Accelerate Product Recommendation Optimization

Version 1.0.3

August 2023

Accelerate Product Recommendation Package

Product Recommendation Package provides recommendations on products to add to your quotes based on how often they were bought by the customer or based on other related products/customers. You can modify the criteria for providing recommended products.

In this section:

Product Info (Optimization - Product Recommendation)

Product Recommendation Package provides recommendations of products using three different modes:

- "**Buy it Again**" with Customer Specific product recommendations, coming from how often a customer bought a specific product.
- "**Purchased together**" with Product Specific product recommendations, coming from how often two products were purchased together.
- "**Other customers buy**" with Customer Segment Specific product recommendations, coming from how often customers in a segment bought a specific product.

Usage

The Product Recommendations can be used:

- In Quotes – when adding new line items, you can make use of the Recommended Items options.
- In other parts of the Pricefx solution (as needed).

How Product Recommendations Are Defined

This section provides some theory behind Product Recommendations. Their methodology applies frequency based recommendations at three different levels:

- Customer Specific – How often did a customer buy a specific product?
- Product Specific – How often were two products purchased together?
- Customer Segment Specific – How often did customers in a segment buy a specific product?

This gives recommendations based on the quoted customers buying history, the quoted products buying history, and the buying history of similar customers.

In this section:

Customer Specific Recommendation Methodology

A frequency rate / probability metric is calculated using the count of transactions by the specific Customer as the denominator and the transaction count of Customer-Product purchases as the numerator.

- Customer A transaction Count: 100
- Customer A Product A transaction Count: 20
- Customer A Product A Frequency Rate: 20%

Next, the frequency rate is multiplied by the products historical profitability metric to come up with a recommendation **Score**.

- Product A Historical Margin: $200
- Customer A Product A Frequency Rate: 20%
- Customer A Product A **Score**: 20% x $200 = 40

The **Score** is used to rank recommendations in descending order and the Top N recommendations for each Customer are stored based on thresholds defined in the Model Class definitions.

Data of Customer Recommendations

Export

CustomerId	ProductId	Customer	Product	Count_Customer_Ba...	Count_Customer_Pro...	Probability	Avg_Product_Margin	Score	Product_Rank
Search...	Search...	Search...	Search...	Search...	Search...	Search...	Search...	Search...	Search...
CID-0042	BR1600SI	Edu SA	Back UPS Pro BR 160...	1,056	185	0.175	844.616	147.968	1
CID-0042	TR47513	Edu SA	Energy Efficiency - El...	1,056	149	0.141	812.559	114.651	2
CID-0042	BN1350M2	Edu SA	Back UPS PRO BN 13...	1,056	169	0.16	646.851	103.521	3
CID-0042	TR47512	Edu SA	Energy Efficiency - El...	1,056	132	0.125	771.366	96.421	4
CID-0042	CN9789	Edu SA	Energy Efficiency - E...	1,056	115	0.109	833.274	90.745	5

Product Specific Recommendation Methodology

A frequency rate / probability metric is calculated using the count of transactions by the quoted Product as the denominator and the transaction count of Product and Co-product purchases as the numerator.

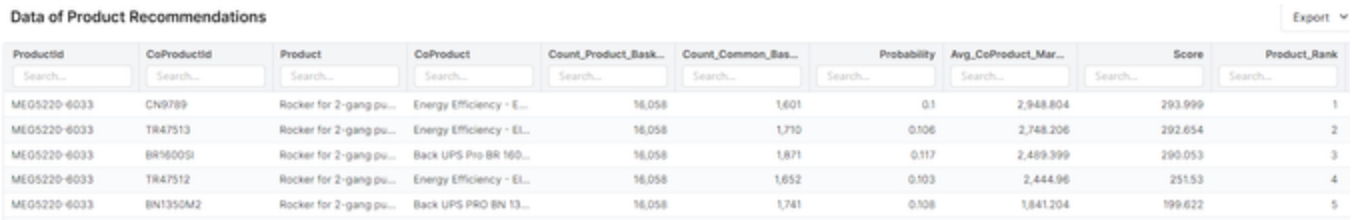
Product and Co-product relationships are identified using a **BasketId**. The **BasketId** is join/grouping key such as "InvoiceNumber" or "TransactionID" that is used to identify Co-occurences of product purchases. Once Products and Co-products relationships are established using the **BasketId** we apply the same frequency and score calculation.

- Product A transaction Count: 100
- Product A Product B (Co-product) transaction Count: 20
- Product A Product B (Co-product) Frequency Rate: 20 / 100 = 20%

Next, the frequency rate is multiplied by the Co-products historical profitability metric to come up with a recommendation **Score**.

- Product B (Co-product) Historical Margin: $200
- Product A Product B (Co-product) Frequency Rate: 20%
- Product A Product B (Co-product) **Score**: 20% x $200 = 40

The **Score** is used to rank recommendations in descending order and the Top N recommendations for each Product are stored based on thresholds defined in the Model Class definitions.



