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Technology Fundamentals for Business Analytics

Final Project

This project is based on the Kaggle competition Bike Sharing Demand which can be found here https://www.kaggle.com/c/bike-sharing-demand.

Executive Summary

Citizens of most metro areas are growing accustomed to seeing rows of branded bikes appear in their city streets as bike sharing programs grow in popularity. A bike sharing program allows a user to check out a bike from a rack near them, ride the bike somewhere else in the city, and then return the bike to another bike share rack. This is a modern convenience that allows city dwellers to use a bike when they need it and not have to worry about maintaining or storing a bike. Bike sharing programs can be used by anyone simply by using their credit card however most bike sharing programs also offer monthly memberships that include a certain number of rides every day. The bike sharing program this data is from, Capital Bikeshare in Washington DC, offered service to both nonmembers (casual riders) and members. Bike sharing programs are not just convenient for their customers, they are also a huge source of data.

Bike sharing programs use highly connected digital infrastructure which means that during normal use they produce a large amount of data that can be valuable if analyzed correctly. Everytime a user rents or returns a bike a data point in generated by the bike sharing system. This data can be at the granular level, specifying exactly who rented which bike at what time from what station and when and where they returned it, however, the data from the Bike Sharing Demand Kaggle competition is much more zoomed out. In this Kaggle competition analysts are provided a tabular dataset where each row represents a single hor. In each row of data there is information about the weather, the type of day (for example a holiday or a weekend) and how many casual, registered and total bike rentals there were that hour.

The goal of the Bike Sharing Demand Kaggle competition is to predict the number of bike rentals there would be given information about the future date and time as well as weather conditions. The metric used to score this competition is Root Mean Squared Logarithmic Error (RMSLE) which is similar to Root Mean Squared Error however the error is the difference in the logs of predicted values vs actual values instead of simply the difference in values.
Many analysts tried their hand the this Kaggle competition and submitted kernels. While many analysts tried using many models the best performing technique was Random Forest. Gradient Boosting came in at a close second with nearly twice the error and linear, ridge and lasso regression all tied for a distant third with nine times the error.

Data description and initial processing

The data for this Kaggle competition is supplied at a CSV with X rows and Y columns. Each row in the dataset represents an hour with information about that hour and how many people used the capital bike share that day. In the data, there are 12 rows datetime, season, holiday, workingday, weather, temp, atemp, humidity, windspeed, casual, registered and count. Thankfully this is nicely prepared data and there are no NA values in any column.

The datetime column is self descriptive. The season column represents spring, summer, fall and winter in that order from 1 to 10. The holiday column represents if the day is considered a holiday however unfortunately Kaggle does not specify which holidays of the many observed are counted in this dataset. The workingday column specifies if the day is neither a weekend or a holiday. The weather column specifies how bad the weather is with 1 being nice and 4 being terrible. More information about specific descriptions of each weather condition is available on Kaggle and in the accompanying code. The temp column specifies the temperature in Celsius and the atemp column specifies the “feels like” temperature in Celsius. The humidity column specifies the relative humidity. The windpseed column specifies the wind speed that hour in unknown units. The casual column specifies how many nonmember bike rentals while the registered column specifies how many member bike rentals and the count column specifies the total number of bike rentals.

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
1	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000	3	13	16
2	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000	8	32	40
3	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000	5	27	32
4	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000	3	10	13
5	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000	0	1	1
6	2011-01-01 05:00:00	1	0	0	2	9.84	12.880	75	6.0032	0	1	1
7	2011-01-01 06:00:00	1	0	0	1	9.02	13.635	80	0.0000	2	0	2
8	2011-01-01 07:00:00	1	0	0	1	8.20	12.880	86	0.0000	1	2	3
9	2011-01-01 08:00:00	1	0	0	1	9.84	14.395	75	0.0000	1	7	8
10	2011-01-01 09:00:00	1	0	0	1	13.12	17.425	76	0.0000	8	6	14

First 10 rows of Data Raw

It is important to know that merely reading in the CSV file will have unintended effects. There are several columns of ambiguous coded categorical data. These columns use integers to represent a categorical or logical variable so when reading in the data using tools such as R or Pandas an analyst must be sure to specify how to interpret these columns. Once the categorical variable `season` and the logical variables `holiday` and `workingday` have been transformed appropriately the analysis can begin.

