### ANALYTICS 95% DASHBOARD Last Updated: Evolution Metric Actual Target Products positioning \$3.4M 82.0% \$1.2M 108.7% Avg. Order Size On Time Delivery **New Customers** Cust. Satisfaction Market Share op 10 products Sales per countries

## Eastern Analytics, Inc

We Are Data Analytics People



+1 (781) 783-7610





### PREDICTING THE FUTURE

# COMBINING MICROSOFT POWER BI & AZURE ML FOR ACCURATE FORECASTING

January 11, 2023





### About Us

Eastern Analytics' architects
have been building platforms
and helping customers unlock
the true value of data for over
25 years.

We specialize in Microsoft
Analytics, Azure Al/ML and
Power Bl.

## What Sets Eastern Analytics Apart From the Rest?



### We have extensive experience

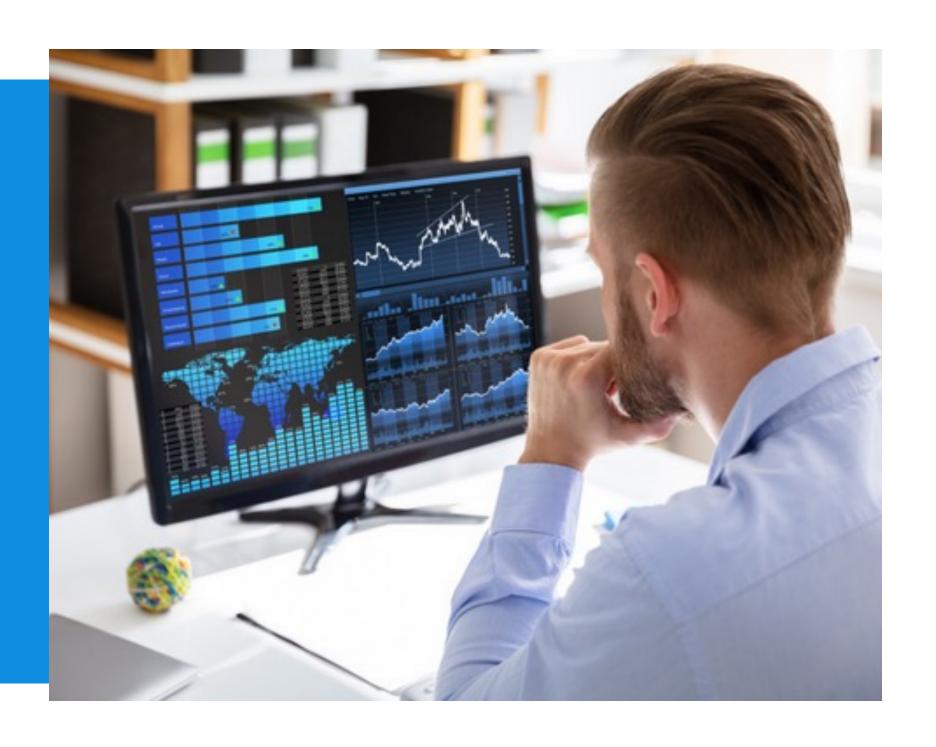
in all aspects of business intelligence (BI) and Machine Learning (ML).

#### Our functional knowledge

allows us to understand your sources and requirements to build solutions that meet your needs.

#### Our technical knowledge

allows us to design systems that are robust, flexible, and secure helping you maximize ROI for years to come.



### **Our Services**

- **Solution Architecture**
- **Azure AI & Machine Learning**
- **Dashboards & Visualizations**
- **Data Engineering**
- **Technology Advisory**
- **Staff Augmentation**

## About Us



### **Scott Pietroski**

As Eastern Analytics' founding partner, Scott's focus is Solution Architecture, customer engagement and project delivery.

Scott.Pietroski@eastern-analytics.us



### **Kerrilee Pietroski**

Kerrilee is Eastern Analytics' Director of Marketing & Communications, leading strategic marketing initiatives and corporate communications.

Kerrilee.Pietroski@eastern-analytics.us

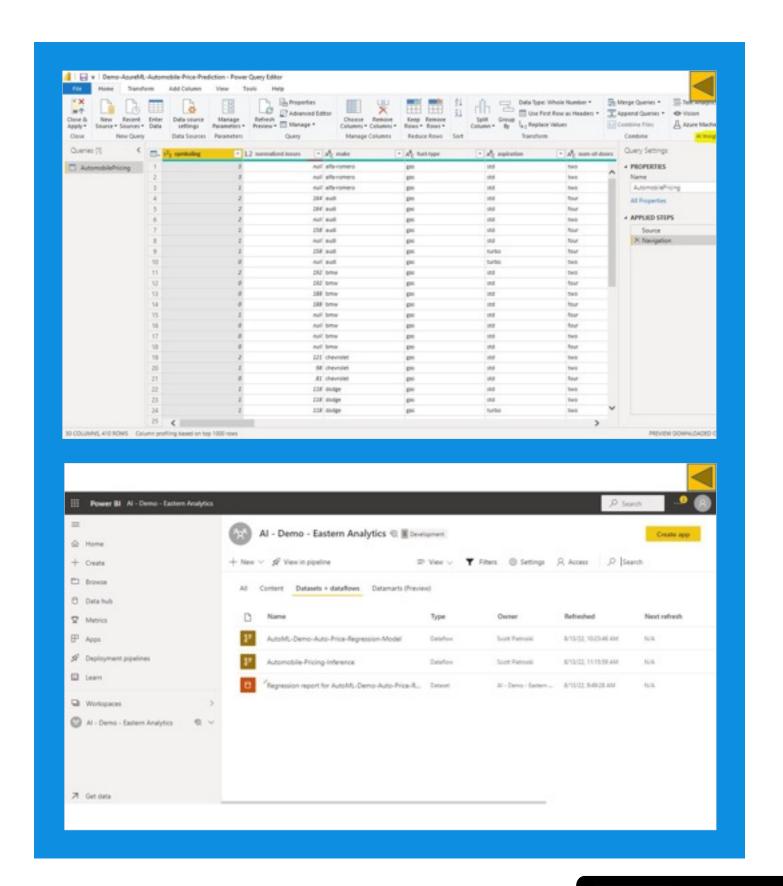
### Today's Presentation:

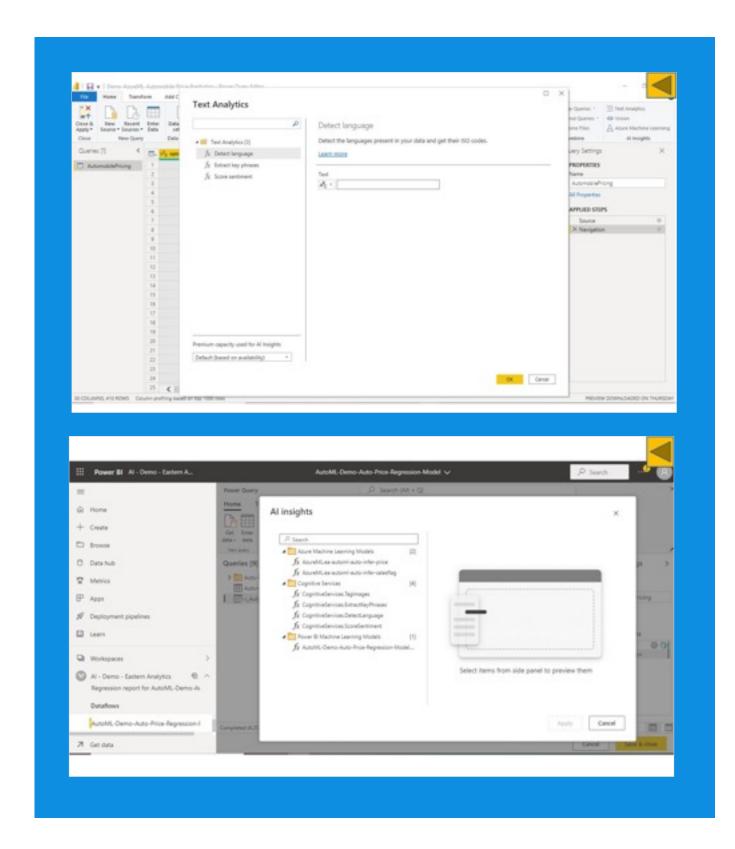
- Overview of Microsoft Power BI & Azure ML
- Azure ML- Predict automobile Prices multiple regression using Auto ML
- Display simple use case while consuming the model in Power BI
- Azure ML Predict Beer/Wine demand -time series forecast
- Consumption of the model in Power BI
- Considerations when designing a reliable forecasting model
- Q&A



### Power BI Desktop & Service

- Two flavors of PBI available
  - **PBI Desktop** Stand-alone application, development work stored locally
  - **PBI Service** A web service similar to PBI Desktop + web-publishing and access control capabilities.
  - AI/ML Integration Both the desktop and the web service allow consumption of Azure ML models.



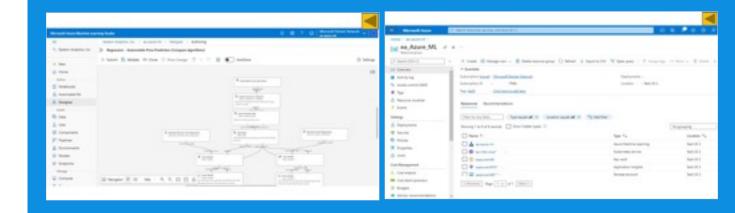


### AI/ML Consumption in PBI

### Things to Know – Using Power Query

- Wizard Based System Automatically suggests column mappings based on target data types
- Data Preparation Inference data goes thru the same data guardrail and preparation steps that were applied to the training set

Azure ML – You can consume/apply any ML model created on the Azure ML platform.



## Azure ML – High Level

### **Functional**

- A stand-alone environment for machine learning
- Seamless integration with Power BI
- Includes Auto ML functionality and an entire toolkit for building and deploying ML models
- It is an ML platform, designed for Enterprise level ML. GUI or code driven
- Provides a framework of common data science tools (Jupyter notebooks etc.)

### **Technical**

- Data volume/size is unlimited
- All data is stored in your own ADLS storage account
- Access Control: Role Based Authorizations
- Model retraining orchestrated thru the Azure **Data Factory**

INTRODUCTION OVERVIEW EXAMPLES

## Example 1: Auto Sales Forecast – The Datasets

### Training Data – Historical Sales

YearSold	ZipCode(3)	Make	Model	ModelYear	Milage	Price
2020	460	Subaru	Legacy	2001	91369	\$2,150.00
2019	460	Subaru	Legacy	2005	193737	\$1,180.00
2019	460	Subaru	Legacy	2007	174236	\$3,250.00
2019	460	Subaru	Outback	2011	93517	\$7,750.00
2019	460	Subaru	Tribeca	2007	140673	\$3,530.00
2020	460	Honda	Odyssey	2005	214091	\$790.00

Inference Set – We want to predict Price

ID	ZipCode(3)	Make	Model	ModelYear	Milage	ListPrice	Price
1	460	Subaru	Legacy	2001	91369	1800	?
2	460	Subaru	Legacy	2005	193737	700	?
3	460	Subaru	Legacy	2007	174236	2500	?
4	460	Subaru	Outback	2011	93517	7700	?
5	460	Subaru	Tribeca	2007	140673	3500	?
6	460	Honda	Odyssey	2005	214091	500	?

CONSIDERATIONS

Data Source: Kaggle – Ebay Used Car Sales. Data staged in Azure SQL Database

## Example 1: Auto Sales Forecast – Multiple Linear Regression

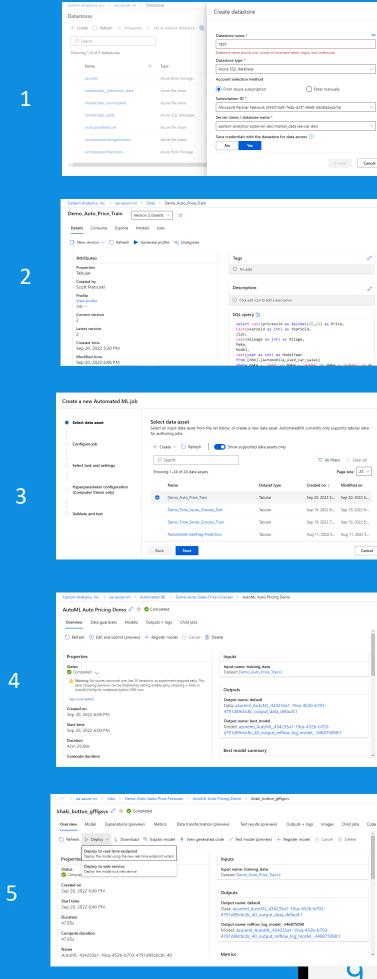
### **Azure ML**

### **Auto ML: Supervised Machine Learning Problem**

- 1. Connect Azure ML to a Data Store
- 2. Register a Data Asset (Training Set)
- 3. Create new Automated ML Job
- 4. Review job results
- 5. Publish a model

Data Source: Kaggle – Ebay Used Car Sales

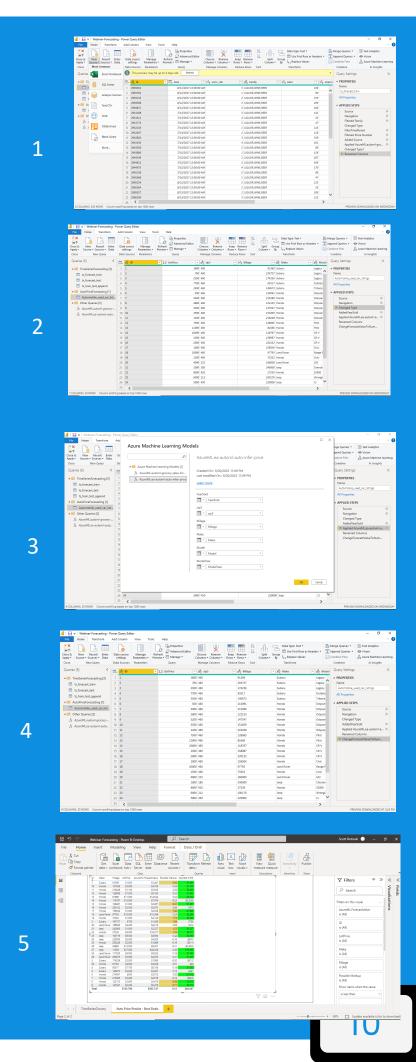
\*Data pre-staged in Azure SQL Database



## Example 1: Auto Sales Forecast – Power BI Consumption

### **Power BI**

- 1. Connect Power BI to Inference Set
- 2. Power Query type fields for alignment with ML Model
- 3. Power Query assign ML model to data set
- 4. Power Query assign proper types for reporting
- 5. Consume your data on a Power BI Reporting screen



## Example 2: Time Series Forecast – The Datasets

### Training Data – Historical Sales

date	store_nbr	family	OnPromotion	Sales
1/1/2013	1	LIQUOR, WINE, BEER	О	\$0.00
1/2/2013	1	LIQUOR, WINE, BEER	О	\$67.00
1/3/2013	1	LIQUOR, WINE, BEER	О	\$66.00
1/4/2013	1	LIQUOR, WINE, BEER	О	\$102.00
1/5/2013	1	LIQUOR, WINE, BEER	2	\$159.00
1/6/2013	1	LIQUOR, WINE, BEER	3	\$0.00
1/7/2013	1	LIQUOR, WINE, BEER	О	\$109.00
1/8/2013	1	LIQUOR, WINE, BEER	О	\$86.00
1/9/2013	1	LIQUOR, WINE, BEER	3	\$104.00
1/10/2013	1	LIQUOR, WINE, BEER	0	\$67.00

Testing Data – We want to predict future sales

<u> </u>							
Features							
date	store_nbr	family	OnPromotion	Sales			
1/11/2013	1	LIQUOR, WINE, BEER	3	?			
1/12/2013	1	LIQUOR, WINE, BEER	3	?			
1/13/2013	1	LIQUOR, WINE, BEER	3	?			
1/14/2013	1	LIQUOR, WINE, BEER	О	?			
1/15/2013	1	LIQUOR, WINE, BEER	О	?			
1/16/2013	1	LIQUOR, WINE, BEER	1	?			
1/17/2013	1	LIQUOR, WINE, BEER	О	?			
1/18/2013	1	LIQUOR, WINE, BEER	О	?			
1/19/2013	1	LIQUOR, WINE, BEER	0	?			
1/20/2013	1	LIQUOR, WINE, BEER	0	?			