Data of Product Recommendations

Export

ProductId	CoProductId	Product	CoProduct	Count_Product_Bask...	Count_Common_Bas...	Probability	Avg_CoProduct_Mar...	Score	Product_Rank
Search...	Search...	Search...	Search...	Search...	Search...	Search...	Search...	Search...	Search...
MEG5220-6033	CN9789	Rocker for 2-gang pu...	Energy Efficiency - E...	16,058	1,601	0.1	2,948.804	293.999	1
MEG5220-6033	TR47513	Rocker for 2-gang pu...	Energy Efficiency - El...	16,058	1,710	0.106	2,748.206	292.654	2
MEG5220-6033	BR1600SI	Rocker for 2-gang pu...	Back UPS Pro BR 160...	16,058	1,871	0.117	2,489.399	290.053	3
MEG5220-6033	TR47512	Rocker for 2-gang pu...	Energy Efficiency - El...	16,058	1,652	0.103	2,444.96	251.53	4
MEG5220-6033	BN1350M2	Rocker for 2-gang pu...	Back UPS PRO BN 13...	16,058	1,741	0.108	1,841.204	199.622	5

Customer Segment Specific Recommendation Methodology

A frequency rate / probability metric is calculated using the count of transactions by the Customer Segment as the denominator and the transaction count of Customer Segment - Product purchases as the numerator.

First we create a mapping table of Customer Segments to individual Customers, this is done either from the transaction source or it is generated within the model using a hierarchical clustering algorithm (future iteration will also allow for external clustering model class).

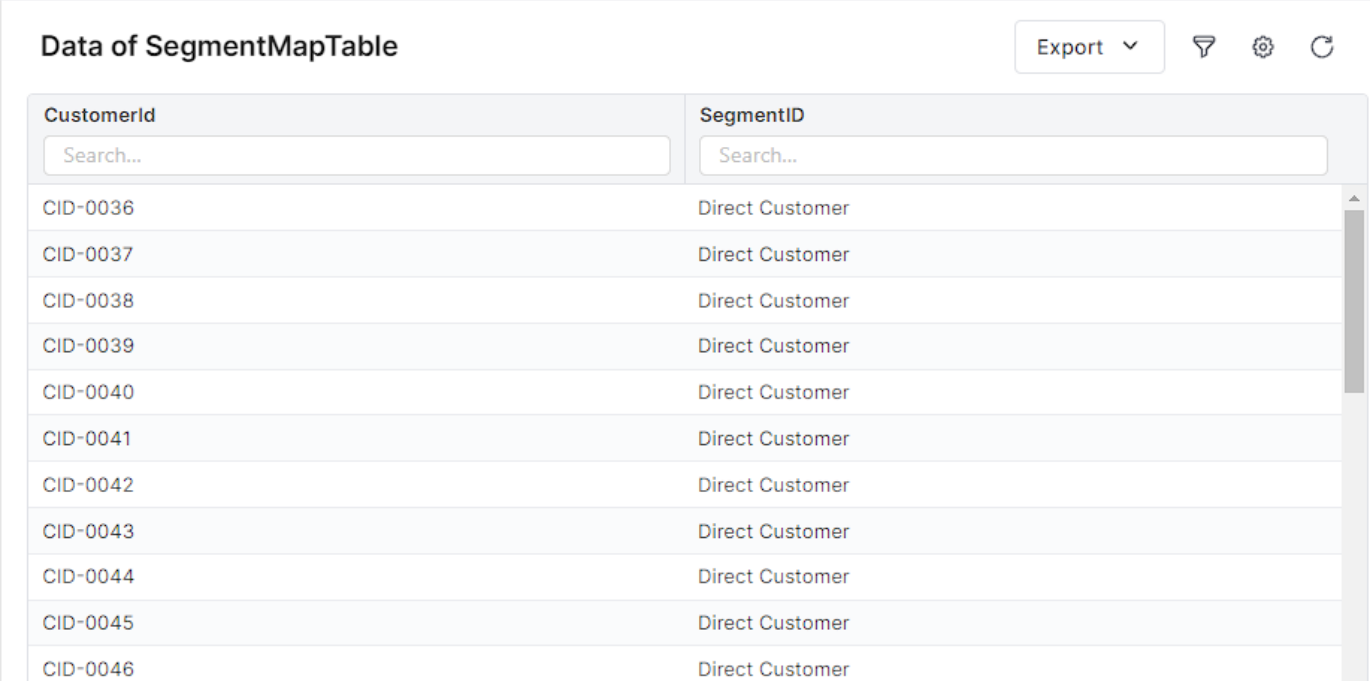
Once the mapping table is created, Customer Segments are mapped to historical transactions to allow for the frequency and score calculation to be done at the segment level.

