

Predictive Modeling

Lesson 3

Logistical Regression and Neural Networks

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Introduction

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
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)
> 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
0.0130190	0.6274385	1.5478081	1.7756171
DURATION	HISTORY1	HISTORY2	HISTORY3
-0.0213973	0.6218902	1.0542574	0.9128612
HISTORY4	NEW_CAR	USED_CAR	FURNITURE
1.9196216	-0.2966938	1.5245519	0.7469575
RADIO.TV	EDUCATION	RETRAINING	AMOUNT
0.6227738	-0.3288723	0.3219821	-0.0001606
SAV_ACCT1	SAV_ACCT2	SAV_ACCT3	SAV_ACCT4
0.1330299	0.3061612	1.2335501	1.0533710
EMPLOYMENT1	EMPLOYMENT2	EMPLOYMENT3	EMPLOYMENT4
-0.2979299	0.1749510	0.4841481	-0.2144694
INSTALL_RATE	MALE_DIV	MALE_SINGLE	MALE_MAR_or_WID
-0.3948298	0.1672193	0.7121614	0.1611906
CO.APPLICANT	GUARANTOR	PRESENT_RESIDENT	REAL_ESTATE
-0.7918356	0.9532831	0.0169459	0.5110658
PROP_UNKN_NONE	AGE	OTHER_INSTALL	RENT
-0.1388947	0.0097773	-0.4422190	-0.2464168
OWN_RES	NUM_CREDITS	JOB1	JOB2
0.2746791	0.0027873	-0.2988528	-0.2699509
JOB3	NUM_DEPENDENTS	TELEPHONE	FOREIGN
0.2313653	-0.4014251	0.4155514	0.3403382

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

Null Deviance: 724.4

Residual Deviance: 520.1 AIC: 608.1

> 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
-2.9686	-0.6543	0.3575	0.6694	2.1016

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.302e-02	1.605e+00	0.008	0.993529
CHK_ACCT1	6.274e-01	2.846e-01	2.205	0.027471 *
CHK_ACCT2	1.548e+00	5.064e-01	3.057	0.002239 **
CHK_ACCT3	1.776e+00	3.051e-01	5.821	5.86e-09 ***
DURATION	-2.140e-02	1.302e-02	-1.644	0.100179
HISTORY1	6.219e-01	7.124e-01	0.873	0.382692
HISTORY2	1.054e+00	5.711e-01	1.846	0.064890 .
HISTORY3	9.129e-01	6.232e-01	1.465	0.142966
HISTORY4	1.920e+00	5.942e-01	3.231	0.001235 **
NEW_CAR	-2.967e-01	6.039e-01	-0.491	0.623239
USED_CAR	1.525e+00	7.304e-01	2.087	0.036868 *
FURNITURE	7.470e-01	6.284e-01	1.189	0.234582
RADIO_TV	6.228e-01	6.049e-01	1.029	0.303258
EDUCATION	-3.289e-01	7.172e-01	-0.459	0.646553
RETRAINING	3.220e-01	6.680e-01	0.482	0.629820
AMOUNT	-1.606e-04	6.272e-05	-2.560	0.010471 *
SAV_ACCT1	1.330e-01	3.926e-01	0.339	0.734702
SAV_ACCT2	3.062e-01	5.367e-01	0.570	0.568363
SAV_ACCT3	1.234e+00	6.603e-01	1.868	0.061757 .
SAV_ACCT4	1.053e+00	3.452e-01	3.051	0.002278 **
EMPLOYMENT1	-2.979e-01	6.147e-01	-0.485	0.627913
EMPLOYMENT2	1.750e-01	6.060e-01	0.289	0.772825
EMPLOYMENT3	4.841e-01	6.461e-01	0.749	0.453681
EMPLOYMENT4	-2.145e-01	5.992e-01	-0.358	0.720383
INSTALL_RATE	-3.948e-01	1.165e-01	-3.390	0.000699 ***
MALE_DIV	1.672e-01	5.252e-01	0.318	0.750180
MALE_SINGLE	7.122e-01	2.872e-01	2.480	0.013136 *
MALE_MAR_or_WID	1.612e-01	4.036e-01	0.399	0.689600
CO.APPLICANT	-7.918e-01	4.855e-01	-1.631	0.102869
GUARANTOR	9.533e-01	5.439e-01	1.753	0.079671 .
PRESENT_RESIDENT	1.695e-02	1.175e-01	0.144	0.885307
REAL_ESTATE	5.111e-01	2.919e-01	1.751	0.079948 .
PROP_UNKN_NONE	-1.389e-01	5.371e-01	-0.259	0.795927
AGE	9.777e-03	1.242e-02	0.788	0.430972
OTHER_INSTALL	-4.422e-01	2.787e-01	-1.587	0.112531
RENT	-2.464e-01	6.414e-01	-0.384	0.700847
OWN_RES	2.747e-01	6.029e-01	0.456	0.648703
NUM_CREDITS	2.787e-03	2.402e-01	0.012	0.990743
JOB1	-2.989e-01	9.660e-01	-0.309	0.757048
JOB2	-2.700e-01	9.374e-01	-0.288	0.773358
JOB3	2.314e-01	9.346e-01	0.248	0.804472

