

## Using Data Analytics to Retain Human Resources

Import the data

```
> View(HR_comma_sep)
> attach(HR_comma_sep)
> hrdata<-HR_comma_sep
> View(hrdata)
```

Analyze and check data quality

```
> summary(hrdata)
```

```
satisfaction_level last_evaluation number_project average_monthly_hours time_spend_company
Min. :0.0900      Min. :0.3600      Min. :2.000      Min. : 96.0      Min. : 2.000
1st Qu.:0.4400     1st Qu.:0.5600     1st Qu.:3.000     1st Qu.:156.0     1st Qu.: 3.000
Median :0.6400     Median :0.7200     Median :4.000     Median :200.0     Median : 3.000
Mean :0.6128       Mean :0.7161       Mean :3.803       Mean :201.1       Mean : 3.498
3rd Qu.:0.8200     3rd Qu.:0.8700     3rd Qu.:5.000     3rd Qu.:245.0     3rd Qu.: 4.000
Max. :1.0000       Max. :1.0000       Max. :7.000       Max. :310.0       Max. :10.000

work_accident      left promotion_last_5years      Dept
Min. :0.0000      Min. :0.0000      Min. :0.00000      Length:14999
1st Qu.:0.0000     1st Qu.:0.0000     1st Qu.:0.00000      Class :character
Median :0.0000     Median :0.0000     Median :0.00000      Mode :character
Mean :0.1446       Mean :0.2381       Mean :0.02127
3rd Qu.:0.0000     3rd Qu.:0.0000     3rd Qu.:0.00000
Max. :1.0000       Max. :1.0000       Max. :1.00000

salary
Length:14999
Class :character
Mode :character
```

Splitting the data into training and testing dataset

```
> library(caTools)
> split<-sample.split(hrdata,SplitRatio = 0.8)
> split
[1] TRUE FALSE TRUE TRUE TRUE TRUE TRUE FALSE TRUE TRUE
> training<- subset(hrdata,split=="TRUE")
> testing<- subset(hrdata,split=="FALSE")
```

View training data

```
> View(training)
```

View testing Data

```
> View(testing)
```

Create a logistic regression model on training dataset

```
> model<- glm(left~.,training, family="binomial")
> summary(model)
```

Call:

```
glm(formula = left ~ ., family = "binomial", data = training)
```

Deviance Residuals:

```
      Min       1Q   Median       3Q      Max
-2.2397  -0.6633  -0.4032  -0.1148   3.1293
```

Coefficients:

```
Estimate Std. Error z value Pr(>|z|)
```

(Intercept)	-1.4412900	0.2147004	-6.713	1.91e-11	***
satisfaction_level	-4.1361302	0.1098570	-37.650	< 2e-16	***
last_evaluation	0.6674703	0.1670034	3.997	6.42e-05	***
number_project	-0.3094176	0.0236712	-13.072	< 2e-16	***
average_monthly_hours	0.0043747	0.0005772	7.579	3.49e-14	***
time_spend_company	0.2707020	0.0173423	15.609	< 2e-16	***
work_accident	-1.5121485	0.0998091	-15.150	< 2e-16	***
promotion_last_5years	-1.6329003	0.3184333	-5.128	2.93e-07	***
Depthr	0.1990695	0.1445491	1.377	0.168458	
DeptIT	-0.2513547	0.1338220	-1.878	0.060343	.
Deptmanagement	-0.4469871	0.1767391	-2.529	0.011436	*
Deptmarketing	-0.0614583	0.1438805	-0.427	0.669271	
Deptproduct_mng	-0.1565207	0.1425095	-1.098	0.272066	
DeptRandD	-0.5733537	0.1590852	-3.604	0.000313	***
Deptsales	-0.0689375	0.1112058	-0.620	0.535318	
Deptsupport	0.0111727	0.1190611	0.094	0.925236	
Depttechnical	0.0366984	0.1159269	0.317	0.751574	
salarylow	1.9760651	0.1438844	13.734	< 2e-16	***
salarymedium	1.4529393	0.1447543	10.037	< 2e-16	***

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

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 13170 on 11998 degrees of freedom  
 Residual deviance: 10298 on 11980 degrees of freedom  
 AIC: 10336

Number of Fisher Scoring iterations: 5

# removed variable Department in model one but this AIC increased and also  
 residual deviance increased  
 therefore we continue with the previous model having all variables  
 > model1<- glm(left~.-Dept,training, family="binomial")  
 > summary(model1)

Call:  
 glm(formula = left ~ . - Dept, family = "binomial", data = training)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.2206	-0.6652	-0.4079	-0.1190	3.1503

