Power BI

for

Data Science and Machine Learning

Rui Quintino, DevScope

AI & Analytics Advisor

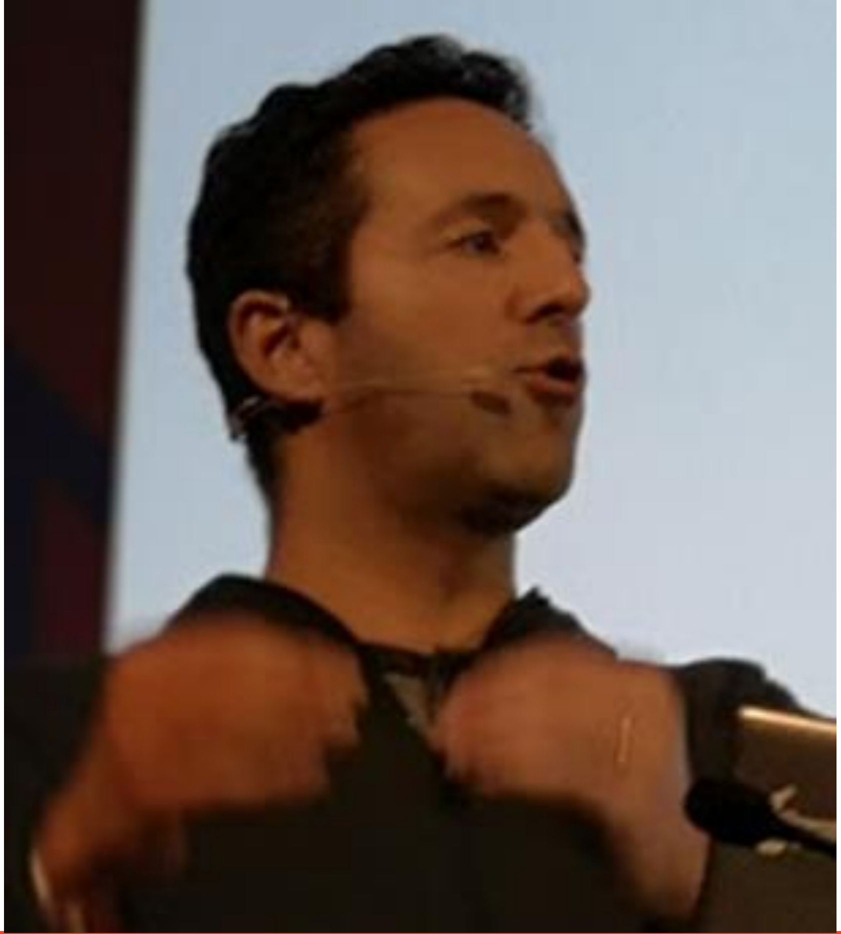
rui.quintino@devscope.net

Linkedin.com/ in/rquintino

Twitter @rquintino

Medium /devscope-ai

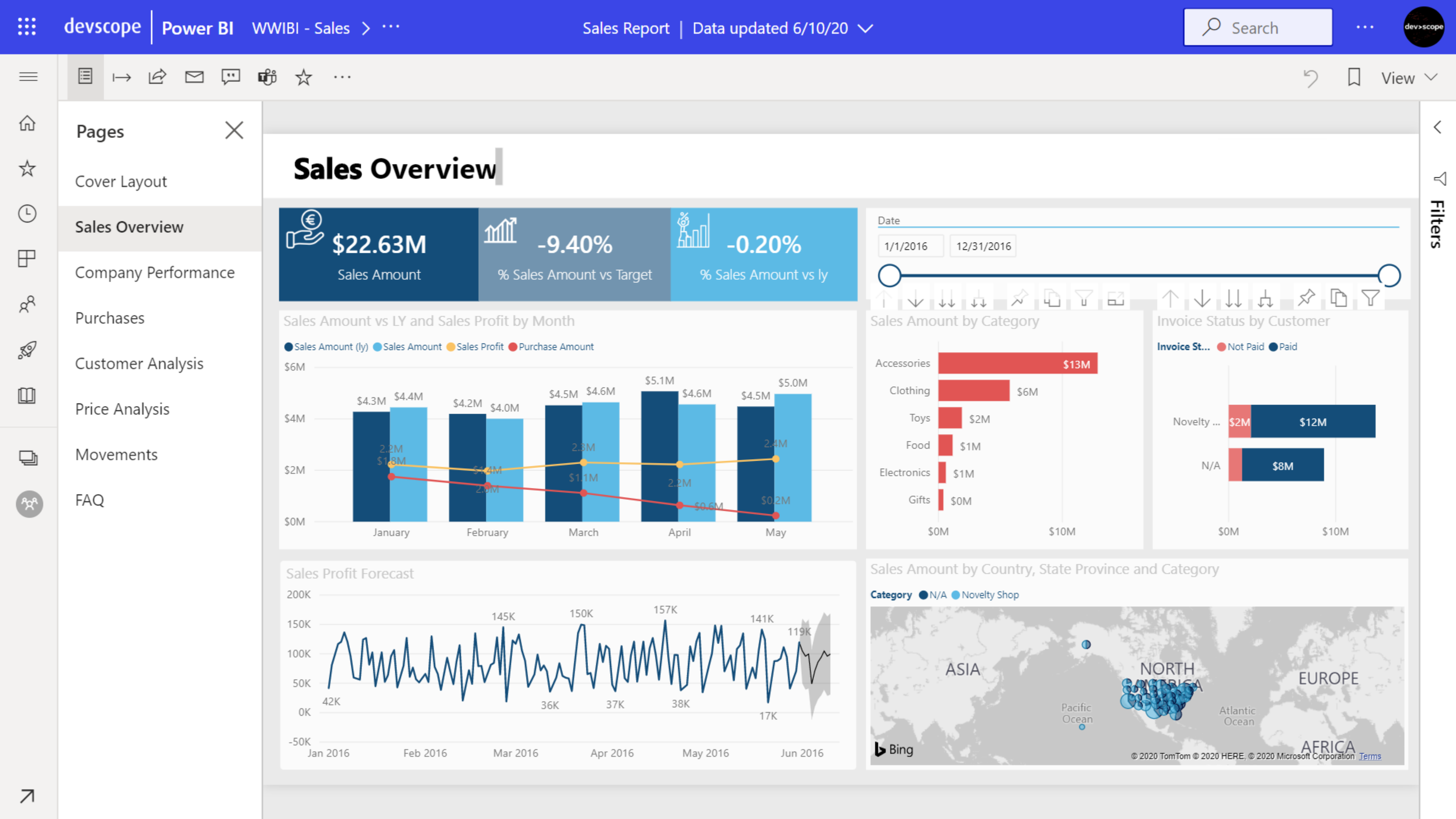
Github /DevScope/ai-lab



What's Power BI anyway?

(Very Successful & Powerful ☺)

