Modelling The Linear Relationship Between Sales and Advertising

Submitted in partial fulfillment of the requirements of the degree **BACHELOR OF ENGINEERING** IN **COMPUTER ENGINEERING**

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CERTIFICATE

This is to certify that the Mini Project entitled "**Modelling The Linear Relationship between Sales and Advertising"** is a bonafide work of **Sanket Chandrashekhar Harvande_19, Sajid Inayat Hurzuk_20, Priyanka Santosh Inamdar_21** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Engineering".**

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Modelling the linear relationship between Sales and Advertising

Project overview

In this project, we build a Simple Linear Regression model to study the linear relationship between Sales and Advertising dataset for a dietary weight control product.

Linear Regression

Linear Regression is a statistical technique which is used to find the linear relationship between dependent and one or more independent variables. This technique is applicable for Supervised learning Regression problems where we try to predict a continuous variable.

Linear Regression can be further classified into two types – Simple and Multiple Linear Regression. In this project, I employ Simple Linear Regression technique where I have one independent and one dependent variable. It is the simplest form of Linear Regression where we fit a straight line to the data.

Simple Linear Regression (SLR)

Simple Linear Regression (or SLR) is the simplest model in machine learning. It models the linear relationship between the independent and dependent variables.

In this project, there is one independent or input variable which represents the Sales data and is denoted by X. Similarly, there is one dependent or output variable which represents the Advertising data and is denoted by y. We want to build a linear relationship between these variables. This linear relationship can be modelled by mathematical equation of the form:-

```
              Y = β0   + β1*X    -------------   (1)
```

In this equation, X and Y are called independent and dependent variables respectively,

β1 is the coefficient for independent variable and

β0 is the constant term.

β0 and β1 are called parameters of the model.

For simplicity, we can compare the above equation with the basic line equation of the form:-

```
               y = ax + b       ----------------- (2)
```

We can see that

slope of the line is given by, a = β1, and

intercept of the line by b = β0.

In this Simple Linear Regression model, we want to fit a line which estimates the linear relationship between X and Y. So, the question of fitting reduces to estimating the parameters of the model β0 and β1.

Ordinary Least Square Method

As I have described earlier, the Sales and Advertising data are given by X and y respectively. We can draw a scatter plot between X and y which shows the relationship between them.

Now, our task is to find a line which best fits this scatter plot. This line will help us to predict the value of any Target variable for any given Feature variable. This line is called **Regression line**.

We can define an error function for any line. Then, the regression line is the one which minimizes the error function. Such an error function is also called a **Cost function**.

Cost Function

We want the Regression line to resemble the dataset as closely as possible. In other words, we want the line to be as close to actual data points as possible. It can be achieved by minimizing the vertical distance between the actual data point and fitted line. I calculate the vertical distance between each data point and the line. This distance is called the **residual**.

So, in a regression model, we try to minimize the residuals by finding the line of best fit. The residuals are represented by the vertical dotted lines from actual data points to the line.

We can try to minimize the sum of the residuals, but then a large positive residual would cancel out a large negative residual. For this reason, we minimize the sum of the squares of the residuals.

Mathematically, we denote actual data points by yi and predicted data points by ŷi. So, the residual for a data point i would be given as

```
        di = yi -  ŷi
```

Sum of the squares of the residuals is given as:

```
        D = Σ di**2       for all data points
```

This is the **Cost function**. It denotes the total error present in the model which is the sum of the total errors of each individual data point.

We can estimate the parameters of the model β0 and β1 by minimize the error in the model by minimizing D. Thus, we can find the regression line given by equation (1).

This method of finding the parameters of the model and thus regression line is called **Ordinary Least Square Method**.

The problem statement

The aim of building a machine learning model is to solve a problem and to define a metric to measure model performance.

The problem is to model and investigate the linear relationship between Sales and Advertising dataset for a dietary weight control product.

I have used two performance metrics RMSE (Root Mean Square Value) and R2 Score value to compute our model performance.

Software information

I did this project using Jupyter notebook (Jupyter notebook server 5.5.0).

The server is running on Python (Python 3.6.5), Anaconda distribution.

Python libraries

I have Anaconda Python distribution installed on my system. It comes with most of the standard Python libraries I need for this project. The basic Python libraries used in this project are:-

• Numpy – It provides a fast numerical array structure and operating functions.

• pandas – It provides tools for data storage, manipulation and analysis tasks.

• Scikit-Learn – The required machine learning library in Python.

• Matplotlib – It is the basic plotting library in Python. It provides tools for making plots.

```
# Import necessary libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
% matplotlib inline

# The above command sets the backend of matplotlib to the 'inline' backend.
# It means the output of plotting commands is displayed inline.
```

About the dataset

The data set has been imported from the econometrics website with the following url:-

http://www.econometrics.com/intro/sales.htm

This data set contains Sales and Advertising expenditures for a dietary weight control product. It contains monthly data for 36 months. The variables in this data set are Sales and Advertising

```
# Import the data

url = "C:/project_datasets/SALES.txt"
df = pd.read_csv(url, sep='\t', header=None)
```

Exploratory data analysis

First, I import the dataset into the dataframe with the standard read_csv () function of pandas library and assign it to the df variable. Then, I conducted exploratory data analysis to get a feel for the data.

pandas shape attribute

The shape attribute of the pandas dataframe gives the dimensions of the dataframe.

```
# Exploratory data analysis

# View the dimensions of df

print(df.shape)
```

```
(36, 2)
```

pandas head() method

I viewed the top 5 rows of the pandas dataframe with the pandas head() method.

```
# View the top 5 rows of df

print(df.head())
```

```
      0     1
0  12.0  15.0
1  20.5  16.0
2  21.0  18.0
3  15.5  27.0
4  15.3  21.0
```

pandas columns attribute

I renamed the column labels of the dataframe with the columns attribute.

```
# Rename columns of df dataframe

df.columns = ['Sales', 'Advertising']
```

column names renamed

I viewed the renamed column names.

```
# View the top 5 rows of df with column names renamed

print(df.head())
```

```
   Sales  Advertising
0   12.0         15.0
1   20.5         16.0
2   21.0         18.0
3   15.5         27.0
4   15.3         21.0
```

pandas info() method

I viewed the summary of the dataframe with the pandas info() method.

```
# View dataframe summary

print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36 entries, 0 to 35
Data columns (total 2 columns):
Sales          36 non-null float64
Advertising    36 non-null float64
dtypes: float64(2)
memory usage: 656.0 bytes
None
```

pandas describe() method

I look at the descriptive statistics of the dataframe with the pandas describe() method.

```
# View descriptive statistics

print(df.describe())
```

```
           Sales  Advertising
count  36.000000    36.000000
mean   24.255556    28.527778
std     6.185118    18.777625
min    12.000000     1.000000
```

```
25%    20.300000    15.750000
50%    24.250000    23.000000
75%    28.600000    41.000000
max    36.500000    65.000000
```

Independent and Dependent Variables

In this project, I refer Independent variable as Feature variable and Dependent variable as Target variable. These variables are also recognized by different names as follows: -

Independent variable

Independent variable is also called Input variable and is denoted by X. In practical applications, independent variable is also called Feature variable or Predictor variable. We can denote it as:-

Independent or Input variable (X) = Feature variable = Predictor variable

Dependent variable

Dependent variable is also called Output variable and is denoted by y.