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-1.5398795	0.1914579	-8.043	8.77e-16	***
satisfaction_level	-4.1344256	0.1095259	-37.748	< 2e-16	***
last_evaluation	0.6693286	0.1665202	4.020	5.83e-05	***
number_project	-0.3090173	0.0235950	-13.097	< 2e-16	***
average_monthly_hours	0.0043464	0.0005751	7.557	4.12e-14	***
time_spend_company	0.2641438	0.0171475	15.404	< 2e-16	***
work_accident	-1.5186137	0.0997111	-15.230	< 2e-16	***
promotion_last_5years	-1.6816057	0.3167320	-5.309	1.10e-07	***
salarylow	2.0306533	0.1426226	14.238	< 2e-16	***
salarymedium	1.5065106	0.1435910	10.492	< 2e-16	***

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

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 13170 on 11998 degrees of freedom  
Residual deviance: 10340 on 11989 degrees of freedom  
AIC: 10360

Number of Fisher Scoring iterations: 5

Test the model on the testing dataset and print the response

```
> test<- predict(model,testing,type="response")
```

```
> test
```

	1	2	3	4	5	6
7	0.172375966	0.137929828	0.752518562	0.354923520	0.524371596	0.480583988
129355						0.508
	8	9	10	11	12	13
14	0.447303656	0.478779972	0.633166706	0.469291225	0.781868064	0.547444291
182481						0.158
	15	16	17	18	19	20
21	0.676029096	0.365579801	0.545040085	0.429725513	0.159057458	0.742639739
266543						0.410
	22	23	24	25	26	27
28	0.346651371	0.364348110	0.731356941	0.501977150	0.370639720	0.540014408
914294						0.360
	29	30	31	32	33	34
35	0.412719411	0.725935106	0.463269069	0.784341383	0.189246857	0.481995128
410314						0.159
	36	37	38	39	40	41
42	0.379997629	0.628736878	0.421200115	0.035123659	0.776795768	0.512608101
649290						0.271
	43	44	45	46	47	48
49	0.538102375	0.129345235	0.491368913	0.529833890	0.184531533	0.444972131
521793						0.529
	50	51	52	53	54	55
56	0.433152545	0.269070605	0.363938579	0.171291407	0.103912576	0.617368154
152218						0.301
	57	58	59	60	61	62
63	0.731766581	0.380979117	0.125937324	0.350716308	0.727136583	0.792944062
267792						0.493
	64	65	66	67	68	69
70	0.526251010	0.183730690	0.215874050	0.693439162	0.386263848	0.411392808
747261						0.642
	71	72	73	74	75	76
77	0.702846520	0.555053350	0.325104594	0.442531062	0.479679758	0.365865242
646255						0.443
	78	79	80	81	82	83
84	0.526310804	0.453239360	0.802131409	0.294933772	0.744901037	0.219394224
987784						0.639
	85	86	87	88	89	90
91						

0.677867432	0.292339962	0.530913042	0.503597105	0.674287403	0.780717613	0.107
635730						
	92	93	94	95	96	97
98						
0.136146159	0.347651454	0.670017021	0.461276655	0.740817772	0.731939921	0.750
532510						
	99	100	101	102	103	104
105						
0.448157835	0.119467080	0.037570704	0.544323161	0.592248618	0.739217049	0.272
617390						
	106	107	108	109	110	111
112						
0.687377978	0.153811839	0.101264409	0.255546798	0.519815489	0.257715378	0.486
966270						
	113	114	115	116	117	118
119						
0.513891656	0.711875517	0.252504102	0.440509932	0.132966764	0.251123275	0.400
746312						
	120	121	122	123	124	125
126						
0.691258425	0.194603153	0.549854279	0.361752433	0.163171244	0.601080304	0.173
737206						
	127	128	129	130	131	132
133						
0.360618677	0.467728197	0.362118313	0.339238064	0.660731934	0.111098717	0.378
714791						
	134	135	136	137	138	139
140						
0.276926580	0.697850426	0.281400225	0.472945004	0.552946502	0.362697074	0.752
089967						
	141	142	143	144	145	146
147						
0.117924332	0.231057347	0.516827917	0.748163900	0.562015676	0.387813440	0.188
312792						
	148	149	150	151	152	153
154						
0.372449878	0.277551586	0.403060712	0.103886947	0.528733898	0.736901893	0.241
230052						
	155	156	157	158	159	160
161						
0.664005971	0.650432163	0.178505333	0.508874587	0.769160519	0.822393017	0.377
426758						
	162	163	164	165	166	167
168						
0.114885348	0.616520494	0.629427451	0.269989731	0.071267016	0.275165705	0.686
459122						
	169	170	171	172	173	174
175						
0.661396856	0.164209427	0.388417262	0.636496693	0.457828000	0.481161921	0.272
115944						
	176	177	178	179	180	181
182						
0.284991130	0.113837828	0.368191937	0.042493869	0.425214457	0.422197523	0.746
372395						
	183	184	185	186	187	188
189						
0.458454935	0.542131007	0.357346346	0.501379657	0.080676693	0.735419729	0.462
398765						
	190	191	192	193	194	195
196						
0.569150992	0.576798543	0.399107926	0.048933626	0.173654842	0.214020042	0.780
809385						
	197	198	199	200	201	202
203						

