



Dynamics 365 Customer Insights

Lab 4: Intelligence



Contents

| | |
|--|----|
| Module Introduction | 3 |
| Out of the Box (OOB) models | 3 |
| Objectives | 3 |
| Prerequisites..... | 3 |
| Approximate Time - 45 mins..... | 3 |
| Exercise 1 – Transaction Churn Model | 4 |
| Task 1 – Run the OOB Transaction Churn Model | 4 |
| Task 2 – Create a Segment of High Churn-Risk Customers..... | 9 |
| Optional – Building OOB Subscription Churn Model | 10 |
| Task 1 – Ingest the Subscription Data..... | 10 |
| Task 2 – Unify the Subscription Data with Existing Data | 14 |
| Task 3 – Create a Subscription Activity..... | 16 |
| Task 4 – Create a UserLog Activity | 19 |
| Task 5 - Building Subscription Churn Model..... | 21 |
| Task 6 – Set up a Segment of High Churn-risk Users | 26 |
| Optional - Customer Lifetime Value (CLV) Prediction Tasks..... | 27 |
| Task 1: Configuring the OOB Customer Lifetime Value prediction | 27 |
| Task 2 – Visualize Model Training Results and Explanation | 32 |
| Model Results and Explanation page | 32 |
| Task 3 – Create a segment of high value customers..... | 36 |



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

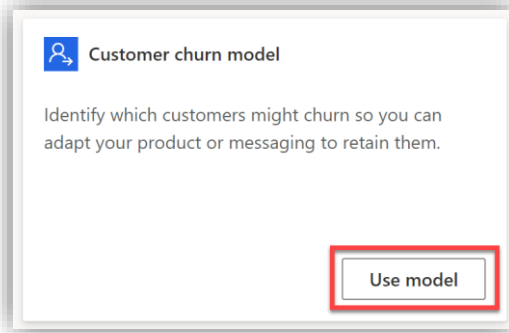
Approximate Time - 45 mins



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**



Add data ×

Step 1 of 2: Select activities

Customer transaction history
Select the activity that contains your template entity. If you haven't set up one in Activities, you'll need to do that [here](#).

SalesOrder ▼

Activities
Choose the activities you'd like the calculation to focus on.

☐ Purchases : PoS [Edit](#)

☒ Purchases : eCommerce [Edit](#)

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

Add data ×

Step 1 of 2: Select activities

Customer activity entity
Select the activity that contains your template entity. If you haven't set up one in Activities, you'll need to do that [here](#).

WebsiteReview ▼

Activities
Choose the activities you'd like the calculation to focus on.

☒ Reviews : Website [Edit](#)

☐ Purchases : PoS [Edit](#)

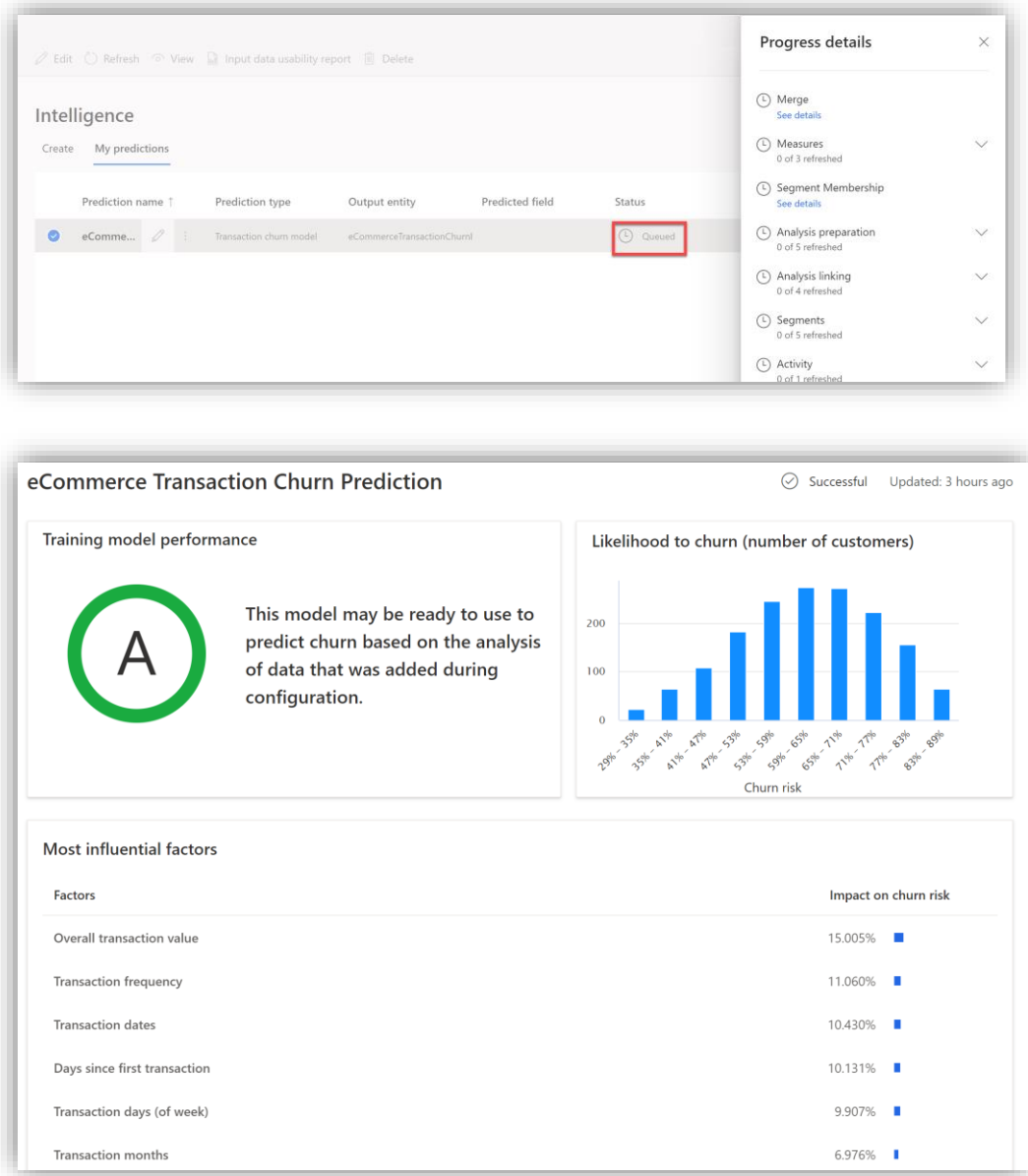
11. Click **Next**, leave the defaults selected and click **Save**

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:

A 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.

