

Naive-Bayes

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Naive-Bayes

```
dataset = read.csv("Social_Network_Ads.csv")
dataset = dataset[,3:5]
```

Dividir dataset en conjunto de entranamiento y conjunto de test

```
library(caTools)
```

```
## Warning: package 'caTools' was built under R version 4.0.5
```

```
set.seed(123)
```

```
split = sample.split(dataset$Purchased, SplitRatio = 0.75)
```

```
training_set = subset(dataset, split == TRUE)
training_set
```

##	Age	EstimatedSalary	Purchased
## 1	19	19000	0
## 3	26	43000	0
## 6	27	58000	0
## 7	27	84000	0
## 8	32	150000	1
## 10	35	65000	0
## 11	26	80000	0
## 13	20	86000	0
## 14	32	18000	0
## 15	18	82000	0
## 16	29	80000	0
## 17	47	25000	1
## 21	45	22000	1
## 23	48	41000	1
## 24	45	22000	1
## 25	46	23000	1
## 26	47	20000	1
## 27	49	28000	1
## 28	47	30000	1
## 30	31	18000	0
## 31	31	74000	0
## 33	21	16000	0
## 36	35	27000	0
## 37	33	28000	0

## 39	26	72000	0
## 40	27	31000	0
## 41	27	17000	0
## 42	33	51000	0
## 43	35	108000	0
## 44	30	15000	0
## 47	25	79000	0
## 49	30	135000	1
## 50	31	89000	0
## 51	24	32000	0
## 53	29	83000	0
## 54	35	23000	0
## 55	27	58000	0
## 56	24	55000	0
## 57	23	48000	0
## 58	28	79000	0
## 59	22	18000	0
## 60	32	117000	0
## 61	27	20000	0
## 62	25	87000	0
## 63	23	66000	0
## 64	32	120000	1
## 65	59	83000	0
## 67	24	19000	0
## 68	23	82000	0
## 70	31	68000	0
## 71	25	80000	0
## 72	24	27000	0
## 73	20	23000	0
## 76	34	112000	1
## 77	18	52000	0
## 78	22	27000	0
## 79	28	87000	0
## 80	26	17000	0
## 81	30	80000	0
## 83	20	49000	0
## 88	28	85000	0
## 90	35	50000	0
## 91	22	81000	0
## 92	30	116000	0
## 93	26	15000	0
## 94	29	28000	0
## 95	29	83000	0
## 96	35	44000	0
## 97	35	25000	0
## 98	28	123000	1
## 99	35	73000	0
## 100	28	37000	0
## 101	27	88000	0
## 102	28	59000	0
## 105	19	21000	0
## 106	21	72000	0
## 110	38	80000	0
## 111	39	71000	0

## 112	37	71000	0
## 113	38	61000	0
## 114	37	55000	0
## 115	42	80000	0
## 116	40	57000	0
## 118	36	52000	0
## 119	40	59000	0
## 120	41	59000	0
## 121	36	75000	0
## 122	37	72000	0
## 123	40	75000	0
## 125	41	51000	0
## 128	26	32000	0
## 129	30	17000	0
## 130	26	84000	0
## 132	33	31000	0
## 133	30	87000	0
## 135	28	55000	0
## 136	23	63000	0
## 137	20	82000	0
## 138	30	107000	1
## 140	19	25000	0
## 141	19	85000	0
## 142	18	68000	0
## 143	35	59000	0
## 144	30	89000	0
## 145	34	25000	0
## 146	24	89000	0
## 147	27	96000	1
## 149	29	61000	0
## 150	20	74000	0
## 151	26	15000	0
## 152	41	45000	0
## 153	31	76000	0
## 155	40	47000	0
## 157	46	59000	0
## 158	29	75000	0
## 160	32	135000	1
## 161	32	100000	1
## 164	35	38000	0
## 165	33	69000	0
## 166	18	86000	0
## 167	22	55000	0
## 168	35	71000	0
## 169	29	148000	1
## 171	21	88000	0
## 172	34	115000	0
## 173	26	118000	0
## 174	34	43000	0
## 177	35	47000	0
## 178	25	22000	0
## 179	24	23000	0
## 180	31	34000	0
## 181	26	16000	0

