Dynamics 365 Customer Insights

Lab 4: Intelligence

Contents

Module Introduction

Out of the Box (OOB) models

Customer Insights offers out of the box models to predict key insights of your business. Currently, Customer Insights provides the following OOB models:

- **Subscription churn model**
- **Product recommendations**
- **Customer lifetime value**
- **Customer sentiment analysis**

Objectives

- Use OOB Subscription Churn model to predict customers at risk of not using Contoso subscription service.
- Create a quick segment using Intelligence.

Prerequisites

To complete this lab, you need to have completed Lab 3

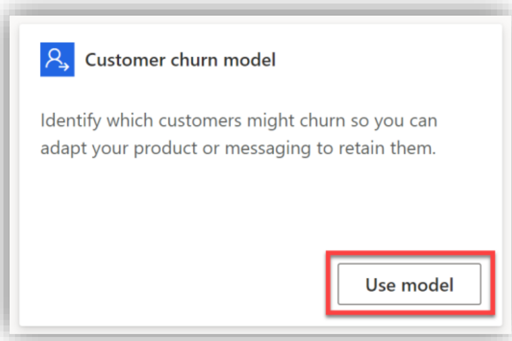
Approximate Time - 45 mins

Exercise 1 – Transaction Churn Model

Task 1 – Run the OOB Transaction Churn Model

1. Go to **Intelligence -> Predictions**

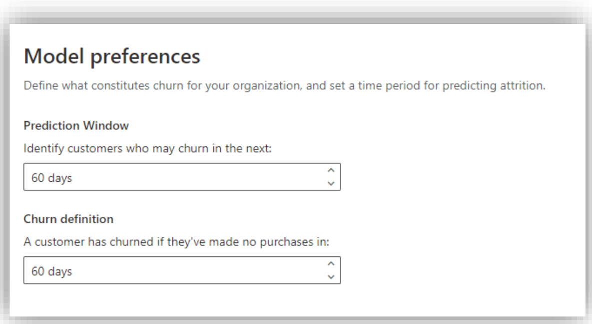
2. Click **Create** and click **Use model** on the **Customer Churn model** card



3. Select the **Transaction** option and click **Get started**

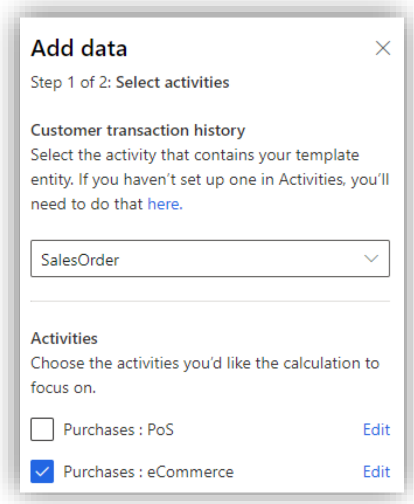
4. Name the model **eCommerce Transaction Churn Prediction** and the output entity **eCommerceTransactionChurnPrediction** then click **Next**

5. Define the two conditions for the churn model as both **60 days** then click **Next**



6. On the **Add required data** screen click **Add data**

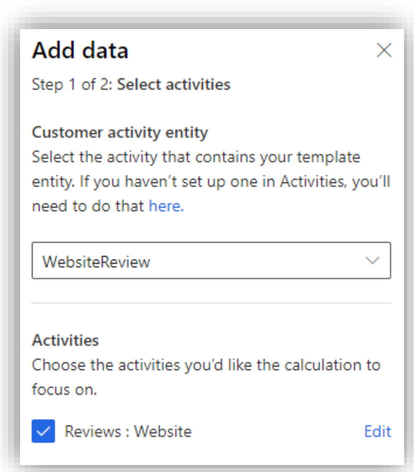
7. Select **SalesOrder** (this is the semantic type used when creating the order activities) and then select **Purchases : eCommerce**



8. Click **Next.** You will see that all the attributes have already been mapped since you did that when you created the activity. Had you not done that then, you would do the mapping here.

9. Click **Save** and then **Next**

10. Click **Add data**, select **WebsiteReview** as the Customer activity entity and select **Reviews : Website** as the Activity



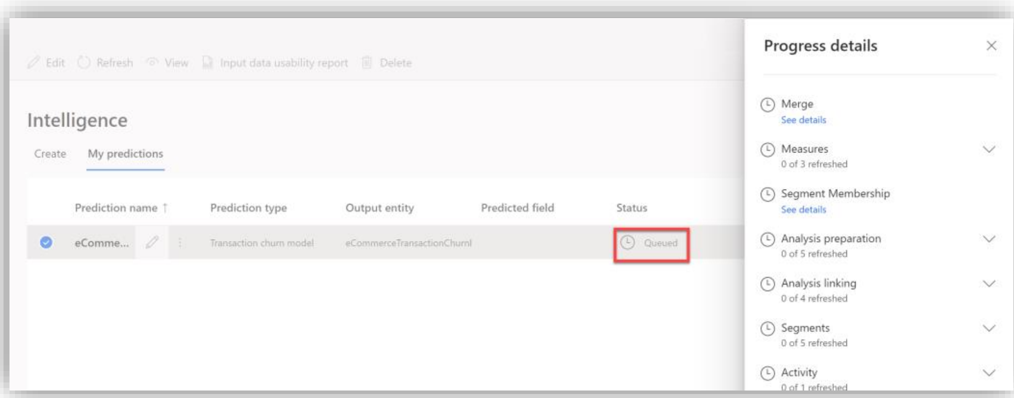
11. Click **Next**, leave the defaults selected and click **Save**

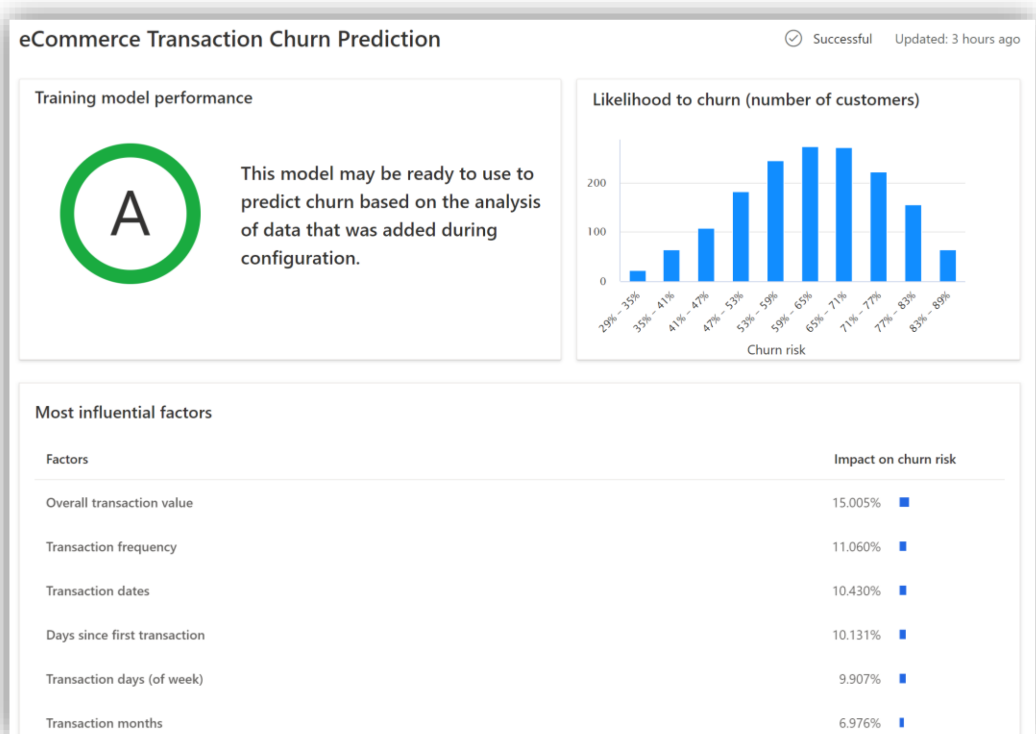
12. Click **Next**

13. Select the **Monthly** update setting and click **Next**

14. Click **Save and run** and then click **Done**

15. Monitor the run status, and once the run has succeeded, click on the **created prediction to see the results.** It will take a while to run, so can check the run progress by clicking on the **Status** and you can jump to the next exercise, page 9, and come back and complete this later





Training Model Performance

The model is graded A, B or C depending on the following conditions:

<u>**A**</u> when the model accurately predicted at least 50% of the total predictions, and when the percentage of accurate predictions for customers who churned is greater than the historical average churn rate by at least 10% of the historical average churn rate.

B when the model accurately predicted at least 50% of the total predictions, and when the percentage of accurate predictions for customers who churned is up to 10% greater than the historical average churn rate of the historical average churn rate.

C when the model accurately predicted less 50% of the total predictions, or when the percentage of accurate predictions for customers who churned is less than the historical average churn rate.

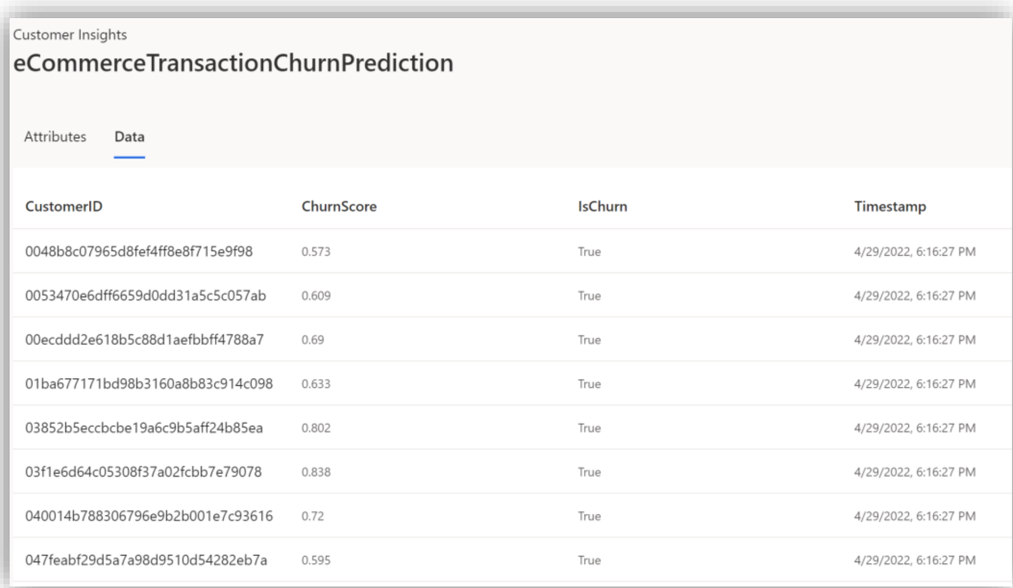
Likelihood to churn (number of customers)

Likelihood of churn shows Groups of customers based on their predicted risk of churn. This data can help you later if you want to create a segment of customers with high churn risk. Such segments help to understand where your cutoff should be for segment membership.

Most Influential Factors

There are many factors that are taken into account when creating your prediction. Each of the factors has their importance calculated for the aggregated predictions a model creates. You can use these factors to help validate your prediction results. Or you can use this information later to create segments that could help influence churn risk for customers.

