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Driver vs Driverless

An Analysis of Driverless Al Feature Creation



Overview

- Analyze two recent problems with an emphasis on feature generation
- Overview of the problem
- Discussion of my approach
- Show the features Driverless created
 - Feature creation
 - Feature representation
- Results



Who am I?

- Data scientist @ H2O since 2015, user since 2014
- 15 top 20 finishes in Kaggle, highest rank 33
- R | H2O | data.table | GBM
- The "driver"



mlandry

Mountain View, CA, United States Joined 5 years ago · last seen in the past day





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Problem #1

How Many Attempts will a Student Make

- Online question/answer platform with computer science problems
- Predict the number of attempts a particular student will make on a particular problem
- Data
 - Student: level, ranking, highest ranking
 - Problem: type, 3-tier level, points awarded
 - Training: 124,000 attempt counts
 - Testing: 60,000 attempt counts



Regression as Classification

- Natural problem is numerical
- End user prefers buckets
- Volume
 - 1: 53%
 - 2 31%
 - 3 9%
 - 4 4%
 - 5 1%
 - 6 2%

attempts_range	No. of attempts	
1	1-1	
2	2-3	
3	4-5	
4	6-7	
5	8-9	
6	>=10	





- Think of it like a recommender problem
 - Standard: Matrix factorization, collaborative filtering
 - GBM: use deep categorical encodings
- Frequent use of target encoding

N	F1	itx	
46471	0.3728824	Rank	
46328	0.4334152	User	
46471	0.4510425	Level	
38589	0.4616374	UserLevel	- interaction
46471	0.4581436	RankLevel	interaction
44039	0.5149664	Problem	
40704	0.5283645	RankProblem	interaction

Table 1: Standalone F1 rates using median-based calculation when 3 records are present per interaction level





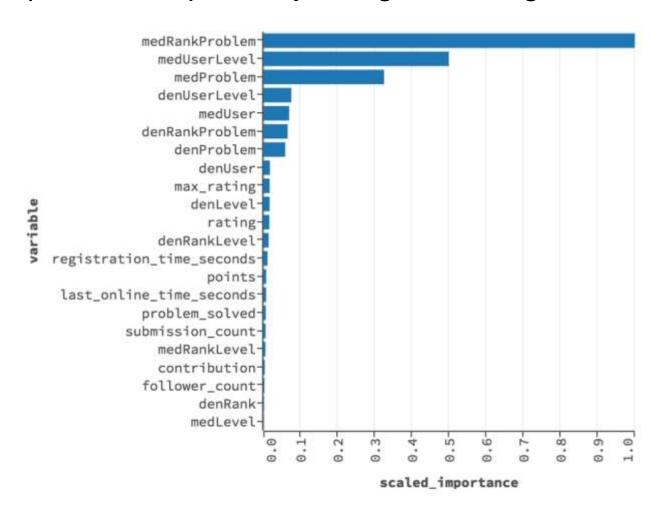
A messy chain of hierarchical target encoding and if/else statements

```
## RANK-LEVEL
all[,denRankLevel:=sum(isTrain),.(rank,level_type)]
all[,medLowRankLevel:=as.numeric(median(c(1,ifelse(isTrain,attempts_range,NA)),na.rm=TRUE)),.(rank,level_type)]
all[,medHiRankLevel:=as.numeric(median(c(6,ifelse(isTrain,attempts_range,NA)),na.rm=TRUE)),.(rank,level_type)]
all[,medRankLevel:=round(as.numeric(
  ifelse(!isTrain,medLowRankLevel*0.5+medHiRankLevel*0.5
         ,ifelse(denRankLevel==1,NA
                 ,ifelse(attempts_range<=medLowRankLevel,medHiRankLevel
                         ,ifelse(attempts_range>=medLowRankLevel,medHiRankLevel
                                 ,medLowRankLevel*0.5+medHiRankLevel*0.5)))))]
## RANK-PROBLEM
all[,denRankProblem:=sum(isTrain),.(rank,problem_id)]
all[,medLowRankProblem:=as.numeric(median(c(1,ifelse(isTrain,attempts_range,NA)),na.rm=TRUE)),.(rank,problem_id)]
all[,medHiRankProblem:=as.numeric(median(c(6,ifelse(isTrain,attempts_range,NA)),na.rm=TRUE)),.(rank.problem_id)]
all[,medRankProblem:=round(as.numeric(
  ifelse(!isTrain,medLowRankProblem*0.5+medHiRankProblem*0.5
         ,ifelse(denRankProblem==1,NA
                 ,ifelse(attempts_range<=medLowRankProblem,medHiRankProblem
                         ,ifelse(attempts_range>=medLowRankProblem,medHiRankProblem
                                 ,medLowRankProblem*0.5+medHiRankProblem*0.5))))))
```