### Additional Features?

date	type	locale	locale_name	description
1/1/2013	Holiday	National	Ecuador	Primer dia del ano
1/5/2013	Work Day	National	Ecuador	Recupero puente Nav
1/12/2013	Work Day	National	Ecuador	Recupero puente prir
2/11/2013	Holiday	National	Ecuador	Carnaval
2/12/2013	Holiday	National	Ecuador	Carnaval
3/2/2013	Holiday	Local	Manta	Fundacion de Manta

store_nbr	city	state	type	cluster
1	Quito	Pichincha	D	13
2	Quito	Pichincha	D	13
3	Quito	Pichincha	D	8
4	Quito	Pichincha	D	9

Data Source: Kaggle – Grocery Sales in Ecuador. Data staged in Azure SQL Database

## Example 2: Time Series Forecast / Regression

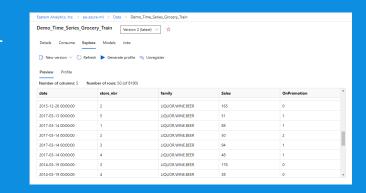
### **Azure ML**

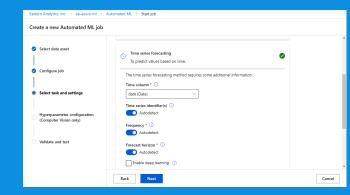
### **Auto ML: Supervised Machine Learning Problem**

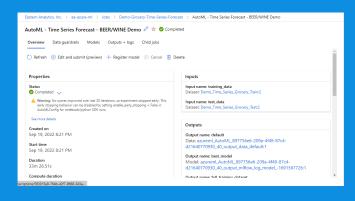
- Create Data Assets You want a training set and testing set. Testing set should occur later than training set
- 2. Create new Automated ML Job
- 3. Review job results
- 4. Publish a model

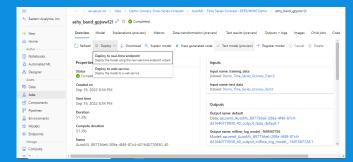
Data Source: Kaggle – Grocery Sales in Ecuador

\*Data pre-staged in Azure SQL Database





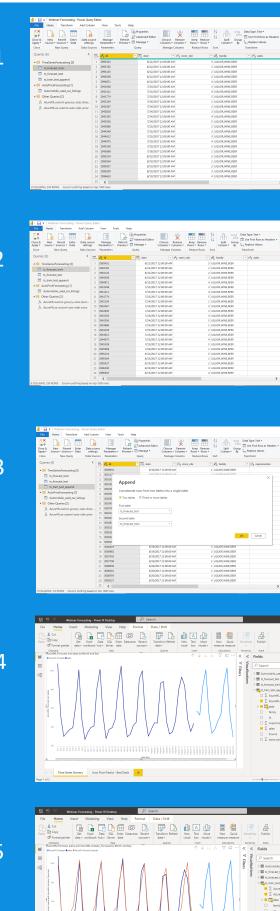


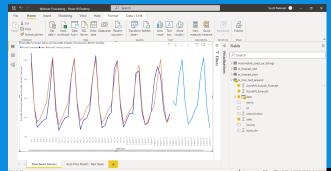


## Example 2: Time Series Forecast – Power BI Consumption

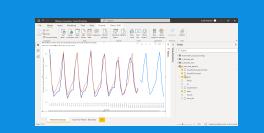
### **Power BI**

- 1. Connect Power BI to Training and Inference Set
- 2. Power Query prep your data for ML model consumption
- 3. Power Query assign ML model to both data sets
- 4. Power Query create append table to combine data
- 5. Present your data showing history + forecast values
- 6. Present your data showing history/actuals vs. history/forecast





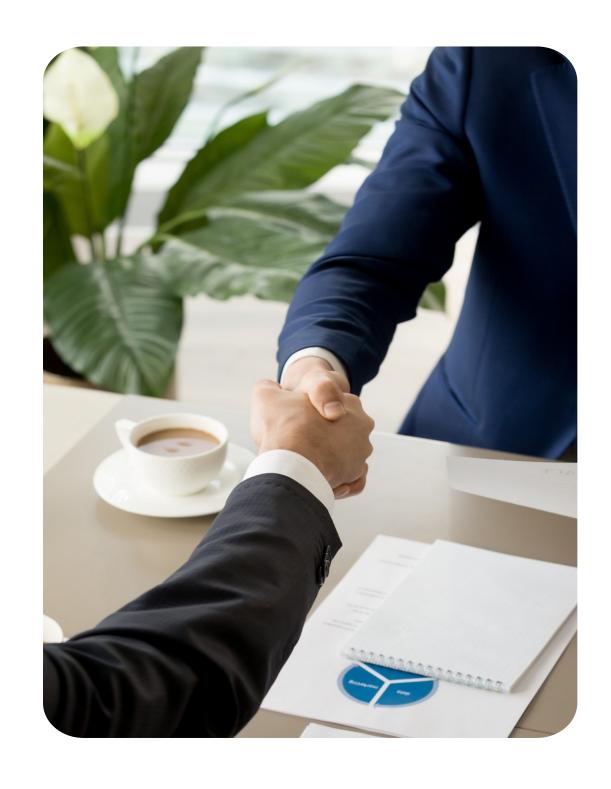
### Creating Better Forecasts



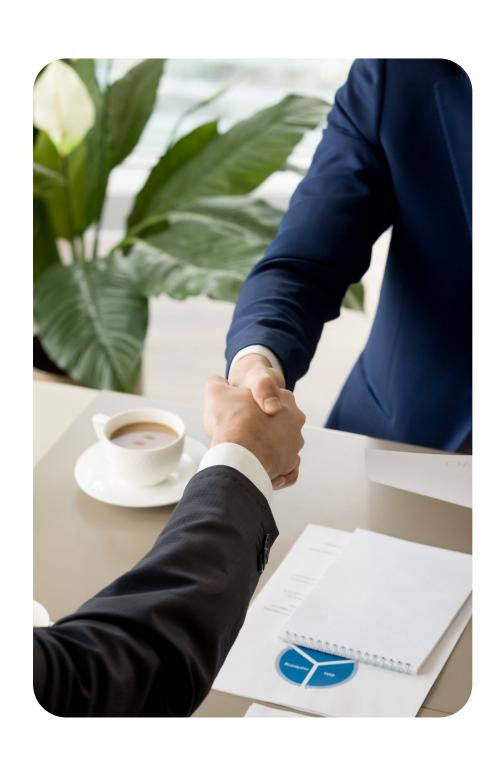


### **ML Considerations**

- Can you add or engineer relevant features? Time/Product/Store/Geography/Others?
   \*Azure ML automatically adds time features like year, week, month, day of week
- 2. Should you use a 'Rolling Window' / Sum / Moving Average function to smooth a forecast? \*Auto ML does not do this automatically, it is available in the SDK
- 3. Can you remove any features that are not significant?\*Auto ML does this as part of its 'Data guardrails'
- 4. Are you dealing with seasonality? Seasonality is a cyclical pattern over time.
- 5. Are there patterns that are predictable? Like the Super Bowl? Do these patterns apply across your entire data set?
- 6. Be careful not to train with features that not available at inference time. Ex. Sales Quantity
- 7. Consider risk when combining forecasts. Are you forecasting the weather and using it as a feature
- 8. Experiment, experiment, experiment







## Thank You

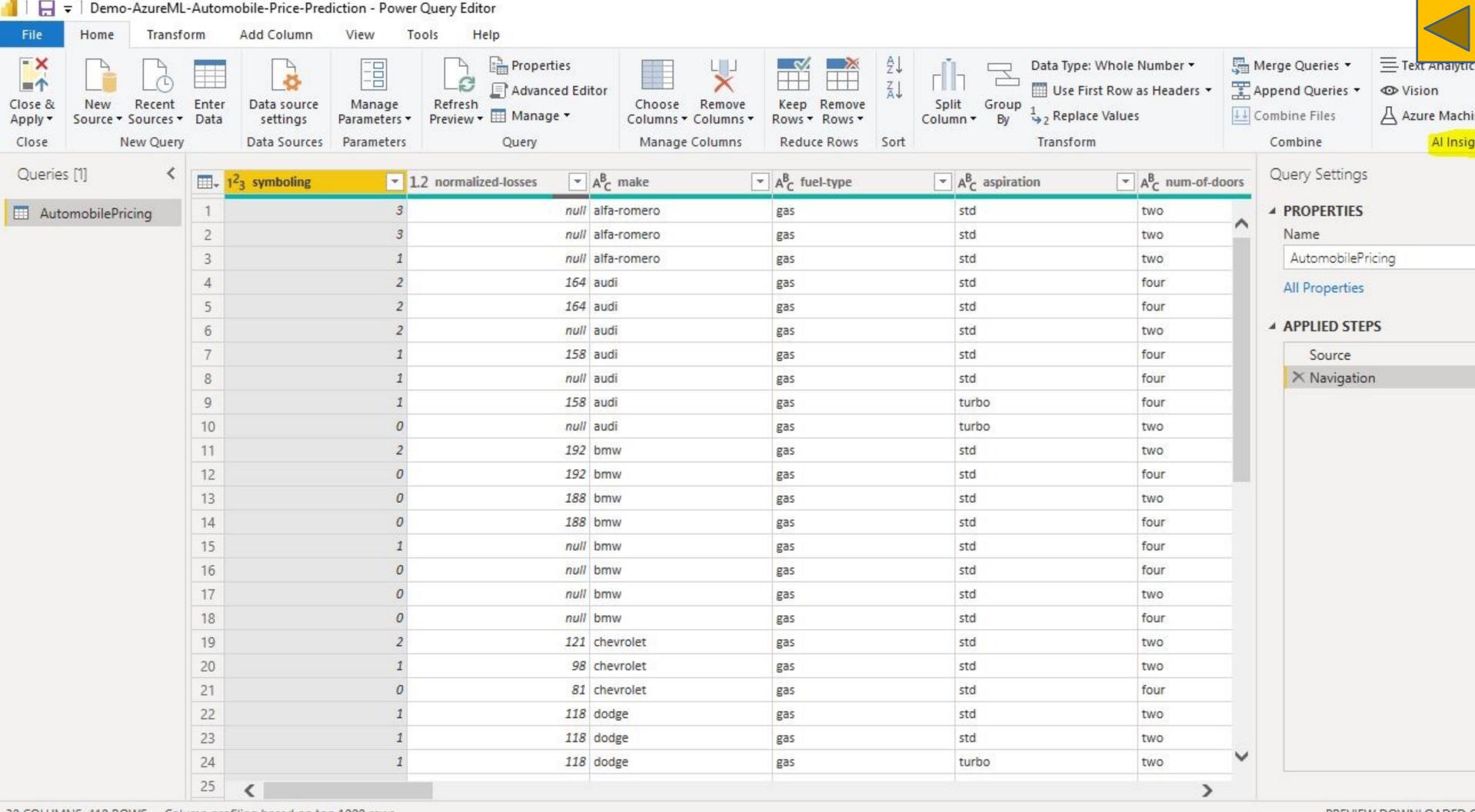
We Are Here to Help

Let us know how we can help take your company to the next level to gain the competitive advantage.