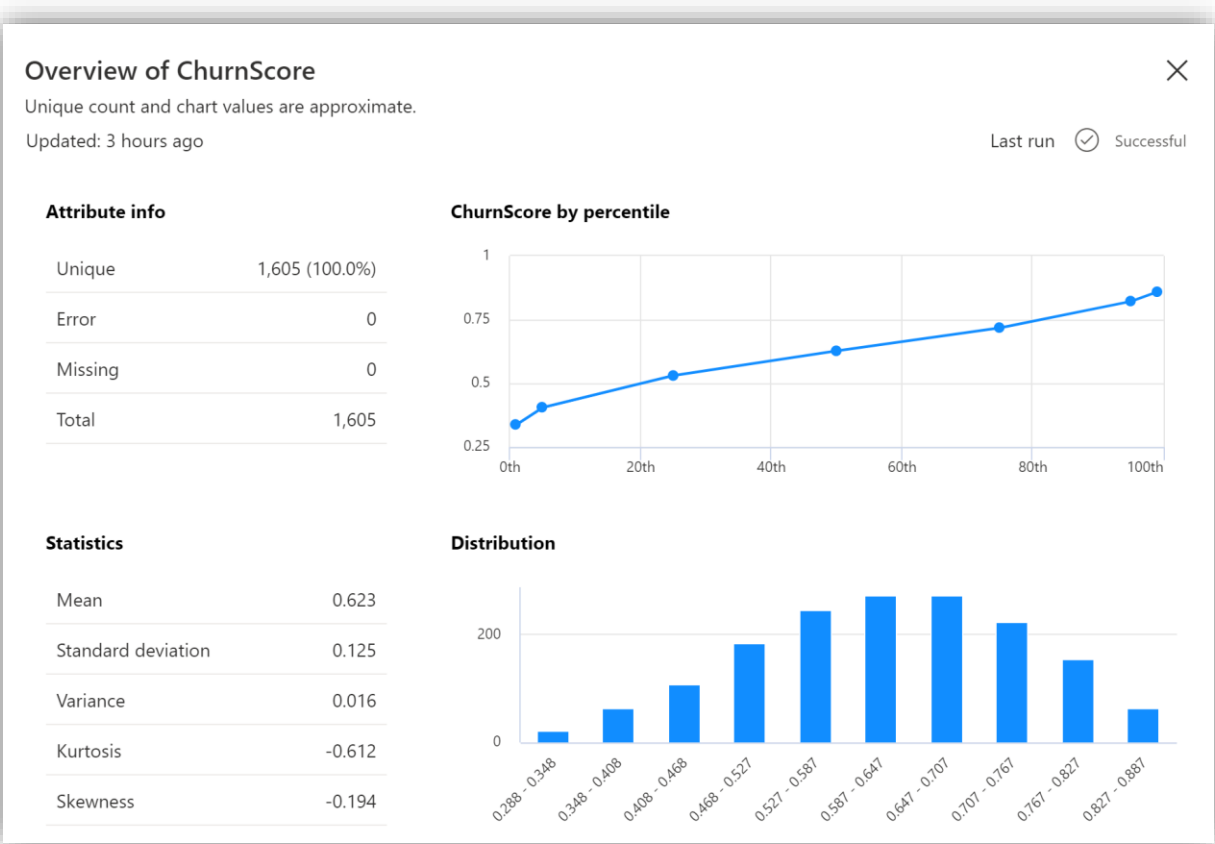
Most Influential Factors

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

| Attributes <u>Data</u> | | | |
|----------------------------------|------------|---------|-----------------------|
| 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 |
| 03f1e6d64c05308f37a02fcb7e79078 | 0.838 | True | 4/29/2022, 6:16:27 PM |
| 040014b78830679e9b2b001e7c93616 | 0.72 | True | 4/29/2022, 6:16:27 PM |
| 047feabf29d5a7a98d9510d54282eb7a | 0.595 | True | 4/29/2022, 6:16:27 PM |

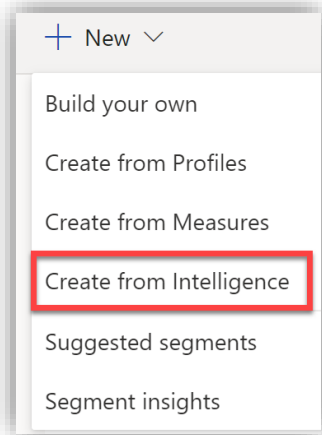
17. Click on **Attributes** and then the mini graph under the **Summary** column for **ChurnScore** to see an overview





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**

The screenshot shows the 'New quick segment' form with the following details:

- Name:** High Risk Transaction Churn
- Output entity name:** HighRiskTransactionChurn
- Tags:** Type to select tags
- Condition:** ChurnScore is greater than .6.
- Estimated segment size:** 986 customers, 61.43% of total
- Buttons:** Back, Save (highlighted with a red box), Cancel



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**

Choose your import method

☒ Microsoft Power Query
Files, databases, Microsoft Azure services, third-party online services, and on-premise data (gateway required)
[Learn more](#)

☐ Azure Synapse Analytics (Preview)
Get data from Azure Synapse Analytics

☐ Azure data lake storage
Azure Data Lake storage accounts
[Learn more](#)

☐ Microsoft Dataverse
Data sets in the Common Data Service data lake
[Learn more](#)

☐ Customer Insights data library
Get data from Datahub catalog

Data stored in an online service such as Azure Data Lake Storage may be stored in a different location than where data is processed or data can be transferred to, and stored with, Dynamics 365 Customer Insights. Learn more at the [Microsoft Trust Center](#)

Provide a name to identify your data source.

Save data source as: *

SubscriptionData

Use both letters and numbers—no spaces or special characters (3-64 characters).

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

Choose data source


Select a connector or directly drag a file from your computer.

All categories | File | Database | Power Platform | Azure | Online services | Other

Search

| | | | | | |
|---|--|---------------------------------------|--|---------------------------------------|---|
| Excel workbook File | Folder File | JSON File | PDF File | Parquet File | SharePoint folder File |
| Text/CSV File | XML File | Access Database | Amazon Redshift Database | Google BigQuery Database | IBM Db2 database Database |
| Impala Database | MySQL database Database | Oracle database Database | PostgreSQL database Database | SAP BW Application Server Database | SAP BW Message Server Database |
| SAP HANA database Database | SQL Server Analysis Services Database | SQL Server database Database | Snowflake Database | Teradata database Database | Azure Analysis Services Azure |
| Azure Blobs Azure | Azure Data Explorer (Kusto) Azure | Azure Data Lake Storage Gen2 Azure | Azure HDInsight Spark Azure | Azure SQL database Azure | Azure Synapse Analytics (SQL DW) Azure |
| Azure Tables Azure | Adobe Analytics Online services | Google Analytics Online services | Microsoft Exchange Online Online services | Salesforce objects Online services | Salesforce reports Online services |
| SharePoint Online list Online services | FHIR Other | OData Other | Odbc Other | SharePoint list Other | Spark Other |
| Web API Other | Web page Other | Dataflows Power Platform | Dataverse Power Platform | Blank table Other | Blank query Other |

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




Text/CSV File

Connection settings

File path or URL

Connection credentials

On-premises data gateway

(none) 

