Different goals, different models: How to use models to sharpen up your questions

Ron Kenett and Chris Gotwalt





Agenda

- Intro and a simple example Ron
 - What is the role of models?
 - The sensor data case study
- A complex example and conclusions Chris
 - Variable importance and SHAP values
 - More complex models









Yes, but which ones?

through analytics

The purpose of models is not to fit the data but to sharpen the question

Sam Karlin, 1924-2007

Yes, but how?

This is the key difference between a model and a computer program

RSK



Pablo Picasso, 1881-1973

"Computers are useless. They can only give you answers"



3





63 sensors, one response



SENSORS.jmp

	sensor01	sensor02	sens	
1	395.333333	735.771429	556.	Brate
2	657.8	385.87619	833.	
3	604.104762	678.171429	743.	
4	348.771429	621.590476	506	
5	333.009524	624.771429	540.4	
6	752.342857	241.028571	840.5	14200
7	287.390476	718.428571	410.	stati
8	463.180952	631.07619	590.	
om 9	270.095238	542.514286	391.	
est 10	359.266667	707.780952	546.	
11	387.27619	635.952381	483.	
12	497.514286	684.47619	694.	
13	372.438095	520.857143	541.	
14	516.390476	550.485714	613	
	1 1 2 3 4 5 6 7 8 0 9 est 10 11 12 13 14	sensor01 1 395.333333 2 657.8 3 604.104762 4 348.771429 5 333.009524 6 752.342857 7 287.390476 8 463.180952 9 270.095238 9 270.095238 10 359.266667 11 387.27619 12 497.514286 13 372.438095 14 516.390476	sensor01 sensor02 1 395.33333 735.771429 2 657.8 385.87619 3 604.104762 678.171429 4 348.771429 621.590476 5 333.009524 624.771429 6 752.342857 241.028571 7 287.390476 718.428571 8 463.180952 631.07619 9 270.095238 542.514286 10 359.266667 707.780952 11 387.27619 635.952381 12 497.514286 684.47619 13 372.438095 520.857143 14 516.390476 550.485714	sensor01 sensor02 sens 1 395.33333 735.771429 556. 2 657.8 385.87619 833. 3 604.104762 678.171429 743. 4 348.771429 621.590476 506 5 333.009524 624.771429 540. 6 752.342857 241.028571 840.5 7 287.390476 718.428571 410. 8 463.180952 631.07619 590. 9 270.095238 542.514286 391. 9 270.095238 542.514286 391. 10 359.266667 707.780952 546. 11 387.27619 635.952381 483. 12 497.514286 684.47619 694. 13 372.438095 520.857143 541. 14 516.390476 550.485714 615.



testResult

Frequencies		
Level	Count	Prob
Brake	6	0.03448
Good	82	0.47126
Grippers	14	0.08046
IMP	5	0.02874
ITM	33	0.18966
Motor	16	0.09195
SOS	2	0.01149
Velocity Type I	11	0.06322
Velocity Type II	5	0.02874
Total	174	1.00000
N Missing 9 Levels	0	



	82	0.47126
l i	174	1.00000
issing 2 Lev	/els	0
	4	



int Prob 92 0.52874

ts through analytics

Goal: Determine system status from the sensor data



Achieving this goal would enable us to create on-line quality control and avoid the cost and delays of testing





	Boosted Tree - JMP Pro				—		×	
	Builds a decision tree that is a sequence	of smal	ller trees to pred	ict a response.				
	Select Columns		Cast Selected	Columns into Roles	5	Actio	n	
	💌 66 Columns		Y. Response	📕 status			ОК	
	Enter column name	₽ -		optional			ncel	
	 sensor01 etc. (63/0) testResult status 		X, Factor	sensor01	^	Rer	nove	
ВГ				sensor02		Re	ecall	
				sensor04	\sim	Н	elp	
			Weight	optional numeric				
			Freq	optional numeric				
			Validation	L Validation				
			By	optional				
			L					
	Options	The	ere are two	main differe	nces b	oetwe	een th	e gradient
	Method Boosted Tree	boc	osting trees	(BT) and th	e ranc	lom f	orests	(RF). We train
	Validation Portion	the	former se	equentially,	one tr	ee a	t a tim	e, each to
		cor	rect the e	rrors of the	previo	ous d	ones.	In contrast, we
	✓ Ordinal Restricts Order	cor	nstruct the	e trees in a r	ando	m foi	rest ir	dependently
KPA								
Insights through analytics							V	JI IP. dis

7





	Boosted Tree Gradient-Boosted	Boosted trees (BT can be used to so regression which) are derived by optimizing an objective function. They lve most objective functions. This includes Poisson is harder to achieve with RF .
BT	Boosting Number of La Splits per Tre Learning Rate Overfit Penal Minimum Siz	ayers: 122 e: 2 e: 0.036 ty: 0.0001 xe Split: 5	Multiple Fits Multiple Fits over Splits and Learning Rate Max Splits Per Tree 3 Max Learning Rate 0.1 Use Tuning Design Table
	Stochastic Boo Row Samplin Column Sam	osting Ig Rate 1.0000 pling Rate 1.0000	Reproducibility Suppress Multithreading Random Seed 0

BT training generally takes longer than RF because trees are built sequentially. There are typically three parameters: number of trees, depth of trees and learning rate.



8





oosted Tre	e for	status									⊿	Column	ontrib	utions		
Specificati	ions												Number			
Target	s	tatus		Numb	er of tr	aining r	ows:	131				Term	of Splits	G^2		
Validation Co	lumn: V	/alidatio	n	Numb	er of v	alidation	rows:	43				sensor56	82	4634.8525	I I	
Number of La	yers:	122	2									sensor18	27	4200.54219		
Splits per Tree	2	2	2									sensor11	21	2735.54419		
Learning Rate	8	0.036	6									sensor61	19	2431.70533		
Overfit Penalt	y:	0.000	1									sensor48	17	2414.82121	1 1	
Overall Sta	atistic	<u>د</u>										sensor57	22	2016.84895		
overanou		-										sensor58	10	1456.34648		
Measure		Trai	ining	Valid	ation	Definiti	on					sensor59	8	726.693834		
Entropy RSq	uare	0.	9981	0	.5788	1-Loglik	(model)	/Loglik	ce(0)			sensor26	2	343.87221		
Generalized	RSquar	e 0.	9991	0	.7352	(1-(L(0))	/L(model))^(2/n	n))/(1-L(0)^(2/n))		sensor52	2	323.166652		
DACE	0	0.	0013	0	2640	2 -Log()	o(j))/n					sensor09	6	286.922646		
Mean Abs D	ev/	0.	0025	0	0875	Z [v[i]-0	(111/n					sensor01	9	194.974174		
Misclassifica	cv ition Ra	te 0.	0000	Ő.	.0930	Σ (o[i]≠	oMax)/n					sensor55	2	165.247012		
N		1	31	4	3	n	p		K			sensor24	4	151.216612		
												sensor07	4	128.858022		
Confusio	on Ma	trix										sensor12	4	117.421132		
Т	raining	1		Va	lidatio	n						sensor15	2	44.7671089		
	Predi	cted			Pred	icted						sensor44	1	37.6713347		
Actual	Cou	int	A	ctual	Со	unt		~				sensor54	1	15.5711294		
status	Fail	Pass	st	atus	Fail	Pass		9	0.3%			sensor27	1	12.8974036		
Fail	69	0	Fa	ail	20	3	_								i i	i
Pass	0	62	Pa	ass	1	19		Act	ual Valida	ation Pas	SS :	= 20				
	Pred	licted			Pre	dicted										
Actual	R	ate	A	ctual	R	ate		of th	ese, prec	dicted Pa	ass	= 19	64		orfitting	
status	Fail	Pass	st	atus	Fai	Pass							50		enning	
Fail	1.000	0.000	Fa	ail	0.870	0.130	E	alse	nredicte	d Pass -	- 3	(13%)				
Pass	0.000	1.000	I P:	226	0.050	0.950			predicte	un ass –						

Pass

0.000 1.000

Pass

0.050 0.950



Portion 0.2065 0.1872 0.1219 0.1084 0.1076 0.0899 0.0649 0.0324 0.0153 0.0144 0.0128 0.0087 0.0074 0.0067 0.0057 0.0052 0.0020 0.0017 0.0007 0.0006









12

RF algorithm with a large number of trees is slow. For categorical variables with different number of levels, RF are biased in favor of attributes with more levels. RF is much easier to tune than BT

OK

Cancel

券 Bootstrap Forest		×
Bootstrap Forest Specification		
Number of Rows: 174 Number of Terms: 63 Forest Number of Trees in the Forest Number of Terms Sampled per Split: Bootstrap Sample Rate Minimum Splits per Tree: Maximum Splits per Tree	1000 49 1 10 2000	Multiple Fits Multiple Fits over Number of Terms Max Number of Terms 49 Use Tuning Design Table Reproducibility Suppress Multithreading Random Seed 0
Minimum Size Split:	5	There are typically two parameters in RF: number of tre and number of features to be selected at each node.



