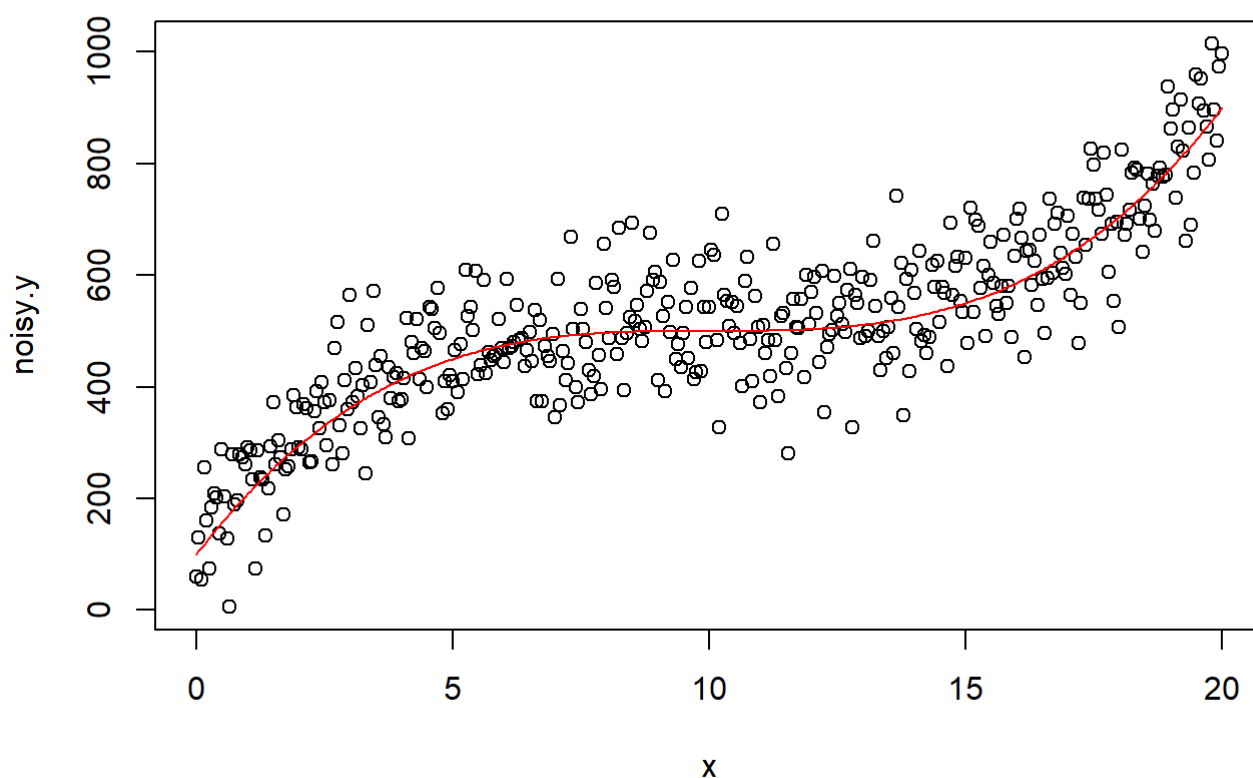


title: "Problem Set 2: Bias, Variance, Cross-Validation" author: "51709" date: || 01 March 2023 output: pdf_document

1a. With predictor x and outcome noisy_y , split the data into a training and test set

```
library(boot)
set.seed(1)
x <- seq(from=0, to=20, by=0.05)
y <- 500 + 0.4 * (x-10)^3
noise <- rnorm(length(x), mean=10, sd=80)
noisy.y <- y + noise
{
  plot(x, noisy.y)
  lines(x, y, col='red')
}
```



Assign the data to a dataframe. Randomly sample the data, assigning 80% to training set and 20% to test set.

```
df <- data.frame(x, noisy.y)
N <- floor(.8*nrow(df))
train_idx <- sample(1:nrow(df), N)
df_train <- df[train_idx,]
df_test <- df[-train_idx,]
```

1b. Perform 10-fold CV for polynomials from degree 1 to 5 (use MSE as your error measure). This should be done from scratch using a for loop.

Randomly permute the training set and split into 10 evenly sized folds. Then create a for loop: for every polynomial model of degree 1 through 5, split the training set again into a training set and test set, with 1 fold in the test set and the rest in the training set. Change which fold is in the test set each time by inserting a nested for loop for i (fold used for test) 1 through 10 (for 10-fold cross-validation).

Calculate the mean-squared error of the test sub-set (validation set) for each fold. Store results from each loop in a results table with column headings for the degree of the model, the fold number and the mean-squared error.

```
folds <- sample(rep(1:10, each = nrow(df_train)/10), replace=FALSE)
degree <- 1:5
results <- data.frame(results_degree=numeric(0), results_i=numeric(0), results_error=numeric(0))
for (d in degree){
  for (i in 1:10){
    cv.te <- df_train[folds==i,]
    cv.tr <- df_train[folds!=i,]
    cv.tr.x <- cv.tr[,1]
    cv.tr.y <- cv.tr[,2]
    cv.te.x <- cv.te[,1]
    cv.te.y <- cv.te[,2]
    mod <- glm(noisy.y ~ poly(x, d, raw = T), data=df_train)
    row <- data.frame(results_degree=d, results_i=i, results_error=mean((predict(mod, cv.te) - cv.te$noisy.y)^2))
    results <- rbind(results, row)
  }
}
results
```

##	results_degree	results_i	results_error
## 1	1	1	6420.144
## 2	1	2	10231.589
## 3	1	3	8808.168
## 4	1	4	12982.480
## 5	1	5	10610.066
## 6	1	6	8595.007
## 7	1	7	5252.368
## 8	1	8	6735.810
## 9	1	9	8653.017
## 10	1	10	13536.145
## 11	2	1	6421.101
## 12	2	2	10225.078
## 13	2	3	8810.706
## 14	2	4	12985.486
## 15	2	5	10619.164
## 16	2	6	8590.346
## 17	2	7	5251.758
## 18	2	8	6728.594
## 19	2	9	8656.569
## 20	2	10	13535.819
## 21	3	1	6285.938
## 22	3	2	6064.201
## 23	3	3	5801.355
## 24	3	4	8317.196
## 25	3	5	6565.344
## 26	3	6	4450.438
## 27	3	7	4031.181
## 28	3	8	4730.678
## 29	3	9	5092.755
## 30	3	10	9157.154
## 31	4	1	6279.820
## 32	4	2	6069.129
## 33	4	3	5813.017
## 34	4	4	8311.775
## 35	4	5	6572.819
## 36	4	6	4446.706
## 37	4	7	4025.874
## 38	4	8	4731.683
## 39	4	9	5088.472
## 40	4	10	9155.785
## 41	5	1	6218.422
## 42	5	2	6214.448
## 43	5	3	5759.784
## 44	5	4	8135.461
## 45	5	5	6536.950
## 46	5	6	4413.713
## 47	5	7	3970.983
## 48	5	8	4600.303
## 49	5	9	5245.364
## 50	5	10	9121.421

To calculate the overall cross-validation error for each model, create a table which summarises the cross-validation error for each fold. For each degree 1 through 5, calculate the sum of the MSE's across the 10 folds (a) using an ifelse condition, and calculate the number of folds (b). Then divide a by b to give the average