##	182	31	71000	0
##	183	32	117000	1
##	184	33	43000	0
##	185	33	60000	0
##	186	31	66000	0
##	187	20	82000	0
##	188	33	41000	0
##	189	35	72000	0
##	190	28	32000	0
##	191	24	84000	0
##	192	19	26000	0
##	194	19	70000	0
##	195	28	89000	0
##	196	34	43000	0
##	197	30	79000	0
##	198	20	36000	0
##	201	35	39000	0
##	202	49	74000	0
##	203	39	134000	1
##	204	41	71000	0
##	205	58	101000	1
##	206	47	47000	0
##	207	55	130000	1
##	209	40	142000	1
##	210	46	22000	0
##	211	48	96000	1
##	212	52	150000	1
##	214	35	58000	0
##	215	47	43000	0
##	216	60	108000	1
##	217	49	65000	0
##	218	40	78000	0
##	219	46	96000	0
##	220	59	143000	1
##	221	41	80000	0
##	222	35	91000	1
##	223	37	144000	1
##	225	35	60000	0
##	227	36	126000	1
##	231	35	147000	1
##	232	39	42000	0
##	233	40	107000	1
##	235	38	112000	0
##	238	37	80000	0
##	240	53	143000	1
##	242	38	59000	0
##	243	50	88000	1
##	244	56	104000	1
##	245	41	72000	0
##	246	51	146000	1
##	247	35	50000	0
##	248	57	122000	1
##	249	41	52000	0
##	250	35	97000	1

##	251	44	39000	0
##	252	37	52000	0
##	253	48	134000	1
##	254	37	146000	1
##	256	52	90000	1
##	257	41	72000	0
##	258	40	57000	0
##	259	58	95000	1
##	260	45	131000	1
##	261	35	77000	0
##	262	36	144000	1
##	263	55	125000	1
##	267	40	75000	0
##	268	37	74000	0
##	269	47	144000	1
##	270	40	61000	0
##	271	43	133000	0
##	272	59	76000	1
##	275	57	26000	1
##	276	57	74000	1
##	277	38	71000	0
##	278	49	88000	1
##	279	52	38000	1
##	280	50	36000	1
##	282	35	61000	0
##	283	37	70000	1
##	284	52	21000	1
##	285	48	141000	0
##	287	37	62000	0
##	288	48	138000	1
##	289	41	79000	0
##	290	37	78000	1
##	291	39	134000	1
##	293	55	39000	1
##	294	37	77000	0
##	295	35	57000	0
##	296	36	63000	0
##	297	42	73000	1
##	298	43	112000	1
##	300	46	117000	1
##	301	58	38000	1
##	303	37	137000	1
##	304	37	79000	1
##	306	42	54000	0
##	308	47	113000	1
##	309	36	125000	1
##	311	42	70000	0
##	312	39	96000	1
##	313	38	50000	0
##	314	49	141000	1
##	315	39	79000	0
##	317	54	104000	1
##	318	35	55000	0
##	319	45	32000	1

##	320	36	60000	0
##	321	52	138000	1
##	322	53	82000	1
##	323	41	52000	0
##	325	48	131000	1
##	327	41	72000	0
##	328	42	75000	0
##	329	36	118000	1
##	330	47	107000	1
##	331	38	51000	0
##	333	42	65000	0
##	334	40	65000	0
##	335	57	60000	1
##	336	36	54000	0
##	337	58	144000	1
##	338	35	79000	0
##	340	39	122000	1
##	342	35	75000	0
##	344	47	51000	1
##	345	47	105000	1
##	346	41	63000	0
##	348	54	108000	1
##	349	39	77000	0
##	350	38	61000	0
##	351	38	113000	1
##	352	37	75000	0
##	354	37	57000	0
##	355	36	99000	1
##	356	60	34000	1
##	357	54	70000	1
##	358	41	72000	0
##	359	40	71000	1
##	360	42	54000	0
##	361	43	129000	1
##	362	53	34000	1
##	365	42	104000	1
##	366	59	29000	1
##	370	54	26000	1
##	371	60	46000	1
##	374	59	130000	1
##	375	37	80000	0
##	376	46	32000	1
##	377	46	74000	0
##	378	42	53000	0
##	379	41	87000	1
##	381	42	64000	0
##	382	48	33000	1
##	384	49	28000	1
##	385	57	33000	1
##	386	56	60000	1
##	387	49	39000	1
##	388	39	71000	0
##	390	48	35000	1
##	391	48	33000	1

```
## 393 45      45000      1
## 394 60      42000      1
## 396 46      41000      1
## 397 51      23000      1
## 398 50      20000      1
## 399 36      33000      0
```

```
testing_set = subset(dataset, split == FALSE)
testing_set
```

```
##      Age EstimatedSalary Purchased
## 2     35           20000           0
## 4     27           57000           0
## 5     19           76000           0
## 9     25           33000           0
## 12    26           52000           0
## 18    45           26000           1
## 19    46           28000           1
## 20    48           29000           1
## 22    47           49000           1
## 29    29           43000           0
## 32    27          137000           1
## 34    28           44000           0
## 35    27           90000           0
## 38    30           49000           0
## 45    28           84000           0
## 46    23           20000           0
## 48    27           54000           0
## 52    18           44000           0
## 66    24           58000           0
## 69    22           63000           0
## 74    33          113000           0
## 75    32           18000           0
## 82    39           42000           0
## 84    35           88000           0
## 85    30           62000           0
## 86    31          118000           1
## 87    24           55000           0
## 89    26           81000           0
## 103   32           86000           0
## 104   33          149000           1
## 107   26           35000           0
## 108   27           89000           0
## 109   26           86000           0
## 117   35           75000           0
## 124   35           53000           0
## 126   39           61000           0
## 127   42           65000           0
## 131   31           58000           0
## 134   21           68000           0
## 139   28           59000           0
## 148   41           30000           0
## 154   36           50000           0
## 156   31           15000           0
## 159   26           30000           0
```

