Analyzing the Effects of Variables on Car Fuel Economy: Developing Prediction Models for Sustainable Transportation

THE ISSUE:

The report aims to explore the correlation between several variables and car fuel efficiency, but the project has encountered several issues that require resolution. One of the primary concerns is the quality and comprehensiveness of the dataset. While the Auto dataset is commonly used in the industry, it may not include all the crucial factors that influence fuel economy. Moreover, inaccurate or missing data in the dataset may affect the accuracy of the analysis. Thus, the project must carefully clean and examine the data to ensure that it accurately reflects the variables being studied. The selection of a statistical model requires careful consideration to obtain reliable and significant results. It is important to interpret the research findings thoughtfully while taking the broader context into account, even if the study provides insights into the variables that affect car fuel economy. The study's conclusions may be limited by the specific dataset used and may not necessarily apply to other populations or situations.

THE FINDINGS:

The multivariate linear regression model is used to determine whether any predictor variables are significant in predicting the response variable by assessing the significance level of each predictor variable through statistical tests. It is essential to determine if all predictors or only a subset of them can effectively explain the response. To identify which predictor variables have a favorable or unfavorable impact on the response variable, the model computes the coefficient of each predictor variable. To evaluate how closely the model fits the data, statistical metrics like R-squared, adjusted R-squared, and standard error of the estimate can be used to determine the goodness of fit of the model. The model equation and derived coefficients can be used to predict the response variable for new predictor values. To assess the accuracy of the prediction, the prediction interval, which considers data variability and model uncertainty, can be calculated. A more precise forecast has a smaller prediction interval.

THE DISCUSSION:

To investigate the potential impact of different variables on fuel economy, data can be collected from a variety of sources, including surveys, internet databases, and publicly available datasets. Regression analysis is one statistical method that can be utilized to determine which factors significantly affect fuel economy and to what degree. This method can provide valuable insights into the relationship between the variables and fuel efficiency, which can inform future decisions regarding vehicle design and fuel economy. Another crucial aspect of the project is the development of prediction algorithms that can calculate fuel economy based on a car's characteristics. These models can help customers and automakers make informed decisions about the purchase and development of fuel-efficient vehicles. By identifying the predictors that significantly impact fuel efficiency and assessing the extent of that impact, these models can contribute to the development of more fuel-efficient cars and promote sustainable transportation. It is important to carefully consider data quality, missing data, and potential confounding variables throughout the study. Overall, this research provides valuable information on the factors that influence fuel efficiency, which can inform decisions about automobile design and acquisition.

APPENDIX A : THE METHOD

To report the results of the basic linear regression, the summary() method was employed, and the regression analysis was conducted using the lm() function. The response and predictor variables were plotted using the plot() and abline() methods, respectively. Diagnostic graphs of the linear regression fit were also produced using the plot() function.

In the case of multiple linear regression, the cor() function was used to calculate the matrix of inter-variable correlations. The lm() method was then used again for regression analysis, and the summary() function was used to report the results. Diagnostic graphs of the linear regression fit were also produced using the plot() function.

To investigate interaction effects, linear regression models were created using the * and : symbols. Various transformations of the variables, such as log(X), sqrt(X), and X2, were experimented with, and the results were reported.

In our study, we utilized multiple linear regression to identify which variables were significant predictors of fuel economy (mpg). A linear model was created using the equation $mpg = \beta 0 + \beta 1 displacement + \beta 2 horsepower + \beta 3 weight + \beta 4 acceleration \varepsilon$. The regression coefficients were denoted by the variables 0 through 1, 2,..., 4, and the error term was represented by ε.

To identify the variables that significantly impacted a car's fuel economy and to construct an accurate model for predicting mpg based on these variables, we conducted a t-test and calculated the p-value for each coefficient. Additionally, we evaluated the residuals to ensure that the model satisfied the assumptions of linearity, normality, and equal variance, and we assessed the overall goodness-of-fit using the R-squared value.