Dependent variable is also called Target variable or Response variable. It can be denoted it as follows:-

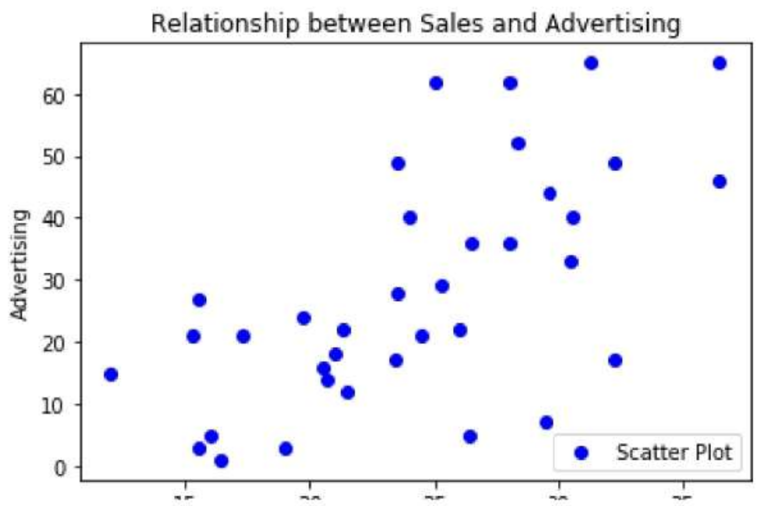
Dependent or Output variable (y) = Target variable = Response variable

```
# Declare feature variable and target variable

X = df['Sales'].values
y = df['Advertising'].values

# Sales and Advertising data values are given by X and y respectively.

# Values attribute of pandas dataframe returns the numpy arrays.
```

Visual exploratory data analysis

I visualize the relationship between X and y by plotting a scatterplot between X and y.

```
# Plot scatter plot between X and y

plt.scatter(X, y, color = 'blue', label='Scatter Plot')
plt.title('Relationship between Sales and Advertising')
plt.xlabel('Sales')
plt.ylabel('Advertising')
plt.legend(loc=4)
plt.show()
```



Checking dimensions of X and y

We need to check the dimensions of X and y to make sure they are in right format for Scikit-Learn API.

It is an important precursor to model building.

```
# Print the dimensions of X and y

print(X.shape)
print(y.shape)
```

```
     (36,)
     (36,)
```

Reshaping X and y

Since we are working with only one feature variable, so we need to reshape using Numpy reshape() method.

It specifies first dimension to be -1, which means "unspecified".

Its value is inferred from the length of the array and the remaining dimensions.

```
# Reshape X and y

X = X.reshape(-1,1)
y = y.reshape(-1,1)
```

```
# Print the dimensions of X and y after reshaping

print(X.shape)
print(y.shape)
```

```
    (36, 1)
    (36, 1)
```

Difference in dimensions of X and y after reshaping

We can see the difference in diminsions of X and y before and after reshaping.

It is essential in this case because getting the feature and target variable right is an important precursor to model building.

Train test split

I split the dataset into two sets namely - train set and test set.

The model learn the relationships from the training data and predict on test data.

```
# Split X and y into training and test data sets

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

```
# Print the dimensions of X_train,X_test,y_train,y_test

print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
    (24, 1)
    (24, 1)
    (12, 1)
    (12, 1)
```

Mechanics of the model

I split the dataset into two sets – the training set and the test set. Then, I instantiate the regressor lm and fit it on the training set with the fit method.

In this step, the model learned the relationships between the training data (X_train, y_train).

Now the model is ready to make predictions on the test data (X_test). Hence, I predict on the test data using the predict method.

```
# Fit the linear model

# Instantiate the linear regression object lm
```

```
from sklearn.linear_model import LinearRegression
lm = LinearRegression()


# Train the model using training data sets
lm.fit(X_train,y_train)


# Predict on the test data
y_pred=lm.predict(X_test)
```

Model slope and intercept term

The model slope is given by lm.coef_ and model intercept term is given by lm.intercept_.

The estimated model slope and intercept values are 1.60509347 and -11.16003616.

So, the equation of the fitted regression line is

y = 1.60509347 * x - 11.16003616

```
# Compute model slope and intercept

a = lm.coef_
b = lm.intercept_,
print("Estimated model slope, a:" , a)
print("Estimated model intercept, b:" , b)
```

```
     Estimated model slope, a: [[1.60509347]]
     Estimated model intercept, b: (array([-11.16003616]),)
```

```
# So, our fitted regression line is

# y = 1.60509347 * x - 11.16003616

# That is our linear model.
```

Making predictions

I have predicted the Advertising values on first five 5 Sales datasets by writing code

```
lm.predict(X) [0:5]
```

If I remove [0:5], then I will get predicted Advertising values for the whole Sales dataset.

To make prediction, on an individual Sales value, I write

```
lm.predict(Xi)
```

where Xi is the Sales data value of the ith observation.

```
# Predicting Advertising values

lm.predict(X)[0:5]

# Predicting Advertising values on first five Sales values.
```

```
     array([[ 8.10108551],
            [21.74438002],
            [22.54692675],
            [13.71891266],
            [13.39789396]])
```

```
# To make an individual prediction using the linear regression model.

print(str(lm.predict(24)))
```

```
     [[27.36220717]]
```

Regression metrics for model performance

Now, it is the time to evaluate model performance.

For regression problems, there are two ways to compute the model performance. They are RMSE (Root Mean Square Error) and R-Squared Value. These are explained below:-

RMSE

RMSE is the standard deviation of the residuals. So, RMSE gives us the standard deviation of the unexplained variance by the model. It can be calculated by taking square root of Mean Squared Error. RMSE is an absolute measure of fit. It gives us how spread the residuals are, given by the standard deviation of the residuals. The more concentrated the data is around the regression line, the lower the residuals and hence lower the standard deviation of residuals. It results in lower values of RMSE. So, lower values of RMSE indicate better fit of data.

```
# Calculate and print Root Mean Square Error(RMSE)

from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print("RMSE value: {:.4f}".format(rmse))
```

```
     RMSE value: 11.2273
```

R2 Score

R2 Score is another metric to evaluate performance of a regression model. It is also called coefficient of determination. It gives us an idea of goodness of fit for the linear regression models. It indicates the percentage of variance that is explained by the model.

Mathematically,

R2 Score = Explained Variation/Total Variation

In general, the higher the R2 Score value, the better the model fits the data. Usually, its value ranges from 0 to 1. So, we want its value to be as close to 1. Its value can become negative if our model is wrong.