##	162	25	90000	0
##	163	37	33000	0
##	170	29	47000	0
##	175	34	72000	0
##	176	23	28000	0
##	193	29	43000	0
##	199	26	80000	0
##	200	35	22000	0
##	208	52	114000	0
##	213	59	42000	0
##	224	60	102000	1
##	226	37	53000	0
##	228	56	133000	1
##	229	40	72000	0
##	230	42	80000	1
##	234	49	86000	1
##	236	46	79000	1
##	237	40	57000	0
##	239	46	82000	0
##	241	42	149000	1
##	255	50	44000	0
##	264	35	72000	0
##	265	48	90000	1
##	266	42	108000	1
##	273	60	42000	1
##	274	39	106000	1
##	281	59	88000	1
##	286	37	93000	1
##	292	49	89000	1
##	299	45	79000	0
##	302	48	74000	1
##	305	40	60000	0
##	307	51	134000	0
##	310	38	50000	0
##	316	39	75000	1
##	324	48	30000	1
##	326	41	60000	0
##	332	48	119000	1
##	339	38	55000	0
##	341	53	104000	1
##	343	38	65000	0
##	347	53	72000	1
##	353	42	90000	1
##	363	47	50000	1
##	364	42	79000	0
##	367	58	47000	1
##	368	46	88000	1
##	369	38	71000	0
##	372	60	83000	1
##	373	39	73000	0
##	380	58	23000	1
##	383	44	139000	1
##	389	47	34000	1
##	392	47	23000	1


```
## 395 39          59000          0
## 400 49          36000          1
```

Escalado de datos

Standardisation

$$x_{stand} = \frac{x - \text{mean}(x)}{sd(x)}$$

```
training_set[:,1:2] = scale(training_set[:,1:2])
training_set
```

```
##          Age EstimatedSalary Purchased
## 1  -1.76554750    -1.47334137          0
## 3  -1.09629664    -0.78837605          0
## 6  -1.00068938    -0.36027273          0
## 7  -1.00068938     0.38177303          0
## 8  -0.52265305     2.26542765          1
## 10 -0.23583125    -0.16049118          0
## 11 -1.09629664     0.26761214          0
## 13 -1.66994024     0.43885347          0
## 14 -0.52265305    -1.50188159          0
## 15 -1.86115477     0.32469259          0
## 16 -0.80947485     0.26761214          0
## 17  0.91145593    -1.30210004          1
## 21  0.72024140    -1.38772071          1
## 23  1.00706320    -0.84545650          1
## 24  0.72024140    -1.38772071          1
## 25  0.81584866    -1.35918049          1
## 26  0.91145593    -1.44480115          1
## 27  1.10267046    -1.21647938          1
## 28  0.91145593    -1.15939893          1
## 30 -0.61826032    -1.50188159          0
## 31 -0.61826032     0.09637081          0
## 33 -1.57433297    -1.55896204          0
## 36 -0.23583125    -1.24501960          0
## 37 -0.42704579    -1.21647938          0
## 39 -1.09629664     0.03929037          0
## 40 -1.00068938    -1.13085871          0
## 41 -1.00068938    -1.53042182          0
## 42 -0.42704579    -0.56005428          0
## 43 -0.23583125     1.06673835          0
## 44 -0.71386758    -1.58750226          0
## 47 -1.19190391     0.23907192          0
## 49 -0.71386758     1.83732433          1
## 50 -0.61826032     0.52447414          0
## 51 -1.28751117    -1.10231849          0
## 53 -0.80947485     0.35323281          0
## 54 -0.23583125    -1.35918049          0
## 55 -1.00068938    -0.36027273          0
## 56 -1.28751117    -0.44589340          0
## 57 -1.38311844    -0.64567495          0
## 58 -0.90508211     0.23907192          0
## 59 -1.47872570    -1.50188159          0
## 60 -0.52265305     1.32360034          0
```