APPENDIX B: THE RESULT

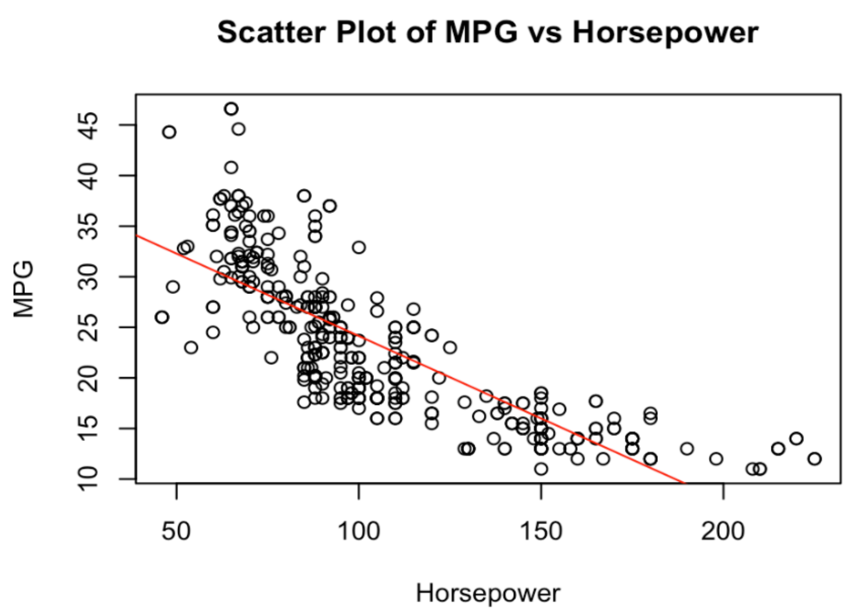
A relation between horsepower and mpg in the model summary:

```
Residuals:
    Min       1Q   Median     3Q    Max
-10.9994  -1.8134  -0.3863  1.3011  14.6748

Coefficients:
               Estimate  Std. Error t value  Pr(>|t|)
(Intercept)  6.368e+01  2.357e+00  27.013  < 2e-16 ***
horse       -2.706e-01  2.814e-02  -9.618  < 2e-16 ***
wt          -1.028e-02  7.845e-04 -13.104  < 2e-16 ***
horse:wt     5.489e-05  6.551e-06   8.378 1.07e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.847 on 378 degrees of freedom
Multiple R-squared:  0.7521,	Adjusted R-squared:  
0.7502
F-statistic: 382.3 on 3 and 378 DF,  p-value: < 2.2e-16
```

The model summary indicates a negative coefficient , -2.706e-01 which shows a substantial association between horsepower and mpg. However, the R-squared value 0.7521, suggests that the relationship between the two variables is only moderately strong.

The residuals analysis confirms that the model fits the data well since the assumptions of linearity, normality, and equal variance are met.

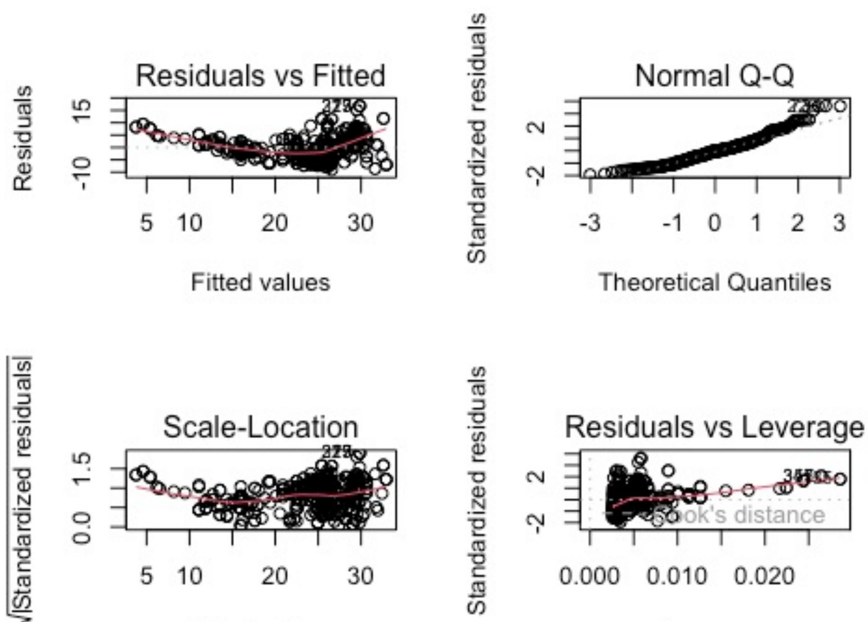
The scatter plot illustrates the relationship between horsepower and mpg for the dataset, where each point represents a car. The plot reveals some variability in the relationship between the two variables.