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
1	2011-01-01 00:00:00	spring	FALSE	FALSE	Good	9.84	14.395	81	0.0000	3	13	16
2	2011-01-01 01:00:00	spring	FALSE	FALSE	Good	9.02	13.635	80	0.0000	8	32	40
3	2011-01-01 02:00:00	spring	FALSE	FALSE	Good	9.02	13.635	80	0.0000	5	27	32
4	2011-01-01 03:00:00	spring	FALSE	FALSE	Good	9.84	14.395	75	0.0000	3	10	13
5	2011-01-01 04:00:00	spring	FALSE	FALSE	Good	9.84	14.395	75	0.0000	0	1	1
6	2011-01-01 05:00:00	spring	FALSE	FALSE	Fair	9.84	12.880	75	6.0032	0	1	1
7	2011-01-01 06:00:00	spring	FALSE	FALSE	Good	9.02	13.635	80	0.0000	2	0	2
8	2011-01-01 07:00:00	spring	FALSE	FALSE	Good	8.20	12.880	86	0.0000	1	2	3
9	2011-01-01 08:00:00	spring	FALSE	FALSE	Good	9.84	14.395	75	0.0000	1	7	8
10	2011-01-01 09:00:00	spring	FALSE	FALSE	Good	13.12	17.425	76	0.0000	8	6	14

First 10 rows of data Transformed

A good first step in analyzing any dataset is to look at 6 number summaries and box plots of numerical data and counts of categorical and logical data.

```
      temp            atemp           humidity         windspeed
 Min.   : 0.82   Min.   : 0.76   Min.   :  0.00   Min.   : 0.000
 1st Qu.:13.94   1st Qu.:16.66   1st Qu.: 47.00   1st Qu.: 7.002
 Median :20.50   Median :24.24   Median : 62.00   Median :12.998
 Mean   :20.23   Mean   :23.66   Mean   : 61.89   Mean   :12.799
 3rd Qu.:26.24   3rd Qu.:31.06   3rd Qu.: 77.00   3rd Qu.:16.998
 Max.   :41.00   Max.   :45.45   Max.   :100.00   Max.   :56.997

     casual          registered         count
 Min.   :  0.00   Min.   :  0.0   Min.   :  1.0
 1st Qu.:  4.00   1st Qu.: 36.0   1st Qu.: 42.0
 Median : 17.00   Median :118.0   Median :145.0
 Mean   : 36.02   Mean   :155.6   Mean   :191.6
 3rd Qu.: 49.00   3rd Qu.:222.0   3rd Qu.:284.0
 Max.   :367.00   Max.   :886.0   Max.   :977.0
```

6 Number Summaries of Numerical Data

```
    season       holiday          workingday       weather
 spring:2686   Mode :logical    Mode :logical    Good:7192
 summer:2733   FALSE:10575      FALSE:3474       Fair:2834
 fall  :2733   TRUE :311        TRUE :7412       Poor: 859
```