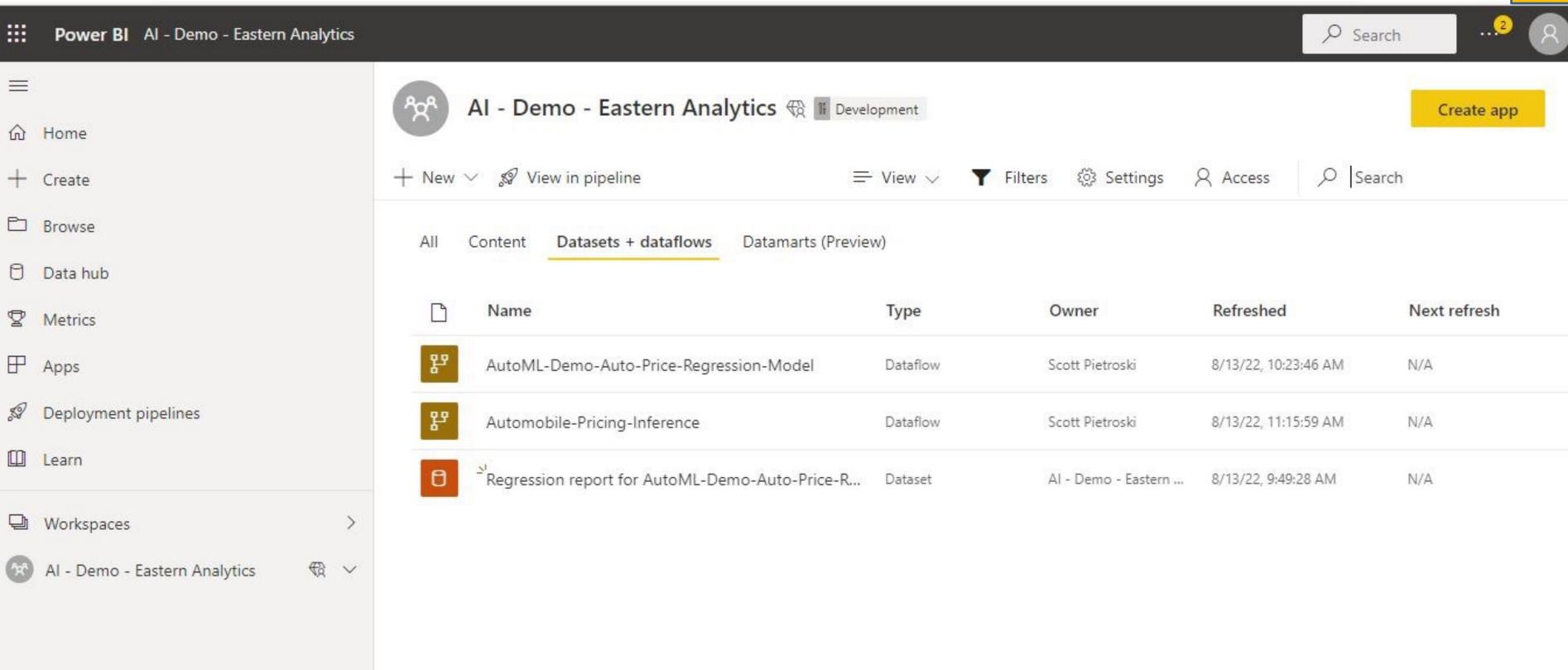




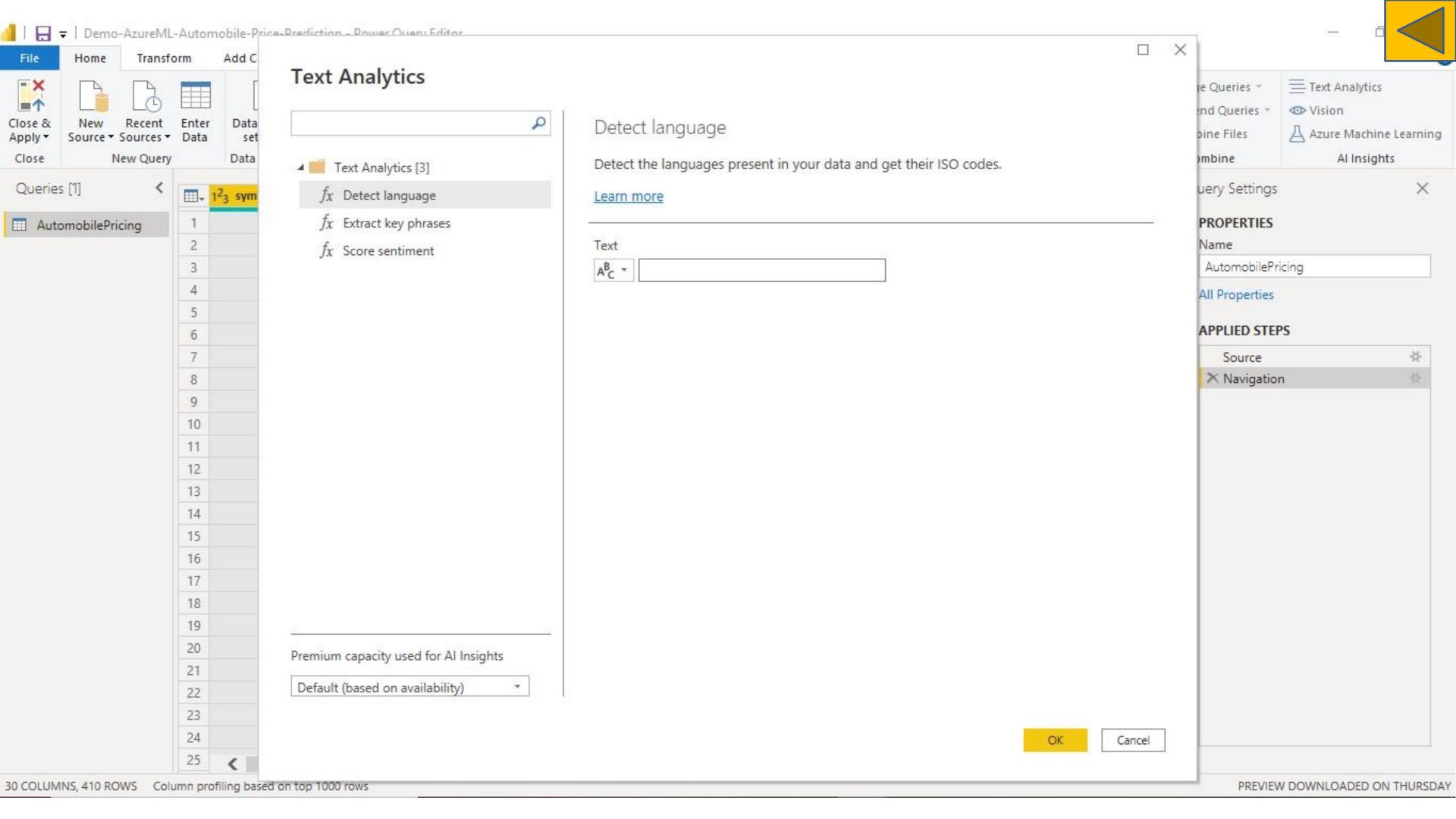


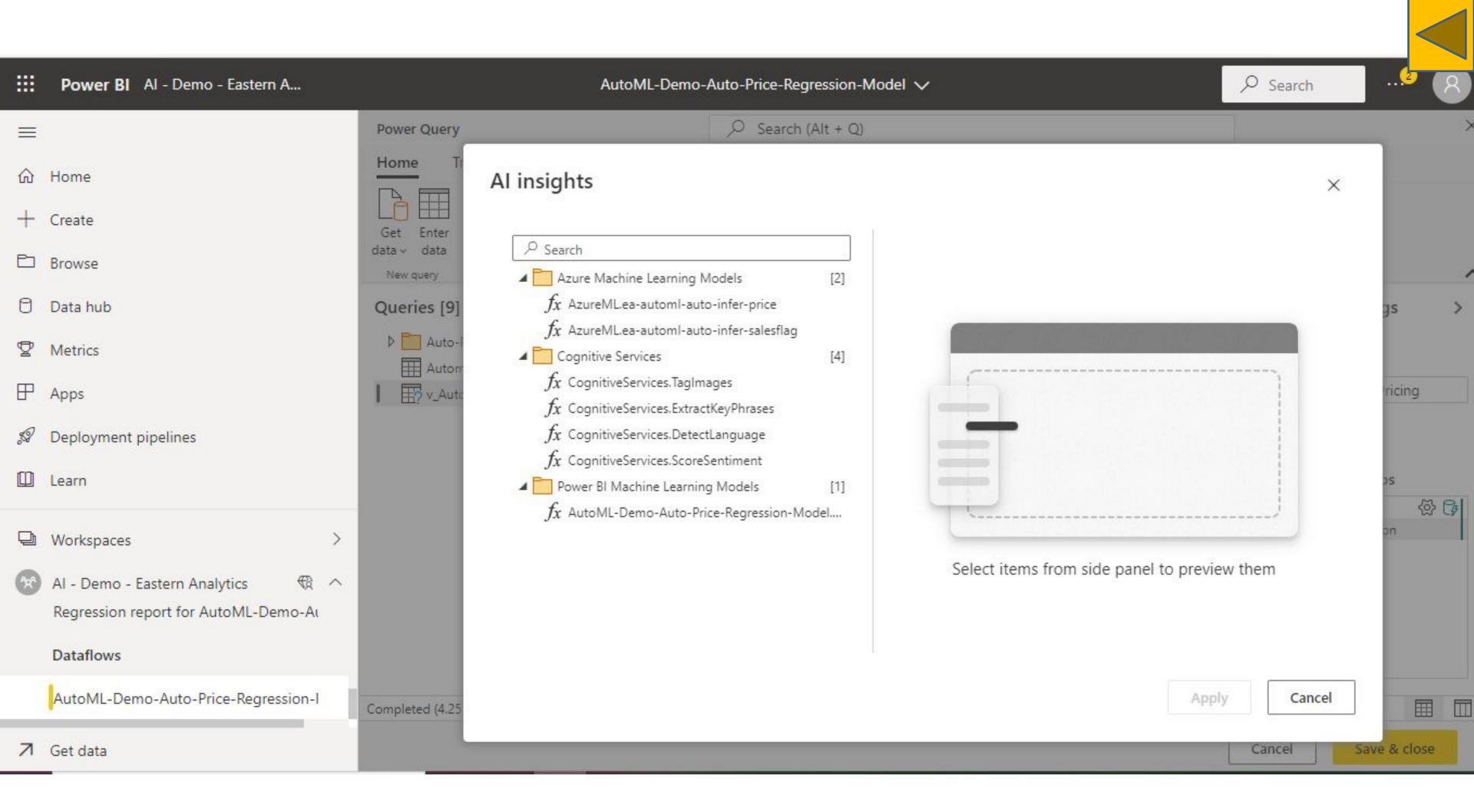


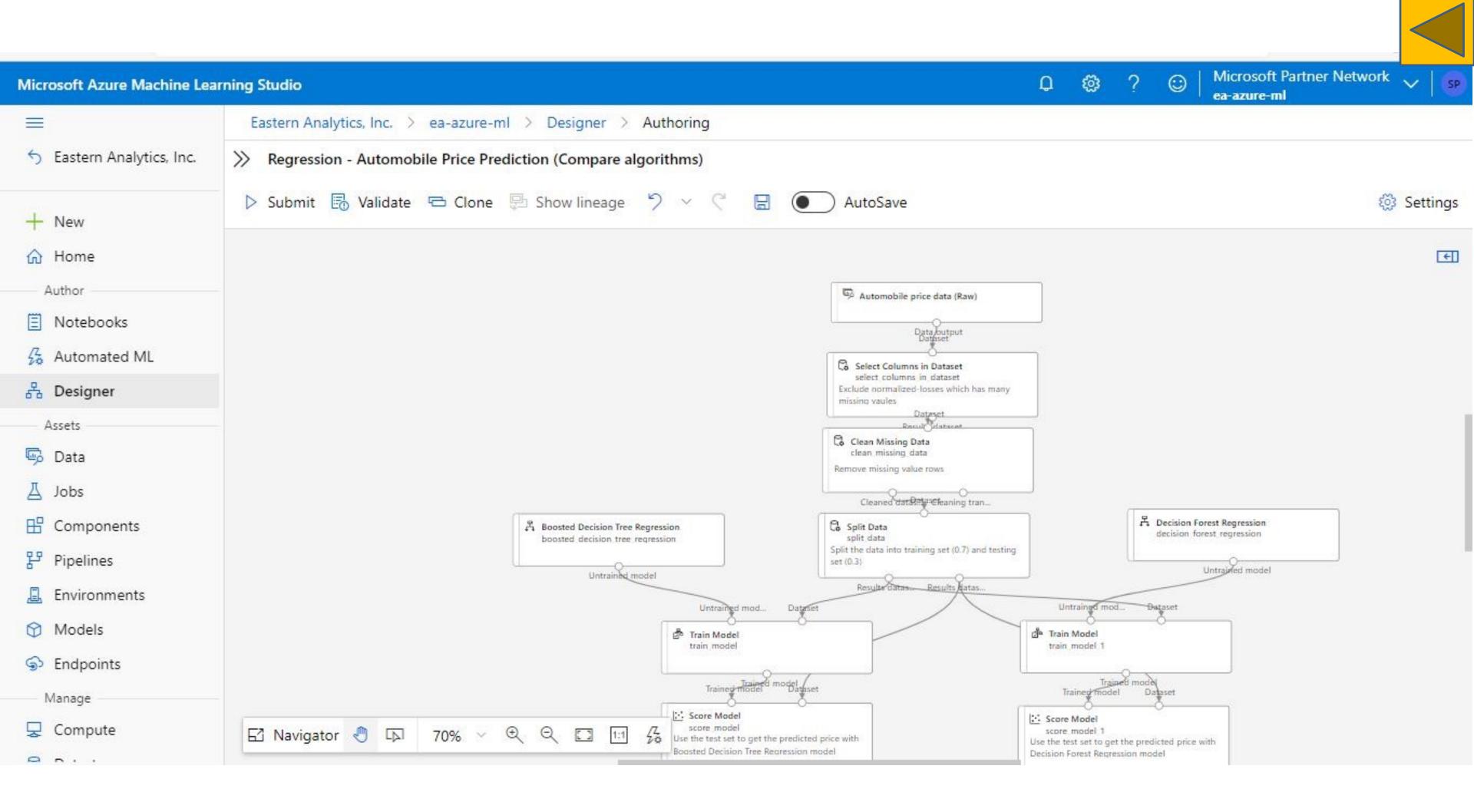




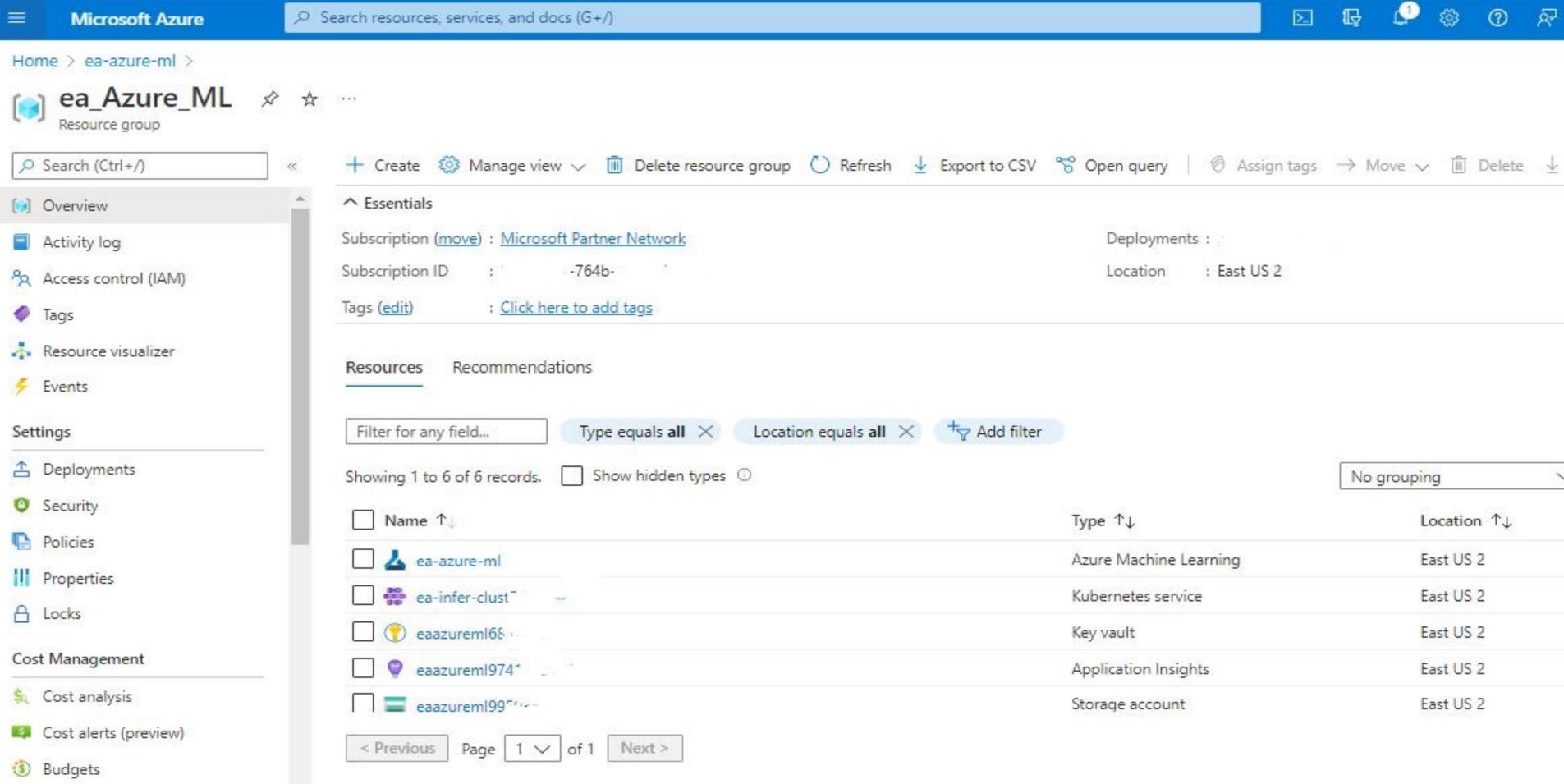
7 Get data











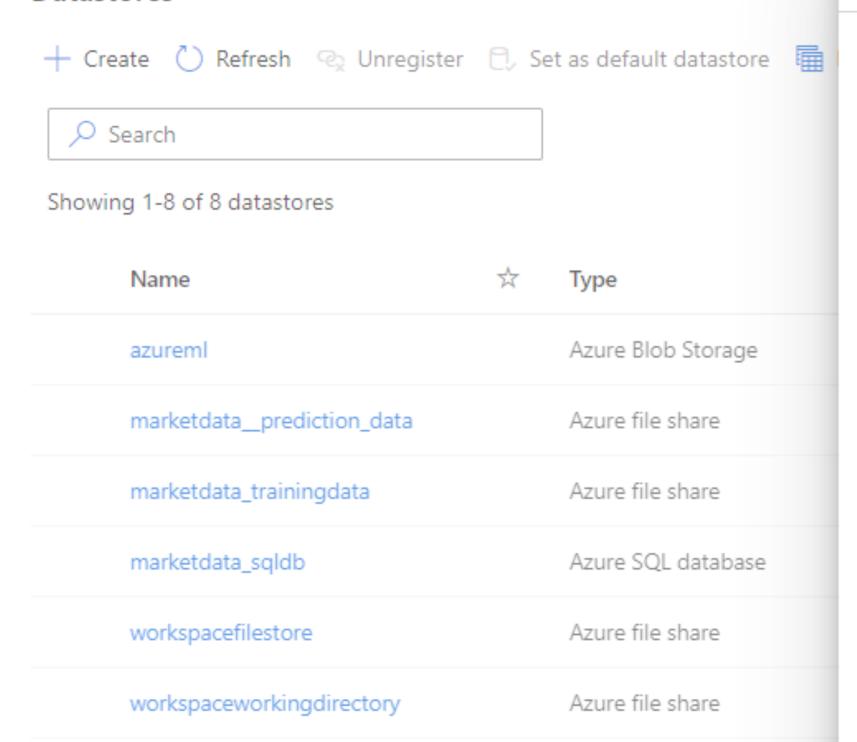
Advisor recommendations

•		Features							
e	Pr	Milage	ModelYear	Model	Make	ZipCode(3)	YearSold		
2,150.		91369	2001	Legacy	Subaru	460	2020		
1,180.		193737	2005	Legacy	Subaru	460	2019		
3,250.		174236	2007	Legacy	Subaru	460	2019		
7,750.		93517	2011	Outback	Subaru	460	2019		
3,530.		140673	2007	Tribeca	Subaru	460	2019		
\$790.		214091	2005	Odyssey	Honda	460	2020		

ID	ZipCode(3)	Make	Model	ModelYear	Milage	ListPrice	Price	
1	460	Subaru	Legacy	2001	91369	1800	?	
2	460	Subaru	Legacy	2005	193737	700	?	
3	460	Subaru	Legacy	2007	174236	2500	?	
4	460	Subaru	Outback	2011	93517	7700	?	
5	460	Subaru	Tribeca	2007	140673	3500	?	
6	460	Honda	Odyssey	2005	214091	500	?	

workspaceartifactstore

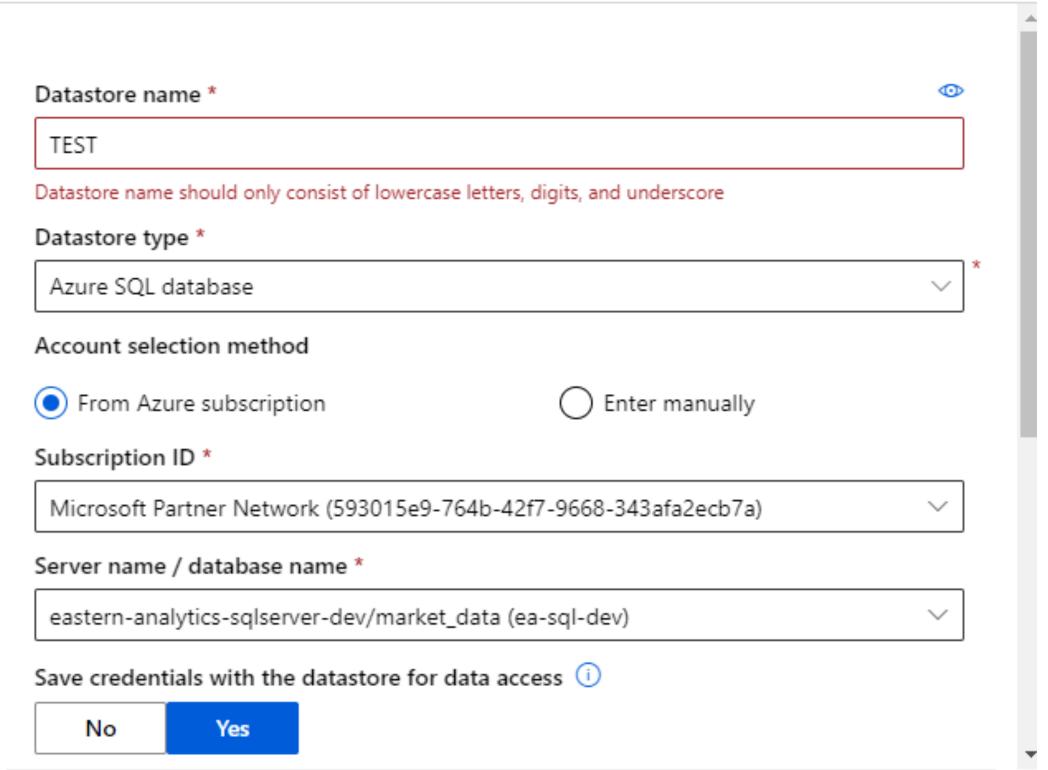
### Datastores



Azure Blob Storage

### Create datastore

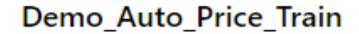




Create

Cancel





Version 2 (latest) ∨ ☆

Details Consume Explore Models Jobs

New version V C Refresh > Generate profile Q Unregister

#### Attributes

Properties

Tabular

Created by

Scott Pietroski

#### Profile

View profile

Job: --

Current version

2

Latest version

2

Created time

Sep 20, 2022 5:20 PM

Modified time

Sep 20, 2022 6:06 PM

### Tags

No data

### Description

i Click edit icon to add a description

### SQL query 🛅

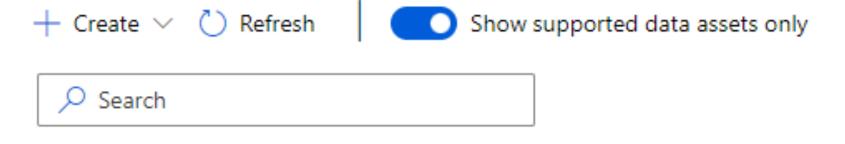
```
select cast(pricesold as decimal(15,2)) as Price,
Cast(yearsold as int) as YearSold,
zip3,
cast(mileage as int) as Milage,
Make,
Model,
cast(year as int) as ModelYear