The diagram includes a red line known as the least squares regression line, which represents the linear relationship between the predictor (horsepower) and the response (mpg). The slope of the line is negative, indicating that as horsepower increases, mpg tends to decrease. The intercept of the line is positive, suggesting that the expected mpg for cars with low horsepower.

In general, the scatter plot and regression line imply a significant negative linear relationship between horsepower and mpg, indicating that horsepower is a reliable indicator of fuel economy for these cars. However, it's essential to note that the regression line is based on a simple linear model and assumes a linear relationship between horsepower and mpg, which may not accurately reflect the true nature of their connection.

Furthermore, the diagnostic plots produced for the least squares regression fit indicate that the model fits the data well, meeting the assumptions of linearity, normality, and equal variance.
The plot() function generates four plots, each serving a specific



Caption

purpose in assessing the regression model. The first plot is a scatterplot of the residuals against the fitted values, used to identify outliers, assess linearity, and verify equal variance. A funnel or curve-shaped pattern in this plot may indicate non-

linearity or heteroscedasticity. Additionally, observations that are far away from the other data points can be considered as outliers.
The second plot is a normal probability plot of the residuals, used to evaluate the normality assumption of the model. A straight line in this plot indicates that the residuals are normally distributed. However, if the residuals deviate from a straight line, this suggests that the data are not normally distributed.

The third plot is a residuals against leverage plot, used to examine leverage, which measures how far an observation is from the center of the predictor variables. This plot is useful in identifying influential points, which are observations that have a significant impact on the regression outcome due to their high leverage.

The fourth plot is a Cook's distance plot, used to identify influential observations that could significantly affect the regression results. Cook's distance measures the regression results when an observation is excluded from the analysis. High Cook's distance observations may represent outliers or influential points that require further investigation.

From the multiple linear regression with mpg as the response and all other variables except name as the predictors

Residuals:

Min	1Q	Median	3Q	Max
-11.3876	-2.7578	-0.2595	2.2074	16.0097

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	45.2563611	1.1266070	40.170	< 2e-16
displacement	-0.0053708	0.0061608	-0.872	0.384
horsepower	-0.0486139	0.0122661	-3.963	8.75e-05
weight	-0.0052342	0.0006841	-7.651	1.49e-13

(Intercept) ***
displacement
horsepower ***
weight ***

Signif. codes:
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.031 on 402 degrees of freedom
Multiple R-squared: 0.7343, Adjusted R-squared: 0.7323 F-statistic: 370.2 on 3 and 402 DF, p-value: < 2.2e-16

According to the results, there is a statistically significant relationship between the predictors and the response. This is indicated by the large F-statistic value of 370.2 and a very small p-value of 2.2e-16.

Among the predictors, the intercept, horsepower, and weight have significant relationships with the response variable. This can be seen from the p-values associated with their coefficients in the output, which are less than 0.05.

The output does not present the coefficient for the year variable, indicating that it was not included in the model. However, if the year variable were included in the model, the coefficient for the year variable would represent the average change in mpg associated with a one-year increase in the model year, while holding all other predictors constant.