MSE for each of the 5 models being tested.

```
summary_table <- data.frame(summary_degree=numeric(0), sum_error =numeric(0), count_error=n
umeric(0), mean_error=numeric(0))

a <- 0
b <- 0
c <- 0

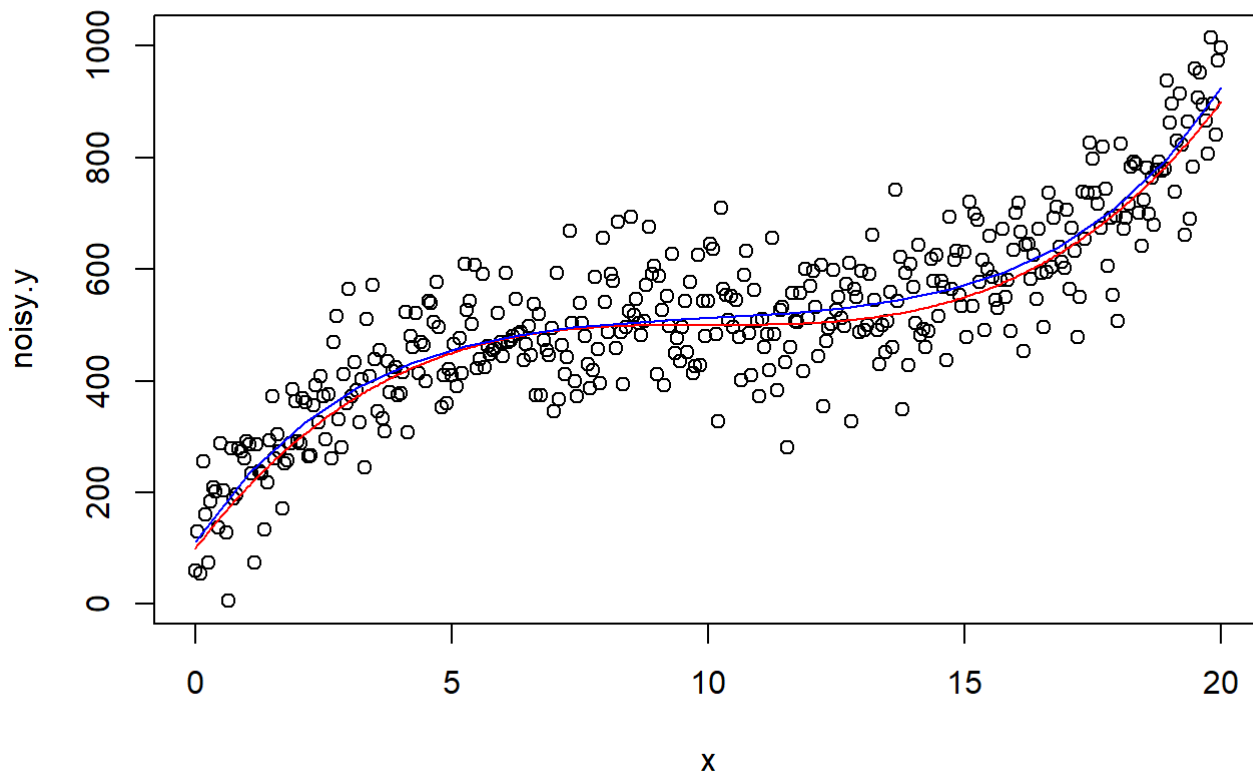
for (k in 1:5){
  for (j in 1:nrow(results)){
    ifelse(results[j,1] == k, a <- a + results[j,3], a <- a)
    ifelse(results[j,1] == k, b <- b + 1, b <- b)
  }
  c = a / b
  row <- data.frame(summary_degree = k, sum_error = a, count_error = b, mean_error = c)
  summary_table <- rbind(summary_table, row)
  a = 0
  b = 0
  c = 0
}
summary_table
```

##	summary_degree	sum_error	count_error	mean_error
## 1	1	91824.79	10	9182.479
## 2	2	91824.62	10	9182.462
## 3	3	60496.24	10	6049.624
## 4	4	60495.08	10	6049.508
## 5	5	60216.85	10	6021.685

1c. Plot the best model's fitted line in blue and compare to the true function (the red line from the previous plot).

From the table above, the model with the lowest MSE (and therefore the best model) is the degree 5 polynomial.

```
plot(x,noisy.y)
lines(x, y, col='red')
poly5_mod <-lm(noisy.y ~ poly(x, 5, raw = T), data = df_train)
x <- seq(min(df$x), max(df$x), length.out=20)
y <- predict(poly5_mod, newdata = data.frame(x = x))
lines(x, y, col = "blue")
```



1.d Comment on the results of (c). Why was performance better or worse at different order polynomials?

Since we generated the data, we know that the true underlying function is a cubic function (with noise added). My 10-fold cross-validation shows that the degree 5 polynomial has the lowest cross-validation error (though this error value is very similar to the polynomials of degrees 3 and 4). We can see from this plot that the 5 degree polynomial model is still visually a good fit to the data points, and stays fairly close to the true function.

We can hazard that the reason a degree 5 model has slightly lower error than degree 3 model may be due to the noise we added to the true function, therefore the 4 and 5 degree models are over-fitting to the noise as the higher the degree of polynomial, the more flexible it is. Cross-validation is only an approximation of the test error so it is possible for over-fitting to occur, however this is more common when the sample size is small.

1e. Report the CV error and test error at each order of polynomial. Which achieves the lowest CV error? How does the

CV error compare to the test error? Comment on the results.

```
degree <- 1:5
test_results <- data.frame(degree=numeric(0), test_error=numeric(0))
for (d in degree){
  mod <- glm(noisy.y ~ poly(x, d, raw = T), data=df_test)
  test_row <- data.frame(degree=d, test_error = mean((predict(mod, df_test) - df_test$noisy.y)^2))
  test_results <- rbind(test_results, test_row)
}
test_results <- cbind(test_results, summary_table[,4, drop=FALSE])
names(test_results)[names(test_results) == "mean_error"] <- "cross-validation_error"
test_results
```

```
## degree test_error cross-validation_error
## 1      1  10474.458          9182.479
## 2      2  10299.480          9182.462
## 3      3   5596.121          6049.624
## 4      4   5560.176          6049.508
## 5      5   5558.305          6021.685
```

For both test error and cross-validation error, the error decreases as the degree of the polynomial increases (from 1 through to 5).

The lowest cross-validation error and test error are both for the polynomial of degree 5.

While test error is higher than validation error for degrees 1 and 2, it is lower for degrees 3, 4 and 5. It may be that the test set contains more “easy” y’s to predict based on x’s than in the validation set, so the model performs better at degrees 3, 4 and 5 on test error, compared to cross-validation. However, since my randomisation of the dataset into a training and test split was intended to try to mitigate this issue.

2a. Pick a new dataset from the `mlbench` package (one we haven’t used in class that is 2-dimensional with two classes). Experiment with classifying the data using KNN at different values of `k`. Use cross-validation to choose your best model.

```
library(mlbench)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

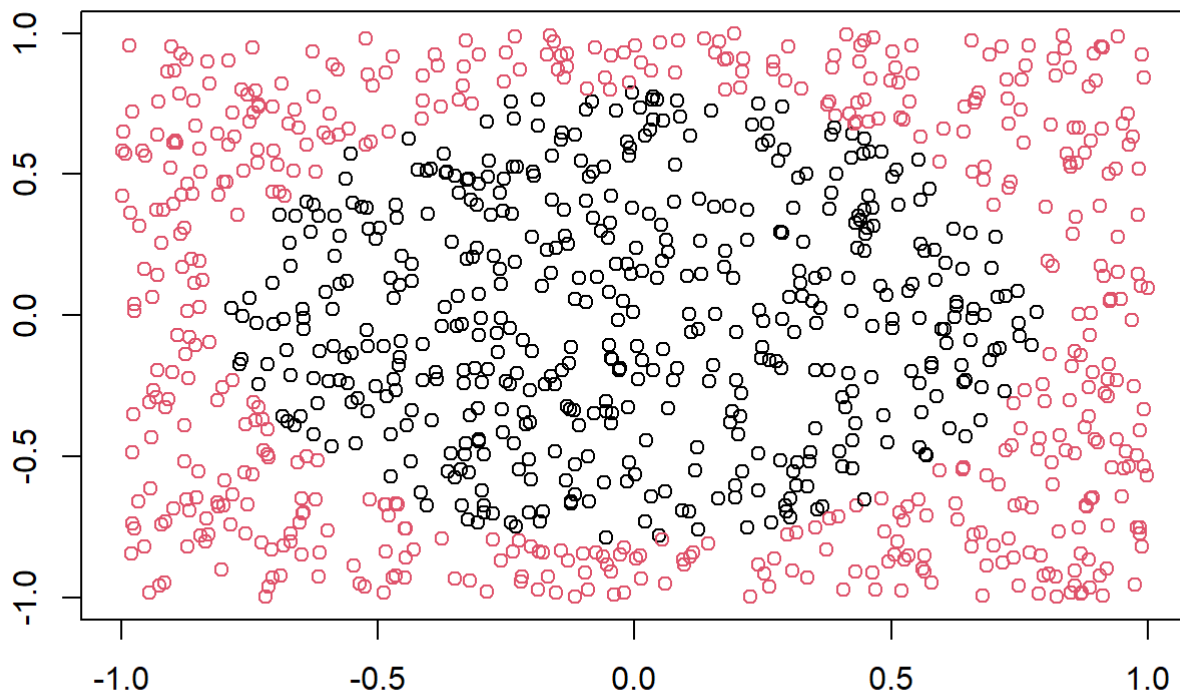
```
## The following objects are masked from 'package:stats':
##
## filter, lag
```

```
## The following objects are masked from 'package:base':
##
## intersect, setdiff, setequal, union
```

```
set.seed(1)
ls(package:mlbench)
```

```
## [1] "bayesclass"      "mlbench.1spiral"  "mlbench.2dnormals"
## [4] "mlbench.cassini"  "mlbench.circle"   "mlbench.corners"
## [7] "mlbench.cuboids"  "mlbench.friedman1" "mlbench.friedman2"
## [10] "mlbench.friedman3" "mlbench.hypercube" "mlbench.peak"
## [13] "mlbench.ringnorm" "mlbench.shapes"   "mlbench.simplex"
## [16] "mlbench.smiley"   "mlbench.spirals"  "mlbench.threenorm"
## [19] "mlbench.twonorm"  "mlbench.waveform" "mlbench.xor"
```

```
c <- mlbench.circle(1000,2)
plot(c)
```



Move the dataset into a dataframe so it's easier to work with. Rename variables and set levels of classes.