```
# Calculate and print r2_score

from sklearn.metrics import r2_score
print ("R2 Score value: {:.4f}".format(r2_score(y_test, y_pred)))
```

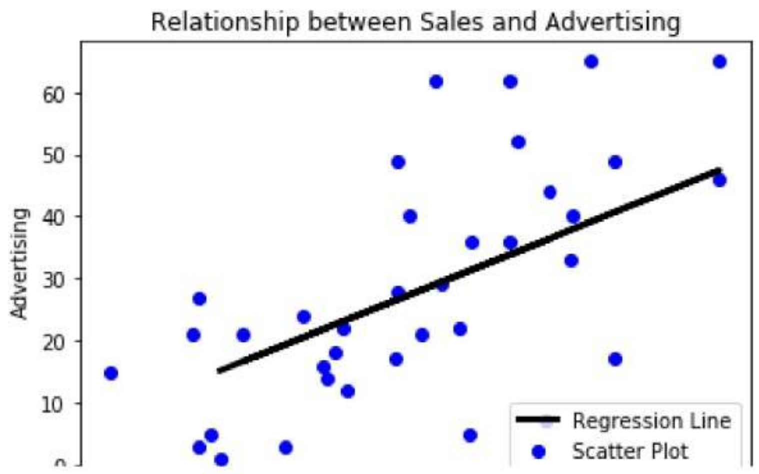
```
    R2 Score value: 0.5789
```

Interpretation and Conclusion

The RMSE value has been found to be 11.2273. It means the standard deviation for our prediction is 11.2273. So, sometimes we expect the predictions to be off by more than 11.2273 and other times we expect less than 11.2273. So, the model is not good fit to the data.

In business decisions, the benchmark for the R2 score value is 0.7. It means if R2 score value >= 0.7, then the model is good enough to deploy on unseen data whereas if R2 score value < 0.7, then the model is not good enough to deploy. Our R2 score value has been found to be .5789. It means that this model explains 57.89 % of the variance in our dependent variable. So, the R2 score value confirms that the model is not good enough to deploy because it does not provide good fit to the data.

```
# Plot the Regression Line


plt.scatter(X, y, color = 'blue', label='Scatter Plot')
plt.plot(X_test, y_pred, color = 'black', linewidth=3, label = 'Regression Line')
plt.title('Relationship between Sales and Advertising')
plt.xlabel('Sales')
plt.ylabel('Advertising')
plt.legend(loc=4)
plt.show()
```



Residual analysis

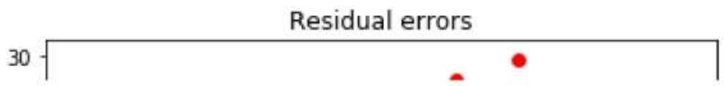
A linear regression model may not represent the data appropriately. The model may be a poor fit to the data. So, we should validate our model by defining and examining residual plots.

The difference between the observed value of the dependent variable (y) and the predicted value (ŷi) is called the residual and is denoted by e. The scatter-plot of these residuals is called residual plot.

If the data points in a residual plot are randomly dispersed around horizontal axis and an approximate zero residual mean, a linear regression model may be appropriate for the data. Otherwise a non-linear model may be more appropriate.

If we take a look at the generated 'Residual errors' plot, we can clearly see that the train data plot pattern is non-random. Same is the case with the test data plot pattern. So, it suggests a better-fit for a non-linear model.

```
# Plotting residual errors

plt.scatter(lm.predict(X_train), lm.predict(X_train) - y_train, color = 'red', label = 'Tr
plt.scatter(lm.predict(X_test), lm.predict(X_test) - y_test, color = 'blue', label = 'Test
plt.hlines(xmin = 0, xmax = 50, y = 0, linewidth = 3)
plt.title('Residual errors')
plt.legend(loc = 4)
plt.show()
```



Checking for Overfitting and Underfitting

I calculate training set score as 0.2861. Similarly, I calculate test set score as 0.5789. The training set score is very poor. So, the model does not learn the relationships appropriately from the training data. Thus, the model performs poorly on the training data. It is a clear sign of Underfitting. Hence, I validated my finding that the linear regression model does not provide good fit to the data.

Underfitting means our model performs poorly on the training data. It means the model does not capture the relationships between the training data. This problem can be improved by increasing model complexity. We should use more powerful models like Polynomial regression to increase model complexity.

```
# Checking for Overfitting or Underfitting the data

print("Training set score: {:.4f}".format(lm.score(X_train,y_train)))

print("Test set score: {:.4f}".format(lm.score(X_test,y_test)))
```

```
     Training set score: 0.2861
     Test set score: 0.5789
```

```
# Save model for future use

from sklearn.externals import joblib
joblib.dump(lm, 'lm_regressor.pkl')

