ANOMALY DETECTION

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Detect anomalies in product sales with ML.NET

https://docs.microsoft.com/en-us/dotnet/machine-learning/tutorials/sales-anomaly-detection

Learn how to build an anomaly detection application for product sales data. This exercise creates a .NET Core console application using C# in Visual Studio.

In this exercise, you learn how to:

- Load the data
- Create a transform for spike anomaly detection
- Detect spike anomalies with the transform
- Create a transform for change point anomaly detection
- Detect change point anomalies with the transform

Prerequisites

- Visual Studio 2017 version 15.6 or later with the ".NET Core cross-platform development" workload installed.
- The product-sales.csv dataset

Create a console application

1. Create a .NET Core Console Application called "ProductSalesAnomalyDetection".
2. Create a directory named Data in your project to save your data set files.
3. Install the Microsoft.ML NuGet Package:
    a. In Solution Explorer, right-click on your project and select Manage NuGet Packages. Choose "nuget.org" as the Package source, select the Browse tab, search for Microsoft.ML and select the Install button. Select the OK button on the Preview Changes dialog and then select the I Accept button on the License Acceptance dialog if you agree with the license terms for the packages listed. Repeat these steps for Microsoft.ML.TimeSeries.
4. Add the following using statements at the top of your Program.cs file:

```
using System;
using System.IO;
using Microsoft.ML;
using System.Collections.Generic;
```

Download your data

1. Download the dataset and save it to the Data folder you previously created:
    a. Right click on product-sales.csv and select "Save Link (or Target) As..."

    Make sure you either save the *.csv file to the Data folder, or after you save it elsewhere, move the *.csv file to the Data folder.

2. In Solution Explorer, right-click the *.csv file and select Properties. Change the value of Copy to Output Directory to Copy if newer.

The following table is a data preview from your *.csv file:

Month	ProductSales
1-Jan	271
2-Jan	150.9
.....	.....
1-Feb	199.3
.....	.....

Create classes and define paths

Next, define your input and prediction class data structures.

Add a new class to your project:

1. In Solution Explorer, right-click the project, and then select Add > New Item.
2. In the Add New Item dialog box, select Class and change the Name field to ProductSalesData.cs. Then, select the Add button.

    The ProductSalesData.cs file opens in the code editor.

3. Add the following using statement to the top of ProductSalesData.cs:

```
using Microsoft.ML.Data;
```

4. Remove the existing class definition and add the following code, which has two classes ProductSalesData and ProductSalesPrediction, to the ProductSalesData.cs file:

```
public class ProductSalesData
 {
     [LoadColumn(0)]
     public string Month;

     [LoadColumn(1)]
     public float numSales;
 }

 public class ProductSalesPrediction
 {
     //vector to hold alert,score,p-value values
     [VectorType(3)]
     public double[] Prediction { get; set; }
    }
```

ProductSalesData specifies an input data class. The LoadColumn attribute specifies which columns (by column index) in the dataset should be loaded.

ProductSalesPrediction specifies the prediction data class. For anomaly detection, the prediction consists of an alert to indicate whether there is an anomaly, a raw score, and p-value. The closer the p-value is to 0, the more likely an anomaly has occurred.

5. Create two global fields to hold the recently downloaded dataset file path and the saved model file path:
    - _dataPath has the path to the dataset used to train the model.
    - _docsize has the number of records in dataset file. You'll use _docSize to calculate pvalueHistoryLength.
6. Add the following code to the line right above the Main method to specify those paths:

```
static readonly string _dataPath = Path.Combine(Environment.CurrentDirectory, "Data",
"product-sales.csv");
//assign the Number of records in dataset file to constant variable
const int _docsize = 36;
```

Initialize variables in Main

1. Replace the Console.WriteLine("Hello World!") line in the Main method with the following code to declare and initialize the mlContext variable:

```
MLContext mlContext = new MLContext();
```

The MLContext class is a starting point for all ML.NET operations, and initializing mlContext creates a new ML.NET environment that can be shared across the model creation workflow objects. It's similar, conceptually, to DBContext in Entity Framework.

Load the data

Data in ML.NET is represented as an IDataView interface. IDataView is a flexible, efficient way of describing tabular data (numeric and text). Data can be loaded from a text file or from other sources (for example, SQL database or log files) to an IDataView object.

