



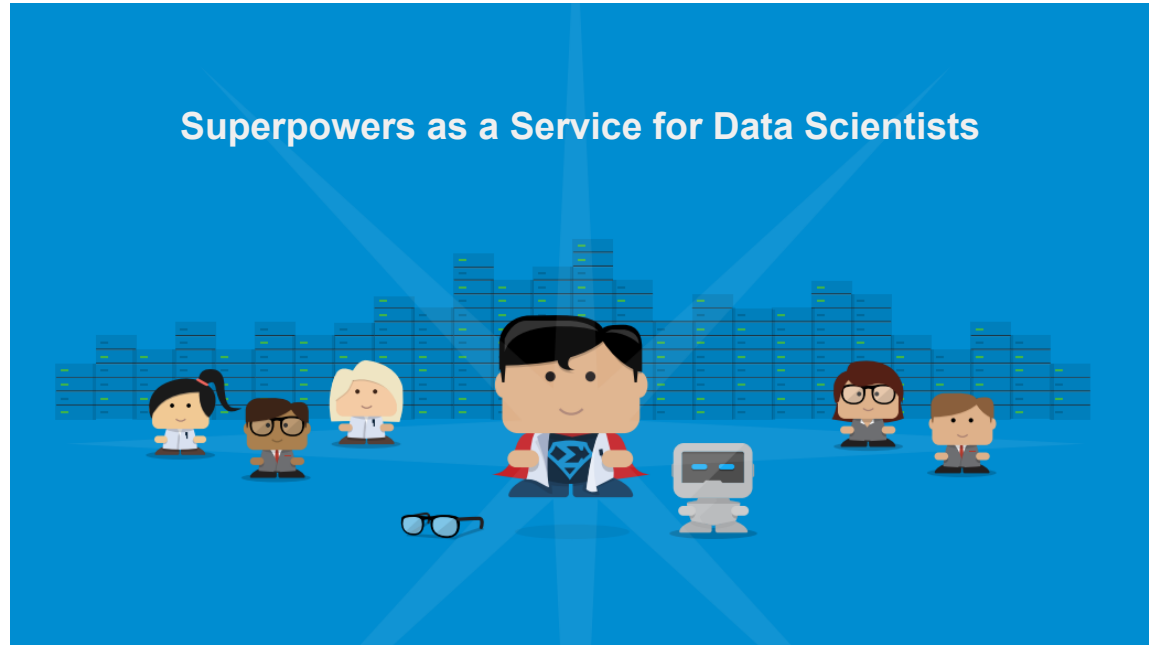
Winning the Liberty Mutual Kaggle Competition

Disclaimer:

- We do NOT state or imply Liberty Mutual endorses me, our team, our submission, Data Robot, Inc. or other companies I am involved with, or any of its or their products
- We thank Liberty Mutual for hosting the competition and identifying us as the winner of this competition.

AGENDA

1. Team
2. Competition Summary
3. Challenges
4. Our Approach
5. Key Takeaways



DATAROBOT TEAM



Xavier Conort

Chief Data Scientist

Kaggle Rank: #1 2012-2013

Experience:

Principal Research Engineer, I2R
Actuary, Risk Manager and CFO
at CNP Assurances and AXA



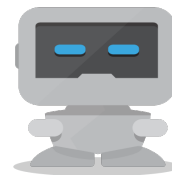
Owen Zhang

Chief Product Officer

Kaggle Rank: #1 2013-present

Experience:

VP, Science, AIG
Sr. Director, Analytics at
Travelers Insurance



DataRobot

Data Science Master

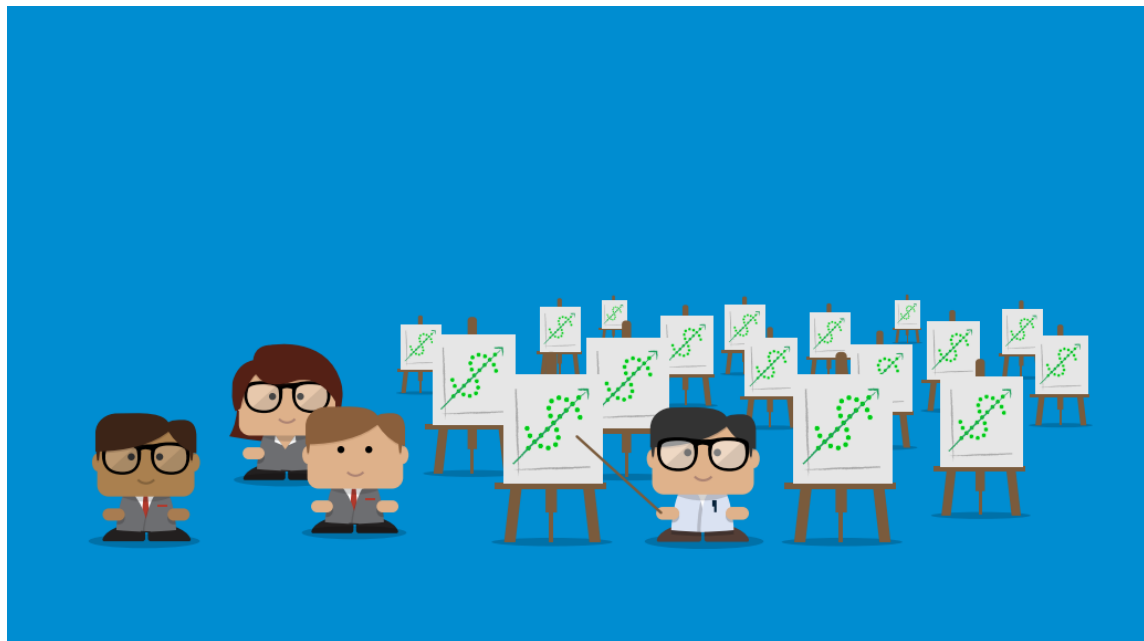
Kaggle Rank: Master (top 1%)

Experience:

10+ million predictive models
and counting ...

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COMPETITION SUMMARY

Fire Peril Loss Cost:

- Organized by Liberty Mutual
- Business problem: Predict expected fire losses for insurance policies
 - Significant portion of property losses
 - Volatile and hard to model correctly
- Started **July 8, 2014**
- Finished **Sept 2, 2014**



Completed • \$25,000 • 634 teams

Liberty Mutual Group - Fire Peril Loss Cost

Tue 8 Jul 2014 - Tue 2 Sep 2014 (12 days ago)

Dashboard

- Home
- Data
- Make a submission

Information

- Description
- Evaluation
- Rules
- Prizes
- Timeline
- Winners

Forum

Leaderboard

- Public
- Private

Leaderboard
1. DataRobot
2. Ivanhoe
3. barisumog
4. datalab.se
5. pauperly

Competition Details » [Get the Data](#) » [Make a submission](#)

Predict expected fire losses for insurance policies



A Fortune 100 company, Liberty Mutual Insurance has provided a wide range of insurance products and services designed to meet our customers' ever-changing needs for over 100 years.

Within the business insurance industry, fire losses account for a significant portion of total property losses. High severity and low frequency, fire losses are inherently volatile, which makes modeling them difficult. In this challenge, your task is to predict the target, a transformed ratio of loss to total insured value, using the provided information. This will enable more accurate identification of each policyholder's risk

Team DataRobot finished 1st out of 634 teams competing globally!

DATA OVERVIEW

- ~1 million insurance records
- 300 variables:

target : The transformed ratio of loss to total insured value

id : A unique identifier of the data set

dummy : Nuisance variable used to control the model, but not a predictor

var1 – var17 : A set of normalized variables representing policy characteristics

crimeVar1 – crimeVar9 : Normalized Crime Rate variables

geodemVar1 – geodemVar37 : Normalized geodemographic variables

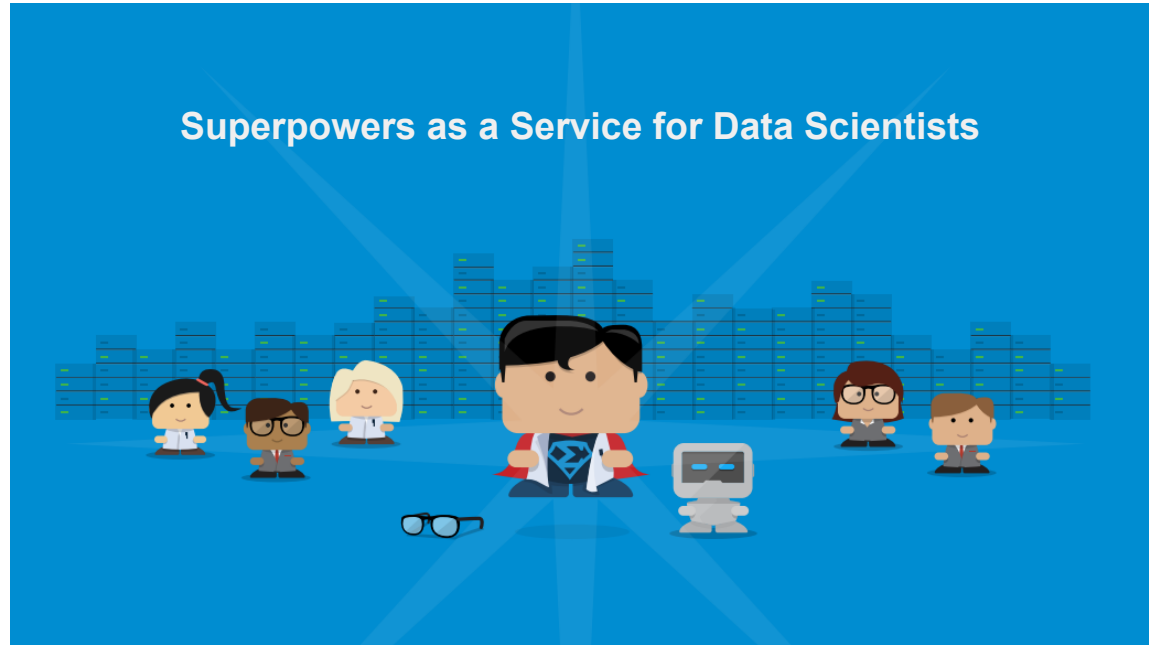
weatherVar1 – weatherVar236 : Normalized weather station variables

Numeric Variable Name	Variable Type
target	Continuous
id	Discrete
var10	Continuous
var11	Continuous
var12	Continuous
var13	Continuous
var14	Continuous
var15	Continuous
var16	Continuous
var17	Continuous
crimeVar1 – crimeVar9	Continuous
geoDemVar1 – geoDemVar37	Continuous

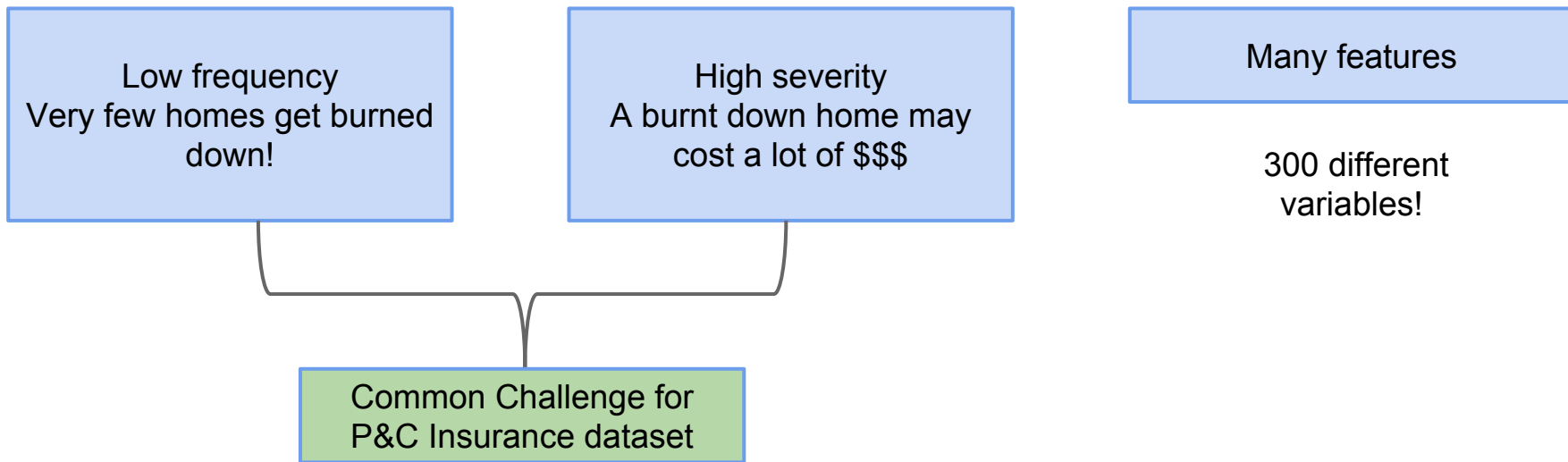
Categorical Variable Name	Variable Type	Possible Values
var1	Ordinal	1, 2, 3, 4, 5, Z*
var2	Nominal	A, B, C, Z*
var3	Ordinal	1, 2, 3, 4, 5, 6, Z*
var4*	Nominal	A1, B1, C1, D1, D2, D3, D4, E1, E2, E3, E4, E5, E6, F1, G1, G2, H1, H2, H3, I1, J1, J2, J3, J4, J5, J6, K1, L1, M1, N1, O1, O2, P1, R1, R2, R3, R4, R5, R6, R7, R8, S1, Z*
var5	Nominal	A, B, C, D, E, F, Z*
var6	Nominal	A, B, C, Z*
var7	Ordinal	1, 2, 3, 4, 5, 6, 7, 8, Z*
var8	Ordinal	1, 2, 3, 4, 5, 6, Z*
var9	Nominal	A, B, Z*
dummy	Nominal	A, B