Sootstrap Forest for status								
Specifications								
Target	status	Training Rows:	131					
Validation Column:	Validation	Validation Rows:	43					
		Test Rows:	0					
Number of Trees in the Forest:	1000	Number of Terms:	63					
Number of Terms Sampled per Split:	49	Bootstrap Samples:	131					
		Minimum Splits per Tree:	10					
		Minimum Size Split:	5					

Actual Validation Pass = 20 of these, predicted Pass = 20 False predicted Pass = 3 (13%)

Overall Statistics

Measure	Training	Validatio
Entropy RSquare	0.9186	0.673
Generalized RSquare	0.9601	0.80
Mean -Log p	0.0563	0.22
RASE	0.1016	0.254
Mean Abs Dev	0.0491	0.12
Misclassification Rate	0.0076	0.06
N	131	43





Confusion Matrix

is through analysics

T	raining			Va	lidatio	n				
Actual	Predicted Count		Predicted Count		Predicted Count			Actual	Predi Cou	cted int
status	Fail	Pass		status	Fail	Pass				
Fail	68	1		Fail	20	3				
Pass	0 62			Pass	0	20				
L										
	Pred	licted			Prec	licted				
Actual	Pred Ra	licted ate		Actual	Prec R	licted ate				
Actual status	Pred Ra Fail	licted ate Pass	5	Actual status	Prec R Fail	licted ate Pass				
Actual status Fail	Pred Ra Fail 0.986	licted ate Pase 0.014	5	Actual status Fail	Prec R Fail 0.870	dicted ate Pass 0.130				





ootstrap Forest for test	Result					
Specifications						
Target	testResult	Training Rows:	131			
Validation Column:	Validation	Validation Rows:	43			Actual Validation Good
		Test Rows:	0			/ lotal / and alloh 0000
Number of Trees in the Forest:	1000	Number of Terms:	63			
Number of Terms Sampled per	Split: 49	Bootstrap Samples:	131			of those prodicted Good
		Minimum Splits per Tree	: 10			or these, predicted 6000
		Minimum Size Split:	5		DE	
Overall Statistics						False predicted Good = 5
Measure Train	ing Validation [Definition				
Entropy RSquare 0.82	203 0.5474 1	l - Loglike(model)/Loglike(0)		00 40		
Generalized RSquare 0.96	669 0.8703 (1-(L(0)/L(model))^(2/n))/(1-	L(0)^/2	Z3.4`	70	
Mean -Log p 0.28	871 0.7564 2	Σ -Log(ρ[j])/n				
RASE 0.30	070 0.4699 v	/∑(y[j] ₁ ρ[j])²/n				For detailed testResult
Mean Abs Dev 0.19	982 0.3136 ∑	Z W MARK				
Misclassification Rate 0.0	534 0.2326 ∑	Σ (ρ[J]∓pMax)/n				
N 13	1 43 m	1				

Confusion Matrix

Training															
	Predicted Count														
Actual		Velocity Velocity													
testResult	Brake	Good	Grippers	IMP	ITM	Motor	SOS	Type I	Type II						
Brake	2	0	0	0	0	1	0	0	0						
Good	0	62	0	0	0	0	0	0	0						
Grippers	0	1	7	0	1	0	0	0	0						
IMP	0	1	0	3	0	0	0	0	0						
ITM	0	1	0	0	25	1	0	0	0						
Motor	0	0	0	0	0	13	0	0	0						
SOS	0	0	0	0	1	0	1	0	0						
Velocity Type I	0	0	0	0	0	0	0	9	0						
Velocity Type II	0	0	0	0	0	0	0	0	2						

			V	/alidati	on				
				Pred	licted	Count			
Actual								Velocity	Velocity
testResult	Brake	Good	Grippers	IMP	ITM	Motor	SOS	Type I	Type II
Brake	0	1	0	2	0	0	0	0	0
Good	0	20	0	0	0	0	0	0	0
Grippers	0	1	1	0	2	1	0	0	0
IMP	0	1	0	0	0	0	0	0	0
ITM	0	0	0	0	6	0	0	0	0
Motor	0	0	0	0	0	3	0	0	0
SOS	0	0	0	0	0	0	0	0	0
Velocity Type I	0	0	0	0	0	0	0	2	0
Velocity Type II	0	2	0	0	0	0	0	0	1

				Pre	dicted	Rate					Predicted Rate								
Actual								Velocity	Velocity	Actual								Velocity	Velocity
testResult	Brake	Good	Grippers	IMP	ITM	Motor	SOS	Type I	Type II	testResult	Brake	Good	Grippers	IMP	ITM	Motor	SOS	Type I	Type II
Brake	0.667	0.000	0.000	0.000	0.000	0.333	0.000	0.000	0.000	Brake	0.000	0.333	0.000	0.667	0.000	0.000	0.000	0.000	0.000
Good	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	Good	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Grippers	0.000	0.111	0.778	0.000	0.111	0.000	0.000	0.000	0.000	Grippers	0.000	0.200	0.200	0.000	0.400	0.200	0.000	0.000	0.000
IMP	0.000	0.250	0.000	0.750	0.000	0.000	0.000	0.000	0.000	IMP	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ITM	0.000	0.037	0.000	0.000	0.926	0.037	0.000	0.000	0.000	ITM	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000
Motor	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	Motor	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
SOS	0.000	0.000	0.000	0.000	0.500	0.000	0.500	0.000	0.000	SOS									
Velocity Type I	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	Velocity Type I	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
Velocity Type II	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	Velocity Type I	0.000	0.667	0.000	0.000	0.000	0.000	0.000	0.000	0.333



1	LCD A
CI	KPA
~	
2	Insights through any

Lift Curve on Validation Data





R	E

R	F

	🛛 💌 Bootst	rap Fore	st for testR	lesult	
	⊿ Colum	n Contrib	utions 🔺		
Portion	Term	Number of Splits	G^2		Portion
0.5024	sensor18	5	54.8827138		0.2325
0.1714	sensor52	3	29.2773568		0.1240
0.1201	sensor48	2	18.0919607		0.0766
0.0482	sensor61	1	12,7377835		0.0540
0.0232	sensor04	4	11,2268386		0.0476
0.0225	sensor62	3	9.74427579		0.0413
0.0123	sensor19	4	8.91209343		0.0378
0.0093	sensor17	2	7.31785078		0.0310
0.0067	sensor40	1	6.4025967		0.0271
0.0062	sensor50	1	5.95404634		0.0252
0.0048	sensor63	1	5.83025113		0.0247
0.0047	sensor28	1	5.71751006		0.0242
0.0038	sensor42	1	5.48313999		0.0232
0.0030	sensor41	1	5.20440640		0.0220
0.0032	sensor36				0.0214
0.0028	sensor07	F	or detai	iled testResi	ults ²⁰⁷
	sensor05				J.0181
	sensor57	4	4.200000		0.0180
	sensor53	2	3.88027473		0.0164

💌 Booste	d Tree f	or status			Bootst	 Bootstrap Forest for status 						
⊿ Columr	Contrib	utions			⊿ Colum	n Contrib	utions					
Term	Number of Splits	G^2		Portion	Term	Number of Splits	G^2		Portic			
sensor56	82	4634.8525		0.2065	sensor18	579	54.9167342		0.50			
sensor18	27	4200.54219		0.1872	sensor61	198	18.7389273		0.17			
sensor11	21	2735.54419		0.1219	sensor52	145	13.1320295		0.12			
sensor61	19	2431.70533		0,1084	sensor53	56	5.26374221		0.04			
sensor48	17	2414.82121		0,1076	sensor44	33	2.53070023		0.02			
sensor57	22	2016.84895	\rightarrow	0.0899	sensor48	42	2.45696551		0.02			
sensor58	10	1456.34648		0.0649	sensor46	31	2.08993095		0.01			
sensor59	8	726 692634		0.0324	sensor11	114	1.34630042		0.01			
sensor26	2	343 87221		0.0153	sensor54	12	1.01688952		0.00			
sensor52	2	323 166652		0.0144	sensor58	111	0.73127415		0.00			
sensor09	6	286 922646		0.0128	sensor07	61	0.68014104		0.00			
sonsor01	9	10/ 07/17/		0.0027	sensor26	89	0.5292647		0.004			
concor55	2	165 247012		0.0074	sensor12	40	0.51092374		0.004			
sensor34	2	151 216612		0.0074	sensor50	8	0.41943383		0.00			
sensor07	4	120.050012		0.0007	sensor57	75	0.3901658		0.00			
sensor07	4	128.858022		0.0057	sensor01	44	0.35310066		0.00			
sensor12	4	117.421132		0.0052	sensor05	47	0.3400086		0.00			
sensor15	2	44.7671089		0.0020	sensor21	8	0.30245908		0.00			
sensor44	1	37.6713347		0.0017								
sensor54	1	15.5711294		0.0007								
sensor27	1	12.8974036		0.0006								

What is your goal?









Bootstrap Forest		>
Bootstrap Forest Specification		
Number of Rows: 174 Number of Terms: 63		Multiple Fits Multiple Fits over Number of Terms Max Number of Terms 49
Number of Trees in the Forest	1000	Use Tuning Design Table
Number of Terms Sampled per Split:	49	Reproducibility
Bootstrap Sample Rate	1	Suppress Multithreading Random Seed 0
Minimum Splits per Tree:	10	
Maximum Splits per Tree	2000	
Minimum Size Split:	5	
Early Stopping		
		OK Cancel



⊿ Column	Contrib	utions	R	RF
Term	Number of Splits	G^2	Portion	
sensor18	522	36.5630568	0.3709	\sim
sensor53	248	19.0040464	0.1928	
sensor55	163	9.18530792	0.0932	
sensor48	107	7.43395874	0.0754	
sensor52	88	4.51699905	0.0458	
sensor54	65	3.1209684	0.0317	
sensor61	48	3.08165918	0.0313	
sensor11	76	2.20715869	0.0224	
sensor21	44	1.8102253	0.0184	
sensor46	31	0.98045171	0.0099	
sensor24	37	0.97068784	0.0098	
sensor50	33	0.77981921	0.0079	
sensor44	15	0.75054722	0.0076	
sensor26	67	0.74422853	0.0075	
sensor17	36	0.52835424	0.0054	





