

INDENG142 Predicting NBA MVP

CASEY LI

12/17/2019

Data loading and cleaning and splitting

```
# Loading data  
set.seed(679)  
  
# we cleaned this csv already  
nba_csv <- read.csv("NBASStats (1).csv")  
summary(nba_csv)
```

```

##          X          fga          fg3a          fta
## Min.   : 0   Min.   : 3.70   Min.   : 0.000   Min.   : 1.300
## 1st Qu.:162   1st Qu.:13.90   1st Qu.: 0.100   1st Qu.: 4.800
## Median :324   Median :16.80   Median : 1.100   Median : 6.300
## Mean   :324   Mean   :16.53   Mean   : 2.069   Mean   : 6.446
## 3rd Qu.:486   3rd Qu.:19.20   3rd Qu.: 3.700   3rd Qu.: 7.900
## Max.   :648   Max.   :27.80   Max.   :13.200   Max.   :13.100
##
##          per          ts_pct          usg_pct          bpm
## Min.   :10.10   Min.   :0.4410   Min.   : 7.10   Min.   : -2.800
## 1st Qu.:19.90   1st Qu.:0.5430   1st Qu.:23.70   1st Qu.: 2.600
## Median :22.60   Median :0.5680   Median :26.70   Median : 4.500
## Mean   :22.51   Mean   :0.5687   Mean   :26.53   Mean   : 4.601
## 3rd Qu.:24.80   3rd Qu.:0.5960   3rd Qu.:29.90   3rd Qu.: 6.100
## Max.   :31.70   Max.   :0.6990   Max.   :41.70   Max.   :15.600
##
##          vorp          season          player          age
## Min.   : -0.500   1980-81: 31   LeBron James   : 16   Min.   :19.00
## 1st Qu.: 3.100   1981-82: 25   Tim Duncan    : 16   1st Qu.:25.00
## Median : 4.400   1982-83: 23   Karl Malone   : 15   Median :27.00
## Mean   : 4.587   1984-85: 23   Shaquille O'Neal: 14   Mean   :27.47
## 3rd Qu.: 5.800   1998-99: 21   Hakeem Olajuwon: 13   3rd Qu.:30.00
## Max.   :12.400   1990-91: 20   Kobe Bryant   : 13   Max.   :38.00
##          (Other):506   (Other)       :562
##          win_pct          votes_first          points_won          points_max
## Min.   :0.2195   Min.   : 0.000   Min.   : 1.0   Min.   : 690
## 1st Qu.:0.5610   1st Qu.: 0.000   1st Qu.: 3.0   1st Qu.: 800
## Median :0.6463   Median : 0.000   Median : 23.0   Median :1130
## Mean   :0.6310   Mean   : 6.401   Mean   :166.4   Mean   :1039
## 3rd Qu.:0.7000   3rd Qu.: 1.000   3rd Qu.:184.0   3rd Qu.:1230
## Max.   :0.8902   Max.   :131.000   Max.   :1310.0   Max.   :1310
##
##          award_share          g          mp_per_g          pts_per_g
## Min.   :0.0010   Min.   :17   Min.   :23.60   Min.   : 4.7
## 1st Qu.:0.0040   1st Qu.:73   1st Qu.:34.60   1st Qu.:18.8
## Median :0.0210   Median :79   Median :36.70   Median :22.0
## Mean   :0.1562   Mean   :75   Mean   :36.33   Mean   :22.0
## 3rd Qu.:0.1770   3rd Qu.:81   3rd Qu.:38.30   3rd Qu.:25.7
## Max.   :1.0000   Max.   :82   Max.   :43.70   Max.   :37.1
##
##          trb_per_g          ast_per_g          stl_per_g          blk_per_g
## Min.   : 1.900   Min.   : 0.800   Min.   :0.200   Min.   :0.0000
## 1st Qu.: 4.800   1st Qu.: 2.800   1st Qu.:1.000   1st Qu.:0.3000
## Median : 6.900   Median : 4.300   Median :1.400   Median :0.6000
## Mean   : 7.459   Mean   : 5.002   Mean   :1.428   Mean   :0.9817
## 3rd Qu.:10.400   3rd Qu.: 6.700   3rd Qu.:1.800   3rd Qu.:1.4000
## Max.   :18.700   Max.   :14.500   Max.   :3.700   Max.   :5.6000
##
##          fg_pct          fg3_pct          ft_pct          ws
## Min.   :0.3840   Min.   :0.0000   Min.   :0.4220   Min.   : 2.3
## 1st Qu.:0.4630   1st Qu.:0.1670   1st Qu.:0.7370   1st Qu.: 8.5
## Median :0.4920   Median :0.3020   Median :0.7900   Median :10.6
## Mean   :0.4944   Mean   :0.2576   Mean   :0.7802   Mean   :10.7

```

```
## 3rd Qu.:0.5230    3rd Qu.:0.3650    3rd Qu.:0.8430    3rd Qu.:12.9
## Max.    :0.6700    Max.    :1.0000    Max.    :0.9480    Max.    :21.2
##
## ws_per_48
## Min.    :0.0460
## 1st Qu.:0.1550
## Median :0.1870
## Mean    :0.1877
## 3rd Qu.:0.2180
## Max.    :0.3220
##
```

```
#variable selection
nba_csv <- select(nba_csv, fg_pct, fg3_pct, ft_pct,
                  trb_per_g, ast_per_g, stl_per_g, blk_per_g,
                  per, ts_pct, usg_pct, ws, bpm, vorp, season,
                  age, award_share, win_pct, pts_per_g)

#separate to training vs. testing set
nba_csv.train <- filter(nba_csv, season != "2018-19")
nba_csv.test <- filter(nba_csv, season == "2018-19")

nba_csv.train <- select(nba_csv.train, -season)
nba_csv.test <- select(nba_csv.test, -season)
```

Baseline linear model

```
# baseline model -----
baseline <- mean(nba_csv.train$award_share)
pred.base <- rep(baseline, nrow(nba_csv.test))

# OSR2
SSE <- sum((nba_csv.test$award_share - pred.base)^2)
SST = sum((nba_csv.test$award_share - mean(nba_csv.train$award_share))^2)
OSR2 = 1 - SSE/SST
OSR2 #0 as expected! since sse = sst
```

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

Naive linear regression

```
##Linear regression model
testlm <- lm(award_share ~ ., data = nba_csv.train)
summary(testlm)
```

```
##
## Call:
## lm(formula = award_share ~ ., data = nba_csv.train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.40274 -0.11786 -0.03753  0.09231  0.69770
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.6529754  0.2288151  -2.854 0.004465 **
## fg_pct       0.5290393  0.3817452   1.386 0.166293
## fg3_pct     -0.0667063  0.0596292  -1.119 0.263708
## ft_pct       0.1576860  0.1352366   1.166 0.244062
## trb_per_g    0.0071437  0.0039831   1.793 0.073381 .
## ast_per_g    0.0163803  0.0046416   3.529 0.000448 ***
## stl_per_g   -0.0447344  0.0186352  -2.401 0.016665 *
## blk_per_g    0.0045502  0.0122848   0.370 0.711213
## per          0.0005473  0.0092639   0.059 0.952907
## ts_pct     -1.3495734  0.4553094  -2.964 0.003152 **
## usg_pct      0.0038880  0.0058959   0.659 0.509854
## ws          0.0237721  0.0097291   2.443 0.014828 *
## bpm         0.0140661  0.0164185   0.857 0.391929
## vorp        0.0085559  0.0244173   0.350 0.726154
## age         0.0018868  0.0020919   0.902 0.367426
## win_pct     0.6003816  0.0898235   6.684 5.19e-11 ***
## pts_per_g   0.0104445  0.0044217   2.362 0.018479 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1783 on 620 degrees of freedom
## Multiple R-squared:  0.5303, Adjusted R-squared:  0.5181
## F-statistic: 43.74 on 16 and 620 DF,  p-value: < 2.2e-16
```

```
testlm$coefficients
```

```
##      (Intercept)      fg_pct      fg3_pct      ft_pct      trb_per_g
## -0.6529753819  0.5290393304 -0.0667062644  0.1576860037  0.0071437321
##      ast_per_g      stl_per_g      blk_per_g      per      ts_pct
##  0.0163803226 -0.0447344375  0.0045502399  0.0005473181 -1.3495734159
##      usg_pct      ws      bpm      vorp      age
##  0.0038880487  0.0237721109  0.0140660859  0.0085559299  0.0018868444
##      win_pct      pts_per_g
##  0.6003815569  0.0104444661
```

```
testlm$fitted.values
```

##	1	2	3	4	5
##	0.3972906118	0.2916581793	0.3594884314	0.1993401127	0.1624579346
##	6	7	8	9	10
##	0.2147955046	0.2154722659	0.0350259089	-0.0589241505	0.0297343558
##	11	12	13	14	15
##	0.0885785342	0.0922945096	-0.2112985691	-0.0617071877	-0.2187128273
##	16	17	18	19	20
##	-0.0637384935	-0.0691877979	-0.0106819405	0.0264315739	-0.0688684067
##	21	22	23	24	25
##	-0.0610597527	0.0219044207	-0.0774595865	-0.2117189962	-0.0560655893
##	26	27	28	29	30
##	-0.2113985352	0.0414616602	-0.2139183151	-0.0582458470	-0.1094189856
##	31	32	33	34	35
##	-0.1195729109	0.3798380306	0.3958375379	0.3154756571	0.2087001326
##	36	37	38	39	40
##	0.1747815062	0.1971712924	0.1797696935	0.2800780058	0.1998916974
##	41	42	43	44	45
##	0.2261494109	-0.0338753795	-0.1361760292	0.1479482157	-0.0056570763
##	46	47	48	49	50
##	0.0354081373	0.0028759112	-0.1874816730	-0.0294870068	-0.0377728547
##	51	52	53	54	55
##	-0.2869335512	-0.0299859784	0.0449853754	-0.2319481805	-0.0200816963
##	56	57	58	59	60
##	-0.1276560415	0.3810857245	0.3798848301	0.2773002294	0.1782551794
##	61	62	63	64	65
##	0.2660436783	0.2175688987	0.0121898546	0.0634733313	0.1016404280
##	66	67	68	69	70
##	0.1816038097	0.0680002057	0.0099041576	-0.1061899541	-0.0208888189
##	71	72	73	74	75
##	-0.2615872467	-0.0231199347	-0.0724331019	-0.0484033035	0.0598843630
##	76	77	78	79	80
##	0.0001164818	0.1760449005	-0.0945440380	0.0422575085	0.4607651897
##	81	82	83	84	85
##	0.1277977964	0.1692539986	0.0933294478	0.1330411785	0.1622708841
##	86	87	88	89	90
##	0.2235146215	0.1337276646	-0.0199162344	0.0740147508	0.1296931373
##	91	92	93	94	95
##	0.0497300998	-0.1157686670	-0.2275910100	0.0754248231	0.5651062663
##	96	97	98	99	100
##	0.2964140129	0.2152980481	0.2495141359	0.2393991395	0.2414150315
##	101	102	103	104	105
##	-0.0218312096	0.1908948211	0.2385215484	-0.0028557656	0.0988968475
##	106	107	108	109	110
##	0.1689760146	0.0692480212	0.0512158342	-0.1016887179	-0.1684487839
##	111	112	113	114	115
##	0.0833802641	-0.0704482056	-0.0474338351	-0.1014580300	-0.2061901511
##	116	117	118	119	120
##	-0.0467824444	0.0588340294	0.5485016823	0.2255040542	0.3133382257
##	121	122	123	124	125
##	0.1269333208	0.2673610796	0.1467539149	0.1221774615	0.1766752978
##	126	127	128	129	130
##	0.0760933393	0.0616564975	0.0539584230	0.1066611894	0.2511496383
##	131	132	133	134	135

##	0.0830623377	-0.1425847923	0.1916543275	-0.1859185553	0.0629914075
##	136	137	138	139	140
##	0.5505936853	0.4431377734	0.4963458117	0.3543969927	0.3164025261
##	141	142	143	144	145
##	0.1851487704	0.1425950248	0.1045610563	0.0627110386	0.0749202261
##	146	147	148	149	150
##	-0.2070096665	-0.0476501164	0.0902816348	0.0450707472	0.1280898977
##	151	152	153	154	155
##	-0.0058145069	-0.1013492495	0.6435355211	0.4909543444	0.3038973946
##	156	157	158	159	160
##	0.2664241078	0.3199673969	0.2150042519	0.1241270757	0.1435291862
##	161	162	163	164	165
##	0.2010242045	0.0534988670	0.1527539107	0.0779074322	-0.0970659812
##	166	167	168	169	170
##	-0.1393687167	0.1538468443	-0.0045354729	-0.3759730112	0.4824391599
##	171	172	173	174	175
##	0.6038916276	0.3256121344	0.1378877341	0.1852858100	0.3272939319
##	176	177	178	179	180
##	0.1846989439	0.2253351013	0.1340769873	0.0928675085	0.0644146218
##	181	182	183	184	185
##	0.0382743230	-0.1410676510	0.0811748639	0.0874044658	0.1056544324
##	186	187	188	189	190
##	0.0339469554	-0.0037865435	0.1074438670	0.4979090700	0.3760578386
##	191	192	193	194	195
##	0.5844865604	0.4009488401	0.2607127947	0.3299225644	0.1882687979
##	196	197	198	199	200
##	0.1648916237	0.2037271630	0.2957021013	-0.0459284286	0.3085042573
##	201	202	203	204	205
##	0.0431050342	0.1212627625	0.6359032968	0.4140381274	0.4313950629
##	206	207	208	209	210
##	0.2695938546	0.4029921390	0.3203995910	0.2290042195	0.1570796380
##	211	212	213	214	215
##	0.1244123724	0.1554239678	0.1603209640	0.1928117616	-0.0806575671
##	216	217	218	219	220
##	-0.0144751477	0.0526305755	-0.1117966994	-0.0630058446	0.1470418841
##	221	222	223	224	225
##	0.0808047232	0.0105841321	0.6091494637	0.3648177724	0.2684030535
##	226	227	228	229	230
##	0.3626741179	0.2475786360	0.1182449365	0.0379832498	0.1550542683
##	231	232	233	234	235
##	0.3797606469	0.0515001160	0.2042012694	0.0926412763	0.1744586967
##	236	237	238	239	240
##	0.1097527419	0.1308838425	0.0474664250	-0.0565397787	0.4397763005
##	241	242	243	244	245
##	0.4851069388	0.5549538297	0.2523358110	0.1472741115	0.2774255022
##	246	247	248	249	250
##	0.1013358223	0.3397837546	0.0501789429	0.1697483450	0.0582189030
##	251	252	253	254	255
##	-0.0532288389	0.0597979040	0.0058044398	0.4376235050	0.6531149024
##	256	257	258	259	260
##	0.2310999456	0.4367468762	0.3248808135	0.0638498489	0.1999928553
##	261	262	263	264	265
##	0.3433020874	0.0330149448	0.1642114058	0.1435191340	0.0545589017
##	266	267	268	269	270