0.138870241 927423	0.596452270	0.269663280	0.100370790	0.610502690	0.128000042	0.336
204	205	206	207	208	209	
210						
0.202561277 536627	0.293798984	0.782752089	0.832326883	0.595635462	0.138037991	0.147
211	212	213	214	215	216	
217						
0.591508756 413879	0.463176216	0.106620281	0.443557267	0.073605459	0.134906603	0.132
218	219	220	221	222	223	
224						
0.347659979 623069	0.334020710	0.565122239	0.712941945	0.294005882	0.475945775	0.186
225	226	227	228	229	230	
231						
0.401588787 208939	0.493176467	0.491664647	0.210496549	0.411251624	0.215458415	0.266
232	233	234	235	236	237	
238						
0.104384693 003988	0.587391851	0.094030710	0.774631498	0.287957482	0.510241423	0.788
239	240	241	242	243	244	
245						
0.685990738 180577	0.136596609	0.687148740	0.109815028	0.692892270	0.214322870	0.230
246	247	248	249	250	251	
252						
0.496753093 530677	0.613447630	0.195794868	0.344942935	0.548672807	0.210396632	0.259
253	254	255	256	257	258	
259						
0.488241451 505132	0.511747996	0.668520344	0.226796729	0.038427878	0.646925458	0.697
260	261	262	263	264	265	
266						
0.497755359 851267	0.471738049	0.441155552	0.374877976	0.377918405	0.314993160	0.497
267	268	269	270	271	272	
273						
0.811715505 867799	0.517066293	0.162920485	0.679981254	0.624046871	0.252982614	0.147
274	275	276	277	278	279	
280						
0.434148299 968650	0.343019130	0.394947106	0.128386384	0.355682250	0.113641039	0.342
281	282	283	284	285	286	
287						
0.618844944 765412	0.314575084	0.792041233	0.827933223	0.045572446	0.245904044	0.432
288	289	290	291	292	293	
294						
0.106977492 233440	0.563967907	0.603594478	0.276017529	0.713322254	0.474246749	0.557
295	296	297	298	299	300	
301						
0.369440448 746535	0.518114247	0.752380071	0.473436621	0.526791225	0.523375022	0.526
302	303	304	305	306	307	
308						
0.356581626 513346	0.287607021	0.300525372	0.156960141	0.508761152	0.571052737	0.512
309	310	311	312	313	314	
315						

0.222350890	0.609314010	0.110256098	0.212331864	0.795954654	0.502033501	0.326929918
316	317	318	319	320	321	322
0.574893028	0.064713008	0.571693951	0.336357890	0.097439745	0.036373689	0.190355960
323	324	325	326	327	328	329
0.720873241	0.295074409	0.088963800	0.397333650	0.636633394	0.705826735	0.529070436
330	331	332	333	334	335	336
0.512716848	0.655347015	0.723740807	0.435080641	0.070951383	0.103799478	0.390279108
337	338	339	340	341	342	343
0.255597752	0.484005443	0.529901221	0.702207914	0.693189426	0.325400577	0.537244205
344	345	346	347	348	349	350
0.792443863	0.741744650	0.751823131	0.499754844	0.645787201	0.273563369	0.366158275
351	352	353	354	355	356	357
0.394776696	0.535058251	0.632462040	0.294631680	0.724262824	0.386926825	0.320184350
358	359	360	361	362	363	364
0.383881156	0.569263492	0.463959472	0.735948349	0.756002958	0.467021768	0.341981393
365	366	367	368	369	370	371
0.599924035	0.267511492	0.319134692	0.652673637	0.186039930	0.742183569	0.438641787
372	373	374	375	376	377	378
0.603855030	0.639647718	0.489109267	0.156385032	0.522832308	0.506588383	0.485471230
379	380	381	382	383	384	385
0.541191594	0.511473111	0.300685481	0.079736713	0.246271314	0.520220793	0.188540200
386	387	388	389	390	391	392
0.757591472	0.445452885	0.422766998	0.252067879	0.191811913	0.095616071	0.270117431
393	394	395	396	397	398	399
0.765478554	0.181840240	0.085179425	0.333501439	0.155943644	0.114735246	0.524977188
400	401	402	403	404	405	406
0.500969263	0.197557505	0.052607311	0.397705804	0.420395105	0.038620199	0.065879483
407	408	409	410	411	412	413
0.336064537	0.228663808	0.095333899	0.090342744	0.084618474	0.081665109	0.014117636
414	415	416	417	418	419	420
0.112561297	0.071714780	0.213575202	0.052361468	0.256945507	0.340535899	0.021984698
421	422	423	424	425	426	427

