

Baseball Assignment

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Problem 1 - nHits

Subgroups

```
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
```

```
infield <- filter(dat, Position == '1B' | Position == '2B' | Position == 'SS' | Position  
== '3B')  
outfield <- filter(dat, Position == 'CF' | Position == 'RF' | Position == 'LF' | Positio  
n == 'OF')  
catcher <- filter(dat, Position == 'C')  
CrHits2 <- dat$CrHits*dat$CrHits
```

Plot League by Division

```
library("arsenal")  
tab.lbyd <- table(dat$League, dat$Division)  
lbyd <- freqlist(tab.lbyd)  
summary(lbyd)
```

```
##
##
## |Var1      |Var2 | Freq| Cumulative Freq| Percent| Cumulative Percent|
## |:-----|:----|----:|-----:|-----:|-----:|
## |American |East | 85|          85| 26.40|          26.40|
## |          |West | 90|         175| 27.95|          54.35|
## |National |East | 72|         247| 22.36|          76.71|
## |          |West | 75|         322| 23.29|         100.00|
```

Plot Division for American Leagues

```
library("arsenal")
library("dplyr")
data <- filter(dat, League == 'American')
tab.adiv <- table(data$Division)
adiv <- freqlist(tab.adiv)
summary(adiv)
```

```
##
##
## |Var1 | Freq| Cumulative Freq| Percent| Cumulative Percent|
## |:----|----:|-----:|-----:|-----:|
## |East | 85|          85| 48.57|          48.57|
## |West | 90|         175| 51.43|         100.00|
```

Arrange by Division

```
data <- filter(dat, League == 'American')
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,
nError, nHits, nHome, nRuns))
print(data[order(data$Division),])
```

##	Salary	Team	Division	YrMajor	logSalary	nAtBat	nBB	nError	nHits
## 1	NA	Cleveland	East	1	NA	293	14	20	66
## 5	1100.000	Cleveland	East	13	7.003065	401	65	0	92
## 6	517.143	Detroit	East	10	6.248319	574	59	22	159
## 7	700.000	Baltimore	East	6	6.551080	239	22	6	60
## 13	776.667	Boston	East	18	6.655012	629	40	14	168
## 14	765.000	Cleveland	East	6	6.639876	587	70	3	163
## 17	612.500	Cleveland	East	5	6.417549	583	56	25	168
## 19	NA	New York	East	4	NA	161	17	12	36
## 20	NA	Milwaukee	East	16	NA	346	30	0	98
## 21	67.500	Milwaukee	East	2	4.212128	181	33	5	41
## 22	180.000	Milwaukee	East	4	5.192957	217	9	1	46
## 23	NA	New York	East	11	NA	194	30	2	40
## 24	305.000	Cleveland	East	6	5.720312	254	22	4	68
## 25	247.500	Cleveland	East	5	5.511411	205	9	4	57
## 26	NA	Milwaukee	East	16	NA	542	41	9	140
## 28	NA	Toronto	East	15	NA	336	52	0	84
## 30	675.000	Detroit	East	12	6.514713	403	39	5	101
## 31	NA	Milwaukee	East	14	NA	235	21	4	61
## 32	1350.000	Baltimore	East	6	7.207860	627	70	13	177
## 33	90.000	Cleveland	East	1	4.499810	416	16	10	113
## 36	950.000	Boston	East	17	6.856462	585	62	0	139
## 38	105.000	Detroit	East	4	4.653960	521	45	23	142
## 39	NA	Detroit	East	12	NA	419	44	1	113
## 41	535.000	Detroit	East	18	6.282267	507	91	2	122
## 42	933.333	Boston	East	15	6.838762	529	97	5	137
## 43	850.000	Toronto	East	9	6.745236	424	13	8	119
## 47	1975.000	New York	East	5	7.588324	677	53	6	238
## 50	110.000	New York	East	2	4.700480	280	47	2	82
## 54	70.000	Milwaukee	East	1	4.248495	317	32	26	78
## 56	1861.460	New York	East	14	7.529116	565	77	5	148
## 57	2460.000	Baltimore	East	10	7.807917	495	78	13	151
## 58	NA	Milwaukee	East	2	NA	524	54	20	132
## 59	375.000	Boston	East	8	5.926926	233	18	10	49
## 60	NA	Toronto	East	10	NA	395	35	7	106
## 61	NA	Baltimore	East	13	NA	397	53	4	114
## 62	NA	Baltimore	East	6	NA	210	15	15	37
## 64	1175.000	Toronto	East	5	7.069023	641	41	10	198
## 65	70.000	Milwaukee	East	1	4.248495	215	11	12	51
## 70	362.500	Toronto	East	8	5.893024	327	20	12	85
## 78	1237.500	Toronto	East	6	7.120848	589	69	3	170
## 79	430.000	Baltimore	East	15	6.063785	343	40	13	103
## 80	NA	Baltimore	East	5	NA	284	25	5	69
## 83	250.000	Cleveland	East	4	5.521461	663	32	6	200
## 85	275.000	Baltimore	East	14	5.616771	160	22	0	39
## 86	775.000	Cleveland	East	5	6.652863	599	32	18	183
## 87	850.000	Milwaukee	East	11	6.745236	497	26	10	136
## 88	365.000	Detroit	East	15	5.899897	210	28	0	70
## 96	2412.500	Boston	East	13	7.788419	618	62	8	200
## 97	300.000	Baltimore	East	6	5.703782	404	18	5	92
## 100	NA	Baltimore	East	2	NA	212	18	5	54
## 102	1300.000	Detroit	East	8	7.170120	441	68	2	118

## 103	1000.000	New York	East	14	6.907755	490	35	3	150
## 107	225.000	Detroit	East	12	5.416100	283	27	2	70
## 108	525.000	Baltimore	East	15	6.263398	491	37	2	141
## 109	787.500	Toronto	East	7	6.668863	589	64	6	149
## 110	800.000	Detroit	East	10	6.684612	327	38	6	84
## 112	145.000	Baltimore	East	3	4.976734	338	21	0	92
## 114	420.000	Detroit	East	10	6.040255	584	63	11	157
## 115	575.000	Boston	East	5	6.354370	625	65	14	179
## 117	700.000	New York	East	13	6.551080	490	49	0	148
## 118	550.000	Cleveland	East	6	6.309918	442	33	7	131
## 121	175.000	New York	East	3	5.164786	504	54	19	120
## 124	350.000	Baltimore	East	5	5.857933	369	49	6	93
## 129	1260.000	Milwaukee	East	9	7.138867	437	40	15	123
## 131	190.000	Detroit	East	5	5.247024	236	21	4	56
## 132	580.000	Cleveland	East	6	6.363028	473	29	9	154
## 135	250.000	Milwaukee	East	12	5.521461	216	15	4	56
## 136	215.000	Milwaukee	East	3	5.370638	466	72	8	108
## 137	400.000	Baltimore	East	18	5.991465	327	45	7	68
## 138	NA	Boston	East	7	NA	462	37	6	119
## 139	560.000	New York	East	9	6.327937	341	46	4	110
## 140	1670.000	New York	East	8	7.420579	608	89	6	160
## 145	250.000	Toronto	East	6	5.521461	246	13	1	76
## 146	400.000	Milwaukee	East	12	5.991465	205	17	2	52
## 147	450.000	Toronto	East	10	6.109248	348	43	6	90
## 148	70.000	Boston	East	1	4.248495	312	24	15	68
## 152	1000.000	Milwaukee	East	13	6.907755	522	62	1	163
## 159	NA	Boston	East	11	NA	425	24	8	112
## 160	530.000	Cleveland	East	8	6.272877	562	53	17	169
## 161	341.667	Detroit	East	8	5.833837	281	20	7	76
## 163	350.000	Toronto	East	4	5.857933	687	27	13	213
## 167	NA	Baltimore	East	5	NA	181	17	9	46
## 170	1600.000	Boston	East	5	7.377759	580	105	19	207
## 172	875.000	New York	East	12	6.774224	492	94	20	136
## 174	960.000	Toronto	East	8	6.866933	573	78	12	144
## 2	480.000	Seattle	West	3	6.173786	479	76	14	130
## 3	750.000	Oakland	West	11	6.620073	594	35	25	169
## 4	100.000	Kansas City	West	3	4.605170	298	7	9	73
## 8	NA	Minneapolis	West	3	NA	183	11	0	39
## 9	175.000	Kansas City	West	5	5.164786	190	15	16	46
## 10	NA	Oakland	West	12	NA	407	65	9	104
## 11	115.000	Chicago	West	1	4.744932	426	62	2	109
## 12	NA	California	West	15	NA	442	43	11	98
## 15	900.000	California	West	14	6.802395	513	90	3	137
## 16	NA	California	West	17	NA	313	39	7	84
## 18	300.000	Seattle	West	7	5.703782	204	12	5	49
## 27	875.000	Chicago	West	17	6.774224	457	22	4	101
## 29	1200.000	Oakland	West	9	7.090077	591	39	4	168
## 34	230.000	Texas	West	4	5.438079	236	11	13	56
## 35	NA	Oakland	West	19	NA	242	27	0	58
## 37	75.000	Chicago	West	3	4.317488	199	21	5	53
## 40	850.000	California	West	14	6.745236	512	52	12	131
## 44	325.000	Seattle	West	6	5.783825	388	39	4	103

## 45	275.000	Oakland	West	4	5.616771	339	23	9	96
## 46	NA	Oakland	West	16	NA	561	33	8	118
## 48	NA	Kansas City	West	5	NA	227	12	2	46
## 49	600.000	Oakland	West	9	6.396930	329	56	2	83
## 51	260.000	Texas	West	16	5.560682	155	22	1	41
## 52	475.000	California	West	4	6.163315	458	48	18	114
## 53	431.500	Texas	West	5	6.067268	314	16	4	83
## 55	145.000	Seattle	West	3	4.976734	511	61	8	138
## 63	750.000	Kansas City	West	14	6.620073	566	43	10	154
## 66	1500.000	Kansas City	West	14	7.313220	441	80	16	128
## 67	900.000	Minneapolis	West	6	6.802395	596	52	21	171
## 68	155.000	Minneapolis	West	4	5.043425	472	30	26	118
## 69	700.000	California	West	16	6.551080	283	26	5	77
## 71	400.000	California	West	5	5.991465	539	69	7	139
## 72	NA	Seattle	West	13	NA	315	58	0	59
## 73	500.000	Chicago	West	5	6.214608	282	29	5	78
## 74	600.000	Texas	West	8	6.396930	380	31	1	120
## 75	950.000	Chicago	West	7	6.856462	570	38	5	169
## 76	325.000	Kansas City	West	18	5.783825	278	18	0	70
## 77	87.500	Seattle	West	4	4.471639	445	29	16	99
## 81	100.000	Chicago	West	2	4.605170	438	71	9	103
## 82	165.000	Oakland	West	2	5.105945	600	65	14	144
## 84	NA	Chicago	West	10	NA	209	42	5	45
## 89	NA	Chicago	West	11	NA	225	26	0	61
## 90	95.000	California	West	2	4.553877	151	19	2	41
## 91	80.000	Seattle	West	5	4.382027	399	34	3	102
## 92	NA	Kansas City	West	15	NA	336	23	0	93
## 93	200.000	Seattle	West	3	5.298317	616	32	15	163
## 94	NA	Kansas City	West	12	NA	219	17	4	47
## 95	75.000	Minneapolis	West	3	4.317488	165	16	2	39
## 98	110.000	Chicago	West	4	4.700480	315	16	3	73
## 99	825.000	Kansas City	West	13	6.715383	429	57	4	91
## 101	NA	Oakland	West	3	NA	161	22	2	43
## 104	1310.000	Minneapolis	West	6	7.177782	550	71	10	147
## 105	300.000	Seattle	West	7	5.703782	344	88	0	85
## 106	365.000	Minneapolis	West	3	5.899897	680	34	6	223
## 111	587.500	Texas	West	13	6.375876	464	52	0	128
## 113	NA	Kansas City	West	9	NA	508	46	9	146
## 116	780.000	Oakland	West	7	6.659294	489	34	9	131
## 119	NA	Minneapolis	West	8	NA	317	19	4	88
## 120	68.000	Kansas City	West	1	4.219508	209	12	3	54
## 122	137.000	Minneapolis	West	3	4.919981	258	18	8	60
## 123	120.000	Oakland	West	3	4.787492	211	39	8	43
## 125	175.000	Chicago	West	2	5.164786	547	12	22	137
## 126	200.000	Texas	West	2	5.298317	572	65	3	152
## 127	750.000	Seattle	West	4	6.620073	526	77	1	163
## 128	172.000	Texas	West	1	5.147494	540	55	14	135
## 130	NA	Texas	West	5	NA	551	87	11	160
## 133	450.000	California	West	12	6.109248	271	33	3	77
## 134	300.000	Minneapolis	West	5	5.703782	357	39	4	96
## 141	487.500	California	West	20	6.189290	419	92	0	101
## 142	NA	California	West	11	NA	393	64	4	90