##	-0.0724093291	-0.0560118081	0.1413972241	0.0131052507	0.1031591960
##	271	272	273	274	275
##	0.5127593147	0.4017993440	0.3695351133	0.1846791855	0.2434262271
##	276	277	278	279	280
##	0.2427020446	0.1452753090	0.1630967564	0.1498564072	0.1166625696
##	281	282	283	284	285
##	-0.0244534565	-0.0783888995	-0.2711467691	0.0844513004	-0.1519106289
##	286	287	288	289	290
##	0.6754691688	0.5265069310	0.2726951859	0.2123914072	0.3346789889
##	291	292	293	294	295
##	0.1839569039	0.3854044001	0.1421588108	0.2027522146	0.1720069621
##	296	297	298	299	300
##	0.0964786602	0.1018918351	-0.1529203937	0.0557838077	0.0356600415
##	301	302	303	304	305
##	0.1298851865	-0.1073350671	0.5759807021	0.5925164560	0.3723969641
##	306	307	308	309	310
##	0.2886361909	0.0527791256	0.2488176198	0.1721828614	0.1725231196
##	311	312	313	314	315
##	0.1416229339	0.2583806222	0.3367462913	0.0996400901	0.0734099288
##	316	317	318	319	320
##	-0.0115412307	0.1420356117	0.1726953571	-0.0631088225	-0.2676841750
##	321	322	323	324	325
##	0.0075989455	0.0310160099	0.4547717182	0.4937551757	0.2388624895
##	326	327	328	329	330
##	0.3182775521	0.2889096306	0.2026247901	0.3406526970	0.1043198074
##	331	332	333	334	335
##	0.0946830229	0.1073807719	-0.0242678095	-0.1425502496	0.0218473476
##	336	337	338	339	340
##	-0.0454342904	-0.1795787294	0.0589440775	0.0112058018	-0.2012647130
##	341	342	343	344	345
##	0.0473286205	0.2827174908	0.1104186216	0.2056320401	0.0488571816
##	346	347	348	349	350
##	0.0426866942	0.2113561972	-0.0543326756	0.1021685191	0.0312985168
##	351	352	353	354	355
##	0.0116338360	-0.1305942693	0.1261982554	-0.0400401604	-0.0381475952
##	356	357	358	359	360
##	-0.0809917541	-0.1838096964	-0.0638212588	-0.1662626945	-0.1539933938
##	361	362	363	364	365
##	-0.0992972190	-0.2000240707	0.7518793147	0.2629045110	0.2310265738
##	366	367	368	369	370
##	0.4207412507	0.3261598385	0.3123144386	0.0748923396	0.1398683916
##	371	372	373	374	375
##	0.2089471384	0.1706762766	0.0978933305	0.2717219537	-0.0849083885
##	376	377	378	379	380
##	0.0120082629	-0.0231967310	-0.0044980131	0.2955677828	0.3409694031
##	381	382	383	384	385
##	0.5101685406	0.3543101636	0.2438922165	0.2347969567	0.2986949701
##	386	387	388	389	390
##	0.1347352462	0.2640186099	0.1663920229	0.1560350422	0.2552806599
##	391	392	393	394	395
##	-0.0268584633	0.0771730730	0.0701336769	0.0840772540	-0.0198988233
##	396	397	398	399	400
##	0.5541818708	0.1434521102	0.4151199967	0.2114993287	0.3078507897
##	401	402	403	404	405

##	0.2525881053	0.2716862758	0.2075810494	0.1058123254	0.0024866901
##	406	407	408	409	410
##	0.1606126894	0.3097576893	-0.0216198066	0.0712699715	-0.0117237312
##	411	412	413	414	415
##	-0.0786940550	0.1141863768	0.0598296074	0.5055873820	0.4545650523
##	416	417	418	419	420
##	0.3738324722	0.4242792031	0.3417190884	0.1192522821	0.3656799833
##	421	422	423	424	425
##	0.0009865580	0.2044291653	0.2205610144	0.0971571942	0.1655458362
##	426	427	428	429	430
##	0.1252376917	0.6222301662	0.3821802498	0.2055959013	0.1208260350
##	431	432	433	434	435
##	0.2049859192	0.2311936860	0.0726137876	0.0600129005	-0.1193174654
##	436	437	438	439	440
##	0.2388294366	0.0393077360	0.1275300220	0.0395334939	-0.1248931990
##	441	442	443	444	445
##	0.0299705095	-0.0375466543	0.1412967430	0.3028676155	0.3671230655
##	446	447	448	449	450
##	0.2885955517	0.1717485048	0.3103513373	0.2939121416	0.2499642446
##	451	452	453	454	455
##	0.2853173546	0.1313096556	0.4147423914	0.0875501986	0.0876352596
##	456	457	458	459	460
##	-0.3260388892	-0.0826642721	0.2002130318	0.1826344976	0.4978785172
##	461	462	463	464	465
##	0.4568226373	0.3912972646	0.2858952458	0.3706454185	0.2931539653
##	466	467	468	469	470
##	0.2609887046	0.1242843550	0.1879032142	0.2104383710	0.4650738959
##	471	472	473	474	475
##	0.2266249078	0.2477688589	0.3297937109	0.3418850003	0.2313973623
##	476	477	478	479	480
##	0.0572553288	0.1131500422	0.1440386829	0.1057884734	0.0664411684
##	481	482	483	484	485
##	-0.1766805599	0.1746594614	0.0880567587	0.0545105124	-0.0569501919
##	486	487	488	489	490
##	0.0858021939	0.3343997339	0.4482708251	0.3385180182	0.4643158179
##	491	492	493	494	495
##	0.1245032474	0.2273514190	0.2536885914	0.0945787154	0.0689771121
##	496	497	498	499	500
##	0.1394859743	0.2397800795	0.1199733949	0.0403149811	0.1384325136
##	501	502	503	504	505
##	-0.0455375356	0.1996603580	-0.0186272146	0.7479513246	0.3592312891
##	506	507	508	509	510
##	0.4192197380	0.2587521795	0.4537657841	-0.0977996549	0.1078486447
##	511	512	513	514	515
##	0.1492435669	0.2493614994	0.1430246011	0.2232322124	0.0470581456
##	516	517	518	519	520
##	0.6828542433	0.3022433780	0.2171480860	0.2219942794	0.3411190131
##	521	522	523	524	525
##	0.1017282697	0.2068840203	0.1041113051	0.1226431847	0.0581861609
##	526	527	528	529	530
##	0.0194981166	-0.0037236448	0.0173314272	-0.1620522282	0.0644666630
##	531	532	533	534	535
##	0.4071098911	0.2350743535	0.4642265111	0.2401642703	0.1832273014
##	536	537	538	539	540


```
## 0.1713661222 0.3041568912 0.0994611354 -0.0110512405 0.0099821954
##          541          542          543          544          545
## -0.0298439333 0.0596330567 0.1250847756 0.4436245018 0.2597127397
##          546          547          548          549          550
## 0.1784332673 0.1156220949 0.1152796829 0.0206909056 0.0145201226
##          551          552          553          554          555
## -0.0789239465 -0.2026512648 0.1446220773 0.1722155800 -0.0369104644
##          556          557          558          559          560
## 0.1352739503 0.0630749572 -0.0768576577 0.6351406025 0.4657458941
##          561          562          563          564          565
## 0.1762673642 0.2195649413 0.1946656498 0.1448003329 0.1529103111
##          566          567          568          569          570
## 0.1295497713 0.3018088651 0.1910605142 0.1063599355 -0.1565167091
##          571          572          573          574          575
## 0.1705731941 -0.0396804970 0.0655790197 -0.0342479090 0.5666388623
##          576          577          578          579          580
## 0.3876921964 0.2508491256 0.1510339862 0.1876706611 0.2579452923
##          581          582          583          584          585
## 0.2307947276 0.0258071992 0.1224271653 0.1211974817 0.2833279841
##          586          587          588          589          590
## 0.1357306606 -0.0068033097 0.0667963046 0.0861510717 0.0052273728
##          591          592          593          594          595
## -0.0208128934 0.4224504356 0.4031673460 0.2609821527 0.3697239643
##          596          597          598          599          600
## 0.2391993075 0.3483503599 0.0877582441 0.1518206918 0.1714648424
##          601          602          603          604          605
## 0.1069709819 -0.0232385474 0.0816534859 0.6079772493 0.2741201940
##          606          607          608          609          610
## 0.4211225832 0.4673510961 0.3687107001 0.2637359703 0.2303198017
##          611          612          613          614          615
## 0.0986823029 0.2387959324 0.1662542860 0.6544219717 0.5206176929
##          616          617          618          619          620
## 0.2988363183 0.3648256025 0.2448380467 0.3206963365 0.1791531761
##          621          622          623          624          625
## 0.1629478848 0.0819950458 0.3325198717 0.1157292559 0.5587262244
##          626          627          628          629          630
## 0.4365125411 0.2365969130 0.2585384265 0.3725967368 0.2019674734
##          631          632          633          634          635
## 0.2344634968 0.1412535188 0.1384792308 -0.0036472864 0.1466540818
##          636          637
## 0.0507897436 -0.0023127817
```

```
## testing multicollinearity
vif(testlm)
```

```
## fg_pct fg3_pct ft_pct trb_per_g ast_per_g stl_per_g blk_per_g
## 5.920908 1.690224 2.797433 3.440902 3.472220 2.389805 2.630610
## per ts_pct usg_pct ws bpm vorp age
## 23.899302 6.350981 16.487403 21.594223 39.249989 53.801023 1.215793
## win_pct pts_per_g
## 1.884890 10.375766
```

```
## predicting
predictions_testlm <- predict(testlm, newdata=nba_csv.test)
predictions_testlm
```

```
##          1          2          3          4          5          6          7
## 0.4918244 0.5519403 0.1647240 0.3149604 0.1654079 0.2545112 0.1870386
##          8          9         10         11         12
## 0.2452853 0.1413281 0.2404894 0.1355675 0.1319142
```

```
nba_csv.test
```

```
##      fg_pct fg3_pct ft_pct trb_per_g ast_per_g stl_per_g blk_per_g per
## 1  0.578   0.256   0.729    12.5      5.9      1.3      1.5 30.9
## 2  0.442   0.368   0.879     6.6      7.5      2.0      0.7 30.6
## 3  0.438   0.386   0.839     8.2      4.1      2.2      0.4 23.3
## 4  0.511   0.307   0.821    10.8      7.3      1.4      0.7 26.3
## 5  0.472   0.437   0.916     5.3      5.2      1.3      0.4 24.4
## 6  0.444   0.369   0.912     4.6      6.9      1.1      0.4 23.7
## 7  0.484   0.300   0.804    13.6      3.7      0.7      1.9 26.1
## 8  0.521   0.353   0.885     6.4      5.9      0.7      1.1 24.2
## 9  0.496   0.371   0.854     7.3      3.3      1.8      0.4 25.8
## 10 0.428   0.290   0.656    11.1    10.7      1.9      0.5 21.1
## 11 0.669   0.000   0.636    12.9      2.0      0.8      2.3 24.6
## 12 0.510   0.339   0.665     8.5      8.3      1.3      0.6 25.6
##      ts_pct usg_pct  ws  bpm vorp age award_share win_pct pts_per_g
## 1  0.644   32.3 14.4 10.8 7.6 24      0.932 0.7317073      27.7
## 2  0.616   40.5 15.2 11.7 9.9 29      0.768 0.6463415      36.1
## 3  0.583   29.5 11.9 5.5 5.3 28      0.352 0.5975610      28.0
## 4  0.589   27.4 11.8 9.5 7.3 23      0.210 0.6585366      20.1
## 5  0.641   30.4 9.7 6.3 4.9 30      0.173 0.6951220      27.3
## 6  0.588   29.3 12.1 5.5 5.4 28      0.068 0.6463415      25.8
## 7  0.593   33.3 8.7 4.1 3.3 24      0.049 0.6219512      27.5
## 8  0.631   29.0 11.5 4.3 4.3 30      0.025 0.6951220      26.0
## 9  0.606   30.3 9.5 5.0 3.6 27      0.013 0.7073171      26.6
## 10 0.501   30.9 6.8 6.5 5.6 30      0.008 0.5975610      22.9
## 11 0.682   17.8 14.4 7.0 5.9 26      0.001 0.6097561      15.9
## 12 0.588   31.6 7.2 8.1 4.9 34      0.001 0.4512195      27.4
```

```
SSE <- sum((nba_csv.test$award_share - predictions_testlm)^2)
SST = sum((nba_csv.test$award_share - mean(nba_csv.train$award_share))^2)
OSR2 = 1 - SSE/SST
OSR2 #0.5684896
```

```
## [1] 0.5684896
```

Backwards stepwise linear regression

```
# backwards stepwise regression -----
set.seed(679)

# training model
step.model <- train(award_share ~., data = nba_csv.train,
                    method = "leapBackward",
                    tuneGrid = data.frame(nvmax = 1:17),
                    trControl = trainControl(method = "cv", number = 5)
)
step.model$results
```

