Weekly Exercise 6-P1-DM

1. **Lesson 1 - evaluating models for the same scenario**
2. **Lesson 2 – using data mining queries to make predictions for new cases with models**

We will complete the lessons in the same project created from the previous tutorial.

1. Locate your DM5-YourWindowsLoginName.zip, e.g., DM5-chenx.zip.
2. Rename the zip file as DM6-YourWindowsLoginName.zip, e.g., DM6-chenx.zip
3. Unzip DM6-YourWindowsLoginName.zip
4. Now you can delete the zip file: DM6-YourWindowsLoginName.zip because after you finish the exercise, you will create a new DM6-YourWindowsLoginName.zip
5. Open your project in Visual Studio by double clicking the DM-YourWindowsLoginName.sln (the solution file for the project) in the project's top folder
6. IMPORTANT: your username/password for the data source Adventure Works DW2012.ds were not saved. You need to reset the username/password
    a. Double click the data source in Solution Explorer window
    b. On the Data Source Designer window, click the Edit… button
    c. Type your SQL Server username and password again for the corresponding text box. Click the Test Connection button to make sure you can make a connection to the data source. Also, make sure the checkbox for Save my password is checked
    d. Click the Save All button 💾 to save all the changes
    e. Open the Target Mailing and Call Center mining structure by double clicking them in the Solution Explorer window. Click the Mining Model menu, then select Process Mining Structure and All Mining Models… to reprocess all the structure and models
7. Save your project from time to time by clicking the Save All button 💾 to protect the work you have done in case of computer crash

Lesson 1: Evaluating models for the same scenario

Open the Target Mailing and Call Center mining structure by double clicking them in the Solution Explorer window. Click the Mining Model menu, then select Process Mining Structure and All Mining Models… to reprocess all the structure and models. After the models in your project have been processed, you can evaluate the performances of different models for the same scenario, such as classification, prediction, etc., with the same mining structure.

1. Evaluating the performances of decision trees, Naïve Bayes, and clustering for classification

Refer to the lecture slide and the book about general measures to evaluate classification performance: overall error rate, accuracy rate, cutoff value that affect the results, and propensity. Also pay attention to the terms: sensitivity, specificity, and precision. Before you start the testing process, you may want to note the results on the Mining Accuracy Chart tab for the training set so that you can compare the results for the training set with the results for the testing set

To evaluate the performances of the models for the targeted mailing structure, open up the mining structure YourWindowsLoginName-Targeted Mailing in your project.

To test accuracy with Lift charts:

On the Mining Accuracy Chart tab of Data Mining Designer, you can calculate how well each of your models makes predictions, and compare the results of each model directly against the results of the other models. This method of comparison is referred to as a lift chart. Typically, the predictive accuracy of a mining model is measured by either lift or classification accuracy. For this tutorial we will use the lift chart only.

Choosing the Input Data

The first step in testing the accuracy of your mining models is to select the data source that you will use for testing. You will test how well the models perform against your testing data and then you will use them with external data.

To select the data set

1. Switch to the Mining Accuracy Chart tab in Data Mining Designer in SQL Server Data Tools (SSDT) and select the Input Selection tab.
2. In the Select data set to be used for Accuracy Chart group box, select Use mining structure test cases. This is the testing data that you set aside when you created the mining structure. It is a subset of the full set of testing cases for the entire mining structure.

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For more information on the other options, see Choose an Accuracy Chart Type and Set Chart Options.

Setting Accuracy Chart Parameters

To create an accuracy chart, you must define three things:

1. Which models should you include in the accuracy chart?
2. Which predictable attribute do you want to measure? Some models might have multiple targets, but each chart can measure only one outcome at a time.
   To use a column as the Predictable Column Name in an accuracy chart, the columns must have the usage type of Predict or Predict Only. Also, the content type of the target column must be either Discrete or Discretized. In other words, you cannot measure accuracy against continuous numeric outputs using the lift chart.
3. Do you want to measure the model's general accuracy, or its accuracy in predicting a particular value (such as [Bike Buyer] = 'Yes')