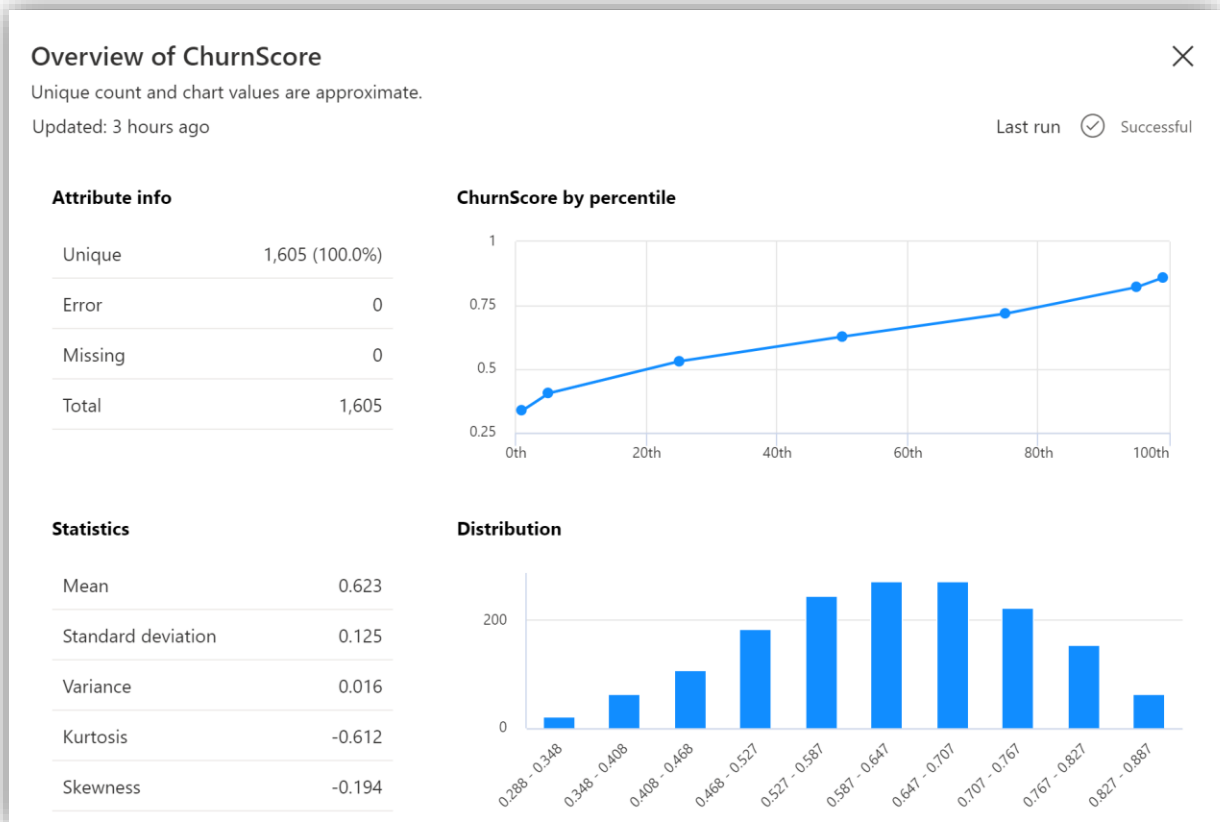
16. You can find the list of customers and their churn score under **Data -> Entities-> Intelligence -> eCommerceTransactionChurnPrediction** and then the **Data** tab


Customer Insights
eCommerceTransactionChurnPrediction

Attributes Data

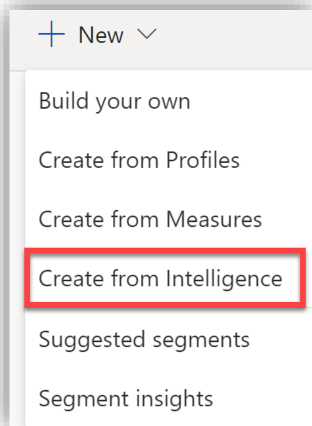
CustomerID	ChurnScore	IsChurn	Timestamp
0048b8c07965d8fef4ff8e8f715e9f98	0.573	True	4/29/2022, 6:16:27 PM
0053470e6dff6659d0dd31a5c5c057ab	0.609	True	4/29/2022, 6:16:27 PM
00ecddd2e618b5c88d1aefbbff4788a7	0.69	True	4/29/2022, 6:16:27 PM
01ba677171bd98b3160a8b83c914c098	0.633	True	4/29/2022, 6:16:27 PM
03852b5eccbcbe19a6c9b5aff24b85ea	0.802	True	4/29/2022, 6:16:27 PM
03f1e6d64c05308f37a02fcbb7e79078	0.838	True	4/29/2022, 6:16:27 PM
040014b788306796e9b2b001e7c93616	0.72	True	4/29/2022, 6:16:27 PM
047feabf29d5a7a98d9510d54282eb7a	0.595	True	4/29/2022, 6:16:27 PM

17. Click on **Attributes** and then the mini graph under the **Summary** column for **ChurnScore** to see an overview



Task 2 – Create a Segment of High Churn-Risk Customers

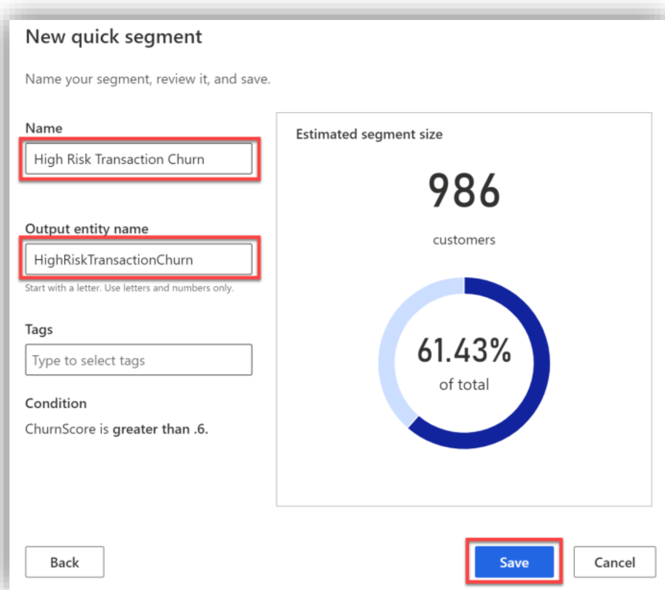
1. Go to **Segments**, select **+New** and choose **Create from Intelligence**.



2. Select the **eCommerceTransactionChurnPrediction** entity:

   - Field: **ChurnScore**
   - Operator: **greater than**
   - Value: **0.6**

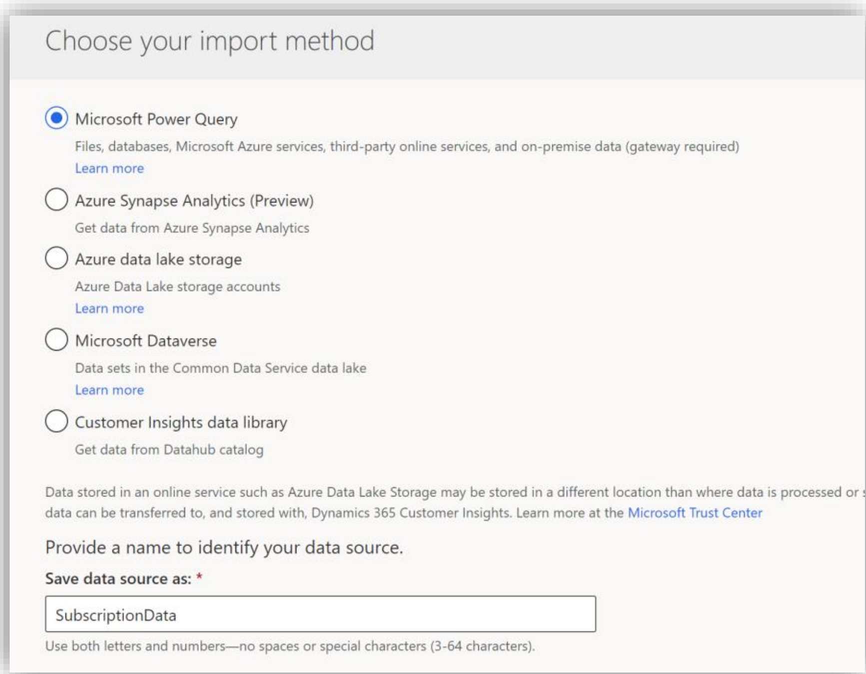
3. Click Review, name your segment **High Risk Transaction Churn,** name the Output entity **HighRiskTransactionChurn** and then click **Save**



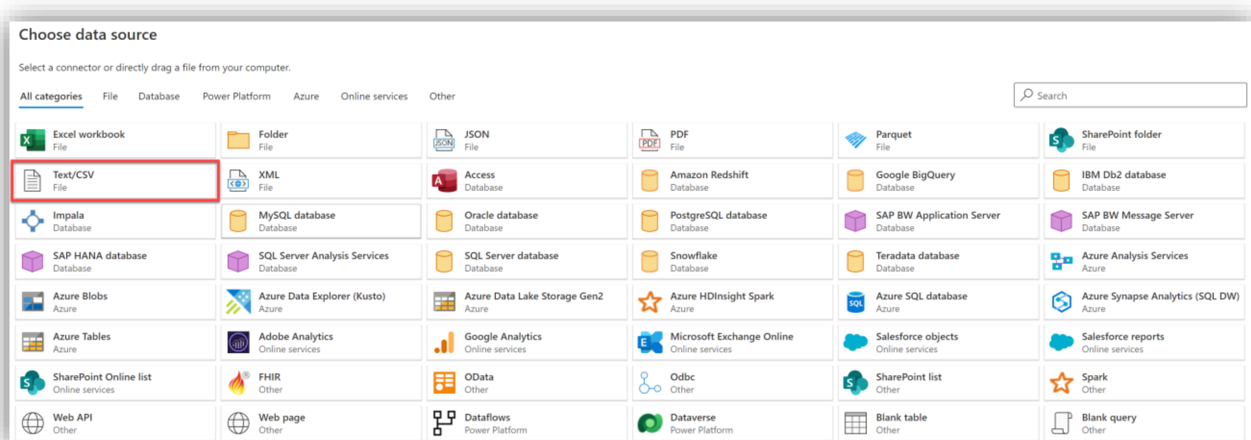
Optional – Building OOB Subscription Churn Model

Task 1 – Ingest the Subscription Data

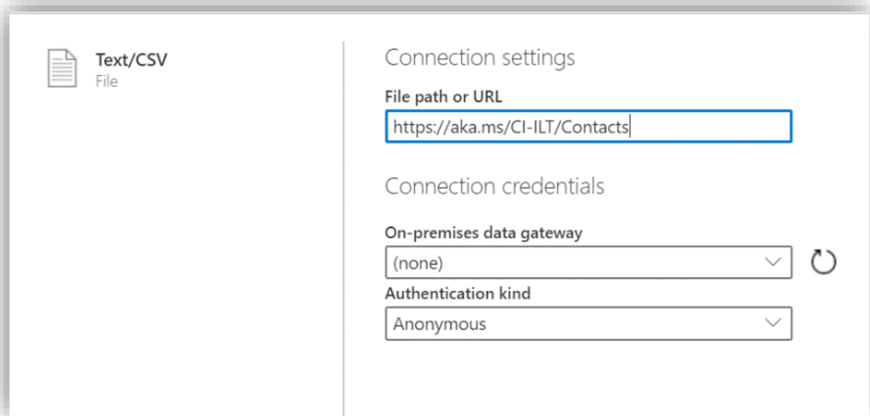
1. Click **Data -> Data sources -> Add Data Source**, choose **Microsoft Power Query,** name the source **SubscriptionData**, then click **Next button**



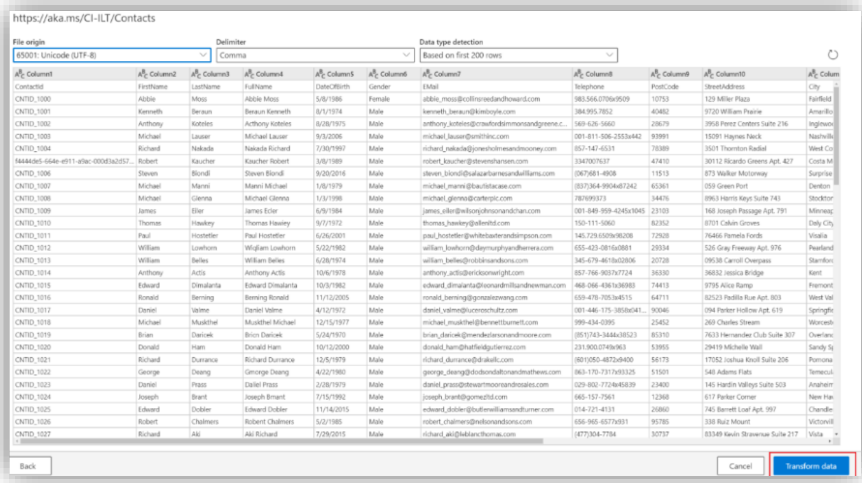
2. Select the **Text/CSV** Connector.



