

Machine Learning for Agriculture

Emmanuel Blanchard
Snr Application Engineer



([University of Cambridge](#))

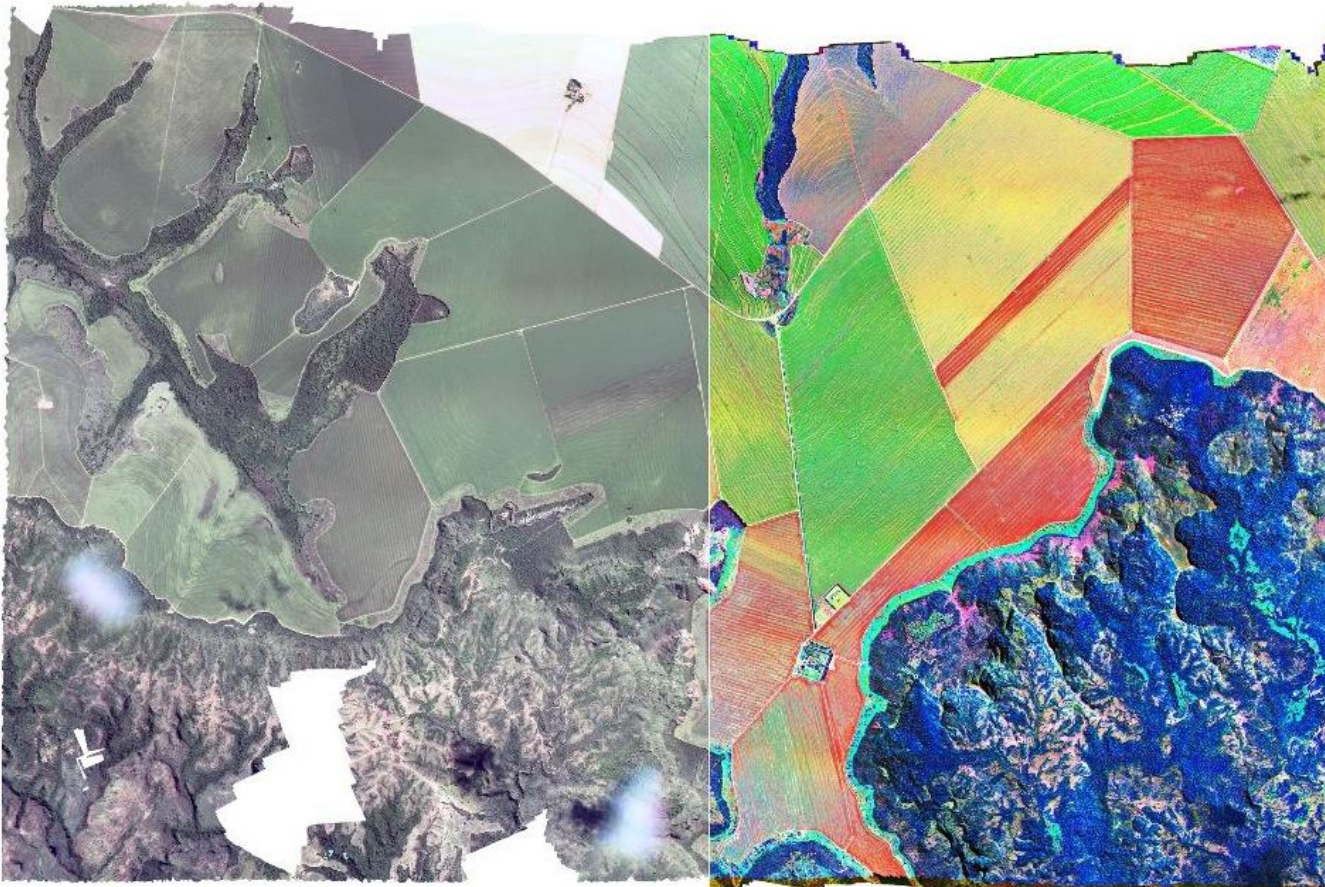


([allmanhall.co.uk](#))

ML is beginning to match or exceed human performance

Imagine what you could do with it

Getting into the Weeds:
Farmers Rely on Artificial Intelligence to Boost Production



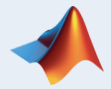
“ We use algorithms to discriminate early-season vegetation that is barely visible due to its size, and generate a health score and anomaly algorithms that identify unusually high or unusually low stress ... These algorithms generate metrics so that farmers can rank and prioritize the actions they need to take”

- Greg Rose, VP of Product, IntelinAir

Image courtesy of Gamaya

[Link to MathWorks story](#)

Agenda - Machine Learning (ML) for Agriculture



How do you get started quickly?

- How to make your ML projects successful?
- What does success look like?
- Conclusion / How we can help you?

50% of organizations are at least beginning to plan for AI

Source: *Real Truth of Artificial Intelligence* by Whit Andrews. Presented at Gartner Data & Analytics Summit 2018

... but they are facing a main obstacle:

 menu

GOVERNMENT NEWS
News, views and analysis of government in Australia

TECHNOLOGY  Amy Cheng

Supply of AI workers failing to meet demand

18 November, 2019

The *Artificial Intelligence: Solving problems, growing the economy and improving our quality of life* report found that Australia currently has 6,600 AI specialist workers, which is up from 650 AI workers in 2014 and is predicted to grow.

However it is well short of the up to 160,000 workers that may be required in the next ten years.

<https://www.governmentnews.com.au/supply-of-ai-workers-failing-to-meet-demand/>

What Are The Challenges To AI Adoption In Agriculture? 8 Experts Share Their Insights

Brad Constantinescu, President and CTO of **Stone Soup Tech**



“AI engineers know little about agriculture, the problems and the opportunities in this field”

Gary Morgan, Director of **MPT Innovation Group**



“The majority of farmers don’t have the time or digital skills experience to explore the AI solutions space by themselves.”

<https://www.disruptordaily.com/ai-challenges-agriculture/>

You don't have to be a data science expert



You are the domain experts

Shortage of data scientists

You need the right tools

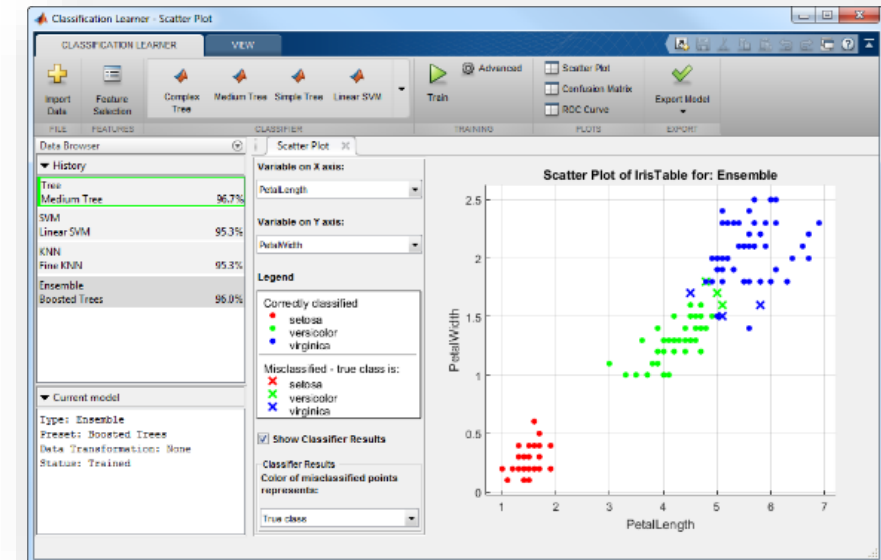
Lund University Develops an Artificial Neural Network for Matching Heart Transplant Donors with Recipients



“I spend a lot of time in the clinic, and don't have the time or the technical expertise to learn, configure, and maintain software. MATLAB makes it easy for physicians like me to get work done and produce meaningful results.”

- Dr. Johan Nilsson, Skåne University Hospital, Lund University

Later in this webinar:



Machine Learning Made Easy for Entire Workflow using MATLAB

Access and
explore data

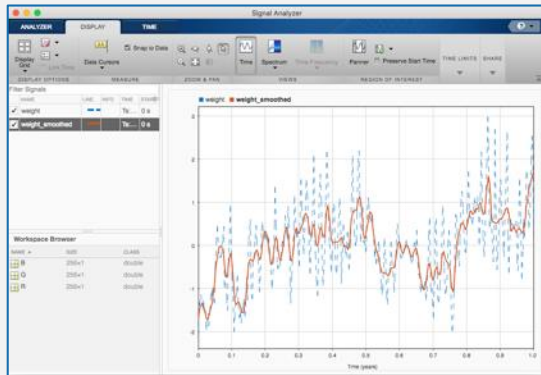
Preprocessing

Feature
Engineering

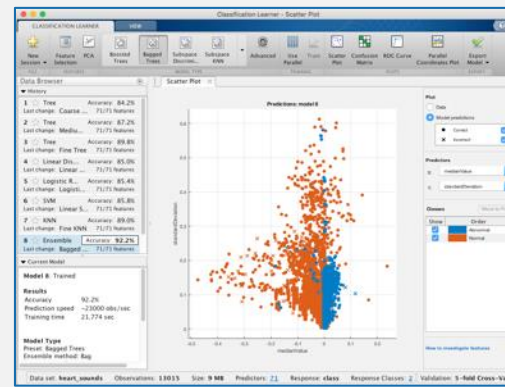
Model
Training

Model
Tuning

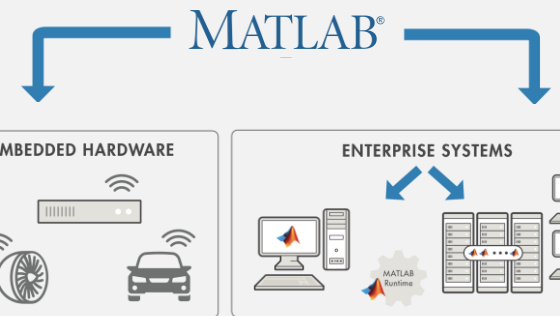
Integrate
Analytics



Datatypes and tools for missing data, outliers, time-alignment, etc.



Machine Learning apps



C/C++ Code Generation and
Enterprise IT Integration

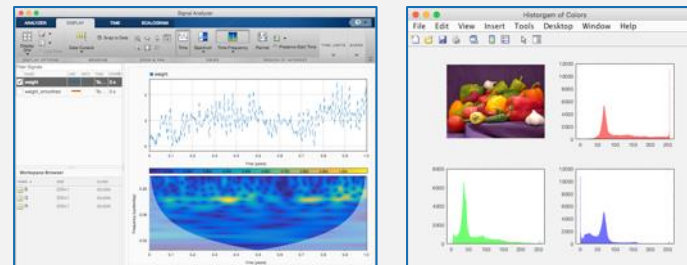
Import - (Applications\MATLAB_92093b\app\toolbox\matlab\import\outages.csv)

Column delimiter: Range: A1:F1469 Output Type: Table

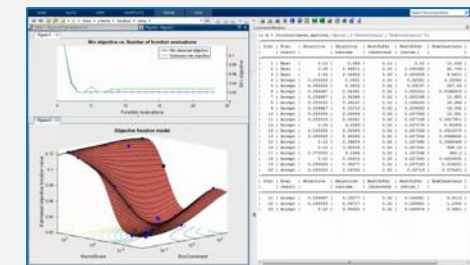
Fixed Width: Variable Names Row: 1 Text Options: Import

Region	OutageTime	Loss	Customers	RestorationTime	Cause
SouthWest	2002-02-01 12:18	418.977218	182019.482	2002-02-07 18:50	winter storm
SouthEast	2003-01-23 00:49	510.1199497	212015.3001	2003-02-07 18:50	winter storm
SouthEast	2003-02-07 21:15	289.4035493	142918.6282	2003-02-17 08:14	winter storm
West	2004-04-06 05:44	414.8053124	340371.0838	2004-04-06 06:10	equipment fault
MidWest	2002-03-18 06:18	186.4367788	212754.0	2002-03-18 10:54	attack
West	2003-06-18 02:49	0	0.0	2003-06-18 10:54	attack
West	2004-06-20 14:39	211.2947226		2004-06-20 19:16	equipment fault

Text files, spreadsheets, databases, binary
files, data feeds, web, cloud storage



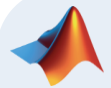
Domain-specific techniques for
Signals, Images, Video, Audio, and Text



Automated Parameter Tuning

Agenda - Machine Learning (ML) for Agriculture

- How do you get started quickly?



How to make your ML projects successful?

- Designing intelligent algorithms
- Using insights from domain experts
- Implementing these algorithms
- Making intelligent algorithms interactive

- What does success look like?
- Conclusion / How we can help you?

