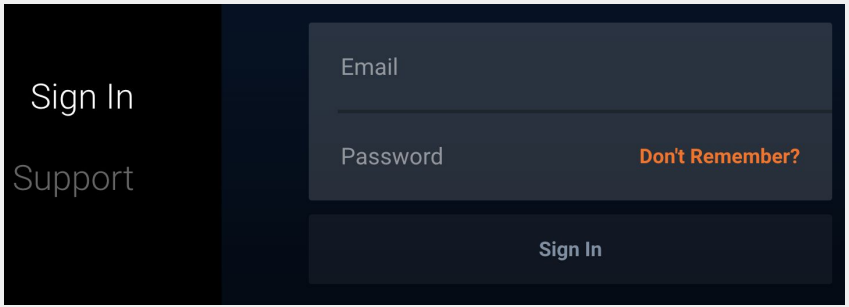
DataRobot
Essentials

DataRobot UNIVERSITY

Logins

Using google chrome

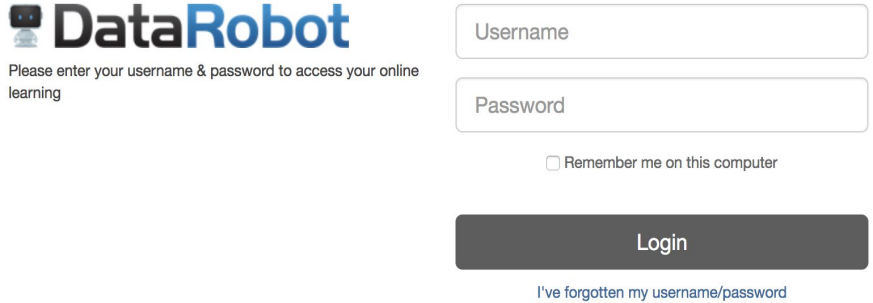
https://app.datarobot.com



Username: {_____}+dru{DMMMYYYY}@{_____}.com

Password: DataRobot123!

https://datarobot.litmos.com



Username: {_____}@{_____}.com

Password: [check your email]

Who We Are

Founders

Jeremy Achin
CEO & Co-Founder

Tom de Godoy
CTO & Co-Founder

Top Data Scientists

Xavier Conort
Chief Data Scientist

Owen Zhang
Data Science Advisor

Sergey Yurgenson
Data Scientist

kaggle hosts worldwide data science competitions with over 1 million registered competitors as of June 2017. 12 members of the DataRobot team have been ranked in Kaggle's top 100 data scientists. Six are Kaggle Grandmasters.

Objectives

You Will Be Able To

- Follow a workflow giving you the best chance of success in machine learning projects
- Use DataRobot to approach and solve typical machine learning problems
- Discuss basic machine learning terminology with peers
- Tailor modeling decisions to meet business objectives

Not Covered

- Programming
- Advanced Extract-Transform-Load (ETL)
- Mathematical Theory / Machine Learning Algorithms

Structure

Explanation

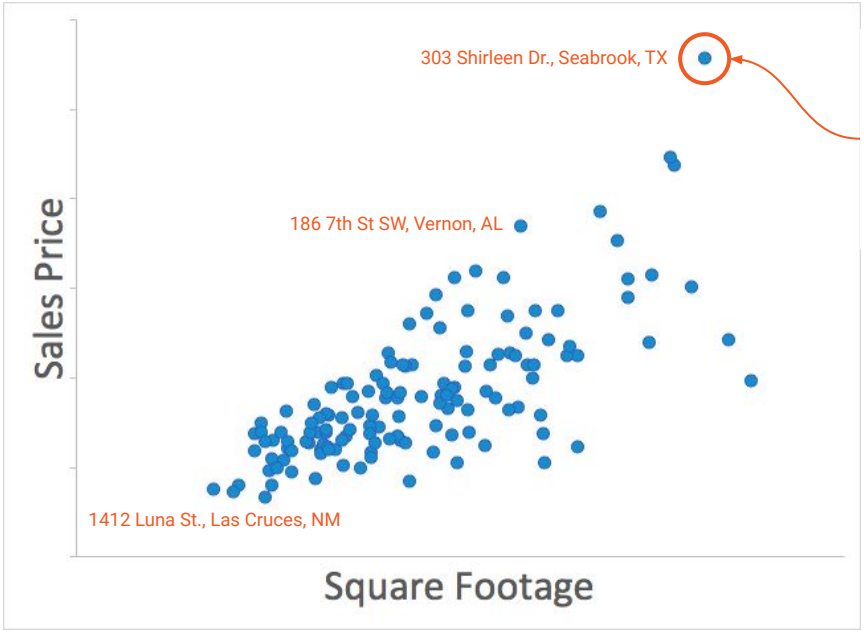
Hands-on Exercises

Hands-on Project

Surveys/Exam

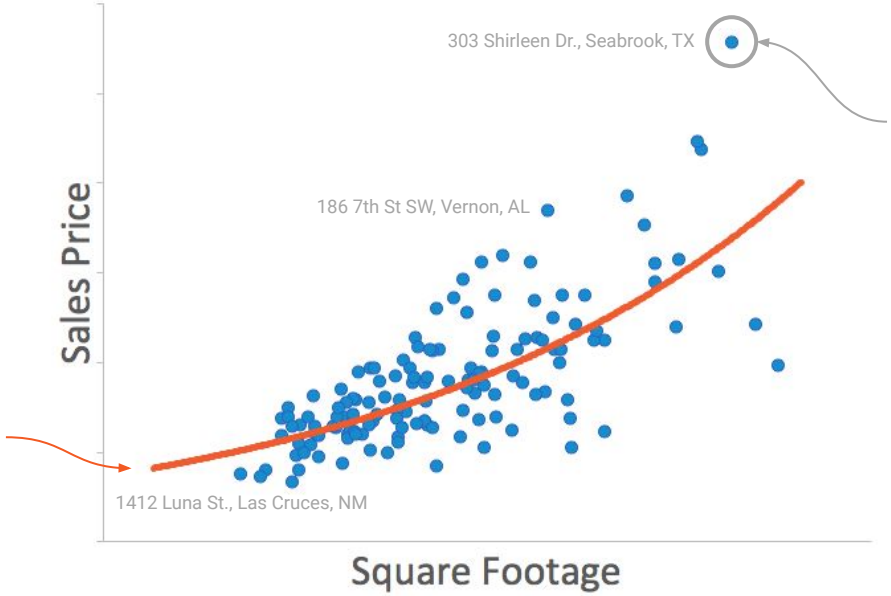
What is Machine Learning? AI?

Why do they call it “Machine Learning”?



Every point is **an example** that the machine learns from

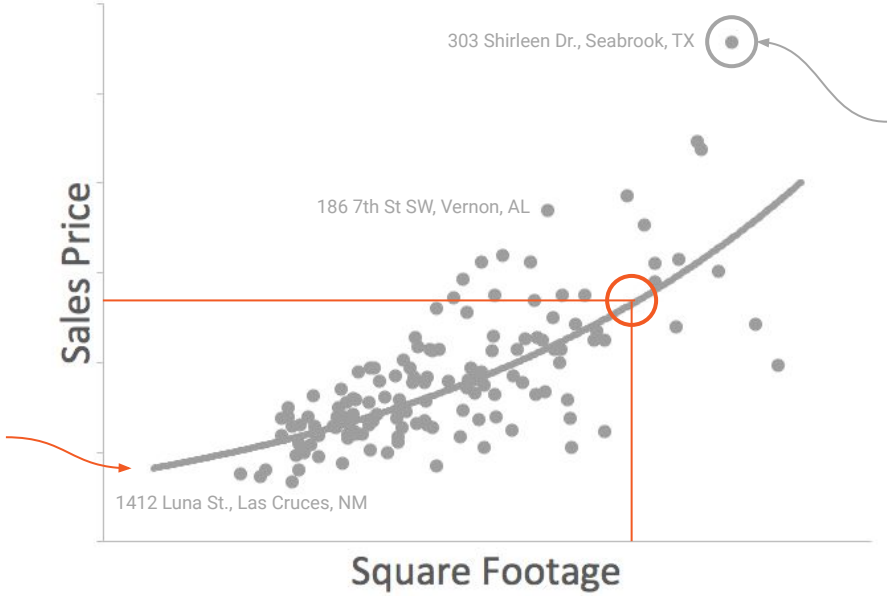
Why do they call it “Machine Learning”?



Every point is **an example** that the machine learns from

The line is a model. If you tell the model a square footage, it will make a prediction.

Why do they call it “Machine Learning”?



Every point is **an example** that the machine learns from

The line is a model. If you tell the model a square footage, it will make a prediction.

ML Working Definition

Using computer algorithms to uncover insights, determine relationships, and make predictions about future trends.

What About Deep Learning?

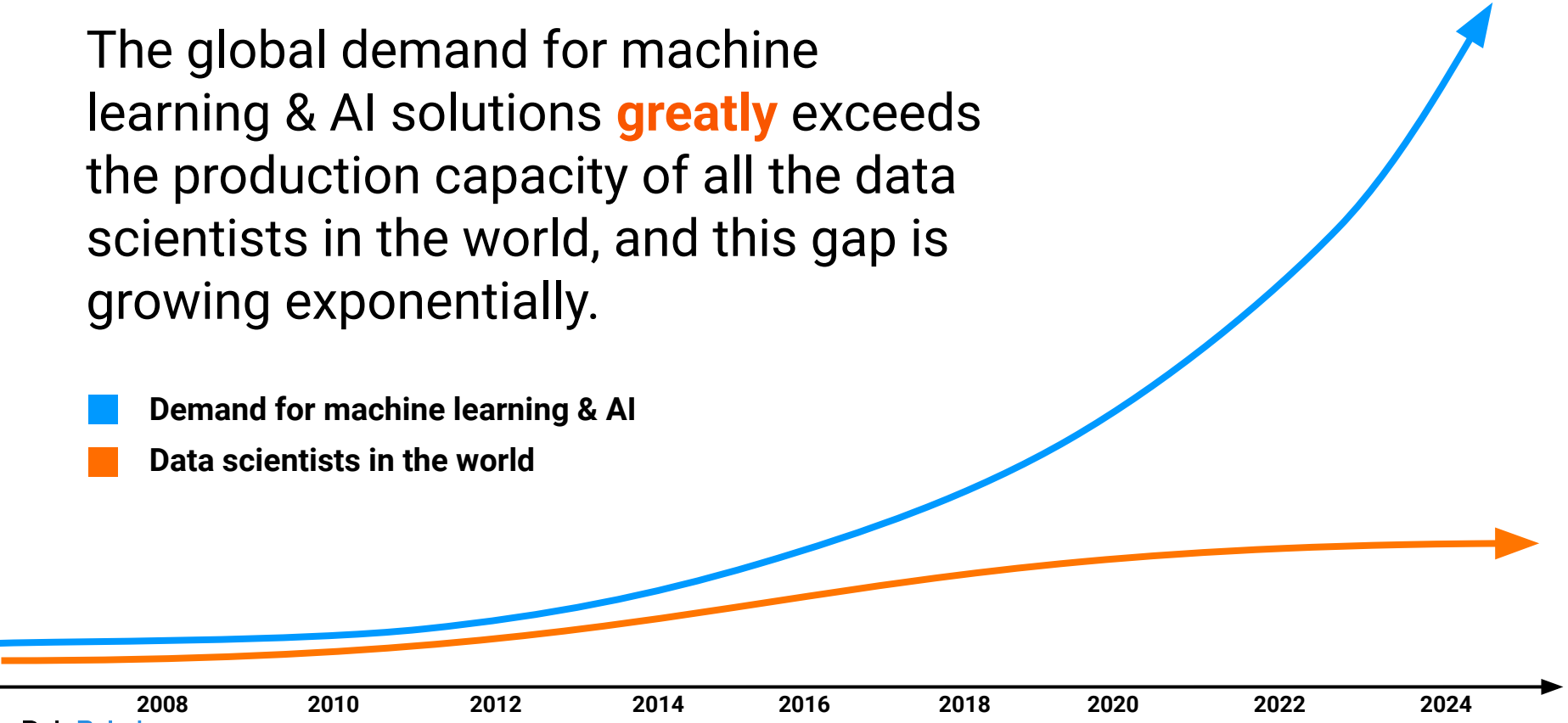
AI Working Definition

Enabling computer *systems* to perform tasks that ordinarily require human intelligence.

We use machine learning methods to create AI systems.

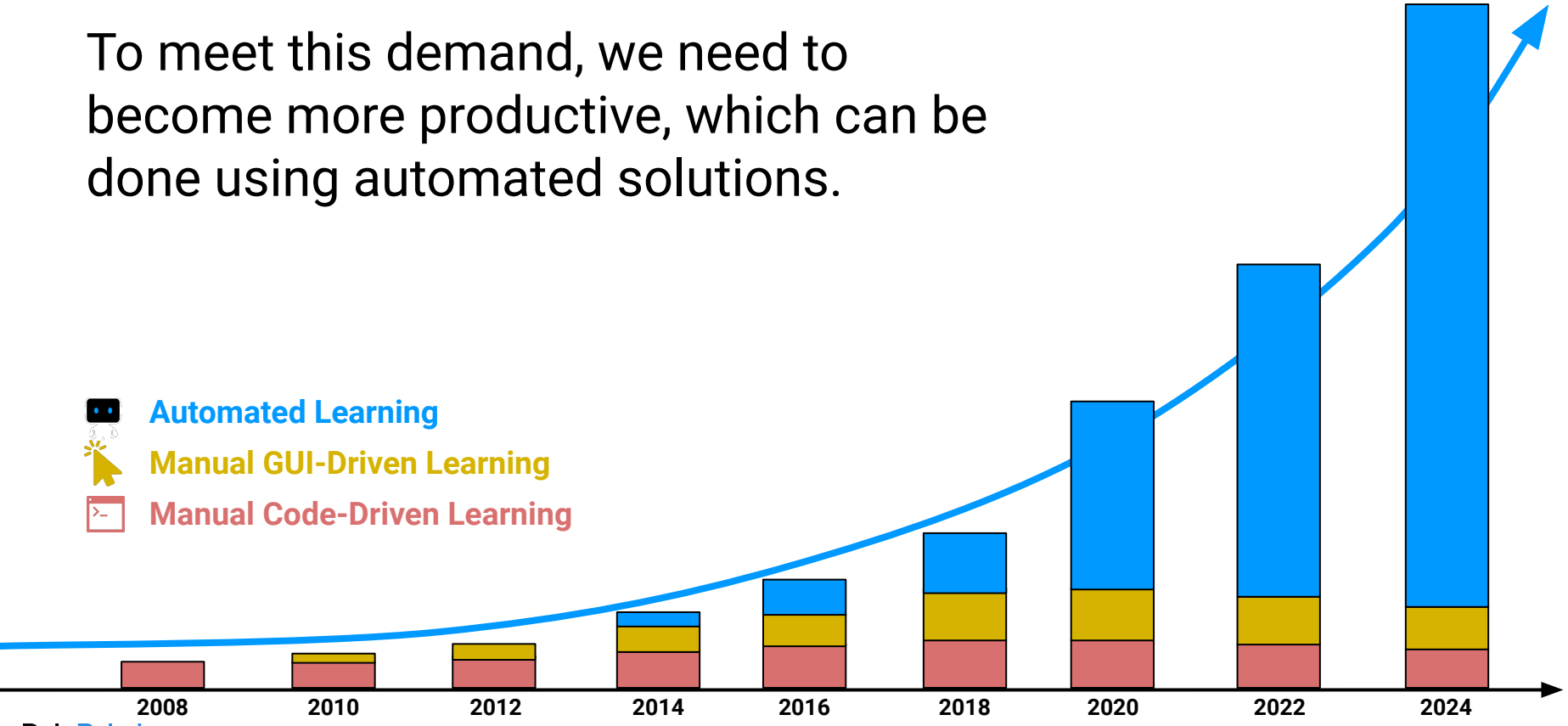
The Demand for AI

The global demand for machine learning & AI solutions **greatly** exceeds the production capacity of all the data scientists in the world, and this gap is growing exponentially.

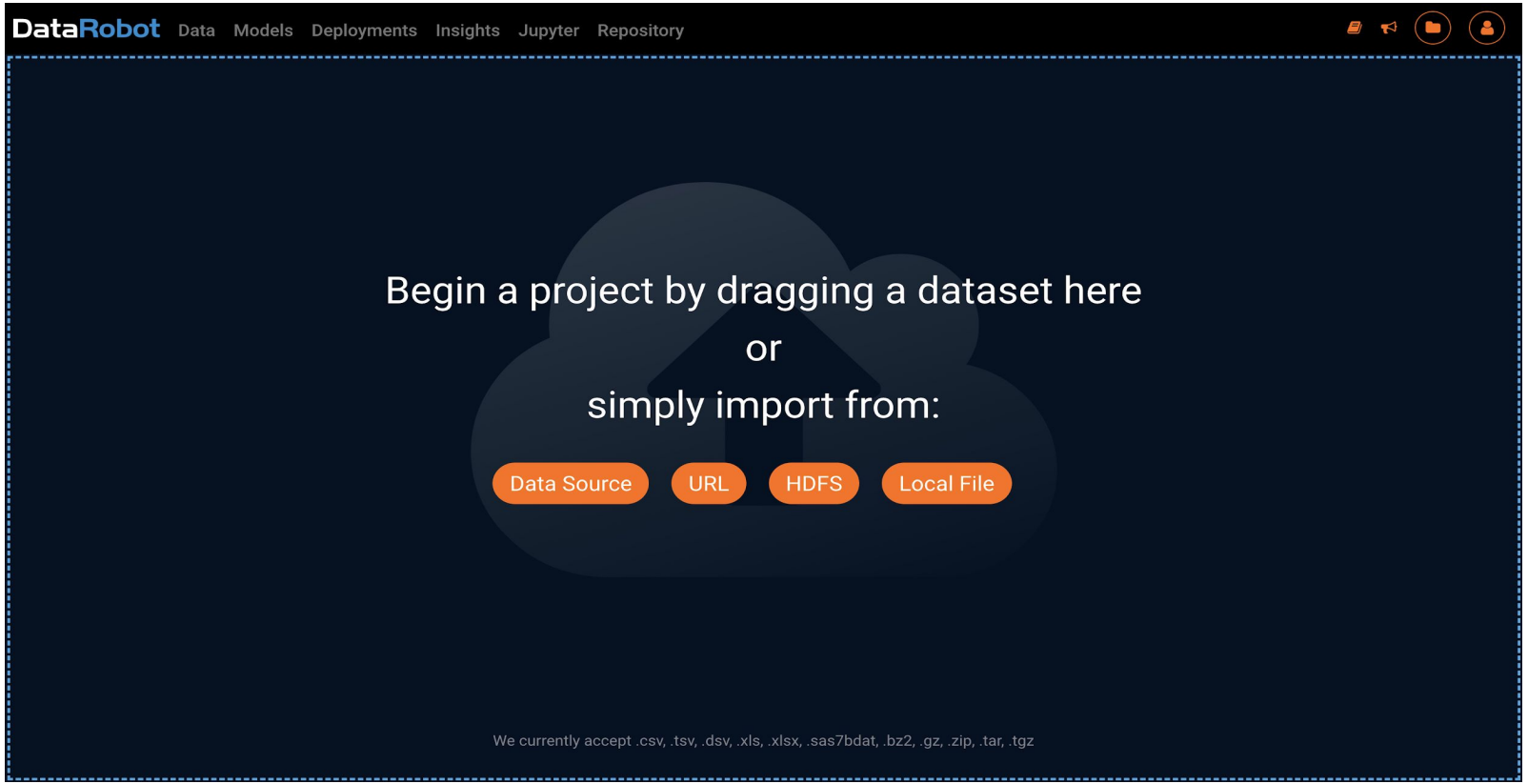


Bridging the Gap

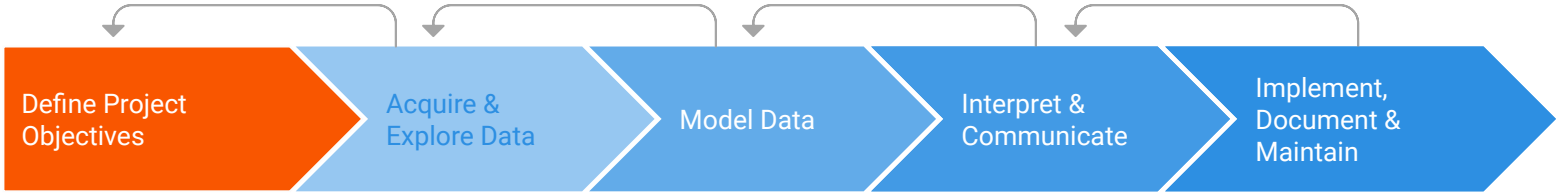
To meet this demand, we need to become more productive, which can be done using automated solutions.