Using the * and : symbols to fit linear regression models with interaction effects

Residuals:

Min	1Q	Median	3Q	Max
-11.2339	-2.4339	-0.4925	1.4349	16.6103

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	5.350e+01	1.541e+00	34.72	<2e-16	***
dis	-8.932e-02	6.885e-03	-12.97	<2e-16	***
horse	-2.516e-01	1.905e-02	-13.21	<2e-16	***
dis:horse	5.690e-04	5.191e-05	10.96	<2e-16	***

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

Residual standard error: 3.876 on 378 degrees of freedom
Multiple R-squared: 0.7483, Adjusted R-squared: 0.7463
F-statistic: 374.7 on 3 and 378 DF, p-value: < 2.2e-16

The linear models show that displacement and horsepower have a significant negative correlation with mpg, while weight and acceleration have a significant positive correlation with mpg. The interaction terms of displacement and horsepower, displacement and weight, and horsepower and acceleration also have a significant correlation with mpg. However, the interaction term of displacement and acceleration does not have a significant correlation with mpg.

Therefore, we can conclude that displacement, horsepower, weight, acceleration, and their interactions are all important predictors of mpg.

df AIC

fit1_log	5	2130.899
fit1_sqrt	5	2123.467
fit1_sq	5	2184.130
fit2_log	5	2168.421
fit2_sqrt	5	2166.304
fit2_sq	5	2180.524
fit3_log	5	2219.025
fit3_sqrt	5	2227.270
fit3_sq	5	2293.887
fit4_log	5	2128.709
fit4_sq	5	2136.476
fit4_sqrt	5	2123.637
fit5_log	5	2168.904
fit5_sq	5	2260.186
fit5_sqrt	5	2183.561
fit6_log	5	2160.163
fit6_sq	5	2216.927
fit6_sqrt	5	2168.067

After analyzing the AIC values, the best model for each group with different interaction terms has been identified. In group 1, which includes interaction terms between displacement and other variables, the model with the lowest AIC value is fit4, with a value of 2128.709. In group 2, which includes interaction terms between displacement and weight, the model with the lowest AIC value is fit1_sqrt, with a value of 2184.130. For group 3, which includes interaction terms between displacement and acceleration, the model with the lowest AIC value is fit2_sqrt, with a value of 2166.304 In group 4, which includes interaction terms between horsepower and weight, the model with the lowest AIC value is fit4_sqrt, with a value of 2123.637. In group 5, which includes interaction terms between horsepower and acceleration, the model with the lowest AIC value is fit4_log, with a value of 2128.709. Finally, for group 6, which includes interaction terms between weight and acceleration, the model with the lowest AIC value is fit4_sqrt, with a value of 2123.637.