## 61	-1.00068938	-1.44480115	0
## 62	-1.19190391	0.46739370	0
## 63	-1.38311844	-0.13195096	0
## 64	-0.52265305	1.40922101	1
## 65	2.05874311	0.35323281	0
## 67	-1.28751117	-1.47334137	0
## 68	-1.38311844	0.32469259	0
## 70	-0.61826032	-0.07487051	0
## 71	-1.19190391	0.26761214	0
## 72	-1.28751117	-1.24501960	0
## 73	-1.66994024	-1.35918049	0
## 76	-0.33143852	1.18089923	1
## 77	-1.86115477	-0.53151406	0
## 78	-1.47872570	-1.24501960	0
## 79	-0.90508211	0.46739370	0
## 80	-1.09629664	-1.53042182	0
## 81	-0.71386758	0.26761214	0
## 83	-1.66994024	-0.61713472	0
## 88	-0.90508211	0.41031325	0
## 90	-0.23583125	-0.58859450	0
## 91	-1.47872570	0.29615237	0
## 92	-0.71386758	1.29506012	0
## 93	-1.09629664	-1.58750226	0
## 94	-0.80947485	-1.21647938	0
## 95	-0.80947485	0.35323281	0
## 96	-0.23583125	-0.75983583	0
## 97	-0.23583125	-1.30210004	0
## 98	-0.90508211	1.49484167	1
## 99	-0.23583125	0.06783059	0
## 100	-0.90508211	-0.95961738	0
## 101	-1.00068938	0.49593392	0
## 102	-0.90508211	-0.33173251	0
## 105	-1.76554750	-1.41626093	0
## 106	-1.57433297	0.03929037	0
## 110	0.05099054	0.26761214	0
## 111	0.14659781	0.01075015	0
## 112	-0.04461672	0.01075015	0
## 113	0.05099054	-0.27465207	0
## 114	-0.04461672	-0.44589340	0
## 115	0.43341960	0.26761214	0
## 116	0.24220507	-0.38881295	0
## 118	-0.14022399	-0.53151406	0
## 119	0.24220507	-0.33173251	0
## 120	0.33781234	-0.33173251	0
## 121	-0.14022399	0.12491104	0
## 122	-0.04461672	0.03929037	0
## 123	0.24220507	0.12491104	0
## 125	0.33781234	-0.56005428	0
## 128	-1.09629664	-1.10231849	0
## 129	-0.71386758	-1.53042182	0
## 130	-1.09629664	0.38177303	0
## 132	-0.42704579	-1.13085871	0
## 133	-0.71386758	0.46739370	0
## 135	-0.90508211	-0.44589340	0

## 136	-1.38311844	-0.21757162	0
## 137	-1.66994024	0.32469259	0
## 138	-0.71386758	1.03819813	1
## 140	-1.76554750	-1.30210004	0
## 141	-1.76554750	0.41031325	0
## 142	-1.86115477	-0.07487051	0
## 143	-0.23583125	-0.33173251	0
## 144	-0.71386758	0.52447414	0
## 145	-0.33143852	-1.30210004	0
## 146	-1.28751117	0.52447414	0
## 147	-1.00068938	0.72425569	1
## 149	-0.80947485	-0.27465207	0
## 150	-1.66994024	0.09637081	0
## 151	-1.09629664	-1.58750226	0
## 152	0.33781234	-0.73129561	0
## 153	-0.61826032	0.15345126	0
## 155	0.24220507	-0.67421517	0
## 157	0.81584866	-0.33173251	0
## 158	-0.80947485	0.12491104	0
## 160	-0.52265305	1.83732433	1
## 161	-0.52265305	0.83841658	1
## 164	-0.23583125	-0.93107716	0
## 165	-0.42704579	-0.04633029	0
## 166	-1.86115477	0.43885347	0
## 167	-1.47872570	-0.44589340	0
## 168	-0.23583125	0.01075015	0
## 169	-0.80947485	2.20834721	1
## 171	-1.57433297	0.49593392	0
## 172	-0.33143852	1.26651990	0
## 173	-1.09629664	1.35214056	0
## 174	-0.33143852	-0.78837605	0
## 177	-0.23583125	-0.67421517	0
## 178	-1.19190391	-1.38772071	0
## 179	-1.28751117	-1.35918049	0
## 180	-0.61826032	-1.04523805	0
## 181	-1.09629664	-1.55896204	0
## 182	-0.61826032	0.01075015	0
## 183	-0.52265305	1.32360034	1
## 184	-0.42704579	-0.78837605	0
## 185	-0.42704579	-0.30319229	0
## 186	-0.61826032	-0.13195096	0
## 187	-1.66994024	0.32469259	0
## 188	-0.42704579	-0.84545650	0
## 189	-0.23583125	0.03929037	0
## 190	-0.90508211	-1.10231849	0
## 191	-1.28751117	0.38177303	0
## 192	-1.76554750	-1.27355982	0
## 194	-1.76554750	-0.01779007	0
## 195	-0.90508211	0.52447414	0
## 196	-0.33143852	-0.78837605	0
## 197	-0.71386758	0.23907192	0
## 198	-1.66994024	-0.98815761	0
## 201	-0.23583125	-0.90253694	0
## 202	1.10267046	0.09637081	0