To generate the lift chart

1. On the **Input Selection** tab of Data Mining Designer, under **Select predictable mining model columns to show in the lift chart**, select the checkbox for **Synchronize Prediction Columns and Values.** When this is checked, Analysis Services analyze the data in the predictable columns of the model and the test data, and to find the best match.
2. In the **Predictable Column Name** column, verify that **Bike Buyer** is selected for each model.
3. In the **Show** column, select each of the models.
   By default, all the models in the mining structure are selected. You can decide not to include a model, but for this tutorial leave all the models selected.
4. In the Predict Value column, select 1. The same value is automatically filled in for each model that has the same predictable column.
5. Select the Lift Chart tab.
   When you click the tab, a prediction query is executed to get predictions for the test data, and the results are compared against the known values. The results are plotted on the graph.
   If you specified a particular target outcome using the Predict Value option, the lift chart plots the results of random guesses and the results of an ideal model.
   - The random guess line shows how accurate the model would be without using any data to inform its predictions: that is, a 50-50 split between two outcomes. The lift chart helps you visualize how much better your model performs in comparison to a random guess.
   - The ideal model line represents the upper bound of accuracy. It shows you the maximum possible benefit you could achieve if your model always predicted accurately.
   - The mining models you created will usually fall between these two extremes. Any improvement from the random guess is considered to be lift.
6. Use the legend to locate the colored lines representing the Ideal Model and the Random Guess Model.
   You'll notice that the TM_Decision_Tree model provides the greatest lift, outperforming both the Clustering and Naive Bayes models.
   For an in-depth explanation of a lift chart similar to the one created in this lesson, see Lift Chart (Analysis Services - Data Mining).

You can change the chart type from Lift Chart to Profit Chart to find in certain profit chart settings how you could reach the maximum profit. For an in-depth explanation of a profit chart, see Profit Chart (Analysis Services – Data Minig). You can also go to Classification Matrix tab to see the actual numbers of predictions from different models. You can calculate the accuracy rate, sensitivity, specificity, and precision for evaluating the prediction performances of different models. Following this link for more information about Classification Matrix.

The last test and validation tool is Cross Validation. In this tool, you can set Target Threshold for a state, which will affect the accuracy of the model. Specific settings for Cross Validation can be found at Cross Validation (Analysis Services – Data Mining). The results can be copied and pasted to an Excel file for further calculations and analyses (Click the completed result area, Ctrl+A to select all contents in the area, then Ctrl + V to paste it to an Excel worksheet).

Lesson 2: Using data mining queries to make predictions for new cases with models

In SSDT, prediction queries are used to make predictions for new data. Click this link for more information about prediction queries. After you have tested the accuracy of your mining models and decided that you are satisfied with the results, you can then generate predictions by using the Prediction Query Builder on the Mining Model Prediction tab in the Data Mining Designer.

The Prediction Query Builder has three views. With the Design and Query views, you can build and examine your query. You can then run the query and view the results in the Result view.

To make predictions for new cases with the decision tree model

The first step in creating a prediction query is to select a mining model and input table.

To select a model and input table

1. Open the Targeted Mailing mining structure
2. On the **Mining Model Prediction** tab of Data Mining Designer, in the **Mining Model**box, click **Select Model**.
3. In the **Select Mining Model** dialog box, navigate through the tree to the **Targeted Mailing** structure, expand the structure, select TM_Decision_Tree, and then click **OK**.
4. In the **Select Input Table(s)** box, click **Select Case Table**.

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5. In the **Select Table** dialog box, in the **Data Source** list, select the data source view your_Windows_login-Targeted Mailing.
6. In **Table/View Name**, select the **ProspectiveBuyer (dbo)** table, and then click **OK**.The ProspectiveBuyer table most closely resembles the **vTargetMail** case table.

Mapping the Columns

After you select the input table, Prediction Query Builder creates a default mapping between the mining model and the input table, based on the names of the columns. At least one column from the structure must match a column in the external data. NOTE: The data that you use to determine the accuracy of the models must contain a column that can be mapped to the predictable column. If such a column does not exist, you can create one with empty values, but it must have the same data type as the predictable column.