## 143	425.000	Chicago	West	5	6.052089	376	35	0	82
## 144	NA	Kansas City	West	7	NA	307	29	2	80
## 149	97.500	Texas	West	1	4.579852	382	22	6	101
## 150	740.000	Minneapolis	West	12	6.606650	459	68	0	113
## 151	341.667	California	West	10	5.833837	288	16	7	63
## 153	100.000	Kansas City	West	6	4.605170	512	43	18	117
## 154	90.000	Seattle	West	3	4.499810	220	13	3	66
## 155	135.000	Texas	West	2	4.905275	461	35	11	112
## 156	475.000	Texas	West	6	6.163315	530	47	15	159
## 157	105.000	Minneapolis	West	2	4.653960	453	52	6	103
## 158	350.000	Seattle	West	4	5.857933	528	51	17	122
## 162	940.000	Minneapolis	West	6	6.845880	593	53	6	152
## 164	NA	Texas	West	17	NA	289	44	7	63
## 165	185.000	Chicago	West	4	5.220356	520	21	11	120
## 166	245.000	Minneapolis	West	6	5.501258	193	24	5	47
## 168	235.000	Texas	West	17	5.459586	213	3	4	61
## 169	425.000	Oakland	West	5	6.052089	441	76	11	113
## 171	165.000	California	West	1	5.105945	593	57	15	172
## 173	385.000	Chicago	West	6	5.953243	475	52	7	126
## 175	1000.000	Kansas City	West	11	6.907755	631	31	3	170
##	nHome	nRuns							
## 1	1	30							
## 5	17	49							
## 6	21	107							
## 7	0	30							
## 13	18	73							
## 14	4	92							
## 17	17	83							
## 19	0	19							
## 20	5	31							
## 21	1	15							
## 22	7	32							
## 23	7	19							
## 24	2	28							
## 25	8	34							
## 26	12	46							
## 28	15	48							
## 30	12	45							
## 31	3	24							
## 32	25	98							
## 33	24	58							
## 36	31	93							
## 38	20	67							
## 39	1	44							
## 41	29	78							
## 42	26	86							
## 43	6	57							
## 47	31	117							
## 50	16	44							
## 54	7	35							
## 56	24	90							
## 57	17	61							

## 58	9	69
## 59	2	41
## 60	16	48
## 61	23	67
## 62	8	15
## 64	31	101
## 65	4	19
## 70	3	30
## 78	40	107
## 79	6	48
## 80	1	33
## 83	29	108
## 85	8	18
## 86	10	80
## 87	7	58
## 88	13	32
## 96	20	98
## 97	11	54
## 100	13	28
## 102	28	84
## 103	21	69
## 107	8	33
## 108	11	77
## 109	21	89
## 110	22	53
## 112	18	42
## 114	20	95
## 115	4	94
## 117	14	64
## 118	18	68
## 121	28	71
## 124	9	43
## 129	9	62
## 131	6	41
## 132	6	61
## 135	4	22
## 136	33	75
## 137	13	42
## 138	16	49
## 139	9	45
## 140	28	130
## 145	5	35
## 146	8	31
## 147	11	50
## 148	2	32
## 152	9	82
## 159	11	40
## 160	17	88
## 161	3	42
## 163	10	91
## 167	1	19
## 170	8	107

## 172	5	76
## 174	9	85
## 2	18	66
## 3	4	74
## 4	0	24
## 8	3	20
## 9	2	24
## 10	6	57
## 11	3	55
## 12	7	48
## 15	20	90
## 16	9	42
## 18	6	23
## 27	14	42
## 29	19	80
## 34	0	27
## 35	4	25
## 37	5	29
## 40	26	69
## 44	15	59
## 45	4	37
## 46	35	70
## 48	7	23
## 49	9	50
## 51	12	21
## 52	13	67
## 53	13	39
## 55	25	76
## 63	22	76
## 66	16	70
## 67	34	91
## 68	12	63
## 69	14	45
## 71	5	93
## 72	16	45
## 73	13	37
## 74	5	54
## 75	21	72
## 76	7	22
## 77	1	46
## 81	2	65
## 82	33	85
## 84	0	38
## 89	5	32
## 90	4	26
## 91	3	56
## 92	9	35
## 93	27	83
## 94	8	24
## 95	2	13
## 98	5	23
## 99	12	41


```
## 101      4      17
## 104     29     85
## 105     24     69
## 106     31    119
## 111     28     67
## 113      8     80
## 116     19     77
## 119      3     40
## 120      3     25
## 122      8     28
## 123     10     26
## 125      2     58
## 126     18    105
## 127     12     88
## 128     30     82
## 130     23     86
## 133      5     35
## 134      7     50
## 141     18     65
## 142     17     73
## 143     21     42
## 144      1     42
## 149     16     50
## 150     20     59
## 151      3     25
## 153     29     54
## 154      5     20
## 155     18     54
## 156      3     82
## 157      8     53
## 158      1     67
## 162     23     69
## 164      7     36
## 165     17     53
## 166     10     21
## 168      4     17
## 169      5     76
## 171     22     82
## 173      3     61
## 175      9     77
```

```
subdata <-
  data %>%
  group_by(Division) %>%
  summarize(c(total_count = n()), (mean_hits = mean(nHits)), (sd_hits = sd(nHits)), (se_
hits = sd(nHits)/sqrt(n())), (min_hits = min(nHits)), (max_hits = max(nHits)))
print(subdata)
```

```
## # A tibble: 2 × 7
##   Division `c(total_count = n())` (mean_hits = mean(nHits)...1 (sd_hits = sd(nHits))...2
##   <chr>           <int>           <dbl>           <dbl>
## 1 East             85             113.             48.8
## 2 West             90             102.             41.2
## # i abbreviated names: 1`(mean_hits = mean(nHits))`, 2`(sd_hits = sd(nHits))`
## # i 3 more variables: `(se_hits = sd(nHits)/sqrt(n()))` <dbl>,
## #   `(min_hits = min(nHits))` <int>, `(max_hits = max(nHits))` <int>
```

Assuming Normal Data

Pooled T-test

```
data <- filter(dat, League == 'American')
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,
nError, nHits, nHome, nRuns))
t.test_res <- t.test(data$nHits ~ data$Division, var.equal = TRUE)
print(t.test_res)
```

```
##
## Two Sample t-test
##
## data: data$nHits by data$Division
## t = 1.6116, df = 173, p-value = 0.1089
## alternative hypothesis: true difference in means between group East and group West is
not equal to 0
## 95 percent confidence interval:
## -2.466278 24.413990
## sample estimates:
## mean in group East mean in group West
##           113.3294           102.3556
```

Satterthwaite T-test

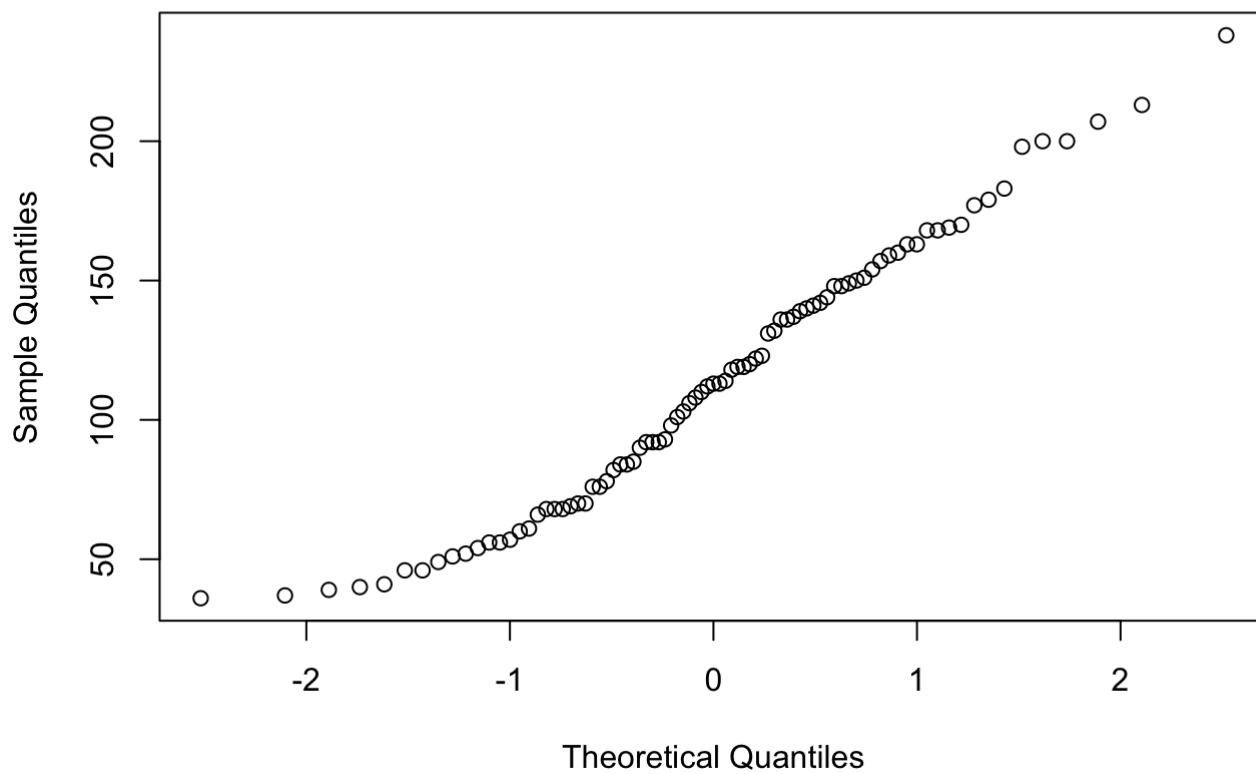
```
data <- filter(dat, League == 'American')
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,
nError, nHits, nHome, nRuns))
t.test(data$nHits ~ data$Division)
```

```
##  
## Welch Two Sample t-test  
##  
## data: data$nHits by data$Division  
## t = 1.6038, df = 164.7, p-value = 0.1107  
## alternative hypothesis: true difference in means between group East and group West is  
## not equal to 0  
## 95 percent confidence interval:  
## -2.536073 24.483786  
## sample estimates:  
## mean in group East mean in group West  
## 113.3294 102.3556
```

Plots

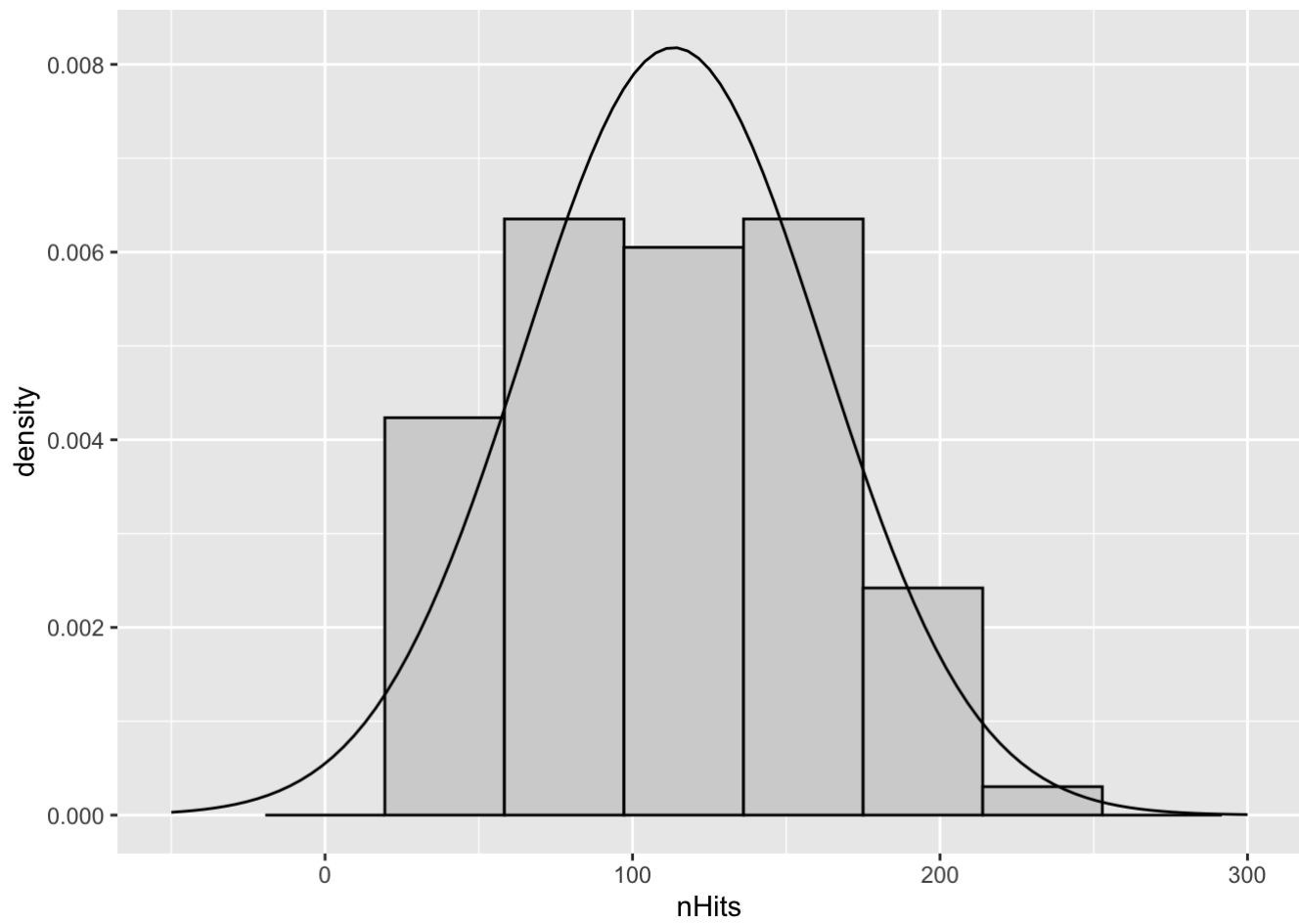
```
library("ggplot2")  
data <- filter(dat, League == 'American')  
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,  
nError, nHits, nHome, nRuns))  
eastsubdata <- filter(data, Division == 'East')  
westsubdata <- filter(data, Division == 'West')  
  
# East Plots  
qqnorm(eastsubdata$nHits)
```