0.124145392	0.071316873	0.010783257	0.037684268	0.160674250	0.053794388	0.038
437101						
428	429	430	431	432	433	
434						
0.244542180	0.334034153	0.339536586	0.242748592	0.196938657	0.051034858	0.056
243289						
435	436	437	438	439	440	
441						
0.155925444	0.522440876	0.006926426	0.464428138	0.190949984	0.049648598	0.779
224425						
442	443	444	445	446	447	
448						
0.030024798	0.191840591	0.020842932	0.104008298	0.306448598	0.181555924	0.145
549403						
449	450	451	452	453	454	
455						
0.057609863	0.017922960	0.221961564	0.099904506	0.141747182	0.471022007	0.269
044933						
456	457	458	459	460	461	
462						
0.231030475	0.565385056	0.425624327	0.059761976	0.046731900	0.144500099	0.307
882119						
463	464	465	466	467	468	
469						
0.152718604	0.198646650	0.022937936	0.325906229	0.120194158	0.149868928	0.179
339109						
470	471	472	473	474	475	
476						
0.164725197	0.048464140	0.145081320	0.156040822	0.127358215	0.050385324	0.113
523819						
477	478	479	480	481	482	
483						
0.425478104	0.105738622	0.021227809	0.059294608	0.054646559	0.134547228	0.031
933495						
484	485	486	487	488	489	
490						
0.058128895	0.358354159	0.113576752	0.163141433	0.090852263	0.198443190	0.329
602696						
491	492	493	494	495	496	
497						
0.024815518	0.123605741	0.776045099	0.085743099	0.321019991	0.147517518	0.132
120338						
498	499	500	501	502	503	
504						
0.148606053	0.059615533	0.065610228	0.052322403	0.026597430	0.273797208	0.173
142762						
505	506	507	508	509	510	
511						
0.133202061	0.131400763	0.246975645	0.175773937	0.116387821	0.085519953	0.243
057872						
512	513	514	515	516	517	
518						
0.153793624	0.138569515	0.082749033	0.078999366	0.172134024	0.147845152	0.096
420906						
519	520	521	522	523	524	
525						
0.467535625	0.164769263	0.065181478	0.056213158	0.054711759	0.290917470	0.022
892979						
526	527	528	529	530	531	
532						
0.140717168	0.168043224	0.294708385	0.060549733	0.014806764	0.110830961	0.349
840866						
533	534	535	536	537	538	
539						

0.115261424 112354	0.201603488	0.084588037	0.140717446	0.081756970	0.146990311	0.061
540	541	542	543	544	545	
546						
0.207253202 442046	0.209478274	0.078552574	0.138891611	0.123679836	0.430213809	0.471
547	548	549	550	551	552	
553						
0.594934361 094304	0.282164291	0.112372569	0.047148343	0.031817804	0.198974439	0.177
554	555	556	557	558	559	
560						
0.159688559 215295	0.227176354	0.089396962	0.218465965	0.453058778	0.685967644	0.069
561	562	563	564	565	566	
567						
0.390863496 014536	0.061009594	0.093622409	0.013627981	0.159213324	0.179522015	0.281
568	569	570	571	572	573	
574						
0.132154651 988425	0.233858701	0.152253950	0.040825378	0.699467187	0.019721694	0.425
575	576	577	578	579	580	
581						
0.070312332 750112	0.288736662	0.596470555	0.037143813	0.397449739	0.004074694	0.488
582	583	584	585	586	587	
588						
0.548595161 491067	0.438057258	0.090525382	0.108473736	0.229948410	0.577037602	0.071
589	590	591	592	593	594	
595						
0.401058607 102368	0.070957655	0.142061392	0.102454684	0.073746358	0.051378372	0.054
596	597	598	599	600	601	
602						
0.239258613 671056	0.079194773	0.193402899	0.062999798	0.033489442	0.028178510	0.073
603	604	605	606	607	608	
609						
0.126946983 962002	0.014472214	0.193498472	0.266594740	0.005947501	0.179180981	0.086
610	611	612	613	614	615	
616						
0.284913899 721356	0.076010568	0.066456390	0.380513967	0.082325247	0.416531782	0.016
617	618	619	620	621	622	
623						
0.090865348 851123	0.867464760	0.138150612	0.236590396	0.154540680	0.132583516	0.051
624	625	626	627	628	629	
630						
0.076974946 280050	0.074204126	0.197181535	0.506583754	0.143555721	0.020097126	0.210
631	632	633	634	635	636	
637						
0.093802643 894982	0.208747282	0.064594523	0.039572365	0.455288142	0.172394497	0.158
638	639	640	641	642	643	
644						
0.169434602 422952	0.043755202	0.008259291	0.020708435	0.342146378	0.053020921	0.078
645	646	647	648	649	650	
651						