NUM_DEPENDENTS	-4.014e-01	3.255e-01	-1.233	0.217500
TELEPHONE	4.156e-01	2.630e-01	1.580	0.114081
FOREIGN	3.403e-01	7.422e-01	0.459	0.646558

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

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 724.36 on 599 degrees of freedom
 Residual deviance: 520.15 on 556 degrees of freedom
 AIC: 608.15

Number of Fisher Scoring iterations: 5

> confint(logit)

	2.5 %	97.5 %
(Intercept)	-3.1088217929	3.205295e+00
CHK_ACCT1	0.0730383976	1.190740e+00
CHK_ACCT2	0.6033382534	2.608454e+00
CHK_ACCT3	1.1893883645	2.388138e+00
DURATION	-0.0471800654	4.028345e-03
HISTORY1	-0.7641375436	2.043542e+00
HISTORY2	-0.0420924161	2.213788e+00
HISTORY3	-0.2860916509	2.170036e+00
HISTORY4	0.7802222009	3.123767e+00
NEW_CAR	-1.5256645097	8.645935e-01
USED_CAR	0.0854573119	2.968877e+00
FURNITURE	-0.5220082124	1.963286e+00
RADIO_TV	-0.6057609977	1.789263e+00
EDUCATION	-1.7666887512	1.062207e+00
RETRAINING	-1.0136186649	1.624869e+00
AMOUNT	-0.0002847035	-3.794786e-05
SAV_ACCT1	-0.6231690751	9.217988e-01
SAV_ACCT2	-0.6920073338	1.440611e+00
SAV_ACCT3	0.0378169851	2.675750e+00
SAV_ACCT4	0.3951067980	1.753439e+00
EMPLOYMENT1	-1.5252554394	8.991256e-01
EMPLOYMENT2	-1.0343351917	1.356605e+00
EMPLOYMENT3	-0.7968523911	1.750967e+00
EMPLOYMENT4	-1.4174238024	9.456194e-01
INSTALL_RATE	-0.6271862178	-1.696799e-01
MALE_DIV	-0.8480863667	1.225398e+00
MALE_SINGLE	0.1522385488	1.280286e+00
MALE_MAR_or_WID	-0.6208394998	9.674190e-01
CO.APPLICANT	-1.7543180324	1.630764e-01

GUARANTOR	-0.0535686993	2.105975e+00
PRESENT_RESIDENT	-0.2136948389	2.477828e-01
REAL_ESTATE	-0.0547834291	1.092135e+00
PROP_UNKN_NONE	-1.1850501887	9.279768e-01
AGE	-0.0142842077	3.450442e-02
OTHER_INSTALL	-0.9872548856	1.079713e-01
RENT	-1.5077823881	1.013876e+00
OWN_RES	-0.9061387196	1.465613e+00
NUM_CREDITS	-0.4682461593	4.782817e-01
JOB1	-2.3045383941	1.533273e+00
JOB2	-2.2278672639	1.499925e+00
JOB3	-1.7166728082	2.005040e+00
NUM_DEPENDENTS	-1.0371197579	2.424741e-01
TELEPHONE	-0.0965757578	9.364935e-01
FOREIGN	-1.0238410353	1.938145e+00