To map the inputs to the model

1. Click the Mining Model menu, then select **Modify Connections**.
   Notice that not every column is mapped. We will add mappings for several **Table Columns**. We will also generate a new birth date column based on the current date column, so that the columns match better.
2. Under **Table Column**, click the Bike Buyer cell and select ProspectiveBuyer.Unknown from the dropdown.
   This maps the predictable column, [Bike Buyer], to an input table column.
3. Click **OK**.
4. In **Solution Explorer**, right-click the your_Windows_login-**Targeted Mailing** data source view and select **View Designer**.
5. Right-click the table, ProspectiveBuyer, and select **New Named Calculation**.
6. In the **Create Named Calculation** dialog box, for **Column name**, type calcAge.
7. For **Description**, type **Calculate age based on birthdate**.
8. In the **Expression** box, type DATEDIFF(YYYY,[BirthDate],getdate()) and then click **OK**.
   Because the input table has no **Age** column corresponding to the one in the model, you can use this expression to calculate customer age from the BirthDate column in the input table. Since **Age** was identified as the most influential column for predicting bike buying, it must exist in both the model and in the input table.
9. In Data Mining Designer, select the **Mining Model Prediction** tab and re-open the **Modify Connections** window.
10. Under **Table Column**, click the **Age** cell and select ProspectiveBuyer.calcAge from the dropdown.
    Warning If you do not see the column in the list, you might have to refresh the definition of the data source view that is loaded in the designer. To do this, from the **File** menu, select **Save all**, and then close and re-open the project in the designer.
11. Click **OK**.

Designing the Prediction Query

1. The first button on the toolbar of the **Mining Model Prediction** tab is the **Switch to design view / Switch to result view / Switch to query view** button. Click the down arrow on this button, and select **Design**.
2. In the grid on the **Mining Model Prediction** tab, click the cell in the first empty row in the **Source** column, and then select **Prediction Function**.
3. In the **Prediction Function** row, in the **Field** column, select PredictProbability.
   In the **Alias** column of the same row, type **Probability of result**.
4. From the **Mining Model** window above, select and drag [Bike Buyer] into the **Criteria/Argument** cell.
   When you let go, [TM_Decision_Tree].[Bike Buyer] appears in the **Criteria/Argument** cell.
   This specifies the target column for the PredictProbability function. For more information about functions, see Data Mining Extensions (DMX) Function Reference.
5. Click the next empty row in the **Source** column, and then select **TM_Decision_Tree** mining model.
6. In the TM_Decision_Tree row, in the **Field** column, select Bike Buyer.
7. In the TM_Decision_Tree row, in the **Criteria/Argument** column, type =1 (we want to see all those records that would be predicted with value 1 for Bike Buyer in our dataset. If you do not type =1 in the column, the result will show the predictions for all records in the dataset, some with 0, some with 1 for the Bike Buyer column).
8. Click the next empty row in the **Source** column, and then select **ProspectiveBuyer table**.
9. In the ProspectiveBuyer row, in the **Field** column, select **ProspectiveBuyerKey**.
   This adds the unique identifier to the prediction query so that you can identify who is and who is not likely to buy a bicycle.
10. Add five more rows to the grid. For each row, select **ProspectiveBuyer table** as the **Source** and then add the following columns in the **Field** cells:
    - calcAge
    - LastName
    - FirstName
    - AddressLine1
    - AddressLine2

To run the query and view results

1. In the **Mining Model Prediction** tab, select the **Result** button (Switch to query result view at the far left of the buttons row under Mining Model Prediction tab).
2. After the query runs and the results are displayed, you can review the results.
   The **Mining Model Prediction** tab displays contact information for potential customers who are likely to be bike buyers.
   The **Probability of result** column indicates the probability of the prediction being correct. You can use these results to determine which potential customers to target for the mailing.
3. At this point, you can save the results. You have three options. We will use the third option:

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- Right-click a row of data in the results, and select **Copy** to save just that value (and the column heading) to the Clipboard.
- Right-click any row in the results, and select **Copy All** to copy the entire result set, including column headings, to the Clipboard. Then, you can paste the results to a file, such as an Excel file
- Click **Save query result** to save the results directly to a database: on the Save Data Mining Query Result window
  1. Create a new data source to your individual database (Click the New button to create the new data source)
  2. The name for the table: DM-Bike Buyer Prediction-Decision Trees
  3. Check the Overwrite if exists checkbox to save the latest result.
  4. Click Save
  5. After it is saved, you can use SQL Server Management Studio or other tools, such as Excel or Power BI to view the result

To make predictions for new cases with the call center models

Continue with the call center example. Now that you have learned something about the interactions between shifts, the number of operators, calls, and service grade, you are ready to create some prediction queries that can be used in business analysis and planning. You will first create some predictions on the exploratory model to test some assumptions. Next, you will create bulk predictions by using the logistic regressino model.

This lesson assumes that you are already familiar with the concept of prediction queries.

Creating Predictions using the Neural Network Model

The following example demonstrates how to make a singleton prediction using the neural network model that was created for exploration. Singleton predictions are a good way to try out different values to see the effect in the model. In this scenario, you will predict the service grade for the midnight shift (no day of the week specified) if six experienced operators are on duty.

To create a singleton query by using the neural network model

1. In SQL Server Data Tools (SSDT) in Visual Studio, open the solution that contains the model that you want to use.
2. In Data Mining Designer, click the **Mining Model Prediction** tab.
3. In the **Mining Model** pane, click **Select Model**.
4. The **Select Mining Model** dialog box shows a list of mining structures. Expand the mining structure to view a list of mining models associated with that structure.
5. Expand the mining structure Call Center, and select the neural network model, Call Center Binned NN.
6. From the **Mining Model** menu, select **Singleton Query**.
   The **Singleton Query Input** dialog box appears, with columns mapped to the columns in the mining model. **A singleton query** *is useful when you have a model that you want to use for prediction, but don't want to map it to an external input data set or make bulk predictions. With a singleton query, you can provide a value or values to the model and instantly see the predicted value.* Click here for more information about prediction queries.
7. In the **Singleton Query Input** dialog box, click the row for Shift, and then select *midnight*.
8. Click the row for Level Two Operators, and type 6.
9. In the bottom half of the **Mining Model Prediction** tab, click the first row in the grid.
10. In the **Source** column, click the down arrow, and select **Prediction function**. In the **Field** column, select **PredictHistogram**.
    A list of arguments that you can use with this prediction function automatically appears in the **Criteria/Arguments** box.
11. Drag the Service Grade column from the list of columns in the **Mining Model** pane to the **Criteria/Arguments** box.
    The name of the column is automatically inserted as the argument. You can choose any predictable attribute column to drag into this text box.
12. Click the button **Switch to query results view**, in the upper corner of the Prediction Query Builder.
13. Click the plus sign left to Expression to see the results.

The expected results contain the possible predicted values for each service grade given these inputs, together with support and probability values for each prediction. You can return to design view at any time and change the inputs, or add more inputs.

Creating Predictions by using a Logistic Regression Model

If you already know the attributes that are relevant to the business problem, you can use a logistic regression model to predict the effect of making changes in some attributes. Logistic regression is a statistical method that is commonly used to make predictions based on changes in independent variables: for example, it is used in financial scoring, to predict customer behavior based on customer demographics. In this task, you will learn how to create a data source that will be used for predictions, and then make predictions to help answer several business questions.

Important: when you create the logistic regression model in WE5, the earlier version of WE5 asked you to ignore Service Grade Binned column and make Service Grade column to have the value of ‘Predict’. It should be the other way around: Service Grade Binned column-Predict; Service Grade column-Ignore. To change the model, double click the Call Center mining structure, on the Mining Models tab, under Call Center – LR, change the values for those two columns.

Generating Data used for Bulk Prediction

There are many ways to provide input data: for example, you might import staffing levels from a spreadsheet, and run that data through the model to predict service quality for the next month. In this lesson, you will use the Data Source View designer to create a named query. This named query is a custom Transact-SQL statement that for each shift on the schedule calculates the maximum number of operators on staff, the minimum calls received, and the average number of issues that are generated. You will then join that data to a mining model to make predictions about a series of upcoming dates.