from [dbo].[Automobile_used_car_sales]
where make = 'leen' or Make = 'Honda' or Make = 'Subaru' or Make
```

### Create a new Automated ML job

Select data asset Configure job Select task and settings Hyperparameter configuration (Computer Vision only) Validate and test

### Select data asset

Select an input data asset from the list below, or create a new data asset. AutomatedML currently only supports tabular data for authoring jobs.



Showing 1-24 of 24 data assets

	Name	Dataset type	Created on $\downarrow$	Modified on
•	Demo_Auto_Price_Train	Tabular	Sep 20, 2022 5:	Sep 20, 2022 6:
	Demo_Time_Series_Grocery_Test	Tabular	Sep 19, 2022 8:	Sep 19, 2022 8:
	Demo_Time_Series_Grocery_Train	Tabular	Sep 19, 2022 7:	Sep 19, 2022 8:
	Automobile-SaleFlag-Prediction	Tabular	Aug 11, 2022 5	Aug 11, 2022 5

Back Next

Cancel

Page size:



### AutoML Auto Pricing Demo 🖉 🔯 Completed





Overview

Data guardrails

Models

Outputs + logs

Child jobs

Refresh

▶ Edit and submit (preview) + Register model ⊗ Cancel Delete

### **Properties**

#### Status



✓ Completed 
✓



▲ Warning: No scores improved over last 20 iterations, so experiment stopped early. This early stopping behavior can be disabled by setting enable\_early\_stopping = False in AutoMLConfig for notebook/python SDK runs.

See more details

#### Created on

Sep 20, 2022 6:08 PM

#### Start time

Sep 20, 2022 6:09 PM

#### Duration

42m 29.99s

Compute duration

### Inputs

Input name: training\_data

Dataset: Demo\_Auto\_Price\_Train:2

### Outputs

Output name: default

Data: azureml\_AutoML\_434235a1-19ca-452b-b703-4791d89cbc8c\_output\_data\_default:1

Output name: best\_model

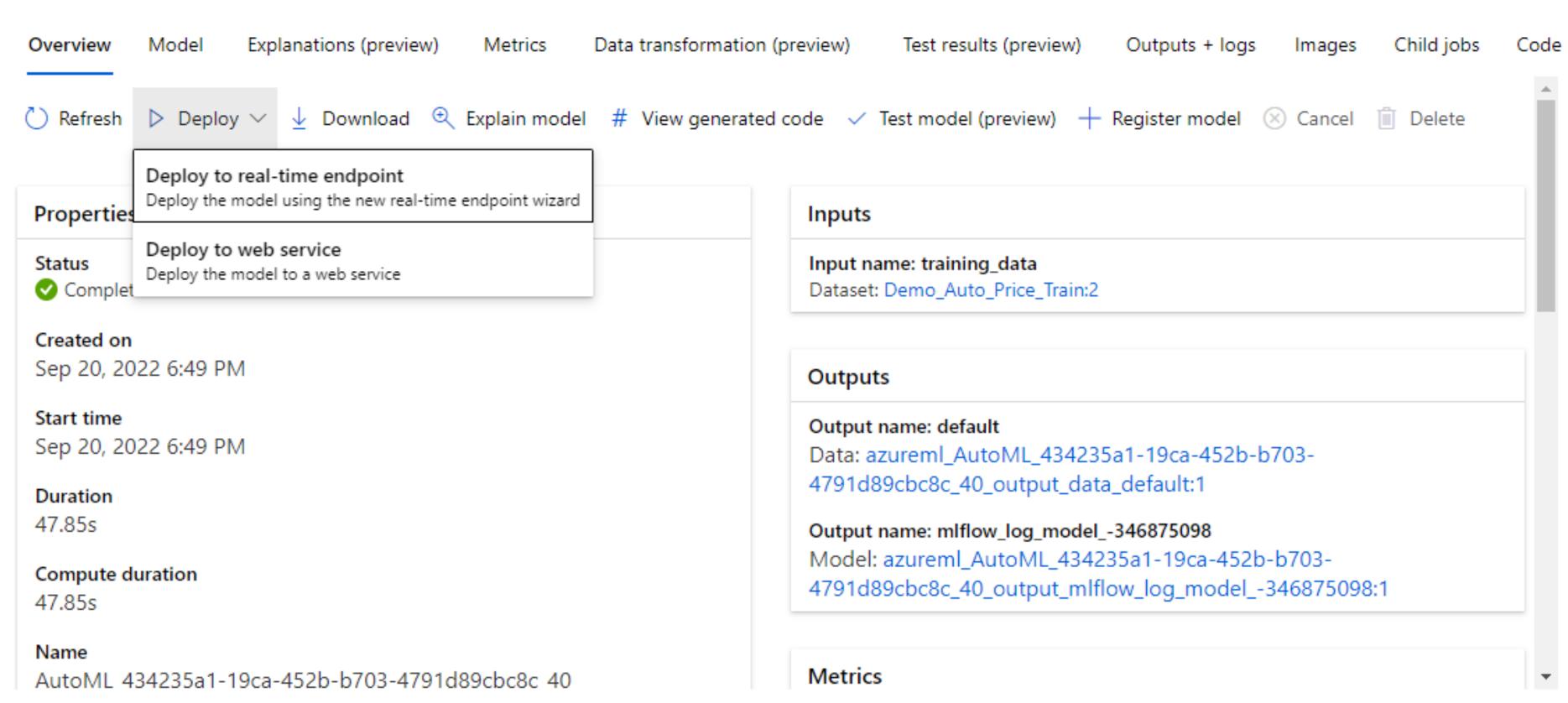
Model: azureml\_AutoML\_434235a1-19ca-452b-b703-