Low/no-code platform
for
Data & Business Understanding



devscope
Power BI
WWIBI - Sales
Sales Report | Data updated 6/10/20
Search
View
Pages
Cover Layout
Sales Overview
Company Performance
Purchases
Customer Analysis
Price Analysis
Movements
FAQ
Sales Overview
$22.63M
Sales Amount
-9.40%
% Sales Amount vs Target
-0.20%
% Sales Amount vs ly
Date
1/1/2016
12/31/2016
Filters
Sales Amount vs LY and Sales Profit by Month
Sales Amount (ly)
Sales Amount
Sales Profit
Purchase Amount
$6M
$4M
$2M
$0M
$4.3M
$4.4M
$4.2M
$4.0M
$4.5M
$4.6M
$5.1M
$4.6M
$4.5M
$5.0M
January
February
March
April
May
Sales Amount by Category
Accessories
Clothing
Toys
Food
Electronics
Gifts
$13M
$6M
$2M
$1M
$1M
$0M
$0M
$10M
Invoice Status by Customer
Invoice St...
Not Paid
Paid
Novelty ...
$2M
$12M
N/A
$8M
$0M
$10M
Sales Profit Forecast
200K
150K
100K
50K
0K
-50K
145K
150K
157K
141K
119K
42K
36K
37K
38K
17K
Jan 2016
Feb 2016
Mar 2016
Apr 2016
May 2016
Jun 2016
Sales Amount by Country, State Province and Category
Category
N/A
Novelty Shop
ASIA
NORTH
EUROPE
Pacific Ocean
Atlantic Ocean
AFRICA
Bing
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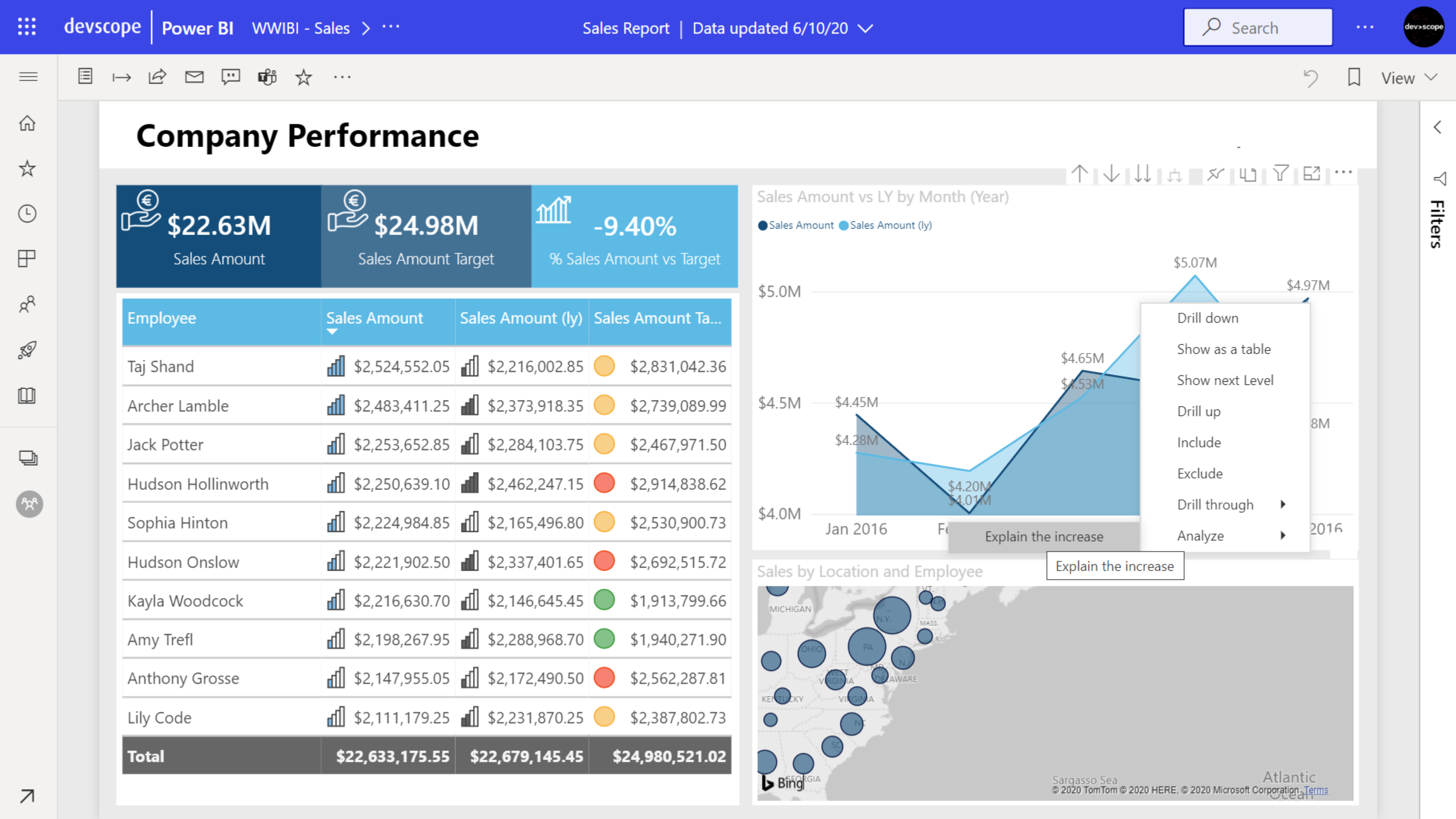
devscope
Power BI
WWIBI - Sales
Sales Report | Data updated 6/10/20
Search
View
Company Performance
$22.63M
Sales Amount
$24.98M
Sales Amount Target
-9.40%
% Sales Amount vs Target
Employee
Sales Amount
Sales Amount (ly)
Sales Amount Ta...
Taj Shand $2,524,552.05 $2,216,002.85 $2,831,042.36
Archer Lamble $2,483,411.25 $2,373,918.35 $2,739,089.99
Jack Potter $2,253,652.85 $2,284,103.75 $2,467,971.50
Hudson Hollinworth $2,250,639.10 $2,462,247.15 $2,914,838.62
Sophia Hinton $2,224,984.85 $2,165,496.80 $2,530,900.73
Hudson Onslow $2,221,902.50 $2,337,401.65 $2,692,515.72
Kayla Woodcock $2,216,630.70 $2,146,645.45 $1,913,799.66
Amy Trefl $2,198,267.95 $2,288,968.70 $1,940,271.90
Anthony Grosse $2,147,955.05 $2,172,490.50 $2,562,287.81
Lily Code $2,111,179.25 $2,231,870.25 $2,387,802.73
Total $22,633,175.55 $22,679,145.45 $24,980,521.02
Sales Amount vs LY by Month (Year)
Sales Amount
Sales Amount (ly)
$5.0M
$4.5M
$4.0M
$5.07M
$4.97M
$4.65M
$4.53M
$4.45M
$4.28M
$4.20M
$4.01M
Jan 2016
Drill down
Show as a table
Show next Level
Drill up
Include
Exclude
Drill through
Analyze
Explain the increase
Explain the increase
Sales by Location and Employee
MICHIGAN
N.Y.
MASS.
PA
OHIO
N.J.
DELAWARE
KENTUCKY
VIRGINIA
Bing
Sargasso Sea
Atlantic
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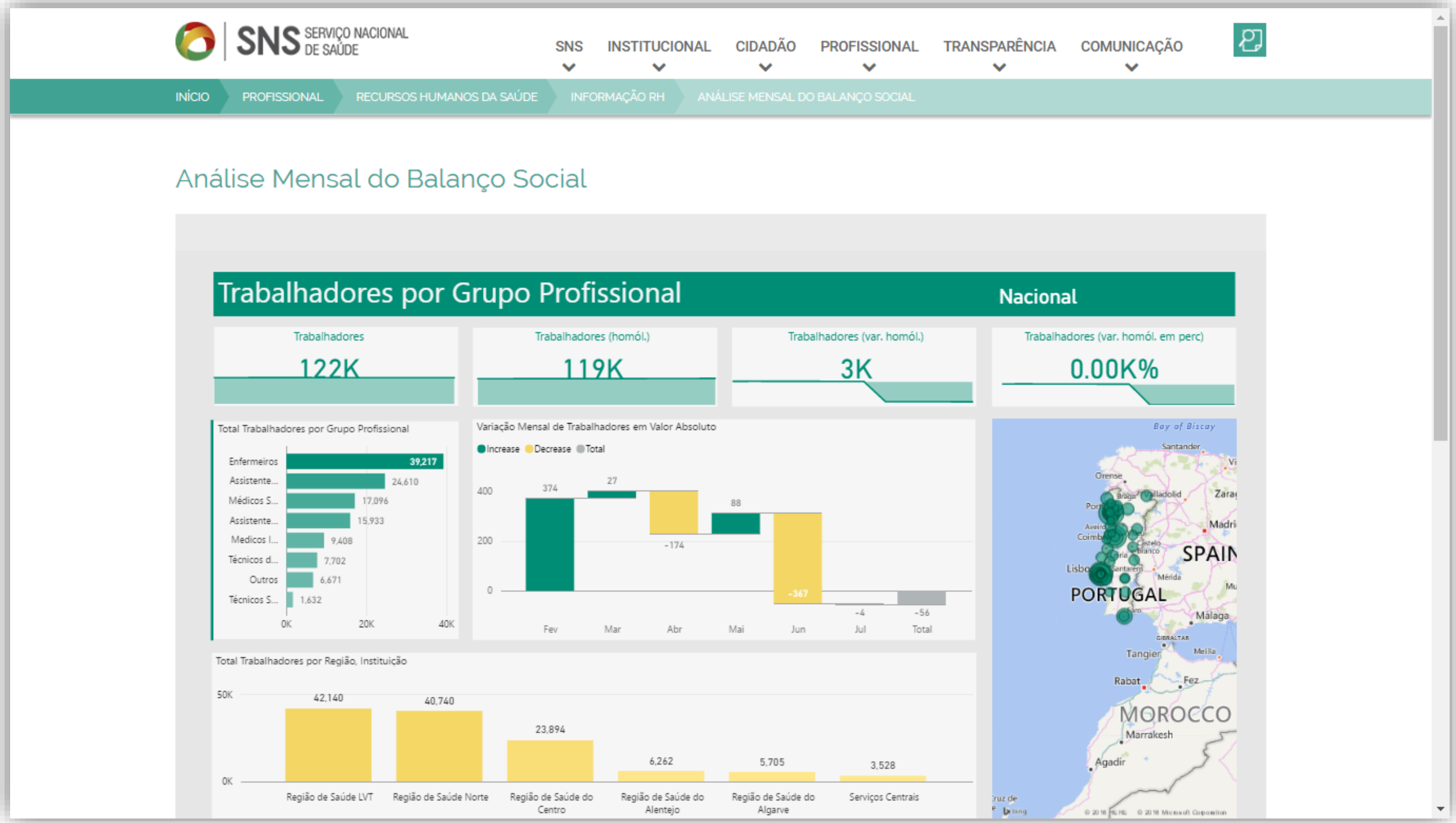
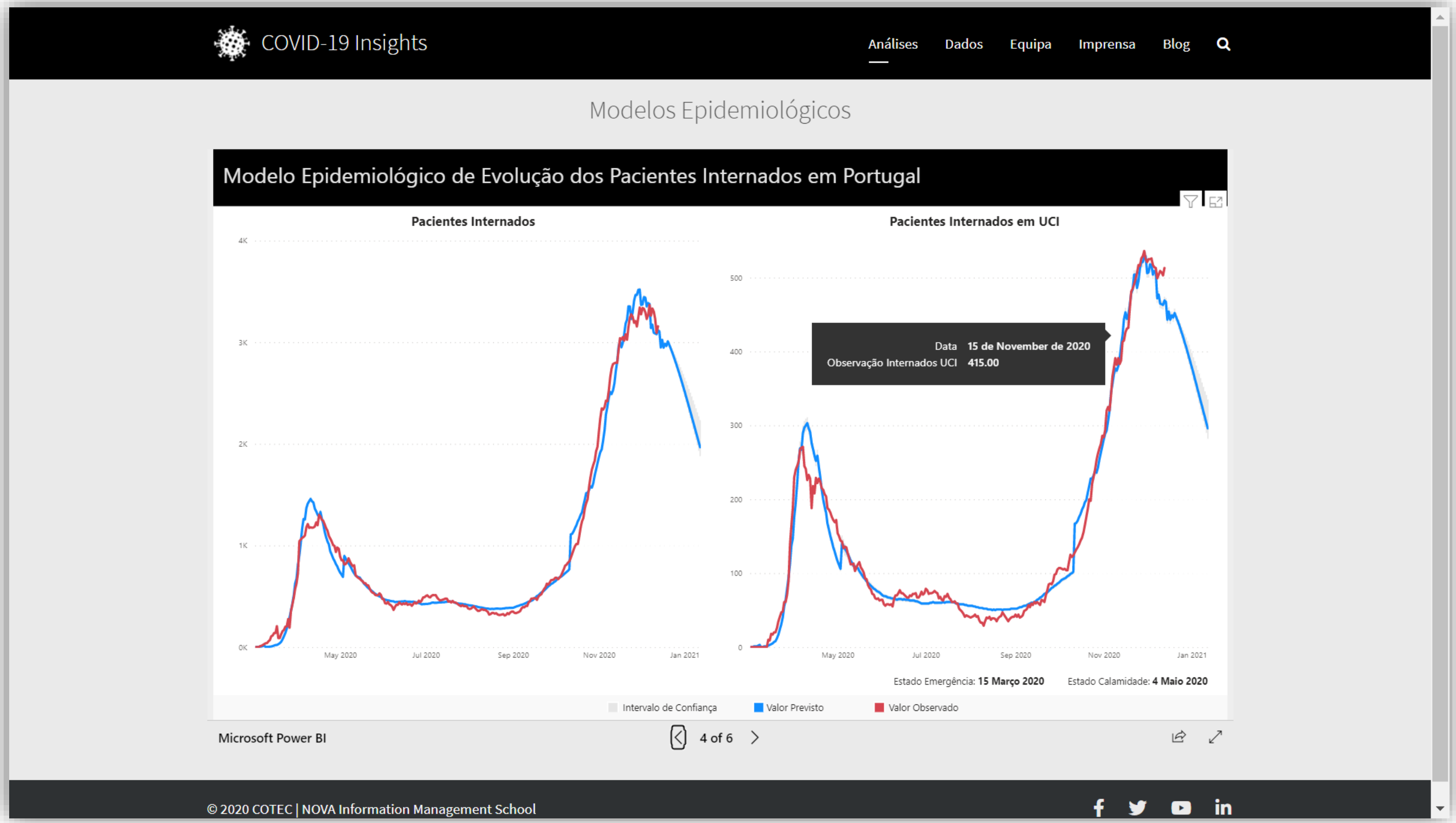
Filters