# To load the model

# lm2=joblib.load('lm_regressor.pkl')
```

```
     ['lm_regressor.pkl']
```

Simple Linear Regression - Model Assumptions

The Linear Regression Model is based on several assumptions which are listed below:-

i. Linear relationship ii. Multivariate normality iii. No or little multicollinearity iv. No auto-correlation v. Homoscedasticity

i. Linear relationship

The relationship between response and feature variables should be linear. This linear relationship assumption can be tested by plotting a scatter-plot between response and feature variables.

ii. Multivariate normality

The linear regression model requires all variables to be multivariate normal. A multivariate normal distribution means a vector in multiple normally distributed variables, where any linear combination of the variables is also normally distributed.

iii. No or little multicollinearity

It is assumed that there is little or no multicollinearity in the data. Multicollinearity occurs when the features (or independent variables) are highly correlated.

iv. No auto-correlation

Also, it is assumed that there is little or no auto-correlation in the data. Autocorrelation occurs when the residual errors are not independent from each other.

v. Homoscedasticity

Homoscedasticity describes a situation in which the error term (that is, the noise in the model) is the same across all values of the independent variables. It means the residuals are same across the regression line. It can be checked by looking at scatter plot.

References

The concepts and ideas in this project have been taken from the following websites and books:-

i. Machine learning notes by Andrew Ng

ii. https://en.wikipedia.org/wiki/Linear_regression

iii.https://en.wikipedia.org/wiki/Simple_linear_regression

iv. https://en.wikipedia.org/wiki/Ordinary_least_squares

v. https://en.wikipedia.org/wiki/Root-mean-square_deviation

vi. https://en.wikipedia.org/wiki/Coefficient_of_determination

vii.https://www.statisticssolutions.com/assumptions-of-linear-regression/

viii.Python Data Science Handbook by Jake VanderPlas

ix. Hands-On Machine Learning with Scikit Learn and Tensorflow by Aurilien Geron

x. Introduction to Machine Learning with Python by Andreas C Muller and Sarah Guido

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Sub : Artificial Intelligence

Sem : VI

A case study of Intelligent Vehicle Control

Introduction :

From the beginning of the 1970s, the transportation engineers throughout the world have gradually used electronic, information, system engineering and other high-tech means that develop rapidly to improve traffic conditions. Advanced technologies are used to replace partial driving tasks, providing the automobiles with increasingly perfect driving assistance. The intelligentization of automobiles is gradually being achieved. The intelligent vehicle, as the key technology of the intelligent transportation system, is one of the numerous high-tech integrated carriers. It is a general term that refers to a comprehensive vehicle technology to complete one or many driving tasks entirely or partially. The main functions are to ride along the regulated road accurately and maintain on the right lane position, to keep a safe distance between the cars, to adjust the speed according to the traffic conditions and road characteristics, to change lanes and overtake automatically to avoid collision and rear-end accidents, to park the car safely on the urban roads and to let the driver assistant system find the best route to the destination under an intelligent traffic network environment, etc. Its existence is a necessity of the development of vehicle technology and the people's urgent demand for traffic safety. With the continuous progress of the informatization and intelligentization of human society, intelligent vehicles are increasingly widely applied, which has become one of the important symbols to measure a country's social civilization and the progress of science and technology.

Methodology :

The control system is the "brain" of an intelligent vehicle, reflecting the intelligence degree of the autonomous controller and organizational flexibility. With the rapid development of modern science and technology such as computers, materials, energy and others and the unceasing expansion of the production system, a complex control system has been formed, contributing to more complicated control objects, controller and control tasks, etc. At the same time, there are more requirements about the degree of automation, facing the challenges of the complex systems including the flexibility control system, intelligent robot system, CNC system, computer integrated manufacturing system and others. The classical and modern control theory and technology is no longer suitable for the control of complex systems. Intelligent control is a kind of advanced information and control technology which is gradually formed on the basis of control theory, information theory, artificial intelligence, bionics, neurophysiology and the development of computer science. Intelligent control theory breaks through the traditional control framework based on the mathematical model. It basically controls according to the actual effect, which is not dependent on or not entirely dependent on the mathematical model of the control object, but also inherits the nonlinear characteristics of human thinking. Some intelligent

Control methods also have functions including online identification and decision-making or overall self optimizing ability and the processing and decision of hierarchical information.

Applications :

Most people usually do not consider the car sitting in their driveway to be on the leading edge of new technology. However, for most people, the personal automobile has now become their initial exposure to new intelligent computational technologies such as fuzzy logic, neural networks, adaptive computing, voice recognition and others. In this chapter we will discuss the various intelligent vehicle systems that are now being deployed into motor vehicles. These intelligent system applications impact every facet of the driver experience and improve both vehicle safety and performance. We will also describe recent developments in autonomous vehicle design and demonstrate that this type of technology is not that far away from deployment. Other applications of intelligent system design apply to adapting the vehicle to the driver's preferences and helping the driver stay aware. The automobile industry is very competitive and there are many other new advances in vehicle technology that cannot be discussed yet. However, this chapter provides an introduction into those technologies that have already been announced or deployed and shows how the automobile has evolved from a basic transportation device into an advanced vehicle with a host of on-board computational technologies.

Conclusion :

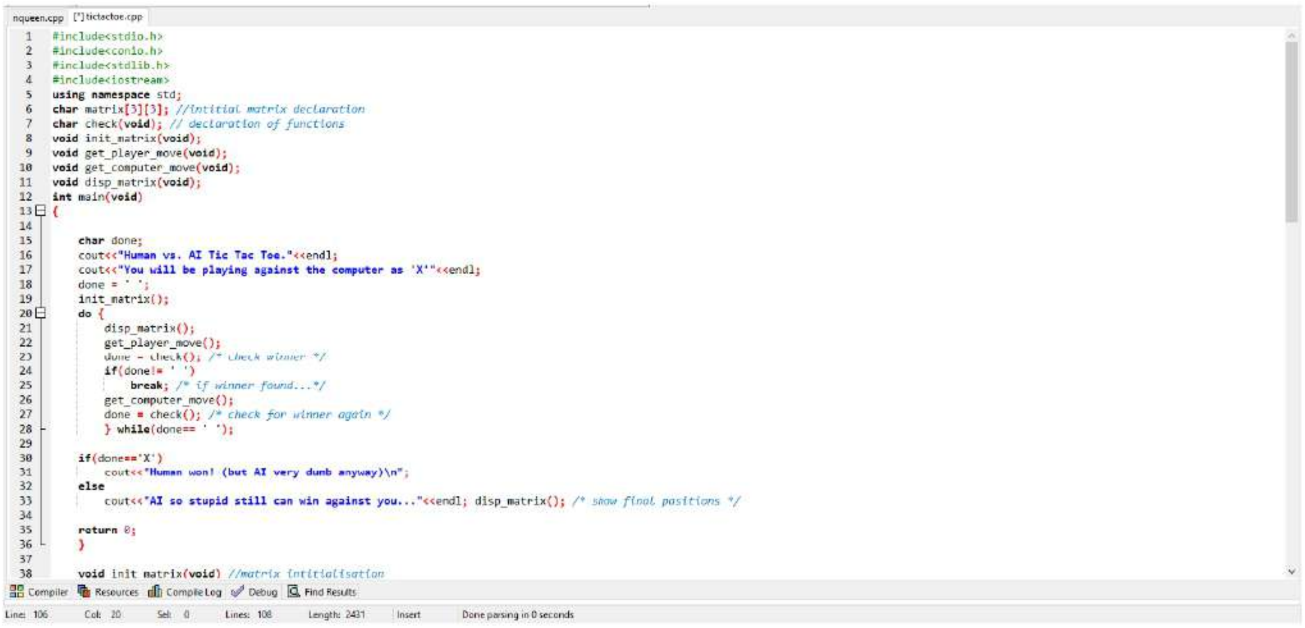
Intelligent vehicles are a research frontier and hot spot in the field of vehicle engineering in the world. Based on the scientific research and technology conditions in our country, the paper implements a systematic research on the key technology of intelligent vehicle control. The main work of this paper is to put forward an inference model by combining cloud theory, inspired by a fuzzy model. The model softens and divides the whole area into several cloud sub areas. The corresponding input of each cloud sub area is the linear expression of input value. The degree of the input value to some cloud sub area is considered as the random confidence of the rule.
The characteristics of the entire nonlinear system are the weighting sum of the local linear models, which not only inherits the success of cloud theory but also can overcome the shortcomings of the traditional inference mechanism based on cloud model. It has strong function approximation ability that can be used for system identification, intelligent control and other fields.
Forward cloud is generated by using the golden ratio method to make the concept of expression more reasonable. The inference model is treated as the reasoning mechanism of the controller, softening and dividing the entire area into several sub areas. In the corresponding sub areas the use of radial basis function neural network approximation equation of the driving can make the controller have a learning function, well simulating the driver's learning process. The area neural network

output. The value corresponding to each cloud sub area is the output of this area. The belonging degree of the output value to some cloud sub area is considered as the random confidence of the rule. The random output of the entire nonlinear system is the weighting sum of the local random output which can identify the nonlinear system quite well.

References :

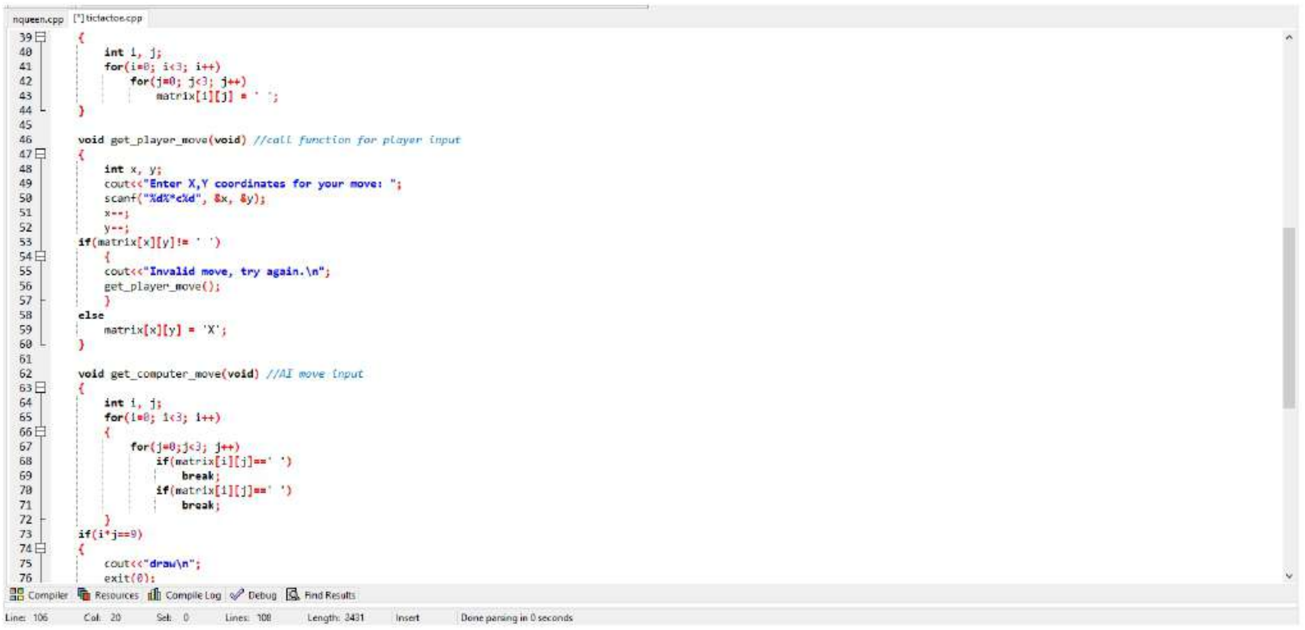
1. Bishop R. A survey of intelligent vehicle applications worldwide[C]//Intelligent Vehicles Symposium, 2000. IV 2000. Proceedings of the IEEE. IEEE, 2000: 25-30.
2. Vahidi A, Eskandarian A. Research advances in intelligent collision avoidance and adaptive cruise control[J]. Intelligent Transportation Systems, IEEE Transactions on, 2003, 4(3): 143-153.
3. Tsugawa S. Inter-vehicle communications and their applications to intelligent vehicles: an overview[C]//Intelligent Vehicle Symposium, 2002. IEEE. IEEE, 2002, 2: 564-569.
4. Xiwen L, Yinggang O, Zuo Xi Z, et al. Research and development of intelligent flexible chassis for precision farming[J]. Transactions of The Chinese Society of Agricultural Engineering, 2005, 2: 019.

Expt 5:



```
#include<stdio.h>
#include<conio.h>
#include<stdlib.h>
#include<iostream>
using namespace std;
char matrix[3][3]; //intitial matrix declaration
char check(void); // declaration of functions
void init_matrix(void);
void get_player_move(void);
void get_computer_move(void);
void disp_matrix(void);
int main(void)
{

    char done;
    cout<<"Human vs. AI Tic Tac Toe."<<endl;
    cout<<"You will be playing against the computer as 'X'"<<endl;
    done = ' ';
    init_matrix();
    do {
        disp_matrix();
        get_player_move();
        done = check(); /* check winner */
        if(done!= ' ')
            break; /* if winner found...*/
        get_computer_move();
        done = check(); /* check for winner again */
        } while(done== ' ');

    if(done=='X')
        cout<<"Human won! (but AI very dumb anyway)\n";
    else
        cout<<"AI so stupid still can win against you..."<<endl; disp_matrix(); /* show final positions */

    return 0;
    }

    void init matrix(void) //matrix intitialisation
```

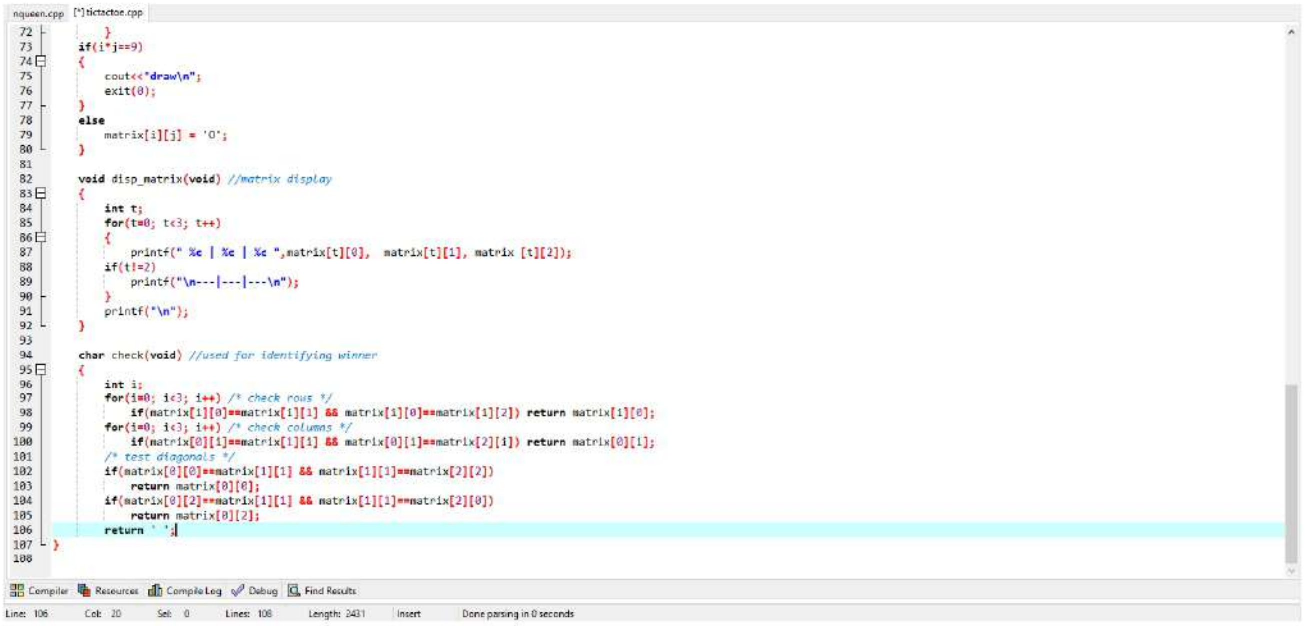
Compiler
Resources
Compile Log
Debug
Find Results
Line: 106 Col: 20 Sel: 0 Lines: 108 Length: 2431 Insert Done parsing in 0 seconds



nqueen.cpp
[*] tictactoe.cpp

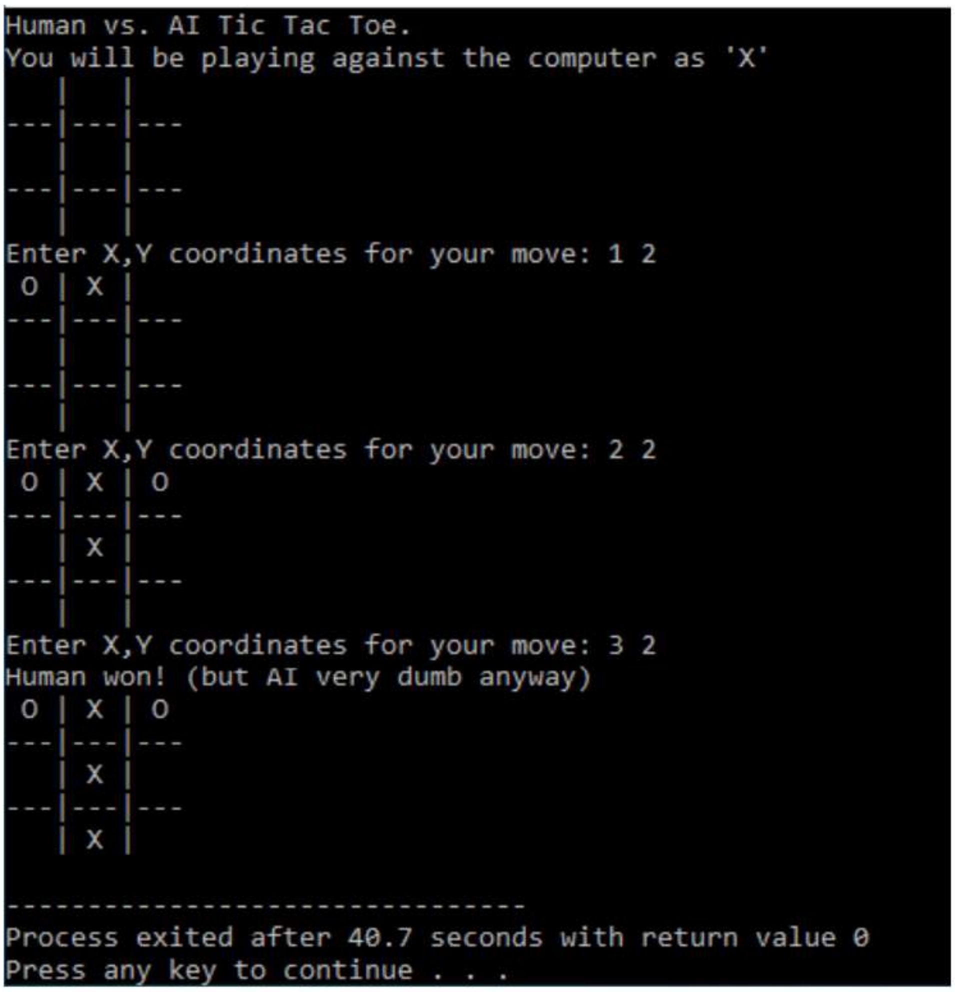
```
    {
        int i, j;
        for(i=0; i<3; i++)
            for(j=0; j<3; j++)
                matrix[i][j] = ' ';
    }