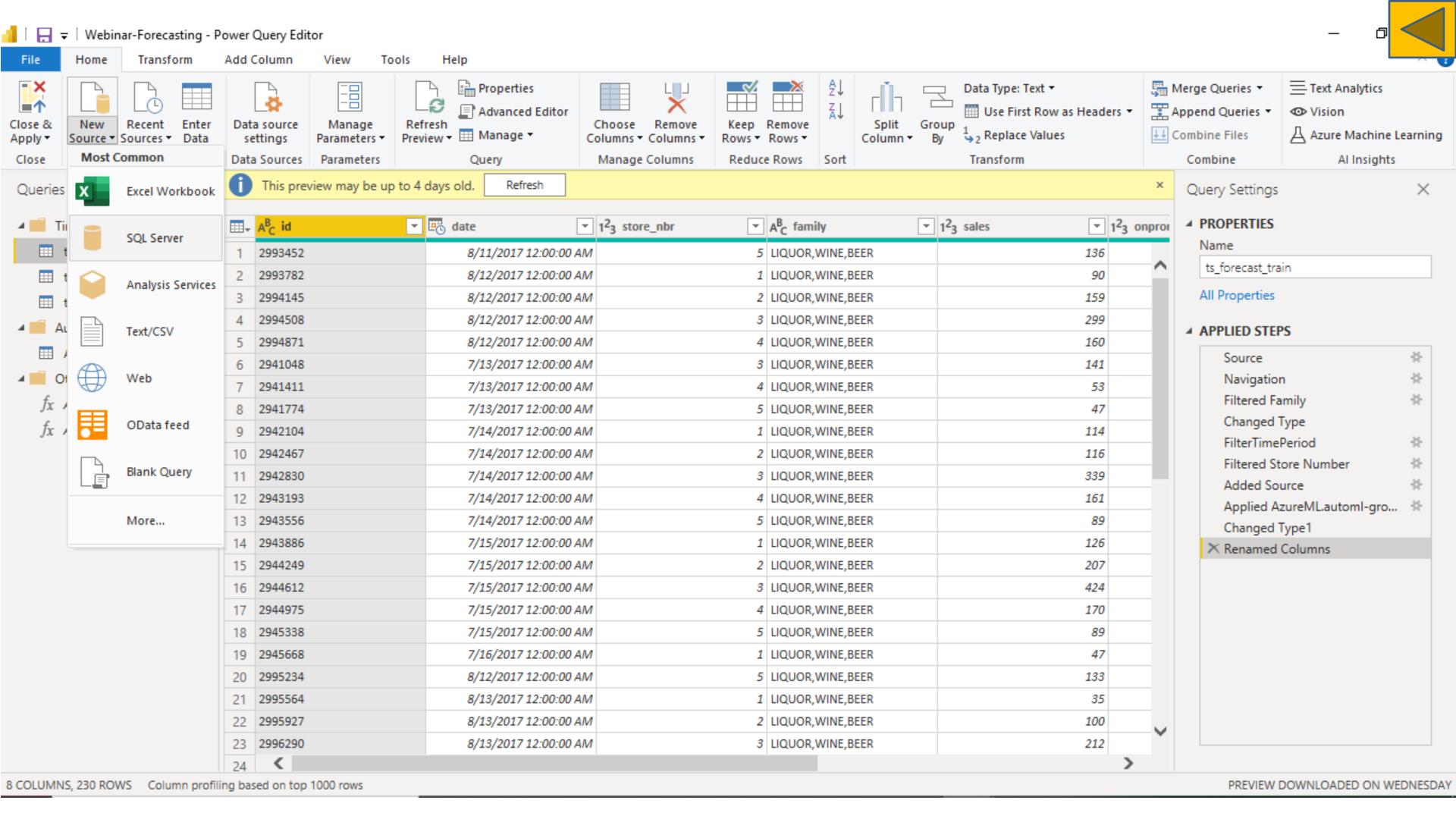
4791d89cbc8c\_40\_output\_mlflow\_log\_model\_-346875098:1