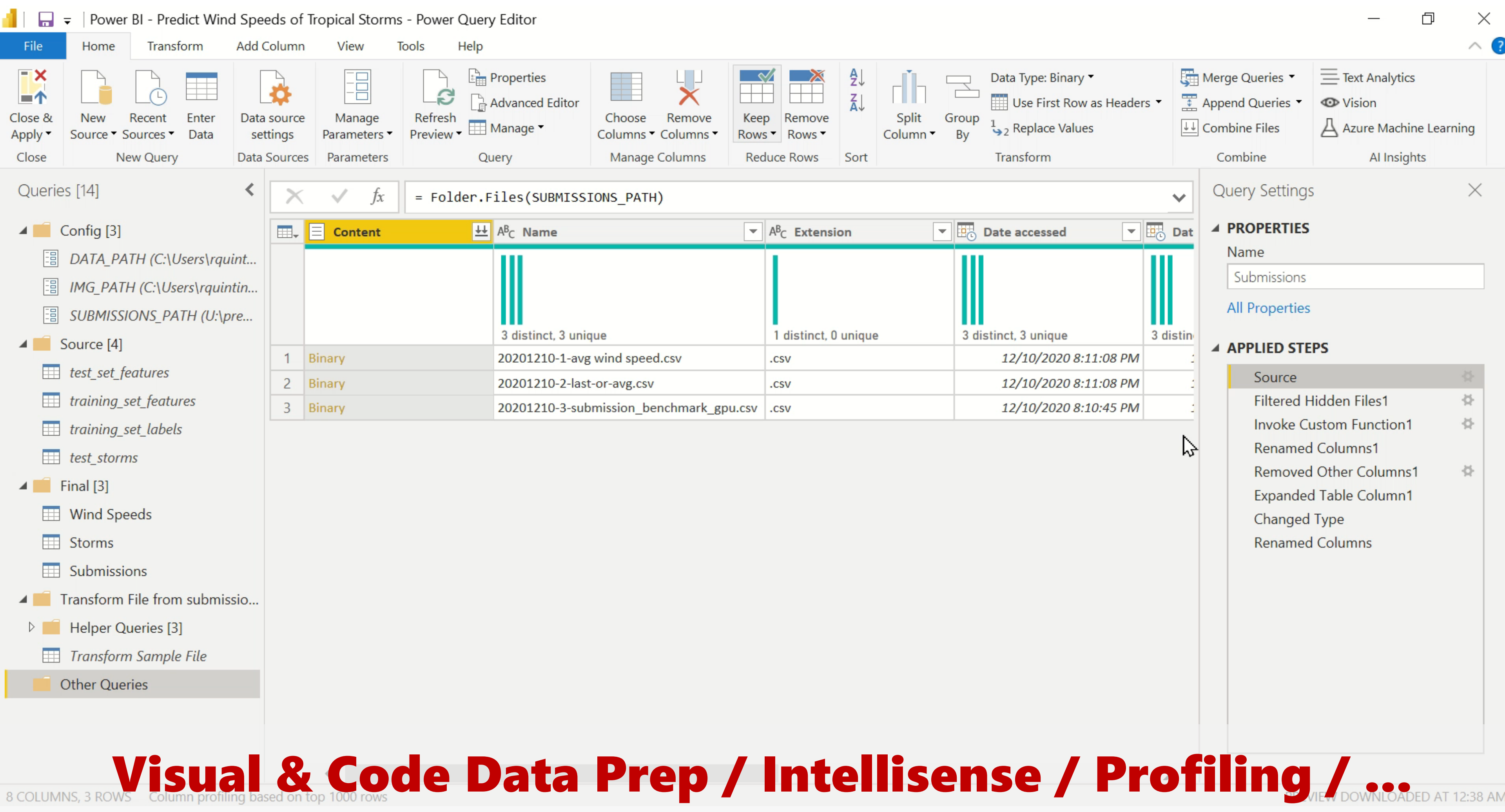


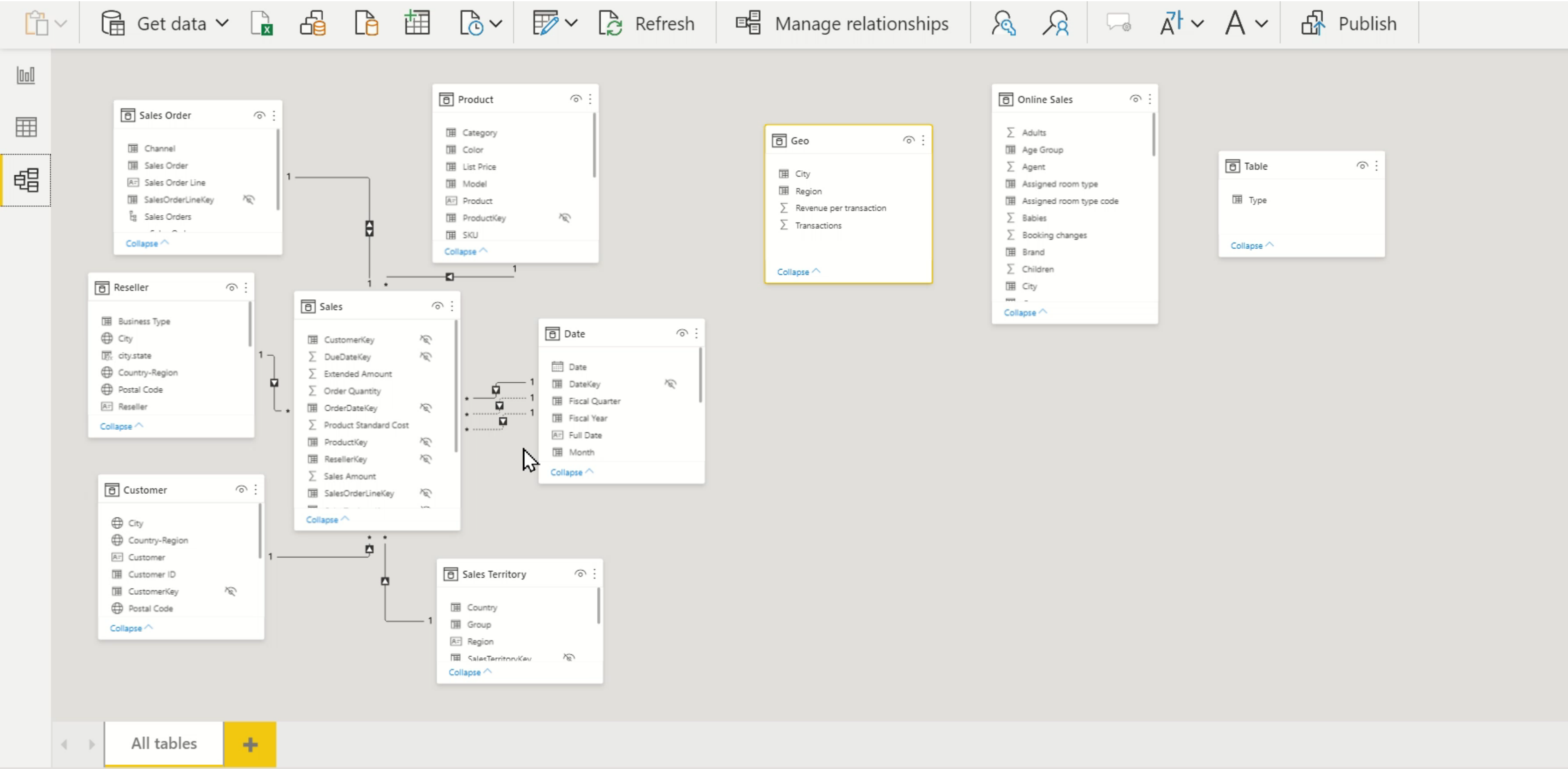
https://www.sns.gov.pt/profissional/recursos-humanos-da-saude/informacao-rh/analise-mensal-do-balanco-social/