The DataRobot Interface



The Machine Learning Life Cycle



1. **Define Project Objectives**
   - Specify problem
   - Acquire subject matter expertise
   - Define target and unit of analysis
   - Prioritize modeling criteria
   - Consider success criteria and risks
   - Decide whether to continue

2. **Acquire & Explore Data**
   - Find appropriate data
   - Format data into single table
   - Conduct exploratory data analysis
   - Find and remove any target leakage
   - Perform feature engineering

3. **Model Data**
   - Select features
   - Build candidate models
   - Validate models

4. **Interpret & Communicate**
   - Assess model quality
   - Determine important features
   - Identify relationships
   - Explain predictions

5. **Implement, Document & Maintain**
   - Select a model for deployment
   - Document modeling process
   - Create model monitoring and maintenance plan

Specify the Business Problem

Criteria

- State problem in language of business (no technical jargon)
- Specify actions that might result
- Include specifics (number of customers affected, costs etc.)
- Explain impact to the bottom line

Critique These Project Statements

Readmissions cost our hospital $65m last year, and we don't have a way to determine which patients are at risk of readmission.

Criteria

- State problem in language of business (no technical jargon)
- Specify actions that might result
- Include specifics (number of customers affected, costs etc.)
- Explain impact to the bottom line

Critique These Project Statements

Warehouse operators want to know how long each truck will take to unload, so they can tell drivers of subsequent deliveries when the warehouse bay will be ready.

Criteria

- State problem in language of business (no technical jargon)
- Specify actions that might result
- Include specifics (number of customers affected, costs etc.)
- Explain impact to the bottom line

Critique These Project Statements

Our hedge fund is considering investing $40 Million/yr in loans on LendingClub.com. These loans are an appealing investment with interest rates averaging 17%. However, 5% of invested money on the site is lost due to borrower defaults. You would like to be able to screen out the riskiest borrowers. If successful, your organization will use your approach to justify investing on the site. They will then apply the method in an automated fashion to choose which loans to fund.

Criteria

- State problem in language of business (no technical jargon)
- Specify actions that might result
- Include specifics (number of customers affected, costs etc.)
- Explain impact to the bottom line

Acquire Subject Matter Expertise

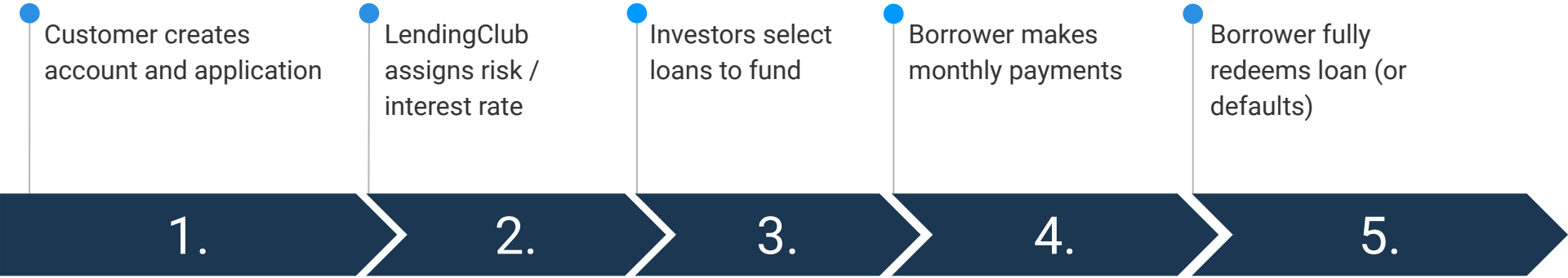
Why

- Indicates obstacles and opportunities
- Suggests data collection and modeling ideas
- Finds data quality problems and improvement opportunities
- Sets expectations for model performance
- Clarifies alternatives to building model

How

- Talk to colleagues or subject matter experts (SMEs)
- Read (trade journals, Google, etc)

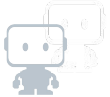
Subject Matter Expertise on Lending Club



Has disbursed $42B in loans (as of 2018)

Mix of individual and institutional investors

Define Target



Retail Sales Data

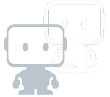
Date	Customer ID	Store ID	Purchase Amount	Number of Items
10/2/2015	1037	17	$107.23	3
10/2/2015	1038	17	$99.50	2
10/5/2015	1037	17	$212.49	5
10/5/2015	1091	19	$37.04	2
10/5/2015	1302	19	$18.02	1

What do you want to predict?


Classification


Regression

Define Unit of Analysis

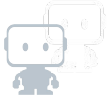


Retail Sales Data

Date	Customer ID	Store ID	Purchase Amount	Number of Items
10/2/2015	1037	17	$107.23	3
10/2/2015	1038	17	$99.50	2
10/5/2015	1037	17	$212.49	5
10/5/2015	1091	19	$37.04	2
10/5/2015	1302	19	$18.02	1

What does each row represent?

Define Unit of Analysis



Retail Sales Data

Date	Store ID	Purchase Amount	Number of Items
10/2/2015	17	$206.73	5
10/5/2015	17	$212.49	5
10/5/2015	19	$55.06	3

What would be a good target and unit of analysis for Lending Club?

Prioritize Modeling Criteria

- Predictive performance
- Familiarity
- Prediction speed
- Speed to build model
- Interpretability?

Success Criteria

Who uses the model?

How much value can the model drive?

What modeling criteria will help get you there?

Risk Scenarios

Play devil's advocate. Be creative.

Examples:

- Change in underlying patterns so past is no longer predictive
- Business loses interest in outcome being modeled
- Model insufficiently predictive

Decide Whether To Continue

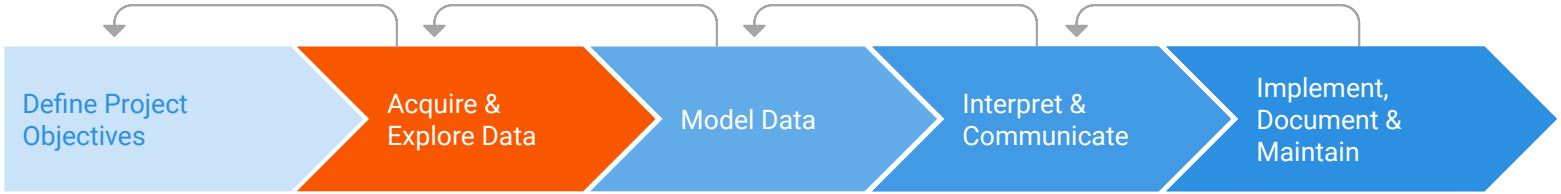
Estimate resources required

Understand alternatives to creating model

Consider organizational risks

Estimate model's business value

The Machine Learning Life Cycle



1. **Define Project Objectives**
   - Specify problem
   - Acquire subject matter expertise
   - Define target and unit of analysis
   - Prioritize modeling criteria
   - Consider success criteria and risks
   - Decide whether to continue

2. **Acquire & Explore Data**
   - Find appropriate data
   - Format data into single table
   - Conduct exploratory data analysis
   - Find and remove any target leakage
   - Perform feature engineering

3. **Model Data**
   - Select features
   - Build candidate models
   - Validate models

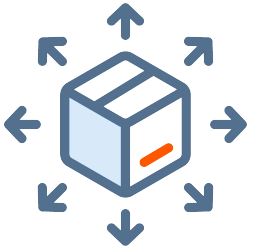
4. **Interpret & Communicate**
   - Assess model quality
   - Determine important features
   - Identify relationships
   - Explain predictions

5. **Implement, Document & Maintain**
   - Select a model for deployment
   - Document modeling process
   - Create model monitoring and maintenance plan

Find Appropriate Data

Internal

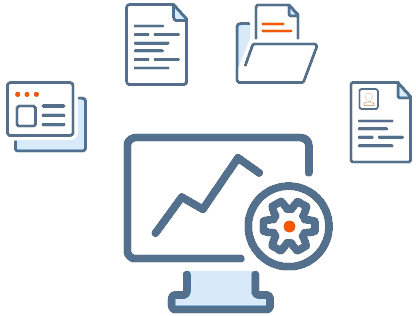
External



Public

What about for LendingClub?

Format Data for Modeling



Modeling requires data be in one “table”

Result should match desired unit of analysis

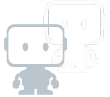
First Steps in Exploratory Data Analysis

View raw table contents

Descriptive statistics

Verify variable/column types match expectation

Defining our Target *loan_is_bad*



FALSE

Fully Paid, Current

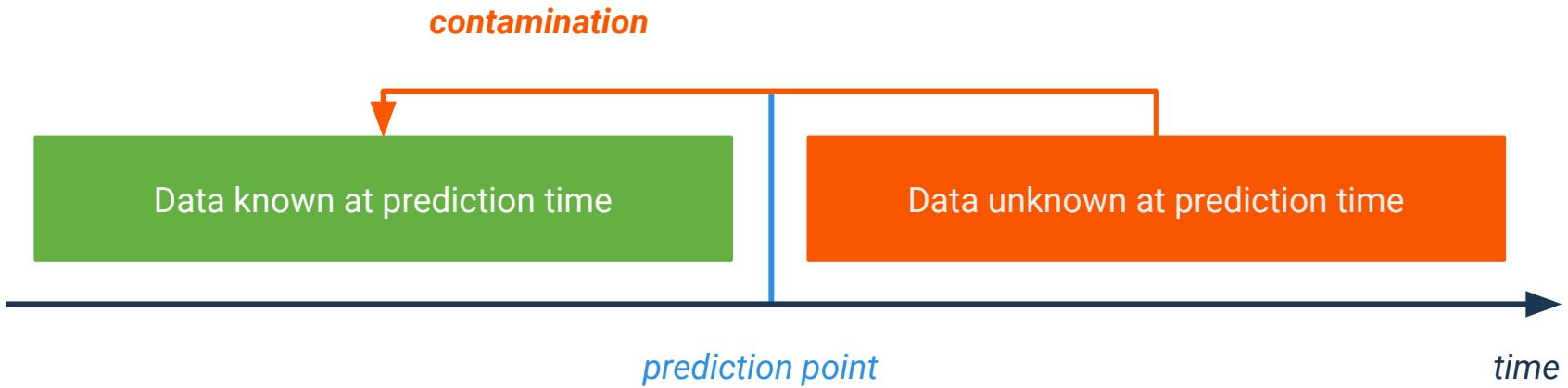
TRUE

In Grace Period, Late (16-30 days), Late (31-120 days), Default, Charged Off

Load Data Into DataRobot

- Start a new project by clicking on the DataRobot icon.
- Load *early_2012_2013_loan_sample_with_outcome.csv.zip* into DataRobot.
- Explore the raw data in DataRobot and view some of the features.
- Set the target to loan_is_bad when prompted and run manual mode.
- Which features are most important according to the green bars?

Visualizing Target Leakage



Target Leakage Examples

Employee ID	Title	Experience Years	Monthly Salary GBP	Annual Income USD
315981	Data Scientist	3	5,000.00	78,895.44
4691	Data Scientist	4	5,500.00	86,784.98
23598	Data Scientist	5	6,200.00	97,830.35

Target Leakage Examples

Employee ID	Title	Experience Years	Monthly Salary GBP	Annual Income USD
315981	Data Scientist	3	5,000.00	78,895.44
4691	Data Scientist	4	5,500.00	86,784.98
23598	Data Scientist	5	6,200.00	97,830.35

Target Leakage Examples

Subscriber ID	Group	Daily Voice Usage	Daily SMS Usage	Daily Data Usage	Gender
24092091	M18-25	15.31	25	135.10	0
4092034091	F40-60	35.81	3	5.01	1
329815	F25-40	13.09	32	128.52	1
94721835	M25-40	18.52	21	259.34	0

Target Leakage Examples

Subscriber ID	Group	Daily Voice Usage	Daily SMS Usage	Daily Data Usage	Gender
24092091	M18-25	15.31	25	135.10	0
4092034091	F40-60	35.81	3	5.01	1
329815	F25-40	13.09	32	128.52	1
94721835	M25-40	18.52	21	259.34	0

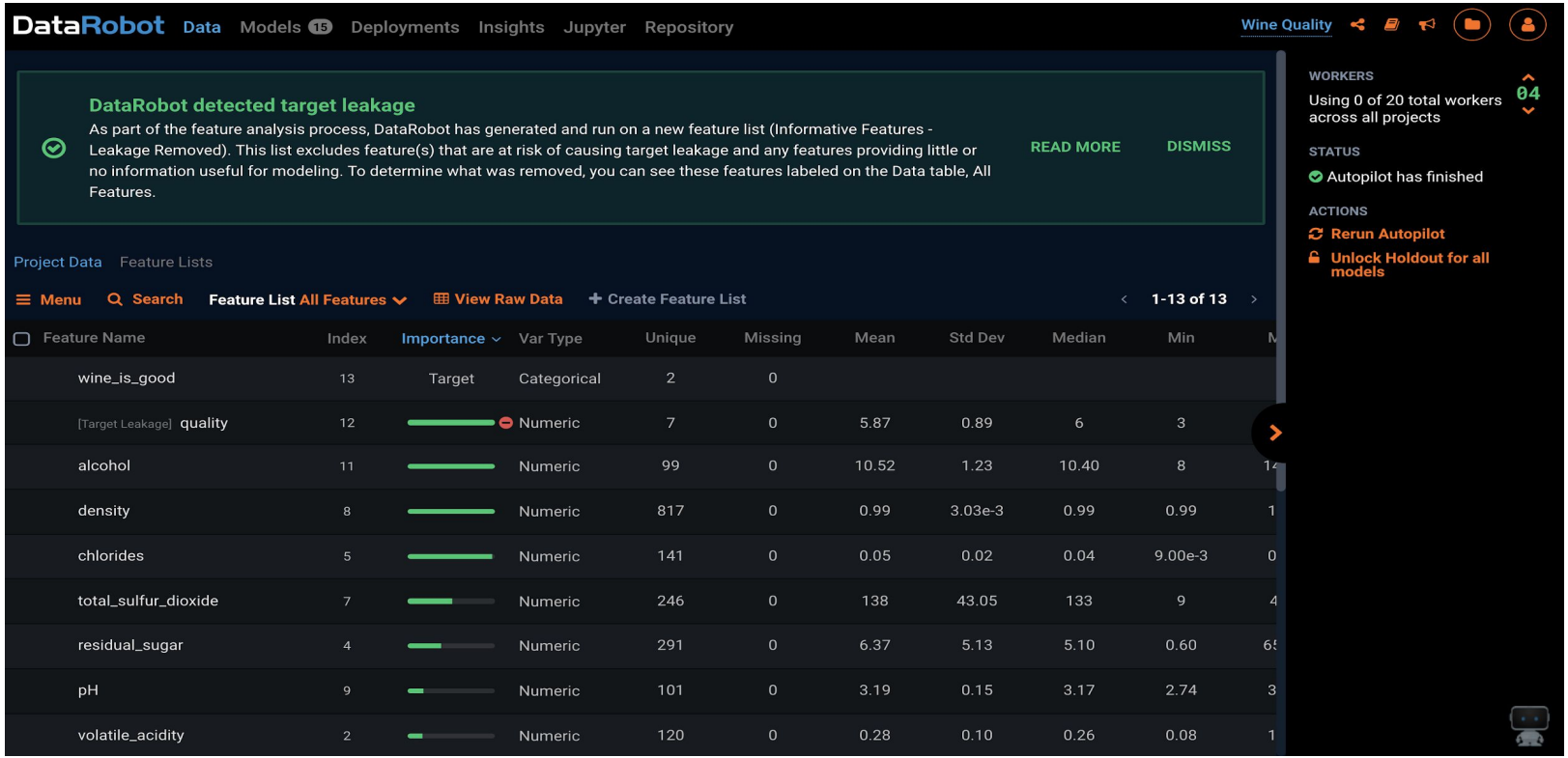
Target Leakage Examples

Education	Married	Annual Income	Purpose	Late Payment Reminders	Is Bad Loan
1	Y	80k	Car Purchase	0	0
3	N	120k	Small Business	3	1
1	Y	85k	House Purchase	5	1
2	N	72k	Marriage	1	0

Target Leakage Examples

Education	Married	Annual Income	Purpose	Late Payment Reminders	Is Bad Loan
1	Y	80k	Car Purchase	0	0
3	N	120k	Small Business	3	1
1	Y	85k	House Purchase	5	1
2	N	72k	Marriage	1	0

How Can DataRobot Help?



Load Data Into DataRobot

- Start a new project again by clicking on the DataRobot icon.
- Load *early_2012_2013_train.csv.zip* into DataRobot.
- Set the target to *loan_is_bad* and run autopilot.

