

# Predictive Modeling

## Lesson 3

### *Logistical Regression and Neural Networks*

Kevin Zollicoffer

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## Introduction

I chose to use R for the assignments. This is my first class in the PASS program and one of my goals upon completion of PASS is to be proficient in R.

The RStudio project files and accompanying artifacts, including the tex file that created this PDF, are publicly available on GitHub  
<https://github.com/zollie/PASS-PredictiveModeling-LogisticalRegression>

## Data Setup

I took the Excel spreadsheet and saved it as a CSV for easy import into R

```
> gc <- read.csv("~/R/PASS/PredictiveModeling/LogisticRegression/GermanCredit.csv")
> head(gc)
```

	OBS.	CHK_ACCT	DURATION	HISTORY	NEW_CAR	USED_CAR	FURNITURE	RADIO.TV	EDUCATION
1	1	0	6	4	0	0	0	1	0
2	2	1	48	2	0	0	0	1	0
3	3	3	12	4	0	0	0	0	1
4	4	0	42	2	0	0	1	0	0
5	5	0	24	3	1	0	0	0	0
6	6	3	36	2	0	0	0	0	1

	RETRAINING	AMOUNT	SAV_ACCT	EMPLOYMENT	INSTALL_RATE	MALE_DIV	MALE_SINGLE
1	0	1169	4	4	4	0	1
2	0	5951	0	2	2	0	0
3	0	2096	0	3	2	0	1
4	0	7882	0	3	2	0	1
5	0	4870	0	2	3	0	1
6	0	9055	4	2	2	0	1

	MALE_MAR_or_WID	CO.APPLICANT	GUARANTOR	PRESENT_RESIDENT	REAL_ESTATE
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1	0	0	0	4	1
2	0	0	0	2	1
3	0	0	0	3	1
4	0	0	1	4	0
5	0	0	0	4	0
6	0	0	0	4	0

	PROP_UNKN_NONE	AGE	OTHER_INSTALL	RENT	OWN_RES	NUM_CREDITS	JOB	NUM_DEPENDENTS
1	0	67	0	0	1	2	2	1
2	0	22	0	0	1	1	2	1
3	0	49	0	0	1	1	1	2
4	0	45	0	0	0	1	2	2
5	1	53	0	0	0	2	2	2
6	1	35	0	0	0	1	1	2

	TELEPHONE	FOREIGN	RESPONSE
1	1	0	1
2	0	0	0
3	0	0	1
4	0	0	1
5	0	0	0
6	1	0	1

The categorical predictors are turned into factors for R

```
> gc$RESPONSE <- factor(gc$RESPONSE)
> gc$JOB <- factor(gc$JOB)
> gc$EMPLOYMENT <- factor(gc$EMPLOYMENT)
> gc$SAV_ACCT <- factor(gc$SAV_ACCT)
> gc$HISTORY <- factor(gc$HISTORY)
> gc$CHK_ACCT <- factor(gc$CHK_ACCT)
```

## Partitioning

Next, the data is partitioned into 60% Train and 40% Test sets. I set the RNG seed for reproducibility

```
> n <- nrow(gc)
> a <- sort(sample(1:n, floor(n*.6)))
> gc.train <- gc[a,]
> gc.test <- gc[-a,]
```

## Logistical Regression

A Logistical Regression model is fit to the train data.

```
> logit <- glm(RESPONSE ~ CHK_ACCT+DURATION+HISTORY+NEW_CAR+USED_CAR+FURNITURE+RADIO.TV+EDUCATION, data=gc.train, family="binomial")
> logit
```

```
Call: glm(formula = RESPONSE ~ CHK_ACCT + DURATION + HISTORY + NEW_CAR +
  USED_CAR + FURNITURE + RADIO.TV + EDUCATION + RETRAINING +
  AMOUNT + SAV_ACCT + EMPLOYMENT + INSTALL_RATE + MALE_DIV +
  MALE_SINGLE + MALE_MAR_or_WID + CO.APPLICANT + GUARANTOR +
  PRESENT_RESIDENT + REAL_ESTATE + PROP_UNKN_NONE + AGE + OTHER_INSTALL +
  RENT + OWN_RES + NUM_CREDITS + JOB + NUM_DEPENDENTS + TELEPHONE +
  FOREIGN, family = binomial("logit"), data = gc.train)
```

Coefficients:

(Intercept)	CHK_ACCT1	CHK_ACCT2	CHK_ACCT3
1.9382673	0.5023131	1.3497380	1.9452021
DURATION	HISTORY1	HISTORY2	HISTORY3
-0.0276555	-0.2593253	0.3418115	0.5251609
HISTORY4	NEW_CAR	USED_CAR	FURNITURE
1.4275518	-0.6117829	0.3965193	0.1576746
RADIO.TV	EDUCATION	RETRAINING	AMOUNT
0.4949101	-0.1705930	-0.0767318	-0.0001219
SAV_ACCT1	SAV_ACCT2	SAV_ACCT3	SAV_ACCT4
0.8681562	0.7210853	1.1493753	1.2641500
EMPLOYMENT1	EMPLOYMENT2	EMPLOYMENT3	EMPLOYMENT4
0.1620601	0.4523329	1.3759836	0.6672299
INSTALL_RATE	MALE_DIV	MALE_SINGLE	MALE_MAR_or_WID
-0.3684956	-0.3868091	0.4472375	0.2917269
CO.APPLICANT	GUARANTOR	PRESENT_RESIDENT	REAL_ESTATE
-0.6288904	1.1317737	-0.1494562	0.0599302
PROP_UNKN_NONE	AGE	OTHER_INSTALL	RENT
-0.8477059	0.0153764	-0.6176907	-0.7773178
OWN_RES	NUM_CREDITS	JOB1	JOB2
-0.5930748	-0.1931763	-0.4742573	-0.7608312
JOB3	NUM_DEPENDENTS	TELEPHONE	FOREIGN
-0.3479994	-0.2218640	0.5463572	2.8128361

Degrees of Freedom: 599 Total (i.e. Null); 556 Residual

Null Deviance: 738

Residual Deviance: 516.1 AIC: 604.1

> summary(logit)

