Credit Ri$k

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Intro to Business Analytics
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Executive Summary

- Business Problem
  - Help a large bank in European Union to figure out what types of customers are most likely to default on a loan in order to lower bad debt risk of the bank.
  - Build a model to predict the probability that a borrower will default on his loan.
- Proposed Solution
  - Restrict loan to customers that are predicted to be in bad risk. (loan amounts, more strict evaluation, etc.)
  - Improve quality of data gathering/storing and keeping the data up to date.

Introduction

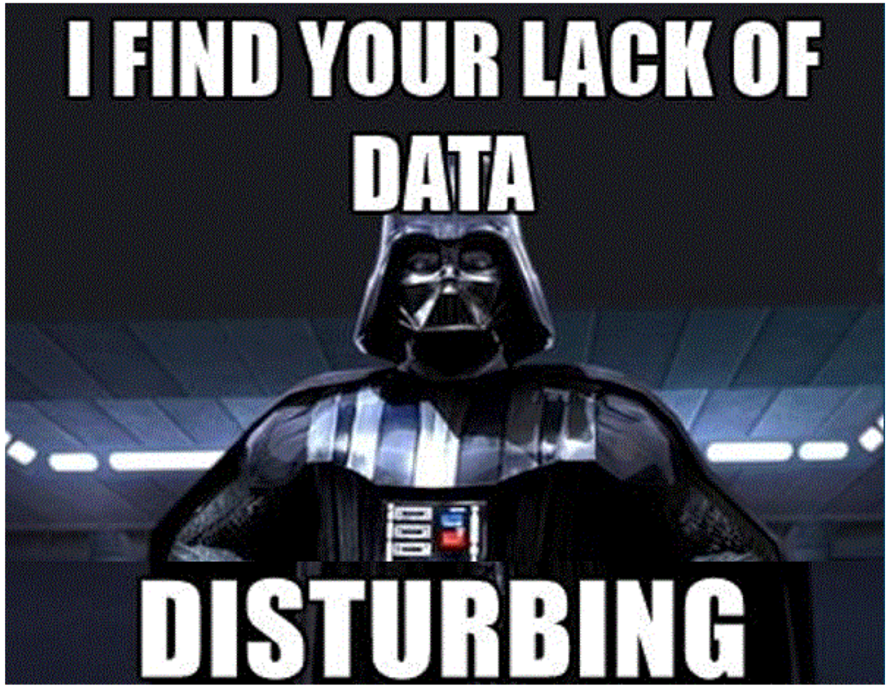
- Why it matters
  - The global financial crisis put credit risk management into the regulatory spotlight
  - Credit risk management requires the bank to have thorough knowledge of customers and their associated credit risk
  - Having profound implications for consumer banking policy

*Reference:https://www.researchgate.netfile.PostFileLoader.html?id=5675b5ad7dfbf936088b4567&assetKey=AS%3A308463333249025%401450554797366

- How analytics helps
    - Compare several model (solutions) method and select the most suitable one
    - Use an assumptions on the cost of a bad loan or revenue from a good loan to test the model
    - The model we build helps us make a better decision

Methods

- Data Quality
  - High number of variables and a few highly correlated variables
  - Significant difference in number of good creditors and bad creditors
  - Outliers
  - Missing information on :
    - Being an owner or renting
    - Time at current address (not critical)
    - Time at current job (not many)
- Some Key Variables
  - Age
  - Income
  - Profession (many unknown)
  - Request cash loan amount
  - Time at current job
  - Being an Owner vs. Renting



- Model
  - Chose a decision tree model
  - Our decision tree model has 29 splits ; Splits on
    - Age (Ages above 28 and below 28)
    - Credit (second split – Visa Mybank, other credit cards and no credit cards in one group and Cheque Card, Master Card, Visa others in other group for ages below 28
    - Ages above 28 is again split into ages 45 and above and ages below 45

Results

Model Performance:

- Low misc. rate of **5.06%**
- Improving accuracy in predicting **bad risk** by lowering true negative rate to **83.4%**
- The top **15%** of the model predicts the bad risk outcome **2.5** times higher than randomly choosing 15% data
- Profit analysis: expected **€821,822** profit

Validation

Actual Risk	Predicted Count: Bad Risk	Predicted Count: Good Risk
Bad Risk	29	332
Good Risk	0	11322

Specified Profit Matrix

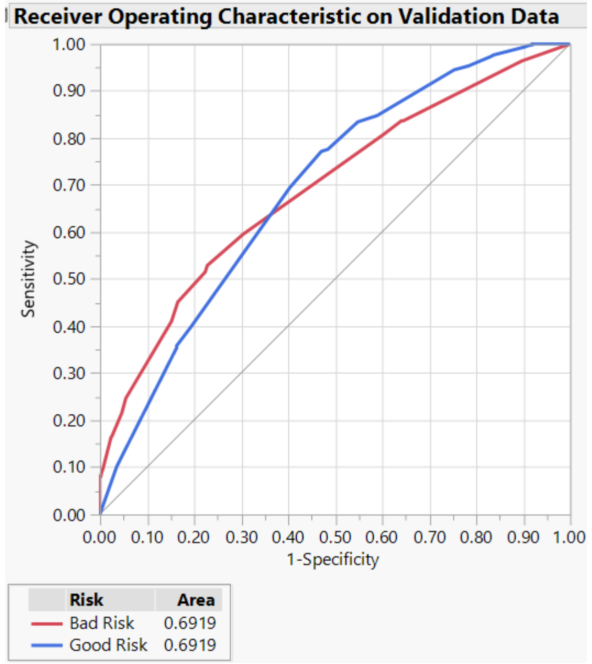
Actual	Decision: Bad Risk	Decision: Good Risk
Bad Risk	0	-2952
Good Risk	-100	100

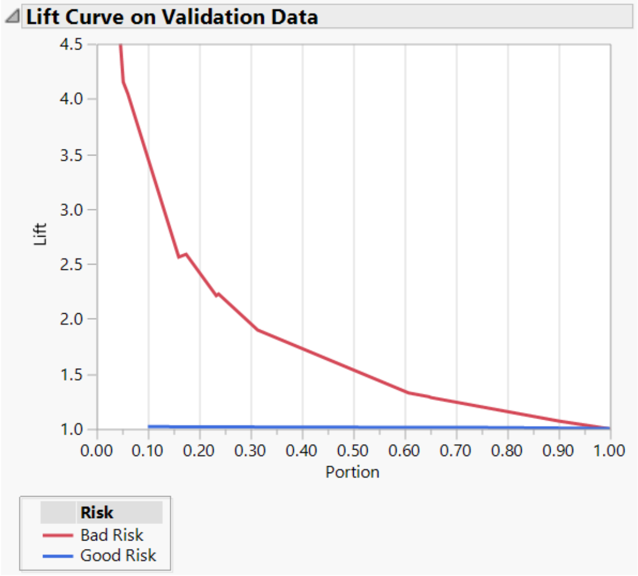
Validation

Actual Risk	Decision Count: Bad Risk	Decision Count: Good Risk
Bad Risk	60	301
Good Risk	290	11032

Actual Risk	Decision Rate: Bad Risk	Decision Rate: Good Risk
Bad Risk	0.166	0.834
Good Risk	0.026	0.974