Normal Q-Q Plot

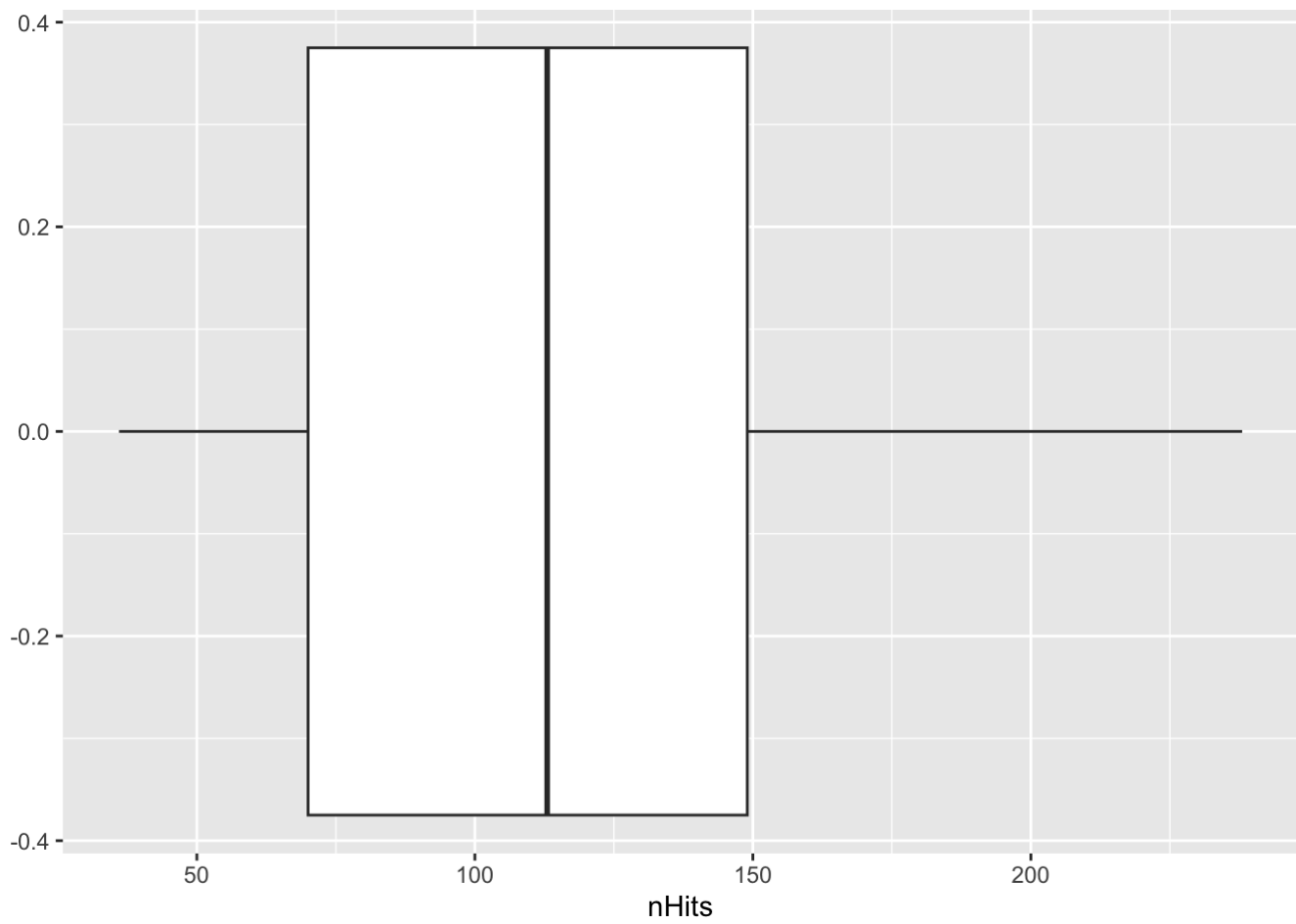


```
ggplot((eastsubdata), aes(x=nHits)) +
  geom_histogram(aes(y = after_stat(density)), fill='lightgray', col='black', bins = 10)
+
  scale_x_continuous(limits = c(-50,300)) +
  stat_function(fun = dnorm, args = list(mean=mean(eastsubdata$nHits), sd=sd(eastsubdata
$nHits)))
```

```
## Warning: Removed 2 rows containing missing values (`geom_bar()`).
```

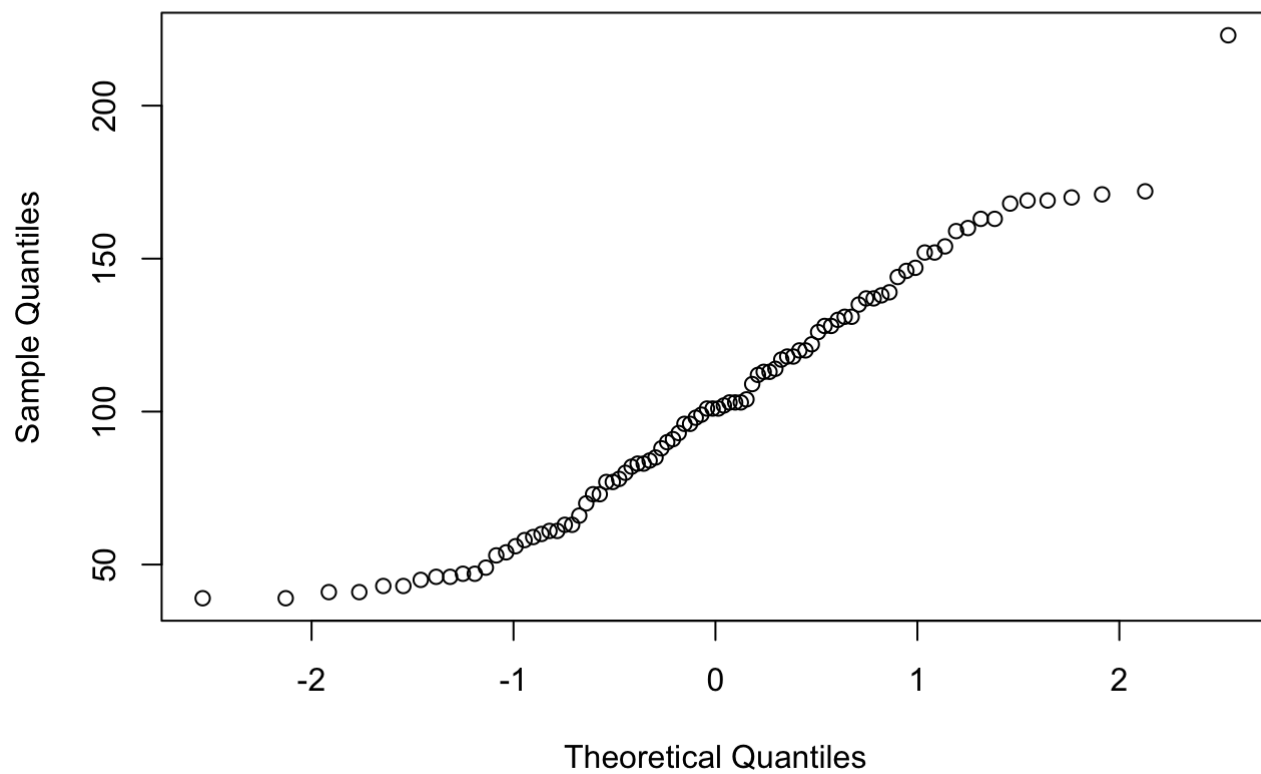


```
ggplot(eastsubdata, aes(x=nHits)) + geom_boxplot()
```

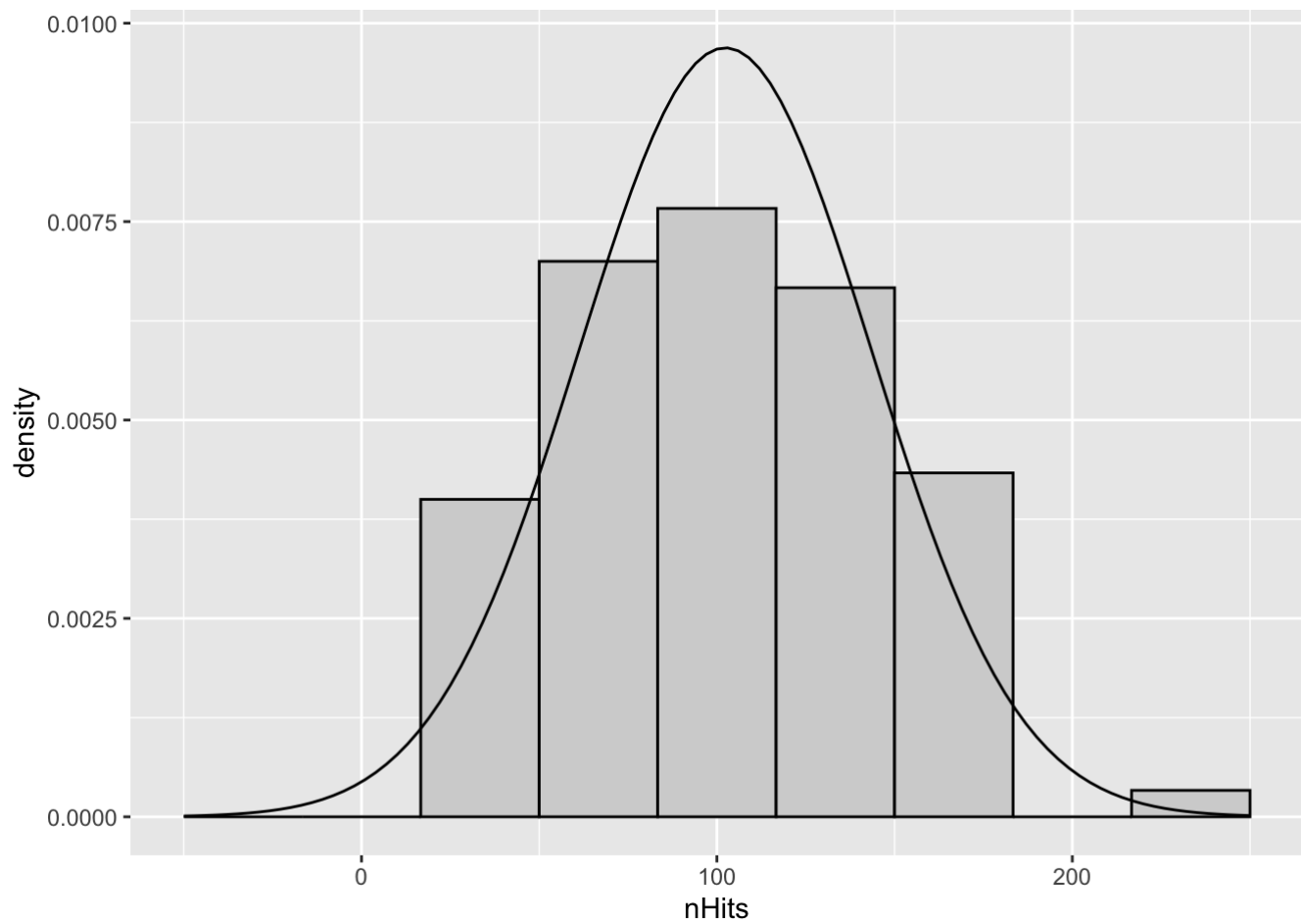


```
# West Plots  
qqnorm(westsubdata$nHits)
```

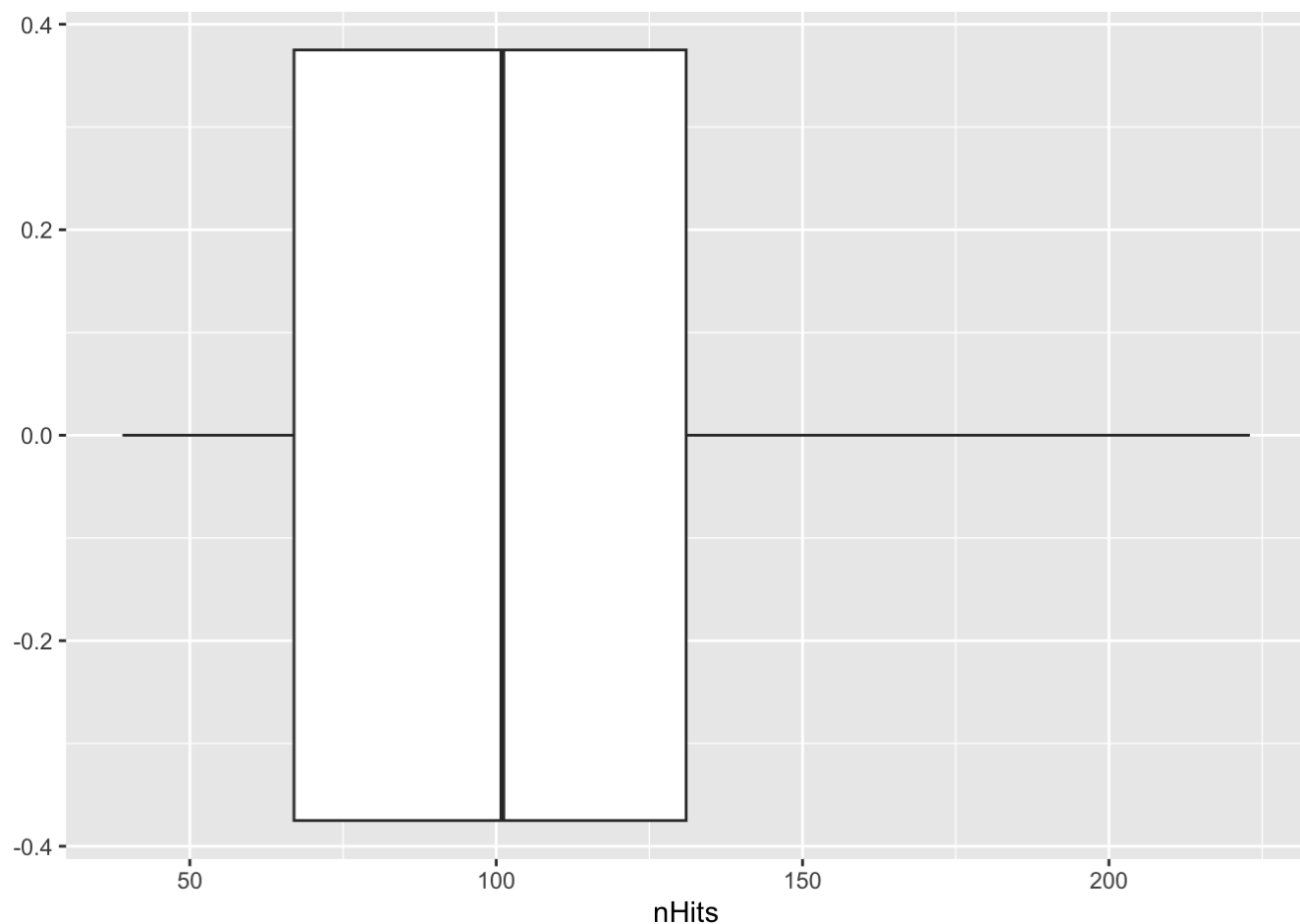
Normal Q-Q Plot



```
ggplot((westsubdata), aes(x=nHits)) +
  geom_histogram(aes(y = after_stat(density)), fill='lightgray', col='black', bins = 10)
+
  scale_x_continuous(limits = c(-50,250)) +
  stat_function(fun = dnorm, args = list(mean=mean(westsubdata$nHits), sd=sd(westsubdata
$nHits)))
```



```
ggplot(westsubdata, aes(x=nHits)) + geom_boxplot()
```