```
cdf <- data.frame(c)
cdf <- cdf %>% rename(Y.1 = classes, X.1 = x.1, X.2 = x.2)
levels(cdf$Y.1) <- c("0", "1")
```

Randomly permute the training set and split into 10 evenly sized folds. Then create a for loop: for values 1 through 100 of K, split the training set again into a training set and test set, with 1 fold in the test set and the rest in the training set. Change which fold is in the test set each time by inserting a nested for loop for i (fold used for test) 1 through 10 (for 10-fold cross-validation). Calculate the mean-squared error of the test sub-set (validation sub-set) for each fold. Store results from each loop in a results table with column headings for the value of the k parameter, the fold number and the classification error.

```
library(class)
n_test <- floor(nrow(cdf)*0.2)
idx <- sample(1:nrow(cdf), n_test)
train <- cdf[-idx,]
test <- cdf[idx,]
folds <- sample(rep(1:10, each = nrow(train)/10), replace=FALSE)
results <- data.frame(results_k=numeric(0), results_i=numeric(0), results_error=numeric(0))
range <- 1:100
for (k in range){
  for (i in 1:10){
    cv.te <- train[folds==i,]
    cv.tr <- train[folds!=i,]
    cv.tr.x <- cv.tr[,1:2]
    cv.tr.y <- cv.tr[,3]
    cv.te.x <- cv.te[,1:2]
    cv.te.y <- cv.te[,3]
    pred.Y <- knn(cv.tr.x, cv.te.x, cv.tr.y, k)
    row <- data.frame(results_k=k, results_i=i, results_error=mean(cv.te.y != pred.Y))
    results <- rbind(results, row)
  }
}
results
```


##	results_k	results_i	results_error
## 1	1	1	0.0625
## 2	1	2	0.0000
## 3	1	3	0.0375
## 4	1	4	0.0125
## 5	1	5	0.0250
## 6	1	6	0.0250
## 7	1	7	0.0000
## 8	1	8	0.0125
## 9	1	9	0.0250
## 10	1	10	0.0125
## 11	2	1	0.1000
## 12	2	2	0.0000
## 13	2	3	0.0500
## 14	2	4	0.0500
## 15	2	5	0.0375
## 16	2	6	0.0500
## 17	2	7	0.0000
## 18	2	8	0.0250
## 19	2	9	0.0250
## 20	2	10	0.0250
## 21	3	1	0.0625
## 22	3	2	0.0125
## 23	3	3	0.0250
## 24	3	4	0.0625
## 25	3	5	0.0250
## 26	3	6	0.0250
## 27	3	7	0.0125
## 28	3	8	0.0250
## 29	3	9	0.0125
## 30	3	10	0.0375
## 31	4	1	0.0625
## 32	4	2	0.0250
## 33	4	3	0.0375
## 34	4	4	0.0750
## 35	4	5	0.0000
## 36	4	6	0.0250
## 37	4	7	0.0000
## 38	4	8	0.0375
## 39	4	9	0.0375
## 40	4	10	0.0500
## 41	5	1	0.0500
## 42	5	2	0.0125
## 43	5	3	0.0125
## 44	5	4	0.0875
## 45	5	5	0.0250
## 46	5	6	0.0250
## 47	5	7	0.0125
## 48	5	8	0.0250
## 49	5	9	0.0125
## 50	5	10	0.0250
## 51	6	1	0.0625
## 52	6	2	0.0250
## 53	6	3	0.0125
## 54	6	4	0.0625

## 55	6	5	0.0250
## 56	6	6	0.0250
## 57	6	7	0.0250
## 58	6	8	0.0250
## 59	6	9	0.0125
## 60	6	10	0.0500
## 61	7	1	0.0375
## 62	7	2	0.0375
## 63	7	3	0.0250
## 64	7	4	0.0750
## 65	7	5	0.0500
## 66	7	6	0.0250
## 67	7	7	0.0125
## 68	7	8	0.0250
## 69	7	9	0.0375
## 70	7	10	0.0250
## 71	8	1	0.0500
## 72	8	2	0.0500
## 73	8	3	0.0250
## 74	8	4	0.0750
## 75	8	5	0.0500
## 76	8	6	0.0375
## 77	8	7	0.0250
## 78	8	8	0.0125
## 79	8	9	0.0500
## 80	8	10	0.0375
## 81	9	1	0.0375
## 82	9	2	0.0625
## 83	9	3	0.0125
## 84	9	4	0.0875
## 85	9	5	0.0500
## 86	9	6	0.0375
## 87	9	7	0.0250
## 88	9	8	0.0250
## 89	9	9	0.0500
## 90	9	10	0.0375
## 91	10	1	0.0375
## 92	10	2	0.0625
## 93	10	3	0.0250
## 94	10	4	0.0750
## 95	10	5	0.0375
## 96	10	6	0.0750
## 97	10	7	0.0250
## 98	10	8	0.0250
## 99	10	9	0.0500
## 100	10	10	0.0250
## 101	11	1	0.0250
## 102	11	2	0.0500
## 103	11	3	0.0250
## 104	11	4	0.0625
## 105	11	5	0.0250
## 106	11	6	0.0500
## 107	11	7	0.0250
## 108	11	8	0.0250
## 109	11	9	0.0500
## 110	11	10	0.0250

## 111	12	1	0.0375
## 112	12	2	0.0500
## 113	12	3	0.0375
## 114	12	4	0.0500
## 115	12	5	0.0500
## 116	12	6	0.0500
## 117	12	7	0.0250
## 118	12	8	0.0375
## 119	12	9	0.0625
## 120	12	10	0.0250
## 121	13	1	0.0250
## 122	13	2	0.0500
## 123	13	3	0.0250
## 124	13	4	0.0500
## 125	13	5	0.0250
## 126	13	6	0.0375
## 127	13	7	0.0250
## 128	13	8	0.0375
## 129	13	9	0.0375
## 130	13	10	0.0250
## 131	14	1	0.0500
## 132	14	2	0.0250
## 133	14	3	0.0375
## 134	14	4	0.0500
## 135	14	5	0.0250
## 136	14	6	0.0375
## 137	14	7	0.0250
## 138	14	8	0.0500
## 139	14	9	0.0375
## 140	14	10	0.0375
## 141	15	1	0.0250
## 142	15	2	0.0250
## 143	15	3	0.0250
## 144	15	4	0.0375
## 145	15	5	0.0125
## 146	15	6	0.0375
## 147	15	7	0.0250
## 148	15	8	0.0375
## 149	15	9	0.0250
## 150	15	10	0.0250
## 151	16	1	0.0250
## 152	16	2	0.0250
## 153	16	3	0.0375
## 154	16	4	0.0625
## 155	16	5	0.0125
## 156	16	6	0.0375
## 157	16	7	0.0250
## 158	16	8	0.0125
## 159	16	9	0.0250
## 160	16	10	0.0125
## 161	17	1	0.0375
## 162	17	2	0.0500
## 163	17	3	0.0250
## 164	17	4	0.0500
## 165	17	5	0.0125
## 166	17	6	0.0250

## 167	17	7	0.0250
## 168	17	8	0.0250
## 169	17	9	0.0250
## 170	17	10	0.0250
## 171	18	1	0.0250
## 172	18	2	0.0500
## 173	18	3	0.0250
## 174	18	4	0.0375
## 175	18	5	0.0250
## 176	18	6	0.0250
## 177	18	7	0.0125
## 178	18	8	0.0375
## 179	18	9	0.0250
## 180	18	10	0.0250
## 181	19	1	0.0375
## 182	19	2	0.0375
## 183	19	3	0.0250
## 184	19	4	0.0375
## 185	19	5	0.0125
## 186	19	6	0.0250
## 187	19	7	0.0125
## 188	19	8	0.0500
## 189	19	9	0.0375
## 190	19	10	0.0375
## 191	20	1	0.0375
## 192	20	2	0.0250
## 193	20	3	0.0125
## 194	20	4	0.0250
## 195	20	5	0.0500
## 196	20	6	0.0250
## 197	20	7	0.0125
## 198	20	8	0.0250
## 199	20	9	0.0250
## 200	20	10	