##	nvmax	RMSE	Rsquared	MAE	RMSESD	RsquaredSD	MAESD
## 1	1	0.2031545	0.3777678	0.1494879	0.013038205	0.06766914	0.009339134
## 2	2	0.1980863	0.4130157	0.1495969	0.009385366	0.06155075	0.008390312
## 3	3	0.1889702	0.4656558	0.1435723	0.009611728	0.03700280	0.008884902
## 4	4	0.1882616	0.4697285	0.1436825	0.009994344	0.03384342	0.008142159
## 5	5	0.1841933	0.4921710	0.1417201	0.011991674	0.04868312	0.009469273
## 6	6	0.1836906	0.4947454	0.1412724	0.011580542	0.05086569	0.008098952
## 7	7	0.1819367	0.5038802	0.1405544	0.011323619	0.04721548	0.008132983
## 8	8	0.1815373	0.5057130	0.1394399	0.010978828	0.04708293	0.007602473
## 9	9	0.1807420	0.5093612	0.1390457	0.010185091	0.04485822	0.006754325
## 10	10	0.1807905	0.5091646	0.1393108	0.010052605	0.04357026	0.006941399
## 11	11	0.1808864	0.5086471	0.1394837	0.009905718	0.04480604	0.006538665
## 12	12	0.1812204	0.5069891	0.1397146	0.010475619	0.04806086	0.006904193
## 13	13	0.1811344	0.5073143	0.1397867	0.010223272	0.04627425	0.006816784
## 14	14	0.1808260	0.5089978	0.1395601	0.010537676	0.04727980	0.007043144
## 15	15	0.1807655	0.5094014	0.1395333	0.010362966	0.04689159	0.006909715
## 16	16	0.1808619	0.5089869	0.1396446	0.010010337	0.04627448	0.006591465
## 17	17	0.1808619	0.5089869	0.1396446	0.010010337	0.04627448	0.006591465

```
step.model$bestTune
```

```
##   nvmax
## 9      9
```

```
summary(step.model$finalModel) # tells us which variables to include
```

```
## Subset selection object
## 16 Variables (and intercept)
##           Forced in Forced out
## fg_pct      FALSE      FALSE
## fg3_pct      FALSE      FALSE
## ft_pct       FALSE      FALSE
## trb_per_g    FALSE      FALSE
## ast_per_g    FALSE      FALSE
## stl_per_g    FALSE      FALSE
## blk_per_g    FALSE      FALSE
## per          FALSE      FALSE
## ts_pct       FALSE      FALSE
## usg_pct       FALSE      FALSE
## ws           FALSE      FALSE
## bpm          FALSE      FALSE
## vorp         FALSE      FALSE
## age          FALSE      FALSE
## win_pct      FALSE      FALSE
## pts_per_g    FALSE      FALSE
## 1 subsets of each size up to 9
## Selection Algorithm: backward
##           fg_pct fg3_pct ft_pct trb_per_g ast_per_g stl_per_g blk_per_g per
## 1 ( 1 ) " "      " "      " "      " "      " "      " "      " "
## 2 ( 1 ) " "      " "      " "      " "      " "      " "      " "
## 3 ( 1 ) " "      " "      " "      " "      " "      " "      " "
## 4 ( 1 ) " "      " "      " "      " "      " "      " "      " "
## 5 ( 1 ) " "      " "      " "      " "      " "      " "      " "
## 6 ( 1 ) " "      " "      " "      " "      " "      "*"      " "
## 7 ( 1 ) " "      " "      " "      " "      "*"      "*"      " "
## 8 ( 1 ) " "      " "      " "      "*"      "*"      "*"      " "
## 9 ( 1 ) "*"      " "      " "      "*"      "*"      "*"      " "
##           ts_pct usg_pct ws bpm vorp age win_pct pts_per_g
## 1 ( 1 ) " "      " "      " "      "*"      " "      " "      " "
## 2 ( 1 ) " "      " "      " "      "*"      " "      " "      "*"
## 3 ( 1 ) " "      " "      " "      "*"      " "      " "      "*"
## 4 ( 1 ) " "      " "      "*"      "*"      " "      " "      "*"
## 5 ( 1 ) "*"      " "      "*"      "*"      " "      " "      "*"
## 6 ( 1 ) "*"      " "      "*"      "*"      " "      " "      "*"
## 7 ( 1 ) "*"      " "      "*"      "*"      " "      " "      "*"
## 8 ( 1 ) "*"      " "      "*"      "*"      " "      " "      "*"
## 9 ( 1 ) "*"      " "      "*"      "*"      " "      " "      "*"

```

```
coef(step.model$finalModel, id = 9)
```

```
## (Intercept)      fg_pct      trb_per_g      ast_per_g      stl_per_g
## -0.387387572  0.425193698  0.006473243  0.016045291 -0.054028684
##           ts_pct      ws      bpm      win_pct      pts_per_g
## -1.364878622  0.025383895  0.020137578  0.613492903  0.013981895

```

```
#building final linear model
```

```
bswr.mod <- lm(award_share ~ fg_pct + trb_per_g + ast_per_g + stl_per_g +
               ts_pct + ws + bpm + win_pct + pts_per_g,
               data = nba_csv.train)
summary(bswr.mod)
```

```
##
## Call:
## lm(formula = award_share ~ fg_pct + trb_per_g + ast_per_g + stl_per_g +
##     ts_pct + ws + bpm + win_pct + pts_per_g, data = nba_csv.train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.38158 -0.11672 -0.03796  0.09170  0.69670
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.387388   0.153987  -2.516  0.01213 *
## fg_pct       0.425194   0.260576   1.632  0.10323
## trb_per_g     0.006473   0.003485   1.858  0.06369 .
## ast_per_g     0.016045   0.003737   4.294 2.03e-05 ***
## stl_per_g    -0.054029   0.017149  -3.151  0.00171 **
## ts_pct       -1.364879   0.332031  -4.111 4.47e-05 ***
## ws           0.025384   0.003995   6.354 4.03e-10 ***
## bpm          0.020138   0.004676   4.307 1.92e-05 ***
## win_pct      0.613493   0.075165   8.162 1.81e-15 ***
## pts_per_g    0.013982   0.001792   7.803 2.53e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.178 on 627 degrees of freedom
## Multiple R-squared:  0.5266, Adjusted R-squared:  0.5198
## F-statistic: 77.51 on 9 and 627 DF,  p-value: < 2.2e-16
```

```
vif(bswr.mod) # acceptable vifs
```

```
##      fg_pct trb_per_g ast_per_g stl_per_g      ts_pct      ws      bpm
## 2.768500 2.642912 2.258271 2.031006 3.389390 3.653558 3.194391
## win_pct pts_per_g
## 1.324580 1.709839
```

```
# testing for OSR2
```

```
pred.bswr <- predict(bswr.mod, newdata=nba_csv.test)
pred.bswr
```

```
##           1           2           3           4           5           6           7
## 0.5039477 0.5375057 0.1740437 0.3132550 0.1671717 0.2550683 0.1880855
##           8           9          10          11          12
## 0.2396639 0.1470319 0.2419638 0.1414766 0.1506761
```

```
nba_csv.test$award_share
```

```
## [1] 0.932 0.768 0.352 0.210 0.173 0.068 0.049 0.025 0.013 0.008 0.001
## [12] 0.001
```

```
SSE <- sum((nba_csv.test$award_share - pred.bswr)^2)
SST = sum((nba_csv.test$award_share - mean(nba_csv.train$award_share))^2)
OSR2 = 1 - SSE/SST
OSR2 # 0.5691312 # slight improvement!
```

```
## [1] 0.5691312
```

Random forests – basic and cross-validated

```
##basic random forest model
set.seed(144)
mod.rf <- randomForest(award_share ~ ., data = nba_csv.train, mtry = 5, nodesize = 5, ntree = 500)
pred.rf <- predict(mod.rf, newdata = nba_csv.test) # just to illustrate

importance(mod.rf) #most important features: ws, vorp, win_pct, bpm
```

```
##          IncNodePurity
## fg_pct      1.0813085
## fg3_pct     0.8731366
## ft_pct      1.2082597
## trb_per_g   0.9318022
## ast_per_g   1.2053944
## stl_per_g   0.5994095
## blk_per_g   0.7338723
## per         5.0909337
## ts_pct      0.9842470
## usg_pct     1.8279452
## ws          9.0585303
## bpm         3.9519190
## vorp        5.5728829
## age         0.7868769
## win_pct     4.3633348
## pts_per_g   2.2574873
```

```
#cross validation on mtry
set.seed(849)
train.rf <- train(award_share ~ .,
                  data = nba_csv.train,
                  method = "rf",
                  tuneGrid = data.frame(mtry=1:16),
                  trControl = trainControl(method="cv",
                                           number=5, verboseIter = TRUE),
                  metric = "RMSE")
```

```
## + Fold1: mtry= 1
## - Fold1: mtry= 1
## + Fold1: mtry= 2
## - Fold1: mtry= 2
## + Fold1: mtry= 3
## - Fold1: mtry= 3
## + Fold1: mtry= 4
## - Fold1: mtry= 4
## + Fold1: mtry= 5
## - Fold1: mtry= 5
## + Fold1: mtry= 6
## - Fold1: mtry= 6
## + Fold1: mtry= 7
## - Fold1: mtry= 7
## + Fold1: mtry= 8
## - Fold1: mtry= 8
## + Fold1: mtry= 9
## - Fold1: mtry= 9
## + Fold1: mtry=10
## - Fold1: mtry=10
## + Fold1: mtry=11
## - Fold1: mtry=11
## + Fold1: mtry=12
## - Fold1: mtry=12
## + Fold1: mtry=13
## - Fold1: mtry=13
## + Fold1: mtry=14
## - Fold1: mtry=14
## + Fold1: mtry=15
## - Fold1: mtry=15
## + Fold1: mtry=16
## - Fold1: mtry=16
## + Fold2: mtry= 1
## - Fold2: mtry= 1
## + Fold2: mtry= 2
## - Fold2: mtry= 2
## + Fold2: mtry= 3
## - Fold2: mtry= 3
## + Fold2: mtry= 4
## - Fold2: mtry= 4
## + Fold2: mtry= 5
## - Fold2: mtry= 5
## + Fold2: mtry= 6
## - Fold2: mtry= 6
## + Fold2: mtry= 7
## - Fold2: mtry= 7
## + Fold2: mtry= 8
## - Fold2: mtry= 8
## + Fold2: mtry= 9
## - Fold2: mtry= 9
## + Fold2: mtry=10
## - Fold2: mtry=10
## + Fold2: mtry=11
```



```
## - Fold2: mtry=11
## + Fold2: mtry=12
## - Fold2: mtry=12
## + Fold2: mtry=13
## - Fold2: mtry=13
## + Fold2: mtry=14
## - Fold2: mtry=14
## + Fold2: mtry=15
## - Fold2: mtry=15
## + Fold2: mtry=16
## - Fold2: mtry=16
## + Fold3: mtry= 1
## - Fold3: mtry= 1
## + Fold3: mtry= 2
## - Fold3: mtry= 2
## + Fold3: mtry= 3
## - Fold3: mtry= 3
## + Fold3: mtry= 4
## - Fold3: mtry= 4
## + Fold3: mtry= 5
## - Fold3: mtry= 5
## + Fold3: mtry= 6
## - Fold3: mtry= 6
## + Fold3: mtry= 7
## - Fold3: mtry= 7
## + Fold3: mtry= 8
## - Fold3: mtry= 8
## + Fold3: mtry= 9
## - Fold3: mtry= 9
## + Fold3: mtry=10
## - Fold3: mtry=10
## + Fold3: mtry=11
## - Fold3: mtry=11
## + Fold3: mtry=12
## - Fold3: mtry=12
## + Fold3: mtry=13
## - Fold3: mtry=13
## + Fold3: mtry=14
## - Fold3: mtry=14
## + Fold3: mtry=15
## - Fold3: mtry=15
## + Fold3: mtry=16
## - Fold3: mtry=16
## + Fold4: mtry= 1
## - Fold4: mtry= 1
## + Fold4: mtry= 2
## - Fold4: mtry= 2
## + Fold4: mtry= 3
## - Fold4: mtry= 3
## + Fold4: mtry= 4
## - Fold4: mtry= 4
## + Fold4: mtry= 5
## - Fold4: mtry= 5
## + Fold4: mtry= 6
```

```
## - Fold4: mtry= 6
## + Fold4: mtry= 7
## - Fold4: mtry= 7
## + Fold4: mtry= 8
## - Fold4: mtry= 8
## + Fold4: mtry= 9
## - Fold4: mtry= 9
## + Fold4: mtry=10
## - Fold4: mtry=10
## + Fold4: mtry=11
## - Fold4: mtry=11
## + Fold4: mtry=12
## - Fold4: mtry=12
## + Fold4: mtry=13
## - Fold4: mtry=13
## + Fold4: mtry=14
## - Fold4: mtry=14
## + Fold4: mtry=15
## - Fold4: mtry=15
## + Fold4: mtry=16
## + Fold5: mtry= 1
## - Fold5: mtry= 1
## + Fold5: mtry= 2
## - Fold5: mtry= 2
## + Fold5: mtry= 3
## - Fold5: mtry= 3
## + Fold5: mtry= 4
## - Fold5: mtry= 4
## + Fold5: mtry= 5
## - Fold5: mtry= 5
## + Fold5: mtry= 6
## - Fold5: mtry= 6
## + Fold5: mtry= 7
## - Fold5: mtry= 7
## + Fold5: mtry= 8
## - Fold5: mtry= 8
## + Fold5: mtry= 9
## - Fold5: mtry= 9
## + Fold5: mtry=10
## - Fold5: mtry=10
## + Fold5: mtry=11
## - Fold5: mtry=11
## + Fold5: mtry=12
## - Fold5: mtry=12
## + Fold5: mtry=13
## - Fold5: mtry=13
## + Fold5: mtry=14
## - Fold5: mtry=14
## + Fold5: mtry=15
## - Fold5: mtry=15
## + Fold5: mtry=16
## - Fold5: mtry=16
## Aggregating results
```

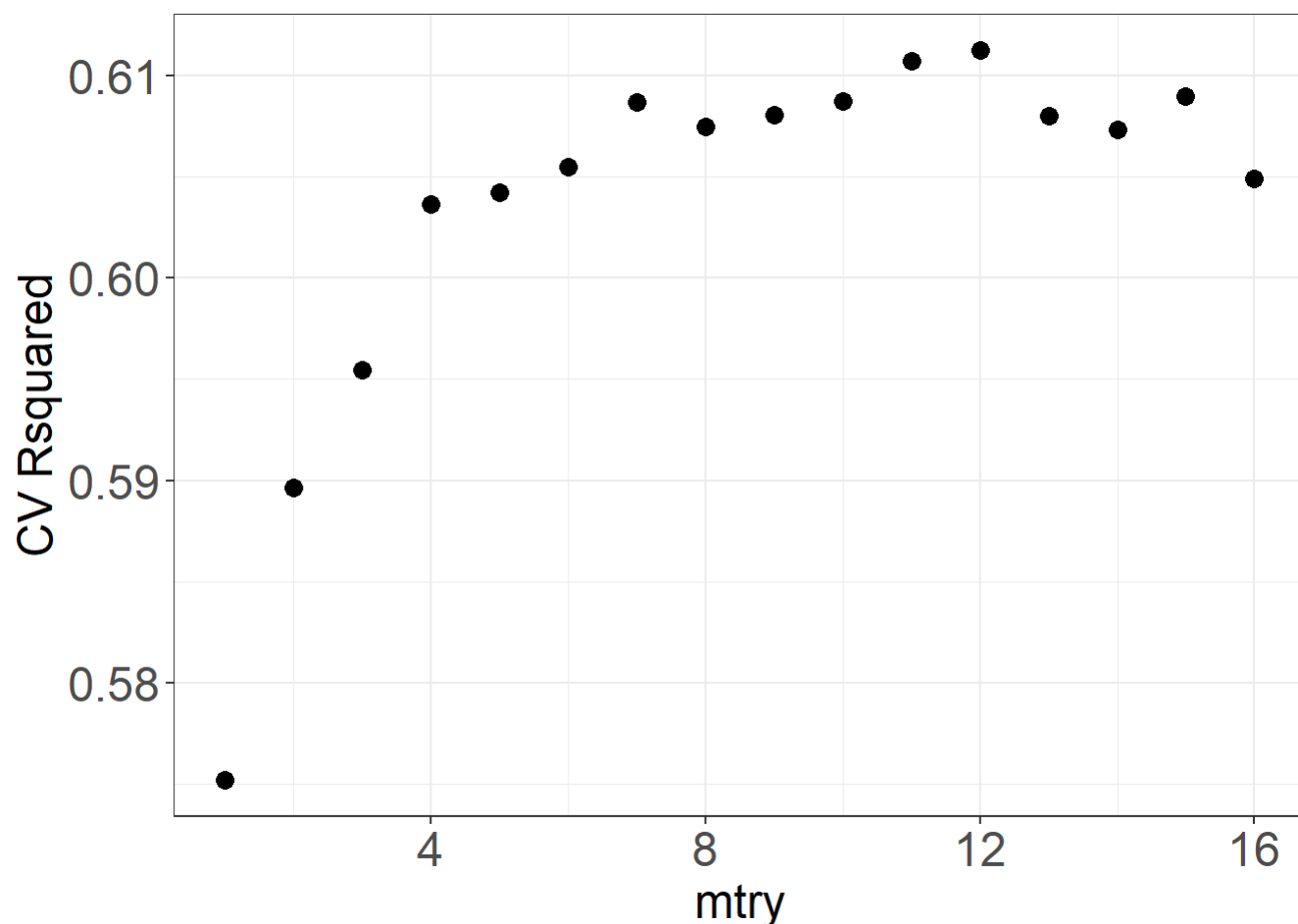
```
## Selecting tuning parameters
## Fitting mtry = 12 on full training set
```

```
train.rf #mtry=12
```

```
## Random Forest
##
## 637 samples
## 16 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 509, 508, 510, 512, 509
## Resampling results across tuning parameters:
##
##  mtry  RMSE      Rsquared  MAE
##  1     0.1729006  0.5751842  0.1148861
##  2     0.1677458  0.5896253  0.1091635
##  3     0.1659232  0.5954343  0.1067127
##  4     0.1642990  0.6036294  0.1052672
##  5     0.1640126  0.6042265  0.1045772
##  6     0.1636150  0.6054612  0.1041081
##  7     0.1628583  0.6086627  0.1030604
##  8     0.1630133  0.6074687  0.1027573
##  9     0.1627223  0.6080682  0.1025852
## 10     0.1626249  0.6087426  0.1023939
## 11     0.1624621  0.6107147  0.1020349
## 12     0.1621851  0.6112369  0.1018550
## 13     0.1631822  0.6079965  0.1023682
## 14     0.1631774  0.6073143  0.1027458
## 15     0.1628195  0.6089939  0.1024110
## 16     0.1637064  0.6049178  0.1031926
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 12.
```

```
best.rf <- train.rf$finalModel
pred.best.rf <- predict(best.rf, newdata = nba_csv.test) # can use same model matrix

ggplot(train.rf$results, aes(x = mtry, y = Rsquared)) + geom_point(size = 3) +
  ylab("CV Rsquared") + theme_bw() + theme(axis.title=element_text(size=18), axis.text=element_text(size=18))
```



```
SSE = sum((nba_csv.test$award_share - pred.best.rf)^2)
SST = sum((nba_csv.test$award_share - mean(nba_csv.train$award_share))^2)
OSR2 = 1 - SSE/SST
OSR2 #0.7677164
```

```
## [1] 0.7677164
```

