

Phil's Code in Markdown

Ronald Maxseiner

2/12/2022

```
#Group 1: Diabetes Dataset
#Members: Phil, Ron, Kelly, Jane

#Libraries used
library(caret) #ML Model buidling package

## Loading required package: ggplot2
## Loading required package: lattice
library(tidyverse) #ggplot and dplyr

## -- Attaching packages ----- tidyverse 1.3.1 --
## v tibble  3.1.6      v dplyr   1.0.7
## v tidyr   1.1.4      v stringr 1.4.0
## v readr   2.1.1      v forcats 0.5.1
## v purrr   0.3.4

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## x purrr::lift()    masks caret::lift()

library(MASS) #Modern Applied Statistics with S

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##      select

library(mlbench) #data sets from the UCI repository.
library(summarytools)

##
## Attaching package: 'summarytools'

## The following object is masked from 'package:tibble':
##
##      view

library(corrplot) #Correlation plot

## corrplot 0.92 loaded
```

```

library(gridExtra) #Multiple plot in single grip space

##
## Attaching package: 'gridExtra'
## The following object is masked from 'package:dplyr':
##
##      combine
library(timeDate)
library(pROC) #ROC

## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
## The following objects are masked from 'package:stats':
##
##      cov, smooth, var
library(caTools) #AUC
library(rpart.plot) #CART Decision Tree

## Loading required package: rpart
library(e1071) #imports graphics, grDevices, class, stats, methods, utils

##
## Attaching package: 'e1071'
## The following objects are masked from 'package:timeDate':
##
##      kurtosis, skewness
library(doParallel)

## Loading required package: foreach
##
## Attaching package: 'foreach'
## The following objects are masked from 'package:purrr':
##
##      accumulate, when
## Loading required package: iterators
## Loading required package: parallel
library(AppliedPredictiveModeling)
library(rpart)
library(partykit)

## Loading required package: grid
## Loading required package: libcoin
## Loading required package: mvtnorm
library(randomForest)

## randomForest 4.6-14

```

```
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:gridExtra':
##
##     combine
##
## The following object is masked from 'package:dplyr':
##
##     combine
##
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
registerDoParallel(cores=7)
```

```
set.seed(100)
```

```
#Pima Indians Diabetes Dataset Found Inside Caret Function
data(PimaIndiansDiabetes)# There are two of them, versions
df <- PimaIndiansDiabetes
df
```

	pregnant	glucose	pressure	triceps	insulin	mass	pedigree	age	diabetes
## 1	6	148	72	35	0	33.6	0.627	50	pos
## 2	1	85	66	29	0	26.6	0.351	31	neg
## 3	8	183	64	0	0	23.3	0.672	32	pos
## 4	1	89	66	23	94	28.1	0.167	21	neg
## 5	0	137	40	35	168	43.1	2.288	33	pos
## 6	5	116	74	0	0	25.6	0.201	30	neg
## 7	3	78	50	32	88	31.0	0.248	26	pos
## 8	10	115	0	0	0	35.3	0.134	29	neg
## 9	2	197	70	45	543	30.5	0.158	53	pos
## 10	8	125	96	0	0	0.0	0.232	54	pos
## 11	4	110	92	0	0	37.6	0.191	30	neg
## 12	10	168	74	0	0	38.0	0.537	34	pos
## 13	10	139	80	0	0	27.1	1.441	57	neg
## 14	1	189	60	23	846	30.1	0.398	59	pos
## 15	5	166	72	19	175	25.8	0.587	51	pos
## 16	7	100	0	0	0	30.0	0.484	32	pos
## 17	0	118	84	47	230	45.8	0.551	31	pos
## 18	7	107	74	0	0	29.6	0.254	31	pos
## 19	1	103	30	38	83	43.3	0.183	33	neg
## 20	1	115	70	30	96	34.6	0.529	32	pos
## 21	3	126	88	41	235	39.3	0.704	27	neg
## 22	8	99	84	0	0	35.4	0.388	50	neg
## 23	7	196	90	0	0	39.8	0.451	41	pos
## 24	9	119	80	35	0	29.0	0.263	29	pos
## 25	11	143	94	33	146	36.6	0.254	51	pos
## 26	10	125	70	26	115	31.1	0.205	41	pos
## 27	7	147	76	0	0	39.4	0.257	43	pos
## 28	1	97	66	15	140	23.2	0.487	22	neg
## 29	13	145	82	19	110	22.2	0.245	57	neg

## 30	5	117	92	0	0	34.1	0.337	38	neg
## 31	5	109	75	26	0	36.0	0.546	60	neg
## 32	3	158	76	36	245	31.6	0.851	28	pos
## 33	3	88	58	11	54	24.8	0.267	22	neg
## 34	6	92	92	0	0	19.9	0.188	28	neg
## 35	10	122	78	31	0	27.6	0.512	45	neg
## 36	4	103	60	33	192	24.0	0.966	33	neg
## 37	11	138	76	0	0	33.2	0.420	35	neg
## 38	9	102	76	37	0	32.9	0.665	46	pos
## 39	2	90	68	42	0	38.2	0.503	27	pos
## 40	4	111	72	47	207	37.1	1.390	56	pos
## 41	3	180	64	25	70	34.0	0.271	26	neg
## 42	7	133	84	0	0	40.2	0.696	37	neg
## 43	7	106	92	18	0	22.7	0.235	48	neg
## 44	9	171	110	24	240	45.4	0.721	54	pos
## 45	7	159	64	0	0	27.4	0.294	40	neg
## 46	0	180	66	39	0	42.0	1.893	25	pos
## 47	1	146	56	0	0	29.7	0.564	29	neg
## 48	2	71	70	27	0	28.0	0.586	22	neg
## 49	7	103	66	32	0	39.1	0.344	31	pos
## 50	7	105	0	0	0	0.0	0.305	24	neg
## 51	1	103	80	11	82	19.4	0.491	22	neg
## 52	1	101	50	15	36	24.2	0.526	26	neg
## 53	5	88	66	21	23	24.4	0.342	30	neg
## 54	8	176	90	34	300	33.7	0.467	58	pos
## 55	7	150	66	42	342	34.7	0.718	42	neg
## 56	1	73	50	10	0	23.0	0.248	21	neg
## 57	7	187	68	39	304	37.7	0.254	41	pos
## 58	0	100	88	60	110	46.8	0.962	31	neg
## 59	0	146	82	0	0	40.5	1.781	44	neg
## 60	0	105	64	41	142	41.5	0.173	22	neg
## 61	2	84	0	0	0	0.0	0.304	21	neg
## 62	8	133	72	0	0	32.9	0.270	39	pos
## 63	5	44	62	0	0	25.0	0.587	36	neg
## 64	2	141	58	34	128	25.4	0.699	24	neg
## 65	7	114	66	0	0	32.8	0.258	42	pos
## 66	5	99	74	27	0	29.0	0.203	32	neg
## 67	0	109	88	30	0	32.5	0.855	38	pos
## 68	2	109	92	0	0	42.7	0.845	54	neg
## 69	1	95	66	13	38	19.6	0.334	25	neg
## 70	4	146	85	27	100	28.9	0.189	27	neg
## 71	2	100	66	20	90	32.9	0.867	28	pos
## 72	5	139	64	35	140	28.6	0.411	26	neg
## 73	13	126	90	0	0	43.4	0.583	42	pos
## 74	4	129	86	20	270	35.1	0.231	23	neg
## 75	1	79	75	30	0	32.0	0.396	22	neg
## 76	1	0	48	20	0	24.7	0.140	22	neg
## 77	7	62	78	0	0	32.6	0.391	41	neg
## 78	5	95	72	33	0	37.7	0.370	27	neg
## 79	0	131	0	0	0	43.2	0.270	26	pos
## 80	2	112	66	22	0	25.0	0.307	24	neg
## 81	3	113	44	13	0	22.4	0.140	22	neg
## 82	2	74	0	0	0	0.0	0.102	22	neg
## 83	7	83	78	26	71	29.3	0.767	36	neg

## 84	0	101	65	28	0	24.6	0.237	22	neg
## 85	5	137	108	0	0	48.8	0.227	37	pos
## 86	2	110	74	29	125	32.4	0.698	27	neg
## 87	13	106	72	54	0	36.6	0.178	45	neg
## 88	2	100	68	25	71	38.5	0.324	26	neg
## 89	15	136	70	32	110	37.1	0.153	43	pos
## 90	1	107	68	19	0	26.5	0.165	24	neg
## 91	1	80	55	0	0	19.1	0.258	21	neg
## 92	4	123	80	15	176	32.0	0.443	34	neg
## 93	7	81	78	40	48	46.7	0.261	42	neg
## 94	4	134	72	0	0	23.8	0.277	60	pos
## 95	2	142	82	18	64	24.7	0.761	21	neg
## 96	6	144	72	27	228	33.9	0.255	40	neg
## 97	2	92	62	28	0	31.6	0.130	24	neg
## 98	1	71	48	18	76	20.4	0.323	22	neg
## 99	6	93	50	30	64	28.7	0.356	23	neg
## 100	1	122	90	51	220	49.7	0.325	31	pos
## 101	1	163	72	0	0	39.0	1.222	33	pos
## 102	1	151	60	0	0	26.1	0.179	22	neg
## 103	0	125	96	0	0	22.5	0.262	21	neg
## 104	1	81	72	18	40	26.6	0.283	24	neg
## 105	2	85	65	0	0	39.6	0.930	27	neg
## 106	1	126	56	29	152	28.7	0.801	21	neg
## 107	1	96	122	0	0	22.4	0.207	27	neg
## 108	4	144	58	28	140	29.5	0.287	37	neg
## 109	3	83	58	31	18	34.3	0.336	25	neg
## 110	0	95	85	25	36	37.4	0.247	24	pos
## 111	3	171	72	33	135	33.3	0.199	24	pos
## 112	8	155	62	26	495	34.0	0.543	46	pos
## 113	1	89	76	34	37	31.2	0.192	23	neg
## 114	4	76	62	0	0	34.0	0.391	25	neg
## 115	7	160	54	32	175	30.5	0.588	39	pos
## 116	4	146	92	0	0	31.2	0.539	61	pos
## 117	5	124	74	0	0	34.0	0.220	38	pos
## 118	5	78	48	0	0	33.7	0.654	25	neg
## 119	4	97	60	23	0	28.2	0.443	22	neg
## 120	4	99	76	15	51	23.2	0.223	21	neg
## 121	0	162	76	56	100	53.2	0.759	25	pos
## 122	6	111	64	39	0	34.2	0.260	24	neg
## 123	2	107	74	30	100	33.6	0.404	23	neg
## 124	5	132	80	0	0	26.8	0.186	69	neg
## 125	0	113	76	0	0	33.3	0.278	23	pos
## 126	1	88	30	42	99	55.0	0.496	26	pos
## 127	3	120	70	30	135	42.9	0.452	30	neg
## 128	1	118	58	36	94	33.3	0.261	23	neg
## 129	1	117	88	24	145	34.5	0.403	40	pos
## 130	0	105	84	0	0	27.9	0.741	62	pos
## 131	4	173	70	14	168	29.7	0.361	33	pos
## 132	9	122	56	0	0	33.3	1.114	33	pos
## 133	3	170	64	37	225	34.5	0.356	30	pos
## 134	8	84	74	31	0	38.3	0.457	39	neg
## 135	2	96	68	13	49	21.1	0.647	26	neg
## 136	2	125	60	20	140	33.8	0.088	31	neg
## 137	0	100	70	26	50	30.8	0.597	21	neg

## 138	0	93	60	25	92	28.7	0.532	22	neg
## 139	0	129	80	0	0	31.2	0.703	29	neg
## 140	5	105	72	29	325	36.9	0.159	28	neg
## 141	3	128	78	0	0	21.1	0.268	55	neg
## 142	5	106	82	30	0	39.5	0.286	38	neg
## 143	2	108	52	26	63	32.5	0.318	22	neg
## 144	10	108	66	0	0	32.4	0.272	42	pos
## 145	4	154	62	31	284	32.8	0.237	23	neg
## 146	0	102	75	23	0	0.0	0.572	21	neg
## 147	9	57	80	37	0	32.8	0.096	41	neg
## 148	2	106	64	35	119	30.5	1.400	34	neg
## 149	5	147	78	0	0	33.7	0.218	65	neg
## 150	2	90	70	17	0	27.3	0.085	22	neg
## 151	1	136	74	50	204	37.4	0.399	24	neg
## 152	4	114	65	0	0	21.9	0.432	37	neg
## 153	9	156	86	28	155	34.3	1.189	42	pos
## 154	1	153	82	42	485	40.6	0.687	23	neg
## 155	8	188	78	0	0	47.9	0.137	43	pos
## 156	7	152	88	44	0	50.0	0.337	36	pos
## 157	2	99	52	15	94	24.6	0.637	21	neg
## 158	1	109	56	21	135	25.2	0.833	23	neg
## 159	2	88	74	19	53	29.0	0.229	22	neg
## 160	17	163	72	41	114	40.9	0.817	47	pos
## 161	4	151	90	38	0	29.7	0.294	36	neg
## 162	7	102	74	40	105	37.2	0.204	45	neg
## 163	0	114	80	34	285	44.2	0.167	27	neg
## 164	2	100	64	23	0	29.7	0.368	21	neg
## 165	0	131	88	0	0	31.6	0.743	32	pos
## 166	6	104	74	18	156	29.9	0.722	41	pos
## 167	3	148	66	25	0	32.5	0.256	22	neg
## 168	4	120	68	0	0	29.6	0.709	34	neg
## 169	4	110	66	0	0	31.9	0.471	29	neg
## 170	3	111	90	12	78	28.4	0.495	29	neg
## 171	6	102	82	0	0	30.8	0.180	36	pos
## 172	6	134	70	23	130	35.4	0.542	29	pos
## 173	2	87	0	23	0	28.9	0.773	25	neg
## 174	1	79	60	42	48	43.5	0.678	23	neg
## 175	2	75	64	24	55	29.7	0.370	33	neg
## 176	8	179	72	42	130	32.7	0.719	36	pos
## 177	6	85	78	0	0	31.2	0.382	42	neg
## 178	0	129	110	46	130	67.1	0.319	26	pos
## 179	5	143	78	0	0	45.0	0.190	47	neg
## 180	5	130	82	0	0	39.1	0.956	37	pos
## 181	6	87	80	0	0	23.2	0.084	32	neg
## 182	0	119	64	18	92	34.9	0.725	23	neg
## 183	1	0	74	20	23	27.7	0.299	21	neg
## 184	5	73	60	0	0	26.8	0.268	27	neg
## 185	4	141	74	0	0	27.6	0.244	40	neg
## 186	7	194	68	28	0	35.9	0.745	41	pos
## 187	8	181	68	36	495	30.1	0.615	60	pos
## 188	1	128	98	41	58	32.0	1.321	33	pos
## 189	8	109	76	39	114	27.9	0.640	31	pos
## 190	5	139	80	35	160	31.6	0.361	25	pos
## 191	3	111	62	0	0	22.6	0.142	21	neg