0.105777800	0.147501329	0.005867490	0.007965451	0.221535823	0.139569668	0.104592031
652	653	654	655	656	657	658
0.133437271	0.054555467	0.028241159	0.198049102	0.052125776	0.052821104	0.097320846
659	660	661	662	663	664	665
0.156066257	0.388066891	0.257731511	0.030298787	0.038023172	0.083267756	0.015509658
666	667	668	669	670	671	672
0.379675308	0.044893395	0.069640965	0.198157458	0.256701917	0.153611362	0.014948615
673	674	675	676	677	678	679
0.049101684	0.029446696	0.041055456	0.721721351	0.218546977	0.002913202	0.029502827
680	681	682	683	684	685	686
0.129328173	0.155897975	0.279395320	0.274500347	0.185119984	0.226349795	0.133626035
687	688	689	690	691	692	693
0.018001109	0.117243161	0.237135688	0.064404620	0.204449117	0.019093759	0.058026694
694	695	696	697	698	699	700
0.068058754	0.098887590	0.303744632	0.300315639	0.718127134	0.129170756	0.168199382
701	702	703	704	705	706	707
0.237553430	0.068244164	0.203919656	0.460490098	0.166307179	0.269580565	0.010554265
708	709	710	711	712	713	714
0.075218751	0.210074832	0.227959269	0.333593791	0.140735810	0.088708027	0.132640137
715	716	717	718	719	720	721
0.016586589	0.182191260	0.149514657	0.056707102	0.032397543	0.205348019	0.214198530
722	723	724	725	726	727	728
0.216379936	0.210912301	0.537233933	0.043220542	0.651606599	0.431215509	0.057473530
729	730	731	732	733	734	735
0.589283221	0.040204577	0.114170662	0.018359007	0.002621570	0.066195390	0.250031237
736	737	738	739	740	741	742
0.019754711	0.476996408	0.077315275	0.019615439	0.113290845	0.052956394	0.422034445
743	744	745	746	747	748	749
0.218329563	0.112360123	0.028576798	0.154192629	0.040275599	0.553213077	0.073139399
750	751	752	753	754	755	756
0.066891931	0.097767270	0.032981484	0.080020664	0.050449485	0.177881618	0.078582533
757	758	759	760	761	762	763

0.339746234	0.039452874	0.045020540	0.212682360	0.079303369	0.013740590	0.029
812182						
764	765	766	767	768	769	
770						
0.323472948	0.104341512	0.232124085	0.011029826	0.198215398	0.071517389	0.072
149958						
771	772	773	774	775	776	
777						
0.701233415	0.164862318	0.243352258	0.030159273	0.241865578	0.218257979	0.023
515091						
778	779	780	781	782	783	
784						
0.096979214	0.073250849	0.258322336	0.107965551	0.057238878	0.117264603	0.161
791600						
785	786	787	788	789	790	
791						
0.529144584	0.170432871	0.560426160	0.343316840	0.109171149	0.058973580	0.079
593417						
792	793	794	795	796	797	
798						
0.226784799	0.009463697	0.503883449	0.232869902	0.268820696	0.278377581	0.302
103659						
799	800	801	802	803	804	
805						
0.387085491	0.211244286	0.752055652	0.065809236	0.201495559	0.212075425	0.066
307017						
806	807	808	809	810	811	
812						
0.187639997	0.291866225	0.039646185	0.541448347	0.068516821	0.890996181	0.044
699452						
813	814	815	816	817	818	
819						
0.242342164	0.744102712	0.098810009	0.166971469	0.125107115	0.036875964	0.306
552951						
820	821	822	823	824	825	
826						
0.211870100	0.007079116	0.221614203	0.481209445	0.399520080	0.062400102	0.027
495649						
827	828	829	830	831	832	
833						
0.019683937	0.123925162	0.112008641	0.084489363	0.176599846	0.029067663	0.034
184116						
834	835	836	837	838	839	
840						
0.437073866	0.119048036	0.089010058	0.626913661	0.440341898	0.174252260	0.036
550281						
841	842	843	844	845	846	
847						
0.141670752	0.194744516	0.097946805	0.233435006	0.011986392	0.164113363	0.714
408178						
848	849	850	851	852	853	
854						
0.044976962	0.016900883	0.180015159	0.132890823	0.154189837	0.051917676	0.010
839990						
855	856	857	858	859	860	
861						
0.105410229	0.044231449	0.181258513	0.094438928	0.078077056	0.023779744	0.115
504904						
862	863	864	865	866	867	
868						
0.105138830	0.055579221	0.097118940	0.042011327	0.170152701	0.102163801	0.119
405027						
869	870	871	872	873	874	
875						