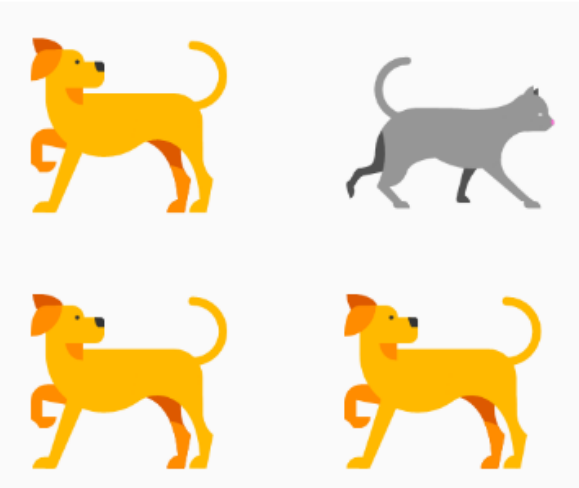
1. Add the following code as the next line of the Main() method:

```
IDataView dataView = mlContext.Data.LoadFromTextFile<ProductSalesData>(path:
_dataPath, hasHeader: true, separatorChar: ',');
```

The LoadFromTextFile() defines the data schema and reads in the file. It takes in the data path variables and returns an IDataView.

Time series anomaly detection

Anomaly detection flags unexpected or unusual events or behaviors. It gives clues where to look for problems and helps you answer the question "Is this weird?".



Anomaly detection is the process of detecting time-series data outliers; points on a given input time-series where the behavior isn't what was expected, or "weird".

Anomaly detection can be useful in lots of ways. For instance:

If you have a car, you might want to know: Is this oil gauge reading normal, or do I have a leak?
If you're monitoring power consumption, you'd want to know: Is there an outage?

There are two types of time series anomalies that can be detected:

- Spikes indicate temporary bursts of anomalous behavior in the system.
- Change points indicate the beginning of persistent changes over time in the system.

In ML.NET, The IID Spike Detection or IID Change point Detection algorithms are suited for independent and identically distributed datasets.

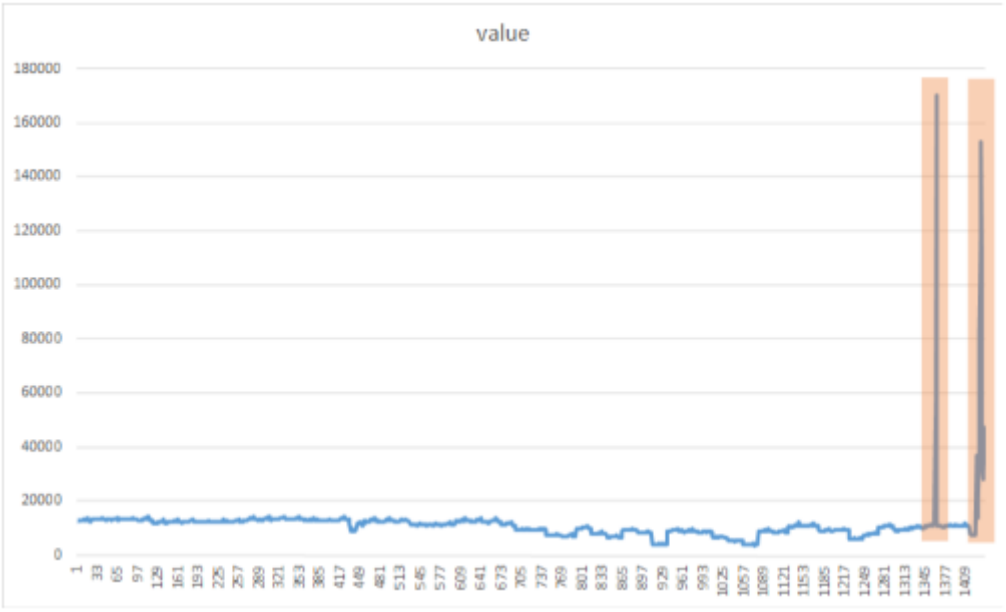
Unlike the models in the other exercises, the time series anomaly detector transforms operate directly on input data. The IEstimator.Fit() method does not need training data to produce the transform. It does need the data schema though, which is provided by a data view generated from an empty list of ProductSalesData.

You'll analyze the same product sales data to detect spikes and change points. The building and training model process is the same for spike detection and change point detection; the main difference is the specific detection algorithm used.

Spike detection

The goal of spike detection is to identify sudden yet temporary bursts that significantly differ from the majority of the time series data values. It's important to detect these suspicious rare items, events, or observations in a timely manner to be minimized.