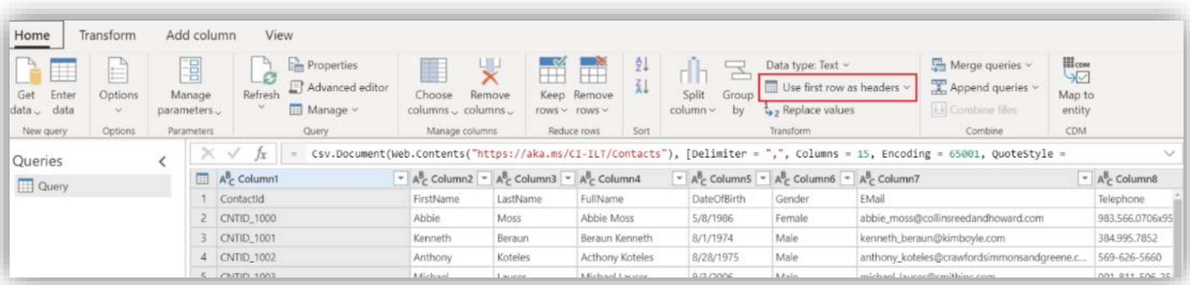
3. Enter the URL **https://aka.ms/CI-ILT/SubscriberContacts** and click **Next**.



4. Click **Transform data**

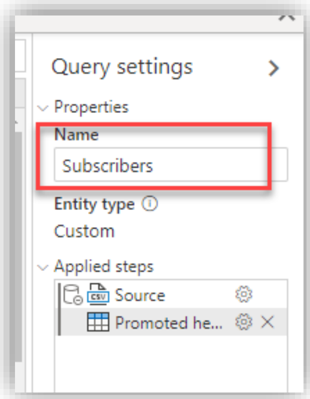


5. Click **Transform** and **Use first row as headers.**

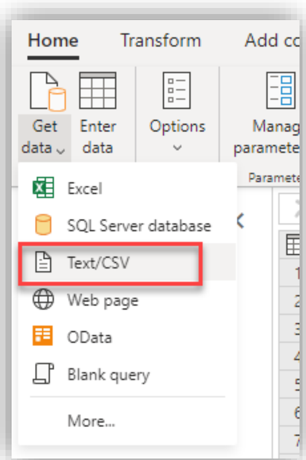


6. Change the datatype for **DateOfBirth** to **Date/Time** (click **ABC** in column header to change it)

7. In the 'Name' field on the right-hand pane, name your data **Subscribers**



8. Click **Get Data**, then choose **Text/CSV**



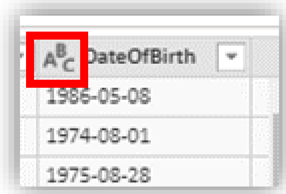
9. Enter the URL for the Subscriber History data set, **https://aka.ms/CI-ILT/SubHistory**, and click **Next**.

10. Click **Create** to configure the datatypes and formats for the data you ingest.

11. Click **Transform** and **Use first row as headers.**

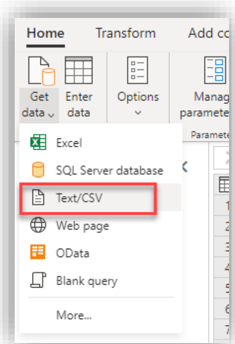
12. Set the datatypes for non-text columns. Click the **ABC** icon within the column heading. Update the datatype for the columns listed below.

Column Heading	New Data Type
SubscriptionAmount	Whole Number
SubscriptionEndDate	Date/Time
SubscriptionStartDate	Date/Time
TransactionDate	Date/Time
IsRecurring	True/False
Is_auto_renew	True/False
RecurringFrequencyInMonths	Whole Number



13. In the 'Name' field on the right-hand pane, name your data source **SubscriberHistory**

14. Click **Get Data**, then choose **Text/CSV**



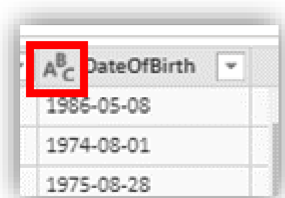
15. Enter the URL for the Userlog data set, **https://aka.ms/CI-ILT/Userlogs**, and click **Next**.

16. Click **Create** to configure the datatypes and formats for the data you ingest.

17. Click **Transform** and **Use first row as headers.**

18. Change the datatype for non-text columns by clicking the **ABC** icon within the column heading. Update the datatype for the columns listed below.

Column Heading	New Data Type
TransactionDate	Date/Time
TransactionValue	Whole Number



19. In the 'Name' field on the right-hand pane, name your data source **UserLogs** and then click **Next**

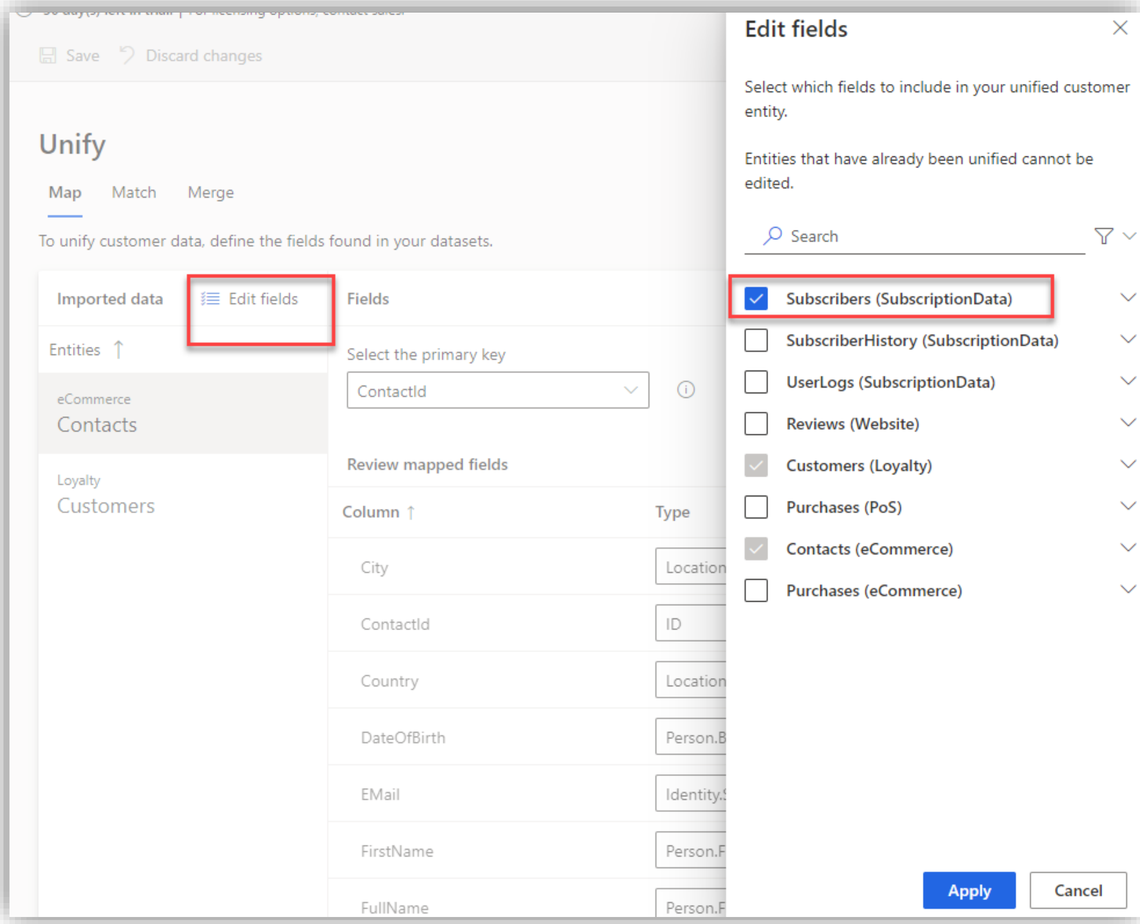
20. Leave the refresh schedule set to **Refresh manually** and click **Save**

Task 2 – Unify the Subscription Data with Existing Data

When the data source is finishes loading you need to Unify it. This can take a while as there is a lot of data in the SubscriptonData tables you are importing.

1. Click on **Data** -> **Unify** in the left-hand menu

2. Click on **Edit Fields** and check **Subscribers (SubscriptionData)**, then press **Apply**



3. Click on **SubscriptionData : Subscribers : SubscriptionData** in the entities list and select **ContactId** for the Primary Key

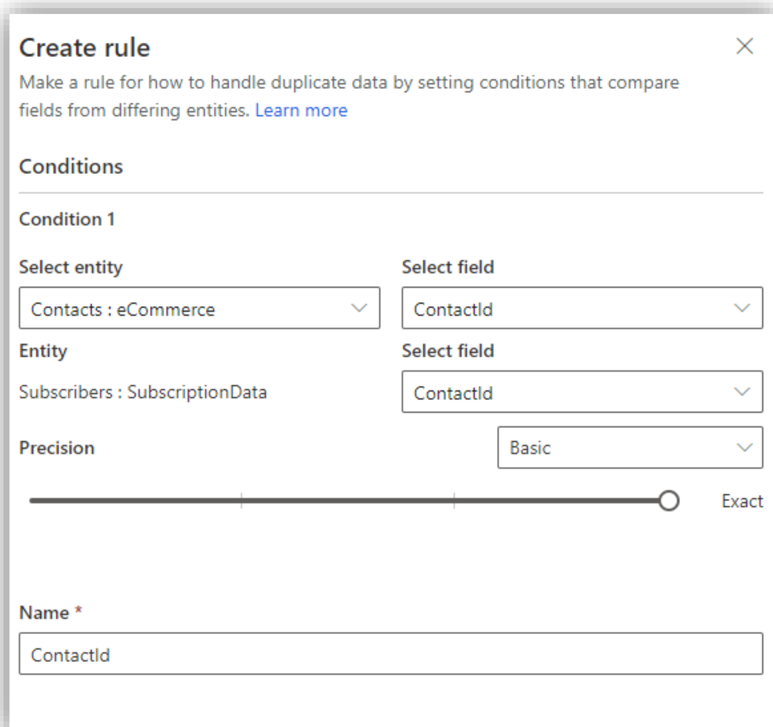
4. Click **Save** and then the **Match** tab.