Authentication kind

Anonymous

4. Click **Transform data**

https://aka.ms/CI-ILT/Contacts

File origin: 85001: Unicode (UTF-8) | Delimiter: Comma | Data type detection: Based on first 200 rows

| Column1 | Column2 | Column3 | Column4 | Column5 | Column6 | Column7 | Column8 | Column9 | Column10 | Column11 |
|---------------------------------|-----------|----------|------------------|-------------|---------|---|-----------------------|----------|---------------------------------|-----------|
| ContactId | FirstName | LastName | FullName | DateOfBirth | Gender | Email | Telephone | PostCode | StreetAddress | City |
| CNTID_1000 | Abbie | Moss | Abbie Moss | 5/8/1986 | Female | abbie_moss@collinsreedandhoward.com | 983.566.0706/9509 | 10753 | 129 Miller Place | Fairfield |
| CNTID_1001 | Kenneth | Beraun | Beraun Kenneth | 8/1/1974 | Male | kenneth_beraun@kimboyle.com | 384.995.7852 | 45482 | 9720 William Penn | Annapolis |
| CNTID_1002 | Anthony | Koteles | Anthony Koteles | 8/28/1975 | Male | anthony_koteles@crawfordsimmonsandgreene.c... | 569.626.5660 | 28879 | 3964 Forest Lakes Suite 276 | Highland |
| CNTID_1003 | Michael | Lauzer | Michael Lauzer | 9/3/2006 | Male | michael_lauzer@earthlink.com | 001-811-506-2553x442 | 89891 | 15091 Haynes Road | Nashville |
| CNTID_1004 | Richard | Nakade | Nakade Richard | 7/30/1987 | Male | michael_nakade@jonesdineandmccoy.com | 657-147-6531 | 78889 | 3501 Thornton Road | West Co |
| NAKADE5-6646e911afac-0003a3a357 | Robert | Kaucher | Kaucher Robert | 3/8/1989 | Male | robert_kaucher@stevenshansen.com | 334707637 | 47410 | 3012 Hards Greens Apt. 427 | Costa M |
| CNTID_1006 | Steven | Bond | Steven Bond | 9/20/2018 | Male | steve_bond@bushnellandsondall.com | 0075491-4908 | 11013 | 873 Walker Motorway | Surgeon |
| CNTID_1007 | Michael | Morre | Morre Michael | 1/8/1979 | Male | michael_morre@earthlink.com | 007384-990487342 | 65361 | 059 Green Port | Darden |
| CNTID_1008 | Michael | Genna | Michael Genna | 1/3/1998 | Male | michael_genna@earthlink.com | 787090373 | 14476 | 8963 Harris Mays Suite 146 | Doctor |
| CNTID_1009 | James | Eder | James Eder | 6/9/1984 | Male | james_eder@wiscorsyandsonandchat.com | 001-848-959-4245x1045 | 23103 | 160 Joseph Passage Apt. 791 | Minneap |
| CNTID_1010 | Thomas | Howley | Thomas Howley | 9/7/1972 | Male | thomas_howley@earthlink.com | 193-119-5862 | 84262 | 8701 Colum Groves | Daly City |
| CNTID_1011 | Paul | Howell | Paul Howell | 6/26/2001 | Male | paul_howell@bushnellandsondall.com | 140-123-0209/9638 | 72838 | 16446 Menlo Park | Visalia |
| CNTID_1012 | William | Loehorn | William Loehorn | 5/22/1982 | Male | william_loehorn@daymurrayandbenes.com | 655-423-0815/0881 | 20334 | 520 Gray Freeway Apt. 876 | Pearland |
| CNTID_1013 | William | Belles | William Belles | 6/28/1974 | Male | william_belles@robbsandsons.com | 345-478-4615/0286 | 20728 | 09538 Carroll Overpass | Stanford |
| CNTID_1014 | Anthony | Acts | Anthony Acts | 10/6/1978 | Male | anthony_acts@ericksonwright.com | 857-788-9579/7724 | 36330 | 36332 Jessica Bridge | Kent |
| CNTID_1015 | Edward | Orndorff | Edward Orndorff | 10/3/1982 | Male | edward_orndorff@jonesdineandmccoy.com | 440-586-4261/0683 | 74413 | 9795 Alice Camp | Hampton |
| CNTID_1016 | Ronald | Berning | Berning Ronald | 11/12/2005 | Male | ronald_berning@protonmail.com | 650-475-7053/4815 | 64711 | 62123 Padilla Rue Apt. 903 | West Val |
| CNTID_1017 | Daniel | Valme | Daniel Valme | 4/12/1972 | Male | daniel_valme@earthlink.com | 001-446-175-3858x41 | 90046 | 094 Parker Hollow Apt. 619 | Springfi |
| CNTID_1018 | Michael | Muskthal | Muskthal Michael | 12/15/1977 | Male | michael_muskthal@earthlink.com | 999-434-0395 | 25452 | 269 Charles Stream | Waco |
| CNTID_1019 | Brian | Dennis | Brian Dennis | 12/4/1970 | Male | brian_dennis@jonesdineandmccoy.com | 0071745-3446/8823 | 80110 | 2633 Newmanster Club Suite 307 | Charmes |
| CNTID_1020 | Donald | Hram | Donald Hram | 10/12/2000 | Male | donald_hram@earthlink.com | 231-9003704963 | 53865 | 29419 Michelle Walk | Sandy Sp |
| CNTID_1021 | Richard | Dumancia | Richard Dumancia | 12/5/1979 | Male | richard_dumancia@earthlink.com | 887080-4870/4640 | 56173 | 17752 Joshua Knoll Suite 206 | Pomona |
| CNTID_1022 | George | Deang | George Deang | 4/22/1980 | Male | george_deang@bushnellandsondall.com | 963-170-7317/05125 | 51501 | 541 Adams Flats | Temecula |
| CNTID_1023 | Daniel | Pross | Daniel Pross | 2/28/1979 | Male | daniel_pross@stevenshansen.com | 029-882-7724/6839 | 23400 | 145 Hardin Village Suite 503 | Annapolis |
| CNTID_1024 | Joseph | Bent | Joseph Bent | 7/15/1982 | Male | joseph_bent@earthlink.com | 940-153-7561 | 12648 | 617 Parker Corner | New Has |
| CNTID_1025 | Edward | Dobler | Edward Dobler | 11/14/2015 | Male | edward_dobler@bushnellandsondall.com | 074-321-4131 | 20680 | 743 Bennett Loop Apt. 997 | Chowche |
| CNTID_1026 | Robert | Chalmers | Robert Chalmers | 5/2/1985 | Male | robert_chalmers@bushnellandsondall.com | 656-985-6577/001 | 95785 | 338 Ruiz Mount | Victorvil |
| CNTID_1027 | Richard | Ali | Ali Richard | 7/29/2015 | Male | richard_ali@earthlink.com | 077304-7794 | 30737 | 83349 Kevin Stranewer Suite 217 | Vista |

Back Cancel Transform data

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

Home Transform Add column View

Get data Enter data Options Manage parameters Refresh Advanced editor Choose columns Remove columns Keep rows Remove rows Sort Split column Group by Data type: Text Use first row as headers Merge queries Append queries Combine files Map to entity CDM

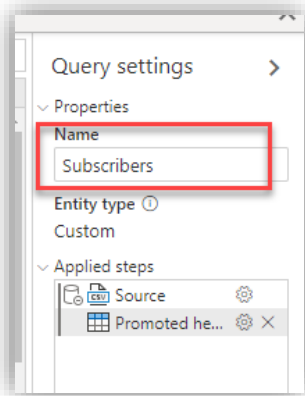
Queries

Query = Csv.Document(Web.Contents("https://aka.ms/CI-ILT/Contacts"), [Delimiter = ",", Columns = 15, Encoding = 65001, QuoteStyle = ...])