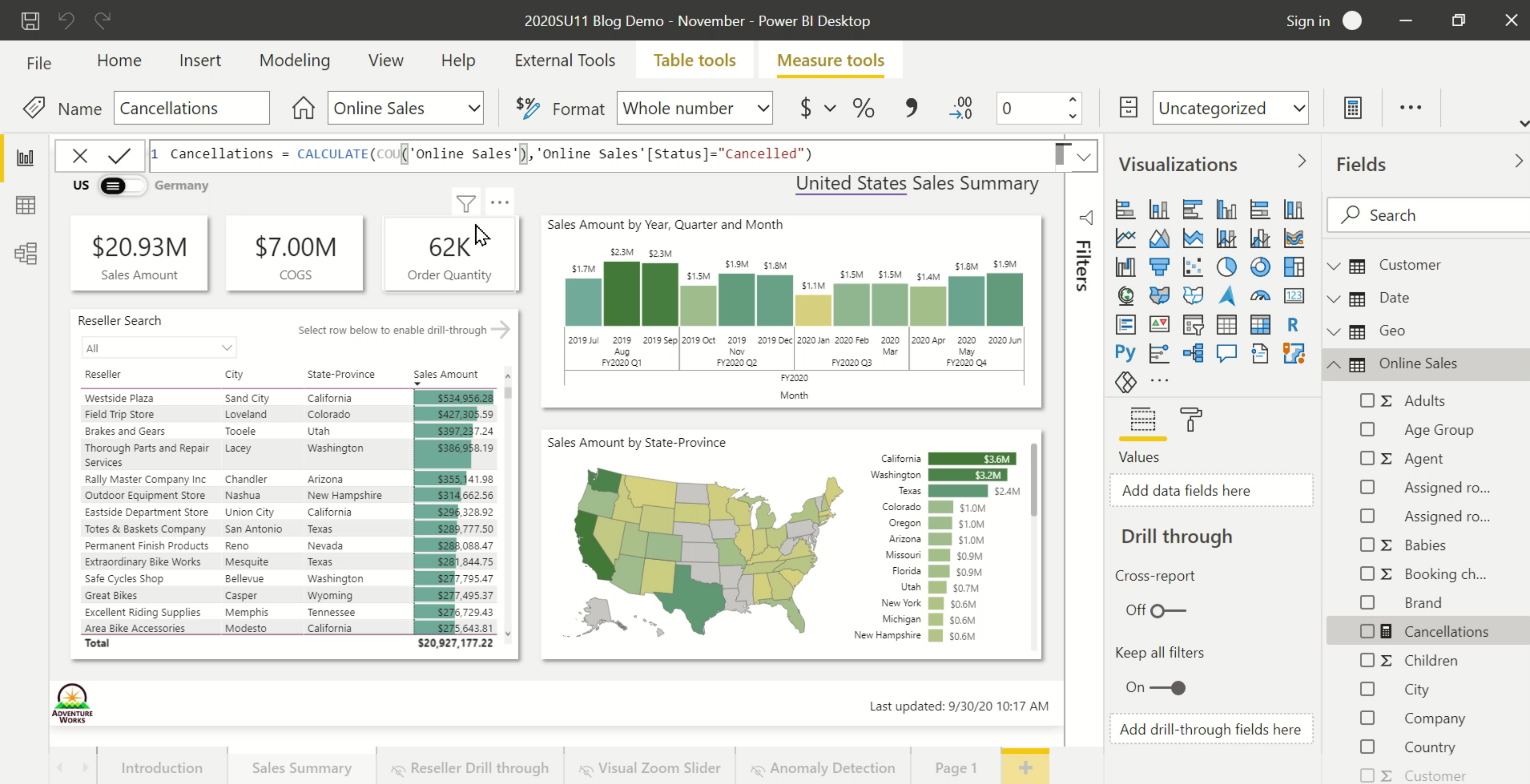
https://insights.cotec.pt/

Why so Powerful?

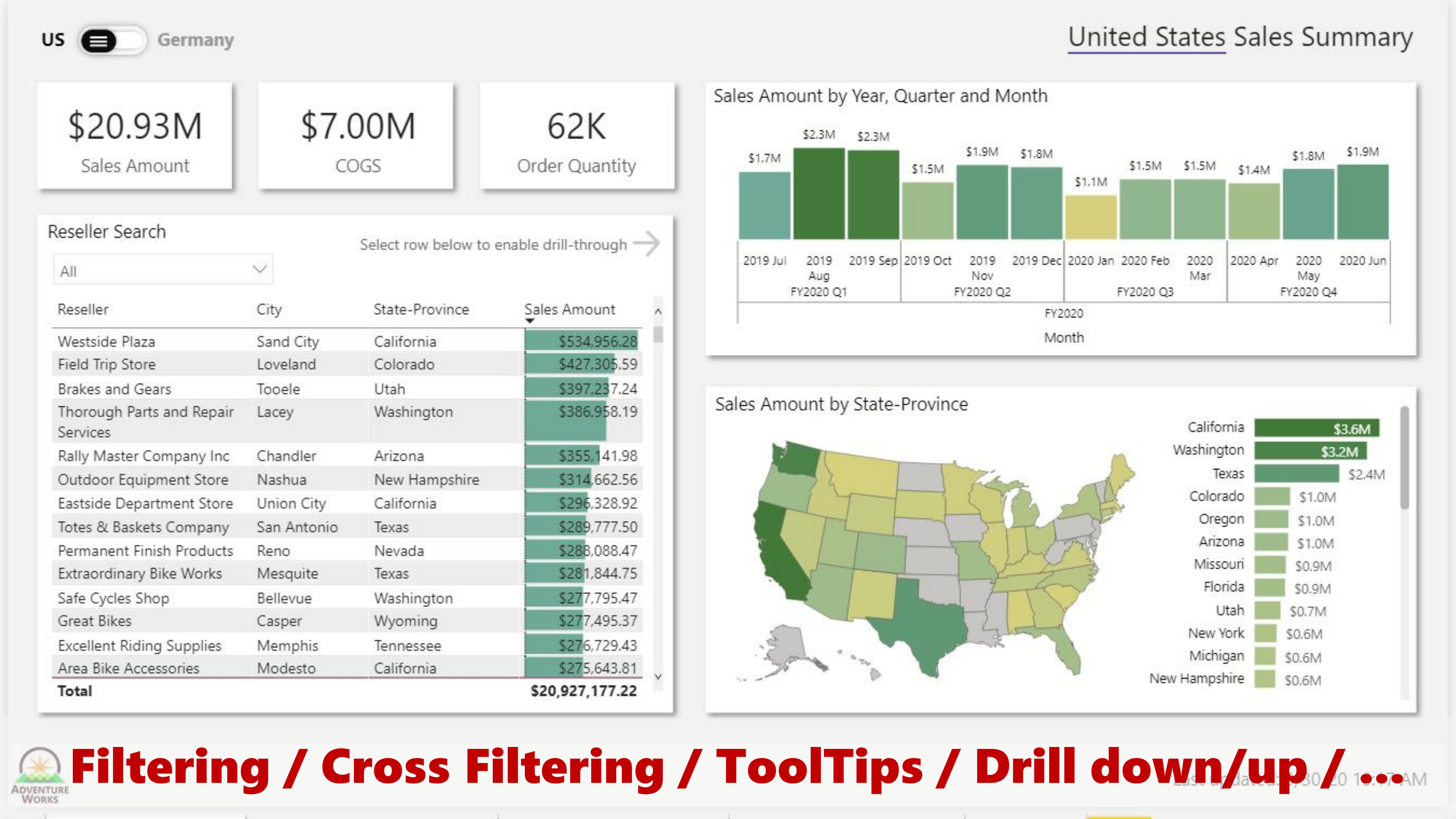

Power BI - Predict Wind Speeds of Tropical Storms - Power Query Editor
File
Home
Transform
Add Column
View
Tools
Help
Close & Apply
New Source
Recent Sources
Enter Data
Data source settings
Manage Parameters
Refresh Preview
Properties
Advanced Editor
Manage
Choose Columns
Remove Columns
Keep Rows
Remove Rows
Split Column
Group By
Data Type: Binary
Use First Row as Headers
Replace Values
Merge Queries
Append Queries
Combine Files
Text Analytics
Vision
Azure Machine Learning
Close
New Query
Data Sources
Parameters
Query
Manage Columns
Reduce Rows
Sort
Transform
Combine
AI Insights
Queries [14]
Config [3]
DATA_PATH (C:\Users\rquint...
IMG_PATH (C:\Users\rquintin...
SUBMISSIONS_PATH (U:\pre...
Source [4]
test_set_features
training_set_features
training_set_labels
test_storms
Final [3]
Wind Speeds
Storms
Submissions
Transform File from submissio...
Helper Queries [3]
Transform Sample File
Other Queries
= Folder.Files(SUBMISSIONS_PATH)
Content
Name
Extension
Date accessed
Dat
3 distinct, 3 unique
1 distinct, 0 unique
3 distinct, 3 unique
3 distin
1 Binary 20201210-1-avg wind speed.csv .csv 12/10/2020 8:11:08 PM
2 Binary 20201210-2-last-or-avg.csv .csv 12/10/2020 8:11:08 PM
3 Binary 20201210-3-submission_benchmark_gpu.csv .csv 12/10/2020 8:10:45 PM
Query Settings
PROPERTIES
Name
Submissions
All Properties
APPLIED STEPS
Source
Filtered Hidden Files1
Invoke Custom Function1
Renamed Columns1
Removed Other Columns1
Expanded Table Column1
Changed Type
Renamed Columns
8 COLUMNS, 3 ROWS
Column profiling based on top 1000 rows
Visual & Code Data Prep / Intellisense / Profiling / ...



Fast (column store) Semantic Models



Powerful Analytical Engine for Metric Modelling



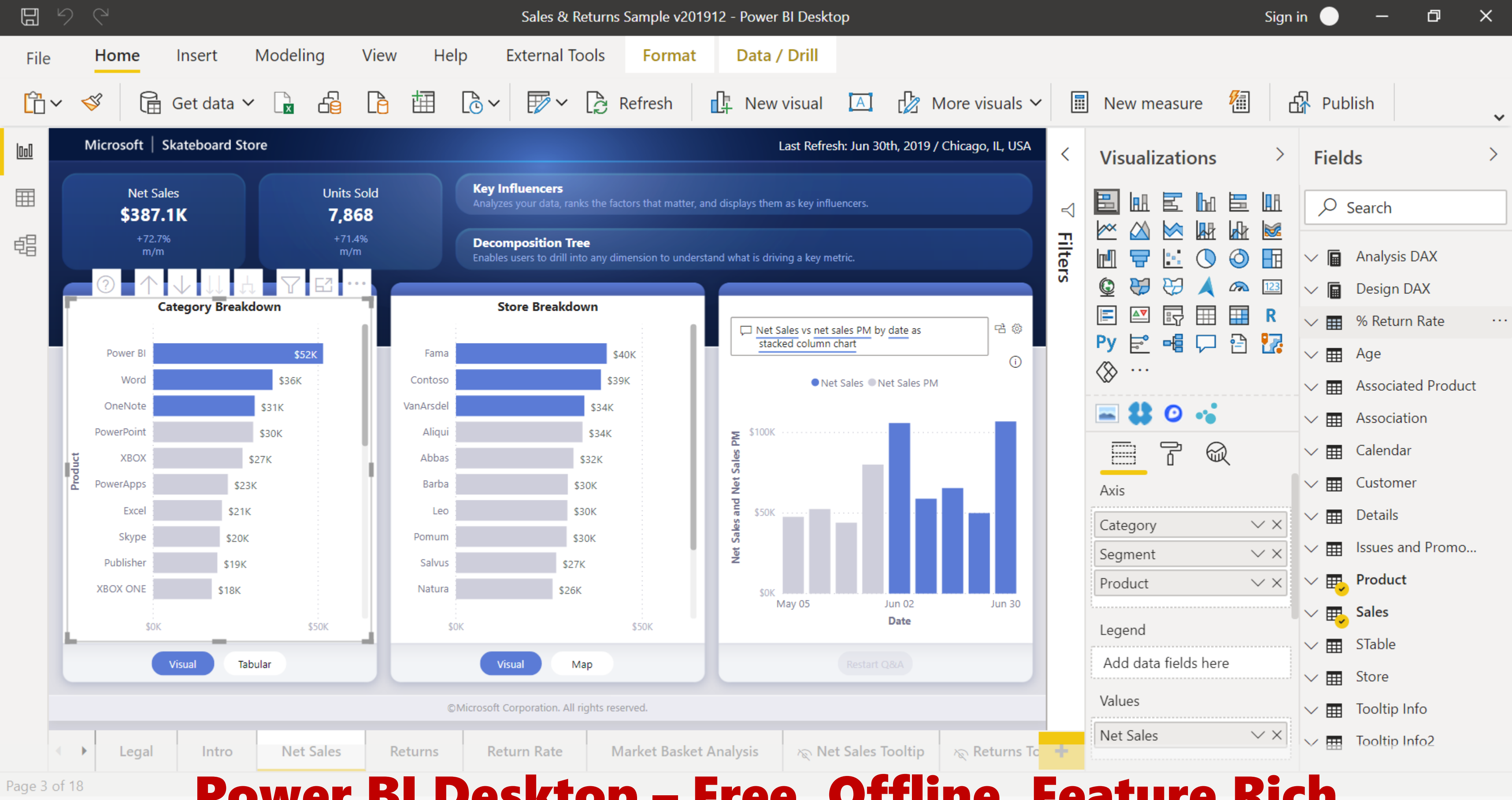
Filtering / Cross Filtering / ToolTips / Drill down/up / …

We don’t go EDA from raw data directly!