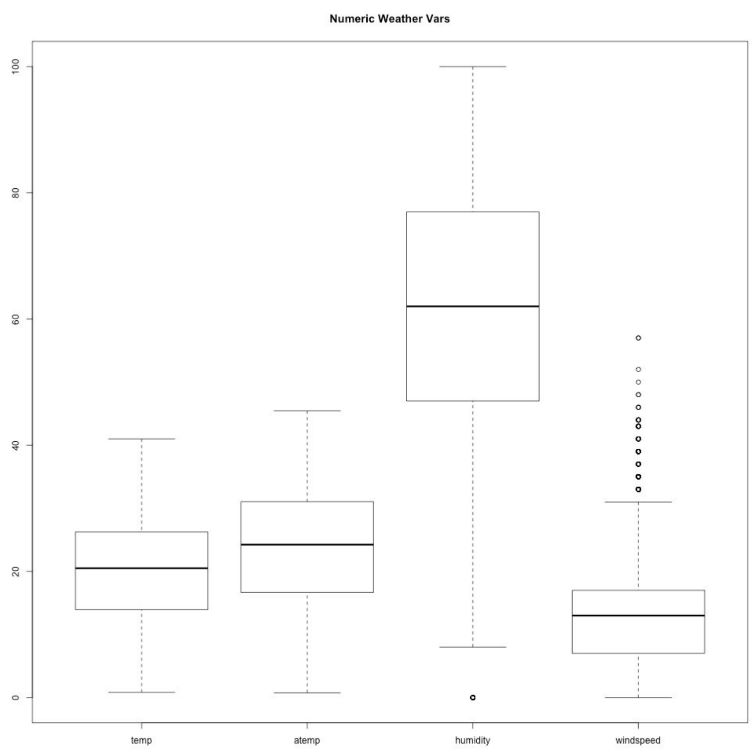
```
 winter:2734   NA's :0          NA's :0          Bad :   1
```

Counts of Categorical and Logical Data

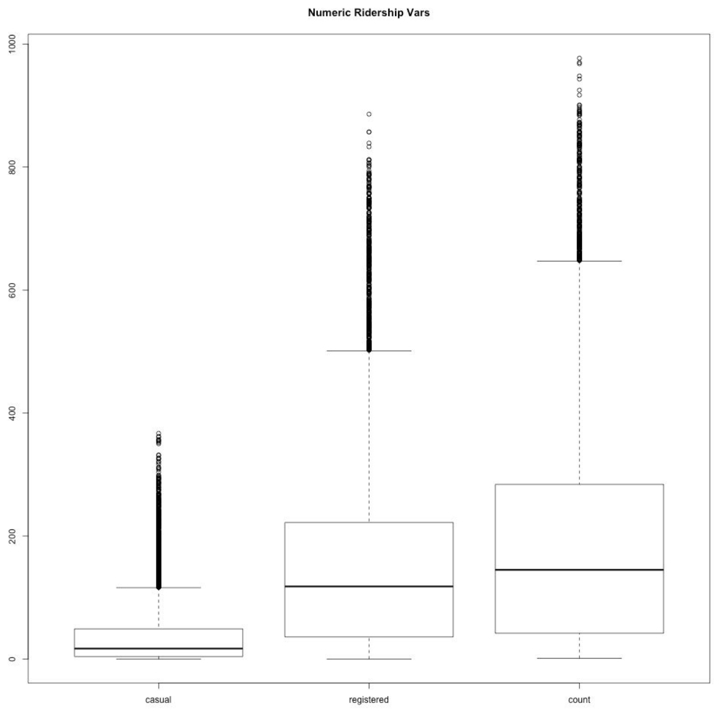
An interesting attribute of the temp, atemp, humidity and windspeed variables is that the mean is close to the median and the 1st quartile is a similar distance from the mean as the 3rd quartile. This suggests that these columns are not skewed, although this will be confirmed or denied by looking at the box plots. The count column however looks significantly skewed because the mean and median are far apart.

Looking at the season variable we can see that we have a relatively even number of each value. In the holiday variable we can see that most of the data points were not from a holiday day. Contrastingly most of the data points are from a workingday. The weather overall was good with many fair days, a few poor days and one bad day.

Box plots are a good tool to quickly analyze the skewness of data and detect outliers.