0.0500
## 201	21	1	0.0250
## 202	21	2	0.0375
## 203	21	3	0.0250
## 204	21	4	0.0375
## 205	21	5	0.0250
## 206	21	6	0.0250
## 207	21	7	0.0250
## 208	21	8	0.0375
## 209	21	9	0.0375
## 210	21	10	0.0500
## 211	22	1	0.0375
## 212	22	2	0.0500
## 213	22	3	0.0250
## 214	22	4	0.0500
## 215	22	5	0.0000
## 216	22	6	0.0625
## 217	22	7	0.0375
## 218	22	8	0.0375
## 219	22	9	0.0250
## 220	22	10	0.0500
## 221	23	1	0.0250
## 222	23	2	0.0375

## 223	23	3	0.0250
## 224	23	4	0.0500
## 225	23	5	0.0125
## 226	23	6	0.0375
## 227	23	7	0.0250
## 228	23	8	0.0375
## 229	23	9	0.0250
## 230	23	10	0.0500
## 231	24	1	0.0375
## 232	24	2	0.0375
## 233	24	3	0.0250
## 234	24	4	0.0500
## 235	24	5	0.0375
## 236	24	6	0.0375
## 237	24	7	0.0125
## 238	24	8	0.0500
## 239	24	9	0.0375
## 240	24	10	0.0375
## 241	25	1	0.0250
## 242	25	2	0.0375
## 243	25	3	0.0375
## 244	25	4	0.0375
## 245	25	5	0.0250
## 246	25	6	0.0375
## 247	25	7	0.0125
## 248	25	8	0.0625
## 249	25	9	0.0375
## 250	25	10	0.0500
## 251	26	1	0.0250
## 252	26	2	0.0625
## 253	26	3	0.0375
## 254	26	4	0.0375
## 255	26	5	0.0500
## 256	26	6	0.0500
## 257	26	7	0.0125
## 258	26	8	0.0375
## 259	26	9	0.0250
## 260	26	10	0.0250
## 261	27	1	0.0375
## 262	27	2	0.0500
## 263	27	3	0.0375
## 264	27	4	0.0375
## 265	27	5	0.0250
## 266	27	6	0.0375
## 267	27	7	0.0000
## 268	27	8	0.0750
## 269	27	9	0.0125
## 270	27	10	0.0500
## 271	28	1	0.0625
## 272	28	2	0.0500
## 273	28	3	0.0375
## 274	28	4	0.0500
## 275	28	5	0.0375
## 276	28	6	0.0375
## 277	28	7	0.0125
## 278	28	8	0.0750

## 279	28	9	0.0125
## 280	28	10	0.0625
## 281	29	1	0.0375
## 282	29	2	0.0500
## 283	29	3	0.0375
## 284	29	4	0.0375
## 285	29	5	0.0250
## 286	29	6	0.0500
## 287	29	7	0.0000
## 288	29	8	0.0750
## 289	29	9	0.0125
## 290	29	10	0.0375
## 291	30	1	0.0625
## 292	30	2	0.0625
## 293	30	3	0.0375
## 294	30	4	0.0375
## 295	30	5	0.0375
## 296	30	6	0.0500
## 297	30	7	0.0125
## 298	30	8	0.0875
## 299	30	9	0.0125
## 300	30	10	0.0375
## 301	31	1	0.0375
## 302	31	2	0.0625
## 303	31	3	0.0375
## 304	31	4	0.0500
## 305	31	5	0.0375
## 306	31	6	0.0500
## 307	31	7	0.0125
## 308	31	8	0.0750
## 309	31	9	0.0125
## 310	31	10	0.0375
## 311	32	1	0.0500
## 312	32	2	0.0625
## 313	32	3	0.0500
## 314	32	4	0.0375
## 315	32	5	0.0375
## 316	32	6	0.0500
## 317	32	7	0.0000
## 318	32	8	0.0875
## 319	32	9	0.0125
## 320	32	10	0.0500
## 321	33	1	0.0625
## 322	33	2	0.0625
## 323	33	3	0.0375
## 324	33	4	0.0375
## 325	33	5	0.0375
## 326	33	6	0.0500
## 327	33	7	0.0000
## 328	33	8	0.0750
## 329	33	9	0.0125
## 330	33	10	0.0250
## 331	34	1	0.0625
## 332	34	2	0.0625
## 333	34	3	0.0375
## 334	34	4	0.0250

## 335	34	5	0.0375
## 336	34	6	0.0500
## 337	34	7	0.0250
## 338	34	8	0.0750
## 339	34	9	0.0250
## 340	34	10	0.0375
## 341	35	1	0.0500
## 342	35	2	0.0750
## 343	35	3	0.0500
## 344	35	4	0.0375
## 345	35	5	0.0500
## 346	35	6	0.0500
## 347	35	7	0.0000
## 348	35	8	0.0625
## 349	35	9	0.0250
## 350	35	10	0.0375
## 351	36	1	0.0750
## 352	36	2	0.0750
## 353	36	3	0.0625
## 354	36	4	0.0500
## 355	36	5	0.0500
## 356	36	6	0.0500
## 357	36	7	0.0125
## 358	36	8	0.0500
## 359	36	9	0.0125
## 360	36	10	0.0375
## 361	37	1	0.0875
## 362	37	2	0.0750
## 363	37	3	0.0625
## 364	37	4	0.0500
## 365	37	5	0.0500
## 366	37	6	0.0500
## 367	37	7	0.0000
## 368	37	8	0.0625
## 369	37	9	0.0125
## 370	37	10	0.0500
## 371	38	1	0.0500
## 372	38	2	0.0750
## 373	38	3	0.0625
## 374	38	4	0.0375
## 375	38	5	0.0500
## 376	38	6	0.0500
## 377	38	7	0.0000
## 378	38	8	0.0625
## 379	38	9	0.0250
## 380	38	10	0.0500
## 381	39	1	0.0500
## 382	39	2	0.0875
## 383	39	3	0.0500
## 384	39	4	0.0500
## 385	39	5	0.0500
## 386	39	6	0.0500
## 387	39	7	0.0000
## 388	39	8	0.0625
## 389	39	9	0.0125
## 390	39	10	0.0375

## 391	40	1	0.0125
## 392	40	2	0.0625
## 393	40	3	0.0500
## 394	40	4	0.0500
## 395	40	5	0.0500
## 396	40	6	0.0500
## 397	40	7	0.0000
## 398	40	8	0.0625
## 399	40	9	0.0375
## 400	40	10	0.0500
## 401	41	1	0.0375
## 402	41	2	0.0625
## 403	41	3	0.0625
## 404	41	4	0.0250
## 405	41	5	0.0500
## 406	41	6	0.0625
## 407	41	7	0.0000
## 408	41	8	0.0625
## 409	41	9	0.0125
## 410	41	10	0.0375
## 411	42	1	0.0500
## 412	42	2	0.0875
## 413	42	3	0.0625
## 414	42	4	0.0125
## 415	42	5	0.0500
## 416	42	6	0.0625
## 417	42	7	0.0000
## 418	42	8	0.0750
## 419	42	9	0.0250
## 420	42	10	0.0500
## 421	43	1	0.0500
## 422	43	2	0.0750
## 423	43	3	0.0875
## 424	43	4	0.0250
## 425	43	5	0.0375
## 426	43	6	0.0625
## 427	43	7	0.0000
## 428	43	8	0.0625
## 429	43	9	0.0125
## 430	43	10	0.0500
## 431	44	1	0.0500
## 432	44	2	0.0750
## 433	44	3	0.0875
## 434	44	4	0.0375
## 435	44	5	0.0250
## 436	44	6	0.0625
## 437	44	7	0.0000
## 438	44	8	0.0625
## 439	44	9	0.0250
## 440	44	10	0.0625
## 441	45	1	0.0375
## 442	45	2	0.0750
## 443	45	3	0.0875
## 444	45	4	0.0250
## 445	45	5	0.0375
## 446	45	6	0.0625

## 447	45	7	0.0000
## 448	45	8	0.0750
## 449	45	9	0.0125
## 450	45	10	0.0625
## 451	46	1	0.0625
## 452	46	2	0.0875
## 453	46	3	0.0875
## 454	46	4	0.0250
## 455	46	5	0.0375
## 456	46	6	0.0625
## 457	46	7	0.0125
## 458	46	8	0.0750
## 459	46	9	0.0250
## 460	46	10	0.0750
## 461	47	1	0.0500
## 462	47	2	0.0875
## 463	47	3	0.0875
## 464	47	4	0.0250
## 465	47	5	0.0500
## 466	47	6	0.0625
## 467	47	7	