5. Click the **Edit** button on the **Matched customer records** heading

6. Click **+ Add** (bottom left), select **Subscribers : SubscriptionData** as the entity, check **Include all** and then click **Done**

7. Click **+ Add rule** under (or the + to the right of) **Subscribers**.

8. Create the rule as follows:



9. Name the rule **ContactId**, click **Done**. Then **Save** and **Run** the match.

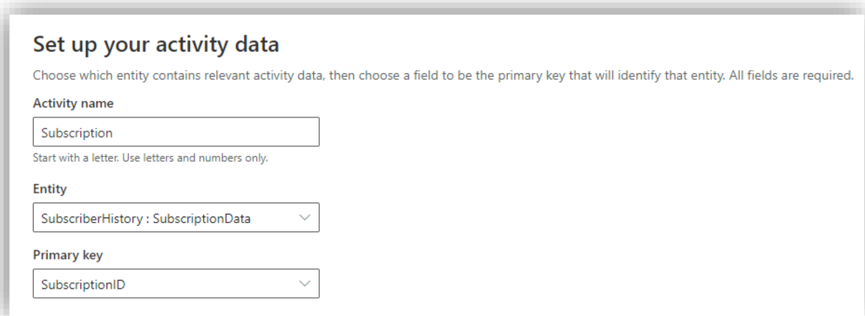
10. When the match finishes running you can click the **Merge** tab**.** Everything here is setup as we need it so just click **Run -> Run Merge and downstream processes** to complete the process. Once the Merge is done running, which can take some time, you can proceed to the next Task.

Task 3 – Create a Subscription Activity

1. Within Customer Insights, Expand **Data -> Activities** on the left menu and click **Add Activity**

2. On the **Activity data** screen set the following values:

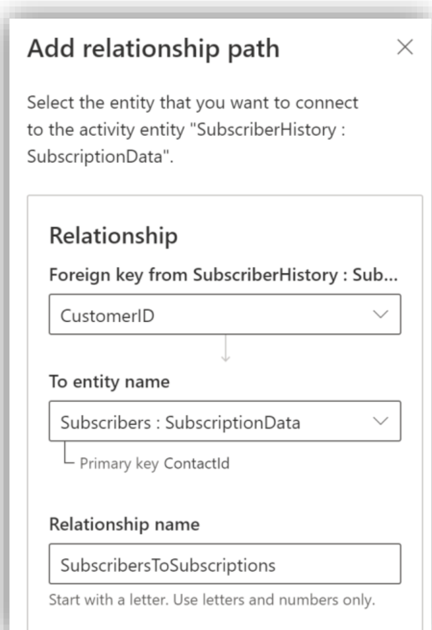
   - Activity name: **Subscription**
   - Entity: **SubscriberHistory : SubscriptionData**
   - Primary Key: **SubscriptionID**



3. Click **Next**

4. Click **+Add relationship** and setup as following :

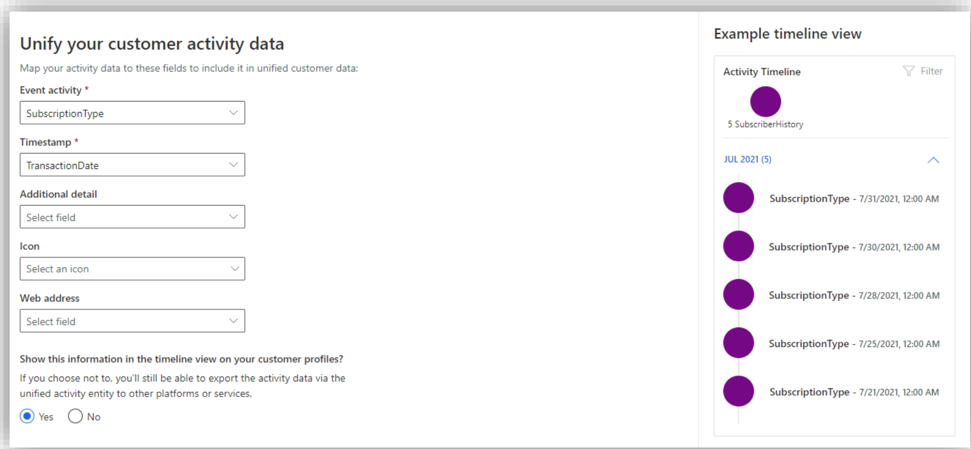
   - Foreign key: **CustomerID**
   - To entity name: **Subscribers : SubscriptionData**
   - Relationshiop name: **SubscribersToSubscriptions**



5. Click **Apply** and then **Next**

6. On the **Unify your customer activity data** screen set the following values:

   - Event activity: **SubscriptionType**
   - Timestamp: **TransactionDate**
   - Additional detail: **<blank> or None**
   - Icon: **<blank> or None**
   - Web address: **<blank> or None**
   - Show this information...: **Yes**

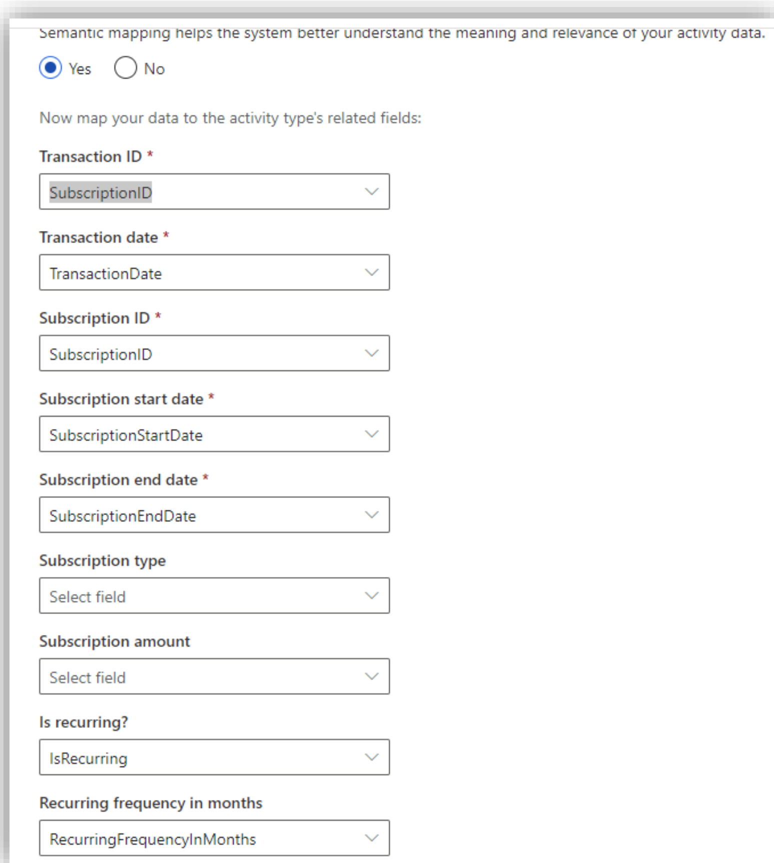


7. Click **Next**

8. Set activity type to **Subscription** (under Semantic types) and select **Yes** for Provide semantic mapping for your activity's attributes

9. Map the data to the activity type related fields as follows:

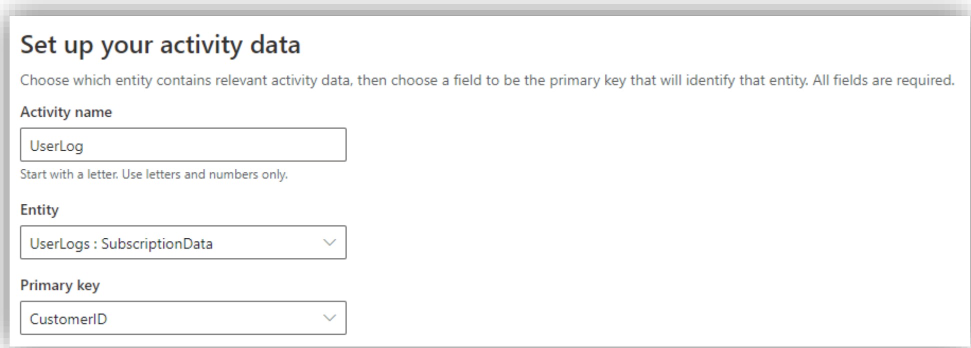
- Transaction ID: **SubscriptionID**
- Transaction date: **TransactionDate**
- Subscription ID: **SubscriptionID**
- Subscription start date: **SubscriptionStartDate**
- Subscription end date: **SubscriptionEndDate**
- Subscription type: **<blank> or None**
- Subscription amount: **<blank> or None**
- Is recurring?: **IsRecurring**
- Recurring frequency in months: **RecurringFrequencyInMonths**



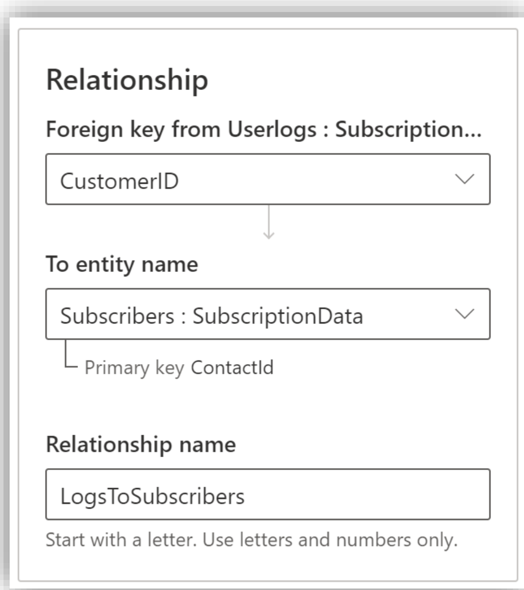
10. Click **Next**, review your entries then click **Save activity** and **Done**

Task 4 – Create a UserLog Activity

1. Go to **Data -> Activities** and click **+Add Activity**
2. On the **Activity data** screen set the following values:
    - Activity name: **UserLog**
    - Entity: **UserLogs : SubscriptionData**
    - Primary Key: **CustomerID**



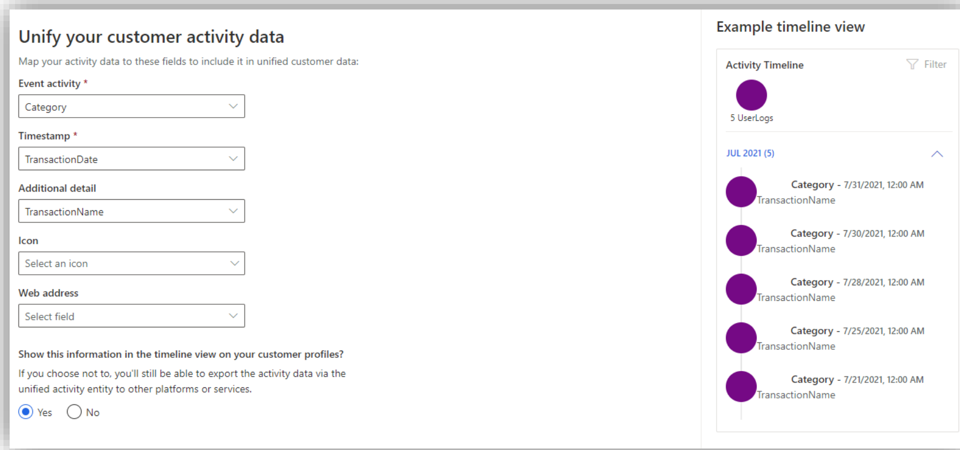
3. Click **Next**
4. Click **+Add relationship** and set the following values:
    - Foreign key: **CustomerID**
    - To entity name: **Subscribers : SubscriptionData**
    - Relationshiop name: **LogsToSubscribers**



