# AI and Machine Learning in Action Using SAS® Viya®: A Detailed Use Case

Ask The Expert

Carlos Pinheiro, Distinguished Data Scientist
Robert Blanchard, Principal Data Scientist

# Carlos Pinheiro

## Distinguished Data Scientist

In addition to his role at SAS, Carlos Pinheiro is an Adjunct Faculty Member at SKEMA Business School and a Lecturer at the Data Science Academy at North Carolina State University. He has been working in analytics since 1996, most of the time for telecommunications providers in Brazil. He worked as a Senior Data Scientist at EMC and as a Lead Data Scientist at Teradata. Pinheiro has a BSc in applied mathematics and computer science, a MSc in computing, and a DSc in engineering from Federal University of Rio de Janeiro. He has accomplished a series of post-doctoral research terms in different fields, including dynamic systems at IMPA, Brazil; in social network analysis at Dublin City University, Ireland; and in transportation systems at Université de Savoie, France. Pinheiro has published several papers in international journals and conferences and been granted US patents. He has written four books, most recently Network Science: Analysis and Optimization Algorithms for Real-World Applications.

# Robert Blanchard

## Principal Data Scientist

Robert Blanchard builds end-to-end artificial intelligence applications. He also researches, consults and teaches machine learning with an emphasis on deep learning and computer vision for SAS. Blanchard has authored an introductory book on computer vision and has written several professional courses on topics including neural networks, deep learning and optimization modeling. Before joining SAS, Blanchard worked under the Senior Vice Provost at North Carolina State University, where he built models pertaining to student success, faculty development and resource management. Prior to working in academia, he was a member of the research and development group on the Workforce Optimization team at Travelers Insurance. His models at Travelers focused on forecasting and optimizing resources. Blanchard holds a master's degree in business analytics and project management from the University of Connecticut and a master's degree in applied and resource economics from East Carolina University.

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# Outline

## Overview

Use case description and analytic lifecycle overview.

## Data Preparation

Detail strategies for data preparation, exploration and feature engineering.

## Machine Learning

Examine best practices for unsupervised and supervised machine learning. We'll also cover forecasting and optimization modeling.

## Deep Learning and Computer Vision

Examine point-and-click computer vision model development with neural architecture search.

## Network Sciences and Deployment

Explore relationships using network sciences and detail deployment best practices.

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# Use Case: Data Description

## Customer Information Table

- The data contains information of the CDA Company customers including:
  - customer demographics,
  - churn status,
  - product spending,
  - ads exposure,
  - returns, and
  - other interactions with the company.
- Target is Binary outcome representing customer churn.