    void get_player_move(void) //call function for player input
    {
        int x, y;
        cout<<"Enter X,Y coordinates for your move: ";
        scanf("%d%*c%d", &x, &y);
        x--;
        y--;
    if(matrix[x][y]!= ' ')
        {
        cout<<"Invalid move, try again.\n";
        get_player_move();
        }
    else
        matrix[x][y] = 'X';
    }

    void get_computer_move(void) //AI move input
    {
        int i, j;
        for(i=0; i<3; i++)
        {
            for(j=0;j<3; j++)
                if(matrix[i][j]==' ')
                    break;
                if(matrix[i][j]==' ')
                    break;
        }
    if(i*j==9)
    {
        cout<<"draw\n";
        exit(0);
```

Compiler
Resources
Compile Log
Debug
Find Results
Line: 106 Col: 20 Sel: 0 Lines: 108 Length: 2431 Insert Done parsing in 0 seconds



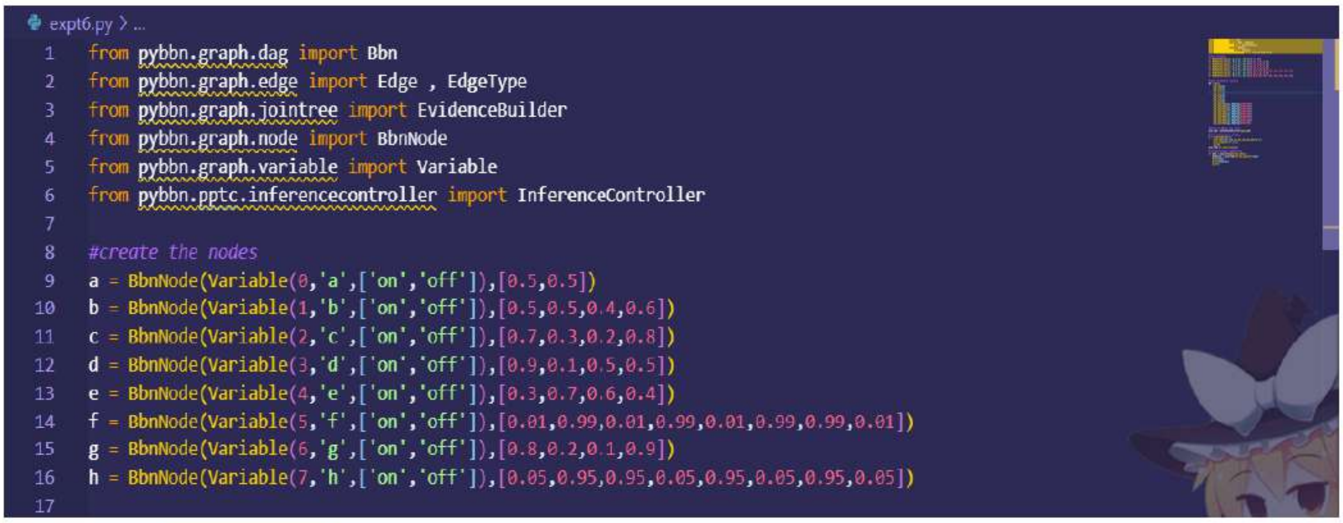
```
        }
    if(i*j==9)
    {
        cout<<"draw\n";
        exit(0);
    }
    else
        matrix[i][j] = 'O';
    }

    void disp_matrix(void) //matrix display
    {
        int t;
        for(t=0; t<3; t++)
        {
            printf(" %c | %c | %c ",matrix[t][0],  matrix[t][1], matrix [t][2]);
        if(t!=2)
            printf("\n---|---|---\n");
        }
        printf("\n");
    }