> residuals(logit)

1	2	4	6	9	10
0.24762860	-1.21427984	0.99415371	0.78194692	0.14388602	-1.08584589
12	13	14	16	17	18
-0.41187164	0.54221809	-1.21270868	-1.02217785	0.23278129	1.82708699
20	23	24	26	27	28
0.50908094	0.75460042	0.31096173	0.41574845	0.93225559	0.34908713
29	30	31	32	35	37
0.32423566	-0.70947614	0.57133002	1.08781747	0.66048002	0.66894075
38	39	40	42	43	44
-1.66666261	0.35734468	0.56299870	0.59781397	0.83662433	0.60768594
45	46	47	48	49	50
-0.79459969	0.60772598	0.60482268	0.46128567	0.39021223	0.71370251
51	53	55	58	59	60
0.87859713	0.37976129	-0.73886534	0.82124259	0.94087228	-0.47350270
61	64	65	66	67	68
0.62933676	-0.50793516	0.82330960	0.61503667	0.70856848	0.68839058
69	70	72	75	76	79
-1.33132911	0.53336746	0.19110584	-1.38032193	0.44059609	0.66861140
80	81	85	86	87	90
1.13684281	-2.40308121	0.76400942	0.15239383	0.88821966	-1.02879570
91	92	93	94	95	96
0.22924883	0.38063697	-2.19421182	0.62746997	0.45626522	-0.24070372
97	98	99	100	103	105
0.31261933	0.91371105	0.63681670	0.46660626	0.41229081	0.22457524
106	113	115	117	118	124
-1.17392065	1.21530388	0.89494465	-1.38006600	0.62009275	0.49042993
125	127	130	134	135	136
-1.54602580	0.93889623	-0.95574227	0.64209963	0.73000774	0.18351204

137	138	139	140	142	146
0.24355414	-2.20380844	0.14719867	0.50381967	1.35381410	1.32126102
147	149	150	151	153	154
0.75978213	0.60113285	0.19335876	0.45733607	0.90018618	0.53986815
159	161	162	163	164	166
0.83838591	0.26214578	0.82640198	0.36600298	1.03184946	0.17685672
168	169	171	172	174	175
0.59573324	0.51680993	-0.34713454	0.37670167	0.31258457	-0.82745183
177	178	179	183	184	186
0.88698489	0.55766824	0.40669257	-1.00862405	0.11787603	0.30490007
187	188	190	192	193	194
-1.54110660	0.41813025	1.07973227	-0.56101852	-1.23060219	0.34898800
196	197	198	199	202	206
-1.93385685	0.18348132	-0.88726734	0.54804285	1.40193167	0.94466340
207	208	209	211	212	213
0.20698744	0.60569371	1.73684946	0.10151912	0.29105270	-0.78096448
215	217	218	219	220	222
0.23798728	1.45719464	0.35578645	1.09216514	0.45547222	1.49035945
223	227	228	229	232	234
0.41512509	-1.40237701	-1.13874246	-2.27426574	0.58053610	0.53543527
235	237	238	239	242	247
0.14686943	-1.55461797	-0.75035435	0.40734304	0.33860355	0.23490793
250	251	254	255	257	259
-1.58167508	0.32897359	0.39706064	0.22581971	0.28806558	0.28420911
260	261	262	265	266	268
0.28504319	0.55213452	1.46876896	0.35655209	-1.35280874	0.85057032
269	271	272	273	276	277
-1.15980608	0.35821882	0.24281990	2.10154673	0.25688979	0.33664300
279	280	281	282	283	285
-2.06892280	0.40864956	0.14320935	0.30748791	0.38954531	1.19125853
286	287	289	291	292	294
1.97048387	1.21042453	0.39404435	0.25087576	-1.50869965	0.48925919
295	296	297	298	299	302
0.80685775	-0.94769654	0.30140368	0.58011798	0.24101173	-0.76700125
305	307	308	310	312	315
-1.34087339	0.37540515	-1.16083247	1.27739107	0.77216528	0.25494271
317	320	322	324	326	330
0.48233411	1.14809405	-0.83483623	0.64707753	0.37833175	0.98064542
331	334	337	340	341	343
0.35767461	-1.52239299	0.65285107	0.91265019	1.34190587	0.76389926
344	345	346	347	349	350
0.73809917	0.50443526	0.41615382	0.31727211	0.22123995	-1.69532129
352	353	354	355	356	359
-2.12151980	0.06599396	-0.63539061	0.62512847	-0.94457055	0.44429318
360	361	362	363	366	368
-1.00484242	0.79165904	0.21919169	0.82154575	0.24290014	1.38768214

