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Automatic Predictive Braking Systems using Naive Bayes Theorem

Abstract:

In order to avoid accidents and mitigate their consequences - we propose an integrated approach is developed for driver's safety and compliance which incorporates Naive Bayes techniques and discuss a particular braking assistance systems which derives sensory inputs from various factors to avoid high speed collisions. We process the sample data taken, pre-process it and built the naive bayes model using the trained data. On formulating and comparing our results with actual results where we have calculated various performance metrics by making confusing

matrix.

Introduction:

Today, the machine learning algorithms are widely used to find the solutions to various challenges arising in manufacturing self-driving cars. The brake system should be very reliable to promote safety on the road. Here, an efficient brake system is mainly designed for the safety and stability of the vehicle. An automatic braking system has become an integral part of safety technology for automobiles. It is a system specifically designed to either prevent possible collision, or reduce the speed of the moving vehicle, prior to a collision with another vehicle or an obstacle of some sort.

These systems combine sensors to not only scan for possible objects in front of the vehicle but also the concentration of the driver and then use brake control to prevent collision if the object is detected. Automatic brakes are one of many car features and are often integrated with other enhanced features such as pre-collision systems. Sadly, only about 40% of drivers alert vigilantly and hit the brakes in crashes. Here, we can detect an imminent rear-end collision and apply the brakes to mitigate or prevent the impact.

Problem:

According to the statistics, In 2013, 54 million people worldwide sustained injuries from traffic collisions. This resulted in 1.4 million deaths in 2013, up from 1.1 million deaths in 1990. Few of the main reasons behind these accidents are lack of concentration of driver, obstacles, visibility of other cars (blind spots) etc. As per the reports by the National Highway Traffic

Safety Administration, Drowsy driving is a factor in more than 100,000 crashes, resulting in 6,550 deaths and 80,000 injuries annually in the USA. Millions of drivers fall asleep at the wheel each month, and roughly 15 percent of all fatal crashes involve a drowsy driver. Today, in this era of vehicle technology, it has been proven among many safety systems, Automatic Emergency Braking (AEB) systems prevents accidents and reduces them simultaneously. This braking assistance combines sensor inputs from various external factors such as obstacles, visibility, concentration of driver, the type of vehicle (heavy or light) and brake controls to help prevent high-speed collisions. Some of these braking systems provide assistance to the driver and others are capable of activating brakes without driver input. High-speed crashes are more fatal than low-speed crashes, this technology provides a visible, audible or alert to warn the driver to impend collision coming in the same path. If the vehicle is equipped with AEB senses a collision and driver don't react on time it applies brake. According to the new reports, with the implementation of AEB systems in vehicle, the rate of crashes has reduced by 50% and 56% for the same with injuries.

Analysis:

We have used Naive Bayes theorem to make our prediction. It is a powerful algorithm for predictive modeling. It is stated as P(X|Y) = (P(Y|X) * P(X)) / P(Y),

where,

- **P(X|Y)** is the probability of hypothesis X given the data Y. This is called the posterior probability.

- **P(Y|X)** is the probability of data X given that the hypothesis Y was true.
- **P(X)** is the probability of hypothesis X being true (regardless of the data). This is called the prior probability of X.
- **P(Y)** is the probability of the data (regardless of the hypothesis)

The estimated results are reported below

```
Naive Bayes Classifier for Discrete Predictors

Call:
naiveBayes.default(x = X, y = Y, laplace = laplace)

A-priori probabilities:
Y
    brake  continue      slow 
0.3000000 0.1666667 0.5333333 

Conditional probabilities:
          relative.speed
Y              [,1]     [,2]
  brake    12.66667 4.582576
  continue 15.80000 4.207137
  slow     18.06250 5.246824

          range
Y              [,1]     [,2]
  brake    31.77778 18.01234
  continue 35.60000 18.62257
  slow     57.18750 30.55535

          reaction.time
Y               [,1]      [,2]
  brake    0.1358889 0.1193822
  continue 0.3600000 0.1140175
  slow     0.4062500 0.2174665

          obstacles
Y              no    yes
  brake    0.0000 1.0000
  continue 0.2000 0.8000
  slow     0.3125 0.6875

          type
Y              heavy     light
  brake    0.6666667 0.3333333
  continue 0.4000000 0.6000000
  slow     0.6250000 0.3750000

          alertness
Y             active    drowsy unattentive
  brake    0.1111111 0.5555556   0.3333333
  continue 0.8000000 0.0000000   0.2000000
  slow     0.1250000 0.3125000   0.5625000
```

Fig:1

Fig:1 is the result of the built Naive Bayes model using train data which shows the A-priori probabilities of each class. It also depicts the conditional probabilities of each class label given the attributes. For continuous attributes, it gives the mean and standard deviation for each class label.

```
> NBpredict=predict(NB,test)
> z<-table(NBpredict,test$class)
> z

NBpredict  brake continue slow
  brake        5        0    1
  continue     0        1    1
  slow         2        1    9
> library(caret)
> a<-confusionMatrix(z)
> a
Confusion Matrix and Statistics


NBpredict  brake continue slow
  brake        5        0    1
  continue     0        1    1
  slow         2        1    9

Overall Statistics

               Accuracy : 0.75
                 95% CI : (0.509, 0.9134)
    No Information Rate : 0.55
    P-Value [Acc > NIR] : 0.05533

                  Kappa : 0.5495

 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: brake Class: continue Class: slow
Sensitivity                0.7143          0.5000      0.8182
Specificity                0.9231          0.9444      0.6667
Pos Pred Value             0.8333          0.5000      0.7500
Neg Pred Value             0.8571          0.9444      0.7500
Prevalence                 0.3500          0.1000      0.5500
Detection Rate             0.2500          0.0500      0.4500
Detection Prevalence       0.3000          0.1000      0.6000
Balanced Accuracy          0.8187          0.7222      0.7424
```

Fig:2

Fig:2 shows us the results after predicting the test data output class using the built model. It also gives the confusion matrix of the prediction results from which we got various performance metrics of the model like accuracy along with its confidence interval, sensitivity, specificity, etc.

Hence, given a situation our model is 75% percent accurate and these coefficients are all significant based on the 95% Confidence Interval of their posterior distribution of value (0.509,0.9134).

Conclusions:

In this paper, we present a machine learning approach for automotive predictive braking system in vehicle using Bayes theorem. The performance of Naïve Bayes algorithm is presented. By using Naïve Bayes classifier in our experiment, we created a predictive model. The efficiency of the model has been tested by running the testing data set on the model and using a Confusion matrix to evaluate the accuracy of the model. The final results show that we built a Naïve Bayes classifier that can predict whether a car should brake or not based on predictor variables, with an accuracy of 75%.

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