Bike Sharing Demand Prediction

Akash K,
Data science Trainee,
AlmaBetter, Bangalore.

Abstract:

The bike sharing demand is calculated using various variables like 'Date', 'Rented Bike Count', 'Hour', 'Temperature(°C)', 'Humidity(%)', 'Wind speed (m/s)', 'Visibility (10m)', 'Dew point temperature(°C)', 'Solar Radiation (MJ/m2)', 'Rainfall(mm)', 'Snowfall (cm)', 'Seasons', 'Holiday', and Functioning Day.
The dependent variable is rented bike count. In this model, the rented bike count is determined with the models to obtain an R2 Score of about 90-92%.
Keywords:machine learning,surge pricing,dynamic pricing,classified labels

1.Problem Statement

Currently Rental bikes are introduced in many urban cities for the enhancement of mobility comfort. It is important to make the rental bike available and accessible to the public at the right time as it lessens the waiting time. Eventually, providing the city with a stable supply of rental bikes becomes a major concern. The crucial part is the prediction of bike count required at each hour for the stable supply of rental bikes.

2. Introduction

The rented bike count is the dependent variable with the independent variables such as 'Date', 'Rented Bike Count', 'Hour', 'Temperature(°C)','Humidity(%)','Wind speed (m/s)', 'Visibility (10m)', 'Dew point temperature(°C)', 'Solar Radiation (MJ/m2)', 'Rainfall(mm)', 'Snowfall (cm)', 'Seasons', 'Holiday', and Functioning Day.

These values are treated for null values at first, then the EDA part is carried out to enhance the normality of the data, to determine the correlation between the variables and finally the multicollinearity is checked between the variables.

Each of the variables are defined below:

Date : year-month-day
Rented Bike count - Count of bikes rented at each hour
Hour - Hour of he day
Temperature-Temperature in Celsius
Humidity - %
Wind Speed - m/s
Visibility - 10m
Dew point temperature - Celsius
Solar radiation - MJ/m2
Rainfall - mm
Snowfall - cm
Seasons - Winter, Spring, Summer, Autumn
Holiday - Holiday/No holiday
Functional Day - NoFunc(Non Functional Hours), Fun(Functional hours)

3. Steps involved:

- **Exploratory Data Analysis**
  After loading the dataset I performed this method by comparing our target variable that is Rented_bike_count with other independent variables. This process helped us figuring out various aspects and relationships among the target and the independent variables. It gave us a better idea of which feature behaves in which manner compared to the target variable.

- **Null values Treatment**
  Our dataset contains a large number of null values which might tend to disturb our accuracy hence I dropped them at the beginning of our project inorder to get a better result.

- **Encoding of categorical columns**
  I used One Hot Encoding to produce binary integers of 0 and 1 to encode our categorical features because categorical features that are in string format cannot be understood by the machine and needs to be converted to numerical format.

- **Feature Selection**
  In these steps I used algorithms like ExtraTree classifier to check the results of each feature i.e which feature is more important compared to our model and which is of less importance.

- **Standardization of features**
  Our main motive through this step was to scale our data into a uniform format that would allow us to utilize the data in a better way while performing fitting and applying different algorithms to it.
  The basic goal was to enforce a level of consistency or uniformity to certain practices or operations within the selected environment.

- **Fitting different models**
  For modelling I tried various classification algorithms like:

1. **Linear Regression**
2. **Random Forest Regressor**
3. **Gradient Boosting Machine**
4. **XGBoost Regressor**

- **Tuning the hyperparameters for better accuracy**
  Tuning the hyperparameters of respective algorithms is necessary for getting better accuracy and to avoid overfitting in case of tree based models like Random Forest Classifier, **Gradient Boosting Machine** and XGBoost classifier.

- **SHAP Values for features**
  I have applied SHAP value plots on the Random Forest model to determine the features that were most important while model building and the features that didn't put much weight on the performance of our model.

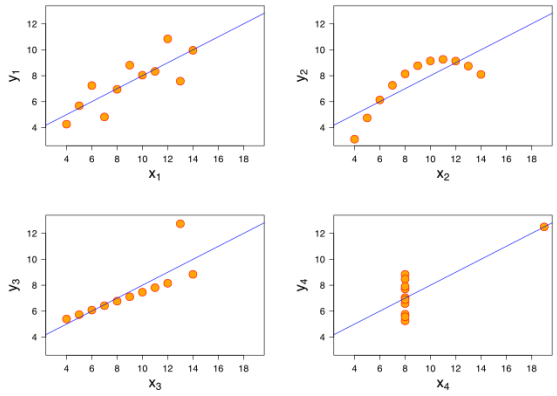
7.1. Algorithms:

1. Linear Regression:

In statistics, **linear regression** is a linear approach to modelling the relationship between a scalar response and one or more explanatory variables (also known as dependent and independent variables). The case of one explanatory variable is called *simple linear regression*; for more than one, the process is called **multiple linear regression**. This term is distinct from multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable.

