(Clean) Vehicle Data

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Introduction

This is a presentation of my findings while investigating the dataset car_prices

The dataset has been cleaned and filtered:

- Removed irrelevant columns such as: trim, vin, body, state, interior, body, seller, and sell date;
- Cleared non-sensical data, missing values, and NAs;
- Made unique makes and colors uniform;
- Converted variables into factors & normalised

Summary & Structure

```
summary(data)
```

```
##       year          make              odometer         color
##  Min.   :1984   Length:511711      Min.   :     1   Length:511711
##  1st Qu.:2008   Class :character   1st Qu.: 28430   Class :character
##  Median :2012   Mode  :character   Median : 51838   Mode  :character
##  Mean   :2010                      Mean   : 67566
##  3rd Qu.:2013                      3rd Qu.: 97762
##  Max.   :2015                      Max.   :999999
##       mmr          sellingprice    transmission         condition
##  Min.   :    25   Min.   :     1   Length:511711      Min.   : 1.00
##  1st Qu.:  7300   1st Qu.:  7000   Class :character   1st Qu.:23.00
##  Median : 12300   Median : 12200   Mode  :character   Median :34.00
##  Mean   : 13806   Mean   : 13651                      Mean   :30.57
##  3rd Qu.: 18300   3rd Qu.: 18200                      3rd Qu.:41.00
##  Max.   :182000   Max.   :230000                      Max.   :49.00
```

```
head(data)
```

```
##   year   make odometer color   mmr sellingprice transmission condition
## 1 2015    kia    16639 white 20500        21500    automatic         5
## 2 2015    kia     9393 white 20800        21500    automatic         5
## 3 2014    bmw     1331  gray 31900        30000    automatic        45
## 4 2015  volvo    14282 white 27500        27750    automatic        41
## 5 2014    bmw     2641  gray 66000        67000    automatic        43
## 6 2015 nissan     5554  gray 15350        10900    automatic         1
```

```r
str(data)
```

```
## 'data.frame':    511711 obs. of  8 variables:
##  $ year        : int  2015 2015 2014 2015 2014 2015 2014 2014 2014 2014 ...
##  $ make        : chr  "kia" "kia" "bmw" "volvo" ...
##  $ odometer    : int  16639 9393 1331 14282 2641 5554 14943 28617 9557 4809 ...
##  $ color       : chr  "white" "white" "gray" "white" ...
##  $ mmr         : int  20500 20800 31900 27500 66000 15350 69000 11900 32100 26300 ...
##  $ sellingprice: int  21500 21500 30000 27750 67000 10900 65000 9800 32250 17500 ...
##  $ transmission: chr  "automatic" "automatic" "automatic" "automatic" ...
##  $ condition   : int  5 5 45 41 43 1 34 2 42 3 ...
```

Correlation & Feature Selection

Correlation Matrix (char & num)

- Cramer's V for Categorical vs Categorical comparison
- Pearson's for Numerical vs Numerical comparison
- Cramer's V for Categorical vs Numerical comparison

```
##                year  make odometer color    mmr sellingprice transmission
## year          1.000 0.403   -0.773 0.337  0.593        0.583        0.244
## make          0.403 1.000    0.214 0.282  0.635        0.623        0.403
## odometer     -0.773 0.214    1.000 0.187 -0.584       -0.578        0.120
## color         0.337 0.282    0.187 1.000  0.194        0.161        0.245
## mmr           0.593 0.635   -0.584 0.194  1.000        0.984        0.117
## sellingprice  0.583 0.623   -0.578 0.161  0.984        1.000        0.091
## transmission  0.244 0.403    0.120 0.245  0.117        0.091        1.000
## condition     0.537 0.221    0.316 0.189  0.284        0.239        0.208
##              condition
## year             0.537
## make             0.221
## odometer         0.316
## color            0.189
## mmr              0.284
## sellingprice     0.239
## transmission     0.208
## condition        1.000
```

Correlation Matrix Continued (char & num)

- Some of the correlation coefficient's are below 0.2, so I increased the threshold and filtered out the small correlations

```
## [1] "year"         "make"         "odometer"     "mmr"          "sellingprice"
## [6] "condition"
```

```
##                year   make odometer    mmr condition sellingprice
## year          1.000 -0.011   -0.773  0.593     0.356        0.583
## make         -0.011  1.000   -0.022 -0.065     0.033       -0.063
## odometer     -0.773 -0.022    1.000 -0.584    -0.338       -0.578
```

```
## mmr           0.593 -0.065   -0.584  1.000     0.301        0.984
## condition     0.356  0.033   -0.338  0.301     1.000        0.344
## sellingprice  0.583 -0.063   -0.578  0.984     0.344        1.000
```