Assuming Non-Normal Data

```
library("DescrTab2")
library("tidyverse")
```

```
## — Attaching packages — tidyverse 1.3.2 —
## ✓ tibble 3.2.1      ✓ purrr 0.3.4
## ✓ tidyr 1.2.0      ✓ stringr 1.4.1
## ✓ readr 2.1.2      ✓ forcats 0.5.2
## — Conflicts — tidyverse_conflicts() —
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag() masks stats::lag()
```

```
library("rstatix")
```

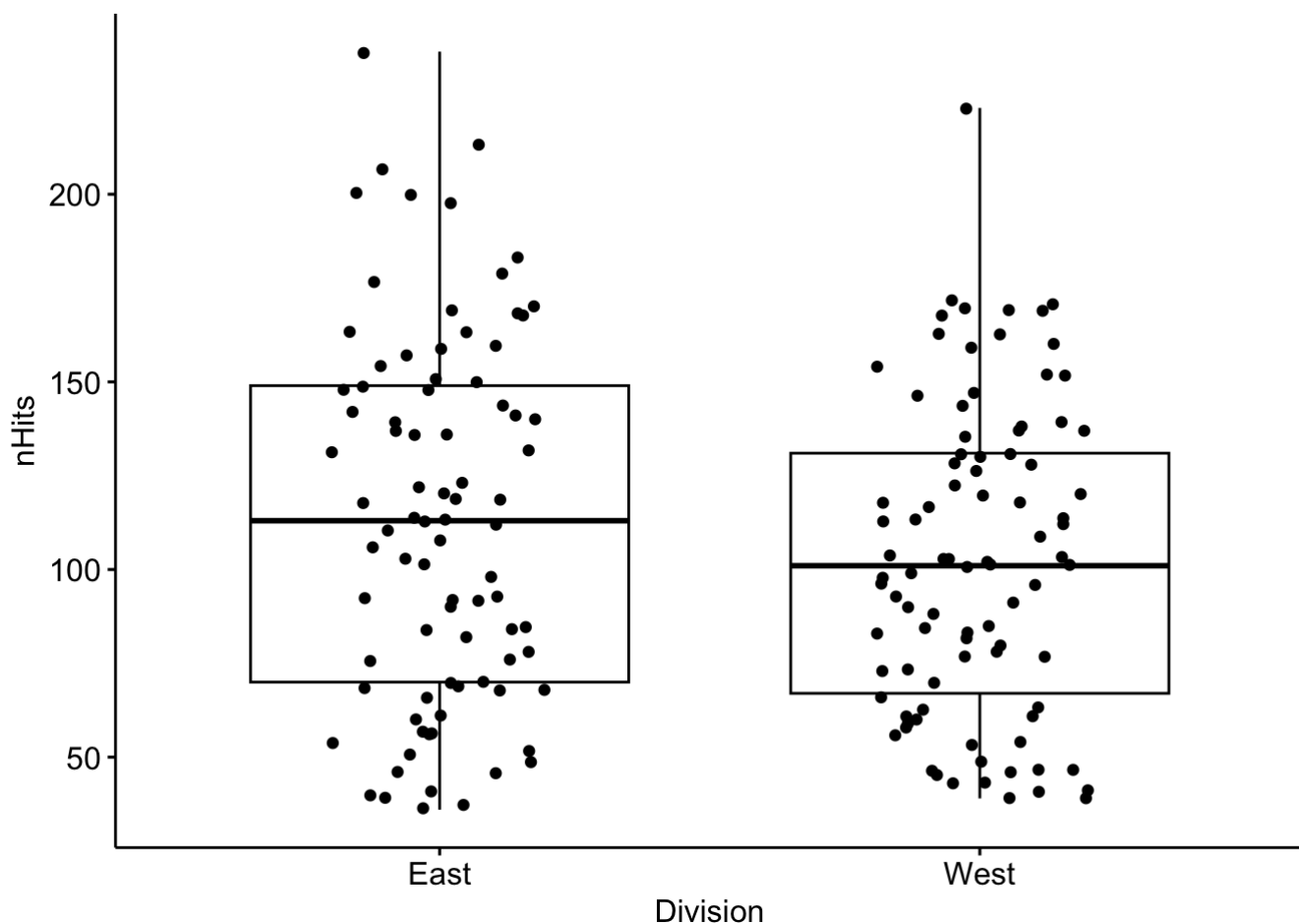
```
##
## Attaching package: 'rstatix'
##
## The following object is masked from 'package:stats':
##
## filter
```

```
library("ggpubr")
data <- filter(dat, League == 'American')
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,
nError, nHits, nHome, nRuns))

data %>%
  group_by(Division) %>%
  get_summary_stats(nHits, type = "median_iqr")
```

```
## # A tibble: 2 × 5
##   Division variable      n median   iqr
##   <chr>      <chr>    <dbl> <dbl> <dbl>
## 1 East      nHits        85    113    79
## 2 West      nHits        90    101    64
```

```
bxp <- ggboxplot(
  data, x = "Division", y = "nHits",
  ylab = "nHits", xlab = "Division", add = "jitter"
)
bxp
```



```
stat.test <- data %>%
  wilcox_test(nHits ~ Division) %>%
  add_significance
stat.test
```

```
## # A tibble: 1 × 8
##   .y.   group1 group2    n1    n2 statistic      p p.signif
##   <chr> <chr>  <chr>  <int> <int>      <dbl> <dbl> <chr>
## 1 nHits East   West     85    90    4288. 0.167 ns
```

```
wilcox.test(data$nHits~data$Division)
```

```
##
## Wilcoxon rank sum test with continuity correction
##
## data: data$nHits by data$Division
## W = 4288.5, p-value = 0.1669
## alternative hypothesis: true location shift is not equal to 0
```

```
kruskal.test(data$nHits~data$Division)
```

```
##
## Kruskal-Wallis rank sum test
##
## data: data$nHits by data$Division
## Kruskal-Wallis chi-squared = 1.915, df = 1, p-value = 0.1664
```

```
ks.test(data$nHits~data$Division)
```

```
##
## Exact two-sample Kolmogorov-Smirnov test
##
## data: data$nHits by data$Division
## D = 0.14379, p-value = 0.2608
## alternative hypothesis: two-sided
```

Summary for Problem 1

There was little reason to believe that there is a difference in the mean and median number of hits for each division. Put differently, the p-value for the t-test assuming normal data was not significant. This means that the assumption of normality is likely okay. Overall, there was not sufficient evidence to claim the mean and median differ between division.

Problem 2

```
library("mosaic")
```

```
## Registered S3 method overwritten by 'mosaic':  
##   method                                from  
##   fortify.SpatialPolygonsDataFrame ggplot2
```

```
##  
## The 'mosaic' package masks several functions from core packages in order to add  
## additional features. The original behavior of these functions should not be affected  
## by this.
```

```
##  
## Attaching package: 'mosaic'
```

```
## The following object is masked from 'package:Matrix':  
##  
##   mean
```

```
## The following objects are masked from 'package:rstatix':  
##  
##   cor_test, prop_test, t_test
```

```
## The following object is masked from 'package:purrr':  
##  
##   cross
```

```
## The following object is masked from 'package:ggplot2':  
##  
##   stat
```

```
## The following objects are masked from 'package:arsenal':  
##  
##   iqr, relrisk
```

```
## The following objects are masked from 'package:dplyr':  
##  
##   count, do, tally
```

```
## The following objects are masked from 'package:stats':  
##  
##   binom.test, cor, cor.test, cov, fivenum, IQR, median, prop.test,  
##   quantile, sd, t.test, var
```

```
## The following objects are masked from 'package:base':
##
##      max, mean, min, prod, range, sample, sum
```

```
library("ggplot2")
```

```
datb <- filter(dat, League == 'National' | Division == 'East')
dim(datb)
```

```
## [1] 232  28
```

```
new_df = subset(datb, select = c(CrAtBat, CrBB, CrHits, CrHits2, CrRbi, CrRuns, Div, Salary, YrMajor, nBB, nHits, nHome));

x = datb$nHits
y = (datb$CrHits)/(datb$YrMajor)

favstats(x)
```

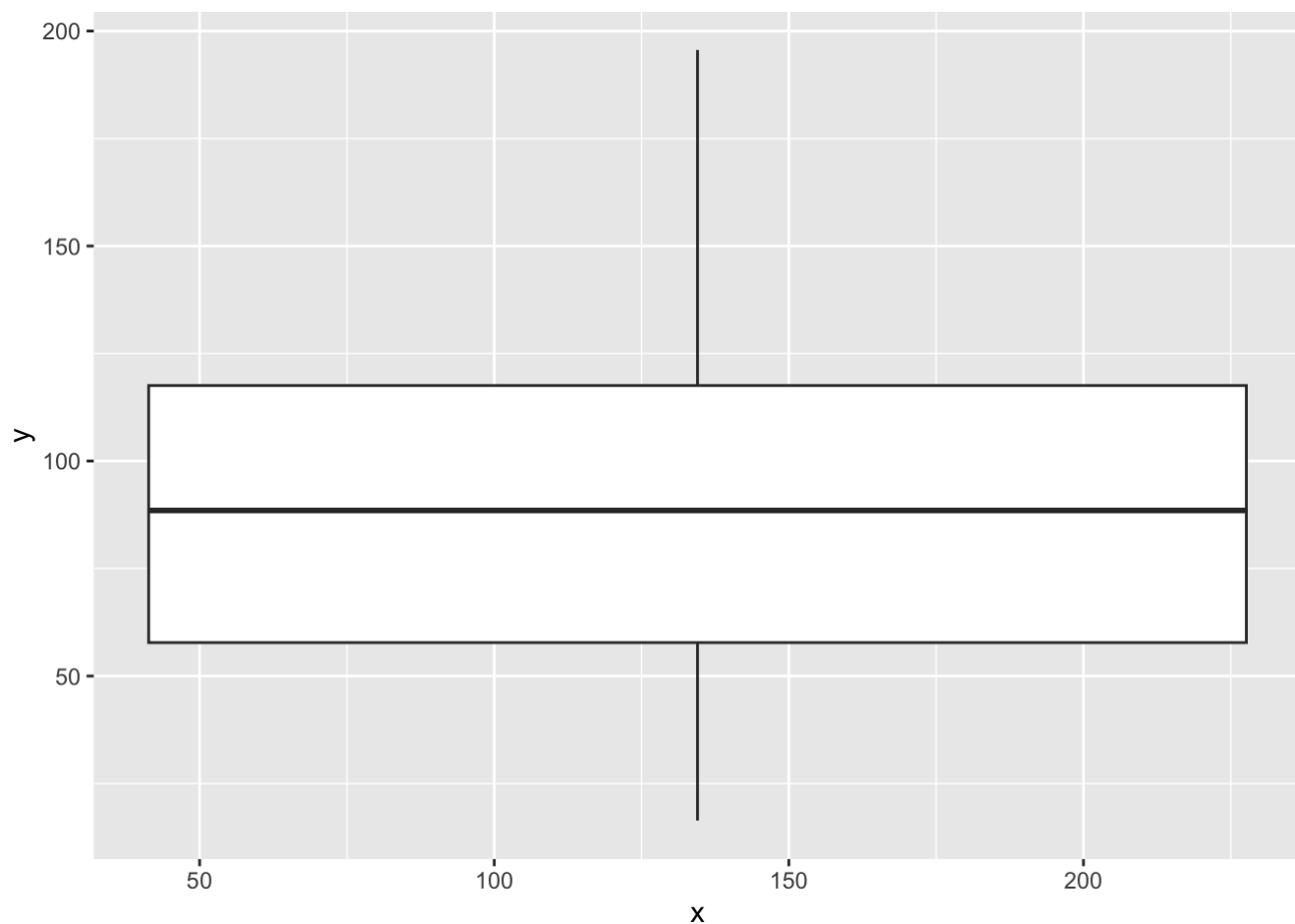
```
##   min Q1 median   Q3 max      mean      sd  n missing
##   31 68    96 140 238 103.8017 45.37286 232      0
```

```
favstats(y)
```

```
##   min      Q1 median      Q3   max      mean      sd  n missing
##  16.4 57.775   88.5 117.5625 195.6 89.18716 37.39127 232      0
```

```
ggplot(datb, aes(x=x, y=y)) + geom_boxplot()
```

```
## Warning: Continuous x aesthetic
## i did you forget `aes(group = ...)`?
```



```
t.test(x,y)
```

```
##
##  Welch Two Sample t-test
##
## data:  x and y
## t = 3.7861, df = 445.72, p-value = 0.000174
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##   7.02840 22.20073
## sample estimates:
## mean of x mean of y
## 103.80172  89.18716
```

```
wilcox.test(x,y)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  x and y
## W = 31464, p-value = 0.001624
## alternative hypothesis: true location shift is not equal to 0
```

```
ks.test(x,y)
```

```
## Warning in ks.test.default(x, y): p-value will be approximate in the presence of
## ties
```

```
##
## Asymptotic two-sample Kolmogorov-Smirnov test
##
## data: x and y
## D = 0.17672, p-value = 0.001426
## alternative hypothesis: two-sided
```

Summary for Problem 2

There is a difference in the mean and median number of hits when comparing the 1986 national league east team with the average career number. The p-value for the t-test is significant indicating that the difference in means is not equal to zero. Further, the p-value of the wilcoxon test is significant indicating that the true location shift is not equal to zero.