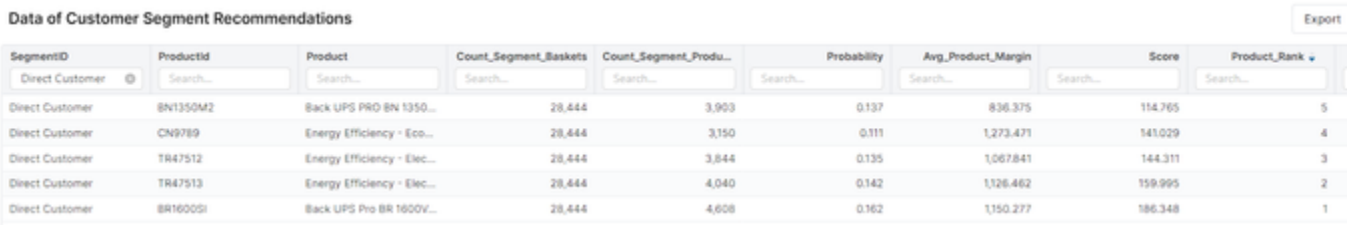
- Segment A transaction Count: 100
- Segment A Product A transaction Count: 20
- Segment A Product A Frequency Rate: 20 / 100 = 20%

Next, the frequency rate is multiplied by the products historical profitability metric to come up with a recommendation **Score**.

- Product A Historical Margin: $200
- Segment A Product A Frequency Rate: 20%
- Segment A Product A **Score**: 20% x $200 = 40

The **Score** is used to rank recommendations in descending order and the Top N recommendations for each Segment are stored based on thresholds defined in the Model Class definitions.





Communicating Recommendations to Individual Quotes

Recommendations are stored in three model tables, one for each category (Customer Specific, Product Specific, Customer Segment Specific). When a quote is created in the Quoting module, a user can look to add "Recommended Products". The recommended products are queries of the recommendation model tables:

- Customer Specific – Uses quoted Customer's ID as key to query Customer Specific Recommendations Model Table.
- Product Specific – Uses quoted Product's ID as key to query Product Specific Recommendations Model Table.
- Customer Segment – Uses quoted Customer's ID to map to Segment ID which is then utilized as key to query Customer Segment Specific recommendations Model Table.

Model Generated Segmentation Methodology

If no customer segment is present in the transaction source, users can generate a customer segment in the model class. We segment based on Product Affinity, meaning customers who buy similar products.

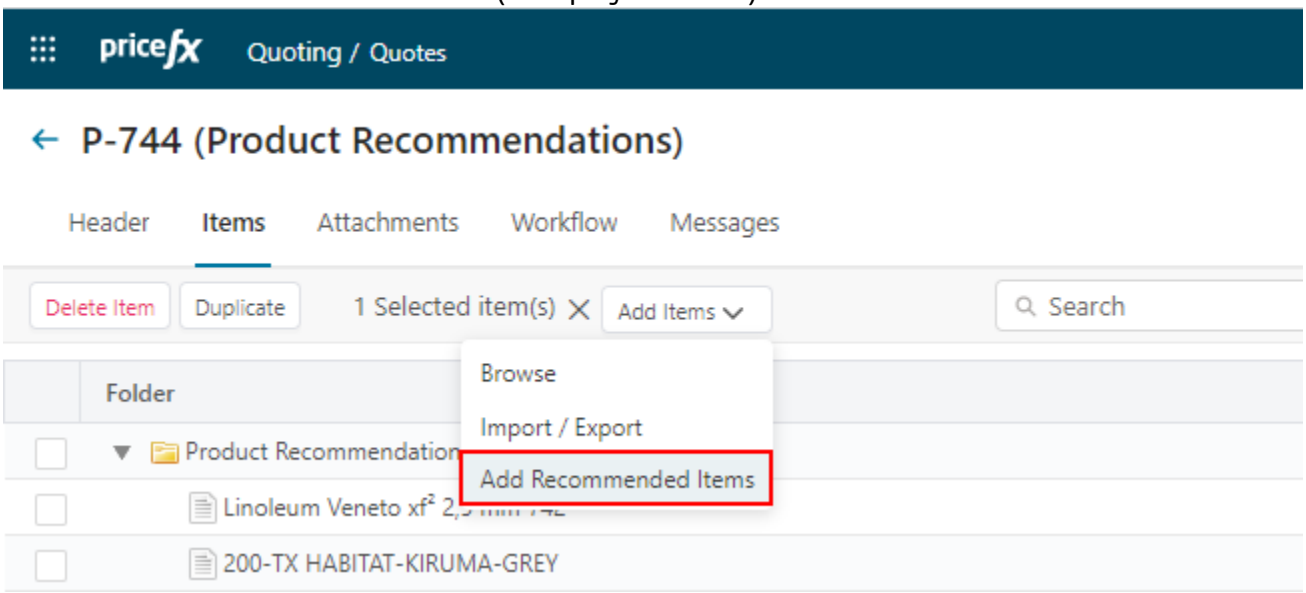
1. Frequency matrix of Customer x Products is created.
2. Frequency matrix is then normalized using chi-square based standardized residuals.
   Standardized Residuals: (Actual Frequency - Expected Frequency) / SQRT(Expected Frequency)
   The reason for using Standardized Residuals vs. Absolute Frequency count is because most B2B have long tail distributions so Large Enterprise Customers would tend to be clustered together, which we don't want since we are trying to cluster based on similar product purchases.