## 192	9	123	70	44	94 33.1	0.374	40	neg
## 193	7	159	66	0	0 30.4	0.383	36	pos
## 194	11	135	0	0	0 52.3	0.578	40	pos
## 195	8	85	55	20	0 24.4	0.136	42	neg
## 196	5	158	84	41	210 39.4	0.395	29	pos
## 197	1	105	58	0	0 24.3	0.187	21	neg
## 198	3	107	62	13	48 22.9	0.678	23	pos
## 199	4	109	64	44	99 34.8	0.905	26	pos
## 200	4	148	60	27	318 30.9	0.150	29	pos
## 201	0	113	80	16	0 31.0	0.874	21	neg
## 202	1	138	82	0	0 40.1	0.236	28	neg
## 203	0	108	68	20	0 27.3	0.787	32	neg
## 204	2	99	70	16	44 20.4	0.235	27	neg
## 205	6	103	72	32	190 37.7	0.324	55	neg
## 206	5	111	72	28	0 23.9	0.407	27	neg
## 207	8	196	76	29	280 37.5	0.605	57	pos
## 208	5	162	104	0	0 37.7	0.151	52	pos
## 209	1	96	64	27	87 33.2	0.289	21	neg
## 210	7	184	84	33	0 35.5	0.355	41	pos
## 211	2	81	60	22	0 27.7	0.290	25	neg
## 212	0	147	85	54	0 42.8	0.375	24	neg
## 213	7	179	95	31	0 34.2	0.164	60	neg
## 214	0	140	65	26	130 42.6	0.431	24	pos
## 215	9	112	82	32	175 34.2	0.260	36	pos
## 216	12	151	70	40	271 41.8	0.742	38	pos
## 217	5	109	62	41	129 35.8	0.514	25	pos
## 218	6	125	68	30	120 30.0	0.464	32	neg
## 219	5	85	74	22	0 29.0	1.224	32	pos
## 220	5	112	66	0	0 37.8	0.261	41	pos
## 221	0	177	60	29	478 34.6	1.072	21	pos
## 222	2	158	90	0	0 31.6	0.805	66	pos
## 223	7	119	0	0	0 25.2	0.209	37	neg
## 224	7	142	60	33	190 28.8	0.687	61	neg
## 225	1	100	66	15	56 23.6	0.666	26	neg
## 226	1	87	78	27	32 34.6	0.101	22	neg
## 227	0	101	76	0	0 35.7	0.198	26	neg
## 228	3	162	52	38	0 37.2	0.652	24	pos
## 229	4	197	70	39	744 36.7	2.329	31	neg
## 230	0	117	80	31	53 45.2	0.089	24	neg
## 231	4	142	86	0	0 44.0	0.645	22	pos
## 232	6	134	80	37	370 46.2	0.238	46	pos
## 233	1	79	80	25	37 25.4	0.583	22	neg
## 234	4	122	68	0	0 35.0	0.394	29	neg
## 235	3	74	68	28	45 29.7	0.293	23	neg
## 236	4	171	72	0	0 43.6	0.479	26	pos
## 237	7	181	84	21	192 35.9	0.586	51	pos
## 238	0	179	90	27	0 44.1	0.686	23	pos
## 239	9	164	84	21	0 30.8	0.831	32	pos
## 240	0	104	76	0	0 18.4	0.582	27	neg
## 241	1	91	64	24	0 29.2	0.192	21	neg
## 242	4	91	70	32	88 33.1	0.446	22	neg
## 243	3	139	54	0	0 25.6	0.402	22	pos
## 244	6	119	50	22	176 27.1	1.318	33	pos
## 245	2	146	76	35	194 38.2	0.329	29	neg

## 246	9	184	85	15	0 30.0	1.213	49	pos
## 247	10	122	68	0	0 31.2	0.258	41	neg
## 248	0	165	90	33	680 52.3	0.427	23	neg
## 249	9	124	70	33	402 35.4	0.282	34	neg
## 250	1	111	86	19	0 30.1	0.143	23	neg
## 251	9	106	52	0	0 31.2	0.380	42	neg
## 252	2	129	84	0	0 28.0	0.284	27	neg
## 253	2	90	80	14	55 24.4	0.249	24	neg
## 254	0	86	68	32	0 35.8	0.238	25	neg
## 255	12	92	62	7	258 27.6	0.926	44	pos
## 256	1	113	64	35	0 33.6	0.543	21	pos
## 257	3	111	56	39	0 30.1	0.557	30	neg
## 258	2	114	68	22	0 28.7	0.092	25	neg
## 259	1	193	50	16	375 25.9	0.655	24	neg
## 260	11	155	76	28	150 33.3	1.353	51	pos
## 261	3	191	68	15	130 30.9	0.299	34	neg
## 262	3	141	0	0	0 30.0	0.761	27	pos
## 263	4	95	70	32	0 32.1	0.612	24	neg
## 264	3	142	80	15	0 32.4	0.200	63	neg
## 265	4	123	62	0	0 32.0	0.226	35	pos
## 266	5	96	74	18	67 33.6	0.997	43	neg
## 267	0	138	0	0	0 36.3	0.933	25	pos
## 268	2	128	64	42	0 40.0	1.101	24	neg
## 269	0	102	52	0	0 25.1	0.078	21	neg
## 270	2	146	0	0	0 27.5	0.240	28	pos
## 271	10	101	86	37	0 45.6	1.136	38	pos
## 272	2	108	62	32	56 25.2	0.128	21	neg
## 273	3	122	78	0	0 23.0	0.254	40	neg
## 274	1	71	78	50	45 33.2	0.422	21	neg
## 275	13	106	70	0	0 34.2	0.251	52	neg
## 276	2	100	70	52	57 40.5	0.677	25	neg
## 277	7	106	60	24	0 26.5	0.296	29	pos
## 278	0	104	64	23	116 27.8	0.454	23	neg
## 279	5	114	74	0	0 24.9	0.744	57	neg
## 280	2	108	62	10	278 25.3	0.881	22	neg
## 281	0	146	70	0	0 37.9	0.334	28	pos
## 282	10	129	76	28	122 35.9	0.280	39	neg
## 283	7	133	88	15	155 32.4	0.262	37	neg
## 284	7	161	86	0	0 30.4	0.165	47	pos
## 285	2	108	80	0	0 27.0	0.259	52	pos
## 286	7	136	74	26	135 26.0	0.647	51	neg
## 287	5	155	84	44	545 38.7	0.619	34	neg
## 288	1	119	86	39	220 45.6	0.808	29	pos
## 289	4	96	56	17	49 20.8	0.340	26	neg
## 290	5	108	72	43	75 36.1	0.263	33	neg
## 291	0	78	88	29	40 36.9	0.434	21	neg
## 292	0	107	62	30	74 36.6	0.757	25	pos
## 293	2	128	78	37	182 43.3	1.224	31	pos
## 294	1	128	48	45	194 40.5	0.613	24	pos
## 295	0	161	50	0	0 21.9	0.254	65	neg
## 296	6	151	62	31	120 35.5	0.692	28	neg
## 297	2	146	70	38	360 28.0	0.337	29	pos
## 298	0	126	84	29	215 30.7	0.520	24	neg
## 299	14	100	78	25	184 36.6	0.412	46	pos

## 300	8	112	72	0	0	23.6	0.840	58	neg
## 301	0	167	0	0	0	32.3	0.839	30	pos
## 302	2	144	58	33	135	31.6	0.422	25	pos
## 303	5	77	82	41	42	35.8	0.156	35	neg
## 304	5	115	98	0	0	52.9	0.209	28	pos
## 305	3	150	76	0	0	21.0	0.207	37	neg
## 306	2	120	76	37	105	39.7	0.215	29	neg
## 307	10	161	68	23	132	25.5	0.326	47	pos
## 308	0	137	68	14	148	24.8	0.143	21	neg
## 309	0	128	68	19	180	30.5	1.391	25	pos
## 310	2	124	68	28	205	32.9	0.875	30	pos
## 311	6	80	66	30	0	26.2	0.313	41	neg
## 312	0	106	70	37	148	39.4	0.605	22	neg
## 313	2	155	74	17	96	26.6	0.433	27	pos
## 314	3	113	50	10	85	29.5	0.626	25	neg
## 315	7	109	80	31	0	35.9	1.127	43	pos
## 316	2	112	68	22	94	34.1	0.315	26	neg
## 317	3	99	80	11	64	19.3	0.284	30	neg
## 318	3	182	74	0	0	30.5	0.345	29	pos
## 319	3	115	66	39	140	38.1	0.150	28	neg
## 320	6	194	78	0	0	23.5	0.129	59	pos
## 321	4	129	60	12	231	27.5	0.527	31	neg
## 322	3	112	74	30	0	31.6	0.197	25	pos
## 323	0	124	70	20	0	27.4	0.254	36	pos
## 324	13	152	90	33	29	26.8	0.731	43	pos
## 325	2	112	75	32	0	35.7	0.148	21	neg
## 326	1	157	72	21	168	25.6	0.123	24	neg
## 327	1	122	64	32	156	35.1	0.692	30	pos
## 328	10	179	70	0	0	35.1	0.200	37	neg
## 329	2	102	86	36	120	45.5	0.127	23	pos
## 330	6	105	70	32	68	30.8	0.122	37	neg
## 331	8	118	72	19	0	23.1	1.476	46	neg
## 332	2	87	58	16	52	32.7	0.166	25	neg
## 333	1	180	0	0	0	43.3	0.282	41	pos
## 334	12	106	80	0	0	23.6	0.137	44	neg
## 335	1	95	60	18	58	23.9	0.260	22	neg
## 336	0	165	76	43	255	47.9	0.259	26	neg
## 337	0	117	0	0	0	33.8	0.932	44	neg
## 338	5	115	76	0	0	31.2	0.343	44	pos
## 339	9	152	78	34	171	34.2	0.893	33	pos
## 340	7	178	84	0	0	39.9	0.331	41	pos
## 341	1	130	70	13	105	25.9	0.472	22	neg
## 342	1	95	74	21	73	25.9	0.673	36	neg
## 343	1	0	68	35	0	32.0	0.389	22	neg
## 344	5	122	86	0	0	34.7	0.290	33	neg
## 345	8	95	72	0	0	36.8	0.485	57	neg
## 346	8	126	88	36	108	38.5	0.349	49	neg
## 347	1	139	46	19	83	28.7	0.654	22	neg
## 348	3	116	0	0	0	23.5	0.187	23	neg
## 349	3	99	62	19	74	21.8	0.279	26	neg
## 350	5	0	80	32	0	41.0	0.346	37	pos
## 351	4	92	80	0	0	42.2	0.237	29	neg
## 352	4	137	84	0	0	31.2	0.252	30	neg
## 353	3	61	82	28	0	34.4	0.243	46	neg

## 354	1	90	62	12	43 27.2	0.580	24	neg
## 355	3	90	78	0	0 42.7	0.559	21	neg
## 356	9	165	88	0	0 30.4	0.302	49	pos
## 357	1	125	50	40	167 33.3	0.962	28	pos
## 358	13	129	0	30	0 39.9	0.569	44	pos
## 359	12	88	74	40	54 35.3	0.378	48	neg
## 360	1	196	76	36	249 36.5	0.875	29	pos
## 361	5	189	64	33	325 31.2	0.583	29	pos
## 362	5	158	70	0	0 29.8	0.207	63	neg
## 363	5	103	108	37	0 39.2	0.305	65	neg
## 364	4	146	78	0	0 38.5	0.520	67	pos
## 365	4	147	74	25	293 34.9	0.385	30	neg
## 366	5	99	54	28	83 34.0	0.499	30	neg
## 367	6	124	72	0	0 27.6	0.368	29	pos
## 368	0	101	64	17	0 21.0	0.252	21	neg
## 369	3	81	86	16	66 27.5	0.306	22	neg
## 370	1	133	102	28	140 32.8	0.234	45	pos
## 371	3	173	82	48	465 38.4	2.137	25	pos
## 372	0	118	64	23	89 0.0	1.731	21	neg
## 373	0	84	64	22	66 35.8	0.545	21	neg
## 374	2	105	58	40	94 34.9	0.225	25	neg
## 375	2	122	52	43	158 36.2	0.816	28	neg
## 376	12	140	82	43	325 39.2	0.528	58	pos
## 377	0	98	82	15	84 25.2	0.299	22	neg
## 378	1	87	60	37	75 37.2	0.509	22	neg
## 379	4	156	75	0	0 48.3	0.238	32	pos
## 380	0	93	100	39	72 43.4	1.021	35	neg
## 381	1	107	72	30	82 30.8	0.821	24	neg
## 382	0	105	68	22	0 20.0	0.236	22	neg
## 383	1	109	60	8	182 25.4	0.947	21	neg
## 384	1	90	62	18	59 25.1	1.268	25	neg
## 385	1	125	70	24	110 24.3	0.221	25	neg
## 386	1	119	54	13	50 22.3	0.205	24	neg
## 387	5	116	74	29	0 32.3	0.660	35	pos
## 388	8	105	100	36	0 43.3	0.239	45	pos
## 389	5	144	82	26	285 32.0	0.452	58	pos
## 390	3	100	68	23	81 31.6	0.949	28	neg
## 391	1	100	66	29	196 32.0	0.444	42	neg
## 392	5	166	76	0	0 45.7	0.340	27	pos
## 393	1	131	64	14	415 23.7	0.389	21	neg
## 394	4	116	72	12	87 22.1	0.463	37	neg
## 395	4	158	78	0	0 32.9	0.803	31	pos
## 396	2	127	58	24	275 27.7	1.600	25	neg
## 397	3	96	56	34	115 24.7	0.944	39	neg
## 398	0	131	66	40	0 34.3	0.196	22	pos
## 399	3	82	70	0	0 21.1	0.389	25	neg
## 400	3	193	70	31	0 34.9	0.241	25	pos
## 401	4	95	64	0	0 32.0	0.161	31	pos
## 402	6	137	61	0	0 24.2	0.151	55	neg
## 403	5	136	84	41	88 35.0	0.286	35	pos
## 404	9	72	78	25	0 31.6	0.280	38	neg
## 405	5	168	64	0	0 32.9	0.135	41	pos
## 406	2	123	48	32	165 42.1	0.520	26	neg
## 407	4	115	72	0	0 28.9	0.376	46	pos

## 408	0	101	62	0	0 21.9	0.336	25	neg
## 409	8	197	74	0	0 25.9	1.191	39	pos
## 410	1	172	68	49	579 42.4	0.702	28	pos
## 411	6	102	90	39	0 35.7	0.674	28	neg
## 412	1	112	72	30	176 34.4	0.528	25	neg
## 413	1	143	84	23	310 42.4	1.076	22	neg
## 414	1	143	74	22	61 26.2	0.256	21	neg
## 415	0	138	60	35	167 34.6	0.534	21	pos
## 416	3	173	84	33	474 35.7	0.258	22	pos
## 417	1	97	68	21	0 27.2	1.095	22	neg
## 418	4	144	82	32	0 38.5	0.554	37	pos
## 419	1	83	68	0	0 18.2	0.624	27	neg
## 420	3	129	64	29	115 26.4	0.219	28	pos
## 421	1	119	88	41	170 45.3	0.507	26	neg
## 422	2	94	68	18	76 26.0	0.561	21	neg
## 423	0	102	64	46	78 40.6	0.496	21	neg
## 424	2	115	64	22	0 30.8	0.421	21	neg
## 425	8	151	78	32	210 42.9	0.516	36	pos
## 426	4	184	78	39	277 37.0	0.264	31	pos
## 427	0	94	0	0	0 0.0	0.256	25	neg
## 428	1	181	64	30	180 34.1	0.328	38	pos
## 429	0	135	94	46	145 40.6	0.284	26	neg
## 430	1	95	82	25	180 35.0	0.233	43	pos
## 431	2	99	0	0	0 22.2	0.108	23	neg
## 432	3	89	74	16	85 30.4	0.551	38	neg
## 433	1	80	74	11	60 30.0	0.527	22	neg
## 434	2	139	75	0	0 25.6	0.167	29	neg
## 435	1	90	68	8	0 24.5	1.138	36	neg
## 436	0	141	0	0	0 42.4	0.205	29	pos
## 437	12	140	85	33	0 37.4	0.244	41	neg
## 438	5	147	75	0	0 29.9	0.434	28	neg
## 439	1	97	70	15	0 18.2	0.147	21	neg
## 440	6	107	88	0	0 36.8	0.727	31	neg
## 441	0	189	104	25	0 34.3	0.435	41	pos
## 442	2	83	66	23	50 32.2	0.497	22	neg
## 443	4	117	64	27	120 33.2	0.230	24	neg
## 444	8	108	70	0	0 30.5	0.955	33	pos
## 445	4	117	62	12	0 29.7	0.380	30	pos
## 446	0	180	78	63	14 59.4	2.420	25	pos
## 447	1	100	72	12	70 25.3	0.658	28	neg
## 448	0	95	80	45	92 36.5	0.330	26	neg
## 449	0	104	64	37	64 33.6	0.510	22	pos
## 450	0	120	74	18	63 30.5	0.285	26	neg
## 451	1	82	64	13	95 21.2	0.415	23	neg
## 452	2	134	70	0	0 28.9	0.542	23	pos
## 453	0	91	68	32	210 39.9	0.381	25	neg
## 454	2	119	0	0	0 19.6	0.832	72	neg
## 455	2	100	54	28	105 37.8	0.498	24	neg
## 456	14	175	62	30	0 33.6	0.212	38	pos
## 457	1	135	54	0	0 26.7	0.687	62	neg
## 458	5	86	68	28	71 30.2	0.364	24	neg
## 459	10	148	84	48	237 37.6	1.001	51	pos
## 460	9	134	74	33	60 25.9	0.460	81	neg
## 461	9	120	72	22	56 20.8	0.733	48	neg