    char check(void) //used for identifying winner
    {
        int i;
        for(i=0; i<3; i++) /* check rows */
            if(matrix[i][0]==matrix[i][1] && matrix[i][0]==matrix[i][2]) return matrix[i][0];
        for(i=0; i<3; i++) /* check columns */
            if(matrix[0][i]==matrix[1][i] && matrix[0][i]==matrix[2][i]) return matrix[0][i];
        /* test diagonals */
        if(matrix[0][0]==matrix[1][1] && matrix[1][1]==matrix[2][2])
            return matrix[0][0];
        if(matrix[0][2]==matrix[1][1] && matrix[1][1]==matrix[2][0])
            return matrix[0][2];
        return ' ';
}
```

Line: 106 Col: 20 Sel: 0 Lines: 108 Length: 2431 Insert Done parsing in 0 seconds



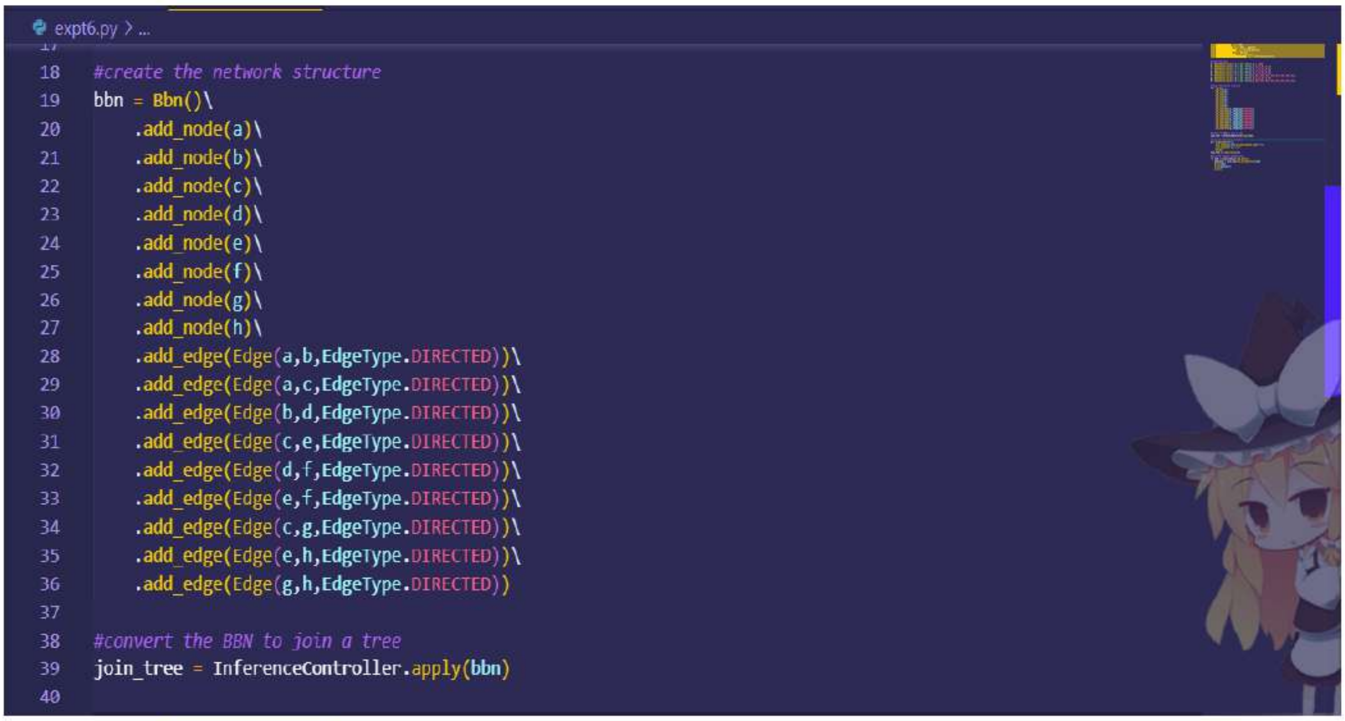
```
Human vs. AI Tic Tac Toe.
You will be playing against the computer as 'X'
   |   |
---|---|---
   |   |
---|---|---
   |   |
Enter X,Y coordinates for your move: 1 2
 O | X |
---|---|---
   |   |
---|---|---
   |   |
Enter X,Y coordinates for your move: 2 2
 O | X | O
---|---|---
   | X |
---|---|---
   |   |
Enter X,Y coordinates for your move: 3 2
Human won! (but AI very dumb anyway)
 O | X | O
---|---|---
   | X |
---|---|---
   | X |

--------------------------------
Process exited after 40.7 seconds with return value 0
Press any key to continue . . .
```

Expt 7:



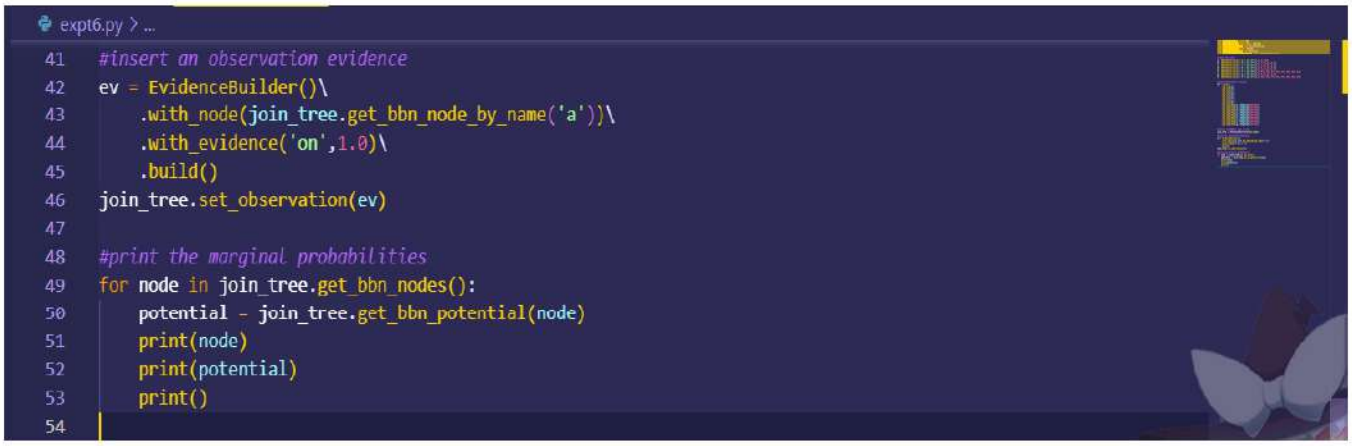
expt6.py > ...