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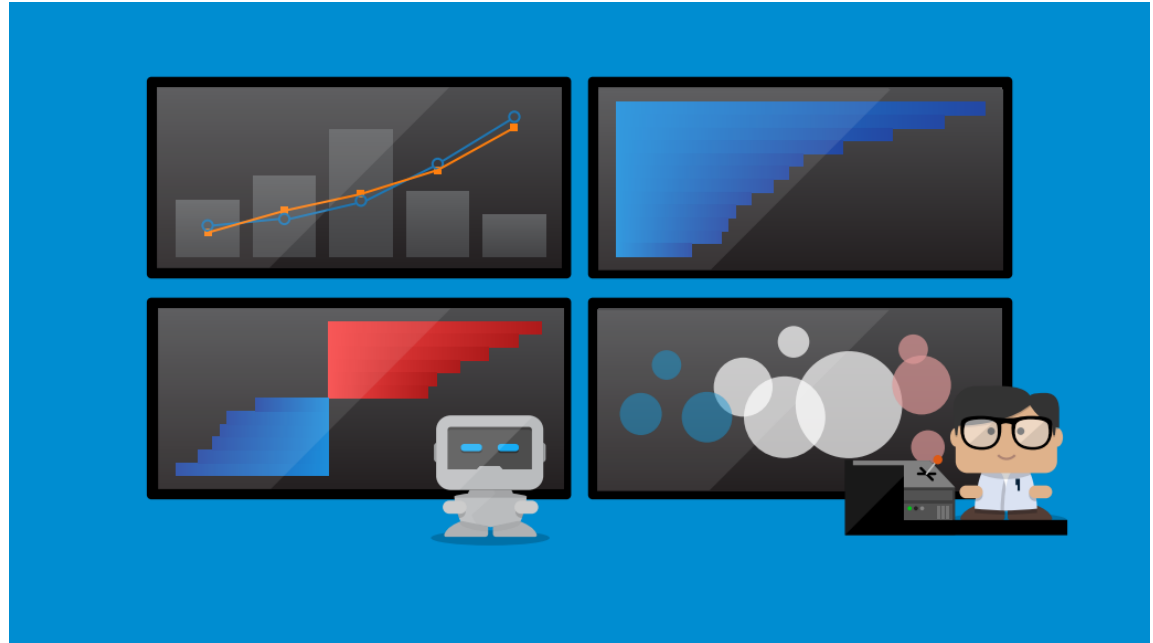