0.225711648	0.666629455	0.082225532	0.158683342	0.127163444	0.045306938	0.803
512984	876	877	878	879	880	881
882						
0.154703964	0.227651989	0.234305221	0.154496397	0.009498935	0.391269764	0.166
400762	883	884	885	886	887	888
889						
0.692971606	0.016385068	0.275414624	0.086258438	0.574478631	0.039948502	0.312
953522	890	891	892	893	894	895
896						
0.062412901	0.069419865	0.443700816	0.342672013	0.014746905	0.300354628	0.175
172410	897	898	899	900	901	902
903						
0.102375001	0.253998731	0.814374074	0.223719260	0.043726015	0.043148760	0.037
039376	904	905	906	907	908	909
910						
0.238953963	0.441449532	0.071135373	0.012169931	0.058782527	0.111972159	0.015
431422	911	912	913	914	915	916
917						
0.036362146	0.076602211	0.049358690	0.204838797	0.080975237	0.205974626	0.185
596401	918	919	920	921	922	923
924						
0.087030700	0.010176772	0.003253672	0.826632409	0.125272617	0.073796093	0.016
200046	925	926	927	928	929	930
931						
0.431882460	0.226322434	0.002753454	0.162354882	0.127540266	0.196784058	0.027
717472	932	933	934	935	936	937
938						
0.012793899	0.171695094	0.015845128	0.033500036	0.264639784	0.268108059	0.014
255005	939	940	941	942	943	944
945						
0.047113483	0.135991496	0.417476782	0.265072526	0.055894205	0.203485070	0.398
204574	946	947	948	949	950	951
952						
0.003984705	0.005323905	0.029378900	0.047481444	0.090853296	0.246243509	0.080
090753	953	954	955	956	957	958
959						
0.080633282	0.134659864	0.062541035	0.029564621	0.124304535	0.049355841	0.240
621349	960	961	962	963	964	965
966						
0.017828108	0.822847987	0.192490421	0.058188103	0.370399792	0.042232740	0.119
890086	967	968	969	970	971	972
973						
0.036607283	0.676623951	0.257493017	0.037699842	0.453571490	0.351253771	0.238
882632	974	975	976	977	978	979
980						
0.308209231	0.055438584	0.167156380	0.292975739	0.257167995	0.011373043	0.078
005143	981	982	983	984	985	986
987						

```

0.011169971 0.187375565 0.172286988 0.125668965 0.168455551 0.201699602 0.233
990101
988      989      990      991      992      993
994
0.220010102 0.383127512 0.322209428 0.353186856 0.065709235 0.027587530 0.044
488113
995      996      997      998      999      1000
0.100895382 0.210538186 0.083568677 0.327669991 0.039697865 0.169904372
[ reached getOption("max.print") -- omitted 2000 entries ]

```

Confusion matrix For threshold 0.5

```
> table(ActualValue=testing$left,PredictedValue=test>0.5)
```

```

      PredictedValue
ActualValue FALSE TRUE
0          2102  183
1          434  281

```

Calculate accuracy from confusion matrix

```
> accuracy=(2102+281)/(2102+281+183+434)
```

```
> accuracy
```

```
[1] 0.7943333
```

Plotting the the ROC curve

```
> test1<- predict(model,training,type="response")
```

```
> library(ROCR)
```