## 462	1	71	62	0	0	21.8	0.416	26	neg
## 463	8	74	70	40	49	35.3	0.705	39	neg
## 464	5	88	78	30	0	27.6	0.258	37	neg
## 465	10	115	98	0	0	24.0	1.022	34	neg
## 466	0	124	56	13	105	21.8	0.452	21	neg
## 467	0	74	52	10	36	27.8	0.269	22	neg
## 468	0	97	64	36	100	36.8	0.600	25	neg
## 469	8	120	0	0	0	30.0	0.183	38	pos
## 470	6	154	78	41	140	46.1	0.571	27	neg
## 471	1	144	82	40	0	41.3	0.607	28	neg
## 472	0	137	70	38	0	33.2	0.170	22	neg
## 473	0	119	66	27	0	38.8	0.259	22	neg
## 474	7	136	90	0	0	29.9	0.210	50	neg
## 475	4	114	64	0	0	28.9	0.126	24	neg
## 476	0	137	84	27	0	27.3	0.231	59	neg
## 477	2	105	80	45	191	33.7	0.711	29	pos
## 478	7	114	76	17	110	23.8	0.466	31	neg
## 479	8	126	74	38	75	25.9	0.162	39	neg
## 480	4	132	86	31	0	28.0	0.419	63	neg
## 481	3	158	70	30	328	35.5	0.344	35	pos
## 482	0	123	88	37	0	35.2	0.197	29	neg
## 483	4	85	58	22	49	27.8	0.306	28	neg
## 484	0	84	82	31	125	38.2	0.233	23	neg
## 485	0	145	0	0	0	44.2	0.630	31	pos
## 486	0	135	68	42	250	42.3	0.365	24	pos
## 487	1	139	62	41	480	40.7	0.536	21	neg
## 488	0	173	78	32	265	46.5	1.159	58	neg
## 489	4	99	72	17	0	25.6	0.294	28	neg
## 490	8	194	80	0	0	26.1	0.551	67	neg
## 491	2	83	65	28	66	36.8	0.629	24	neg
## 492	2	89	90	30	0	33.5	0.292	42	neg
## 493	4	99	68	38	0	32.8	0.145	33	neg
## 494	4	125	70	18	122	28.9	1.144	45	pos
## 495	3	80	0	0	0	0.0	0.174	22	neg
## 496	6	166	74	0	0	26.6	0.304	66	neg
## 497	5	110	68	0	0	26.0	0.292	30	neg
## 498	2	81	72	15	76	30.1	0.547	25	neg
## 499	7	195	70	33	145	25.1	0.163	55	pos
## 500	6	154	74	32	193	29.3	0.839	39	neg
## 501	2	117	90	19	71	25.2	0.313	21	neg
## 502	3	84	72	32	0	37.2	0.267	28	neg
## 503	6	0	68	41	0	39.0	0.727	41	pos
## 504	7	94	64	25	79	33.3	0.738	41	neg
## 505	3	96	78	39	0	37.3	0.238	40	neg
## 506	10	75	82	0	0	33.3	0.263	38	neg
## 507	0	180	90	26	90	36.5	0.314	35	pos
## 508	1	130	60	23	170	28.6	0.692	21	neg
## 509	2	84	50	23	76	30.4	0.968	21	neg
## 510	8	120	78	0	0	25.0	0.409	64	neg
## 511	12	84	72	31	0	29.7	0.297	46	pos
## 512	0	139	62	17	210	22.1	0.207	21	neg
## 513	9	91	68	0	0	24.2	0.200	58	neg
## 514	2	91	62	0	0	27.3	0.525	22	neg
## 515	3	99	54	19	86	25.6	0.154	24	neg

## 516	3	163	70	18	105	31.6	0.268	28	pos
## 517	9	145	88	34	165	30.3	0.771	53	pos
## 518	7	125	86	0	0	37.6	0.304	51	neg
## 519	13	76	60	0	0	32.8	0.180	41	neg
## 520	6	129	90	7	326	19.6	0.582	60	neg
## 521	2	68	70	32	66	25.0	0.187	25	neg
## 522	3	124	80	33	130	33.2	0.305	26	neg
## 523	6	114	0	0	0	0.0	0.189	26	neg
## 524	9	130	70	0	0	34.2	0.652	45	pos
## 525	3	125	58	0	0	31.6	0.151	24	neg
## 526	3	87	60	18	0	21.8	0.444	21	neg
## 527	1	97	64	19	82	18.2	0.299	21	neg
## 528	3	116	74	15	105	26.3	0.107	24	neg
## 529	0	117	66	31	188	30.8	0.493	22	neg
## 530	0	111	65	0	0	24.6	0.660	31	neg
## 531	2	122	60	18	106	29.8	0.717	22	neg
## 532	0	107	76	0	0	45.3	0.686	24	neg
## 533	1	86	66	52	65	41.3	0.917	29	neg
## 534	6	91	0	0	0	29.8	0.501	31	neg
## 535	1	77	56	30	56	33.3	1.251	24	neg
## 536	4	132	0	0	0	32.9	0.302	23	pos
## 537	0	105	90	0	0	29.6	0.197	46	neg
## 538	0	57	60	0	0	21.7	0.735	67	neg
## 539	0	127	80	37	210	36.3	0.804	23	neg
## 540	3	129	92	49	155	36.4	0.968	32	pos
## 541	8	100	74	40	215	39.4	0.661	43	pos
## 542	3	128	72	25	190	32.4	0.549	27	pos
## 543	10	90	85	32	0	34.9	0.825	56	pos
## 544	4	84	90	23	56	39.5	0.159	25	neg
## 545	1	88	78	29	76	32.0	0.365	29	neg
## 546	8	186	90	35	225	34.5	0.423	37	pos
## 547	5	187	76	27	207	43.6	1.034	53	pos
## 548	4	131	68	21	166	33.1	0.160	28	neg
## 549	1	164	82	43	67	32.8	0.341	50	neg
## 550	4	189	110	31	0	28.5	0.680	37	neg
## 551	1	116	70	28	0	27.4	0.204	21	neg
## 552	3	84	68	30	106	31.9	0.591	25	neg
## 553	6	114	88	0	0	27.8	0.247	66	neg
## 554	1	88	62	24	44	29.9	0.422	23	neg
## 555	1	84	64	23	115	36.9	0.471	28	neg
## 556	7	124	70	33	215	25.5	0.161	37	neg
## 557	1	97	70	40	0	38.1	0.218	30	neg
## 558	8	110	76	0	0	27.8	0.237	58	neg
## 559	11	103	68	40	0	46.2	0.126	42	neg
## 560	11	85	74	0	0	30.1	0.300	35	neg
## 561	6	125	76	0	0	33.8	0.121	54	pos
## 562	0	198	66	32	274	41.3	0.502	28	pos
## 563	1	87	68	34	77	37.6	0.401	24	neg
## 564	6	99	60	19	54	26.9	0.497	32	neg
## 565	0	91	80	0	0	32.4	0.601	27	neg
## 566	2	95	54	14	88	26.1	0.748	22	neg
## 567	1	99	72	30	18	38.6	0.412	21	neg
## 568	6	92	62	32	126	32.0	0.085	46	neg
## 569	4	154	72	29	126	31.3	0.338	37	neg

## 570	0	121	66	30	165	34.3	0.203	33	pos
## 571	3	78	70	0	0	32.5	0.270	39	neg
## 572	2	130	96	0	0	22.6	0.268	21	neg
## 573	3	111	58	31	44	29.5	0.430	22	neg
## 574	2	98	60	17	120	34.7	0.198	22	neg
## 575	1	143	86	30	330	30.1	0.892	23	neg
## 576	1	119	44	47	63	35.5	0.280	25	neg
## 577	6	108	44	20	130	24.0	0.813	35	neg
## 578	2	118	80	0	0	42.9	0.693	21	pos
## 579	10	133	68	0	0	27.0	0.245	36	neg
## 580	2	197	70	99	0	34.7	0.575	62	pos
## 581	0	151	90	46	0	42.1	0.371	21	pos
## 582	6	109	60	27	0	25.0	0.206	27	neg
## 583	12	121	78	17	0	26.5	0.259	62	neg
## 584	8	100	76	0	0	38.7	0.190	42	neg
## 585	8	124	76	24	600	28.7	0.687	52	pos
## 586	1	93	56	11	0	22.5	0.417	22	neg
## 587	8	143	66	0	0	34.9	0.129	41	pos
## 588	6	103	66	0	0	24.3	0.249	29	neg
## 589	3	176	86	27	156	33.3	1.154	52	pos
## 590	0	73	0	0	0	21.1	0.342	25	neg
## 591	11	111	84	40	0	46.8	0.925	45	pos
## 592	2	112	78	50	140	39.4	0.175	24	neg
## 593	3	132	80	0	0	34.4	0.402	44	pos
## 594	2	82	52	22	115	28.5	1.699	25	neg
## 595	6	123	72	45	230	33.6	0.733	34	neg
## 596	0	188	82	14	185	32.0	0.682	22	pos
## 597	0	67	76	0	0	45.3	0.194	46	neg
## 598	1	89	24	19	25	27.8	0.559	21	neg
## 599	1	173	74	0	0	36.8	0.088	38	pos
## 600	1	109	38	18	120	23.1	0.407	26	neg
## 601	1	108	88	19	0	27.1	0.400	24	neg
## 602	6	96	0	0	0	23.7	0.190	28	neg
## 603	1	124	74	36	0	27.8	0.100	30	neg
## 604	7	150	78	29	126	35.2	0.692	54	pos
## 605	4	183	0	0	0	28.4	0.212	36	pos
## 606	1	124	60	32	0	35.8	0.514	21	neg
## 607	1	181	78	42	293	40.0	1.258	22	pos
## 608	1	92	62	25	41	19.5	0.482	25	neg
## 609	0	152	82	39	272	41.5	0.270	27	neg
## 610	1	111	62	13	182	24.0	0.138	23	neg
## 611	3	106	54	21	158	30.9	0.292	24	neg
## 612	3	174	58	22	194	32.9	0.593	36	pos
## 613	7	168	88	42	321	38.2	0.787	40	pos
## 614	6	105	80	28	0	32.5	0.878	26	neg
## 615	11	138	74	26	144	36.1	0.557	50	pos
## 616	3	106	72	0	0	25.8	0.207	27	neg
## 617	6	117	96	0	0	28.7	0.157	30	neg
## 618	2	68	62	13	15	20.1	0.257	23	neg
## 619	9	112	82	24	0	28.2	1.282	50	pos
## 620	0	119	0	0	0	32.4	0.141	24	pos
## 621	2	112	86	42	160	38.4	0.246	28	neg
## 622	2	92	76	20	0	24.2	1.698	28	neg
## 623	6	183	94	0	0	40.8	1.461	45	neg

## 624	0	94	70	27	115	43.5	0.347	21	neg
## 625	2	108	64	0	0	30.8	0.158	21	neg
## 626	4	90	88	47	54	37.7	0.362	29	neg
## 627	0	125	68	0	0	24.7	0.206	21	neg
## 628	0	132	78	0	0	32.4	0.393	21	neg
## 629	5	128	80	0	0	34.6	0.144	45	neg
## 630	4	94	65	22	0	24.7	0.148	21	neg
## 631	7	114	64	0	0	27.4	0.732	34	pos
## 632	0	102	78	40	90	34.5	0.238	24	neg
## 633	2	111	60	0	0	26.2	0.343	23	neg
## 634	1	128	82	17	183	27.5	0.115	22	neg
## 635	10	92	62	0	0	25.9	0.167	31	neg
## 636	13	104	72	0	0	31.2	0.465	38	pos
## 637	5	104	74	0	0	28.8	0.153	48	neg
## 638	2	94	76	18	66	31.6	0.649	23	neg
## 639	7	97	76	32	91	40.9	0.871	32	pos
## 640	1	100	74	12	46	19.5	0.149	28	neg
## 641	0	102	86	17	105	29.3	0.695	27	neg
## 642	4	128	70	0	0	34.3	0.303	24	neg
## 643	6	147	80	0	0	29.5	0.178	50	pos
## 644	4	90	0	0	0	28.0	0.610	31	neg
## 645	3	103	72	30	152	27.6	0.730	27	neg
## 646	2	157	74	35	440	39.4	0.134	30	neg
## 647	1	167	74	17	144	23.4	0.447	33	pos
## 648	0	179	50	36	159	37.8	0.455	22	pos
## 649	11	136	84	35	130	28.3	0.260	42	pos
## 650	0	107	60	25	0	26.4	0.133	23	neg
## 651	1	91	54	25	100	25.2	0.234	23	neg
## 652	1	117	60	23	106	33.8	0.466	27	neg
## 653	5	123	74	40	77	34.1	0.269	28	neg
## 654	2	120	54	0	0	26.8	0.455	27	neg
## 655	1	106	70	28	135	34.2	0.142	22	neg
## 656	2	155	52	27	540	38.7	0.240	25	pos
## 657	2	101	58	35	90	21.8	0.155	22	neg
## 658	1	120	80	48	200	38.9	1.162	41	neg
## 659	11	127	106	0	0	39.0	0.190	51	neg
## 660	3	80	82	31	70	34.2	1.292	27	pos
## 661	10	162	84	0	0	27.7	0.182	54	neg
## 662	1	199	76	43	0	42.9	1.394	22	pos
## 663	8	167	106	46	231	37.6	0.165	43	pos
## 664	9	145	80	46	130	37.9	0.637	40	pos
## 665	6	115	60	39	0	33.7	0.245	40	pos
## 666	1	112	80	45	132	34.8	0.217	24	neg
## 667	4	145	82	18	0	32.5	0.235	70	pos
## 668	10	111	70	27	0	27.5	0.141	40	pos
## 669	6	98	58	33	190	34.0	0.430	43	neg
## 670	9	154	78	30	100	30.9	0.164	45	neg
## 671	6	165	68	26	168	33.6	0.631	49	neg
## 672	1	99	58	10	0	25.4	0.551	21	neg
## 673	10	68	106	23	49	35.5	0.285	47	neg
## 674	3	123	100	35	240	57.3	0.880	22	neg
## 675	8	91	82	0	0	35.6	0.587	68	neg
## 676	6	195	70	0	0	30.9	0.328	31	pos
## 677	9	156	86	0	0	24.8	0.230	53	pos