```python
from pybbn.graph.dag import Bbn
from pybbn.graph.edge import Edge , EdgeType
from pybbn.graph.jointree import EvidenceBuilder
from pybbn.graph.node import BbnNode
from pybbn.graph.variable import Variable
from pybbn.pptc.inferencecontroller import InferenceController

#create the nodes
a = BbnNode(Variable(0,'a',['on','off']),[0.5,0.5])
b = BbnNode(Variable(1,'b',['on','off']),[0.5,0.5,0.4,0.6])
c = BbnNode(Variable(2,'c',['on','off']),[0.7,0.3,0.2,0.8])
d = BbnNode(Variable(3,'d',['on','off']),[0.9,0.1,0.5,0.5])
e = BbnNode(Variable(4,'e',['on','off']),[0.3,0.7,0.6,0.4])
f = BbnNode(Variable(5,'f',['on','off']),[0.01,0.99,0.01,0.99,0.01,0.99,0.99,0.01])
g = BbnNode(Variable(6,'g',['on','off']),[0.8,0.2,0.1,0.9])
h = BbnNode(Variable(7,'h',['on','off']),[0.05,0.95,0.95,0.05,0.95,0.05,0.95,0.05])

```



expt6.py > ...

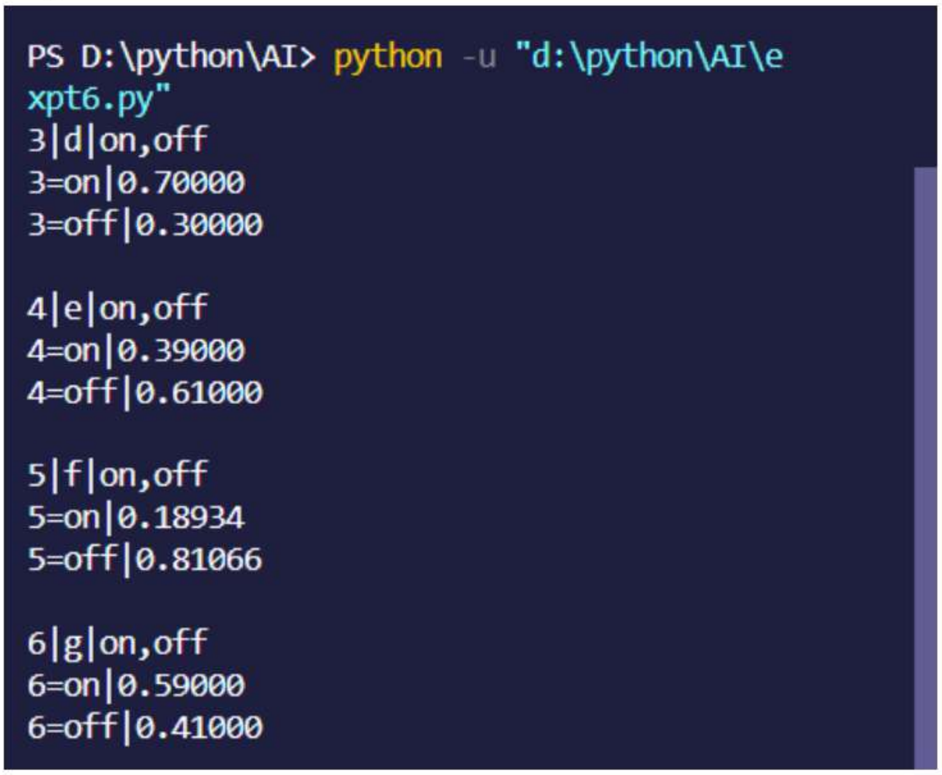
```python
#create the network structure
bbn = Bbn()\
    .add_node(a)\
    .add_node(b)\
    .add_node(c)\
    .add_node(d)\
    .add_node(e)\
    .add_node(f)\
    .add_node(g)\
    .add_node(h)\
    .add_edge(Edge(a,b,EdgeType.DIRECTED))\
    .add_edge(Edge(a,c,EdgeType.DIRECTED))\
    .add_edge(Edge(b,d,EdgeType.DIRECTED))\
    .add_edge(Edge(c,e,EdgeType.DIRECTED))\
    .add_edge(Edge(d,f,EdgeType.DIRECTED))\
    .add_edge(Edge(e,f,EdgeType.DIRECTED))\
    .add_edge(Edge(c,g,EdgeType.DIRECTED))\
    .add_edge(Edge(e,h,EdgeType.DIRECTED))\
    .add_edge(Edge(g,h,EdgeType.DIRECTED))

#convert the BBN to join a tree
join_tree = InferenceController.apply(bbn)

```



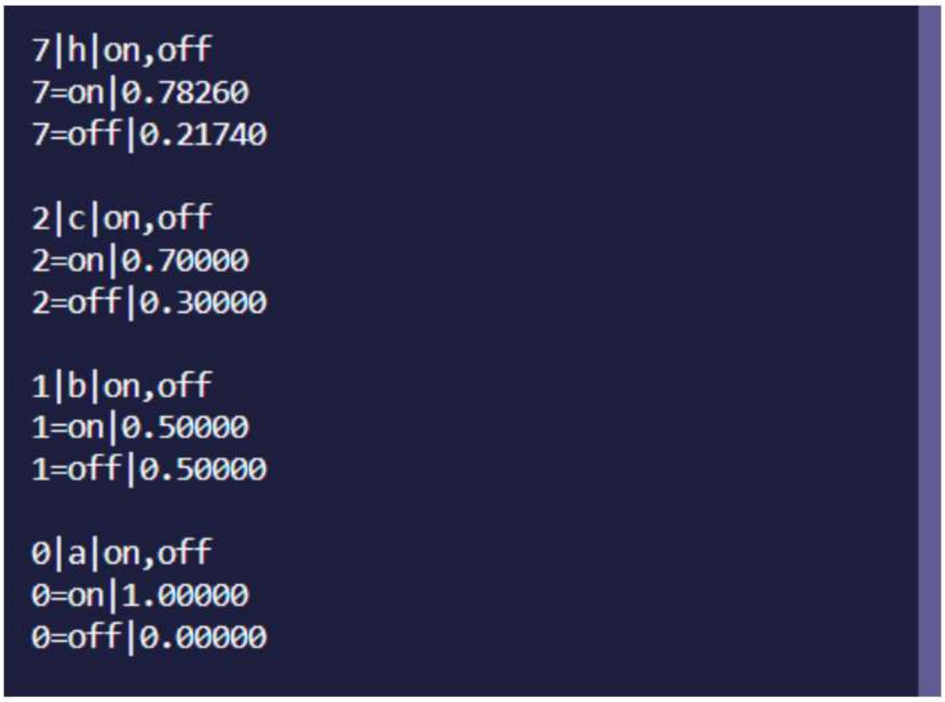
expt6.py > ...

```python
#insert an observation evidence
ev = EvidenceBuilder()\
    .with_node(join_tree.get_bbn_node_by_name('a'))\
    .with_evidence('on',1.0)\
    .build()
join_tree.set_observation(ev)

#print the marginal probabilities
for node in join_tree.get_bbn_nodes():
    potential = join_tree.get_bbn_potential(node)
    print(node)
    print(potential)
    print()

```

Output:



```
PS D:\python\AI> python -u "d:\python\AI\e
xpt6.py"
3|d|on,off
3=on|0.70000
3=off|0.30000

4|e|on,off
4=on|0.39000
4=off|0.61000

5|f|on,off
5=on|0.18934
5=off|0.81066

6|g|on,off
6=on|0.59000
6=off|0.41000
```



```
7|h|on,off
7=on|0.78260
7=off|0.21740

2|c|on,off
2=on|0.70000
2=off|0.30000

1|b|on,off
1=on|0.50000
1=off|0.50000

0|a|on,off
0=on|1.00000
0=off|0.00000
```