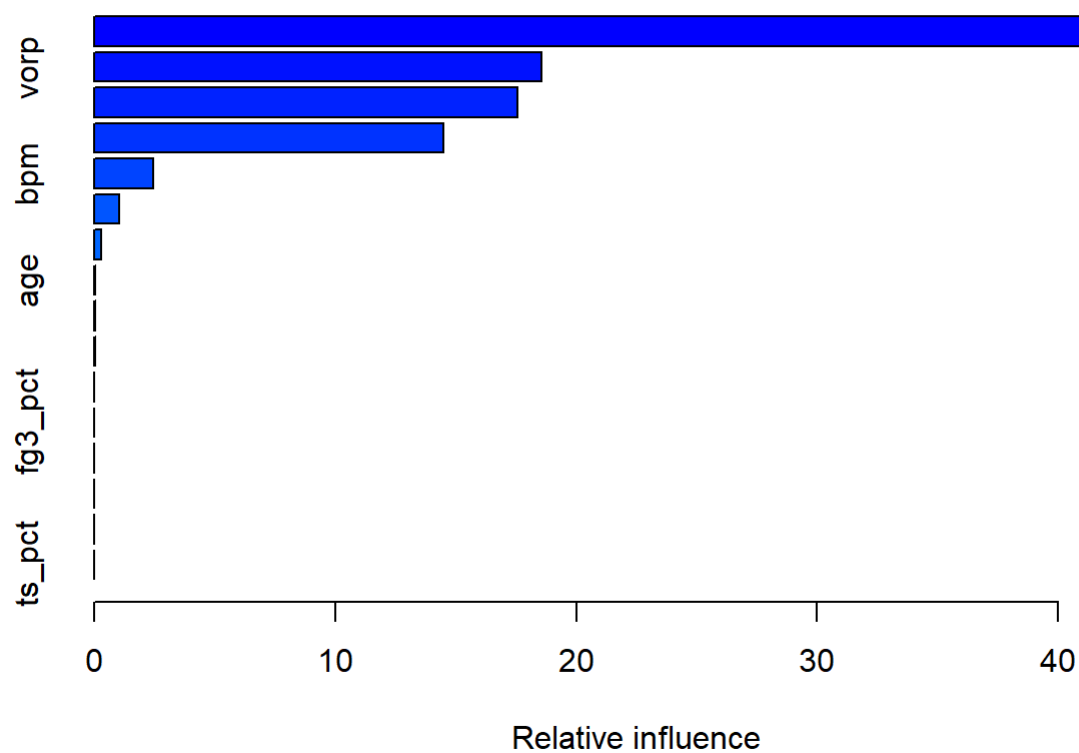
Boosting – basic and cross-validated

```
#boosting model
mod.boost <- gbm(award_share ~ .,
  data = nba_csv.train,
  distribution = "gaussian",
  n.trees = 1000,
  shrinkage = 0.001,
  interaction.depth = 2)

pred.boost <- predict(mod.boost, newdata = nba_csv.test, n.trees=1000)

pred.boost.earlier <- predict(mod.boost, newdata = nba_csv.test, n.trees=330)

summary(mod.boost) #most influential features are ws, vorp, per, win_pct
```



```
##          var      rel.inf
## ws          ws 45.46286772
## vorp        vorp 18.55601031
## per          per 17.57885978
## win_pct    win_pct 14.47977396
## bpm         bpm  2.44925995
## usg_pct    usg_pct 1.05795822
## pts_per_g  pts_per_g 0.29577981
## age         age  0.04456713
## ft_pct     ft_pct  0.04326546
## ast_per_g  ast_per_g 0.03165767
## fg_pct     fg_pct  0.00000000
## fg3_pct    fg3_pct  0.00000000
## trb_per_g  trb_per_g 0.00000000
## stl_per_g  stl_per_g 0.00000000
## blk_per_g  blk_per_g 0.00000000
## ts_pct     ts_pct  0.00000000
```

```
#cross validation on n.trees and interaction depth
tGrid = expand.grid(n.trees = (1:75)*500, interaction.depth = c(1,2,4,6,8,10),
                   shrinkage = 0.001, n.minobsinnode = 10)

set.seed(849)
train.boost <- train(award_share ~ .,
                    data = nba_csv.train,
                    method = "gbm",
                    tuneGrid = tGrid,
                    trControl = trainControl(method="cv", number=5,
                                             verboseIter = TRUE),
                    metric = "RMSE",
                    distribution = "gaussian")
```

```
## + Fold1: shrinkage=0.001, interaction.depth= 1, n.minobsinnode=10, n.trees=37500
```

## Iter	TrainDeviance	ValidDeviance	StepSize	Improve
## 1	0.0665	nan	0.0010	0.0001
## 2	0.0665	nan	0.0010	0.0000
## 3	0.0664	nan	0.0010	0.0000
## 4	0.0663	nan	0.0010	0.0000
## 5	0.0663	nan	0.0010	0.0000
## 6	0.0662	nan	0.0010	0.0000
## 7	0.0662	nan	0.0010	0.0001
## 8	0.0662	nan	0.0010	0.0000
## 9	0.0661	nan	0.0010	0.0000
## 10	0.0661	nan	0.0010	0.0000
## 20	0.0656	nan	0.0010	0.0000
## 40	0.0646	nan	0.0010	0.0000
## 60	0.0637	nan	0.0010	0.0000
## 80	0.0628	nan	0.0010	0.0000
## 100	0.0620	nan	0.0010	0.0000
## 120	0.0611	nan	0.0010	0.0000
## 140	0.0603	nan	0.0010	0.0001
## 160	0.0595	nan	0.0010	0.0000
## 180	0.0587	nan	0.0010	0.0000
## 200	0.0579	nan	0.0010	0.0000
## 220	0.0572	nan	0.0010	0.0000
## 240	0.0565	nan	0.0010	0.0000
## 260	0.0558	nan	0.0010	0.0000
## 280	0.0551	nan	0.0010	0.0000
## 300	0.0545	nan	0.0010	0.0000
## 320	0.0539	nan	0.0010	0.0000
## 340	0.0533	nan	0.0010	0.0000
## 360	0.0527	nan	0.0010	0.0000
## 380	0.0521	nan	0.0010	0.0000
## 400	0.0516	nan	0.0010	0.0000
## 420	0.0510	nan	0.0010	0.0000
## 440	0.0505	nan	0.0010	0.0000
## 460	0.0500	nan	0.0010	0.0000
## 480	0.0495	nan	0.0010	0.0000
## 500	0.0490	nan	0.0010	0.0000
## 520	0.0486	nan	0.0010	0.0000
## 540	0.0481	nan	0.0010	0.0000
## 560	0.0477	nan	0.0010	0.0000
## 580	0.0472	nan	0.0010	0.0000
## 600	0.0468	nan	0.0010	0.0000
## 620	0.0464	nan	0.0010	0.0000
## 640	0.0460	nan	0.0010	0.0000
## 660	0.0456	nan	0.0010	0.0000
## 680	0.0452	nan	0.0010	0.0000
## 700	0.0449	nan	0.0010	0.0000
## 720	0.0445	nan	0.0010	0.0000
## 740	0.0442	nan	0.0010	0.0000
## 760	0.0438	nan	0.0010	0.0000
## 780	0.0435	nan	0.0010	0.0000
## 800	0.0432	nan	0.0010	0.0000
## 820	0.0428	nan	0.0010	0.0000

##	840	0.0425	nan	0.0010	0.0000
##	860	0.0422	nan	0.0010	0.0000
##	880	0.0419	nan	0.0010	0.0000
##	900	0.0417	nan	0.0010	0.0000
##	920	0.0414	nan	0.0010	0.0000
##	940	0.0411	nan	0.0010	0.0000
##	960	0.0408	nan	0.0010	0.0000
##	980	0.0406	nan	0.0010	0.0000
##	1000	0.0403	nan	0.0010	0.0000
##	1020	0.0400	nan	0.0010	0.0000
##	1040	0.0398	nan	0.0010	0.0000
##	1060	0.0396	nan	0.0010	0.0000
##	1080	0.0393	nan	0.0010	0.0000
##	1100	0.0391	nan	0.0010	0.0000
##	1120	0.0388	nan	0.0010	0.0000
##	1140	0.0386	nan	0.0010	0.0000
##	1160	0.0384	nan	0.0010	0.0000
##	1180	0.0382	nan	0.0010	0.0000
##	1200	0.0380	nan	0.0010	0.0000
##	1220	0.0378	nan	0.0010	0.0000
##	1240	0.0376	nan	0.0010	0.0000
##	1260	0.0374	nan	0.0010	0.0000
##	1280	0.0372	nan	0.0010	0.0000
##	1300	0.0370	nan	0.0010	0.0000
##	1320	0.0368	nan	0.0010	0.0000
##	1340	0.0366	nan	0.0010	0.0000
##	1360	0.0365	nan	0.0010	0.0000
##	1380	0.0363	nan	0.0010	0.0000
##	1400	0.0361	nan	0.0010	0.0000
##	1420	0.0359	nan	0.0010	0.0000
##	1440	0.0358	nan	0.0010	0.0000
##	1460	0.0356	nan	0.0010	0.0000
##	1480	0.0355	nan	0.0010	0.0000
##	1500	0.0353	nan	0.0010	0.0000
##	1520	0.0351	nan	0.0010	0.0000
##	1540	0.0350	nan	0.0010	0.0000
##	1560	0.0348	nan	0.0010	0.0000
##	1580	0.0347	nan	0.0010	0.0000
##	1600	0.0345	nan	0.0010	0.0000
##	1620	0.0344	nan	0.0010	0.0000
##	1640	0.0342	nan	0.0010	0.0000
##	1660	0.0341	nan	0.0010	0.0000
##	1680	0.0339	nan	0.0010	0.0000
##	1700	0.0338	nan	0.0010	0.0000
##	1720	0.0337	nan	0.0010	0.0000
##	1740	0.0335	nan	0.0010	0.0000
##	1760	0.0334	nan	0.0010	0.0000
##	1780	0.0333	nan	0.0010	0.0000
##	1800	0.0331	nan	0.0010	0.0000
##	1820	0.0330	nan	0.0010	0.0000
##	1840	0.0329	nan	0.0010	0.0000
##	1860	0.0328	nan	0.0010	0.0000
##	1880	0.0327	nan	0.0010	0.0000
##	1900	0.0325	nan	0.0010	0.0000

##	1920	0.0324	nan	0.0010	0.0000
##	1940	0.0323	nan	0.0010	0.0000
##	1960	0.0322	nan	0.0010	0.0000
##	1980	0.0321	nan	0.0010	0.0000
##	2000	0.0320	nan	0.0010	0.0000
##	2020	0.0319	nan	0.0010	-0.0000
##	2040	0.0318	nan	0.0010	0.0000
##	2060	0.0317	nan	0.0010	0.0000
##	2080	0.0316	nan	0.0010	0.0000
##	2100	0.0315	nan	0.0010	0.0000
##	2120	0.0314	nan	0.0010	0.0000
##	2140	0.0313	nan	0.0010	0.0000
##	2160	0.0312	nan	0.0010	0.0000
##	2180	0.0311	nan	0.0010	0.0000
##	2200	0.0310	nan	0.0010	0.0000
##	2220	0.0309	nan	0.0010	0.0000
##	2240	0.0308	nan	0.0010	0.0000
##	2260	0.0307	nan	0.0010	0.0000
##	2280	0.0306	nan	0.0010	0.0000
##	2300	0.0305	nan	0.0010	0.0000
##	2320	0.0304	nan	0.0010	0.0000
##	2340	0.0304	nan	0.0010	0.0000
##	2360	0.0303	nan	0.0010	0.0000
##	2380	0.0302	nan	0.0010	0.0000
##	2400	0.0301	nan	0.0010	0.0000
##	2420	0.0300	nan	0.0010	0.0000
##	2440	0.0300	nan	0.0010	0.0000
##	2460	0.0299	nan	0.0010	0.0000
##	2480	0.0298	nan	0.0010	0.0000
##	2500	0.0297	nan	0.0010	0.0000
##	2520	0.0297	nan	0.0010	0.0000
##	2540	0.0296	nan	0.0010	0.0000
##	2560	0.0295	nan	0.0010	0.0000
##	2580	0.0294	nan	0.0010	0.0000
##	2600	0.0294	nan	0.0010	0.0000
##	2620	0.0293	nan	0.0010	0.0000
##	2640	0.0292	nan	0.0010	0.0000
##	2660	0.0291	nan	0.0010	0.0000
##	2680	0.0291	nan	0.0010	0.0000
##	2700	0.0290	nan	0.0010	0.0000
##	2720	0.0289	nan	0.0010	0.0000
##	2740	0.0289	nan	0.0010	0.0000
##	2760	0.0288	nan	0.0010	0.0000
##	2780	0.0288	nan	0.0010	0.0000
##	2800	0.0287	nan	0.0010	0.0000
##	2820	0.0286	nan	0.0010	0.0000
##	2840	0.0286	nan	0.0010	0.0000
##	2860	0.0285	nan	0.0010	0.0000
##	2880	0.0285	nan	0.0010	0.0000
##	2900	0.0284	nan	0.0010	0.0000
##	2920	0.0284	nan	0.0010	0.0000
##	2940	0.0283	nan	0.0010	0.0000
##	2960	0.0282	nan	0.0010	0.0000
##	2980	0.0282	nan	0.0010	0.0000