369	371	372	375	376	378
-0.81147686	0.46289861	0.36079797	-0.26435426	-0.74438017	0.30907600
383	384	385	388	389	392
0.71775013	0.76757079	0.55462777	0.66005878	0.48365189	0.41902753
393	394	396	397	399	400
1.35127025	0.46300971	1.72566368	1.06983155	-1.42630069	0.19708431
403	404	409	411	412	413
-1.45214533	0.73780869	0.43336537	1.18621358	0.16616668	-2.49475279
415	417	418	420	421	423
-1.03945472	-0.77837582	1.41930666	-1.37669719	0.51024354	0.40503235
424	426	427	428	429	433
0.24414512	0.48387125	0.47252142	0.12040749	0.28845132	0.52352184
435	436	437	438	440	442
0.67089767	-2.55174224	0.37305800	0.29741909	-1.58959481	1.24561423
444	448	449	454	455	456
-1.29067059	0.26939858	0.17507147	0.27226539	-0.96367408	0.45172766
458	459	461	467	470	471
-1.67592838	1.43839020	0.63223019	-0.68829900	0.26111935	-1.12223469
472	475	476	477	478	479
-0.65199980	-1.76328599	-0.66069646	0.37076908	0.80649025	0.44224778
480	483	484	485	486	487
0.73827145	1.11071114	0.25091516	0.23074367	-1.67349412	0.25496228
488	490	491	492	493	497
1.56387835	0.43845092	0.27857178	-0.67462236	0.20962751	-0.65222734
499	500	501	502	503	505
0.64070388	0.47984595	-0.45095929	1.21281975	0.33952068	-0.41146712
506	512	513	514	515	517
-2.60003358	0.25644739	0.41398411	1.32806884	0.57665701	0.66405961
519	523	525	526	527	530
1.02436547	-0.43140114	0.69077622	0.80470256	0.63436379	1.03818167
531	534	535	537	538	539
1.27229983	0.44399031	0.45215652	0.72477944	0.66570123	-0.33461756
540	541	542	544	545	546
0.66799949	-1.67506690	0.88012075	-2.33191031	0.37365273	-0.76886895
547	549	550	553	554	555
0.60089871	-0.95235048	0.17138690	-1.90110866	0.95781259	0.74686988
557	558	559	561	563	565
-0.54724250	-1.62349998	-1.09599189	0.83113570	0.71449080	0.65050298
567	568	569	570	571	573
-1.24786076	0.16275426	0.67514066	-0.76698791	-0.85417044	0.23575863
574	576	578	579	581	583
1.44290497	0.49413023	0.31459517	-0.88726946	-2.06122386	0.59160600
585	586	589	590	592	594
0.52993720	-1.30672685	-1.28862909	-1.89843689	1.15273826	-0.85200831
595	597	598	600	601	602
-1.35030344	-0.58216627	-1.70594254	0.52277949	0.37339065	-1.44661218