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To generate input data for a bulk prediction query

1. In Solution Explorer, right-click **Data Source Views**, and then select **New Data Source View**.
2. In the Data Source View wizard, select Adventure Works DW 2012 as the data source, and then click **Next**.
3. On the **Select Tables and Views** page, click **Next** without selecting any tables.
4. On the **Completing the Wizard** page, type the name, Shifts. Double click the new data source view to open it.
5. Right-click the empty design pane, then select **New Named Query**.

   NOTE: If you get an error related to login, double click the data source Adventure Works 2012 in the Solution Explorer pane. In the Data Source Designer window, click the Edit… button to open the Connection Manager window to check the following:

   ✓ Your username and password are filled correctly
   ✓ The checkbox for Save my password is checked
   ✓ Then, click OK to close the Connection Manager window

   Click the Impersonation Information tab in the Data Source Designer window, make sure the option Use the Service Account is selected.
6. In the **Create Named Query** dialog box, for **Name**, type Shifts for Call Center.
   This name will appear in Data Source View designer only as the name of the named query.
7. In the SQL text pane in the bottom window of the dialog box, there may be the words SELECT FROM already there. Delete SELECT FROM first if they exist, then paste the following query in the window.

```
SELECT DISTINCT WageType, Shift, AVG (AverageTimePerIssue) AS AverageTimePerIssue, AVG(Orders) as AvgOrders,
MIN(Orders) as MinOrders, MAX(Orders) as MaxOrders,  AVG(Calls) as AvgCalls, MIN(Calls) as MinCalls, MAX(Calls) as MaxCalls,
AVG(LevelTwoOperators) as AvgOperators, MIN(LevelTwoOperators) as MinOperators, MAX(LevelTwoOperators) as MaxOperators,
AVG(IssuesRaised) as AvgIssues, MIN(IssuesRaised) as MinIssues, MAX(IssuesRaised) as MaxIssues
FROM dbo.FactCallCenter  GROUP BY Shift, WageType
```

8. Click OK to exit the dialog. In the design pane, right-click the table, Shifts for Call Center, and select **Explore Data** to preview the data as returned by the T-SQL query.
9. Right-click the tab, **Shifts.dsv (Design),** and then click **Save Selected Item** to save the new data source view definition.

Predicting Service Metrics for Each Shift

Now that you have generated some values for each shift, you will use those values as input to the logistic regression model that you built, to generate some predictions that can be used in business planning.

To use the new DSV as input to a prediction query

1. In Data Mining Designer for Call Center, click the **Mining Model Prediction** tab.
2. In the **Mining Model** pane, click **Select Model**, and choose Call Center – LR from the list of available models.
3. From the **Mining Model** menu, clear the option, **Singleton Query**. A warning tells you that the singleton query inputs will be lost. Click **OK**. The **Singleton Query Input** dialog box is replaced with the **Select Input Table(s)** dialog box.
4. Click **Select Case Table**.
5. In the **Select Table** dialog box, select Shifts from the list of data sources. In the **Table/View name** list, select Shifts for Call Center (it might be automatically selected), and then click **OK. NOTE:** for some reason, the new data source view Shifts is not available sometime. If that happens to you, close the Call Center mining structure tab, then double click it from the Solution Explorer window. After it is re-opened, Shifts is available.
   The **Mining Model Prediction** design surface is updated to show mappings that are created based on the names and data types of columns in the input data and in the model.
6. Drag a column from Mining Model and drop it onto a column in Select Input Tables pane to create column mappings. Alternatively, you can click the Mining Model menu, then select Modify Connections… to bring up the Modify Mapping window to make connections. The mining model contains columns for Calls, Orders, Issues Raised, and Total Operators, which you can map to any of the aggregates that you created based on these columns in the source data. In this scenario, you will map to the corresponding averages.

