and make available to users

What is data?

- Data is a collection of information stored somewhere
  - Spreadsheets
  - Databases
  - On paper
  - In somebody's head

Dataset 1	Dataset 2
20	11
21	16
22	19
25	23
29	32
34	46

Why do we want it?

- Data is created to represent attributes about real world things, experiences, interactions or results
- We used it to make decisions
  - Daily weather
  - Scientific results
  - Surveys
  - Sensor data
  - Sales

We tend to use the data at face value

The data on the spreadsheet certainly tells you a lot about what you want to know. Sometimes it's all you need.

However, all data is multi-dimensional and has hidden features

- Face value
- Design/settings
- Physical limitations
- Original purpose
- Implied data
- Derived data

You can discover the extra dimensions by asking the right questions

- What does this data mean?
- How is it captured?
- Why is it captured?
- What insights does the subject matter have?

Simple case study: widget paint process

- At face value, there is not a lot we know about this process
  - Some fail
  - Some pass
  - Some red
  - Some blue

Serial Number	Paint Color	Quality
A12177521P1	Red	Fail
A06117522P2	Blue	Pass
A07147322P1	Red	Pass
A01087322P2	Blue	Fail

What else can we derive from this data

Derived data = can be pulled from other characteristics of the data	• SN provides: Date, factory data, paint booth number
Implied data = can be assumed from other characteristics of the data	• Pass/fail has criteria that can be added • SMEs provide insight into what might drive failures, like air temperature

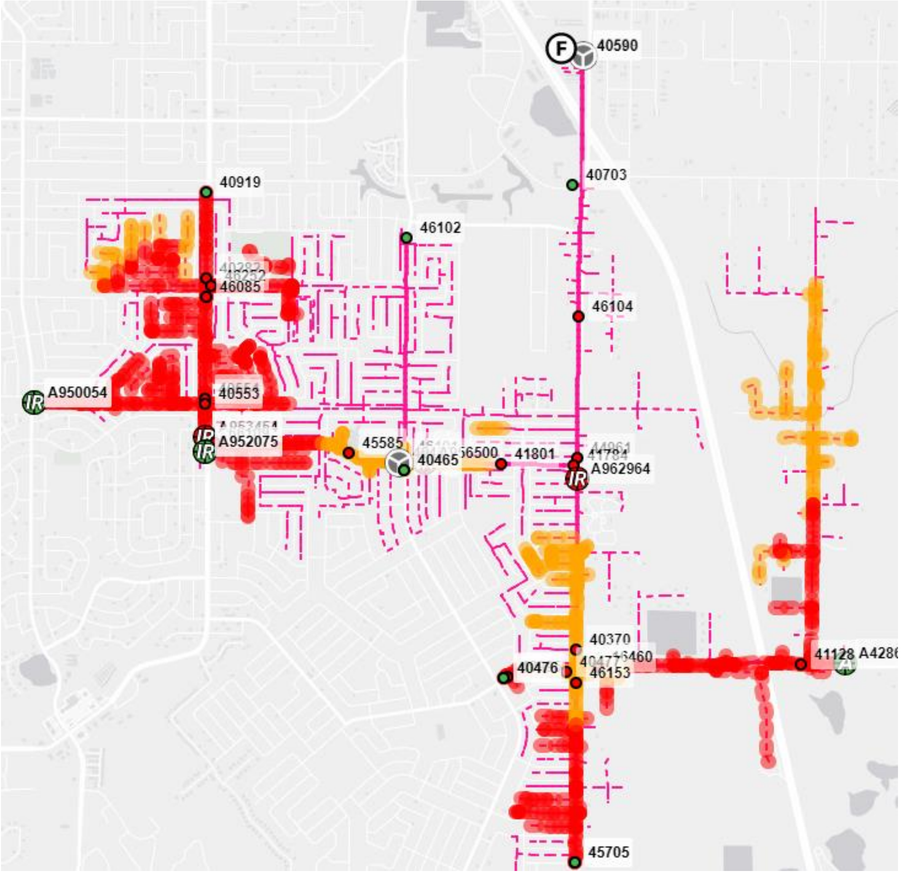
New data set with additional features

Serial Number	Date	Factory #	High Temp	Humidity	Paint Booth	Paint Color	Quality	Thickness
A12177521P1	12/17/21	75	37	62%	1	Red	Fail	> 5m
A06117522P2	06/11/22	75	78	75%	2	Blue	Pass	>1M <5M
A07147322P1	07/14/22	73	82	78%	1	Red	Pass	>1M <5M
A01087322P2	01/08/22	73	32	65%	2	Blue	Fail	>5M