ML is more than just the intelligence of the algorithm



engadget

AI's intelligence and
stupidity in one photo
stitch fail

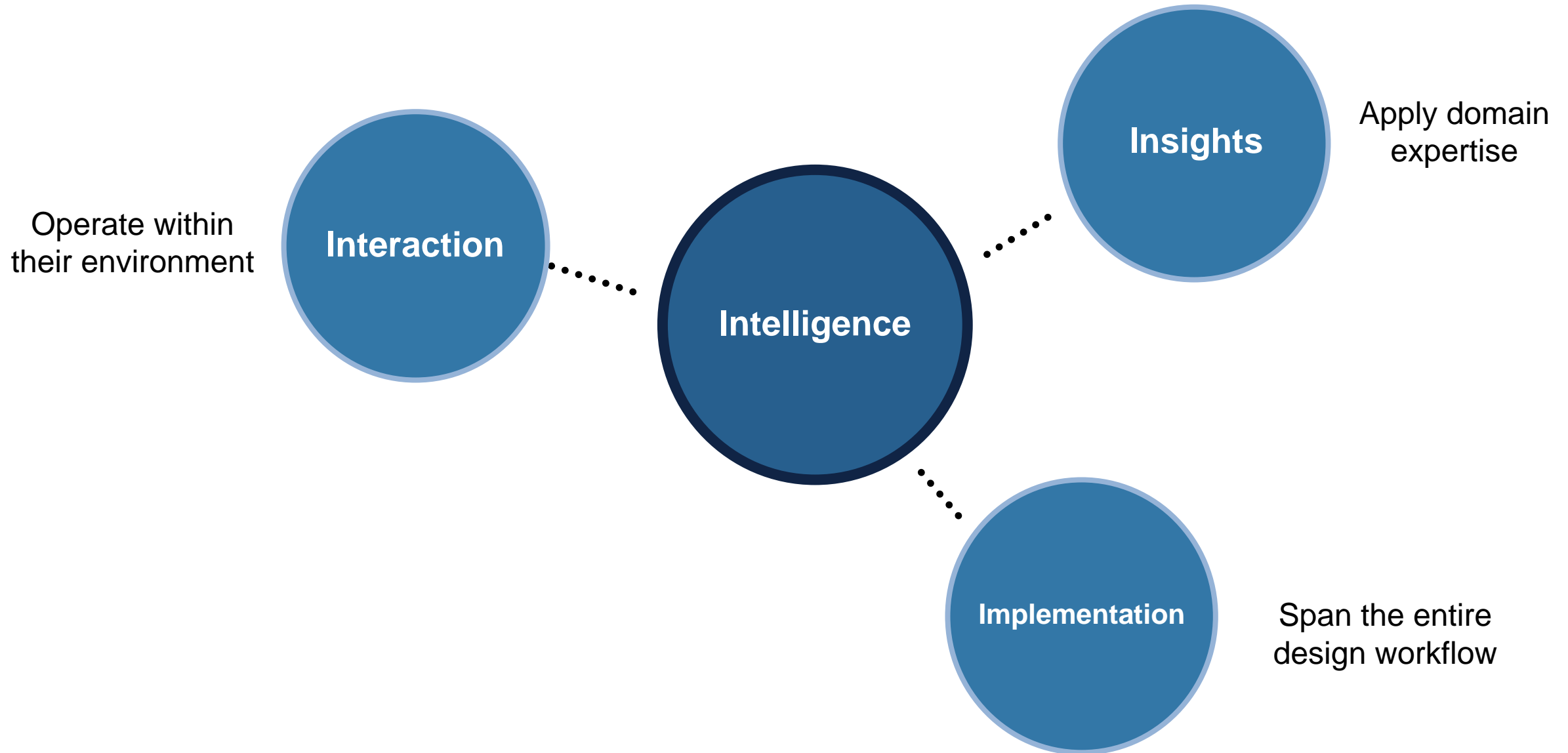
01.23.2018

THE VERGE

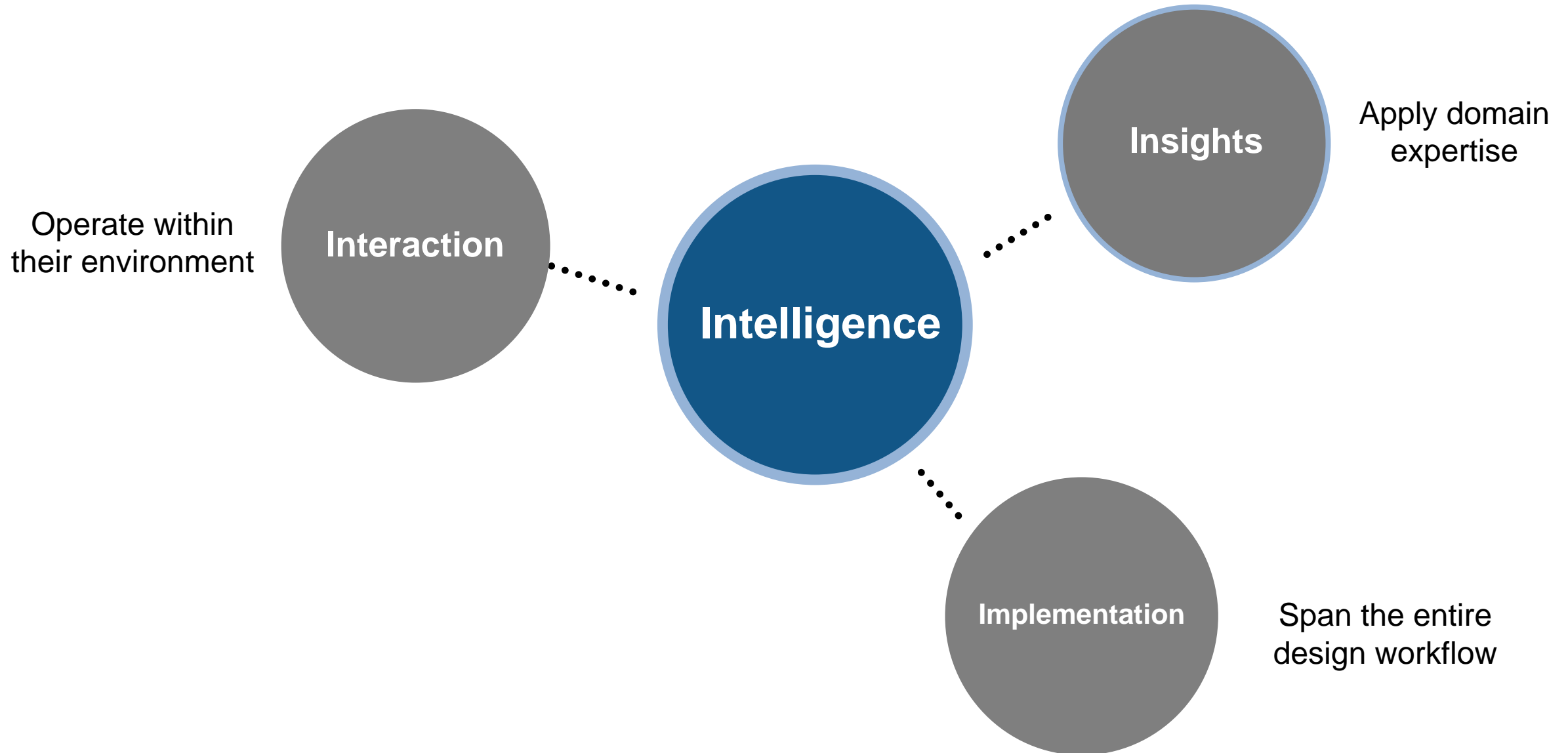
I can't stop looking at this
wonderfully bad Google
Photos panorama stitch

By Natt Garun | @nattgarun | Jan 18, 2018, 6:51pm EST

ML is more than just the intelligence of the algorithm



Being able to design intelligent algorithms is at the center of ML



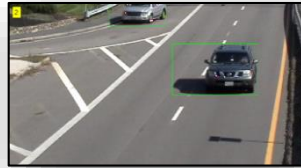
What is Machine Learning?

Ability to learn from data without being explicitly programmed

Solution is too complex for hand written rules or equations



Speech Recognition



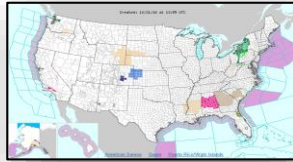
Object Recognition



Engine Health Monitoring

learn complex non-linear relationships

Solution needs to adapt with changing data



Weather Forecasting



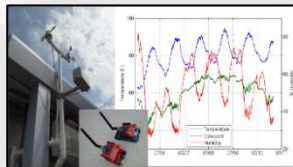
Energy Load Forecasting



Stock Market Prediction

update as more data becomes available

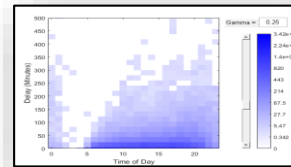
Solution needs to scale



IoT Analytics



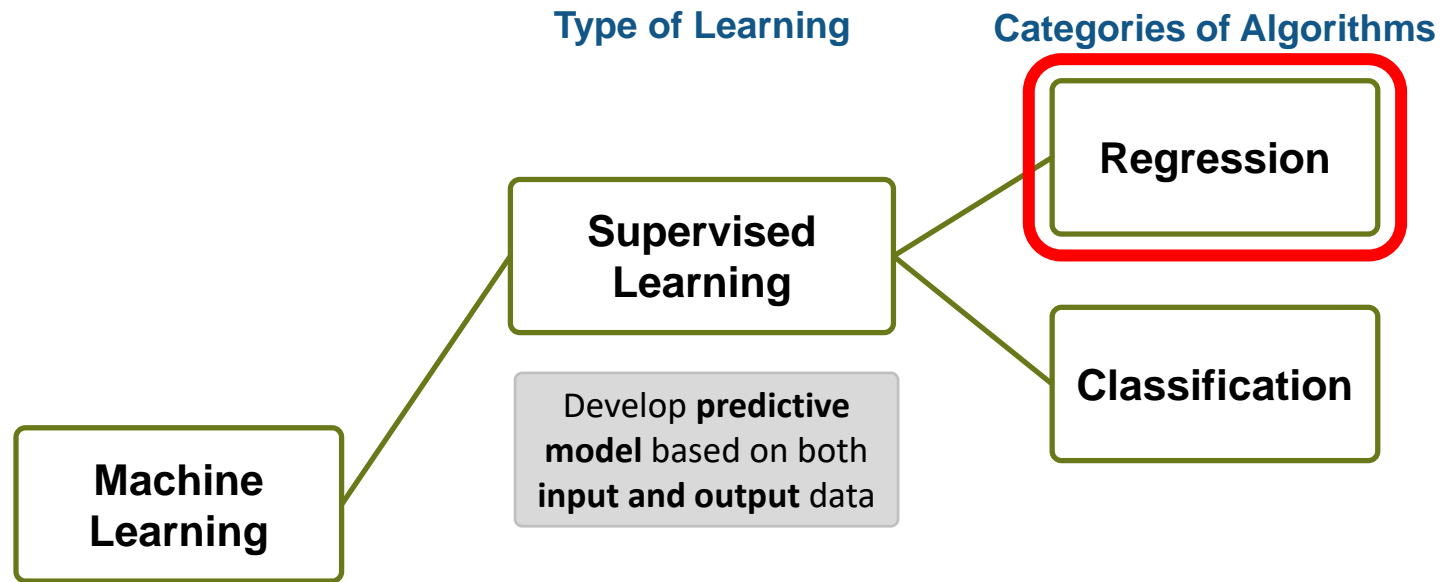
Taxi Availability



Airline Flight Delays

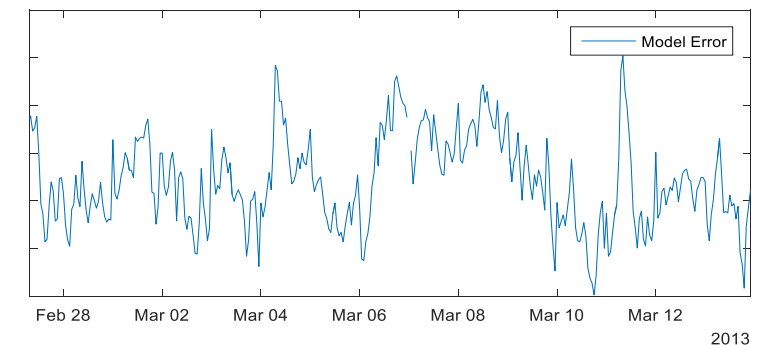
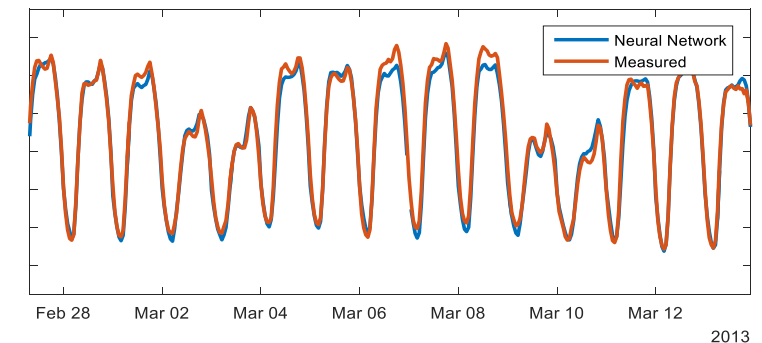
learn efficiently from very large data sets

There are different types of Machine Learning

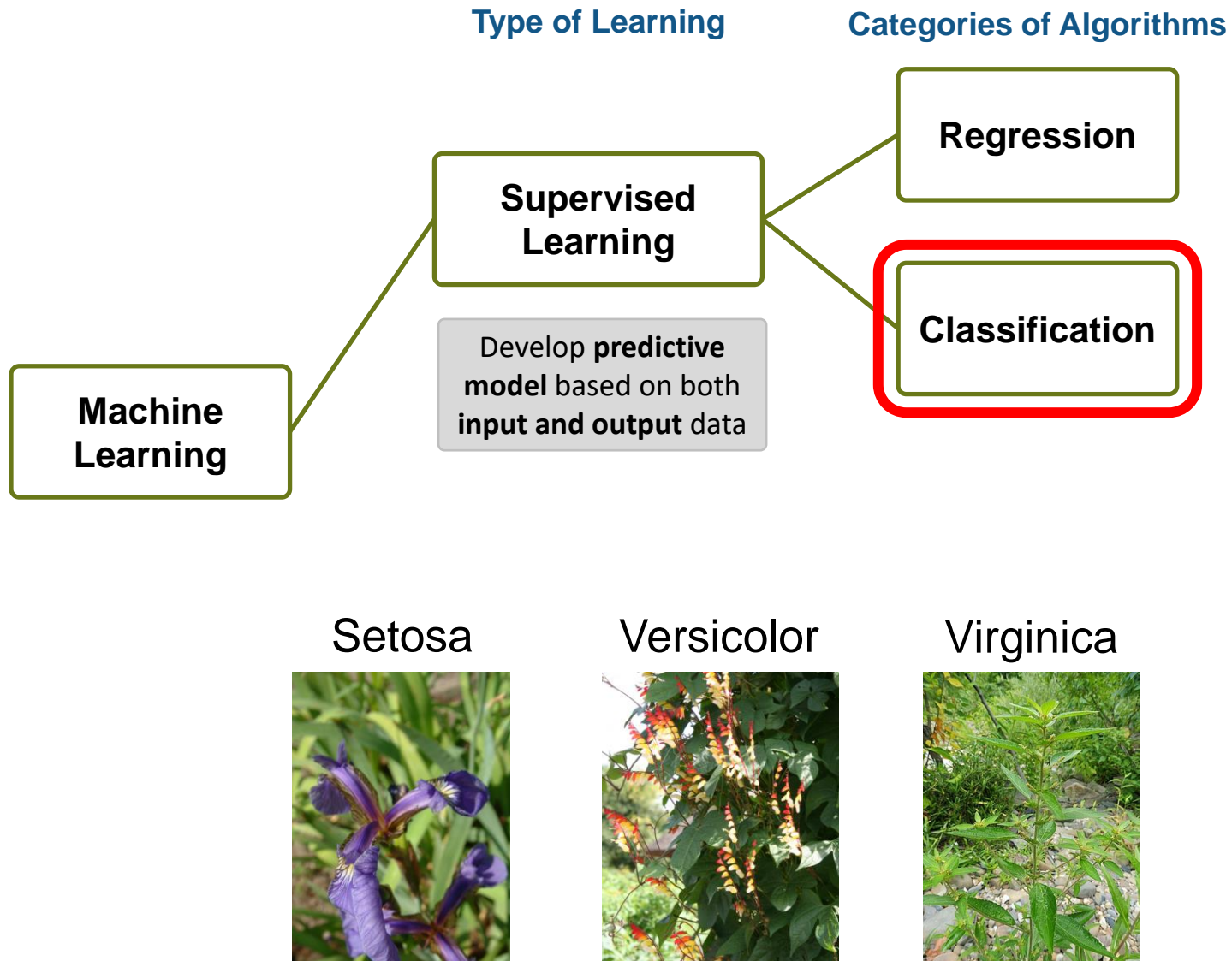


Objective:

Predict continuous variable (crop yield, rain forecast, solar radiation, ...)