CHALLENGES

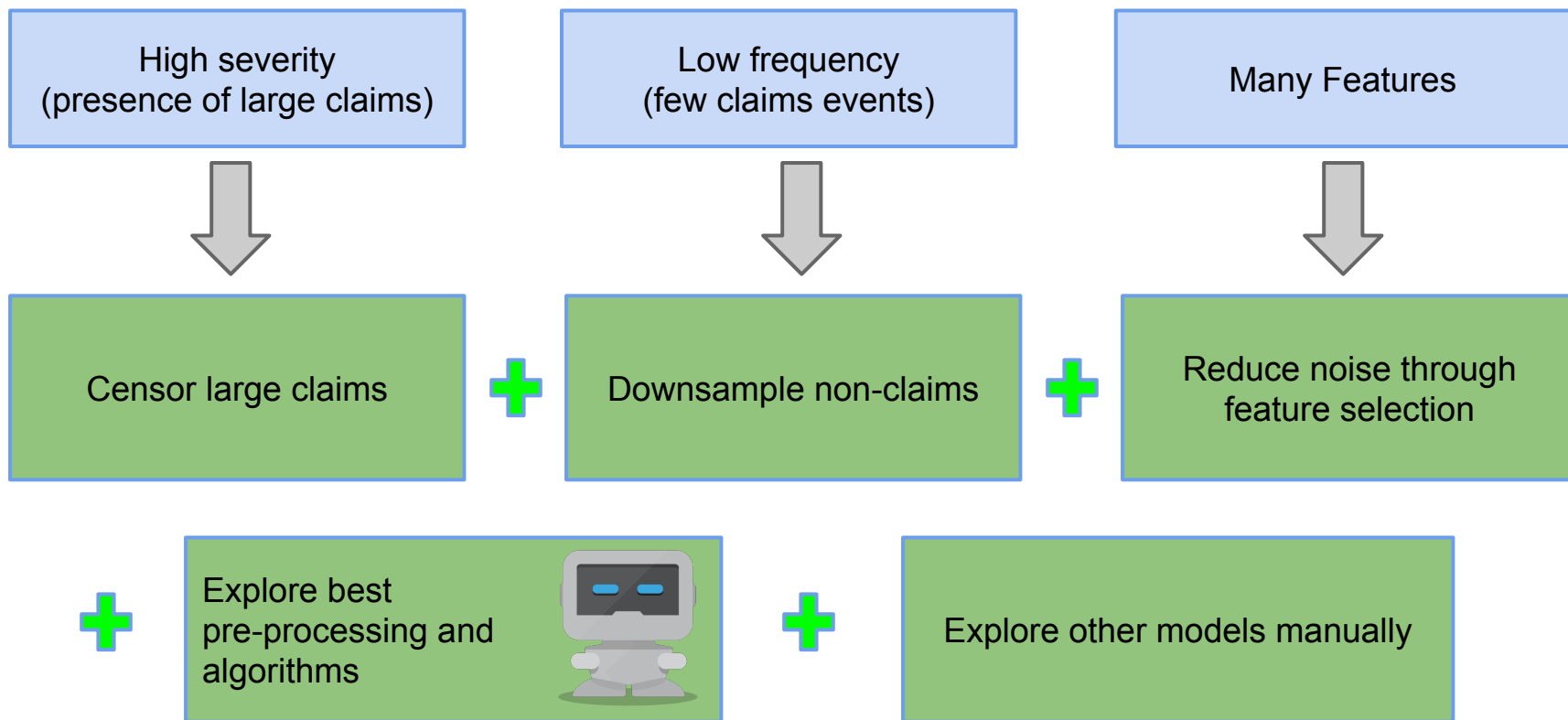


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OUR APPROACH



CENSORING LARGE CLAIMS

Technique

- To censor large claims, we capped the target at the 80% quantile of non-zero losses

Impact

- More accurate and robust results than modeling with the raw target or its log transformation