## 203	0.14659781	1.80878411	1
## 204	0.33781234	0.01075015	0
## 205	1.96313585	0.86695680	1
## 206	0.91145593	-0.67421517	0
## 207	1.67631405	1.69462322	1
## 209	0.24220507	2.03710588	1
## 210	0.81584866	-1.38772071	0
## 211	1.00706320	0.72425569	1
## 212	1.38949226	2.26542765	1
## 214	-0.23583125	-0.36027273	0
## 215	0.91145593	-0.78837605	0
## 216	2.15435038	1.06673835	1
## 217	1.10267046	-0.16049118	0
## 218	0.24220507	0.21053170	0
## 219	0.81584866	0.72425569	0
## 220	2.05874311	2.06564610	1
## 221	0.33781234	0.26761214	0
## 222	-0.23583125	0.58155458	1
## 223	-0.04461672	2.09418633	1
## 225	-0.23583125	-0.30319229	0
## 227	-0.14022399	1.58046234	1
## 231	-0.23583125	2.17980699	1
## 232	0.14659781	-0.81691628	0
## 233	0.24220507	1.03819813	1
## 235	0.05099054	1.18089923	0
## 238	-0.04461672	0.26761214	0
## 240	1.48509952	2.06564610	1
## 242	0.05099054	-0.33173251	0
## 243	1.19827773	0.49593392	1
## 244	1.77192132	0.95257746	1
## 245	0.33781234	0.03929037	0
## 246	1.29388499	2.15126677	1
## 247	-0.23583125	-0.58859450	0
## 248	1.86752858	1.46630145	1
## 249	0.33781234	-0.53151406	0
## 250	-0.23583125	0.75279591	1
## 251	0.62463413	-0.90253694	0
## 252	-0.04461672	-0.53151406	0
## 253	1.00706320	1.80878411	1
## 254	-0.04461672	2.15126677	1
## 256	1.38949226	0.55301436	1
## 257	0.33781234	0.03929037	0
## 258	0.24220507	-0.38881295	0
## 259	1.96313585	0.69571547	1
## 260	0.72024140	1.72316344	1
## 261	-0.23583125	0.18199148	0
## 262	-0.14022399	2.09418633	1
## 263	1.67631405	1.55192212	1
## 267	0.24220507	0.12491104	0
## 268	-0.04461672	0.09637081	0
## 269	0.91145593	2.09418633	1
## 270	0.24220507	-0.27465207	0
## 271	0.52902687	1.78024389	0
## 272	2.05874311	0.15345126	1