Call:

```
glm(formula = RESPONSE ~ CHK_ACCT + DURATION + HISTORY + NEW_CAR +
  USED_CAR + FURNITURE + RADIO.TV + EDUCATION + RETRAINING +
  AMOUNT + SAV_ACCT + EMPLOYMENT + INSTALL_RATE + MALE_DIV +
  MALE_SINGLE + MALE_MAR_or_WID + CO.APPLICANT + GUARANTOR +
  PRESENT_RESIDENT + REAL_ESTATE + PROP_UNKN_NONE + AGE + OTHER_INSTALL +
  RENT + OWN_RES + NUM_CREDITS + JOB + NUM_DEPENDENTS + TELEPHONE +
  FOREIGN, family = binomial("logit"), data = gc.train)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.6286	-0.6632	0.3267	0.6882	2.3683

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	1.9382673	1.4776338	1.312	0.189609
CHK_ACCT1	0.5023131	0.2868664	1.751	0.079940 .
CHK_ACCT2	1.3497380	0.4836687	2.791	0.005261 **
CHK_ACCT3	1.9452021	0.3192069	6.094	1.1e-09 ***
DURATION	-0.0276555	0.0124606	-2.219	0.026457 *
HISTORY1	-0.2593253	0.7520851	-0.345	0.730238
HISTORY2	0.3418115	0.5779081	0.591	0.554210
HISTORY3	0.5251609	0.6465567	0.812	0.416652
HISTORY4	1.4275518	0.6074964	2.350	0.018779 *
NEW_CAR	-0.6117829	0.4710751	-1.299	0.194049
USED_CAR	0.3965193	0.5901390	0.672	0.501642
FURNITURE	0.1576746	0.4957144	0.318	0.750428
RADIO_TV	0.4949101	0.4771533	1.037	0.299636
EDUCATION	-0.1705930	0.6203380	-0.275	0.783316
RETRAINING	-0.0767318	0.5454558	-0.141	0.888127
AMOUNT	-0.0001219	0.0000594	-2.053	0.040091 *
SAV_ACCT1	0.8681562	0.3898857	2.227	0.025968 *
SAV_ACCT2	0.7210853	0.5510039	1.309	0.190644
SAV_ACCT3	1.1493753	0.6084248	1.889	0.058878 .
SAV_ACCT4	1.2641500	0.3468265	3.645	0.000267 ***
EMPLOYMENT1	0.1620601	0.6197901	0.261	0.793726
EMPLOYMENT2	0.4523329	0.5973562	0.757	0.448915
EMPLOYMENT3	1.3759836	0.6467280	2.128	0.033370 *
EMPLOYMENT4	0.6672299	0.5917302	1.128	0.259492
INSTALL_RATE	-0.3684956	0.1254429	-2.938	0.003308 **
MALE_DIV	-0.3868091	0.5679873	-0.681	0.495861
MALE_SINGLE	0.4472375	0.2796380	1.599	0.109744
MALE_MAR_or_WID	0.2917269	0.4283643	0.681	0.495855
CO.APPLICANT	-0.6288904	0.5098314	-1.234	0.217379
GUARANTOR	1.1317737	0.5825667	1.943	0.052048 .
PRESENT_RESIDENT	-0.1494562	0.1192233	-1.254	0.209994
REAL_ESTATE	0.0599302	0.2879804	0.208	0.835147
PROP_UNKN_NONE	-0.8477059	0.5776286	-1.468	0.142223
AGE	0.0153764	0.0119257	1.289	0.197275
OTHER_INSTALL	-0.6176907	0.2814590	-2.195	0.028192 *
RENT	-0.7773178	0.6646814	-1.169	0.242219
OWN_RES	-0.5930749	0.6382663	-0.929	0.352787
NUM_CREDITS	-0.1931763	0.2533597	-0.762	0.445786
JOB1	-0.4742573	0.8666457	-0.547	0.584219

JOB2	-0.7608312	0.8284276	-0.918	0.358407
JOB3	-0.3479994	0.8215027	-0.424	0.671848
NUM_DEPENDENTS	-0.2218640	0.3296838	-0.673	0.500973
TELEPHONE	0.5463572	0.2722419	2.007	0.044762 *
FOREIGN	2.8128361	1.1654728	2.413	0.015801 *

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 738.05 on 599 degrees of freedom  
 Residual deviance: 516.08 on 556 degrees of freedom  
 AIC: 604.08

Number of Fisher Scoring iterations: 6

> confint(logit)

	2.5 %	97.5 %
(Intercept)	-0.9483086330	4.863639e+00
CHK_ACCT1	-0.0578207835	1.068824e+00
CHK_ACCT2	0.4378136712	2.350091e+00
CHK_ACCT3	1.3330469901	2.587685e+00
DURATION	-0.0522896603	-3.314751e-03
HISTORY1	-1.7402640699	1.223633e+00
HISTORY2	-0.7808915320	1.504650e+00
HISTORY3	-0.7256874803	1.825148e+00
HISTORY4	0.2565070787	2.656288e+00
NEW_CAR	-1.5571580335	2.974326e-01
USED_CAR	-0.7578591898	1.565918e+00
FURNITURE	-0.8287903738	1.122608e+00
RADIO_TV	-0.4569724061	1.422208e+00
EDUCATION	-1.3959785104	1.045972e+00
RETRAINING	-1.1572272270	9.894845e-01
AMOUNT	-0.0002399121	-6.296406e-06
SAV_ACCT1	0.1201717191	1.653509e+00
SAV_ACCT2	-0.2962365829	1.891110e+00
SAV_ACCT3	0.0224850597	2.440544e+00
SAV_ACCT4	0.6034520555	1.967469e+00
EMPLOYMENT1	-1.0576078319	1.383995e+00
EMPLOYMENT2	-0.7198677682	1.633857e+00
EMPLOYMENT3	0.1169650710	2.664044e+00
EMPLOYMENT4	-0.4959761843	1.834425e+00
INSTALL_RATE	-0.6188734195	-1.261201e-01
MALE_DIV	-1.4930941050	7.473492e-01
MALE_SINGLE	-0.1006843166	9.977084e-01

MALE_MAR_or_WID	-0.5325003697	1.155354e+00
CO.APPLICANT	-1.6384002108	3.774832e-01
GUARANTOR	0.0533049350	2.374182e+00
PRESENT_RESIDENT	-0.3847713927	8.363036e-02
REAL_ESTATE	-0.5023666600	6.291340e-01
PROP_UNKN_NONE	-1.9879964697	2.860277e-01
AGE	-0.0077129936	3.914491e-02
OTHER_INSTALL	-1.1706848175	-6.451552e-02
RENT	-2.0954129284	5.165607e-01
OWN_RES	-1.8648210754	6.464762e-01
NUM_CREDITS	-0.6927616526	3.028382e-01
JOB1	-2.1958101803	1.234842e+00
JOB2	-2.4111794352	8.720063e-01
JOB3	-1.9856813573	1.268323e+00
NUM_DEPENDENTS	-0.8654599921	4.310456e-01
TELEPHONE	0.0180926715	1.087650e+00
FOREIGN	0.9137954618	5.869858e+00

> residuals(logit)

	3	7	8	9	11	12
	0.16418010	0.38743896	0.88183793	0.16138331	-0.79806588	-0.34783101
	14	17	18	21	23	26
-1.27817393	0.18993479	1.91211963	0.47009851	0.24084261	0.66508158	
	27	28	29	30	31	33
0.46612077	0.56632233	0.45196101	-0.50626160	0.86255313	0.88515134	
	34	35	36	37	38	39
0.25407197	0.82795004	-1.21375613	0.62542921	-1.22484012	0.41397534	
	40	41	42	43	44	45
0.93169606	0.46806015	0.63093058	0.84193263	0.51087077	-0.67149662	
	47	51	55	57	58	59
0.49474831	0.92723575	-0.69986926	-2.11506595	0.80617703	0.95772000	
	61	62	63	64	65	66
0.86888228	0.14056573	-1.19715252	-0.58020034	0.81347650	0.53626890	
	67	68	69	70	71	72
0.69149104	0.92964847	-1.23700996	0.58120364	0.97603122	0.08928786	
	73	74	75	77	78	79
0.75778204	0.86492679	-1.23621285	-0.65529291	0.48560410	0.59023426	
	82	84	86	88	89	91
0.31894771	0.74325594	0.18638107	-1.13665340	0.75973216	0.23294774	
	92	94	96	97	98	100
0.61423719	0.87604452	-0.24028419	0.14146960	1.03768538	0.53804572	
	101	102	103	106	108	109
0.62053161	1.10790167	0.43053256	-1.26732506	0.93236258	0.22733145	
	110	111	112	113	114	115
0.39063804	0.89703985	1.16314516	1.17626016	-1.10867082	0.63683688	

116	118	119	120	121	122
0.15956435	0.21663286	-1.47975769	0.39036034	-1.19742448	0.32575020
123	125	126	127	128	131
0.48225038	-1.27801048	1.26805930	0.96544487	-1.25979820	1.02044056
134	135	136	137	138	139
1.02914582	0.52959194	0.13391115	0.40215164	-2.12305620	0.15365805
140	141	143	145	146	149
0.39035052	0.08537530	1.10778951	0.54541784	1.19740625	0.80234167
151	153	155	156	157	158
0.26043147	1.05608187	0.61907344	-0.94353693	0.07784126	1.51549140
159	160	161	162	163	164
0.74644018	0.08634070	0.16911524	0.75458797	0.25418888	1.39146749
165	166	169	171	175	176
0.77286307	0.18342711	0.44690093	-0.53470996	-0.95686950	-1.78526898
179	181	182	184	185	186
0.27355059	-1.13309268	-0.89075949	0.19747089	-1.25684083	0.33268185
188	189	190	191	192	193
0.35667671	-1.98153451	1.32263712	-2.62865356	-1.07373046	-1.05997863
194	198	200	201	204	205
0.24613905	-0.69903817	-0.94197597	0.17050405	-1.09532798	0.41218709
206	207	208	209	210	213
1.19435880	0.30336066	0.52938651	1.76910644	0.03202403	-0.58389118
214	216	218	219	220	221
-2.05470585	0.16127266	0.57751285	1.53149790	0.49221629	0.72852244
222	224	226	228	233	234
1.34904479	0.43478980	1.11484024	-1.15207256	0.24571077	0.56901357
236	237	241	244	245	246
