

REGRESSION ANALYSIS

FOR

KELOWNA WEATHER-CRASH PROJECT

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1 Predicting Number of Crashes

1.1 Multiple Linear Regression

With backwards and forward selection using 'step()':

Call:

```
lm(formula = crashes ~ month + day + relhum + precip + wind.dir +
    wind.spd + visibility, data = train, x = TRUE, y = TRUE)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-82.657	-17.998	0.226	19.747	166.522

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	248.3339	39.4690	6.292	1.06e-09	***
monthAUGUST	21.4353	9.7515	2.198	0.028671	*
monthDECEMBER	40.8051	11.7764	3.465	0.000604	***
monthFEBRUARY	41.5961	10.6586	3.903	0.000117	***
monthJANUARY	57.8888	12.1759	4.754	3.04e-06	***
monthJULY	30.3272	9.1724	3.306	0.001055	**
monthJUNE	26.1346	8.5632	3.052	0.002468	**
monthMARCH	13.7881	8.8537	1.557	0.120403	
monthMAY	18.7967	8.4966	2.212	0.027670	*
monthNOVEMBER	35.4994	11.1850	3.174	0.001654	**
monthOCTOBER	35.2250	9.7665	3.607	0.000361	***
monthSEPTEMBER	23.1569	8.6477	2.678	0.007801	**
dayMONDAY	-24.6982	6.3687	-3.878	0.000128	***
daySATURDAY	-44.2414	6.3844	-6.930	2.41e-11	***
daySUNDAY	-64.2965	6.3471	-10.130	< 2e-16	***
dayTHURSDAY	-8.4554	6.3670	-1.328	0.185142	
dayTUESDAY	-9.6025	6.3569	-1.511	0.131908	
dayWEDNESDAY	-9.2981	6.3458	-1.465	0.143858	
relhum	-0.8501	0.3610	-2.355	0.019151	*
precip	0.9424	0.4563	2.065	0.039718	*
wind.dir	1.9817	0.9429	2.102	0.036376	*
wind.spd	-2.6151	1.0352	-2.526	0.012023	*
visibility	-5.0721	1.6142	-3.142	0.001838	**

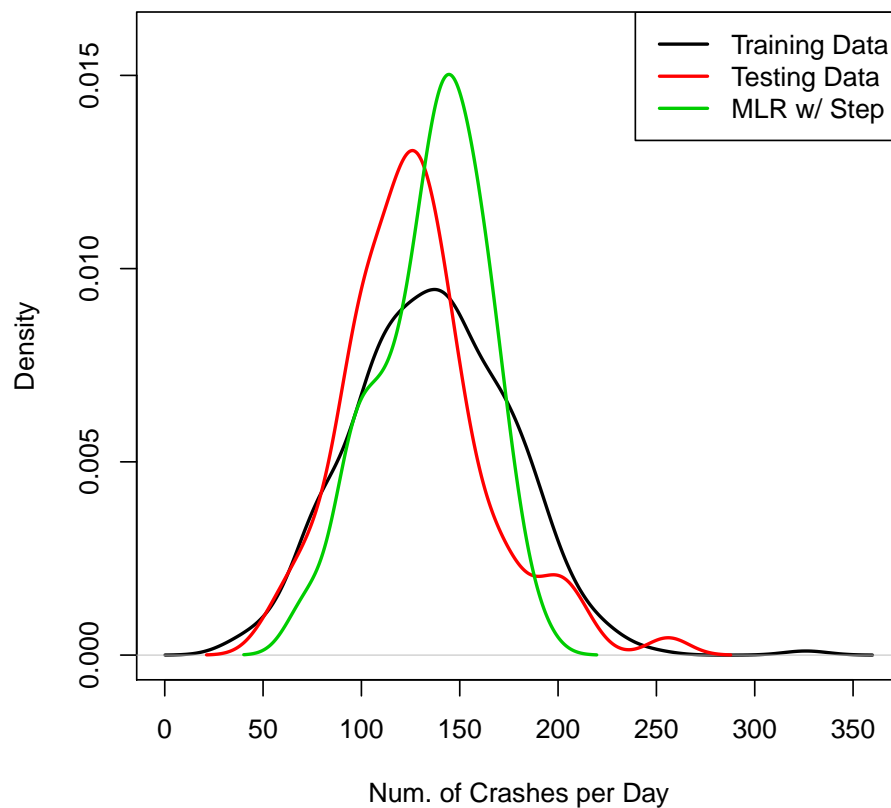
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 30.97 on 313 degrees of freedom

Multiple R-squared: 0.4441, Adjusted R-squared: 0.405

F-statistic: 11.37 on 22 and 313 DF, p-value: < 2.2e-16

MLR MSE: 990.7888



Consistent Model Specification Test

Parametric null model: `lm(formula = crashes ~ month + day + temp + relhum +
precip + wind.dir + wind.spd + visibility + pressure,
data = train, x = TRUE, y = TRUE)`

Number of regressors: 9

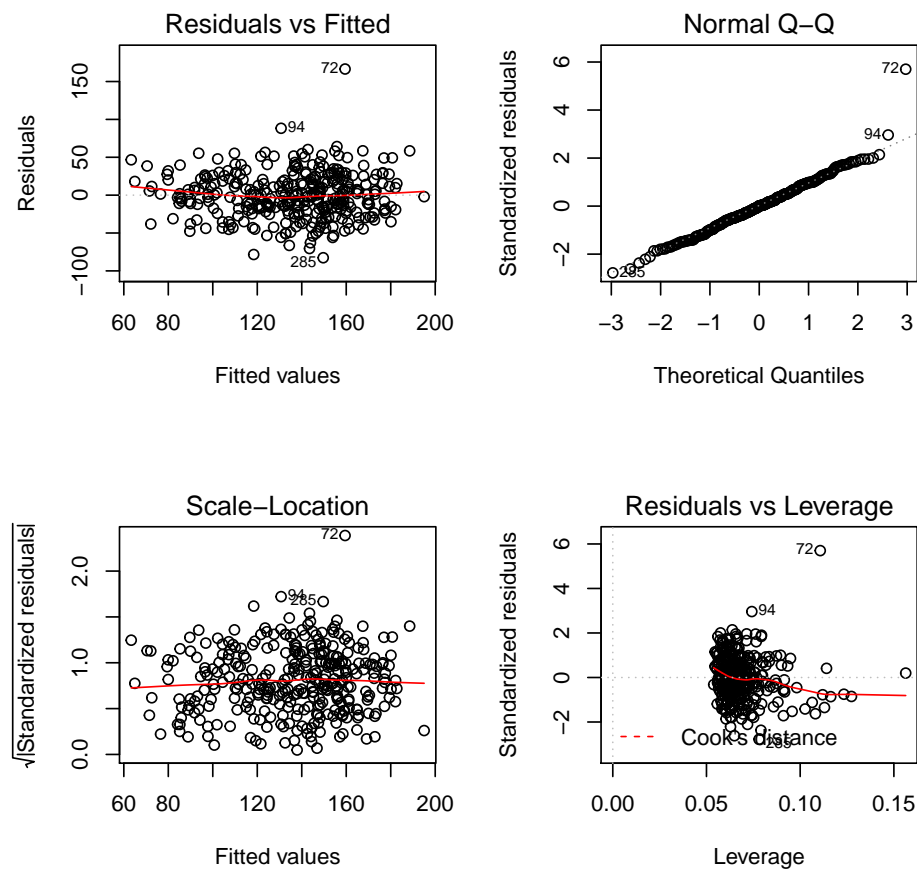
IID Bootstrap (399 replications)

Test Statistic 'Jn': 2.125212 P Value: 0.0075188 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null of correct specification is rejected at the 1% level

MLR Model Diagnostics:



Point 72:

```

linker month day temp relhum precip wind.dir
72 2017 NOVEMBER THURSDAY NOVEMBER THURSDAY 3.244167 88.5 18.7 19.20085
wind.spd visibility pressure crashes victims parked HWY97 HARVEY HWY33
72 11.43333 13.09917 95.80075 326 147 70 33 10 21
GORDON year
72 14 2017

```

1.2 MLR Outliers Removed

With backwards and forward selection using 'step()':

Call:

```
lm(formula = crashes ~ month + day + relhum + wind.dir + wind.spd +
    visibility, data = train, x = TRUE, y = TRUE)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-77.259	-18.539	-1.277	19.245	87.761

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	226.0928	36.2392	6.239	1.43e-09	***
monthAUGUST	22.8495	9.2334	2.475	0.013866	*
monthDECEMBER	34.9678	10.6659	3.278	0.001161	**
monthFEBRUARY	35.5950	9.4245	3.777	0.000190	***
monthJANUARY	51.1036	10.7197	4.767	2.87e-06	***
monthJULY	33.1438	8.5406	3.881	0.000127	***
monthJUNE	28.8859	8.0154	3.604	0.000365	***
monthMARCH	11.2022	8.2851	1.352	0.177321	
monthMAY	22.0047	7.8938	2.788	0.005635	**
monthNOVEMBER	22.9119	10.2012	2.246	0.025401	*
monthOCTOBER	30.8668	9.0629	3.406	0.000746	***
monthSEPTEMBER	21.7934	8.1734	2.666	0.008066	**
dayMONDAY	-25.1623	6.0412	-4.165	4.03e-05	***
daySATURDAY	-44.6592	6.0515	-7.380	1.44e-12	***
daySUNDAY	-64.3616	6.0213	-10.689	< 2e-16	***
dayTHURSDAY	-12.4378	6.0778	-2.046	0.041549	*
dayTUESDAY	-9.8105	6.0302	-1.627	0.104769	
dayWEDNESDAY	-9.6708	6.0203	-1.606	0.109202	
relhum	-0.5819	0.2980	-1.953	0.051731	.
wind.dir	2.1891	0.8938	2.449	0.014864	*
wind.spd	-3.2337	0.9844	-3.285	0.001136	**
visibility	-4.3765	1.5345	-2.852	0.004632	**