New Variable - nRuns

Problem 1

Subgroups

```
library("dplyr")
infield <- filter(dat, Position == '1B' | Position == '2B' | Position == 'SS' | Position == '3B')
outfield <- filter(dat, Position == 'CF' | Position == 'RF' | Position == 'LF' | Position == 'OF')
catcher <- filter(dat, Position == 'C')
CrOuts2 <- dat$CrOuts*dat$CrOuts
```

Plot League by Division

```
library("arsenal")
tab.lbyd <- table(dat$League, dat$Division)
lbyd <- freqlist(tab.lbyd)
summary(lbyd)
```

```
##
##
## |Var1      |Var2 | Freq| Cumulative Freq| Percent| Cumulative Percent|
## |:-----|:----|----:|-----:|-----:|-----:|
## |American |East | 85|          85| 26.40|          26.40|
## |          |West | 90|         175| 27.95|          54.35|
## |National |East | 72|         247| 22.36|          76.71|
## |          |West | 75|         322| 23.29|         100.00|
```

Plot Division for American Leagues

```
library("arsenal")
library("dplyr")
data <- filter(dat, League == 'American')
tab.adiv <- table(data$Division)
adiv <- freqlist(tab.adiv)
summary(adiv)
```

```
##
##
## |Var1 | Freq| Cumulative Freq| Percent| Cumulative Percent|
## |:----|----:|-----:|-----:|-----:|
## |East | 85|          85| 48.57|          48.57|
## |West | 90|         175| 51.43|         100.00|
```

Arrange by Division

```
data <- filter(dat, League == 'American')
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,
nError, nHits, nHome, nRuns, nRuns))
print(data[order(data$Division),])
```


##	Salary	Team	Division	YrMajor	logSalary	nAtBat	nBB	nError	nHits
## 1	NA	Cleveland	East	1	NA	293	14	20	66
## 5	1100.000	Cleveland	East	13	7.003065	401	65	0	92
## 6	517.143	Detroit	East	10	6.248319	574	59	22	159
## 7	700.000	Baltimore	East	6	6.551080	239	22	6	60
## 13	776.667	Boston	East	18	6.655012	629	40	14	168
## 14	765.000	Cleveland	East	6	6.639876	587	70	3	163
## 17	612.500	Cleveland	East	5	6.417549	583	56	25	168
## 19	NA	New York	East	4	NA	161	17	12	36
## 20	NA	Milwaukee	East	16	NA	346	30	0	98
## 21	67.500	Milwaukee	East	2	4.212128	181	33	5	41
## 22	180.000	Milwaukee	East	4	5.192957	217	9	1	46
## 23	NA	New York	East	11	NA	194	30	2	40
## 24	305.000	Cleveland	East	6	5.720312	254	22	4	68
## 25	247.500	Cleveland	East	5	5.511411	205	9	4	57
## 26	NA	Milwaukee	East	16	NA	542	41	9	140
## 28	NA	Toronto	East	15	NA	336	52	0	84
## 30	675.000	Detroit	East	12	6.514713	403	39	5	101
## 31	NA	Milwaukee	East	14	NA	235	21	4	61
## 32	1350.000	Baltimore	East	6	7.207860	627	70	13	177
## 33	90.000	Cleveland	East	1	4.499810	416	16	10	113
## 36	950.000	Boston	East	17	6.856462	585	62	0	139
## 38	105.000	Detroit	East	4	4.653960	521	45	23	142
## 39	NA	Detroit	East	12	NA	419	44	1	113
## 41	535.000	Detroit	East	18	6.282267	507	91	2	122
## 42	933.333	Boston	East	15	6.838762	529	97	5	137
## 43	850.000	Toronto	East	9	6.745236	424	13	8	119
## 47	1975.000	New York	East	5	7.588324	677	53	6	238
## 50	110.000	New York	East	2	4.700480	280	47	2	82
## 54	70.000	Milwaukee	East	1	4.248495	317	32	26	78
## 56	1861.460	New York	East	14	7.529116	565	77	5	148
## 57	2460.000	Baltimore	East	10	7.807917	495	78	13	151
## 58	NA	Milwaukee	East	2	NA	524	54	20	132
## 59	375.000	Boston	East	8	5.926926	233	18	10	49
## 60	NA	Toronto	East	10	NA	395	35	7	106
## 61	NA	Baltimore	East	13	NA	397	53	4	114
## 62	NA	Baltimore	East	6	NA	210	15	15	37
## 64	1175.000	Toronto	East	5	7.069023	641	41	10	198
## 65	70.000	Milwaukee	East	1	4.248495	215	11	12	51
## 70	362.500	Toronto	East	8	5.893024	327	20	12	85
## 78	1237.500	Toronto	East	6	7.120848	589	69	3	170
## 79	430.000	Baltimore	East	15	6.063785	343	40	13	103
## 80	NA	Baltimore	East	5	NA	284	25	5	69
## 83	250.000	Cleveland	East	4	5.521461	663	32	6	200
## 85	275.000	Baltimore	East	14	5.616771	160	22	0	39
## 86	775.000	Cleveland	East	5	6.652863	599	32	18	183
## 87	850.000	Milwaukee	East	11	6.745236	497	26	10	136
## 88	365.000	Detroit	East	15	5.899897	210	28	0	70
## 96	2412.500	Boston	East	13	7.788419	618	62	8	200
## 97	300.000	Baltimore	East	6	5.703782	404	18	5	92
## 100	NA	Baltimore	East	2	NA	212	18	5	54
## 102	1300.000	Detroit	East	8	7.170120	441	68	2	118

## 103	1000.000	New York	East	14	6.907755	490	35	3	150
## 107	225.000	Detroit	East	12	5.416100	283	27	2	70
## 108	525.000	Baltimore	East	15	6.263398	491	37	2	141
## 109	787.500	Toronto	East	7	6.668863	589	64	6	149
## 110	800.000	Detroit	East	10	6.684612	327	38	6	84
## 112	145.000	Baltimore	East	3	4.976734	338	21	0	92
## 114	420.000	Detroit	East	10	6.040255	584	63	11	157
## 115	575.000	Boston	East	5	6.354370	625	65	14	179
## 117	700.000	New York	East	13	6.551080	490	49	0	148
## 118	550.000	Cleveland	East	6	6.309918	442	33	7	131
## 121	175.000	New York	East	3	5.164786	504	54	19	120
## 124	350.000	Baltimore	East	5	5.857933	369	49	6	93
## 129	1260.000	Milwaukee	East	9	7.138867	437	40	15	123
## 131	190.000	Detroit	East	5	5.247024	236	21	4	56
## 132	580.000	Cleveland	East	6	6.363028	473	29	9	154
## 135	250.000	Milwaukee	East	12	5.521461	216	15	4	56
## 136	215.000	Milwaukee	East	3	5.370638	466	72	8	108
## 137	400.000	Baltimore	East	18	5.991465	327	45	7	68
## 138	NA	Boston	East	7	NA	462	37	6	119
## 139	560.000	New York	East	9	6.327937	341	46	4	110
## 140	1670.000	New York	East	8	7.420579	608	89	6	160
## 145	250.000	Toronto	East	6	5.521461	246	13	1	76
## 146	400.000	Milwaukee	East	12	5.991465	205	17	2	52
## 147	450.000	Toronto	East	10	6.109248	348	43	6	90
## 148	70.000	Boston	East	1	4.248495	312	24	15	68
## 152	1000.000	Milwaukee	East	13	6.907755	522	62	1	163
## 159	NA	Boston	East	11	NA	425	24	8	112
## 160	530.000	Cleveland	East	8	6.272877	562	53	17	169
## 161	341.667	Detroit	East	8	5.833837	281	20	7	76
## 163	350.000	Toronto	East	4	5.857933	687	27	13	213
## 167	NA	Baltimore	East	5	NA	181	17	9	46
## 170	1600.000	Boston	East	5	7.377759	580	105	19	207
## 172	875.000	New York	East	12	6.774224	492	94	20	136
## 174	960.000	Toronto	East	8	6.866933	573	78	12	144
## 2	480.000	Seattle	West	3	6.173786	479	76	14	130
## 3	750.000	Oakland	West	11	6.620073	594	35	25	169
## 4	100.000	Kansas City	West	3	4.605170	298	7	9	73
## 8	NA	Minneapolis	West	3	NA	183	11	0	39
## 9	175.000	Kansas City	West	5	5.164786	190	15	16	46
## 10	NA	Oakland	West	12	NA	407	65	9	104
## 11	115.000	Chicago	West	1	4.744932	426	62	2	109
## 12	NA	California	West	15	NA	442	43	11	98
## 15	900.000	California	West	14	6.802395	513	90	3	137
## 16	NA	California	West	17	NA	313	39	7	84
## 18	300.000	Seattle	West	7	5.703782	204	12	5	49
## 27	875.000	Chicago	West	17	6.774224	457	22	4	101
## 29	1200.000	Oakland	West	9	7.090077	591	39	4	168
## 34	230.000	Texas	West	4	5.438079	236	11	13	56
## 35	NA	Oakland	West	19	NA	242	27	0	58
## 37	75.000	Chicago	West	3	4.317488	199	21	5	53
## 40	850.000	California	West	14	6.745236	512	52	12	131
## 44	325.000	Seattle	West	6	5.783825	388	39	4	103

## 45	275.000	Oakland	West	4	5.616771	339	23	9	96
## 46	NA	Oakland	West	16	NA	561	33	8	118
## 48	NA	Kansas City	West	5	NA	227	12	2	46
## 49	600.000	Oakland	West	9	6.396930	329	56	2	83
## 51	260.000	Texas	West	16	5.560682	155	22	1	41
## 52	475.000	California	West	4	6.163315	458	48	18	114
## 53	431.500	Texas	West	5	6.067268	314	16	4	83
## 55	145.000	Seattle	West	3	4.976734	511	61	8	138
## 63	750.000	Kansas City	West	14	6.620073	566	43	10	154
## 66	1500.000	Kansas City	West	14	7.313220	441	80	16	128
## 67	900.000	Minneapolis	West	6	6.802395	596	52	21	171
## 68	155.000	Minneapolis	West	4	5.043425	472	30	26	118
## 69	700.000	California	West	16	6.551080	283	26	5	77
## 71	400.000	California	West	5	5.991465	539	69	7	139
## 72	NA	Seattle	West	13	NA	315	58	0	59
## 73	500.000	Chicago	West	5	6.214608	282	29	5	78
## 74	600.000	Texas	West	8	6.396930	380	31	1	120
## 75	950.000	Chicago	West	7	6.856462	570	38	5	169
## 76	325.000	Kansas City	West	18	5.783825	278	18	0	70
## 77	87.500	Seattle	West	4	4.471639	445	29	16	99
## 81	100.000	Chicago	West	2	4.605170	438	71	9	103
## 82	165.000	Oakland	West	2	5.105945	600	65	14	144
## 84	NA	Chicago	West	10	NA	209	42	5	45
## 89	NA	Chicago	West	11	NA	225	26	0	61
## 90	95.000	California	West	2	4.553877	151	19	2	41
## 91	80.000	Seattle	West	5	4.382027	399	34	3	102
## 92	NA	Kansas City	West	15	NA	336	23	0	93
## 93	200.000	Seattle	West	3	5.298317	616	32	15	163
## 94	NA	Kansas City	West	12	NA	219	17	4	47
## 95	75.000	Minneapolis	West	3	4.317488	165	16	2	39
## 98	110.000	Chicago	West	4	4.700480	315	16	3	73
## 99	825.000	Kansas City	West	13	6.715383	429	57	4	91
## 101	NA	Oakland	West	3	NA	161	22	2	43
## 104	1310.000	Minneapolis	West	6	7.177782	550	71	10	147
## 105	300.000	Seattle	West	7	5.703782	344	88	0	85
## 106	365.000	Minneapolis	West	3	5.899897	680	34	6	223
## 111	587.500	Texas	West	13	6.375876	464	52	0	128
## 113	NA	Kansas City	West	9	NA	508	46	9	146
## 116	780.000	Oakland	West	7	6.659294	489	34	9	131
## 119	NA	Minneapolis	West	8	NA	317	19	4	88
## 120	68.000	Kansas City	West	1	4.219508	209	12	3	54
## 122	137.000	Minneapolis	West	3	4.919981	258	18	8	60
## 123	120.000	Oakland	West	3	4.787492	211	39	8	43
## 125	175.000	Chicago	West	2	5.164786	547	12	22	137
## 126	200.000	Texas	West	2	5.298317	572	65	3	152
## 127	750.000	Seattle	West	4	6.620073	526	77	1	163
## 128	172.000	Texas	West	1	5.147494	540	55	14	135
## 130	NA	Texas	West	5	NA	551	87	11	160
## 133	450.000	California	West	12	6.109248	271	33	3	77
## 134	300.000	Minneapolis	West	5	5.703782	357	39	4	96
## 141	487.500	California	West	20	6.189290	419	92	0	101
## 142	NA	California	West	11	NA	393	64	4	90