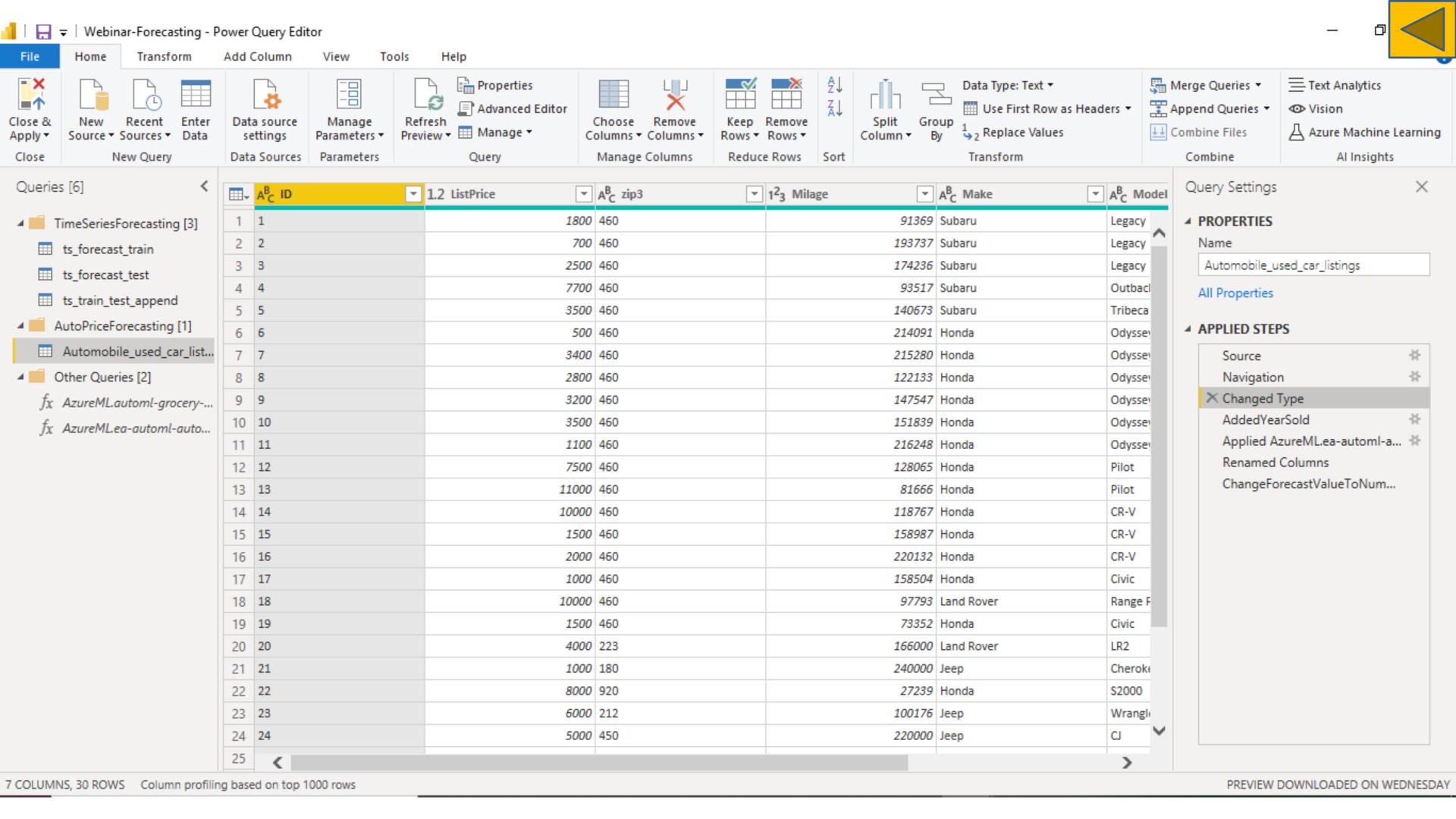
### Best model summary

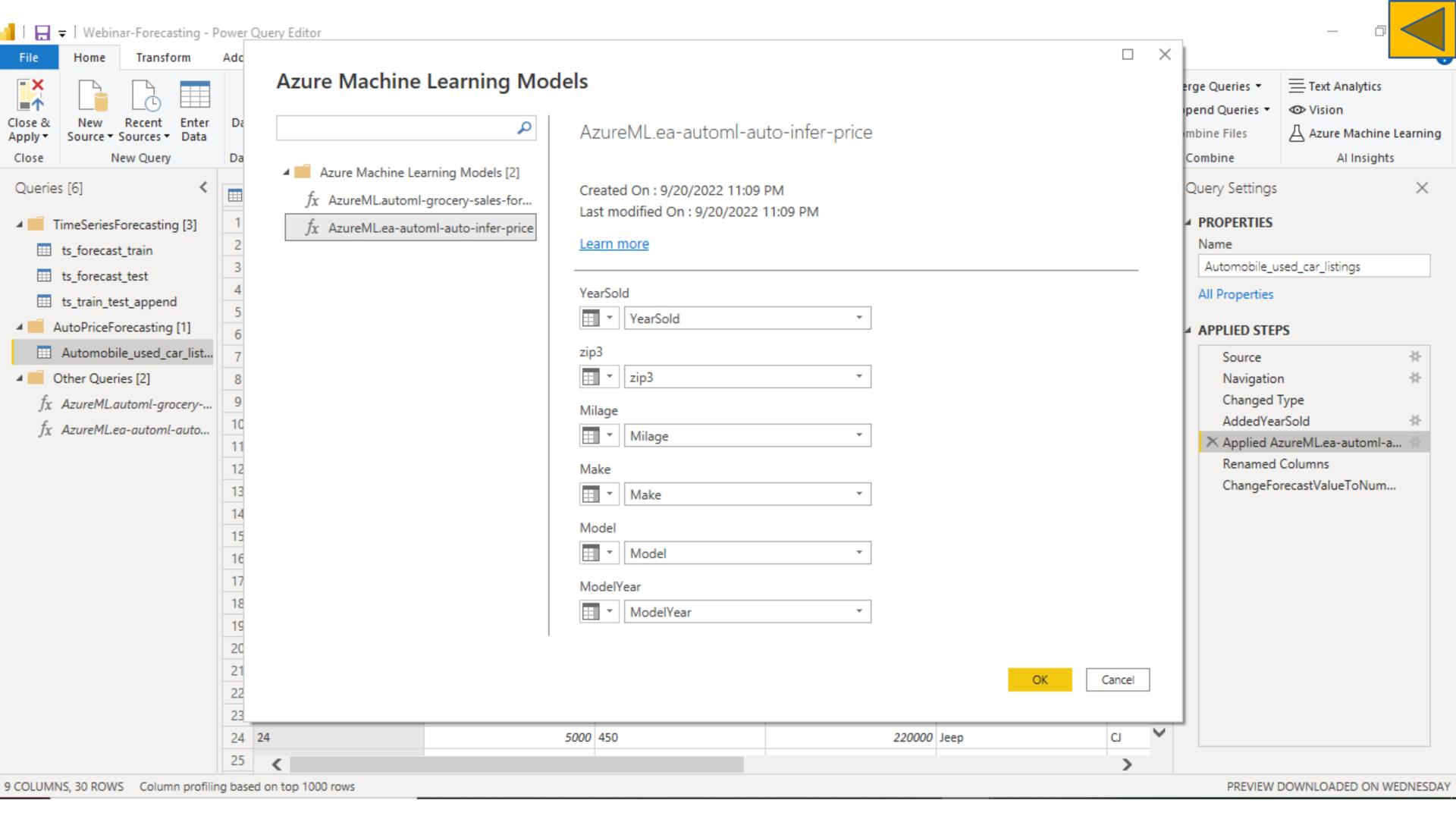


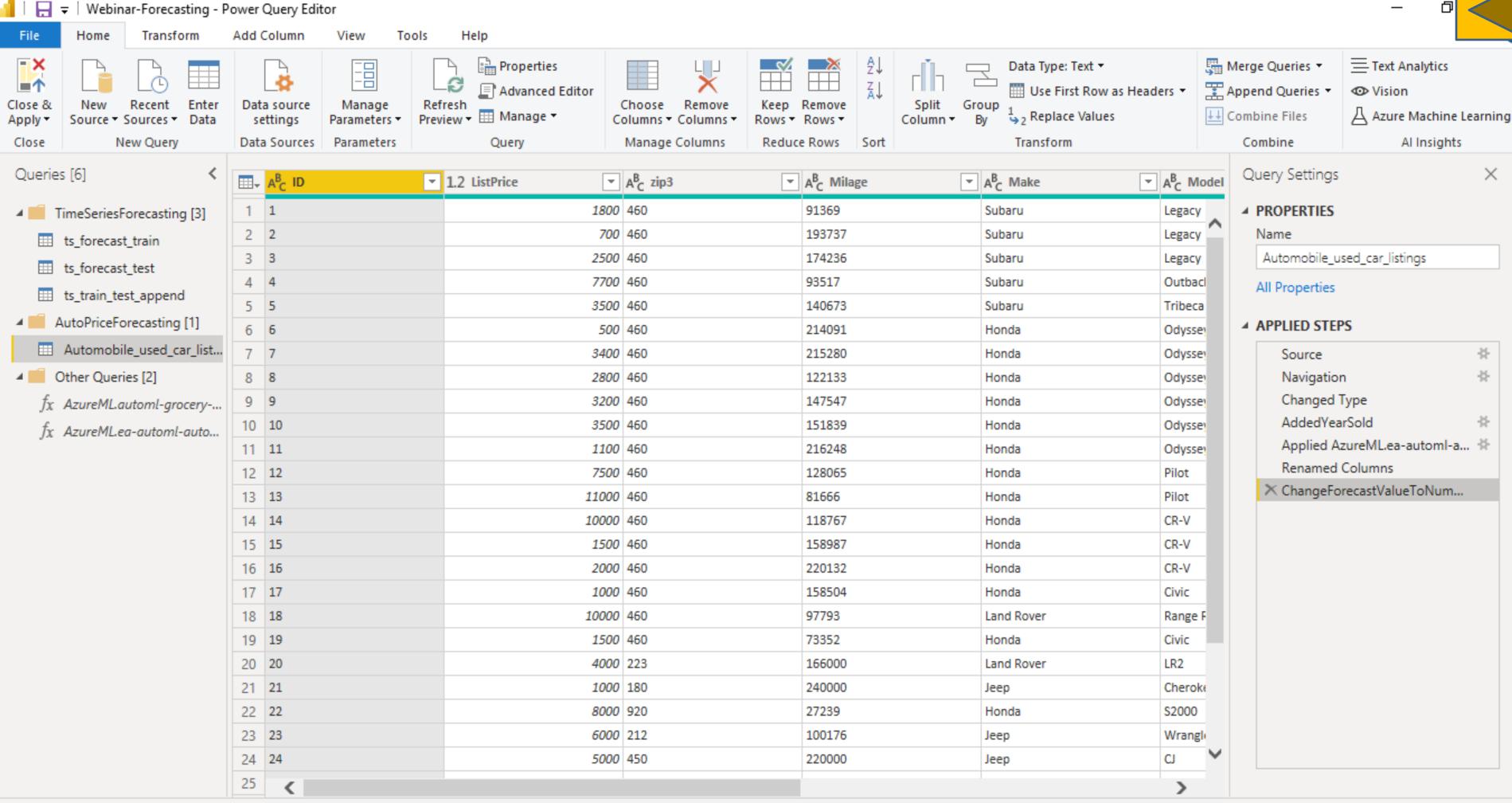




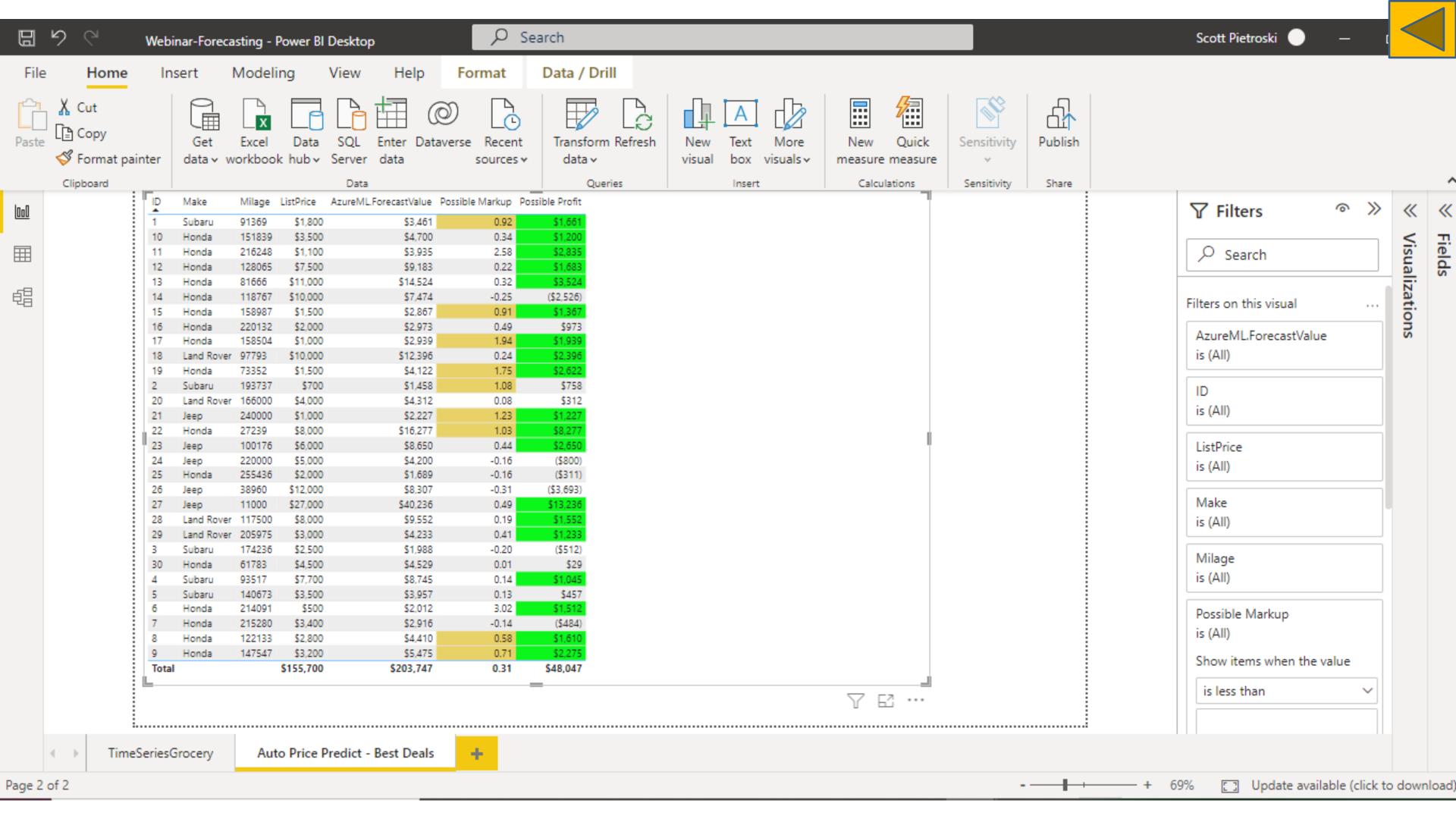








9 COLUMNS, 30 ROWS Column profiling based on top 1000 rows PREVIEW DOWNLOADED AT 2:25 PM



		Features		
date	store_nbr	family	OnPromotion	Sales
1/1/2013	1	LIQUOR, WINE, BEER	0	\$0.00
1/2/2013	1	LIQUOR, WINE, BEER	0	\$67.00
1/3/2013	1	LIQUOR, WINE, BEER	0	\$66.00
1/4/2013	1	LIQUOR, WINE, BEER	0	\$102.00
1/5/2013	1	LIQUOR, WINE, BEER	2	\$159.00
1/6/2013	1	LIQUOR, WINE, BEER	3	\$0.00
1/7/2013	1	LIQUOR, WINE, BEER	0	\$109.00
1/8/2013	1	LIQUOR, WINE, BEER	0	\$86.00
1/9/2013	1	LIQUOR, WINE, BEER	3	\$104.00
1/10/2013	1	LIQUOR, WINE, BEER	0	\$67.00

		Features		
date	store_nbr	family	OnPromotion	Sale
1/11/2013	1	LIQUOR, WINE, BEER	3	?
1/12/2013	1	LIQUOR, WINE, BEER	3	?
1/13/2013	1	LIQUOR, WINE, BEER	3	?
1/14/2013	1	LIQUOR, WINE, BEER	O	?
1/15/2013	1	LIQUOR, WINE, BEER	O	?
1/16/2013	1	LIQUOR, WINE, BEER	1	?
1/17/2013	1	LIQUOR, WINE, BEER	O	?
1/18/2013	1	LIQUOR, WINE, BEER	O	?
1/19/2013	1	LIQUOR, WINE, BEER	O	?
1/20/2013	1	LIQUOR, WINE, BEER	O	?

date	type	locale	locale_name	description	
1/1/2013	Holiday	National	Ecuador	Primer dia del ano	
1/5/2013	Work Day	National	Ecuador	Recupero puente l	Nav
1/12/2013	Work Day	National	Ecuador	Recupero puente p	orir
2/11/2013	Holiday	National	Ecuador	Carnaval	
2/12/2013	Holiday	National	Ecuador	Carnaval	
3/2/2013	Holiday	Local	Manta	Fundacion de Man	ta

store_nbr	city	state	type	cluster
1	Quito	Pichincha	D	13
2	Quito	Pichincha	D	13
3	Quito	Pichincha	D	8
4	Quito	Pichincha	D	9



# Demo\_Time\_Series\_Grocery\_Train

Version 2 (latest) ∨ ☆

Details Consume Explore Models Jobs

New version ∨ ○ Refresh

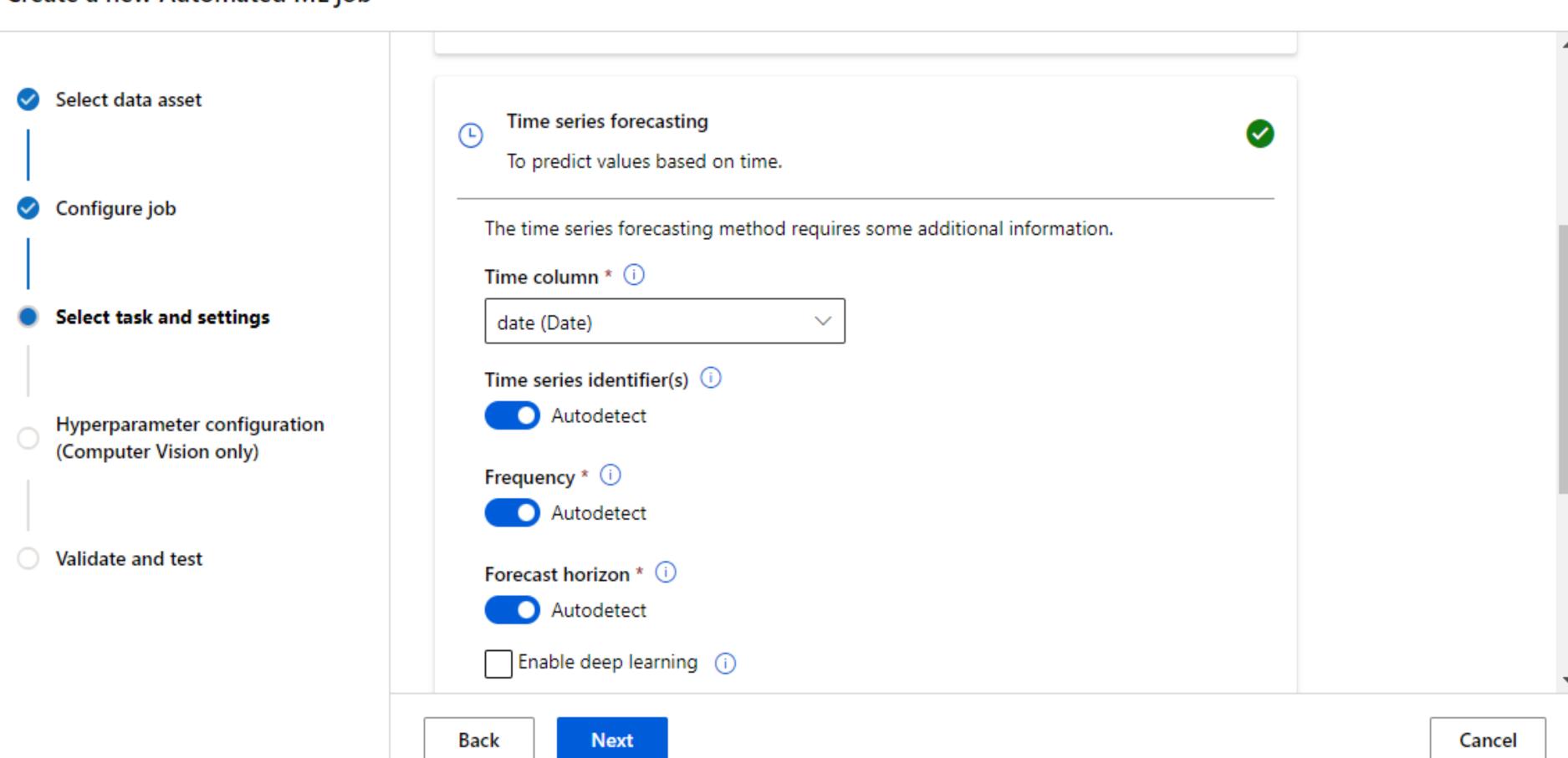
Concrete Profile Concrete Unregister

Preview Profile

Number of columns: 5 Number of rows: 50 (of 8190)

date	store_nbr	family	Sales	OnPromotion	•
2015-12-28 00:00:00	2	LIQUOR,WINE,BEER	165	0	
2017-03-13 00:00:00	5	LIQUOR,WINE,BEER	51	1	
2017-03-14 00:00:00	1	LIQUOR,WINE,BEER	88	1	
2017-03-14 00:00:00	2	LIQUOR,WINE,BEER	50	2	
2017-03-14 00:00:00	3	LIQUOR,WINE,BEER	94	1	
2017-03-14 00:00:00	4	LIQUOR,WINE,BEER	48	1	
2014-03-19 00:00:00	3	LIQUOR,WINE,BEER	176	0	
2014-03-19 00:00:00	4	LIQUOR,WINE,BEER	38	0	•

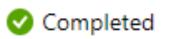
# Create a new Automated ML job





# AutoML - Time Series Forecast - BEER/WINE Demo 🖉 🛣 😵 Completed





Overview

Data guardrails

Models

Outputs + logs

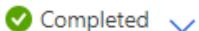
Child jobs

Refresh

▶ Edit and submit (preview) + Register model ⊗ Cancel Delete

# Properties

#### Status





▲ Warning: No scores improved over last 20 iterations, so experiment stopped early. This early stopping behavior can be disabled by setting enable\_early\_stopping = False in AutoMLConfig for notebook/python SDK runs.