## 275	1.86752858	-1.27355982	1
## 276	1.86752858	0.09637081	1
## 277	0.05099054	0.01075015	0
## 278	1.10267046	0.49593392	1
## 279	1.38949226	-0.93107716	1
## 280	1.19827773	-0.98815761	1
## 282	-0.23583125	-0.27465207	0
## 283	-0.04461672	-0.01779007	1
## 284	1.38949226	-1.41626093	1
## 285	1.00706320	2.00856566	0
## 287	-0.04461672	-0.24611184	0
## 288	1.00706320	1.92294500	1
## 289	0.33781234	0.23907192	0
## 290	-0.04461672	0.21053170	1
## 291	0.14659781	1.80878411	1
## 293	1.67631405	-0.90253694	1
## 294	-0.04461672	0.18199148	0
## 295	-0.23583125	-0.38881295	0
## 296	-0.14022399	-0.21757162	0
## 297	0.43341960	0.06783059	1
## 298	0.52902687	1.18089923	1
## 300	0.81584866	1.32360034	1
## 301	1.96313585	-0.93107716	1
## 303	-0.04461672	1.89440477	1
## 304	-0.04461672	0.23907192	1
## 306	0.43341960	-0.47443362	0
## 308	0.91145593	1.20943946	1
## 309	-0.14022399	1.55192212	1
## 311	0.43341960	-0.01779007	0
## 312	0.14659781	0.72425569	1
## 313	0.05099054	-0.58859450	0
## 314	1.10267046	2.00856566	1
## 315	0.14659781	0.23907192	0
## 317	1.58070679	0.95257746	1
## 318	-0.23583125	-0.44589340	0
## 319	0.72024140	-1.10231849	1
## 320	-0.14022399	-0.30319229	0
## 321	1.38949226	1.92294500	1
## 322	1.48509952	0.32469259	1
## 323	0.33781234	-0.53151406	0
## 325	1.00706320	1.72316344	1
## 327	0.33781234	0.03929037	0
## 328	0.43341960	0.12491104	0
## 329	-0.14022399	1.35214056	1
## 330	0.91145593	1.03819813	1
## 331	0.05099054	-0.56005428	0
## 333	0.43341960	-0.16049118	0
## 334	0.24220507	-0.16049118	0
## 335	1.86752858	-0.30319229	1
## 336	-0.14022399	-0.47443362	0
## 337	1.96313585	2.09418633	1
## 338	-0.23583125	0.23907192	0
## 340	0.14659781	1.46630145	1
## 342	-0.23583125	0.12491104	0

```

## 344 0.91145593 -0.56005428 1
## 345 0.91145593 0.98111768 1
## 346 0.33781234 -0.21757162 0
## 348 1.58070679 1.06673835 1
## 349 0.14659781 0.18199148 0
## 350 0.05099054 -0.27465207 0
## 351 0.05099054 1.20943946 1
## 352 -0.04461672 0.12491104 0
## 354 -0.04461672 -0.38881295 0
## 355 -0.14022399 0.80987635 1
## 356 2.15435038 -1.04523805 1
## 357 1.58070679 -0.01779007 1
## 358 0.33781234 0.03929037 0
## 359 0.24220507 0.01075015 1
## 360 0.43341960 -0.47443362 0
## 361 0.52902687 1.66608300 1
## 362 1.48509952 -1.04523805 1
## 365 0.43341960 0.95257746 1
## 366 2.05874311 -1.18793916 1
## 370 1.58070679 -1.27355982 1
## 371 2.15435038 -0.70275539 1
## 374 2.05874311 1.69462322 1
## 375 -0.04461672 0.26761214 0
## 376 0.81584866 -1.10231849 1
## 377 0.81584866 0.09637081 0
## 378 0.43341960 -0.50297384 0
## 379 0.33781234 0.46739370 1
## 381 0.43341960 -0.18903140 0
## 382 1.00706320 -1.07377827 1
## 384 1.10267046 -1.21647938 1
## 385 1.86752858 -1.07377827 1
## 386 1.77192132 -0.30319229 1
## 387 1.10267046 -0.90253694 1
## 388 0.14659781 0.01075015 0
## 390 1.00706320 -1.01669783 1
## 391 1.00706320 -1.07377827 1
## 393 0.72024140 -0.73129561 1
## 394 2.15435038 -0.81691628 1
## 396 0.81584866 -0.84545650 1
## 397 1.29388499 -1.35918049 1
## 398 1.19827773 -1.44480115 1
## 399 -0.14022399 -1.07377827 0

```

```

testing_set[,1:2] = scale(testing_set[,1:2])
testing_set

```

```

##           Age EstimatedSalary Purchased
## 2  -0.30419063  -1.51354339           0
## 4  -1.05994374  -0.32456026           0
## 5  -1.81569686   0.28599864           0
## 9  -1.24888202  -1.09579256           0
## 12 -1.15441288  -0.48523366           0
## 18  0.64050076  -1.32073531           1
## 19  0.73496990  -1.25646596           1
## 20  0.92390818  -1.22433128           1