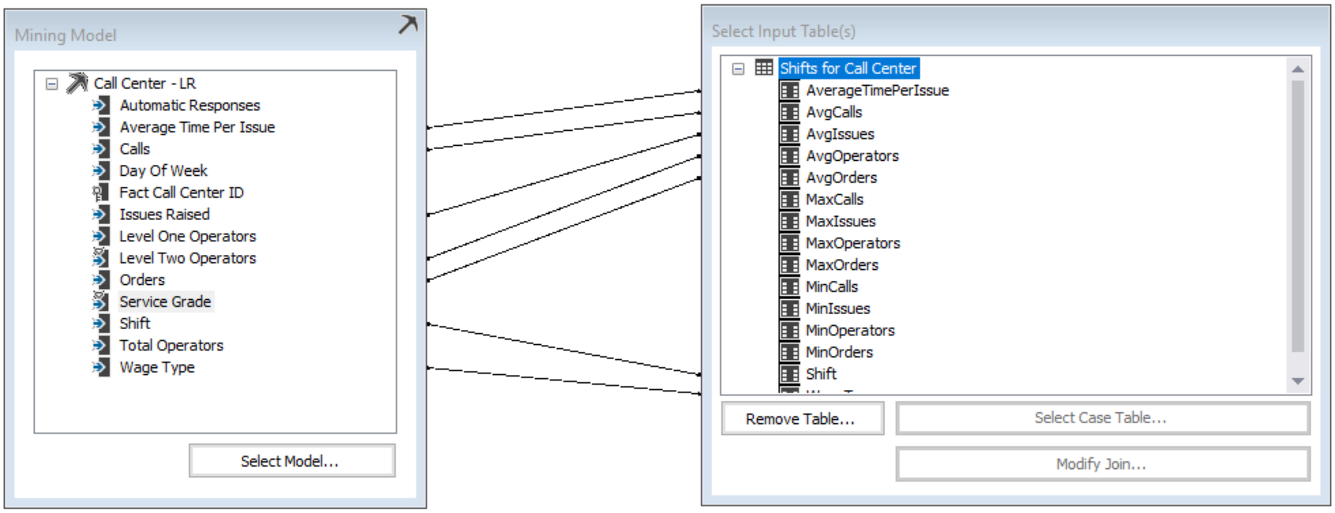

Figure 1: Column mappings

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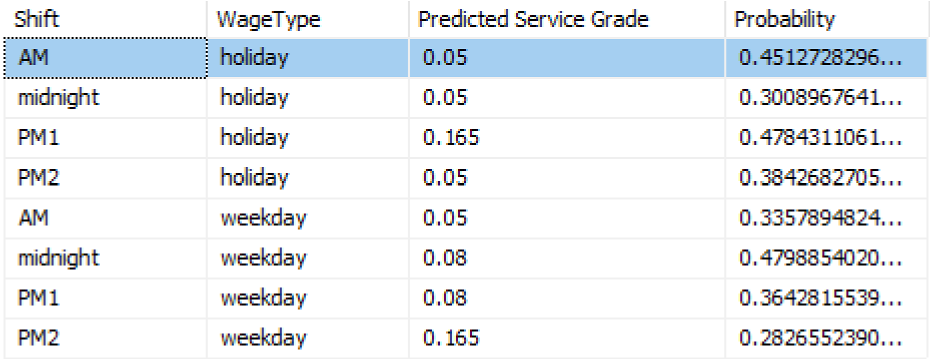
To create the predictions for each shift

1. In the grid at the bottom half of the **Prediction Query Builder**, click the empty cell under **Source,** and then select Shifts for Call Center.
2. In the empty cell under **Field**, select Shift.
3. Click the next empty line in the grid and repeat the procedure described above to add another row for WageType.
4. Click the next empty line in the grid. In the **Source** column, select **Prediction Function**. In the **Field** column, select **Predict**.
5. Drag the column Service Grade Binned from the **Mining Model** pane down to the grid, and into the **Criteria/Argument** cell. In the **Alias** field, type **Predicted Service Grade**.
6. Click the next empty line in the grid. In the **Source** column, select **Prediction Function**. In the **Field** column, select **PredictProbability**.
7. Drag the column Service Grade Binned from the **Mining Model** pane down to the grid, and into the **Criteria/Argument** cell. In the **Alias** field, type **Probability**.
8. Click **Switch to query result view** to view the predictions.
9. Click **Save query result** to save the result directly to your individual database: on the Save Data Mining Query Result window
    1. Use the data source for your individual database
    2. The name for the table: DM-Service Grade Prediction LR
    3. Check the Overwrite if exists checkbox to save the latest result.
    4. Click Save