There are different types of Machine Learning



Objective:

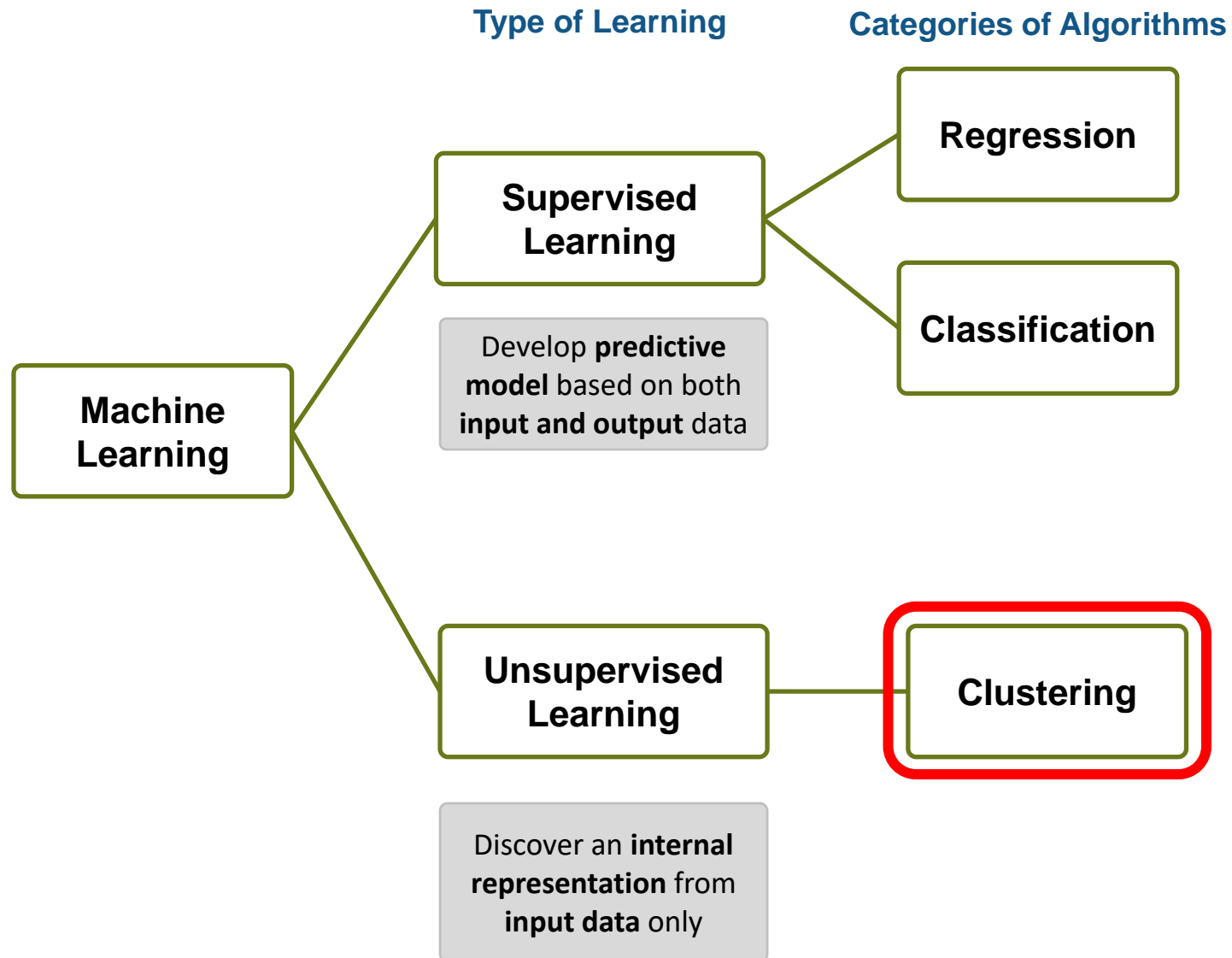
Train a classifier to classify flowers from petal and sepal length and width measurements

Data:

Inputs	Petal length Petal width Sepal length Sepal width
Outputs	Setosa Versicolor Virginica

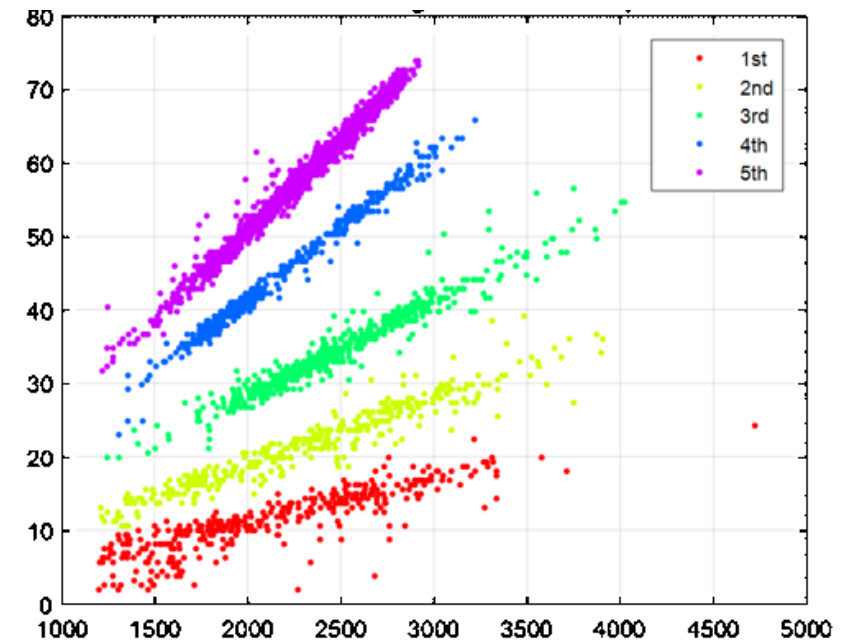
[MATLAB Doc - Classification](#)

There are different types of Machine Learning



Objective:

Identify clusters based on some similarity/characteristic in your data



Beyond traditional Machine Learning: Deep Learning

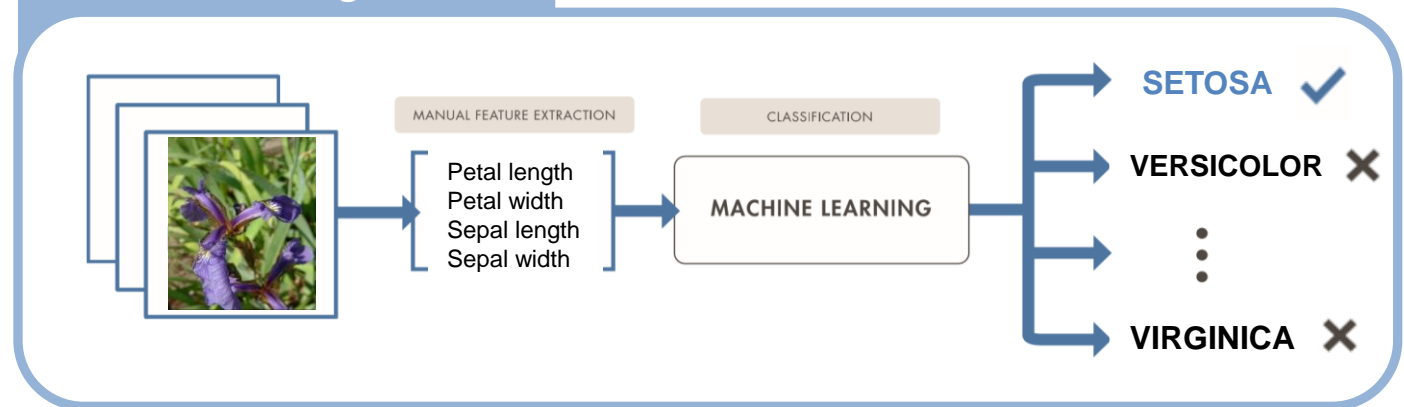
Machine Learning

Deep Learning

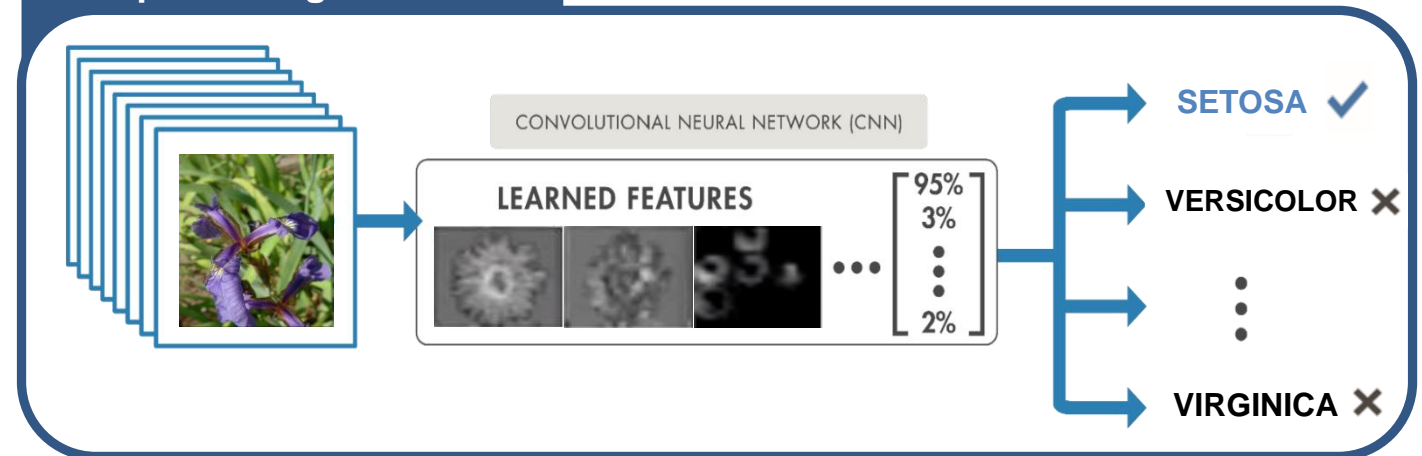
Neural Networks
with many Hidden
Layers

- Learns directly from data
- Computationally Intensive
- Requires a lot of labelled data
- **Not interpretable**