##	34900	0.0003	nan	0.0010	-0.0000
##	34920	0.0003	nan	0.0010	-0.0000
##	34940	0.0003	nan	0.0010	-0.0000
##	34960	0.0003	nan	0.0010	-0.0000
##	34980	0.0003	nan	0.0010	-0.0000
##	35000	0.0003	nan	0.0010	-0.0000
##	35020	0.0003	nan	0.0010	-0.0000
##	35040	0.0003	nan	0.0010	-0.0000
##	35060	0.0003	nan	0.0010	-0.0000
##	35080	0.0003	nan	0.0010	-0.0000
##	35100	0.0003	nan	0.0010	-0.0000
##	35120	0.0003	nan	0.0010	-0.0000
##	35140	0.0003	nan	0.0010	-0.0000
##	35160	0.0003	nan	0.0010	-0.0000
##	35180	0.0003	nan	0.0010	-0.0000
##	35200	0.0003	nan	0.0010	-0.0000
##	35220	0.0003	nan	0.0010	-0.0000
##	35240	0.0003	nan	0.0010	-0.0000
##	35260	0.0003	nan	0.0010	-0.0000
##	35280	0.0003	nan	0.0010	-0.0000
##	35300	0.0003	nan	0.0010	-0.0000
##	35320	0.0003	nan	0.0010	-0.0000
##	35340	0.0003	nan	0.0010	-0.0000
##	35360	0.0003	nan	0.0010	-0.0000
##	35380	0.0003	nan	0.0010	-0.0000
##	35400	0.0003	nan	0.0010	-0.0000
##	35420	0.0003	nan	0.0010	-0.0000
##	35440	0.0003	nan	0.0010	-0.0000
##	35460	0.0003	nan	0.0010	-0.0000
##	35480	0.0003	nan	0.0010	-0.0000
##	35500	0.0003	nan	0.0010	-0.0000
##	35520	0.0003	nan	0.0010	-0.0000
##	35540	0.0003	nan	0.0010	-0.0000
##	35560	0.0003	nan	0.0010	-0.0000
##	35580	0.0003	nan	0.0010	-0.0000
##	35600	0.0003	nan	0.0010	-0.0000
##	35620	0.0003	nan	0.0010	-0.0000
##	35640	0.0003	nan	0.0010	-0.0000
##	35660	0.0003	nan	0.0010	-0.0000
##	35680	0.0003	nan	0.0010	-0.0000
##	35700	0.0003	nan	0.0010	-0.0000
##	35720	0.0003	nan	0.0010	-0.0000
##	35740	0.0003	nan	0.0010	-0.0000
##	35760	0.0003	nan	0.0010	-0.0000
##	35780	0.0003	nan	0.0010	-0.0000
##	35800	0.0003	nan	0.0010	-0.0000
##	35820	0.0003	nan	0.0010	-0.0000
##	35840	0.0003	nan	0.0010	-0.0000
##	35860	0.0003	nan	0.0010	-0.0000
##	35880	0.0003	nan	0.0010	-0.0000
##	35900	0.0003	nan	0.0010	-0.0000
##	35920	0.0003	nan	0.0010	-0.0000
##	35940	0.0003	nan	0.0010	-0.0000
##	35960	0.0003	nan	0.0010	-0.0000

##	35980	0.0003	nan	0.0010	-0.0000
##	36000	0.0003	nan	0.0010	-0.0000
##	36020	0.0003	nan	0.0010	-0.0000
##	36040	0.0003	nan	0.0010	-0.0000
##	36060	0.0003	nan	0.0010	-0.0000
##	36080	0.0003	nan	0.0010	-0.0000
##	36100	0.0003	nan	0.0010	-0.0000
##	36120	0.0003	nan	0.0010	-0.0000
##	36140	0.0003	nan	0.0010	-0.0000
##	36160	0.0003	nan	0.0010	-0.0000
##	36180	0.0003	nan	0.0010	-0.0000
##	36200	0.0003	nan	0.0010	-0.0000
##	36220	0.0003	nan	0.0010	-0.0000
##	36240	0.0003	nan	0.0010	-0.0000
##	36260	0.0003	nan	0.0010	-0.0000
##	36280	0.0003	nan	0.0010	-0.0000
##	36300	0.0003	nan	0.0010	-0.0000
##	36320	0.0003	nan	0.0010	-0.0000
##	36340	0.0003	nan	0.0010	-0.0000
##	36360	0.0003	nan	0.0010	-0.0000
##	36380	0.0003	nan	0.0010	-0.0000
##	36400	0.0003	nan	0.0010	-0.0000
##	36420	0.0003	nan	0.0010	-0.0000
##	36440	0.0003	nan	0.0010	-0.0000
##	36460	0.0003	nan	0.0010	-0.0000
##	36480	0.0003	nan	0.0010	-0.0000
##	36500	0.0003	nan	0.0010	-0.0000
##	36520	0.0003	nan	0.0010	-0.0000
##	36540	0.0003	nan	0.0010	-0.0000
##	36560	0.0003	nan	0.0010	-0.0000
##	36580	0.0003	nan	0.0010	-0.0000
##	36600	0.0003	nan	0.0010	-0.0000
##	36620	0.0003	nan	0.0010	-0.0000
##	36640	0.0003	nan	0.0010	-0.0000
##	36660	0.0003	nan	0.0010	-0.0000
##	36680	0.0003	nan	0.0010	-0.0000
##	36700	0.0003	nan	0.0010	-0.0000
##	36720	0.0003	nan	0.0010	-0.0000
##	36740	0.0003	nan	0.0010	-0.0000
##	36760	0.0003	nan	0.0010	-0.0000
##	36780	0.0003	nan	0.0010	-0.0000
##	36800	0.0003	nan	0.0010	-0.0000
##	36820	0.0003	nan	0.0010	-0.0000
##	36840	0.0003	nan	0.0010	-0.0000
##	36860	0.0003	nan	0.0010	-0.0000
##	36880	0.0003	nan	0.0010	-0.0000
##	36900	0.0003	nan	0.0010	-0.0000
##	36920	0.0003	nan	0.0010	-0.0000
##	36940	0.0003	nan	0.0010	-0.0000
##	36960	0.0003	nan	0.0010	-0.0000
##	36980	0.0003	nan	0.0010	-0.0000
##	37000	0.0003	nan	0.0010	-0.0000
##	37020	0.0003	nan	0.0010	-0.0000
##	37040	0.0003	nan	0.0010	-0.0000

```
## 37060      0.0003      nan      0.0010     -0.0000
## 37080      0.0003      nan      0.0010     -0.0000
## 37100      0.0003      nan      0.0010     -0.0000
## 37120      0.0003      nan      0.0010     -0.0000
## 37140      0.0003      nan      0.0010     -0.0000
## 37160      0.0003      nan      0.0010     -0.0000
## 37180      0.0003      nan      0.0010     -0.0000
## 37200      0.0003      nan      0.0010     -0.0000
## 37220      0.0003      nan      0.0010     -0.0000
## 37240      0.0003      nan      0.0010     -0.0000
## 37260      0.0003      nan      0.0010     -0.0000
## 37280      0.0003      nan      0.0010     -0.0000
## 37300      0.0003      nan      0.0010     -0.0000
## 37320      0.0003      nan      0.0010     -0.0000
## 37340      0.0003      nan      0.0010     -0.0000
## 37360      0.0003      nan      0.0010     -0.0000
## 37380      0.0003      nan      0.0010     -0.0000
## 37400      0.0003      nan      0.0010     -0.0000
## 37420      0.0003      nan      0.0010     -0.0000
## 37440      0.0003      nan      0.0010     -0.0000
## 37460      0.0003      nan      0.0010     -0.0000
## 37480      0.0003      nan      0.0010     -0.0000
## 37500      0.0003      nan      0.0010     -0.0000
```

```
##
```

```
## - Fold5: shrinkage=0.001, interaction.depth=10, n.minobsinnode=10, n.trees=37500
```

```
## Aggregating results
```

```
## Selecting tuning parameters
```

```
## Fitting n.trees = 4000, interaction.depth = 4, shrinkage = 0.001, n.minobsinnode = 10 on full training set
```

## Iter	TrainDeviance	ValidDeviance	StepSize	Improve
## 1	0.0658	nan	0.0010	0.0001
## 2	0.0657	nan	0.0010	0.0001
## 3	0.0657	nan	0.0010	0.0001
## 4	0.0656	nan	0.0010	0.0001
## 5	0.0655	nan	0.0010	0.0001
## 6	0.0655	nan	0.0010	0.0001
## 7	0.0654	nan	0.0010	0.0001
## 8	0.0653	nan	0.0010	0.0001
## 9	0.0652	nan	0.0010	0.0001
## 10	0.0652	nan	0.0010	0.0001
## 20	0.0644	nan	0.0010	0.0001
## 40	0.0631	nan	0.0010	0.0000
## 60	0.0617	nan	0.0010	0.0001
## 80	0.0604	nan	0.0010	0.0001
## 100	0.0592	nan	0.0010	0.0000
## 120	0.0580	nan	0.0010	0.0000
## 140	0.0568	nan	0.0010	0.0001
## 160	0.0556	nan	0.0010	0.0001
## 180	0.0546	nan	0.0010	0.0000
## 200	0.0535	nan	0.0010	0.0000
## 220	0.0524	nan	0.0010	0.0000
## 240	0.0514	nan	0.0010	0.0000
## 260	0.0505	nan	0.0010	0.0000
## 280	0.0495	nan	0.0010	0.0000

##	300	0.0486	nan	0.0010	0.0000
##	320	0.0477	nan	0.0010	0.0000
##	340	0.0469	nan	0.0010	0.0000
##	360	0.0461	nan	0.0010	0.0000
##	380	0.0453	nan	0.0010	0.0000
##	400	0.0445	nan	0.0010	0.0000
##	420	0.0437	nan	0.0010	0.0000
##	440	0.0430	nan	0.0010	0.0000
##	460	0.0423	nan	0.0010	0.0000
##	480	0.0416	nan	0.0010	0.0000
##	500	0.0409	nan	0.0010	0.0000
##	520	0.0403	nan	0.0010	0.0000
##	540	0.0397	nan	0.0010	0.0000
##	560	0.0390	nan	0.0010	0.0000
##	580	0.0385	nan	0.0010	0.0000
##	600	0.0379	nan	0.0010	0.0000
##	620	0.0374	nan	0.0010	0.0000
##	640	0.0368	nan	0.0010	0.0000
##	660	0.0363	nan	0.0010	0.0000
##	680	0.0358	nan	0.0010	0.0000
##	700	0.0353	nan	0.0010	0.0000
##	720	0.0348	nan	0.0010	0.0000
##	740	0.0344	nan	0.0010	0.0000
##	760	0.0339	nan	0.0010	0.0000
##	780	0.0335	nan	0.0010	0.0000
##	800	0.0331	nan	0.0010	0.0000
##	820	0.0326	nan	0.0010	0.0000
##	840	0.0322	nan	0.0010	0.0000
##	860	0.0318	nan	0.0010	0.0000
##	880	0.0315	nan	0.0010	0.0000
##	900	0.0311	nan	0.0010	0.0000
##	920	0.0308	nan	0.0010	0.0000
##	940	0.0304	nan	0.0010	0.0000
##	960	0.0301	nan	0.0010	0.0000
##	980	0.0297	nan	0.0010	0.0000
##	1000	0.0294	nan	0.0010	0.0000
##	1020	0.0291	nan	0.0010	0.0000
##	1040	0.0288	nan	0.0010	0.0000
##	1060	0.0285	nan	0.0010	0.0000
##	1080	0.0282	nan	0.0010	0.0000
##	1100	0.0280	nan	0.0010	0.0000
##	1120	0.0277	nan	0.0010	0.0000
##	1140	0.0274	nan	0.0010	0.0000
##	1160	0.0272	nan	0.0010	0.0000
##	1180	0.0269	nan	0.0010	0.0000
##	1200	0.0267	nan	0.0010	0.0000
##	1220	0.0264	nan	0.0010	0.0000
##	1240	0.0262	nan	0.0010	0.0000
##	1260	0.0260	nan	0.0010	0.0000
##	1280	0.0257	nan	0.0010	0.0000
##	1300	0.0255	nan	0.0010	0.0000
##	1320	0.0253	nan	0.0010	0.0000
##	1340	0.0251	nan	0.0010	0.0000
##	1360	0.0249	nan	0.0010	0.0000

##	1380	0.0247	nan	0.0010	0.0000
##	1400	0.0245	nan	0.0010	0.0000
##	1420	0.0243	nan	0.0010	0.0000
##	1440	0.0242	nan	0.0010	0.0000
##	1460	0.0240	nan	0.0010	0.0000
##	1480	0.0238	nan	0.0010	0.0000
##	1500	0.0236	nan	0.0010	0.0000
##	1520	0.0235	nan	0.0010	0.0000
##	1540	0.0233	nan	0.0010	0.0000
##	1560	0.0231	nan	0.0010	0.0000
##	1580	0.0230	nan	0.0010	0.0000
##	1600	0.0228	nan	0.0010	0.0000
##	1620	0.0227	nan	0.0010	0.0000
##	1640	0.0225	nan	0.0010	0.0000
##	1660	0.0224	nan	0.0010	0.0000
##	1680	0.0222	nan	0.0010	0.0000
##	1700	0.0221	nan	0.0010	0.0000
##	1720	0.0220	nan	0.0010	0.0000
##	1740	0.0218	nan	0.0010	0.0000
##	1760	0.0217	nan	0.0010	0.0000
##	1780	0.0216	nan	0.0010	0.0000
##	1800	0.0215	nan	0.0010	0.0000
##	1820	0.0214	nan	0.0010	0.0000
##	1840	0.0212	nan	0.0010	0.0000
##	1860	0.0211	nan	0.0010	0.0000
##	1880	0.0210	nan	0.0010	0.0000
##	1900	0.0209	nan	0.0010	0.0000
##	1920	0.0208	nan	0.0010	0.0000
##	1940	0.0207	nan	0.0010	0.0000
##	1960	0.0206	nan	0.0010	0.0000
##	1980	0.0205	nan	0.0010	0.0000
##	2000	0.0204	nan	0.0010	0.0000
##	2020	0.0203	nan	0.0010	-0.0000
##	2040	0.0202	nan	0.0010	0.0000
##	2060	0.0201	nan	0.0010	0.0000
##	2080	0.0200	nan	0.0010	0.0000
##	2100	0.0199	nan	0.0010	0.0000
##	2120	0.0198	nan	0.0010	0.0000
##	2140	0.0197	nan	0.0010	0.0000
##	2160	0.0196	nan	0.0010	0.0000
##	2180	0.0195	nan	0.0010	0.0000
##	2200	0.0194	nan	0.0010	0.0000
##	2220	0.0194	nan	0.0010	0.0000
##	2240	0.0193	nan	0.0010	0.0000
##	2260	0.0192	nan	0.0010	-0.0000
##	2280	0.0191	nan	0.0010	0.0000
##	2300	0.0190	nan	0.0010	-0.0000
##	2320	0.0190	nan	0.0010	0.0000
##	2340	0.0189	nan	0.0010	0.0000
##	2360	0.0188	nan	0.0010	0.0000
##	2380	0.0188	nan	0.0010	0.0000
##	2400	0.0187	nan	0.0010	0.0000
##	2420	0.0186	nan	0.0010	0.0000
##	2440	0.0185	nan	0.0010	0.0000