5. Click **Apply** and then **Next**

6. Set the following values to **Unify your customer activity data**:

    - Event activity: **Category**
    - Timestamp: **TransactionDate**
    - Additional detail: **TransactionName**
    - Icon: **<blank> or None**
    - Web address: **<blank> or None**
    - Show this information...: **Yes**



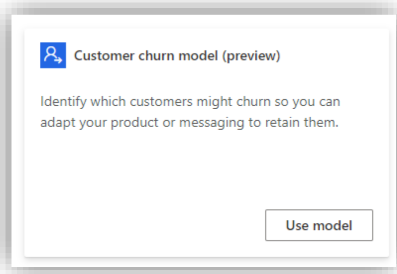
7. Click **Next**

8. Set activity type to **Other**

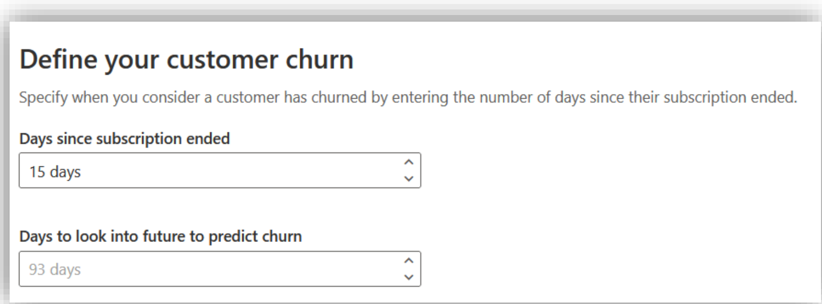
9. Click **Next**, review your entries then click **Save activity** and **Done**

Task 5 - Building Subscription Churn Model

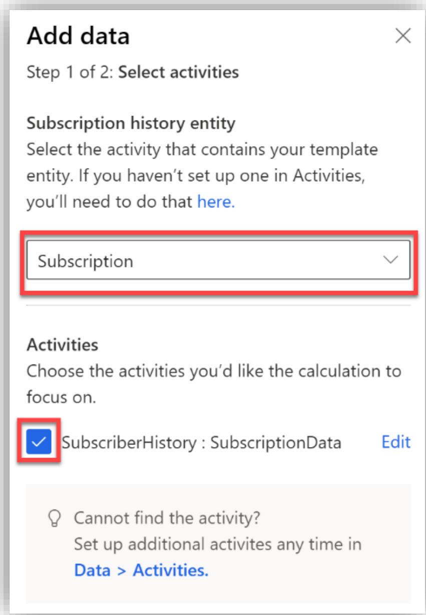
1. Go to **Intelligence -> Predictions -> Create**
2. Click **Use model** on the **Customer churn model** card

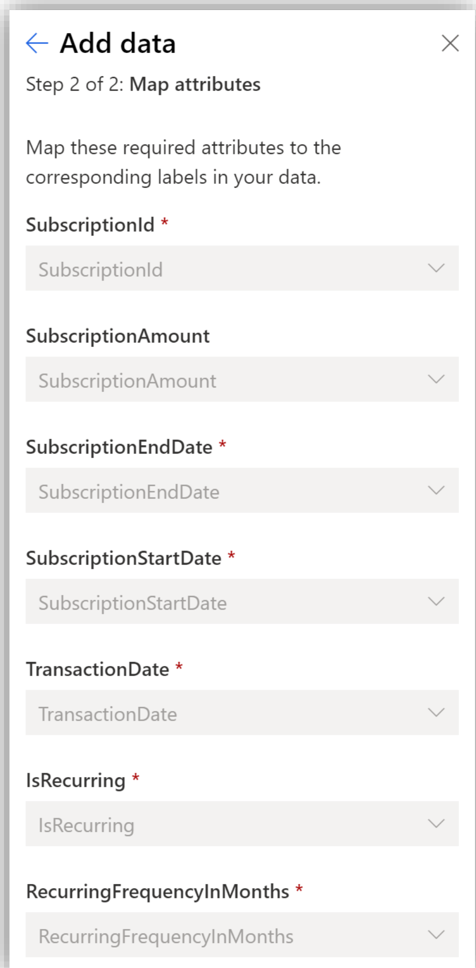


3. Select **Subscription** and click **Get started**
4. Enter the model name **Subscription Churn Model**, Output entity name **SubscriptionChurnModel** and click **Next.**
5. Set the days since subscription ended to **15 days**, leave days to predict churn at **93 days** and click **Next.**



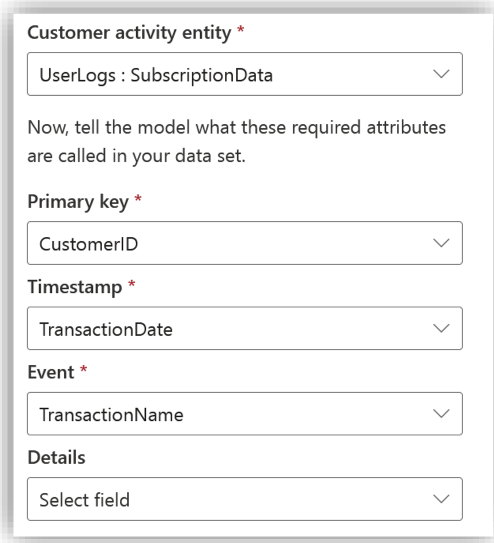
6. Under Subscription history, click **Add data**, select the **Subscription** as the Subscription history entity, check **SubsciberHistory : SubscriptionData**, click **Next** and then **Save.**





7. Within Customer activities, click on **Add data** and choose **UserLogs** entity from the list and map the fields as below.

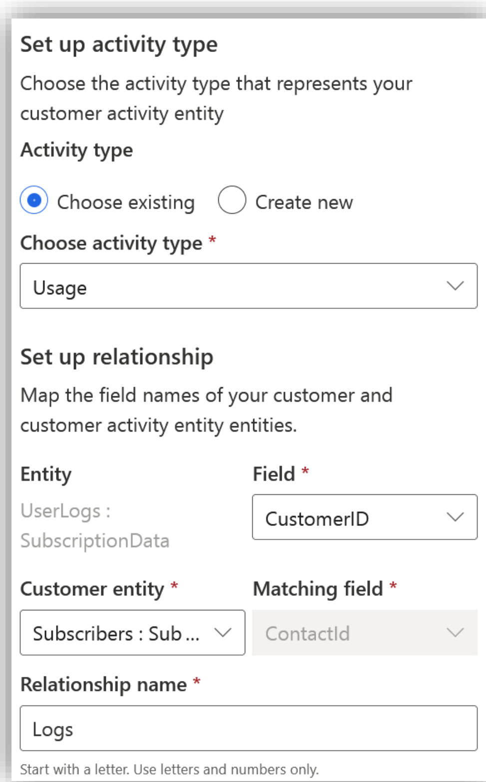
   - Customer activity entity: **UserLogs : SubscriptionData**
   - Primary key: **CustomerID**
   - Timestamp: **TransactionDate**
   - Event: **TransactionName**



8. Click **Next**

9. Set the activity type to **Usage** and set up relationship between **UserLogs** and **Subscribers** entity as below and hit **Save.**

   - Activity type: **Usage**
   - Corresponding label: **CustomerID**
   - Customer entity: **Subscribers : SubscriptionData**
   - Relationship: **Logs**

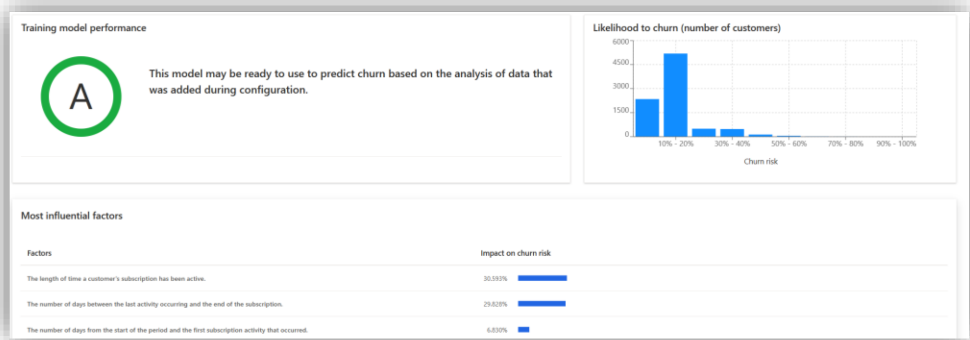


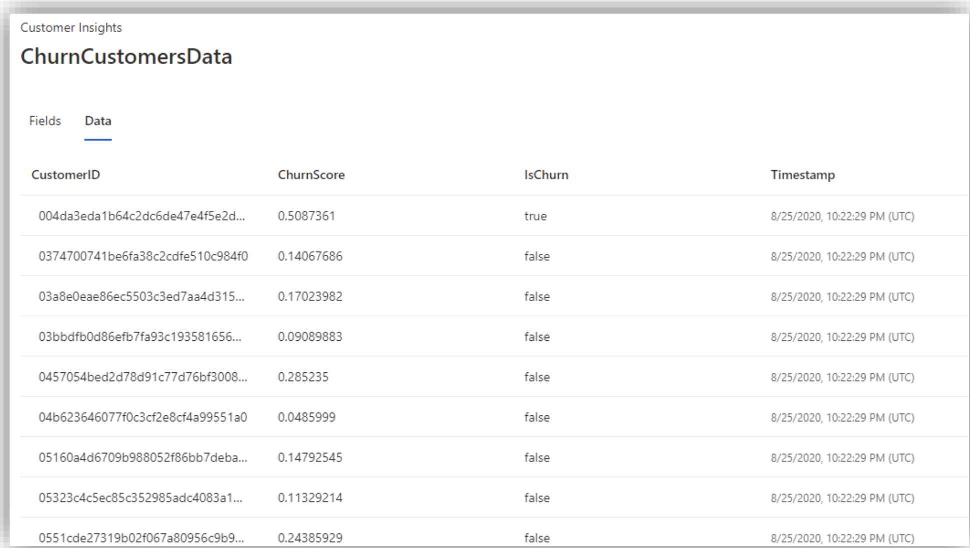
10. Click **Next** and set training schedule as **Monthly** and click **Next.**

11. Review the details and click **Save and Run** and then **Done**

The model will initiate Activity entity to run for the first time and adds SubscriptionHistory and Userlogs to customer timeline. After that, the model run begins. This can take a long time as we have ingested a large amount of data inside the logs and subscription history.

You can check the run status in the **System** page. Once the run has succeeded, you can go back to Intelligence and click on the created prediction 'Churn Model' to see the results and you can find the list of customers and their churn score in **Entities-> ChurnModel.**





CustomerID	ChurnScore	IsChurn	Timestamp
004da3eda1b64c2dc6de47e4f5e2d...	0.5087361	true	8/25/2020, 10:22:29 PM (UTC)
0374700741be6fa38c2cdfe510c984f0	0.14067686	false	8/25/2020, 10:22:29 PM (UTC)
03a8e0eae86ec5503c3ed7aa4d315...	0.17023982	false	8/25/2020, 10:22:29 PM (UTC)
03bbdfb0d86efb7fa93c193581656...	0.09089883	false	8/25/2020, 10:22:29 PM (UTC)
0457054bed2d78d91c77d76bf3008...	0.285235	false	8/25/2020, 10:22:29 PM (UTC)
04b623646077f0c3cf2e8cf4a99551a0	0.0485999	false	8/25/2020, 10:22:29 PM (UTC)
05160a4d6709b988052f86bb7deba...	0.14792545	false	8/25/2020, 10:22:29 PM (UTC)
05323c4c5ec85c352985adc4083a1...	0.11329214	false	8/25/2020, 10:22:29 PM (UTC)
0551cde27319b02f067a80956c9b9...	0.24385929	false	8/25/2020, 10:22:29 PM (UTC)

Training Model Performance

The model is graded A, B or C depending on the following conditions:

<u>A</u> when the model accurately predicted at least 50% of the total predictions, and when the percentage of accurate predictions for customers who churned is greater than the historical average churn rate by at least 10% of the historical average churn rate.