Looking at data as multi-dimensional will produce larger, more complete data sets that allow for stronger models and analysis

Utility case study: FPL fault location

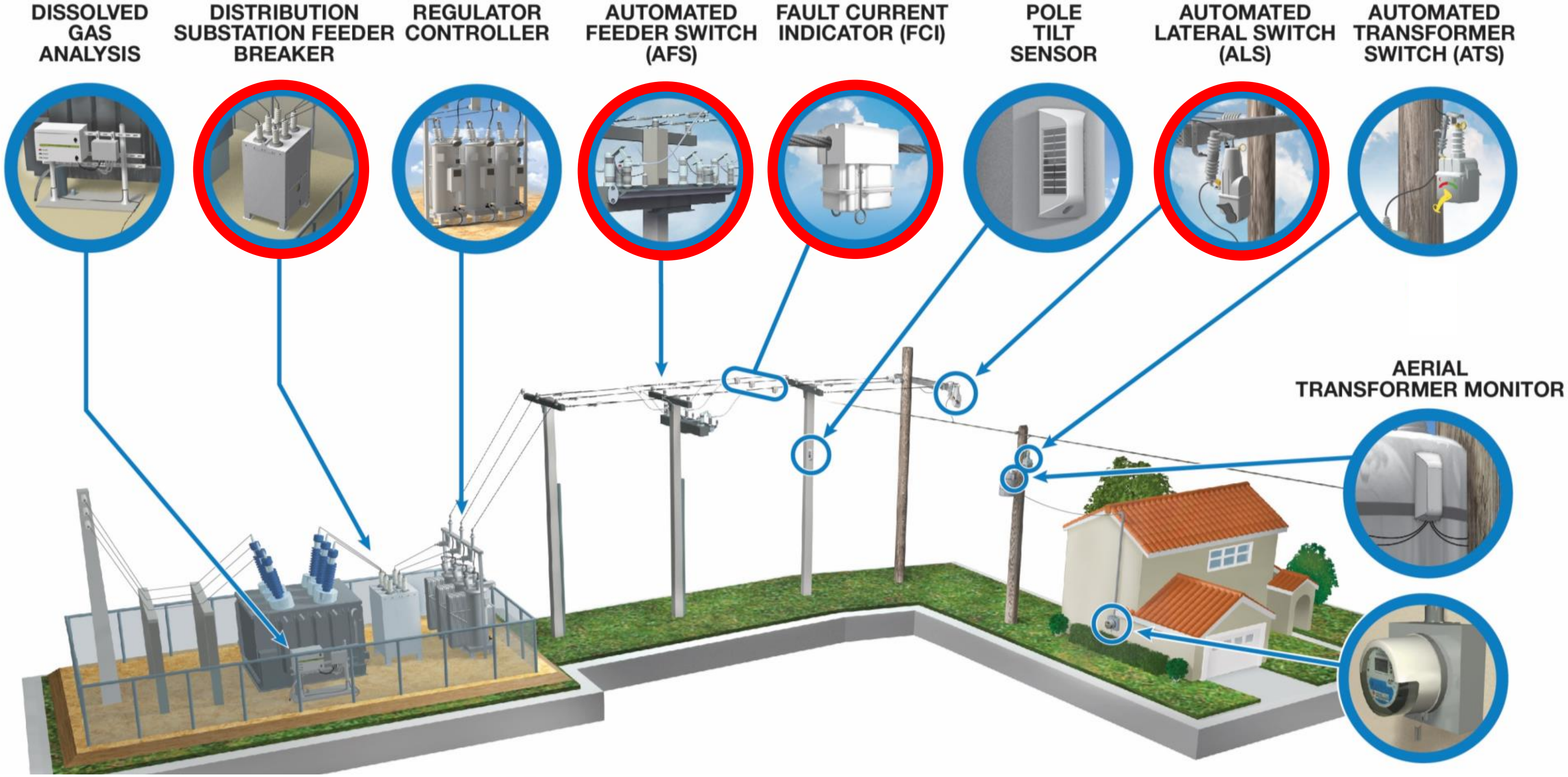
- Goal: Determine where temporary faults were occurring on our circuits
  - Feeder backbone vs. lateral circuit
- Available data
  - Feeder telemetry data
  - Automated feeder switch data (AFS)
  - Fault current indicator data (FCI)
  - Ticket data
  - Topology information