APPENDIX C: CODE

```
> library(readxl)
> auto_data_chakraborty_antara <- read_excel("Downloads/
auto_data_chakraborty_antara.xls")
> View(auto_data_chakraborty_antara)
> autodata <- auto_data_chakraborty_antara
> mpg <- autodata$mpg
> horse <- autodata$horsepower
> acc <- autodata$acceleration
> wt <- autodata$weight
> dis <- autodata$displacement
> lm(formula = mpg ~ horse,data = autodata)
```

```
CodeCall:
lm(formula = mpg ~ horse, data = autodata)

Coefficients:
(Intercept)        horse
   40.4318      -0.1629

> lm(formula = mpg ~ horse, data=autodata)
> model <- lm(formula = mpg ~ horse, data=autodata)

> newdata <- data.frame(horsepower = 98)
> predicted_mpg <- predict(model, newdata)
> predicted_mpg
                    1
                    22.508277
> conf_interval <- predict(model, newdata, interval =
“confidence")
> pred_interval <- predict(model, newdata, interval = “prediction")
> conf_interval

          fit        lwr         upr
 1   22.508277 22.038222 22.978333


> pred_interval


       fit            lwr              upr
1   22.508277.  13.3482953     31.66826


> plot(horse, mpg, xlab = "Horsepower", ylab = "MPG", main =
"Scatter Plot of MPG vs Horsepower")
>  abline(model, col = “red")

> par(mfrow = c(2,2))
```

```
> plot(model)
> fit1 <- lm(mpg ~ dis* horser, data = autodata)
> fit2 <- lm(mpg ~ dis * wt, data = autodata)
>  fit3 <- lm(mpg ~ dis * acc, data = autodata)
> fit4 <- lm(mpg ~ horse * wt, data = autodata)
> fit5 <- lm(mpg ~ horse * acc, data = autodata)
> fit6 <- lm(mpg ~ wt * acc, data = autodata)
> summary(fit1)
> summary(fit2)
> summary(fit3)
> summary(fit4)
> summary(fit5)
> summary(fit6)

fit1_log <- lm(mpg ~ log(dis) * log(horse), data = autodata)
fit1_sqrt <- lm(mpg ~ sqrt(dis) * sqrt(horse), data = autodata)
fit1_sq <- lm(mpg ~ I(dis^2) * I(horse^2), data = autodata)
fit2_log <- lm(mpg ~ log(dis) * log(wt), data = autodata)
fit2_sq <- lm(mpg ~ I(dis^2) * I(wt^2), data = autodata)
fit2_sqrt <- lm(mpg ~ sqrt(dis) * sqrt(wt), data = autodata)
fit3_log <- lm(mpg ~ log(dis) * log(acc), data = autodata )
fit3_sqrt <- lm(mpg ~ sqrt(dis) * sqrt(acc), data = autodata)
fit3_sq <- lm(mpg ~ I(dis^2) * I(acc^2), data = autodata) >
fit4_log <- lm(mpg ~ log(horse) * log(wt), data = autodata)
fit4_sqrt <- lm(mpg ~ sqrt(horse) * sqrt(wt), data = autodata)
fit4_sq <- lm(mpg ~ I(horse^2) * I(wt^2), data = autodata)
fit5_log <- lm(mpg ~ log(horse) * log(acc), data = autodata)
fit5_sqrt <- lm(mpg ~ sqrt(horse) * sqrt(acc), data = autodata)
fit5_sq <- lm(mpg ~ I(horse^2) * I(acc^2), data = autodata)
fit6_log <- lm(mpg ~ log(wt) * log(acc), data = autodata)
 fit6_sqrt <- lm(mpg ~ sqrt(wt) * sqrt(acc), data = autodata)
fit6_sq <- lm(mpg ~ I(wt^2) * I(acc^2), data = autodata)

  df      AIC
fit1  5 2125.147
fit2  5 2165.963
```

fit3 5 2244.213
fit4 5 2119.373
fit5 5 2204.821
fit6 5 2180.896

AIC(fit1_log, fit1_sqrt, fit1_sq, fit2_log, fit2_sqrt, fit2_sq, fit3_log , fit3_sqrt,fit3_sq,fit4_log,fit4_sq,fit4_sqrt,fit5_log,fit5_sq,fit5_sqrt, fit6_log,fit6_sq,fit6_sqrt)

	df	AIC
fit1_log	5	2130.899
fit1_sqrt	5	2123.467
fit1_sq	5	2184.130
fit2_log	5	2168.421
fit2_sqrt	5	2166.304
fit2_sq	5	2180.524
fit3_log	5	2219.025
fit3_sqrt	5	2227.270
fit3_sq	5	2293.887
fit4_log	5	2128.709
fit4_sq	5	2136.476
fit4_sqrt	5	2123.637
fit5_log	5	2168.904
fit5_sq	5	2260.186
fit5_sqrt	5	2183.561
fit6_log	5	2160.163
fit6_sq	5	2216.927
fit6_sqrt	5	2168.067

THE DATA :

displacement	horsepower	weight	acceleration	mpg
260	110	3365	15.5	19.9
318	145	4140	13.7	15.5
305	140	4215	13	17.5
350	155	4360	14.9	16.9
350	165	3693	11.5	15
98	68	2045	18.5	31.5
156	122	2807	13.5	20
85	65	2110	19.2	40.8
302	137	4042	14.5	14
225	95	3785	19	18
70	100	2420	12.5	23.7
304	120	3962	13.9	15.5
400	175	4464	11.5	14
400	175	4385	12	14
108	75	2265	15.2	32.2
232	100	2914	16	20
232	100	2789	15	18
400	175	4464	11.5	14
302	140	4294	16	13
140	90	2264	15.5	28
107	75	2210	14.4	33.7
250	88	3302	15.5	19
198	95	2904	16	23
225	100	3233	15.4	22