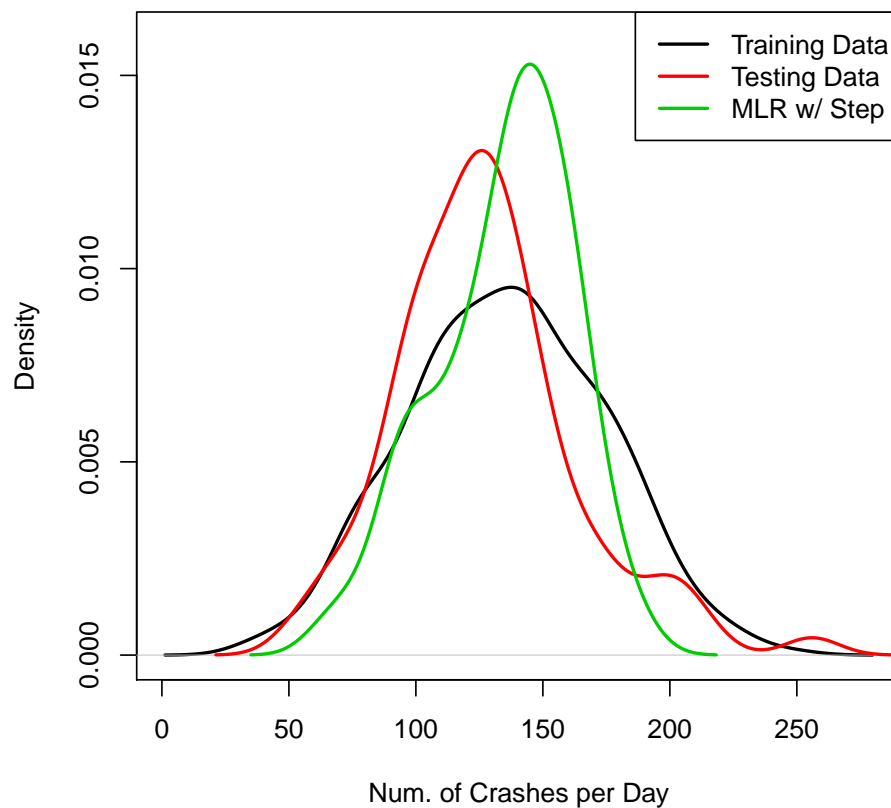
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 29.38 on 313 degrees of freedom

Multiple R-squared: 0.4638, Adjusted R-squared: 0.4278

F-statistic: 12.89 on 21 and 313 DF, p-value: < 2.2e-16

MLR MSE: 1029.308



Consistent Model Specification Test

Parametric null model: `lm(formula = crashes ~ month + day + relhum + wind.dir + wind.spd + visibility, data = train, x = TRUE, y = TRUE)`

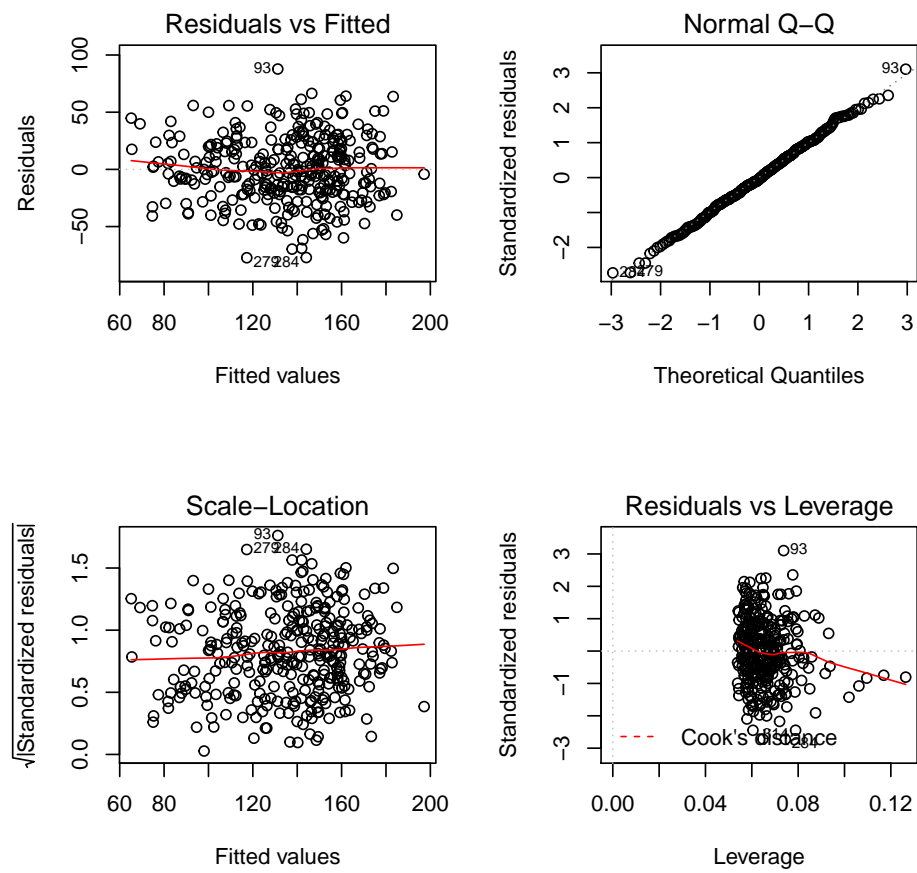
Number of regressors: 9

IID Bootstrap (399 replications)

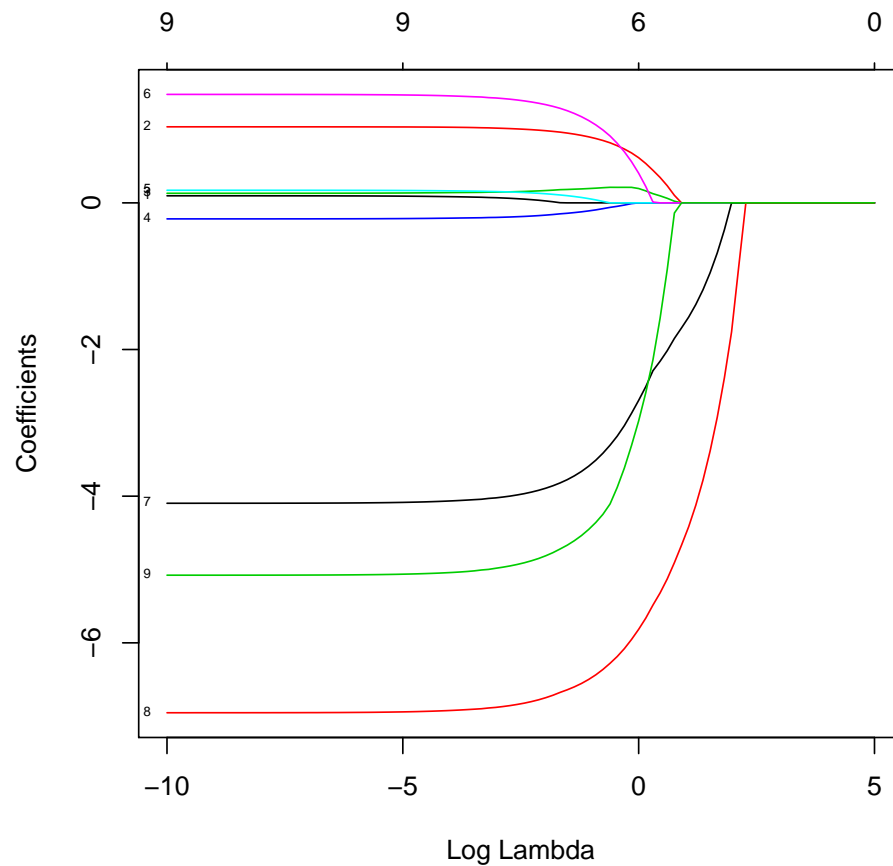
Test Statistic 'Jn': 1.956675 P Value: 0.0075188 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null of correct specification is rejected at the 1% level

MLR Model Diagnostics:

1.3 LASSO Variable Selection



Value of lambda that results in the lowest MSE: 1.833195

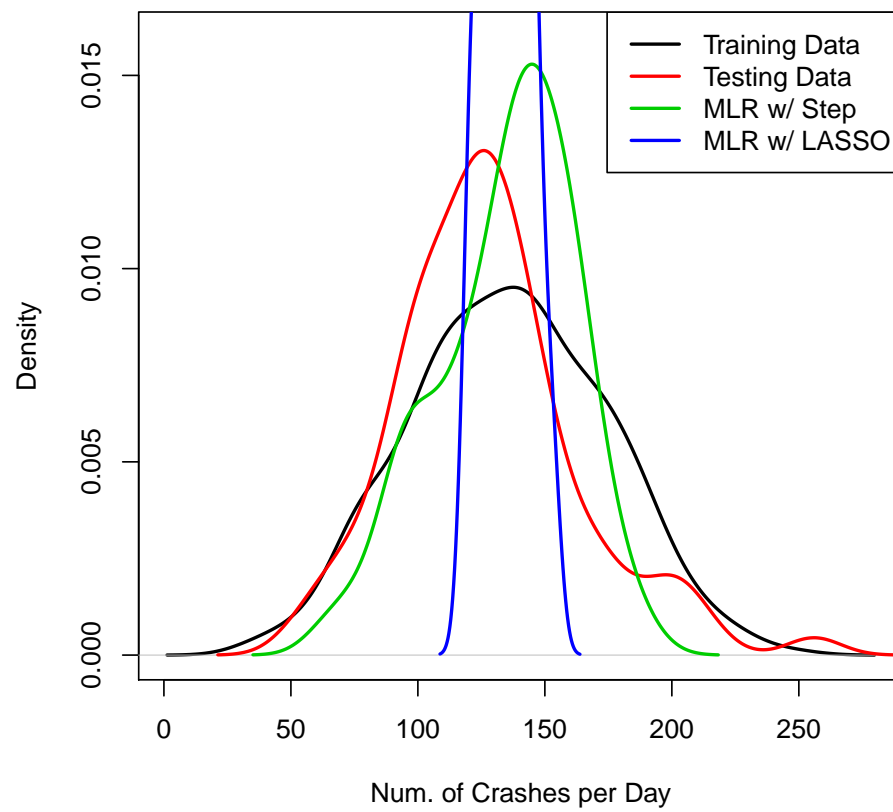
10 x 1 sparse Matrix of class "dgCMatrix"

```

              s0
(Intercept) 316.42924787
month        .
day          0.23352977
temp         0.06176113
relhum       .
precip       .
wind.dir     .
wind.spd     -2.01652421
visibility   -5.12835456
pressure     -0.91108125

```

MLR w/ LASSO MSE: 1334.424



This is clearly a terrible fit.....