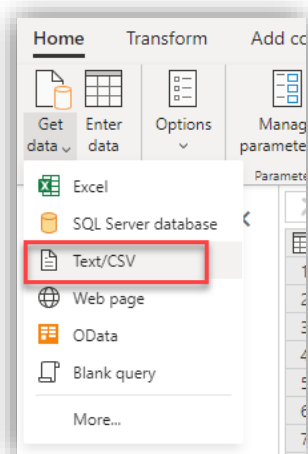
| Column1 | Column2 | Column3 | Column4 | Column5 | Column6 | Column7 | Column8 |
|-----------|-----------|----------|-----------------|-------------|---------|---|----------------------|
| ContactId | FirstName | LastName | FullName | DateOfBirth | Gender | Email | Telephone |
| 1 | Abbie | Moss | Abbie Moss | 5/8/1986 | Female | abbie_moss@collinsreedandhoward.com | 983.566.0706/9509 |
| 2 | Kenneth | Beraun | Beraun Kenneth | 8/1/1974 | Male | kenneth_beraun@kimboyle.com | 384.995.7852 |
| 3 | Anthony | Koteles | Anthony Koteles | 8/28/1975 | Male | anthony_koteles@crawfordsimmonsandgreene.c... | 569.626.5660 |
| 4 | Michael | Lauzer | Michael Lauzer | 9/3/2006 | Male | michael_lauzer@earthlink.com | 001-811-506-2553x442 |



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**



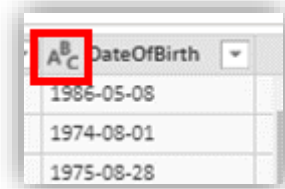
8. Click **Get Data**, then choose **Text/CSV**



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**.

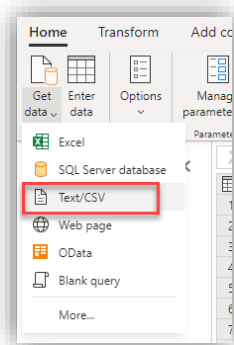
12. Set the datatypes for non-text columns. Click the **ABC** icon within the column heading. Update the datatype for the columns listed below.

| 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**



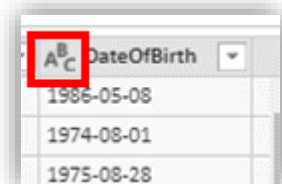
15. Enter the URL for the Userlog data set, <https://aka.ms/CI-ILT/Userlogs>, and click **Next**.

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**

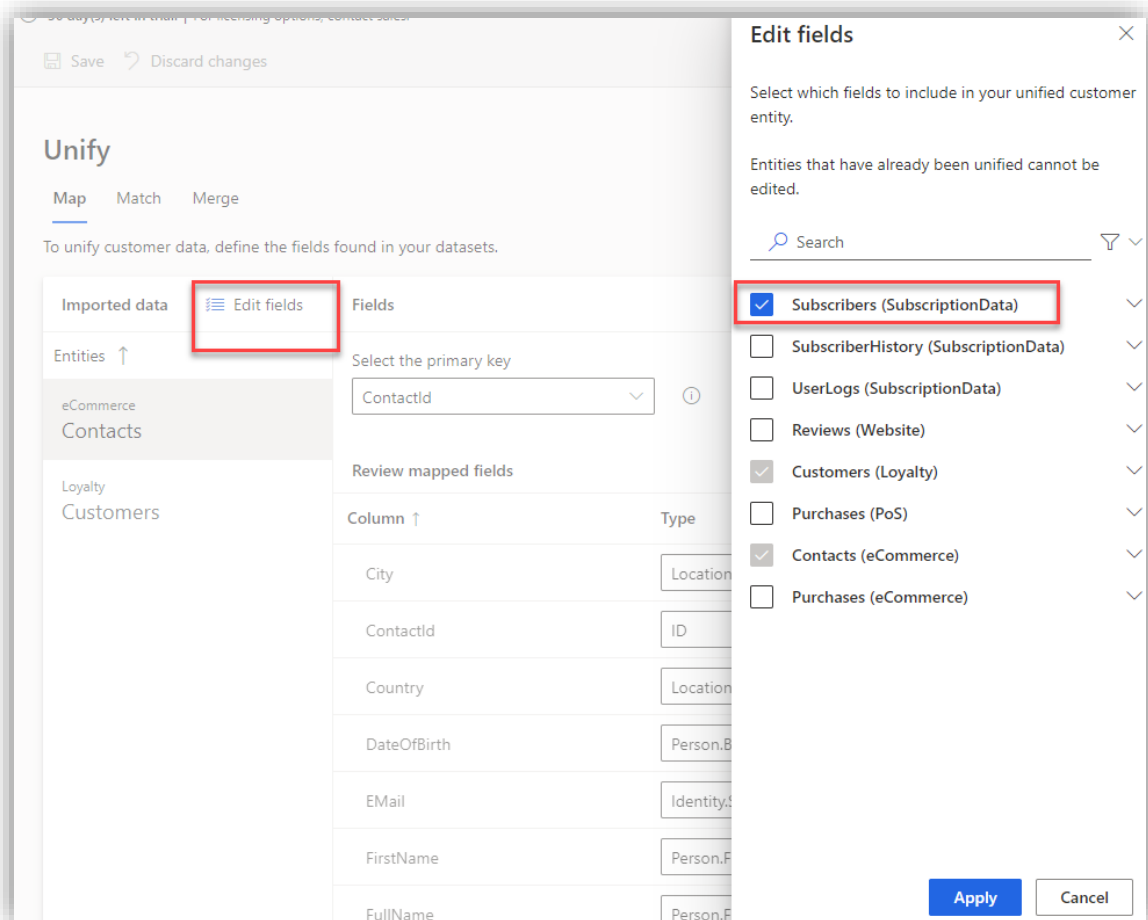
20. Leave the refresh schedule set to **Refresh manually** and click **Save**



Task 2 – Unify the Subscription Data with Existing Data

When the data source is finished loading you need to Unify it. This can take a while as there is a lot of data in the SubscriptionData 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

View last run

Matched records details

+ Add entity | Custom match | **Edit**

| Order | Name | Source records | Unique records | Records matched | Include all records |
|-----------------|----------------------|----------------|----------------|-----------------|---------------------|
| 1 | eCommerce : Contacts | 5,002 | 5,002 | | ✓ |
| 2 | Loyalty : Customers | 5,002 | 5,002 | 99.0% matched | ✓ |
| FullName, Email | | | | 99.0% | |

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:

Create rule ×

Make a rule for how to handle duplicate data by setting conditions that compare fields from differing entities. [Learn more](#)

Conditions

Condition 1

Select entity: Contacts : eCommerce | Select field: ContactId

Entity: Subscribers : SubscriptionData | Select field: ContactId

Precision: Basic | Exact

Name *: ContactId

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**

Set up your activity data

Choose which entity contains relevant activity data, then choose a field to be the primary key that will identify that entity. All fields are required.

Activity name

Subscription

Start with a letter. Use letters and numbers only.