Results of unsupervised machine learning models

- Best models provided accurate results for feeder vs. lateral 51% of the time
  - Used FCI and AFS data to narrow down the map location
  - Used unsupervised models to predict Feeder vs laterals
  - ~4/10 times we rolled a truck to the wrong place

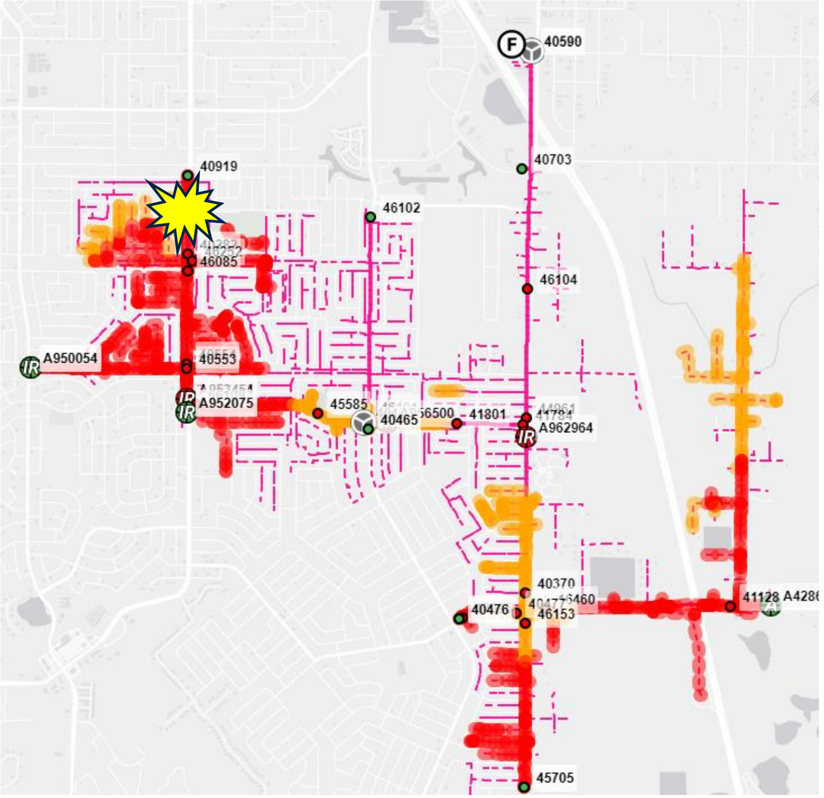
Smart Grid sensors at FPL

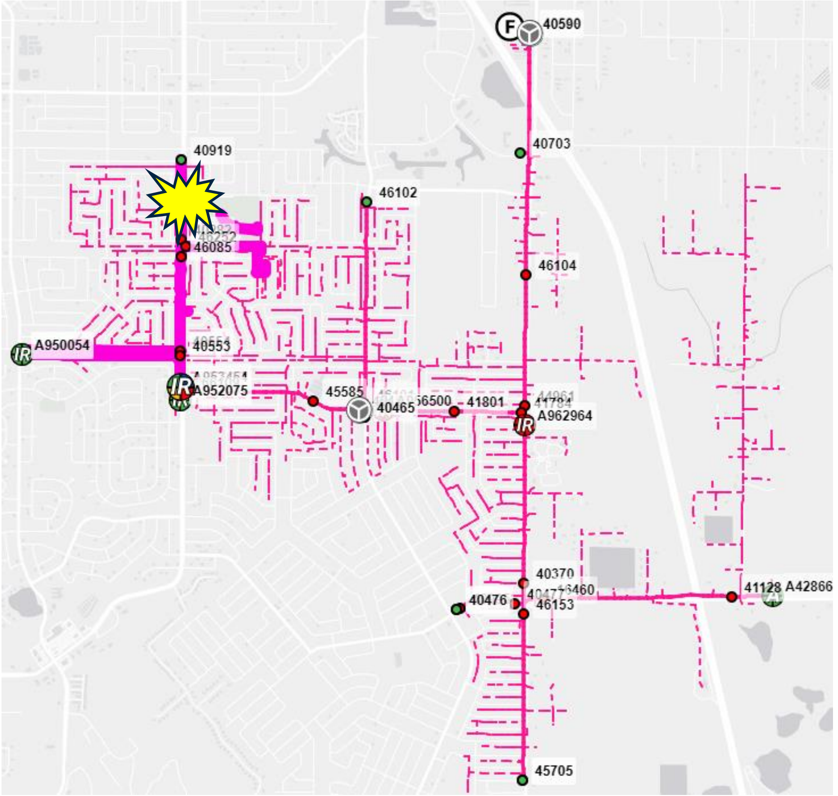


The hidden obvious

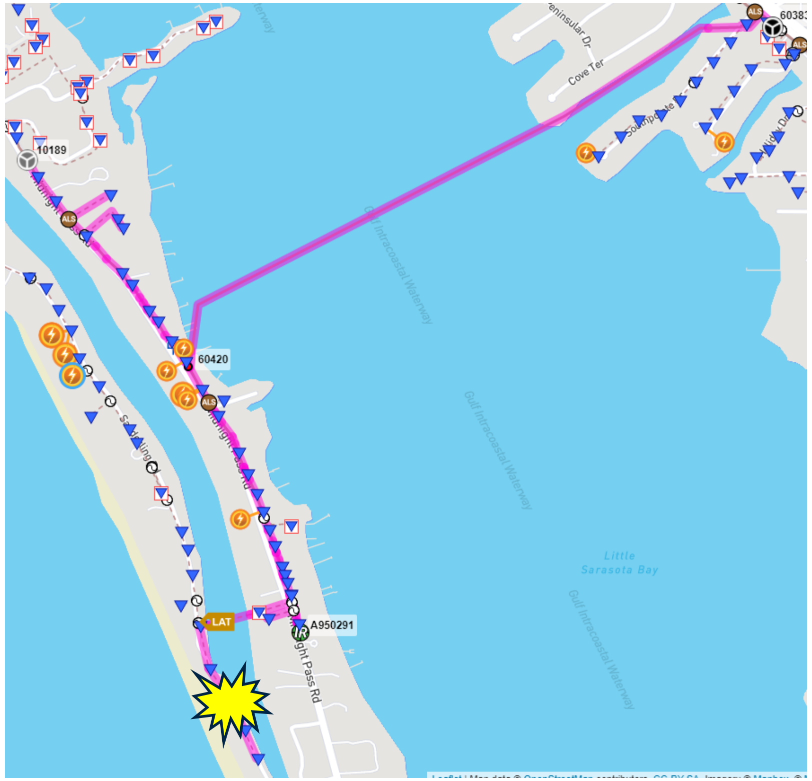
- Protection scheme knowledge
  - Our protective equipment is programed to respond to faults and to coordinate with other equipment down stream
  - The behavior of our protective equipment is recorded in our SCADA system
  - Faults should be cleared by the nearest upstream device
    - If your breaker operates, it most likely cleared a backbone fault
    - If your breaker did not operate, something else did

Case study results – Example 1





Case study results – Example 2



The answer was in the data…we just needed to know how to interpret it!

Local knowledge of our system was key to exploring new algorithms

- Subject matter experts provided insight into protection schemes

We Built in-house situational intelligence software application

- Agile process to quickly validate and improve

Determined if faults were occurring on feeder or lateral line with >95% accuracy

Questions?