Misclassification Rate
0.0506





Result Interpretation

Column Contributions

Term	Number of Splits	G^2	Portion
AGE	4	303.279684	0.2927
CASH	4	117.862282	0.1138
TMJOB1	3	82.2075824	0.0793
TEL	2	60.0007594	0.0579
CHILDREN	2	55.0835336	0.0532
CARDS	1	50.9552482	0.0492
EC_CARD	1	44.5943956	0.0430
PRODUCT	2	44.4426531	0.0429
PROF	1	39.8341124	0.0384
CAR	2	39.1724194	0.0378
PERS_H	1	38.5382595	0.0372
REGN	1	37.0185961	0.0357
INCOME	1	33.3496714	0.0322
STATUS	1	31.2576587	0.0302
RESID	1	21.4888696	0.0207
BUREAU	1	19.685138	0.0190
FINLOAN	1	17.3382431	0.0167
TITLE	0	0	0.0000
TMADD	0	0	0.0000
NMBLOAN	0	0	0.0000
LOCATION	0	0	0.0000
LOANS	0	0	0.0000
DIV	0	0	0.0000
NAT	0	0	0.0000

Typical bad risk customers

- Predicted bad risk: 93.38%
  - Age<23
  - Request cash loan > 1900
  - Current job < 18 months
- Predicted bad risk: 91.42%
  - Age<28
  - Current job < 9 months
  - More than 2 persons in the household

Conclusion

- Concerns
  - Missing data
  - Up-to-date data
  - Manual data input

- Next steps
  - Update data regularly
  - Minimize split size(working with key variables)
  - Further gathering data about cost and revenue related to credit risk