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**
 - Relationship name: **SubscribersToSubscriptions**

Add relationship path

Select the entity that you want to connect to the activity entity "SubscriberHistory : SubscriptionData".

Relationship

Foreign key from SubscriberHistory : Sub...

CustomerID

To entity name

Subscribers : SubscriptionData

Primary key ContactId

Relationship name

SubscribersToSubscriptions

Start with a letter. Use letters and numbers only.



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**

Unify your customer activity data

Map your activity data to these fields to include it in unified customer data:

Event activity *

SubscriptionType

Timestamp *

TransactionDate

Additional detail

Select field

Icon

Select an icon

Web address

Select field

Show this information in the timeline view on your customer profiles?

If you choose not to, you'll still be able to export the activity data via the unified activity entity to other platforms or services.

☒ Yes ☐ No

Example timeline view

Activity Timeline Filter

5 SubscriberHistory

JUL 2021 (5)

SubscriptionType - 7/31/2021, 12:00 AM

SubscriptionType - 7/30/2021, 12:00 AM

SubscriptionType - 7/28/2021, 12:00 AM

SubscriptionType - 7/25/2021, 12:00 AM

SubscriptionType - 7/21/2021, 12:00 AM

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**

Semantic mapping helps the system better understand the meaning and relevance of your activity data.

☒ Yes ☐ No

Now map your data to the activity type's related fields:

Transaction ID *

SubscriptionID

Transaction date *

TransactionDate

Subscription ID *

SubscriptionID

Subscription start date *

SubscriptionStartDate

Subscription end date *

SubscriptionEndDate

Subscription type

Select field

Subscription amount

Select field

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**

Set up your activity data

Choose which entity contains relevant activity data, then choose a field to be the primary key that will identify that entity. All fields are required.

Activity name

Start with a letter. Use letters and numbers only.

Entity

Primary key

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

Relationship

Foreign key from Userlogs : Subscription...

↓

To entity name

└ Primary key ContactId

Relationship name

Start with a letter. Use letters and numbers only.

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**

The screenshot shows a configuration window titled "Unify your customer activity data" with a subtitle "Map your activity data to these fields to include it in unified customer data:". The window contains several dropdown menus: "Event activity *" (set to "Category"), "Timestamp *" (set to "TransactionDate"), "Additional detail" (set to "TransactionName"), "Icon" (set to "Select an icon"), and "Web address" (set to "Select field"). Below these is a section "Show this information in the timeline view on your customer profiles?" with a note "If you choose not to, you'll still be able to export the activity data via the unified activity entity to other platforms or services." and two radio buttons, "Yes" (selected) and "No". To the right, an "Example timeline view" shows a list of activity items, each with a purple circle icon, the text "Category - [date], [time] AM", and "TransactionName". The items are grouped under "JUL 2021 (5)".

7. Click **Next**

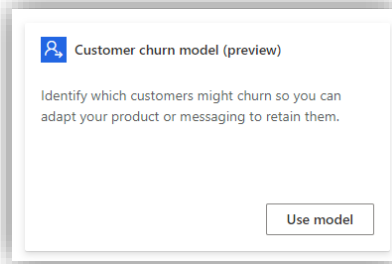
8. Set activity type to **Other**

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**.

Define your customer churn

Specify when you consider a customer has churned by entering the number of days since their subscription ended.

Days since subscription ended

15 days

Days to look into future to predict churn

93 days



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

Add data

Step 1 of 2: Select activities

Subscription history entity

Select the activity that contains your template entity. If you haven't set up one in Activities, you'll need to do that [here](#).

Subscription

Activities

Choose the activities you'd like the calculation to focus on.

☒ SubscriberHistory : SubscriptionData [Edit](#)

?

Cannot find the activity?

Set up additional activities any time in [Data > Activities](#).

Add data

Step 2 of 2: Map attributes

Map these required attributes to the corresponding labels in your data.

SubscriptionId *

SubscriptionId

SubscriptionAmount

SubscriptionAmount

SubscriptionEndDate *

SubscriptionEndDate

SubscriptionStartDate *

SubscriptionStartDate

TransactionDate *

TransactionDate

IsRecurring *

IsRecurring

RecurringFrequencyInMonths *

RecurringFrequencyInMonths



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**

Customer activity entity *

UserLogs : SubscriptionData

Now, tell the model what these required attributes are called in your data set.

Primary key *

CustomerID

Timestamp *

TransactionDate

Event *

TransactionName

Details

Select field

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**

Set up activity type

Choose the activity type that represents your customer activity entity

Activity type

☒ Choose existing ☐ Create new

Choose activity type *

Usage

Set up relationship

Map the field names of your customer and customer activity entity entities.

| | |
|--------------------------------|-------------------------|
| Entity | Field * |
| UserLogs : SubscriptionData | CustomerID |
| Customer entity * | Matching field * |
| Subscribers : Sub ... | ContactId |
| Relationship name * | |
| Logs | |

Start with a letter. Use letters and numbers only.

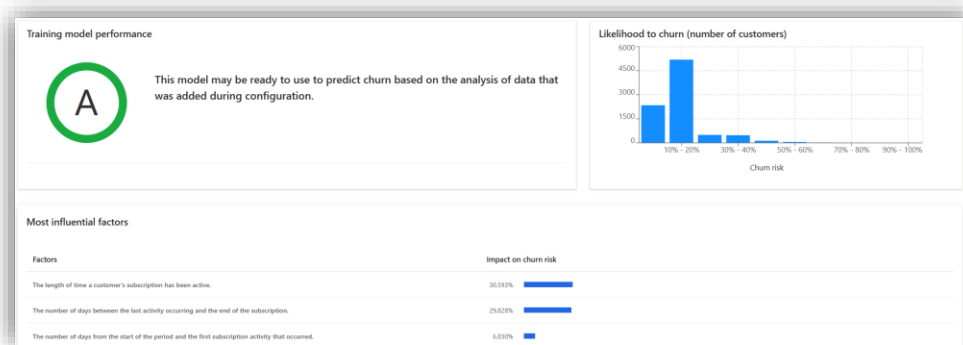


10. Click **Next** and set training schedule as **Monthly** and click **Next**.

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**.



Customer Insights

ChurnCustomersData

Fields Data

| CustomerID | ChurnScore | IsChurn | Timestamp |
|----------------------------------|------------|---------|------------------------------|
| 004da3eda1b64c2dc6de47e4f5e2d... | 0.5087361 | true | 8/25/2020, 10:22:29 PM (UTC) |
| 0374700741be6fa38c2cde510c984f0 | 0.14067686 | false | 8/25/2020, 10:22:29 PM (UTC) |
| 03a8e0eae86ec5503c3ed7aa4d315... | 0.17023982 | false | 8/25/2020, 10:22:29 PM (UTC) |
| 03bbdbf0d86efb7fa93c193581656... | 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) |
| 05323c4c5ec85c52985adc4083a1... | 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:



A 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.