PCA (char & num)

```
## Importance of components:
##                            PC1    PC2    PC3    PC4     PC5    PC6
## Standard deviation     1.8032 1.0149 0.8953 0.8223 0.47512 0.1225
## Proportion of Variance 0.5419 0.1717 0.1336 0.1127 0.03762 0.0025
## Cumulative Proportion  0.5419 0.7136 0.8472 0.9599 0.99750 1.0000
```

```
##                  PC1    PC2    PC3    PC4    PC5    PC6
## year         -0.462  0.080  0.032 -0.521  0.712  0.021
## make          0.022  0.937 -0.315  0.147  0.031  0.000
## odometer      0.458 -0.115  0.008  0.535  0.701 -0.001
## mmr          -0.497 -0.147 -0.290  0.385  0.009 -0.707
## condition    -0.284  0.251  0.870  0.313 -0.022 -0.038
## sellingprice -0.498 -0.135 -0.244  0.418 -0.012  0.706
```

```
##   Principal_Component Variance_Explained
## 1                 PC1         54.1918858
## 2                 PC2         17.1673249
## 3                 PC3         13.3601557
## 4                 PC4         11.2683595
## 5                 PC5          3.7622722
## 6                 PC6          0.2500018
```

Correlation Matrix (num)

- Seeing as there are many PCs and it takes about 4 of them to explain most of the data, I have decided to do correlation with just numerical variables (low correlation) and see if PCA improves

```
##                year odometer    mmr sellingprice
## year          1.000   -0.773  0.593        0.583
## odometer     -0.773    1.000 -0.584       -0.578
## mmr           0.593   -0.584  1.000        0.984
## sellingprice  0.583   -0.578  0.984        1.000
```

PCA (num)

```
## Importance of components:
##                            PC1    PC2     PC3     PC4
## Standard deviation     1.7471 0.8395 0.47614 0.12739
## Proportion of Variance 0.7631 0.1762 0.05668 0.00406
## Cumulative Proportion  0.7631 0.9393 0.99594 1.00000
```

```
##                  PC1    PC2    PC3    PC4
## year         -0.478 -0.515  0.711 -0.013
## odometer      0.476  0.529  0.703 -0.003
## mmr          -0.523  0.471  0.003  0.710
## sellingprice -0.521  0.483 -0.014 -0.704
```

```
##   Principal_Component Variance_Explained
## 1                 PC1         76.3060869
## 2                 PC2         17.6203358
## 3                 PC3          5.6678479
## 4                 PC4          0.4057294
```

Lasso Regression

- I used Lasso Regression for feature selection as it's easy to interpret and I expect a small amount of variables to be useful in predicting the Selling Price

```
## [1] "Selected Features by Lasso:"
```

```
## [1] "year"     "odometer" "mmr"
```

Random Forest

- I used Random forest with a sample of 10% to confirm the useful numerical variables

```
##  num [1:3, 1] 6.08e+11 7.53e+11 2.95e+12
##  - attr(*, "dimnames")=List of 2
##   ..$ : chr [1:3] "year" "odometer" "mmr"
##   ..$ : chr "IncNodePurity"
```

```
## [1] "Selected Features by Random Forest:"
```

```
## [1] "year"     "odometer" "mmr"
```

Feature Selection Conclusion

- Numerical variables explain the data better and the dimensions are reduced therefore, categorical variables have been filtered out for a better model

Regression Models

Linear Regression

```
##
## Call:
## lm(formula = response ~ ., data = as.data.frame(predictors))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.9777 -0.0675  0.0100  0.0822 21.4964
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  9.189e-16  2.513e-04    0.00        1
## year        -8.716e-03  4.122e-04  -21.15   <2e-16 ***
## odometer    -1.169e-02  4.088e-04  -28.59   <2e-16 ***
```

```
## mmr          9.820e-01  3.220e-04 3050.17   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1798 on 511707 degrees of freedom
## Multiple R-squared:  0.9677, Adjusted R-squared:  0.9677
## F-statistic: 5.108e+06 on 3 and 511707 DF,  p-value: < 2.2e-16
```