##	2460	0.0185	nan	0.0010	0.0000
##	2480	0.0184	nan	0.0010	-0.0000
##	2500	0.0183	nan	0.0010	-0.0000
##	2520	0.0183	nan	0.0010	0.0000
##	2540	0.0182	nan	0.0010	0.0000
##	2560	0.0182	nan	0.0010	0.0000
##	2580	0.0181	nan	0.0010	-0.0000
##	2600	0.0180	nan	0.0010	0.0000
##	2620	0.0180	nan	0.0010	-0.0000
##	2640	0.0179	nan	0.0010	0.0000
##	2660	0.0179	nan	0.0010	-0.0000
##	2680	0.0178	nan	0.0010	-0.0000
##	2700	0.0178	nan	0.0010	-0.0000
##	2720	0.0177	nan	0.0010	-0.0000
##	2740	0.0176	nan	0.0010	-0.0000
##	2760	0.0176	nan	0.0010	-0.0000
##	2780	0.0175	nan	0.0010	0.0000
##	2800	0.0175	nan	0.0010	0.0000
##	2820	0.0174	nan	0.0010	0.0000
##	2840	0.0174	nan	0.0010	-0.0000
##	2860	0.0173	nan	0.0010	-0.0000
##	2880	0.0173	nan	0.0010	0.0000
##	2900	0.0172	nan	0.0010	-0.0000
##	2920	0.0172	nan	0.0010	0.0000
##	2940	0.0171	nan	0.0010	-0.0000
##	2960	0.0171	nan	0.0010	0.0000
##	2980	0.0170	nan	0.0010	-0.0000
##	3000	0.0170	nan	0.0010	-0.0000
##	3020	0.0169	nan	0.0010	-0.0000
##	3040	0.0169	nan	0.0010	-0.0000
##	3060	0.0168	nan	0.0010	0.0000
##	3080	0.0168	nan	0.0010	-0.0000
##	3100	0.0168	nan	0.0010	-0.0000
##	3120	0.0167	nan	0.0010	0.0000
##	3140	0.0167	nan	0.0010	-0.0000
##	3160	0.0166	nan	0.0010	-0.0000
##	3180	0.0166	nan	0.0010	-0.0000
##	3200	0.0165	nan	0.0010	-0.0000
##	3220	0.0165	nan	0.0010	-0.0000
##	3240	0.0165	nan	0.0010	0.0000
##	3260	0.0164	nan	0.0010	-0.0000
##	3280	0.0164	nan	0.0010	-0.0000
##	3300	0.0163	nan	0.0010	-0.0000
##	3320	0.0163	nan	0.0010	-0.0000
##	3340	0.0163	nan	0.0010	-0.0000
##	3360	0.0162	nan	0.0010	-0.0000
##	3380	0.0162	nan	0.0010	0.0000
##	3400	0.0161	nan	0.0010	-0.0000
##	3420	0.0161	nan	0.0010	-0.0000
##	3440	0.0161	nan	0.0010	-0.0000
##	3460	0.0160	nan	0.0010	0.0000
##	3480	0.0160	nan	0.0010	-0.0000
##	3500	0.0160	nan	0.0010	-0.0000
##	3520	0.0159	nan	0.0010	-0.0000

##	3540	0.0159	nan	0.0010	-0.0000
##	3560	0.0158	nan	0.0010	-0.0000
##	3580	0.0158	nan	0.0010	-0.0000
##	3600	0.0158	nan	0.0010	-0.0000
##	3620	0.0157	nan	0.0010	-0.0000
##	3640	0.0157	nan	0.0010	0.0000
##	3660	0.0157	nan	0.0010	0.0000
##	3680	0.0156	nan	0.0010	-0.0000
##	3700	0.0156	nan	0.0010	-0.0000
##	3720	0.0156	nan	0.0010	-0.0000
##	3740	0.0155	nan	0.0010	-0.0000
##	3760	0.0155	nan	0.0010	0.0000
##	3780	0.0155	nan	0.0010	-0.0000
##	3800	0.0154	nan	0.0010	-0.0000
##	3820	0.0154	nan	0.0010	-0.0000
##	3840	0.0154	nan	0.0010	-0.0000
##	3860	0.0153	nan	0.0010	-0.0000
##	3880	0.0153	nan	0.0010	-0.0000
##	3900	0.0153	nan	0.0010	-0.0000
##	3920	0.0152	nan	0.0010	-0.0000
##	3940	0.0152	nan	0.0010	-0.0000
##	3960	0.0152	nan	0.0010	-0.0000
##	3980	0.0152	nan	0.0010	0.0000
##	4000	0.0151	nan	0.0010	-0.0000

```
train.boost #ntrees=4000,interaction.depth=4
```



```

## Stochastic Gradient Boosting
##
## 637 samples
## 16 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 509, 508, 510, 512, 509
## Resampling results across tuning parameters:
##
##  interaction.depth  n.trees  RMSE      Rsquared  MAE
##      1              500    0.2214558  0.4792111  0.16511538
##      1             1000    0.2020549  0.4969852  0.14811466
##      1             1500    0.1907759  0.5191214  0.13683499
##      1             2000    0.1831320  0.5373833  0.12848911
##      1             2500    0.1778574  0.5505235  0.12209313
##      1             3000    0.1742092  0.5597227  0.11716936
##      1             3500    0.1716621  0.5664189  0.11334564
##      1             4000    0.1701625  0.5703639  0.11062390
##      1             4500    0.1691255  0.5734536  0.10869947
##      1             5000    0.1685429  0.5752649  0.10789840
##      1             5500    0.1681944  0.5763153  0.10764586
##      1             6000    0.1679193  0.5772218  0.10766962
##      1             6500    0.1676691  0.5782582  0.10781953
##      1             7000    0.1675026  0.5791145  0.10807441
##      1             7500    0.1674431  0.5794730  0.10839219
##      1             8000    0.1673553  0.5798363  0.10872500
##      1             8500    0.1672696  0.5802706  0.10906576
##      1             9000    0.1671723  0.5808824  0.10944028
##      1             9500    0.1671933  0.5809542  0.10978272
##      1            10000    0.1671539  0.5812307  0.11012546
##      1            10500    0.1671547  0.5813962  0.11046063
##      1            11000    0.1671482  0.5815500  0.11076698
##      1            11500    0.1670776  0.5818552  0.11103891
##      1            12000    0.1670899  0.5819566  0.11134365
##      1            12500    0.1670744  0.5820467  0.11163698
##      1            13000    0.1670629  0.5820531  0.11185851
##      1            13500    0.1671021  0.5820431  0.11212352
##      1            14000    0.1671688  0.5819046  0.11242023
##      1            14500    0.1672609  0.5815236  0.11271889
##      1            15000    0.1672414  0.5815486  0.11294315
##      1            15500    0.1672694  0.5814595  0.11315290
##      1            16000    0.1672855  0.5815873  0.11336020
##      1            16500    0.1672617  0.5816539  0.11356570
##      1            17000    0.1673041  0.5815828  0.11375661
##      1            17500    0.1673724  0.5814112  0.11394510
##      1            18000    0.1674393  0.5811127  0.11415674
##      1            18500    0.1675226  0.5809154  0.11436165
##      1            19000    0.1675932  0.5806968  0.11456401
##      1            19500    0.1675779  0.5808066  0.11469208
##      1            20000    0.1676236  0.5806323  0.11487004
##      1            20500    0.1676828  0.5804456  0.11500101
##      1            21000    0.1677423  0.5802403  0.11517986

```

##	1	21500	0.1678338	0.5799192	0.11536466
##	1	22000	0.1678938	0.5796839	0.11554429
##	1	22500	0.1678971	0.5797352	0.11565831
##	1	23000	0.1679281	0.5796376	0.11579512
##	1	23500	0.1679813	0.5795677	0.11591496
##	1	24000	0.1680311	0.5794820	0.11604862
##	1	24500	0.1680568	0.5792360	0.11615515
##	1	25000	0.1680816	0.5792260	0.11628105
##	1	25500	0.1681189	0.5791069	0.11638408
##	1	26000	0.1682174	0.5787820	0.11652927
##	1	26500	0.1682819	0.5786252	0.11663353
##	1	27000	0.1683325	0.5782847	0.11673454
##	1	27500	0.1683847	0.5781400	0.11682979
##	1	28000	0.1684494	0.5778956	0.11696772
##	1	28500	0.1685378	0.5776667	0.11708884
##	1	29000	0.1685966	0.5773497	0.11720647
##	1	29500	0.1686372	0.5771779	0.11731944
##	1	30000	0.1686736	0.5770251	0.11742131
##	1	30500	0.1687696	0.5767262	0.11751840
##	1	31000	0.1688152	0.5765563	0.11758834
##	1	31500	0.1688788	0.5763740	0.11768664
##	1	32000	0.1689261	0.5761759	0.11776235
##	1	32500	0.1689816	0.5760901	0.11785943
##	1	33000	0.1690188	0.5758197	0.11793775
##	1	33500	0.1690658	0.5757314	0.11801278
##	1	34000	0.1691419	0.5755570	0.11812002
##	1	34500	0.1691867	0.5754365	0.11818911
##	1	35000	0.1692360	0.5751593	0.11825524
##	1	35500	0.1692954	0.5749372	0.11836039
##	1	36000	0.1693476	0.5747394	0.11842810
##	1	36500	0.1694348	0.5744117	0.11853231
##	1	37000	0.1694931	0.5742627	0.11859583
##	1	37500	0.1695597	0.5741320	0.11868027
##	2	500	0.2137503	0.5604232	0.15977050
##	2	1000	0.1900088	0.5781564	0.13913312
##	2	1500	0.1765877	0.5921661	0.12559398
##	2	2000	0.1688755	0.6028566	0.11634537
##	2	2500	0.1643709	0.6105790	0.10959152
##	2	3000	0.1619216	0.6152882	0.10496616
##	2	3500	0.1606477	0.6185082	0.10192181
##	2	4000	0.1598136	0.6211583	0.09998822
##	2	4500	0.1593077	0.6231082	0.09880187
##	2	5000	0.1590381	0.6241381	0.09823526
##	2	5500	0.1589199	0.6245225	0.09810074
##	2	6000	0.1588604	0.6248718	0.09824476
##	2	6500	0.1589107	0.6249419	0.09854758
##	2	7000	0.1590157	0.6245981	0.09897750
##	2	7500	0.1590626	0.6243050	0.09928272
##	2	8000	0.1591175	0.6241695	0.09964640
##	2	8500	0.1592280	0.6238063	0.09997356
##	2	9000	0.1594571	0.6228850	0.10036185
##	2	9500	0.1596208	0.6221653	0.10070837
##	2	10000	0.1597952	0.6215747	0.10105302
##	2	10500	0.1600374	0.6206522	0.10140356

##	2	11000	0.1602157	0.6199648	0.10172315
##	2	11500	0.1604588	0.6191029	0.10203659
##	2	12000	0.1606167	0.6184754	0.10230569
##	2	12500	0.1608240	0.6176909	0.10255068
##	2	13000	0.1609856	0.6170830	0.10275346
##	2	13500	0.1610696	0.6165900	0.10293637
##	2	14000	0.1612863	0.6158137	0.10317954
##	2	14500	0.1614250	0.6152745	0.10330915
##	2	15000	0.1616299	0.6144505	0.10354205
##	2	15500	0.1617791	0.6139780	0.10371125
##	2	16000	0.1619087	0.6134491	0.10383206
##	2	16500	0.1621331	0.6126041	0.10402804
##	2	17000	0.1622810	0.6121171	0.10422085
##	2	17500	0.1624086	0.6117243	0.10436348
##	2	18000	0.1626084	0.6109255	0.10451729
##	2	18500	0.1627691	0.6103134	0.10465935
##	2	19000	0.1628951	0.6098289	0.10477137
##	2	19500	0.1631061	0.6090511	0.10497543
##	2	20000	0.1632228	0.6087294	0.10511400
##	2	20500	0.1633785	0.6080979	0.10522949
##	2	21000	0.1635344	0.6075315	0.10536598
##	2	21500	0.1636318	0.6071449	0.10544792
##	2	22000	0.1638008	0.6065304	0.10558707
##	2	22500	0.1639156	0.6060297	0.10570732
##	2	23000	0.1640671	0.6054805	0.10580877
##	2	23500	0.1641638	0.6051929	0.10589365
##	2	24000	0.1643228	0.6044657	0.10599951
##	2	24500	0.1644884	0.6037854	0.10613654
##	2	25000	0.1646500	0.6031625	0.10628593
##	2	25500	0.1647519	0.6026876	0.10637125
##	2	26000	0.1648764	0.6022171	0.10648756
##	2	26500	0.1649698	0.6017583	0.10656465
##	2	27000	0.1650527	0.6014732	0.10663942
##	2	27500	0.1651658	0.6010775	0.10675308
##	2	28000	0.1652546	0.6007621	0.10684296
##	2	28500	0.1653858	0.6001812	0.10696463
##	2	29000	0.1655380	0.5995648	0.10710268
##	2	29500	0.1656556	0.5990614	0.10718974
##	2	30000	0.1658216	0.5984188	0.10729817
##	2	30500	0.1659337	0.5979505	0.10738733
##	2	31000	0.1659881	0.5977160	0.10743805
##	2	31500	0.1660786	0.5974156	0.10753321
##	2	32000	0.1661791	0.5969972	0.10762031
##	2	32500	0.1663089	0.5963877	0.10774770
##	2	33000	0.1664091	0.5960499	0.10782755
##	2	33500	0.1665558	0.5954389	0.10793625
##	2	34000	0.1666956	0.5949787	0.10807434
##	2	34500	0.1668367	0.5943526	0.10819605
##	2	35000	0.1669858	0.5937913	0.10831560
##	2	35500	0.1670568	0.5935155	0.10836493
##	2	36000	0.1671539	0.5930449	0.10843982
##	2	36500	0.1672478	0.5926805	0.10853983
##	2	37000	0.1673684	0.5922293	0.10863388
##	2	37500	0.1674849	0.5917337	0.10872547