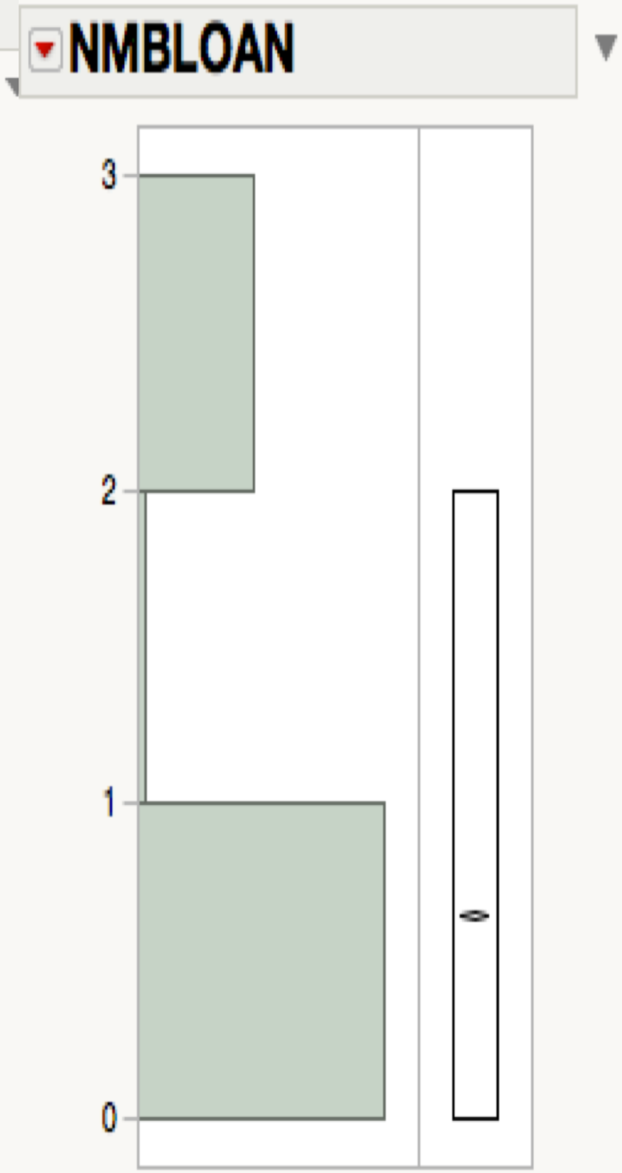
Appendix

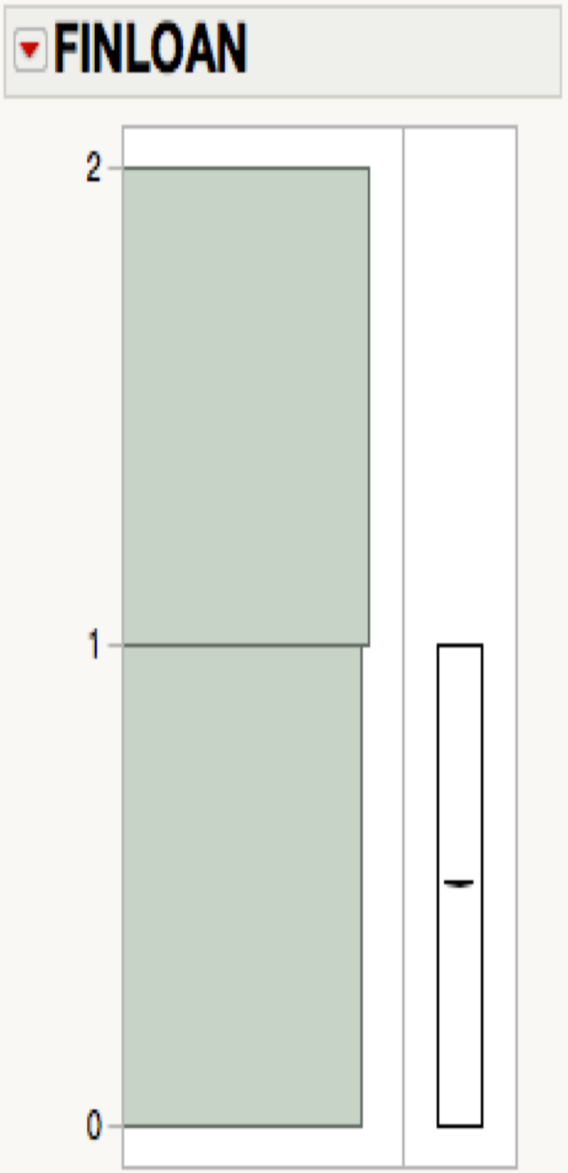
Model Comparison

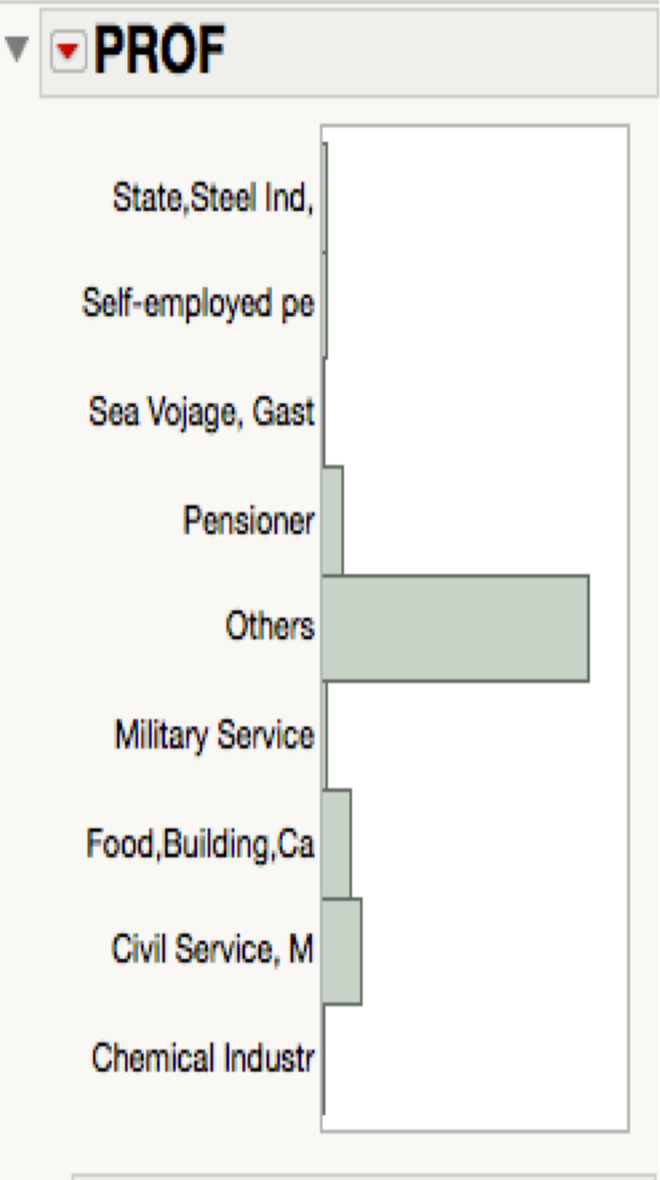
Predictors

Measures of Fit for Risk

Validation	Creator	.2 .4 .6 .8	Entropy RSquare	Generalized RSquare	Mean -Log p	RMSE	Mean Abs Dev	Misclassification Rate	N
Training	Fit Ordinal Logistic		0.1052	0.1191	0.1278	0.1725	0.0598	0.0321	18119
Training	Partition		0.1823	0.2040	0.116	0.1610	0.0523	0.0273	23142
Validation	Fit Ordinal Logistic		0.0969	0.1093	0.1233	0.1686	0.0585	0.0305	9205
Validation	Partition		0.1411	0.1582	0.1176	0.1611	0.0522	0.0273	11847
Test	Fit Ordinal Logistic		0.0719	0.0827	0.1436	0.1826	0.0633	0.0359	8965
Test	Partition		0.0835	0.0954	0.137	0.1724	0.0560	0.0309	11511

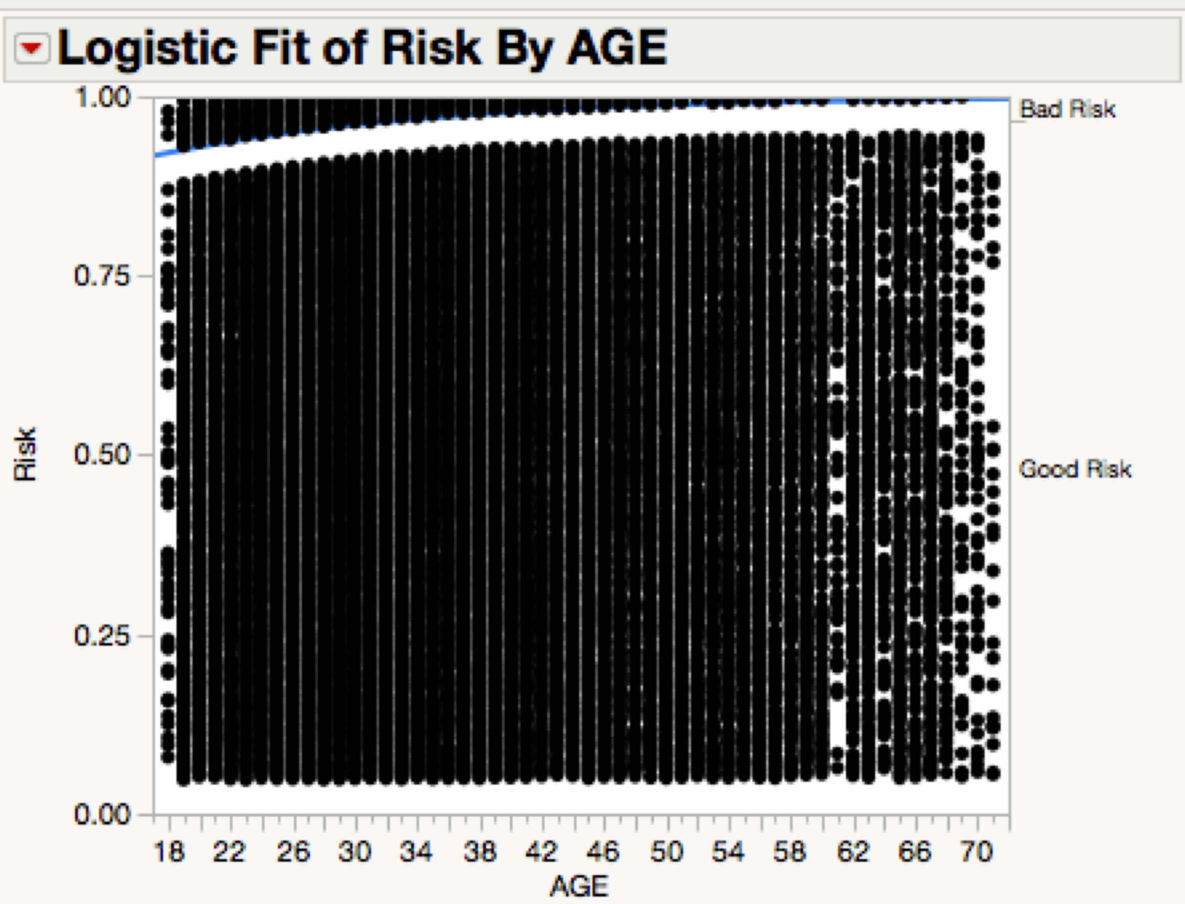


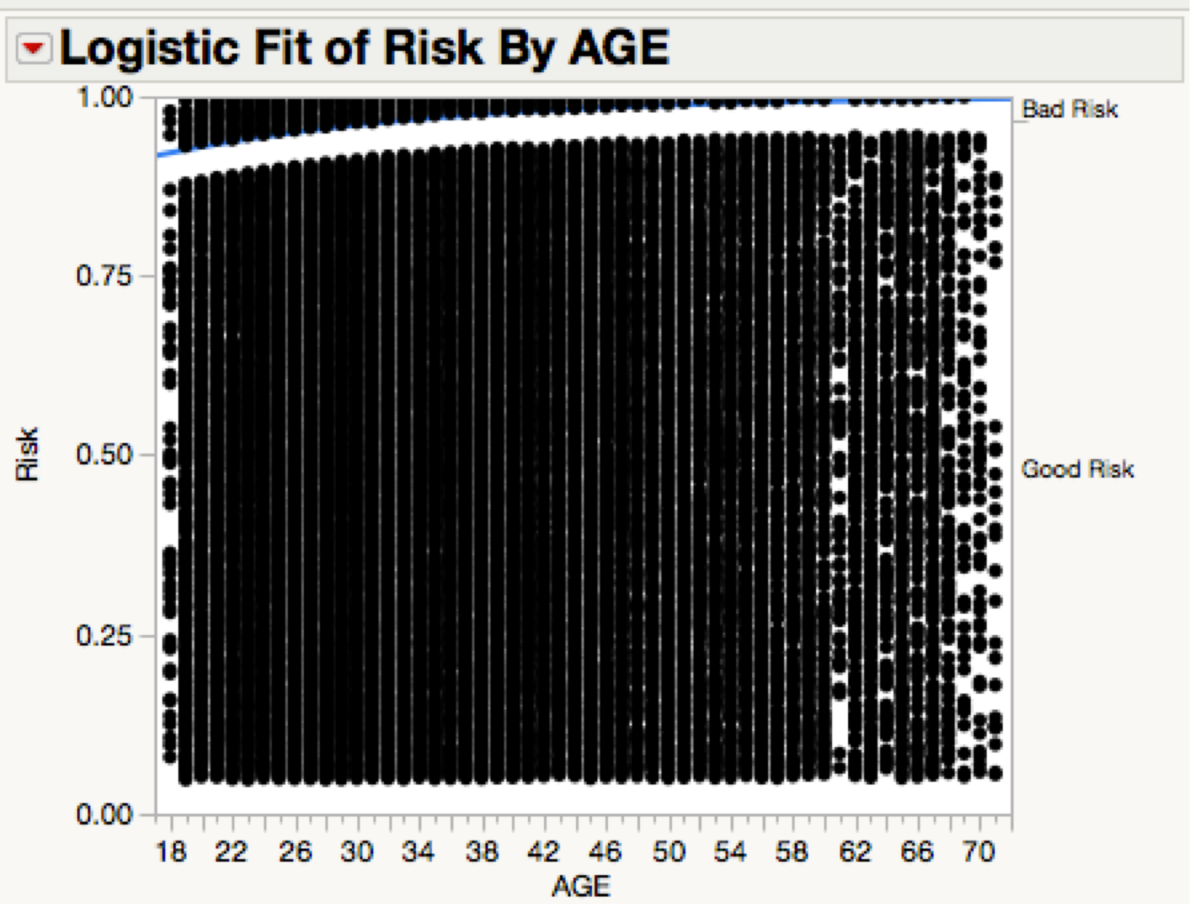




Frequencies

Level	Count	Prob
Good Risk	45000	0.96774
Bad Risk	1500	0.03226
Total	46500	1.00000
N Missing	0	