Lunch

Feature Engineering is the Art Part of Data Science

Sergey Yurgenson

Former #1 ranked modeler on Kaggle.com

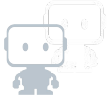
Feature Engineering - Dates

Manufacture Date	Is Defective
10/5/15	True
10/6/15	False
10/7/15	False
10/8/15	False
10/9/15	True

Feature Engineering - Dates

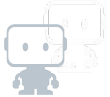
Manufacture Date	Day of the Week	Is Defective
10/5/15	Monday	True
10/6/15	Tuesday	False
10/7/15	Wednesday	False
10/8/15	Thursday	False
10/9/15	Friday	True

Feature Engineering - Generalizing



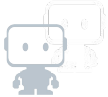
Birth Year	Is Bad
10 Apr 1982	True
3 Dec 1978	False
5 Jan 1993	False
15 Jul 1994	False
1 Jan 1980	True

Feature Engineering - Generalizing



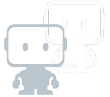
Birth Year	Age at Application Time	Is Bad
10 Apr 1982	30	True
3 Dec 1978	36	False
5 Jan 1993	24	False
15 Jul 1994	22	False
1 Jan 1980	31	True

Feature Engineering - Aggregation



Date	Customer ID	Store ID	Purchase Amount	Number of Items
10/2/2015	1037	17	$107.23	3
10/2/2015	1038	17	$99.50	2
10/5/2015	1037	17	$212.49	5
10/5/2015	1091	19	$37.04	2
10/5/2015	1302	19	$18.02	1

Feature Engineering - Aggregation



Date	Store ID	Purchase Amount	Number of Items	Number of Customers
10/2/2015	17	$206.73	5	2
10/5/2015	17	$212.49	5	1
10/5/2015	19	$55.06	3	2

Feature Types

- **Numerical**
- **Categorical**
- **Text**

Numeric Features

Impute missing value and create flag for what was imputed

Scaling transformations (Ridit, Standardize, Squared, Log)

Differences of features

Ratios of features

Categorical Features

One-hot encoding

Count / ordinal encoding

Credibility estimates

One-hot Encoding

Group
A
B
C
A
A

Group_A	Group_B	Group_C
1	0	0
0	1	0
0	0	1
1	0	0
1	0	0

Count Encoding

Group
A
B
C
A
A

Count Encoding
3
1
1
3
3

Ordinal Encoding

Group
A
B
C
A
A

Ordinal Encoding
0
1
2
0
0

Credibility Estimates

$$count_k \times (\bar{y}_k - \bar{y}_.)$$

The more we see a group, the more we “trust” the group’s deviation from the overall mean

Credibility Estimates

Defaulted	Group
0	A
0	B
1	C
1	A
0	A

Credibility Estimates
3 * (0.33 - 0.4)
1 * (0 - 0.4)
1 * (1 - 0.4)
3 * (0.33 - 0.4)
3 * (0.33 - 0.4)

Feature Types

- ✓ Numerical
- ✓ Categorical
- • Text

Text Features

Churn	Comments
0	I like AAA coffee
1	I dislike AAA coffee
1	I like AAA coffee, but prefer BBB coffee

Text Features (Tokenizing)

Churn	Comments	I	like	dislike	coffee	AAA	BBB	but	prefer
0	I like AAA coffee	1	1	0	1	1	0	0	0
1	I dislike AAA coffee	1	0	1	1	1	0	0	0
1	I like AAA coffee, but prefer BBB coffee	1	1	0	2	1	1	1	1

Text Features (N-grams)

Churn	Comments	Like AAA	Dislike AAA	Prefer BBB	...
0	I like AAA coffee	1	0	0	...
1	I dislike AAA coffee	0	1	0	...
1	I like AAA coffee, but prefer BBB coffee	1	0	1	...

TF-IDF

Term Frequency

$$\frac{\{\text{number of times the word appears in the document}\}}{\{\text{total number of words in the document}\}}$$

Inverse Document Frequency

$$\frac{\{\text{number of documents}\}}{\{\text{number of documents that contain word}\}}$$

TF * IDF

Text Features (TF-IDF)

Churn	Comments	I	like	dislike	coffee	AAA	BBB	but	prefer
0	I like AAA coffee	(1/4) * (3/3) = 0.25	0.375	0	0.25	0.25	0	0	0
1	I dislike AAA coffee	0.25	0	0.75	0.25	0.25	0	0	0
1	I like AAA coffee, but prefer BBB coffee	0.125	0.188	0	(2/8) * (3/3) = 0.25	0.125	0.375	0.375	0.375

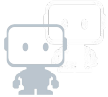
Other Text Pre-processing

- Word embeddings (word2vec, fastText)
- Deep learning methods (such as autoencoders)
- Cosine similarity between pairs of text columns (on datasets with 2+ text columns)
- Support for multiple languages, including English, Japanese, French, Spanish, Chinese, Portuguese, etc.

Feature Types

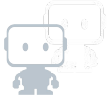
- ✓ **Numerical**
- ✓ **Categorical**
- ✓ **Text**

Domain-Specific Feature Engineering



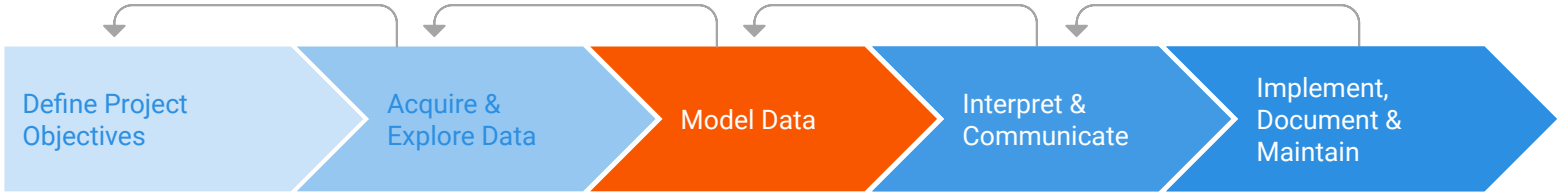
Loan Amount	Term Length	Annual Income
$11,200	36	$108,000
$10,000	60	$65,000
$8,000	36	$35,000
$16,000	36	$110,000
$4,000	60	$155,000

Domain-Specific Feature Engineering



Loan Amount	Term Length	Annual Income	Loan To Income Ratio
$11,200	36	$108,000	(11200/36) / (108,000/12) = 0.035
$10,000	60	$65,000	0.031
$8,000	36	$35,000	0.076
$16,000	36	$110,000	0.048
$4,000	60	$155,000	0.005

The Machine Learning Life Cycle



1. **Define Project Objectives**
   - Specify problem
   - Acquire subject matter expertise
   - Define target and unit of analysis
   - Prioritize modeling criteria
   - Consider success criteria and risks
   - Decide whether to continue

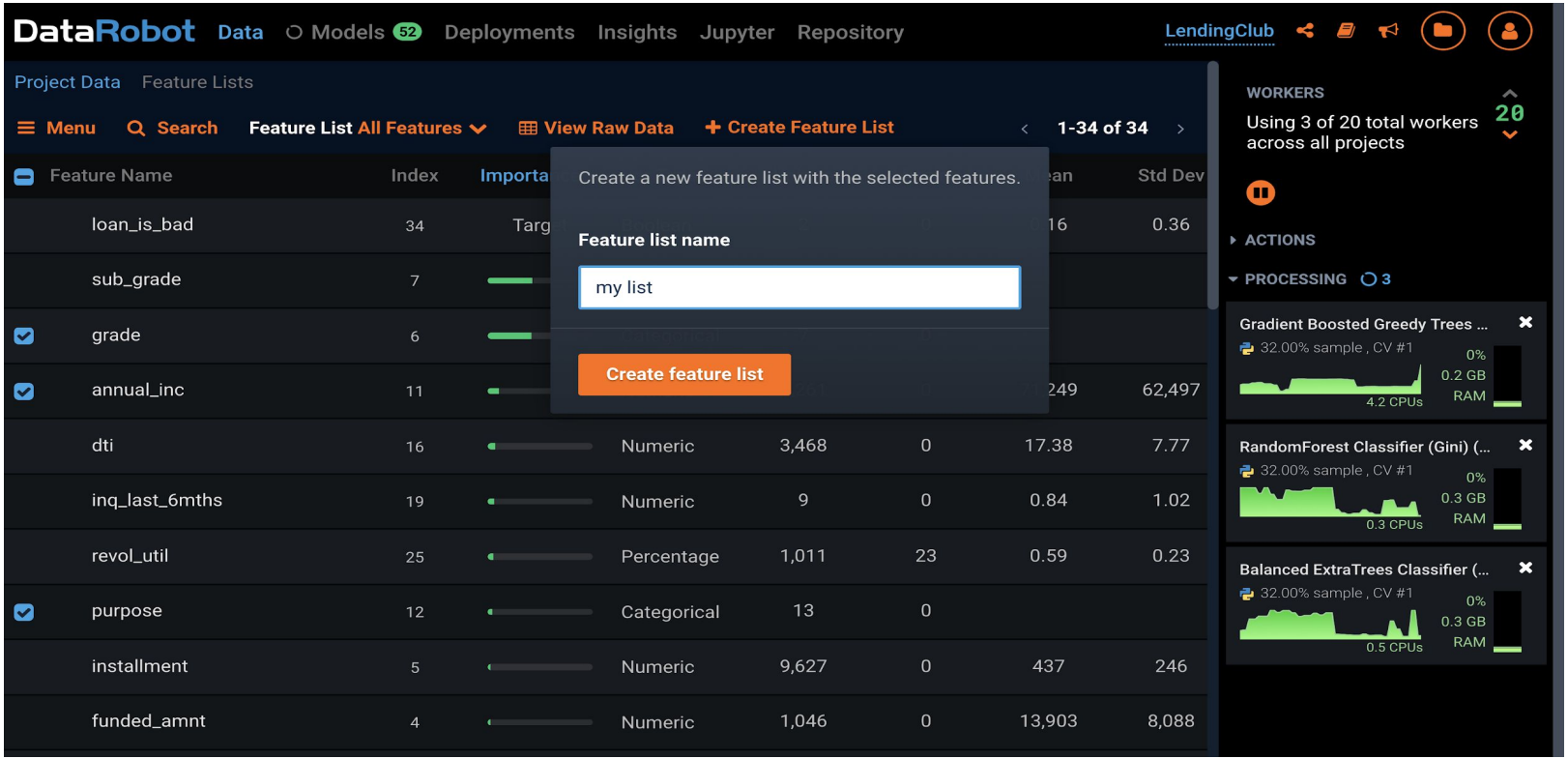
2. **Acquire & Explore Data**
   - Find appropriate data
   - Format data into single table
   - Conduct exploratory data analysis
   - Find and remove any target leakage
   - Perform feature engineering

3. **Model Data**
   - Select features
   - Build candidate models
   - Validate models

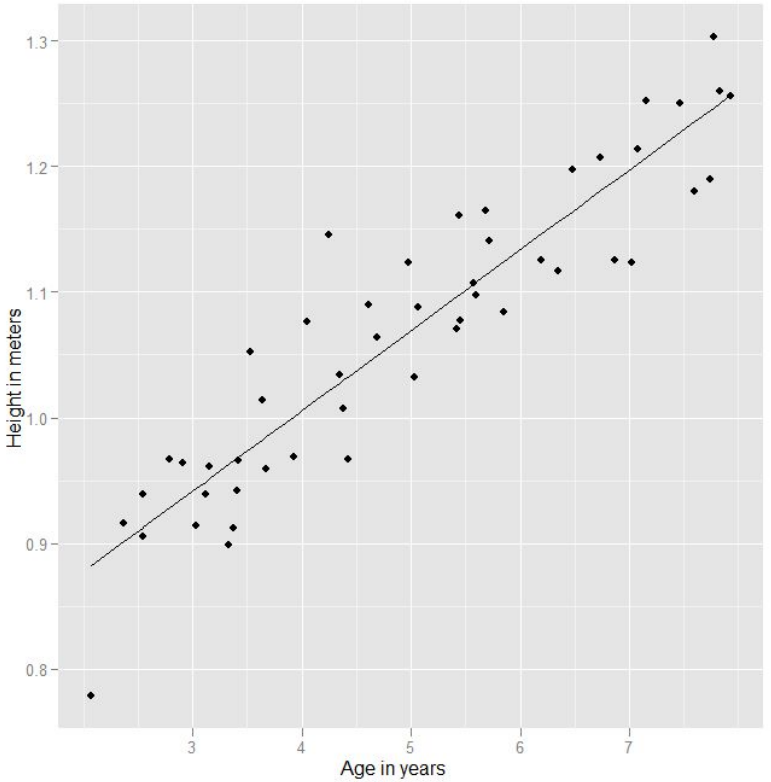
4. **Interpret & Communicate**
   - Assess model quality
   - Determine important features
   - Identify relationships
   - Explain predictions

5. **Implement, Document & Maintain**
   - Select a model for deployment
   - Document modeling process
   - Create model monitoring and maintenance plan