3. Matrix of standardized residuals is used as input for Cosine Similarity calculation between Customers.
   Similarity metric range from 1.00 to -1.00.
   Example: Customer A - Customer B similarity score is 1.00 which means they buy all the same products.
4. Cosine Similarity matrix is then converted to distance matrix by taking 1 - Cosine Similarity.
5. Distance Matrix is utilized as input into hierarchical clustering algorithm using complete linkage.
6. Customers and their Segment IDs are extracted from clustering algorithm and exported as a mapping table into the model class.

Business User Reference (Optimization - Product Recommendation)

After the package is installed and set up, the end users can start using Recommended Items when creating their quotes.

1. Create a new quote and add an item.
2. After adding an item click **Add Recommended Items** to view recommendations that come from the Product Recommendation model (set up by an admin).



Recommended Items are sorted in descending order based on their recommendation score. Category Name tells you how the recommendation was generated:

- Customer - Queried recommendations from Customer Specific Model Table.
- Product History - Queried recommendations from Product Specific Model Table.
- Customer Segment - Queried recommendations from Customer Segment Specific Model Table.

Part-ID	Score	Category Name
24524007	99999	Customer
3942034	99992	Customer segment
711450001	37000	Customer
25133111	3313	Product history
25206027	147	Customer segment
25206015	101	Customer segment
25223500	97	Customer
25206050	52	Customer
25213011	52	Customer segment
25094005	43	Customer
25188228	37	Customer
25207027	34	Customer segment

To learn more about these three types of recommendations, see How Product Recommendations Are Defined.

Pricing Analyst Reference (Optimization - Product Recommendation)

Before the end users can start using Product Recommendations in their quotes, it is necessary to do the following:

1. Deploy the package. This step is done by the admin user.
2. Define a new Product Recommendation Model to reflect company specific pricing strategy and priorities. This step is done by Pricing Analyst.
3. Link the new model with quotes. This is done in Advanced Configuration Options by the admin user.

In this section:

- Model Setup Overview (Optimization - Product Recommendation)
- Set up Product Recommendation Model
- Revise Product Recommendations

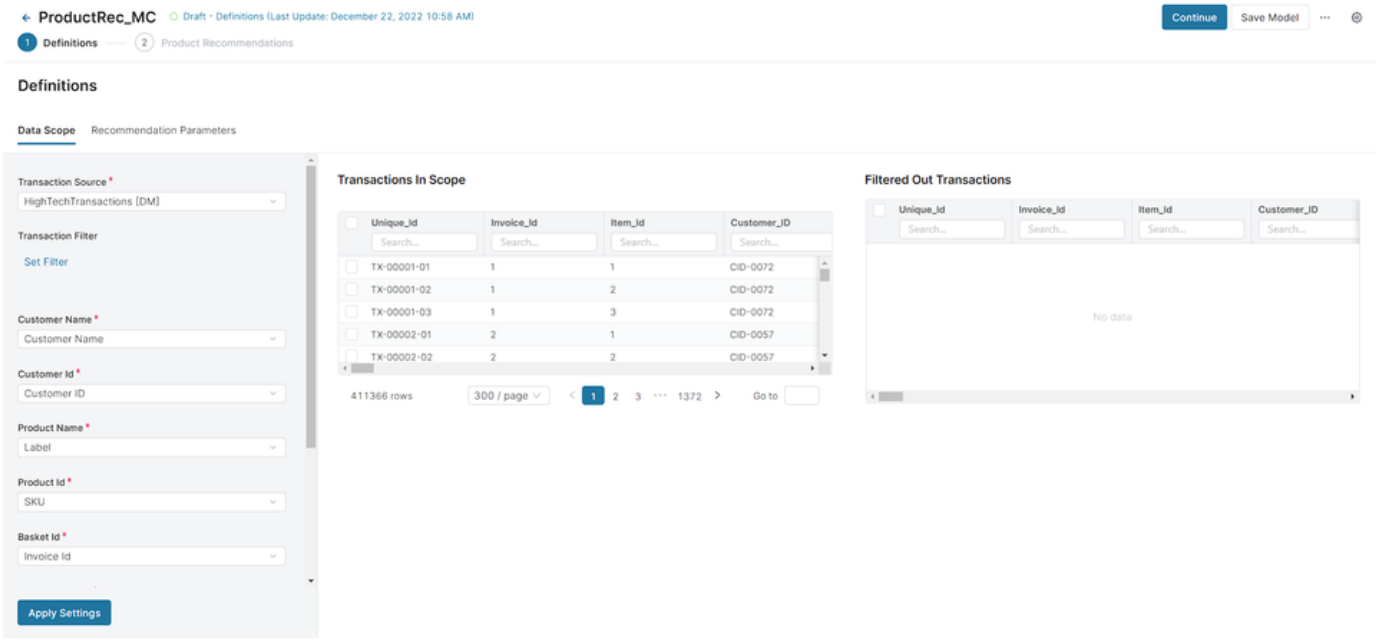
Model Setup Overview (Optimization - Product Recommendation)

Product Recommendation Model setup consists of two steps with the following tabs:

- Step 1: **Definitions**
  - Tab 1: **Data Scope** – Defines mapping, and scope of input data.