603	604	606	607	608	612
-0.54079114	-1.93628430	1.01230862	0.16548569	-0.72702051	-1.49813426
614	615	616	617	618	620
0.77061541	-2.07401659	1.30253511	0.94891761	0.78394476	0.62023322
621	625	626	627	629	630
0.46353939	-1.21750663	0.34681135	0.19445205	0.24674001	0.22718818
632	633	635	636	637	640
-1.05297614	0.63443719	-0.96964723	0.91177674	0.54321220	-0.94642238
641	642	643	646	649	650
-0.90596601	1.13466379	-2.16150944	-1.48324228	-1.19488506	-0.72346344
651	653	654	655	657	658
1.73625177	-0.66034984	-1.19392405	0.15801378	-0.83277017	0.64636745
662	663	665	666	667	668
-1.19630397	0.42851514	0.42191704	0.87437836	0.82892642	0.83941054
669	670	672	673	674	675
-0.83108913	0.49710284	0.42202140	1.04998991	0.30105762	-1.61177524
678	679	681	683	684	691
-0.94781960	1.38214472	0.63625679	0.61369541	0.55290035	0.59037445
693	694	695	698	700	701
0.79046973	0.50532072	0.39120627	0.32845743	0.77853339	-1.82780462
703	705	706	708	709	710
0.81073544	1.57289839	0.90920454	-0.54288547	0.94800833	0.51223809
712	714	715	716	717	719
-0.45713770	0.53017150	-0.54316526	0.12675770	0.23109643	0.17239592
720	722	726	728	730	731
1.35208437	-0.66447965	0.19574254	-0.65098200	0.12641667	0.92917190
735	736	737	739	742	744
0.31678592	1.60500400	-1.40087146	0.24691306	0.87985831	0.99049628
745	746	747	748	749	751
0.74966262	1.03439369	1.60745314	-0.89569030	0.14628173	0.90225474
752	754	755	756	757	758
-0.92479851	0.61917490	-1.95302026	-0.91122416	0.15535924	-2.96863698
759	761	763	764	766	767
0.21782112	0.25738567	1.07396601	-1.78616461	0.58422773	-1.05334445
769	770	773	774	775	777
0.41276068	0.13410559	0.09963273	0.44665004	0.36827162	0.47063281
778	784	785	788	790	791
0.79899331	-0.68096714	0.16689341	0.21232407	-0.74105984	-1.18857035
792	794	795	798	799	800
0.21066476	0.82205477	0.62481707	0.44754157	0.54876164	0.60419488
803	804	805	806	808	809
0.83736578	0.19939165	0.88525707	-0.85847378	0.13286953	0.80733767
812	813	818	820	821	822
0.39794865	-1.65881596	0.20886824	-1.10436316	0.48119373	0.63291696
825	827	828	829	831	834
0.30424501	-1.16473376	-1.30949017	-1.42686141	0.54557364	0.62413971

835	837	838	841	843	844
-1.99334056	0.38573194	0.46800350	-1.07442513	-1.47563999	0.57352129
845	848	849	850	851	854
0.69906876	0.95795943	0.49165099	-1.39974974	-1.13595370	-0.63014344
855	856	857	859	862	863
1.31015041	0.75177921	0.32616390	-0.84132638	-1.78960999	-1.11455204
864	866	868	872	875	876
0.27869581	0.51529861	0.30961598	0.24165664	1.27222035	0.57591314
877	879	881	885	886	887
1.58191114	-1.17176081	0.23724247	-1.72710610	-0.68470330	0.40635110
888	889	890	891	893	894
-0.74207728	0.65695310	0.32009468	1.02125191	1.07089308	0.39525224
895	896	899	900	901	902
0.15026935	0.29677044	0.23496467	-1.23544064	-1.65670168	0.23328267
904	906	909	910	911	914
0.28701137	0.58090699	0.36087269	0.51081011	0.80706815	0.17105163
915	916	917	919	921	922
-0.81943340	-0.34411669	0.23309525	-1.51826681	0.46908333	0.76635887
923	924	930	932	933	934
-0.84847660	1.05625352	1.34761269	-1.28531996	0.28893871	0.26698293
935	936	938	939	941	942
1.53309477	-1.20608706	0.97846318	-0.51605688	0.30969593	0.46926446
943	944	945	947	948	949
0.24226079	0.23002836	1.25267918	-0.80500187	0.33699978	-1.20461581
951	952	955	958	960	961
0.71459651	-1.53755862	1.12200181	0.30623929	1.16031268	0.31075935
962	964	965	966	968	970
0.96869881	-2.12397630	1.18530215	0.81680090	0.82618611	0.67144014
971	972	974	975	977	978
0.53023410	0.79090669	-0.23520975	0.45662335	0.28260660	0.74966711
979	980	981	984	985	986
-1.22359937	-0.96775859	-1.99555852	-1.21604779	0.19725846	1.13222746
987	988	993	994	997	998
1.61956530	0.29464690	0.70837795	1.00968580	0.76624459	0.49362119