⊿	Binomial	Ridge wit	h Validati	on Column		⊿ Bir	nomial	Lasso wit	h Validatio	on Column		⊿ Bino	mial	Elastic Ne	t with Val	idation Col	umn
	⊿ Parame	ter Estima	ates for Or	iginal Pred	ictors	⊿₣	Parame	ter Estima	ates for Or	iginal Pred	ictors	⊿ Pa	rame	ter Estima	ates for Or	iginal Pred	ictors
	Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare		「erm	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Ter	m	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare
L	Intercept	-5.678926	10.351753	0.3009571	0.5833	s	ensor17	1.0154108	0.4506304	5.077413	0.0242*	Inte	rcept	-4.563879	2.0946723	4.7471847	0.0293*
L	sensor57	0.0074349	0.0192829	0.1486652	0.6998	1	ntercept	-3.287154	2.1404982	2.3583615	0.1246	ser	sor17	0.9999637	0.7369391	1.8412183	0.1748
L	sensor58	-0.004759	0.0174843	0.0740924	0.7855	s	ensor21	0.0003969	0.0003088	1.6521055	0.1987	ser	sor52	0.0524902	0.0574976	0.8334072	0.3613
L	sensor22	0.0001382	0.0007282	0.0360128	0.8495	s	ensor52	0.0493613	0.0486158	1.0309056	0.3099	ser	sor29	0.0002216	0.0002958	0.5615393	0.4536
L	sensor59	0.0027809	0.0155676	0.0319105	0.8582	s	ensor20	0.0001786	0.0002831	0.3980931	0.5281	ser	sor20	0.0002296	0.0003917	0.3437918	0.5576
L	sensor23	0.0001047	0.0007698	0.0184902	0.8918	s	ensor18	0.3648566	0.6438341	0.3211415	0.5709	ser	sor21	0.0002095	0.000441	0.2255527	0.6348
L	sensor49	-0.023623	0.1845799	0.0163801	0.8982	s	ensor29	8.7425e-5	0.0003001	0.0848859	0.7708	ser	sor22	0.0001835	0.0004571	0.1611644	0.6881
L	sensor20	0.0000964	0.0010633	0.0082211	0.9278	s	ensor01	6.9577e-5	0.000528	0.0173639	0.8952	ser	sor18	0.3325641	0.8331405	0.1593361	0.6898
L	sensor21	8.8042e-5	0.0011147	0.006238	0.9370	s	ensor02	0	0	0	1.0000	ser	sor01	0.0001942	0.0006893	0.0793924	0.7781
L	sensor29	0.0001312	0.0017377	0.0056977	0.9398	s	ensor03	0	0	0	1.0000	ser	sor04	0.0001689	0.0006879	0.0602512	0.8061
L	sensor17	0.3125492	4.2247778	0.005473	0.9410	s	ensor04	0	0	0	1.0000	ser	sor11	-5.539e-5	0.0011937	0.0021528	0.9630
L	sensor56	-0.00097	0.0160737	0.0036419	0.9519	s	ensor05	0	0	0	1.0000	ser	sor57	9.2889e-5	0.014103	4.3382e-5	0.9947
	sensor41	-0.000499	0.0085741	0.0033923	0.9536	s	ensor06	0	0	0	1.0000	ser	sor02	0	0	0	1.0000
	sensor37	-0.000381	0.0074011	0.0026455	0.9590	s	ensor07	0	0	0	1.0000	ser	sor03	0	0	0	1.0000
	sensor63	0.0080211	0.1920101	0.0017451	0.9667	s	ensor08	0	0	0	1.0000	ser	sor05	0	0	0	1.0000



Parame	ter Estimates for Original Predictors									
Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare						
Intercept	-4.563879	2.0946723	4.7471847	0.0293*						
sensor17	0.9999637	0.7369391	1.8412183	0.1748						
sensor52	0.0524902	0.0574976	0.8334072	0.3613						
sensor29	0.0002216	0.0002958	0.5615393	0.4536						
sensor20	0.0002296	0.0003917	0.3437918	0.5576						
sensor21	0.0002095	0.000441	0.2255527	0.6348						
sensor22	0.0001835	0.0004571	0.1611644	0.6881						
sensor18	0.3325641	0.8331405	0.1593361	0.6898						
sensor01	0.0001942	0.0006893	0.0793924	0.7781						
sensor04	0.0001689	0.0006879	0.0602512	0.8061						
sensor11	-5.539e-5	0.0011937	0.0021528	0.9630						
sensor57	9.2889e-5	0.014103	4.3382e-5	0.9947						
sensor02	0	0	0	1.0000						
sensor03	0	0	0	1.0000						
sensor05	0	0	0	1.0000						

⊿ Binomial Elastic Net with Validation Column

-		-		
Column	Contrib	utions		
Term	Number of Splits	G^2	Portion	
sensor18	522	36.5630568	0.3709	1
sensor 53	248	19.0040464	0.1928	
sensor 55	163	9.18530792	0.0932	
sensor 48	107	7.43395874	0.0754	
sensor 52	88	4.51699905	0.0458	
sensor 54	65	3.1209684	0.0317	
sensor 61	48	3.08165918	0.0313	
sensor11	76	2.20715869	0.0224	
sensor21	44	1.8102253	0.0184	
sensor46	31	0.98045171	0.0099	
sensor24	37	0.97068784	0.0098	T
sensor 50	33	0.77981921	0.0079	
sensor44	15	0.75054722	0.0076	
sensor26	67	0.74422853	0.0075	
sensor17	36	0.52835424	0.0054	





Gener	ralized Regression for stat	tus = Fail									
- Bind	omial Elastic Net with Vali	dation Col	umn								
	astic Net Prediction Profil	er									
	Optimization and Desirability	•									1
	Assess Variable Importance	Ind	ependent Uniform Inp	outs							
CAC.	Save Bagged Predictions	Ind	Independent Resampled Inputs		Calculates the indi	ces that are used in			A		
	Simulator	Dep	pendent Resampled In	puts	the Assess Variable	Importance option data table					
	Design Space Profiler	Lin	Linearly Constrained Inputs		assuming that the inputs are		000	0 0 0 0 0 00	0 0 0	0 0 0 0	0000000
	Interaction Profiler	-	-	40 80	independent.		800	100 200 200 200 -700	-500	300 500 900	- (1 (1) 1)
~	Confidence Intervals	10.73	2.657	2212	1197.8	2293	1764	1207.6	-1076.4	7432.5	16.73
		ensor52	sensor18	sensor21	sensorul	sensor20	sensor22	sensor04	sensor11	sensor29	sensor5/





Summa	ry Report					
Column	Main Effect	Total Effect	.2	.4	.6	.8
sensor17	0.179	0.233				
sensor 52	0.178	0.227				
sensor18	0.173	0.216				
sensor20	0.098	0.136				
sensor21	0.093	0.128				
sensor22	0.036	0.063				
sensor01	0.02	0.038				
sensor29	0.02	0.036				
sensor04	0.014	0.026				
sensor11	0.001	0.002				
sensor57	9e-6	3e-5				

Elastic Net Prediction Profiler

Column	Contrib	utions	R	RF
Term	Number of Splits	G^2	Portion	
sensor18	522	36.5630568	0.3709	\sim
sensor53	248	19.0040464	0.1928	
sensor55	163	9.18530792	0.0932	
sensor48	107	7.43395874	0.0754	
sensor52	88	4.51699905	0.0458	
sensor54	65	3.1209684	0.0317	
sensor61	48	3.08165918	0.0313	
sensor11	76	2.20715869	0.0224	
sensor21	44	1.8102253	0.0184	
sensor46	31	0.98045171	0.0099	
sensor24	37	0.97068784	0.0098	
sensor50	33	0.77981921	0.0079	
sensor44	15	0.75054722	0.0076	
sensor26	67	0.74422853	0.0075	
sensor17	36	0.52835424	0.0054	

KPA Insights through analytics

⊿



Model Driven Multivariate Control Chart - JMP		—		\times
Creates multivariate control charts based on principal co squares methods.	omponents or partial least			
Select Columns	Cast Selected Columns into	Roles —	Action	I —
157 Columns	Process / sensor01	^	0	к
Enter column name 🔎 🔻	sensor02		Can	icel
Sensor Measurements (63/0)	a sensor03			
testResult	sensor04	~	Deres	
status	Time ID optional numer	ic	Rem	ove
stratified Validation	By optional		Red	all
Historical Data End at Row 81			He	lp
		0) 🏠 🗌] 🕶 🔡





PCA Model Driven Multivariate Control Chart

Monitor the Process

⊿ ■ T² for 13 Principal Components







PCA Model Driven Multivariate Control Chart

Monitor the Process

T² for 13 Principal Components







PCA Model Driven Multivariate Control Chart

Monitor the Process

⊿ **▼**T² for 13 Principal Components















Variable

Variable

Variable

Variable

Variable

Variable

Variable

Variable

Variable

F Sensors July 13 2022 - Distribution 2 - JMP

File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help Image: Second and the second













E Sensors July 13 2022 - Distribution 2 - JMP Х File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help i 🕮 🐚 💕 🛃 | 3 🛍 🖺 | 9, , i 🗎 🝈 🧛 , i 💊 ? ↔ 🐵 | 🖤 🖉 ዖ �, + ∥ | 🗉 ☴ () ⊂ , j Distributions ⊿ 💌 sensor02 ⊿ ▼ sensor03 ⊿ ▼ sensor01 3000 2000 2000 2000 1000 1000 1000 0 Compare Distributions Compare Distributions Compare Distributions Show Distribution AICc ^ BIC -2*LogLikelihood AICc ^ BIC -2*LogLikelihood AICc ^ BIC -2*LogLikelił Show Distribution Show Distribution ~ Johnson Sb 2788.5753 2800.9748 2780.3386 ~ Johnson Su -2706.2838 2718.6833 2698.0471 1 2880.6212 2893.0207 2872 Fitted Johnson Sb Distribution Fitted Johnson Su Distribution Fitted Johnson Sb Distribution ~ Density Curve Error Lower 95% Upper 95% Estimate Std Error Lower 95% Upper 95% Estimate Std Error Lower 95% Upper 95% Parameter Parameter **Diagnostic Plots** 8516 0.5992993 0.9789505 Shape v -1.107392 0.1247941 -1.351984 -0.8628 Shape y 0.7891857 0.1150968 0.5636002 1.0147712 8686 0.3526331 0.4543076 Shape δ 0.6756394 0.0374785 0.6060352 0.7532377 Shape δ 0.4247852 0.0279451 0.3733978 0.4832445 Profilers 532.62753 θ 194.59048 52.238366 92.205161 Location θ 486.20761 23.684068 439.78769 Location 296.97579 Save Columns Save Density Formula Scale σ 113.62197 0 113.62197 113.62197 Scale σ 6780.8524 0 6780.8524 6780.8524 Process Capability Save Distribution Formula Measures Measures Remove Fit Save Simulation Formula -2*LogLikelihood 2698.0471 -2*LogLikelihood 2872.3845 AICc 2788.5753 Save Transformed Saves a column to the data table that 38 AICc 2880.6212 contains a formula used to transform BIC 2800.9748 BIC 2893.0207 the analysis column to normality using the specified fitted distribution. 0 1 🛛 🗸 🖓