DOWNSAMPLING MAJORITY EVENTS

Technique

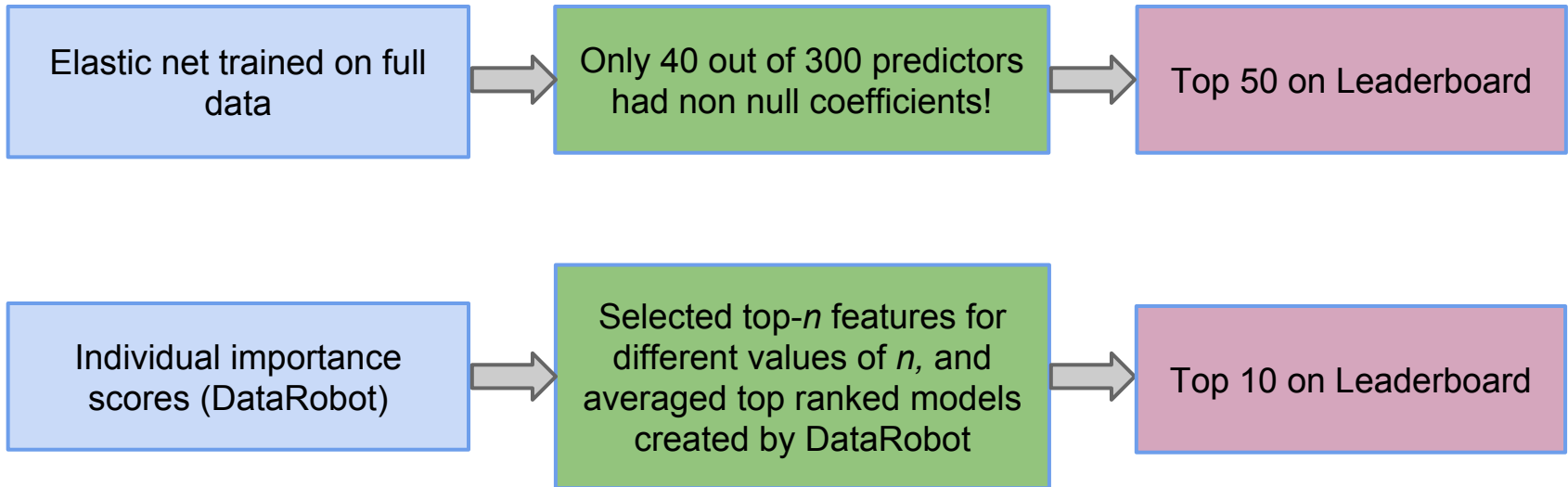
- Kept all non-0 records but only small % of 0 records from the training dataset

Impact

- Sped up model training significantly, and improved accuracy of certain ML algorithms (RandomForest, ExtraTrees, etc.)