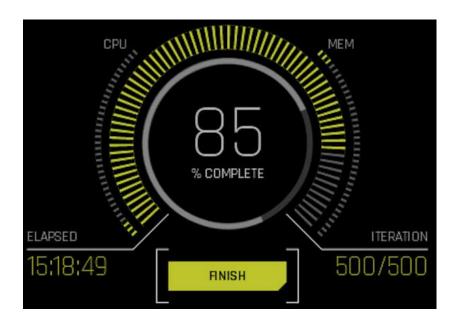
h2o.gbm feature importance - primarily using three target encodings





















VARIABLE IMPORTANCE	
16_CV_TE_problem_id_0	1.00
51_CV_TE_points_problem_id_0	0.74
3_max_rating	0.29
32_Freq_last_online_time_seconds_rating	0.25
61_NumToCatTE_rating_max_rating_points_last_online_ti	0.18
6_rating	0.16
24_CV_CatNumEnc_problem_idrating_mean	0.15
49_NumToCatTE_max_rating_follower_count_rating_0	0.15
16_CV_TE_problem_id_5	0.12
51_CV_TE_points_problem_id_1	0.11
16_CV_TE_problem_id_1	0.09
60_NumToCatTE_points_max_rating_0	0.07
60_NumToCatTE_points_max_rating_2	0.07
51_CV_TE_points_problem_id_5	0.06



Top 5 Features: divided into components



- {16} {CV TE} {problem_id} {0}
- {51} {CV TE} {points * problem_id} {0}
- {3} {max_rating}
- {32} {freq} {last_online_time_seconds * rating}
- {61} {NumToCatTE} {rating * max_rating * points * last_online_time_seconds} {0}





Feature #1: same base target encoding I found to be the best

- {16} {CV TE} {problem_id} {0}
 - 16: indicator of base features 16 is later used twice more in the top
 - CV TE: Cross-Fold target encoding
 - Problem_id: feature used as basis for target encoding
 - 0: the target; multinomial, so the two other uses are for class 1 & 5
- {51} {CV TE} {points * problem_id} {0}
- {3} {max_rating}
- {32} {freq} {last_online_time_seconds * rating}
- {61} {NumToCatTE} {rating * max_rating * points * last_online_time_seconds} {0}



13.45510 (10.50) (10.5

Feature #2: deeper interaction

- {16} {CV TE} {problem_id} {0}
- {51} {CV TE} {points * problem_id} {0}
 - 51: base feature ID
 - CV TE: out of sample target encoding result
 - points * problem: interaction of two different features, both related to the problem; it is subdividing the problem further
 - 0: again, rate of class 0 as the target
- {3} {max_rating}
- {32} {freq} {last_online_time_seconds * rating}
- {61} {NumToCatTE} {rating * max_rating * points * last_online_time_seconds} {0}





Feature #3: no transformation

- {16} {CV TE} {problem_id} {0}
- {51} {CV TE} {points * problem_id} {0}
- {3} {max_rating}
 - max rating
 - used as is no alternate encoding; was first natural feature in my model as well
 - this is the first variable of the student dimension.
 - a 4-digit number with close to a normal distribution
- {32} {freq} {last_online_time_seconds * rating}
- {61} {NumToCatTE} {rating * max_rating * points * last_online_time_seconds} {0}



Feature #4: frequency encoding



- {16} {CV TE} {problem_id} {0}
- {51} {CV TE} {points * problem_id} {0}
- {3} {max_rating}
- {32} {freq} {last_online_time_seconds * rating}
 - Counting the occurrences of two fields
 - Last online & rating are both numerics in the student dimension
- {61} {NumToCatTE} {rating * max_rating * points * last_online_time_seconds} {0}





Feature 5: four-way interaction w/ target encoding

- {16} {CV TE} {problem_id} {0}
- {51} {CV TE} {points * problem_id} {0}
- {3} {max_rating}
- {32} {freq} {last_online_time_seconds * rating}
- {61} {NumToCatTE} {rating * max_rating * points * last_online_time_seconds} {0}
 - Target encoding of class 0
 - Finding the rate for each value of the result of a four way interaction