We prepare a **rich semantic model**
(reusable relationships, metrics, behaviors,etc)

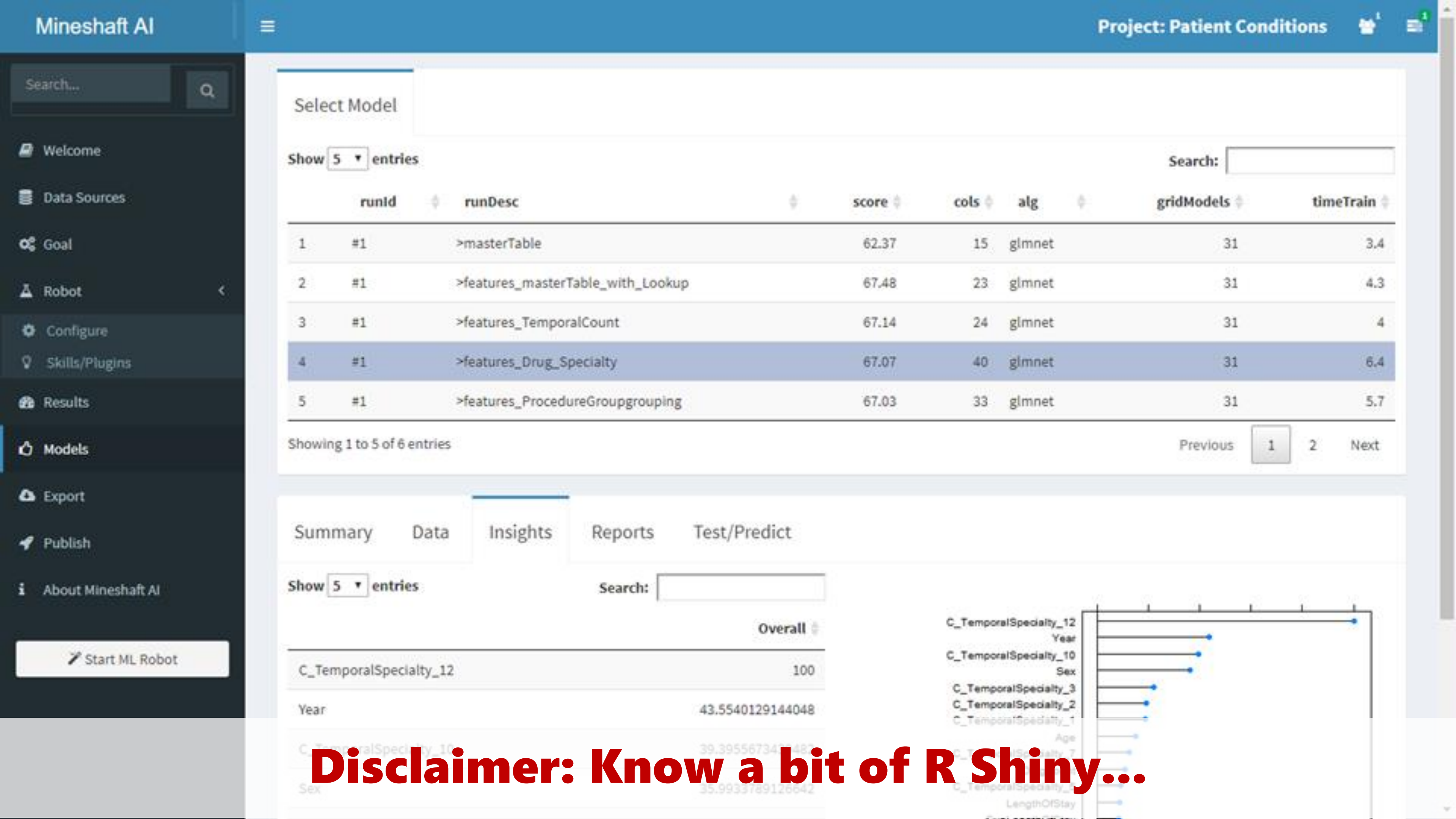
EDA then reuses this semantic model

Power BI Use Cases in DS/ML

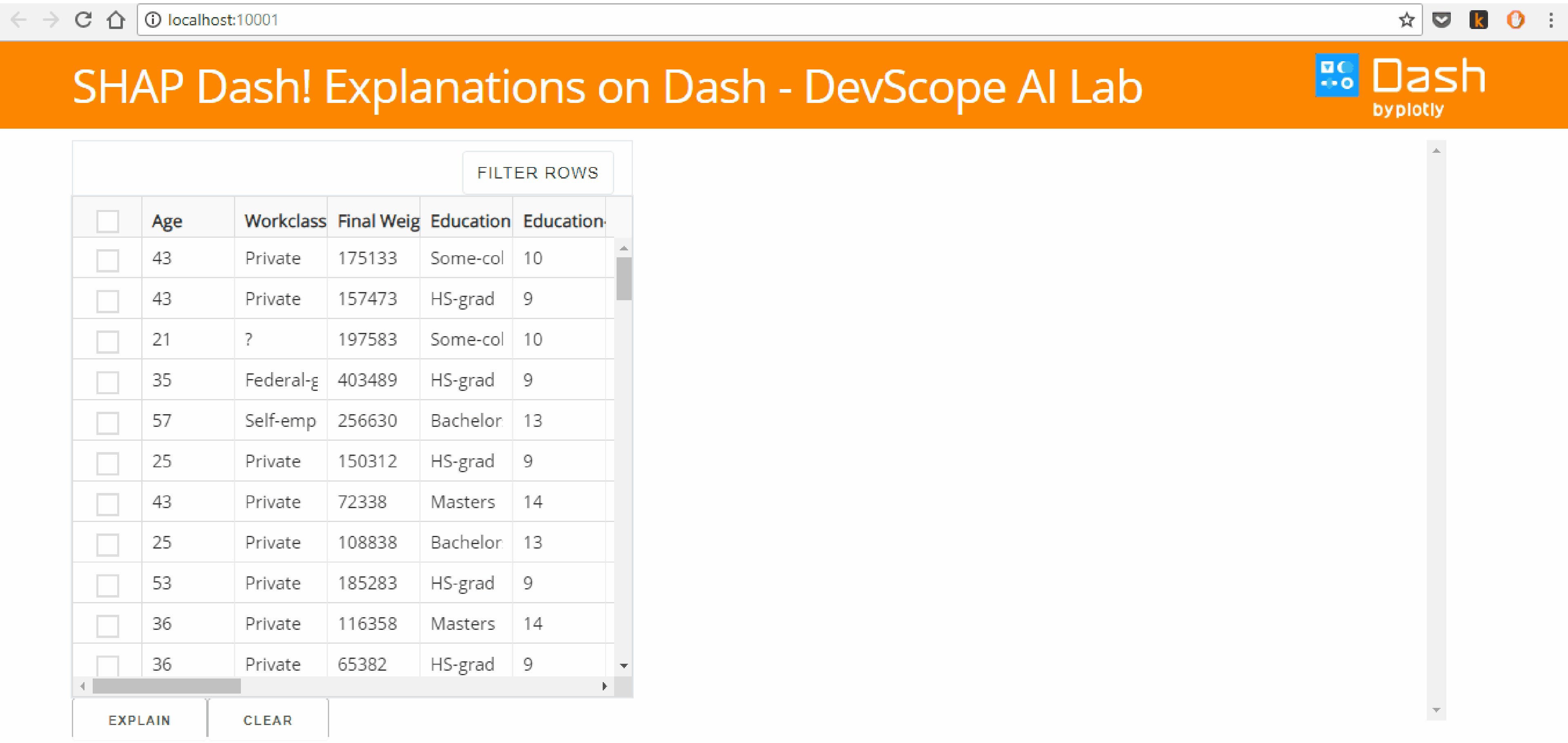


Power BI Desktop – Free, Offline, Feature Rich

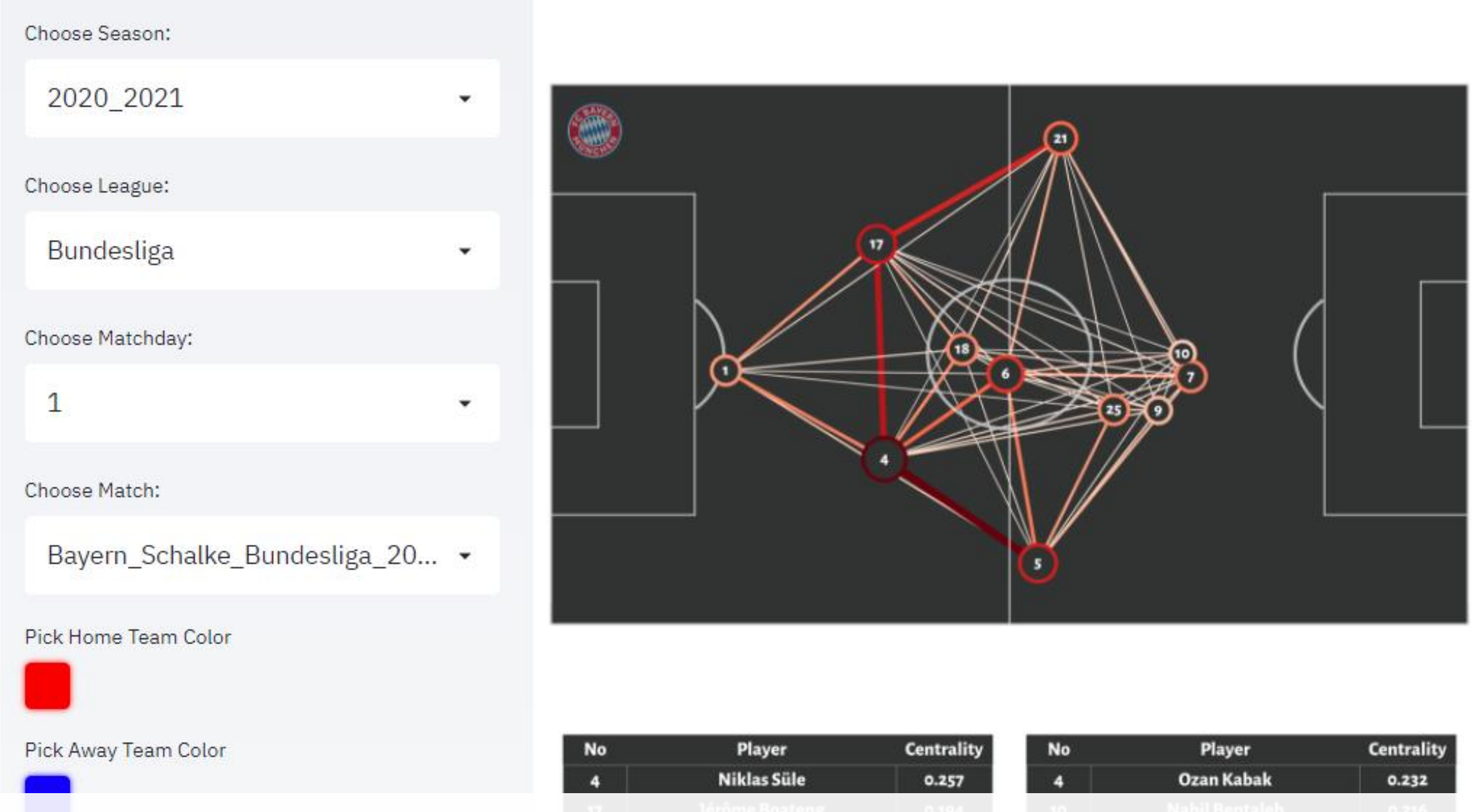