Logistic Fit of Risk By AGE
1.00
0.75
0.50
0.25
0.00
Risk
Bad Risk
Good Risk
18 22 26 30 34 38 42 46 50 54 58 62 66 70
AGE

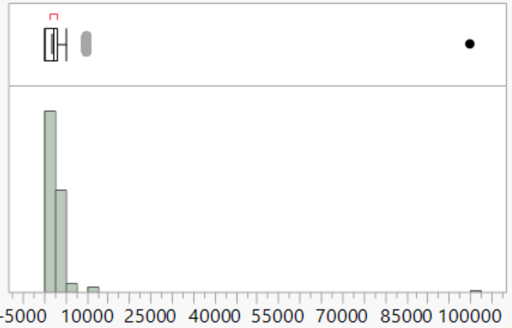

Logistic Fit of Risk By AGE
1.00
0.75
0.50
0.25
0.00
Risk
Bad Risk
Good Risk
18 22 26 30 34 38 42 46 50 54 58 62 66 70
AGE

	Risk	TITLE	CHILDREN	PERS_H	AGE	TMADD	TMJOB1	TEL	NMBLOAN	FINLOAN	INCOME	EC_CARD	STATUS	BUREAU	LOCATION	LOANS	REGN	DIV	CASH	PROD
46469	Good Risk	H	6	8	48	192	30	1	0	0	0	1	V	3	1	0	0	0	1100	Radio, T
46470	Bad Risk	H	8	10	33	72	9	2	0	1	0	1	V	1	1	3	0	0	1300	Radio, T
46471	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46472	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46473	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46474	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46475	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46476	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46477	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46478	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46479	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46480	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46481	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46482	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46483	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46484	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46485	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46486	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46487	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46488	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46489	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46490	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46491	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46492	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46493	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46494	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46495	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46496	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46497	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46498	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46499	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur
46500	Good Risk	H	23	25	32	6	6	2	0	0	2700	0	V	3	1	0	5	1	1800	Furnitur

Abnormal records in CHILDREN and PERS_H

Distributions

INCOME



Quantiles

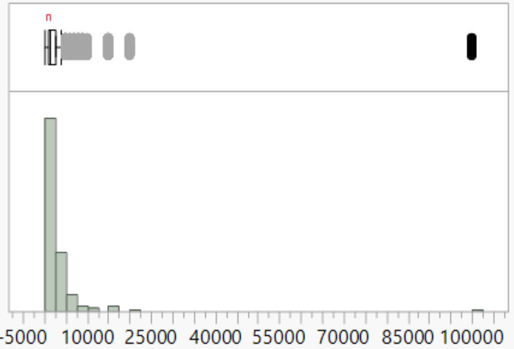
100.0%	maximum	100000
99.5%		10000
97.5%		5000
90.0%		3500
75.0%	quartile	2800
50.0%	median	2100
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	1875.2163
Std Dev	1653.0156
Std Err Mean	7.6681502
Upper 95% Mean	1890.246
Lower 95% Mean	1860.1866
N	46470

Distributions

CASH



Quantiles

100.0%	maximum	100000
99.5%		20000
97.5%		10000
90.0%		4000
75.0%	quartile	2500
50.0%	median	1500
25.0%	quartile	1000
10.0%		700
2.5%		500
0.5%		500
0.0%	minimum	0

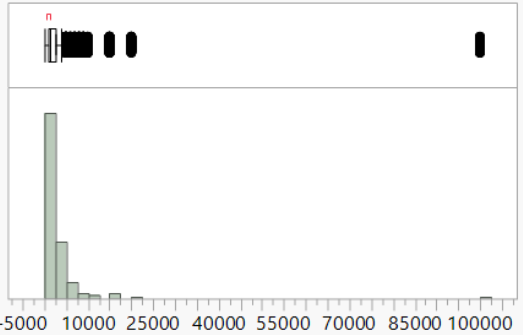
Summary Statistics

Mean	2592.1195
Std Dev	6170.9801
Std Err Mean	28.626779
Upper 95% Mean	2648.2284
Lower 95% Mean	2536.0106
N	46469