-0.73492128	-1.69533505	-0.82978916	0.43322951	0.78580515	0.35154016
247	248	250	251	252	255
0.29203656	0.30634876	-1.29945450	0.33383713	0.46039825	0.21129086
257	258	259	262	263	264
0.33305966	-0.61885831	0.32143737	1.35663790	0.97676200	0.51789630
265	266	267	270	271	272
0.10748130	-1.41134690	0.41115184	0.31745964	0.09067402	0.14704807
273	274	277	285	286	287
2.36830510	-1.11710084	0.33226082	1.03821359	1.90325825	1.58674787
288	290	292	294	295	296
1.13248427	-0.77905962	-1.16104627	0.71111647	0.76909214	-0.81555471
297	299	302	303	304	306
0.39074950	0.44274313	-1.06436524	-2.35336286	0.80500895	0.44358480
307	309	310	311	314	315
0.37935035	-1.16766978	1.48902854	1.14034256	-1.40554219	0.08827811
316	317	321	323	324	325
-0.42456482	0.56723104	-0.90118492	0.49138842	0.95316407	0.70750161
327	328	329	330	331	332
0.12676987	0.40781455	0.92294935	0.98792956	0.69424798	-2.28003053

333	334	337	338	341	342
-0.47574329	-1.55029430	0.63701916	-1.20693914	1.23766863	0.95025427
343	344	345	348	350	351
0.71395464	0.87085899	0.42728549	1.08401390	-1.93496707	0.49721657
354	355	357	359	361	365
-0.89895599	0.36359816	0.08747561	0.50706995	0.80203951	-1.10964313
366	367	369	370	371	373
0.25025188	0.21438429	-0.79784752	0.84744380	0.73239990	0.38910242
375	376	381	382	384	386
-0.41651368	-0.83527290	0.50205179	-0.76317879	1.09348863	0.30818599
387	389	391	394	396	397
0.35816812	0.66177881	0.44693745	0.38339510	1.16633133	1.47496187
398	400	401	402	403	406
0.83557445	0.19230992	0.45189381	0.82232714	-1.42648560	-1.80756757
408	409	411	412	413	414
0.41047036	0.33550169	1.15453116	0.20374057	-2.19817736	0.18584591
415	418	419	420	421	422
-0.99282875	0.94877792	0.37380913	-1.27556167	0.39635336	0.58385245
423	428	429	431	432	433
0.43077428	0.18133394	0.36760207	0.17580689	-0.67836890	0.93254920
434	435	437	439	440	442
0.54281357	1.13568416	0.21246230	1.46958171	-1.41185464	1.51294777
445	446	448	450	451	452
-1.61860890	0.26003740	0.37959578	-1.64963525	0.25542841	0.41170185
454	455	457	458	460	461
0.41602697	-1.04498508	1.14254815	-1.35306425	0.47242804	0.81113477
463	464	465	470	471	472
1.09794402	0.69811449	0.48018900	0.27593575	-1.65921863	-0.65326398
474	476	478	479	483	484
0.30126505	-0.74522663	0.83272884	0.41422238	1.09882067	0.22602770
485	486	488	489	491	492
0.27069296	-1.31992333	1.20543428	0.10121052	0.32622448	-0.90670733
495	496	499	500	504	505
0.30430107	-1.44974916	0.50188025	0.42010725	-1.13173929	-0.37192082
506	510	511	513	515	517
-2.59570506	0.38074154	-1.17103727	0.43881637	0.50711803	0.24631658
518	519	520	521	522	524
-1.70395823	0.67218856	0.17268538	0.54125335	-1.16243995	0.36802689
525	526	528	530	531	532
0.82197791	1.43526599	0.10194763	1.23736460	1.08742450	-1.28576459
533	535	537	538	540	541
0.57943510	0.45828981	0.78472506	0.66460061	0.74046724	-1.69032014
548	549	551	554	555	556
0.43318754	-0.62755633	0.20244093	0.73158246	0.62096495	-1.37689289
559	560	562	563	564	565
-0.75419099	-1.94471986	-1.30257431	0.66581727	-1.15770634	0.79498898



566	567	573	576	578	579
0.45823436	-1.07633938	0.37296552	0.48870006	0.22704287	-0.52146438
580	581	582	583	584	586
0.89121939	-1.73925359	0.92247748	0.74147748	-0.62754968	-0.78270506
588	590	591	595	601	602
0.72655770	-1.81751894	0.42240933	-1.39286285	0.38618126	-1.22036339
603	605	608	609	611	612
-0.66252914	1.04112698	-0.90578040	0.56436667	-0.92520614	-2.03617258
613	615	616	617	618	619
1.44823353	-2.15962965	1.18305917	0.92898066	1.05698933	-0.94197492
620	622	623	624	625	626
0.85175047	-1.81015443	-1.24529016	1.70935345	-1.00133217	0.25136629
628	629	632	633	634	635
-1.38713020	0.38574712	-0.61107740	0.62864087	-1.41168833	-0.87918749
636	639	641	649	651	652
0.83662574	0.79904194	-0.92173888	-1.11892820	1.27448954	-1.43468353
653	656	661	662	663	664
-0.65471128	1.80366833	0.74632470	-1.19731095	0.56945536	0.94650193
665	675	679	682	683	687
0.36855466	-1.78348957	1.34115393	0.26993117	0.75224448	0.11116485
688	689	690	691	692	694
1.39247831	0.29663012	0.93192772	1.05609777	0.81737090	0.52584644
695	697	698	699	700	701
0.30626223	0.10488674	0.28781510	0.37449504	0.64166696	-1.97420657
702	703	704	705	708	710
-1.07018837	0.43692030	1.17126433	1.51378530	-0.60152881	0.61807077
711	713	716	720	722	724
0.18901522	0.19020272	0.15852567	1.13469018	-0.76030022	0.55943485
725	726	728	729	730	731
-1.12754010	0.24807753	-0.51545133	-0.28910753	0.32771115	0.89926661
732	733	734	735	736	737
-1.14702521	0.31905571	0.32235379	0.22402710	1.75854527	-0.86573903
738	741	742	743	748	749
1.14315937	1.29341881	1.43460362	0.23011667	-0.87405183	0.25892045
750	751	753	754	755	760
0.26088749	0.82127676	0.52124073	0.43756740	-2.26548533	-1.22277850
761	762	763	765	767	772
0.16264350	-0.94674051	1.16172305	0.26286001	-0.68318945	-0.72498329
773	774	775	776	778	779
0.14007626	0.31146821	0.46434721	-0.78246885	0.66126840	0.18240384
782	784	786	787	790	792
0.21552038	-0.87879487	0.54058838	0.34967221	-0.51870461	0.24848690
793	795	796	797	798	801
0.11894946	0.63567448	0.51967567	-2.31479624	0.43940280	0.57494422
806	807	810	813	814	815
-1.02303876	0.21780879	-0.99203375	-1.30598893	-0.73791851	-0.52180889

816	817	818	822	823	824
1.73509443	0.31774577	0.12011733	0.63058520	-0.86582214	0.93790727
825	827	829	830	831	832
0.41354409	-1.02486357	-1.19405046	1.29663163	0.44443527	-0.55538188
833	834	835	838	841	842
-0.35297381	0.50067271	-1.78454093	0.48766565	-0.98850566	0.61992941
843	844	846	847	850	852
-1.27453093	0.67187509	0.29801587	-2.07077514	-1.27898361	0.10592325
854	855	856	857	858	859
-0.63037047	0.93234965	0.63056172	0.19530659	0.35612416	-0.80588539
860	861	868	870	873	874
0.06185781	0.29323844	0.34873352	1.60366807	0.38428740	0.46574408
876	877	878	879	881	883
0.80047833	1.80554876	0.69755071	-1.09443491	0.30433291	0.75185910
884	885	887	888	891	892
0.32720238	-1.46540658	0.50723887	-0.62382360	1.29855954	0.24365319
893	894	896	898	899	900
0.48314249	0.83828788	0.27869852	0.03091816	0.22559449	-0.93378703
901	902	904	905	906	909
-1.86218540	0.35264343	0.22767584	0.28331882	0.68708476	0.40134092
910	916	917	918	921	922
0.58836347	-1.40866965	0.30711153	-0.66532165	0.77484353	0.36040591
926	927	928	929	931	932
-0.54309775	1.45943060	-0.44587276	0.22777702	0.60164468	-1.32021278
933	934	937	939	940	941
0.39629580	0.17405423	-1.99412987	-0.42392682	0.14710558	0.28268214
943	946	947	949	950	952
0.23719309	1.91236353	-0.72097136	-1.55596822	-2.38228069	-1.62949011
955	957	958	959	960	963
1.24553553	0.36032367	0.39469877	-0.82959466	1.07299372	0.67787799
966	967	969	971	972	973
0.80437966	-1.99149693	0.26638332	0.51849902	0.81262513	-0.29331507
974	976	984	985	986	988
-0.17431474	0.43273105	-0.77474869	0.17856783	1.30631820	0.31214321
990	991	993	995	998	999
0.53024466	0.18749295	0.47344358	0.31284069	0.46981155	-0.79483979

>

## Using the model with the test data

The test data is then run through the model