# Use Case: Data Description

## Operations Information Tables

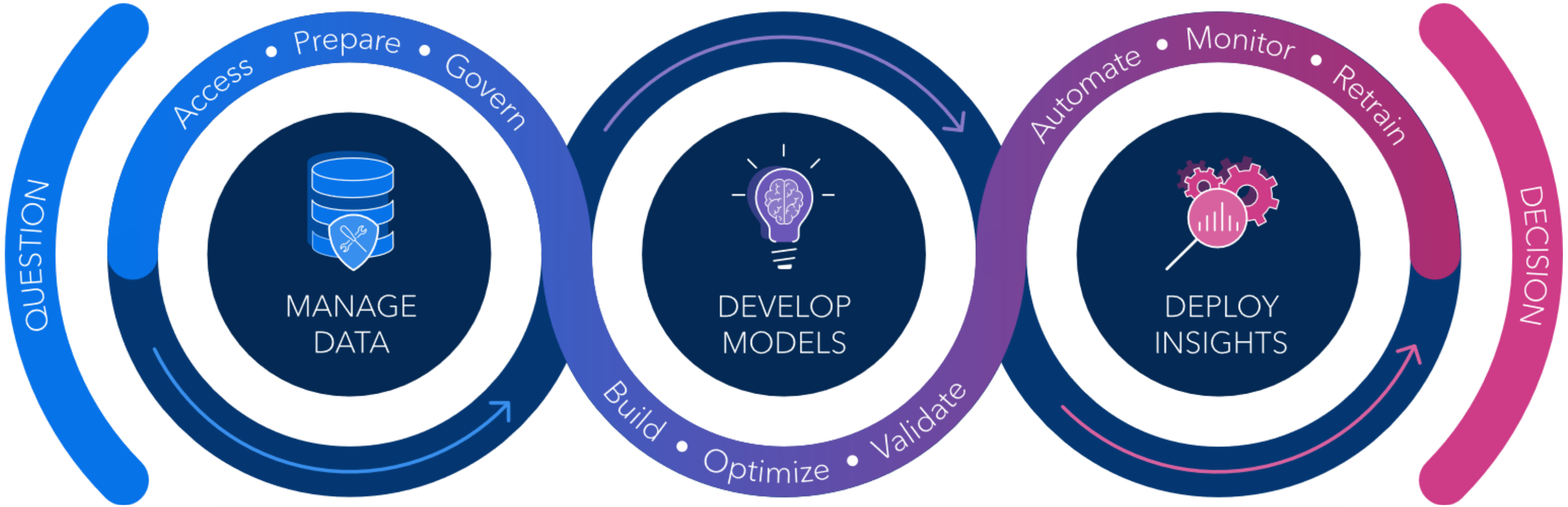
- The data contains information of the CDA Company operations including:
  - Time-stamped data that tracks revenue,
  - cost,
  - profit,
  - returns,
  - churn, across CDA company manufacturing facilities, and
  - overall quality score across CDA company hubs

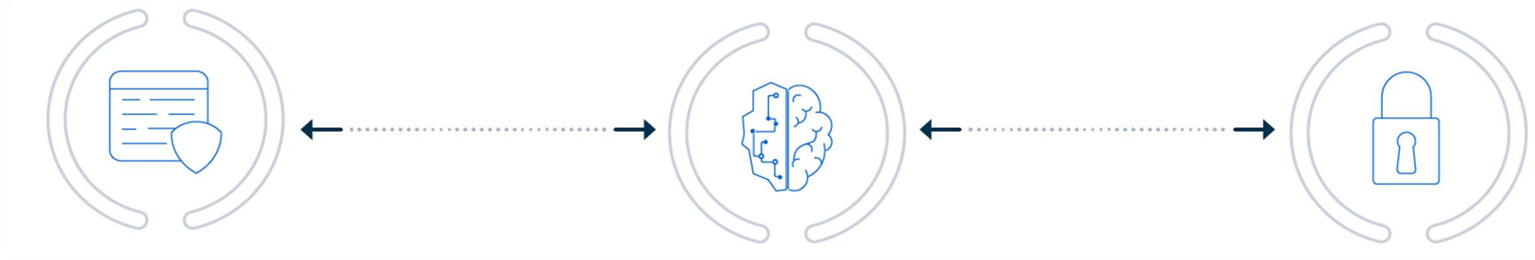
# Use Case: Data Description

## Product Quality Imagery

- The data contains images of products coming off the manufacturing line and includes images of defective and non-defective products.

# Analytics Lifecycle



ROBUST DATA GOVERNANCE

TRANSPARENT AI

SECURE MODEL OPS PROCESSES

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# Demo

## Data Exploration and Visualization


- Explore and visualize data to discover relationships.
- Modify data and create new features for future analyses.