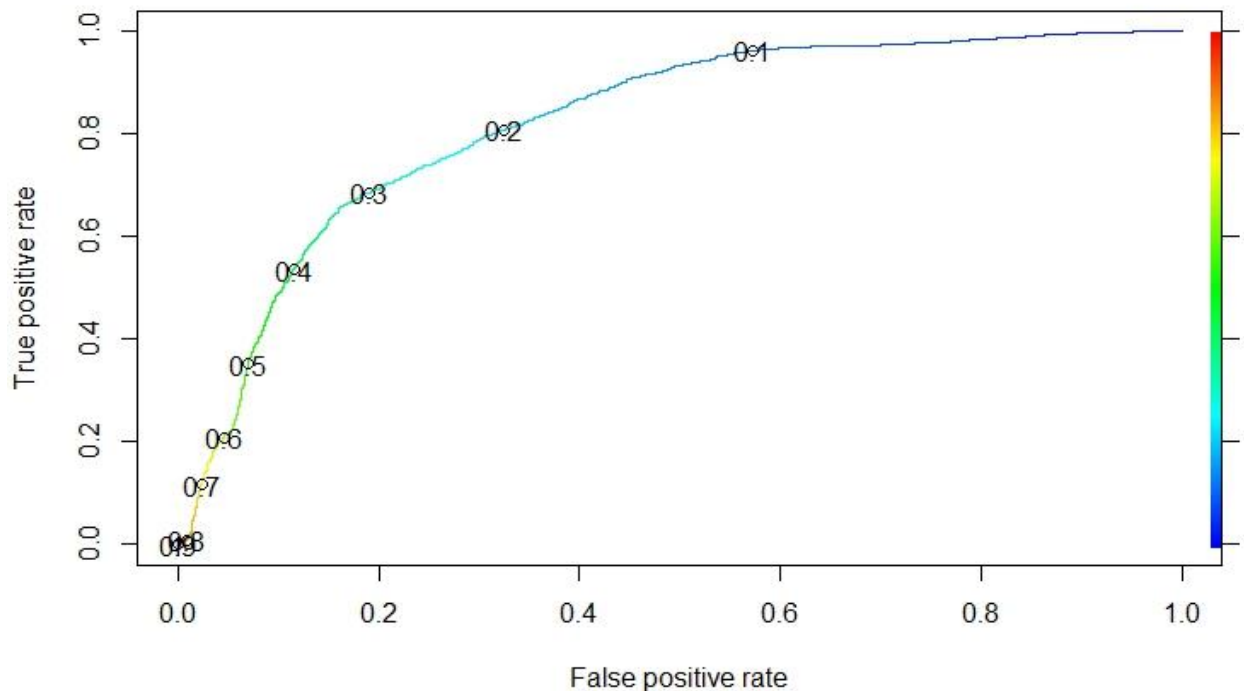
```
> res<- predict(model,training,type="response")
```

```
> library(ROCR)
```

```
> ROCRpred= prediction(res,training$left)
```

```
> ROCRperf<- performance(ROCRpred,"tpr","fpr")
```

```
> plot(ROCRperf,colorize=TRUE,print.cutoffs.at=seq(0.1,by=0.1))
```



Confusion matrix and accuracy for Threshold 0.4

```
> table(ActualValue=testing$left,PredictedValue=test>0.4)
```

```

      PredictedValue
ActualValue FALSE TRUE

```

```

      0  2014  271
      1   321  394
> accuracy1=(2014+394)/(2014+394+271+321)
> accuracy1
[1] 0.8026667

Confusion matrix and accuracy for Threshold 0.2
> table(ActualValue=testing$left,PredictedValue=test>0.2)
      PredictedValue
ActualValue FALSE TRUE
      0    1529   756
      1     135   580
> acc4=(1529+580)/(1529+580+135+756)
> acc4
[1] 0.703

Confusion matrix and accuracy for Threshold 0.35
> table(ActualValue=testing$left,PredictedValue=test>0.35)
      PredictedValue
ActualValue FALSE TRUE
      0    1945   340
      1     254   461
> accuracy2=(1945+461)/(1945+461+254+340)
> accuracy2
[1] 0.802

Confusion matrix and accuracy for Threshold 0.3
> table(ActualValue=testing$left,PredictedValue=test>0.3)
      PredictedValue
ActualValue FALSE TRUE
      0    1846   439
      1     219   496
> acc3=(1846+496)/(1846+496+219+439)
> acc3
[1] 0.7806667

```

## Principal Component Analysis

```

> my_data <-HR_comma_sep
> new_hr_data<-my_data[c(-9,-10)]
> View(new_hr_data)
> library(caTools)

#Splitting data into train and test data
> split<-sample.split(new_hr_data,SplitRatio = 0.8)
> split
[1] TRUE TRUE FALSE TRUE TRUE FALSE TRUE TRUE

> pca.train<- subset(new_hr_data,split=="TRUE")

> View(pca.train)
> pca.test<- subset(new_hr_data,split=="FALSE")
> View(pca.test)
#Principal component analysis and normalization of the variables
> prin_comp <- prcomp(pca.train, scale. = T)

Tprcomp() function results in 5 useful measures:
> names(prin_comp)
[1] "sdev" "rotation" "center" "scale" "x"

```

```
#output of mean of variables
```

```
> prin_comp$center
```

satisfaction_level	last_evaluation	number_project	average_monthly_hours
0.61119388	0.71628234	3.81402791	20

time_spend_company	work_accident	left	promotion_last_5years
3.50644502	0.14650191	0.23806561	0.02115744

```
#output the standard deviation of variables
```

```
> prin_comp$scale
```

satisfaction_level	last_evaluation	number_project	average_monthly_hours
0.2497568	0.1713073	1.2387096	49.8909677

time_spend_company	work_accident	left	promotion_last_5years
1.4610210	0.3536244	0.4259184	0.1439154

```
#rotation measure provides the principal component loading
```

```
> prin_comp$rotation
```