```
> p.test <- predict(logit, gc.test, type="response")
> summary(p.test)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.02806	0.49540	0.81520	0.69740	0.93130	0.99930

## Classification Table

A baseline Classification Table with cutoff = 50% is given

```
> library(gmodels)
> p.test.vals <- sapply(p.test, function(y) { ifelse(y<.5,0, 1) })
> CrossTable(gc.test$RESPONSE, p.test.vals, dnn = c("Actual", "Predicted"))
```

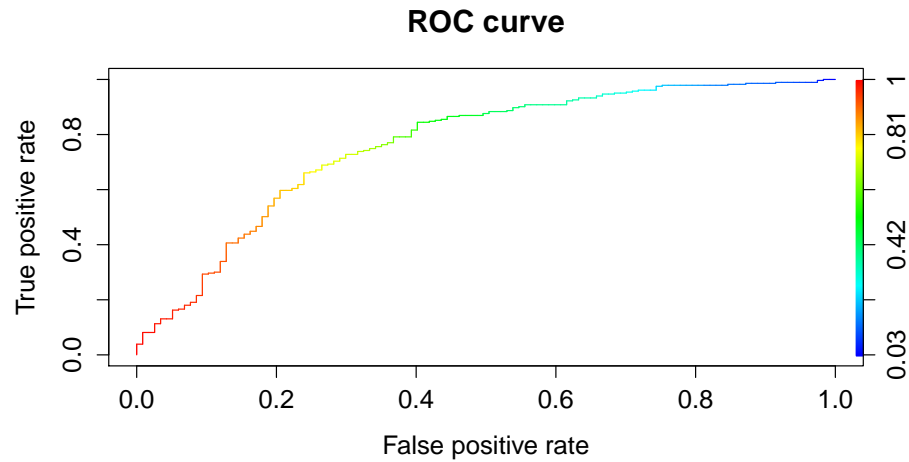
Cell Contents	
	-----
	N
Chi-square contribution	
N / Row Total	
N / Col Total	
N / Table Total	
	-----

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	
0	62	55	117
	35.660	12.046	
	0.530	0.470	0.292
	0.614	0.184	
	0.155	0.138	
1	39	244	283
	14.743	4.980	
	0.138	0.862	0.708
	0.386	0.816	
	0.098	0.610	
Column Total	101	299	400
	0.253	0.748	

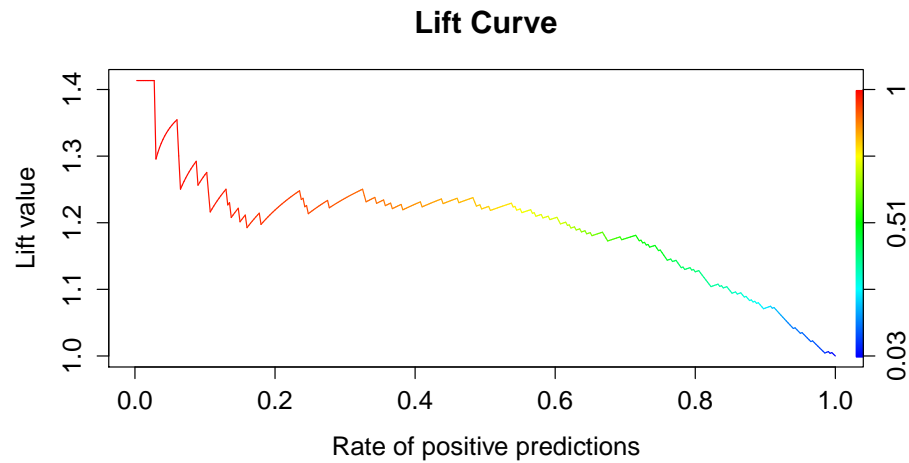
## ROC Curve

```
> library(ROCR)
> p.rocr <- prediction(p.test, gc.test$RESPONSE)
> p.rocr.roc <- performance(p.rocr, "tpr", "fpr")
> plot(p.rocr.roc, main="ROC Curve", colorize=T)
```



### Lift Curve

```
> p.rocr.lift <- performance(p.rocr, "lift", "rpp")
> plot(p.rocr.lift, main="Lift Curve", colorize=T)
```



### 0.1 Classification Table with different cutoff values

```
> calcNetProfit <- function(facts, preds, cutoff) {
+   vals <- sapply(preds, function(y) { ifelse(y<cutoff,0, 1) })
+   ct <- CrossTable(facts, vals, dnn = c("Actual", "Predicted"))
+   print("Profit with cutoff")
+   print(cutoff)
+ }
```

```

+   profitFromCrossTable(ct)
+ }
> profitFromCrossTable <- function(ct) {
+   profit <- ct$t[1,1] * 100
+   loss <- ct$t[2,1] * -500
+   profit - loss
+ }
> s <- seq(0,1, by = .1)
> for(i in s) { print(calcNetProfit(gc.test$RESPONSE, p.test, i)) }

```

```

      Cell Contents
|-----|
|              N |
|      N / Table Total |
|-----|

```

Total Observations in Table: 400

	vals	
facts	1	Row Total
0	117	117
	0.292	
1	283	283
	0.708	
Column Total	400	400

```

[1] "Profit with cutoff"
[1] 0
[1] 153200

```

```

      Cell Contents
|-----|
|              N |
| Chi-square contribution |
|      N / Row Total |
|      N / Col Total |
|      N / Table Total |
|-----|

```

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	
0	6	111	117
	7.630	0.136	
	0.051	0.949	0.292
	0.857	0.282	
	0.015	0.278	
1	1	282	283
	3.154	0.056	
	0.004	0.996	0.708
	0.143	0.718	
	0.003	0.705	
Column Total	7	393	400
	0.018	0.983	

[1] "Profit with cutoff"

[1] 0.1

[1] 1100

#### Cell Contents

N
Chi-square contribution
N / Row Total
N / Col Total
N / Table Total

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	

0	21	96	117
	25.620	1.708	
	0.179	0.821	0.292
	0.840	0.256	
	0.052	0.240	
-----			
1	4	279	283
	10.592	0.706	
	0.014	0.986	0.708
	0.160	0.744	
	0.010	0.698	
-----			
Column Total	25	375	400
	0.062	0.938	
-----			

[1] "Profit with cutoff"  
[1] 0.2  
[1] 4100

Cell Contents	
	N
Chi-square contribution	
N / Row Total	
N / Col Total	
N / Table Total	

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	
0	38	79	117
	29.847	4.758	
	0.325	0.675	0.292
	0.691	0.229	
	0.095	0.198	
1	17	266	283
	12.339	1.967	

	0.060	0.940	0.708
	0.309	0.771	
	0.043	0.665	
-----			
Column Total	55	345	400
	0.138	0.863	
-----			

[1] "Profit with cutoff"  
[1] 0.3  
[1] 12300

Cell Contents	
	-----
	N
Chi-square contribution	
N / Row Total	
N / Col Total	
N / Table Total	
	-----