## 678	0	93	60	0	0 35.3	0.263	25	neg
## 679	3	121	52	0	0 36.0	0.127	25	pos
## 680	2	101	58	17	265 24.2	0.614	23	neg
## 681	2	56	56	28	45 24.2	0.332	22	neg
## 682	0	162	76	36	0 49.6	0.364	26	pos
## 683	0	95	64	39	105 44.6	0.366	22	neg
## 684	4	125	80	0	0 32.3	0.536	27	pos
## 685	5	136	82	0	0 0.0	0.640	69	neg
## 686	2	129	74	26	205 33.2	0.591	25	neg
## 687	3	130	64	0	0 23.1	0.314	22	neg
## 688	1	107	50	19	0 28.3	0.181	29	neg
## 689	1	140	74	26	180 24.1	0.828	23	neg
## 690	1	144	82	46	180 46.1	0.335	46	pos
## 691	8	107	80	0	0 24.6	0.856	34	neg
## 692	13	158	114	0	0 42.3	0.257	44	pos
## 693	2	121	70	32	95 39.1	0.886	23	neg
## 694	7	129	68	49	125 38.5	0.439	43	pos
## 695	2	90	60	0	0 23.5	0.191	25	neg
## 696	7	142	90	24	480 30.4	0.128	43	pos
## 697	3	169	74	19	125 29.9	0.268	31	pos
## 698	0	99	0	0	0 25.0	0.253	22	neg
## 699	4	127	88	11	155 34.5	0.598	28	neg
## 700	4	118	70	0	0 44.5	0.904	26	neg
## 701	2	122	76	27	200 35.9	0.483	26	neg
## 702	6	125	78	31	0 27.6	0.565	49	pos
## 703	1	168	88	29	0 35.0	0.905	52	pos
## 704	2	129	0	0	0 38.5	0.304	41	neg
## 705	4	110	76	20	100 28.4	0.118	27	neg
## 706	6	80	80	36	0 39.8	0.177	28	neg
## 707	10	115	0	0	0 0.0	0.261	30	pos
## 708	2	127	46	21	335 34.4	0.176	22	neg
## 709	9	164	78	0	0 32.8	0.148	45	pos
## 710	2	93	64	32	160 38.0	0.674	23	pos
## 711	3	158	64	13	387 31.2	0.295	24	neg
## 712	5	126	78	27	22 29.6	0.439	40	neg
## 713	10	129	62	36	0 41.2	0.441	38	pos
## 714	0	134	58	20	291 26.4	0.352	21	neg
## 715	3	102	74	0	0 29.5	0.121	32	neg
## 716	7	187	50	33	392 33.9	0.826	34	pos
## 717	3	173	78	39	185 33.8	0.970	31	pos
## 718	10	94	72	18	0 23.1	0.595	56	neg
## 719	1	108	60	46	178 35.5	0.415	24	neg
## 720	5	97	76	27	0 35.6	0.378	52	pos
## 721	4	83	86	19	0 29.3	0.317	34	neg
## 722	1	114	66	36	200 38.1	0.289	21	neg
## 723	1	149	68	29	127 29.3	0.349	42	pos
## 724	5	117	86	30	105 39.1	0.251	42	neg
## 725	1	111	94	0	0 32.8	0.265	45	neg
## 726	4	112	78	40	0 39.4	0.236	38	neg
## 727	1	116	78	29	180 36.1	0.496	25	neg
## 728	0	141	84	26	0 32.4	0.433	22	neg
## 729	2	175	88	0	0 22.9	0.326	22	neg
## 730	2	92	52	0	0 30.1	0.141	22	neg
## 731	3	130	78	23	79 28.4	0.323	34	pos


```
## 732      8      120      86      0      0 28.4      0.259 22      pos
## 733      2      174      88     37     120 44.5      0.646 24      pos
## 734      2      106      56     27     165 29.0      0.426 22      neg
## 735      2      105      75      0      0 23.3      0.560 53      neg
## 736      4       95      60     32      0 35.4      0.284 28      neg
## 737      0      126      86     27     120 27.4      0.515 21      neg
## 738      8       65      72     23      0 32.0      0.600 42      neg
## 739      2       99      60     17     160 36.6      0.453 21      neg
## 740      1      102      74      0      0 39.5      0.293 42      pos
## 741     11      120      80     37     150 42.3      0.785 48      pos
## 742      3      102      44     20      94 30.8      0.400 26      neg
## 743      1      109      58     18     116 28.5      0.219 22      neg
## 744      9      140      94      0      0 32.7      0.734 45      pos
## 745     13      153      88     37     140 40.6      1.174 39      neg
## 746     12      100      84     33     105 30.0      0.488 46      neg
## 747      1      147      94     41      0 49.3      0.358 27      pos
## 748      1       81      74     41      57 46.3      1.096 32      neg
## 749      3      187      70     22     200 36.4      0.408 36      pos
## 750      6      162      62      0      0 24.3      0.178 50      pos
## 751      4      136      70      0      0 31.2      1.182 22      pos
## 752      1      121      78     39      74 39.0      0.261 28      neg
## 753      3      108      62     24      0 26.0      0.223 25      neg
## 754      0      181      88     44     510 43.3      0.222 26      pos
## 755      8      154      78     32      0 32.4      0.443 45      pos
## 756      1      128      88     39     110 36.5      1.057 37      pos
## 757      7      137      90     41      0 32.0      0.391 39      neg
## 758      0      123      72      0      0 36.3      0.258 52      pos
## 759      1      106      76      0      0 37.5      0.197 26      neg
## 760      6      190      92      0      0 35.5      0.278 66      pos
## 761      2       88      58     26      16 28.4      0.766 22      neg
## 762      9      170      74     31      0 44.0      0.403 43      pos
## 763      9       89      62      0      0 22.5      0.142 33      neg
## 764     10      101      76     48     180 32.9      0.171 63      neg
## 765      2      122      70     27      0 36.8      0.340 27      neg
## 766      5      121      72     23     112 26.2      0.245 30      neg
## 767      1      126      60      0      0 30.1      0.349 47      pos
## 768      1       93      70     31      0 30.4      0.315 23      neg
```

```
str(df)
```

```
## 'data.frame': 768 obs. of 9 variables:
## $ pregnant: num 6 1 8 1 0 5 3 10 2 8 ...
## $ glucose : num 148 85 183 89 137 116 78 115 197 125 ...
## $ pressure: num 72 66 64 66 40 74 50 0 70 96 ...
## $ triceps : num 35 29 0 23 35 0 32 0 45 0 ...
## $ insulin : num 0 0 0 94 168 0 88 0 543 0 ...
## $ mass : num 33.6 26.6 23.3 28.1 43.1 25.6 31 35.3 30.5 0 ...
## $ pedigree: num 0.627 0.351 0.672 0.167 2.288 ...
## $ age : num 50 31 32 21 33 30 26 29 53 54 ...
## $ diabetes: Factor w/ 2 levels "neg","pos": 2 1 2 1 2 1 2 1 2 2 ...
```

```
#Summary Statistics
```

```
summary(df)
```

```
##      pregnant      glucose      pressure      triceps
## Min.   : 0.000   Min.    : 0.0   Min.    : 0.00   Min.    : 0.00
```

```
## 1st Qu.: 1.000    1st Qu.: 99.0    1st Qu.: 62.00    1st Qu.: 0.00
## Median : 3.000    Median :117.0    Median : 72.00    Median :23.00
## Mean   : 3.845    Mean   :120.9    Mean   : 69.11    Mean   :20.54
## 3rd Qu.: 6.000    3rd Qu.:140.2    3rd Qu.: 80.00    3rd Qu.:32.00
## Max.   :17.000    Max.   :199.0    Max.   :122.00    Max.   :99.00
##      insulin      mass      pedigree      age      diabetes
## Min.   : 0.0      Min.   : 0.00      Min.   :0.0780      Min.   :21.00      neg:500
## 1st Qu.: 0.0      1st Qu.:27.30      1st Qu.:0.2437      1st Qu.:24.00      pos:268
## Median : 30.5      Median :32.00      Median :0.3725      Median :29.00
## Mean   : 79.8      Mean   :31.99      Mean   :0.4719      Mean   :33.24
## 3rd Qu.:127.2      3rd Qu.:36.60      3rd Qu.:0.6262      3rd Qu.:41.00
## Max.   :846.0      Max.   :67.10      Max.   :2.4200      Max.   :81.00
```

#Confirmation of No Near Zero Variance for Predictor Variables

```
predictors <- PimaIndiansDiabetes[ , -(9)]
print(nearZeroVar(predictors))
```

```
## integer(0)
```

#Check for missing values

#Confirmed No Missing Values

```
sapply(df, function(x) sum(is.na(x)))
```

```
## pregnant glucose pressure triceps insulin mass pedigree age
##          0          0          0          0          0          0          0
## diabetes
##          0
```

#List Zero Markers: 6 out of 9 Variables have zero markers for Predictor Variables

```
list( Column = colSums(df==0),
      Row = sum(rowSums(df==0)))
```

```
## $Column
## pregnant glucose pressure triceps insulin mass pedigree age
##      111          5          35          227          374          11          0          0
## diabetes
##          0
##
## $Row
## [1] 763
```

#Logic Behind 6 Zero Markers

#pregnant- not all woman have a baby, likely 0 is a true value, will keep predictor variable

#glucose- only 5 values are missing, will keep predictor variable, will use numerical mean

#pressure- only 35 values are missing, will keep predictor variable, will use numerical mean

#triceps- approximately 30% of the data contains 0 values, will keep predictor variable, will use numerical mean

#insulin- almost 50% of the data has 0 values, will keep predictor variable, will use numerical mean

#mass- only 11 values are missing, will keep predictor variable

#Predictor Variables After Review of Summary Statistics and Zero Markers

#1.pregnant

#2.glucose

#3.pressure

#4.mass

#5.pedigree

#6.age

#7.triceps

```

#8.insulin

#Outcome Variable
#1.diabetes

#Replace All Zeros
df[df == 0] <- NA

#Return Pregnant NA back to 0(zero)
df$pregnant[is.na(df$pregnant)] <- 0
#df

#Replace NA Values with Mean from respective columns: glucose, pressure, mass, insulin & triceps
df$glucose[is.na(df$glucose)]<-mean(df$glucose,na.rm=TRUE) #glucose
df$pressure[is.na(df$pressure)]<-mean(df$pressure,na.rm=TRUE) #pressure
df$mass[is.na(df$mass)]<-mean(df$mass,na.rm=TRUE) #mass
df$insulin[is.na(df$insulin)]<-mean(df$insulin,na.rm=TRUE) #insulin
df$triceps[is.na(df$triceps)]<-mean(df$triceps,na.rm=TRUE) #triceps
df <- df[,-4]
#df

#Updated Summary Statistics After replacing NA Values with Mean from respective columns: glucose, pressure, mass, insulin & triceps
summary(df)

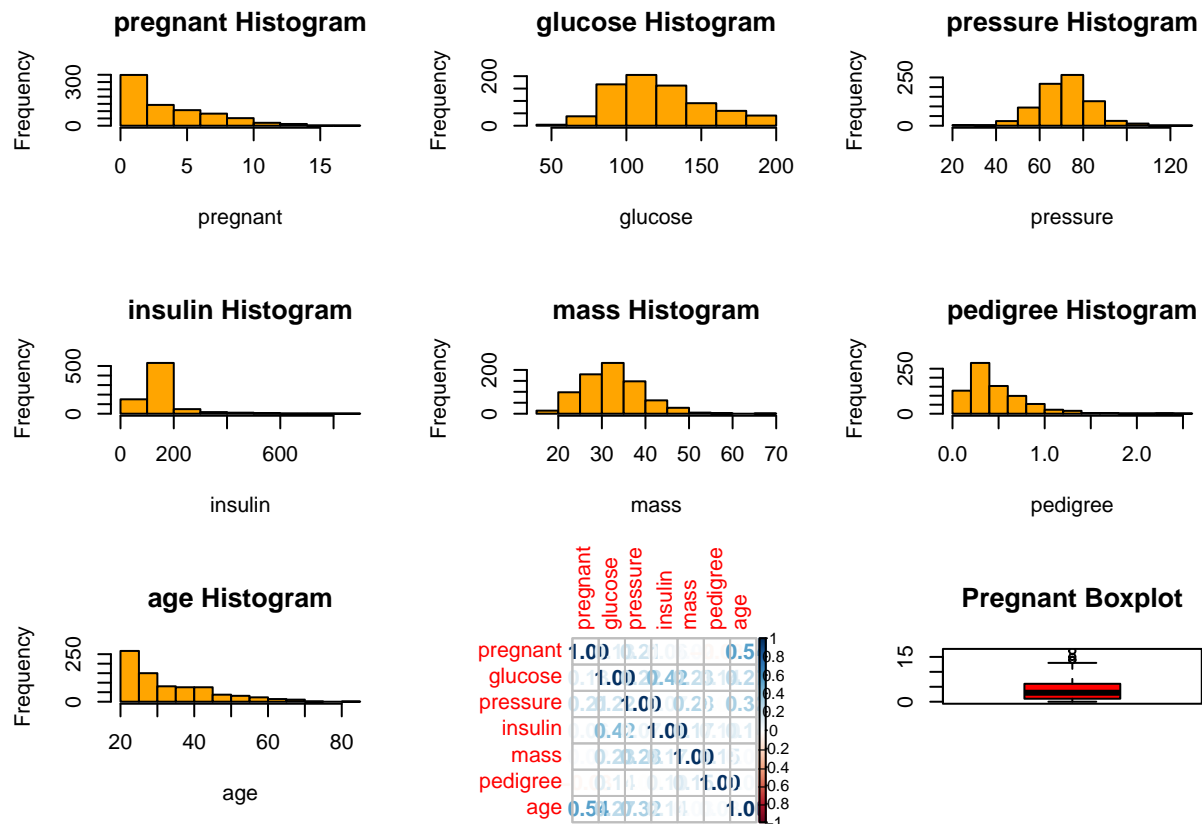
##      pregnant      glucose      pressure      insulin
##  Min.   : 0.000   Min.    : 44.00   Min.    : 24.00   Min.    : 14.0
##  1st Qu.: 1.000   1st Qu.: 99.75   1st Qu.: 64.00   1st Qu.:121.5
##  Median : 3.000   Median :117.00   Median : 72.20   Median :155.5
##  Mean   : 3.845   Mean    :121.69   Mean    : 72.41   Mean    :155.5
##  3rd Qu.: 6.000   3rd Qu.:140.25   3rd Qu.: 80.00   3rd Qu.:155.5
##  Max.    :17.000   Max.    :199.00   Max.    :122.00   Max.    :846.0
##      mass      pedigree      age      diabetes
##  Min.    :18.20   Min.   :0.0780   Min.    :21.00   neg:500
##  1st Qu.:27.50   1st Qu.:0.2437   1st Qu.:24.00   pos:268
##  Median :32.40   Median :0.3725   Median :29.00
##  Mean    :32.46   Mean    :0.4719   Mean     :33.24
##  3rd Qu.:36.60   3rd Qu.:0.6262   3rd Qu.:41.00
##  Max.    :67.10   Max.    :2.4200   Max.     :81.00

#Histograms of Diabetes: Predictor Variables
n <-df[,1:(ncol(df)-1)] #Predictors are variables 1-8
par(mfrow = c(3,3)) #Histograms will be 3x3
for (i in 1:ncol(n))
{hist(n[,i], xlab = names(n[i]), main = paste(names(n[i]), "Histogram"), col="orange")}
}

#Correlation Plot of Diabetes: Predictor Variables
x <- cor(df[1:ncol(df)-1])
corrplot(x, method="number")

#Box Plots of Diabetes: Predictor Variables
boxplot(df$pregnant, main = "Pregnant Boxplot", col = "red")