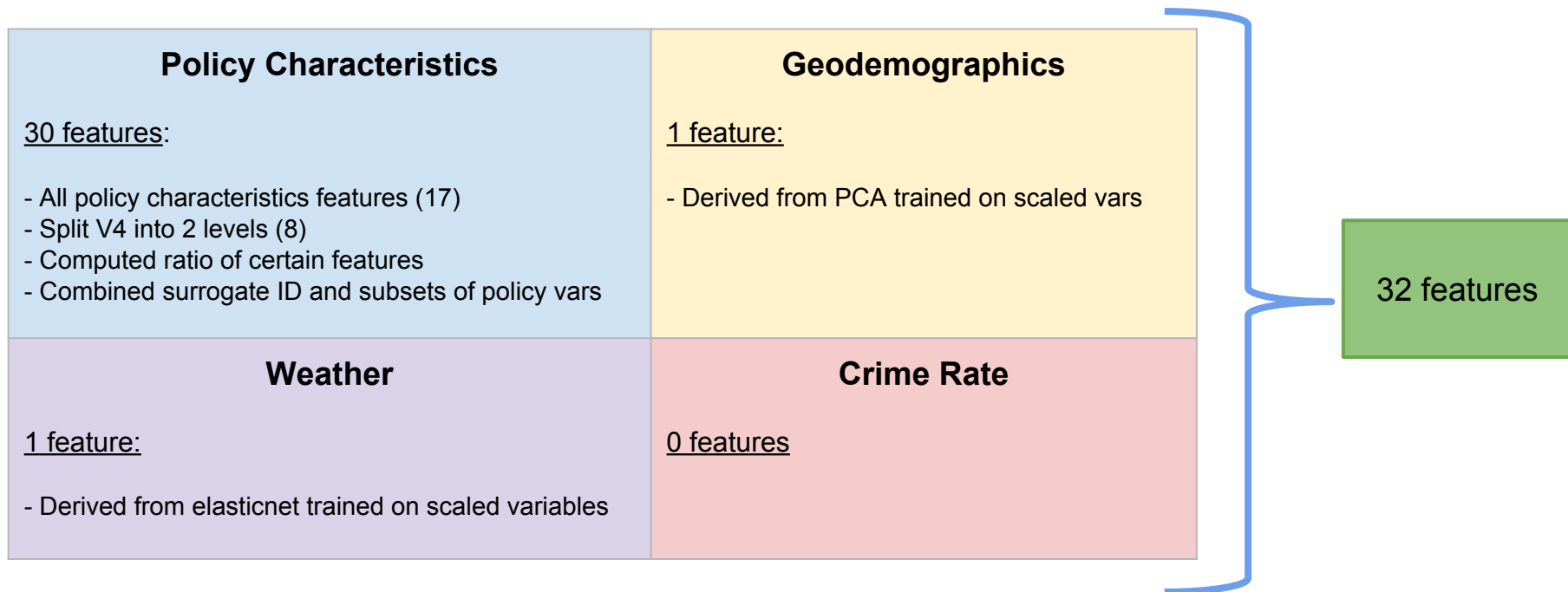
REDUCING NOISE

- Ran 2 automated feature selections to detect large presence of noise
- Produced our own feature list with significantly low noise



FEATURE ENGINEERING

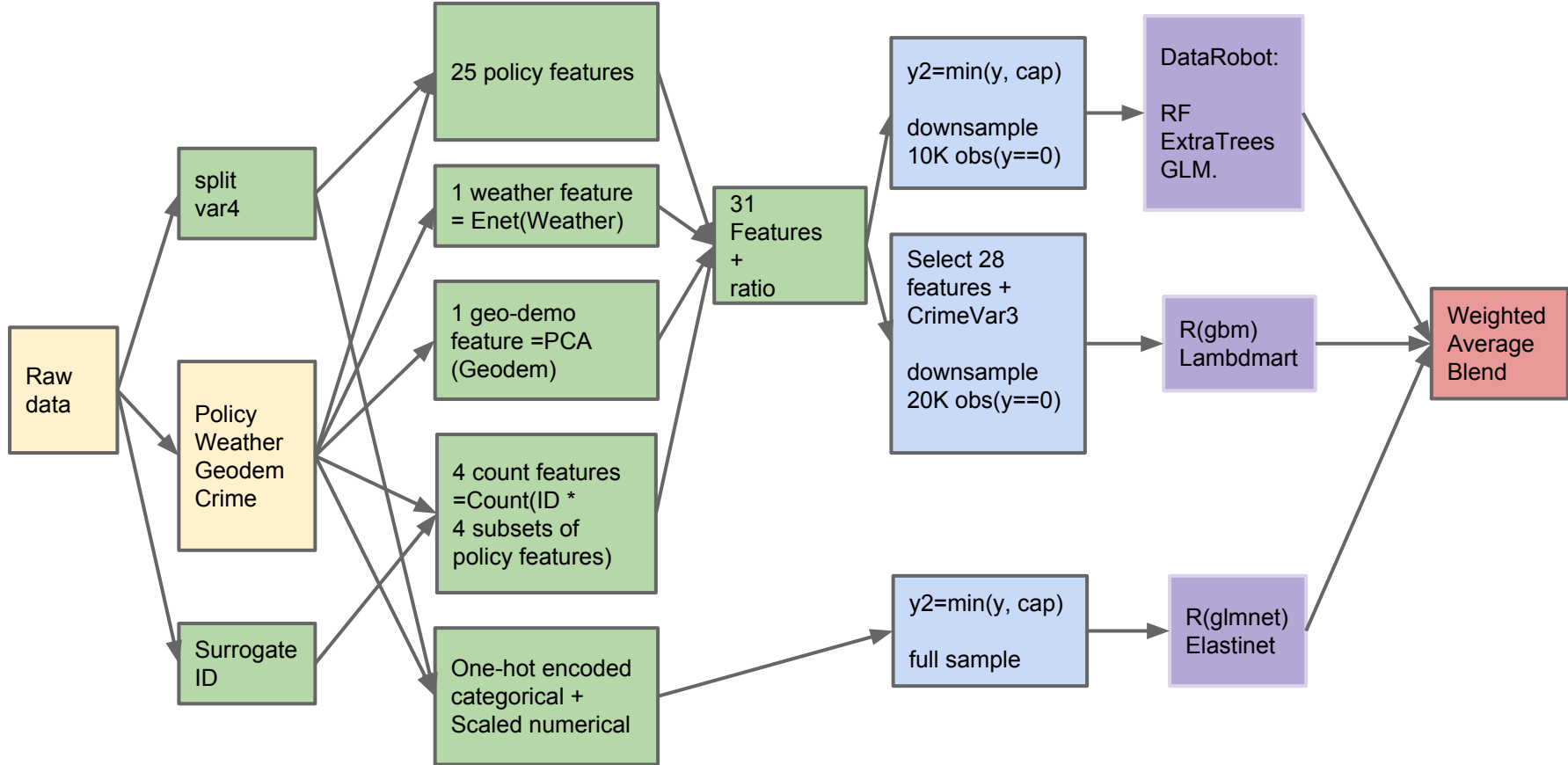
- Broke feature set into 4 components
- Created surrogate ID based on identical crime, geodemographics and weather variables