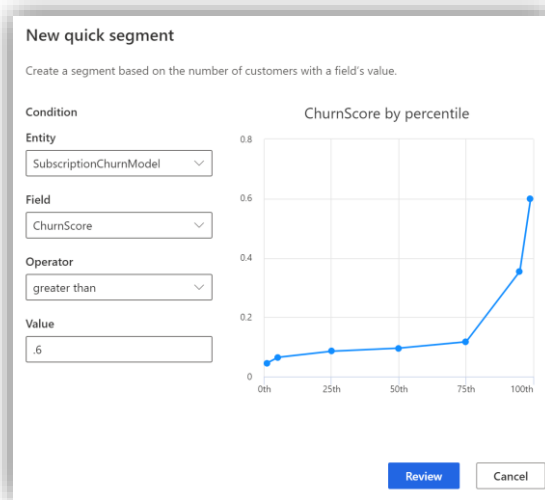


Task 6 – Set up a Segment of High Churn-risk Users

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

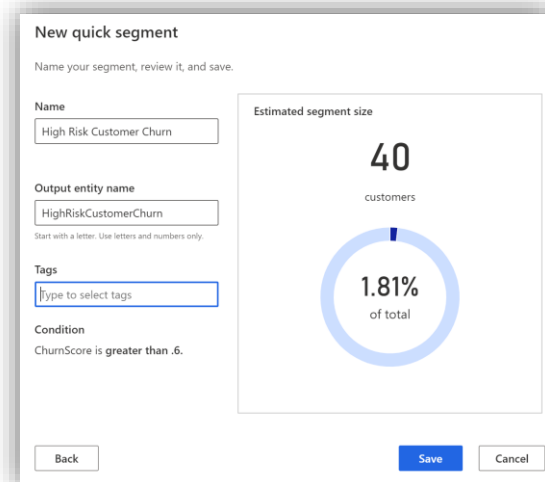
2. Setup your quick segment with these settings:

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



3. Click **Review**

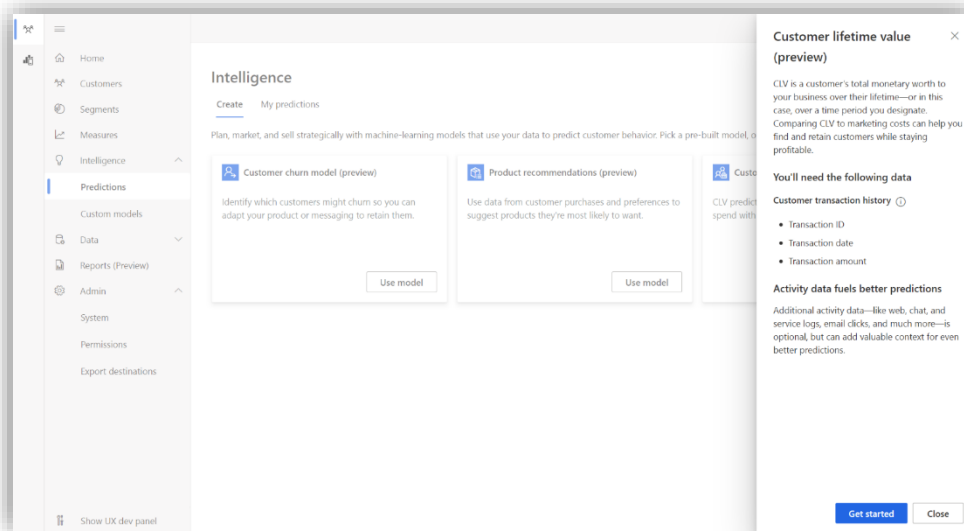
4. Name the segment **High Risk For Subscription Churn** and output entity name **HighRiskForSubscriptionChurn** and click **Save**



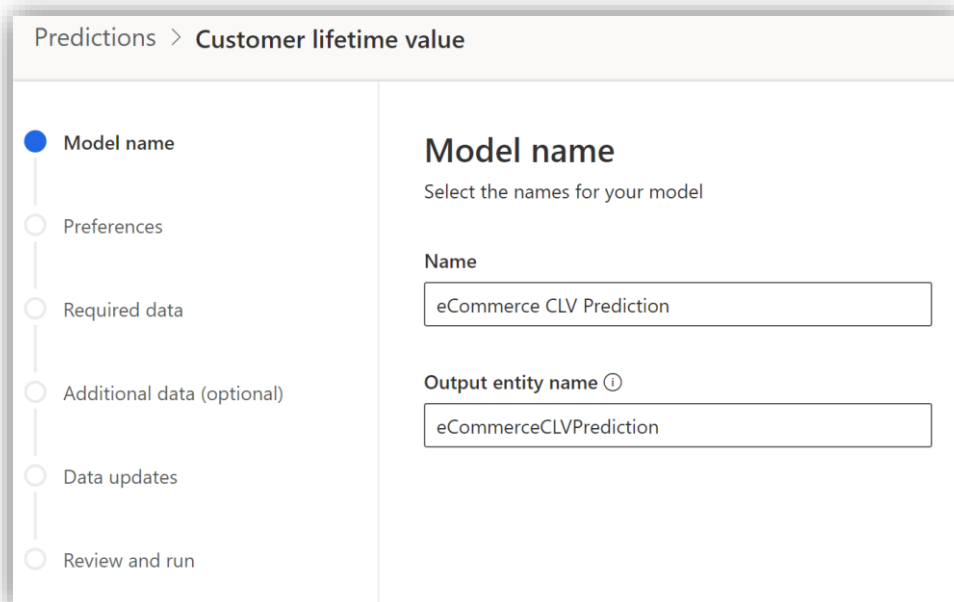
Optional - Customer Lifetime Value (CLV) Prediction Tasks

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**.



Predictions > Customer lifetime value

Model name

Select the names for your model

Name

eCommerce CLV Prediction

Output entity name ⓘ

eCommerceCLVPrediction

Model name
Preferences
Required data
Additional data (optional)
Data updates
Review and run



4. Configure **Model Preferences**:

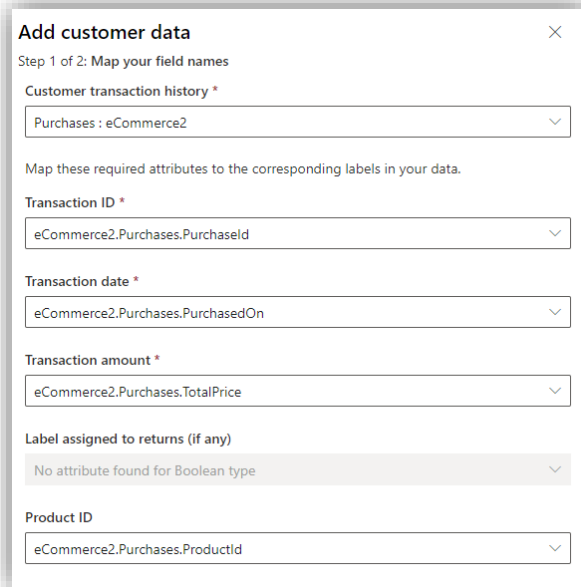
- a. **Prediction time period:** This setting defines how far into the future do we want to predict customer lifetime value. Select **1 year**.
- b. **Active customers:** Specify what **Active customers** mean for your business. Select **Let model calculate purchase interval**.
- c. **High value customers:** 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**.