First Tip…



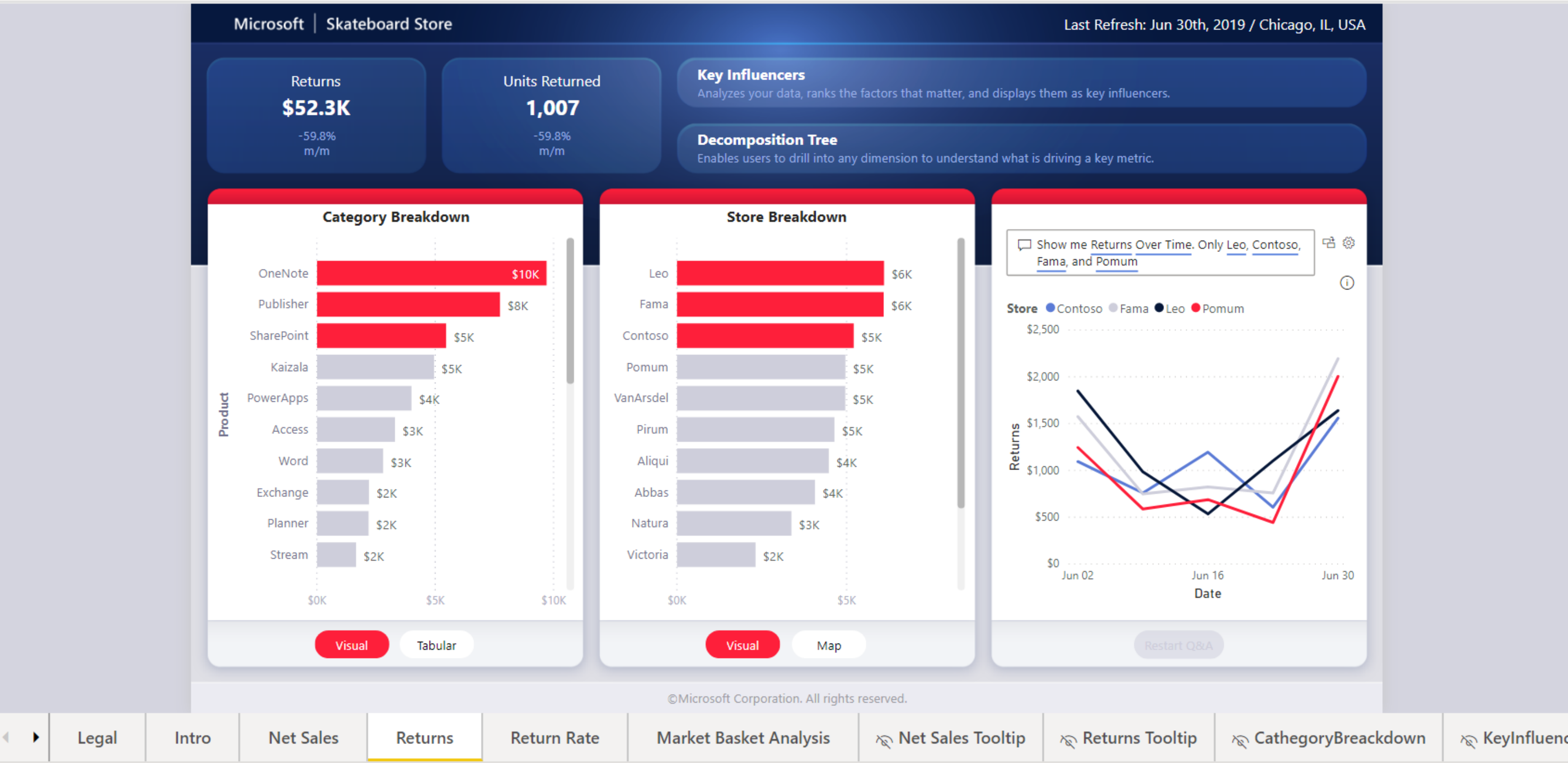
Disclaimer: Know a bit of R Shiny...



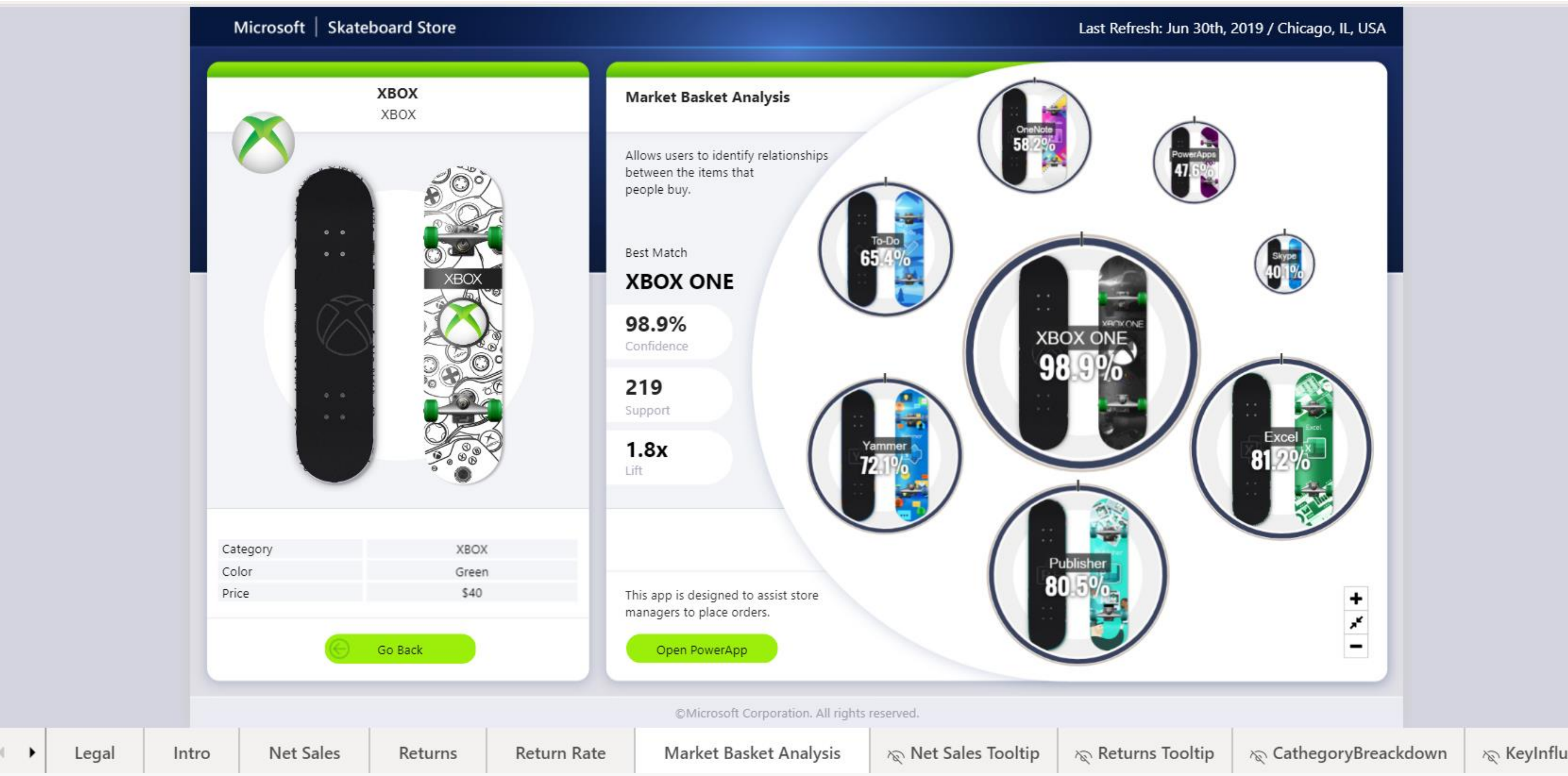
And Python Plotly Dash...



Big fans of Python StreamLit… (credits to Luís Costa ☺)



but… Business Reports/Dashboards with Shiny, Python, StreamLit, just don't!