Total Observations in Table: 400

	Predicted		
Actual	0	1	Row Total
-----			
0	49	68	117
	28.007	7.002	
	0.419	0.581	0.292
	0.613	0.212	
	0.122	0.170	
-----			
1	31	252	283
	11.579	2.895	
	0.110	0.890	0.708
	0.388	0.787	
	0.077	0.630	
-----			
Column Total	80	320	400
	0.200	0.800	
-----			



```
[1] "Profit with cutoff"
[1] 0.4
[1] 20400
```

Cell Contents

	N
Chi-square contribution	
N / Row Total	
N / Col Total	
N / Table Total	

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	
----- ----- ----- -----			
0	62	55	117
	35.660	12.046	
	0.530	0.470	0.292
	0.614	0.184	
	0.155	0.138	
----- ----- ----- -----			
1	39	244	283
	14.743	4.980	
	0.138	0.862	0.708
	0.386	0.816	
	0.098	0.610	
----- ----- ----- -----			
Column Total	101	299	400
	0.253	0.748	
----- ----- ----- -----			

```
[1] "Profit with cutoff"
[1] 0.5
[1] 25700
```

Cell Contents

--	--

	N
Chi-square contribution	
N / Row Total	
N / Col Total	
N / Table Total	
-----	

Total Observations in Table: 400

	Predicted		
Actual	0	1	Row Total
-----			
0	75	42	117
	31.938	16.270	
	0.641	0.359	0.292
	0.556	0.158	
	0.188	0.105	
-----			
1	60	223	283
	13.204	6.727	
	0.212	0.788	0.708
	0.444	0.842	
	0.150	0.557	
-----			
Column Total	135	265	400
	0.338	0.662	
-----			

[1] "Profit with cutoff"  
[1] 0.6  
[1] 37500

Cell Contents	
-----	
	N
Chi-square contribution	
N / Row Total	
N / Col Total	
N / Table Total	
-----	

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	
0	83	34	117
	27.379	18.444	
	0.709	0.291	0.292
	0.516	0.142	
	0.207	0.085	
1	78	205	283
	11.319	7.625	
	0.276	0.724	0.708
	0.484	0.858	
	0.195	0.512	
Column Total	161	239	400
	0.403	0.598	

[1] "Profit with cutoff"

[1] 0.7

[1] 47300

#### Cell Contents

N
Chi-square contribution
N / Row Total
N / Col Total
N / Table Total

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	
0	90	27	117
	19.936	18.588	

		0.769	0.231	0.292
		0.466	0.130	
		0.225	0.068	
-----				
1	103	180	283	
	8.242	7.685		
	0.364	0.636	0.708	
	0.534	0.870		
	0.258	0.450		
-----				
Column Total	193	207	400	
	0.482	0.517		
-----				

[1] "Profit with cutoff"  
[1] 0.8  
[1] 60500

Cell Contents	
-----	
	N
Chi-square contribution	
N / Row Total	
N / Col Total	
N / Table Total	
-----	

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	
-----			
0	103	14	117
	7.516	15.433	
	0.880	0.120	0.292
	0.383	0.107	
	0.258	0.035	
-----			
1	166	117	283
	3.107	6.380	
	0.587	0.413	0.708
	0.617	0.893	

	0.415	0.292	
Column Total	269	131	400
	0.672	0.328	

```
[1] "Profit with cutoff"
[1] 0.9
[1] 93300
```

Cell Contents
N
N / Table Total

Total Observations in Table: 400

facts	vals	
	0	Row Total
0	117	117
	0.292	
1	283	283
	0.708	
Column Total	400	400

```
[1] "Profit with cutoff"
[1] 1
[1] 153200
```

## Neural Network

A Neural Network model is now fit to the train data.

```
> library(nnet)
> nn <- nnet(RESPONSE ~ CHK_ACCT+DURATION+HISTORY+NEW_CAR+USED_CAR+FURNITURE+RADIO.TV+EDUCAT
```

```
# weights: 901
initial value 389.905872
iter 10 value 369.026034
iter 20 value 368.813672
iter 30 value 359.861220
iter 40 value 335.341464
iter 50 value 276.665377
final value 276.665377
stopped after 50 iterations
```

```
> nn
```

```
a 43-20-1 network with 901 weights
```

```
inputs: CHK_ACCT1 CHK_ACCT2 CHK_ACCT3 DURATION HISTORY1 HISTORY2 HISTORY3 HISTORY4 NEW_CAR U
```

```
output(s): RESPONSE
```

```
options were - entropy fitting decay=5e-04
```

```
> summary(nn)
```

```
a 43-20-1 network with 901 weights
```

```
options were - entropy fitting decay=5e-04
```

```

b->h1 i1->h1 i2->h1 i3->h1 i4->h1 i5->h1 i6->h1 i7->h1 i8->h1 i9->h1
0.05 0.05 0.04 -0.08 0.04 -0.02 -0.08 0.07 -0.07 0.00
i10->h1 i11->h1 i12->h1 i13->h1 i14->h1 i15->h1 i16->h1 i17->h1 i18->h1 i19->h1
0.03 -0.07 0.03 0.09 0.03 -0.08 -0.08 0.09 0.08 -0.07
i20->h1 i21->h1 i22->h1 i23->h1 i24->h1 i25->h1 i26->h1 i27->h1 i28->h1 i29->h1
0.02 -0.05 -0.08 -0.03 -0.07 0.01 0.08 0.02 0.00 0.02
i30->h1 i31->h1 i32->h1 i33->h1 i34->h1 i35->h1 i36->h1 i37->h1 i38->h1 i39->h1
0.06 -0.07 -0.09 0.02 0.04 0.03 -0.01 0.04 -0.01 -0.06
i40->h1 i41->h1 i42->h1 i43->h1
0.07 0.05 0.04 0.02
b->h2 i1->h2 i2->h2 i3->h2 i4->h2 i5->h2 i6->h2 i7->h2 i8->h2 i9->h2
-0.07 -0.02 0.04 -0.01 0.04 -0.07 -0.04 0.08 0.06 -0.04
i10->h2 i11->h2 i12->h2 i13->h2 i14->h2 i15->h2 i16->h2 i17->h2 i18->h2 i19->h2
-0.03 -0.07 0.08 -0.02 0.06 0.08 0.04 -0.03 -0.01 -0.05
i20->h2 i21->h2 i22->h2 i23->h2 i24->h2 i25->h2 i26->h2 i27->h2 i28->h2 i29->h2
0.00 -0.06 0.00 0.06 -0.08 0.04 0.09 0.08 0.06 -0.03
i30->h2 i31->h2 i32->h2 i33->h2 i34->h2 i35->h2 i36->h2 i37->h2 i38->h2 i39->h2
0.06 -0.06 -0.09 0.02 0.00 0.02 0.00 0.05 -0.06 -0.02
i40->h2 i41->h2 i42->h2 i43->h2
0.04 0.02 -0.02 -0.05
b->h3 i1->h3 i2->h3 i3->h3 i4->h3 i5->h3 i6->h3 i7->h3 i8->h3 i9->h3
0.09 0.07 0.04 -0.02 -0.08 0.08 -0.03 0.00 0.09 0.05
i10->h3 i11->h3 i12->h3 i13->h3 i14->h3 i15->h3 i16->h3 i17->h3 i18->h3 i19->h3
0.06 0.02 -0.04 -0.02 -0.09 -0.08 -0.04 0.07 -0.06 -0.01
i20->h3 i21->h3 i22->h3 i23->h3 i24->h3 i25->h3 i26->h3 i27->h3 i28->h3 i29->h3
-0.02 -0.05 -0.02 -0.09 -0.02 0.07 0.05 0.07 -0.08 0.07
```