Temp, atemp, humidity, windspeed box plots



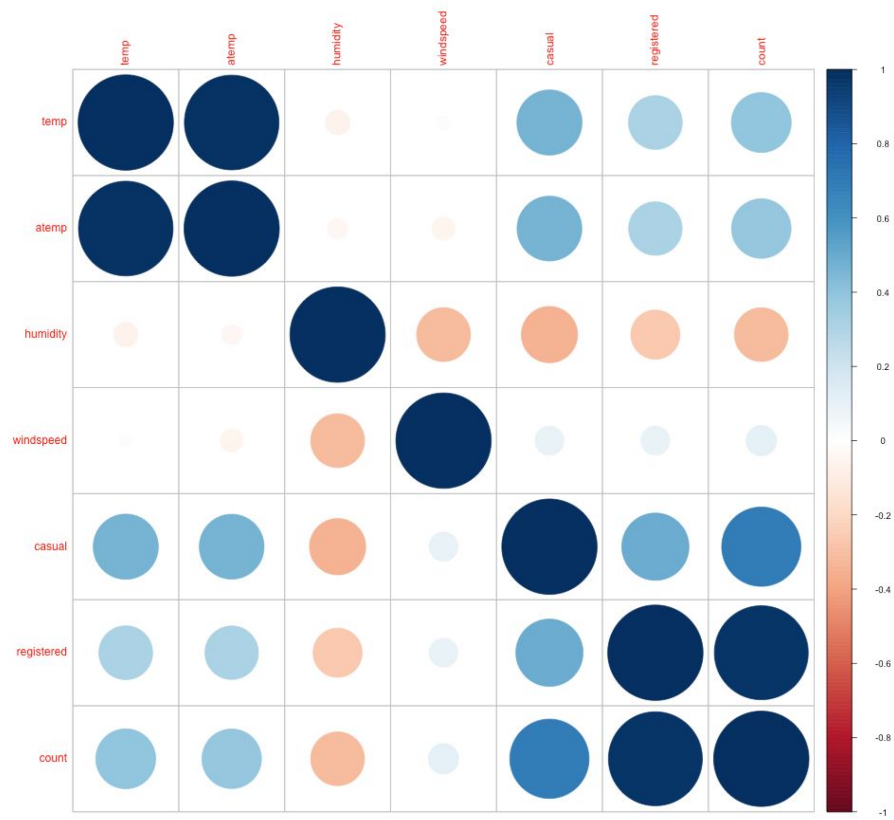
Ridership bot plots

Looking at these box plots we can see. That temp, atemp and humidity are all fairly symmetrical distributions. However windspeed, casual, registered and count are all skewed left. There are many outliers, especially in the ridership variables. It is hard to determine from the plot just how many outliers there are which is typical of a large dataset where event plotting 1% of points looks like a solid line. Based on this information outlier removal should be considered before modeling.

Correlation matrices are a good tool to find multicollinearity in the data.

	temp	atemp	humidity	windspeed	casual	registered	count
temp	1.00000000	0.98494811	-0.06494877	-0.01785201	0.46709706	0.31857128	0.3944536
atemp	0.98494811	1.00000000	-0.04353571	-0.05747300	0.46206654	0.31463539	0.3897844
humidity	-0.06494877	-0.04353571	1.00000000	-0.31860699	-0.34818690	-0.26545787	-0.3173715
windspeed	-0.01785201	-0.05747300	-0.31860699	1.00000000	0.09227619	0.09105166	0.1013695
casual	0.46709706	0.46206654	-0.34818690	0.09227619	1.00000000	0.49724969	0.6904136
registered	0.31857128	0.31463539	-0.26545787	0.09105166	0.49724969	1.00000000	0.9709481
count	0.39445364	0.38978444	-0.31737148	0.10136947	0.69041357	0.97094811	1.0000000