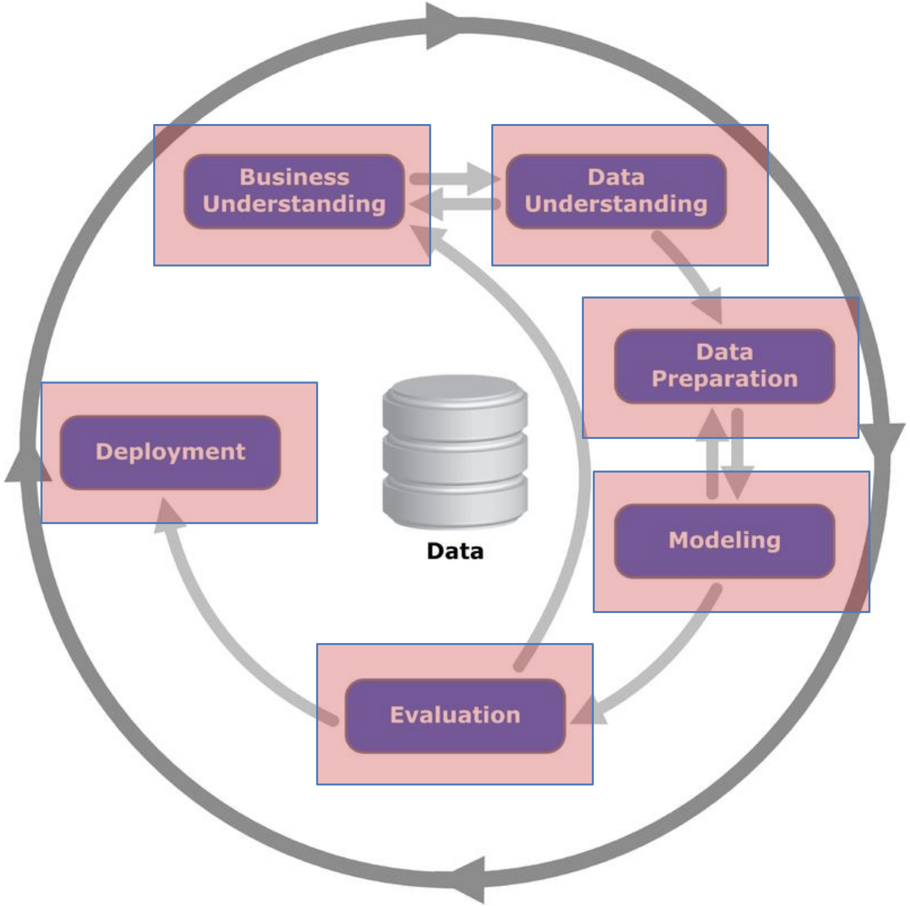


Tip: Delivering/Presenting DS/ML Outputs

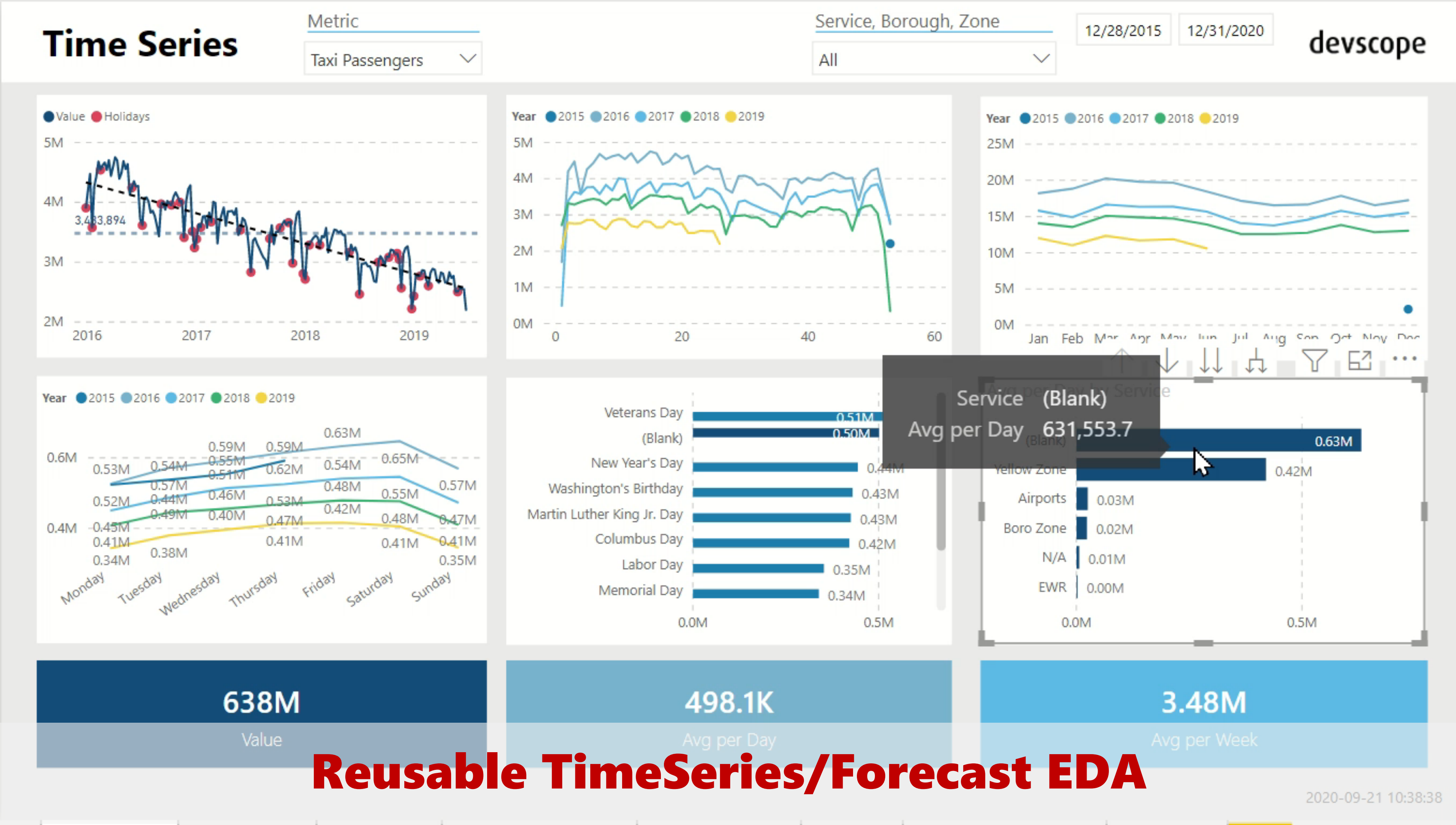
Where Power BI can help?

Actually...

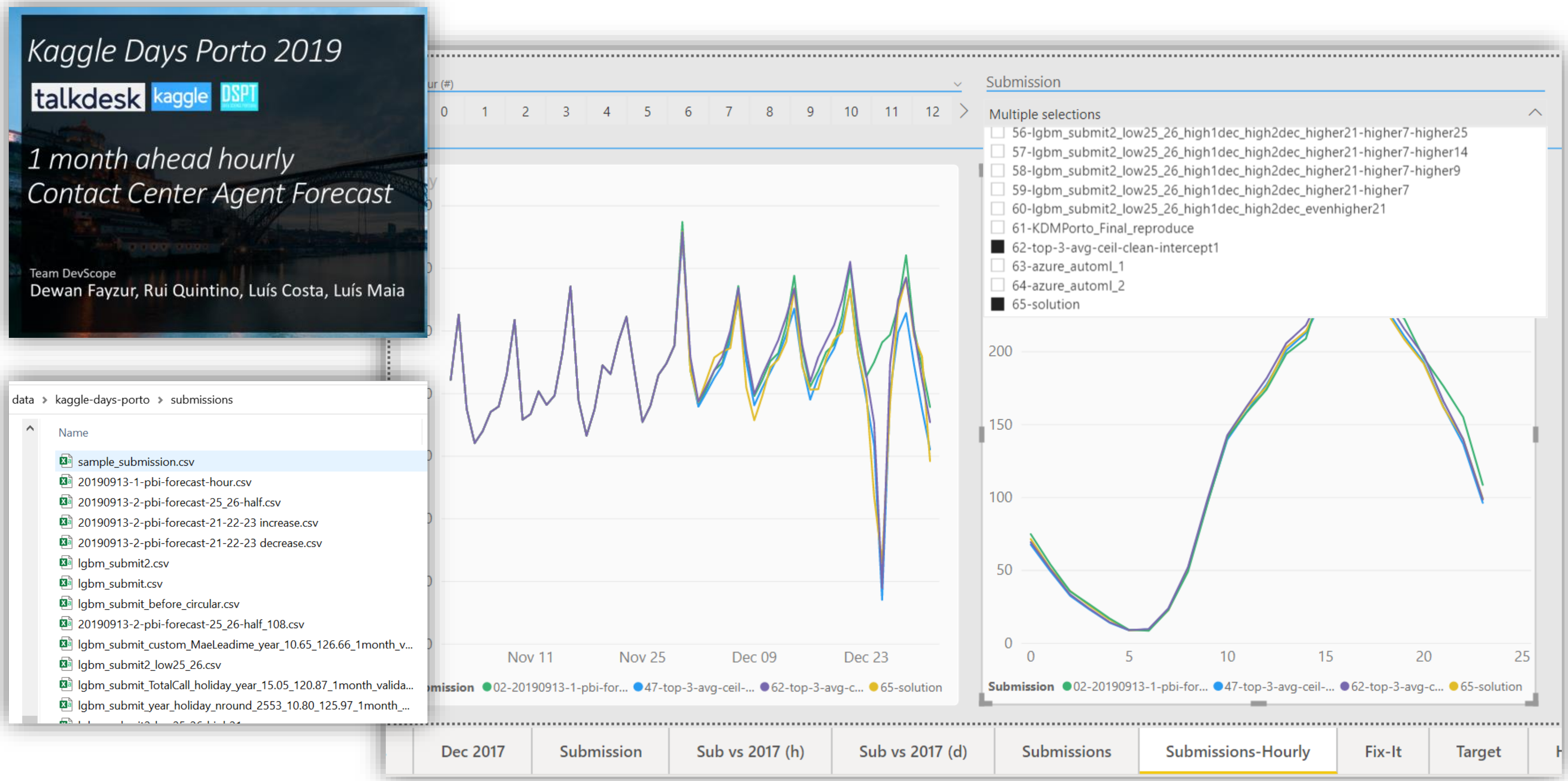
(with new *Auto ML*)



https://en.wikipedia.org/wiki/Cross-industry_standard_process_for_data_mining



Time Series
Metric
Taxi Passengers
Service, Borough, Zone
All
12/28/2015
12/31/2020
devscope
Value
Holidays
3,433,894
Year
2015
2016
2017
2018
2019
Service (Blank)
Avg per Day 631,553.7
Veterans Day
(Blank)
New Year's Day
Washington's Birthday
Martin Luther King Jr. Day
Columbus Day
Labor Day
Memorial Day
Yellow Zone
Airports
Boro Zone
N/A
EWR
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
638M
Value
498.1K
Avg per Day
3.48M
Avg per Week
Reusable TimeSeries/Forecast EDA
2020-09-21 10:38:38



Leaderboards (ex: submission evaluation/validation)

Eval performance & behaviors for different models

Wind-dependent Variables: Predict Wind Speeds of Tropical Storms

Press F11 to exit full screen

HOSTED BY RADIANT EARTH FOUNDATION

$13,000

7 WEEKS LEFT

Submissions

$13,000

BEST	CURRENT RANK	# COMPETITORS	SUBS. MADE
8.8177	2	260	2 of 3

LEADERBOARD

DATA DOWNLOAD

SUBMISSION RESTRICTIONS

Competitors are allowed 3 submissions per 1 day.