1.4 Generalized Linear Model

Call:

```
glm(formula = crashes ~ month + day + temp + relhum + precip +
     wind.dir + wind.spd + visibility + pressure, family = gaussian(link = "identity"),
     data = train)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-79.335	-18.853	-0.679	19.692	88.901

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	791.9625	565.5173	1.400	0.162387
monthAUGUST	28.1143	14.2525	1.973	0.049431 *
monthDECEMBER	38.0453	13.6585	2.785	0.005674 **
monthFEBRUARY	34.8072	14.6491	2.376	0.018106 *
monthJANUARY	52.9286	14.6668	3.609	0.000359 ***
monthJULY	38.2162	14.7552	2.590	0.010050 *
monthJUNE	31.9660	11.8956	2.687	0.007594 **
monthMARCH	10.5997	9.7818	1.084	0.279377
monthMAY	23.4757	10.4261	2.252	0.025046 *
monthNOVEMBER	25.7166	11.7240	2.193	0.029014 *
monthOCTOBER	34.9887	9.5613	3.659	0.000297 ***
monthSEPTEMBER	26.9859	10.7824	2.503	0.012837 *
dayMONDAY	-24.3617	6.1856	-3.938	0.000101 ***
daySATURDAY	-44.0734	6.0752	-7.255	3.25e-12 ***
daySUNDAY	-63.9712	6.0884	-10.507	< 2e-16 ***
dayTHURSDAY	-12.5281	6.1086	-2.051	0.041118 *
dayTUESDAY	-9.7347	6.1057	-1.594	0.111870
dayWEDNESDAY	-9.6339	6.0622	-1.589	0.113041
temp	-0.5824	1.0183	-0.572	0.567779
relhum	-0.8393	0.3532	-2.376	0.018089 *
precip	0.4340	0.4469	0.971	0.332244
wind.dir	2.1701	0.8995	2.413	0.016416 *
wind.spd	-3.5396	1.0086	-3.510	0.000515 ***
visibility	-4.1926	1.5441	-2.715	0.006993 **
pressure	-5.6648	5.8171	-0.974	0.330908

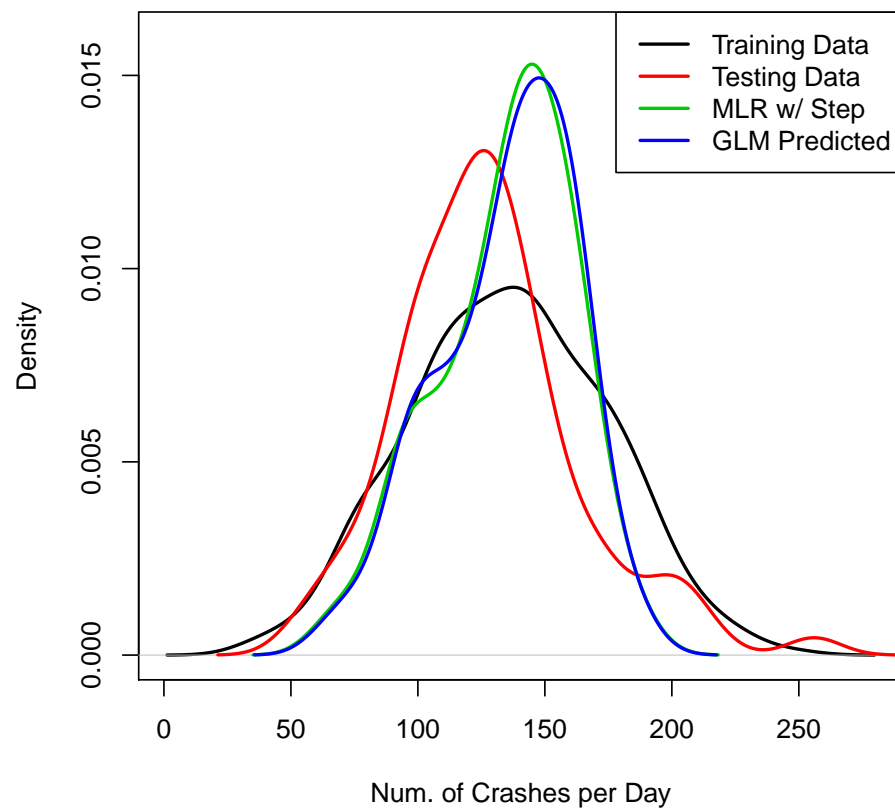
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 865.032)

Null deviance: 503970 on 334 degrees of freedom
 Residual deviance: 268160 on 310 degrees of freedom
 AIC: 3242.2

Number of Fisher Scoring iterations: 2

GLM MSE: 974.3266



1.5 Non-parametric Approach

Kernel Regression Significance Test

Type I Test with IID Bootstrap (399 replications, Pivot = TRUE, joint = FALSE)

Explanatory variables tested for significance:

month (1), day (2), temp (3), relhum (4), precip (5), wind.dir (6), wind.spd (7), visibility

	month	day	temp	relhum	precip	wind.dir	wind.spd
Bandwidth(s):	0.916666	0.4419936	9.705523	12.39832	6428386	20379937	14.35713
	visibility	pressure					
Bandwidth(s):	6167572	6886070					

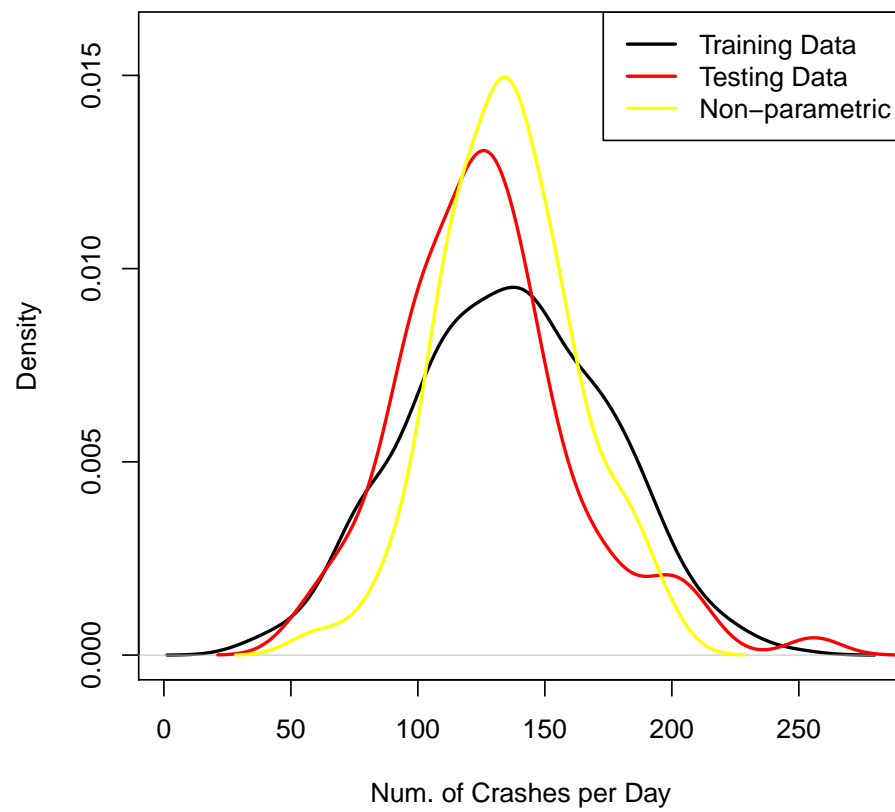
Individual Significance Tests

P Value:

month	0.0075188 **
day	< 2.22e-16 ***
temp	0.0175439 *
relhum	0.6892231
precip	0.2706767
wind.dir	0.0350877 *
wind.spd	< 2.22e-16 ***
visibility	0.0100251 *
pressure	0.1027569

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Non-parametric MSE: 1203.843



1.6 Decision Tree

Regression tree:

```
tree(formula = crashes ~ month + day + temp + relhum + precip +
      wind.dir + wind.spd + visibility + pressure, data = train)
```

Variables actually used in tree construction:

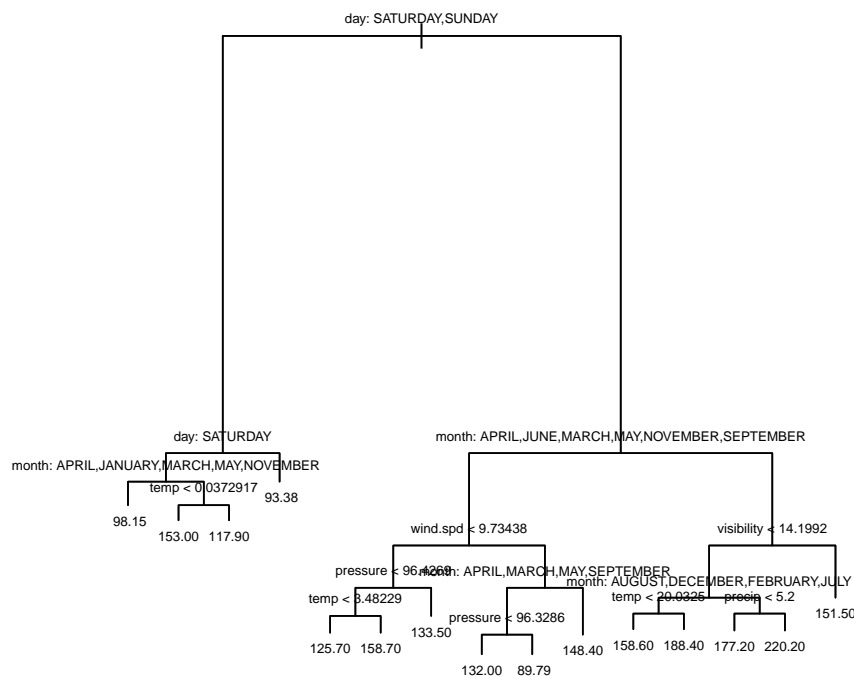
```
[1] "day"      "month"    "temp"     "wind.spd" "pressure"
[6] "visibility" "precip"
```

Number of terminal nodes: 15

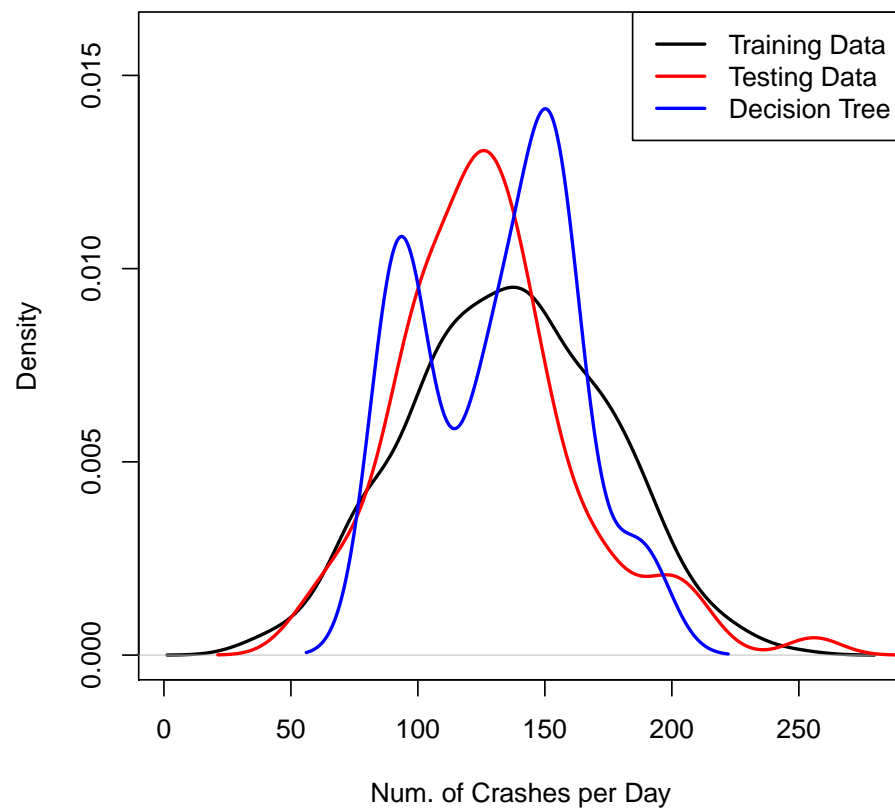
Residual mean deviance: 705.1 = 225600 / 320

Distribution of residuals:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-65.0000	-17.4200	0.1304	0.0000	17.5900	66.0000



Decision Tree MSE: 1164.874



1.7 Random Forest

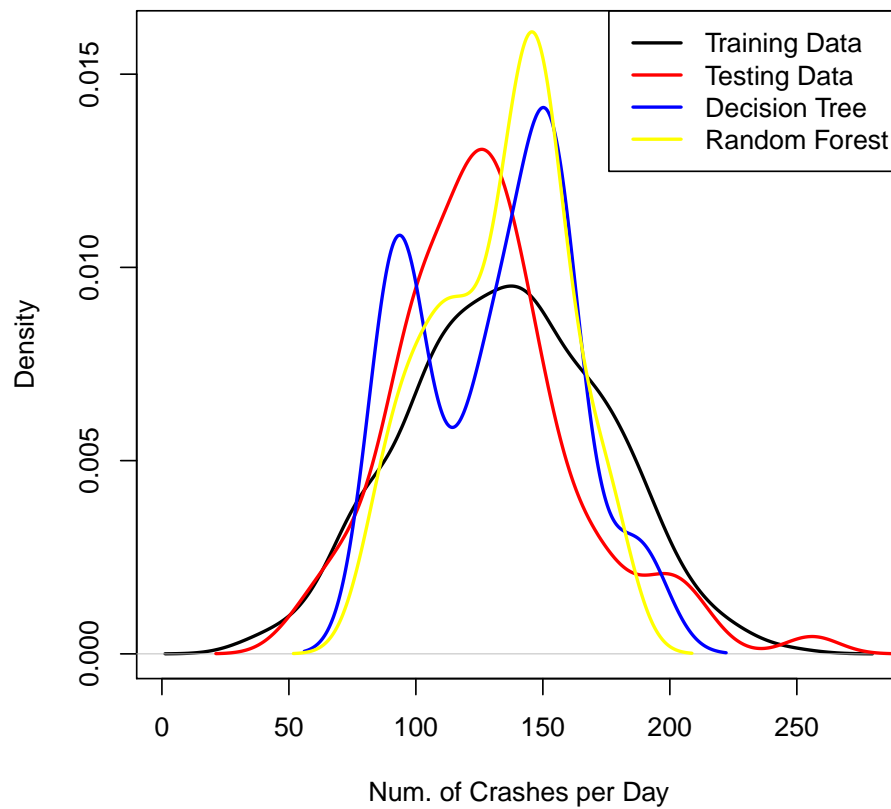
Call:

```
randomForest(formula = crashes ~ month + day + temp + relhum +      precip + wind.dir + win  
              Type of random forest: regression  
              Number of trees: 500
```

No. of variables tried at each split: 3

```
Mean of squared residuals: 837.889  
% Var explained: 44.3
```

Random Forest MSE: 1017.569

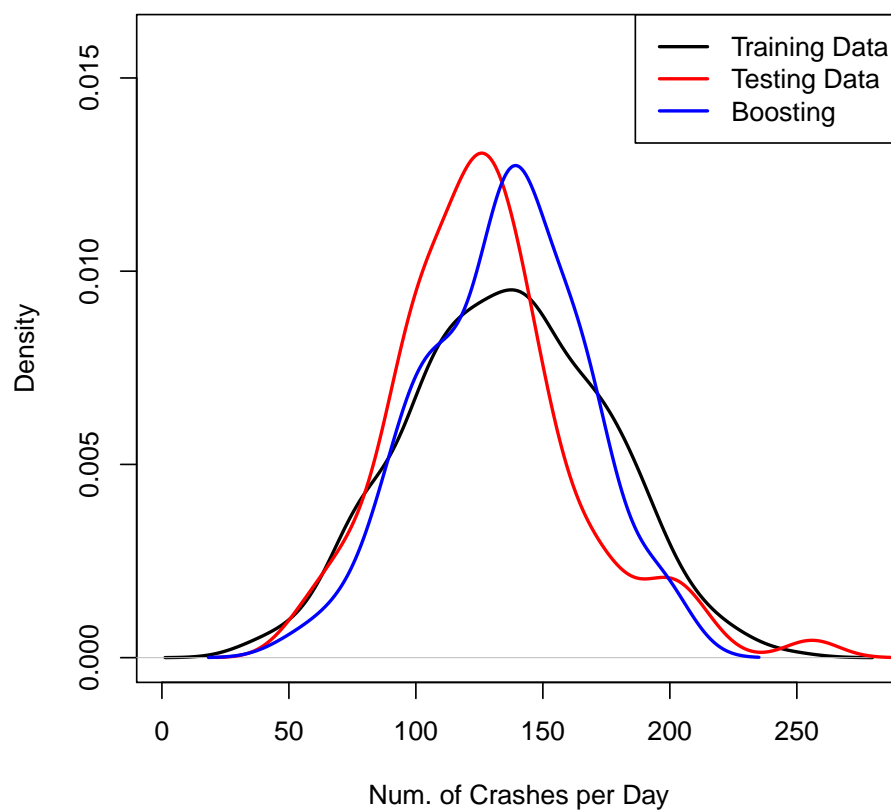


1.8 Boosting

Distribution not specified, assuming gaussian ...

	var	rel.inf
month	month	37.449966
day	day	13.487334
wind.dir	wind.dir	10.802975
wind.spd	wind.spd	8.292799
visibility	visibility	7.510607
pressure	pressure	6.772252
temp	temp	5.864595
relhum	relhum	5.223828
precip	precip	4.595645

Boosting MSE: 1052.224



1.9 Regression Summary

All model MSEs:

MLR	GLM	NP	Tree	RF	Boosting
1029.308	974.3266	1203.843	1164.874	1017.569	1052.224

Winner: GLM!

2 Predicting Number of Victims

2.1 Multiple Linear Regression

Call:

```
lm(formula = victims ~ month + day + wind.spd, data = train,
    x = TRUE, y = TRUE)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-28.201	-6.864	0.272	6.680	37.935

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	48.3371	4.1058	11.773	< 2e-16 ***
monthAUGUST	11.2373	3.0844	3.643	0.000314 ***
monthDECEMBER	10.2125	3.2096	3.182	0.001609 **
monthFEBRUARY	7.8671	3.0711	2.562	0.010882 *
monthJANUARY	9.2144	3.1289	2.945	0.003470 **
monthJULY	12.3294	3.0452	4.049	6.48e-05 ***
monthJUNE	9.2431	3.0452	3.035	0.002603 **
monthMARCH	1.0384	3.0717	0.338	0.735536
monthMAY	6.1042	3.0446	2.005	0.045825 *
monthNOVEMBER	5.1081	3.1965	1.598	0.111040
monthOCTOBER	9.9902	3.1395	3.182	0.001608 **
monthSEPTEMBER	10.5302	3.0902	3.408	0.000740 ***
dayMONDAY	-12.5839	2.3256	-5.411	1.24e-07 ***
daySATURDAY	-21.8174	2.3350	-9.344	< 2e-16 ***
daySUNDAY	-25.5786	2.3266	-10.994	< 2e-16 ***
dayTHURSDAY	-7.6391	2.3499	-3.251	0.001275 **
dayTUESDAY	-6.6192	2.3290	-2.842	0.004773 **
dayWEDNESDAY	-7.3388	2.3275	-3.153	0.001771 **
wind.spd	-0.5891	0.3222	-1.828	0.068447 .

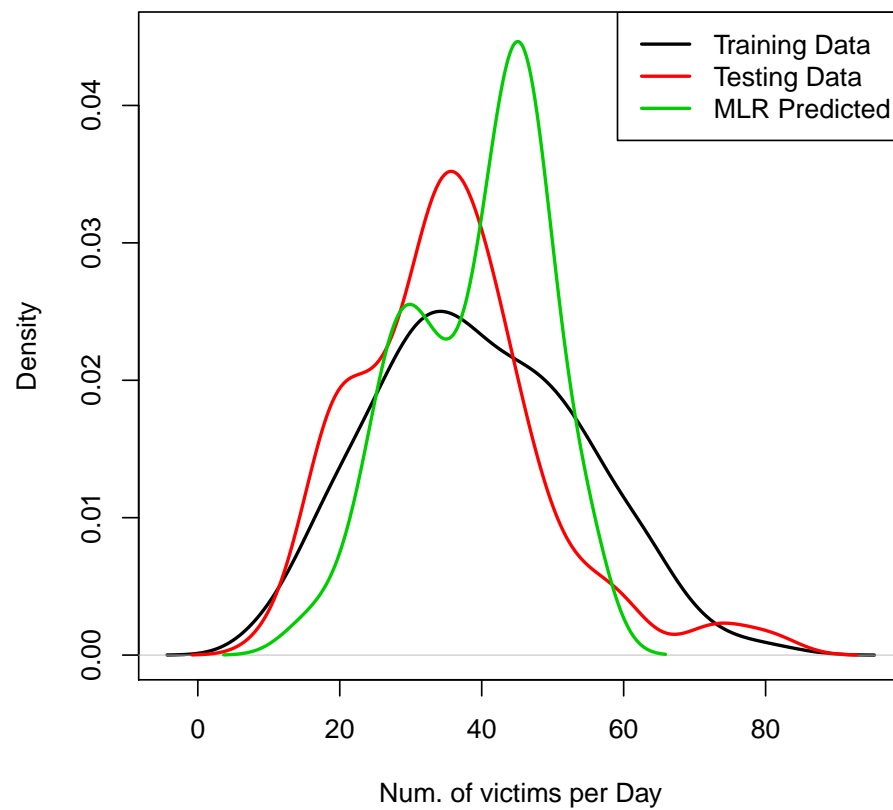
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 11.39 on 316 degrees of freedom