\setminus	Normalized Sensor 01	Normalized Sensor 02	Normalized Sensor 03	Normalized Sensor 04	Normalized Sensor 05	Normalized Sensor 06	Normalized Sensor 07	Normalized Sensor 08	
1	-0.429462541	-0.023164209	-0.180868093	-0.045175325	0.2103355703	-0.013999938	-0.147937751	-0.000344392	
2	-0.055300886	-1.63236901	0.0946350653	-1.649470993	-1.009090647	-1.042115859	-1.120255017	-1.525902819	
3	-0.111839132	-0.187981022	0.0190318601	-0.321027105	0.0413421482	-0.274633425	-0.277695263	-0.53213534	
4	-0.545119593	-0.394709423	-0.250233244	-0.502509817	-0.35310491	-0.19353877	-0.09709766	-0.969841771	
5	-0.592368033	-0.381589246	-0.202267621	-0.067493582	-0.021463294	-0.083870644	-0.131019005	-0.055471228	
6	0.0314637112	-2.059472445	0.0999572363	-1.329631387	-0.047036417	-0.310192693	-0.124253218	-0.525600034	
7	-0.768441134	-0.068940672	-0.417092494	0.0214536018	-0.420836258	-0.424783097	-0.262673168	-0.762969287	
8	-0.30113471	-0.3561646	-0.139427747	-0.229023302	-0.523040338	-0.000297651	-0.046667654	0.133640498	
9	-0.860416254	-0.790455797	-0.458553392	-0.622679123	-1.647412021	-0.44909209	-0.591129387	-0.670397594	
10	-0.516276499	-0.09857755	-0.194884031	-0.159489881	-1.334245723	-0.871892236	-0.866731627	-0.635561702	
11	-0.447437398	-0.337014942	-0.285230865	-0.233164785	0.0729605379	-0.303294366	0.041864424	-0.947967663	
12	-0.247673385	-0.168014048	-0.027250896	-0.184571798	-1.529483355	-1.024703913	-1.240298412	-0.993812537	
13	-0.482567866	-0.919694837	-0.201434875	-0.716976459	-2.034307511	-0.532455295	-0.752553719	-0.648544939	
14	-0.22067253	-0.744586147	-0.112670362	-0.494764669	-0.30377406	-2.456479871	-0.239149348	-1.247260093	
15	-0.291032767	-0.084932408	-0.116938339	-0.205684568	-1.44825592	-1.926141272	-1.261958747	-1.125094932	



















Cluster	Number of Members	Most Representative Variable	Cluster Proportion of Variation Explained	Total Proportion of Variation Explained	.2	.4	.6	
1	25	Normalized Sensor 46	0.797	0.316			1	
2	10	Normalized Sensor 36	0.77	0.122		1		
3	7	Normalized Sensor 38	0.818	0.091				
4	4	Normalized Sensor 31	0.622	0.04	Ê Î.	1		
5	5	Normalized Sensor 51	0.466	0.037			1	
9	3	Normalized Sensor 62	0.747	0.036			Å.	
8	3	Normalized Sensor 35	0.675	0.032			1	
6	4	Normalized Sensor 63	0.478	0.03				
7	2	Normalized Sensor 43	0.861	0.027				l


Cluste	r Members			
Cluster	Mombors	RSquare with	RSquare with	1-RSquare
1	Normalized Sensor 46	0.015	0.514	0.174
1	Normalized Sensor 40	0.915	0.514	0.104
1	Normalized Sensor 50	0.094	0.433	0.107
1	Normalized Sensor 35	0.903	0.472	0.21/
1	Normalized Sensor 44	0.860	0.475	0.214
1	Normalized Sensor 18	0.003	0.667	0.225
1	Normalized Sensor 08	0.922	0.471	0.246
1	Normalized Sensor 53	0.9	0.643	0.28
1	Normalized Sensor 24	0.844	0.465	0.29
1	Normalized Sensor 06	0.812	0.431	0.3
1	Normalized Sensor 61	0.878	0.639	0.336
1	Normalized Sensor 07	0.799	0.411	0.341
1	Normalized Sensor 05	0.798	0.412	0.343
1	Normalized Sensor 54	0.88	0.656	0.349
1	Normalized Sensor 27	0.76	0.354	0.371
1	Normalized Sensor 14	0.773	0.407	0.383
1	Normalized Sensor 13	0.739	0.362	0.408
1	Normalized Sensor 52	0.824	0.582	0.422
1	Normalized Sensor 55	0.851	0.667	0.449
1	Normalized Sensor 15	0.681	0.348	0.489
1	Normalized Sensor 26	0.685	0.36	0.492
1	Normalized Sensor 16	0.683	0.366	0.499
1	Normalized Sensor 21	0.72	0.588	0.679
1	Normalized Sensor 41	0.373	0.217	0.8
1	Normalized Sensor 20	0.655	0.623	0.915



ciuste	Members							
luster	Members	RSquare with Own Cluster	RSquare with Next Closest	1-RSquare Ratio	⊿ Column	Contrib	utions	
	Normalized Sensor 46	0.915	0.514	0.174		Number		
	Normalized Sensor 48	0.894	0.455	0.194	Term	of Solits	6^2	Portion
	Normalized Sensor 50	0.905	0.517	0.197	concor19	522	26 5620560	 0 2700
	Normalized Sensor 25	0.888	0.473	0.214	Sensor To	522	50.5050508	 0.5709
	Normalized Sensor 44	0.869	0.427	0.229	sensor53	248	19.0040464	 0.1928
	Normalized Sensor 18	0.922	0.667	0.235	sensor55	163	9.18530792	0.0932
1	Normalized Sensor 08	0.87	0.471	0.246	sensor48	107	7.43395874	0.0754
	Normalized Sensor 53	0.9	0.643	0.28	sensor52	88	4.51699905	0.0458
I	Normalized Sensor 24	0.844	0.465	0.291	sensor54	65	3,1209684	0.0317
	Normalized Sensor 06	0.812	0.431	0.33	sensor61	49	2 09165019	0.0313
	Normalized Sensor 61	0.878	0.639	0.336	Sensor11	40	3.00105910	0.0313
l	Normalized Sensor 07	0.799	0.411	0.341	sensorii	/0	2.20715809	0.0224
	Normalized Sensor 05	0.798	0.412	0.343	sensor21	44	1.8102253	0.0184
	Normalized Sensor 54	0.88	0.656	0.349	sensor46	31	0.98045171	0.0099
I	Normalized Sensor 27	0.76	0.354	0.371	sensor24	37	0.97068784	0.0098
	Normalized Sensor 14	0.773	0.407	0.383	sensor50	33	0.77981921	0.0079
	Normalized Sensor 13	0.739	0.362	0.408	sensor44	15	0 75054722	0.0076
	Normalized Sensor 52	0.824	0.582	0.422	sonsor26	67	0 74422052	0.0075
	Normalized Sensor 55	0.851	0.667	0.449	Sensor20	07	0.74422033	0.0075
	Normalized Sensor 15	0.681	0.348	0.489	sensor17	36	0.52835424	0.0054
	Normalized Sensor 26	0.685	0.36	0.492				
1	Normalized Sensor 16	0.683	0.366	0.499				
	Normalized Sensor 21	0.72	0.588	0.679				
1	Normalized Sensor 41	0.373	0.217	0.8				
l	Normalized Sensor 20	0.655	0.623	0.915				





					-
Cluster	Members	RSquare with Own Cluster	RSquare with Next Closest	1-RSquare Ratio	
	Normalized Sensor 46	0.915	0.514	0.174	\sim
	Normalized Sensor 48	0.894	0.455	0.194	
	Normalized Sensor 50	0.905	0.517	0.197	
	Normalized Sensor 25	0.888	0.473	0.214	
	Normalized Sensor 44	0.869	0.427	0.229	
	Normalized Sensor 18	0.922	0.667	0.235	
	Normalized Sensor 08	0.87	0.471	0.246	
	Normalized Sensor 53	0.9	0.643	0.28	
	Normalized Sensor 24	0.844	0.465	0.291	
	Normalized Sensor 06	0.812	0.431	0.33	
	Normalized Sensor 61	0.878	0.639	0.336	
	Normalized Sensor 07	0.799	0.411	0.341	
	Normalized Sensor 05	0.798	0.412	0.343	
l .	Normalized Sensor 54	0.88	0.656	0.349	
1	Normalized Sensor 27	0.76	0.354	0.371	
	Normalized Sensor 14	0.773	0.407	0.383	
	Normalized Sensor 13	0.739	0.362	0.408	
	Normalized Sensor 52	0.824	0.582	0.422	
1	Normalized Sensor 55	0.851	0.667	0.449	
1	Normalized Sensor 15	0.681	0.348	0.489	
	Normalized Sensor 26	0.685	0.36	0.492	
	Normalized Sensor 16	0.683	0.366	0.499	
	Normalized Sensor 21	0.72	0.588	0.679	
	Normalized Sensor 41	0.373	0.217	0.8	
	Normalized Sensor 20	0.655	0.623	0.915	





Chusten Mensherr

⊿ Generalized Regression for status = Fail







Binomial Elastic I	Vet with V	alidation	Column		⊿⊂	olumn	Contrib	utions	
Parameter Estima	tes for Ori	iginal Pred	dictors				Number		
			Wald	Prob >	т	erm	of Splits	G^2	 Portion
Term	Estimate	Std Error	ChiSquare	ChiSquare		ensor18	522	36.5630568	0.3709
ntercept	10.090548	1.8017642	31.364152	<.0001*		ensor53	248	19.0040464	0.1928
Normalized Sensor 18	13.755492	2.5555089	28.973268	<.0001*		ensor55	163	9.18530792	0.0932
Normalized Sensor 27	-4.513064	1.9010799	5.6356271	0.0176*		oncor/9	107	7 42205974	0.0754
Normalized Sensor 41	-0.875506	0.4462948	3.8483516	0.0498*	3	ens0140	107	1.43393014	0.0754
Normalized Sensor 26	1.9403476	1.3346853	2.1134955	0.1460		ensor52	88	4.51699905	0.0458
Normalized Sensor 15	-0.622552	0.7173161	0.7532344	0.3855		ensor54	65	3.1209684	0.0317
Normalized Sensor 52	3.841615	4.4366523	0.7497507	0.3866	5	ensor61	48	3.08165918	0.0313
Normalized Sensor 21	0.94501	1.2462852	0.5749604	0.4483		opcor11	76	2 20715960	0.0224
Normalized Sensor 08	0.6791519	1.1816369	0.3303434	0.5655	2	ensorri	/0	2.20713009	0.0224
Normalized Sensor 05	0.3684318	0.8110402	0.2063619	0.6496		ensor21	44	1.8102253	0.0184
Normalized Sensor 55	2.4557393	6.4177539	0.1464193	0.7020	S	ensor46	31	0.98045171	0.0099
Normalized Sensor 61	1.6776547	6.6668107	0.0633241	0.8013	S	ensor24	37	0.97068784	0.0098
Normalized Sensor 06	0.2655408	1.2046963	0.0485856	0.8255		oncor50	22	0.77091021	0.0070
Normalized Sensor 14	-0.113737	0.681085	0.0278868	0.8674	5	ensorbu	55	0.77961921	0.0079
Normalized Sensor 53	0.4410189	5.6487227	0.0060956	0.9378	S	ensor44	15	0.75054722	0.0076
Normalized Sensor 54	0.6979234	9.6499351	0.0052308	0.9423	S	ensor26	67	0.74422853	0.0075
Normalized Sensor 16	-0.003632	0.3813282	9.0716e-5	0.9924	5	ensor17	36	0.52835424	0.0054
Normalized Sensor 07	0	0	0	1.0000	-	choorn	50	0.02000424	0.0004
Normalized Sensor 13	0	0	0	1.0000					
Normalized Sensor 20	0	0	0	1.0000					





"Can the sensor data predict the outcome (test result)?"