In linear regression, the relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models. Most commonly, the conditional mean of the response given the values of the explanatory variables (or predictors) is assumed to be an affine function of those values; less commonly, the conditional median or some other quantile is used. Like all forms of regression analysis, linear regression focuses on the conditional probability distribution of the response given the values of the predictors, rather than on the joint probability distribution of all of these variables, which is the domain of multivariate analysis.

$$f(x)= mx + c$$



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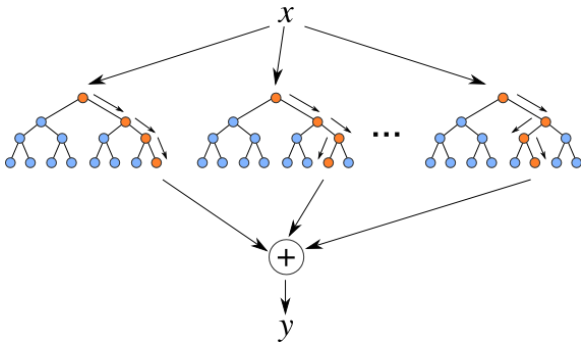
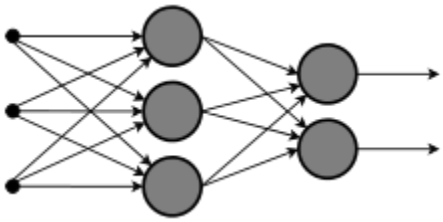
2. Random Forest Regressor:

Random Forest is a bagging type of Decision Tree Algorithm that creates a number of decision trees from a randomly selected subset of the training set, collects the labels from these subsets and then averages the final prediction depending on the most number of times a label has been predicted out of all.



3. Gradient Boosting Machine Regressor:

Gradient boosting is a machine learning technique for regression, classification and other tasks, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. When a decision tree is the weak learner, the resulting algorithm is called gradient boosted trees, which usually outperforms random forest. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.

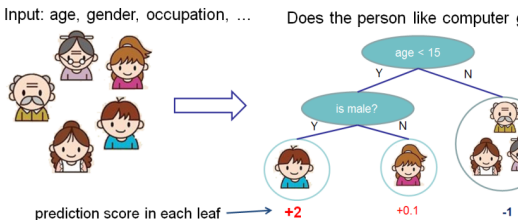


4. XGBoost-

To understand XGBoost I have to know gradient boosting beforehand.

- **Gradient Boosting-**

  Gradient boosted trees consider the special case where the simple model is a decision tree



  In this case, there are going to be 2 kinds of parameters P: the weights at each leaf, w, and the number of leaves T in each tree (so that in the above example, T=3 and w=[2, 0.1, -1]).

  When building a decision tree, a challenge is to decide how to split a current leaf. For instance, in the above image, how could I add another layer to the (age > 15) leaf? A 'greedy' way to do this is to consider every possible split on the remaining features (so, gender and occupation), and calculate the new loss for each split; you could then pick the tree which most reduces your loss.

XGBoost is one of the fastest implementations of gradient boosting. trees. It does this by tackling one of the major inefficiencies of gradient boosted trees: considering the potential loss for all possible splits to create a new branch (especially if you consider the case where there are thousands of features, and therefore thousands of possible splits). XGBoost tackles this inefficiency by looking at the distribution of features across all data points in a leaf and using this information to reduce the search space of possible feature splits.

7.2. Model performance:

Model can be evaluated by various metrics such as:

1. **Mean Squared Error(MSE):**
   In statistics, the mean squared error (MSE) or mean squared deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors—that is, the average squared difference between the estimated values and the actual value. MSE is a risk function, corresponding to the expected value of the squared error loss. The fact that MSE is almost always strictly positive (and not zero) is because of randomness or because the estimator does not account for information that could produce a more accurate estimate.