Expected Profit for Risk	Sum	821822.57429
Actual Profit for Risk	Sum	681000

Distributions

CASH

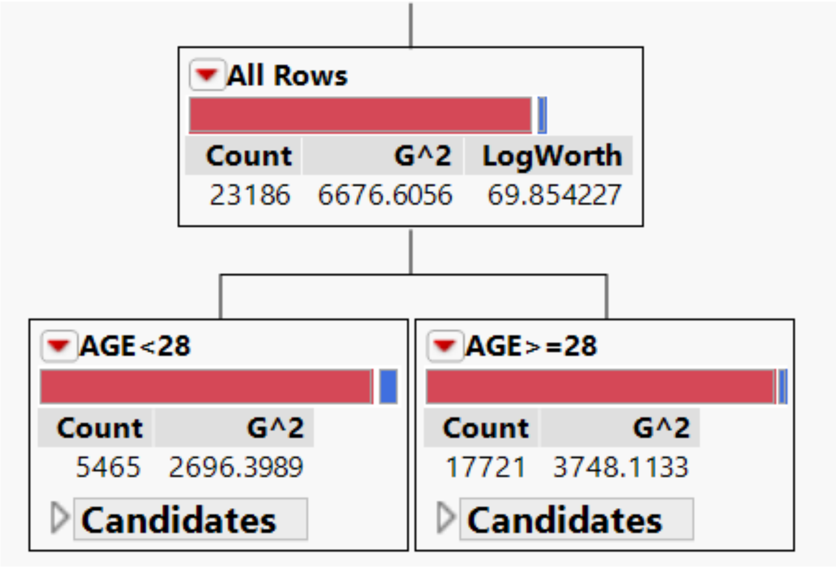


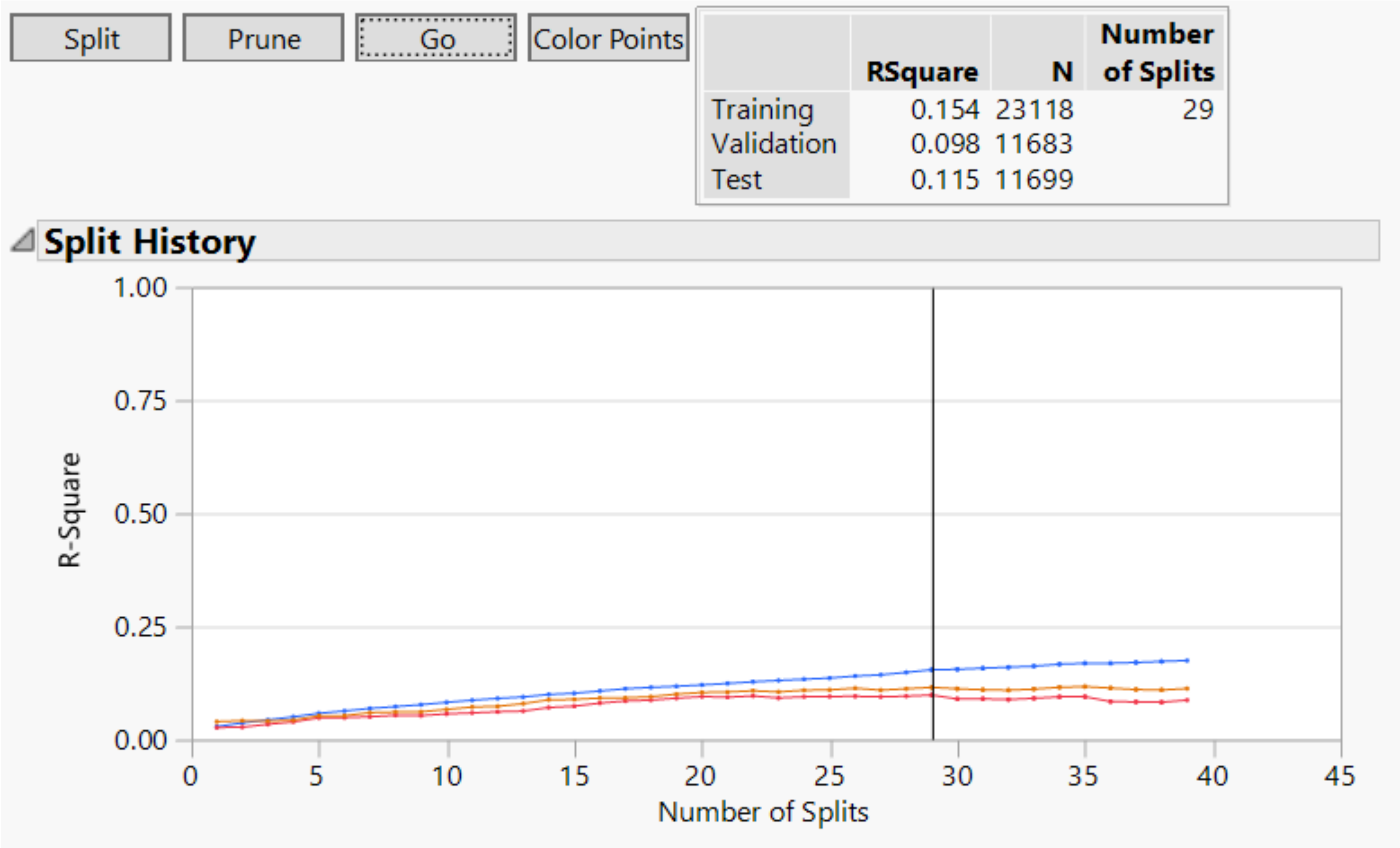
Quantiles

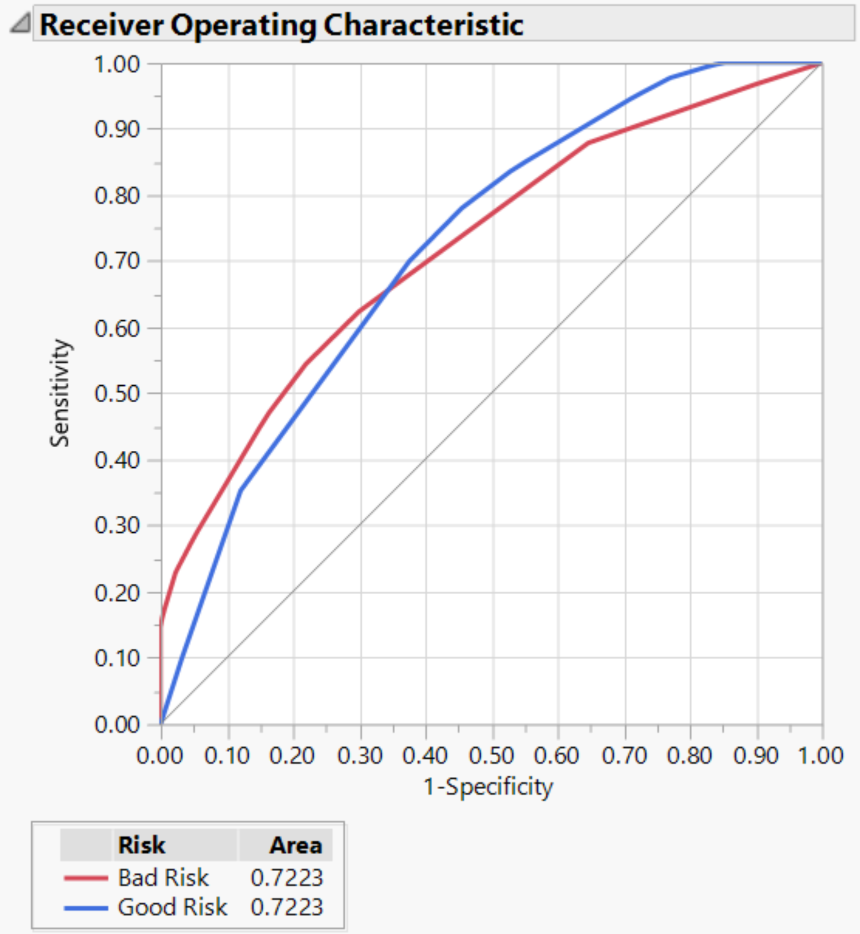
100.0%	maximum	100000
99.5%		20000
97.5%		10000
90.0%		4000
75.0%	quartile	2500
50.0%	median	1500
25.0%	quartile	1000
10.0%		700
2.5%		500
0.5%		500
0.0%	minimum	0