#### See more details

### Created on

Sep 19, 2022 8:21 PM

#### Start time

Sep 19, 2022 8:21 PM

#### Duration

33m 26.51s

#### Compute duration

# Inputs

### Input name: training\_data

Dataset: Demo\_Time\_Series\_Grocery\_Train:2

### Input name: test\_data

Dataset: Demo\_Time\_Series\_Grocery\_Test:2

## Outputs

### Output name: default

Data: azureml\_AutoML\_897756e6-209a-4f49-87c4d21640770930\_40\_output\_data\_default:1

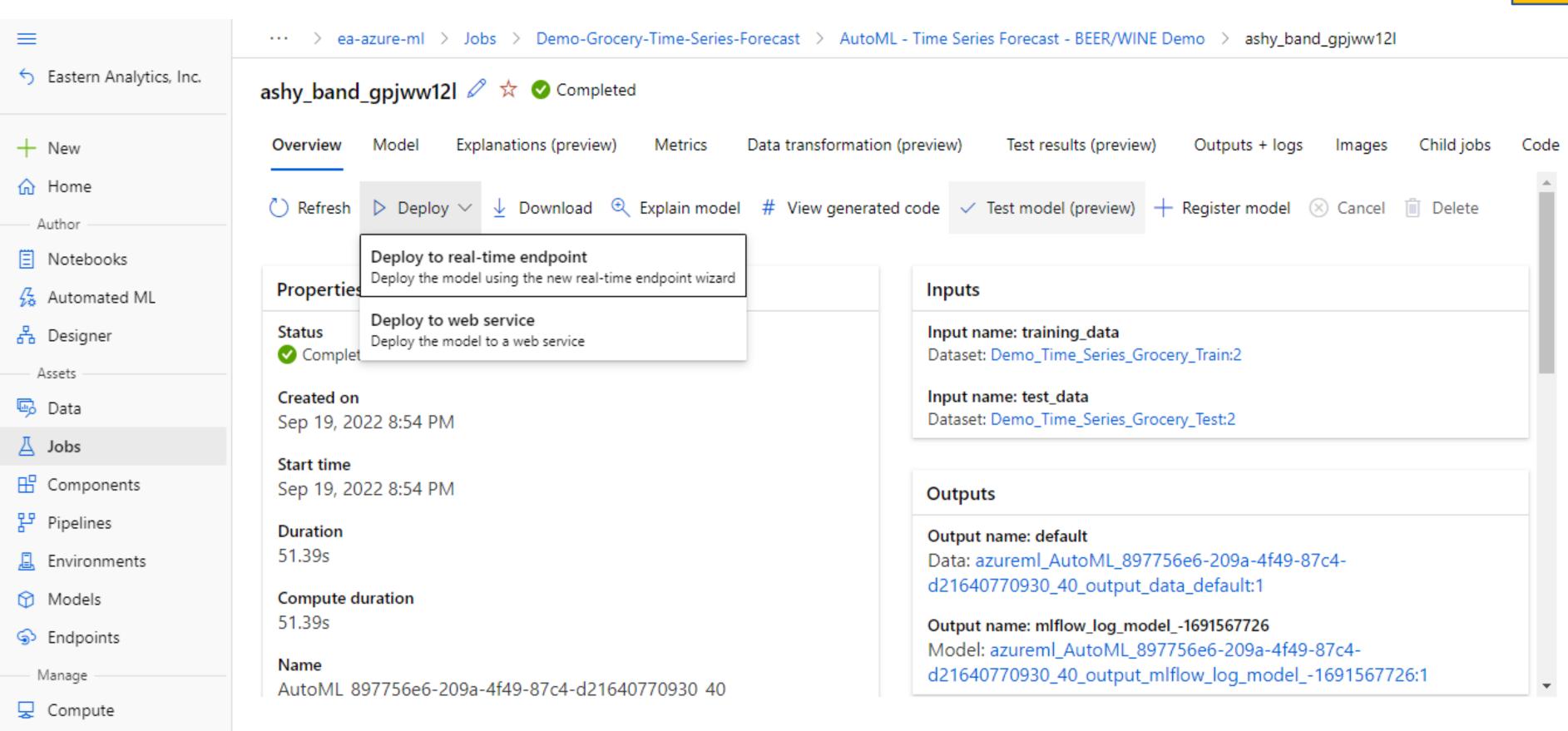
### Output name: best\_model

Model: azureml\_AutoML\_897756e6-209a-4f49-87c4-

d21640770930\_40\_output\_mlflow\_log\_model\_-1691567726:1

Outnut name: full training dataset







 $\times$ 



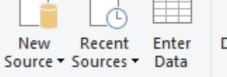
File

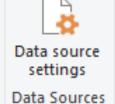
Close



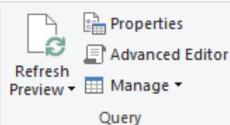


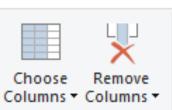
**New Query** 



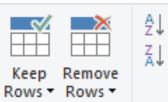






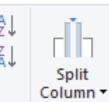


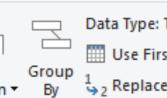
Manage Columns



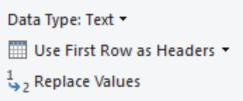
Reduce Rows Sort







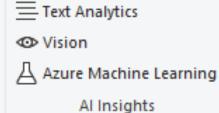
Transform





Combine

Name







- ts\_forecast\_train ts\_forecast\_test
- ts\_train\_test\_append
- AutoPriceForecasting [1]
- Automobile\_used\_car\_listings
- Other Queries [2]
  - $f_X$  AzureML.automl-grocery-sales-forec...
  - $f_X$  AzureML.ea-automl-auto-infer-price

(	→ A <sup>B</sup> <sub>C</sub> id	date 🔻	1 <sup>2</sup> <sub>3</sub> store_nbr	A <sup>B</sup> <sub>C</sub> family	1 <sup>2</sup> <sub>3</sub> sales	
1	2993452	8/11/2017 12:00:00 AM	5	LIQUOR,WINE,BEER	1	
2	2993782	8/12/2017 12:00:00 AM	1	LIQUOR,WINE,BEER	^	
3	2994145	8/12/2017 12:00:00 AM	2	LIQUOR,WINE,BEER	1	
4	2994508	8/12/2017 12:00:00 AM	3	LIQUOR,WINE,BEER	2	
5	2994871	8/12/2017 12:00:00 AM	4	LIQUOR,WINE,BEER	1	
6	2941048	7/13/2017 12:00:00 AM	3	LIQUOR,WINE,BEER	1	
7	2941411	7/13/2017 12:00:00 AM	4	LIQUOR,WINE,BEER		
8	2941774	7/13/2017 12:00:00 AM	5	LIQUOR,WINE,BEER		
9	2942104	7/14/2017 12:00:00 AM	1	LIQUOR,WINE,BEER	1	
10	2942467	7/14/2017 12:00:00 AM	2	LIQUOR,WINE,BEER	1	
11	2942830	7/14/2017 12:00:00 AM	3	LIQUOR,WINE,BEER	3	
12	2943193	7/14/2017 12:00:00 AM	4	LIQUOR,WINE,BEER	1	
13	2943556	7/14/2017 12:00:00 AM	5	LIQUOR,WINE,BEER		
14	1 2943886	7/15/2017 12:00:00 AM	1	LIQUOR,WINE,BEER	1	
15	2944249	7/15/2017 12:00:00 AM	2	LIQUOR,WINE,BEER	2	
16	2944612	7/15/2017 12:00:00 AM	3	LIQUOR,WINE,BEER	4	
17	2944975	7/15/2017 12:00:00 AM	4	LIQUOR,WINE,BEER	1	
18	2945338	7/15/2017 12:00:00 AM	5	LIQUOR,WINE,BEER		
19	2945668	7/16/2017 12:00:00 AM	1	LIQUOR,WINE,BEER		
20	2995234	8/12/2017 12:00:00 AM	5	LIQUOR,WINE,BEER	1	
2	2995564	8/13/2017 12:00:00 AM	1	LIQUOR,WINE,BEER		
22	2995927	8/13/2017 12:00:00 AM	2	LIQUOR,WINE,BEER	1	
23	2996290	8/13/2017 12:00:00 AM	3	LIQUOR,WINE,BEER	2	
24	1 2996653	8/13/2017 12:00:00 AM	4	LIQUOR,WINE,BEER	~	
25	<				>	