```



	pregnant	glucose	pressure	insulin	mass	pedigree	age
pregnant	1.00	0.12	0.5	0.8	0.6	0.4	0.2
glucose	0.12	1.00	0.42	0.2	0.3	0.2	0.1
pressure	0.5	0.42	1.00	0.2	0.3	0.2	0.1
insulin	0.8	0.2	0.2	1.00	0.7	0.1	0.1
mass	0.6	0.3	0.3	0.7	1.00	0.4	0.2
pedigree	0.4	0.2	0.2	0.1	0.4	1.00	0.6
age	0.2	0.1	0.1	0.1	0.2	0.6	1.00

```

boxplot(df$glucose, main = "Glucose Boxplot", col = "red")
boxplot(df$pressure, main = "Pressure Boxplot", col = "red")
#boxplot(df$triceps, main = "Triceps Boxplot", col = "red")
boxplot(df$insulin, main = "Insulin Boxplot", col = "red")
boxplot(df$mass, main = "Mass Boxplot", col = "red")
boxplot(df$pedigree, main = "Pedigree Boxplot", col = "red")
boxplot(df$age, main = "Age Boxplot", col = "red")

#Split Training and Test Data, 80/20
set.seed(100)
split <- caret::createDataPartition(y = df$diabetes, times = 1, p = 0.8, list = FALSE)

#Train_data Split, 80%
train_data <- df[split,]

#Test_data Split, 20%
test_data <- df[-split,]

#Summary Statistics
summary(train_data)

```

```

##      pregnant      glucose      pressure      insulin
##  Min.   : 0.000    Min.   : 56.0    Min.   : 24.00    Min.   : 15.0
## 1st Qu.: 1.000    1st Qu.: 99.0    1st Qu.: 64.00    1st Qu.:125.0
##  Median : 3.000    Median :117.0    Median : 72.41    Median :155.5

```

```
## Mean : 3.881 Mean :121.9 Mean : 72.62 Mean :155.1
## 3rd Qu.: 6.000 3rd Qu.:140.0 3rd Qu.: 80.00 3rd Qu.:155.5
## Max. :17.000 Max. :199.0 Max. :122.00 Max. :846.0
## mass pedigree age diabetes
## Min. :18.2 Min. :0.0780 Min. :21.00 neg:400
## 1st Qu.:27.6 1st Qu.:0.2370 1st Qu.:24.00 pos:215
## Median :32.4 Median :0.3640 Median :29.00
## Mean :32.6 Mean :0.4647 Mean :33.41
## 3rd Qu.:36.8 3rd Qu.:0.6110 3rd Qu.:41.00
## Max. :67.1 Max. :2.2880 Max. :81.00
```

```
#####Training Models#####
```

```
#Logistic Regression: Training Model
```

```
#No Tuning Parameters for Simple Logistic Regression
```

```
lr_train_data <- caret::train(diabetes ~., data = train_data,
                              method = "glm",
                              metric = "ROC",
                              tuneLength = 10,
                              trControl = trainControl(method = "cv", number = 10,
                                                         classProbs = T, summaryFunction = twoClassSummary),
                              preProcess = c("center","scale"))
```

```
lr_train_data
```

```
## Generalized Linear Model
```

```
##
```

```
## 615 samples
```

```
## 7 predictor
```

```
## 2 classes: 'neg', 'pos'
```

```
##
```

```
## Pre-processing: centered (7), scaled (7)
```

```
## Resampling: Cross-Validated (10 fold)
```

```
## Summary of sample sizes: 553, 553, 554, 553, 554, 554, ...
```

```
## Resampling results:
```

```
##
```

```
## ROC Sens Spec
```

```
## 0.8446807 0.885 0.5900433
```

```
summary(lr_train_data)
```

```
##
```

```
## Call:
```

```
## NULL
```

```
##
```

```
## Deviance Residuals:
```

```
## Min 1Q Median 3Q Max
```

```
## -2.6733 -0.7046 -0.3818 0.6726 2.4367
```

```
##
```

```
## Coefficients:
```

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

```
## (Intercept) -0.86976 0.11010 -7.900 2.8e-15 ***
```

```
## pregnant 0.43851 0.12451 3.522 0.000428 ***
```

```
## glucose 1.16594 0.13312 8.758 < 2e-16 ***
```

```
## pressure -0.10367 0.11925 -0.869 0.384630
```

```
## insulin -0.01707 0.11357 -0.150 0.880496
```

```

## mass          0.68502    0.12187    5.621  1.9e-08 ***
## pedigree      0.34252    0.10753    3.185  0.001445 **
## age           0.13217    0.12639    1.046  0.295677
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 796.05  on 614  degrees of freedom
## Residual deviance: 556.89  on 607  degrees of freedom
## AIC: 572.89
##
## Number of Fisher Scoring iterations: 5
#Random Forest: Training Model
rf_train_data <- caret::train(diabetes ~., data = train_data,
                             method = "ranger",
                             metric = "ROC",
                             trControl = trainControl(method = "cv", number = 10,
                                                         classProbs = T, summaryFunction = twoClassSummary),
                             preProcess = c("center","scale"))
rf_train_data

## Random Forest
##
## 615 samples
## 7 predictor
## 2 classes: 'neg', 'pos'
##
## Pre-processing: centered (7), scaled (7)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 554, 553, 554, 553, 553, 553, ...
## Resampling results across tuning parameters:
##
##  mtry  splitrule  ROC      Sens  Spec
##  2     gini      0.8345509 0.8525  0.6183983
##  2     extratrees 0.8445536 0.8800  0.5911255
##  4     gini      0.8339935 0.8550  0.6515152
##  4     extratrees 0.8420049 0.8700  0.6279221
##  7     gini      0.8291288 0.8500  0.6651515
##  7     extratrees 0.8415368 0.8600  0.6324675
##
## Tuning parameter 'min.node.size' was held constant at a value of 1
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were mtry = 2, splitrule = extratrees
## and min.node.size = 1.
plot(rf_train_data)

FinalTree = rf_train_data$finalModel$importance.mode

#K Nearest Neighbor: Training Model
knn_train_data <- caret::train(diabetes ~., data = train_data,
                              method = "knn",

```

```

        metric = "ROC",
        tuneGrid = expand.grid(.k = c(3:10)),
        trControl = trainControl(method = "cv", number = 10,
                                classProbs = T, summaryFunction = twoClassSummary),
        preProcess = c("center", "scale"))

knn_train_data

## k-Nearest Neighbors
##
## 615 samples
## 7 predictor
## 2 classes: 'neg', 'pos'
##
## Pre-processing: centered (7), scaled (7)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 554, 554, 554, 553, 553, 554, ...
## Resampling results across tuning parameters:
##
##  k   ROC       Sens   Spec
##  3  0.7554437  0.7975  0.5679654
##  4  0.7794183  0.8275  0.5722944
##  5  0.7857495  0.8350  0.5816017
##  6  0.8004518  0.8325  0.5543290
##  7  0.8020292  0.8275  0.5913420
##  8  0.8062716  0.8425  0.5956710
##  9  0.8168236  0.8400  0.6145022
## 10  0.8220996  0.8625  0.5731602
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was k = 10.

plot(knn_train_data)

#Classification and Regression Trees (CART): Training Model
cart_train_data <- caret::train(diabetes ~., data = train_data,
                              method = "rpart",
                              metric = "ROC",
                              tuneLength = 20,
                              trControl = trainControl(method = "cv", number = 10,
                                                        classProbs = TRUE, summaryFunction = twoClassSummary),
                              preProcess = c("center", "scale", "pca"))

cart_train_data

## CART
##
## 615 samples
## 7 predictor
## 2 classes: 'neg', 'pos'
##
## Pre-processing: centered (7), scaled (7), principal component signal
## extraction (7)
## Resampling: Cross-Validated (10 fold)

```

```
## Summary of sample sizes: 554, 554, 553, 554, 553, 553, ...
```

```
## Resampling results across tuning parameters:
```

```
##
```

##	cp	ROC	Sens	Spec
##	0.00000000	0.7626028	0.7950	0.56774892
##	0.01223990	0.7785092	0.8200	0.57662338
##	0.02447980	0.7706034	0.8225	0.60043290
##	0.03671971	0.7689935	0.8325	0.55865801
##	0.04895961	0.7709253	0.8350	0.55865801
##	0.06119951	0.7712825	0.8375	0.55389610
##	0.07343941	0.7697944	0.8100	0.59675325
##	0.08567931	0.7697944	0.8100	0.59675325
##	0.09791922	0.7604924	0.7825	0.60670996
##	0.11015912	0.7585606	0.7625	0.65670996
##	0.12239902	0.7556629	0.7450	0.67943723
##	0.13463892	0.7502462	0.7175	0.71277056
##	0.14687882	0.7429167	0.6750	0.76731602
##	0.15911873	0.7432738	0.6600	0.80541126
##	0.17135863	0.7071374	0.6725	0.74177489
##	0.18359853	0.6580465	0.7425	0.57359307
##	0.19583843	0.6341829	0.7675	0.50086580
##	0.20807834	0.6114448	0.8125	0.41038961
##	0.22031824	0.5216071	0.9575	0.08571429
##	0.23255814	0.5000000	1.0000	0.00000000

```
##
```

```
## ROC was used to select the optimal model using the largest value.
```

```
## The final value used for the model was cp = 0.0122399.
```

```
FinalTree = cart_train_data$finalModel
```

```
rpartTree = as.party(FinalTree)
```

```
dev.new()
```

```
plot(rpartTree)
```

```
#Neural Net
```

```
registerDoParallel(cores=7)
```

```
nnetGrid <- expand.grid(.decay = c(0, 0.01, 0.1),
```

```
                        .size = c(1:10),
```

```
                        .bag = FALSE
```

```
)
```

```
nnet_train_data <- caret::train(diabetes ~., data = train_data,
```

```
                                method = "avNNet",
```

```
                                tuneGrid = nnetGrid,
```

```
                                metric = "ROC",
```

```
                                trControl = trainControl(method = "cv", number = 10,
```

```
                                                         classProbs = TRUE, summaryFunction = twoClassS
```

```
                                preProcess = c("center","scale"),
```

```
                                linout = TRUE,
```

```
                                trace = FALSE,
```

```
                                MaxNWts = 10 * (ncol(train_data) + 1) + 10 + 1,
```

```
                                maxit = 500)
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
```

```
## There were missing values in resampled performance measures.
```



```
## Warning in train.default(x, y, weights = w, ...): missing values found in
## aggregated results
nnet_train_data

## Model Averaged Neural Network
##
## 615 samples
## 7 predictor
## 2 classes: 'neg', 'pos'
##
## Pre-processing: centered (7), scaled (7)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 554, 554, 553, 554, 553, 554, ...
## Resampling results across tuning parameters:
##
##  decay  size  ROC      Sens   Spec
##  0.00    1   0.8476569 0.8600 0.6229437
##  0.00    2   0.8470076 0.8500 0.6043290
##  0.00    3   0.8393723 0.8525 0.6225108
##  0.00    4   0.8307576 0.8450 0.6034632
##  0.00    5   0.8203409 0.8550 0.5714286
##  0.00    6   0.8144102 0.8325 0.5857143
##  0.00    7   0.8255087 0.8575 0.5995671
##  0.00    8   0.8115747 0.8425 0.6093074
##  0.00    9   0.8081872 0.8225 0.6127706
##  0.00   10      NaN      NaN      NaN
##  0.01    1   0.8476569 0.8625 0.6231602
##  0.01    2   0.8501948 0.8525 0.6367965
##  0.01    3   0.8438745 0.8600 0.6088745
##  0.01    4   0.8347673 0.8675 0.5904762
##  0.01    5   0.8371861 0.8625 0.6041126
##  0.01    6   0.8318452 0.8250 0.6136364
##  0.01    7   0.8316234 0.8500 0.5904762
##  0.01    8   0.8236364 0.8450 0.5906926
##  0.01    9   0.8211201 0.8475 0.5902597
##  0.01   10      NaN      NaN      NaN
##  0.10    1   0.8478896 0.8625 0.6231602
##  0.10    2   0.8518994 0.8650 0.5861472
##  0.10    3   0.8530790 0.8700 0.5906926
##  0.10    4   0.8437771 0.8525 0.5941558
##  0.10    5   0.8357522 0.8500 0.5857143
##  0.10    6   0.8319210 0.8475 0.5954545
##  0.10    7   0.8302814 0.8425 0.5580087
##  0.10    8   0.8321212 0.8500 0.5854978
##  0.10    9   0.8249188 0.8375 0.5807359
##  0.10   10      NaN      NaN      NaN
##
## Tuning parameter 'bag' was held constant at a value of FALSE
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were size = 3, decay = 0.1 and bag = FALSE.
plot(nnet_train_data)
```

```
##### Support Vector Machines #####

svmFit <- train(diabetes ~., data = train_data,
               method = "svmRadial",
               metric = "ROC",
               tuneLength = 14,
               preProcess = c("center","scale"),
               trControl = trainControl(method = "cv", number = 10,
                                       classProbs = TRUE, summaryFunction = twoClassSummary))

svmFit

## Support Vector Machines with Radial Basis Function Kernel
##
## 615 samples
## 7 predictor
## 2 classes: 'neg', 'pos'
##
## Pre-processing: centered (7), scaled (7)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 554, 553, 554, 553, 553, 553, ...
## Resampling results across tuning parameters:
##
##  C          ROC          Sens    Spec
##  0.25 0.8425271 0.8800 0.6088745
##  0.50 0.8415043 0.8850 0.5900433
##  1.00 0.8384199 0.8875 0.5621212
##  2.00 0.8345184 0.8950 0.5149351
##  4.00 0.8201245 0.8850 0.5432900
##  8.00 0.8038366 0.8850 0.5012987
## 16.00 0.7779221 0.8750 0.4922078
## 32.00 0.7582684 0.8800 0.4411255
## 64.00 0.7406872 0.8775 0.3768398
## 128.00 0.7341721 0.8975 0.3536797
## 256.00 0.7264989 0.9000 0.3112554
## 512.00 0.7167803 0.9100 0.2839827
## 1024.00 0.7156061 0.9175 0.2707792
## 2048.00 0.7101732 0.8975 0.2935065
##
## Tuning parameter 'sigma' was held constant at a value of 0.1441702
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were sigma = 0.1441702 and C = 0.25.

plot(svmFit)

##### Boosted #####

gbmGrid <- expand.grid(.interaction.depth = seq(1, 7, by = 2),
                      .n.trees = seq(100, 1000, by = 50),
                      .shrinkage = c(0.01, 0.1),
                      .n.minobsinnode = 10)

gbmFit <- train(diabetes ~., data = train_data,
               method = "gbm",
               tuneGrid = gbmGrid,
```

```
preProcess = c("center","scale"),
verbose = FALSE,
trControl = trainControl(method = "cv", number = 10,
                           classProbs = TRUE, summaryFunction = twoClassSummary))
```

```
## Warning in train.default(x, y, weights = w, ...): The metric "Accuracy" was not
## in the result set. ROC will be used instead.
```

```
gbmFit
```

```
## Stochastic Gradient Boosting
```

```
##
```

```
## 615 samples
```

```
## 7 predictor
```

```
## 2 classes: 'neg', 'pos'
```

```
##
```

```
## Pre-processing: centered (7), scaled (7)
```

```
## Resampling: Cross-Validated (10 fold)
```

```
## Summary of sample sizes: 553, 553, 553, 554, 554, 554, ...
```

```
## Resampling results across tuning parameters:
```

```
##
```