Multiple R-squared: 0.4259, Adjusted R-squared: 0.3932

F-statistic: 13.02 on 18 and 316 DF, p-value: < 2.2e-16

MLR MSE: 153.6082



Consistent Model Specification Test

Parametric null model: `lm(formula = crashes ~ month + day + temp + relhum +
precip + wind.dir + wind.spd + visibility + pressure,
data = train, x = TRUE, y = TRUE)`

Number of regressors: 9

IID Bootstrap (399 replications)

Test Statistic 'Jn': 2.125212 P Value: 0.0075188 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null of correct specification is rejected at the 1% level

2.2 Generalized Linear Model

Call:

```
glm(formula = victims ~ month + day + temp + relhum + precip +
     wind.dir + wind.spd + visibility + pressure, family = gaussian(link = "identity"),
     data = train)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-29.597	-7.378	0.171	7.247	39.637

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	383.54765	218.89064	1.752	0.080722	.
monthAUGUST	14.79288	5.51660	2.682	0.007721	**
monthDECEMBER	10.36465	5.28669	1.961	0.050830	.
monthFEBRUARY	3.54993	5.67013	0.626	0.531726	
monthJANUARY	7.31513	5.67695	1.289	0.198510	
monthJULY	17.86761	5.71119	3.129	0.001924	**
monthJUNE	13.82776	4.60435	3.003	0.002889	**
monthMARCH	-0.98606	3.78617	-0.260	0.794699	
monthMAY	9.30472	4.03556	2.306	0.021788	*
monthNOVEMBER	6.15255	4.53793	1.356	0.176147	
monthOCTOBER	12.42884	3.70083	3.358	0.000882	***
monthSEPTEMBER	14.63639	4.17346	3.507	0.000520	***
dayMONDAY	-12.67408	2.39423	-5.294	2.27e-07	***
daySATURDAY	-21.74037	2.35150	-9.245	< 2e-16	***
daySUNDAY	-25.43063	2.35661	-10.791	< 2e-16	***
dayTHURSDAY	-7.89874	2.36442	-3.341	0.000938	***
dayTUESDAY	-6.87792	2.36327	-2.910	0.003872	**
dayWEDNESDAY	-7.52565	2.34645	-3.207	0.001480	**
temp	-0.57623	0.39413	-1.462	0.144744	
relhum	-0.19986	0.13670	-1.462	0.144754	
precip	0.02343	0.17298	0.135	0.892338	
wind.dir	0.34939	0.34815	1.004	0.316375	
wind.spd	-0.98698	0.39037	-2.528	0.011958	*
visibility	-0.69167	0.59765	-1.157	0.248031	
pressure	-3.21530	2.25158	-1.428	0.154294	

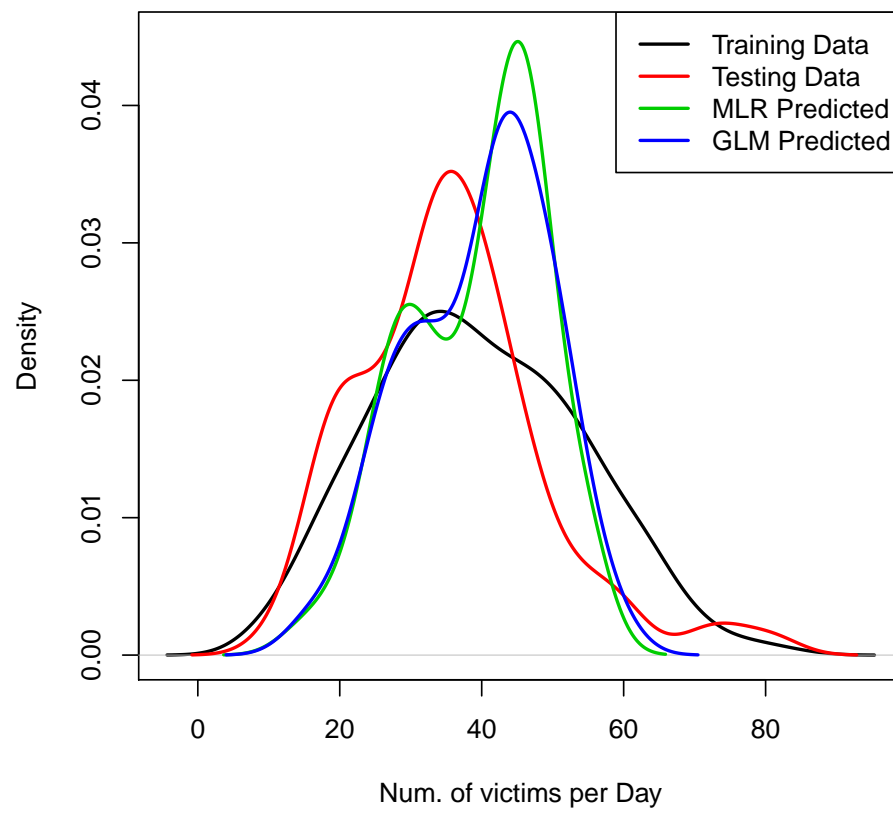
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 129.5969)

Null deviance: 71422 on 334 degrees of freedom
 Residual deviance: 40175 on 310 degrees of freedom
 AIC: 2606.3

Number of Fisher Scoring iterations: 2

GLM MSE: 142.8508



2.3 Non-parametric Approach

Kernel Regression Significance Test

Type I Test with IID Bootstrap (399 replications, Pivot = TRUE, joint = FALSE)

Explanatory variables tested for significance:

month (1), day (2), temp (3), relhum (4), precip (5), wind.dir (6), wind.spd (7), visibility

```

              month      day      temp  relhum  precip wind.dir wind.spd
Bandwidth(s): 0.916666 0.4512622 15.01095 11.0829 9.474667 5925261 11.88198
              visibility pressure
Bandwidth(s): 52101772 3255838

```

Individual Significance Tests

P Value:

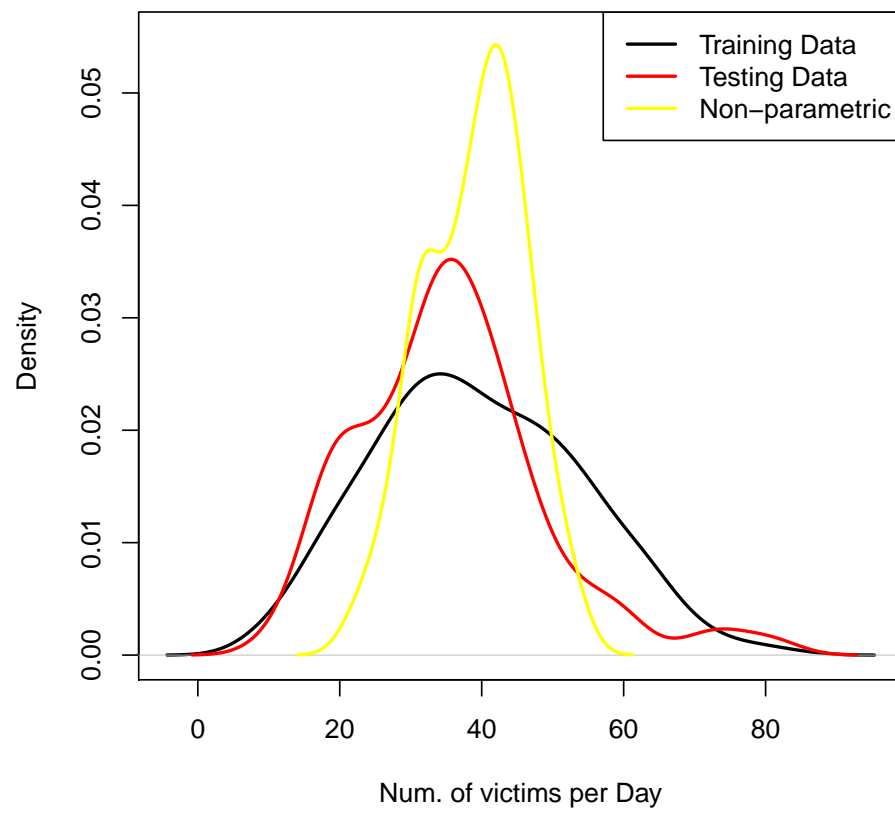
```

month      0.0025063 **
day        < 2.22e-16 ***
temp       0.0075188 **
relhum     0.7969925
precip     0.0350877 *
wind.dir   0.1679198
wind.spd   0.0050125 **
visibility 0.0225564 *
pressure   0.2080201

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Non-parametric MSE: 170.7991



2.4 Decision Tree

Regression tree:

```
tree(formula = victims ~ month + day + temp + relhum + precip +
      wind.dir + wind.spd + visibility + pressure, data = train)
```

Variables actually used in tree construction:

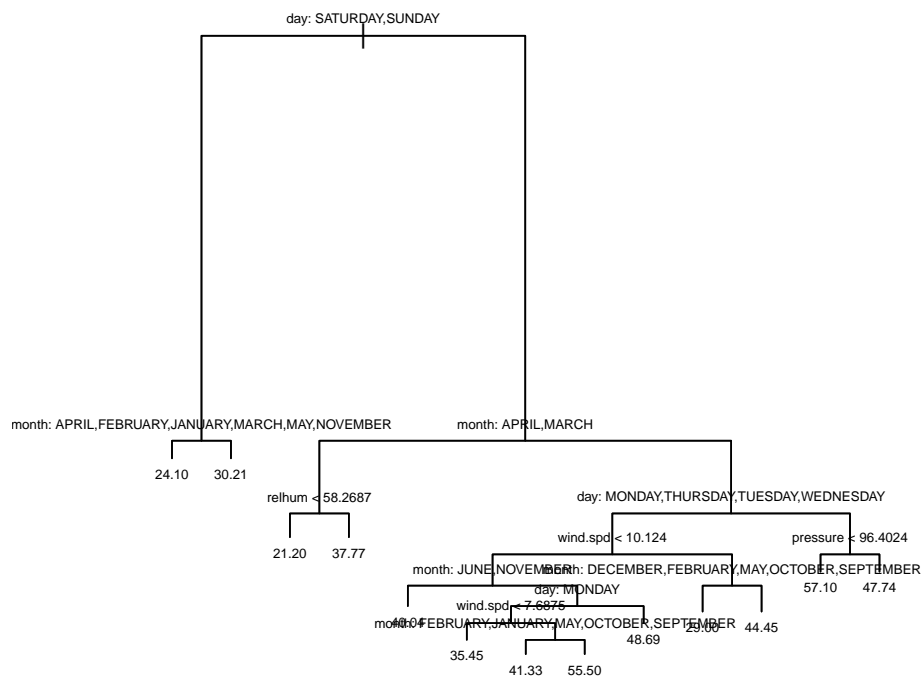
```
[1] "day"      "month"    "relhum"   "wind.spd" "pressure"
```