i30->h3	i31->h3	i32->h3	i33->h3	i34->h3	i35->h3	i36->h3	i37->h3	i38->h3	i39->h3
0.04	-0.04	-0.06	-0.09	0.02	-0.02	-0.03	0.09	0.06	0.05
i40->h3	i41->h3	i42->h3	i43->h3						
0.06	-0.04	0.00	-0.03						
b->h4	i1->h4	i2->h4	i3->h4	i4->h4	i5->h4	i6->h4	i7->h4	i8->h4	i9->h4
0.03	0.08	-0.04	0.05	-0.03	-0.06	0.06	0.04	0.00	0.06
i10->h4	i11->h4	i12->h4	i13->h4	i14->h4	i15->h4	i16->h4	i17->h4	i18->h4	i19->h4
0.01	-0.02	0.00	-0.09	0.08	0.07	-0.06	-0.09	0.04	0.02
i20->h4	i21->h4	i22->h4	i23->h4	i24->h4	i25->h4	i26->h4	i27->h4	i28->h4	i29->h4
0.09	-0.04	0.03	-0.04	-0.04	0.09	0.02	0.02	0.04	-0.07
i30->h4	i31->h4	i32->h4	i33->h4	i34->h4	i35->h4	i36->h4	i37->h4	i38->h4	i39->h4
-0.07	0.01	-0.09	0.09	0.04	0.01	-0.07	0.04	-0.07	0.02
i40->h4	i41->h4	i42->h4	i43->h4						
0.00	0.06	-0.02	0.07						
b->h5	i1->h5	i2->h5	i3->h5	i4->h5	i5->h5	i6->h5	i7->h5	i8->h5	i9->h5
0.03	-0.08	0.08	-0.07	-0.09	-0.05	-0.06	-0.01	0.05	-0.02
i10->h5	i11->h5	i12->h5	i13->h5	i14->h5	i15->h5	i16->h5	i17->h5	i18->h5	i19->h5
0.05	-0.03	0.07	0.03	0.08	0.06	0.02	0.06	0.01	0.08
i20->h5	i21->h5	i22->h5	i23->h5	i24->h5	i25->h5	i26->h5	i27->h5	i28->h5	i29->h5
-0.04	0.07	0.05	-0.07	-0.04	0.03	0.01	0.02	-0.09	0.01
i30->h5	i31->h5	i32->h5	i33->h5	i34->h5	i35->h5	i36->h5	i37->h5	i38->h5	i39->h5
0.08	-0.01	0.04	0.07	-0.02	-0.05	-0.01	-0.06	0.09	-0.03
i40->h5	i41->h5	i42->h5	i43->h5						
0.04	0.00	0.09	0.07						
b->h6	i1->h6	i2->h6	i3->h6	i4->h6	i5->h6	i6->h6	i7->h6	i8->h6	i9->h6
-0.04	-0.05	-0.03	0.03	-0.01	0.03	0.09	0.04	-0.07	0.03
i10->h6	i11->h6	i12->h6	i13->h6	i14->h6	i15->h6	i16->h6	i17->h6	i18->h6	i19->h6
-0.07	-0.04	0.03	0.07	0.05	-0.06	0.02	-0.07	0.00	0.08
i20->h6	i21->h6	i22->h6	i23->h6	i24->h6	i25->h6	i26->h6	i27->h6	i28->h6	i29->h6
0.00	-0.08	-0.02	-0.09	-0.04	0.00	0.08	0.08	0.03	0.08
i30->h6	i31->h6	i32->h6	i33->h6	i34->h6	i35->h6	i36->h6	i37->h6	i38->h6	i39->h6
0.04	-0.01	-0.07	-0.06	0.03	0.03	-0.02	0.05	-0.03	0.02
i40->h6	i41->h6	i42->h6	i43->h6						
0.05	0.01	0.05	0.05						
b->h7	i1->h7	i2->h7	i3->h7	i4->h7	i5->h7	i6->h7	i7->h7	i8->h7	i9->h7
1.08	1.37	0.11	0.24	4.57	-0.22	0.46	-0.95	1.41	0.91
i10->h7	i11->h7	i12->h7	i13->h7	i14->h7	i15->h7	i16->h7	i17->h7	i18->h7	i19->h7
2.12	-1.44	0.26	-0.23	-0.34	-0.02	-0.04	-0.01	0.03	-0.39
i20->h7	i21->h7	i22->h7	i23->h7	i24->h7	i25->h7	i26->h7	i27->h7	i28->h7	i29->h7
-0.32	-0.91	2.53	-0.15	1.04	-0.02	0.61	0.13	-0.05	0.16
i30->h7	i31->h7	i32->h7	i33->h7	i34->h7	i35->h7	i36->h7	i37->h7	i38->h7	i39->h7
0.63	0.15	-1.64	1.80	-1.12	0.65	2.19	2.37	0.20	1.20
i40->h7	i41->h7	i42->h7	i43->h7						
-0.01	2.32	-2.07	0.13						
b->h8	i1->h8	i2->h8	i3->h8	i4->h8	i5->h8	i6->h8	i7->h8	i8->h8	i9->h8
0.06	0.07	-0.04	-0.02	0.06	-0.01	0.07	0.05	0.08	0.06

i10->h8	i11->h8	i12->h8	i13->h8	i14->h8	i15->h8	i16->h8	i17->h8	i18->h8	i19->h8
0.09	-0.05	0.01	0.01	-0.04	-0.06	0.04	0.03	0.07	0.00
i20->h8	i21->h8	i22->h8	i23->h8	i24->h8	i25->h8	i26->h8	i27->h8	i28->h8	i29->h8
-0.03	0.06	0.09	0.02	0.00	-0.01	0.01	0.05	0.05	-0.02
i30->h8	i31->h8	i32->h8	i33->h8	i34->h8	i35->h8	i36->h8	i37->h8	i38->h8	i39->h8
0.06	0.08	-0.03	0.09	-0.05	0.09	0.09	0.01	-0.07	0.09
i40->h8	i41->h8	i42->h8	i43->h8						
0.05	-0.08	-0.03	0.09						
b->h9	i1->h9	i2->h9	i3->h9	i4->h9	i5->h9	i6->h9	i7->h9	i8->h9	i9->h9
-0.05	-0.04	-0.05	-0.02	-0.01	0.08	0.05	-0.04	0.06	-0.01
i10->h9	i11->h9	i12->h9	i13->h9	i14->h9	i15->h9	i16->h9	i17->h9	i18->h9	i19->h9
-0.06	-0.02	0.01	0.00	-0.07	0.08	-0.08	0.05	0.08	-0.02
i20->h9	i21->h9	i22->h9	i23->h9	i24->h9	i25->h9	i26->h9	i27->h9	i28->h9	i29->h9
0.07	-0.01	0.05	-0.02	-0.07	0.00	0.06	0.04	0.00	0.06
i30->h9	i31->h9	i32->h9	i33->h9	i34->h9	i35->h9	i36->h9	i37->h9	i38->h9	i39->h9
0.04	0.06	0.07	-0.09	-0.06	0.08	0.09	-0.09	0.00	-0.07
i40->h9	i41->h9	i42->h9	i43->h9						
0.01	-0.06	-0.02	0.09						
b->h10	i1->h10	i2->h10	i3->h10	i4->h10	i5->h10	i6->h10	i7->h10		
0.02	0.01	0.06	-0.06	0.06	-0.07	-0.03	0.04		
i8->h10	i9->h10	i10->h10	i11->h10	i12->h10	i13->h10	i14->h10	i15->h10		
0.09	0.03	-0.07	0.05	-0.09	-0.05	0.06	-0.06		
i16->h10	i17->h10	i18->h10	i19->h10	i20->h10	i21->h10	i22->h10	i23->h10		
0.07	-0.09	-0.04	-0.07	0.07	0.00	0.06	0.09		
i24->h10	i25->h10	i26->h10	i27->h10	i28->h10	i29->h10	i30->h10	i31->h10		
0.00	0.04	-0.08	-0.08	0.08	0.08	-0.01	0.05		
i32->h10	i33->h10	i34->h10	i35->h10	i36->h10	i37->h10	i38->h10	i39->h10		
-0.01	0.00	0.00	-0.06	0.04	-0.04	-0.09	0.02		
i40->h10	i41->h10	i42->h10	i43->h10						
-0.03	0.02	-0.04	-0.01						
b->h11	i1->h11	i2->h11	i3->h11	i4->h11	i5->h11	i6->h11	i7->h11		
-0.05	0.04	0.02	-0.03	-0.03	0.09	-0.03	-0.03		
i8->h11	i9->h11	i10->h11	i11->h11	i12->h11	i13->h11	i14->h11	i15->h11		
0.01	0.07	-0.02	0.02	-0.03	0.06	0.04	0.09		
i16->h11	i17->h11	i18->h11	i19->h11	i20->h11	i21->h11	i22->h11	i23->h11		
-0.03	0.00	-0.07	0.07	-0.03	-0.06	-0.03	-0.06		
i24->h11	i25->h11	i26->h11	i27->h11	i28->h11	i29->h11	i30->h11	i31->h11		
0.09	0.03	0.05	0.01	-0.06	-0.02	0.08	0.07		
i32->h11	i33->h11	i34->h11	i35->h11	i36->h11	i37->h11	i38->h11	i39->h11		
-0.08	-0.07	-0.07	0.01	0.01	0.03	-0.08	-0.01		
i40->h11	i41->h11	i42->h11	i43->h11						
-0.02	0.03	0.05	-0.04						
b->h12	i1->h12	i2->h12	i3->h12	i4->h12	i5->h12	i6->h12	i7->h12		
0.04	0.03	-0.02	-0.09	0.04	-0.05	-0.08	0.00		
i8->h12	i9->h12	i10->h12	i11->h12	i12->h12	i13->h12	i14->h12	i15->h12		
-0.03	-0.05	-0.07	0.02	-0.07	0.06	-0.08	1.42		