2. **Root Mean Squared Error:**
   The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed. The RMSD represents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences. These deviations are called *residuals* when the calculations are performed over the data sample that was used for estimation and are called *errors* (or prediction errors) when computed out-of-sample. The RMSD serves to aggregate the magnitudes of the errors in predictions for various data points into a single measure of predictive power. RMSD is a measure of accuracy, to compare forecasting errors of different models for a particular dataset and not between datasets, as it is scale-dependent

3. **Mean Absolute Error:**
   In statistics, mean absolute error (MAE) is a measure of errors between paired observations expressing the same phenomenon. Examples of Y versus X include comparisons of predicted versus observed, subsequent time versus initial time, and one technique of measurement versus an alternative technique of measurement.
   It is thus an arithmetic average of the absolute errors $|e_i| = |y_i - x_i|$, where
   y_i is the prediction and x_i is the true value. Note that alternative formulations may include relative frequencies as weight factors. The mean absolute error uses the same scale as the data being measured. This is known as a scale-dependent accuracy measure and therefore cannot be used to make comparisons between series using different scales. The mean absolute error is a common measure of forecast error in time series analysis, sometimes used

in confusion with the more standard definition of mean absolute deviation. The same confusion exists more generally.

4. **R-Squared:**

   In statistics, the coefficient of determination, denoted R^2 or r^2 and pronounced "R squared", is the proportion of the variance in the dependent variable that is predictable from the independent variable(s).

   It is a statistic used in the context of statistical models whose main purpose is either the prediction of future outcomes or the testing of hypotheses, on the basis of other related information. It provides a measure of how well observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model.

7.3. Hyper parameter tuning:

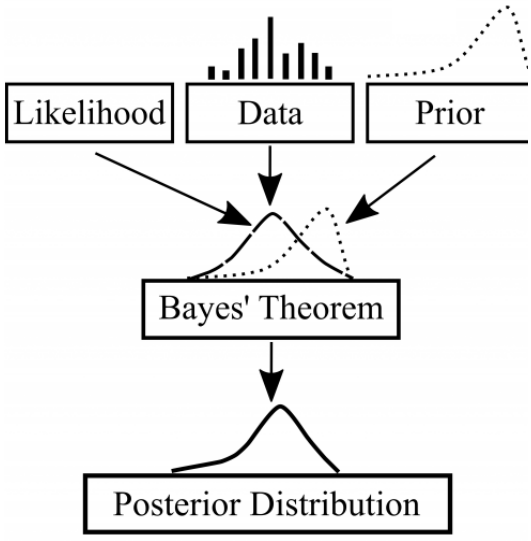
Hyperparameters are sets of information that are used to control the way of learning an algorithm. Their definitions impact parameters of the models, seen as a way of learning, change from the new hyperparameters. This set of values affects performance, stability and interpretation of a model. Each algorithm requires a specific hyperparameters grid that can be adjusted according to the business problem. Hyperparameters alter the way a model learns to trigger this training algorithm after parameters to generate outputs.

I used Grid Search CV, Randomized Search CV and Bayesian Optimization for hyperparameter tuning. This also results in cross validation and in our case I divided the dataset into different folds. The best performance improvement among the three was by Bayesian Optimization.

1. **Grid Search CV-**Grid Search combines a selection of hyperparameters established by the scientist and runs through all of them to evaluate the model's performance. Its advantage is that it is a simple technique that will go through all the programmed combinations. The biggest disadvantage is that it traverses a specific region of the parameter space and cannot understand which movement or which region of the space is important to optimize the model.

2. **Randomized Search CV-** In Random Search, the hyperparameters are chosen at random within a range of values that it can assume. The advantage of this method is that there is a greater chance of finding regions of the cost minimization space with more suitable hyperparameters, since the choice for each iteration is random. The disadvantage of this method is that the combination of hyperparameters is beyond the scientist's control

3. **Bayesian Optimization-** Bayesian Hyperparameter optimization is a very efficient and interesting way to find good hyperparameters. In this approach, in naive interpretation way is to use a support model to find the best hyperparameters.A hyperparameter optimization process based on a probabilistic model, often Gaussian Process, will be used to find data from data observed in the later distribution of the performance of the given models or set of tested hyperparameters.



As it is a Bayesian process at each iteration, the distribution of the model's performance in relation to the hyperparameters used is evaluated and a new probability distribution is generated. With this distribution it is possible to make a more appropriate choice of the set of values that I will use so that our algorithm learns in the best possible way.

8. Conclusion:

That's it! I reached the end of our exercise. Starting with loading the data so far I have done EDA , null values treatment, encoding of categorical columns, feature selection and then model building.
In all of these models our accuracy revolves in the range of 90 to 92%.
And there is no such improvement in accuracy score even after hyperparameter tuning.
So the accuracy of our best model is 92.2% which can be said to be good for this large dataset. This performance could be due to various reasons like: no proper pattern of data, too much data, not enough relevant features.

References-

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