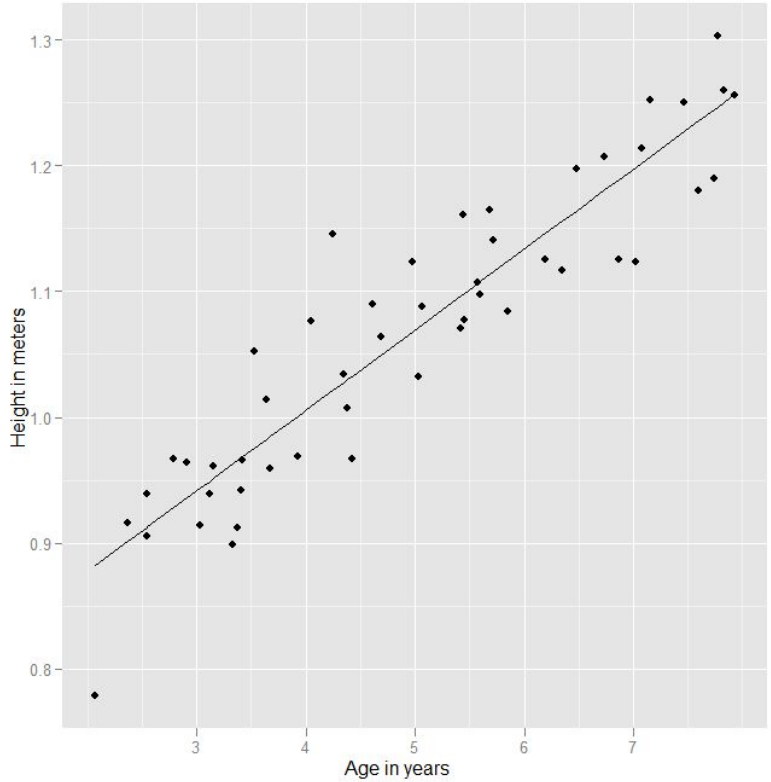
Selecting Features



Linear Regression

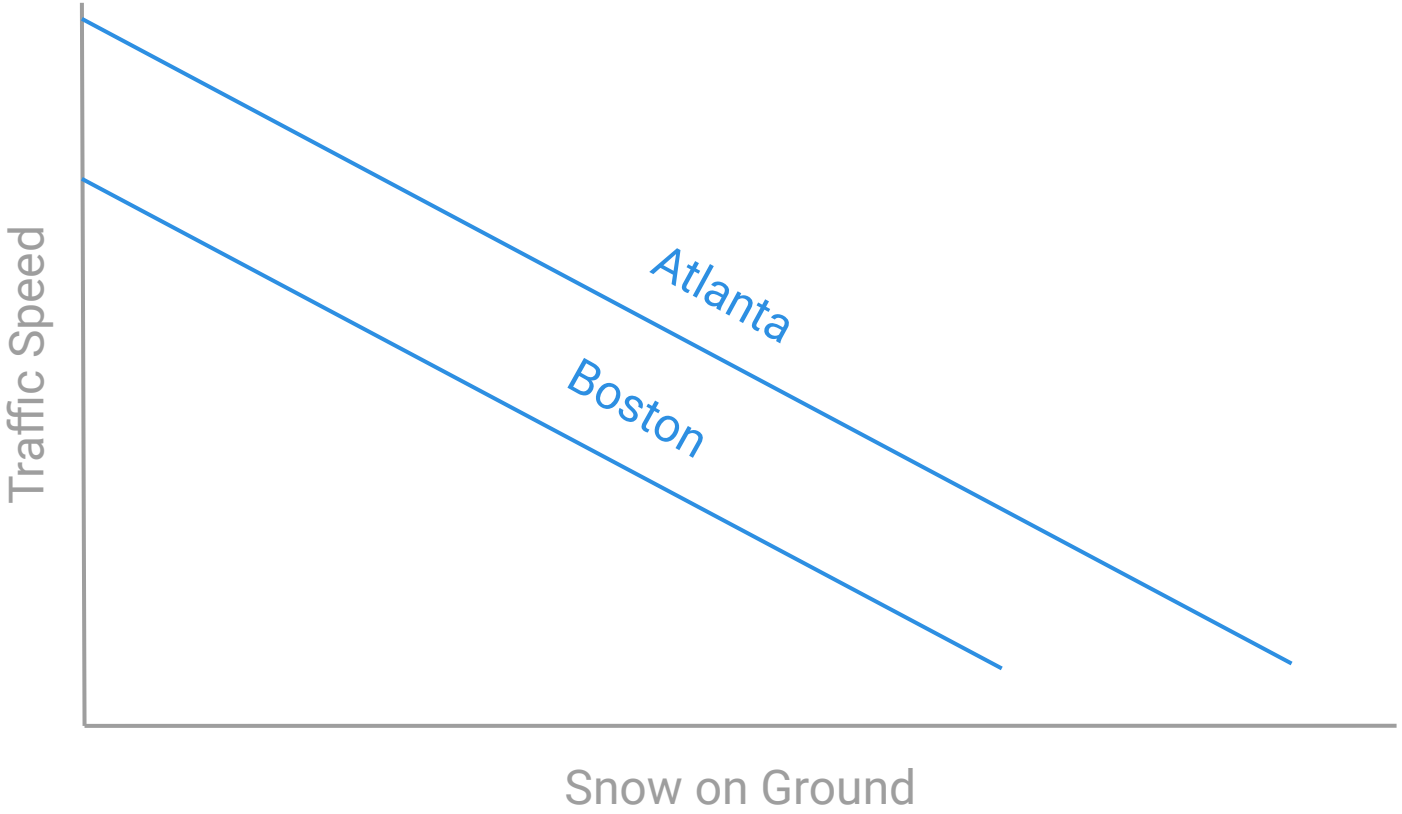


Linear Regression

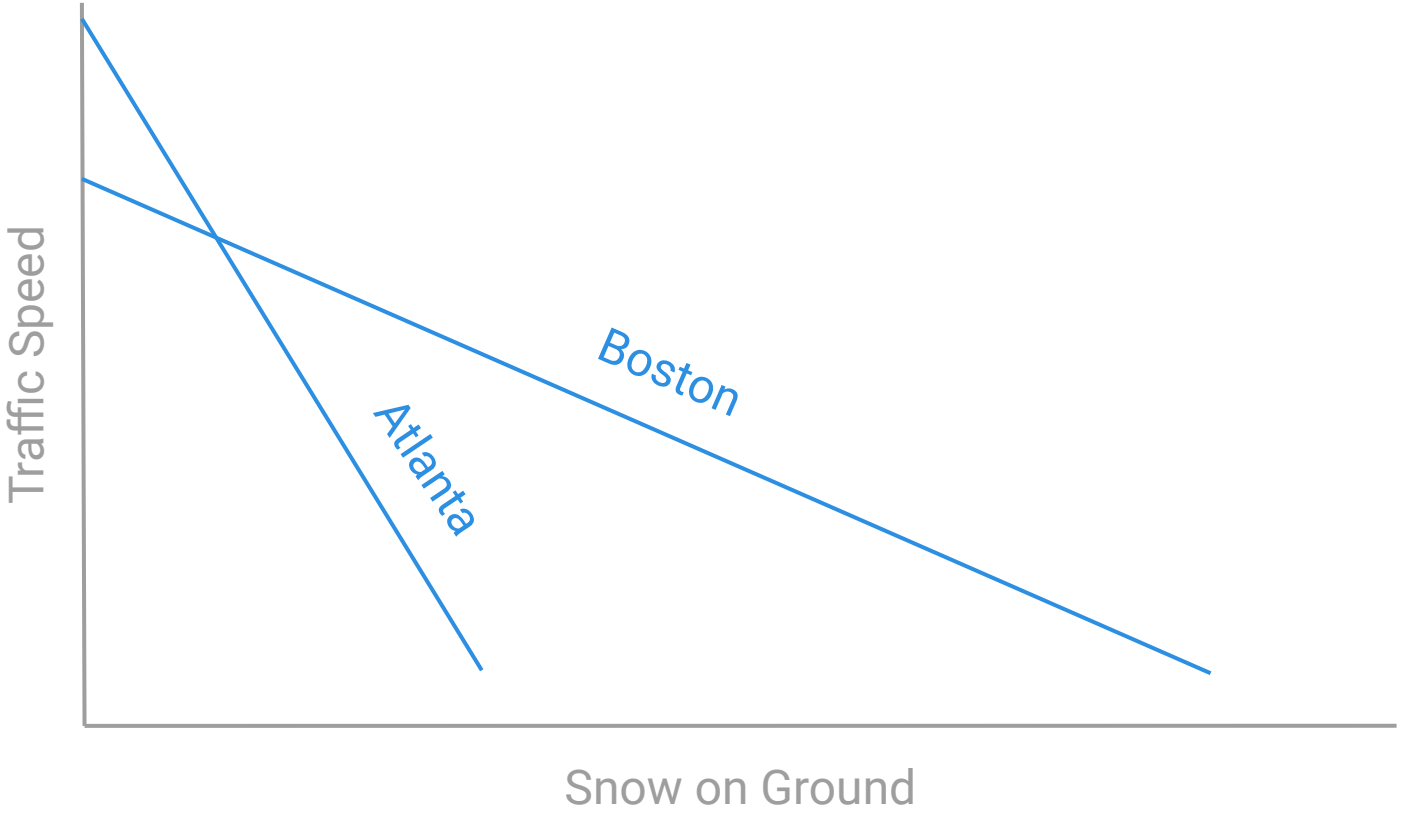


= __ + __ * age

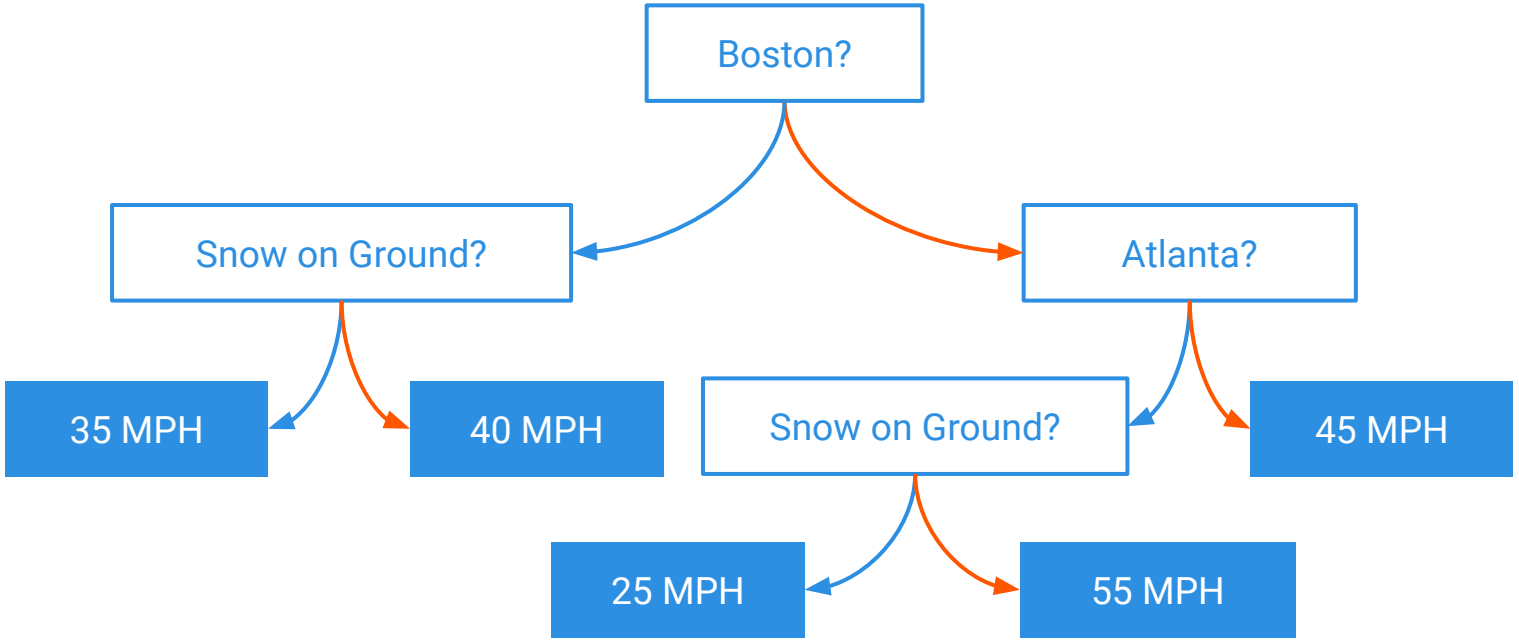
What Linear Models Miss



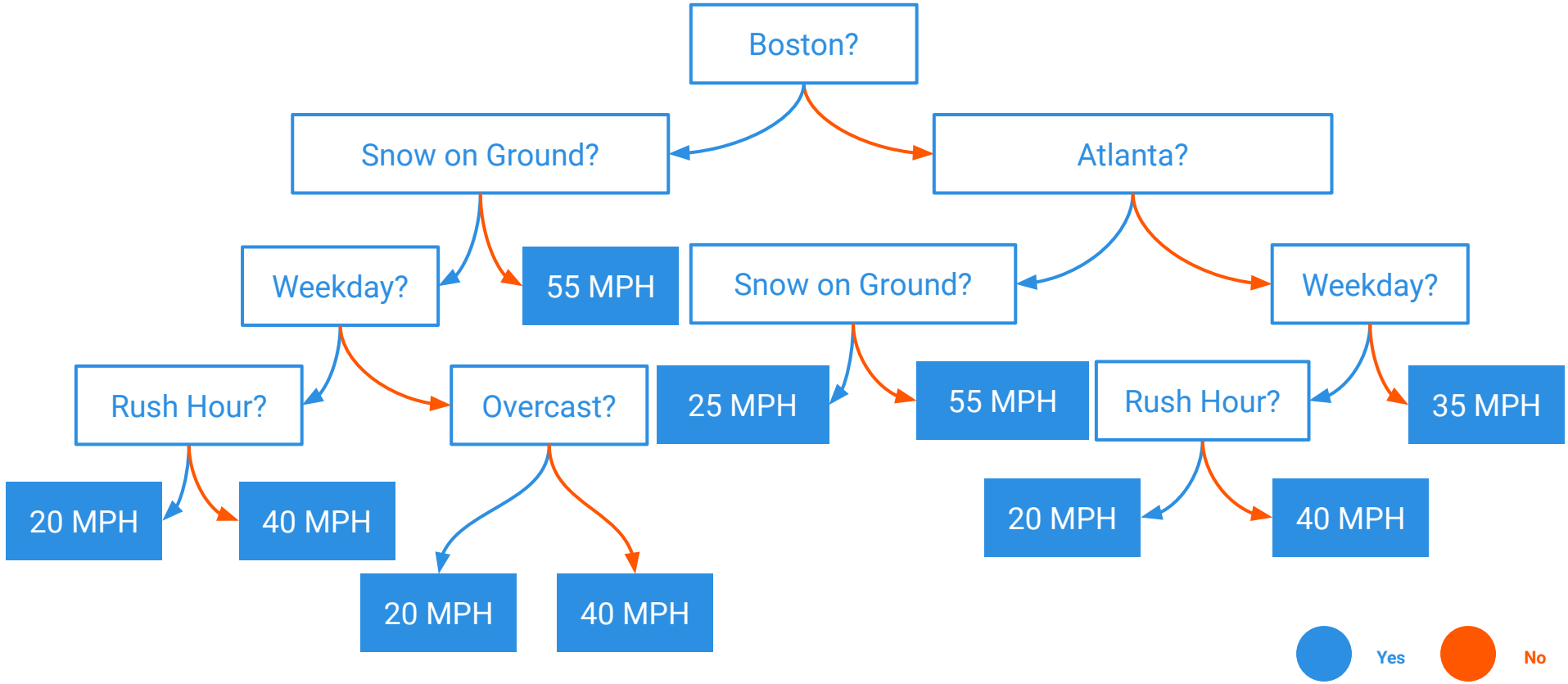
What Linear Models Miss



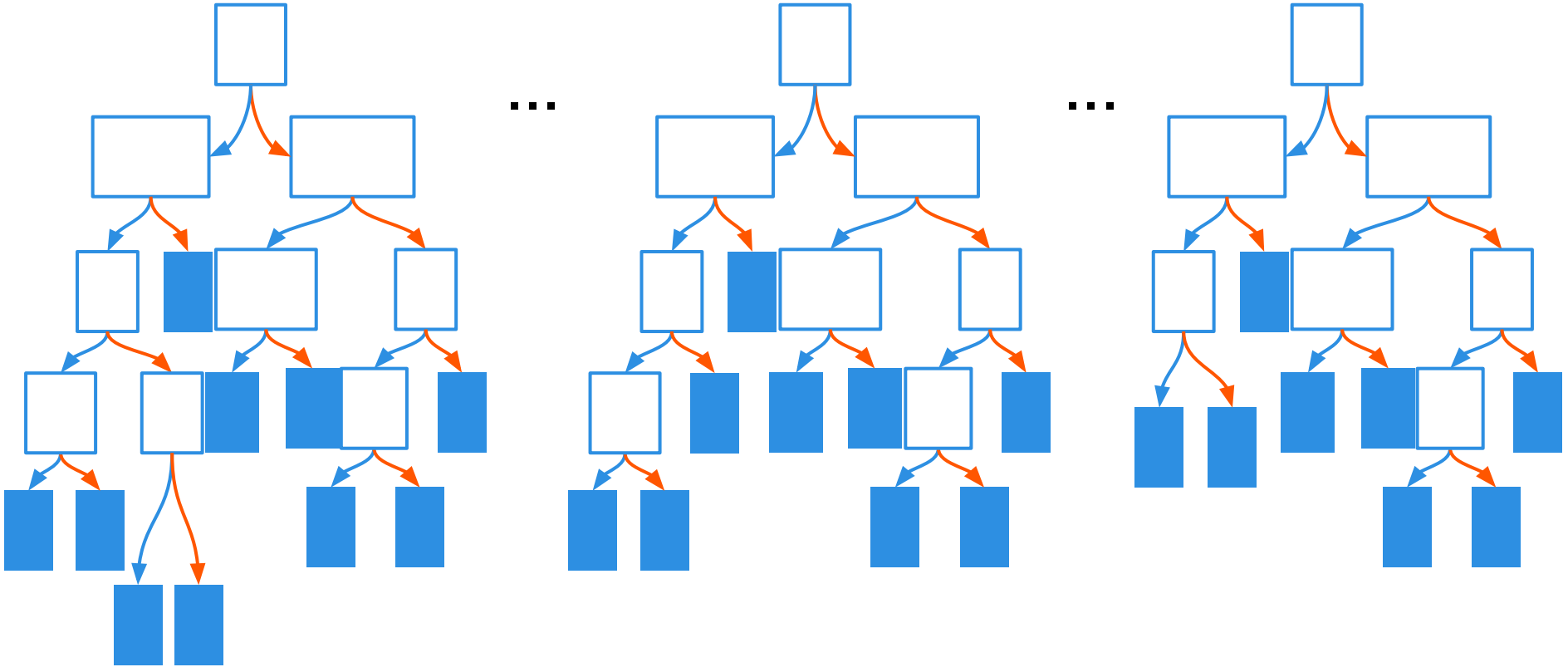
Decision Trees



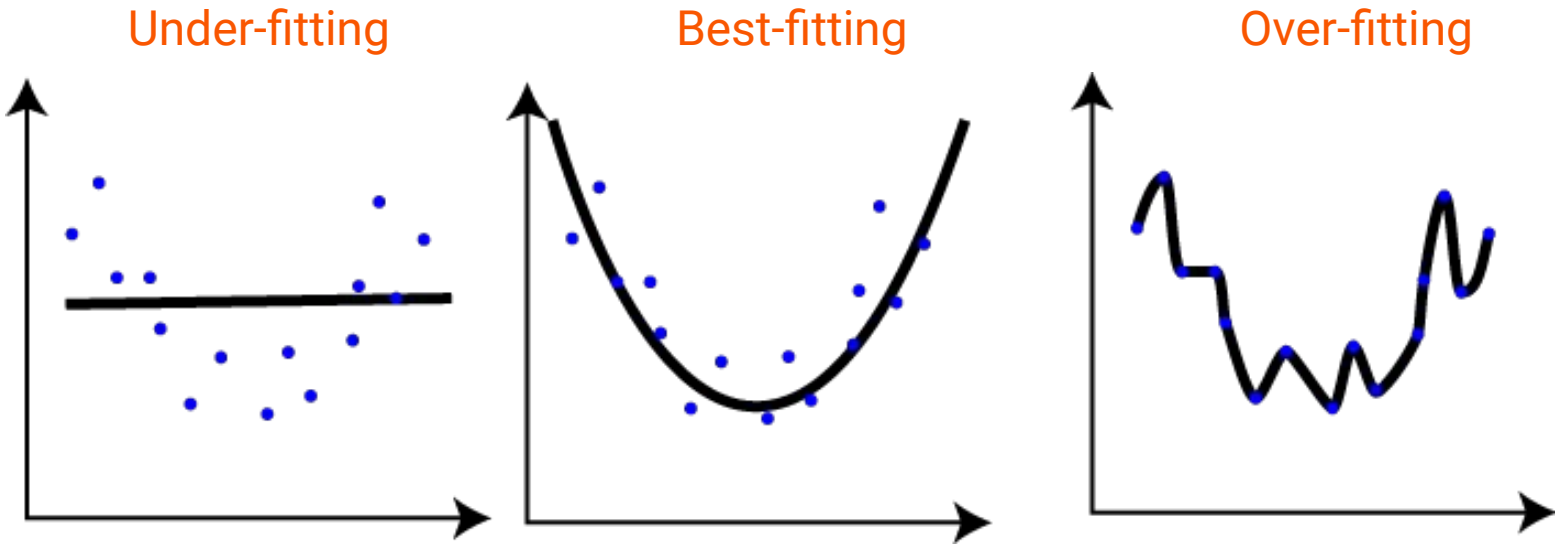
Decision Trees



Tree-based Ensembles

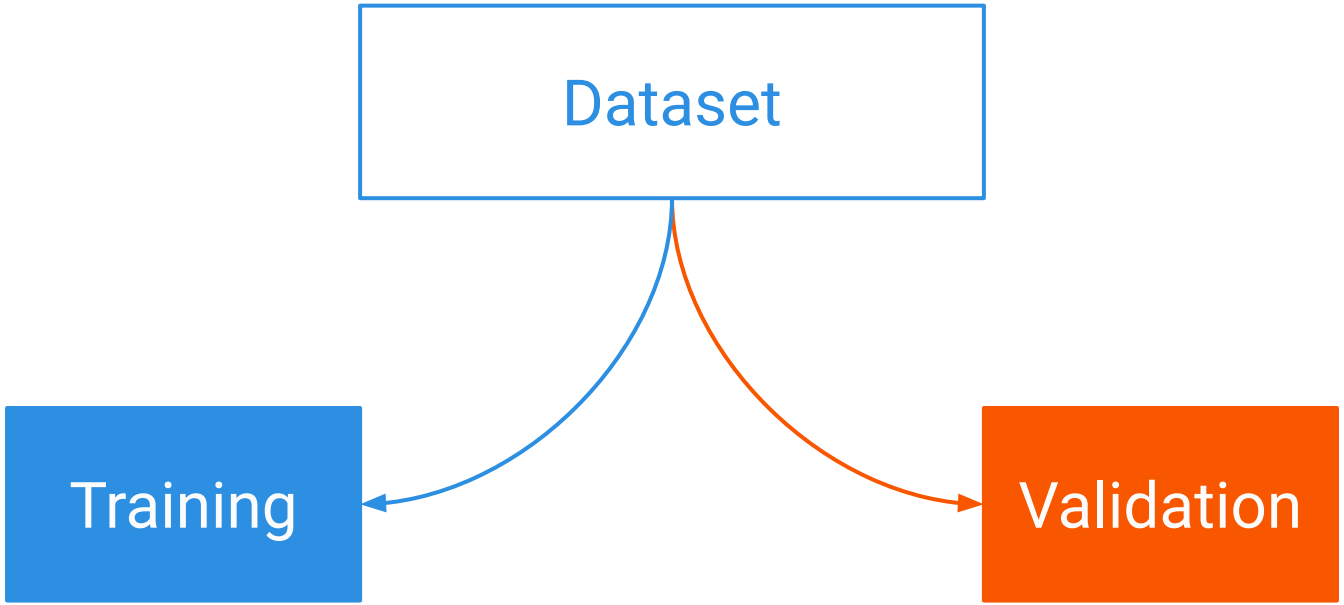


Introduction to Underfitting and Overfitting

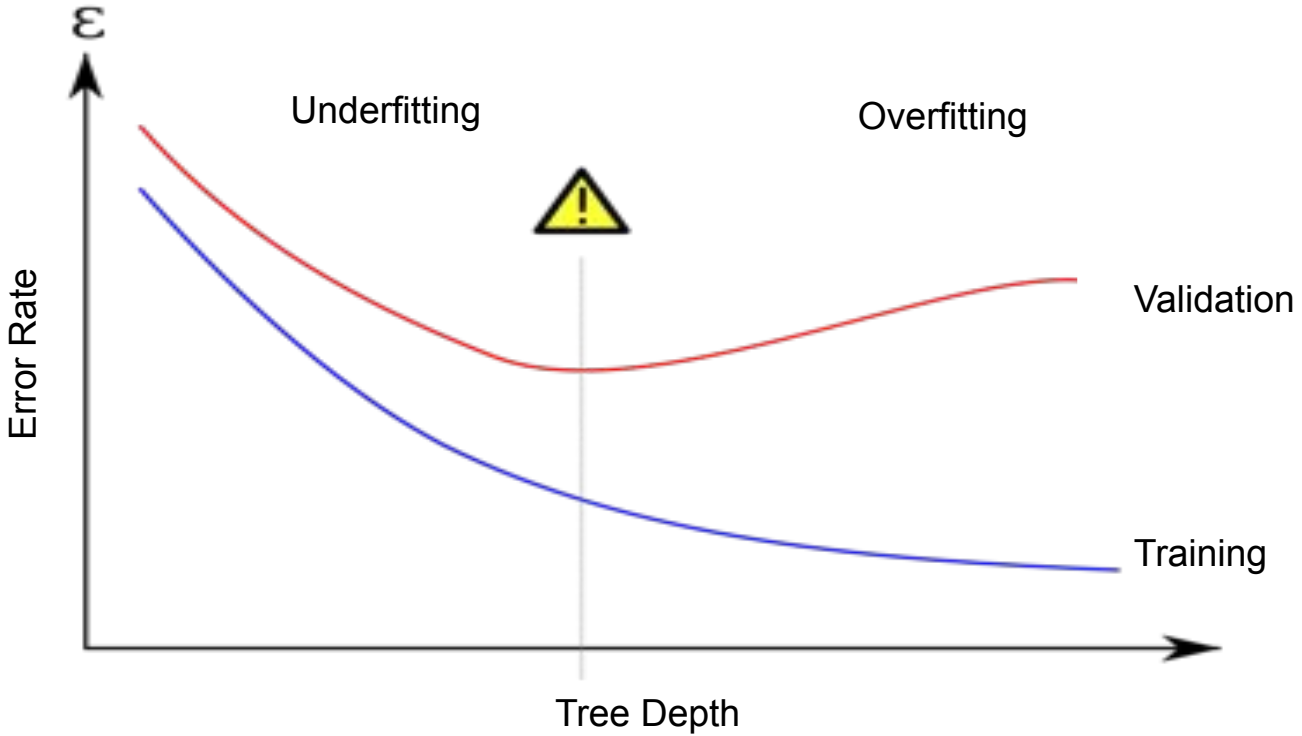


But how do we find the best fit?