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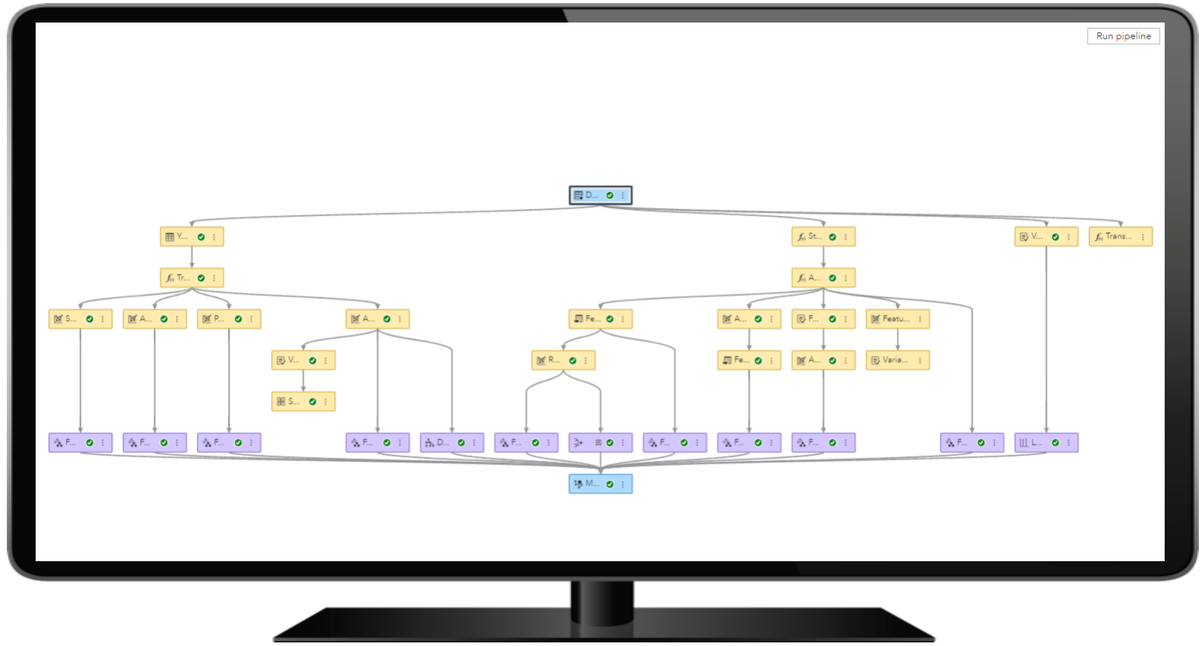
## Machine Learning




- Apply methods of supervised and unsupervised machine learning to build predictive models.
- Build forecast models and optimize decisions for better outcomes.

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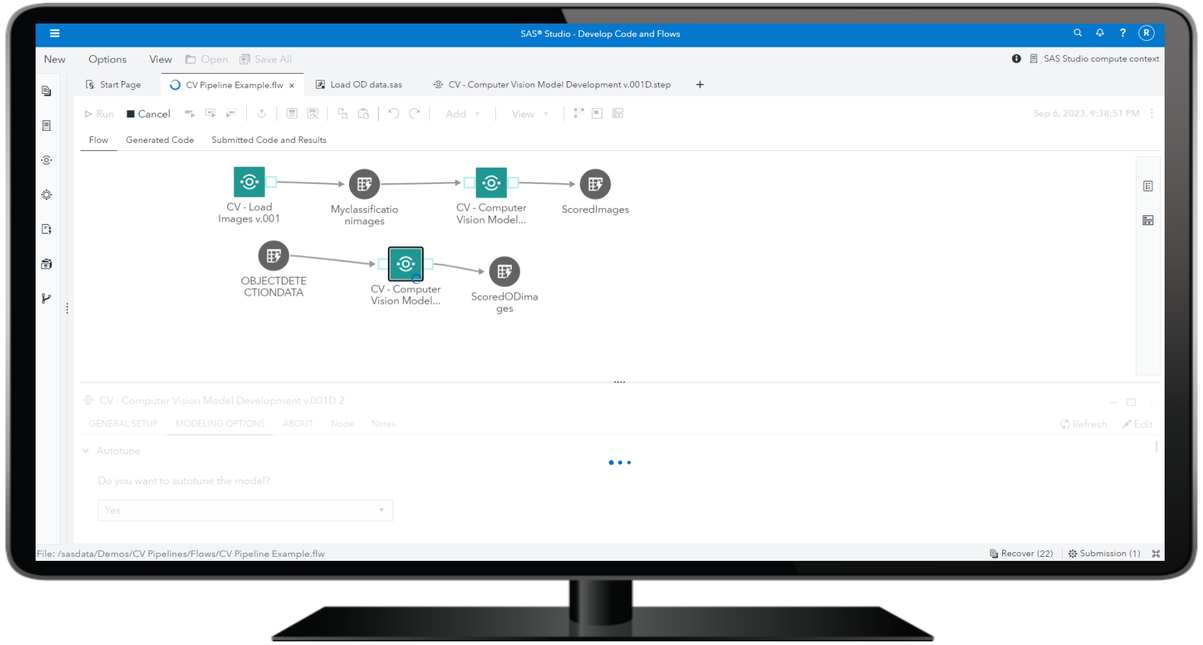
## Deep Learning and Computer Vision