>

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.
0.03299	0.56790	0.80110	0.71260	0.92580	0.99650

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"))
```

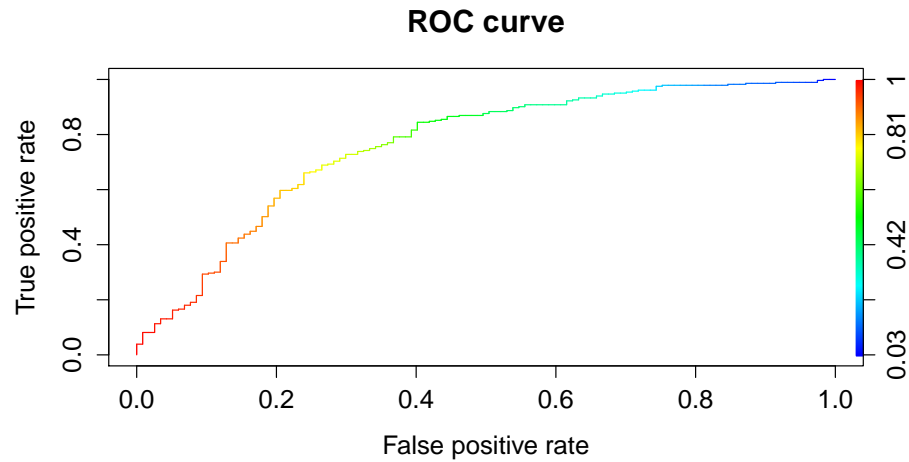
Cell Contents	
	N
Chi-square contribution	
N / Row Total	
N / Col Total	
N / Table Total	

Total Observations in Table: 400

Actual	Predicted		Row Total
	0	1	
0	52	73	125
	28.137	7.145	
	0.416	0.584	0.312
	0.642	0.229	
	0.130	0.182	
1	29	246	275
	12.790	3.248	
	0.105	0.895	0.688
	0.358	0.771	
	0.072	0.615	
Column Total	81	319	400
	0.203	0.797	

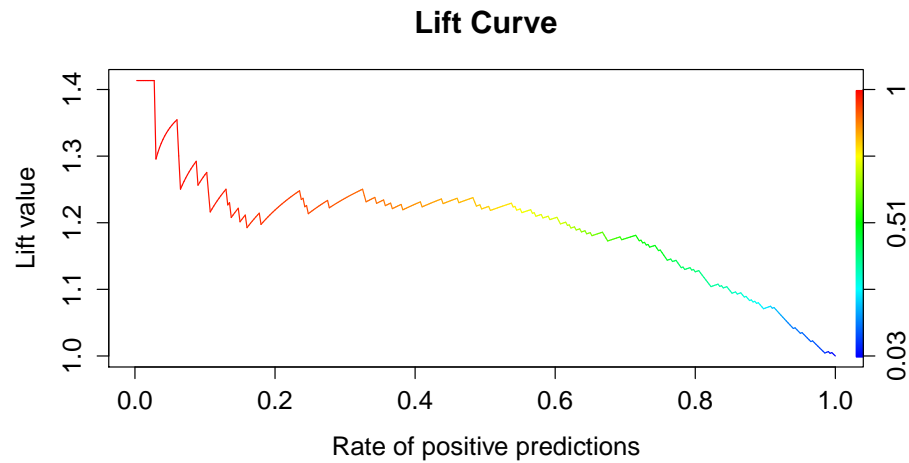
ROC Curve

```
> 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	125	125
	0.312	
1	275	275
	0.688	
Column Total	400	400

```

[1] "Profit with cutoff"
[1] 0
[1] 150000