##	shrinkage	interaction.depth	n.trees	ROC	Sens	Spec
##	0.01	1	100	0.8122078	0.9425	0.3722944
##	0.01	1	150	0.8209578	0.9300	0.4190476
##	0.01	1	200	0.8273295	0.9175	0.4653680
##	0.01	1	250	0.8333144	0.9075	0.5110390
##	0.01	1	300	0.8362013	0.8975	0.5294372
##	0.01	1	350	0.8386742	0.8950	0.5339827
##	0.01	1	400	0.8420563	0.8900	0.5387446
##	0.01	1	450	0.8427922	0.8900	0.5389610
##	0.01	1	500	0.8457197	0.8850	0.5296537
##	0.01	1	550	0.8472457	0.8850	0.5482684
##	0.01	1	600	0.8483117	0.8850	0.5577922
##	0.01	1	650	0.8484253	0.8850	0.5577922
##	0.01	1	700	0.8480519	0.8850	0.5718615
##	0.01	1	750	0.8480574	0.8800	0.5766234
##	0.01	1	800	0.8482089	0.8825	0.5766234
##	0.01	1	850	0.8485552	0.8800	0.5813853
##	0.01	1	900	0.8477435	0.8775	0.5859307
##	0.01	1	950	0.8480952	0.8725	0.5859307
##	0.01	1	1000	0.8478896	0.8725	0.5952381
##	0.01	3	100	0.8378842	0.9200	0.4829004
##	0.01	3	150	0.8409037	0.8975	0.5158009
##	0.01	3	200	0.8405952	0.8875	0.5435065
##	0.01	3	250	0.8439610	0.8800	0.5482684
##	0.01	3	300	0.8438799	0.8775	0.5668831
##	0.01	3	350	0.8439340	0.8700	0.5809524
##	0.01	3	400	0.8446861	0.8700	0.5857143
##	0.01	3	450	0.8445617	0.8700	0.5904762
##	0.01	3	500	0.8436742	0.8675	0.6041126
##	0.01	3	550	0.8437716	0.8700	0.6088745
##	0.01	3	600	0.8432197	0.8675	0.6181818
##	0.01	3	650	0.8403571	0.8700	0.6181818
##	0.01	3	700	0.8362987	0.8700	0.6136364

##	0.01	3	750	0.8352597	0.8675	0.6134199
##	0.01	3	800	0.8352489	0.8650	0.6136364
##	0.01	3	850	0.8340801	0.8675	0.6365801
##	0.01	3	900	0.8343074	0.8650	0.6181818
##	0.01	3	950	0.8343182	0.8625	0.6227273
##	0.01	3	1000	0.8337229	0.8575	0.6318182
##	0.01	5	100	0.8459361	0.9075	0.5017316
##	0.01	5	150	0.8475379	0.8875	0.5389610
##	0.01	5	200	0.8483983	0.8850	0.5666667
##	0.01	5	250	0.8490422	0.8825	0.5852814
##	0.01	5	300	0.8470942	0.8775	0.5945887
##	0.01	5	350	0.8432684	0.8750	0.5948052
##	0.01	5	400	0.8417641	0.8675	0.6088745
##	0.01	5	450	0.8413041	0.8650	0.6134199
##	0.01	5	500	0.8387229	0.8650	0.6086580
##	0.01	5	550	0.8364286	0.8700	0.6179654
##	0.01	5	600	0.8366667	0.8625	0.6086580
##	0.01	5	650	0.8354870	0.8625	0.6274892
##	0.01	5	700	0.8341126	0.8500	0.6322511
##	0.01	5	750	0.8329491	0.8500	0.6274892
##	0.01	5	800	0.8312121	0.8525	0.6274892
##	0.01	5	850	0.8310931	0.8500	0.6320346
##	0.01	5	900	0.8299459	0.8475	0.6415584
##	0.01	5	950	0.8287771	0.8450	0.6367965
##	0.01	5	1000	0.8276245	0.8425	0.6277056
##	0.01	7	100	0.8457684	0.9050	0.5158009
##	0.01	7	150	0.8460606	0.8825	0.5666667
##	0.01	7	200	0.8470022	0.8750	0.5991342
##	0.01	7	250	0.8462229	0.8750	0.6138528
##	0.01	7	300	0.8455574	0.8700	0.6183983
##	0.01	7	350	0.8423160	0.8725	0.6231602
##	0.01	7	400	0.8402597	0.8675	0.6326840
##	0.01	7	450	0.8395671	0.8625	0.6233766
##	0.01	7	500	0.8373918	0.8650	0.6231602
##	0.01	7	550	0.8358658	0.8625	0.6279221
##	0.01	7	600	0.8337662	0.8575	0.6279221
##	0.01	7	650	0.8324188	0.8525	0.6233766
##	0.01	7	700	0.8317262	0.8525	0.6233766
##	0.01	7	750	0.8317208	0.8525	0.6140693
##	0.01	7	800	0.8302327	0.8425	0.6140693
##	0.01	7	850	0.8292478	0.8425	0.6183983
##	0.01	7	900	0.8277273	0.8400	0.6138528
##	0.01	7	950	0.8264448	0.8400	0.6140693
##	0.01	7	1000	0.8256223	0.8375	0.6090909
##	0.10	1	100	0.8444210	0.8650	0.5958874
##	0.10	1	150	0.8391396	0.8600	0.6277056
##	0.10	1	200	0.8363961	0.8600	0.6090909
##	0.10	1	250	0.8355465	0.8475	0.6093074
##	0.10	1	300	0.8349188	0.8600	0.5904762
##	0.10	1	350	0.8332143	0.8600	0.6051948
##	0.10	1	400	0.8292749	0.8550	0.6093074
##	0.10	1	450	0.8287554	0.8475	0.6283550
##	0.10	1	500	0.8285498	0.8450	0.5911255
##	0.10	1	550	0.8251461	0.8400	0.6006494

##	0.10	1	600	0.8237771	0.8475	0.6006494
##	0.10	1	650	0.8205465	0.8450	0.6054113
##	0.10	1	700	0.8231223	0.8425	0.6149351
##	0.10	1	750	0.8216180	0.8400	0.6054113
##	0.10	1	800	0.8220671	0.8375	0.6196970
##	0.10	1	850	0.8217911	0.8400	0.5917749
##	0.10	1	900	0.8197835	0.8400	0.5870130
##	0.10	1	950	0.8207955	0.8425	0.5961039
##	0.10	1	1000	0.8178571	0.8425	0.6054113
##	0.10	3	100	0.8354600	0.8550	0.6231602
##	0.10	3	150	0.8274297	0.8450	0.6090909
##	0.10	3	200	0.8184253	0.8400	0.5948052
##	0.10	3	250	0.8130032	0.8300	0.6000000
##	0.10	3	300	0.8111201	0.8400	0.5906926
##	0.10	3	350	0.8090152	0.8300	0.6002165
##	0.10	3	400	0.8059091	0.8375	0.5954545
##	0.10	3	450	0.8001840	0.8250	0.5948052
##	0.10	3	500	0.7996320	0.8225	0.5950216
##	0.10	3	550	0.8006764	0.8225	0.5857143
##	0.10	3	600	0.7979221	0.8200	0.5995671
##	0.10	3	650	0.7941504	0.8225	0.5900433
##	0.10	3	700	0.7941558	0.8150	0.5989177
##	0.10	3	750	0.7937554	0.8050	0.6086580
##	0.10	3	800	0.7897565	0.8075	0.6086580
##	0.10	3	850	0.7909957	0.8100	0.6043290
##	0.10	3	900	0.7891234	0.8100	0.6045455
##	0.10	3	950	0.7886959	0.8025	0.6088745
##	0.10	3	1000	0.7902976	0.8025	0.6138528
##	0.10	5	100	0.8233496	0.8350	0.6419913
##	0.10	5	150	0.8148701	0.8400	0.6329004
##	0.10	5	200	0.8105628	0.8350	0.6093074
##	0.10	5	250	0.8093344	0.8350	0.6240260
##	0.10	5	300	0.8061580	0.8275	0.6004329
##	0.10	5	350	0.8074188	0.8350	0.6051948
##	0.10	5	400	0.8020887	0.8275	0.5958874
##	0.10	5	450	0.7997781	0.8250	0.5909091
##	0.10	5	500	0.8000541	0.8175	0.6002165
##	0.10	5	550	0.8015801	0.8200	0.5956710
##	0.10	5	600	0.7981872	0.8125	0.5906926
##	0.10	5	650	0.7943615	0.8175	0.5865801
##	0.10	5	700	0.7963799	0.8100	0.6000000
##	0.10	5	750	0.7990747	0.8100	0.5909091
##	0.10	5	800	0.7976353	0.8150	0.5952381
##	0.10	5	850	0.7966126	0.8025	0.5954545
##	0.10	5	900	0.7960065	0.8025	0.5956710
##	0.10	5	950	0.7942478	0.8025	0.5956710
##	0.10	5	1000	0.7940693	0.8000	0.5956710
##	0.10	7	100	0.8148377	0.8275	0.6188312
##	0.10	7	150	0.8056169	0.8200	0.5997835
##	0.10	7	200	0.7975379	0.8125	0.5941558
##	0.10	7	250	0.7982900	0.8075	0.6090909
##	0.10	7	300	0.8018561	0.8150	0.5950216
##	0.10	7	350	0.7985335	0.8050	0.6136364
##	0.10	7	400	0.7969697	0.8100	0.6132035

```

##      0.10      7      450      0.7948701  0.8025  0.6043290
##      0.10      7      500      0.7956926  0.8025  0.6181818
##      0.10      7      550      0.7964123  0.8050  0.6134199
##      0.10      7      600      0.7932143  0.8000  0.6179654
##      0.10      7      650      0.7961526  0.8075  0.5945887
##      0.10      7      700      0.7954762  0.8100  0.6086580
##      0.10      7      750      0.7951569  0.7975  0.5995671
##      0.10      7      800      0.7946916  0.8025  0.6090909
##      0.10      7      850      0.7911797  0.8050  0.5950216
##      0.10      7      900      0.7905844  0.8025  0.5948052
##      0.10      7      950      0.7931494  0.7975  0.6038961
##      0.10      7     1000      0.7927165  0.8000  0.6038961
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were n.trees = 250, interaction.depth =
## 5, shrinkage = 0.01 and n.minobsinnode = 10.
##### Elastinet #####
glmnetGrid <- expand.grid(alpha = c(0, .1, .2, .4, .6, .8, 1),
                          lambda = seq(.01, .2, length = 40))

glmnetFit <- train(diabetes ~., data = train_data,
                  method = "glmnet",
                  tuneGrid = glmnetGrid,
                  preProcess = c("center", "scale"),
                  metric = "ROC",
                  trControl = trainControl(method = "cv", number = 10,
                                           classProbs = TRUE, summaryFunction = twoClassSummary))

glmnetFit

## glmnet
##
## 615 samples
## 7 predictor
## 2 classes: 'neg', 'pos'
##
## Pre-processing: centered (7), scaled (7)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 553, 554, 554, 554, 553, 553, ...
## Resampling results across tuning parameters:
##
##      alpha      lambda      ROC      Sens      Spec
##      0.0      0.01000000  0.8499351  0.8925  0.558008658
##      0.0      0.01487179  0.8499351  0.8925  0.558008658
##      0.0      0.01974359  0.8499351  0.8925  0.558008658
##      0.0      0.02461538  0.8498214  0.8925  0.558008658
##      0.0      0.02948718  0.8498160  0.8950  0.548701299
##      0.0      0.03435897  0.8496753  0.8950  0.548701299
##      0.0      0.03923077  0.8501569  0.8950  0.553463203
##      0.0      0.04410256  0.8501515  0.8975  0.553463203
##      0.0      0.04897436  0.8503842  0.8975  0.548917749
##      0.0      0.05384615  0.8505249  0.8975  0.548917749

```

##	0.0	0.05871795	0.8499459	0.9025	0.539393939
##	0.0	0.06358974	0.8505357	0.9025	0.539393939
##	0.0	0.06846154	0.8502922	0.9025	0.539393939
##	0.0	0.07333333	0.8500703	0.9050	0.539393939
##	0.0	0.07820513	0.8504275	0.9050	0.539393939
##	0.0	0.08307692	0.8503030	0.9075	0.539393939
##	0.0	0.08794872	0.8500541	0.9100	0.539393939
##	0.0	0.09282051	0.8498268	0.9100	0.534848485
##	0.0	0.09769231	0.8497132	0.9100	0.530303030
##	0.0	0.10256410	0.8497132	0.9125	0.525541126
##	0.0	0.10743590	0.8497186	0.9125	0.516450216
##	0.0	0.11230769	0.8491342	0.9125	0.516450216
##	0.0	0.11717949	0.8487879	0.9125	0.516450216
##	0.0	0.12205128	0.8480952	0.9125	0.511904762
##	0.0	0.12692308	0.8480898	0.9125	0.511904762
##	0.0	0.13179487	0.8483225	0.9125	0.511904762
##	0.0	0.13666667	0.8483225	0.9150	0.511904762
##	0.0	0.14153846	0.8485606	0.9150	0.507142857
##	0.0	0.14641026	0.8485660	0.9200	0.493073593
##	0.0	0.15128205	0.8484470	0.9200	0.493073593
##	0.0	0.15615385	0.8484470	0.9225	0.493073593
##	0.0	0.16102564	0.8486742	0.9225	0.493073593
##	0.0	0.16589744	0.8482035	0.9225	0.493073593
##	0.0	0.17076923	0.8483171	0.9225	0.488528139
##	0.0	0.17564103	0.8480790	0.9300	0.488528139
##	0.0	0.18051282	0.8475054	0.9300	0.488528139
##	0.0	0.18538462	0.8475054	0.9300	0.483982684
##	0.0	0.19025641	0.8476245	0.9300	0.479220779
##	0.0	0.19512821	0.8473972	0.9300	0.474458874
##	0.0	0.20000000	0.8469426	0.9300	0.474458874
##	0.1	0.01000000	0.8497998	0.8850	0.571645022
##	0.1	0.01487179	0.8497998	0.8900	0.562554113
##	0.1	0.01974359	0.8494589	0.8900	0.562554113
##	0.1	0.02461538	0.8496807	0.8900	0.562554113
##	0.1	0.02948718	0.8502706	0.8925	0.553246753
##	0.1	0.03435897	0.8506223	0.8950	0.543939394
##	0.1	0.03923077	0.8502760	0.9025	0.539177489
##	0.1	0.04410256	0.8506169	0.9025	0.539177489
##	0.1	0.04897436	0.8507359	0.9075	0.539177489
##	0.1	0.05384615	0.8505032	0.9075	0.539177489
##	0.1	0.05871795	0.8506277	0.9075	0.530086580
##	0.1	0.06358974	0.8509740	0.9100	0.530086580
##	0.1	0.06846154	0.8509740	0.9125	0.530086580
##	0.1	0.07333333	0.8508550	0.9125	0.534848485
##	0.1	0.07820513	0.8509740	0.9125	0.530086580
##	0.1	0.08307692	0.8514502	0.9150	0.525541126
##	0.1	0.08794872	0.8516829	0.9150	0.520995671
##	0.1	0.09282051	0.8508658	0.9150	0.520995671
##	0.1	0.09769231	0.8503950	0.9150	0.520995671
##	0.1	0.10256410	0.8500541	0.9150	0.520995671
##	0.1	0.10743590	0.8502868	0.9150	0.520995671
##	0.1	0.11230769	0.8504113	0.9200	0.520995671
##	0.1	0.11717949	0.8500595	0.9200	0.516450216
##	0.1	0.12205128	0.8499405	0.9200	0.516450216