Top 5 Features: did I try?

```
YES {16} {CV TE} {problem_id} {0}
NO {51} {CV TE} {points * problem_id} {0}
YES {3} {max_rating}
NO {32} {freq} {last_online_time_seconds * rating}
NO {61} {NumToCatTE} {rating * max_rating * points * last_online_time_seconds} {0}
```





VARIABLE IMPORTANCE	
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32_Freq_last_online_time_seconds_rating	0.25
61_NumToCatTE_rating_max_rating_points_last_online_ti	0.18
6_rating	0.16
24_CV_CatNumEnc_problem_idrating_mean	0.15
49_NumToCatTE_max_rating_follower_count_rating_0	0.15
16_CV_TE_problem_id_5	0.12
51_CV_TE_points_problem_id_1	0.11
16_CV_TE_problem_id_1	0.09
60_NumToCatTE_points_max_rating_0	0.07
60_NumToCatTE_points_max_rating_2	0.07
51_CV_TE_points_problem_id_5	0.06



Problem #2

Bank Customer Churn

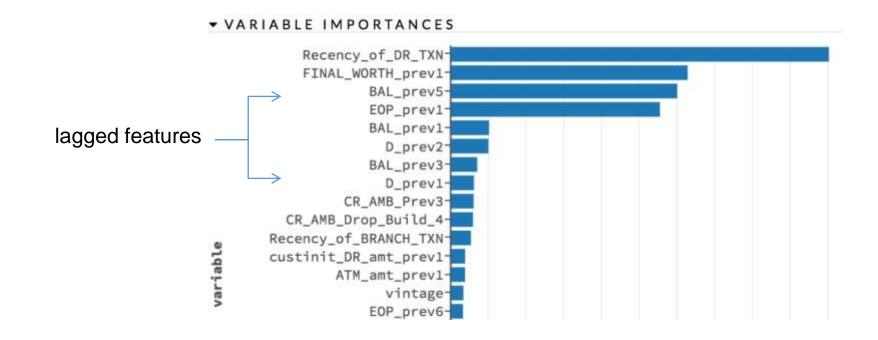
- Identify customers likely to churn balances in the next quarter by 50%
- Data
 - 300,00 training rows; 200,000 testing rows
 - 377 columns
 - Customer: age, gender, demographics
 - Reported assets, liabilities
 - Monthly balance history



Exploit before Explore



- 377 columns made [quick] manual investigation harder
- Rather than iterate: {analyze > model > analyze > ... },
 I changed to {model > analyze > model > ... }





After lagging, try differences and ratios



- Lagging features present the balance features at several time steps.
- But often, the interesting part is not the raw balance itself, but whether it is growing or shrinking
- Decision trees have a hard time "seeing" this so it is wise to engineer mathematical features: + - * /



After lagging, try differences and ratios



- I used the leading monthly feature from the model and created new features representing month-over-month differences and a binary indicator
- One field, one specific length (1 month), two calculations

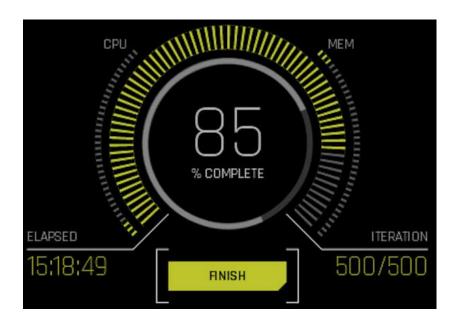
```
trainHex$diff_BAL_5_4<-trainHex$BAL_prev5-trainHex$BAL_prev4
trainHex$diff_BAL_4_3<-trainHex$BAL_prev4-trainHex$BAL_prev3
trainHex$diff_BAL_3_2<-trainHex$BAL_prev3-trainHex$BAL_prev4
trainHex$diff_BAL_2_1<-trainHex$BAL_prev2-trainHex$BAL_prev1

trainHex$rt_BAL_5_4<-trainHex$BAL_prev5/trainHex$BAL_prev4
trainHex$rt_BAL_4_3<-trainHex$BAL_prev4/trainHex$BAL_prev3
trainHex$rt_BAL_3_2<-trainHex$BAL_prev3/trainHex$BAL_prev4
trainHex$rt_BAL_3_1<-trainHex$BAL_prev3/trainHex$BAL_prev4
```