Number of terminal nodes: 13

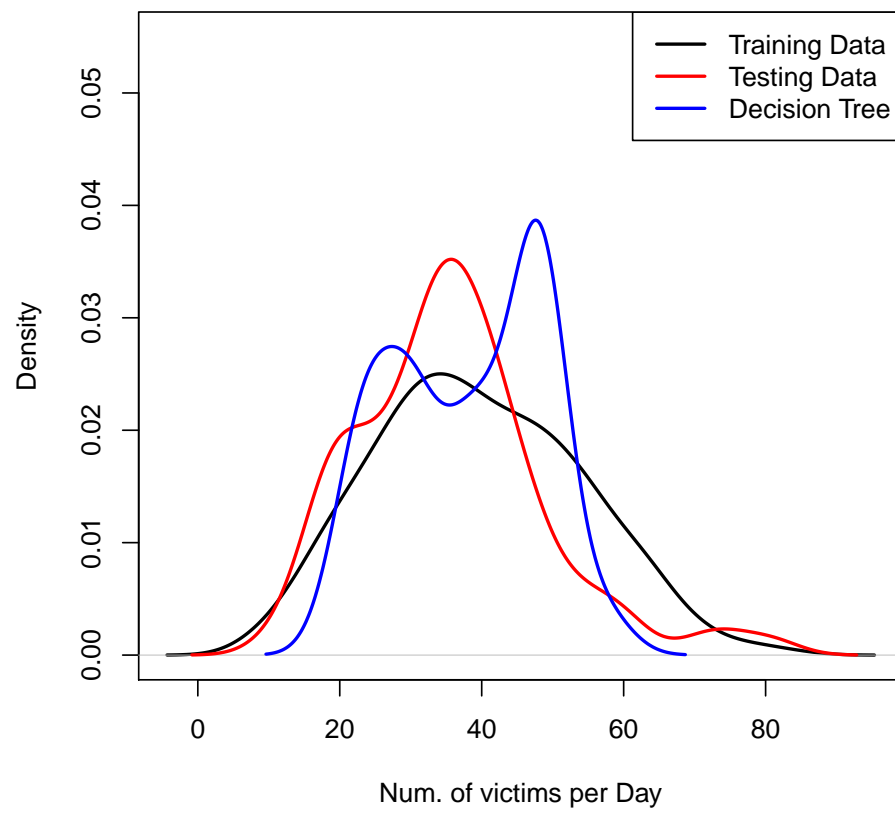
Residual mean deviance: 111.3 = 35840 / 322

Distribution of residuals:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-23.770	-7.331	-0.686	0.000	6.606	45.230



Decision Tree MSE: 180.8277



2.5 Random Forest

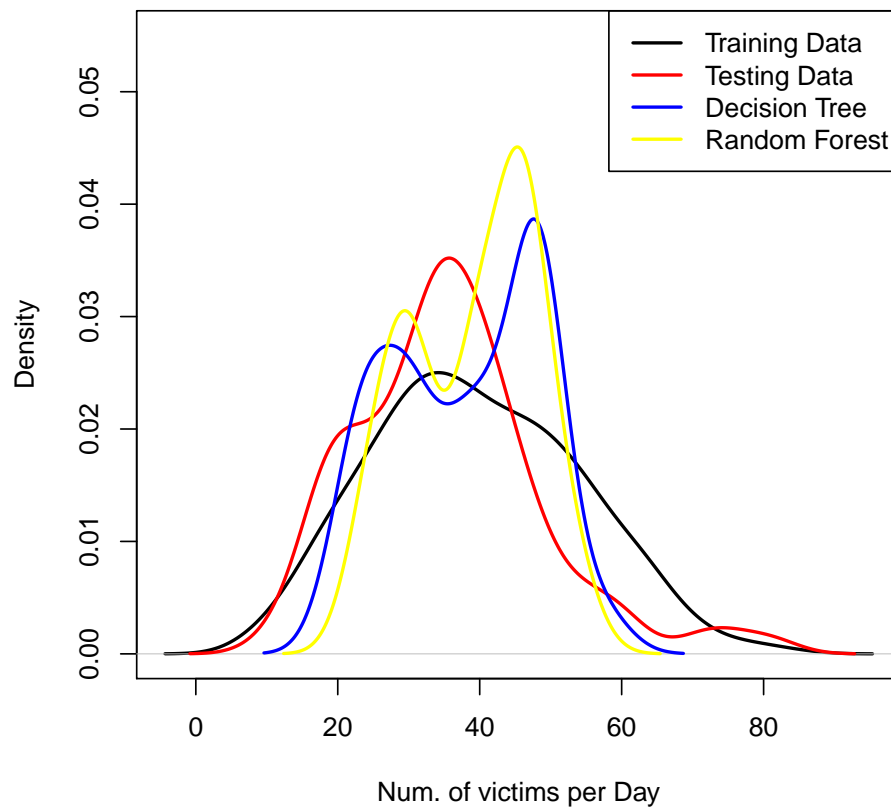
Call:

```
randomForest(formula = victims ~ month + day + temp + relhum +      precip + wind.dir + win  
              Type of random forest: regression  
              Number of trees: 500
```

No. of variables tried at each split: 3

```
Mean of squared residuals: 142.6944  
% Var explained: 33.07
```

Random Forest MSE: 152.5664

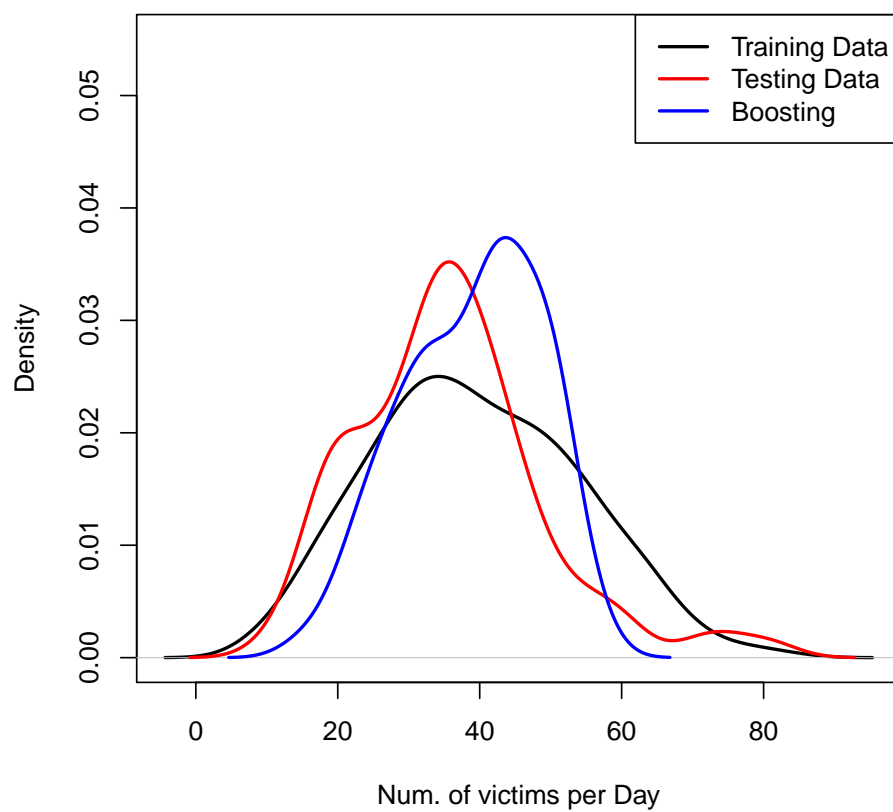


2.6 Boosting

Distribution not specified, assuming gaussian ...

	var	rel.inf
month	month	40.877423
day	day	12.957957
pressure	pressure	9.455169
wind.dir	wind.dir	9.081652
visibility	visibility	6.599191
wind.spd	wind.spd	6.451126
temp	temp	5.749958
relhum	relhum	4.830842
precip	precip	3.996683

Boosting MSE: 143.6589



2.7 Regression Summary

All model MSEs:

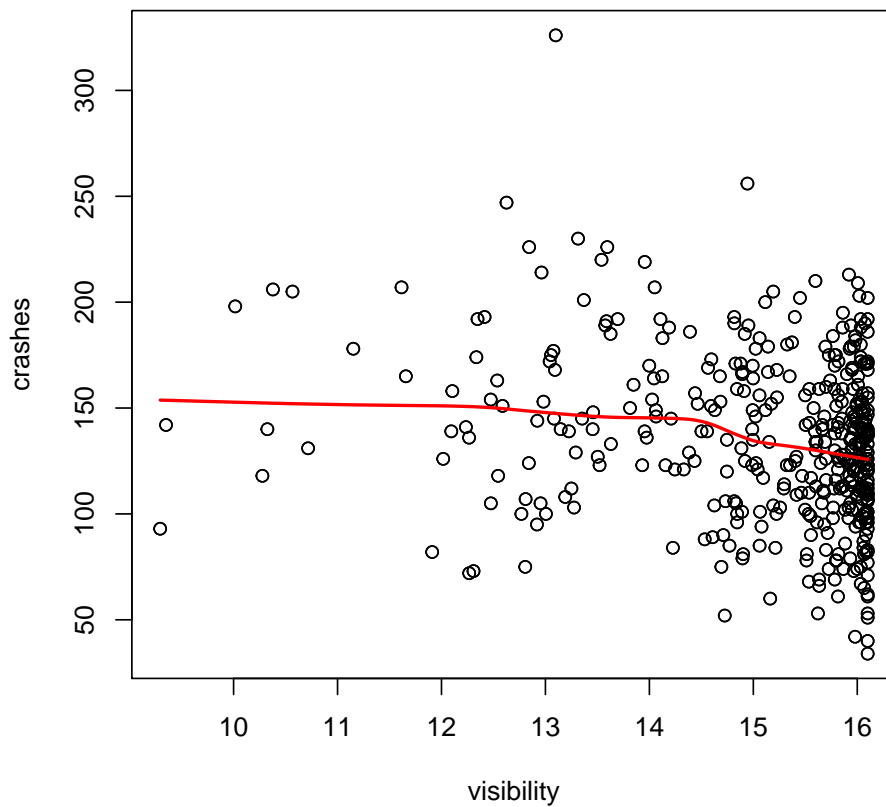
MLR	GLM	NP	Tree	RF	Boosting
153.6082	142.8508	170.7991	180.8277	152.5664	143.6589

Winner: GLM (again)!