Machine Learning



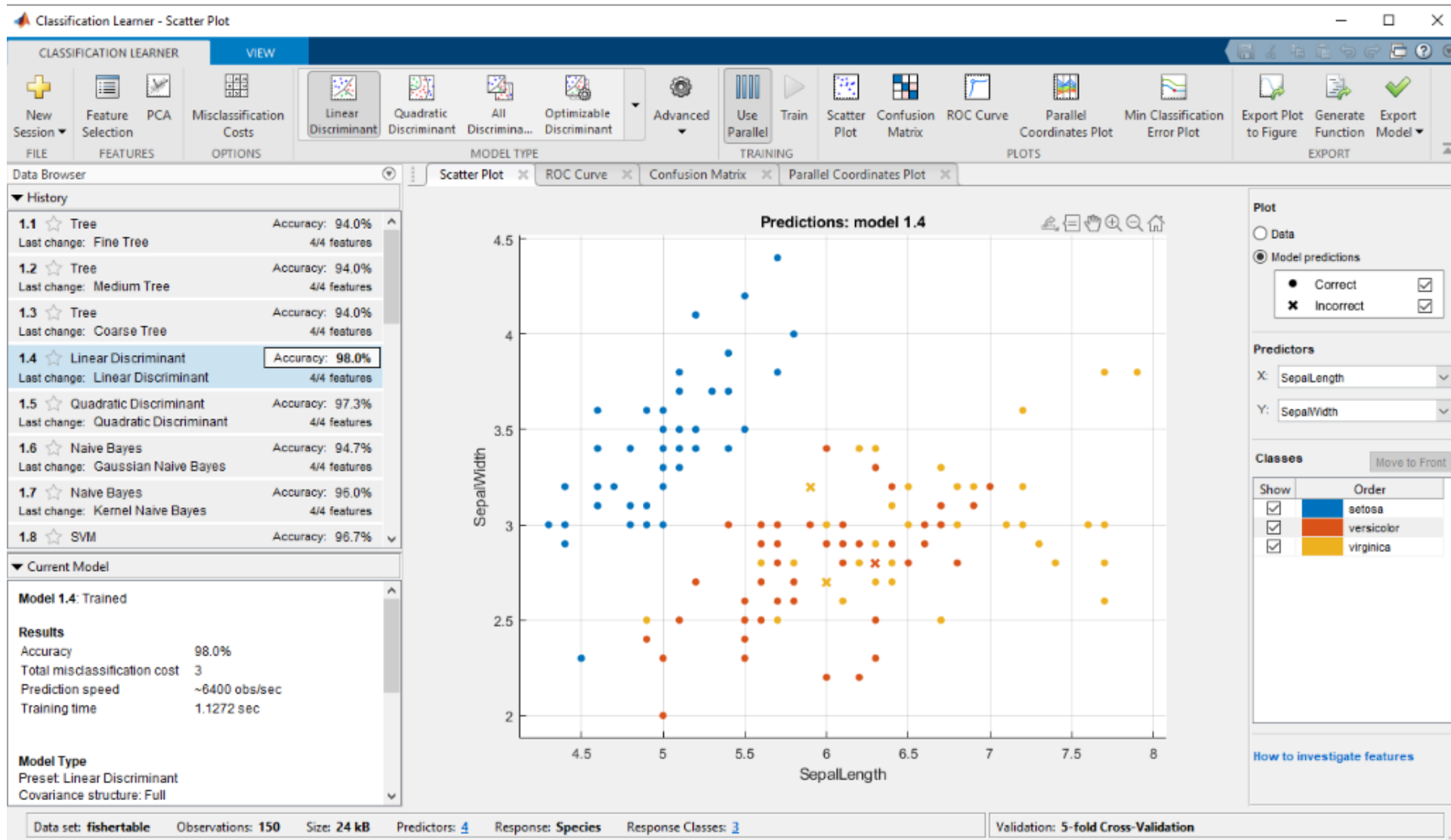
Deep Learning



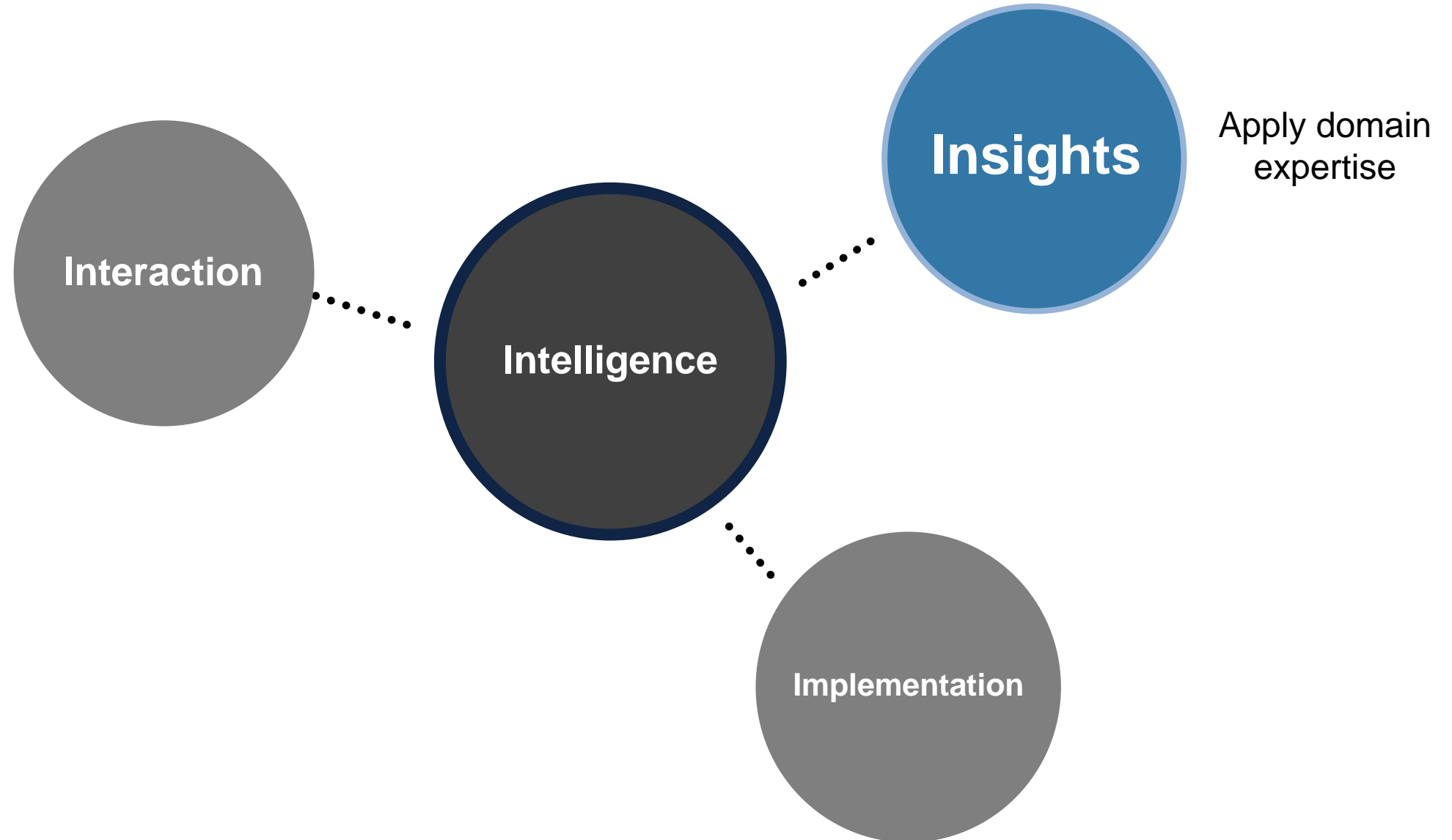
[Deep Learning and Traditional Machine Learning: Choosing the Right Approach](#)

[Webinar: Deep Learning in Agriculture: MATLAB for Plant Classification](#)

Example: Flowers Classification



Building intelligent algorithms require insights from domain experts



Bringing human insights into Machine Learning

- Your ML algorithm depends on your datasets (garbage in = garbage out)
- You can use your domain expertise to:
 - Select data (e.g. no biases in training data sets)
 - Realise that unmodeled dynamics are changing over time (e.g. wear and tear)
 - Make tradeoffs
 - Estimate results (reject unreasonable answers)
- Physical knowledge of the system can be used to build a better data driven model



You are the domain experts

Shortage of data scientists

You need the right tools

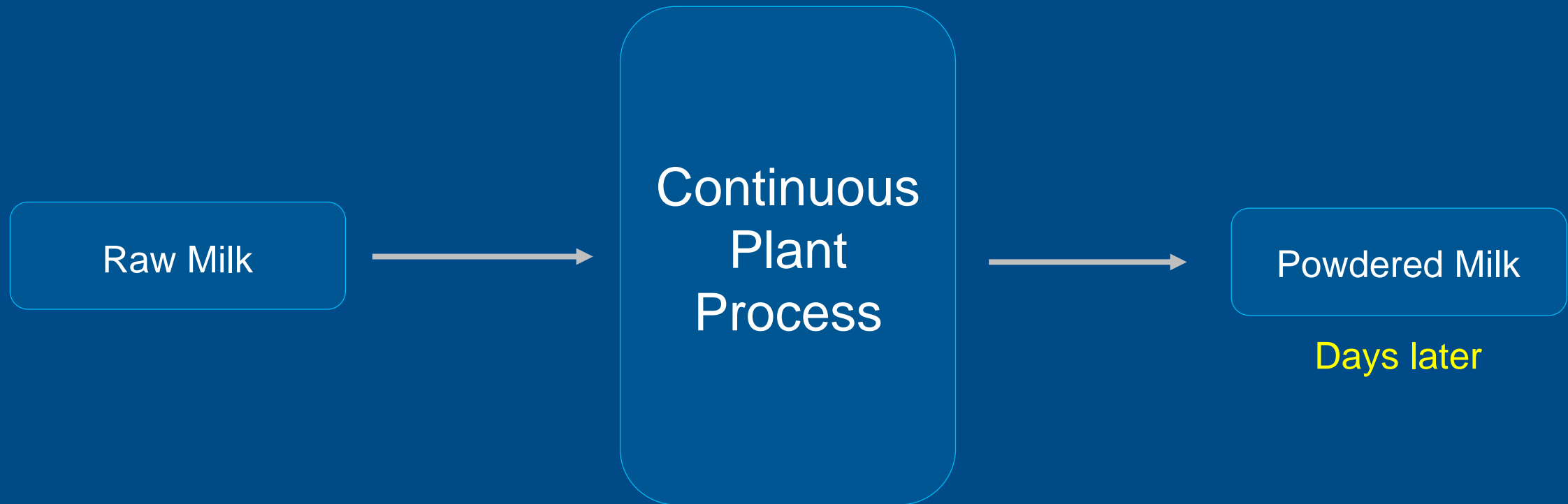
**MATLAB was developed for
Engineers and Scientists and makes
Machine Learning easy and
accessible for domain experts**

Improving New Zealand Dairy Processing

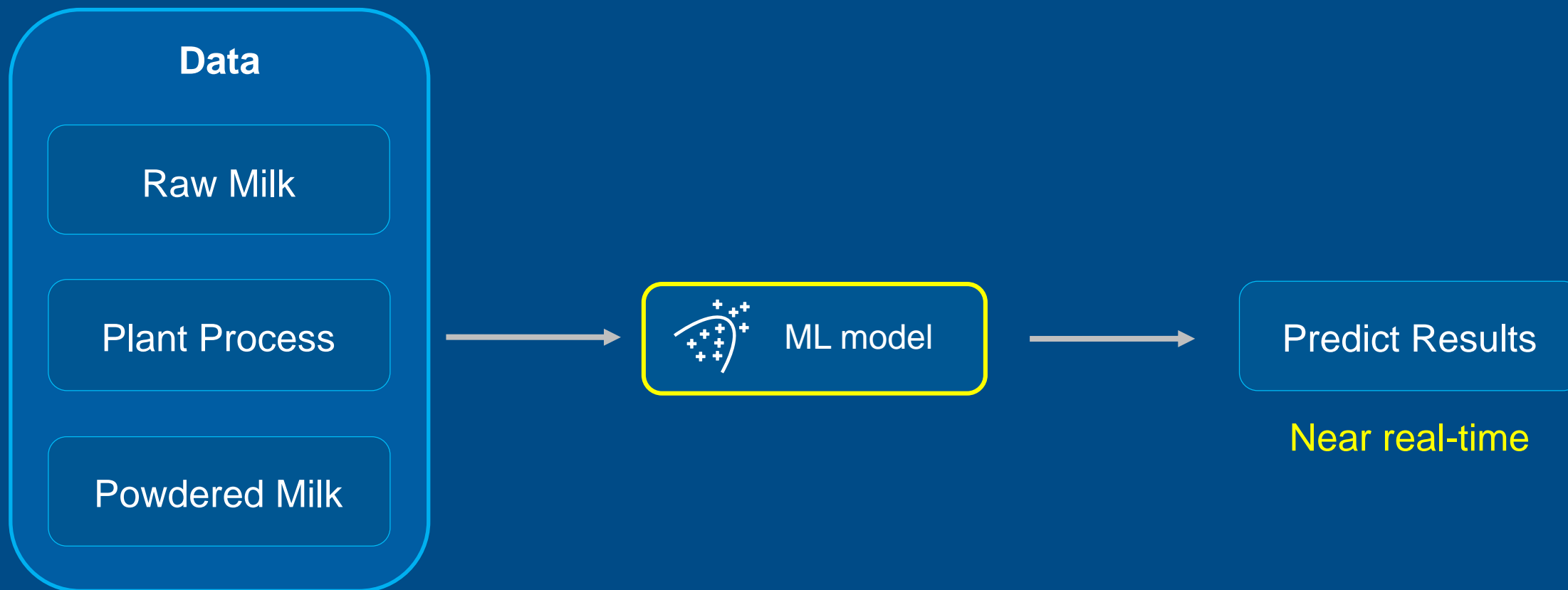
- University of Auckland
- Auckland University of Technology



Wanted to detect a bad product earlier



Wanted to detect a bad product earlier

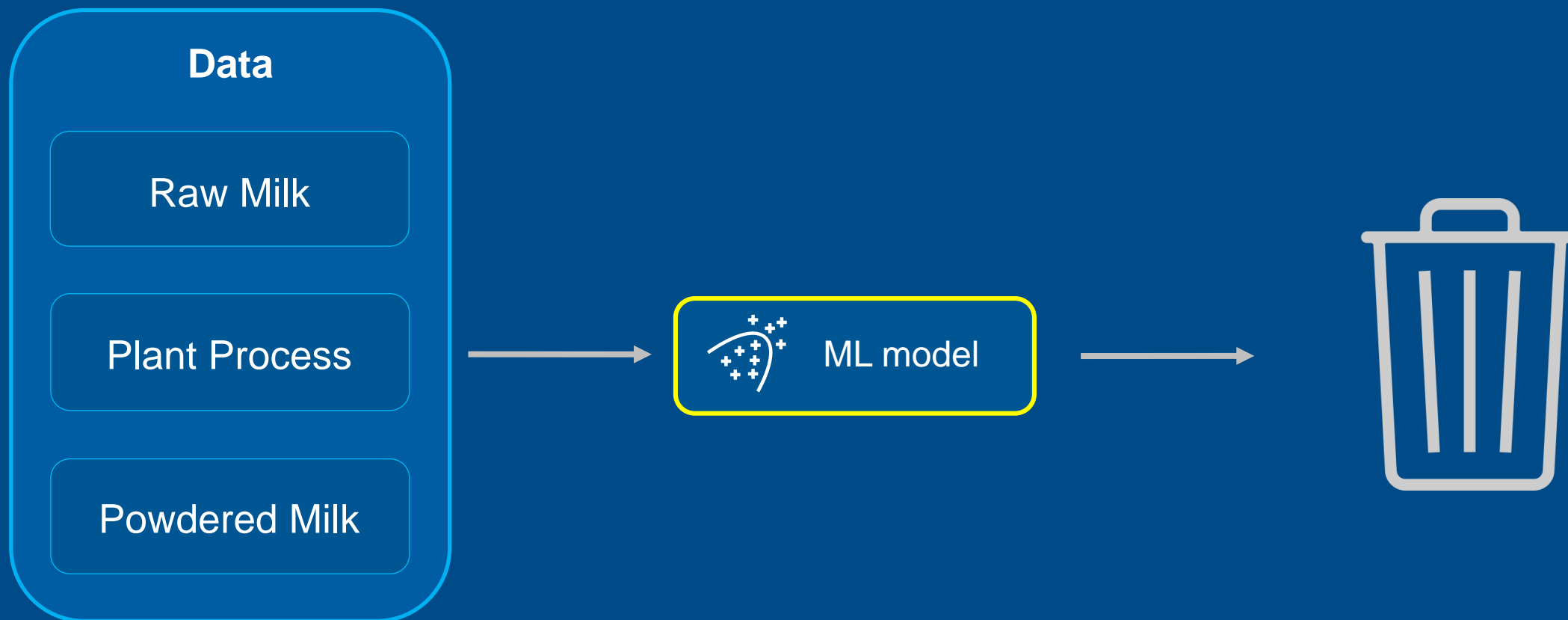


They had **lots** of data



- Millions of data points
- 6 years
- 3 plants

But...