##	0.1	0.12692308	0.8499405	0.9200	0.511904762
##	0.1	0.13179487	0.8498268	0.9200	0.507359307
##	0.1	0.13666667	0.8495996	0.9200	0.507359307
##	0.1	0.14153846	0.8496050	0.9200	0.493506494
##	0.1	0.14641026	0.8490260	0.9200	0.493506494
##	0.1	0.15128205	0.8492641	0.9250	0.493506494
##	0.1	0.15615385	0.8493723	0.9250	0.493506494
##	0.1	0.16102564	0.8493723	0.9250	0.493506494
##	0.1	0.16589744	0.8493777	0.9250	0.488961039
##	0.1	0.17076923	0.8493723	0.9300	0.484199134
##	0.1	0.17564103	0.8491450	0.9300	0.474675325
##	0.1	0.18051282	0.8489123	0.9300	0.469913420
##	0.1	0.18538462	0.8487933	0.9300	0.469913420
##	0.1	0.19025641	0.8487987	0.9300	0.465151515
##	0.1	0.19512821	0.8485660	0.9300	0.460389610
##	0.1	0.20000000	0.8483279	0.9300	0.446320346
##	0.2	0.01000000	0.8496699	0.8875	0.571645022
##	0.2	0.01487179	0.8505032	0.8900	0.567099567
##	0.2	0.01974359	0.8503896	0.8900	0.562554113
##	0.2	0.02461538	0.8502652	0.8950	0.557792208
##	0.2	0.02948718	0.8499080	0.8975	0.553030303
##	0.2	0.03435897	0.8497890	0.9025	0.543722944
##	0.2	0.03923077	0.8498972	0.9050	0.539177489
##	0.2	0.04410256	0.8496591	0.9050	0.534632035
##	0.2	0.04897436	0.8501299	0.9125	0.534632035
##	0.2	0.05384615	0.8503680	0.9125	0.534632035
##	0.2	0.05871795	0.8502543	0.9125	0.534632035
##	0.2	0.06358974	0.8497835	0.9125	0.530086580
##	0.2	0.06846154	0.8494318	0.9125	0.520779221
##	0.2	0.07333333	0.8494156	0.9125	0.520779221
##	0.2	0.07820513	0.8494156	0.9125	0.516233766
##	0.2	0.08307692	0.8494210	0.9125	0.516233766
##	0.2	0.08794872	0.8494210	0.9125	0.516233766
##	0.2	0.09282051	0.8489556	0.9175	0.516233766
##	0.2	0.09769231	0.8489610	0.9200	0.516233766
##	0.2	0.10256410	0.8488528	0.9200	0.506926407
##	0.2	0.10743590	0.8488528	0.9200	0.506926407
##	0.2	0.11230769	0.8488582	0.9225	0.506926407
##	0.2	0.11717949	0.8488690	0.9225	0.506926407
##	0.2	0.12205128	0.8491071	0.9225	0.502380952
##	0.2	0.12692308	0.8487554	0.9225	0.497619048
##	0.2	0.13179487	0.8489827	0.9250	0.492857143
##	0.2	0.13666667	0.8492100	0.9250	0.483766234
##	0.2	0.14153846	0.8491017	0.9250	0.479004329
##	0.2	0.14641026	0.8488636	0.9250	0.464935065
##	0.2	0.15128205	0.8487392	0.9250	0.464935065
##	0.2	0.15615385	0.8485065	0.9275	0.464935065
##	0.2	0.16102564	0.8482792	0.9300	0.464935065
##	0.2	0.16589744	0.8478139	0.9300	0.460389610
##	0.2	0.17076923	0.8475758	0.9375	0.460389610
##	0.2	0.17564103	0.8473431	0.9375	0.455844156
##	0.2	0.18051282	0.8468615	0.9400	0.446753247
##	0.2	0.18538462	0.8469913	0.9400	0.442207792
##	0.2	0.19025641	0.8461797	0.9425	0.437662338

##	0.2	0.19512821	0.8460714	0.9425	0.423376623
##	0.2	0.20000000	0.8459578	0.9475	0.409307359
##	0.4	0.01000000	0.8506061	0.8950	0.571645022
##	0.4	0.01487179	0.8497998	0.8950	0.562337662
##	0.4	0.01974359	0.8503626	0.9000	0.562337662
##	0.4	0.02461538	0.8496699	0.9025	0.553246753
##	0.4	0.02948718	0.8501299	0.9025	0.543722944
##	0.4	0.03435897	0.8502489	0.9050	0.543722944
##	0.4	0.03923077	0.8499134	0.9075	0.543722944
##	0.4	0.04410256	0.8500271	0.9125	0.539177489
##	0.4	0.04897436	0.8502543	0.9150	0.534415584
##	0.4	0.05384615	0.8494426	0.9150	0.534415584
##	0.4	0.05871795	0.8490855	0.9150	0.529870130
##	0.4	0.06358974	0.8485065	0.9150	0.525108225
##	0.4	0.06846154	0.8479221	0.9175	0.520562771
##	0.4	0.07333333	0.8469859	0.9200	0.515800866
##	0.4	0.07820513	0.8468777	0.9200	0.515800866
##	0.4	0.08307692	0.8467695	0.9200	0.511038961
##	0.4	0.08794872	0.8461797	0.9200	0.511038961
##	0.4	0.09282051	0.8452489	0.9200	0.506493506
##	0.4	0.09769231	0.8448972	0.9225	0.501948052
##	0.4	0.10256410	0.8447727	0.9250	0.497186147
##	0.4	0.10743590	0.8439502	0.9250	0.492640693
##	0.4	0.11230769	0.8437175	0.9275	0.487878788
##	0.4	0.11717949	0.8424351	0.9300	0.469480519
##	0.4	0.12205128	0.8420617	0.9350	0.464935065
##	0.4	0.12692308	0.8418074	0.9350	0.455627706
##	0.4	0.13179487	0.8408658	0.9425	0.446536797
##	0.4	0.13666667	0.8406115	0.9425	0.441991342
##	0.4	0.14153846	0.8391180	0.9450	0.432683983
##	0.4	0.14641026	0.8385335	0.9475	0.428138528
##	0.4	0.15128205	0.8375703	0.9475	0.414069264
##	0.4	0.15615385	0.8360552	0.9525	0.395670996
##	0.4	0.16102564	0.8351190	0.9575	0.386363636
##	0.4	0.16589744	0.8346591	0.9575	0.367748918
##	0.4	0.17076923	0.8338420	0.9575	0.358658009
##	0.4	0.17564103	0.8331494	0.9600	0.349350649
##	0.4	0.18051282	0.8312879	0.9625	0.340043290
##	0.4	0.18538462	0.8303571	0.9625	0.335497835
##	0.4	0.19025641	0.8289827	0.9650	0.330735931
##	0.4	0.19512821	0.8276948	0.9650	0.330735931
##	0.4	0.20000000	0.8274784	0.9675	0.316450216
##	0.6	0.01000000	0.8495563	0.8950	0.576406926
##	0.6	0.01487179	0.8494264	0.9025	0.562337662
##	0.6	0.01974359	0.8496591	0.9025	0.557792208
##	0.6	0.02461538	0.8500000	0.9025	0.553030303
##	0.6	0.02948718	0.8502219	0.9050	0.548268398
##	0.6	0.03435897	0.8498972	0.9075	0.538961039
##	0.6	0.03923077	0.8487338	0.9100	0.534415584
##	0.6	0.04410256	0.8478084	0.9100	0.529870130
##	0.6	0.04897436	0.8469751	0.9100	0.529870130
##	0.6	0.05384615	0.8460335	0.9075	0.520562771
##	0.6	0.05871795	0.8456818	0.9150	0.515800866
##	0.6	0.06358974	0.8453139	0.9175	0.511038961

##	0.6	0.06846154	0.8447403	0.9200	0.511038961
##	0.6	0.07333333	0.8426136	0.9225	0.506277056
##	0.6	0.07820513	0.8418939	0.9225	0.501731602
##	0.6	0.08307692	0.8411797	0.9225	0.492424242
##	0.6	0.08794872	0.8401407	0.9250	0.487662338
##	0.6	0.09282051	0.8382468	0.9275	0.483116883
##	0.6	0.09769231	0.8373106	0.9325	0.473809524
##	0.6	0.10256410	0.8353355	0.9325	0.455411255
##	0.6	0.10743590	0.8335985	0.9400	0.450865801
##	0.6	0.11230769	0.8323106	0.9425	0.446320346
##	0.6	0.11717949	0.8299729	0.9425	0.432251082
##	0.6	0.12205128	0.8280249	0.9450	0.409307359
##	0.6	0.12692308	0.8274513	0.9500	0.400000000
##	0.6	0.13179487	0.8241126	0.9500	0.381818182
##	0.6	0.13666667	0.8244481	0.9550	0.372510823
##	0.6	0.14153846	0.8245617	0.9600	0.363203463
##	0.6	0.14641026	0.8237960	0.9625	0.349350649
##	0.6	0.15128205	0.8226542	0.9625	0.330735931
##	0.6	0.15615385	0.8225352	0.9650	0.326190476
##	0.6	0.16102564	0.8223079	0.9675	0.316883117
##	0.6	0.16589744	0.8210200	0.9675	0.307575758
##	0.6	0.17076923	0.8200839	0.9700	0.298051948
##	0.6	0.17564103	0.8199540	0.9725	0.283982684
##	0.6	0.18051282	0.8183306	0.9725	0.274675325
##	0.6	0.18538462	0.8166748	0.9725	0.265584416
##	0.6	0.19025641	0.8151596	0.9725	0.256277056
##	0.6	0.19512821	0.8133144	0.9725	0.242207792
##	0.6	0.20000000	0.8114367	0.9725	0.228138528
##	0.8	0.01000000	0.8496429	0.8975	0.571645022
##	0.8	0.01487179	0.8496483	0.9025	0.557792208
##	0.8	0.01974359	0.8498701	0.9025	0.557792208
##	0.8	0.02461538	0.8500054	0.9000	0.548268398
##	0.8	0.02948718	0.8487284	0.9000	0.538961039
##	0.8	0.03435897	0.8469589	0.9025	0.538961039
##	0.8	0.03923077	0.8461418	0.9050	0.529653680
##	0.8	0.04410256	0.8456710	0.9075	0.525108225
##	0.8	0.04897436	0.8448377	0.9075	0.520346320
##	0.8	0.05384615	0.8424675	0.9100	0.515584416
##	0.8	0.05871795	0.8411634	0.9100	0.510822511
##	0.8	0.06358974	0.8398972	0.9100	0.496969697
##	0.8	0.06846154	0.8379004	0.9150	0.492207792
##	0.8	0.07333333	0.8355628	0.9175	0.483116883
##	0.8	0.07820513	0.8333550	0.9250	0.473809524
##	0.8	0.08307692	0.8301894	0.9275	0.460173160
##	0.8	0.08794872	0.8278842	0.9350	0.460173160
##	0.8	0.09282051	0.8256818	0.9350	0.446320346
##	0.8	0.09769231	0.8247998	0.9375	0.432251082
##	0.8	0.10256410	0.8244264	0.9375	0.418398268
##	0.8	0.10743590	0.8231602	0.9450	0.413852814
##	0.8	0.11230769	0.8226596	0.9475	0.404978355
##	0.8	0.11717949	0.8212473	0.9525	0.386580087
##	0.8	0.12205128	0.8200785	0.9575	0.354112554
##	0.8	0.12692308	0.8187960	0.9600	0.349350649
##	0.8	0.13179487	0.8166802	0.9675	0.330952381

##	0.8	0.13666667	0.8152733	0.9700	0.31666667
##	0.8	0.14153846	0.8124919	0.9700	0.307575758
##	0.8	0.14641026	0.8106196	0.9700	0.298484848
##	0.8	0.15128205	0.8080709	0.9725	0.288961039
##	0.8	0.15615385	0.8063285	0.9725	0.265367965
##	0.8	0.16102564	0.8034064	0.9725	0.256060606
##	0.8	0.16589744	0.8030601	0.9775	0.232683983
##	0.8	0.17076923	0.8019183	0.9775	0.232683983
##	0.8	0.17564103	0.8012338	0.9775	0.204978355
##	0.8	0.18051282	0.8010552	0.9800	0.177056277
##	0.8	0.18538462	0.8010552	0.9825	0.162987013
##	0.8	0.19025641	0.8013393	0.9850	0.153896104
##	0.8	0.19512821	0.8013393	0.9900	0.130519481
##	0.8	0.20000000	0.8013393	0.9925	0.097619048
##	1.0	0.01000000	0.8496483	0.9000	0.571645022
##	1.0	0.01487179	0.8492857	0.8950	0.557792208
##	1.0	0.01974359	0.8501028	0.8975	0.548268398
##	1.0	0.02461538	0.8486039	0.8975	0.543722944
##	1.0	0.02948718	0.8466071	0.9000	0.543506494
##	1.0	0.03435897	0.8455574	0.9000	0.529653680
##	1.0	0.03923077	0.8432900	0.9075	0.524891775
##	1.0	0.04410256	0.8415152	0.9100	0.529653680
##	1.0	0.04897436	0.8394156	0.9100	0.524891775
##	1.0	0.05384615	0.8366180	0.9100	0.501515152
##	1.0	0.05871795	0.8342803	0.9150	0.501515152
##	1.0	0.06358974	0.8303030	0.9175	0.492207792
##	1.0	0.06846154	0.8277652	0.9200	0.483333333
##	1.0	0.07333333	0.8252381	0.9250	0.474242424
##	1.0	0.07820513	0.8239502	0.9250	0.469696970
##	1.0	0.08307692	0.8234443	0.9350	0.451082251
##	1.0	0.08794872	0.8214800	0.9350	0.437229437
##	1.0	0.09282051	0.8202029	0.9375	0.423593074
##	1.0	0.09769231	0.8185633	0.9425	0.404978355
##	1.0	0.10256410	0.8163231	0.9425	0.391125541
##	1.0	0.10743590	0.8130763	0.9475	0.381818182
##	1.0	0.11230769	0.8105005	0.9500	0.358874459
##	1.0	0.11717949	0.8077246	0.9600	0.335281385
##	1.0	0.12205128	0.8051542	0.9625	0.321428571
##	1.0	0.12692308	0.8024865	0.9650	0.316883117
##	1.0	0.13179487	0.8019129	0.9675	0.302813853
##	1.0	0.13666667	0.8018561	0.9700	0.284199134
##	1.0	0.14153846	0.8013393	0.9775	0.265367965
##	1.0	0.14641026	0.8013393	0.9775	0.237229437
##	1.0	0.15128205	0.8013393	0.9775	0.223376623
##	1.0	0.15615385	0.8013393	0.9800	0.200432900
##	1.0	0.16102564	0.8013393	0.9825	0.167748918
##	1.0	0.16589744	0.8013393	0.9875	0.149134199
##	1.0	0.17076923	0.8013393	0.9925	0.106926407
##	1.0	0.17564103	0.8013393	0.9925	0.074675325
##	1.0	0.18051282	0.8013393	0.9975	0.037229437
##	1.0	0.18538462	0.8013393	1.0000	0.004761905
##	1.0	0.19025641	0.8013393	1.0000	0.000000000
##	1.0	0.19512821	0.8013393	1.0000	0.000000000
##	1.0	0.20000000	0.8013393	1.0000	0.000000000

```
##
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were alpha = 0.1 and lambda = 0.08794872.
##### Nearest Shrunken Centroids #####
nscGrid <- data.frame(.threshold = 0:25)
nscFit <- train(diabetes ~., data = train_data,
               method = "pam",
               tuneGrid = nscGrid,
               preProcess = c("center","scale"),
               metric = "ROC",
               trControl = trainControl(method = "cv", number = 10,
                                       classProbs = TRUE, summaryFunction = twoClassSummary))

## 1
nscFit

## Nearest Shrunken Centroids
##
## 615 samples
## 7 predictor
## 2 classes: 'neg', 'pos'
##
## Pre-processing: centered (7), scaled (7)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 553, 553, 554, 554, 553, 554, ...
## Resampling results across tuning parameters:
##
## threshold ROC Sens Spec
## 0 0.8380682 0.9550 0.31580087
## 1 0.8430844 0.9775 0.19047619
## 2 0.8351299 0.9925 0.04155844
## 3 0.8158820 1.0000 0.00000000
## 4 0.7968642 1.0000 0.00000000
## 5 0.7967505 1.0000 0.00000000
## 6 0.7967505 1.0000 0.00000000
## 7 0.5000000 1.0000 0.00000000
## 8 0.5000000 1.0000 0.00000000
## 9 0.5000000 1.0000 0.00000000
## 10 0.5000000 1.0000 0.00000000
## 11 0.5000000 1.0000 0.00000000
## 12 0.5000000 1.0000 0.00000000
## 13 0.5000000 1.0000 0.00000000
## 14 0.5000000 1.0000 0.00000000
## 15 0.5000000 1.0000 0.00000000
## 16 0.5000000 1.0000 0.00000000
## 17 0.5000000 1.0000 0.00000000
## 18 0.5000000 1.0000 0.00000000
## 19 0.5000000 1.0000 0.00000000
## 20 0.5000000 1.0000 0.00000000
## 21 0.5000000 1.0000 0.00000000
## 22 0.5000000 1.0000 0.00000000
## 23 0.5000000 1.0000 0.00000000
## 24 0.5000000 1.0000 0.00000000
## 25 0.5000000 1.0000 0.00000000
```

```

##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was threshold = 1.
##### LDA #####
ldaFit <- train(diabetes ~., data = train_data,
               method = "lda",
               metric = "ROC",
               preProcess = c("center","scale"),
               trControl = trainControl(method = "cv", number = 10,
                                       classProbs = TRUE, summaryFunction = twoClassSummary))

ldaFit

## Linear Discriminant Analysis
##
## 615 samples
## 7 predictor
## 2 classes: 'neg', 'pos'
##
## Pre-processing: centered (7), scaled (7)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 553, 554, 553, 554, 554, 554, ...
## Resampling results:
##
## ROC      Sens   Spec
## 0.8461472 0.8875 0.5722944

#Compare ROC Value by Training Model
allmodels <- list(Logistic_Regression = lr_train_data, Random_Forest = rf_train_data, KNN = knn_train_data)
trainresults <- resamples(allmodels)

#Box Plot: Training Models' ROC Values
#Logistic Regression Performed Best on Training Data
bwplot(trainresults, metric="ROC")

#####Test Data#####
#Logistic Regression: Testing Data
lrpredict <- predict(lr_train_data, test_data)
#Confusion Matrix Accuracy
lrconfusion <- confusionMatrix(lrpredict, test_data$diabetes, positive="pos")
lrconfusion

## Confusion Matrix and Statistics
##
##           Reference
## Prediction neg pos
##      neg  86  26
##      pos  14  27
##
##              Accuracy : 0.7386
##              95% CI : (0.6615, 0.8062)
##      No Information Rate : 0.6536
##      P-Value [Acc > NIR] : 0.01536
##