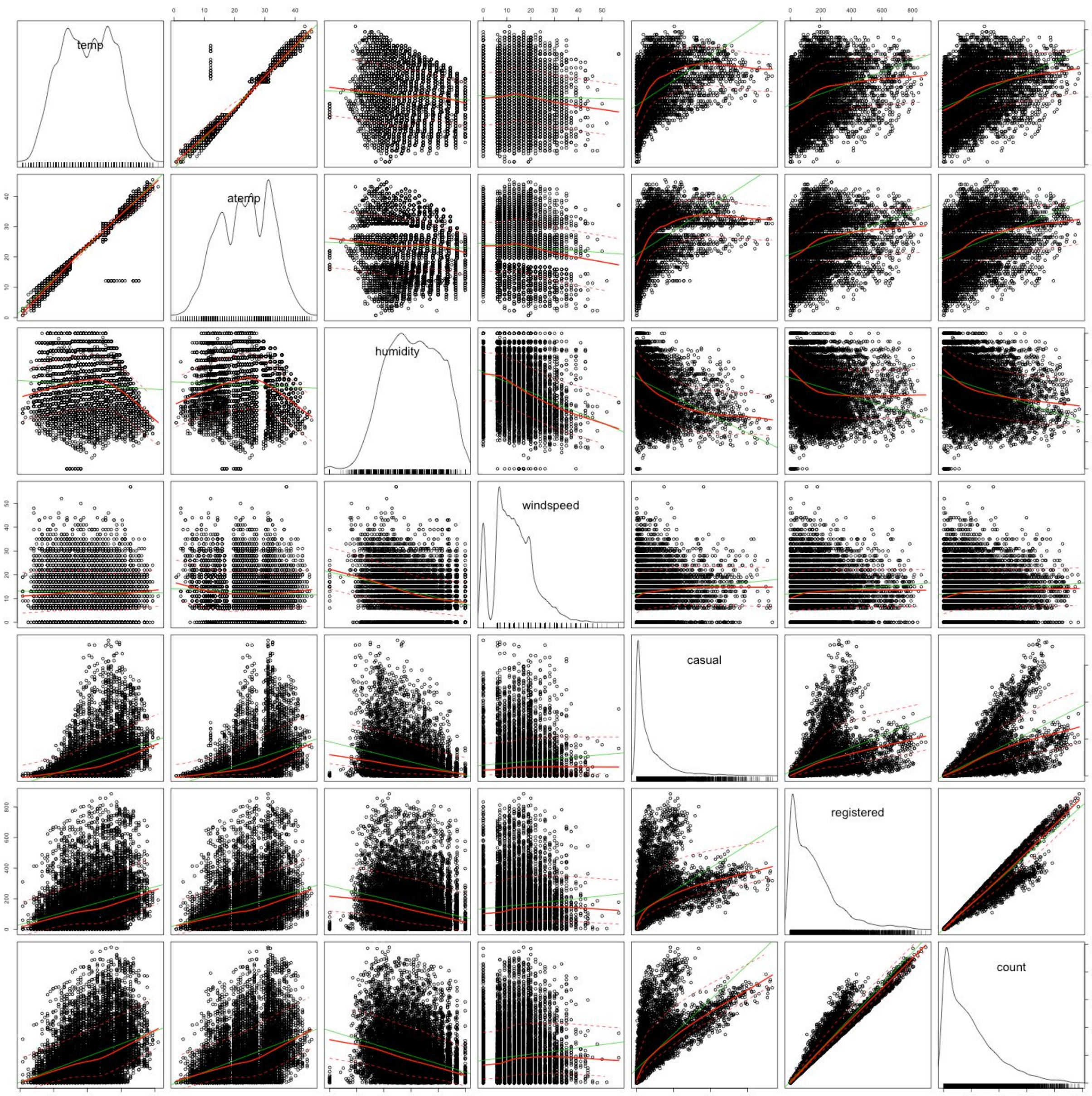
Correlation Matrix



Correlation Matrix Visualization

The correlation matrix shows us the obvious result that temp and atemp are extremely correlated and that casual, registered and count are fairly correlated. It is reasonable to see that humidity is negatively correlated with ridership and that temperature is positively correlated with ridership. Interestingly we see that humidity is negatively correlated with windspeed.

A scatterplot matrix produced by the car R library is a useful tool because it also generates histograms and performs a linear regression for each pair of variables.