	PC1	PC2	PC3	PC4
PC5				
satisfaction_level	0.21981730	-0.59683577	0.144938610	-0.259385721
5146e-01				3.31
last_evaluation	-0.45024694	-0.33450961	0.152266384	-0.093595870
4173e-02				6.78
number_project	-0.55098945	-0.14716969	0.008783725	0.074795059
9125e-01				-1.91
average_monthly_hours	-0.51928533	-0.20122380	0.114143857	-0.002466779
3380e-01				-2.45
time_spend_company	-0.33008364	0.09776795	-0.463184963	-0.039883094
9095e-01				7.85
work_accident	0.07022193	-0.28400759	-0.411381956	0.819537875
9069e-02				-7.74
left	-0.24726698	0.60639451	0.014723828	0.011978125
1029e-05				-2.73
promotion_last_5years	0.02615574	-0.10866123	-0.747468768	-0.494956573
9753e-01				-4.05

	PC6	PC7	PC8
satisfaction_level	-0.23589511	0.30867249	-0.49633876
last_evaluation	-0.53068033	-0.55172267	0.25062671
number_project	0.47556202	-0.22350068	-0.59677304
average_monthly_hours	-0.01382189	0.71156366	0.33183163
time_spend_company	0.16545099	0.08010518	0.11794331
work_accident	-0.24153859	0.04724174	-0.08338854
left	-0.57742389	0.18724000	-0.44978584
promotion_last_5years	-0.13133290	-0.01845405	-0.03757960

```
#principal component score vectors
```

```
> dim(prin_comp$x)
```

```
[1] 11249      8
```

```
#Computing the standard deviation of each principal component
```

```
> std_dev <- prin_comp$sdev
```

```
#computing the variance
```

```
> pr_var <- std_dev^2
```

```
#varaince of components
```

```
> pr_var[1:8]
[1] 1.8809638 1.4406816 1.0647661 0.9575586 0.8439379 0.7098382 0.6266033 0.4756506
```

```
#explaining the proportion of variance
```

```
> prop_varex <- pr_var/sum(pr_var)
```

```
> prop_varex[1:8]
```

```
[1] 0.23512048 0.18008519 0.13309576 0.11969482 0.10549223 0.08872978 0.07832541 0.05945632
```

```
#scree plot used to access components with variability in data, shown in descending value
```

```
> plot(prop_varex, xlab = "Principal Component",
+       ylab = "Proportion of Variance Explained",
+       type = "b")
```

```
#Cumulative variance plot for the principal components
```

```
> plot(cumsum(prop_varex), xlab = "Principal Component",
+       ylab = "Cumulative Proportion of Variance Explained",
+       type = "b")
```

```
#Adding a training set with principal components
```

```
> training<- subset(new_hr_data,split=="TRUE")
```

```
> train.data <- data.frame(left = training$left, prin_comp$x)
```

```
#Selecting the components
```

```
> train.data <- train.data[,1:7]
```

```
Run the logistic regressionmodel
```

```
> lrmodel<- glm(left~.,data = train.data, family="binomial")
```

```
> summary(lrmodel)
```

```
Call:
```

```
glm(formula = left ~ ., family = "binomial", data = train.data)
```

```
Deviance Residuals:
```

Min	1Q	Median	3Q	Max
-0.005429	0.000000	0.000000	0.000000	0.004387

```
Coefficients:
```

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-833.483	6102.722	-0.137	0.891
PC1	-357.504	2652.817	-0.135	0.893
PC2	795.578	5822.952	0.137	0.891
PC3	2.286	193.640	0.012	0.991
PC4	137.348	1020.115	0.135	0.893
PC5	-93.917	724.979	-0.130	0.897
PC6	-489.328	3581.104	-0.137	0.891

```
(Dispersion parameter for binomial family taken to be 1)
```

```
Null deviance: 1.2348e+04 on 11248 degrees of freedom
Residual deviance: 1.0074e-04 on 11242 degrees of freedom
AIC: 14
```

```
Number of Fisher Scoring iterations: 25
```

```
#transforming test to PCA
```

```
> test.data <- predict(prin_comp, newdata = pca.test)
```

```
> test.data <- as.data.frame(test.data)
```

```
> testpredict<- predict(lrmodel,test.data,type="response")
```

```
# Select the components
```

```
> test.data <- test.data[,1:7]
```

```
#making prediction on test data  
> testpredict<- predict(lrmodel,test.data,type="response")
```