<u>B</u> when the model accurately predicted at least 50% of the total predictions, and when the percentage of accurate predictions for customers who churned is up to 10% greater than the historical average churn rate of the historical average churn rate.

<u>C</u> when the model accurately predicted less 50% of the total predictions, or when the percentage of accurate predictions for customers who churned is less than the historical average churn rate.

Likelihood to churn (number of customers)

Likelihood of churn shows Groups of customers based on their predicted risk of churn. This data can help you later if you want to create a segment of customers with high churn risk. Such segments help to understand where your cutoff should be for segment membership.

Most Influential Factors

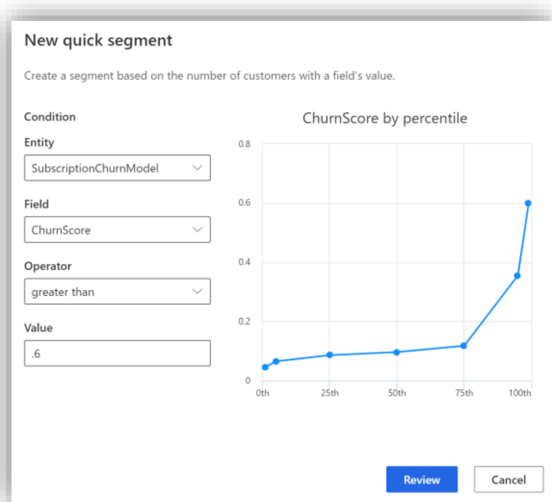
There are many factors that are taken into account when creating your prediction. Each of the factors has their importance calculated for the aggregated predictions a model creates. You can use these factors to help validate your prediction results. Or you can use this information later to create segments that could help influence churn risk for customers.

Task 6 – Set up a Segment of High Churn-risk Users

1. Go to **Segments,** click **New -> Create from Intelligence**

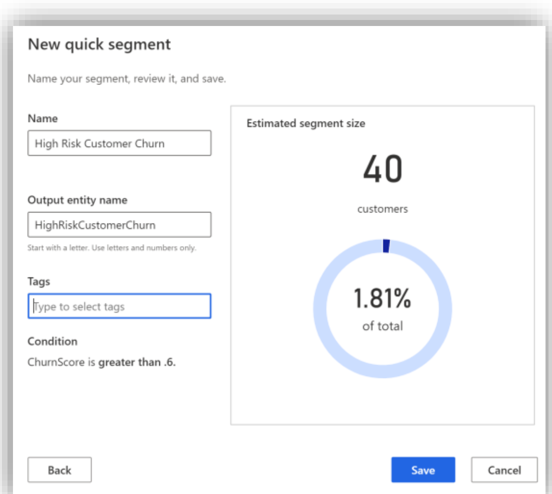
2. Setup your quick segment with these settings:

   - Entity: **SubscriptionChurnModel**
   - Field: **ChurnScore**
   - Operator: **greater than**
   - Value: **0.6**



3. Click **Review**

4. Name the segment **High Risk For Subscription Churn** and output entity name **HighRiskForSubscriptionChurn and** click **Save**

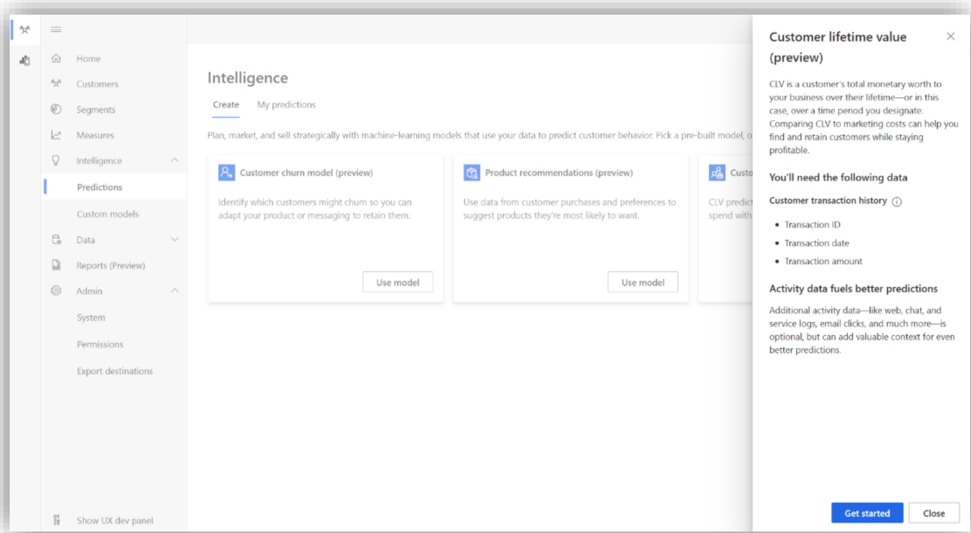


Optional - Customer Lifetime Value (CLV) Prediction Tasks

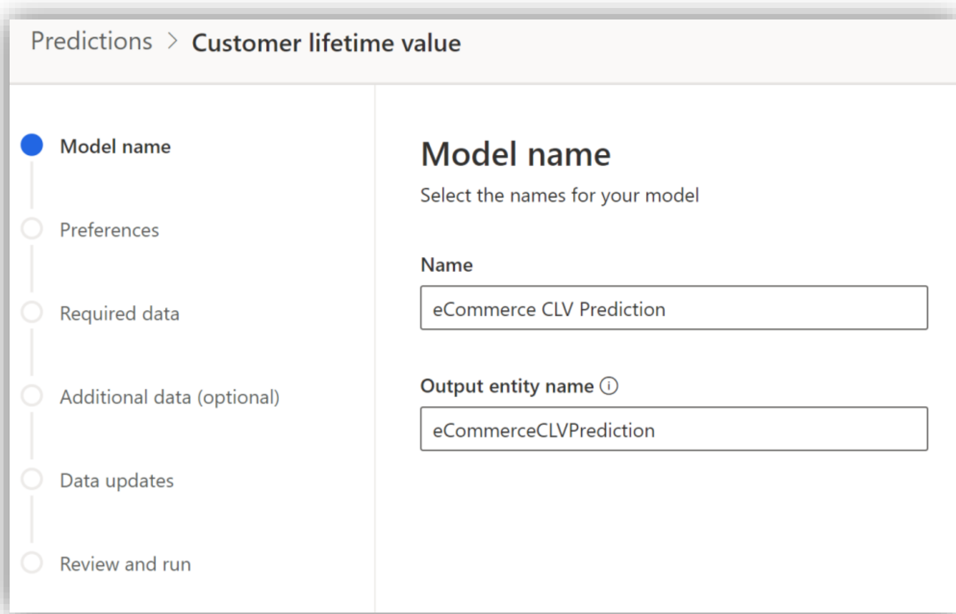
Task 1: Configuring the OOB Customer Lifetime Value prediction

1. Go to **Intelligence** and then **Predictions.**

2. Go to the **Create** tab and click on the **Use model** button on the **Customer Lifetime Value** card. Click on **Get Started**.



3. Name the model **eCommerce CLV Prediction** and the output entity name **eCommerceCLVPrediction.**

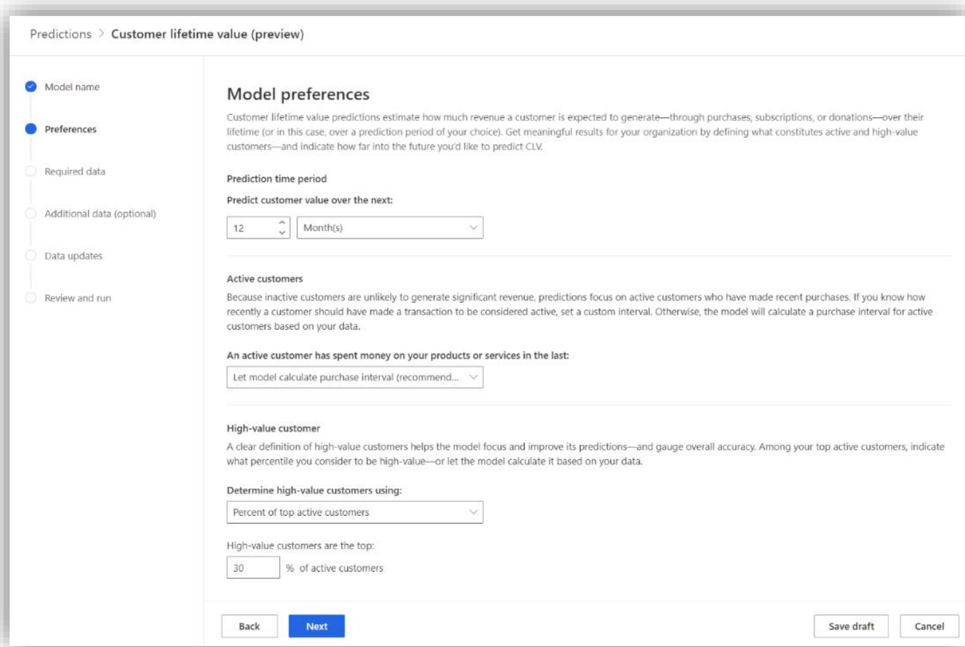


4. Configure **Model Preferences:**

a. **Prediction time period:** This setting defines how far into the future do we want to predict customer lifetime value. Select **1 year.**

b. **Active customers:** Specify what **Active customers** mean for your business. Select **Let model calculate purchase interval**.

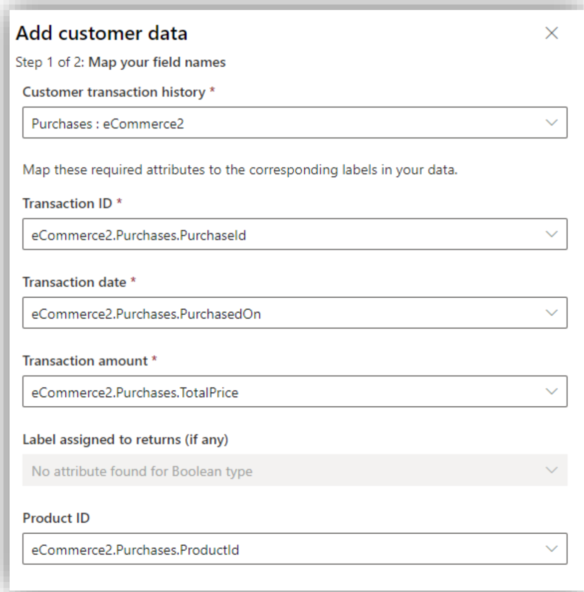
c. **High value customers:** Define High value customers as a percentile of top-paying customers – the model uses this input to provide results that fit your business definition of high value customers. You could choose to rely on the model to define high value customers for your business (the model uses a heuristic rule to derive the percentile of top paying customers for your business) or you could define high value customers in terms of a percentile of top future paying customers. For this scenario, we will **define high value customers as top 30% of active paying customers**.