- Tab 2: **Recommendations Parameters** - Defines thresholds for recommendations.

- Step 2: Product Recommendations
  - Tab 1: **Recommendations Summary** - Dashboard with high level overview of top customer segment recommendations networks, and output summary.
  - Tab 2: **Recommendation Results** - Allows you to simulate quote inputs and returns recommendations.
  - Tab 3: **Add Manual Recommendations** - Allows you to manually add recommendations that are utilized in Quoting.

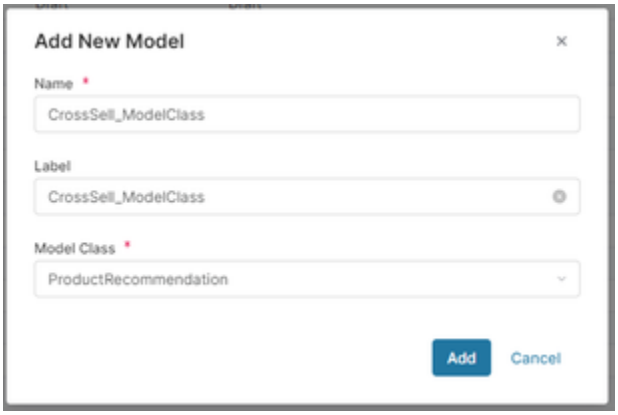


Set up Product Recommendation Model

To be able to generate Product Recommendations, you need to define a Product Recommendation Model which handles the data mapping and input data scope.

Steps:

1. Go to **Optimization** > **Model Objects (MO)** and create a new model.
2. Provide **Name** and **Label** for the new model.
3. As **Model Class** select *ProductRecommendation*.



4. Proceed at the **Definitions** screen. First the **Data Scope** tab opens.

5. Select a **Transaction Source** – Data Source or Datamart with historical transactions to use for generating product recommendations.
6. If needed, define a **Transaction Filter** to scope down transactions to use for generating product recommendations
7. Define the following options:
   - **Customer Name** – Select a field which contains customer's full name.
   - **Customer ID** – Select a field which contains a unique code for each customer (should be the same code utilized in the Customer Master table).
   - **Product Name** – Select a field which contains product name.
   - **Product ID** – Select a field which contains a unique code for each product (should be the same code utilized in the Product Master table).
   - **Basket ID** – Used to determine which products are bought "together" (i.e. Invoice Number, Billing Number). If no predefined Basket ID is available, then **Billing/Invoice Date** is a good proxy. If the Basket ID applies to the same product ID multiple times, their margins will be summed.
   - **Margin Measure** – Select a field which contains profitability metric to be used for calculating recommendation **Score**.
   - **Customer Segment Labels Source** – Defines whether the Customer Segment Label comes from the transaction source, or if it should be generated within the model using a segmentation algorithm.
   - **Transaction Source Customer Segment Label** – Defines dimension in Transaction Source to use as a segment label. Note that segment labels should be unique per customer.
   - **Number of Customer Segments to Create** – If 'Model Generated' is chosen as the Customer Segment Labels Source, this defines the number of segments to generate within the model. This should not be more than the number of customers.
8. Click **Apply Settings**. You will get a list of all transactions in scope.
9. Proceed to the **Recommendation Parameters** tab.
10. Define the following options:
    - **Minimum Number of Customer-Product Transactions** – Minimum number of transactions observations to consider for Customer Specific recommendation.
      Example: Customer A Product A transaction count 1, minimum threshold set at 3 so Customer A Product A recommendation is excluded.
    - **Maximum Number of Recommendations Per Customer** – Maximum number of recommendations to generate for each customer (Top N recommendations Stored).
    - **Minimum Number of Product-CoProduct Transactions** – Minimum number of transactions observations to consider for Product Specific recommendations.
      Example: Product A Product B transaction count 1, minimum threshold set at 3 so Product A Product B recommendation is excluded.
    - **Maximum Number of Recommendations Per Product** – Maximum number of recommendations to generate for each product (Top N recommendations Stored).
    - **Minimum Number of Segment-Product Transactions** – Minimum number of transactions observations to consider for Customer Segment Specific recommendations.
      Example: Customer Segment A Product A transaction count 1, minimum threshold set at 3 so Customer Segment A Product A recommendation is excluded.
    - **Maximum Number of Recommendations Per Segment** – Maximum number of recommendations to generate for each customer segment (Top N recommendations Stored).
11. When finished, click **Save Model**, and continue to the next step at the Product Recommendations tab.