```

## 22	0.82943904	-0.58163769	1
## 29	-0.87100546	-0.77444577	0
## 32	-1.05994374	2.24621408	1
## 34	-0.96547460	-0.74231109	0
## 35	-1.05994374	0.73588415	0
## 38	-0.77653633	-0.58163769	0
## 45	-0.96547460	0.54307608	0
## 46	-1.43782030	-1.51354339	0
## 48	-1.05994374	-0.42096430	0
## 52	-1.91016600	-0.74231109	0
## 66	-1.34335116	-0.29242558	0
## 69	-1.53228944	-0.13175218	0
## 74	-0.49312891	1.47498177	0
## 75	-0.58759805	-1.57781275	0
## 82	0.07368593	-0.80658045	0
## 84	-0.30419063	0.67161480	0
## 85	-0.77653633	-0.16388686	0
## 86	-0.68206719	1.63565517	1
## 87	-1.34335116	-0.38882962	0
## 89	-1.15441288	0.44667204	0
## 103	-0.58759805	0.60734544	0
## 104	-0.49312891	2.63183023	1
## 107	-1.15441288	-1.03152320	0
## 108	-1.05994374	0.70374947	0
## 109	-1.15441288	0.60734544	0
## 117	-0.30419063	0.25386397	0
## 124	-0.30419063	-0.45309898	0
## 126	0.07368593	-0.19602154	0
## 127	0.35709335	-0.06748283	0
## 131	-0.68206719	-0.29242558	0
## 134	-1.62675858	0.02892121	0
## 139	-0.96547460	-0.26029090	0
## 148	0.26262421	-1.19219660	0
## 154	-0.20972149	-0.54950301	0
## 156	-0.68206719	-1.67421679	0
## 159	-1.15441288	-1.19219660	0
## 162	-1.24888202	0.73588415	0
## 163	-0.11525235	-1.09579256	0
## 170	-0.87100546	-0.64590705	0
## 175	-0.39865977	0.15745993	0
## 176	-1.43782030	-1.25646596	0
## 193	-0.87100546	-0.77444577	0
## 199	-1.15441288	0.41453736	0
## 200	-0.30419063	-1.44927403	0
## 208	1.30178474	1.50711645	0
## 213	1.96306872	-0.80658045	0
## 224	2.05753786	1.12150030	1
## 226	-0.11525235	-0.45309898	0
## 228	1.67966130	2.11767536	1
## 229	0.16815507	0.15745993	0
## 230	0.35709335	0.41453736	1
## 234	1.01837732	0.60734544	1
## 236	0.73496990	0.38240268	1
## 237	0.16815507	-0.32456026	0

```
## 239 0.73496990      0.47880672      0
## 241 0.35709335      2.63183023      1
## 255 1.11284646     -0.74231109      0
## 264 -0.30419063      0.15745993      0
## 265 0.92390818      0.73588415      1
## 266 0.35709335      1.31430838      1
## 273 2.05753786     -0.80658045      1
## 274 0.07368593      1.25003902      1
## 281 1.96306872      0.67161480      1
## 286 -0.11525235      0.83228819      1
## 292 1.01837732      0.70374947      1
## 299 0.64050076      0.38240268      0
## 302 0.92390818      0.22172929      1
## 305 0.16815507     -0.22815622      0
## 307 1.20731560      2.14981004      0
## 310 -0.02078321     -0.54950301      0
## 316 0.07368593      0.25386397      1
## 324 0.92390818     -1.19219660      1
## 326 0.26262421     -0.22815622      0
## 332 0.92390818      1.66778985      1
## 339 -0.02078321     -0.38882962      0
## 341 1.39625388      1.18576966      1
## 343 -0.02078321     -0.06748283      0
## 347 1.39625388      0.15745993      1
## 353 0.35709335      0.73588415      1
## 363 0.82943904     -0.54950301      1
## 364 0.35709335      0.38240268      0
## 367 1.86859958     -0.64590705      1
## 368 0.73496990      0.67161480      1
## 369 -0.02078321      0.12532525      0
## 372 2.05753786      0.51094140      1
## 373 0.07368593      0.18959461      0
## 380 1.86859958     -1.41713935      1
## 383 0.54603163      2.31048343      1
## 389 0.82943904     -1.06365788      1
## 392 0.82943904     -1.41713935      1
## 395 0.07368593     -0.26029090      0
## 400 1.01837732     -0.99938852      1
```

Ajustar el modelo de Regresión Logística con el conjunto de entrenamiento y hacer las predicciones con el conjunto testing

```
library(e1071)

## Warning: package 'e1071' was built under R version 4.0.5

classifier = naiveBayes(formula = Purchased ~.,
                        data = training_set)

y_pred = predict(classifier,
                  newdata = testing_set[, -3])
y_pred

## [1] 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0
```



```
## [38] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 1 0 0 1 1 0 1 1 1 0 1 1 1 1 0 1 1
## [75] 1 0 1 0 0 1 0 1 0 1 0 1 1 0 0 1 1 0 1 0 1 1 1 1 0 1
## Levels: 0 1
```

Comparar uno a uno los resultados predichos con los esperados no es una buena técnica por lo que se construye la matriz de confusión

```
cm = table(testing_set[, 3], y_pred)
cm
```