The following table shows sample results for each shift and wage type:



Shift	WageType	Predicted Service Grade	Probability
AM	holiday	0.05	0.4512728296...
midnight	holiday	0.05	0.3008967641...
PM1	holiday	0.165	0.4784311061...
PM2	holiday	0.05	0.3842682705...
AM	weekday	0.05	0.3357894824...
midnight	weekday	0.08	0.4798854020...
PM1	weekday	0.08	0.3642815539...
PM2	weekday	0.165	0.2826552390...

Figure 2: Call Center – LR's Prediction results for different shifts and wage types

Predicting the Effect of Reduced Response Time on Service Grade

You generated some average values for each shift, and used those values as input to the logistic regression model. However, given that the business objective is to keep abandon rate within the range 0.05, you may want to find ways to improve the service grades for the shift PM1 on holidays and PM2 on weekdays. Based on the original model, which showed a strong influence of response time on service grade, the Operations team decides to run some predictions to assess whether reducing the average time for responding to calls might improve service quality. For example, if you cut the call response time to 90 percent or even to 50 percent of the current call response time, what would happen to service grade values? It is easy to create a data source view (DSV) or a new named query in a DSV that calculates the average response times for each shift, and then add columns that calculate 50% or 90% of the average response time

In this example, we will create a new Named Query in the data source view Shifts because we can create a table (a named query) from the same data set.

1. Double click the Shifts data source view from the Solution Explorer window
2. On the Shifts.dsv[Design] tab, the named query Shifts for Call Center is displayed in the right pane
3. Right click an empty area in the pane, select New Named Query…
4. In the Edit Named Query, type Shifts and Reduced Response Time for the Name, then copy and paste the following to the bottom window (make sure to remove the two words SELECT FROM already in the bottom window before you paste the code). Then click OK to create the named query

SELECT DISTINCT WageType, Shift, AVG(Orders) AS AvgOrders, AVG(AverageTimePerIssue) AS AverageTimePerIssue, MIN(Orders) AS MinOrders, MAX(Orders) AS MaxOrders, AVG(Calls) AS AvgCalls, MIN(Calls) AS MinCalls, MAX(Calls) AS MaxCalls, AVG(LevelTwoOperators) AS AvgOperators, MIN(LevelTwoOperators) AS MinOperators, MAX(LevelTwoOperators) AS MaxOperators, AVG(IssuesRaised) AS AvgIssues, MIN(IssuesRaised) AS MinIssues, MAX(IssuesRaised) AS MaxIssues, AVG(AverageTimePerIssue) * 0.9 AS AvgResponseTime90Perc, AVG(AverageTimePerIssue) * 0.5 AS AvgResponseTime50Perc FROM FactCallCenter GROUP BY Shift, WageType

You can then use the new named query as input to the model. The exact steps are not shown here. The outline steps are:

1. Use Call Center – LR as the prediction model
2. Use the new named queries for the predictions when you select the case table
3. Map Average Time Per Issue in Mining Model to AvgResponseTime90Perc in Shifts and Reduced Response Time, and keep other mappings as in the Figure 1
    a. you can click the menu Mining Model -> Modify Connections to change the mappings
    b. switch back the result view to see the new set of predictions
4. Map Average Time Per Issue in Mining Model to AvgResponseTime50Perc, and keep other mappings as in the Figure 1 to get a new set of predictions

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5. The other steps are the same as the above example
   The following table compares the effects on service grade when you reduce response times to 50% or to 90% of current response times (the actual values may vary). From these results, you can make some decisions, e.g., you might conclude that for the PM2 shift on weekdays, you should reduce the response time to 90 percent of the current response time in order to improve service quality to an ideal level. However, it is not necessary to reduce the response time further to 50% of the current response time. To improve the service grade for the PM1 shift on holidays, you need to reduce the response time to 50% since 90% is not enough.
6. Click **Save query result** to save the result directly to your individual database: on the Save Data Mining Query Result window
   1. Use the data source for your individual database
   2. The name for the table (each for the corresponding percentage of reduced response time):
      1. DM-Service Grade Prediction LR-90PercReduced
      2. DM-Service Grade Prediction LR-50PercReduced
   3. Check the Overwrite if exists checkbox to save the latest result.
   4. Click Save
   5. You should have four result tables in your individual database after you finish the exercise:
      1. DM-Bike Buyer Prediction-Decision Trees
      2. DM-Service Grade Prediction LR
      3. DM-Service Grade Prediction LR-90PercReduced
      4. DM-Service Grade Prediction LR-50PercReduced