## 143	425.000	Chicago	West	5	6.052089	376	35	0	82
## 144	NA	Kansas City	West	7	NA	307	29	2	80
## 149	97.500	Texas	West	1	4.579852	382	22	6	101
## 150	740.000	Minneapolis	West	12	6.606650	459	68	0	113
## 151	341.667	California	West	10	5.833837	288	16	7	63
## 153	100.000	Kansas City	West	6	4.605170	512	43	18	117
## 154	90.000	Seattle	West	3	4.499810	220	13	3	66
## 155	135.000	Texas	West	2	4.905275	461	35	11	112
## 156	475.000	Texas	West	6	6.163315	530	47	15	159
## 157	105.000	Minneapolis	West	2	4.653960	453	52	6	103
## 158	350.000	Seattle	West	4	5.857933	528	51	17	122
## 162	940.000	Minneapolis	West	6	6.845880	593	53	6	152
## 164	NA	Texas	West	17	NA	289	44	7	63
## 165	185.000	Chicago	West	4	5.220356	520	21	11	120
## 166	245.000	Minneapolis	West	6	5.501258	193	24	5	47
## 168	235.000	Texas	West	17	5.459586	213	3	4	61
## 169	425.000	Oakland	West	5	6.052089	441	76	11	113
## 171	165.000	California	West	1	5.105945	593	57	15	172
## 173	385.000	Chicago	West	6	5.953243	475	52	7	126
## 175	1000.000	Kansas City	West	11	6.907755	631	31	3	170
##	nHome	nRuns	nRuns.1						
## 1	1	30	30						
## 5	17	49	49						
## 6	21	107	107						
## 7	0	30	30						
## 13	18	73	73						
## 14	4	92	92						
## 17	17	83	83						
## 19	0	19	19						
## 20	5	31	31						
## 21	1	15	15						
## 22	7	32	32						
## 23	7	19	19						
## 24	2	28	28						
## 25	8	34	34						
## 26	12	46	46						
## 28	15	48	48						
## 30	12	45	45						
## 31	3	24	24						
## 32	25	98	98						
## 33	24	58	58						
## 36	31	93	93						
## 38	20	67	67						
## 39	1	44	44						
## 41	29	78	78						
## 42	26	86	86						
## 43	6	57	57						
## 47	31	117	117						
## 50	16	44	44						
## 54	7	35	35						
## 56	24	90	90						
## 57	17	61	61						

## 58	9	69	69
## 59	2	41	41
## 60	16	48	48
## 61	23	67	67
## 62	8	15	15
## 64	31	101	101
## 65	4	19	19
## 70	3	30	30
## 78	40	107	107
## 79	6	48	48
## 80	1	33	33
## 83	29	108	108
## 85	8	18	18
## 86	10	80	80
## 87	7	58	58
## 88	13	32	32
## 96	20	98	98
## 97	11	54	54
## 100	13	28	28
## 102	28	84	84
## 103	21	69	69
## 107	8	33	33
## 108	11	77	77
## 109	21	89	89
## 110	22	53	53
## 112	18	42	42
## 114	20	95	95
## 115	4	94	94
## 117	14	64	64
## 118	18	68	68
## 121	28	71	71
## 124	9	43	43
## 129	9	62	62
## 131	6	41	41
## 132	6	61	61
## 135	4	22	22
## 136	33	75	75
## 137	13	42	42
## 138	16	49	49
## 139	9	45	45
## 140	28	130	130
## 145	5	35	35
## 146	8	31	31
## 147	11	50	50
## 148	2	32	32
## 152	9	82	82
## 159	11	40	40
## 160	17	88	88
## 161	3	42	42
## 163	10	91	91
## 167	1	19	19
## 170	8	107	107

## 172	5	76	76
## 174	9	85	85
## 2	18	66	66
## 3	4	74	74
## 4	0	24	24
## 8	3	20	20
## 9	2	24	24
## 10	6	57	57
## 11	3	55	55
## 12	7	48	48
## 15	20	90	90
## 16	9	42	42
## 18	6	23	23
## 27	14	42	42
## 29	19	80	80
## 34	0	27	27
## 35	4	25	25
## 37	5	29	29
## 40	26	69	69
## 44	15	59	59
## 45	4	37	37
## 46	35	70	70
## 48	7	23	23
## 49	9	50	50
## 51	12	21	21
## 52	13	67	67
## 53	13	39	39
## 55	25	76	76
## 63	22	76	76
## 66	16	70	70
## 67	34	91	91
## 68	12	63	63
## 69	14	45	45
## 71	5	93	93
## 72	16	45	45
## 73	13	37	37
## 74	5	54	54
## 75	21	72	72
## 76	7	22	22
## 77	1	46	46
## 81	2	65	65
## 82	33	85	85
## 84	0	38	38
## 89	5	32	32
## 90	4	26	26
## 91	3	56	56
## 92	9	35	35
## 93	27	83	83
## 94	8	24	24
## 95	2	13	13
## 98	5	23	23
## 99	12	41	41

```
## 101      4      17      17
## 104     29     85     85
## 105     24     69     69
## 106     31    119    119
## 111     28     67     67
## 113      8     80     80
## 116     19     77     77
## 119      3     40     40
## 120      3     25     25
## 122      8     28     28
## 123     10     26     26
## 125      2     58     58
## 126     18    105    105
## 127     12     88     88
## 128     30     82     82
## 130     23     86     86
## 133      5     35     35
## 134      7     50     50
## 141     18     65     65
## 142     17     73     73
## 143     21     42     42
## 144      1     42     42
## 149     16     50     50
## 150     20     59     59
## 151      3     25     25
## 153     29     54     54
## 154      5     20     20
## 155     18     54     54
## 156      3     82     82
## 157      8     53     53
## 158      1     67     67
## 162     23     69     69
## 164      7     36     36
## 165     17     53     53
## 166     10     21     21
## 168      4     17     17
## 169      5     76     76
## 171     22     82     82
## 173      3     61     61
## 175      9     77     77
```

```
subdata <-
  data %>%
  group_by(Division) %>%
  summarize(c(total_count = n()), (mean_outs = mean(nRuns)), (sd_outs = sd(nRuns)), (se_
outs = sd(nRuns)/sqrt(n())), (min_outs = min(nRuns)), (max_outs = max(nRuns)))
print(subdata)
```

```
## # A tibble: 2 × 7
##   Division `c(total_count = n())` (mean_outs = mean(nRu...1 (sd_outs = sd(nRuns)...2
##   <chr>                <int>                <dbl>                <dbl>
## 1 East                  85                  58.5                  28.1
## 2 West                  90                  53.2                  23.9
## # i abbreviated names: 1`(mean_outs = mean(nRuns))`, 2`(sd_outs = sd(nRuns))`
## # i 3 more variables: `(se_outs = sd(nRuns)/sqrt(n()))` <dbl>,
## #   `(min_outs = min(nRuns))` <int>, `(max_outs = max(nRuns))` <int>
```

Assuming Normal Data

Pooled T-test

```
data <- filter(dat, League == 'American')
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,
nError, nHits, nHome, nRuns, nRuns))
t.test_res <- t.test(data$nRuns ~ data$Division, var.equal = TRUE)
print(t.test_res)
```

```
##
## Two Sample t-test
##
## data: data$nRuns by data$Division
## t = 1.3531, df = 173, p-value = 0.1778
## alternative hypothesis: true difference in means between group East and group West is
not equal to 0
## 95 percent confidence interval:
## -2.444213 13.101729
## sample estimates:
## mean in group East mean in group West
##          58.51765          53.18889
```

Satterthwaite T-test

```
data <- filter(dat, League == 'American')
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,
nError, nHits, nHome, nRuns, nRuns))
t.test(data$nRuns ~ data$Division)
```

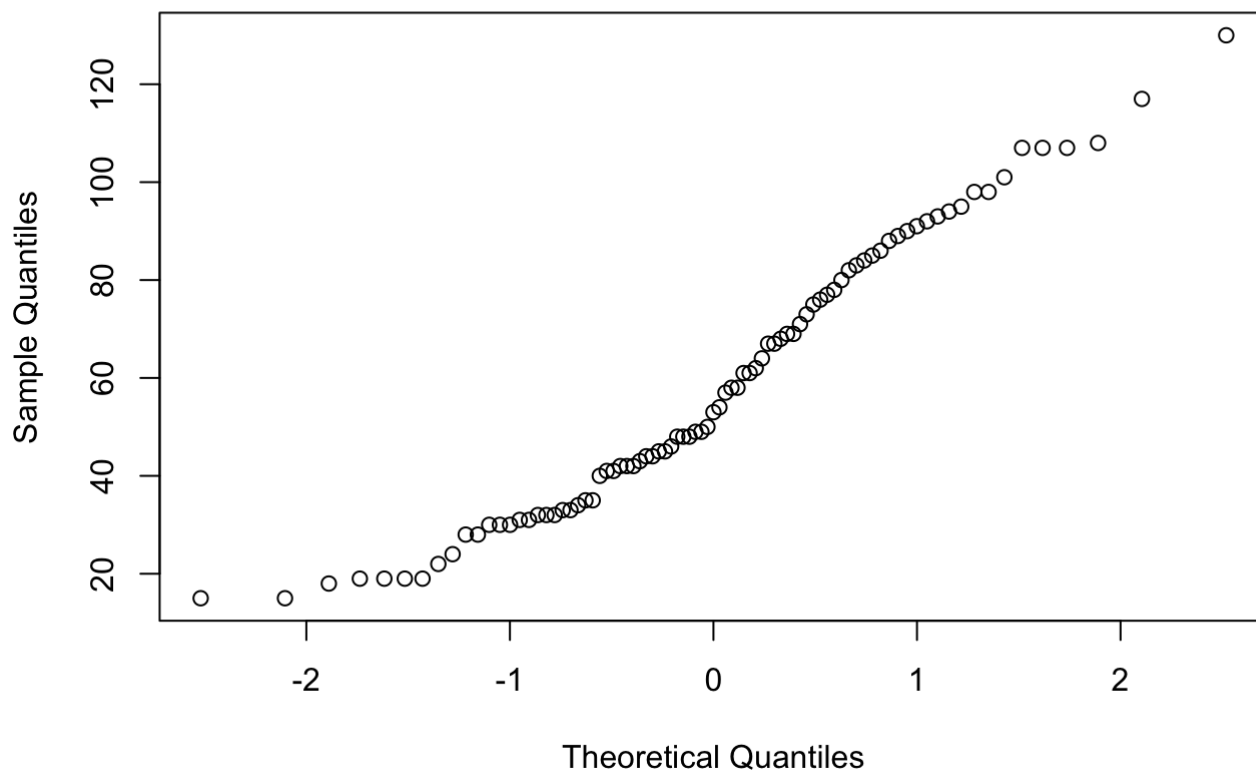


```
##  
## Welch Two Sample t-test  
##  
## data: data$nRuns by data$Division  
## t = 1.3469, df = 165.29, p-value = 0.1798  
## alternative hypothesis: true difference in means between group East and group West is  
## not equal to 0  
## 95 percent confidence interval:  
## -2.482434 13.139951  
## sample estimates:  
## mean in group East mean in group West  
## 58.51765 53.18889
```

Plots

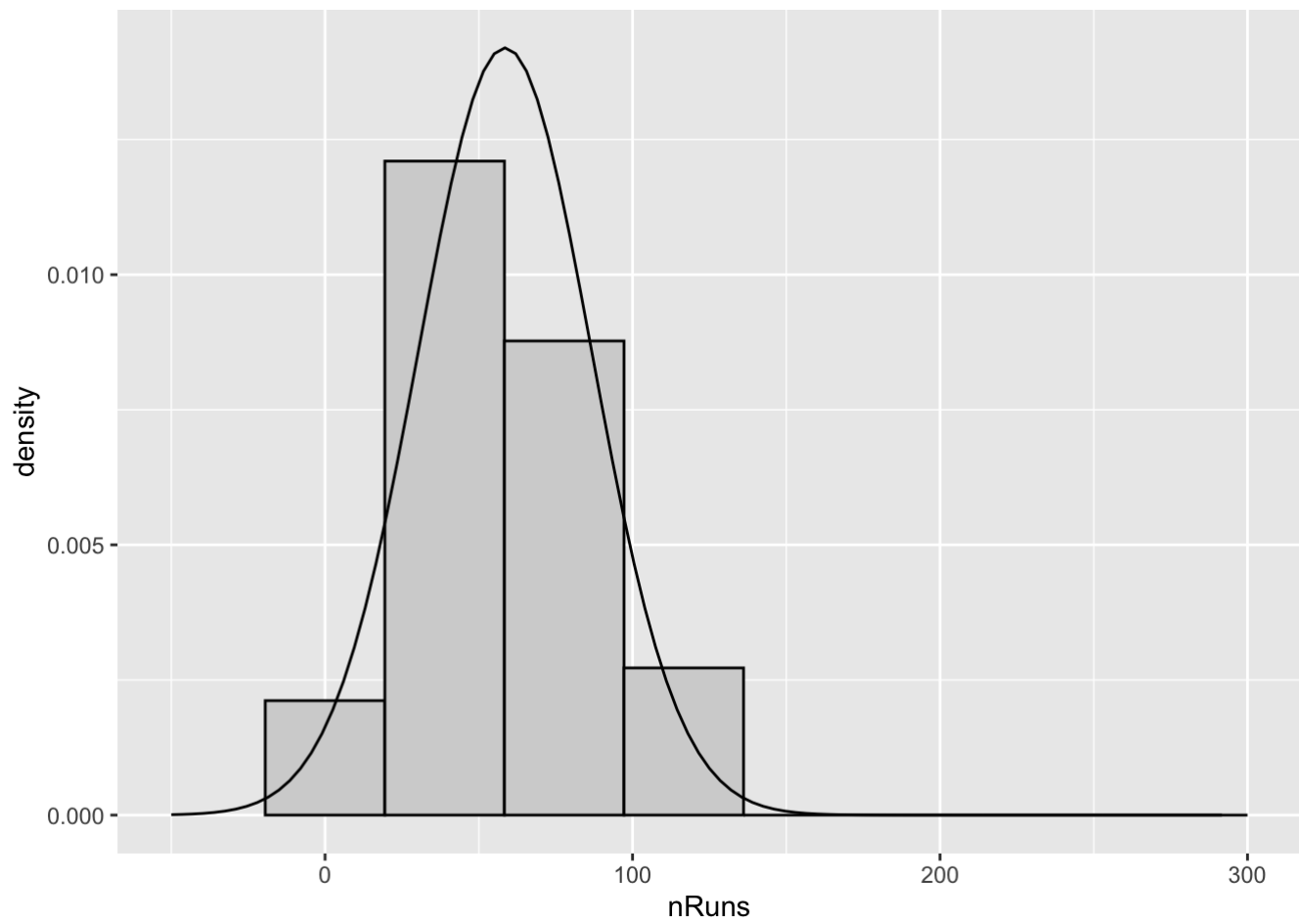
```
library("ggplot2")  
data <- filter(dat, League == 'American')  
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,  
nError, nHits, nHome, nRuns, nRuns))  
eastsubdata <- filter(data, Division == 'East')  
westsubdata <- filter(data, Division == 'West')  
  
# East Plots  
qqnorm(eastsubdata$nRuns)
```