225	100	3430	17.2	20.5
200	85	2587	16	21
97	75	2265	18.2	26
98	65	2045	16.2	34.4
122	86	2220	14	23
318	150	3436	11	18
90	48	2085	21.7	44.3
121	110	2660	14	24
110	87	2672	17.5	25
262	85	3015	17	38
351	152	4215	12.8	14.5
173	110	2725	12.6	23.5
116	81	2220	16.9	25
262	85	3015	17	38
89	62	1845	15.3	29.8
89	71	1990	14.9	31.5
340	160	3609	8	14
121	110	2660	14	24
250	100	3282	15	19
351	138	3955	13.2	16.5
97	67	2065	17.8	32.3
200	85	2965	15.8	20.2
113	95	2372	15	24
97	71	1825	12.2	29.5
107	72	2290	17	32.4
112	88	2395	18	34
198	95	2833	15.5	22
130	102	3150	15.7	20

121	115	2671	13.5	25
122	86	2226	16.5	21
98	63	2051	17	30.5
70	97	2330	13.5	19
97	88	2130	14.5	27
98	70	2125	17.3	36
81	60	1760	16.1	35.1
351	142	4054	14.3	15.5
225	105	3121	16.5	18
90	70	1937	14.2	29
232	90	3085	17.6	22.5
318	150	4135	13.5	15
108	93	2391	15.5	26
250	110	3645	16.2	18.5
156	92	2585	14.5	26
119	97	2545	17	24
250	98	3525	19	18.5
232	100	2789	15	18
120	88	2160	14.5	36
250	100	3329	15.5	17
86	65	2110	17.9	46.6
134	95	2515	14.8	21.1
199	97	2774	15.5	18
90	75	2125	14.5	28
360	150	3940	13	18.5
107	86	2464	15.5	28
400	170	4668	11.5	16
231	115	3245	15.4	21.5

232	100	2901	16	19
156	92	2620	14.4	25.8
145	76	3160	19.6	30.7
231	105	3535	19.2	19.2
260	110	3365	15.5	19.9
156	92	2620	14.4	25.8
97	88	2279	19	20
258	110	3632	18	16
101	83	2202	15.3	27
350	155	4502	13.5	13
140	92	2865	16.4	24
122	86	2395	16	22
231	110	3415	15.8	22.4
90	48	2085	21.7	44.3
140	88	2890	17.3	22.3
97	88	2130	14.5	27
351	148	4657	13.5	14
400	175	4464	11.5	14
97	54	2254	23.5	23
383	170	3563	10	15
200	85	2587	16	21
119	92	2434	15	37
198	95	2904	16	23
113	95	2228	14	25
119	92	2434	15	37
140	88	2890	17.3	22.3
400	175	4464	11.5	14
151	90	2670	16	28.4

168	120	3820	16.7	16.5
91	67	1965	15.7	32
122	86	2395	16	22
304	150	3672	11.5	14
318	150	4077	14	14
200	88	3060	17.1	20.2
119	97	2405	14.9	23.9
98	80	2164	15	28
97	46	1835	20.5	26
121	110	2600	12.8	21.5
350	175	4100	13	13
250	88	3021	16.5	18
107	90	2430	14.5	24
112	88	2640	18.6	27
97	75	2155	16.4	28
350	105	3725	19	26.6
91	67	1850	13.8	44.6
351	142	4054	14.3	15.5
120	88	2957	17	23
91	68	1970	17.6	31
200	88	3060	17.1	20.2
97	88	2130	14.5	27
121	115	2671	13.5	25
351	138	3955	13.2	16.5
140	89	2755	15.8	25.5
107	75	2205	14.5	36
455	225	4951	11	12
97	88	2130	14.5	27