0.0125
## 468	47	8	0.0750
## 469	47	9	0.0125
## 470	47	10	0.0625
## 471	48	1	0.0375
## 472	48	2	0.0875
## 473	48	3	0.0875
## 474	48	4	0.0250
## 475	48	5	0.0250
## 476	48	6	0.0625
## 477	48	7	0.0125
## 478	48	8	0.0875
## 479	48	9	0.0250
## 480	48	10	0.0750
## 481	49	1	0.0375
## 482	49	2	0.0875
## 483	49	3	0.0875
## 484	49	4	0.0375
## 485	49	5	0.0500
## 486	49	6	0.0625
## 487	49	7	0.0125
## 488	49	8	0.0875
## 489	49	9	0.0125
## 490	49	10	0.1000
## 491	50	1	0.0625
## 492	50	2	0.0750
## 493	50	3	0.0875
## 494	50	4	0.0375
## 495	50	5	0.0500
## 496	50	6	0.0625
## 497	50	7	0.0125
## 498	50	8	0.0875
## 499	50	9	0.0125
## 500	50	10	0.0875
## 501	51	1	0.0625
## 502	51	2	0.0875

## 503	51	3	0.0750
## 504	51	4	0.0250
## 505	51	5	0.0375
## 506	51	6	0.0625
## 507	51	7	0.0125
## 508	51	8	0.0875
## 509	51	9	0.0125
## 510	51	10	0.0750
## 511	52	1	0.0625
## 512	52	2	0.0875
## 513	52	3	0.0625
## 514	52	4	0.0500
## 515	52	5	0.0500
## 516	52	6	0.0500
## 517	52	7	0.0250
## 518	52	8	0.0875
## 519	52	9	0.0125
## 520	52	10	0.0750
## 521	53	1	0.0625
## 522	53	2	0.0875
## 523	53	3	0.0750
## 524	53	4	0.0250
## 525	53	5	0.0375
## 526	53	6	0.0500
## 527	53	7	0.0375
## 528	53	8	0.0875
## 529	53	9	0.0125
## 530	53	10	0.0750
## 531	54	1	0.0625
## 532	54	2	0.0875
## 533	54	3	0.0625
## 534	54	4	0.0375
## 535	54	5	0.0375
## 536	54	6	0.0500
## 537	54	7	0.0375
## 538	54	8	0.0875
## 539	54	9	0.0125
## 540	54	10	0.0750
## 541	55	1	0.0625
## 542	55	2	0.0875
## 543	55	3	0.1000
## 544	55	4	0.0375
## 545	55	5	0.0625
## 546	55	6	0.0750
## 547	55	7	0.0375
## 548	55	8	0.0750
## 549	55	9	0.0000
## 550	55	10	0.0750
## 551	56	1	0.0750
## 552	56	2	0.0875
## 553	56	3	0.1125
## 554	56	4	0.0375
## 555	56	5	0.0500
## 556	56	6	0.0750
## 557	56	7	0.0375
## 558	56	8	0.0750

## 559	56	9	0.0000
## 560	56	10	0.0750
## 561	57	1	0.0750
## 562	57	2	0.0875
## 563	57	3	0.0875
## 564	57	4	0.0250
## 565	57	5	0.0500
## 566	57	6	0.0875
## 567	57	7	0.0375
## 568	57	8	0.0875
## 569	57	9	0.0000
## 570	57	10	0.0750
## 571	58	1	0.0875
## 572	58	2	0.0875
## 573	58	3	0.0875
## 574	58	4	0.0375
## 575	58	5	0.0500
## 576	58	6	0.0750
## 577	58	7	0.0375
## 578	58	8	0.0875
## 579	58	9	0.0000
## 580	58	10	0.0750
## 581	59	1	0.0750
## 582	59	2	0.0750
## 583	59	3	0.1000
## 584	59	4	0.0375
## 585	59	5	0.0625
## 586	59	6	0.0750
## 587	59	7	0.0375
## 588	59	8	0.0875
## 589	59	9	0.0125
## 590	59	10	0.0750
## 591	60	1	0.0625
## 592	60	2	0.0875
## 593	60	3	0.0875
## 594	60	4	0.0375
## 595	60	5	0.0625
## 596	60	6	0.0875
## 597	60	7	0.0375
## 598	60	8	0.0875
## 599	60	9	0.0125
## 600	60	10	0.0750
## 601	61	1	0.1000
## 602	61	2	0.0875
## 603	61	3	0.0875
## 604	61	4	0.0375
## 605	61	5	0.0625
## 606	61	6	0.1000
## 607	61	7	0.0250
## 608	61	8	0.0875
## 609	61	9	0.0125
## 610	61	10	0.0750
## 611	62	1	0.0875
## 612	62	2	0.0750
## 613	62	3	0.1000
## 614	62	4	0.0500

## 615	62	5	0.0625
## 616	62	6	0.0750
## 617	62	7	0.0375
## 618	62	8	0.0750
## 619	62	9	0.0125
## 620	62	10	0.1000
## 621	63	1	0.0875
## 622	63	2	0.0750
## 623	63	3	0.1125
## 624	63	4	0.0250
## 625	63	5	0.0625
## 626	63	6	0.1000
## 627	63	7	0.0375
## 628	63	8	0.0875
## 629	63	9	0.0125
## 630	63	10	0.1000
## 631	64	1	0.0875
## 632	64	2	0.1000
## 633	64	3	0.1125
## 634	64	4	0.0500
## 635	64	5	0.0625
## 636	64	6	0.1000
## 637	64	7	0.0375
## 638	64	8	0.0875
## 639	64	9	0.0125
## 640	64	10	0.1000
## 641	65	1	0.0875
## 642	65	2	0.0875
## 643	65	3	0.1000
## 644	65	4	0.0500
## 645	65	5	0.0625
## 646	65	6	0.0875
## 647	65	7	0.0500
## 648	65	8	0.0875
## 649	65	9	0.0125
## 650	65	10	0.1125
## 651	66	1	0.0875
## 652	66	2	0.1125
## 653	66	3	0.1125
## 654	66	4	0.0250
## 655	66	5	0.0625
## 656	66	6	0.0875
## 657	66	7	0.0500
## 658	66	8	0.0750
## 659	66	9	0.0125
## 660	66	10	0.1125
## 661	67	1	0.0875
## 662	67	2	0.1125
## 663	67	3	0.1000
## 664	67	4	0.0375
## 665	67	5	0.0625
## 666	67	6	0.1000
## 667	67	7	0.0375
## 668	67	8	0.0875
## 669	67	9	0.0125
## 670	67	10	0.1125

## 671	68	1	0.0750
## 672	68	2	0.1125
## 673	68	3	0.0875
## 674	68	4	0.0375
## 675	68	5	0.0625
## 676	68	6	0.1000
## 677	68	7	0.0500
## 678	68	8	0.1000
## 679	68	9	0.0125
## 680	68	10	0.1250
## 681	69	1	0.0875
## 682	69	2	0.1000
## 683	69	3	0.0875
## 684	69	4	0.0375
## 685	69	5	0.0625
## 686	69	6	0.1000
## 687	69	7	0.0375
## 688	69	8	0.0875
## 689	69	9	0.0125
## 690	69	10	0.1250
## 691	70	1	0.0875
## 692	70	2	0.0875
## 693	70	3	0.1000
## 694	70	4	0.0375
## 695	70	5	0.0750
## 696	70	6	0.1000
## 697	70	7	0.0375
## 698	70	8	0.0875
## 699	70	9	0.0125
## 700	70	10	0.1250
## 701	71	1	0.0875
## 702	71	2	0.1125
## 703	71	3	0.0875
## 704	71	4	0.0375
## 705	71	5	0.0750
## 706	71	6	0.1000
## 707	71	7	0.0375
## 708	71	8	0.0750
## 709	71	9	0.0250
## 710	71	10	0.1250
## 711	72	1	0.0875
## 712	72	2	0.1125
## 713	72	3	0.0875
## 714	72	4	0.0500
## 715	72	5	0.0750
## 716	72	6	0.0875
## 717	72	7	0.0375
## 718	72	8	0.0750
## 719	72	9	0.0250
## 720	72	10	0.1125
## 721	73	1	0.1000
## 722	73	2	0.1250
## 723	73	3	0.0875
## 724	73	4	0.0500
## 725	73	5	0.0750
## 726	73	6	0.1125

## 727	73	7	0.0375
## 728	73	8	0.0875
## 729	73	9	0.0375
## 730	73	10	0.1375
## 731	74	1	0.1125
## 732	74	2	0.1125
## 733	74	3	0.1000
## 734	74	4	