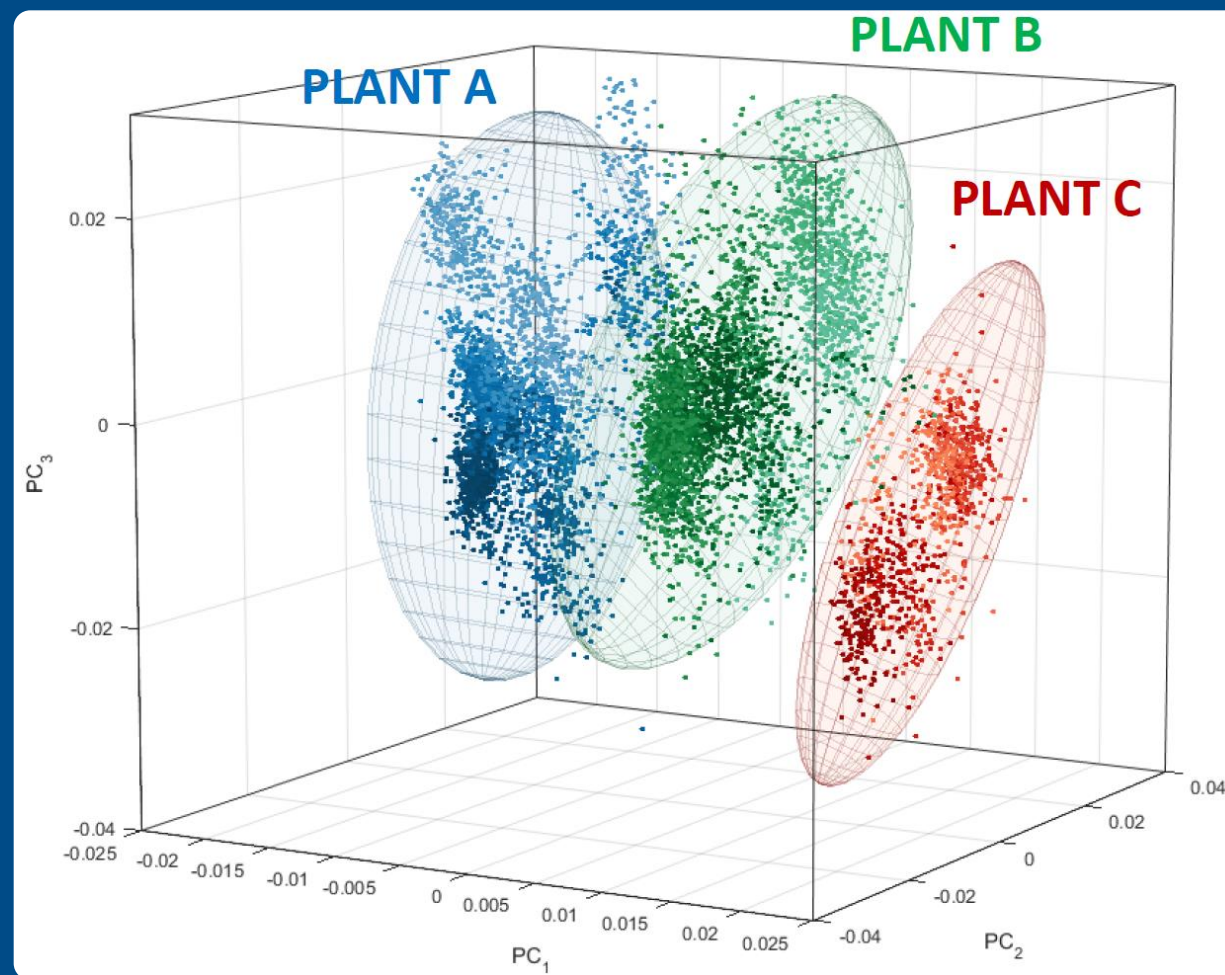
They made several key insights

1. Results were wrong

They made several key insights

1. Results were wrong
2. Need to build a separate model for each plant

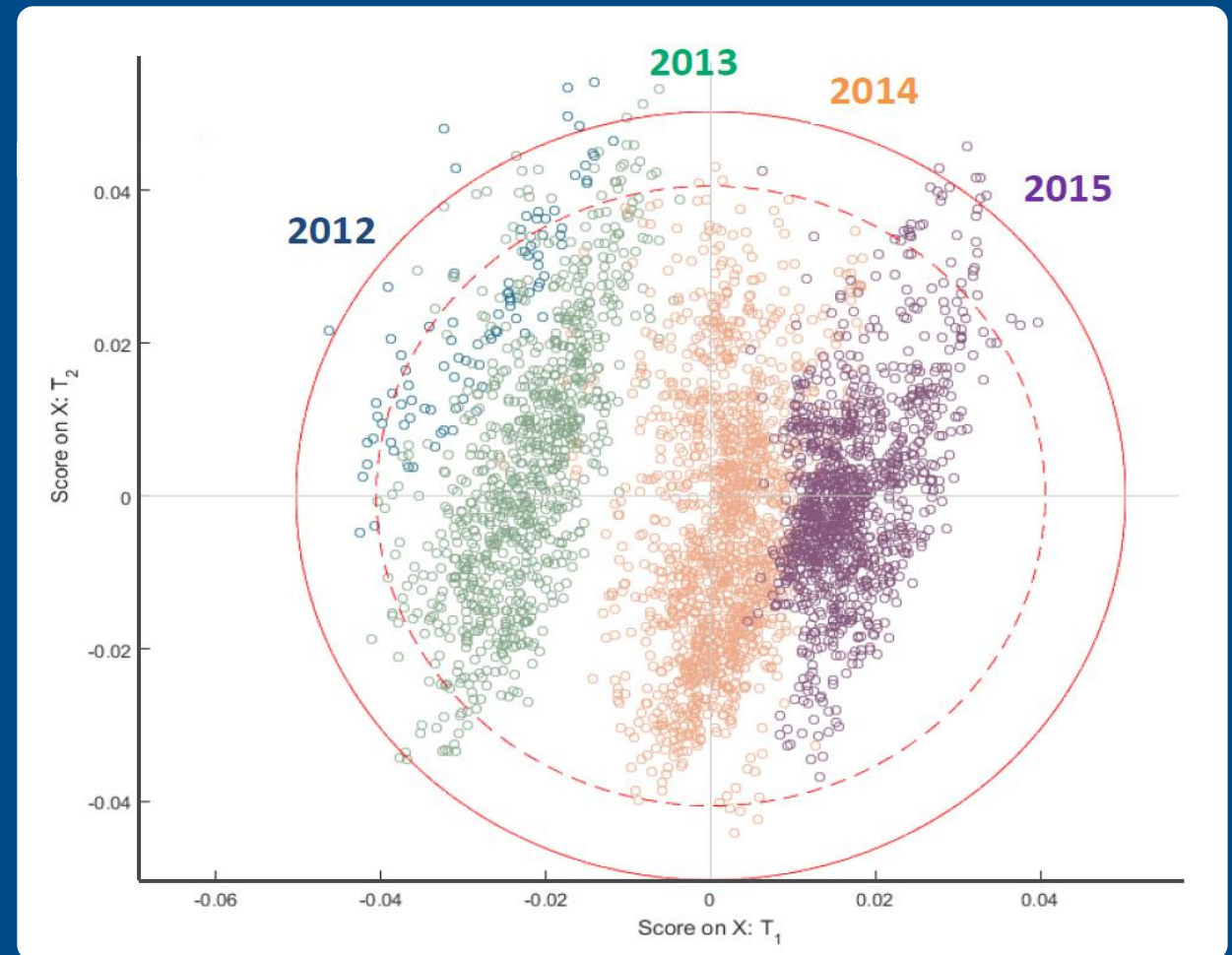
Plants **behaved differently**
from each another



They made several key insights

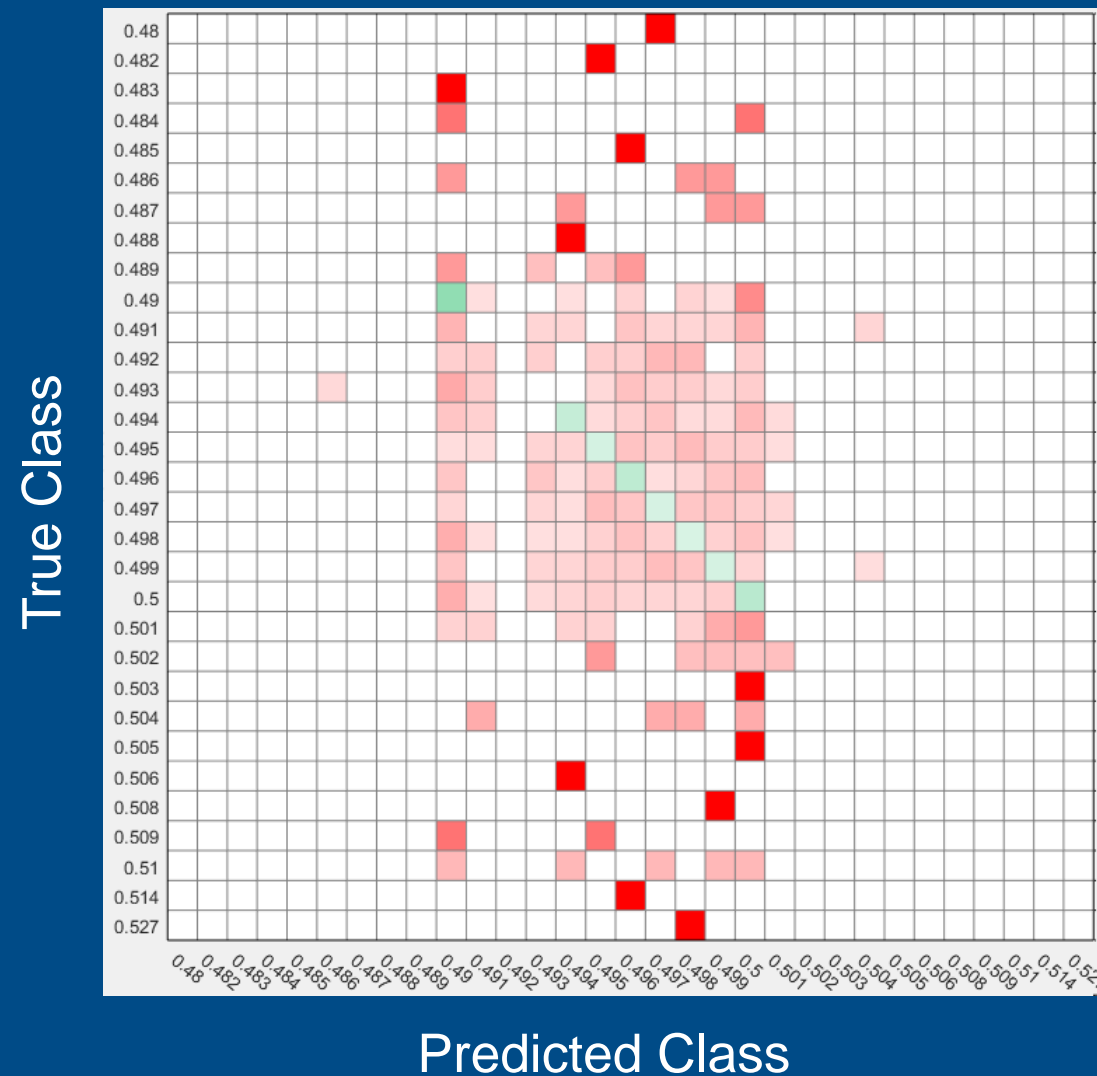
1. Results were wrong
2. Need to build a separate model for each plant
3. Plant's operating state changes each year

Each year was like a
completely different plant



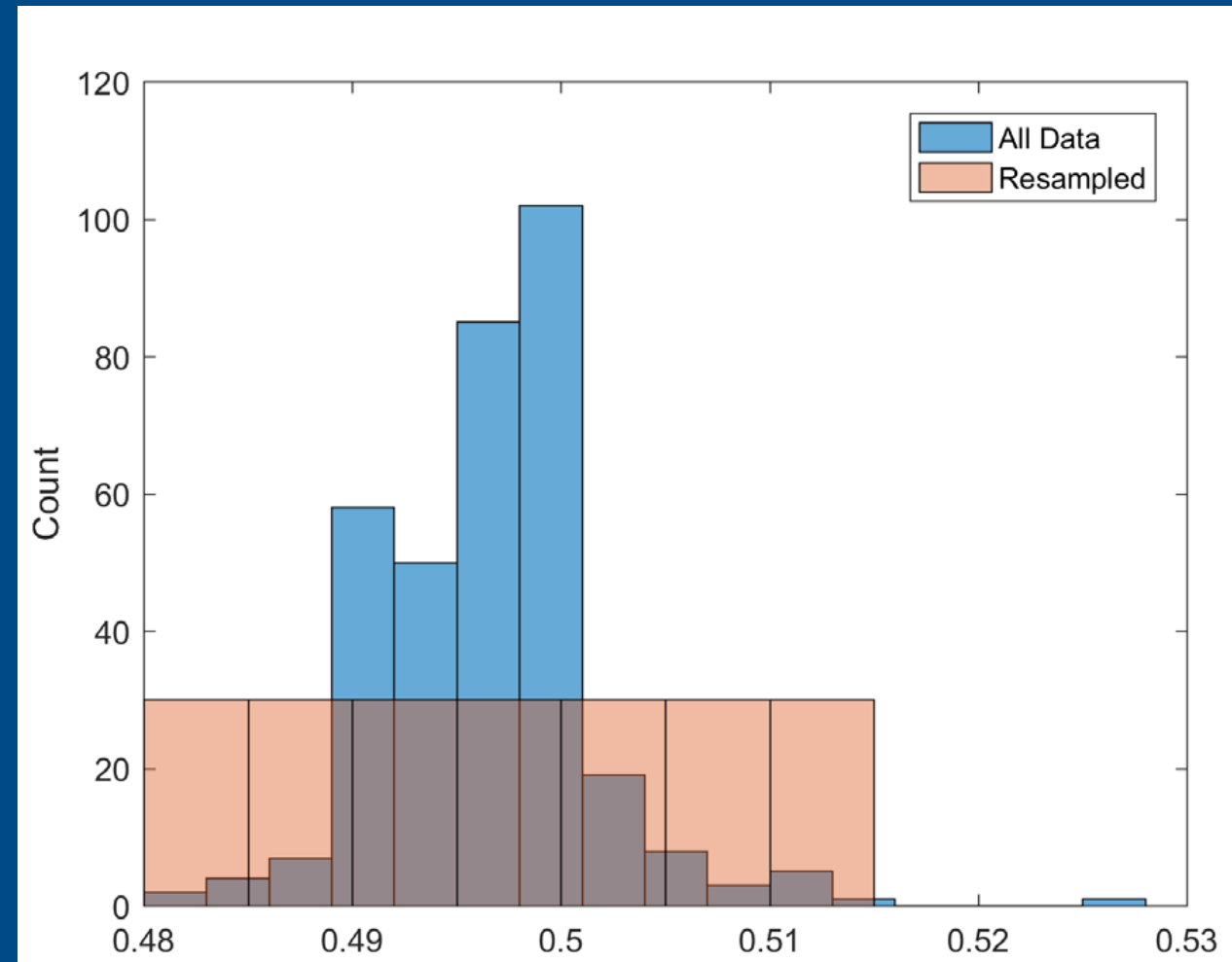
Bulk density prediction results were inaccurate