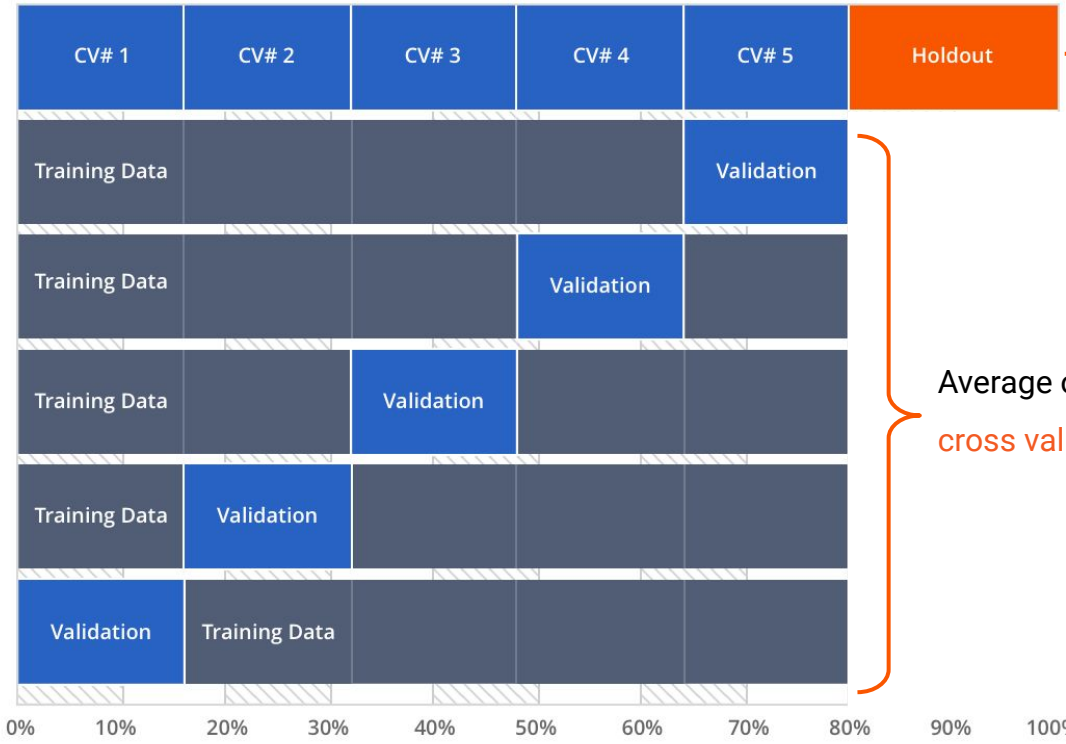
Data Partitioning



Finding the Best Fit



Cross Validation in DataRobot



The holdout is completely hidden from the models during the training process. After you have selected your optimal model, you can score your model on this to get your holdout score.

Average of these 5 validation scores is the cross validation score

Modeling Modes

Autopilot

- Default setting
- Multiple elimination rounds

Quick

- Fewer blueprints
- One elimination round

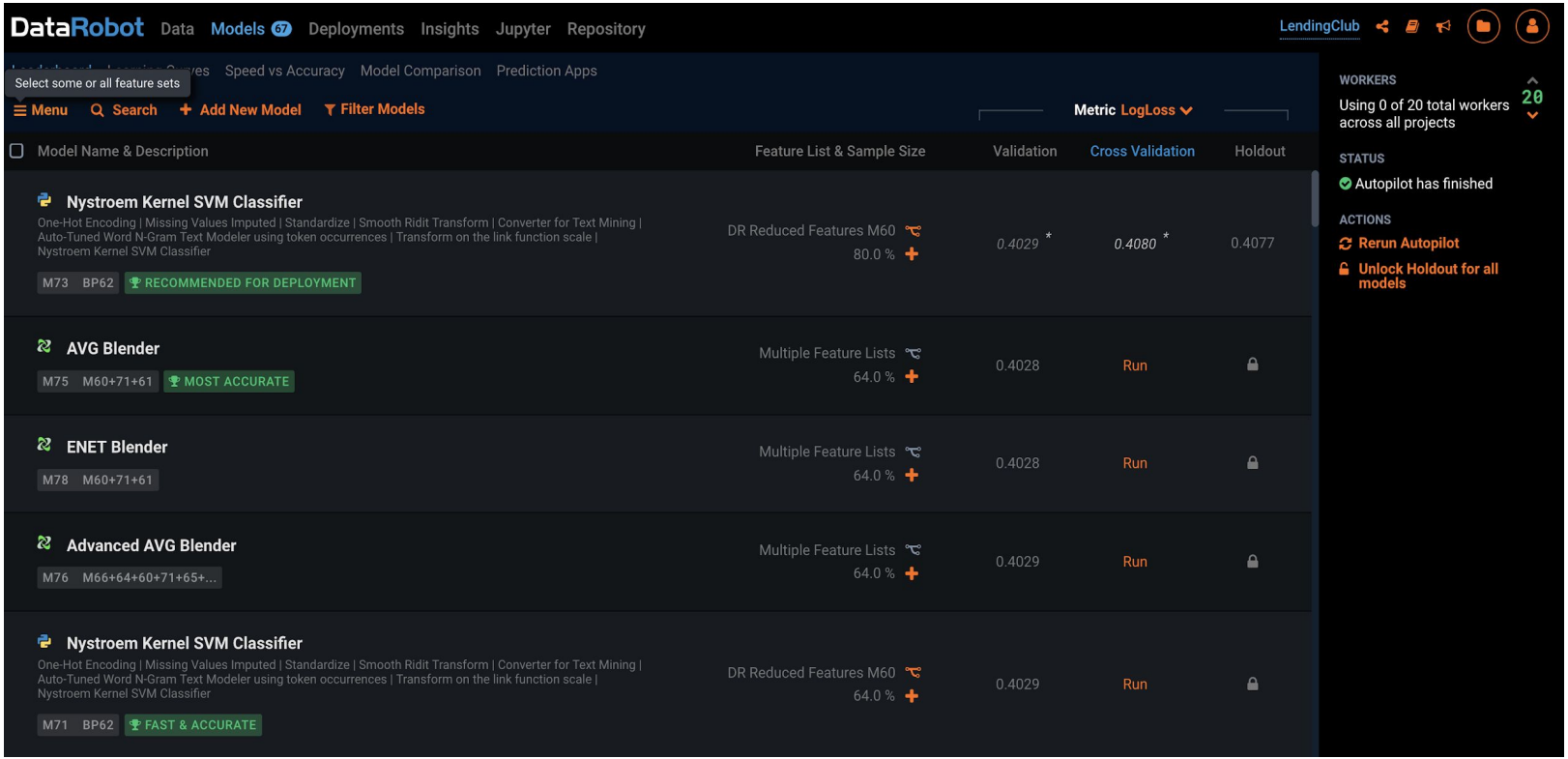
Manual Mode

- User chooses blueprints
- Can customize elimination

Benefits of Automation

Iteration is easy and safe

Leaderboard



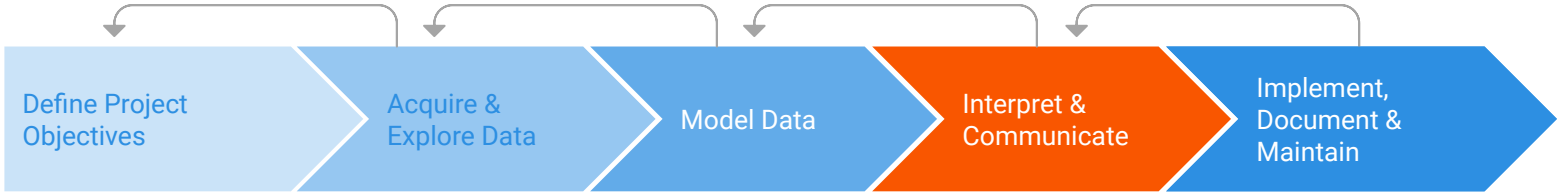
What about Fast Iron?

Go back to the fast_iron_100k project. Run any model(s) from the repository and explore the dataset further using DataRobot.

Discussion Questions

1. Which models did you choose and why? Which performed the best?
2. Are there any other data quality issues in the dataset?
3. What other data sources might be useful to predict the sales price?

The Machine Learning Life Cycle



1. **Define Project Objectives**
   - Specify problem
   - Acquire subject matter expertise
   - Define target and unit of analysis
   - Prioritize modeling criteria
   - Consider success criteria and risks
   - Decide whether to continue

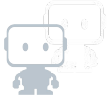
2. **Acquire & Explore Data**
   - Find appropriate data
   - Format data into single table
   - Conduct exploratory data analysis
   - Find and remove any target leakage
   - Perform feature engineering

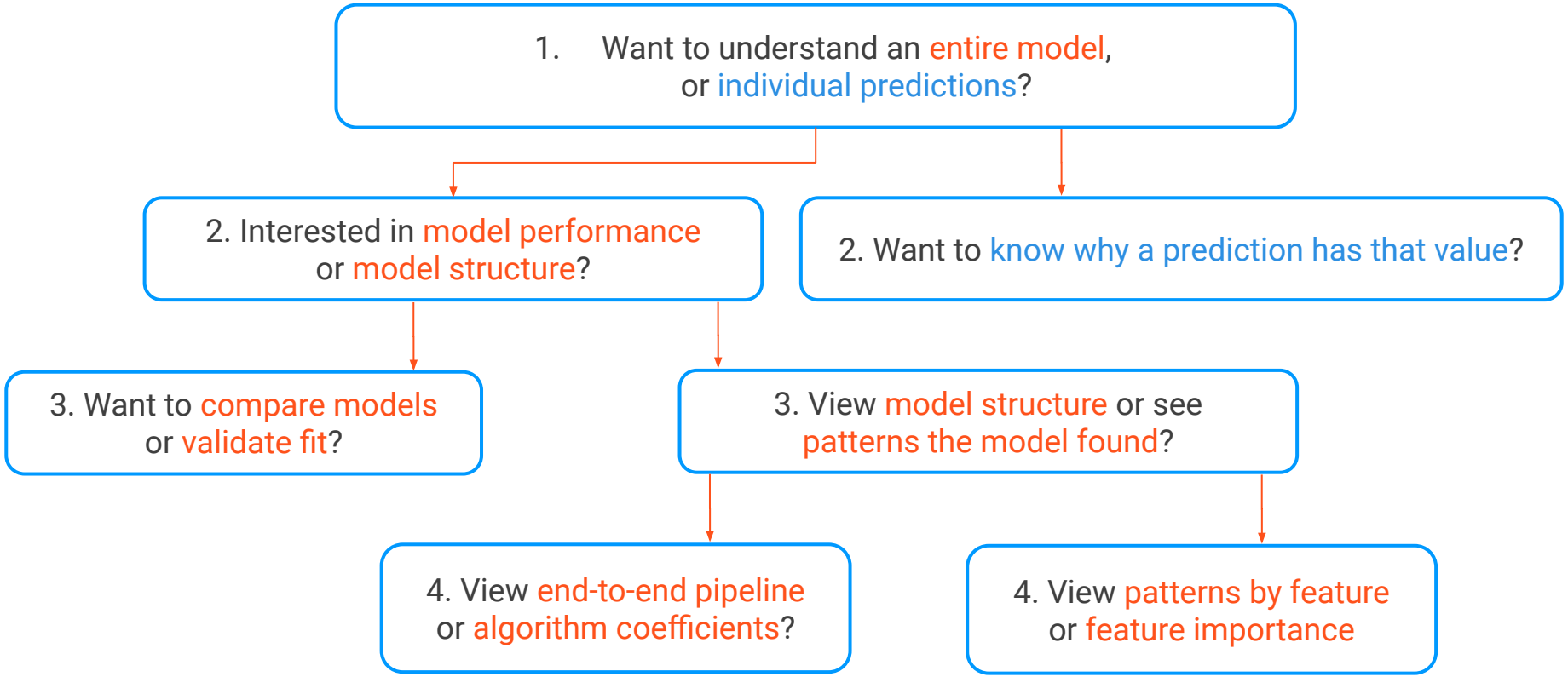
3. **Model Data**
   - Select features
   - Build candidate models
   - Validate models

4. **Interpret & Communicate**
   - Assess model quality
   - Determine important features
   - Identify relationships
   - Explain predictions

5. **Implement, Document & Maintain**
   - Select a model for deployment
   - Document modeling process
   - Create model monitoring and maintenance plan

Interpreting a Model





Confusion Matrix

Strengths

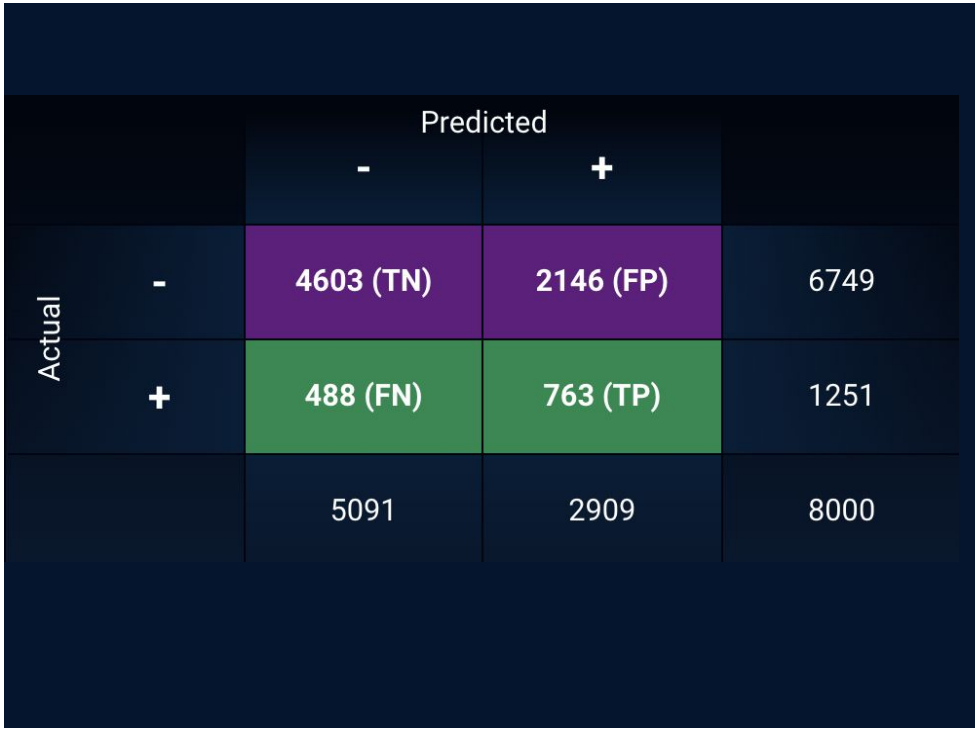
- Straightforward Interpretation

Weaknesses

- Imprecise

Use Cases

- Quick view of model
- Easy to equate to real business value



Calculating Payoffs from a Confusion Matrix

Payoff Matrix

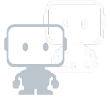
$3,000 (TN)	**$0** (FP)
-$8,000 (FN)	**$0** (TP)

Payoff = $9,905,000

= (**$3K** × 4603) + (**$0** × 2146) +
(**-$8K** × 488) + (**$0** × 763)

		Predicted -	Predicted +	
Actual	-	**4603 (TN)**	**2146 (FP)**	6749
	+	**488 (FN)**	**763 (TP)**	1251
		5091	2909	8000

What a Confusion Matrix Doesn't Show



	Log Loss = 0.31	Log Loss = 1.11	
Actual Value	**Model 1**	**Model 2**	**Are Models Correct?**
True	0.9	0.6	Yes
False	0.51	0.9	No
False	0.1	0.4	Yes

Assume classification threshold = 0.5

Lift Chart

Strengths

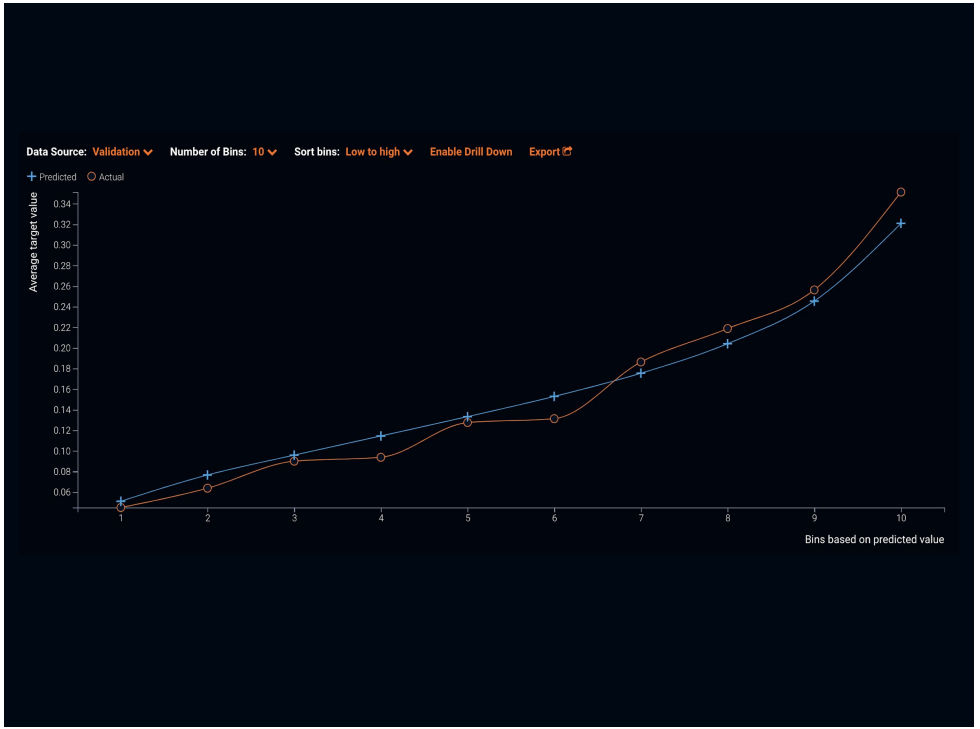
- Straightforward interpretation
- Visualizes the model's error and its ability to discriminate