0.0500
## 735	74	5	0.0750
## 736	74	6	0.1000
## 737	74	7	0.0375
## 738	74	8	0.0875
## 739	74	9	0.0375
## 740	74	10	0.1125
## 741	75	1	0.1125
## 742	75	2	0.1125
## 743	75	3	0.1000
## 744	75	4	0.0500
## 745	75	5	0.0750
## 746	75	6	0.1000
## 747	75	7	0.0375
## 748	75	8	0.0875
## 749	75	9	0.0375
## 750	75	10	0.1250
## 751	76	1	0.1000
## 752	76	2	0.1250
## 753	76	3	0.1000
## 754	76	4	0.0500
## 755	76	5	0.0750
## 756	76	6	0.0875
## 757	76	7	0.0500
## 758	76	8	0.1000
## 759	76	9	0.0375
## 760	76	10	0.1125
## 761	77	1	0.1125
## 762	77	2	0.1125
## 763	77	3	0.1000
## 764	77	4	0.0500
## 765	77	5	0.0750
## 766	77	6	0.0875
## 767	77	7	0.0375
## 768	77	8	0.1000
## 769	77	9	0.0250
## 770	77	10	0.1000
## 771	78	1	0.1125
## 772	78	2	0.1250
## 773	78	3	0.1000
## 774	78	4	0.0500
## 775	78	5	0.0750
## 776	78	6	0.0875
## 777	78	7	0.0500
## 778	78	8	0.1000
## 779	78	9	0.0375
## 780	78	10	0.1125
## 781	79	1	0.1125
## 782	79	2	0.1250

## 783	79	3	0.1000
## 784	79	4	0.0500
## 785	79	5	0.0750
## 786	79	6	0.0875
## 787	79	7	0.0375
## 788	79	8	0.1125
## 789	79	9	0.0500
## 790	79	10	0.1250
## 791	80	1	0.1125
## 792	80	2	0.1250
## 793	80	3	0.1000
## 794	80	4	0.0375
## 795	80	5	0.0750
## 796	80	6	0.0875
## 797	80	7	0.0500
## 798	80	8	0.1125
## 799	80	9	0.0375
## 800	80	10	0.1000
## 801	81	1	0.1125
## 802	81	2	0.1250
## 803	81	3	0.0875
## 804	81	4	0.0500
## 805	81	5	0.0750
## 806	81	6	0.0875
## 807	81	7	0.0375
## 808	81	8	0.1125
## 809	81	9	0.0500
## 810	81	10	0.1375
## 811	82	1	0.1125
## 812	82	2	0.1250
## 813	82	3	0.1000
## 814	82	4	0.0500
## 815	82	5	0.0750
## 816	82	6	0.0875
## 817	82	7	0.0375
## 818	82	8	0.1125
## 819	82	9	0.0500
## 820	82	10	0.1375
## 821	83	1	0.1000
## 822	83	2	0.1500
## 823	83	3	0.1000
## 824	83	4	0.0625
## 825	83	5	0.0875
## 826	83	6	0.0875
## 827	83	7	0.0375
## 828	83	8	0.1125
## 829	83	9	0.0500
## 830	83	10	0.1125
## 831	84	1	0.1125
## 832	84	2	0.1375
## 833	84	3	0.1125
## 834	84	4	0.0750
## 835	84	5	0.0875
## 836	84	6	0.0875
## 837	84	7	0.0500
## 838	84	8	0.1125

## 839	84	9	0.0500
## 840	84	10	0.1500
## 841	85	1	0.1000
## 842	85	2	0.1375
## 843	85	3	0.1125
## 844	85	4	0.0625
## 845	85	5	0.0875
## 846	85	6	0.0750
## 847	85	7	0.0500
## 848	85	8	0.1250
## 849	85	9	0.0500
## 850	85	10	0.1250
## 851	86	1	0.1000
## 852	86	2	0.1375
## 853	86	3	0.1125
## 854	86	4	0.0500
## 855	86	5	0.0875
## 856	86	6	0.0875
## 857	86	7	0.0500
## 858	86	8	0.1125
## 859	86	9	0.0500
## 860	86	10	0.1250
## 861	87	1	0.1000
## 862	87	2	0.1375
## 863	87	3	0.1125
## 864	87	4	0.0750
## 865	87	5	0.0875
## 866	87	6	0.0750
## 867	87	7	0.0250
## 868	87	8	0.1125
## 869	87	9	0.0500
## 870	87	10	0.1125
## 871	88	1	0.1000
## 872	88	2	0.1375
## 873	88	3	0.1125
## 874	88	4	0.0750
## 875	88	5	0.0875
## 876	88	6	0.0750
## 877	88	7	0.0500
## 878	88	8	0.1250
## 879	88	9	0.0500
## 880	88	10	0.1250
## 881	89	1	0.1000
## 882	89	2	0.1375
## 883	89	3	0.1125
## 884	89	4	0.0625
## 885	89	5	0.1000
## 886	89	6	0.0625
## 887	89	7	0.0625
## 888	89	8	0.1250
## 889	89	9	0.0500
## 890	89	10	0.1250
## 891	90	1	0.1000
## 892	90	2	0.1375
## 893	90	3	0.1250
## 894	90	4	0.0500

## 895	90	5	0.1000
## 896	90	6	0.0625
## 897	90	7	0.0625
## 898	90	8	0.1125
## 899	90	9	0.0500
## 900	90	10	0.1250
## 901	91	1	0.1000
## 902	91	2	0.1375
## 903	91	3	0.1250
## 904	91	4	0.0500
## 905	91	5	0.0875
## 906	91	6	0.0625
## 907	91	7	0.0625
## 908	91	8	0.1125
## 909	91	9	0.0500
## 910	91	10	0.1250
## 911	92	1	0.1125
## 912	92	2	0.1375
## 913	92	3	0.1375
## 914	92	4	0.0375
## 915	92	5	0.0875
## 916	92	6	0.0625
## 917	92	7	0.0625
## 918	92	8	0.1125
## 919	92	9	0.0625
## 920	92	10	0.1625
## 921	93	1	0.1250
## 922	93	2	0.1375
## 923	93	3	0.1250
## 924	93	4	0.0500
## 925	93	5	0.0875
## 926	93	6	0.0500
## 927	93	7	0.0625
## 928	93	8	0.1125
## 929	93	9	0.0375
## 930	93	10	0.1250
## 931	94	1	0.1250
## 932	94	2	0.1250
## 933	94	3	0.1125
## 934	94	4	0.0750
## 935	94	5	0.0875
## 936	94	6	0.0625
## 937	94	7	0.0625
## 938	94	8	0.1125
## 939	94	9	0.0375
## 940	94	10	0.1375
## 941	95	1	0.1125
## 942	95	2	0.1250
## 943	95	3	0.1250
## 944	95	4	0.0625
## 945	95	5	0.0875
## 946	95	6	0.0500
## 947	95	7	0.0625
## 948	95	8	0.1000
## 949	95	9	0.0375
## 950	95	10	0.1375

## 951	96	1	0.1125
## 952	96	2	0.1375
## 953	96	3	0.1250
## 954	96	4	0.0625
## 955	96	5	0.0875
## 956	96	6	0.0500
## 957	96	7	0.0625
## 958	96	8	0.1000
## 959	96	9	0.0375
## 960	96	10	0.1375
## 961	97	1	0.1000
## 962	97	2	0.1375
## 963	97	3	0.1375
## 964	97	4	0.0625
## 965	97	5	0.0875
## 966	97	6	0.0375
## 967	97	7	0.0625
## 968	97	8	0.0875
## 969	97	9	0.0375
## 970	97	10	0.1500
## 971	98	1	0.1000
## 972	98	2	0.1375
## 973	98	3	0.1500
## 974	98	4	0.0625
## 975	98	5	0.0875
## 976	98	6	0.0375
## 977	98	7	0.0875
## 978	98	8	0.0750
## 979	98	9	0.0375
## 980	98	10	0.1500
## 981	99	1	0.0875
## 982	99	2	0.1375
## 983	99	3	0.1375
## 984	99	4	0.0625
## 985	99	5	0.1000
## 986	99	6	0.0375
## 987	99	7	0.0750
## 988	99	8	0.0875
## 989	99	9	0.0375
## 990	99	10	0.1375
## 991	100	1	0.1000
## 992	100	2	0.1250
## 993	100	3	0.1375
## 994	100	4	0.0625
## 995	100	5	0.0875
## 996	100	6	0.0375
## 997	100	7	0.0750
## 998	100	8	0.0875
## 999	100	9	0.0500
## 1000	100	10	0.1375