The screenshot shows the 'Model preferences' configuration window for 'Customer lifetime value (preview)'. The window has a sidebar on the left with five steps: 'Model name', 'Preferences' (selected), 'Required data', 'Additional data (optional)', and 'Data updates'. The main content area is titled 'Model preferences' and includes a descriptive paragraph about customer lifetime value predictions. Below this, there are three sections: 'Prediction time period' with a dropdown set to '12' and 'Month(s)'; 'Active customers' with a dropdown set to 'Let model calculate purchase interval (recommend...)'; and 'High-value customer' with a dropdown set to 'Percent of top active customers' and a text input set to '30' followed by '% of active customers'. At the bottom, there are 'Back', 'Next', 'Save draft', and 'Cancel' buttons.

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**



Add customer data ✕

Step 1 of 2: Map your field names

Customer transaction history *

Purchases : eCommerce2

Map these required attributes to the corresponding labels in your data.

Transaction ID *

eCommerce2.Purchases.PurchaseId

Transaction date *

eCommerce2.Purchases.PurchasedOn

Transaction amount *

eCommerce2.Purchases.TotalPrice

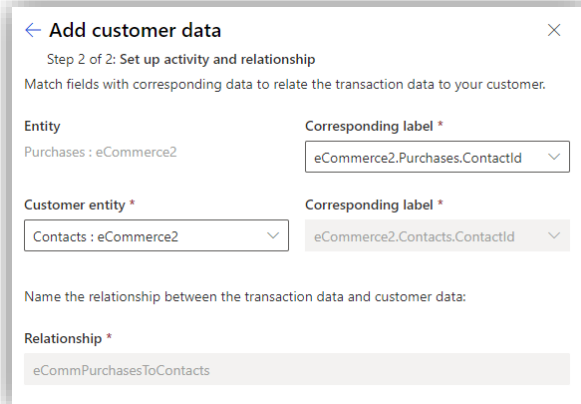
Label assigned to returns (if any)

No attribute found for Boolean type

Product ID

eCommerce2.Purchases.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.



← **Add customer data** ✕

Step 2 of 2: Set up activity and relationship

Match fields with corresponding data to relate the transaction data to your customer.

Entity

Purchases : eCommerce2

Corresponding label *

eCommerce2.Purchases.ContactId

Customer entity *

Contacts : eCommerce2

Corresponding label *

eCommerce2.Contacts.ContactId

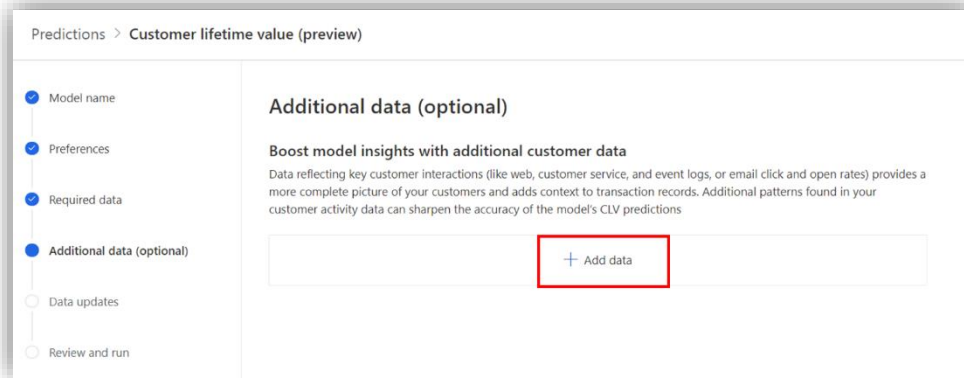
Name the relationship between the transaction data and customer data:

Relationship *

eCommPurchasesToContacts

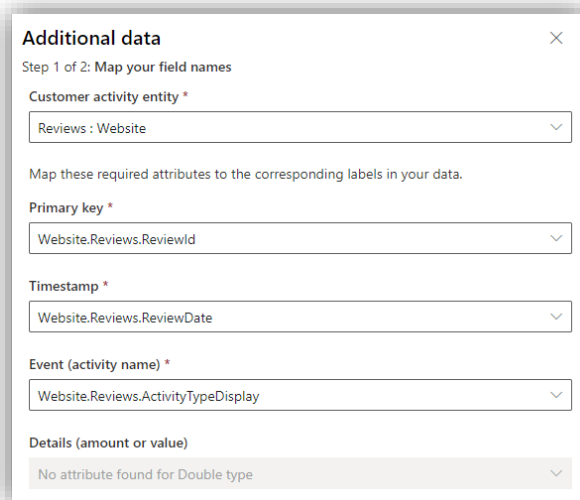
8. Click **Next**

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.

The screenshot shows a configuration window titled "Additional data" with a close button (X) in the top right corner. Below the title is a subtitle "Step 2 of 2: Set up activity and relationship". The main instruction reads: "Select the activity type that best describes this dataset, or add a new one." Under "Activity type", there are two radio buttons: "Choose existing" (which is selected) and "Add new activity". Below this is a section for "Activity label *" with a dropdown menu showing "Review". The next section is titled "Match fields with corresponding data to relate the transaction data to your customer." It contains two rows of fields. The first row has "Entity" (Reviews : Website) and "Corresponding label *" (Website.Reviews.UserId). The second row has "Customer entity *" (Contacts : eCommerce2) and "Corresponding label *" (eCommerce2.Contacts.ContactId). At the bottom, there is a section "Name the relationship between the transaction data and customer data:" with a text field labeled "Relationship *" containing the text "WebReviewsToContacts".

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.

Intelligence

CreateMy predictions

| Prediction name | Prediction type | Output entity | Predicted field | Status | Edited | Last refreshed |
|--|-----------------|----------------------------|-----------------|------------|------------|----------------|
| eCommerce CLV Prediction | CLV model | eCommerceCLVPrediction | | Successful | 2 days ago | 2 days ago |
| eCommerce Transaction Churn Prediction | | eCommerceTransactionChurnI | | Successful | 2 days ago | 2 days ago |
| Subscription Churn Model | | SubscriptionChurnModel | | Successful | 2 days ago | 2 days ago |