MODELING WITH DATAROBOT

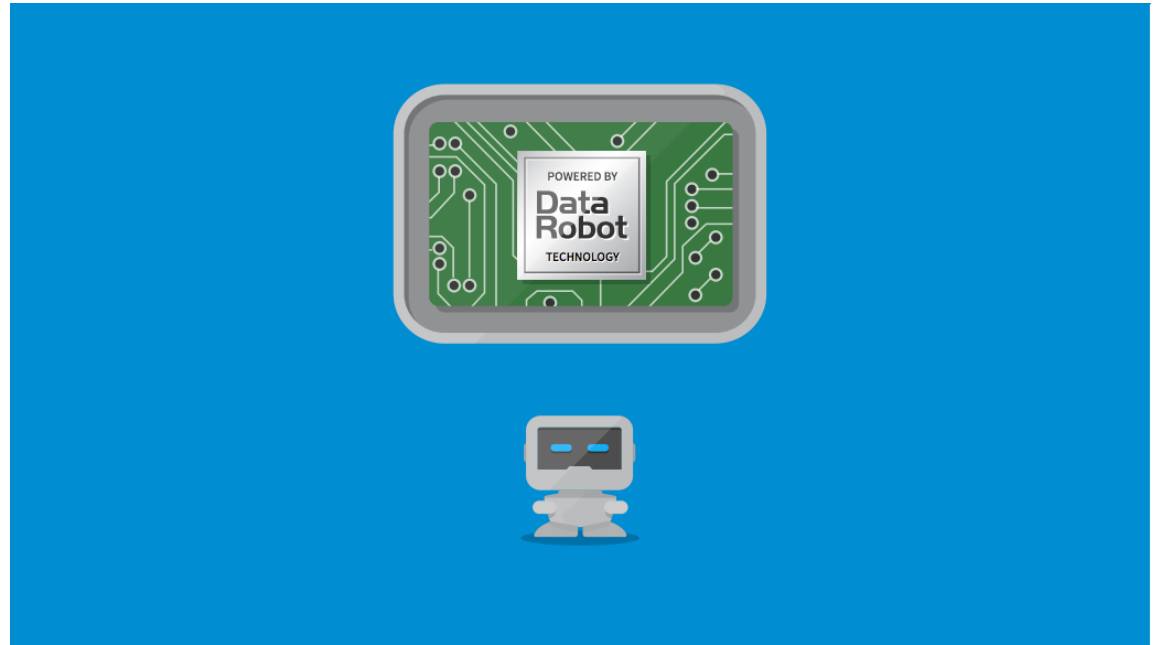
- Uploaded downsampled dataset with 32 features and capped target
- Ran multiple models in parallel with Normalized Gini metric to rank them
- Selected 3 promising models based on their 5-CV scores and trained them on 100% data
 - ExtraTrees Regressor
 - RandomForest Regressor
 - Ordinary Least Squares Regressor

FINAL SOLUTION SUMMARY



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KEY TAKEAWAYS

1. Classic insurance problem set - keys to addressing this problem were:
 - Capping
 - Downsampling
 - Feature selection to reduce noise
 - Extracting value from blocks of features
2. Capabilities of DataRobot
 - Rapidly explore diverse combinations of feature transformations and ML algorithms
 - Build highly accurate models from this search space automatically