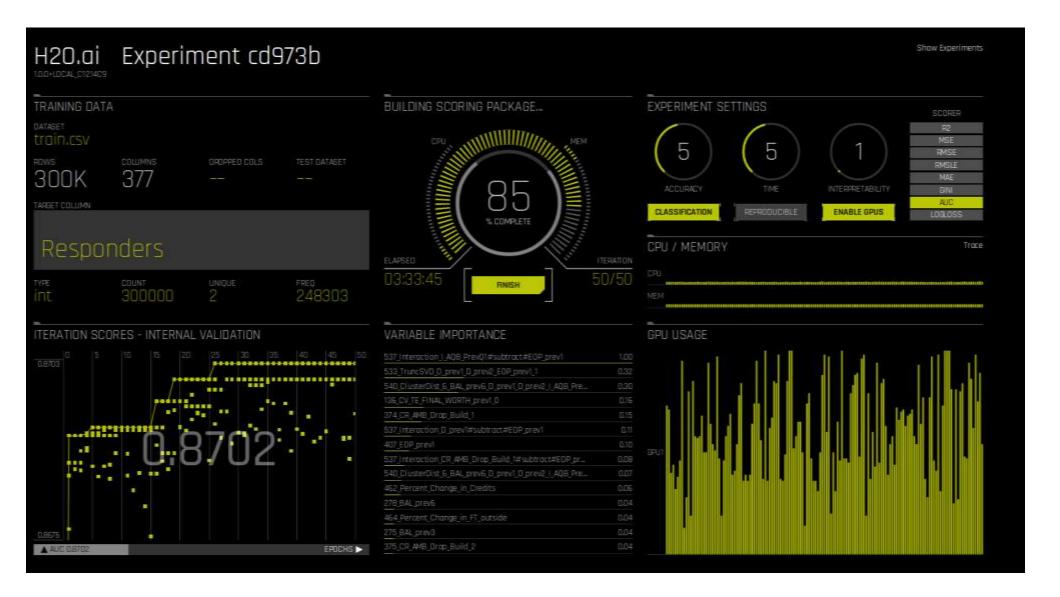
















It knows math!

	VARIABLE IMPORTANCE	
subtraction>	537_Interaction_I_AQB_PrevQ1#subtract#EOP_prev1	1.00
	533_TruncSVD_D_prev1_D_prev2_EOP_prev1_1	0.32
	540_ClusterDist_6_BAL_prev6_D_prev1_D_prev2_I_AQB_Pre	0.30
	136_CV_TE_FINAL_WORTH_prev1_0	0.16
	374_CR_AMB_Drop_Build_1	0.15
subtraction>	537_Interaction_D_prev1#subtract#EOP_prev1	0.11
	407_E0P_prev1	0.10
subtraction>	537_Interaction_CR_AMB_Drop_Build_1#subtract#EOP_pr	0.08
	540_ClusterDist_6_BAL_prev6_D_prev1_D_prev2_I_AQB_Pre	0.07
	462_Percent_Change_in_Credits	0.06
	278_BAL_prev6	0.04



Top 10 Features: divided into categories



- (3) Subtraction: #1, #6, #8
- (1) Truncated SVD components: #2
- (2) Cluster Distances: #3, #9
- (1) Target encoding: #4
- (3) Direct features: #5, #7, #10





- Lagged balances also used in clusters & SVD
- Distance to cluster #1 after segmenting columns into 6 clusters
 - BAL_prev6
 - D_prev1
 - D_prev2
 - I_AQB_PrevQ1
- Component #1 of truncated SVD of
 - D_prev1
 - D_prev2
 - EOP_prev1_1





Final Analysis

- On first iteration, Driverless AI had surpassed my manual modeling
- Features were well beyond what I would have ever attempted
- Accuracy was stable: Driverless AI self-reported scores within 1% of competition submission



Competition Results



Private Leaderboard

	#		Name	Score
	1	**	Team Billa	0.680800
	2	4	ankit2106	0.678672
Kaggle Grandmaster>	3	4	SRK	0.678595
	3	۵	sadz2201	0.678595
100% Driverless AI>	5	4	mark12	0.678440
	5	۵	numb3r303	0.678440
Kaggle Grandmaster>	7	4	Rohan Rao	0.677937
Also Driverless Al>	8	4	ruben_diaz	0.677860



The End Thank You