3 Answering Hypotheses

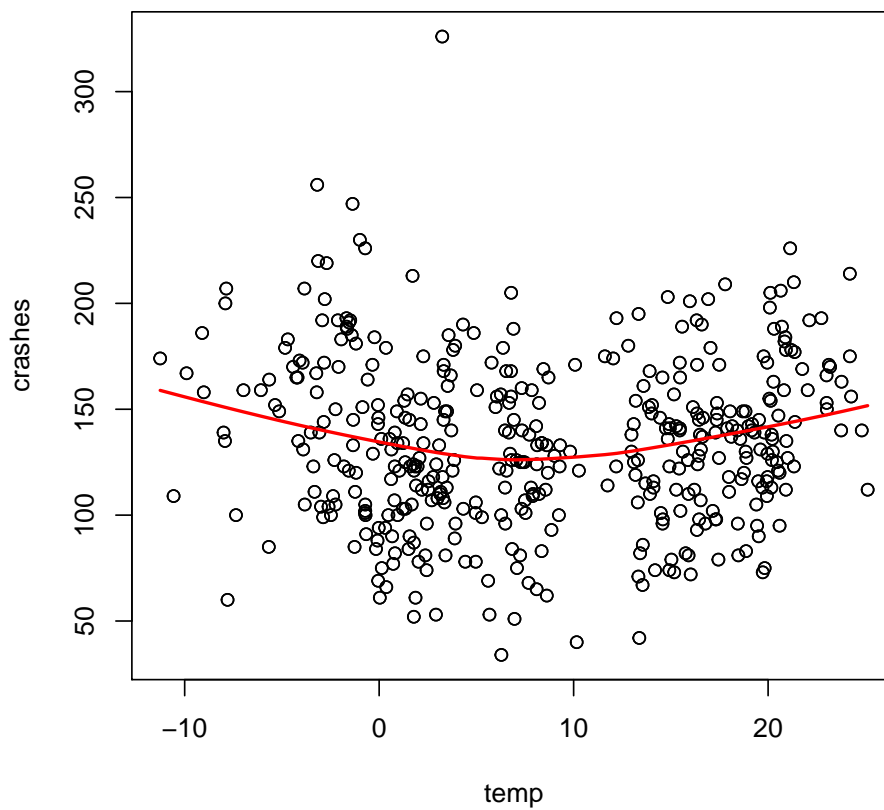
3.1 Visibility on a given day will be inversely correlated with # of crashes per day.

This is true. The GLM (with outlier removed) shows a statistically significant coefficient estimate of -4.1926, meaning that visibility and # of crashes per day is, indeed, inversely related.



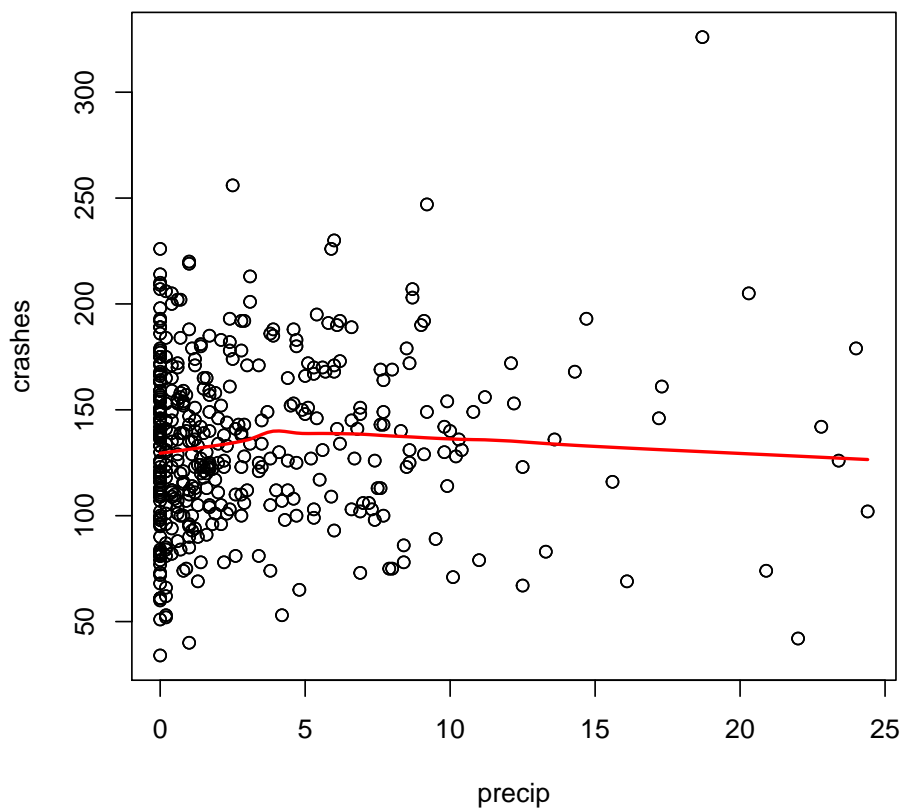
3.2 Temperature will have a weak correlation with # of crashes per day (people drive more recklessly in the summer? also tourism = more traffic in summer).

This is false. The GLM shows that temperature is not a statistically significant predictor, and the months that increase the # of crashes the most are in the winter: January & December.



3.3 Precipitation will be correlated with # of crashes per day.

This is unclear. While the GLM does show increasing precipitation to be associated with increasing # of crashes (0.434), this relationship is not statistically significant ($p=0.332$). Perhaps with more data (or if the current data was not anonymized), this trend would be confirmed.



3.4 Summer will have more crashes involving cyclists and motorcyclists.

A cursory glance at the variable investigation document will confirm this.

We can also cluster the months based on season and perform a proper hypothesis test:

Cyclist ANOVA:

```

              Df Sum Sq Mean Sq F value    Pr(>F)
season         3   3539   1179.6     7.714 0.00955 **
Residuals      8   1223    152.9
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Tukey multiple comparisons of means
95% family-wise confidence level

Fit: aov(formula = bike ~ season, data = kwt)

```

$season
              diff          lwr          upr      p adj
Spring-Fall -13.00000 -45.333361  1.933336e+01 0.5946617
Summer-Fall  14.33333 -18.000028  4.666669e+01 0.5223532
Winter-Fall -32.33333 -64.666694  2.757948e-05 0.0500002
Summer-Spring 27.33333  -5.000028  5.966669e+01 0.1005671
Winter-Spring -19.33333 -51.666694  1.300003e+01 0.2944622
Winter-Summer -46.66667 -79.000028 -1.433331e+01 0.0073984

```

Motorcycle ANOVA:

```

              Df Sum Sq Mean Sq F value    Pr(>F)
season         3   9249    3083    10.04 0.00435 **
Residuals      8   2456     307
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

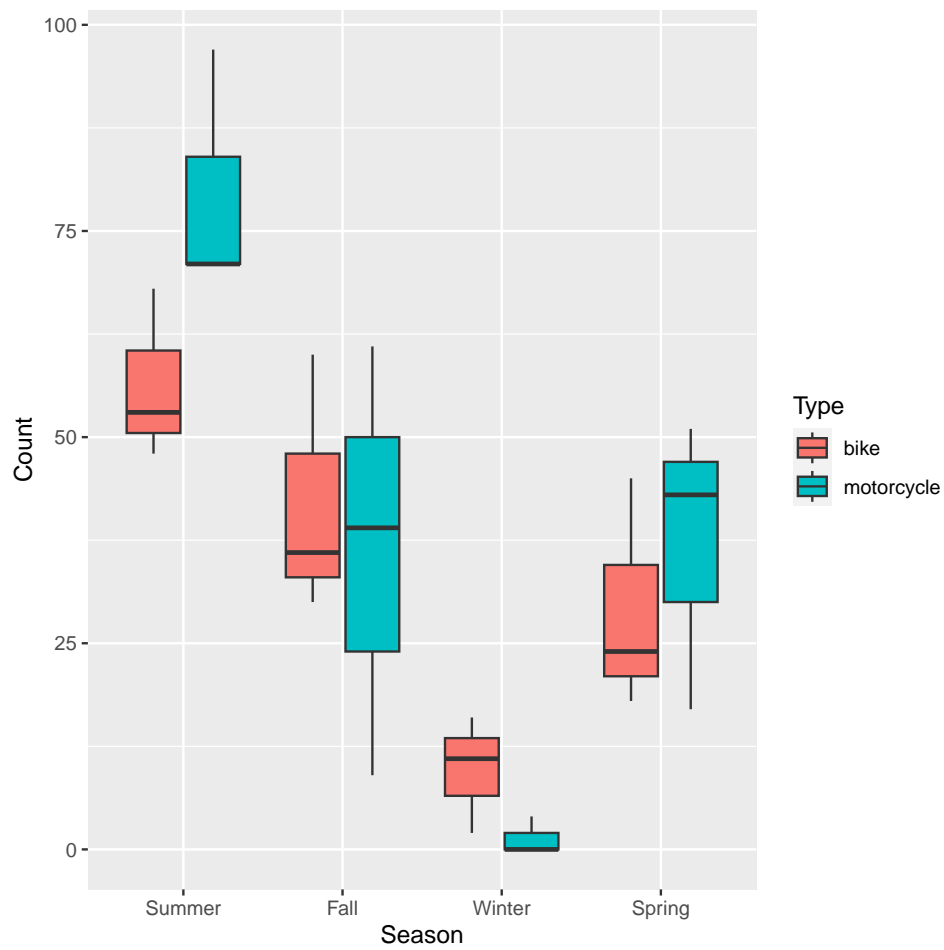
Tukey multiple comparisons of means
95% family-wise confidence level

Fit: aov(formula = motorcycle ~ season, data = kwt)

```

$season
              diff          lwr          upr      p adj
Spring-Fall  0.6666667 -45.146744  46.48008 0.9999604
Summer-Fall  43.3333333  -2.480078  89.14674 0.0638450
Winter-Fall -35.0000000 -80.813411  10.81341 0.1447832
Summer-Spring 42.6666667  -3.146744  88.48008 0.0681892
Winter-Spring -35.6666667 -81.480078  10.14674 0.1357137
Winter-Summer -78.3333333 -124.146744 -32.51992 0.0026273