i16->h12	i17->h12	i18->h12	i19->h12	i20->h12	i21->h12	i22->h12	i23->h12
0.01	0.06	-0.10	0.05	0.06	-0.05	-0.01	0.07
i24->h12	i25->h12	i26->h12	i27->h12	i28->h12	i29->h12	i30->h12	i31->h12
-0.02	-0.09	0.00	0.06	0.04	0.01	0.00	0.02
i32->h12	i33->h12	i34->h12	i35->h12	i36->h12	i37->h12	i38->h12	i39->h12
-0.02	-0.61	0.00	-0.05	0.06	-0.04	-0.03	0.03
i40->h12	i41->h12	i42->h12	i43->h12				
-0.05	-0.09	-0.07	-0.02				
b->h13	i1->h13	i2->h13	i3->h13	i4->h13	i5->h13	i6->h13	i7->h13
0.01	-0.06	0.07	0.00	-0.02	-0.01	-0.06	-0.09
i8->h13	i9->h13	i10->h13	i11->h13	i12->h13	i13->h13	i14->h13	i15->h13
0.05	-0.04	-0.05	0.00	-0.06	0.04	0.02	0.11
i16->h13	i17->h13	i18->h13	i19->h13	i20->h13	i21->h13	i22->h13	i23->h13
0.07	-0.08	0.04	0.02	0.06	0.09	-0.05	0.07
i24->h13	i25->h13	i26->h13	i27->h13	i28->h13	i29->h13	i30->h13	i31->h13
0.03	0.06	0.08	-0.08	-0.03	-0.09	0.01	-0.06
i32->h13	i33->h13	i34->h13	i35->h13	i36->h13	i37->h13	i38->h13	i39->h13
0.06	-0.04	0.00	-0.02	0.08	-0.06	0.08	-0.01
i40->h13	i41->h13	i42->h13	i43->h13				
0.02	0.00	-0.04	-0.09				
b->h14	i1->h14	i2->h14	i3->h14	i4->h14	i5->h14	i6->h14	i7->h14
-0.05	-0.06	-0.06	-0.05	-0.03	0.08	-0.03	-0.07
i8->h14	i9->h14	i10->h14	i11->h14	i12->h14	i13->h14	i14->h14	i15->h14
-0.03	0.02	0.01	0.03	0.02	-0.07	0.04	-0.08
i16->h14	i17->h14	i18->h14	i19->h14	i20->h14	i21->h14	i22->h14	i23->h14
-0.08	0.03	0.03	0.06	-0.08	-0.05	-0.04	-0.09
i24->h14	i25->h14	i26->h14	i27->h14	i28->h14	i29->h14	i30->h14	i31->h14
0.06	-0.03	0.05	0.03	-0.04	0.09	0.05	-0.02
i32->h14	i33->h14	i34->h14	i35->h14	i36->h14	i37->h14	i38->h14	i39->h14
-0.09	-0.05	-0.04	0.07	-0.03	0.07	-0.01	0.02
i40->h14	i41->h14	i42->h14	i43->h14				
-0.01	0.09	-0.06	-0.07				
b->h15	i1->h15	i2->h15	i3->h15	i4->h15	i5->h15	i6->h15	i7->h15
0.01	0.08	-0.08	-0.01	-0.05	-0.06	-0.09	0.08
i8->h15	i9->h15	i10->h15	i11->h15	i12->h15	i13->h15	i14->h15	i15->h15
0.08	-0.03	-0.02	0.06	-0.03	0.06	0.07	-0.07
i16->h15	i17->h15	i18->h15	i19->h15	i20->h15	i21->h15	i22->h15	i23->h15
-0.02	-0.08	0.04	-0.06	0.08	-0.01	0.05	0.03
i24->h15	i25->h15	i26->h15	i27->h15	i28->h15	i29->h15	i30->h15	i31->h15
-0.04	-0.07	0.09	-0.07	-0.03	0.08	-0.03	-0.03
i32->h15	i33->h15	i34->h15	i35->h15	i36->h15	i37->h15	i38->h15	i39->h15
-0.09	0.08	0.09	0.06	-0.02	-0.01	0.05	0.08
i40->h15	i41->h15	i42->h15	i43->h15				
0.03	-0.03	0.02	0.02				
b->h16	i1->h16	i2->h16	i3->h16	i4->h16	i5->h16	i6->h16	i7->h16
-0.02	0.02	0.07	-0.02	-0.06	0.04	0.01	-0.01