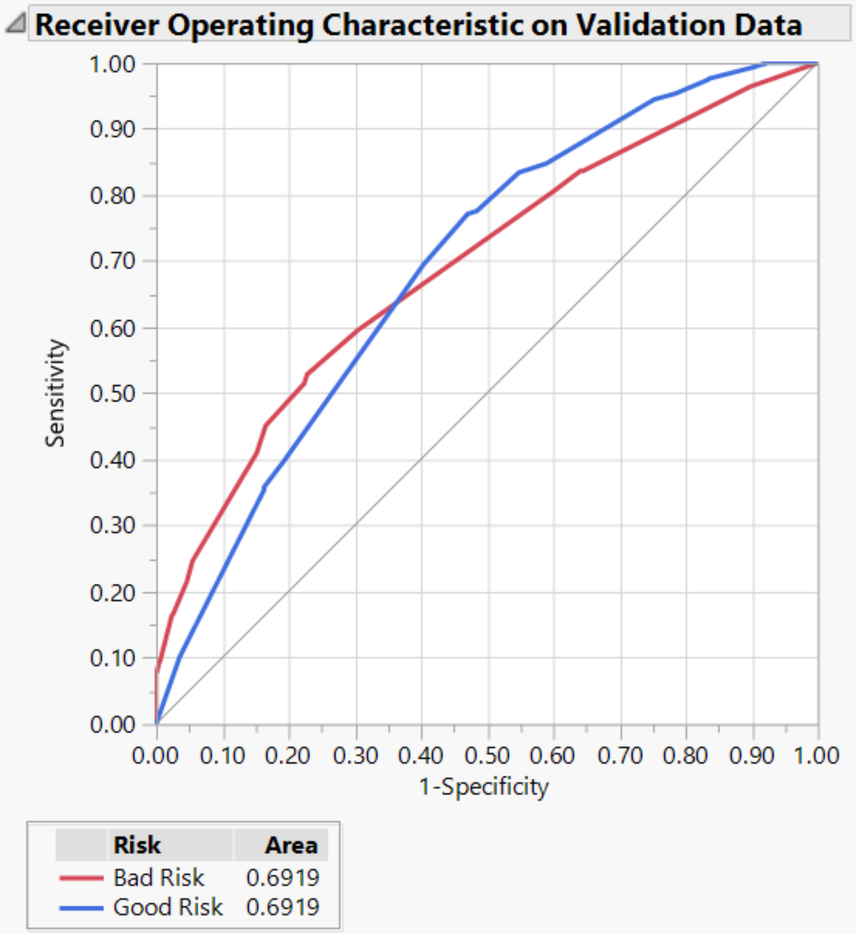
Summary Statistics

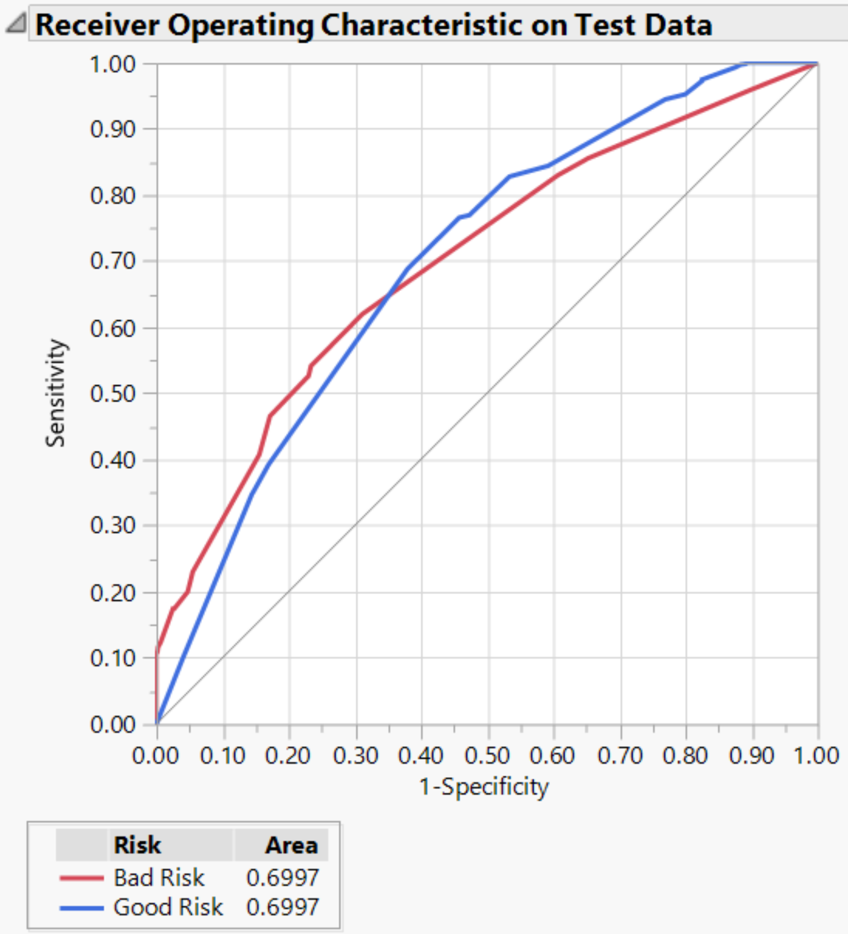
Mean	2591.6172
Std Dev	6168.9558
Std Err Mean	28.607848
Upper 95% Mean	2647.689
Lower 95% Mean	2535.5454
N	46500


All Rows
Count G^2 LogWorth
23186 6676.6056 69.854227
AGE<28
Count G^2
5465 2696.3989
Candidates
AGE>=28
Count G^2
17721 3748.1133
Candidates

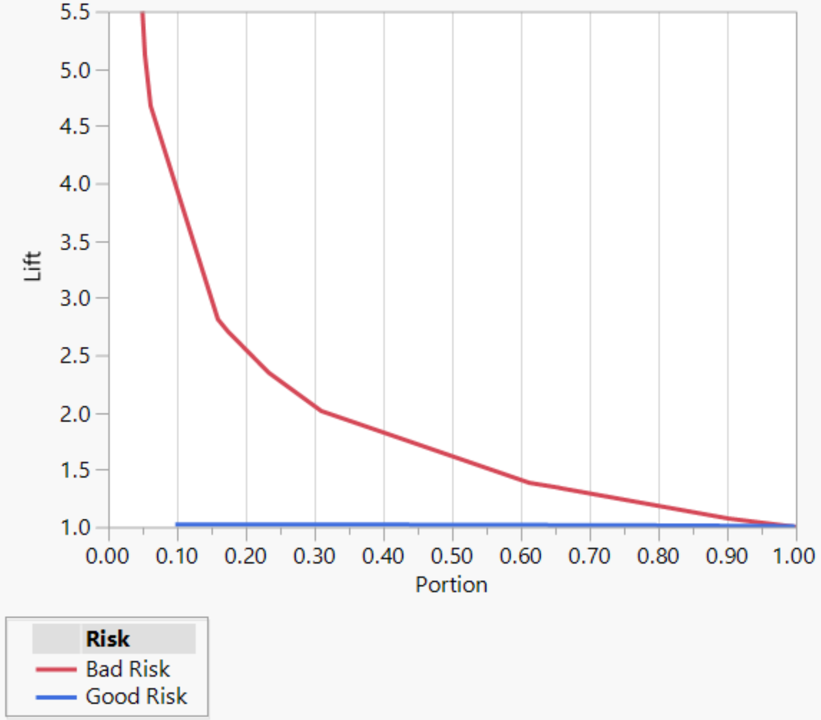

Split
Prune
Go
Color Points
RSquare N Number of Splits
Training 0.154 23118 29
Validation 0.098 11683
Test 0.115 11699
Split History
R-Square
1.00
0.75
0.50
0.25
0.00
0 5 10 15 20 25 30 35 40 45
Number of Splits


Receiver Operating Characteristic
Sensitivity
1-Specificity
0.00
0.10
0.20
0.30
0.40
0.50
0.60
0.70
0.80
0.90
1.00
Risk Area
Bad Risk 0.7223
Good Risk 0.7223

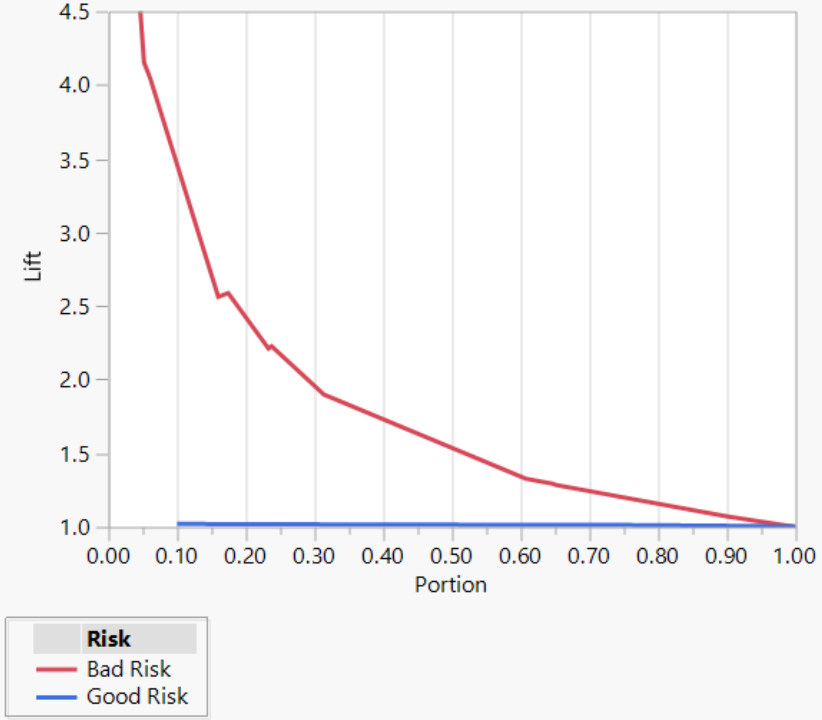

Receiver Operating Characteristic on Validation Data
Sensitivity
1-Specificity
0.00
0.10
0.20
0.30
0.40
0.50
0.60
0.70
0.80
0.90
1.00
Risk Area
Bad Risk 0.6919
Good Risk 0.6919