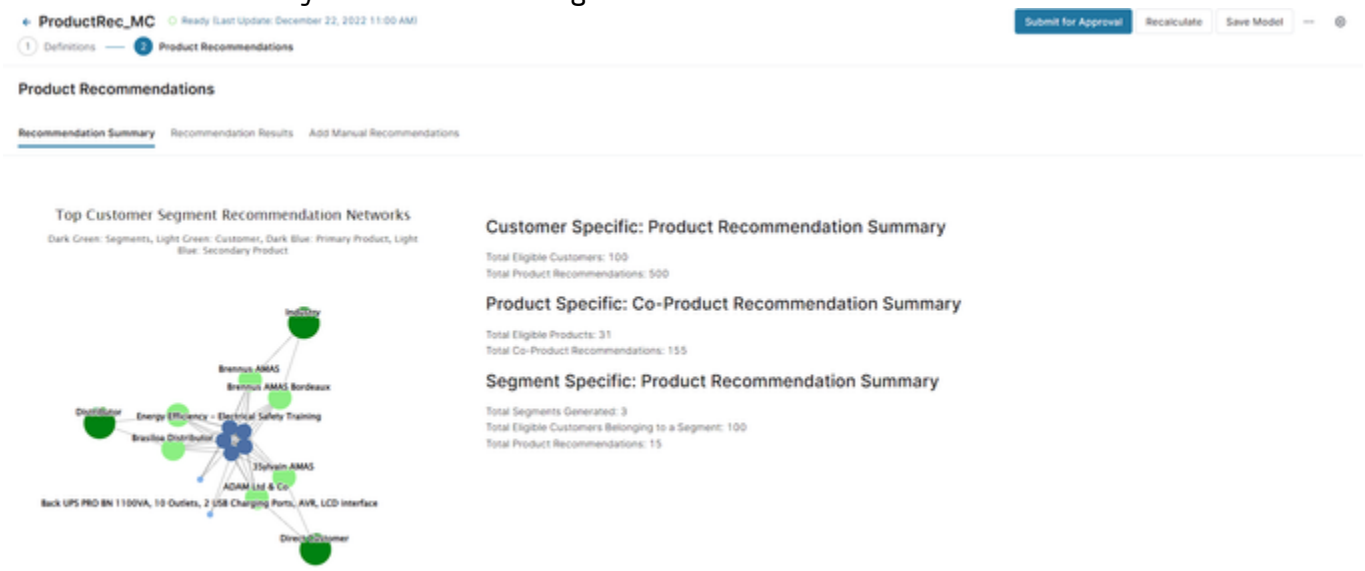
Revise Product Recommendations

The Product Recommendations step has different tabs to allow for better insight into recommendation rules, and for adding manual recommendations.