```
summary_table_k <- data.frame(sum_k=numeric(0), sum_error =numeric(0), count_error=numeric(0), mean_error=numeric(0))

a <- 0
b <- 0
c <- 0

for (k in range){
  for (j in 1:nrow(results)){
    ifelse(results[j,1] == k, a <- a + results[j,3], a <- a)
    ifelse(results[j,1] == k, b <- b + 1, b <- b)
  }
  c = a / b
  row <- data.frame(sum_k = k, sum_error = a, count_error = b, mean_error = c)
  summary_table_k <- rbind(summary_table_k, row)
  a = 0
  b = 0
  c = 0
}
summary_table_k
```

##	sum_k	sum_error	count_error	mean_error
## 1	1	0.2125	10	0.02125
## 2	2	0.3625	10	0.03625
## 3	3	0.3000	10	0.03000
## 4	4	0.3500	10	0.03500
## 5	5	0.2875	10	0.02875
## 6	6	0.3250	10	0.03250
## 7	7	0.3500	10	0.03500
## 8	8	0.4125	10	0.04125
## 9	9	0.4250	10	0.04250
## 10	10	0.4375	10	0.04375
## 11	11	0.3625	10	0.03625
## 12	12	0.4250	10	0.04250
## 13	13	0.3375	10	0.03375
## 14	14	0.3750	10	0.03750
## 15	15	0.2750	10	0.02750
## 16	16	0.2750	10	0.02750
## 17	17	0.3000	10	0.03000
## 18	18	0.2875	10	0.02875
## 19	19	0.3125	10	0.03125
## 20	20	0.2875	10	0.02875
## 21	21	0.3250	10	0.03250
## 22	22	0.3750	10	0.03750
## 23	23	0.3250	10	0.03250
## 24	24	0.3625	10	0.03625
## 25	25	0.3625	10	0.03625
## 26	26	0.3625	10	0.03625
## 27	27	0.3625	10	0.03625
## 28	28	0.4375	10	0.04375
## 29	29	0.3625	10	0.03625
## 30	30	0.4375	10	0.04375
## 31	31	0.4125	10	0.04125
## 32	32	0.4375	10	0.04375
## 33	33	0.4000	10	0.04000
## 34	34	0.4375	10	0.04375
## 35	35	0.4375	10	0.04375
## 36	36	0.4750	10	0.04750
## 37	37	0.5000	10	0.05000
## 38	38	0.4625	10	0.04625
## 39	39	0.4500	10	0.04500
## 40	40	0.4250	10	0.04250
## 41	41	0.4125	10	0.04125
## 42	42	0.4750	10	0.04750
## 43	43	0.4625	10	0.04625
## 44	44	0.4875	10	0.04875
## 45	45	0.4750	10	0.04750
## 46	46	0.5500	10	0.05500
## 47	47	0.5250	10	0.05250
## 48	48	0.5250	10	0.05250
## 49	49	0.5750	10	0.05750
## 50	50	0.5750	10	0.05750
## 51	51	0.5375	10	0.05375
## 52	52	0.5625	10	0.05625
## 53	53	0.5500	10	0.05500
## 54	54	0.5500	10	0.05500

## 55	55	0.6125	10	0.06125
## 56	56	0.6250	10	0.06250
## 57	57	0.6125	10	0.06125
## 58	58	0.6250	10	0.06250
## 59	59	0.6375	10	0.06375
## 60	60	0.6375	10	0.06375
## 61	61	0.6750	10	0.06750
## 62	62	0.6750	10	0.06750
## 63	63	0.7000	10	0.07000
## 64	64	0.7500	10	0.07500
## 65	65	0.7375	10	0.07375
## 66	66	0.7375	10	0.07375
## 67	67	0.7500	10	0.07500
## 68	68	0.7625	10	0.07625
## 69	69	0.7375	10	0.07375
## 70	70	0.7500	10	0.07500
## 71	71	0.7625	10	0.07625
## 72	72	0.7500	10	0.07500
## 73	73	0.8500	10	0.08500
## 74	74	0.8250	10	0.08250
## 75	75	0.8375	10	0.08375
## 76	76	0.8375	10	0.08375
## 77	77	0.8000	10	0.08000
## 78	78	0.8500	10	0.08500
## 79	79	0.8750	10	0.08750
## 80	80	0.8375	10	0.08375
## 81	81	0.8750	10	0.08750
## 82	82	0.8875	10	0.08875
## 83	83	0.9000	10	0.09000
## 84	84	0.9750	10	0.09750
## 85	85	0.9250	10	0.09250
## 86	86	0.9125	10	0.09125
## 87	87	0.8875	10	0.08875
## 88	88	0.9375	10	0.09375
## 89	89	0.9375	10	0.09375
## 90	90	0.9250	10	0.09250
## 91	91	0.9125	10	0.09125
## 92	92	0.9750	10	0.09750
## 93	93	0.9125	10	0.09125
## 94	94	0.9375	10	0.09375
## 95	95	0.9000	10	0.09000
## 96	96	0.9125	10	0.09125
## 97	97	0.9000	10	0.09000
## 98	98	0.9250	10	0.09250
## 99	99	0.9000	10	0.09000
## 100	100	0.9000	10	0.09000

remove $k = 1$ as this is unhelpful. Then find the minimum error.

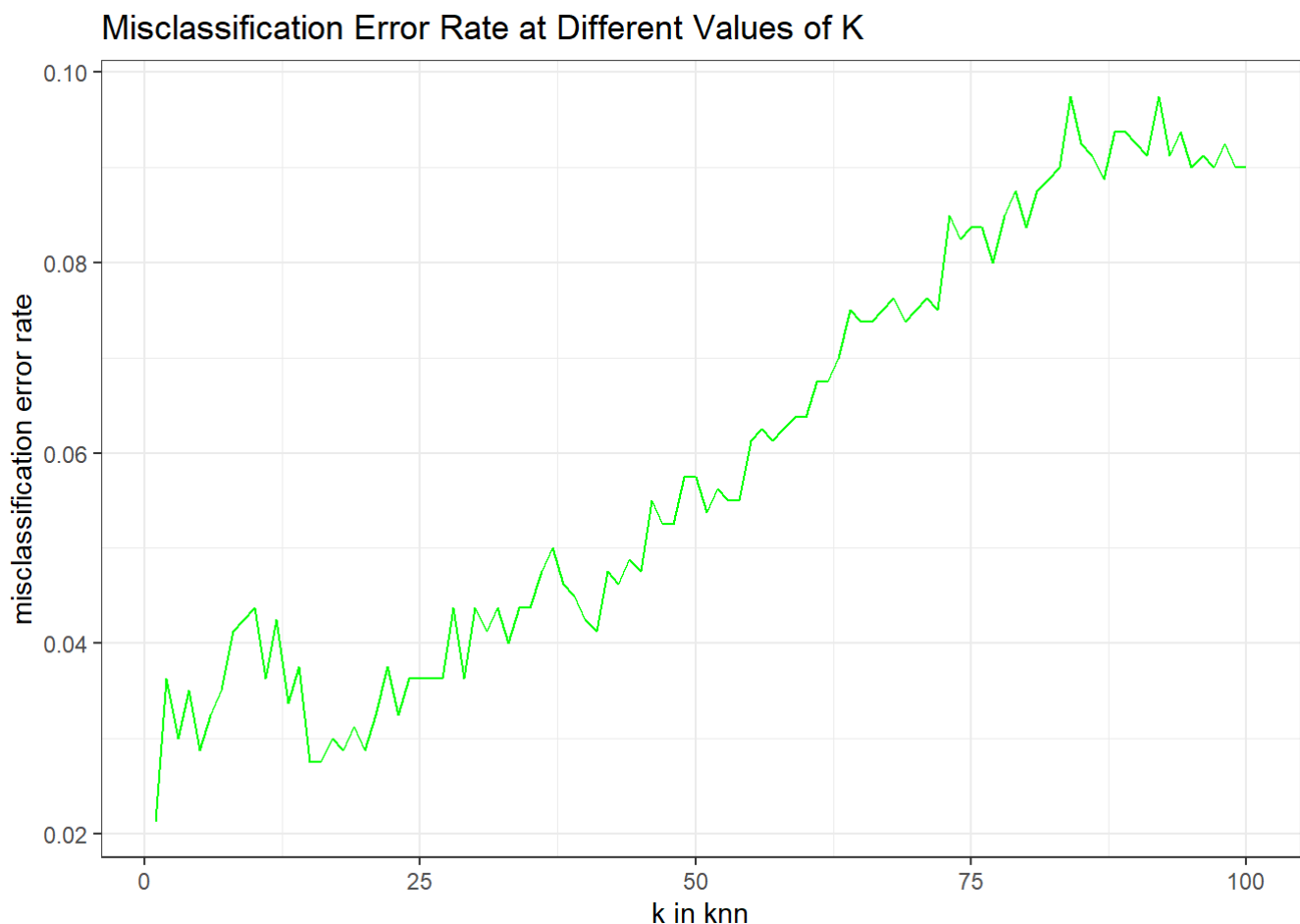
```
summary_table_k_min <- summary_table_k[-1,]
which(summary_table_k_min == min(summary_table_k_min[,4]), arr.ind=TRUE)
```

```
##      row col
## 16   15   4
```

Ignoring $k=1$, minimum cross-validation error is where $k = 15$. So our best model is KNN where $k = 15$.

2b. Plot misclassification error rate at different values of k .