Scatter Plot Matrix of numeric variables

In this scatter plot matrix we can see a similar story to the correlation matrix. Most of the data is relatively uncorrelated with the exceptions of temp with atemp and casual, registered and count alltogether. We can see from this histograms that temp, atemp and humidity are very roughly normal distributions and that windspeed, casual, registered and count are all skewed left.

Modeling and evaluation of 3 other solutions

Solution Overview

Kernel	Features	Modeling Approach	Performance (RSMLE)
EDA & Ensemble Model (Top 10 Percentile)	-New cols from Datetime -Coercing of columns to "categorical" data type	Linear Regression Ridge Regression Lasso Regression Random Forest Gradient Boost	0.977996 0.977996 0.978133 0.102804 0.189973
Comprehensive EDA with XGBoost (Top 10 percentile)	-Transforming count to log(count) -Creation of dummy vars for categorical data	XGBoost Random Forest	Did not put in notebook :-(
bikes	- Creation of dayofweek, hour, month and year columns from the datetime column	Random Forest	0.106703

Solution Commentary

EDA & Ensemble Model (Top 10 Percentile)

This kernel was made by Vivek Srinivasan and can be found here https://www.kaggle.com/viveksrinivasan/eda-ensemble-model-top-10-percentile.

Vivek has the clearest notebook of the three and his exploratory data analysis phase is very easy to follow. First, they read in the data and ascertains the shape, looks at the first 2 rows, and looks at the automatically chosen data types of each row. After that they create several features, hour, weekday, and month from the datatime column and then drops the datetime column for each row and casts the categorical data rows to categorical data. They then check for missing values and finds none. Vivek then makes box plots to find outliers (points above 3 standard deviations) in the count column and decides to remove those rows from the data. After that, they perform a correlation analysis and removes highly correlated variables from the dataset. Then they look at histograms and a probability plot of the count column with and without outliers to visualize the distribution of the data. After creating additional count visualizations they build a random forest model to predict when the wind speed is 0 and then never uses this model. It is unclear why they included this model in the notebook. Vivek then builds models to test linear, ride and lasso regression, random forest and gradient boost models and chooses the one with the best fitting to the training data. They do not use any validation data which raises concerns about overfitting the training data however despite this the model performs reasonably on the test data.

Comprehensive EDA with XGBoost (Top 10 percentile)

This kernel was made by Mitesh Yadav and can be found here https://www.kaggle.com/miteshyadav/comprehensive-eda-with-xgboost-top-10-percentile

This notebook contains the most extensive exploratory data analysis of all the notebooks. Mitesh begins the analysis by viewing the first few rows of data. They then create a bot plot and remove rows where the value of count is higher than 3 standard deviations above the mean. They then continue the exploratory data analysis with a histogram of count with the outliers removed, bar charts to compare the frequency of the categorical and logical variables, and box plots of the continuous variables. After this Mitesh creates a graph of a rolling average of count and shows that over the span of the dataset ridership is cyclic and increasing. After that, they make join plots for every combination of continuous variables which show a few artifacts in the data but mostly show loosely correlated or uncorrelated variables. Mitesh then creates a correlation matrix visualization with a terrible color scheme and begins modeling. Mitesh creates a random forest model from scikit-learn and a gradient boosting model from xgboost however never displays the mean error, merely prints out a list of errors which makes this model difficult to compare to other models.

bikes

This kernel was made by meena and can be found here https://www.kaggle.com/meenaj/bikes
This notebook is the least descriptive of the three so it is fortunate the code is easy to follow. meena first creates new columns for dayofweek, hour, month and year from the datetime column. After this, they make pair plots between count and the other non date columns. meena does not drop or correctly interpret and categorical or logical variables but proceeds to make a correlation matrix anyway. After dropping the casual, registered and datetime columns meena separates the training data into a X and Y dataframe. Despite importing a GradientBoostingRegressor from sklearn.ensembles meena only uses a RandomForestRegressor and despite not correctly interpreting all of the data columns archives

a RSMLE almost identical to the other best. This good result suggests just how powerful the random forest model is.