- Many false positives
- Unused classes



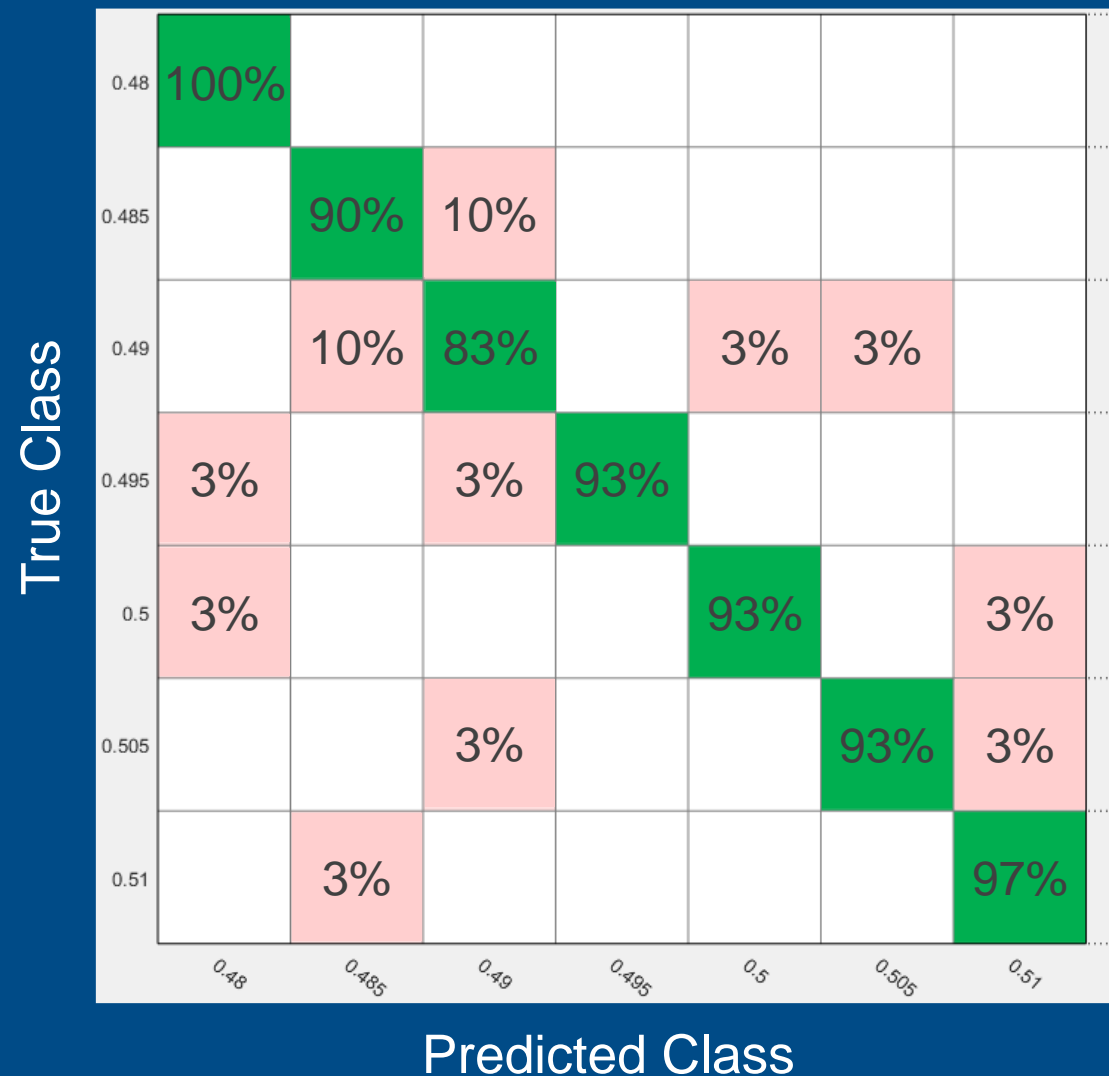
They made several key insights

1. Results were wrong
2. Need to build a separate model for each plant
3. Plant's operating state changes each year
4. Training data was biased



Resampling data resulted in higher predictive accuracy

- Resampled data
- Reduced the number of bins



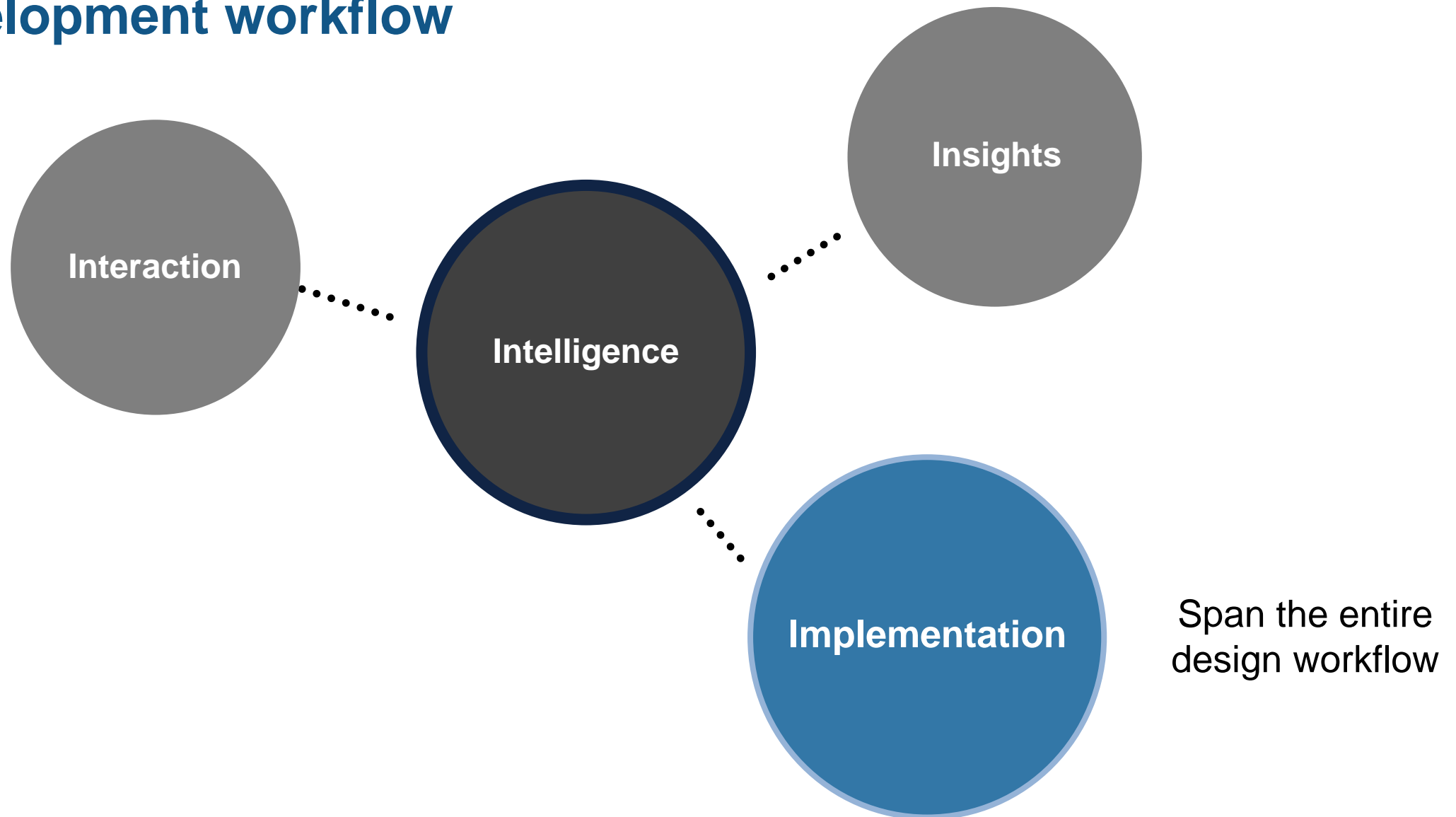
A photograph of a herd of black and white cows grazing in a lush green field. In the background, there are rolling green hills and mountains under a blue sky with some clouds. A semi-transparent blue box is overlaid on the top half of the image, containing white and yellow text.

“It’s great to sit down with our industry partners and watch their jaws drop when they see **how productive we are with MATLAB** and how quickly we can analyze and plot data.

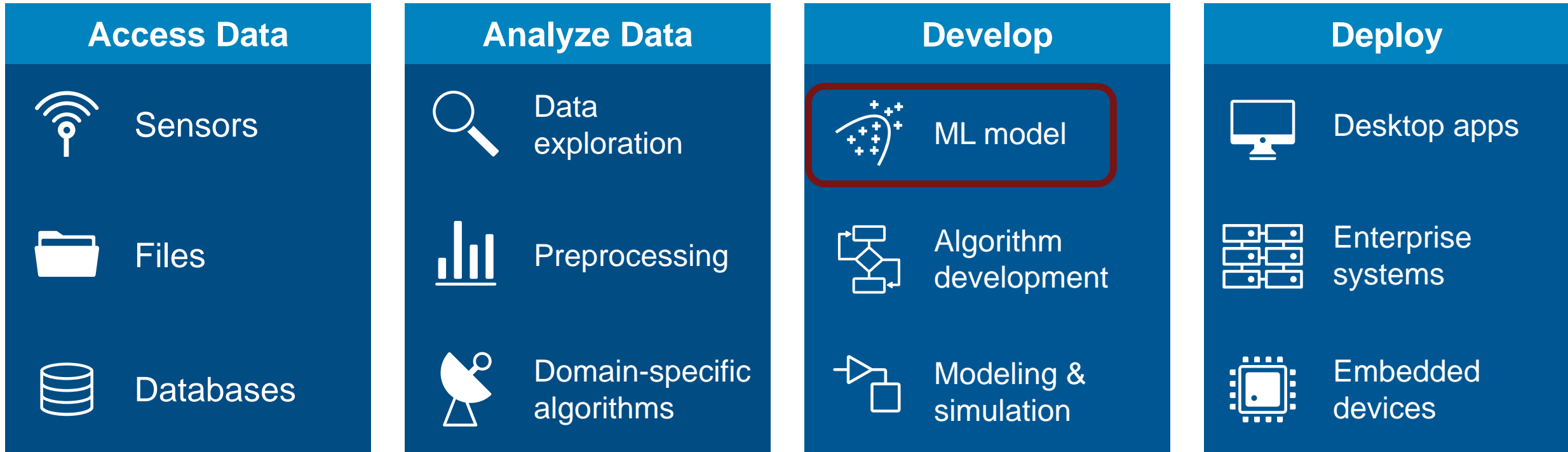
Our results have enabled them to **confirm hypotheses** for which they lacked evidence, and have **sparked new ideas for process improvement.**”

- *David Wilson, Auckland University of Technology*

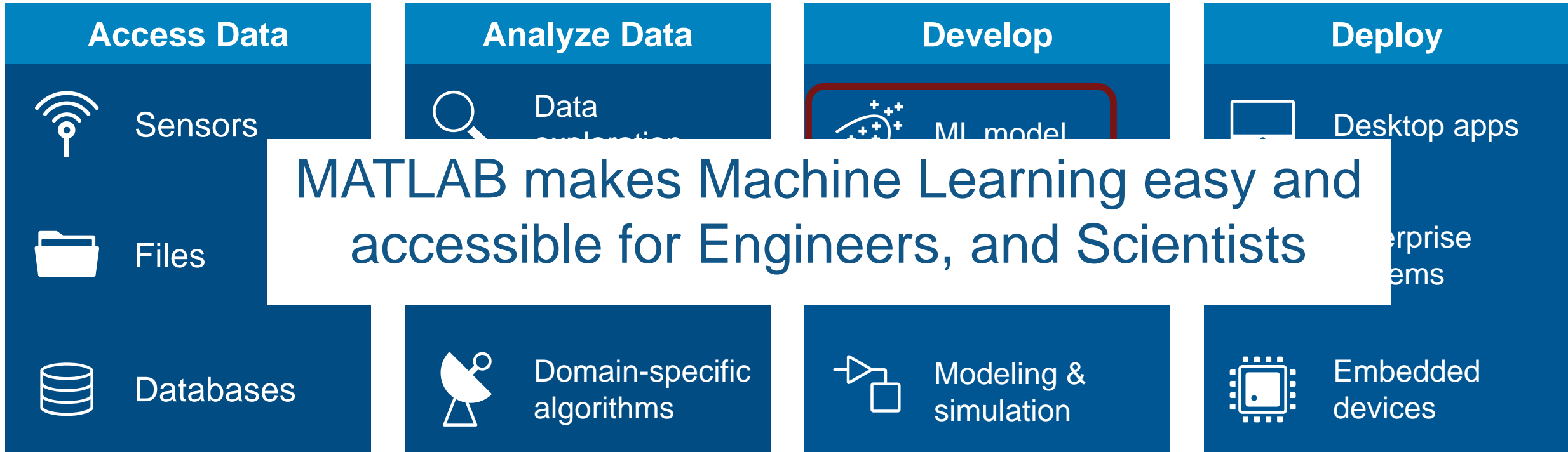
Implementing intelligent algorithms requires an end-to-end development workflow



MATLAB and Simulink provide an algorithm development platform

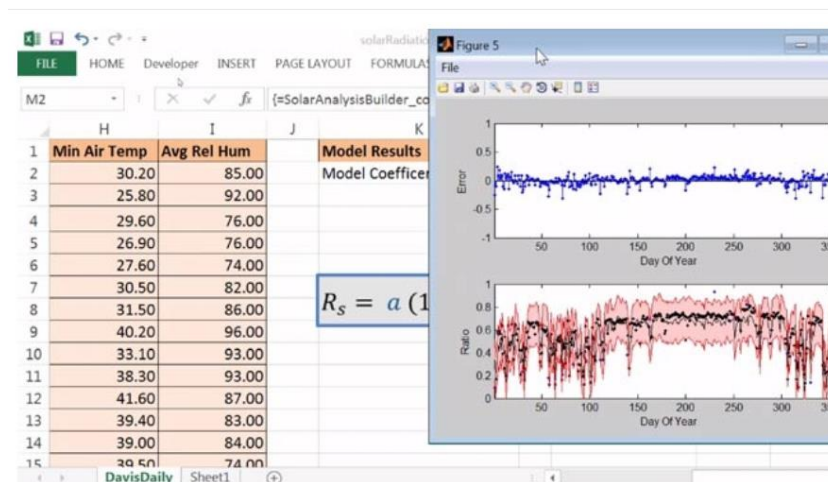
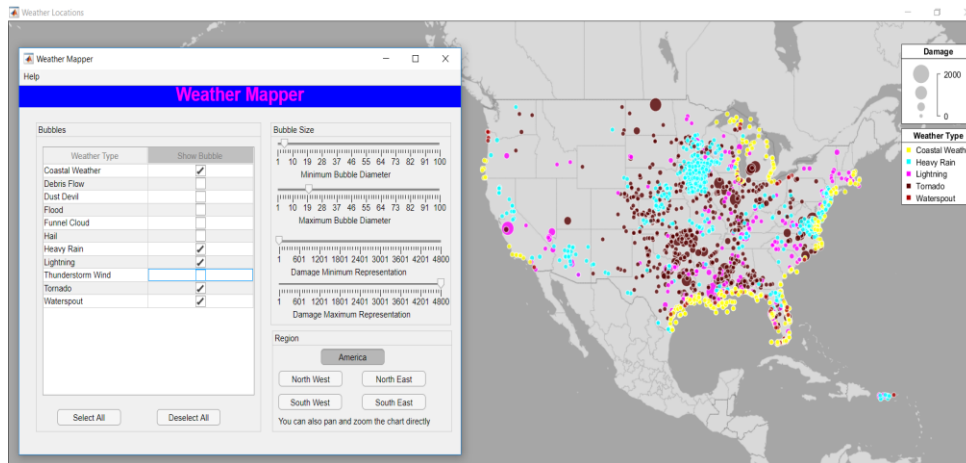


MATLAB and Simulink provide an algorithm development platform



Useful deployment solutions for agriculture industry

- Standalone apps / web apps
- ThingsSpeak



Videos and Webinars

[Videos Home](#) | [Search](#)

Using ThingSpeak and MATLAB for IoT in Agriculture

Collect
Send sensor data privately to the cloud.