Weakness

- Does not display the variation within the bins

Use Cases

- Many



End of Day 1

Please complete *Survey - Day One* in Litmos

Lift Chart Data

Predicted	Actual
4	7
5	3
7	9
12	7
13	8
15	10
17	12
20	12
21	30
23	16

Lift Chart Data

Predicted	Actual
4	7
5	3
7	9
12	7
13	8
15	10
17	12
20	12
21	30
23	16

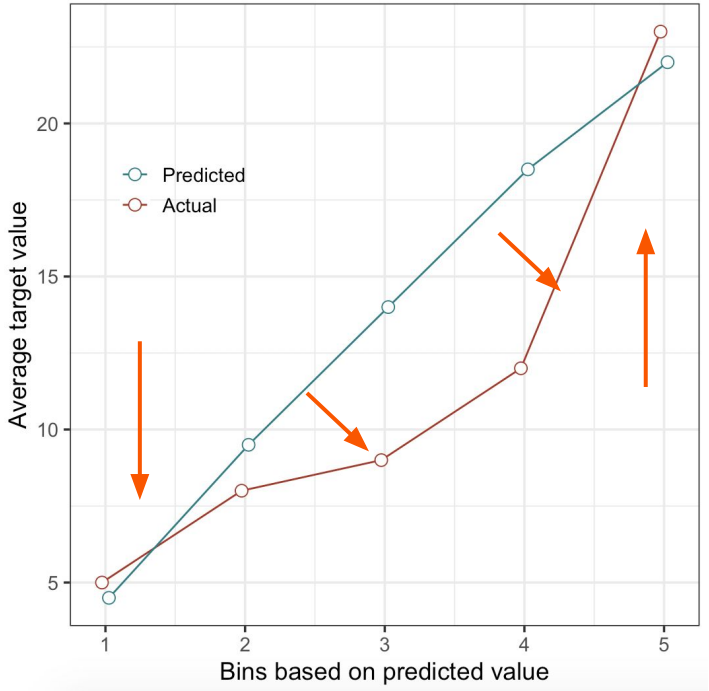
Predicted	Actual
4.5	5

Lift Chart Data

Predicted	Actual
4	7
5	3
7	9
12	7
13	8
15	10
17	12
20	12
21	30
23	16

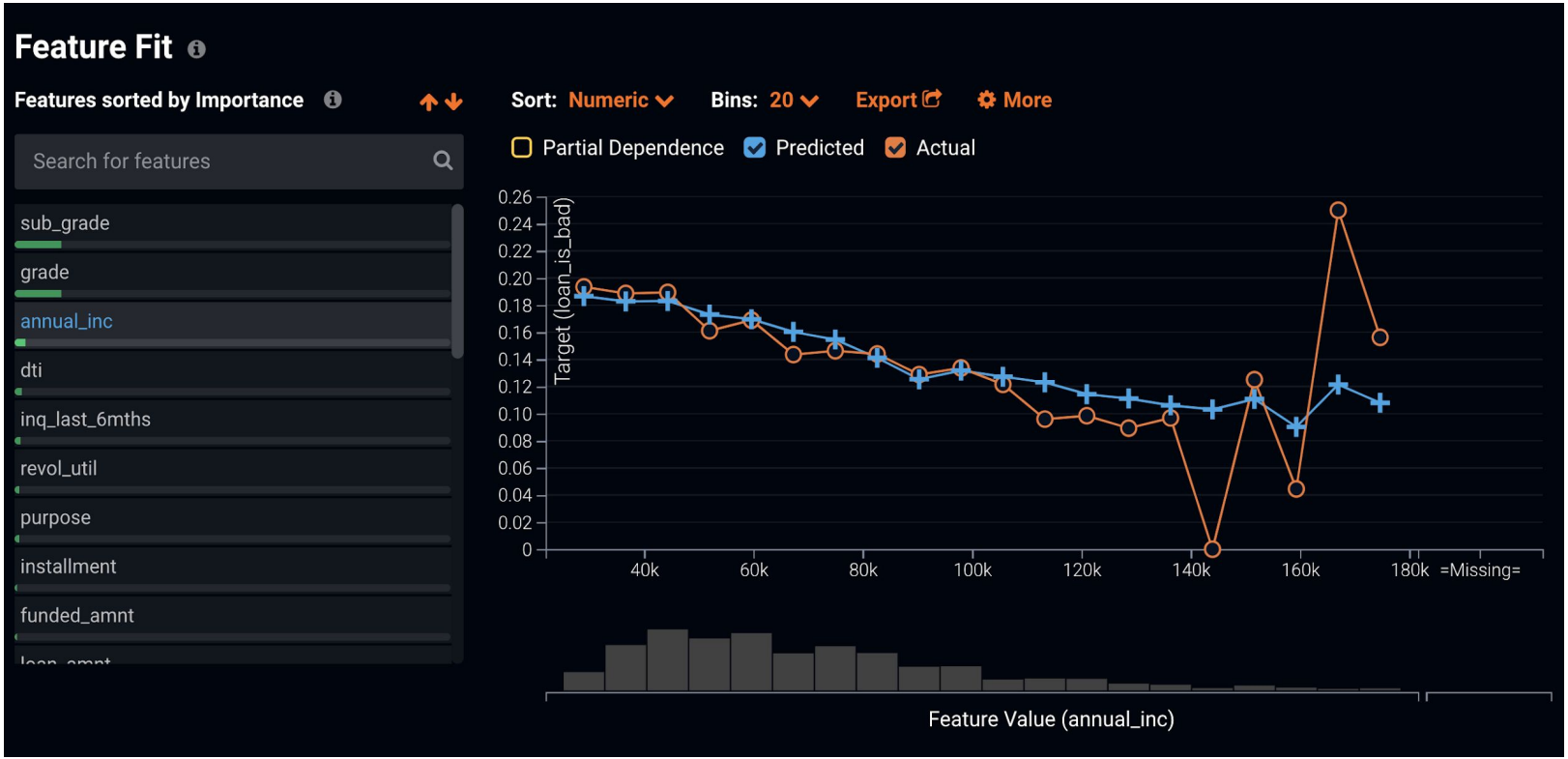
Predicted	Actual
4.5	5
9.5	8
14	9
18.5	12
22	23

1. How close are the lines?



2. How steep is the *actual* line?

Feature Fit



Prediction Distribution

Strengths

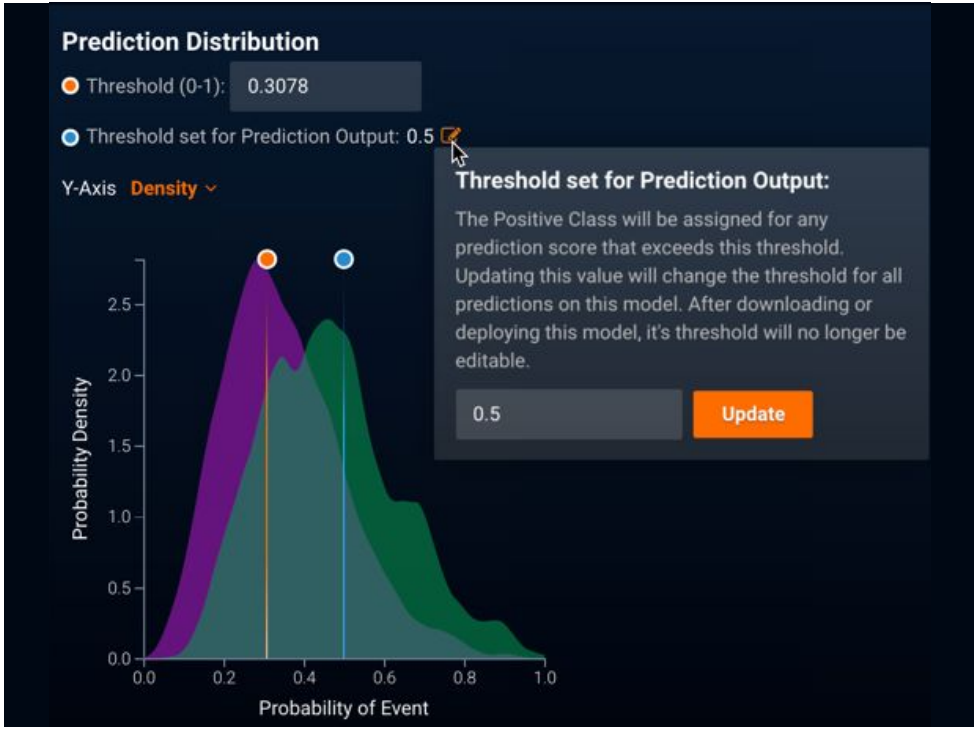
- Visualizes a model's performance by showing how well it separates the two groups in the target

Weakness

- Less "executive friendly" than a simple accuracy score

Use Case

- Set a threshold for model output
- Model comparison



ROC Curve

Strengths

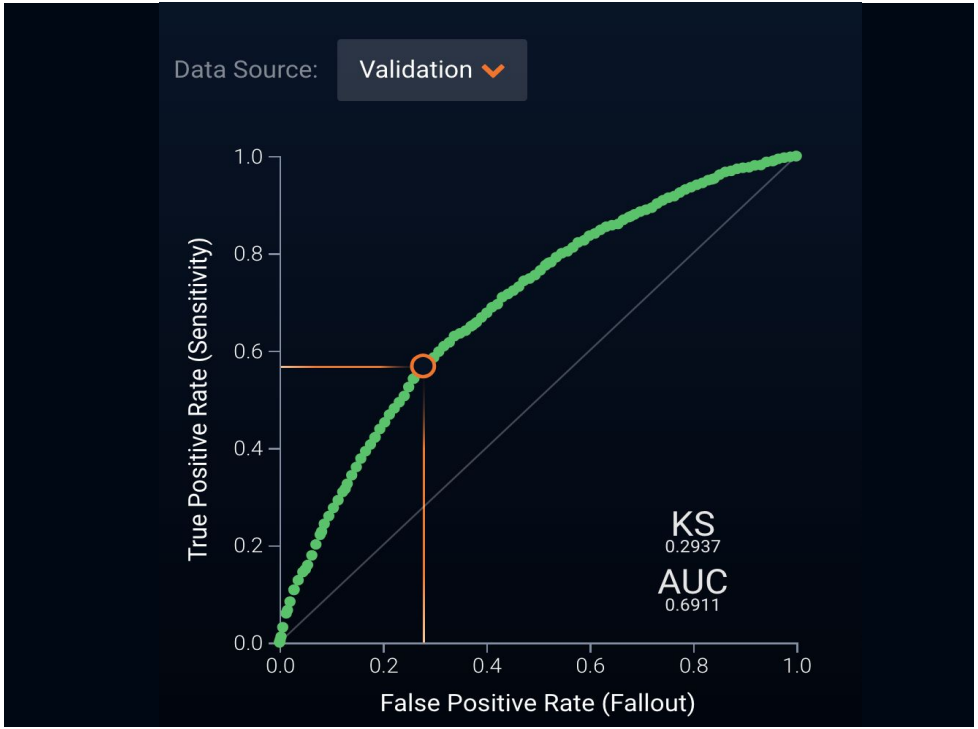
- Precise measure of model's ability to discriminate risk
- Interpretable metrics

Weakness

- Not "executive friendly"
- Only captures rank ordering of probabilities

Use Case

- Model comparison



Cumulative Gain and Lift

Strengths

- Widely used in marketing
- Shows how many predictions of a model are expected to be needed to achieve a certain true positive (or true negative) rate