Receiver Operating Characteristic on Test Data
Sensitivity
1-Specificity
0.00
0.10
0.20
0.30
0.40
0.50
0.60
0.70
0.80
0.90
1.00
Risk Area
Bad Risk 0.6997
Good Risk 0.6997

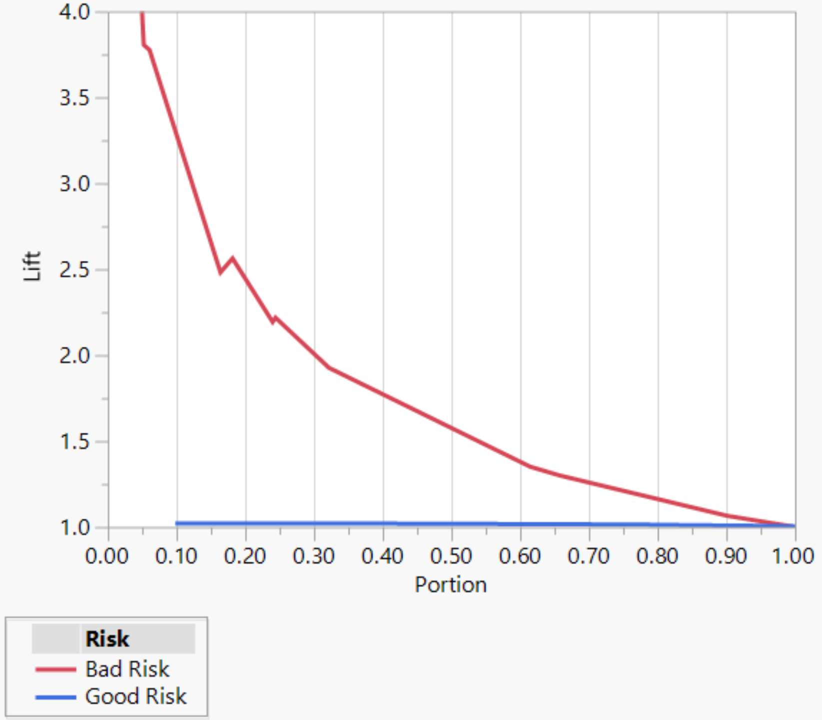
Lift Curve



Lift Curve on Validation Data



Lift Curve on Test Data



Confusion Matrix

Training

Actual	Predicted Count	
Risk	Bad Risk	Good Risk
Bad Risk	110	634
Good Risk	0	22374

Validation

Actual	Predicted Count	
Risk	Bad Risk	Good Risk
Bad Risk	29	332
Good Risk	0	11322

Test

Actual	Predicted Count	
Risk	Bad Risk	Good Risk
Bad Risk	42	353
Good Risk	0	11304

Decision Matrix

Training

Actual	Decision Count	
Risk	Bad Risk	Good Risk
Bad Risk	173	571
Good Risk	542	21832

Actual	Decision Rate	
Risk	Bad Risk	Good Risk
Bad Risk	0.233	0.767
Good Risk	0.024	0.976

Misclassification Rate
0.0481

Validation

Actual	Decision Count	
Risk	Bad Risk	Good Risk
Bad Risk	60	301
Good Risk	290	11032

Actual	Decision Rate	
Risk	Bad Risk	Good Risk
Bad Risk	0.166	0.834
Good Risk	0.026	0.974

Misclassification Rate
0.0506

Test

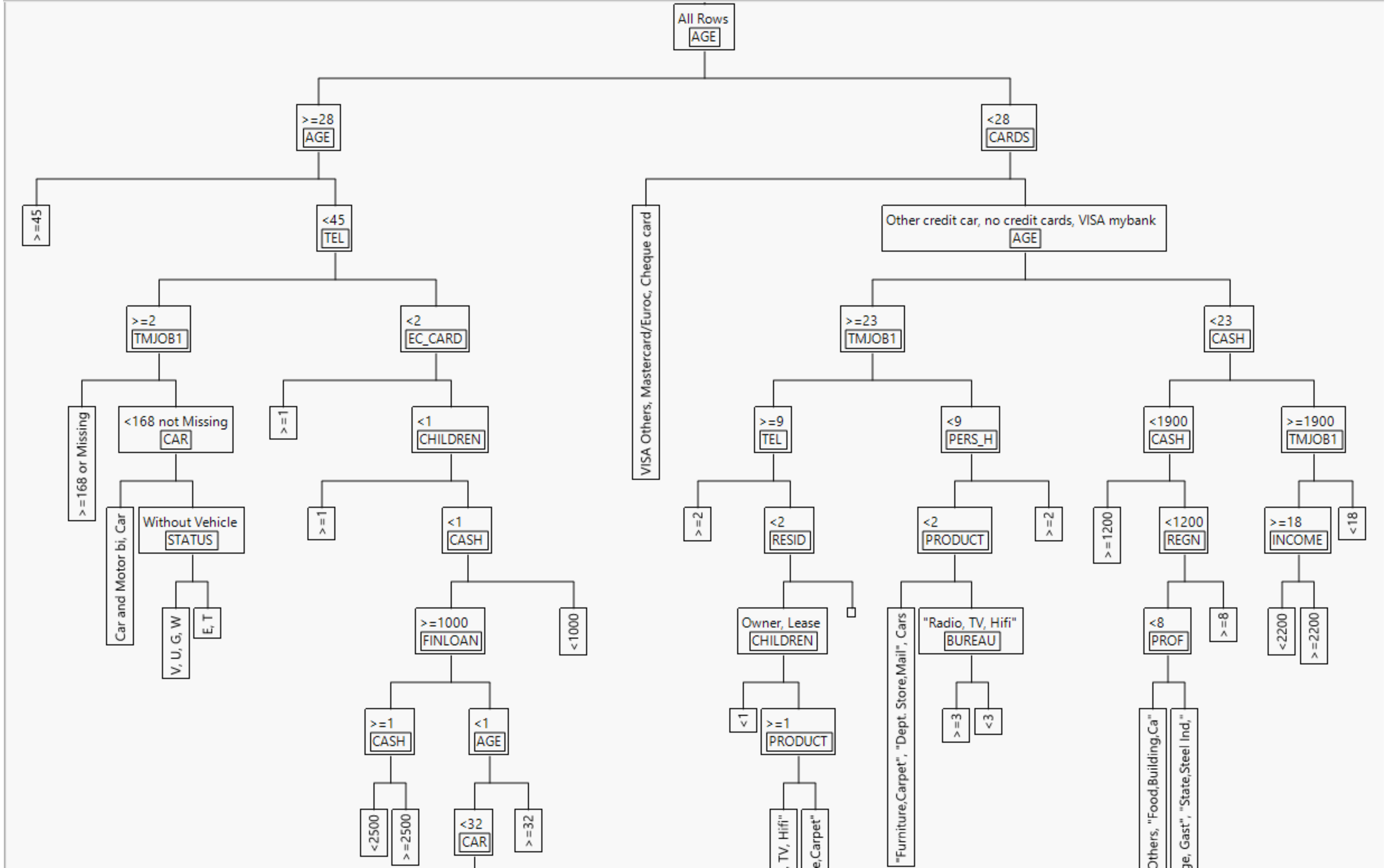
Actual	Decision Count	
Risk	Bad Risk	Good Risk
Bad Risk	70	325
Good Risk	308	10996