##	4	500	0.2081001	0.5930581	0.15506055
##	4	1000	0.1831339	0.6020570	0.13234731
##	4	1500	0.1705480	0.6106607	0.11842771
##	4	2000	0.1642763	0.6177361	0.10947892
##	4	2500	0.1611253	0.6229935	0.10379603
##	4	3000	0.1595433	0.6265126	0.10021965
##	4	3500	0.1588250	0.6284245	0.09816705
##	4	4000	0.1585888	0.6289045	0.09730911
##	4	4500	0.1586172	0.6289872	0.09712436
##	4	5000	0.1586710	0.6287279	0.09721216
##	4	5500	0.1588093	0.6281724	0.09753125
##	4	6000	0.1591624	0.6266933	0.09798206
##	4	6500	0.1594750	0.6252876	0.09844005
##	4	7000	0.1597877	0.6238037	0.09886474
##	4	7500	0.1601182	0.6224451	0.09933991
##	4	8000	0.1604669	0.6210524	0.09971809
##	4	8500	0.1608090	0.6195923	0.10008900
##	4	9000	0.1611486	0.6182290	0.10047200
##	4	9500	0.1614466	0.6169540	0.10078336
##	4	10000	0.1617722	0.6155133	0.10113906
##	4	10500	0.1620352	0.6144409	0.10145201
##	4	11000	0.1623149	0.6133813	0.10172519
##	4	11500	0.1626354	0.6119679	0.10201037
##	4	12000	0.1628977	0.6107972	0.10227710
##	4	12500	0.1631919	0.6096134	0.10252108
##	4	13000	0.1634325	0.6086692	0.10275018
##	4	13500	0.1636501	0.6077203	0.10292078
##	4	14000	0.1638746	0.6067647	0.10310736
##	4	14500	0.1640733	0.6058495	0.10329800
##	4	15000	0.1643461	0.6047095	0.10349918
##	4	15500	0.1645750	0.6037229	0.10366859
##	4	16000	0.1647998	0.6027834	0.10383637
##	4	16500	0.1649999	0.6018412	0.10400886
##	4	17000	0.1652350	0.6008822	0.10417221
##	4	17500	0.1654106	0.6001028	0.10435615
##	4	18000	0.1656218	0.5992080	0.10452839
##	4	18500	0.1658166	0.5982908	0.10468686
##	4	19000	0.1660728	0.5971898	0.10489168
##	4	19500	0.1662586	0.5964464	0.10507368
##	4	20000	0.1664480	0.5956697	0.10522151
##	4	20500	0.1666183	0.5950179	0.10535695
##	4	21000	0.1668123	0.5941862	0.10552806
##	4	21500	0.1669522	0.5936082	0.10564676
##	4	22000	0.1671218	0.5928233	0.10581134
##	4	22500	0.1672841	0.5921121	0.10596674
##	4	23000	0.1674383	0.5915153	0.10610127
##	4	23500	0.1676237	0.5907184	0.10626492
##	4	24000	0.1678090	0.5899697	0.10643673
##	4	24500	0.1679593	0.5892991	0.10658273
##	4	25000	0.1680940	0.5887025	0.10668507
##	4	25500	0.1683023	0.5878532	0.10685865
##	4	26000	0.1684177	0.5874002	0.10695632
##	4	26500	0.1685526	0.5868480	0.10707024
##	4	27000	0.1686666	0.5862840	0.10718260

##	4	27500	0.1688009	0.5856872	0.10729071
##	4	28000	0.1689137	0.5852355	0.10740345
##	4	28500	0.1690462	0.5846803	0.10755196
##	4	29000	0.1692570	0.5838181	0.10771089
##	4	29500	0.1693952	0.5832416	0.10782277
##	4	30000	0.1695108	0.5827616	0.10790706
##	4	30500	0.1696414	0.5823012	0.10801855
##	4	31000	0.1697798	0.5817395	0.10812054
##	4	31500	0.1698884	0.5812252	0.10823241
##	4	32000	0.1700139	0.5807376	0.10835756
##	4	32500	0.1701239	0.5802719	0.10844615
##	4	33000	0.1702166	0.5798486	0.10855412
##	4	33500	0.1703346	0.5794286	0.10864441
##	4	34000	0.1704742	0.5788458	0.10875689
##	4	34500	0.1705881	0.5782908	0.10885696
##	4	35000	0.1706793	0.5779450	0.10892784
##	4	35500	0.1707891	0.5774974	0.10900901
##	4	36000	0.1709009	0.5770026	0.10910501
##	4	36500	0.1710219	0.5765225	0.10918304
##	4	37000	0.1711095	0.5761821	0.10926702
##	4	37500	0.1712092	0.5757935	0.10936477
##	6	500	0.2062742	0.6012482	0.15339828
##	6	1000	0.1809392	0.6101613	0.12998589
##	6	1500	0.1687524	0.6164286	0.11614566
##	6	2000	0.1629721	0.6222686	0.10754441
##	6	2500	0.1603198	0.6261458	0.10229248
##	6	3000	0.1593016	0.6279180	0.09924148
##	6	3500	0.1588865	0.6288074	0.09777288
##	6	4000	0.1588843	0.6286181	0.09740707
##	6	4500	0.1591060	0.6275732	0.09748808
##	6	5000	0.1593639	0.6265285	0.09782845
##	6	5500	0.1597698	0.6246656	0.09834818
##	6	6000	0.1601350	0.6230271	0.09879440
##	6	6500	0.1605253	0.6213253	0.09918451
##	6	7000	0.1610039	0.6193616	0.09963463
##	6	7500	0.1614863	0.6172603	0.10010738
##	6	8000	0.1618985	0.6154619	0.10048556
##	6	8500	0.1622634	0.6139025	0.10082191
##	6	9000	0.1626910	0.6121194	0.10117574
##	6	9500	0.1630061	0.6106655	0.10146560
##	6	10000	0.1633947	0.6089960	0.10178402
##	6	10500	0.1637044	0.6076224	0.10205452
##	6	11000	0.1640731	0.6060814	0.10232065
##	6	11500	0.1644335	0.6045285	0.10261128
##	6	12000	0.1646876	0.6033523	0.10285240
##	6	12500	0.1649701	0.6021348	0.10312565
##	6	13000	0.1652288	0.6010556	0.10333379
##	6	13500	0.1654504	0.6000441	0.10352183
##	6	14000	0.1657430	0.5987300	0.10373237
##	6	14500	0.1660121	0.5975615	0.10395490
##	6	15000	0.1663250	0.5961947	0.10417761
##	6	15500	0.1665370	0.5952758	0.10431987
##	6	16000	0.1667689	0.5942024	0.10447840
##	6	16500	0.1669717	0.5932760	0.10463377

##	6	17000	0.1671798	0.5923788	0.10481005
##	6	17500	0.1673755	0.5916151	0.10496103
##	6	18000	0.1675964	0.5906946	0.10514607
##	6	18500	0.1678058	0.5898655	0.10532107
##	6	19000	0.1679845	0.5891321	0.10545738
##	6	19500	0.1681568	0.5882760	0.10564420
##	6	20000	0.1683034	0.5876082	0.10577413
##	6	20500	0.1684910	0.5868241	0.10595575
##	6	21000	0.1686735	0.5860131	0.10611852
##	6	21500	0.1688634	0.5851839	0.10628469
##	6	22000	0.1690340	0.5844878	0.10643509
##	6	22500	0.1691823	0.5839013	0.10657057
##	6	23000	0.1693301	0.5832654	0.10669796
##	6	23500	0.1694919	0.5825754	0.10683236
##	6	24000	0.1696317	0.5819980	0.10692455
##	6	24500	0.1697697	0.5814524	0.10704839
##	6	25000	0.1699091	0.5809223	0.10715336
##	6	25500	0.1700438	0.5802984	0.10728196
##	6	26000	0.1701859	0.5796818	0.10738237
##	6	26500	0.1703177	0.5791111	0.10749251
##	6	27000	0.1704677	0.5785403	0.10764465
##	6	27500	0.1705798	0.5780616	0.10773864
##	6	28000	0.1706827	0.5776539	0.10783402
##	6	28500	0.1707882	0.5772259	0.10790984
##	6	29000	0.1708922	0.5767972	0.10798989
##	6	29500	0.1710107	0.5762526	0.10809600
##	6	30000	0.1711197	0.5758264	0.10818352
##	6	30500	0.1712382	0.5753036	0.10829063
##	6	31000	0.1713437	0.5748381	0.10838585
##	6	31500	0.1714284	0.5744365	0.10846881
##	6	32000	0.1715349	0.5739525	0.10855328
##	6	32500	0.1716204	0.5736513	0.10862160
##	6	33000	0.1717187	0.5732653	0.10871153
##	6	33500	0.1718129	0.5729223	0.10879245
##	6	34000	0.1718861	0.5726156	0.10884123
##	6	34500	0.1719582	0.5723176	0.10889610
##	6	35000	0.1720431	0.5719629	0.10897737
##	6	35500	0.1721154	0.5716671	0.10902591
##	6	36000	0.1721900	0.5713887	0.10908647
##	6	36500	0.1722616	0.5710899	0.10914798
##	6	37000	0.1723336	0.5707940	0.10919233
##	6	37500	0.1723913	0.5705614	0.10923649
##	8	500	0.2056724	0.6043325	0.15266172
##	8	1000	0.1800684	0.6117354	0.12885505
##	8	1500	0.1682629	0.6170662	0.11515708
##	8	2000	0.1628897	0.6221450	0.10679539
##	8	2500	0.1604849	0.6255679	0.10180923
##	8	3000	0.1596672	0.6263910	0.09924485
##	8	3500	0.1594553	0.6264584	0.09825181
##	8	4000	0.1597797	0.6247565	0.09822361
##	8	4500	0.1601196	0.6230558	0.09851142
##	8	5000	0.1605655	0.6210311	0.09887941
##	8	5500	0.1610580	0.6191105	0.09927876
##	8	6000	0.1615487	0.6169906	0.09971674

##	8	6500	0.1620194	0.6149453	0.10012626
##	8	7000	0.1624932	0.6128172	0.10054394
##	8	7500	0.1629046	0.6109574	0.10083853
##	8	8000	0.1633469	0.6090814	0.10119174
##	8	8500	0.1637542	0.6072844	0.10149558
##	8	9000	0.1641326	0.6056509	0.10179599
##	8	9500	0.1645473	0.6038767	0.10209211
##	8	10000	0.1649385	0.6020996	0.10239276
##	8	10500	0.1652967	0.6005745	0.10267627
##	8	11000	0.1656526	0.5989190	0.10297880
##	8	11500	0.1659840	0.5975343	0.10324656
##	8	12000	0.1663013	0.5960288	0.10349512
##	8	12500	0.1666123	0.5946988	0.10367286
##	8	13000	0.1669615	0.5930681	0.10397115
##	8	13500	0.1672248	0.5919293	0.10417162
##	8	14000	0.1674720	0.5908541	0.10436238
##	8	14500	0.1677548	0.5895907	0.10455701
##	8	15000	0.1679971	0.5885377	0.10475239
##	8	15500	0.1682494	0.5874278	0.10493570
##	8	16000	0.1684328	0.5865559	0.10511171
##	8	16500	0.1686664	0.5855437	0.10532156
##	8	17000	0.1688702	0.5846732	0.10547201
##	8	17500	0.1690614	0.5838019	0.10564713
##	8	18000	0.1692411	0.5830555	0.10580668
##	8	18500	0.1694527	0.5821351	0.10598701
##	8	19000	0.1696136	0.5814892	0.10611391
##	8	19500	0.1697758	0.5807506	0.10624270
##	8	20000	0.1699712	0.5799023	0.10641804
##	8	20500	0.1701448	0.5791349	0.10657525
##	8	21000	0.1703082	0.5784205	0.10671977
##	8	21500	0.1704661	0.5778334	0.10684511
##	8	22000	0.1706072	0.5772613	0.10697183
##	8	22500	0.1707364	0.5767219	0.10708514
##	8	23000	0.1708670	0.5761375	0.10719049
##	8	23500	0.1709795	0.5756785	0.10727387
##	8	24000	0.1711308	0.5750210	0.10738757
##	8	24500	0.1712524	0.5745143	0.10749021
##	8	25000	0.1713637	0.5740602	0.10759146
##	8	25500	0.1714674	0.5736381	0.10767362
##	8	26000	0.1715815	0.5731544	0.10776158
##	8	26500	0.1716972	0.5726663	0.10784594
##	8	27000	0.1717854	0.5722727	0.10790558
##	8	27500	0.1718736	0.5719146	0.10798474
##	8	28000	0.1719573	0.5715688	0.10804256
##	8	28500	0.1720472	0.5711947	0.10811889
##	8	29000	0.1721249	0.5708551	0.10817994
##	8	29500	0.1722156	0.5704617	0.10824505
##	8	30000	0.1722912	0.5701667	0.10830692
##	8	30500	0.1723984	0.5697577	0.10837783
##	8	31000	0.1724673	0.5694767	0.10844187
##	8	31500	0.1725511	0.5691460	0.10851079
##	8	32000	0.1726409	0.5687683	0.10858323
##	8	32500	0.1726979	0.5685351	0.10862665
##	8	33000	0.1727582	0.5682779	0.10866226