i18->h16	i9->h16	i10->h16	i11->h16	i12->h16	i13->h16	i14->h16	i15->h16
-0.03	0.08	0.00	0.08	0.01	0.02	0.00	-0.05
i16->h16	i17->h16	i18->h16	i19->h16	i20->h16	i21->h16	i22->h16	i23->h16
-0.01	0.09	-0.06	-0.05	0.09	0.02	0.08	0.04
i24->h16	i25->h16	i26->h16	i27->h16	i28->h16	i29->h16	i30->h16	i31->h16
0.09	-0.07	-0.07	0.00	0.03	-0.09	0.09	0.06
i32->h16	i33->h16	i34->h16	i35->h16	i36->h16	i37->h16	i38->h16	i39->h16
-0.05	-0.07	0.02	-0.03	-0.01	0.05	-0.07	-0.07
i40->h16	i41->h16	i42->h16	i43->h16				
-0.04	0.03	0.07	-0.01				
b->h17	i1->h17	i2->h17	i3->h17	i4->h17	i5->h17	i6->h17	i7->h17
0.07	0.09	-0.07	0.03	-0.02	-0.05	0.01	-0.04
i8->h17	i9->h17	i10->h17	i11->h17	i12->h17	i13->h17	i14->h17	i15->h17
0.09	-0.08	-0.03	-0.08	0.06	-0.03	0.08	-0.04
i16->h17	i17->h17	i18->h17	i19->h17	i20->h17	i21->h17	i22->h17	i23->h17
0.01	-0.03	-0.06	0.07	0.06	0.09	0.08	-0.04
i24->h17	i25->h17	i26->h17	i27->h17	i28->h17	i29->h17	i30->h17	i31->h17
-0.06	0.06	0.08	-0.04	0.07	-0.07	0.05	-0.08
i32->h17	i33->h17	i34->h17	i35->h17	i36->h17	i37->h17	i38->h17	i39->h17
-0.02	0.00	0.00	0.07	-0.08	0.07	0.04	0.08
i40->h17	i41->h17	i42->h17	i43->h17				
-0.04	-0.07	-0.01	0.06				
b->h18	i1->h18	i2->h18	i3->h18	i4->h18	i5->h18	i6->h18	i7->h18
-0.08	-0.09	-0.04	-0.05	0.08	0.02	-0.01	-0.01
i8->h18	i9->h18	i10->h18	i11->h18	i12->h18	i13->h18	i14->h18	i15->h18
-0.03	0.05	0.09	-0.04	0.02	0.03	0.09	0.09
i16->h18	i17->h18	i18->h18	i19->h18	i20->h18	i21->h18	i22->h18	i23->h18
-0.05	0.08	-0.04	-0.01	0.09	-0.06	0.02	0.03
i24->h18	i25->h18	i26->h18	i27->h18	i28->h18	i29->h18	i30->h18	i31->h18
0.04	-0.03	0.01	0.08	-0.04	-0.02	0.00	-0.02
i32->h18	i33->h18	i34->h18	i35->h18	i36->h18	i37->h18	i38->h18	i39->h18
-0.06	0.00	-0.05	-0.02	0.00	0.00	-0.02	-0.05
i40->h18	i41->h18	i42->h18	i43->h18				
0.08	0.05	-0.01	-0.08				
b->h19	i1->h19	i2->h19	i3->h19	i4->h19	i5->h19	i6->h19	i7->h19
0.01	-0.06	-0.03	-0.09	-0.05	-0.04	-0.03	0.04
i8->h19	i9->h19	i10->h19	i11->h19	i12->h19	i13->h19	i14->h19	i15->h19
0.05	0.02	0.05	0.09	0.06	-0.02	-0.03	0.09
i16->h19	i17->h19	i18->h19	i19->h19	i20->h19	i21->h19	i22->h19	i23->h19
-0.02	-0.01	-0.04	-0.06	0.06	-0.07	0.01	0.03
i24->h19	i25->h19	i26->h19	i27->h19	i28->h19	i29->h19	i30->h19	i31->h19
-0.04	-0.02	0.08	-0.03	-0.01	0.04	0.08	-0.03
i32->h19	i33->h19	i34->h19	i35->h19	i36->h19	i37->h19	i38->h19	i39->h19
-0.06	0.02	0.02	0.05	0.03	-0.05	0.05	-0.09
i40->h19	i41->h19	i42->h19	i43->h19				
0.07	0.02	0.05	0.05				

```

b->h20 i1->h20 i2->h20 i3->h20 i4->h20 i5->h20 i6->h20 i7->h20
1.35 3.90 -1.78 -20.81 1.22 7.35 -0.16 1.65
i8->h20 i9->h20 i10->h20 i11->h20 i12->h20 i13->h20 i14->h20 i15->h20
-8.87 11.30 -2.86 3.77 -5.79 2.40 -2.28 0.00
i16->h20 i17->h20 i18->h20 i19->h20 i20->h20 i21->h20 i22->h20 i23->h20
0.64 -6.01 -5.06 -6.76 8.92 -4.95 -6.09 1.91
i24->h20 i25->h20 i26->h20 i27->h20 i28->h20 i29->h20 i30->h20 i31->h20
6.81 6.63 -6.70 -4.85 4.49 -2.51 -1.12 0.73
i32->h20 i33->h20 i34->h20 i35->h20 i36->h20 i37->h20 i38->h20 i39->h20
8.43 -0.98 -2.59 -0.98 -5.54 -1.58 4.69 5.23
i40->h20 i41->h20 i42->h20 i43->h20
-7.73 3.74 -13.14 -4.54
b->o h1->o h2->o h3->o h4->o h5->o h6->o h7->o h8->o h9->o h10->o
-0.13 -0.06 -0.16 0.05 -0.22 -0.12 -0.04 4.50 -0.01 -0.22 0.02
h11->o h12->o h13->o h14->o h15->o h16->o h17->o h18->o h19->o h20->o
-0.26 -0.47 -0.15 0.09 0.04 0.08 0.13 -0.28 -0.15 -2.76

```

## Using the model with the test data

The test data is then run through the model

```

> nn.pred <- predict(nn, gc.test, type="raw")
> summary(nn.pred)

```

```

      V1
Min.   :0.007196
1st Qu.:0.394270
Median :0.911725
Mean   :0.711669
3rd Qu.:0.911725
Max.   :0.911726

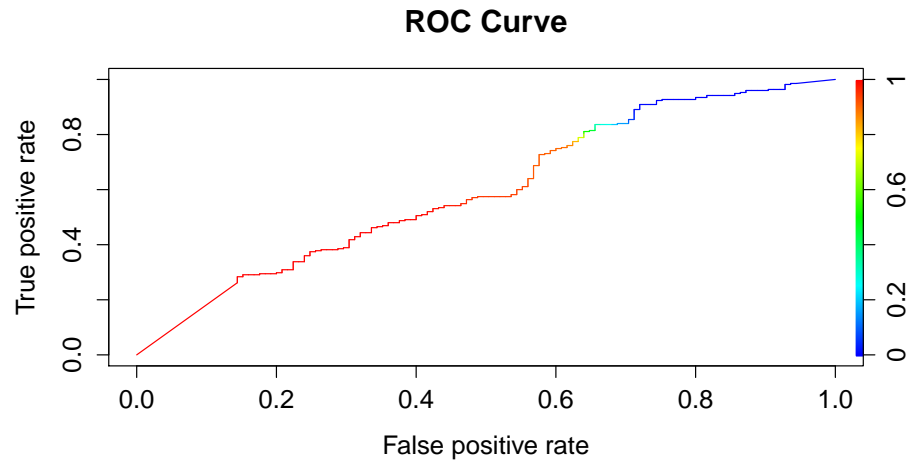
```

## ROC Curve

```

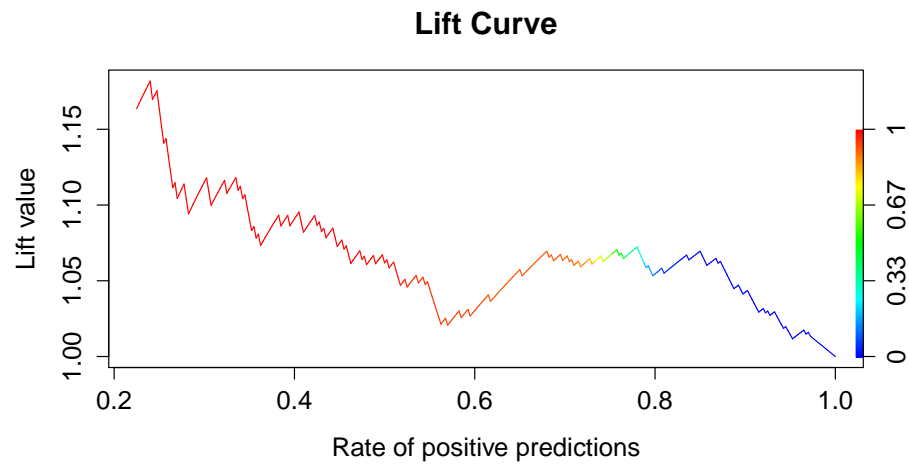
> library(ROCR)
> nn.rocr <- prediction(nn.pred, gc.test$RESPONSE)
> nn.rocr.roc <- performance(nn.rocr, "tpr", "fpr")
> plot(nn.rocr.roc, main="ROC Curve", colorize=T)

```



### Lift Curve

```
> nn.rocr.lift <- performance(nn.rocr, "lift", "rpp")
> plot(nn.rocr.lift, main="Lift Curve", colorize=T)
```



## Lesson 3 Question and Answer

1

*Comments on the models*

I had trouble getting a good fit using a Neural Network. I think the sample size of the data is not sufficiently large to train the network in a more significant way than with the Logistical Regression model. NN is noticeably slower. I generated ROC and Lift Curves for both approaches and Logistical Regression clearly out performs NN for the given data. I think this is a function of the size of the sample though.

I feel NN may outperform Logistical Regression when there may be many predictors with more complex relationships than presently given and the sample train data is sufficiently large. With Neural Networks it is not easy to say what the model is doing and why, and there are no statistical confidence indicators like Degrees of Freedom, etc.

## 2

*If you want to select 275 customers from the validation data set, which model would you adopt for credit rating? Why?*

I would choose the Logistical Regression model as it clearly shows a greater Lift, and is explainable using statistical methods. It also handles categorical data in a more understandable way.

More specifically, I would use the Logistical Regression model with a high cutoff value,  $> 90\%$  approximately.

I should note, I played for hours with NN to get a good fit, and was never completely satisfied. I don't think NN is inferior to Logistical Regression, just not as suited to the current data.