"Can the sensor data predict the outcome (test result)?"

"Can the sensor data predict the 'Good' ones?"





Model Driven Multivariate Control Chart - JMP [2]			_		×
Creates multivariate control charts based on principal co squares methods.	mponents or	partial least			
Select Columns	Cast Select	ed Columns into Role	es —	Action	
 ■67 Columns Enter column name 	Process	sensor01 sensor02	^	Ok	(
Original Sensors (63/63) testResult		sensor03sensor04	>	Cano	cei
L status Validation	Time ID	optional numeric		Remo	ove
Level Validation Random Formula	Ву	optional		Hel	p
Historical Data End at Row 82				L	
			0	☆ 🗆	▼ii





































A T² Contribution Plot for status=Fail











💌 Booste	d Tree f	or status			💌 Bootst	rap Fore	st for stati	ıs	
d Columr	Contrib	outions			⊿ Colum	n Contrib	utions		
Term	Number of Splits	G^2		Portion	Term	Number of Splits	G^2		Portion
sensor56	82	4634.8525		0.2065	sensor18	579	54.9167342		0.5024
sensor18	27	4200.54219		0.1872	sensor61	198	18.7389273		0.1714
sensor11	21	2735.54419		0.1219	sensor52	145	13.1320295		0.1201
sensor61	19	2431.70533		0.1084	sensor53	56	5.26374221		0.0482
sensor48	17	2414.82121		0.1076	sensor44	33	2.53070023		0.0232
sensor57	22	2016.84895		0.0899	sensor48	42	2.45696551		0.0225
sensor58	10	1456.34648		0.0649	sensor46	31	2.08993095		0.0191
sensor59	8	726.693834		0.0324	sensor11	114	1.34630042		0.0123
sensor26	2	343 87221		0.0153	sensor54	12	1.01688952		0.0093
sensor52		323,166652		0.0144	sensor58	111	0.73127415		0.0067
sensor09	6	286 922646		0.0128	sensor07	61	0.68014104		0.0062
sensor01	9	194 974174		0.0087	sensor26	89	0.5292647		0.0048
sensor55	2	165 247012		0.0074	sensor12	40	0.510923/4		0.004/
sensor24	4	151 216612		0.0067	sensor50	8	0.41943383		0.0038
sensor07	4	128 858022	1	0.0057	sensor57	/5	0.3901658		0.0036
sensor12	4	117 421132		0.0052	sensorui	44	0.35310066		0.0032
sensor15	2	44 7671089		0.0020	sensor05	47	0.3400086		0.003
sensor44	1	37 6713347		0.0017	sensor21	8	0.50245908		0.0028
sensor54	1	15 5711294		0.0007					
sensor27	1	12 8974036		0.0007					
30130127		12.0374030		0.0000					







Overall Statistics

Measure	Training	Validation
Entropy RSquare	0.9981	0.5788
Generalized RSquare	0.9991	0.7352
Mean -Log p	0.0013	0.2909
RASE	0.0025	0.2649
Mean Abs Dev	0.0013	0.0875
Misclassification Rate	0.0000	0.0930
N	131	43



Overall Statistics

Measure	Training	Validation
Entropy RSquare	0.9186	0.6736
Generalized RSquare	0.9601	0.8089
Mean -Log p	0.0563	0.2254
RASE	0.1016	0.2543
Mean Abs Dev	0.0491	0.1253
Misclassification Rate	0.0076	0.0698
N	131	43





Boosted Trees vs. Random Forest Folklore



- Fast algorithm
- Highly accurate on big data



- More accurate on small data
- Robust to messy/noisy data
- Often used for variable selection







Pattern Recognition Letters Volume 31, Issue 14, 15 October 2010, Pages 2225-2236



Variable selection using random forests

Robin Genuer ^a 🖾, Jean-Michel Poggi ^{a, b} $\stackrel{\diamond}{\sim}$ $\stackrel{\boxtimes}{\sim}$, Christine Tuleau-Malot ^c $\stackrel{\boxtimes}{\sim}$

Citation Network In Web of Science Core Collection

1,186 Citations

🌲 Create citation alert

1,23538Times Cited in AllCited ReDatabasesView Rel

38 Cited References View Related Records









✓ ■ Boosted Tree for status

	-		
lumn	Con	rıbı	utions

	Number		
Term	of Splits	G^2	Portion
sensor56	82	4634.8525	0.2065
sensor18	27	4200.54219	0.1872
sensor11	21	2735.54419	0.1219
sensor61	19	2431.70533	0.1084
sensor48	17	2414.82121	0.1076
sensor57	22	2016.84895	0.0899
sensor58	10	1456.34648	0.0649
sensor59	8	726.693834	0.0324
sensor26	2	343.87221	0.0153
sensor52	2	323.166652	0.0144
sensor09	6	286.922646	0.0128
sensor01	9	194.974174	0.0087
sensor55	2	165.247012	0.0074
sensor24	4	151.216612	0.0067
sensor07	4	128.858022	0.0057
sensor12	4	117.421132	0.0052
sensor15	2	44.7671089	0.0020
sensor44	1	37.6713347	0.0017
sensor54	1	15.5711294	0.0007
sensor27	1	12.8974036	0.0006

•	 Bootst 	rap Fore	st for state	JS	
1	Column	Contrib	utions		
	Term	Number of Splits	G^2		Portion
	sensor18	579	54.9167342		0.5024
	sensor61	198	18.7389273		0.1714
	sensor52	145	13.1320295		0.1201
	sensor53	56	5.26374221		0.0482
	sensor44	33	2.53070023		0.0232
	sensor48	42	2.45696551		0.0225
	sensor46	31	2.08993095		0.0191
	sensor11	114	1.34630042		0.0123
	sensor54	12	1.01688952		0.0093
	sensor58	111	0.73127415		0.0067
	sensor07	61	0.68014104		0.0062
	sensor26	89	0.5292647		0.0048
	sensor12	40	0.51092374		0.0047
	sensor50	8	0.41943383		0.0038
	sensor57	75	0.3901658		0.0036
	sensor01	44	0.35310066		0.0032
	sensor05	47	0.3400086		0.0031
	sensor21	8	0.30245908		0.0028





Make Validation Column

Stratified Validation Column

Randomly partitions the rows into training, validation and test sets while attempting to evenly distribute across levels of the stratification variable(s). Use this option when you want a balanced representation of a column's levels in each of the training, validation and test sets.

Stratification Columns: status

Adju	isted Rates Rov	v Counts
Training Set 0.75	0.75	129
Validation Set 0.25	0.25	43
Test Set 0	0	0
Excluded Rows		2
Total Rows		172
ptions		
New Celever News		
New Column Name	idation	
Validation Column Type Fo	lidation ormula	~





Column	Contrib	utions				
	Number					
[erm	of Splits	G^2	Portio	n		
ensor18	527	48.0327701	0.447	1 .		
ensor61	303	27.9106906	0.2	Table Style	•	
ensor52	112	9.35593633	0.0	Columns	+	
ensor53	67	5.65325216	0.0	Sort by Colum	n	
ensor48	60	2.90761066	0.0	Make into Dat	a Table	
ensor46	33	1.89183143	0.0	Make into Dat		
ensor54	22	1.68095955	0.0	Make Combine	ed Data lable	
ensor44	16	1.12914783	0.0	Make Into Mat	rix	
ensor11	95	1.00344327	0.0	Select Where		
ensor50	17	0.71366776	0.0	Filter Where		
ensor07	60	0.67747388	0.0	Filler Where		
ensor58	96	0.64091112	0.0	Format Colum	n	
ensor26	92	0.54471308	0.0	Align Decimal	Separator	
ensor12	35	0.43300361	0.0	Show Propertie	es	
ensor57	67	0.37339152	0.0			
ensor55	11	0.34960808	0.0	Copy Column		
ensor24	39	0.34381403	0.0	Copy Table		
ensor45	47	0.30713564	0.0			
ensor27	46	0.24187279	0.0	Simulate		Switch columns to perform
ensor17	17	0.23554353	0.0	Bootstrap		simulation.
ensor08	13	0.2208964	0.002	1		1
ensor49	35	0.21863803	0.002	0		