Linear Regression Model Evaluation & Cross-Validation

```
## Linear Regression RMSE: 0.1749224
```

```
## Linear Regression R-squared: 0.9676856
```

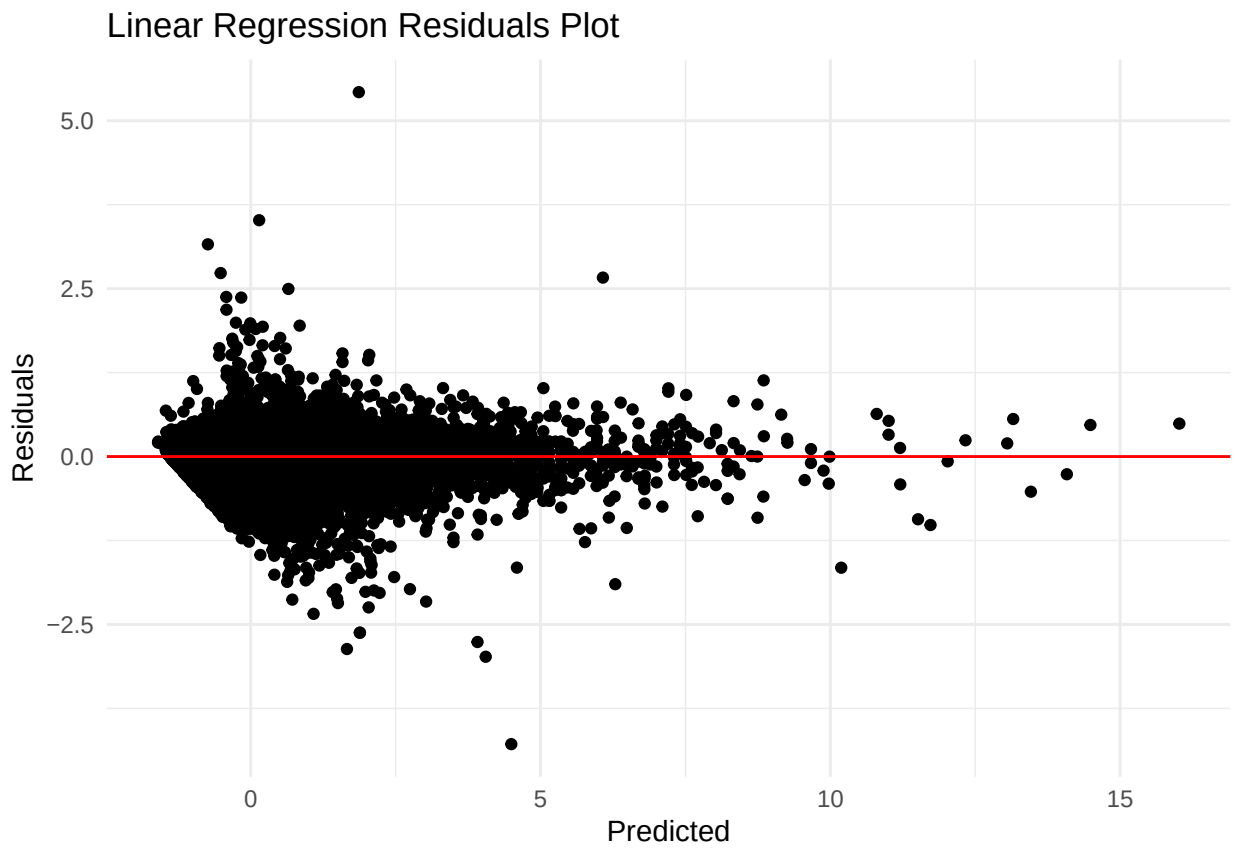
Polynomial Regression

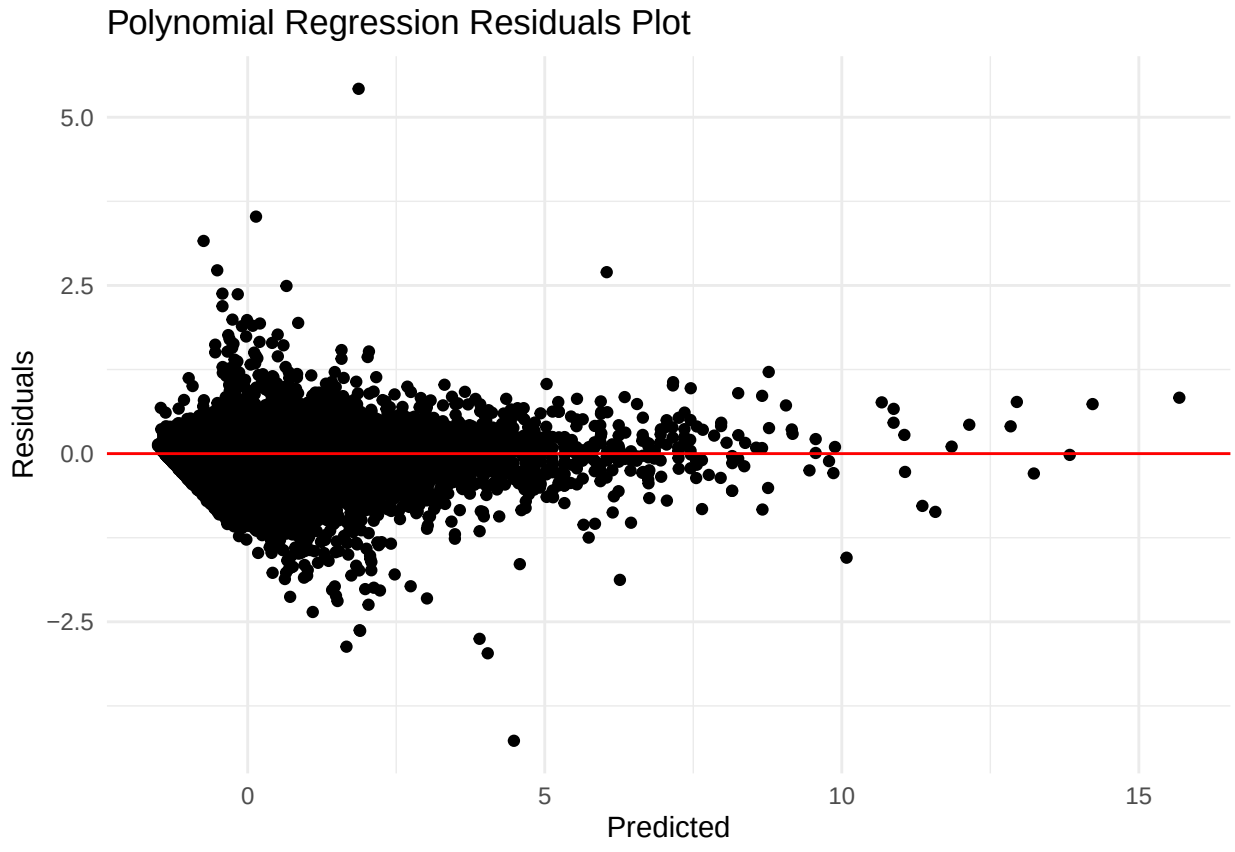
```
##
## Call:
## lm(formula = sellingprice ~ poly(year, 2) + poly(odometer, 2) +
##     poly(mmr, 2), data = as.data.frame(train_data))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.8690 -0.0673  0.0110  0.0824 21.4976
##
## Coefficients:
##                      Estimate Std. Error  t value Pr(>|t|)
## (Intercept)         7.101e-04  2.827e-04    2.512    0.012 *
## poly(year, 2)1     -7.827e+00  3.265e-01  -23.970  < 2e-16 ***
## poly(year, 2)2     -2.336e+00  1.928e-01  -12.114  < 2e-16 ***
## poly(odometer, 2)1 -7.853e+00  3.201e-01  -24.535  < 2e-16 ***
## poly(odometer, 2)2  8.533e-01  1.976e-01    4.319 1.57e-05 ***
## poly(mmr, 2)1       6.311e+02  2.471e-01 2553.583  < 2e-16 ***
## poly(mmr, 2)2      -3.148e+00  2.055e-01  -15.318  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1809 on 409363 degrees of freedom
## Multiple R-squared:  0.9675, Adjusted R-squared:  0.9675
## F-statistic: 2.028e+06 on 6 and 409363 DF,  p-value: < 2.2e-16
```

```
## Polynomial Regression RMSE: 0.1749021
```

```
## Polynomial Regression R-squared: 0.9674528
```

Model Comparison





Conlcusion

- Given that the RMSE for the linear regression and the R-squared are very close but slightly better than the polynomial regression, the linear model is likely the better choice. It's simpler, less prone to overfitting, and has better predictive performance based on RMSE