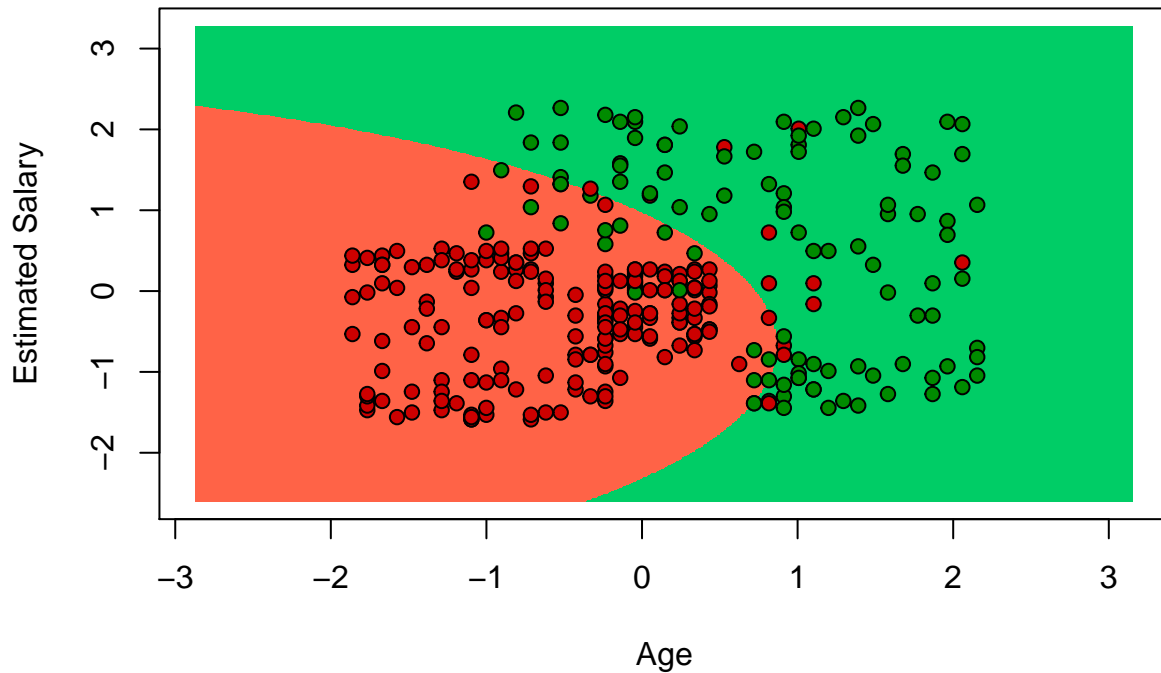
```
##      y_pred
##         0   1
##    0 57   7
##    1   7 29
```

La diagonal principal es la cantidad de datos que son predichos correctamente. La diagonal secundaria son los fallos.

Visualización del conjunto de entranmiento

```
library(ElemStatLearn)
set = training_set
X1 = seq(min(set[, 1]) - 1, max(set[, 1]) + 1, by = 0.01)
X2 = seq(min(set[, 2]) - 1, max(set[, 2]) + 1, by = 0.01)
grid_set = expand.grid(X1, X2)
colnames(grid_set) = c('Age', 'EstimatedSalary')
y_grid = predict(classifier,
                  newdata = grid_set)
plot(set[, -3],
     main = 'Naive-Bayes (Training set)',
     xlab = 'Age', ylab = 'Estimated Salary',
     xlim = range(X1), ylim = range(X2))
contour(X1, X2, matrix(as.numeric(y_grid), length(X1), length(X2)), add = TRUE)
points(grid_set, pch = '.', col = ifelse(y_grid == 1, 'springgreen3', 'tomato'))
points(set, pch = 21, bg = ifelse(set[, 3] == 1, 'green4', 'red3'))
```

Naive-Bayes (Training set)



Visualising the Test set results

```
library(ElemStatLearn)
set = testing_set
X1 = seq(min(set[, 1]) - 1, max(set[, 1]) + 1, by = 0.01)
X2 = seq(min(set[, 2]) - 1, max(set[, 2]) + 1, by = 0.01)
grid_set = expand.grid(X1, X2)
colnames(grid_set) = c('Age', 'EstimatedSalary')
y_grid = predict(classifier,
                  newdata = grid_set)
plot(set[, -3],
      main = 'Naive-Bayes (Test set)',
      xlab = 'Age', ylab = 'Estimated Salary',
      xlim = range(X1), ylim = range(X2))
contour(X1, X2, matrix(as.numeric(y_grid), length(X1), length(X2)), add = TRUE)
points(grid_set, pch = '.', col = ifelse(y_grid == 1, 'springgreen3', 'tomato'))
points(set, pch = 21, bg = ifelse(set[, 3] == 1, 'green4', 'red3'))
```

Naive-Bayes (Test set)