 \sim

 \sim







Bootstrap Forest of	status Simul	ate Results (Portio	on) - JMP					—		\times
File Edit Tables Ro	ows Cols	DOE Analyze	Graph Tools Add	d-Ins Vie	w Wind	ow Help				
! 🔛 😂 💕 📕 🐰 🎙	🗎 🚨	ြ ရ 🏢 🗎	🖬 🖶 🚩 ≽	V .						
 Bootstrap Forest of 	statu ▷	۹ 🔪 💌								
Make Combined D	ata Table	•	Table	Y	SimID.	sensor01	sensor02	sensor03	sensor04	sen
Distribution		× 🛯 1	Sensors No SO	status	0	0.0014	0.0002	0.0013	0.0002	1
		2	Sensors No SO	status	1	0.0055	0.0011	0.0033	0.0036	
		3	Sensors No SO	status	2	0.0086	0.0009	0.0056	0.0043	
Columns (66/0)		4	Sensors No SO	status	3	0.0035	0.0004	0.0022	0.0011	
۹,		5	Sensors No SO	status	4	0.0053	0.0018	0.0030	0.0048	
L Table 🗱	^	6	Sensors No SO	status	5	0.0035	0.0006	0.0014	0.0024	
L Y		7	Sensors No SO	status	6	0.0044	0.0016	0.0022	0.0033	
sensor01		8	Sensors No SO	status	7	0.0108	0.0008	0.0077	0.0017	
sensor02		9	Sensors No SO	status	8	0.0066	0.0007	0.0019	0.0003	
🚄 sensor03		10	Sensors No SO	status	9	0.0033	0.0004	0.0012	0.0020	
sensor04		11	Sensors No SO	status	10	0.0030	0.0003	0.0009	0.0007	
sensor05		12	Sensors No SO	status	11	0.0022	0.0007	0.0015	0.0002	
sensor07		13	Sensors No SO	status	12	0.0013	0.0006	0.0011	0.0003	
a sensor08		14	Sensors No SO	status	13	0.0056	0.0011	0.0022	0.0032	
a sensor09		15	Sensors No SO	status	14	0.0024	0.0003	0.0013	0.0005	
sensor10	\sim	16	Sensors No SO	status	15	0.0084	0.0009	0.0020	0.0030	
Rows		17	Sensors No SO	status	16	0.0037	0.0003	0.0022	0.0030	
All rows	101	18	Sensors No SO	status	17	0.0063	0.0006	0.0016	0.0042	
Selected		19	Sensors No SO	status	18	0.0050	0.0024	0.0029	0.0057	
Excluded	cluded 1		Sensors No SO	status	19	0.0052	0.0011	0.0031	0.0059	
Hidden (20	Sensors No SO	status	20	0.0051	0.0011	0.0019	0.0038	
Labeled	0	21	6	status	20	0.0001	0.0011	0.0015	0.0050	>
		22	`						A 🛆 🗆	





61





ssights through analytics

D STATISTICAL DISCOVERY

















ts through analytics.

 Hold Alt + Click to broadcast to all columns





sen	sor01					4	sensor02					
• Fi	tted Johnson Sb [Dist	ributi	on		4	Fitted .	Joł	nson Su I	Distributi	on	
~	Density Curve		Error	Lower 95%	Upper 95%		Parameter	Estimate		Std Error	Lower 95%	Upper 95%
	Diagnostic Plots	,	3599	0.6185806	0.968865		Shape	Y	-0.992423	0.1262952	-1.239957	-0.744889
	Profilers	,	\$4469	0.3588199	9 0.4588212		Shape	δ	0.6380772	0.0367072	0.5700402	0.7142347
	Save Columns	,		ave Density Fo	ormula		Location	θ	508.94132	23.487057	462.90754	554.97511
-	Process Canability		Con Distillation Committee		Scale		σ	104.31675	0	104.31675	104.31675	
	Remove Fit			Save Distribution Formula Save Simulation Formula			Measures -2*LogLikelihood 2651.8731					
AICC	C 2708.2845 Save Transformed		ed	Saves a column to the data table that			ta table that	26				
sen	3IC 2720.635				the analysis column to normality							



Show	Dist	rib	ution	ution		AICc BIC			-2*LogL	ikelihood
\checkmark	Johr	nso	n Sb	-	_	2789.0762		2801.426	57	2780.8367
💌 Fitt	ed J	loł	inso	n Sb I	Dis	tributi	on			
Param	eter		Est	imate	S	td Error	Lo	wer 95%	Upper 959	6
Shape		γ	0.7	90034	0	.083804	0	.6257812	0.954286	7
Shape		δ	0.42	46405	0.0	271587	0	.3746116	0.481350	6
Locatio	on	θ	194.	59048		0	1	94.59048	194.5904	8
Scale		σ	3925	5.2571		0	3	925.2571	3925.257	1
Measu	ires									
-2*Log AICc BIC	-2*LogLikeliho AICc BIC		od 2 2 2	2780.8367 2789.0762 2801.4267						

Н	\diamond	 	

Comp	oare	Di	stribu	itior	IS				
Show	Dis	trib	n Sh	AIC		Cc ^	BIC	-2*LogLi	kelihood
Fitt	ed .	Joł	nson	Sb I	Distribut	ion	2105.555		2001.0102
Param	eter		Estin	nate	Std Erro	r Lo	wer 95%	Upper 95%	6
Shape		γ	1.398	0018	0.1063894	1 1	.1894824	1.606521	2
Shape		δ	0.602	5777	0.0353684	4 0	.5370956	0.6760434	4
Locatio	on	θ	205.1	9524	2.1311578	3 2	01.01825	209.3722	3
Scale		σ	5347.	2482	() 5	347.2482	5347.248	2
Measu	res								
-2*Log	Like	iho	od 26	84.94	32				
AICc			26	93.18	27				
BIC			27	05.53	31				

Hold Alt + Click to broadcast to all columns





	status	Validation	Validation Random Formula	Johnson Sb Transform to Normal sensor01	Johnson Su Transform to Normal sensor02	Johnson Sb Transform to Normal sensor03	Johnson Sb Transform to Normal sensor04	Johnson Su Transform to Normal sensor05	Johnson Su Transform to Normal sensor06
1	Pass	Validation	Training	-0.429462541	-0.023164209	-0.180868093	-0.045175325	0.2103355703	-0.013999938
2	Pass	Validation	Training	-0.055300886	-1.63236901	0.0946350653	-1.649470993	-1.009090647	-1.042115859
3	Pass	Validation	Training	-0.111839132	-0.187981022	0.0190318601	-0.321027105	0.0413421482	-0.274633425
4	Pass	Training	Training	-0.545119593	-0.394709423	-0.250233244	-0.502509817	-0.35310491	-0.19353877
5	Pass	Validation	Training	-0.592368033	-0.381589246	-0.202267621	-0.067493582	-0.021463294	-0.083870644
6	Pass	Training	Training	0.0314637112	-2.059472445	0.0999572363	-1.329631387	-0.047036417	-0.310192693
7	Pass	Training	Training	-0.768441134	-0.068940672	-0.417092494	0.0214536018	-0.420836258	-0.424783097
8	Pass	Training	Training	-0.30113471	-0.3561646	-0.139427747	-0.229023302	-0.523040338	-0.000297651
9	Pass	Training	Training	-0.860416254	-0.790455797	-0.458553392	-0.622679123	-1.647412021	-0.44909209
10	Pass	Validation	Training	-0.516276499	-0.09857755	-0.194884031	-0.159489881	-1.334245723	-0.871892236
11	Pass	Training	Training	-0.447437398	-0.337014942	-0.285230865	-0.233164785	0.0729605379	-0.303294366
12	Pass	Training	Training	-0.247673385	-0.168014048	-0.027250896	-0.184571798	-1.529483355	-1.024703913













Insights through analytics











Cluster	Number of Members	Most Representative Variable	Cluster Proportion of Variation Explained	Total Proportion of Variation Explained	.2 .4 .6 .8
1	25	Trans Sensor 46	0.797	0.316	
2	10	Trans Sensor 36	0.77	0.122	
3	7	Trans Sensor 38	0.818	0.091	
4	4	Trans Sensor 31	0.622	0.04	
5	5	Trans Sensor 51	0.466	0.037	
9	3	Trans Sensor 62	0.747	0.036	
8	3	Trans Sensor 35	0.675	0.032	
6	4	Trans Sensor 63	0.478	0.03	
7	2	Trans Sensor 43	0.861	0.027	1

Proportion of variation explained by clustering: 0.731

Variable Clustering

Cluster Members

Cluster	Members	RSquare with Own Cluster	RSquare with Next Closest	1-RSquare Ratio
1	Trans Sensor 4	5 0.915	0.514	0.174
1	Trans Sensor 4	0.894	0.455	0.194
1	Trans Sensor 5	0.905	0.517	0.197
1	Trans Sensor 2	5 0.888	0.473	0.214
1	Trans Sensor 4	4 0.869	0.427	0.229
1	Trans Sensor 1	3 0.922	0.667	0.235
1	Trans Sensor 0	0.87	0.471	0.246
1	Trans Sensor 5	3 0.9	0.643	0.28
1	Trans Sensor 2-	4 0.844	0.465	0.29
1	Trans Sensor 0	5 0.812	0.431	0.33
1	Trans Sensor 6	1 0.878	0.639	0.336
1	Trans Sensor 0	7 0.799	0.411	0.34
1	Trans Sensor 0	5 0.798	0.412	0.343
1	Trans Sensor 54	4 0.88	0.656	0.349
1	Trans Sensor 2	0.76	0.354	0.37
1	Trans Sensor 1-	4 0.773	0.407	0.383
1	Trans Sensor 1	0.739	0.362	0.408
1	Trans Sensor 52	0.824	0.582	0.422
1	Trans Sensor 5	5 0.851	0.667	0.449
1	Trans Sensor 1	5 0.681	0.348	0.489
1	Trans Sensor 2	6 0.685	0.36	0.492
1	Trans Sensor 1	5 0.683	0.366	0.499
1	Trans Sensor 2	1 0.72	0.588	0.679
1	Trans Sensor 4	1 0.373	0.217	0.8
1	Trans Sensor 2	0.655	0.623	0.91
2	Trans Sensor 3	5 0.938	0.536	0.134
2	Trans Sensor 4	0.939	0.576	0.14
2	Trans Sensor 1	1 0.896	0.555	0.233
2	Trans Sensor 0	9 0.881	0.498	0.23
2	Trans Sensor 0.	0.877	0.588	0.299
2	Trans Sensor 0	1 0.872	0.585	0.309
2	Trans Sensor 3	0.662	0.165	0.404
2	Trans Sensor 3-	4 0.594	0.125	0.464
2	Trans Sensor 1	9 0.484	0.275	0.71
2	Trans Sensor 1	7 0.554	0.436	0.79
3	Trans Sensor 3	0.92	0.407	0.13