Normal Q-Q Plot

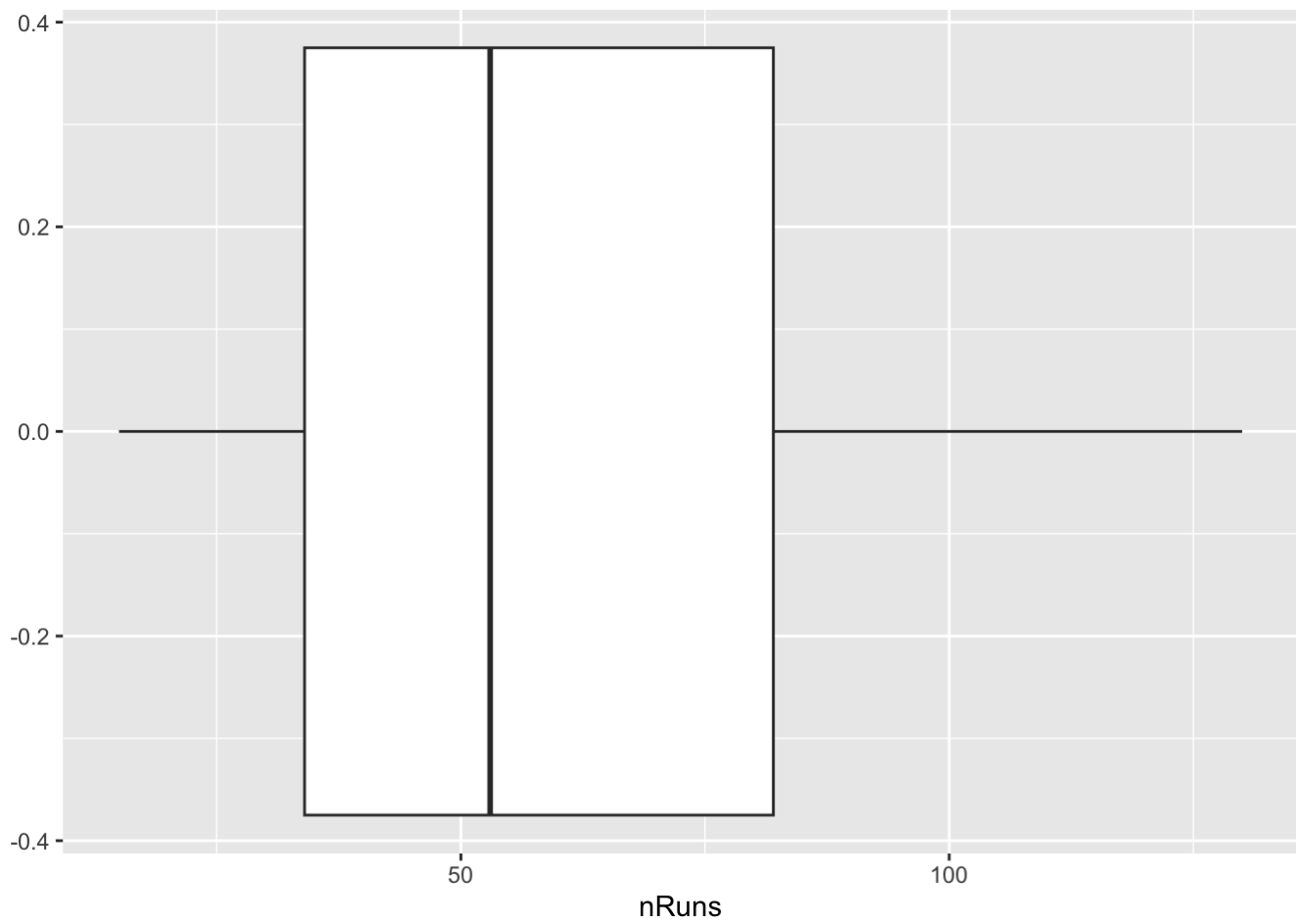


```
ggplot((eastsubdata), aes(x=nRuns)) +
  geom_histogram(aes(y = after_stat(density)), fill='lightgray', col='black', bins = 10)
+
  scale_x_continuous(limits = c(-50,300)) +
  stat_function(fun = dnorm, args = list(mean=mean(eastsubdata$nRuns), sd=sd(eastsubdata
$nRuns)))
```

```
## Warning: Removed 2 rows containing missing values (`geom_bar()`).
```

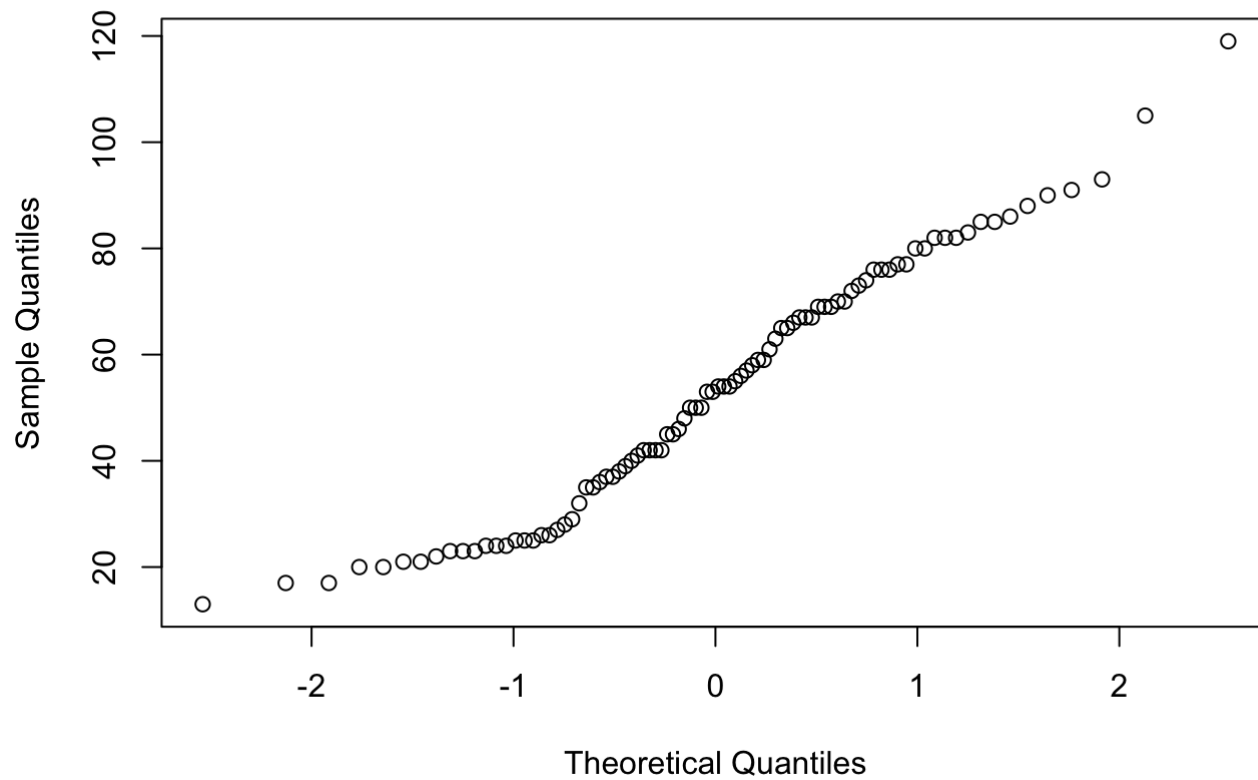


```
ggplot(eastsubdata, aes(x=nRuns)) + geom_boxplot()
```

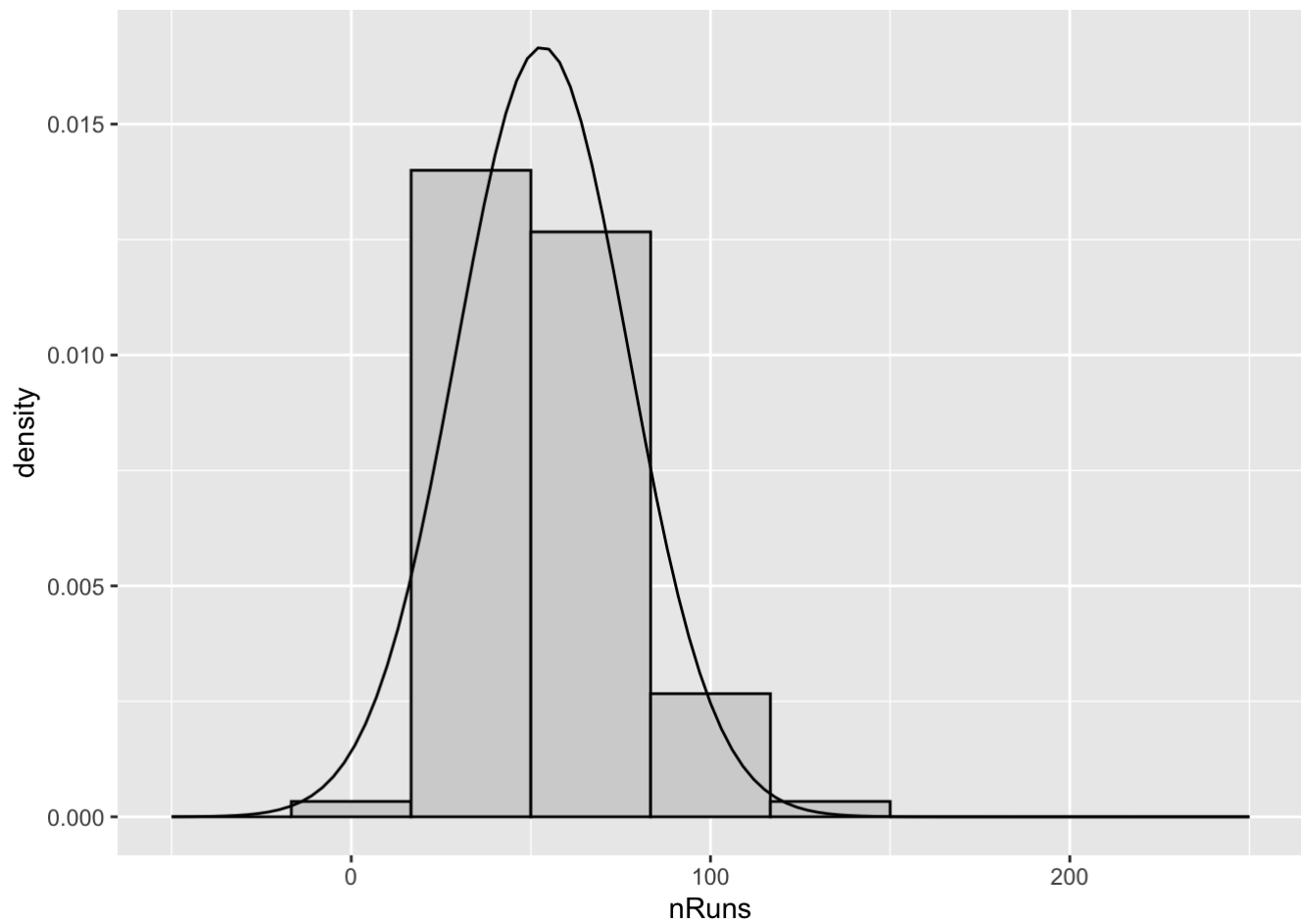


```
# West Plots  
qqnorm(westsubdata$nRuns)
```

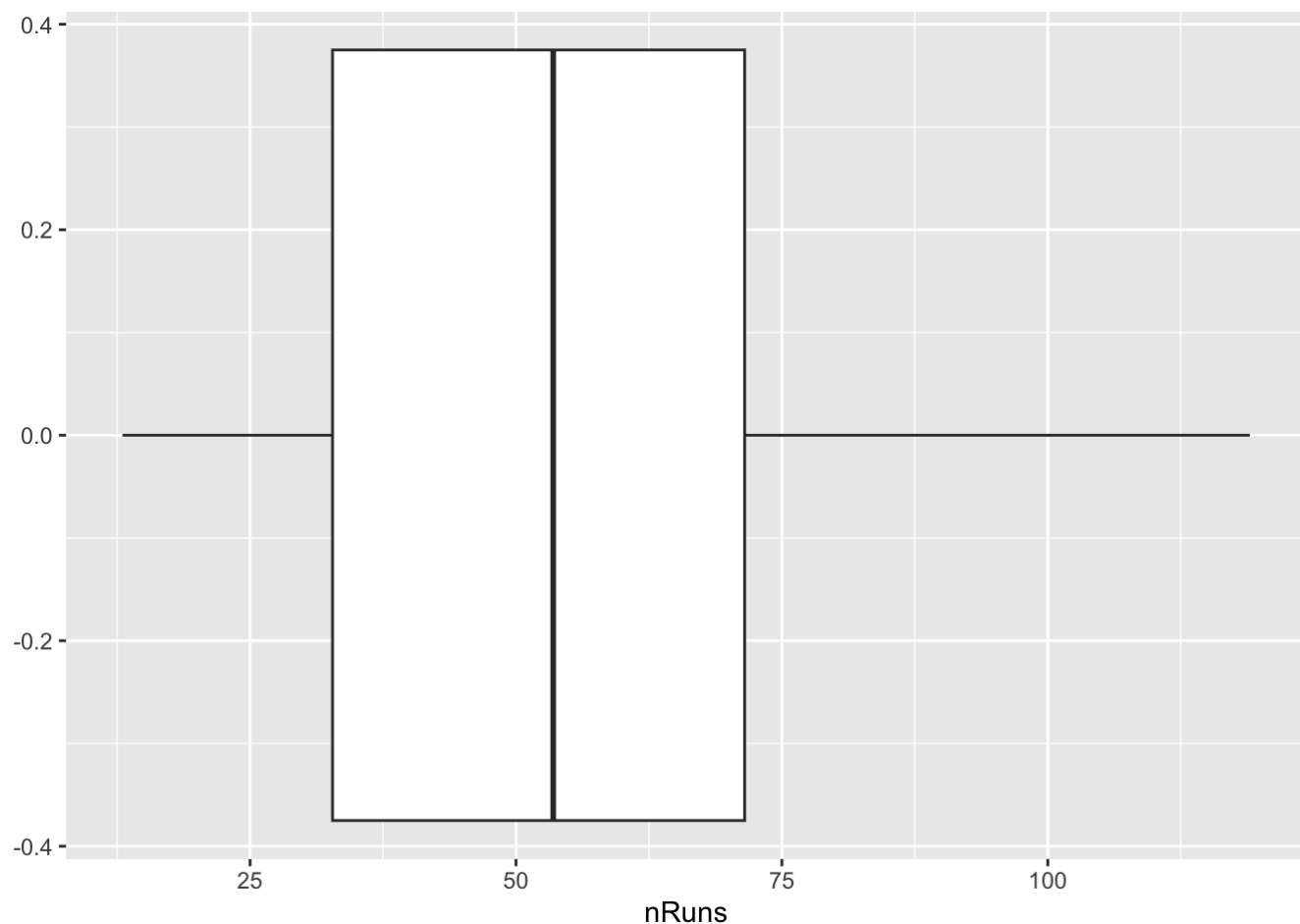
Normal Q-Q Plot



```
ggplot((westsubdata), aes(x=nRuns)) +
  geom_histogram(aes(y = after_stat(density)), fill='lightgray', col='black', bins = 10)
+
  scale_x_continuous(limits = c(-50,250)) +
  stat_function(fun = dnorm, args = list(mean=mean(westsubdata$nRuns), sd=sd(westsubdata
$nRuns)))
```



```
ggplot(westsubdata, aes(x=nRuns)) + geom_boxplot()
```