Edit

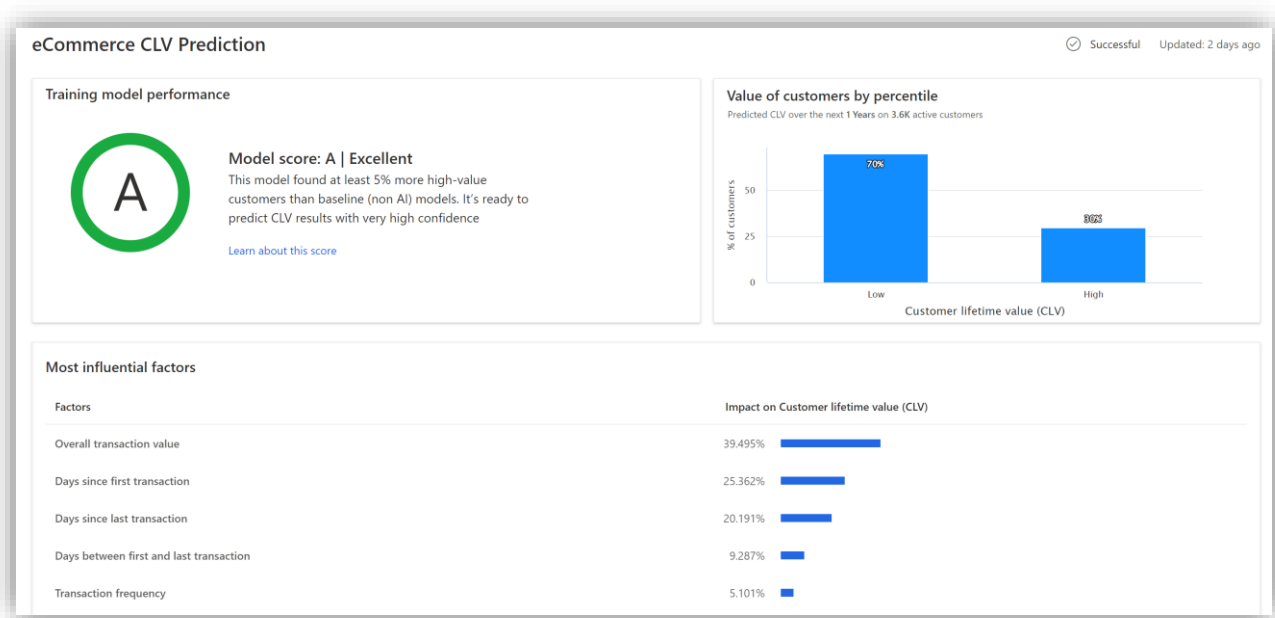
Refresh

View

Input data usability report

Delete

Model Results and Explanation page



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

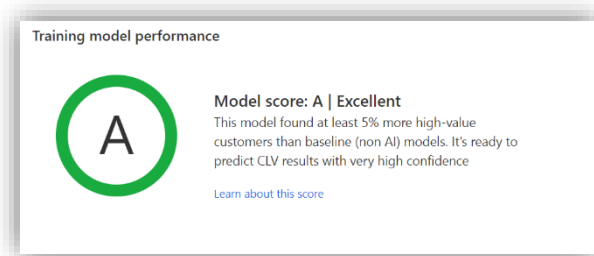
9.287%

Transaction frequency

5.101%



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

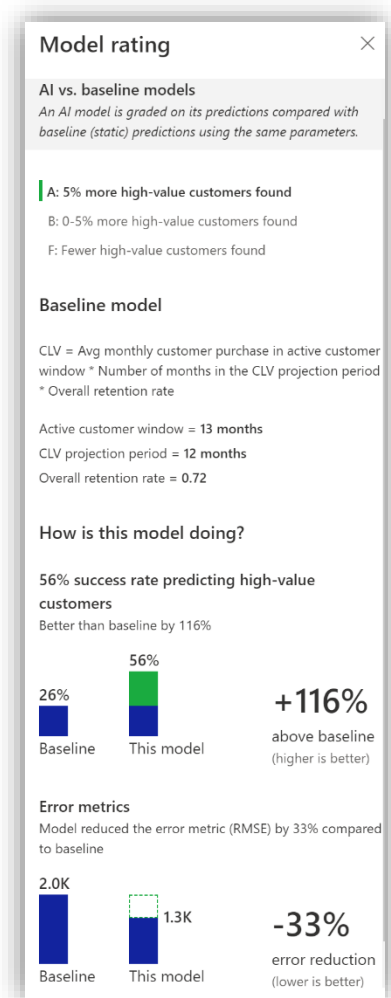
The AI model is compared to the baseline model based on two model performance metrics.

- **Success rate in predicting high-value customers**

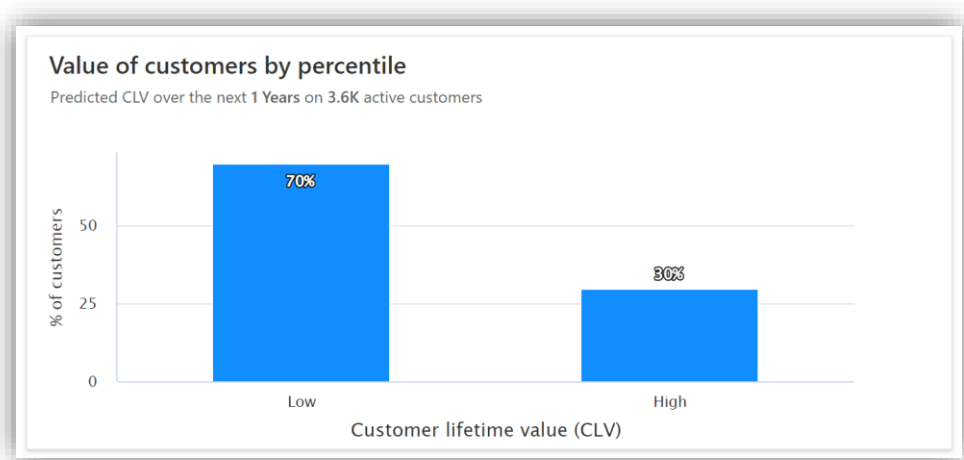
This metric shows the difference in predicting high-value customers using the AI model compared to the baseline model. For example, 33% success rate means that out of all the high-value customers (based on your definition as specified in model preferences), the AI model was able to accurately capture 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.

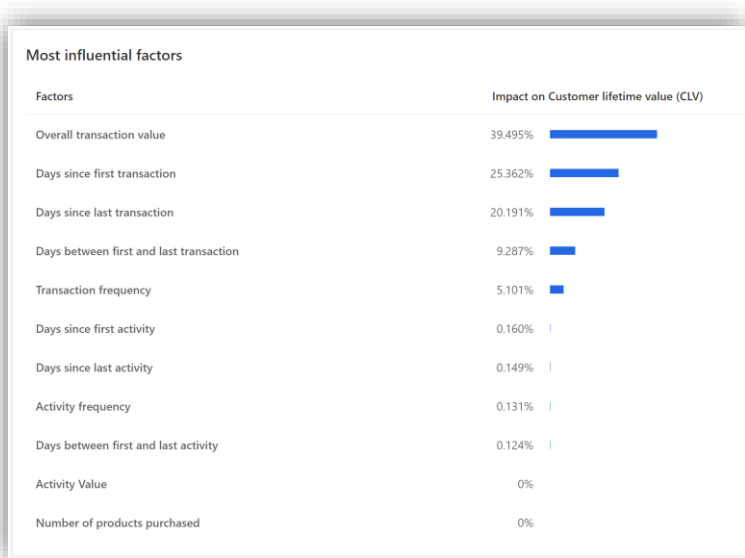


Value of customer by percentile:



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:



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**

New quick segment

Create a segment based on the number of customers with a field's value.

Condition

Entity
eCommerceCLVPrediction

Field
CLVScore

Operator
greater than

Value
223

CLVScore by percentile

| Percentile | CLVScore |
|------------|----------|
| 0th | ~200 |
| 25th | ~200 |
| 50th | ~200 |
| 75th | ~300 |
| 100th | ~4500 |

ReviewCancel



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

New quick segment

Name your segment, review it, and save.

Name

Output entity name

Start with a letter. Use letters and numbers only.

Tags

Condition

CLVScore is **greater than 223**.

Estimated segment size

3588

customers

100.14%

of total

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).