- Bootst	ran Fore	st for status		Cluster	Members	RSquare with Own Cluster	RSquare with Next Closest	1-RSquare Ratio
		······································		1	Normalized Sensor 46	0.915	0.514	0.174
Columr	1 Contrib	utions		1	Normalized Sensor 48	0.894	0.455	0.194
	Number			1	Normalized Sensor 50	0.905	0.517	0.197
Term	of Splits	G^2	Portion	1	Normalized Sensor 25	0.888	0.473	0.214
sensor18	570	54 9167342	0.5024	1	Normalized Sensor 44	0.869	0.427	0.229
sensor61	198	18.7389273	0.1714		Normalized Ser or 18	0.922	0.667	0.235
sensor52	145	13.1320295	0.1201	1	Normalized Sensor 08	0.87	0.471	0.246
sensor53	00	740571477	0.0462	1	Normalized Series 53	0.9	0.643	0.28
sensor44	33	2500	0.0232	1	Normalized Sensor 24	0.844	0.465	0.291
sensor48	42	2.45696551	0.0225		Normalized Sensor 06	0.812	0.431	0.33
sensor46	31	2.08993095	0.0191	1	Normalized Ser or 61	0.878	0.639	0.336
sensor11	114	1.34630042	0.0123	1	Normalized Sensor 07	0.799	0.411	0.341
sensor54	12	1.01688952	0.0993	1	Normalized Sensor 05	0.798	0.412	0.343
sensor58	111	0.73127415	0.0067	1	Normalized Sensor 54	0.88	0.656	0.349
sensor07	61	0 68014104	0.0062	1	Normalized Sensor 27	0.76	0.354	0.371
sensor26	89	0 5292647	0.0048	1	Normalized Sensor 14	0.773	0.407	0.383
concor12	40	0.51002274	0.0047	1	Normalized Sensor 13	0.739	0.362	0.408
sensor 50	40	0.11042292	0.0047	1	Normalized Ser or 52	0.824	0.582	0.422
sensor57	75	0.41945565	0.0038	1	Normalized Sensor 55	0.851	0.667	0.449
sensor57	15	0.3901058	0.0036	1	Normalized Sensor 15	0.681	0.348	0.489
sensoru	44	0.35310000	0.0032	1	Normalized Sensor 26	0.685	0.36	0.492
sensor05	47	0.3400086	0.0031	1	Normalized Sensor 16	0.683	0.366	0.499
sensor21	8	0.30245908	0.0028	1	Normalized Sensor 21	0.72	0.588	0.679
				1	Normalized Sensor 41	0.373	0.217	0.8
				1	Normalized Sensor 20	0.655	0.623	0.915






Cluste	r Members			
Cluster	Members	RSquare with Own Cluster	RSquare with Next Closest	1-RSquar Ratio
1	Trans Sensor 46	0.915	0.514	0.17
1	Trans Sensor 48	0.894	0.455	0.19
1	Trans Sensor 50	0.905	0.517	0.19
1	Trans Sensor 25	0.888	0.473	0.21
1	Trans Sensor 44	0.869	0.427	0.22
1	Trans Sensor 18	0.922	0.667	0.23
1	Trans Sensor 08	0.87	0.471	0.24
1	Trans Sensor 53	0.9	0.643	0.2
1	Trans Sensor 24	0.844	0.465	0.29
1	Trans Sensor 06	0.812	0.431	0.3
1	Trans Sensor 61	0.878	0.639	0.33
1	Trans Sensor 07	0.799	0.411	0.34
1	Trans Sensor 05	0.798	0.412	0.34
1	Trans Sensor 54	0.88	0.656	0.34
1	Trans Sensor 27	0.76	0.354	0.37
1	Trans Sensor 14	0.773	0.407	0.38
1	Trans Sensor 13	0.739	0.362	0.40
1	Trans Sensor 52	0.824	0.582	0.42
1	Trans Sensor 55	0.851	0.667	0.44
1	Trans Sensor 15	0.681	0.348	0.48
1	Trans Sensor 26	0.685	0.36	0.49
1	Trans Sensor 16	0.683	0.366	0.49
1	Trans Sensor 21	0.72	0.588	0.67
1	Trans Sensor 41	0.373	0.217	0.
1	Trans Sensor 20	0.655	0.623	0.91
2	Trans Sensor 36	0.938	0.536	0.13
2	Trans Sensor 40	0.939	0.576	0.14
2	Trans Sensor 11	0.896	0.555	0.23
2	Trans Sensor 09	0.881	0.498	0.23
2	Trans Sensor 03	0.877	0.588	0.29
2	Trans Sensor 01	0.872	0.585	0.30
2	Trans Sensor 32	0.662	0.165	0.40
2	Trans Sensor 34	0.594	0.125	0.46
2	Trans Sensor 19	0.484	0.275	0.71
2	Trans Sensor 17	0.554	0.436	0.79

0.92

0.407

0.135



Trans Sensor 38

3



Cluste	r Members			
cl		RSquare with	RSquare with	1-RSquare
Cluster	Members	Own Cluster	Next Closest	Ratio
	Trans Sensor 46	0.915	0.514	0.17
	Trans Sensor 48	0.894	0.455	0.194
	Trans Sensor 50	0.905	0.517	0.19
	Trans Sensor 25	0.888	0.473	0.21
	Trans Sensor 44	0.009	0.427	0.22
	Trans Sensor To	0.922	0.007	0.25
	Trans Sensor 08	0.87	0.471	0.24
	Trans Sensor 53	0.9	0.643	0.2
	Trans Sensor 24	0.844	0.465	0.29
	Trans Sensor 06	0.812	0.431	0.3
	Trans Sensor 61	0.878	0.639	0.33
	Trans Sensor 07	0.799	0.411	0.34
	Trans Sensor 05	0.798	0.412	0.34
1	Trans Sensor 54	0.88	0.656	0.34
	Trans Sensor 27	0.76	0.354	0.37
1	Trans Sensor 14	0.773	0.407	0.38
1	Trans Sensor 13	0.739	0.362	0.40
1	Trans Sensor 52	0.824	0.582	0.42
1	Trans Sensor 55	0.851	0.667	0.44
	Trans Sensor 15	0.681	0.348	0.48
	Trans Sensor 26	0.685	0.36	0.49
	Trans Sensor 16	0.683	0.366	0.49
	Trans Sensor 21	0.72	0.588	0.67
	Trans Sensor 41	0.373	0.217	
1	Trans Sensor 20	0.655	0.623	0.91
2	Trans Sensor 36	0.938	0.536	0.13
2	Trans Sensor 40	0.939	0.576	0.14
2	Trans Sensor 11	0.896	0.555	0.23
2	Trans Sensor 09	0.881	0.498	0.23
2	Trans Sensor 03	0.877	0.588	0.29
2	Trans Sensor 01	0.872	0.585	0.30
2	Trans Sensor 32	0.662	0.165	0.40
2	Trans Sensor 34	0.594	0.125	0.46
2	Trans Sensor 19	0.484	0.275	0.71
2	Trans Sensor 17	0.554	0.436	0.79
3	Trans Sensor 38	0.92	0.407	0.13



Variable Clustering

4 Cluster Members

Cluster	Members	RSquare with Own Cluster	RSquare with Next Closest	1-RSquare Ratio
1	Trans Sensor 46	0.915	0.514	0.174
	Trans Sensor 48	0.894	0.455	0.194
	Trans Sensor 50	0.905	0.517	0.197
	Trans Sensor 25	0.888	0.473	0.214
	Trans Sensor 44	0.869	0.427	0.229
	Trans Sensor 18	0.922	0.667	0.235
	Trans Sensor 08	0.87	0.471	0.246
	Trans Sensor 53	0.9	0.643	0.28
	Trans Sensor 24	0.844	0.465	0.291
	Trans Sensor 06	0.812	0.431	0.33
	Trans Sensor 61	0.878	0.639	0.336
	Trans Sensor 07	0.799	0.411	0.341
	Trans Sensor 05	0.798	0.412	0.343
	Trans Sensor 54	0.88	0.656	0.349
	Trans Sensor 27	0.76	0.354	0.371
	Trans Sensor 14	0.773	0.407	0.383
	Trans Sensor 13	0.739	0.362	0.408
	Trans Sensor 52	0.824	0.582	0.422
	Trans Sensor 55	0.851	0.667	0.449
	Trans Sensor 15	0.681	0.348	0.489
	Trans Sensor 26	0.685	0.36	0.492
	Trans Sensor 16	0.683	0.366	0.499
	Trans Sensor 21	0.72	0.588	0.679
	Trans Sensor 41	0.373	0.217	0.8
	Trans Sensor 20	0.655	0.623	0.915
2	Trans Sensor 36	0.938	0.536	0.134
2	Trans Sensor 40	0.939	0.576	0.145
2	Trans Sensor 11	0.896	0.555	0.233
2	Trans Sensor 09	0.881	0.498	0.237
2	Trans Sensor 03	0.877	0.588	0.299
2	Trans Sensor 01	0.872	0.585	0.309
2	Trans Sensor 32	0.662	0.165	0.404
2	Trans Sensor 34	0.594	0.125	0.464
2	Trans Sensor 19	0.484	0.275	0.711
2	Trans Sensor 17	0.554	0.436	0.791
3	Trans Sensor 38	0.92	0.407	0.135

Trans	Trans							
Sensor	Sensor							
01	02	03	04	05	06	07	08	09
-0.4294	-0.0231	-0.1808	-0.0451	0.2103	-0.0139	-0.1479	-0.0003	0.045
-0.0553	-1.6323	0.0946	-1.6494	-1.0090	-1.0421	-1.1202	-1.5259	-0.07
-0.1118	-0.1879	0.0190	-0.3210	0.0413	-0.2746	-0.2776	-0.5321	-0.00
-0.5451	-0.3947	-0.2502	-0.5025	-0.3531	-0.1935	-0.0970	-0.9698	0.296
-0.5923	-0.3815	-0.2022	-0.0674	-0.0214	-0.0838	-0.1310	-0.0554	0.205
0.0314	-2.0594	0.0999	-1.3296	-0.0470	-0.3101	-0.1242	-0.5256	-0.20
-0.7684	-0.0689	-0.4170	0.0214	-0.4208	-0.4247	-0.2626	-0.7629	0.208
-0.3011	-0.3561	-0.1394	-0.2290	-0.5230	-0.0002	-0.0466	0.1336	-0.08
-0.8604	-0.7904	-0.4585	-0.6226	-1.6474	-0.4490	-0.5911	-0.6703	0.279
-0.5162	-0.0985	-0.1948	-0.1594	-1.3342	-0.8718	-0.8667	-0.6355	0.130
-0.4474	-0.3370	-0.2852	-0.2331	0.0729	-0.3032	0.0418	-0.9479	0.145
-0.2476	-0.1680	-0.0272	-0.1845	-1.5294	-1.0247	-1.2402	-0.9938	0.077
-0.4825	-0.9196	-0.2014	-0.7169	-2.0343	-0.5324	-0.7525	-0.6485	0.105