Analyze
Analyze and visualize your data with MATLAB.

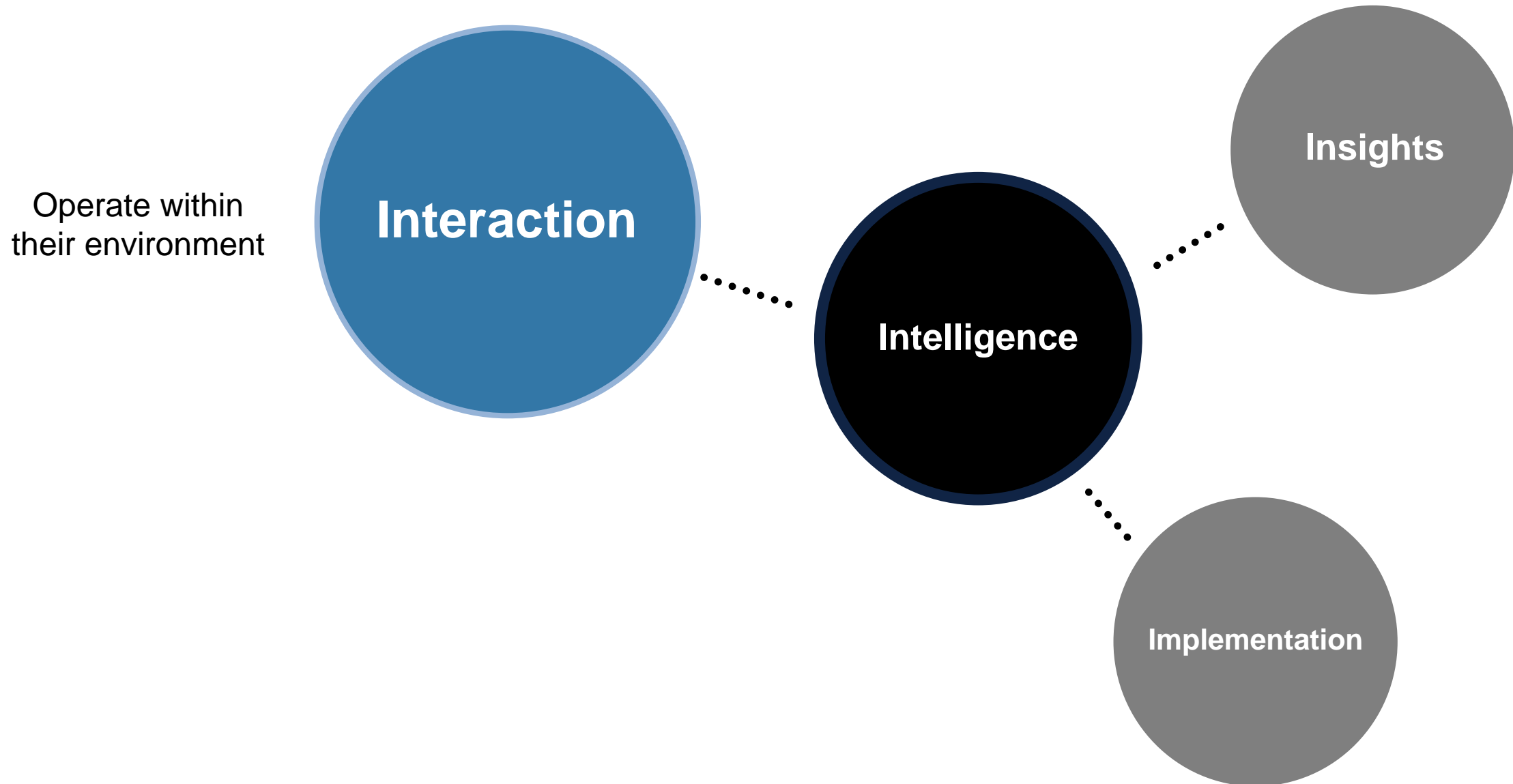
Act
Trigger a reaction.

Daryl Ning
Applications Engineer
MathWorks Australia

0:00 / 34:37

[Webinar: Using ThingSpeak for IOT in Agriculture](#)

For intelligent algorithms to be useful, they need to be interactive



It is easy to interact with colleagues with no MATLAB background

Getting into the Weeds:
Farmers Rely on Artificial Intelligence to Boost Production

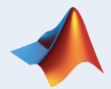


ThingsSpeak



Agenda - Machine Learning (ML) for Agriculture

- How do you get started quickly?
- How to make your ML projects successful?



What does success look like?

- Conclusion / How we can help you?

Getting into the Weeds: Farmers Rely on Artificial Intelligence to Boost Production

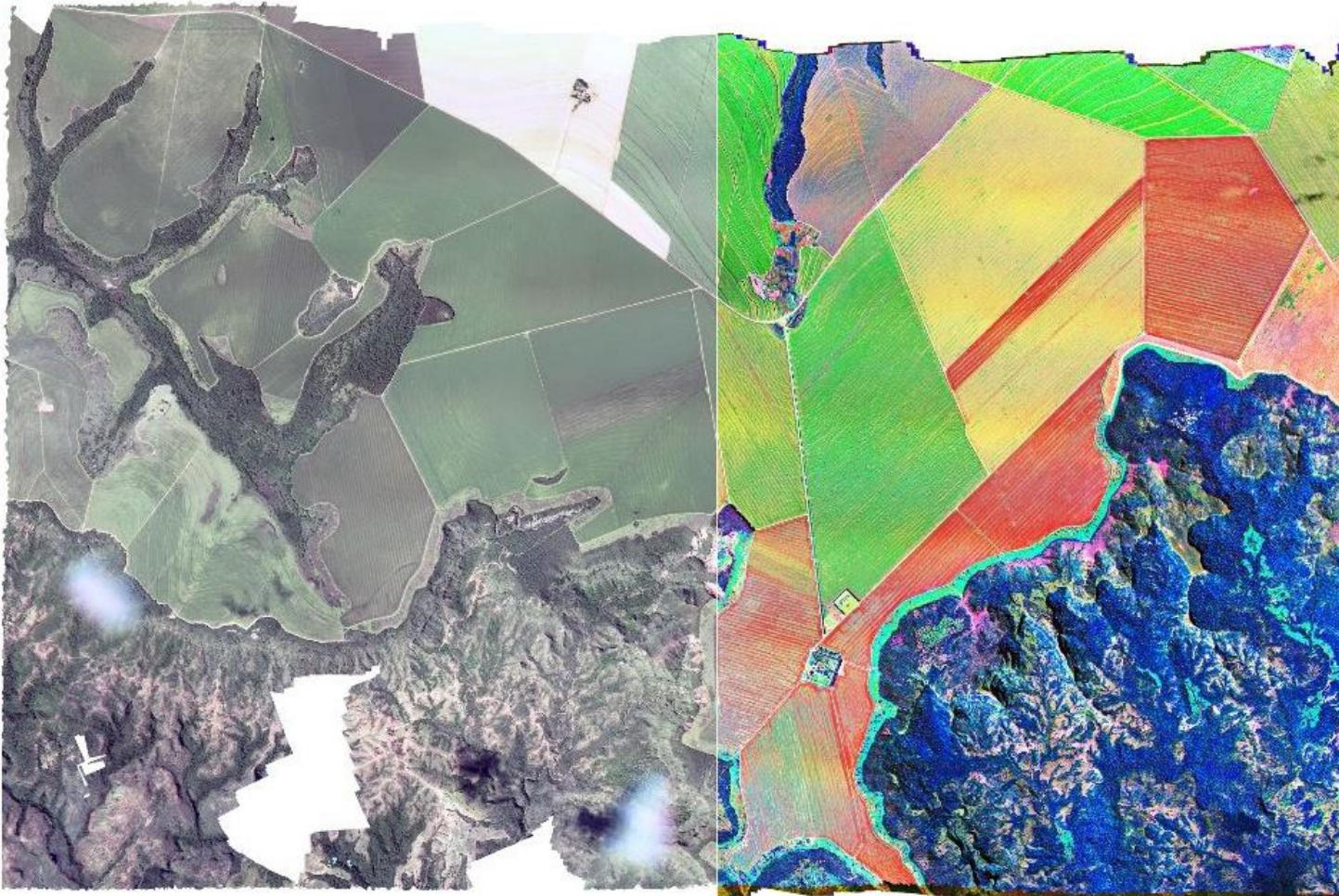


Image courtesy of Gamaya



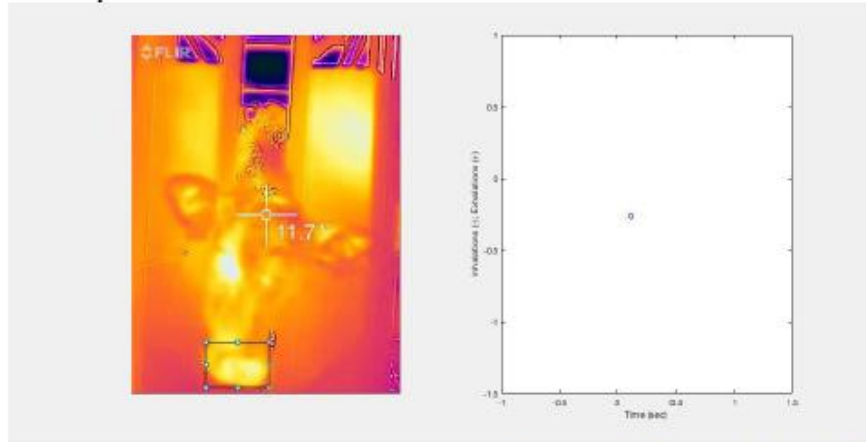
- Exceed human performance
- Boost production
- Achieve greater financial returns
- Be good for the planet

Automated Recognition of Cattle Features for Data Extraction

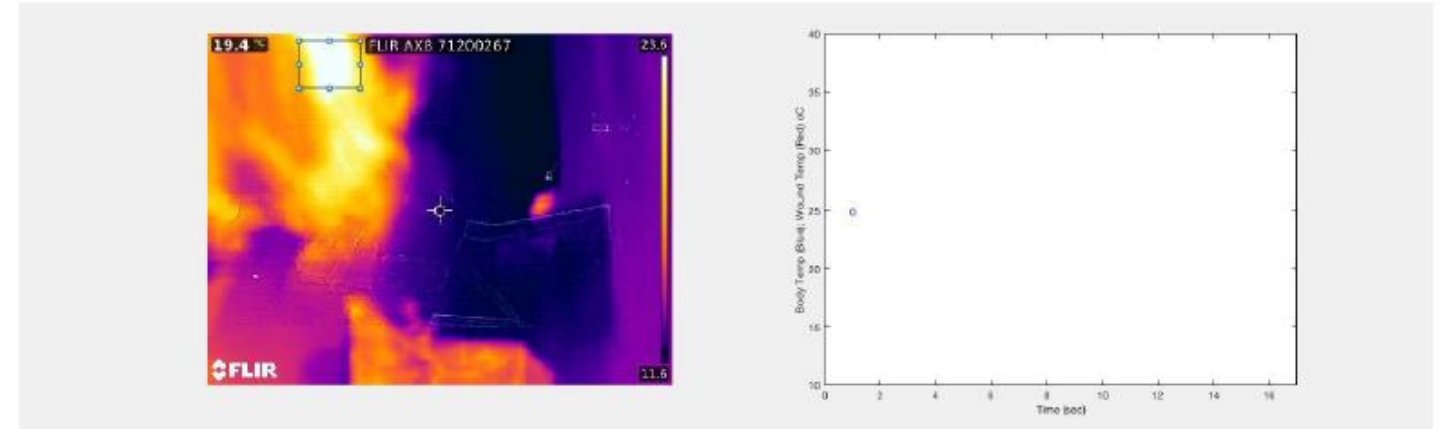


Monitoring Cattle Biometrics

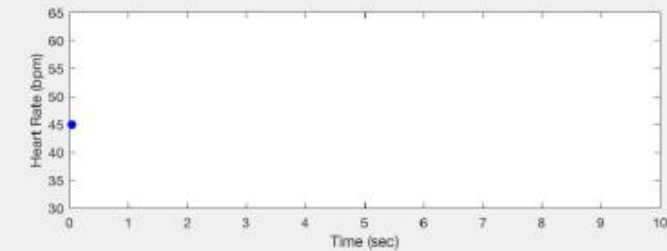
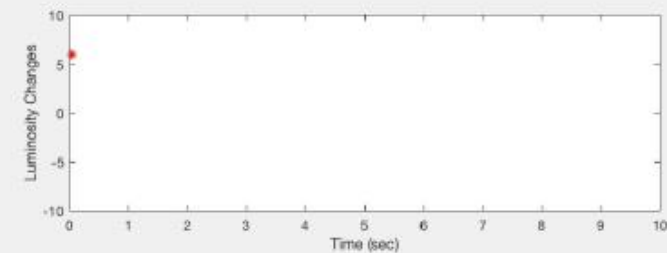
Respiration Rate: IR-Non radiometric