Shift; wage	**Predicted service quality with current average response time**	**Predicted service quality with 50 percent reduction in response time**	**Predicted service quality with 90 percent reduction in response time**
AM; Holiday	0.05	0.05	0.05
Midnight; Holiday	0.05	0.05	0.05
PM1; Holiday	0.165	0.05	0.165
PM2; Holiday	0.05	0.05	0.05
AM; Weekday	0.05	0.05	0.05
Midnight; Weekday	0.08	0.08	0.08
PM1; Weekday	0.08	0.08	0.08
PM2; Weekday	0.165	0.05	0.05

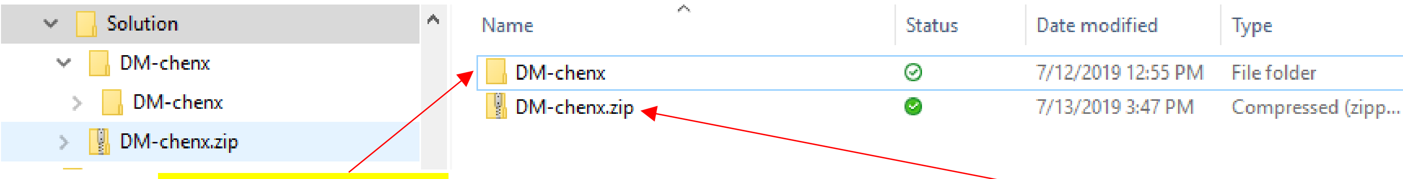
There are a variety of other prediction queries that you can create on this model. For example, you could predict how many operators are required to meet a certain service level or to respond to a certain number of incoming calls. Because you can include multiple outputs in a neural networks model, it is easy to experiment with different independent variables and outcomes without having to create many separate models.

To make predictions for new cases with other models

If you are interested, please go to Microsoft Tutorial to explore how to make predictions for new cases with other models

Submission:

1. **Save your project by clicking the Save All button**
2. **Exit from the Visual Studio (SSDT)**
3. **Zip the project's top folder as a new zipped file DM6-YourWindowsLoginName.zip. The following is the example of how to zip the project's top folder**
   a. **In the Windows Explorer window, locate the project's top folder. As an example, the following Windows Explorer window shows my project DM-chenx stored in a folder called Solution. I expanded the Solution folder in the left navigation pane to show the folder structure of the project. The folder DM-chenx immediately below Solution in the left navigation pane is the top project folder, which is also shown in the right pane of the window.**



Solution
DM-chenx
DM-chenx
DM-chenx.zip

Name	Status	Date modified	Type
DM-chenx	✓	7/12/2019 12:55 PM	File folder
DM-chenx.zip	✓	7/13/2019 3:47 PM	Compressed (zipp...

   b. **Right click the top project folder in the right pane, select Send To -> Compressed (zipped) folder to create a zip file. It should create a zip file with the same name of the top folder, e.g., DM-chenx.zip, right below the top project folder in the right pane of the window as shown in the image above.**
4. **Upload the zip file DM6-YourWindowsLoginName.zip to Canvas**
5. **To make sure you have made the right zip file that contains all needed subfolders and files**

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a. **After the uploading, download the zip file from Canvas and save it in a location other than the original location**
b. **Unzip it. In the unzipped folder, double click DM6-YourWindowsLoginName.sln (the solution file), e.g., DM-chenx.sln. Then, your project should open in Visual Studio**
c. **If it cannot open in Visual Studio, it means you didn't zip the top project folder correctly. You want to recreate the zip file following the instructions above.**

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