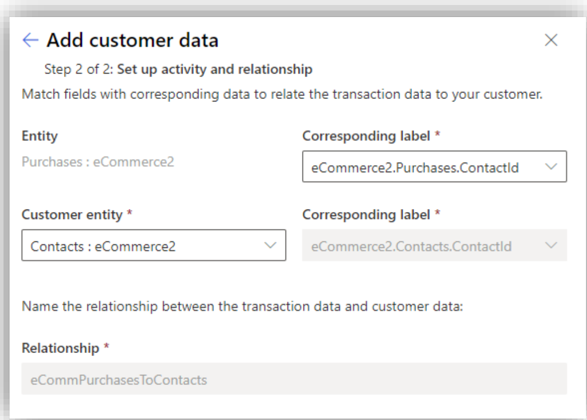
5. Next, in the **Required data** step, select **Add data**. This is where you map the required customer transaction history data for the model.

6. Set the values as defined below, then click **Next**

   - Customer transaction history: **Purchases : eCommerce**
   - Transaction ID: **PurchaseId**
   - Transaction date: **PurchasedOn**
   - Transaction amount: **TotalPrice**
   - Product ID: **ProductId**

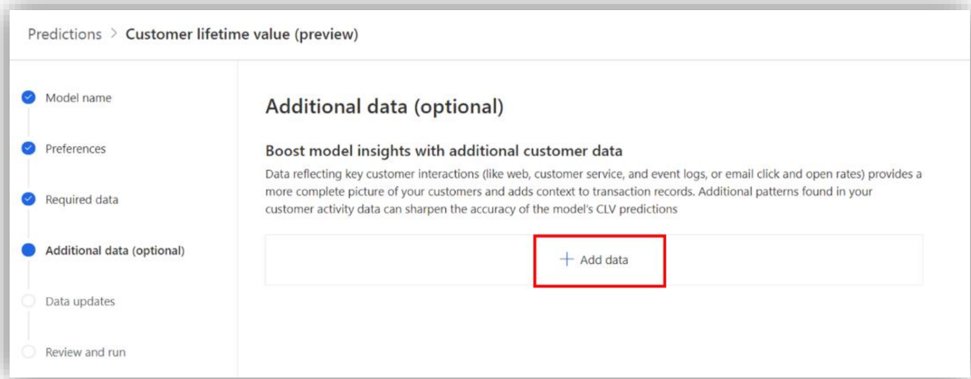


7. Join the **Purchases : eCommerce** entity with **Contacts : eCommerce** on **ContactId**, then **Save**. This may already be done for you based on relationships defined in the system already.



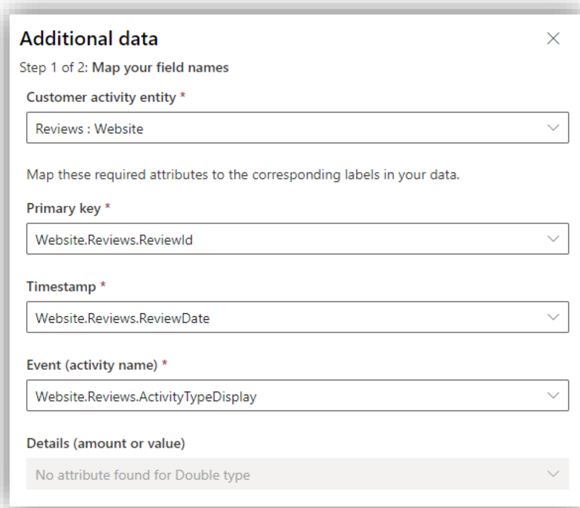
8. Click **Next**

9. Next, the **Additional data (optional)** step allows you to add any other customer activity data that would help provide a holistic view of your customers' interactions with your business. Adding key customer interactions like web logs, customer service logs, rewards program history, email click history, etc can improve the accuracy of predictions.
   Select **Add data** to map additional customer activity data.



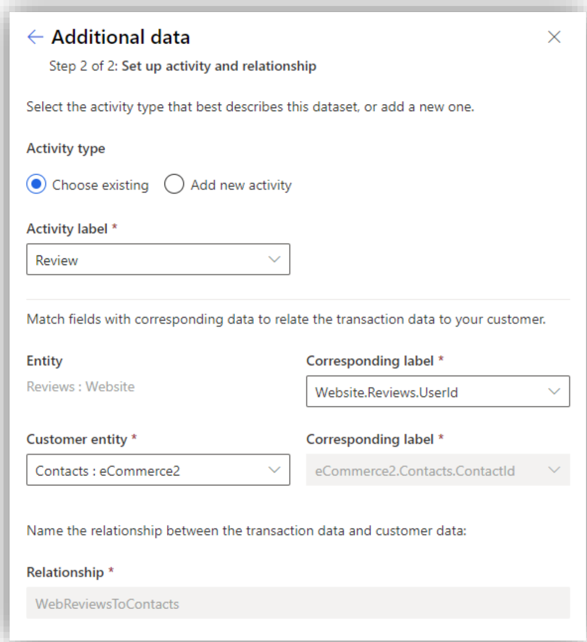
10. Add the **Reviews : Website** Entity and map the fields from the entity to the corresponding fields required by the Model. Click on **Next** when done.

    - Primary key: **ReviewId**
    - Timestamp: **ReviewDate**
    - Event: **ActivityTypeDisplay**



11. Since we have mapped website reviews data, select the **Choose existing** option under **Activity Type** and select **Review** as the **Activity label** from the dropdown.

12. Next, configure the relationship from the **Reviews : Website** entity to the **Contacts : eCommerce** entity by mapping the **UserId** column in the Reviews entity to the **ContactId** column in eCommerceContacts entity as shown below and click on **Save**. This may already be done for you based on relationships defined in the system already.



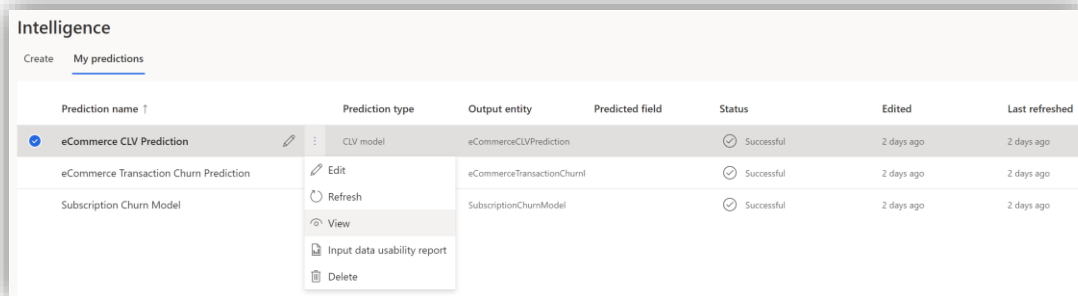
13. Click on **Next** to set the model Schedule. The model needs to train with certain frequency so that it learns new patterns when there is new data ingested. For this example, select **Monthly** and click on **Next**.

14. After reviewing all the details in the next screen, click on **Save and Run.**

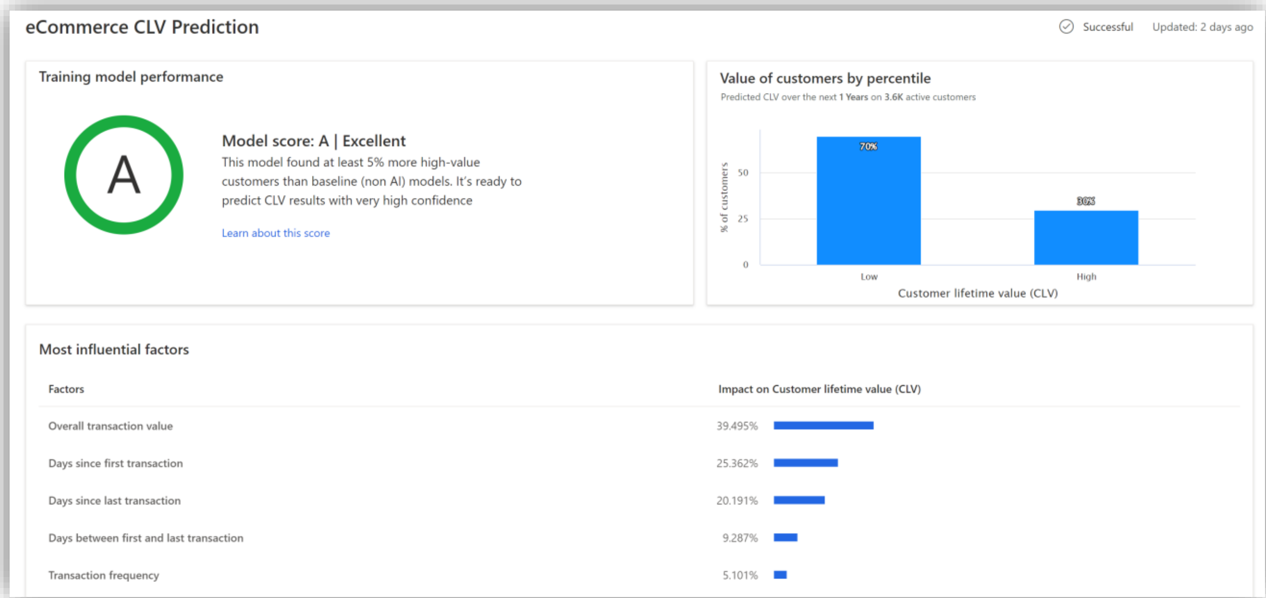
    Note: The model can take some time to finish running.

Task 2 – Visualize Model Training Results and Explanation

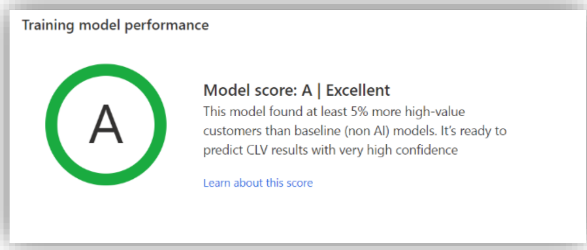
After the model has successfully completed the training and scoring of the data, you can view the Customer Lifetime Value Model Results page by clicking on the Prediction Name, **eCommerce CLV Prediction,** or selecting **View** after clicking on the ellipses next to the prediction name or simply clicking on the model prediction name.



Model Results and Explanation page



Training Model Performance



A, B, or C are possible grades. This grade indicates the performance of the prediction and can help you make the decision to use the results stored in the output entity.
Using the definition of high value customers provided while configuring the prediction, the system assesses how the AI model performed in predicting the high value customers as compared to a baseline model.

Grades are determined based on the following rules:

- **A** when the model accurately predicted at least 5% more high-value customers as compared to the baseline model.
- **B** when the model accurately predicted between 0-5% more high-value customers as compared to the baseline model.
- **C** when the model accurately predicted fewer high-value customers as compared to the baseline model.

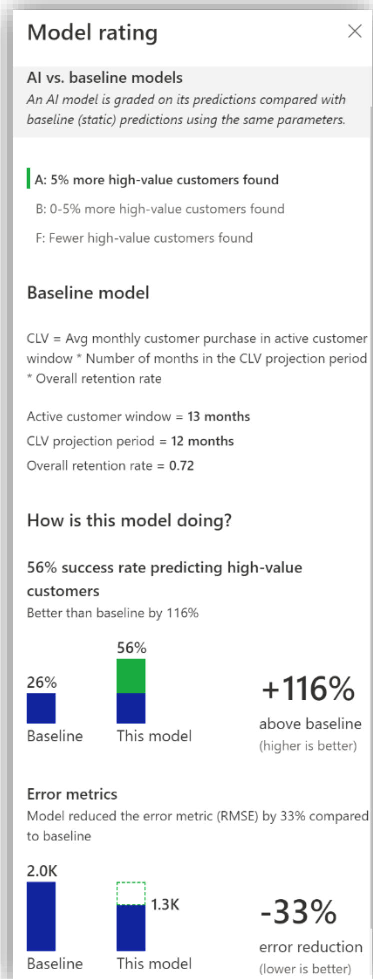
Select **Learn about this score** to understand in more detail the underlying model performance metrics.