```
library(ggplot2)
ggplot(summary_table_k, aes(x = sum_k)) +
  geom_line(aes(y = mean_error), color = "green") + labs(x = "k in knn", y = "misclassification
error rate", title = "Misclassification Error Rate at Different Values of K") + theme_bw()
```



2c. Plot the decision boundary for your classifier using the function at the top code block, `plot_decision_boundary()`. Make sure you load this function into memory before trying to use it.

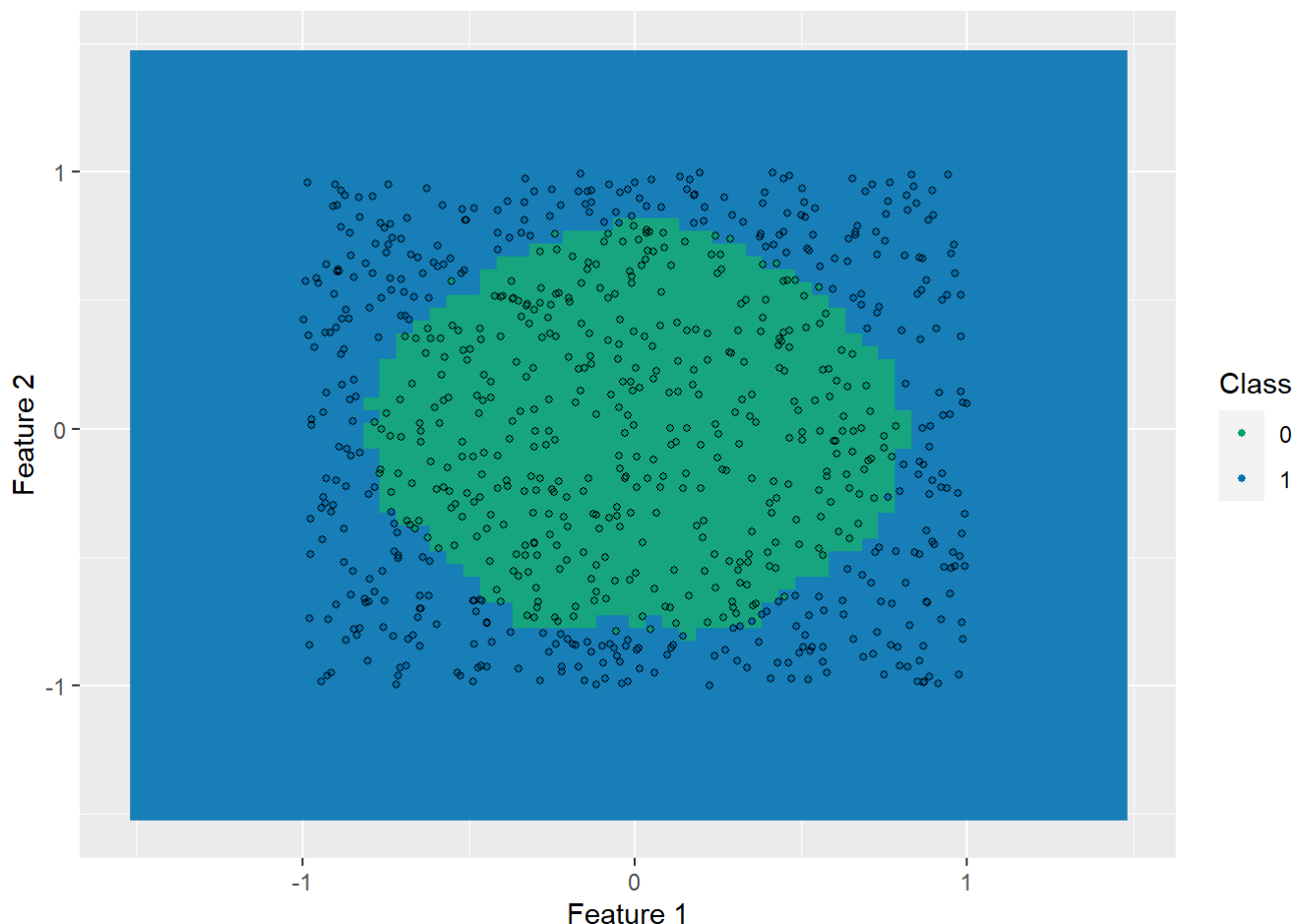
From 2a, the best model is where $k = 15$.

```

library(ggplot2)
plot_decision_boundary <- function(tr.x, tr.y, pred_grid, grid)
{
  cl <- ifelse(tr.Y == 1, "1", "0")
  dataf <- data.frame(grid, prob = as.numeric(pred_grid), class = ifelse(pred_grid==2, "1",
"0"))
  col <- c("#009E73", "#0072B2")
  plot <- ggplot(dataf) + geom_raster(aes(x=X.1, y=X.2, fill=prob), alpha=.9, data=dataf) +
  geom_point(aes(x=X.1, y=X.2, color=class), size=1,
data=data.frame(X.1=tr.X[,1], X.2=tr.X[,2], class=cl)) +
  geom_point(aes(x=X.1, y=X.2), size=1, shape=1,
data=data.frame(X.1=tr.X[,1], X.2=tr.X[,2], class=cl)) +
  scale_colour_manual(values=col, name="Class") +
  scale_fill_gradientn(colors=col[c(1,2)], limits=c(0,1), guide = FALSE) + xlab("Feature 1") +
  ylab("Feature 2")
  return(plot)
}

tr.X <- train[,1:2]
tr.Y <- train[,3]
te.X <- test[,1:2]
te.Y <- test[,3]
grid <- expand.grid(X.1=seq(min(tr.X[,1]-0.5), max(tr.X[,1]+0.5), by=0.05), X.2=seq(min(tr.X
[,2]-0.5), max(tr.X[,2]+0.5), by=0.05))
y_pred15 <- knn(tr.X, te.X, tr.Y, k =15, prob = TRUE)
pred_grid <- as.numeric(knn(tr.X, grid, tr.Y, k=15, prob=TRUE)) - 1
plot_decision_boundary(tr.X, tr.Y, pred_grid, grid)

```



3. Performance measures for classification

Recall the `Caravan` data from the week 2 lab (part of the `ISLR` package). Train a KNN model with $k=2$ using all the predictors in the dataset and the outcome `Purchase`. Create a confusion matrix with the test set predictions and the actual values of `Purchase`. Using the values of the confusion matrix, calculate precision, recall, and F1. (Note that `Yes` is the positive class and the confusion matrix may be differently oriented than the one presented in class.)

```
library(ISLR)
names(Caravan)
```

```
## [1] "MOSTYPE" "MAANTHUI" "MGEMOMV" "MGEMLEEF" "MOSHOOFD" "MGODRK"
## [7] "MGODPR" "MGODOV" "MGODGE" "MRELGE" "MRELSA" "MRELOV"
## [13] "MFALLEEN" "MFGEKIND" "MFEWKIND" "MOPLHOOG" "MOPLMIDD" "MOPLLAAG"
## [19] "MBERHOOG" "MBERZELF" "MBERBOER" "MBERMIDD" "MBERARBG" "MBERARBO"
## [25] "MSKA" "MSKB1" "MSKB2" "MSKC" "MSKD" "MHHUUR"
## [31] "MHKOOP" "MAUT1" "MAUT2" "MAUT0" "MZFONDS" "MZPART"
## [37] "MINKM30" "MINK3045" "MINK4575" "MINK7512" "MINK123M" "MINKGEM"
## [43] "MKOOPKLA" "PWAPART" "PWABEDR" "PWALAND" "PPERSAUT" "PBESAUT"
## [49] "PMOTSCO" "PVRAAUT" "PAANHANG" "PTRACTOR" "PWERKT" "PBROM"
## [55] "PLEVEN" "PPERSONG" "PGEZONG" "PWAOREG" "PBRAND" "PZEILPL"
## [61] "PPLEZIER" "PFIETS" "PINBOED" "PBYSTAND" "AWAPART" "AWABEDR"
## [67] "AWALAND" "APERSAUT" "ABESAUT" "AMOTSCO" "AVRAAUT" "AAANHANG"
## [73] "ATRACTOR" "AWERKT" "ABROM" "ALEVEN" "APERSONG" "AGEZONG"
## [79] "AWAOREG" "ABRAND" "AZEILPL" "APLEZIER" "AFIETS" "AINBOED"
## [85] "ABYSTAND" "Purchase"
```

```
X <- Caravan[,1:85]
Y <- Caravan[,86]
X <- scale(X)
n_test <- floor(nrow(Caravan) * 0.2)
idx <- sample(1:nrow(Caravan), n_test)
tr.X <- X[-idx,]
te.X <- X[idx,]
tr.Y <- Y[-idx]
te.Y <- Y[idx]
set.seed(1)
pred.Y <- knn(tr.X, te.X, tr.Y, k = 2)
matrix <- table(te.Y, pred.Y)
matrix
```

```
##      pred.Y
## te.Y    No  Yes
##   No 1027   70
##   Yes  59    8
```

```
TP <- matrix['Yes', 'Yes']
FP <- matrix['No', 'Yes']
TN <- matrix['No', 'No']
FN <- matrix['Yes', 'No']
Precision = TP / (TP + FP)
Precision
```



```
## [1] 0.1025641
```

```
Recall = TP/ (TP + FN)  
Recall
```

```
## [1] 0.119403
```

```
F1 = 2*((Precision*Recall)/(Precision+Recall))  
F1
```

```
## [1] 0.1103448
```