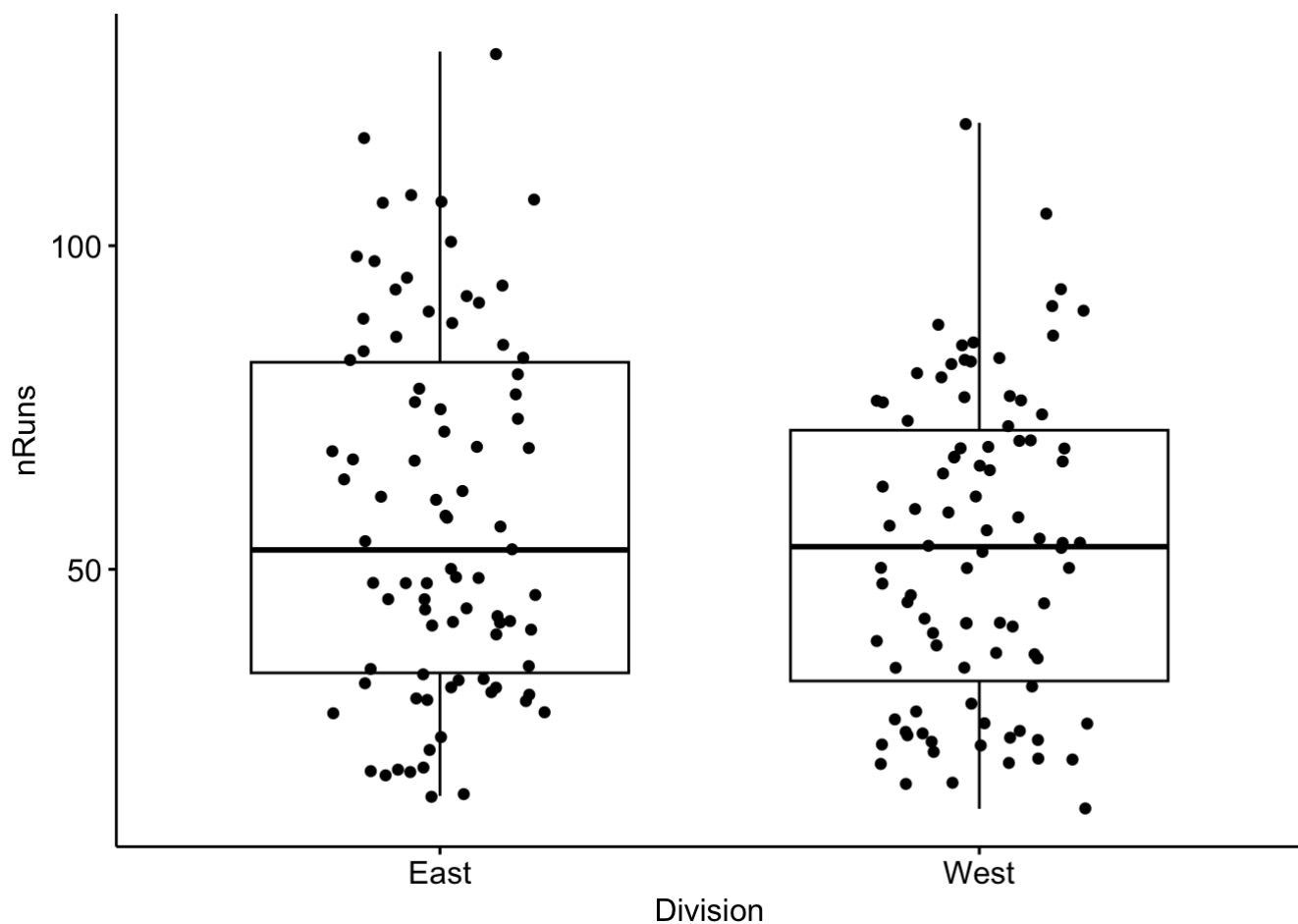
Assuming Non-Normal Data

```
library("DescrTab2")
library("tidyverse")
library("rstatix")
library("ggpubr")
data <- filter(dat, League == 'American')
data <- subset(data, select = c(Salary, Team, Division, YrMajor, logSalary, nAtBat, nBB,
nError, nHits, nHome, nRuns, nRuns))

data %>%
  group_by(Division) %>%
  get_summary_stats(nRuns, type = "median_iqr")
```

```
## # A tibble: 2 × 5
##   Division variable      n median   iqr
##   <chr>      <chr>    <dbl> <dbl> <dbl>
## 1 East      nRuns        85    53    48
## 2 West      nRuns        90   53.5  38.8
```

```
bxp <- ggboxplot(
  data, x = "Division", y = "nRuns",
  ylab = "nRuns", xlab = "Division", add = "jitter"
)
bxp
```



```
stat.test <- data %>%
  wilcox_test(nRuns ~ Division) %>%
  add_significance
stat.test
```

```
## # A tibble: 1 × 8
##   .y.   group1 group2    n1    n2 statistic    p p.signif
##   <chr> <chr>  <chr>  <int> <int>    <dbl> <dbl> <chr>
## 1 nRuns East   West     85    90     4201 0.262 ns
```

```
wilcox.test(data$nRuns~data$Division)
```



```
##
## Wilcoxon rank sum test with continuity correction
##
## data: data$nRuns by data$Division
## W = 4201, p-value = 0.2622
## alternative hypothesis: true location shift is not equal to 0
```

```
kruskal.test(data$nRuns~data$Division)
```

```
##
## Kruskal-Wallis rank sum test
##
## data: data$nRuns by data$Division
## Kruskal-Wallis chi-squared = 1.2604, df = 1, p-value = 0.2616
```

```
ks.test(data$nRuns~data$Division)
```

```
##
## Exact two-sample Kolmogorov-Smirnov test
##
## data: data$nRuns by data$Division
## D = 0.13595, p-value = 0.3119
## alternative hypothesis: two-sided
```

Summary for Problem 1

There was little reason to believe that there is a difference in the mean and median number of runs for each division. Put differently, the p-value for the t-test assuming normal data was not significant. This means that the assumption of normality is likely okay. Overall, there was not sufficient evidence to claim the mean and median differ between division.

Problem 2

```
library("mosaic")
library("ggplot2")

datb <- filter(dat, League == 'National' | Division == 'East')
dim(datb)
```

```
## [1] 232 28
```

```
new_df = subset(datb, select = c(CrAtBat, CrBB, CrHits, CrHits2, CrRbi, CrRuns, Div, Salary, YrMajor, nBB, nHits, nHome, nRuns));

x = datb$nRuns
y = (datb$CrRuns)/(datb$YrMajor)

favstats(x)
```

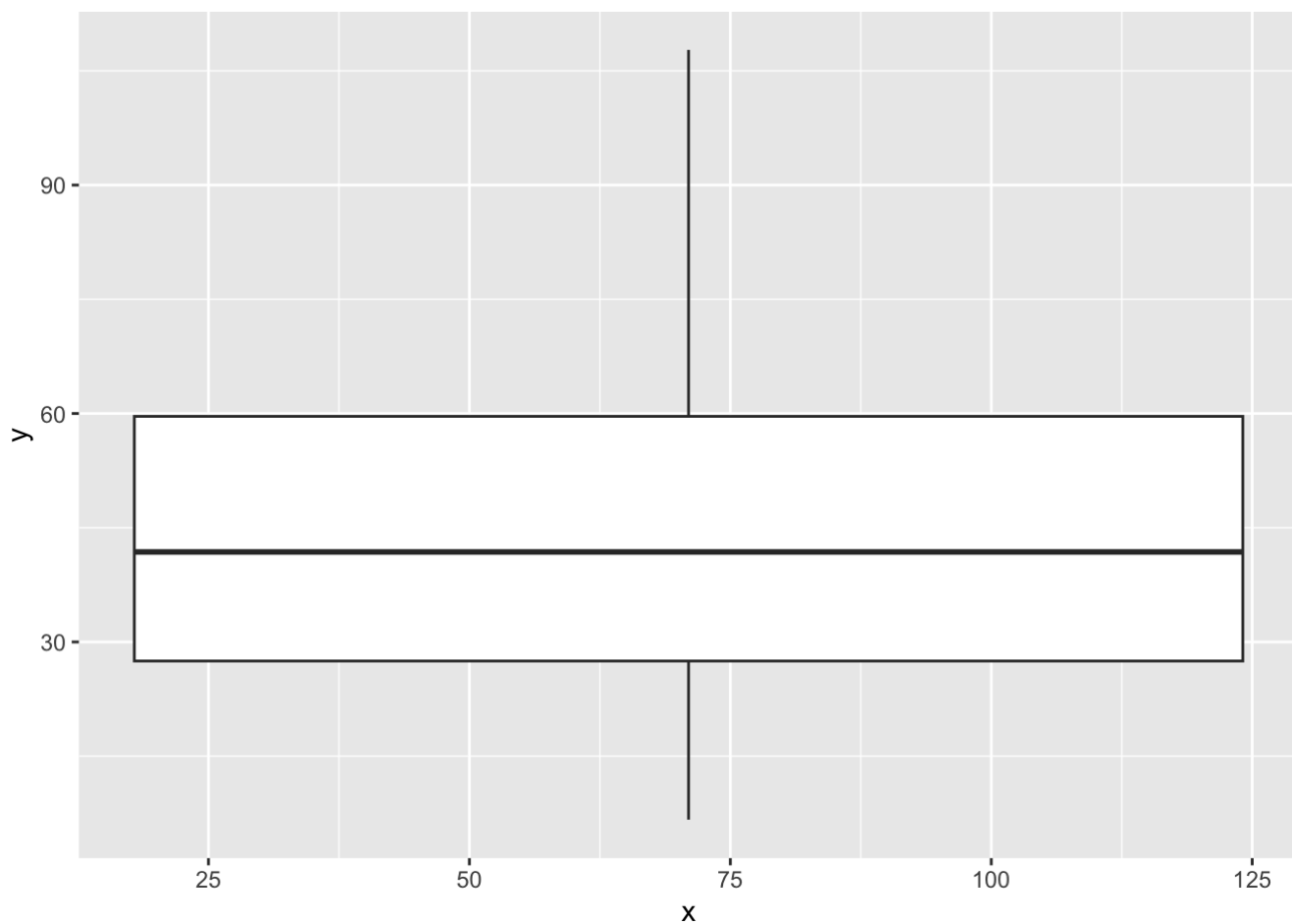
```
##   min      Q1 median Q3 max      mean      sd  n missing
##   12 31.75      48 69 130 51.84052 25.52184 232        0
```

```
favstats(y)
```

```
##           min      Q1   median      Q3      max      mean      sd  n missing
##  6.666667 27.5 41.81944 59.62692 107.75 44.66428 20.69896 232        0
```

```
ggplot(datb, aes(x=x, y=y)) + geom_boxplot()
```

```
## Warning: Continuous x aesthetic
## i did you forget `aes(group = ...)`?
```



```
t.test(x,y)
```

```
##  
##  Welch Two Sample t-test  
##  
## data:  x and y  
## t = 3.3263, df = 443.12, p-value = 0.0009532  
## alternative hypothesis: true difference in means is not equal to 0  
## 95 percent confidence interval:  
##   2.936233 11.416232  
## sample estimates:  
## mean of x mean of y  
##  51.84052  44.66428
```

```
wilcox.test(x,y)
```

```
##  
##  Wilcoxon rank sum test with continuity correction  
##  
## data:  x and y  
## W = 30642, p-value = 0.009798  
## alternative hypothesis: true location shift is not equal to 0
```

```
ks.test(x,y)
```

```
## Warning in ks.test.default(x, y): p-value will be approximate in the presence of  
## ties
```

```
##  
##  Asymptotic two-sample Kolmogorov-Smirnov test  
##  
## data:  x and y  
## D = 0.14655, p-value = 0.01371  
## alternative hypothesis: two-sided
```

Summary for Problem 2

```
# There is a difference in the mean and median number of runs when comparing the 1986 na  
tional league east team with the average career number. The p-value for the t-test is si  
gnificant indicating that the difference in means is not equal to zero. Further, the p-v  
alue of the wilcoxon test is significant indicating that the true location shift is not  
equal to zero.
```