```

```
##           Kappa : 0.3902
##
## Mcnemar's Test P-Value : 0.08199
##
##           Sensitivity : 0.5094
##           Specificity : 0.8600
##           Pos Pred Value : 0.6585
##           Neg Pred Value : 0.7679
##           Prevalence : 0.3464
##           Detection Rate : 0.1765
##           Detection Prevalence : 0.2680
##           Balanced Accuracy : 0.6847
##
##           'Positive' Class : pos
##
```

#Random Forest: Testing Data

```
rfpredict <- predict(rf_train_data, test_data)
```

#Confusion Matrix Accuracy

```
rfconfusion <- confusionMatrix(rfpredict, test_data$diabetes, positive="pos")
rfconfusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction neg pos
##      neg  84  22
##      pos  16  31
##
##           Accuracy : 0.7516
##           95% CI : (0.6754, 0.8179)
##           No Information Rate : 0.6536
##           P-Value [Acc > NIR] : 0.005891
##
##           Kappa : 0.4365
##
## Mcnemar's Test P-Value : 0.417304
##
##           Sensitivity : 0.5849
##           Specificity : 0.8400
##           Pos Pred Value : 0.6596
##           Neg Pred Value : 0.7925
##           Prevalence : 0.3464
##           Detection Rate : 0.2026
##           Detection Prevalence : 0.3072
##           Balanced Accuracy : 0.7125
##
##           'Positive' Class : pos
##
```

#K Nearest Neighbor: Testing Data

```
knnpredict <- predict(knn_train_data, test_data)
```

#Confusion Matrix Accuracy

```
knnconfusion <- confusionMatrix(knnpredict, test_data$diabetes, positive="pos")
knnconfusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction neg pos
##      neg  80  22
##      pos  20  31
##
##           Accuracy : 0.7255
##           95% CI : (0.6476, 0.7945)
##      No Information Rate : 0.6536
##      P-Value [Acc > NIR] : 0.03543
##
##           Kappa : 0.3883
##
##  McNemar's Test P-Value : 0.87737
##
##           Sensitivity : 0.5849
##           Specificity : 0.8000
##      Pos Pred Value : 0.6078
##      Neg Pred Value : 0.7843
##           Prevalence : 0.3464
##      Detection Rate : 0.2026
##      Detection Prevalence : 0.3333
##      Balanced Accuracy : 0.6925
##
##      'Positive' Class : pos
##
```

```
#Classification and Regression Trees (CART): Testing Data
cartpredict <- predict(cart_train_data, test_data)
#Confusion Matrix Accuracy
cartconfusion <- confusionMatrix(cartpredict, test_data$diabetes, positive="pos")
cartconfusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction neg pos
##      neg  85  19
##      pos  15  34
##
##           Accuracy : 0.7778
##           95% CI : (0.7036, 0.8409)
##      No Information Rate : 0.6536
##      P-Value [Acc > NIR] : 0.000586
##
##           Kappa : 0.5004
##
##  McNemar's Test P-Value : 0.606905
##
##           Sensitivity : 0.6415
##           Specificity : 0.8500
##      Pos Pred Value : 0.6939
##      Neg Pred Value : 0.8173
##           Prevalence : 0.3464
```

```
##          Detection Rate : 0.2222
##    Detection Prevalence : 0.3203
##      Balanced Accuracy : 0.7458
##
##      'Positive' Class : pos
##
```

#Neural Net: Testing Data

```
nnetpredict <- predict(nnet_train_data, test_data)
```

#Confusion Matrix Accuracy

```
nnetconfusion <- confusionMatrix(nnetpredict, test_data$diabetes, positive="pos")
nnetconfusion
```

Confusion Matrix and Statistics

```
##
##          Reference
## Prediction neg pos
##      neg  82  25
##      pos  18  28
##
##          Accuracy : 0.719
##          95% CI : (0.6407, 0.7886)
##    No Information Rate : 0.6536
##    P-Value [Acc > NIR] : 0.05152
##
##          Kappa : 0.3595
##
## Mcnemar's Test P-Value : 0.36020
##
##      Sensitivity : 0.5283
##      Specificity : 0.8200
##      Pos Pred Value : 0.6087
##      Neg Pred Value : 0.7664
##      Prevalence : 0.3464
##      Detection Rate : 0.1830
##    Detection Prevalence : 0.3007
##      Balanced Accuracy : 0.6742
##
##      'Positive' Class : pos
##
```

#Support Vector Machines

```
svmpredict <- predict(svmFit, test_data)
```

#Confusion Matrix Accuracy

```
svmconfusion <- confusionMatrix(svmpredict, test_data$diabetes, positive="pos")
svmconfusion
```

Confusion Matrix and Statistics

```
##
##          Reference
## Prediction neg pos
##      neg  81  24
##      pos  19  29
##
##          Accuracy : 0.719
##          95% CI : (0.6407, 0.7886)
```



```
##      No Information Rate : 0.6536
##      P-Value [Acc > NIR] : 0.05152
##
##              Kappa : 0.3653
##
##      McNemar's Test P-Value : 0.54187
##
##              Sensitivity : 0.5472
##              Specificity : 0.8100
##              Pos Pred Value : 0.6042
##              Neg Pred Value : 0.7714
##              Prevalence : 0.3464
##              Detection Rate : 0.1895
##      Detection Prevalence : 0.3137
##      Balanced Accuracy : 0.6786
##
##      'Positive' Class : pos
##
```

```
#Boost
gbmpredict <- predict(gbmFit, test_data)
#Confusion Matrix Accuracy
gbmconfusion <- confusionMatrix(gbmpredict, test_data$diabetes, positive="pos")
gbmconfusion
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction neg pos
##      neg  85  25
##      pos  15  28
##
##              Accuracy : 0.7386
##              95% CI : (0.6615, 0.8062)
##      No Information Rate : 0.6536
##      P-Value [Acc > NIR] : 0.01536
##
##              Kappa : 0.3959
##
##      McNemar's Test P-Value : 0.15473
##
##              Sensitivity : 0.5283
##              Specificity : 0.8500
##              Pos Pred Value : 0.6512
##              Neg Pred Value : 0.7727
##              Prevalence : 0.3464
##              Detection Rate : 0.1830
##      Detection Prevalence : 0.2810
##      Balanced Accuracy : 0.6892
##
##      'Positive' Class : pos
##
```

```
#Elastinet
glmnpredict <- predict(glmnFit, test_data)
```

#Confusion Matrix Accuracy

```
glmncfusion <- confusionMatrix(glmnpredict, test_data$diabetes, positive="pos")
glmncfusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction neg pos
##      neg  90  28
##      pos  10  25
##
##           Accuracy : 0.7516
##           95% CI : (0.6754, 0.8179)
##      No Information Rate : 0.6536
##      P-Value [Acc > NIR] : 0.005891
##
##           Kappa : 0.4039
##
##  McNemar's Test P-Value : 0.005820
##
##           Sensitivity : 0.4717
##           Specificity : 0.9000
##      Pos Pred Value : 0.7143
##      Neg Pred Value : 0.7627
##           Prevalence : 0.3464
##      Detection Rate : 0.1634
##      Detection Prevalence : 0.2288
##      Balanced Accuracy : 0.6858
##
##      'Positive' Class : pos
##
```

Nearest Shrunk Centroid

```
nscpredict <- predict(nscFit, test_data)
```

#Confusion Matrix Accuracy

```
nscconfusion <- confusionMatrix(nscpredict, test_data$diabetes, positive="pos")
nscconfusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction neg pos
##      neg  99  46
##      pos   1   7
##
##           Accuracy : 0.6928
##           95% CI : (0.6132, 0.7648)
##      No Information Rate : 0.6536
##      P-Value [Acc > NIR] : 0.1753
##
##           Kappa : 0.1525
##
##  McNemar's Test P-Value : 1.38e-10
##
##           Sensitivity : 0.13208
```

```
##           Specificity : 0.99000
##           Pos Pred Value : 0.87500
##           Neg Pred Value : 0.68276
##           Prevalence : 0.34641
##           Detection Rate : 0.04575
##           Detection Prevalence : 0.05229
##           Balanced Accuracy : 0.56104
##
##           'Positive' Class : pos
##
```

```
#Boost
ldapredict <- predict(ldaFit, test_data)
#Confusion Matrix Accuracy
ldaconfusion <- confusionMatrix(ldapredict, test_data$diabetes, positive="pos")
ldaconfusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction neg pos
##           neg  86  28
##           pos  14  25
##
##           Accuracy : 0.7255
##           95% CI : (0.6476, 0.7945)
##           No Information Rate : 0.6536
##           P-Value [Acc > NIR] : 0.03543
##
##           Kappa : 0.3537
##
##           Mcnemar's Test P-Value : 0.04486
##
##           Sensitivity : 0.4717
##           Specificity : 0.8600
##           Pos Pred Value : 0.6410
##           Neg Pred Value : 0.7544
##           Prevalence : 0.3464
##           Detection Rate : 0.1634
##           Detection Prevalence : 0.2549
##           Balanced Accuracy : 0.6658
##
##           'Positive' Class : pos
##
```

#Comparing Test Results

```
lrfinal<- c(lrconfusion$byClass['Sensitivity'], lrconfusion$byClass['Specificity'], lrconfusion$byClass[
  lrconfusion$byClass['Recall'], lrconfusion$byClass['F1'])
rffinal <- c(rfconfusion$byClass['Sensitivity'], rfconfusion$byClass['Specificity'], rfconfusion$byClass[
  rfconfusion$byClass['Recall'], rfconfusion$byClass['F1'])

knnfinal <- c(knnconfusion$byClass['Sensitivity'], knnconfusion$byClass['Specificity'], knnconfusion$byClass[
  knnconfusion$byClass['Recall'], knnconfusion$byClass['F1'])

cartfinal <- c(cartconfusion$byClass['Sensitivity'], cartconfusion$byClass['Specificity'], cartconfusion$byClass[
  cartconfusion$byClass['Recall'], cartconfusion$byClass['F1'])
```

```

        cartconfusion$byClass['Recall'], cartconfusion$byClass['F1'])

nnetfinal <- c(nnetconfusion$byClass['Sensitivity'], nnetconfusion$byClass['Specificity'], nnetconfusion$byClass['Precision'],
              nnetconfusion$byClass['Recall'], nnetconfusion$byClass['F1'])

svmfinal <- c(svmconfusion$byClass['Sensitivity'], svmconfusion$byClass['Specificity'], svmconfusion$byClass['Precision'],
              svmconfusion$byClass['Recall'], svmconfusion$byClass['F1'])

gbmfinal <- c(gbmconfusion$byClass['Sensitivity'], gbmconfusion$byClass['Specificity'], gbmconfusion$byClass['Precision'],
              gbmconfusion$byClass['Recall'], gbmconfusion$byClass['F1'])

glmfinal <- c(glmnconfusion$byClass['Sensitivity'], glmnconfusion$byClass['Specificity'], glmnconfusion$byClass['Precision'],
              glmnconfusion$byClass['Recall'], glmnconfusion$byClass['F1'])

nscfinal <- c(nscconfusion$byClass['Sensitivity'], nscconfusion$byClass['Specificity'], nscconfusion$byClass['Precision'],
              nscconfusion$byClass['Recall'], nscconfusion$byClass['F1'])

ldafinal <- c(ldaconfusion$byClass['Sensitivity'], ldaconfusion$byClass['Specificity'], ldaconfusion$byClass['Precision'],
              ldaconfusion$byClass['Recall'], ldaconfusion$byClass['F1'])

allmodelsfinal <- data.frame(rbind(lrfinal, rffinal, knnfinal, cartfinal, nnetfinal, svmfinal, gbmfinal, nscfinal, ldafinal))
names(allmodelsfinal) <- c("Sensitivity", "Specificity", "Precision", "Recall", "F1")
allmodelsfinal

```

##	Sensitivity	Specificity	Precision	Recall	F1
## lrfinal	0.5094340	0.86	0.6585366	0.5094340	0.5744681
## rffinal	0.5849057	0.84	0.6595745	0.5849057	0.6200000
## knnfinal	0.5849057	0.80	0.6078431	0.5849057	0.5961538
## cartfinal	0.6415094	0.85	0.6938776	0.6415094	0.6666667
## nnetfinal	0.5283019	0.82	0.6086957	0.5283019	0.5656566
## svmfinal	0.5471698	0.81	0.6041667	0.5471698	0.5742574
## gbmfinal	0.5283019	0.85	0.6511628	0.5283019	0.5833333
## nscfinal	0.1320755	0.99	0.8750000	0.1320755	0.2295082
## ldafinal	0.4716981	0.86	0.6410256	0.4716981	0.5434783