Generalized Regression for status = Pass

Model Comparison

	Response	Estimation	Validation	Nonzero			Generalized	Validation
Show	Distribution	Method	Method	Parameters	AICc	BIC	RSquare	Generalized RSquare
\checkmark	Binomial	Logistic Regression	Validation Column	26				0.6234149
\checkmark	Binomial	Lasso	Validation Column	13	30.775781	64.788125	0.9958038	0.906737
\checkmark	Binomial	Elastic Net	Validation Column	17	43.746715	86.850012	0.9888577	0.8883607
\checkmark	Binomial	Ridge	Validation Column	26	76.931684	137.5221	0.9697985	0.8336802





Parameter Es	timates f	or Original	Predictors			
Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Trans Sensor 18	-21.50633	1.983503	117.56198	<.0001*	-25.39392	-17.61874
Intercept	-16.15049	2.0322961	63.153519	<.0001*	-20.13372	-12.16726
Trans Sensor 27	7.6947349	1.5130301	25.863792	<.0001*	4.7292504	10.660219
Trans Sensor 26	-4.982007	1.4309036	12.12238	0.0005*	-7.786526	-2.177487
Trans Sensor 15	2.0136856	0.7221117	7.7763279	0.0053*	0.5983727	3.4289985
Trans Sensor 52	-6.155699	3.8026345	2.6205089	0.1055	-13.60873	1.2973273
Trans Sensor 05	-1.227494	0.9327291	1.7319197	0.1882	-3.05561	0.6006214
Trans Sensor 16	0.4251844	0.3580648	1.4100395	0.2350	-0.27661	1.1269786
Trans Sensor 53	-3.442666	3.6166922	0.9060802	0.3412	-10.53125	3.6459207
Trans Sensor 6	-2.92957	3.5324812	0.6877774	0.4069	-9.853105	3.9939665
Trans Sensor 06	-0.67685	0.8698959	0.6054114	0.4365	-2.381815	1.0281144
Trans Sensor 07	-0.165354	0.5695772	0.0842799	0.7716	-1.281705	0.9509968
Trans Sensor 14	0.1156922	0.816768	0.0200637	0.8874	-1.485144	1.7165282
Trans Sensor 08	3 0	0	0	1.0000	0	C
Trans Sensor 13	3 0	0	0	1.0000	0	C
Trans Sensor 20) (0	0	1.0000	0	C











4 💌 Pi	rediction Profiler									
	Optimization and Desirability	* E		1	Di Alta	1	4	1 14		-
	Assess Variable Importance	*	Independ	lent Uniform Inputs						
	Save Bagged Predictions		Independ	lent Resampled Inp	outs					
	Simulator		Depende	nt Resampled Inpu	ts	Calcul	ates the indic	es that are used in		
	Design Space Profiler		Linearly (Constrained Inputs		the As	sess Variable	Importance		
	Interaction Profiler	T	-0.0363	0.0495	0.0297	assum	ing that the ir	nputs are	-0.0035	-0.8164
~	Confidence Intervals	Т	rans	Trans	Trans	depen	dent.	Hans	Trans	Trans
	Sensitivity Indicator	S	Sensor 06	Sensor 07	Sensor 14		Sensor 15	Sensor 16	Sensor 18	Sensor 26







Binomial Lasso with Validation Column

Prediction Profiler

Variable Importance: Dependent Resampled Inputs

Summary Report

Column	Main Effect	Total Effect	.2	.4	.6	.8
Trans Sensor 18	0.053	0.175				
Trans Sensor 27	0.035	0.077				
Trans Sensor 52	0.051	0.051				
Trans Sensor 61	0.051	0.051				
Trans Sensor 53	0.05	0.05				
Trans Sensor 26	0.041	0.041				
Trans Sensor 06	0.038	0.038				
Trans Sensor 07	0.037	0.037				
Trans Sensor 05	0.036	0.036				
Trans Sensor 14	0.034	0.034				
Trans Sensor 16	0.03	0.03				
Trans Sensor 15	0.029	0.029				

Rsq=.9





Binomial Lasso v	vith Validat	ion Column	Bootst	rap Fore	st for stat	us				
Prediction Pro	filer	r		Column Contributions						
🖉 💌 Variable Imp	riable Importance: Dependent Resampled Inputs		Term	Number of Splits	6^2		Portion			
✓ Summary Rep	nmary Report			579	54.9167342	· · · · · · · · ·	0.5024			
Column	Main Effect	Total Effect .2 .4 .0 .8	sensor61	198	18.7389273		0.1714			
Trans Sensor 18	0.053	0.175	sepsor52	145	13.1320295		0.1201			
Trans Sensor 27	0.035	0.022	sepsor53	56	5.26374221		0.0482			
Trans Sensor 52	0.051	0.051	sensor44	33	2.53070023		0.0232			
Trans Sensor 61	0.051	0.051	sensor48	42	2.45696551		0.0225			
Trans Sensor 53	0.05	0.05	sensor46	31	2.08993095		0.0191			
Trans Sensor 35	0.03	0.03	sensor11	114	1.34630042		0.0123			
Trans Sensor 20	0.041	0.041	sensor54	12	1.01688952		0.0093			
Trans Sensor 06	0.038	0.038	sensor58	111	0.73127415		0.0067			
Trans Sensor 07	0.037	0.037	sensor07	61	0.68014104		0.0062			
Trans Sensor 05	0.036	0.036	sensor26	89	0.5292647		0.0048			
Trans Sensor 14	0.034	0.034	sensor12	40	0.51092374		0.0047			
Trans Sensor 16	0.03	0.03	sensor50	8	0.41943383		0.0038			
Trans Sensor 15	0.029	0.029	sensor57	75	0.3901658		0.0036			
The source of th	0.025		sensor01	44	0.35310066		0.0032			
			sensor05	47	0.3400086		0.0031			

Rsq=.8

8 0.30245908



Rsq=.9

4



0.0028

sensor21



Lasso Validation Shuffling Total Effect vs. Column

"How important are the inputs to a predictive model"

Column Contributions

- What predictors explain the most response variation on the training data?
- Partition-based models only
- Based on equivalent Least Sq model
- Includes residual error
- Robust and stable (random forests)
- Results will not change if columns monotonically transformed
- Good early step in modeling process

Variable Importance

- What predictors explain the most variation in predictive model on the data or a region?
- General: applies to all supervised models
- Based on Sobol (1990) sensitivity analysis
- Model variation based, not residual error
- Very sensitive to model over/under fit
- Results change unpredictably if columns are transformed
 - Descriptive tool at the end of the modeling process



"What are the groups of related columns?"

"How representative are each column to its group?"

Variable Clustering

- Unsupervised method
- Based on recursive partitioning of columns guided by PCA/Factor Analysis of groups
- Reference: PROC VARCLUS documentation
- Only seeks linear relationships among columns
- Sensitive to outliers
- Useful in the early stages of data exploration



"How did each input column contribute to this model's prediction at a particular value of X?"

Shapley (SHAP) Values

- Additive decomposition of a single predicted value that can be anywhere (not just data used for fitting the model)
- $\hat{f}(x_1x_2\dots) = SHAP_{Intercept} + SHAP_{\hat{f},1}(x_1) + SHAP_{\hat{f},1}(x_2) + \cdots$
- General: applies to all supervised models
- Based on Shapley (1951) resulted in 2012 Nobel
- Model variation based, not residual error
- Very sensitive to model over/under fit
- Results change unpredictably if columns are transformed
- Descriptive tool at the end of the modeling process











SHAP Trans Sensor 05	SHAP Trans Sensor 06	SHAP Trans Sensor 07	SHAP Trans Sensor 14	SHAP Trans Sensor 15	SHAP Trans Sensor 16	SHAP Trans Sensor 18	SHAP Trans Sensor 26	SHAP Trans Sensor 27	SHAP Trans Sensor 52	SHAP Trans Sensor 53	SHAP Trans Sensor 61	SHAP Interce pt	SHAP Trans Sensor 05+SHAP Trans Sensor 06+SHAP Tns Sensor 53+SHAP Trans Sensor 61+SHAP Intercept	Probability(status=Pass)
-0.01	-0.00	0.000	0.000	0.073	-0.00	0.138	0.038	0.019	0.103	0.078	0.050	0.480	0.9646941837	0.9646941837
0.016	0.007	0.001	0.002	0.019	0.006	0.333	0.052	-0.05	0.060	0.037	0.037	0.480	0.999999949	0.999999949
0.001	0.006	0.001	0.002	-0.01	-0.00	0.255	0 104	-0.08	0.082	0.068	0.060	0.480	0.9669140606	0.9669140606





















































Generalized Regression for testResult

⊿ Model Comparison

	Response		Validation	Nonzero			Generalized	Validation
Show	Distribution	Estimation Method	Method	Parameters	AICc	BIC	RSquare	Generalized RSquare
\checkmark	Multinomial	Maximum Likelihood	Validation Column	156		655.93721	0.999997	-43.17824
\checkmark	Multinomial	Lasso	Validation Column	60	1346.9128	259.19431	0.995714	0.9396993
\checkmark	Multinomial	Elastic Net	Validation Column	64	4304.7032	285.80357	0.988835	0.9282288
\checkmark	Multinomial	Ridge	Validation Column	156		682.86499	0.9804884	0.8778949

- Exclude all the "Pass" rows to focus on the failures
- Same Cluster 1 columns used in the Pass model











▼All Ro	ws	
Count	G^2	Logworth
129	397.84836	55.737136

testResult

- Good
- Grippers
- IMP
- Motor
- ITM
- Brake
- SOS
- Velocity Type I
- Velocity Type II







testResult

- Good
- Grippers
- IMP
- Motor
- ITM
- Brake
- SOS
- Velocity Type I
- Velocity Type II







testResult

- Good
- Grippers
- IMP
- Motor
- ITM
- Brake
- SOS
- Velocity Type I
- Velocity Type II







- SOS
- Velocity Type I
- Velocity Type II

















⊿ Actual By Predicted Category on Training

testResult						
Velocity Type II						
0						
0						
0						
0						
2						

⊿ ■ Actual By Predicted Category on Validation

Velocity Type I Velocity Type II
0 0 1
1 0 2
0 0 0
2 0 0
0 2 0





Thank you for your attention