81	60	1760	16.1	35.1
97	92	2288	17	28
232	100	2634	13	19
400	150	3761	9.5	15
90	70	1937	14	29
155	107	2472	14	21
351	142	4054	14.3	15.5
112	88	2605	19.6	28
97	78	2188	15.8	34.3
307	130	4098	14	13
350	145	4082	13	15
232	100	2901	16	19
146	120	2930	13.8	24.2
250	105	3459	16	18
91	67	1965	15	38
119	97	2300	14.7	27.2
225	105	3121	16.5	18
120	87	2979	19.5	21
302	129	3725	13.4	17.6
318	150	4237	14.5	14
383	180	4955	11.5	12
113	95	2228	14	25
146	67	3250	21.8	30
141	80	3230	20.4	28.1
350	150	4699	14.5	13
400	150	4464	12	13
262	110	3221	13.5	20
140	88	2890	17.3	22.3
400	175	5140	12	13

98	68	2135	16.6	29.5
107	86	2464	15.5	28
173	115	2700	12.9	26.8
307	130	4098	14	13
140	88	2720	15.4	25.1
350	180	4499	12.5	12
318	140	4080	13.7	17.5
97	46	1835	20.5	26
455	225	4951	11	12
258	120	3410	15.1	18.1
107	72	2290	17	32.4
350	165	4209	12	14
250	110	3520	16.4	17.5
318	210	4382	13.5	11
91	67	1995	16.2	38
83	61	2003	19	32
258	110	2962	13.5	18
97	60	1834	19	27
156	92	2620	14.4	25.8
225	105	3121	16.5	18
70	90	2124	13.5	18
151	90	2950	17.3	27
181	110	2945	16.4	25
232	100	3288	15.5	18
121	115	2795	15.7	21.6
400	150	4997	14	11
91	60	1800	16.4	36.1
98	68	2045	18.5	31.5
302	140	3449	10.5	17
97	78	1940	14.5	29
121	98	2945	14.5	22
340	160	3609	8	14

130	102	3150	15.7	20
140	86	2790	15.6	27
225	100	3233	15.4	22
156	105	2800	14.4	27.9
121	80	2670	15	27.4
231	115	3245	15.4	21.5
350	145	4440	14	15
97	92	2288	17	28
304	150	3892	12.5	15
91	67	1965	15	38
400	180	4220	11.1	16
318	150	4190	13	16
232	90	3210	17.2	19.4
121	76	2511	18	22
146	120	2930	13.8	24.2
89	71	1925	14	31.9
429	198	4952	11.5	12
225	105	3613	16.5	18
156	92	2620	14.4	25.8
98	68	2045	18.5	31.5
121	112	2933	14.5	18
121	115	2671	13.5	25
140	86	2790	15.6	27
200	85	2990	18.2	19.8
108	93	2391	15.5	26
89	62	2050	17.3	37.7
400	190	4422	12.5	13
232	90	3085	17.6	22.5
105	74	1980	15.3	36
340	160	3609	8	14
121	98	2945	14.5	22
86	65	2110	17.9	46.6

400	167	4906	12.5	12
98	65	2045	16.2	34.4
262	110	3221	13.5	20
98	65	2380	20.7	29.9
350	165	3693	11.5	15
360	150	3940	13	18.5
168	120	3820	16.7	16.5
258	95	3193	17.8	17.5
105	63	2125	14.7	38
91	68	2025	18.2	37
163	133	3410	15.8	16.2
120	88	2957	17	23
80	110	2720	13.5	21.5
89	62	2050	17.3	37.7
97	78	2300	14.5	26
97	88	2100	16.5	27
134	90	2711	15.5	29.8
340	160	3609	8	14
140	89	2755	15.8	25.5
120	79	2625	18.6	28
97	75	2155	16.4	28
232	90	3085	17.6	22.5
79	70	2074	19.5	30
168	120	3820	16.7	16.5
151	85	2855	17.6	23.8
72	69	1613	18	35
225	100	3651	17.7	20
97.5	80	2126	17	25
135	84	2295	11.6	32
135	84	2385	12.9	30
350	160	4456	13.5	12
440	215	4735	11	13