- Use point-and-click to develop computer vision analyses.
- Detail “human-in-the-loop” neural architecture search to develop better model outcomes.

# Human-in-the-Loop Learning

## Human overrides and adjustments

- The user can alter the search specifications without losing previous search effort. The user may choose to do this for several reasons:

# Human-in-the-Loop Learning

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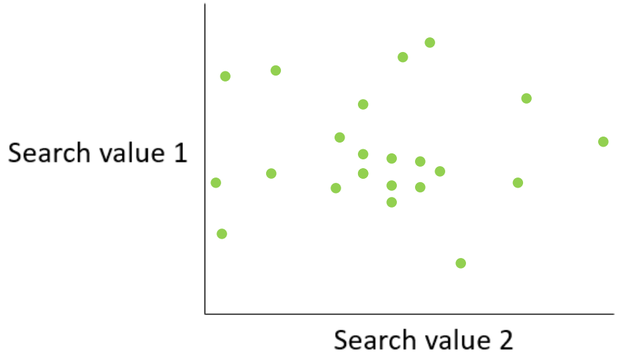

# Human-in-the-Loop Learning

## Human overrides and adjustments

- The user can alter the search specifications without losing previous search effort. The user may choose to do this for several reasons:
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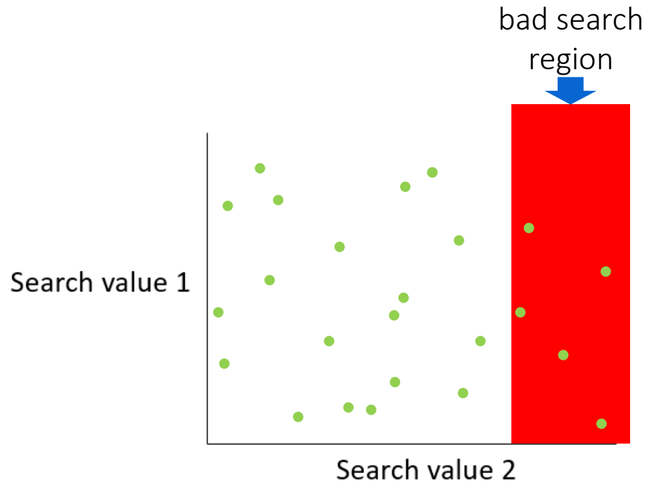
  - Search bounds are deemed to be inefficient



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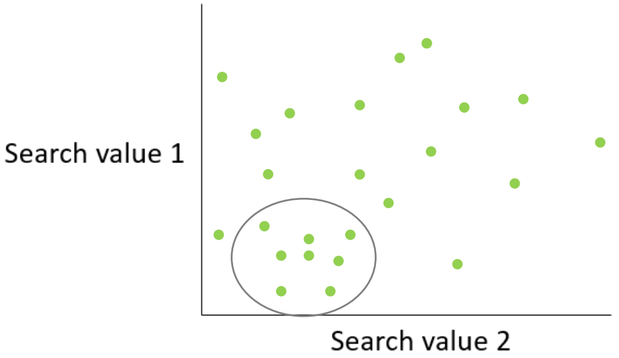

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## Human overrides and adjustments