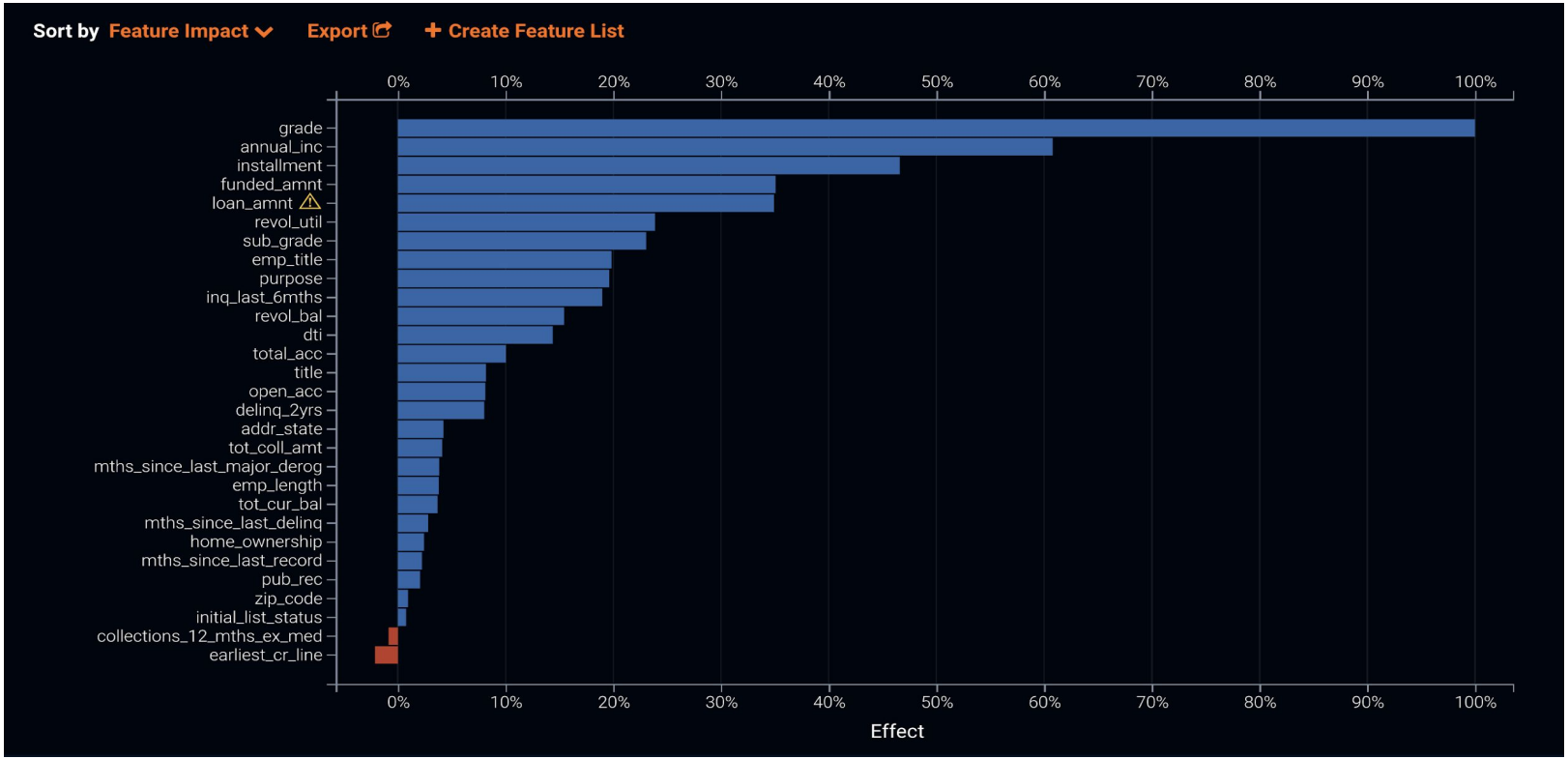
Weakness

- Doesn't show rate of wrong predictions

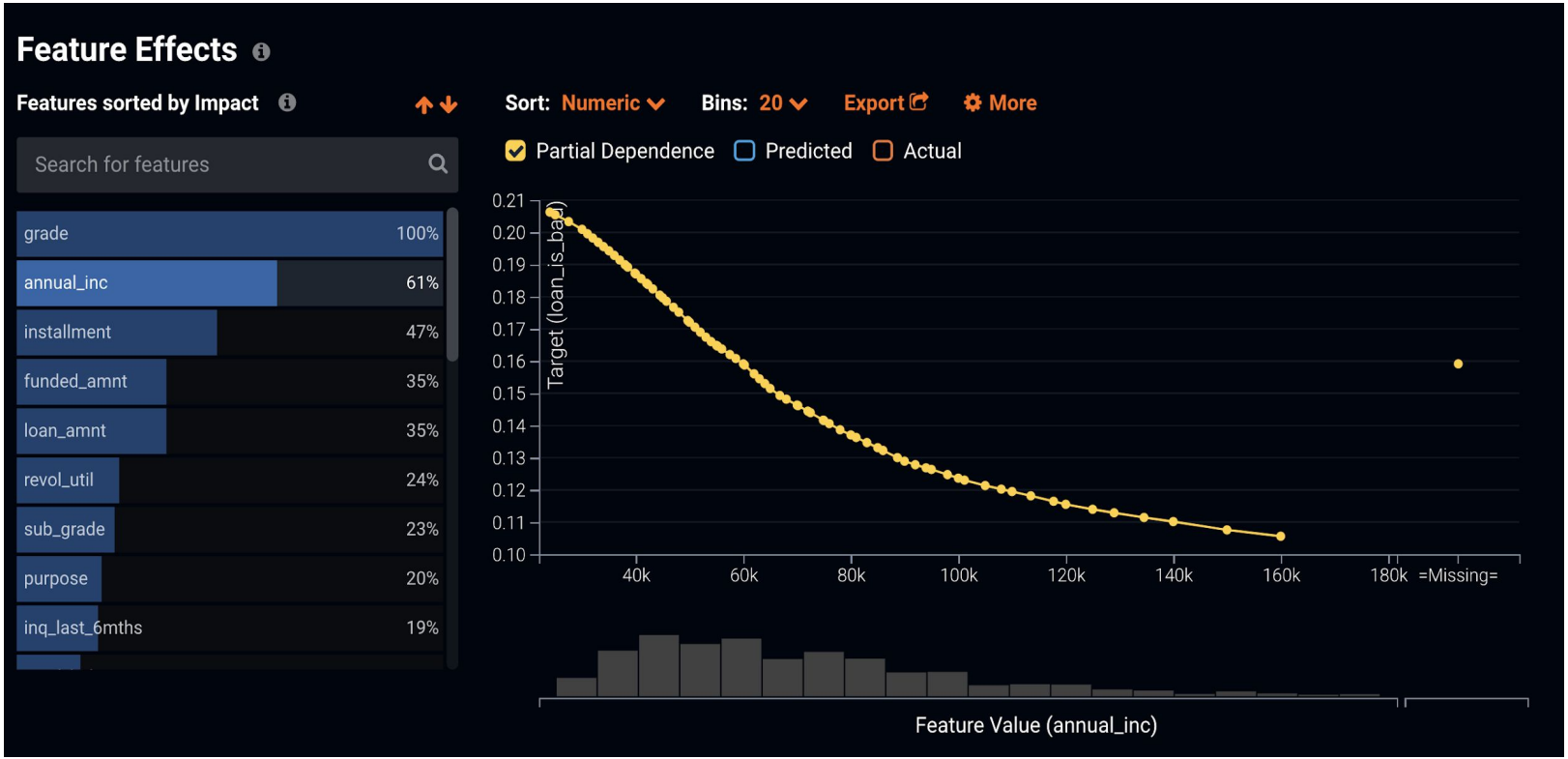
Use Case

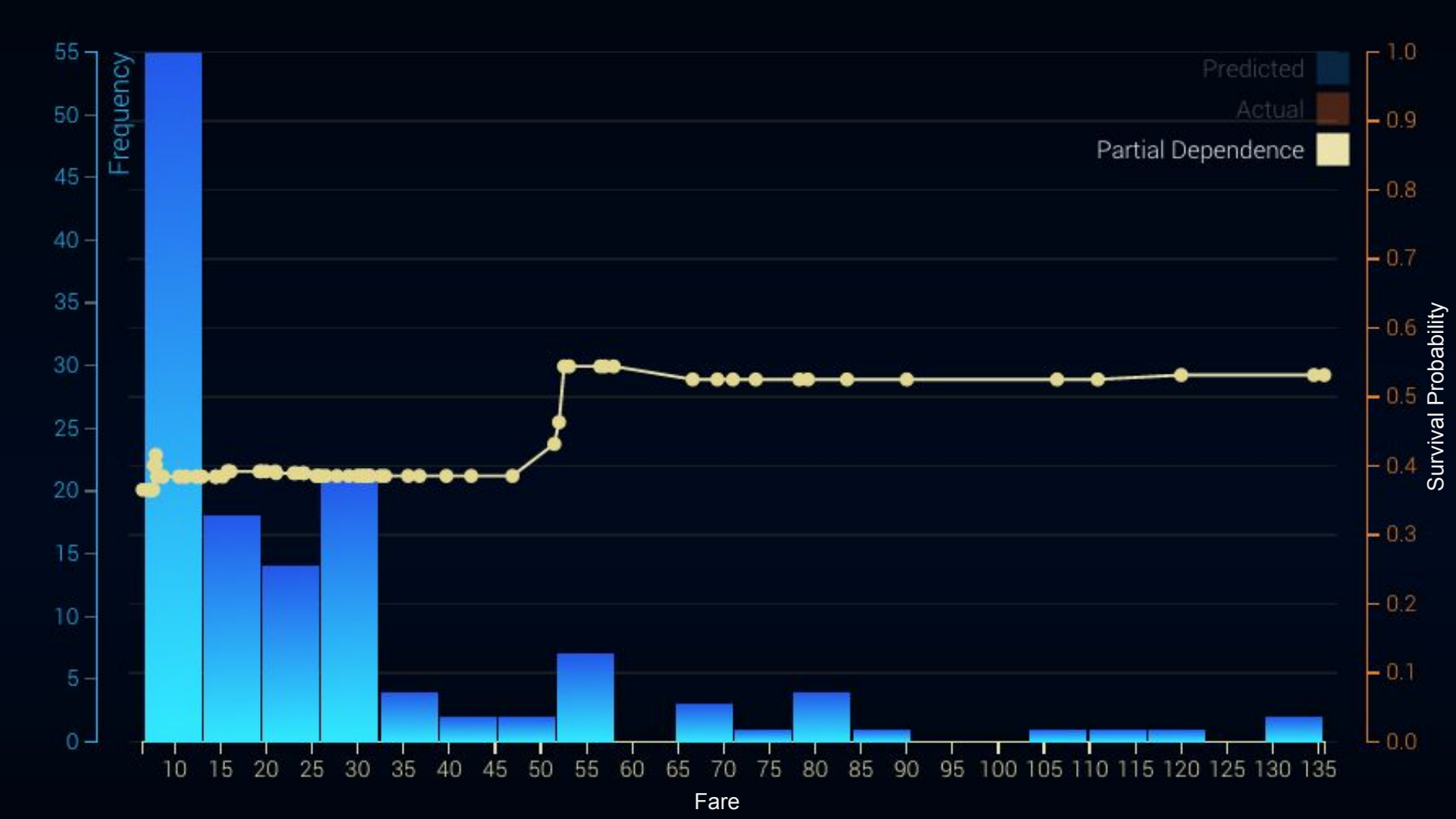
- Model comparison

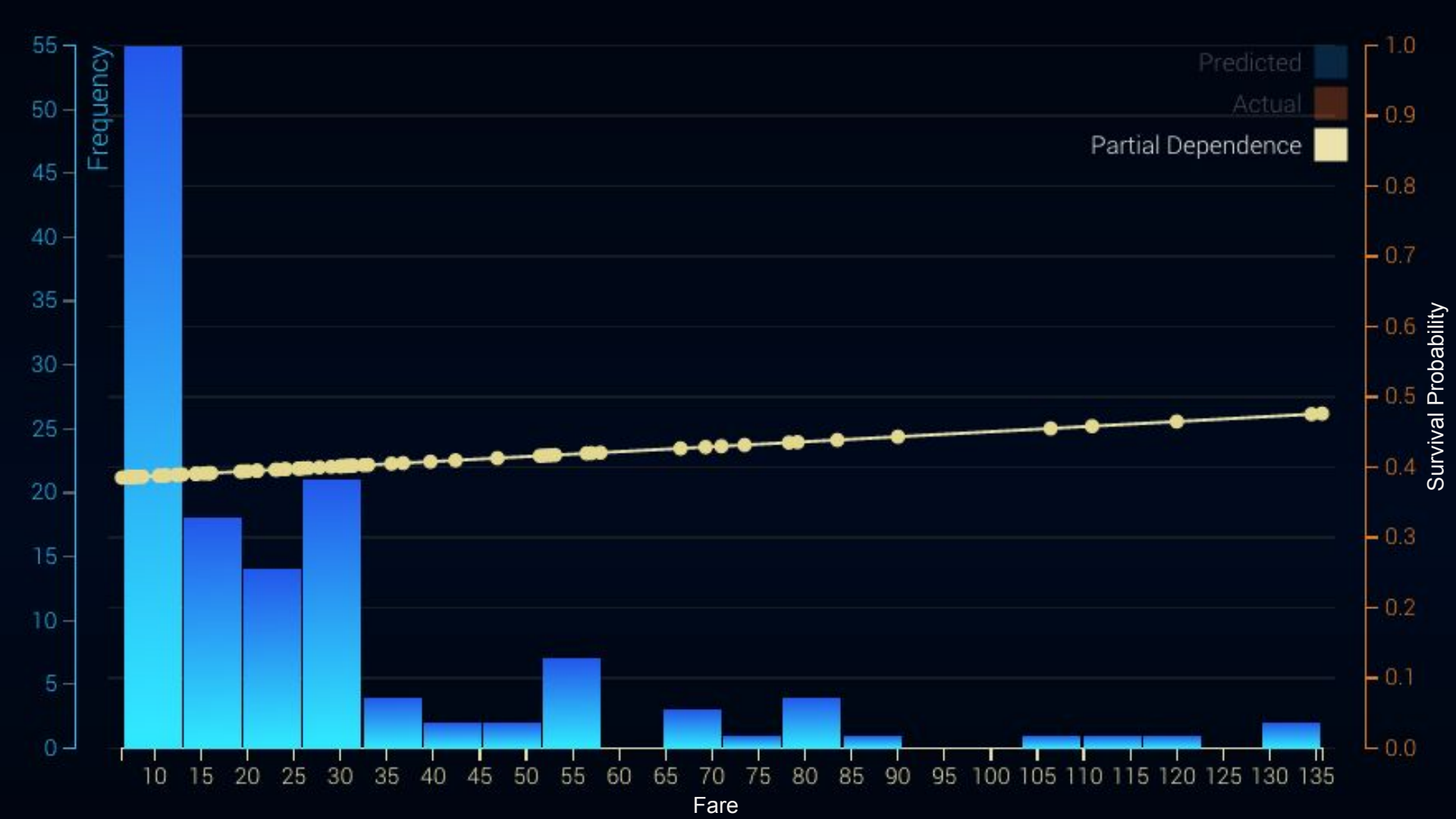
Feature Impact



Feature Effects




Frequency
Predicted
Actual
Partial Dependence
Survival Probability
Fare
55
50
45
40
35
30
25
20
15
10
5
0
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100 105 110 115 120 125 130 135

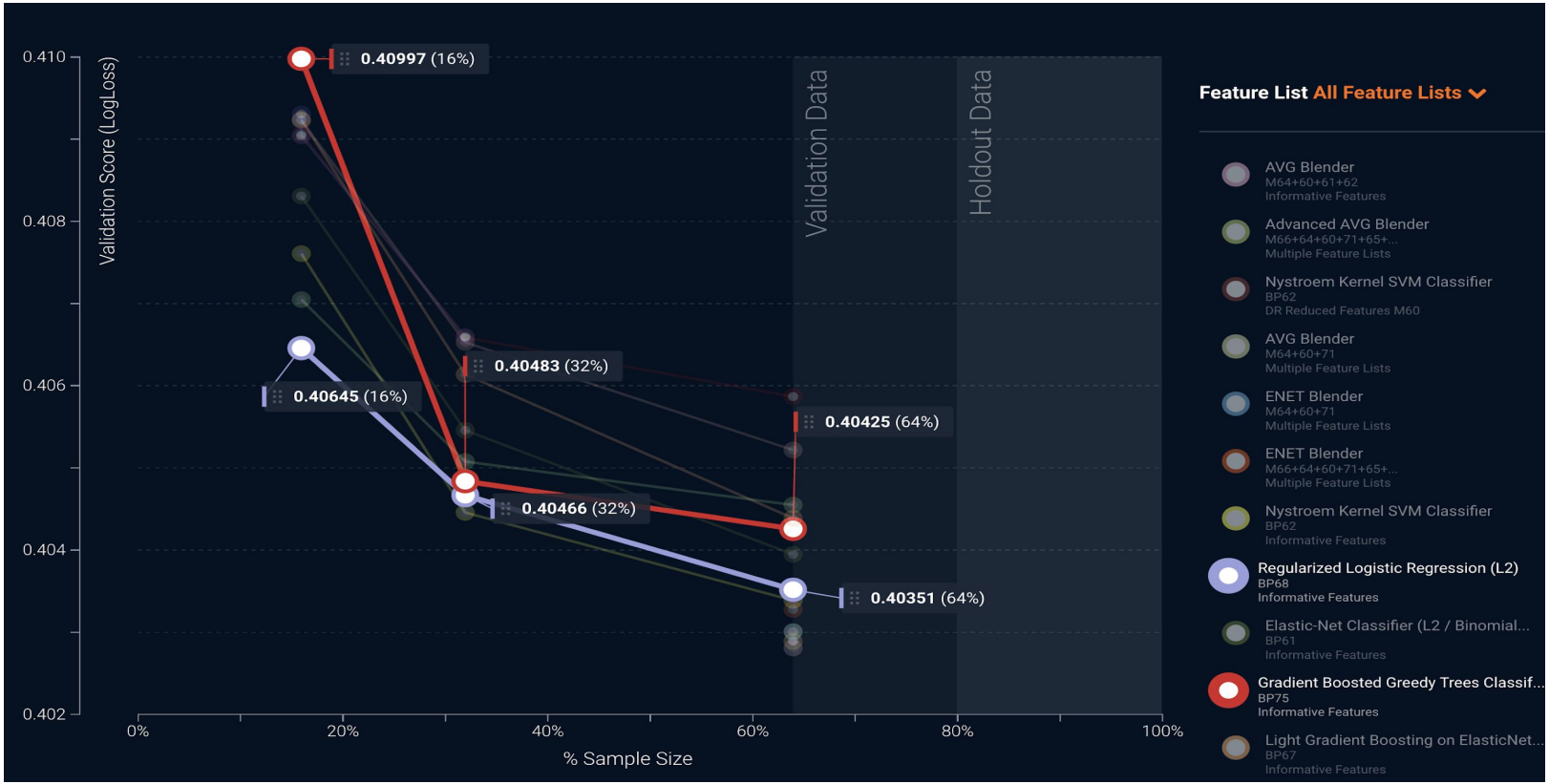

Frequency
Predicted
Actual
Partial Dependence
Survival Probability
Fare
0
5
10
15
20
25
30
35
40
45
50
55
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100 105 110 115 120 125 130 135

Prediction Explanations

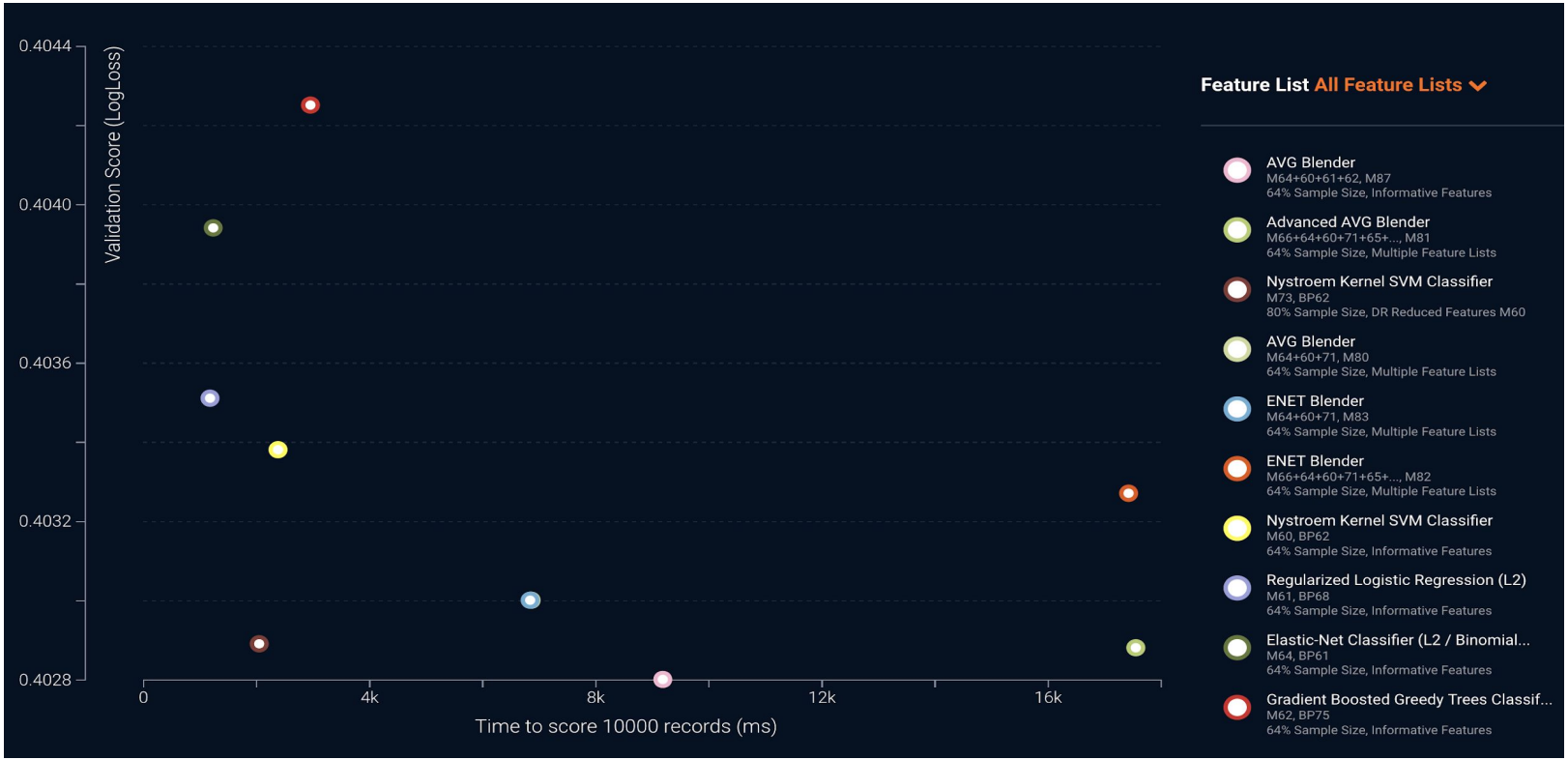
Preview of explanations for predictions from validation data within highlighted area(s):

ID	PREDICTION	EXPLANATIONS		
40078	0.548	+++ purpose = "small_business"	++ grade = "D"	++ inq_last_6mths = 3
21989	0.496	+++ purpose = "small_business"	++ grade = "D"	++ annual_inc = 36000
46728	0.495	+++ grade = "F"	++ inq_last_6mths = 3	++ annual_inc = 43000
19155	0.021	--- grade = "A"	-- annual_inc = 128000	-- sub_grade = "A3"
1367	0.020	-- annual_inc = 190000	-- grade = "A"	-- installment = 782.26
33460	0.020	--- grade = "A"	-- annual_inc = 88000	-- revol_bal = 52720

Learning Curves



Speed vs. Accuracy



More Insights

Insights

Tree-based Variable Importance

For tree/forest models, illustrates the relevancy of different variables on the prediction.

Hotspots

Provides a simple, graphical interpretation of rules describing high predictive performance.

Variable Effects

For some linear models, illustrates the strength and direction of the relationship between each feature in your model and the model prediction.

Word Cloud

Displays the most relevant words and short phrases in word cloud format.

Text Mining

Displays the most relevant words and short phrases in variables detected as text, indicating the strength of correlation with the target.

How to Understand a DataRobot Model

1. Want to understand an entire model, or individual predictions?

2. Interested in model performance or model structure?

2. Want to know why a prediction has that value?

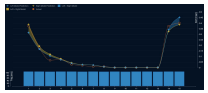
3. Want to compare models or validate fit?

3. View model structure or see patterns the model found?

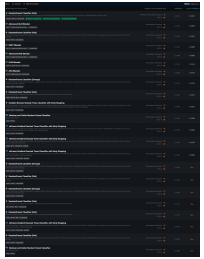
4. View end-to-end pipeline or algorithm coefficients?