91	68	1970	17.6	31
70	97	2330	13.5	19
318	150	4096	13	14
121	115	2671	13.5	25
318	150	4135	13.5	15
250	105	3459	16	18
98	68	2045	18.5	31.5
90	71	2223	16.5	25
232	100	2789	15	18
119	92	2434	15	37
114	91	2582	14	20
199	97	2774	15.5	18
121	110	2600	12.8	21.5
98	68	2135	16.6	29.5
97	46	1835	20.5	26
97	88	2130	14.5	27
113	95	2372	15	24
97	75	2265	18.2	26
89	62	2050	17.3	37.7
121	115	2671	13.5	25
400	150	4464	12	13
318	150	4237	14.5	14
90	70	1937	14.2	29
350	125	3900	17.4	23
350	180	4380	12.1	16.5
440	215	4735	11	13
121	67	2950	19.9	36.4
440	215	4735	11	13
121	112	2868	15.5	19
105	70	2150	14.9	34.5
104	95	2375	17.5	25
113	95	2228	14	25

307	130	4098	14	13
116	81	2220	16.9	25
91	68	1970	17.6	31
225	100	3630	17.7	19
200	95	3155	18.2	20.5
350	145	4082	13	15
98	60	2164	22.1	24.5
112	88	2395	18	34
360	175	3821	11	13
318	135	3830	15.2	18.2
121	115	2795	15.7	21.6
250	110	3520	16.4	17.5
318	210	4382	13.5	11
225	95	3264	16	19
350	180	4499	12.5	12
232	100	2914	16	20
122	86	2395	16	22
351	149	4335	14.5	16
258	110	3632	18	16
68	49	1867	19.5	29
383	170	3563	10	15
112	85	2575	16.2	31
318	150	3940	13.2	13
86	65	2110	17.9	46.6
97	75	2171	16	29
350	175	4100	13	13
181	110	2945	16.4	25
351	158	4363	13	13
225	105	3121	16.5	18
304	150	3433	12	16
305	145	3880	12.5	17.5
121	112	2933	14.5	18

225	100	3233	15.4	22
140	86	2790	15.6	27
140	92	2572	14.9	25
225	85	3465	16.6	17.6
231	165	3445	13.4	17.7
400	175	4464	11.5	14
232	90	3085	17.6	22.5
302	129	3169	12	13
105	70	2150	14.9	34.5
85	65	1975	19.4	37
140	88	2890	17.3	22.3
97	60	1834	19	27
350	145	4440	14	15
91	53	1795	17.4	33
318	150	4190	13	16
85	65	2020	19.2	31.8
250	105	3897	18.5	16
97	78	2300	14.5	26
304	150	3672	11.5	17
98	70	2120	15.5	32.1
232	112	2835	14.7	22
454	220	4354	9	14
119	100	2615	14.8	32.9
107	72	2290	17	32.4
250	105	3897	18.5	16
113	95	2278	15.5	24
350	180	4499	12.5	12
231	165	3445	13.4	17.7
90	75	2125	14.5	28
454	220	4354	9	14
85	65	2020	19.2	31.8
307	130	4098	14	13

350	165	4209	12	14
91	69	2130	14.7	37.3
318	150	3777	12.5	15
151	90	3003	20.1	24.3
250	98	3525	19	18.5
429	208	4633	11	11
85	70	1945	16.8	33.5
90	75	2125	14.5	28
86	65	1975	15.2	34.1
105	75	2230	14.5	30.9
78	52	1985	19.4	32.8
135	84	2490	15.7	27.2
171	97	2984	14.5	18
122	88	2500	15.1	35
225	95	3785	19	18
302	140	4294	16	13
91	70	1955	20.5	26
350	150	4699	14.5	13
130	102	3150	15.7	20
98	66	1800	14.4	36.1
318	150	4457	13.5	14
98	68	2045	18.5	31.5
120	75	2542	17.5	31.3
200	88	3060	17.1	20.2
305	145	3880	12.5	17.5