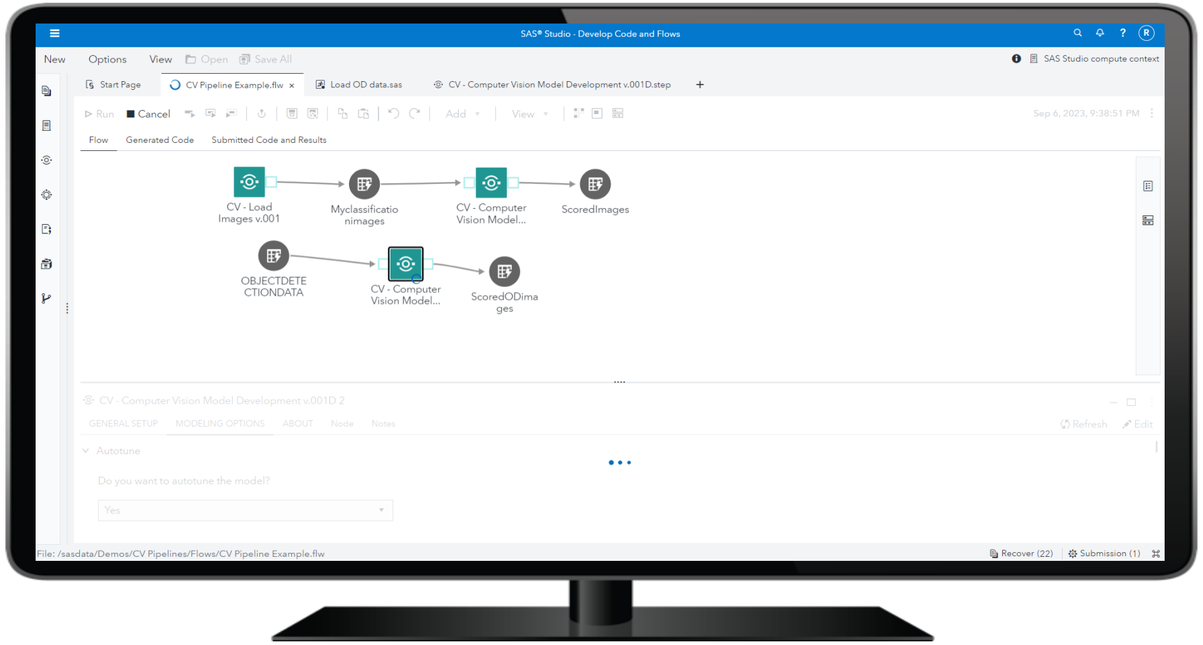
- The user can alter the search specifications without losing previous search effort. The user may choose to do this for several reasons:
  - Search bounds are too restrictive
  - Search bounds are deemed to be inefficient
  - User perspective or knowledge can be  interjected to influence the search
  - Search population can be “re-diversified” to discover new optimal solutions

| Objective Function | Evaluation Time | Backbone Used | Activation Function | Size of First Convo Filter | Gamma Value |
|---|---|---|---|---|---|
| 0.8751645207 | 25.89843 | Tiny-Yolov2 | ReLU | 3 by 3 | 0.7 |
| 0.877042717 | 25.404542 | Tiny-Yolov2 | ReLU | 3 by 3 | 0.7 |
| 0.8861827175 | 77.383928 | resnet50_caffe | ReLU | 3 by 3 | 0.7 |
| 0.8881127868 | 78.142874 | resnet50_caffe | ReLU | 3 by 3 | 0.5 |
| 0.8982402223 | 25.218013 | Tiny-Yolov2 | ReLU | 3 by 3 | 0.69215897 |
| 0.9163502042 | 25.573186 | Tiny-Yolov2 | ReLU | 3 by 3 | 0.7 |
| 0.9173565784 | 24.427719 | Tiny-Yolov2 | ReLU | 3 by 5 | 0.6726658173 |
| 0.917570761 | 77.207966 | resnet50_caffe | ReLU | 3 by 5 | 0.6866390352 |