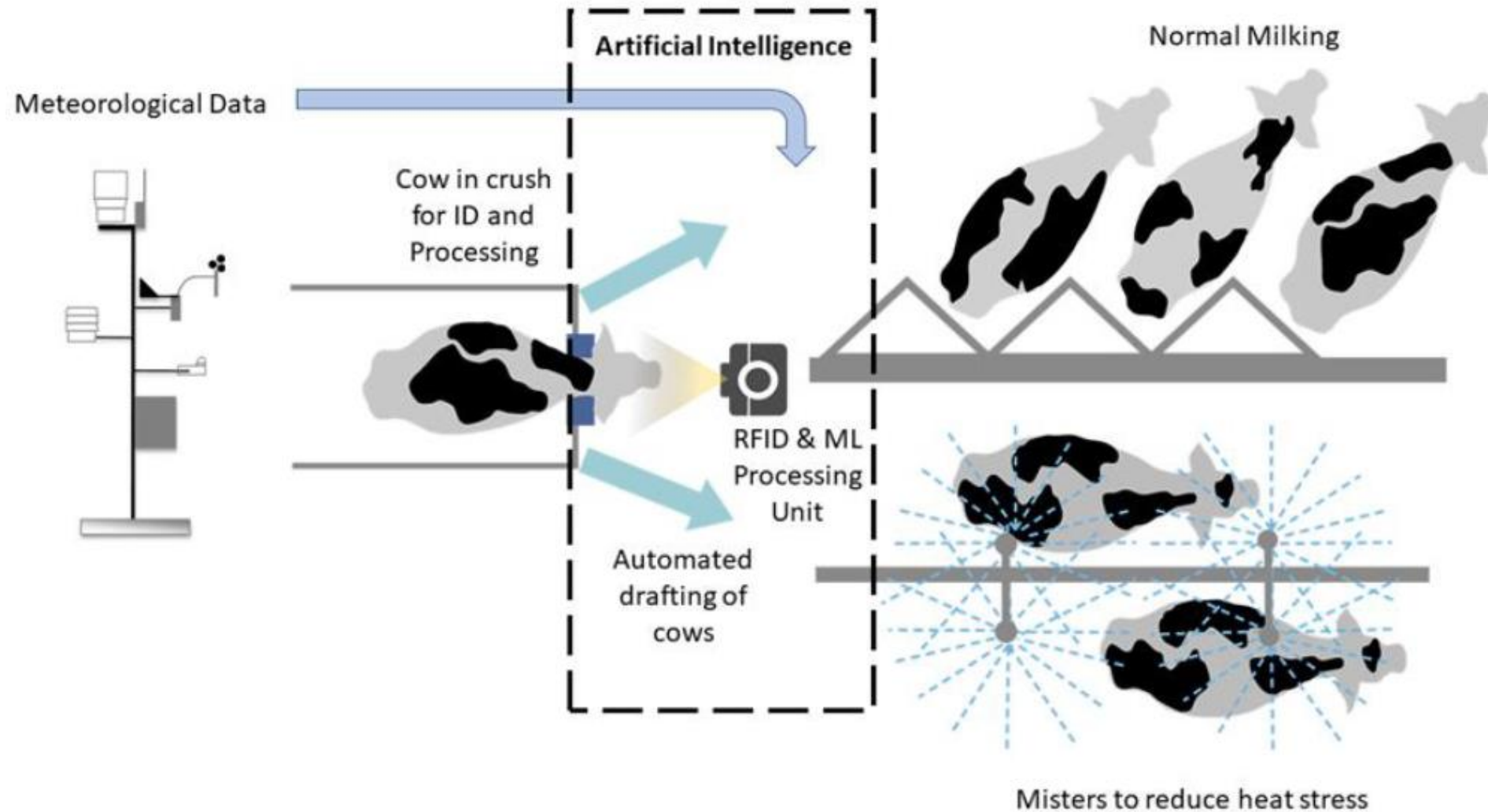
Body Temperature: InfraRed Thermography Radiometric



Heart Rate: Video Magnification Analysis



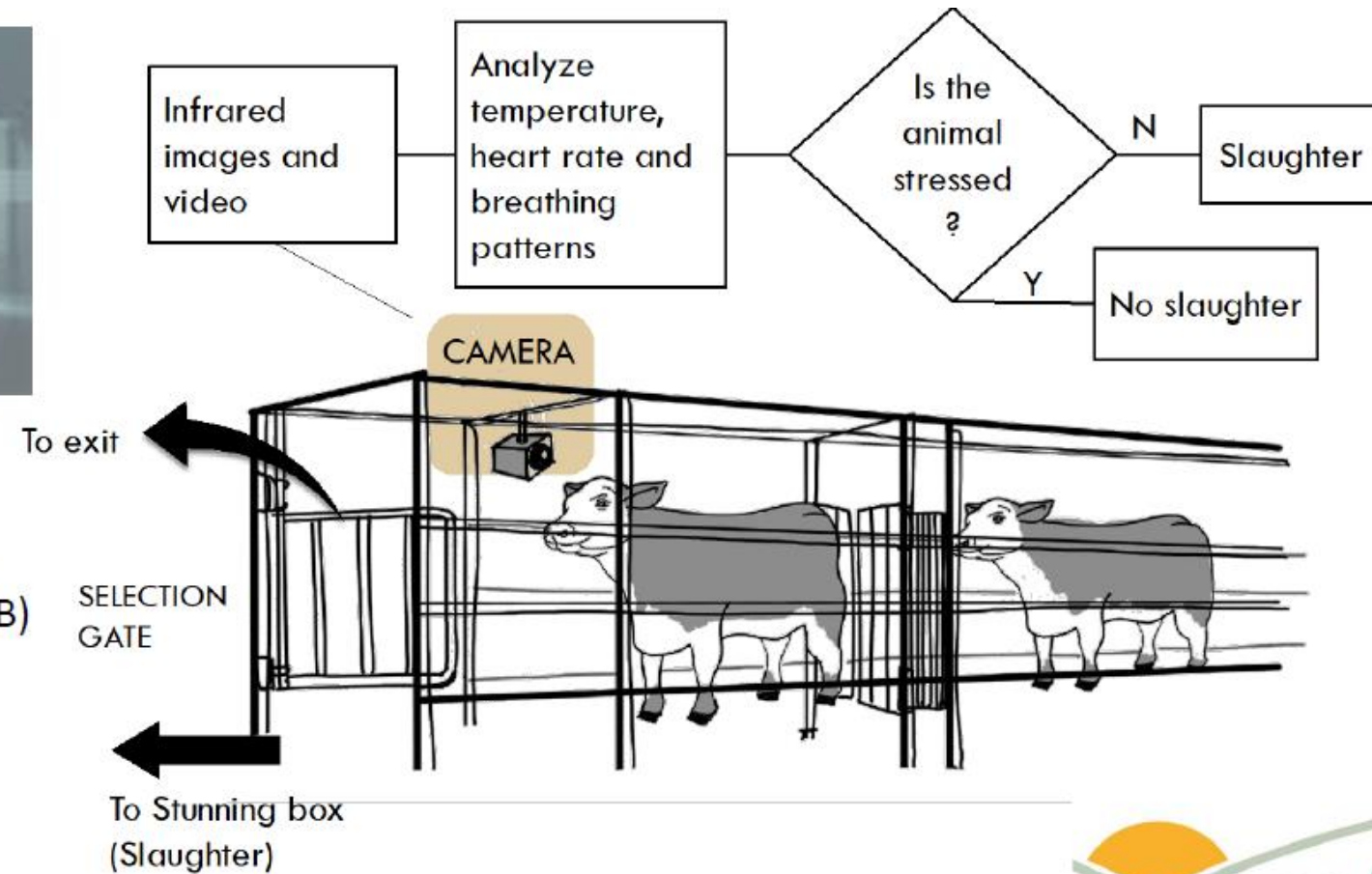
Maximize productivity and quality of milk in a robotic dairy farm



Minimising Dark Cutting Beef



Inputs: Non-contact Animal Biometrics
Target: Minimise Dark Cutting Beef (DCB)



Making Better Beer and Wine with Data and Machine Learning

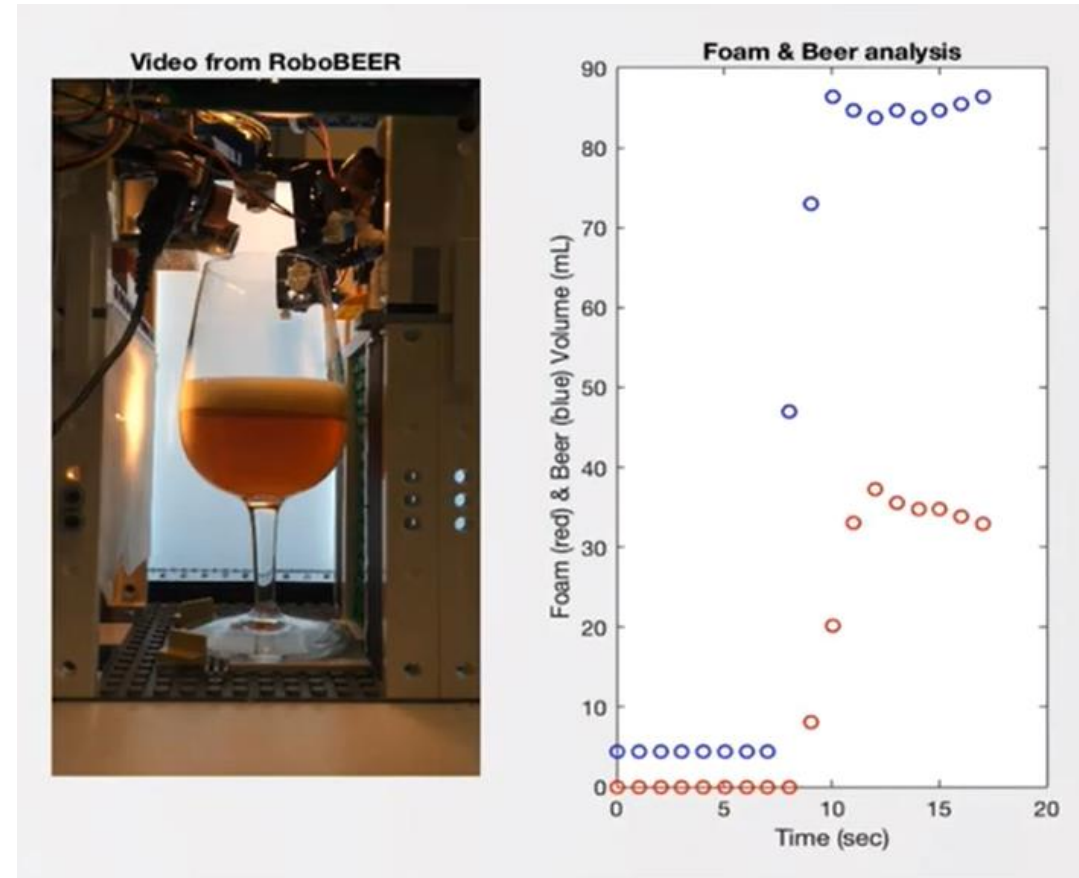
Gas Sensors (x9)



Electronic board + Sensors



FACULTY OF
VETERINARY &
AGRICULTURAL
SCIENCES



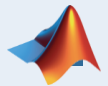
[MATLAB Expo 2020 proceedings](#)

[Mathworks stories: making better beer and wine using machine learning](#)

[Research article on classification of smoke contaminated wines with ML](#)

Agenda - Machine Learning (ML) for Agriculture

- How do you get started quickly?
- How to make your ML projects successful?
- What does success look like?

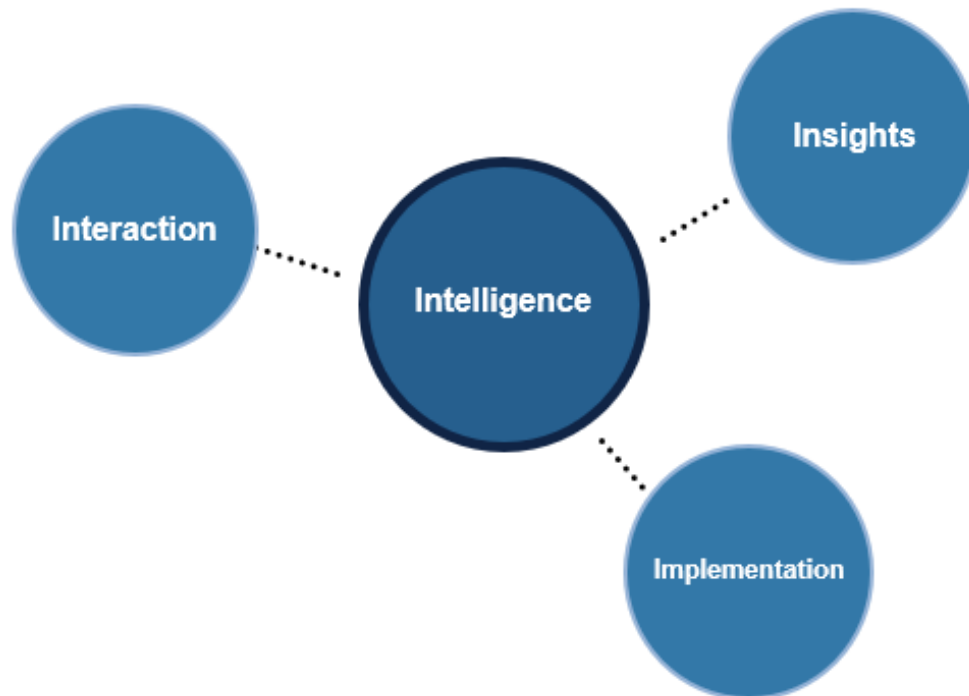


Conclusion / How we can help you?

Summary

ML is already becoming crucial for agriculture

ML is more than just the intelligence of the algorithm



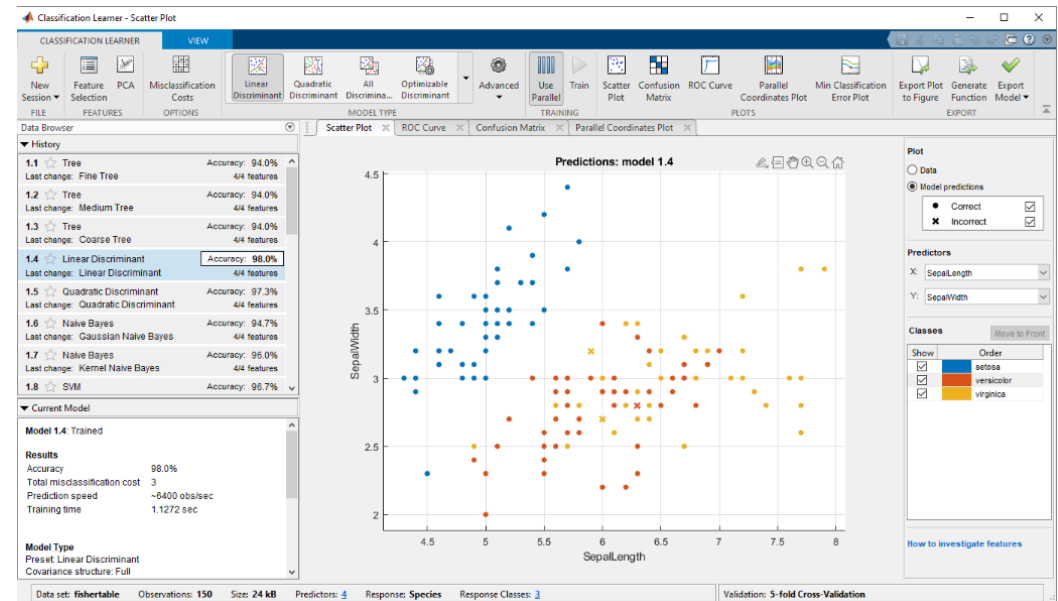
You can empower your domain experts with the right tools



You are the domain experts

Shortage of data scientists

You need the right tools







How MathWorks can support you

- Deep Learning for Agriculture and Internet Of Things for Agriculture webinars
- On-Site Presentations & Proof-of-Concepts
- Trainings

Getting Started

<https://matlabacademy.mathworks.com/>

 <p>MATLAB Onramp</p> <p>Get started quickly with the basics of MATLAB.</p> <p>Launch Details</p>	 <p>Simulink Onramp</p> <p>Get started quickly with the basics of Simulink.</p> <p>Details</p>	 <p>Machine Learning Onramp</p> <p>Learn the basics of practical machine learning methods for classification problems.</p> <p>Launch Details</p>	 <p>Deep Learning Onramp</p> <p>Get started quickly using deep learning methods to perform image recognition.</p> <p>Launch Details</p>
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- Consulting
- Contact us

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