```

```

      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	5	120	125
	3.616	0.064	
	0.040	0.960	0.312
	0.714	0.305	
	0.013	0.300	
1	2	273	275
	1.644	0.029	
	0.007	0.993	0.688
	0.286	0.695	
	0.005	0.682	
Column Total	7	393	400
	0.018	0.983	

[1] "Profit with cutoff"
 [1] 0.1
 [1] 1500

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	16	109	125
	12.111	0.705	
	0.128	0.872	0.312
	0.727	0.288	
	0.040	0.273	

1	6	269	275
	5.505	0.320	
	0.022	0.978	0.688
	0.273	0.712	
	0.015	0.672	

Column Total	22	378	400
	0.055	0.945	

```
[1] "Profit with cutoff"
[1] 0.2
[1] 4600
```

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	32	93	125
	25.642	3.089	
	0.256	0.744	0.312
	0.744	0.261	
	0.080	0.233	
1	11	264	275
	11.656	1.404	

	0.040	0.960	0.688
	0.256	0.739	
	0.028	0.660	
Column Total	43	357	400
	0.107	0.892	

[1] "Profit with cutoff"
[1] 0.3
[1] 8700

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	46	79	125
	32.485	6.303	
	0.368	0.632	0.312
	0.708	0.236	
	0.115	0.198	
1	19	256	275
	14.766	2.865	
	0.069	0.931	0.688
	0.292	0.764	
	0.048	0.640	
Column Total	65	335	400
	0.163	0.838	


```
[1] "Profit with cutoff"
[1] 0.4
[1] 14100
```

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	52	73	125
	28.137	7.145	
	0.416	0.584	0.312
	0.642	0.229	
	0.130	0.182	
1	29	246	275
	12.790	3.248	
	0.105	0.895	0.688
	0.358	0.771	
	0.072	0.615	
Column Total	81	319	400
	0.203	0.797	

```
[1] "Profit with cutoff"
[1] 0.5
[1] 19700
```

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	73	52	125
	35.390	14.809	
	0.584	0.416	0.312
	0.619	0.184	
	0.182	0.130	
1	45	230	275
	16.086	6.731	
	0.164	0.836	0.688
	0.381	0.816	
	0.113	0.575	
Column Total	118	282	400
	0.295	0.705	

[1] "Profit with cutoff"
[1] 0.6
[1] 29800

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	86	39	125
	26.538	17.508	
	0.688	0.312	0.312
	0.541	0.162	
	0.215	0.098	
1	73	202	275
	12.063	7.958	
	0.265	0.735	0.688
	0.459	0.838	
	0.182	0.505	
Column Total	159	241	400
	0.398	0.603	

[1] "Profit with cutoff"

[1] 0.7

[1] 45100

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	100	25	125
	22.992	22.763	

		0.800	0.200	0.312
		0.503	0.124	
		0.250	0.062	

1	99	176	275	
	10.451	10.347		
	0.360	0.640	0.688	
	0.497	0.876		
	0.247	0.440		

Column Total	199	201	400	
	0.497	0.502		

[1] "Profit with cutoff"
[1] 0.8
[1] 59500

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	113	12	125
	8.986	19.316	
	0.904	0.096	0.312
	0.414	0.094	
	0.282	0.030	

1	160	115	275
	4.084	8.780	
	0.582	0.418	0.688
	0.586	0.906	

	0.400	0.287	
Column Total	273	127	400
	0.682	0.318	

```
[1] "Profit with cutoff"
[1] 0.9
[1] 91300
```

Cell Contents
N
N / Table Total

Total Observations in Table: 400

facts	vals	
	0	Row Total
0	125	125
	0.312	
1	275	275
	0.688	
Column Total	400	400

```
[1] "Profit with cutoff"
[1] 1
[1] 150000
```

Lesson 3 Question and Answer

1

Comments on the models

2

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

With a value for k too small we will classify in a way that is very sensitive to the local characteristics of the training data.

With a value of k too large we essentially overfit, ignoring the information contained in the predictor variables. In the extreme with k equal the number of observations in the train data all test data is assigned to the most frequent class in the train data, Owner in the present case.