| Objective Function | Evaluation Time | Backbone Used | Activation Function | Size of First Convo Filter | Gamma Value |
|---|---|---|---|---|---|
| 0.8157730608 | 79.667217 | ShuffleNetV2 | Leaky ReLU | 5 by 7 | 0.9 |
| 0.8163279969 | 80.263945 | ShuffleNetV2 | Leaky ReLU | 5 by 7 | 0.9 |
| 0.8751645207 | 0 | Tiny-Yolov2 | ReLU | 3 by 3 | 0.7 |
| 0.877042717 | 0 | Tiny-Yolov2 | ReLU | 3 by 3 | 0.7 |
| 0.8861827175 | 0 | resnet50_caffe | ReLU | 3 by 3 | 0.7 |
| 0.8881127868 | 0 | resnet50_caffe | ReLU | 3 by 3 | 0.5 |
| 0.8918203447 | 0 | ShuffleNetV2 | Leaky ReLU | 5 by 5 | 0.9 |
| 0.8926189473 | 0 | ShuffleNetV2 | Leaky ReLU | 5 by 5 | 0.5 |

# Demo

## Deep Learning and Computer Vision

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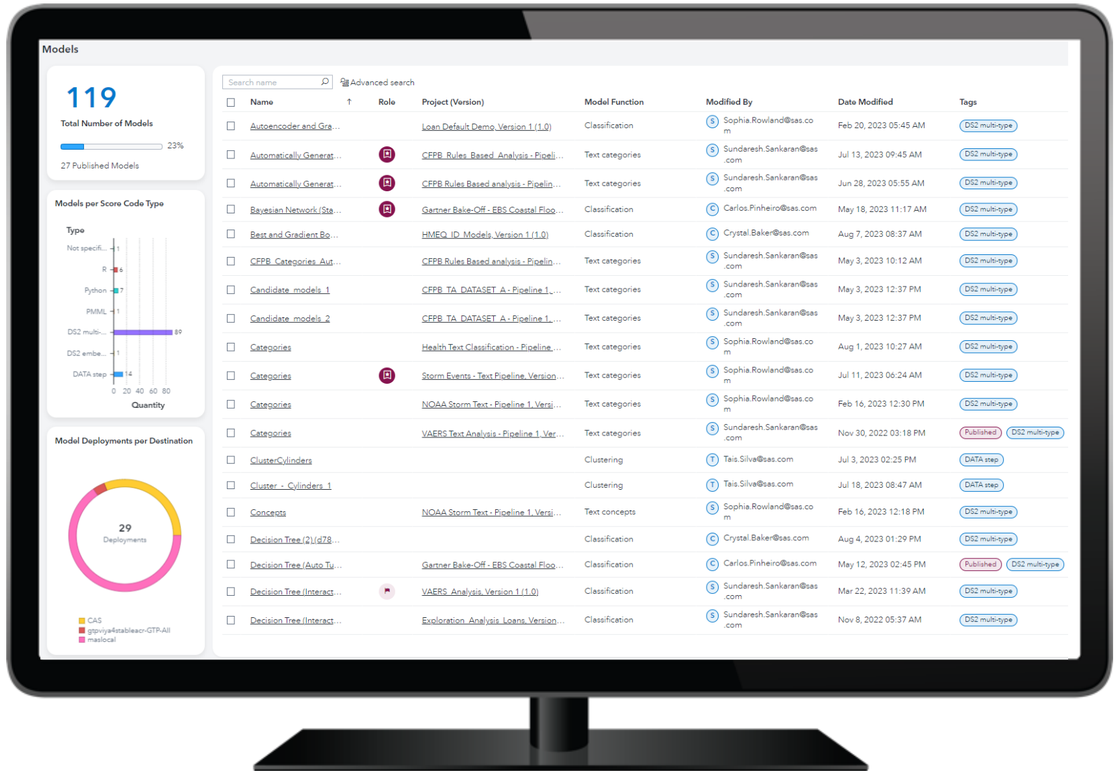
## Network Sciences and Model Deployment




- Examine data using network analyses.
- Deploy and manage models in production.

# Thank you!