The following approach can be used to detect a variety of anomalies such as: outages, cyber-attacks, or viral web content. The following image is an example of spikes in a time series dataset:



Add the CreateEmptyDataView() method

Add the following method to Program.cs:

```
static IDataView CreateEmptyDataView(MLContext mlContext)
        {
            // Create empty DataView. We just need the schema to call Fit() for the
time series transforms
            IEnumerable<ProductSalesData> enumerableData = new
List<ProductSalesData>();
            return mlContext.Data.LoadFromEnumerable(enumerableData);
        }
```

The CreateEmptyDataView() produces an empty data view object with the correct schema to be used as input to the IEstimator.Fit() method.

Create the DetectSpike() method

The DetectSpike() method:

- Creates the transform from the estimator.
- Detects spikes based on historical sales data.
- Displays the results.

1. Create the DetectSpike() method, just after the Main() method, using the following code:

```
static void DetectSpike(MLContext mlContext, int docSize, IDataView productSales)
     {

         }
```

2. Use the IidSpikeEstimator to train the model for spike detection. Add it to the DetectSpike() method with the following code:

```
var iidSpikeEstimator = mlContext.Transforms.DetectIidSpike(outputColumnName:
nameof(ProductSalesPrediction.Prediction), inputColumnName:
nameof(ProductSalesData.numSales), confidence: 95, pvalueHistoryLength: docSize /
4);
```

3. Create the spike detection transform by adding the following as the next line of code in the DetectSpike() method:

```
ITransformer iidSpikeTransform =
iidSpikeEstimator.Fit(CreateEmptyDataView(mlContext));
```

4. Add the following line of code to transform the productSales data as the next line in the DetectSpike() method:

```
IDataView transformedData = iidSpikeTransform.Transform(productSales);
```

The previous code uses the Transform() method to make predictions for multiple input rows of a dataset.

5. Convert your transformedData into a strongly typed IEnumerable for easier display using the CreateEnumerable() method with the following code:

```
var predictions =
mlContext.Data.CreateEnumerable<ProductSalesPrediction>(transformedData,
reuseRowObject: false);
```

6. Create a display header line using the following Console.WriteLine() code:

```
Console.WriteLine("Alert\tScore\tP-Value");
```

You'll display the following information in your spike detection results:

- Alert indicates a spike alert for a given data point.
- Score is the ProductSales value for a given data point in the dataset.
- P-Value The "P" stands for probability. The closer the p-value is to 0, the more likely the data point is an anomaly.

7. Use the following code to iterate through the predictions IEnumerable and display the results:

```
foreach (var p in predictions)
        {
                    var results =
   $"{p.Prediction[0]}\t{p.Prediction[1]:f2}\t{p.Prediction[2]:F2}";

            if (p.Prediction[0] == 1)
            {
                results += " <-- Spike detected";
            }

            Console.WriteLine(results);
        }
           Console.WriteLine("");
```

8. Add the call to the DetectSpike()method in the Main() method:

```
DetectSpike(mlContext, _docsize, dataView);
```

Spike detection results

Your results should be similar to the following. During processing, messages are displayed. You may see warnings, or processing messages. Some of the messages have been removed from the following results for clarity.

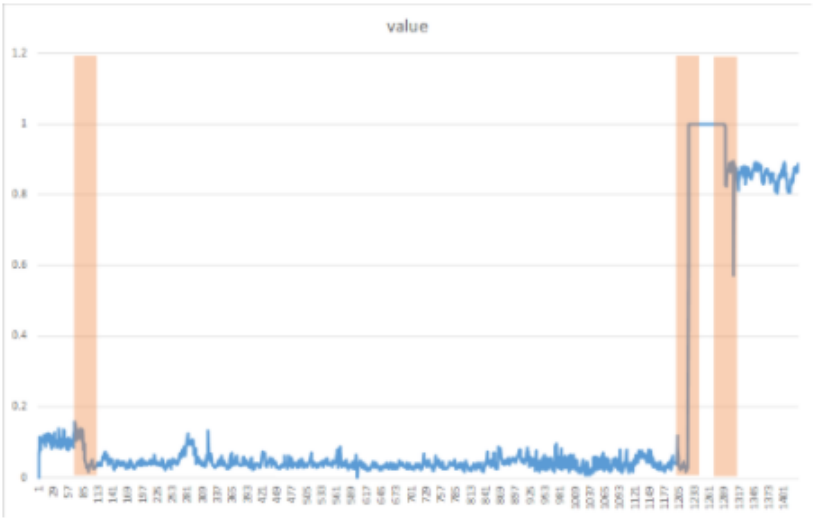
Console Copy

```
Detect temporary changes in pattern
=============== Training the model ===============
=============== End of training process ===============
Alert   Score   P-Value
0       271.00  0.50
0       150.90  0.00
0       188.10  0.41
0       124.30  0.13
0       185.30  0.47
0       173.50  0.47
0       236.80  0.19
0       229.50  0.27
0       197.80  0.48
0       127.90  0.13
1       341.50  0.00 <-- Spike detected
0       190.90  0.48
0       199.30  0.48
0       154.50  0.24
0       215.10  0.42
0       278.30  0.19
0       196.40  0.43
0       292.00  0.17
0       231.00  0.45
0       308.60  0.18
0       294.90  0.19
1       426.60  0.00 <-- Spike detected
0       269.50  0.47
0       347.30  0.21
0       344.70  0.27
0       445.40  0.06
0       320.90  0.49
```