4. View patterns by feature or feature importance

Model Comparison

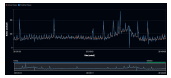


Leaderboard

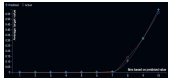


Feature Fit

Accuracy Over Time



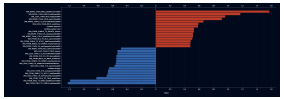
Lift Chart



Distribution Plot

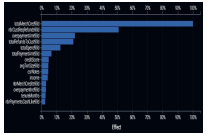
Eureqa Formulae

Model Coefficients



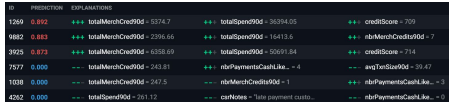
GA2M Rating Tables

Feature Impact



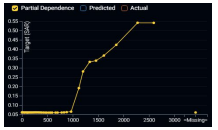
Model Blueprint

Prediction Explanations

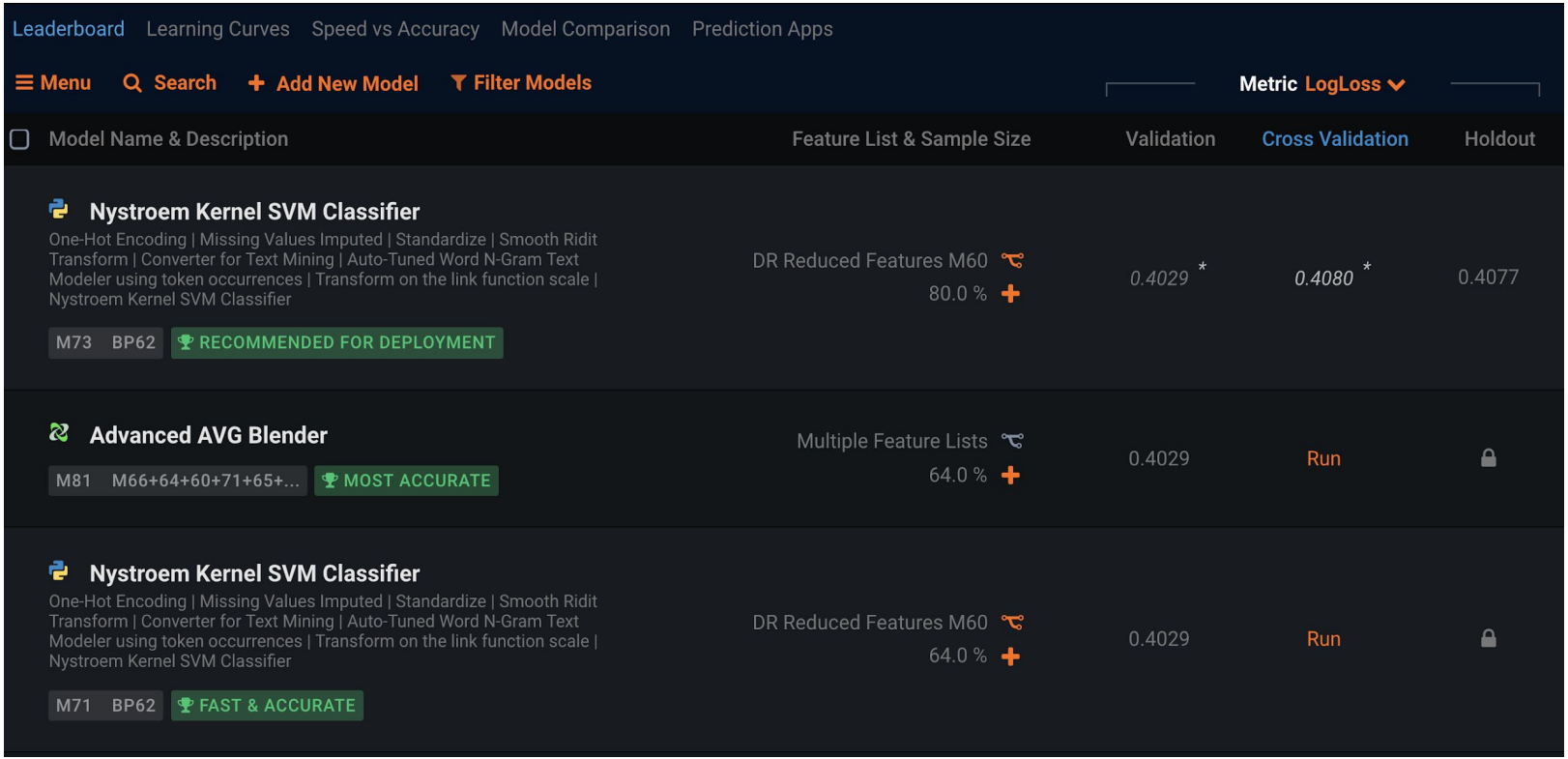


Hotspots

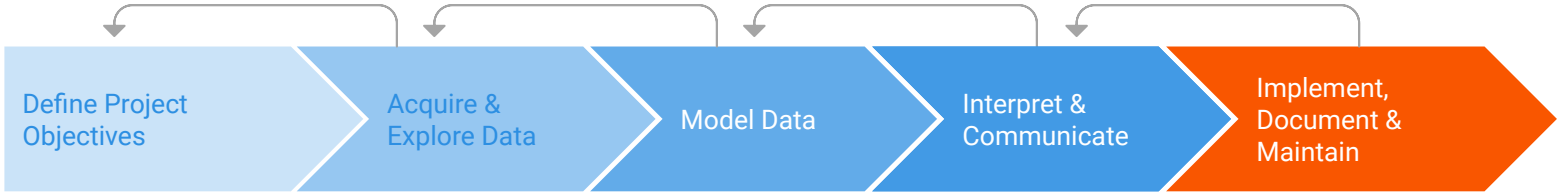
Feature Effects



Model Tags



The Machine Learning Life Cycle



1. **Define Project Objectives**
   - Specify problem
   - Acquire subject matter expertise
   - Define target and unit of analysis
   - Prioritize modeling criteria
   - Consider success criteria and risks
   - Decide whether to continue

2. **Acquire & Explore Data**
   - Find appropriate data
   - Format data into single table
   - Conduct exploratory data analysis
   - Find and remove any target leakage
   - Perform feature engineering

3. **Model Data**
   - Select features
   - Build candidate models
   - Validate models

4. **Interpret & Communicate**
   - Assess model quality
   - Determine important features
   - Identify relationships
   - Explain predictions

5. **Implement, Document & Maintain**
   - Select a model for deployment
   - Document modeling process
   - Create model monitoring and maintenance plan

Deployment Notes

1. **Choose model**
   - Which model satisfies my modeling criteria?
   - Optionally use 100% of data to train model
2. **Choose deployment options**
   - GUI batch predictions
   - Prediction API
   - DataRobot Prime (python, java)
   - Scoring Code JAR (java)

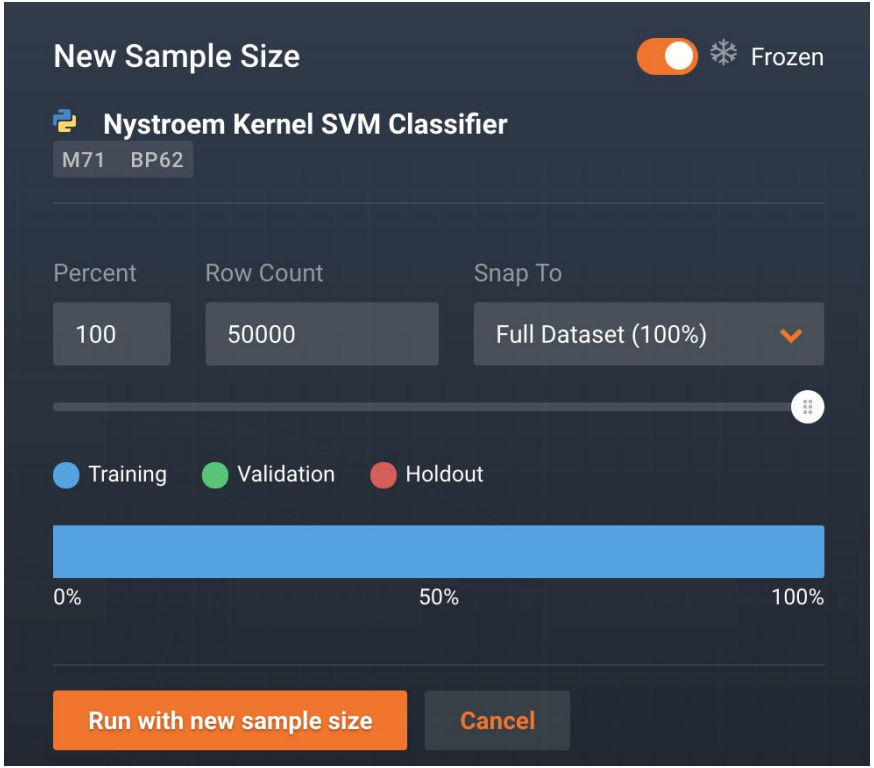
Training on 100%

Pros

- Using 100% of the data gives the model more examples to learn from and may significantly improve predictive performance

Cons

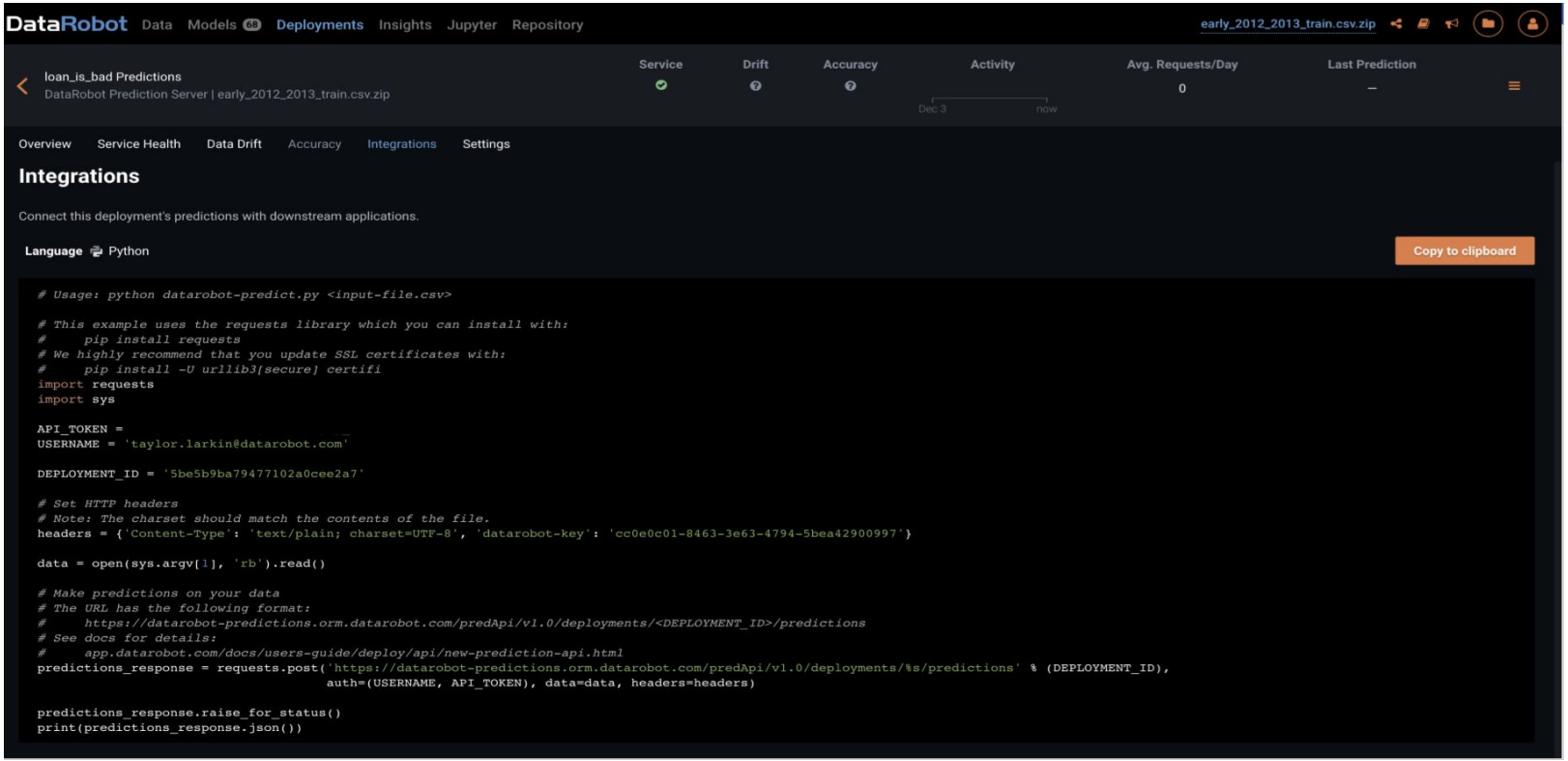
- Can't validate the model directly
- When monitoring the model after deployment, new predictions have no direct comparison



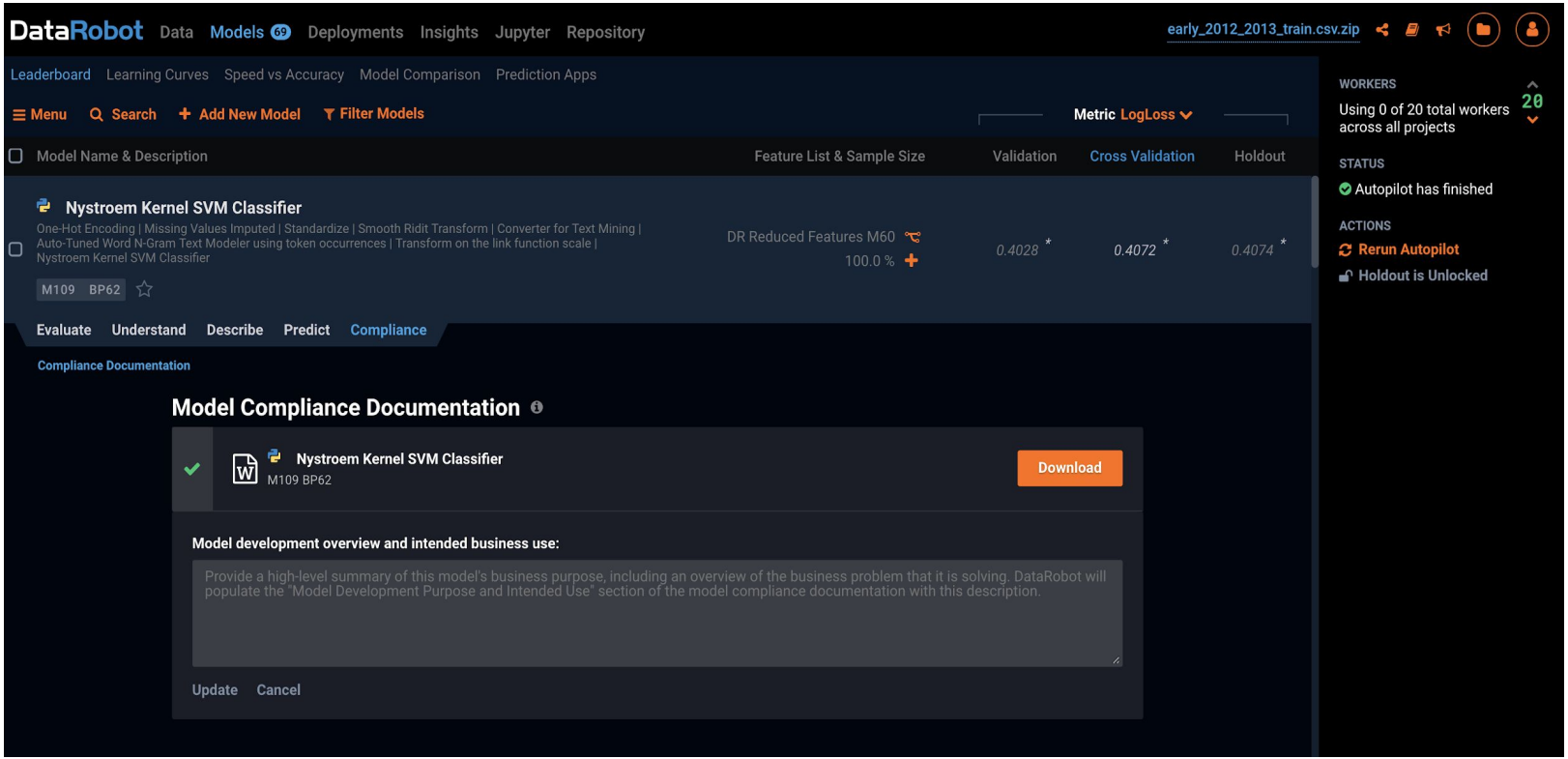
GUI Batch Predictions

- Load *2015_test.csv.zip* into the LendingClub project.
- Add optional features *id*, *member id, grade*, *annual_inc*, and *purpose*.
- Set threshold for prediction output to be 0.2 (under ROC curve tab)
- Make predictions with the chosen model.
- Download the csv and inspect the results.

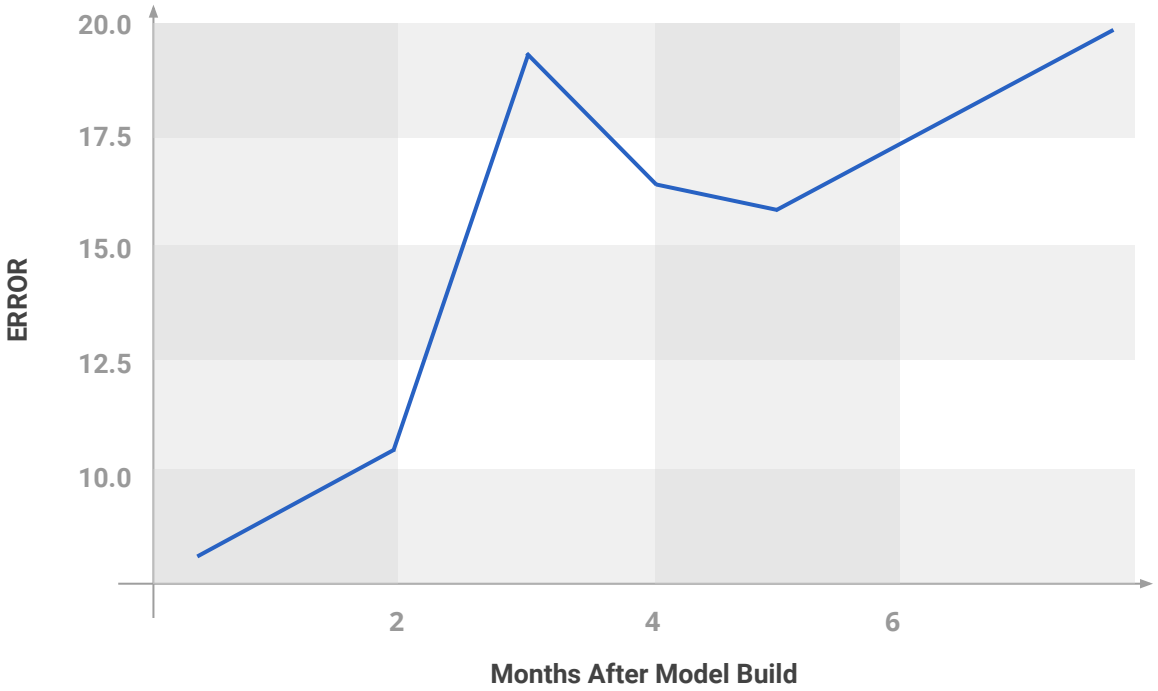
Prediction API



Model Documentation

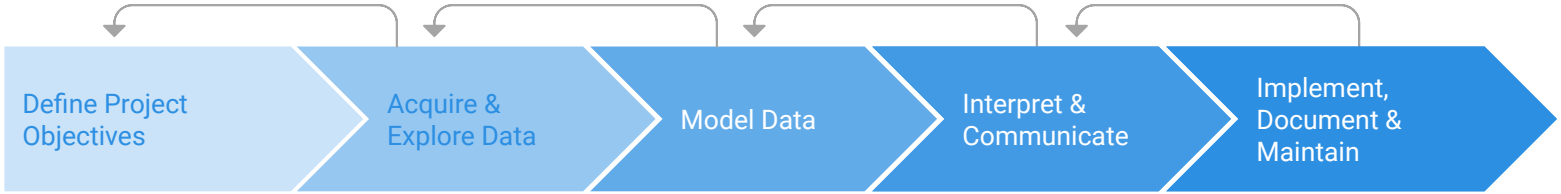


Deteriorating Model Performance



Data Drift

The Machine Learning Life Cycle



1. **Define Project Objectives**
   - Specify problem
   - Acquire subject matter expertise
   - Define target and unit of analysis
   - Prioritize modeling criteria
   - Consider success criteria and risks
   - Decide whether to continue

2. **Acquire & Explore Data**
   - Find appropriate data
   - Format data into single table
   - Conduct exploratory data analysis
   - Find and remove any target leakage
   - Perform feature engineering

3. **Model Data**
   - Select features
   - Build candidate models
   - Validate models

4. **Interpret & Communicate**
   - Assess model quality
   - Determine important features
   - Identify relationships
   - Explain predictions

5. **Implement, Document & Maintain**
   - Select a model for deployment
   - Document modeling process
   - Create model monitoring and maintenance plan

Lunch

Documentation and Support

Roles

Capability	Owner	User	Observer
View everything	✔	✔	✔
Launch IDEs	✔	✔	
Make predictions	✔	✔	
Create and edit feature lists	✔	✔	
Set target	✔	✔	
Delete jobs from queue	✔	✔	
Run Autopilot	✔	✔	
Share project with others	✔	✔	
Rename project	✔	✔	
Delete project	✔		
Unlock holdout	✔		
Clone the project	✔	✔	

DataRobot offers a growing variety of certifications, from introductory to advanced, with many specialties covered including:

- *DataRobot Deeper Dive Certification*
- *DataRobot Time Series Modeling Certification*
- *Advanced DataRobot with Python Certification*
- *Advanced DataRobot with R Certification*

Check out:
datarobot.com/education
for more information

DataRobot UNIVERSITY

Hands-on Project

End of Day

Please complete *Course Exam* and *Course Survey* in Litmos

DataRobot