The **Model rating** pane shows further details about the AI model performance and the baseline model. The **baseline model** uses a non-AI based approach to calculate customer lifetime value which is based primarily on historical purchases made by customers.

The standard formula used to calculate CLV by the baseline model is:

CLV for each customer *= Average monthly purchase made by the customer in the active customer window * Number of months in the CLV prediction period * Overall retention rate of all customers*

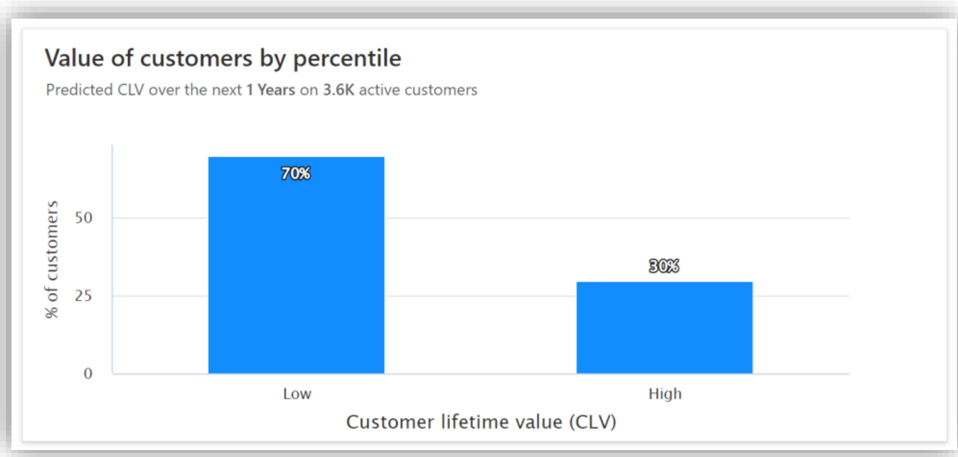
The AI model is compared to the baseline model based on two model performance metrics.



- **Success rate in predicting high-value customers**
  This metric shows the difference in predicting high-value customers using the AI model compared to the baseline model. For example, 33% success rate means that out of all the high-value customers (based on your definition as specified in model preferences), the AI model was able to accurately capture 33%. This is then compared with the success rate of the baseline model (26% in this case) to report the relative change (+24%). The relative change (in percentage) is then used to assign a grade to the model.

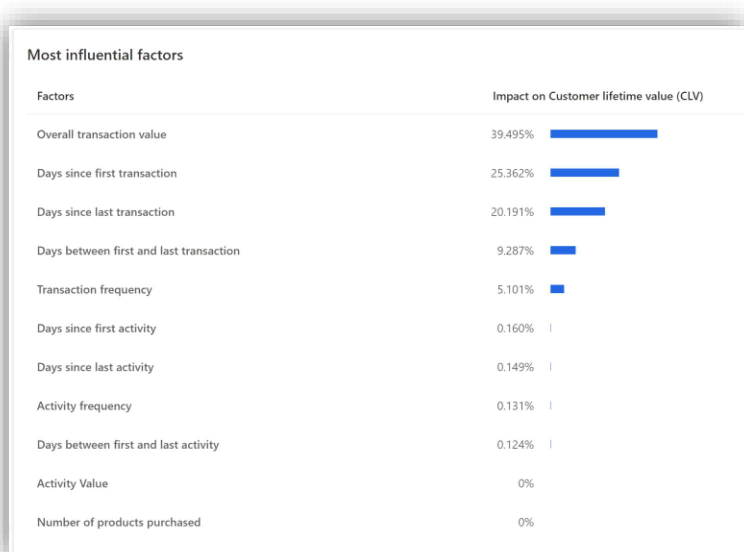
- **Error metrics**
  Another metric lets you review the overall performance of the model in terms of error in predicting future values. The overall Root Mean Squared Error (RMSE) metric is a standard way to measure the error of a model in predicting quantitative data. The AI model's RMSE is compared to the RMSE of the baseline model and the relative difference is reported. In this case, the AI model was able to reduce the overall RMSE by 14% as compared to the baseline model.

Value of customer by percentile:



Using your definition of high-value customers, customers are grouped into **low-value** and **high-value**, based on their CLV predictions, and shown in the above chart. By hovering over the bars in the histogram, you can see the number of customers in each group and the average CLV of that group. This data can be helpful if you want to create segments of customers based on their CLV predictions.

Most influential factors:


Most influential factors

Factors	Impact on Customer lifetime value (CLV)
Overall transaction value	39.495%
Days since first transaction	25.362%
Days since last transaction	20.191%
Days between first and last transaction	9.287%
Transaction frequency	5.101%
Days since first activity	0.160%
Days since last activity	0.149%
Activity frequency	0.131%
Days between first and last activity	0.124%
Activity Value	0%
Number of products purchased	0%

Numerous factors are considered when creating your CLV prediction based on the input data provided to the AI model. The most influential factors that impacted the CLV predictions at an aggregate level (across all customers) is reported along with their percentage impact on the predictions. You can use these factors to help validate your prediction results.

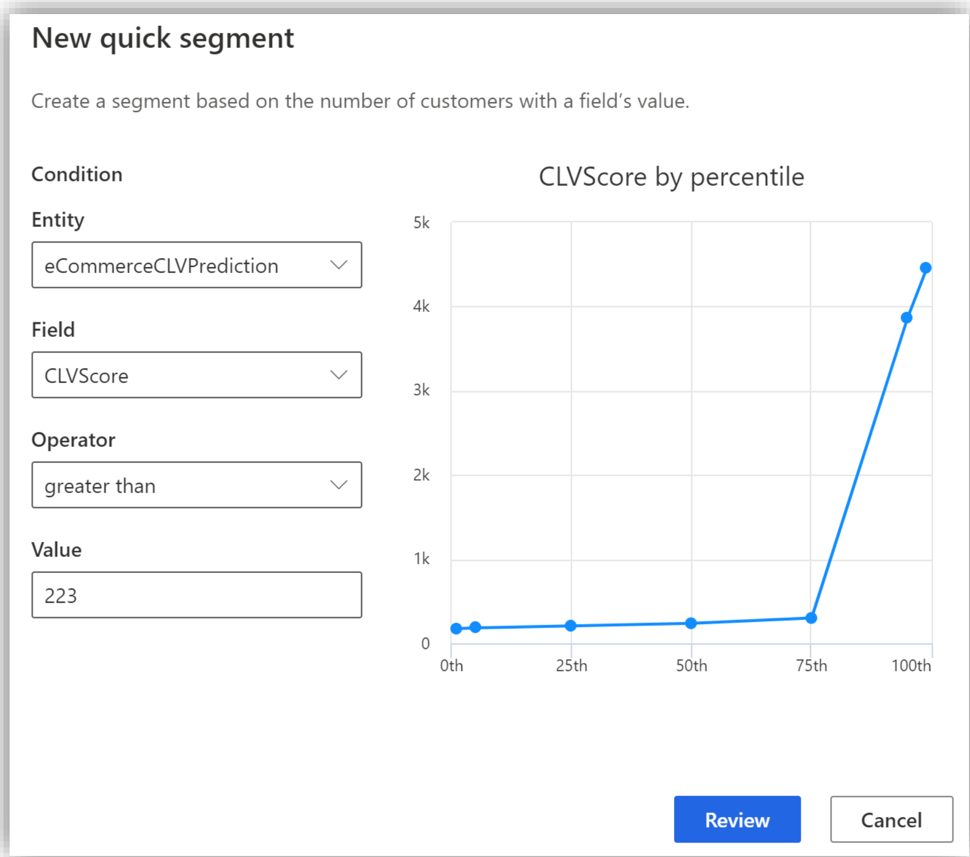
Task 3 – Create a segment of high value customers

Running the production model creates a new entity that you can see in **Data -> Entities -> Intelligence -> eCommerceCLVPrediction**.
Now create a new segment based on the entity created by the model.

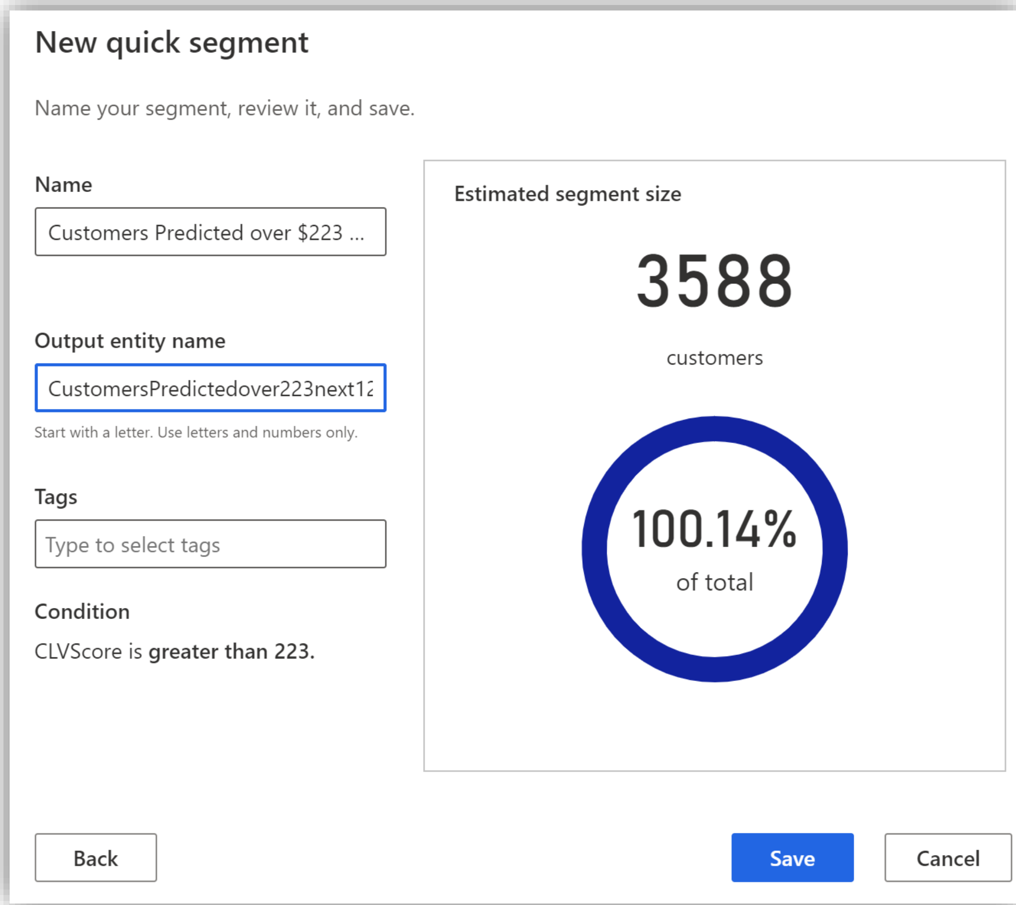
1. Go to **Segments**, select **New** and choose **Create from Intelligence**.

2. **Select** the **eCommerceCLVPrediction** entity and define the segment as follows:

   - Field: **CLVScore**
   - Operator: **greater than**
   - Value: **223**



3. Click **Review**, name the segment **Customers Predicted over $223 next 12 months** and **Save** the segment.



You now have a segment that is dynamically updated which identifies high value customers (customers that are predicted to generate more than $223 of revenue in the next 12 months).