Actual	Decision Rate	
Risk	Bad Risk	Good Risk
Bad Risk	0.177	0.823
Good Risk	0.027	0.973

Misclassification Rate
0.0541

Specified Profit Matrix

	Decision	
Actual	Bad Risk	Good Risk
Bad Risk	0	-2952
Good Risk	-100	100


All Rows
AGE
>=28
AGE
<28
CARDS
>=45
<45
TEL
VISA Others, Mastercard/Euroc, Cheque card
Other credit car, no credit cards, VISA mybank
AGE
>=2
TMJOB1
<2
EC_CARD
>=23
TMJOB1
<23
CASH
>=168 or Missing
<168 not Missing
CAR
>=1
<1
CHILDREN
>=9
TEL
<9
PERS_H
<1900
CASH
>=1900
TMJOB1
Car and Motor bi, Car
Without Vehicle
STATUS
>=1
<1
CASH
>=2
<2
RESID
<2
PRODUCT
>=2
>=1200
<1200
REGN
>=18
INCOME
<18
V, U, G, W
E, T
>=1000
FINLOAN
<1000
Owner, Lease
CHILDREN
"Furniture,Carpet", "Dept. Store,Mail", Cars
"Radio, TV, Hifi"
BUREAU
<8
PROF
>=8
<2200
>=2200
>=1
CASH
<1
AGE
<1
>=1
PRODUCT
>=3
<3
<2500
>=2500
<32
CAR
>=32

Leaf Report

Response Prob

Leaf Label	Bad Risk	Good Risk
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH>=1900&TMJOB1<18	0.9338	0.0662
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN<1&AGE>=32	0.9303	0.0697
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH<1000	0.9276	0.0724
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1<9&PERS_H>=2	0.9142	0.0858
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH>=1900&TMJOB1>=18&INCOME>=2200	0.9086	0.0914
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL<2&RESID(Owner, Lease)&CHILDREN>=1&PRODUCT(Cars, "Dept. Store,Mail", "Furniture,Carpet")	0.9085	0.0915
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH<1900&CASH<1200&REGN<8&PROF(Chemical Industr, "Civil Service, M", "Sea Vojage, Gast", "State,Steel Ind,")	0.9067	0.0933
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH<1900&CASH<1200&REGN>=8	0.9062	0.0938
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1<9&PERS_H<2&PRODUCT("Radio, TV, Hifi")&BUREAU<3	0.8860	0.1140
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN<1&AGE<32&CAR(Without Vehicle)	0.8500	0.1500
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN>=1&CASH>=2500	0.8448	0.1552
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL<2&RESID()	0.8420	0.1580
AGE>=28&AGE<45&TEL>=2&TMJOB1<168 not Missing&CAR(Without Vehicle)&STATUS(E, T)	0.8386	0.1614
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1<9&PERS_H<2&PRODUCT("Radio, TV, Hifi")&BUREAU>=3	0.1514	0.8486
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL<2&RESID(Owner, Lease)&CHILDREN>=1&PRODUCT("Radio, TV, Hifi")	0.1495	0.8505
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH>=1900&TMJOB1>=18&INCOME<2200	0.1122	0.8878
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH<1900&CASH<1200&REGN<8&PROF(Military Service, Others, "Food,Building,Ca")	0.0999	0.9001
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN<1&AGE<32&CAR(Car)	0.0660	0.9340
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN>=1	0.0592	0.9408
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL<2&RESID(Owner, Lease)&CHILDREN<1	0.0576	0.9424
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL>=2	0.0526	0.9474
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH<1900&CASH>=1200	0.0499	0.9501
AGE>=28&AGE<45&TEL>=2&TMJOB1<168 not Missing&CAR(Without Vehicle)&STATUS(V, U, G, W)	0.0420	0.9580
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1<9&PERS_H<2&PRODUCT("Furniture,Carpet", "Dept. Store,Mail", Cars)	0.0333	0.9667
AGE<28&CARDS(VISA Others, Mastercard/Euroc, Cheque card)	0.0318	0.9682
AGE>=28&AGE<45&TEL>=2&TMJOB1<168 not Missing&CAR(Car and Motor bi, Car)	0.0239	0.9761
AGE>=28&AGE<45&TEL<2&EC_CARD>=1	0.0238	0.9762
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN>=1&CASH<2500	0.0120	0.9880
AGE>=28&AGE>=45	0.0115	0.9885
AGE>=28&AGE<45&TEL>=2&TMJOB1>=168 or Missing	0.0106	0.9894

Leaf Label	Bad Risk	Good Risk
AGE>=28&AGE<45&TEL>=2&TMJOB1<168 not Missing&CAR(Car and Motor bi, Car)	167	6828
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL>=2	119	2143
AGE>=28&AGE>=45	65	5576
AGE<28&CARDS(VISA Others, Mastercard/Euroc, Cheque card)	56	1706
AGE>=28&AGE<45&TEL>=2&TMJOB1<168 not Missing&CAR(Without Vehicle)&STATUS(V, U, G, W)	54	1230
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH<1900&CASH<1200&REGN<8&PROF(Military Service, Others, "Food,Building,Ca")	42	378
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN>=1	31	492
AGE>=28&AGE<45&TEL>=2&TMJOB1>=168 or Missing	24	2234
AGE>=28&AGE<45&TEL<2&EC_CARD>=1	23	944
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH<1900&CASH>=1200	17	324
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH>=1900&TMJOB1<18	13	0
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN<1&AGE>=32	12	0
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH<1000	12	0
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL<2&RESID(Owner, Lease)&CHILDREN<1	11	180
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1<9&PERS_H>=2	10	0
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL<2&RESID(Owner, Lease)&CHILDREN>=1&PRODUCT(Cars, "Dept. Store,Mail", "Furniture,Carpet")	9	0
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH<1900&CASH<1200&REGN<8&PROF(Chemical Industr, "Civil Service, M", "Sea Vojage, Gast", "State,Steel Ind,")	9	0
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH<1900&CASH<1200&REGN>=8	9	0
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH>=1900&TMJOB1>=18&INCOME<2200	9	71
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE<23&CASH>=1900&TMJOB1>=18&INCOME>=2200	9	0
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1<9&PERS_H<2&PRODUCT("Radio, TV, Hifi")&BUREAU<3	7	0
AGE>=28&AGE<45&TEL>=2&TMJOB1<168 not Missing&CAR(Without Vehicle)&STATUS(E, T)	5	0
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN>=1&CASH>=2500	5	0
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN<1&AGE<32&CAR(Without Vehicle)	5	0
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL<2&RESID(Owner, Lease)&CHILDREN>=1&PRODUCT("Radio, TV, Hifi")	5	28
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1>=9&TEL<2&RESID()	5	0
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1<9&PERS_H<2&PRODUCT("Radio, TV, Hifi")&BUREAU>=3	4	22
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN<1&AGE<32&CAR(Car)	3	43
AGE<28&CARDS(Other credit car, no credit cards, VISA mybank)&AGE>=23&TMJOB1<9&PERS_H<2&PRODUCT("Furniture,Carpet", "Dept. Store,Mail", Cars)	3	88
AGE>=28&AGE<45&TEL<2&EC_CARD<1&CHILDREN<1&CASH>=1000&FINLOAN>=1&CASH<2500	1	87