Query Settings

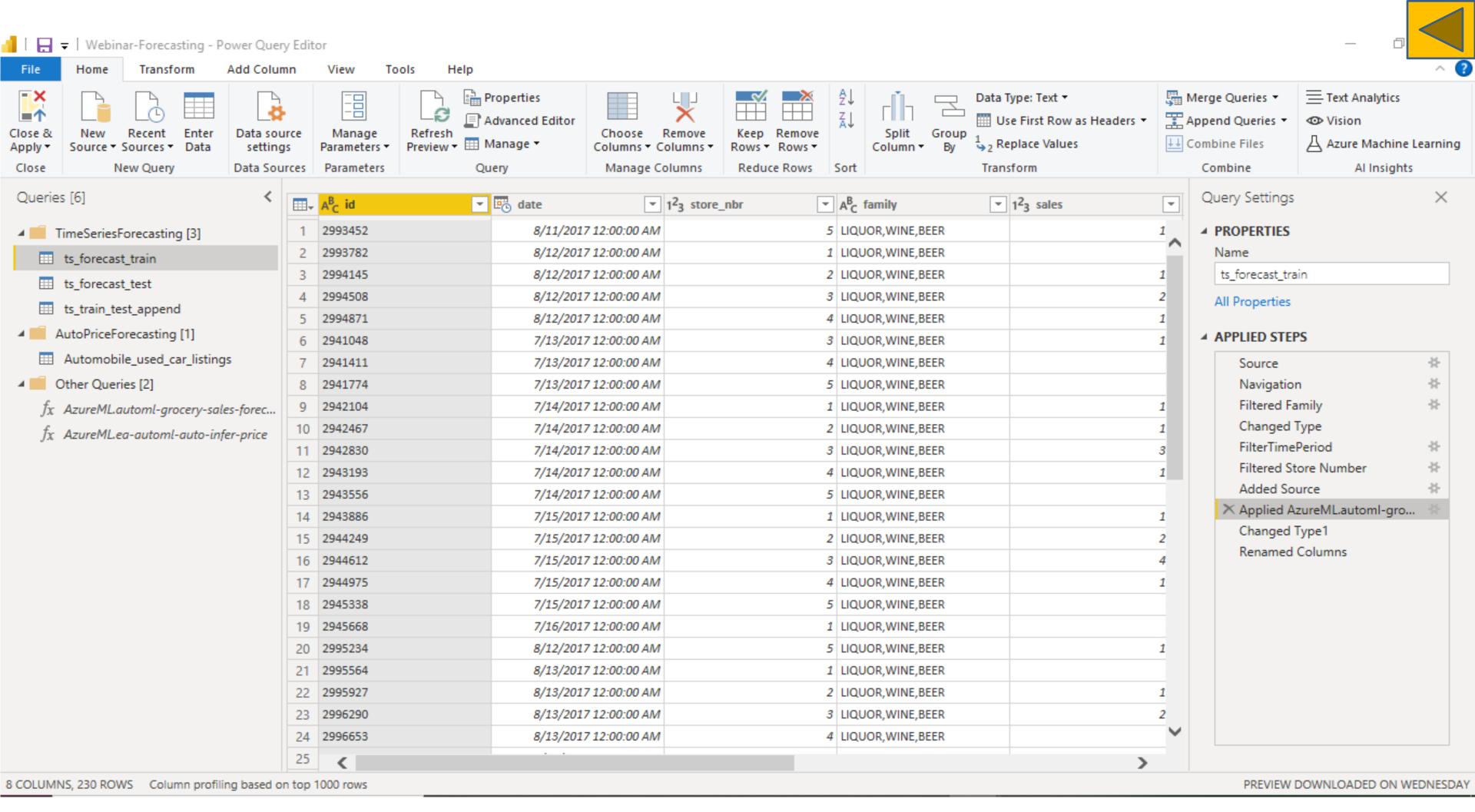
■ PROPERTIES

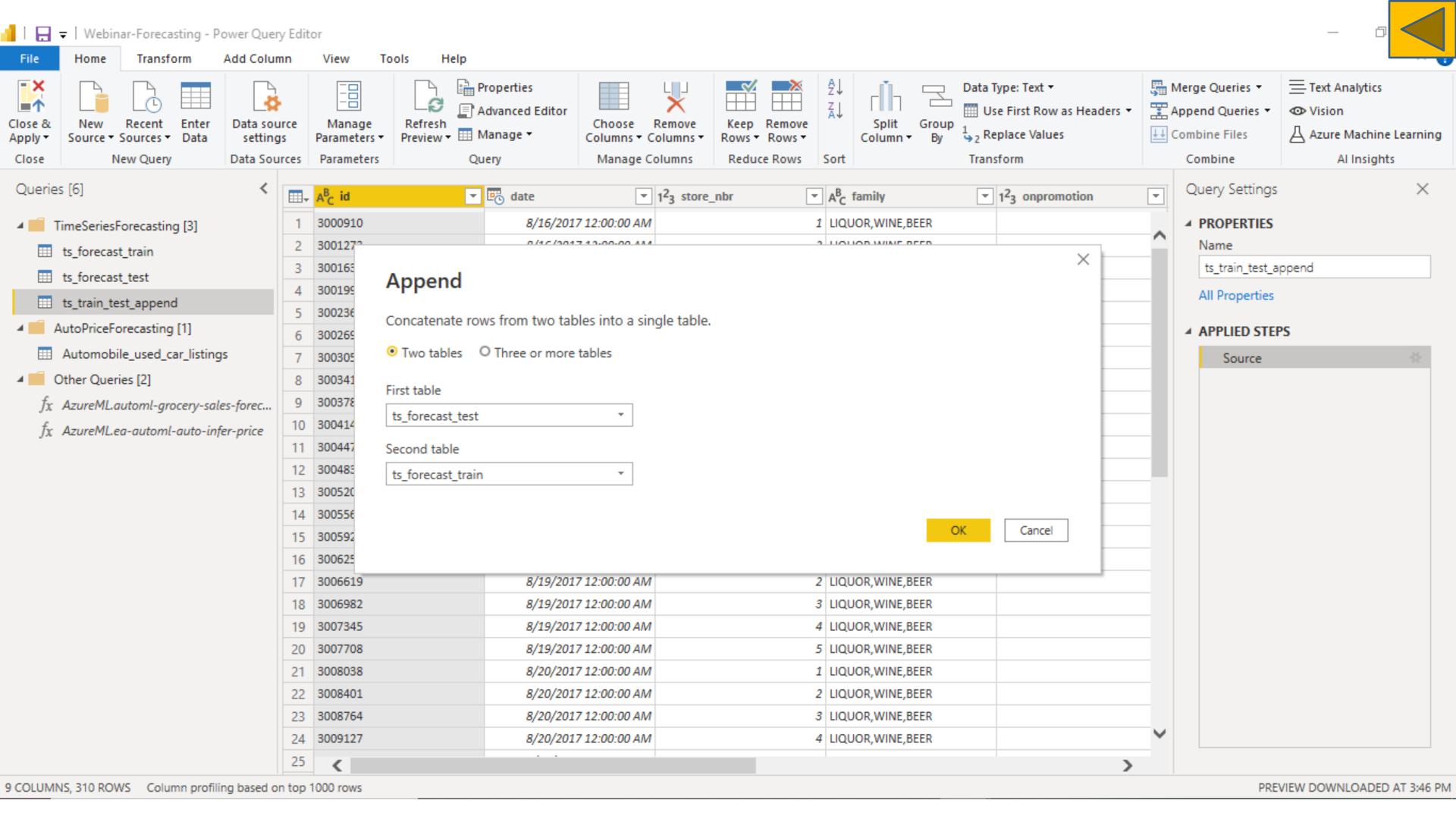
ts\_forecast\_train

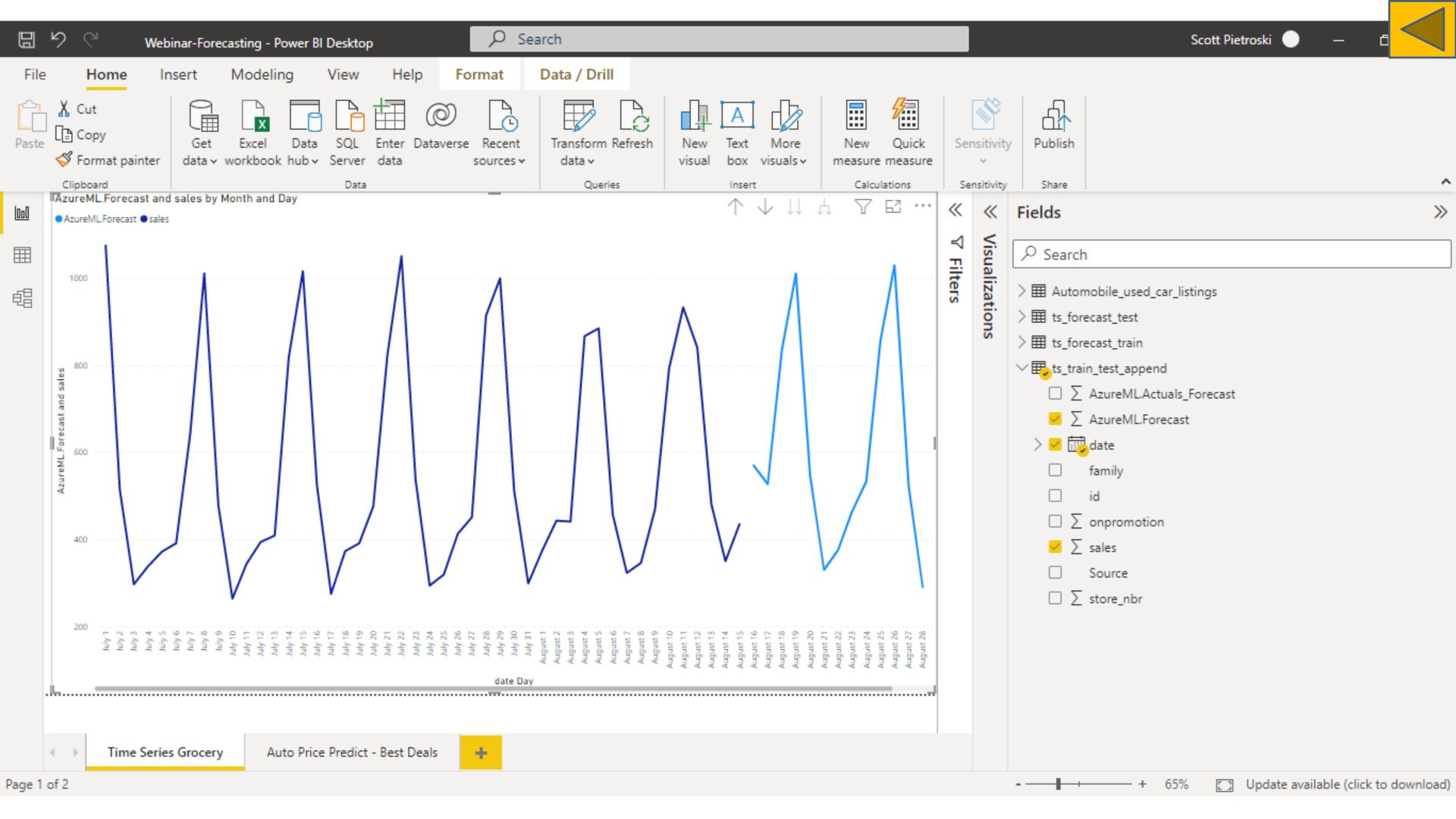
**All Properties** 

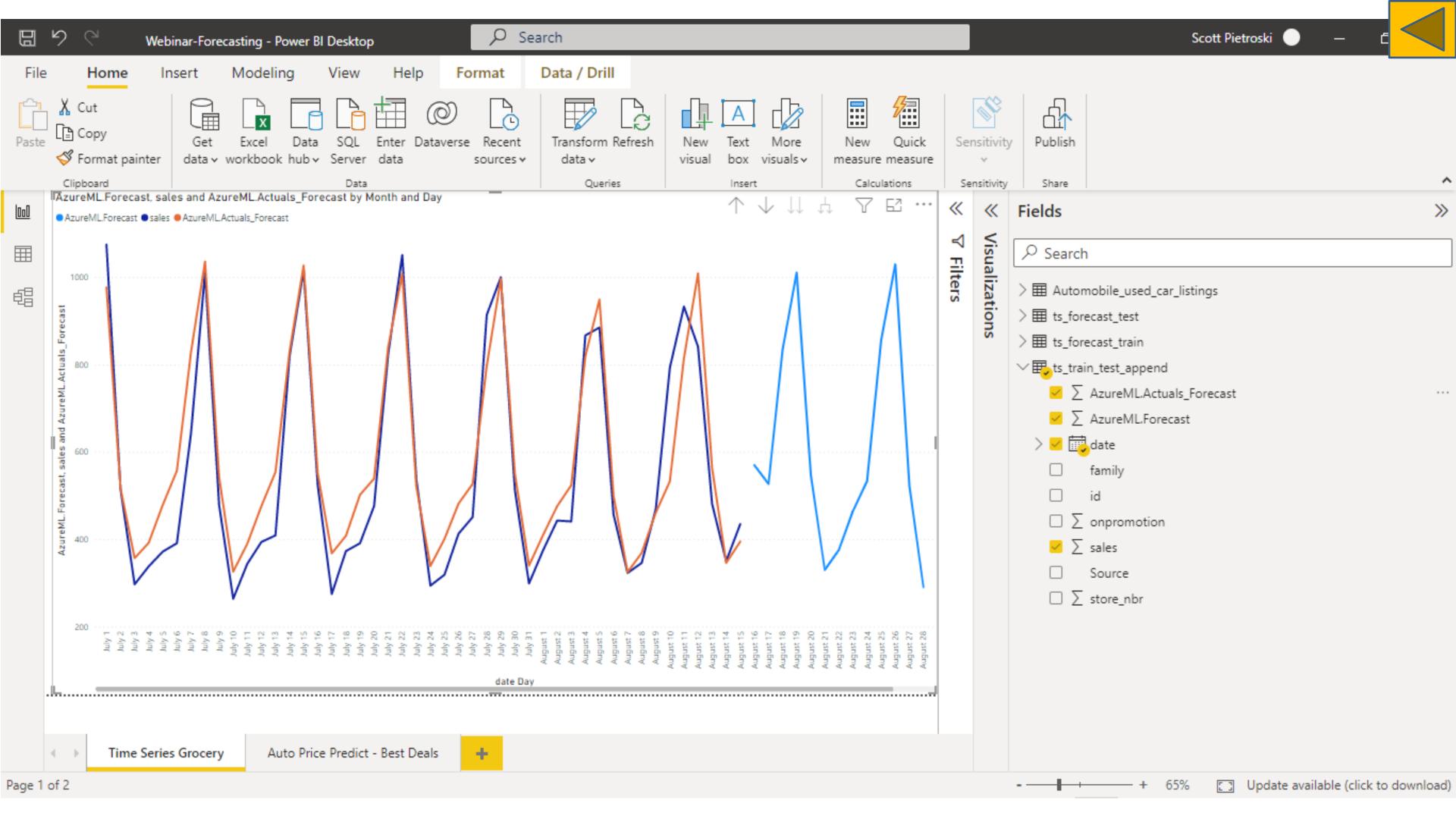
#### ▲ APPLIED STEPS

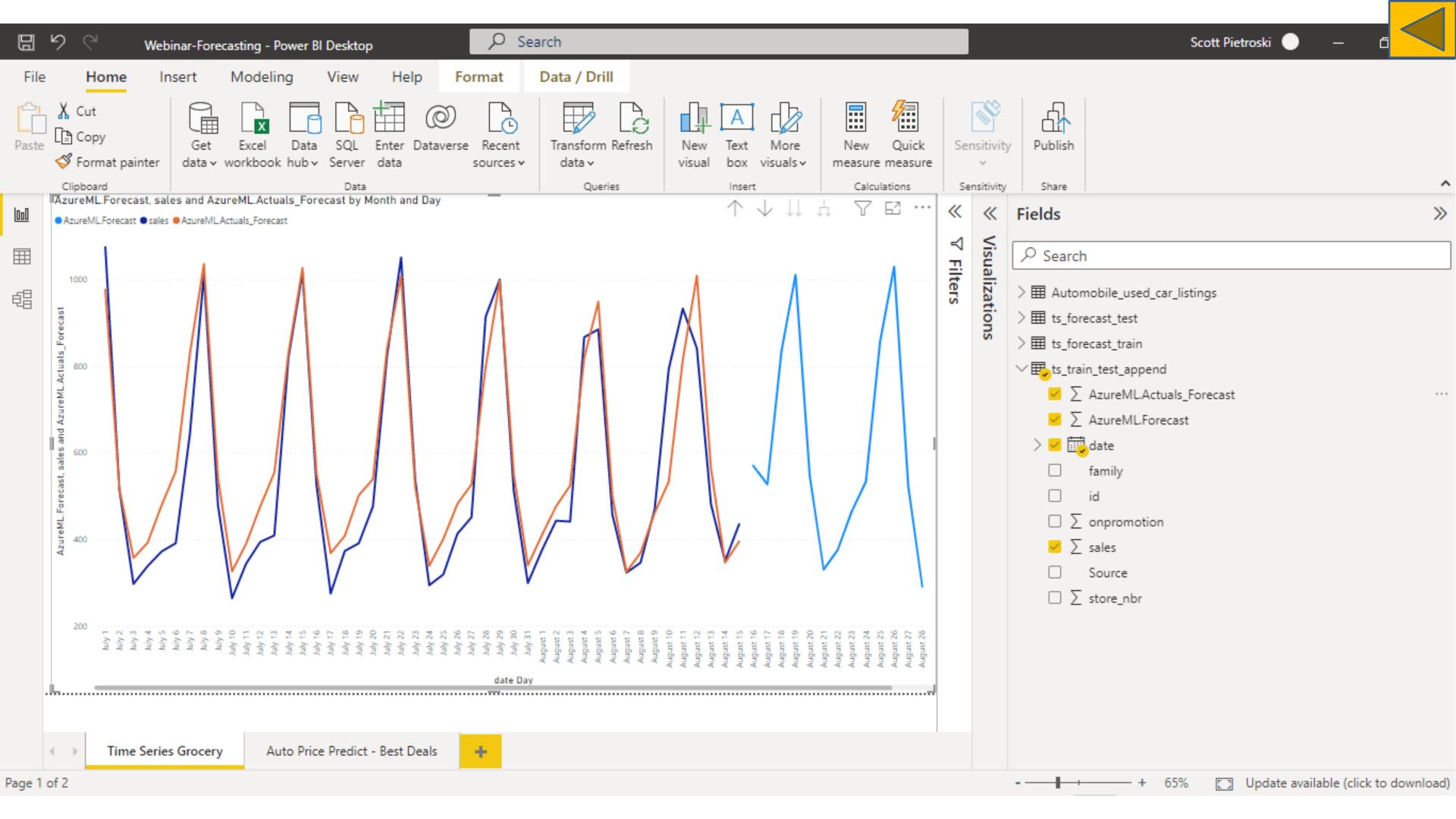
Source Navigation Filtered Family Changed Type FilterTimePeriod Filtered Store Number Added Source Applied AzureML.automl-gro... Changed Type1 X Renamed Columns











# Training Data – Historical Sales

		Features		
date	store_nbr	family	OnPromotion	Sales
1/1/2013	1	LIQUOR, WINE, BEER	0	\$0.00
1/2/2013	1	LIQUOR, WINE, BEER	0	\$67.00
1/3/2013	1	LIQUOR, WINE, BEER	O	\$66.00
1/4/2013	1	LIQUOR, WINE, BEER	0	\$102.00
1/5/2013	1	LIQUOR, WINE, BEER	2	\$159.00
1/6/2013	1	LIQUOR, WINE, BEER	3	\$0.00
1/7/2013	1	LIQUOR, WINE, BEER	0	\$109.00
1/8/2013	1	LIQUOR, WINE, BEER	0	\$86.00
1/9/2013	1	LIQUOR, WINE, BEER	а	\$104.00
1/10/2013	1	LIQUOR, WINE, BEER	0	\$67.00

Testing Data – We want to predict future sales

Features				
date	store_nbr	family	OnPromotion	Sales
1/11/2013	1.	LIQUOR, WINE, BEER	3	7
1/12/2013	1	LIQUOR, WINE, BEER	3	7
1/13/2013	1	LIQUOR, WINE, BEER	3	7
1/14/2013	1	LIQUOR, WINE, BEER	0	?
1/15/2013	1	LIQUOR, WINE, BEER	0	7
1/16/2013	1	LIQUOR, WINE, BEER	1	7
1/17/2013	1	LIQUOR, WINE, BEER	0	9
1/18/2013	1	LIQUOR, WINE, BEER	0	7
1/19/2013	1	LIQUOR, WINE, BEER	0	7
1/20/2013	1	LIQUOR, WINE, BEER	0	9

Additional Features?

date	type	locale	locale_name	description
1/1/2013	Holiday	National	Ecuador	Primer dia del ano
1/5/2013	Work Day	National	Ecuador	Recupero puente Nas
1/12/2013	Work Day	National	Eouador	Recupero puente prir
2/11/2013	Holiday	National	Ecuador	Carnaval
2/12/2013	Holiday	National	Ecuador	Carnaval
1/2/2013	Holiday	Local	Manta	Fundacion de Manta

store_nbr	city	state	type	cluster
1	Quito	Pichincha	D	13
2	Quito	Pichincha	D	13
3	Quito	Pichincha	D	8
4	Quito	Pichincha	D	9

Data Source: Kaggle – Grocery Sales in Ecuador. Data staged in Azure SQL Database