- Recommendation Summary
- Recommendation Results
- Add Manual Recommendations

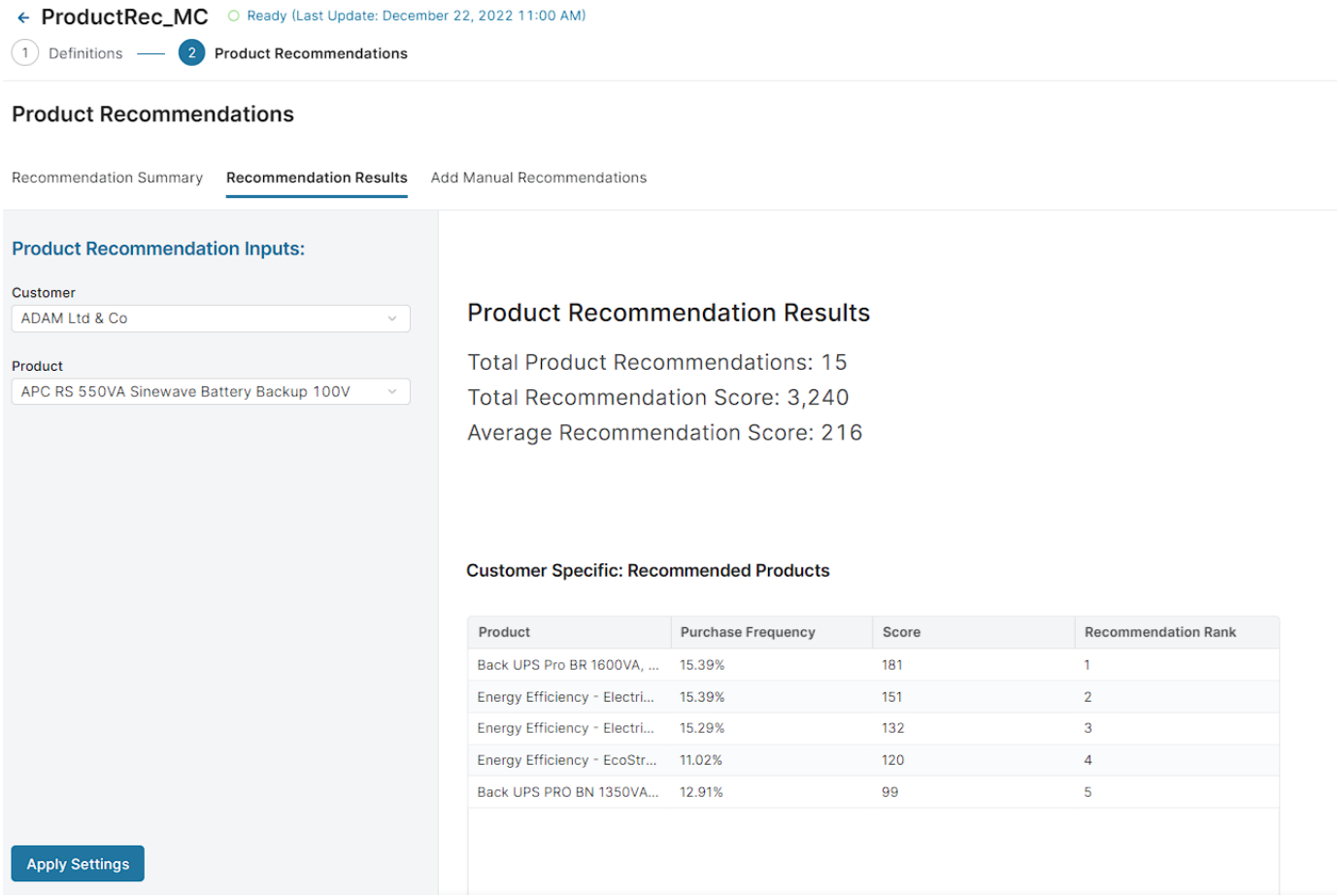
Recommendation Summary

Shows a visual summary of the Customer Segment Recommendation Networks.



Recommendation Results

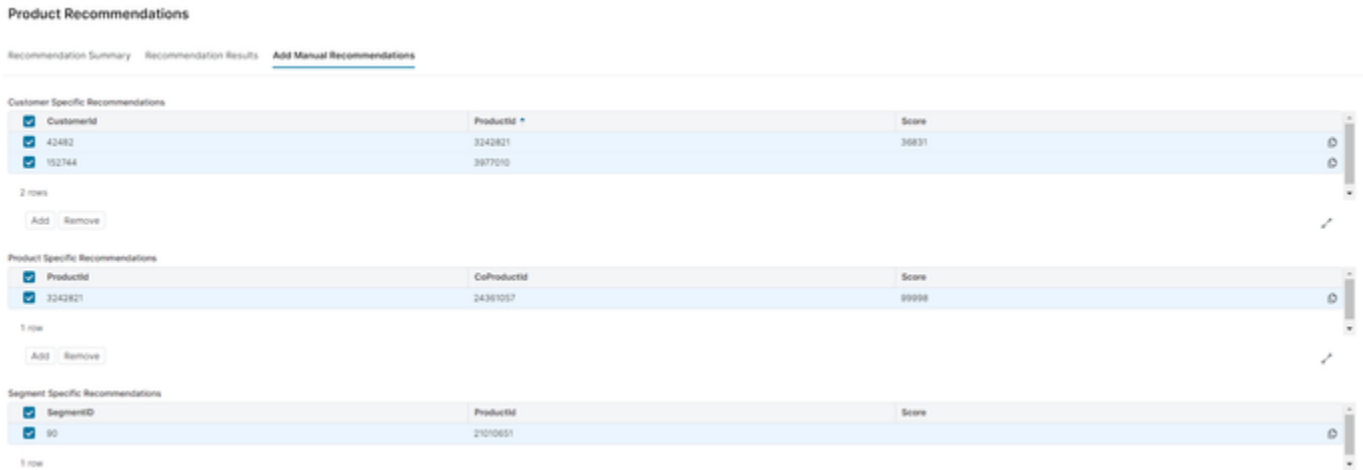
Allows you to simulate a quote by entering Customer and Product to see summary statistics, and recommendation outputs. The result also includes details about the customer segment.



Add Manual Recommendations

Allows you to add manual recommendations if you want to push the sale of certain products, or target specific customers, products, and segments. You can add the recommendation and a Score which is used for ranking recommendations. If Score is left blank, the default is 99,999.

After entering recommended products click **Save Model** for the Quoting module to recognize the manual recommendations.