```

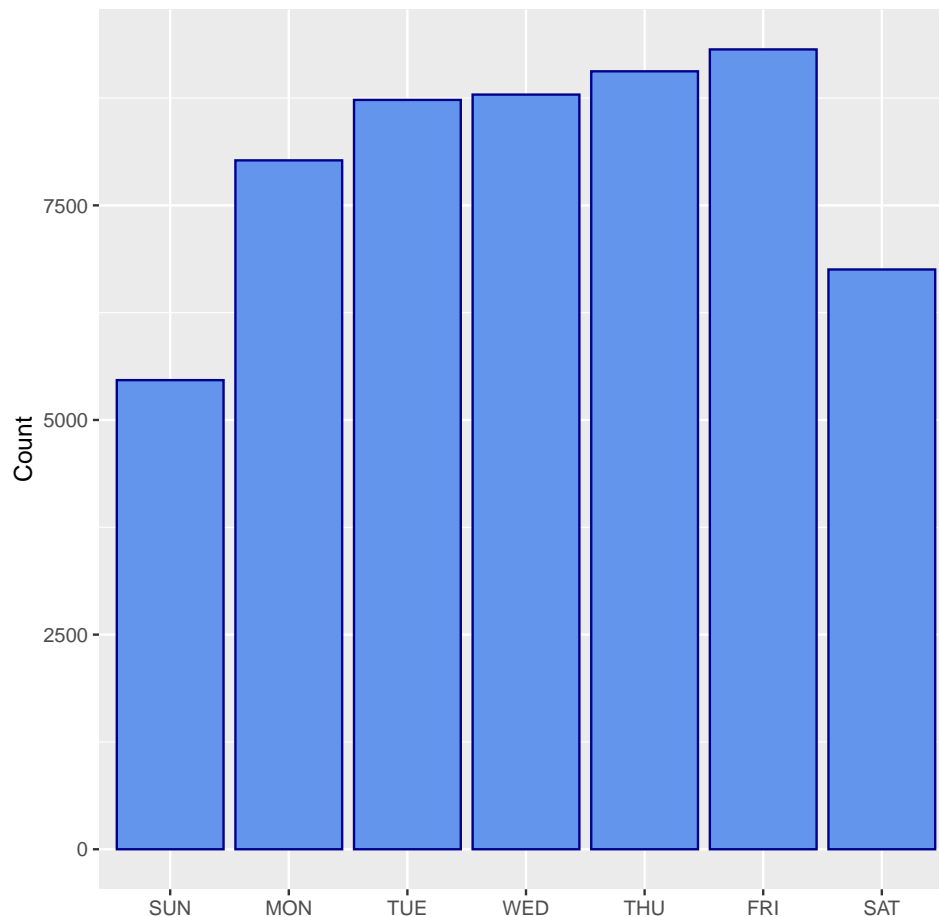


In summary, yes, summer months have significantly more cyclist and motorcycle accidents (than winter months).

3.5 Crash fatality will be higher on weekends when more people are driving under the influence.

This is false. By looking at the barplot of accidents throughout the week in the Variable Investigation document, it is clear that there are more crashes on weekdays (Mon-Fri) compared to weekends (Sat-Sun), with the # of crashes slowly climbing throughout the week. This is the reverse of what was expected.

Reprint of plot from Variable Investigation:



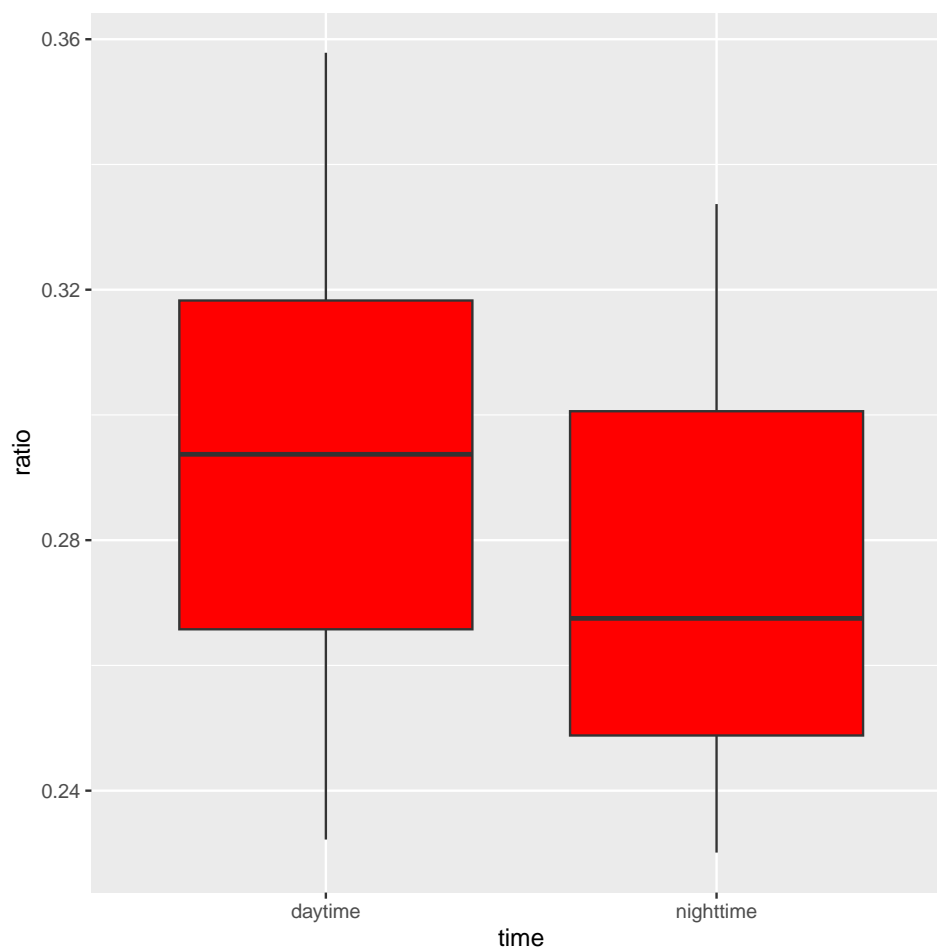
3.6 Fatal, more severe crashes occur proportionately more often at nighttime, as visibility is reduced due to lack of sunlight.

By looking at the barplot of accidents throughout the day in the Variable Investigation document, it is clear that more accidents happen during the daytime. However, this is likely due to the fact that more people are driving and are on the roads during the day. Instead, we want to know if nighttime crashes are *more fatal*.

To determine this, I will give each time block a crash:casualty ratio by dividing the number of fatalities by the number of crashes. This value can then be compared across time categories. I will define 9PM to 6AM as 'nighttime', and 6AM - 9PM as 'daytime'.

Crash-Casualty Ratio ANOVA:

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
time	1	0.000508	0.0005079	0.206	0.666
Residuals	6	0.014781	0.0024636		



As you can see, there is no evidence that nighttime accidents are more fatal than daytime ones.

3.7 Single-vehicle crashes should be proportionally higher during adverse weather, especially snow/ice conditions.

This approach can be similar to the cyclist/motocycle hypothesis above. I will group by season and test for difference using an ANOVA:

```

      Df Sum Sq Mean Sq F value Pr(>F)
Season   3 105547   35182   10.09 0.00429 **
Residuals  8  27905    3488

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    Tukey multiple comparisons of means
      95% family-wise confidence level

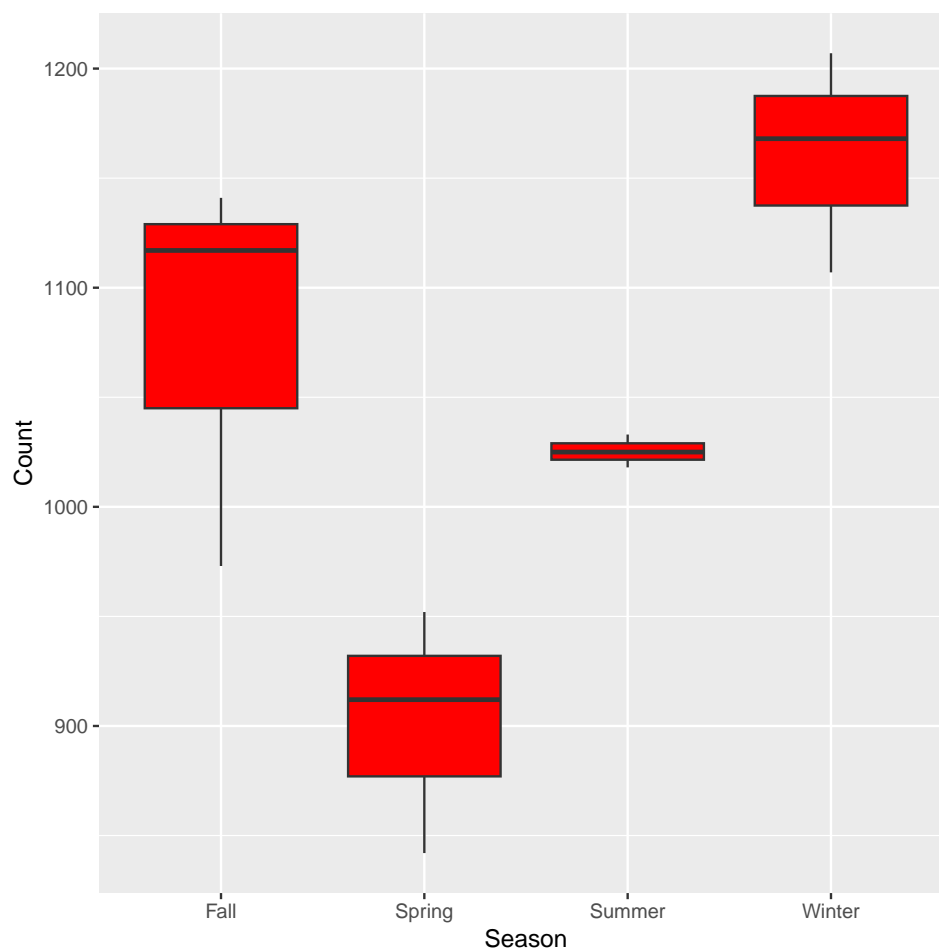
```

```
Fit: aov(formula = Count ~ Season, data = single)
```

```

$Season
      diff      lwr      upr    p adj
Spring-Fall -175.00000 -329.42658 -20.57342 0.0275845
Summer-Fall  -51.66667 -206.09325 102.75991 0.7152015
Winter-Fall   83.66667  -70.75991 238.09325 0.3674538
Summer-Spring 123.33333  -31.09325 277.75991 0.1240470
Winter-Spring 258.66667  104.24009 413.09325 0.0029922
Winter-Summer 135.33333  -19.09325 289.75991 0.0874337

```



It appears that most single vehicle collisions occur in the fall and winter, which seems to confirm our hypothesis. However, spring has the least, whereas we have predicted summer to have the least. The winter-summer comparison barely fails to reject ($p=0.087$), making this hypothesis unclear.