Change point detection

Change points are persistent changes in a time series event stream distribution of values, like level changes and trends. These persistent changes last much longer than spikes and could indicate catastrophic event(s).

Change points are not usually visible to the naked eye, but can be detected in your data using approaches such as in the following method. The following image is an example of a change point detection:



Create the DetectChangepoint() method

The DetectChangepoint() method executes the following tasks:

- Creates the transform from the estimator.
- Detects change points based on historical sales data.
- Displays the results.

1. Create the DetectChangepoint() method, just after the Main() method, using the following code:

```
static void DetectChangepoint(MLContext mlContext, int docSize, IDataView
productSales)
    {

        }
```

2. Create the iidChangePointEstimator in the DetectChangepoint() method with the following code:

```
var iidChangePointEstimator =
mlContext.Transforms.DetectIidChangePoint(outputColumnName:
nameof(ProductSalesPrediction.Prediction), inputColumnName:
nameof(ProductSalesData.numSales), confidence: 95, changeHistoryLength: docSize /
4);
```

3. As you did previously, create the transform from the estimator by adding the following line of code in the DetectChangePoint() method:

```
var iidChangePointTransform =
iidChangePointEstimator.Fit(CreateEmptyDataView(mlContext));
```

4. Use the Transform() method to transform the data by adding the following code to DetectChangePoint():

```
IDataView transformedData = iidChangePointTransform.Transform(productSales);
```

5. As you did previously, convert your transformedData into a strongly typed IEnumerable for easier display using the CreateEnumerable()method with the following code:

```
var predictions =
mlContext.Data.CreateEnumerable<ProductSalesPrediction>(transformedData,
reuseRowObject: false);
```

6. Create a display header with the following code as the next line in the DetectChangePoint() method:

```
Console.WriteLine("Alert\tScore\tP-Value\tMartingale value");
```

You'll display the following information in your change point detection results:

- Alert indicates a change point alert for a given data point.
- Score is the ProductSales value for a given data point in the dataset.
- P-Value The "P" stands for probability. The closer the P-value is to 0, the more likely the data point is an anomaly.
- Martingale value is used to identify how "weird" a data point is, based on the sequence of P-values.

7. Iterate through the predictions IEnumerable and display the results with the following code:

```
    foreach (var p in predictions)
            {
                var results =
$"{p.Prediction[0]}\t{p.Prediction[1]:f2}\t{p.Prediction[2]:F2}\t{p.Prediction[3]:F2}"
;

                if (p.Prediction[0] == 1)
                {
                    results += " <-- alert is on, predicted changepoint";
                }
                Console.WriteLine(results);
            }
                Console.WriteLine("");
```

8. Add the following call to the DetectChangepoint()method in the Main() method:

```
    DetectChangepoint(mlContext, _docsize, dataView);
```

Change point detection results

Your results should be similar to the following. During processing, messages are displayed. You may see warnings, or processing messages. Some messages have been removed from the following results for clarity.

Console Copy

```
Detect Persistent changes in pattern
=============== Training the model Using Change Point Detection Algorithm===========
=============== End of training process ===============
Alert   Score   P-Value Martingale value
0       271.00  0.50    0.00
0       150.90  0.00    2.33
0       188.10  0.41    2.80
0       124.30  0.13    9.16
0       185.30  0.47    9.77
0       173.50  0.47    10.41
0       236.80  0.19    24.46
0       229.50  0.27    42.38
1       197.80  0.48    44.23 <-- alert is on, predicted changepoint
0       127.90  0.13    145.25
0       341.50  0.00    0.01
0       190.90  0.48    0.01
0       199.30  0.48    0.00
0       154.50  0.24    0.00
0       215.10  0.42    0.00
```

Congratulations! You've now successfully built machine learning models for detecting spikes and change point anomalies in sales data.

You can find the source code for this exercise at the dotnet/samples repository.