Admin User Reference (Optimization - Product Recommendation)

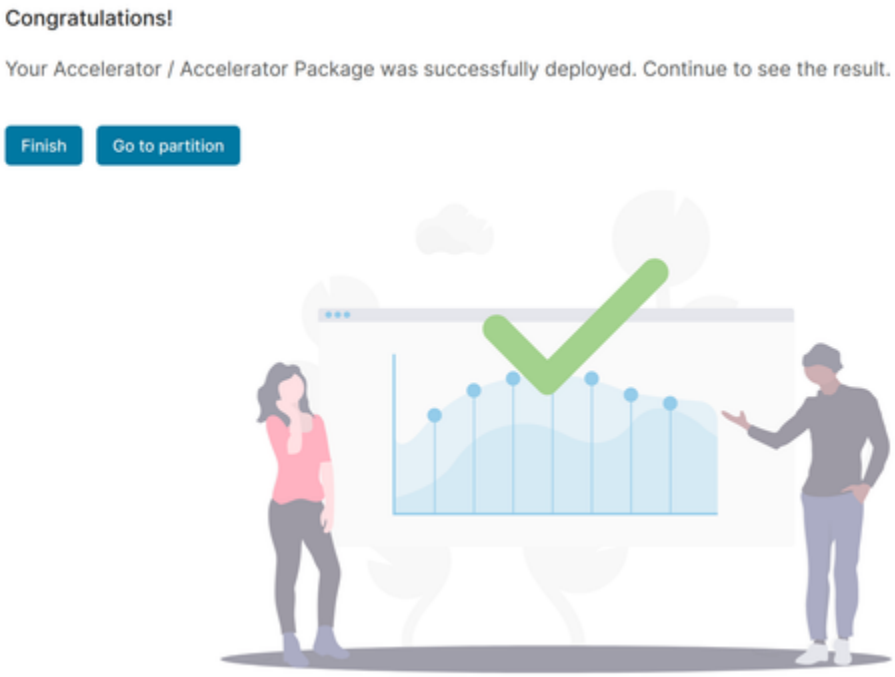
As an admin user, you can expect to handle the following tasks for Product Recommendation Package:

- Deployment (Optimization - Product Recommendation)
- Link Product Recommendation Model with Quotes (PRP)

Product Recommendation Model creation and tuning is typically done by Pricing Analysts.

Deployment (Optimization - Product Recommendation)

1. Access PlatformManager at https://platform.pricefx.com/ and log in with your account or using O365.
2. Go to **Marketplace** > **Accelerator Packages**.
3. Find **Optimization - Product Recommendation Package**.
4. Select your **Target Partition** from the drop-down menu.
5. Click **Continue** and wait until the deployment is complete.



Note: The Accelerator uses a Python Engine image. If the image `cregistry.pricefx.eu /engineering/pricefx-python-engine/datascience` was not yet enabled for your partition, the deployment process takes care of configuring it. For details see Python Engine.

Link Product Recommendation Model with Quotes (PRP)

After you create and define a new Product Recommendation Model, you need to update a specific Advanced Configuration Option to instruct the Quoting module which model to query for recommendations.

A template of the Advanced Configuration Option for Product Recommendations is deployed from PlatformManager and you only need to update it with a proper model name.

1. Go to **Administration** > **Configuration** > **Advanced Configuration Options**.
2. Find the option named "quoteProductRecommendationsConfig".
3. Edit its value - change the `modelName` to the unique name of the model you created.
4. Save the changes.

For an example of the content of this Advanced Configuration Option, see Product Recommendation API.

Release Notes (Optimization - Product Recommendation)

Optimization - Product Recommendation 1.0.3

This document summarizes major improvements and fixes introduced in the Accelerate Product Recommendation Optimization package release version.

Version	1.0.3
Release Date	Aug 10, 2023

Fixed Issues

Bug Description	ID
When adding Manual Recommendations in the Product Specific Recommendations table, not all products from Datamart are available.	PFPCS-7224
Product Recommendations "Segment Specific Recommendations" do not work when they are not selected.	PFPCS-7140

Optimization - Product Recommendation 1.0.2

This document summarizes major improvements and fixes introduced in the Accelerate Product Recommendation Optimization package release version.

Version	1.0.2
Release Date	Jul 18, 2023

New Features and Improvements

Description	ID
Python engine is now automatically deployed to the partition (if not already present) together with the accelerator.	PFPCS-6938

Fixed Issues

Bug Description	ID
Product Recommendation step fails when Pricing Date is used for Basket ID but this field is not unique for each product-customer pair. To fix this issue, this corner case was implemented: transaction date is used for Basket ID and a customer orders the same product multiple times on a single date.	PFPCS-6808
The Product Recommendations step fails with an error "Input X contains NaN. AgglomerativeClustering does not accept missing values encoded as NaN natively..." This happens when the selected data only contains a single customer and model generated segments are selected. To fix this issue, recommendations for a single customer are now produced.	PFPCS-6811
When using model generated customer segments, you can get an error "cannot extract more clusters than samples".	PFPCS-6824
Product Recommendation's SegmentMapTable DMT fields are not classified (dimension vs. measure) and thus cannot be used by the Data Table input.	PFPCS-6831
The Product Recommendation step fails with an error "duplicate key value".	PFPCS-6862