##	8	33500	0.1728055	0.5681233	0.10870440
##	8	34000	0.1728673	0.5678887	0.10875261
##	8	34500	0.1729380	0.5675809	0.10881606
##	8	35000	0.1729945	0.5673634	0.10886621
##	8	35500	0.1730617	0.5670987	0.10891549
##	8	36000	0.1731237	0.5668235	0.10896268
##	8	36500	0.1731733	0.5666317	0.10899807
##	8	37000	0.1732122	0.5665012	0.10903885
##	8	37500	0.1732712	0.5662506	0.10909732
##	10	500	0.2050995	0.6070552	0.15213500
##	10	1000	0.1794826	0.6144966	0.12818444
##	10	1500	0.1678623	0.6190703	0.11473030
##	10	2000	0.1625576	0.6234839	0.10644799
##	10	2500	0.1604984	0.6254875	0.10181403
##	10	3000	0.1597459	0.6265611	0.09946826
##	10	3500	0.1596889	0.6260491	0.09869884
##	10	4000	0.1599152	0.6249949	0.09863401
##	10	4500	0.1602804	0.6235022	0.09885348
##	10	5000	0.1607582	0.6213569	0.09923379
##	10	5500	0.1612263	0.6191451	0.09956037
##	10	6000	0.1617702	0.6167579	0.09996534
##	10	6500	0.1622116	0.6147627	0.10033022
##	10	7000	0.1627188	0.6124314	0.10072645
##	10	7500	0.1632301	0.6101826	0.10110538
##	10	8000	0.1637088	0.6080121	0.10144854
##	10	8500	0.1641718	0.6060066	0.10176423
##	10	9000	0.1645616	0.6042373	0.10204506
##	10	9500	0.1650055	0.6022799	0.10234784
##	10	10000	0.1653673	0.6006051	0.10258157
##	10	10500	0.1656853	0.5991435	0.10284603
##	10	11000	0.1660691	0.5973076	0.10312015
##	10	11500	0.1663792	0.5959649	0.10332460
##	10	12000	0.1667406	0.5943463	0.10359089
##	10	12500	0.1670243	0.5931649	0.10378341
##	10	13000	0.1672967	0.5918803	0.10399682
##	10	13500	0.1675936	0.5906074	0.10421585
##	10	14000	0.1678361	0.5895497	0.10439079
##	10	14500	0.1680878	0.5884447	0.10459422
##	10	15000	0.1683000	0.5875320	0.10477279
##	10	15500	0.1685428	0.5865087	0.10496216
##	10	16000	0.1687551	0.5855014	0.10514819
##	10	16500	0.1689953	0.5844682	0.10533331
##	10	17000	0.1691620	0.5837118	0.10550409
##	10	17500	0.1693429	0.5829502	0.10565185
##	10	18000	0.1695334	0.5821340	0.10579576
##	10	18500	0.1696699	0.5815415	0.10591229
##	10	19000	0.1698174	0.5809213	0.10602152
##	10	19500	0.1700235	0.5800012	0.10616833
##	10	20000	0.1701643	0.5793453	0.10625569
##	10	20500	0.1703184	0.5786641	0.10636889
##	10	21000	0.1704776	0.5779786	0.10649549
##	10	21500	0.1706105	0.5774015	0.10660078
##	10	22000	0.1707360	0.5768998	0.10668013
##	10	22500	0.1708497	0.5764261	0.10676641


```
## 10      23000      0.1709721 0.5759802 0.10687519
## 10      23500      0.1710754 0.5755409 0.10697615
## 10      24000      0.1711622 0.5751896 0.10704606
## 10      24500      0.1712842 0.5746484 0.10713869
## 10      25000      0.1713792 0.5742640 0.10722314
## 10      25500      0.1714736 0.5738752 0.10729927
## 10      26000      0.1715899 0.5733928 0.10739968
## 10      26500      0.1716582 0.5730863 0.10745911
## 10      27000      0.1717587 0.5727277 0.10754360
## 10      27500      0.1718427 0.5723652 0.10760192
## 10      28000      0.1719220 0.5720314 0.10767169
## 10      28500      0.1719854 0.5717694 0.10772143
## 10      29000      0.1720531 0.5714521 0.10778694
## 10      29500      0.1721260 0.5711641 0.10785504
## 10      30000      0.1722062 0.5708877 0.10791577
## 10      30500      0.1722825 0.5705834 0.10797993
## 10      31000      0.1723429 0.5703322 0.10803090
## 10      31500      0.1724014 0.5700926 0.10808018
## 10      32000      0.1724527 0.5699104 0.10811601
## 10      32500      0.1725021 0.5697188 0.10816437
## 10      33000      0.1725510 0.5694976 0.10819819
## 10      33500      0.1726131 0.5692463 0.10825754
## 10      34000      0.1726633 0.5690446 0.10830037
## 10      34500      0.1726951 0.5689104 0.10832944
## 10      35000      0.1727387 0.5687660 0.10836671
## 10      35500      0.1727813 0.5686262 0.10840026
## 10      36000      0.1728243 0.5684690 0.10843440
## 10      36500      0.1728644 0.5683091 0.10847078
## 10      37000      0.1729034 0.5681476 0.10850440
## 10      37500      0.1729425 0.5679821 0.10854408
```

```
##
```

```
## Tuning parameter 'shrinkage' was held constant at a value of 0.001
```

```
##
```

```
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
```

```
## RMSE was used to select the optimal model using the smallest value.
```

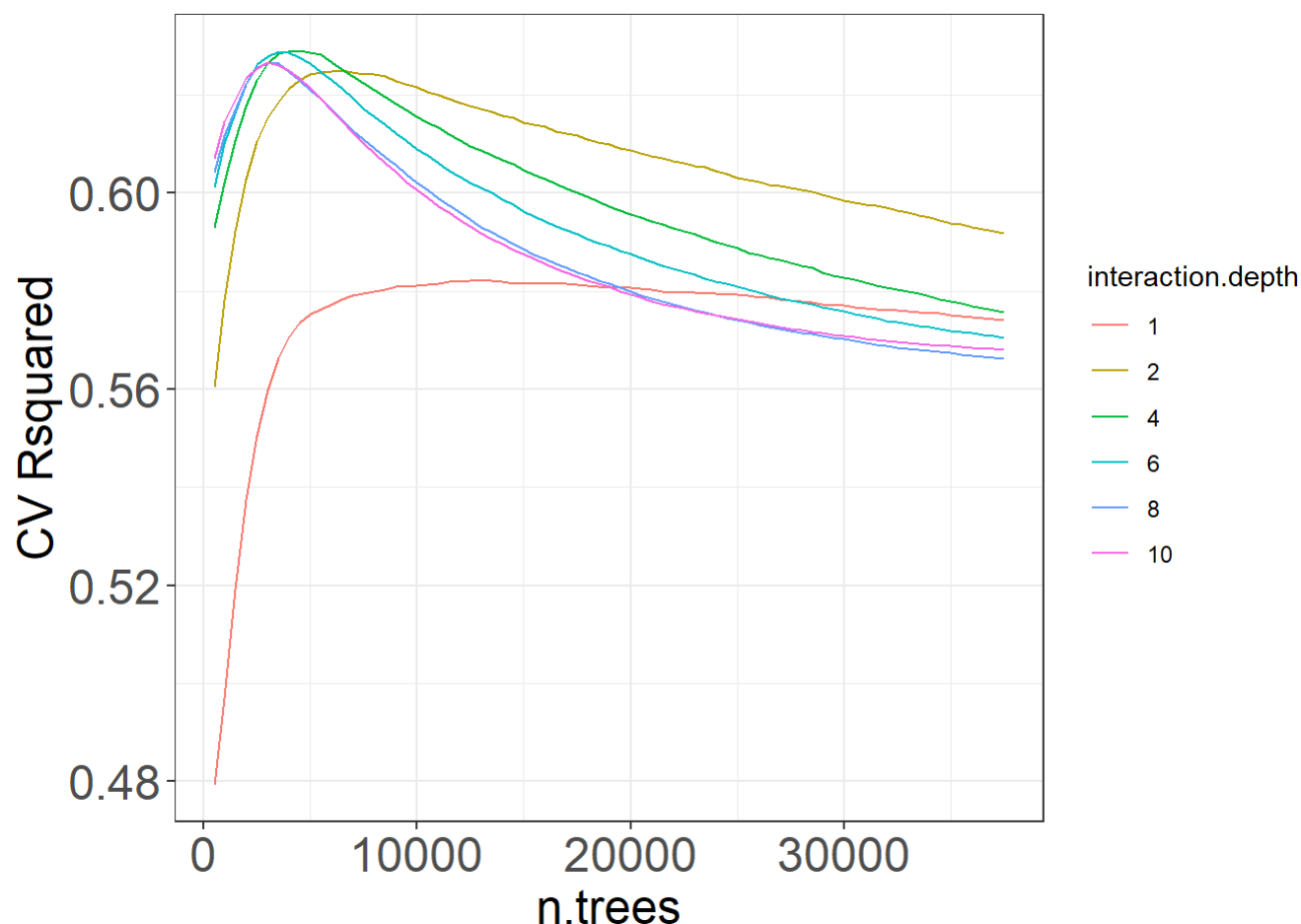
```
## The final values used for the model were n.trees = 4000,
```

```
## interaction.depth = 4, shrinkage = 0.001 and n.minobsinnode = 10.
```

```
best.boost <- train.boost$finalModel
```

```
pred.best.boost <- predict(best.boost, newdata = nba_csv.test, n.trees = 4000) # can use same model matrix
```

```
ggplot(train.boost$results, aes(x = n.trees, y = Rsquared, colour = as.factor(interaction.depth))) +
  geom_line() +
  ylab("CV Rsquared") + theme_bw() + theme(axis.title=element_text(size=18), axis.text=element_text(size=18)) +
  scale_color_discrete(name = "interaction.depth")
```



```
SSE = sum((nba_csv.test$award_share - pred.best.boost)^2)
SST = sum((nba_csv.test$award_share - mean(nba_csv.train$award_share))^2)
OSR2 = 1 - SSE/SST
OSR2 #0.8231889
```

```
## [1] 0.8231889
```

Bootstrapping for performance metrics

```
library(boot)
```

```
##
## Attaching package: 'boot'
```

```
## The following object is masked from 'package:car':
##
##   logit
```

```
## The following object is masked from 'package:lattice':
##
##   melanoma
```

```
boot_osr <- function(data, index) {
  labels <- data$label[index]
  predictions <- data$prediction[index]
  return(1 - (sum((labels - predictions)^2)/
              sum((labels - mean(data$label))^2)))
}

boot_mae <- function(data, index) {
  labels <- data$label[index]
  predictions <- data$prediction[index]
  return(mean(abs(labels-predictions)))
}

boot_rmse <- function(data, index) {
  labels <- data$label[index]
  predictions <- data$prediction[index]
  return(sqrt(mean((labels-predictions)^2)))
}

boot_all_metrics <- function(data, index) {
  osr = boot_osr(data, index)
  mae = boot_mae(data, index)
  rmse = boot_rmse(data, index)
  return(c(osr, mae, rmse))
}

big_B = 10000

##baseline model
#predict.baseline = rep(mean_obs, nrow(nba_csv.test))
#baseline_df = data.frame(labels = nba_csv.test$award_share, predictions = predict.baseline)
#set.seed(6829)
#Baseline_boot = boot(baseline_df, boot_all_metrics, R = big_B)
#Baseline_boot
#boot.ci(Baseline_boot, index = 1, type = "basic")
#boot.ci(Baseline_boot, index = 2, type = "basic")
#boot.ci(Baseline_boot, index = 3, type = "basic")

##naive lin reg
lin_df = data.frame(labels = nba_csv.test$award_share, predictions = predictions_testlm)
set.seed(342)

Lin_boot = boot(lin_df, boot_all_metrics, R = big_B)
Lin_boot
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = lin_df, statistic = boot_all_metrics, R = big_B)
##
##
## Bootstrap Statistics :
##      original      bias    std. error
## t1* 0.5506391 -5.595224e-02  0.17788423
## t2* 0.1772665  3.304536e-05  0.02856057
## t3* 0.2030427 -2.661079e-03  0.03412865
```

```
boot.ci(Lin_boot, index = 1, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Lin_boot, type = "basic", index = 1)
##
## Intervals :
## Level      Basic
## 95%   ( 0.3989,  1.1281 )
## Calculations and Intervals on Original Scale
```

```
boot.ci(Lin_boot, index = 2, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Lin_boot, type = "basic", index = 2)
##
## Intervals :
## Level      Basic
## 95%   ( 0.1165,  0.2289 )
## Calculations and Intervals on Original Scale
```

```
boot.ci(Lin_boot, index = 3, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Lin_boot, type = "basic", index = 3)
##
## Intervals :
## Level      Basic
## 95%      ( 0.1363,  0.2635 )
## Calculations and Intervals on Original Scale
```

```
##backwards stepwise lin reg
stepwise_df = data.frame(labels = nba_csv.test$award_share, predictions = pred.bswr)
set.seed(342)
Step_boot = boot(stepwise_df, boot_all_metrics, R = big_B)
Step_boot
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = stepwise_df, statistic = boot_all_metrics, R = big_B)
##
##
## Bootstrap Statistics :
##      original      bias    std. error
## t1* 0.5513073 -5.822719e-02  0.17656909
## t2* 0.1787127  3.674980e-06  0.02774371
## t3* 0.2028917 -2.379516e-03  0.03215793
```

```
boot.ci(Step_boot, index = 1, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Step_boot, type = "basic", index = 1)
##
## Intervals :
## Level      Basic
## 95%      ( 0.4139,  1.1281 )
## Calculations and Intervals on Original Scale
```

```
boot.ci(Step_boot, index = 2, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Step_boot, type = "basic", index = 2)
##
## Intervals :
## Level      Basic
## 95%      ( 0.1201,  0.2296 )
## Calculations and Intervals on Original Scale
```

```
boot.ci(Step_boot, index = 3, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Step_boot, type = "basic", index = 3)
##
## Intervals :
## Level      Basic
## 95%      ( 0.1397,  0.2602 )
## Calculations and Intervals on Original Scale
```

```
##random forest
rf_df = data.frame(labels = nba_csv.test$award_share, predictions = pred.best.rf)
set.seed(6722)
RF_boot = boot(rf_df, boot_all_metrics, R = big_B)
RF_boot
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = rf_df, statistic = boot_all_metrics, R = big_B)
##
##
## Bootstrap Statistics :
##      original      bias    std. error
## t1* 0.7581074 -5.016702e-02  0.16450474
## t2* 0.1248506  6.594466e-05  0.02327981
## t3* 0.1489708 -1.754376e-03  0.02357759
```

```
boot.ci(RF_boot, index = 1, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = RF_boot, type = "basic", index = 1)
##
## Intervals :
## Level      Basic
## 95%      ( 0.6397,  1.3085 )
## Calculations and Intervals on Original Scale
```

```
boot.ci(RF_boot, index = 2, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = RF_boot, type = "basic", index = 2)
##
## Intervals :
## Level      Basic
## 95%      ( 0.0775,  0.1690 )
## Calculations and Intervals on Original Scale
```

```
boot.ci(RF_boot, index = 3, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = RF_boot, type = "basic", index = 3)
##
## Intervals :
## Level      Basic
## 95%      ( 0.1068,  0.1989 )
## Calculations and Intervals on Original Scale
```

```
##boosting
boost_df = data.frame(labels = nba_csv.test$award_share, predictions = pred.best.boost)
set.seed(9391)
Boost_boot = boot(boost_df, boot_all_metrics, R = big_B)
Boost_boot
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
## Call:
## boot(data = boost_df, statistic = boot_all_metrics, R = big_B)
##
##
## Bootstrap Statistics :
##      original      bias    std. error
## t1* 0.81587466 -0.0509104966  0.19324228
## t2* 0.09692254  0.0002631934  0.02466090
## t3* 0.12997102 -0.0033825419  0.03044758
```

```
boot.ci(Boost_boot, index = 1, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Boost_boot, type = "basic", index = 1)
##
## Intervals :
## Level      Basic
## 95%   ( 0.6919,  1.4153 )
## Calculations and Intervals on Original Scale
```

```
boot.ci(Boost_boot, index = 2, type = "basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Boost_boot, type = "basic", index = 2)
##
## Intervals :
## Level      Basic
## 95%   ( 0.0434,  0.1399 )
## Calculations and Intervals on Original Scale
```

```
boot.ci(Boost_boot, index = 3, type = "basic")
```



```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 10000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = Boost_boot, type = "basic", index = 3)
##
## Intervals :
## Level      Basic
## 95%      ( 0.0746,  0.1925 )
## Calculations and Intervals on Original Scale
```