Your next submission can be on Dec. 15, 2020 UTC.

PRIMARY EVALUATION METRIC

$$\text{Root-mean-square Error} = \sqrt{\frac{1}{N}\sum_{i=0}^{N}(y_i - \hat{y}_i)^2}$$

Root-mean-square error is the square root of the sum of the squared differences betwee[n] values and the actual values. The goal is to minimize RMSE.

- submissions
- test
- train
- validation
- local_val_storms.csv
- Power BI - Predict Wind Speeds of Tropical Stor...
- re-test-images.tgz
- re-train-images.tgz

Facebook Twitter LinkedIn Email

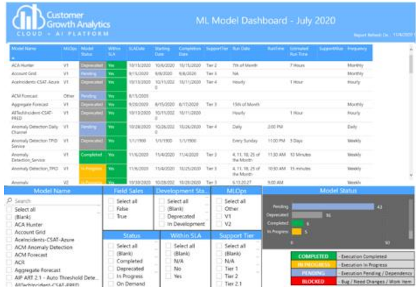
ML Competitions (I kid you not! ☺)

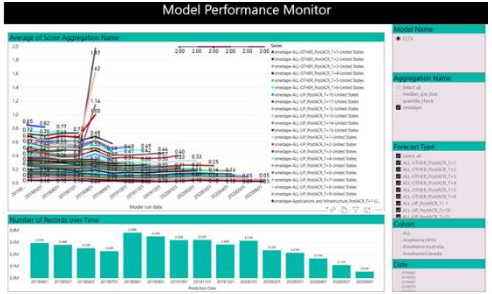
SHARE YOUR WORK!

Machine Learning model governance at scale

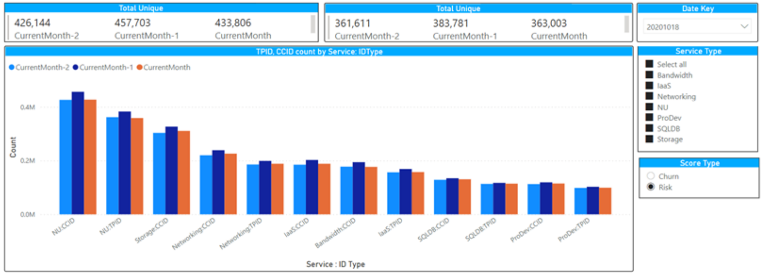
P
Petersaddow Follow
Nov 13 · 13 min read

Author Peter Saddow is joined for this article by co-author Daniel Yehdego



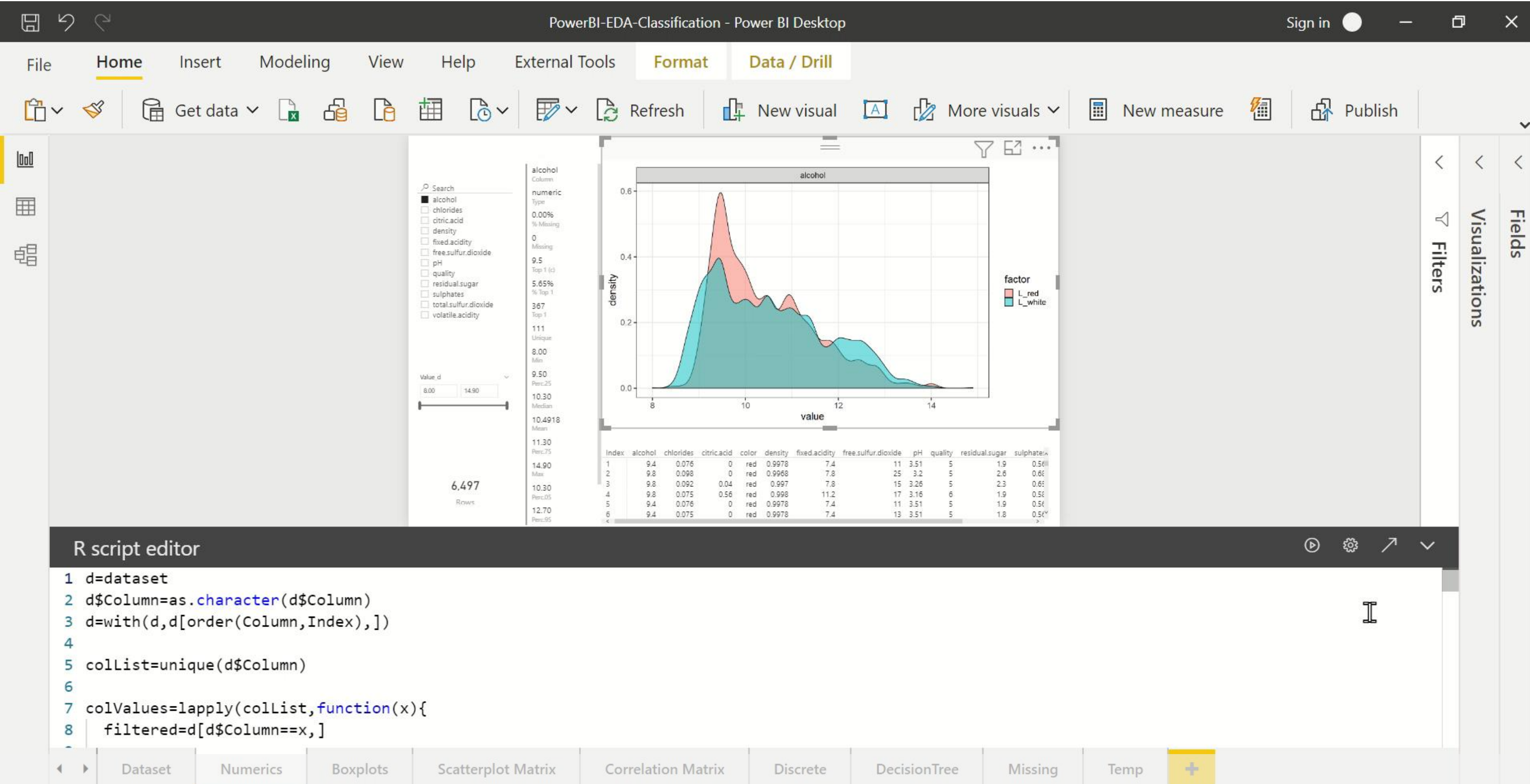


Model Output (MLOps: V2)

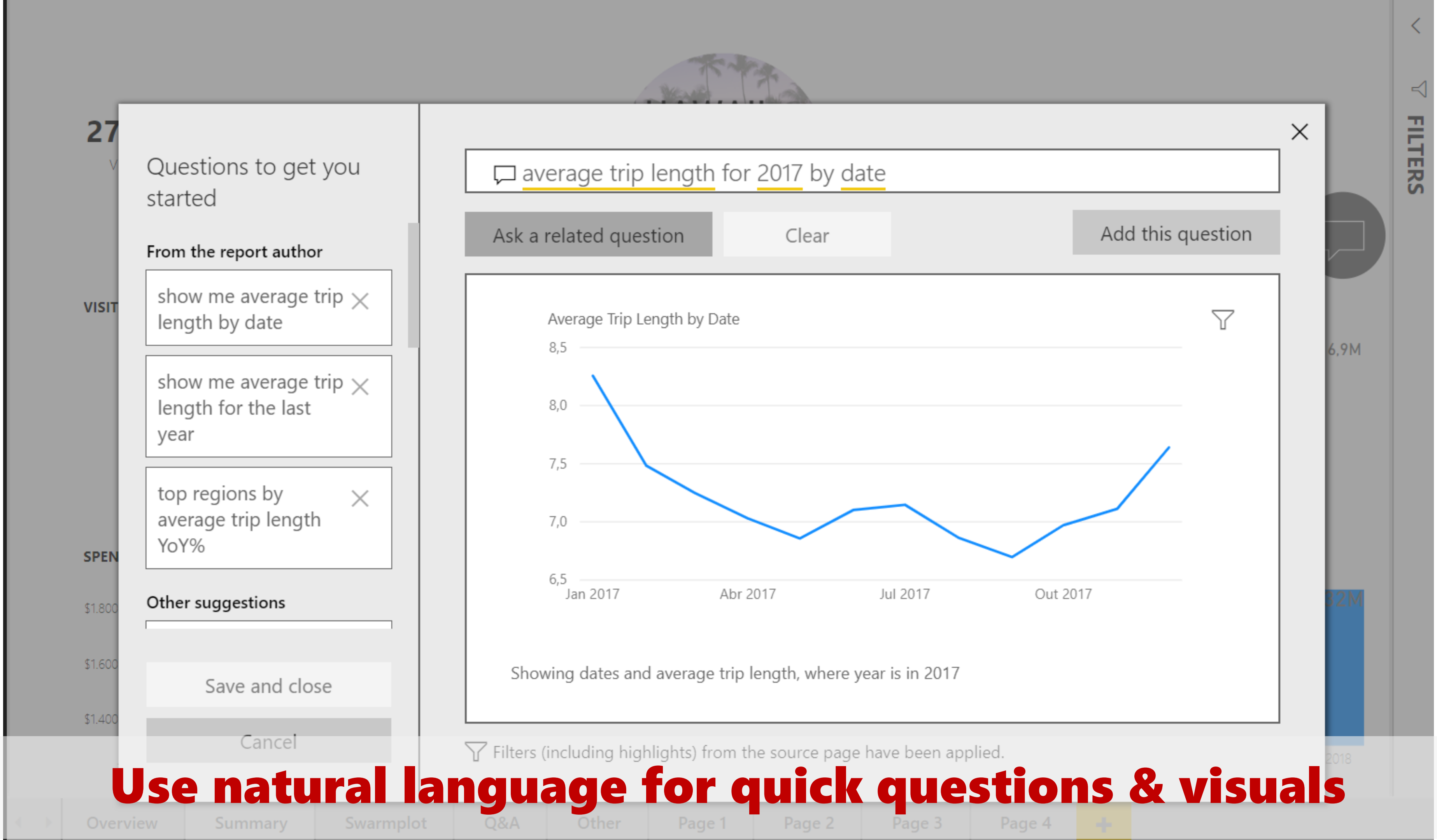


Machine Learning Governance (msft CGA team Cloud+AI)

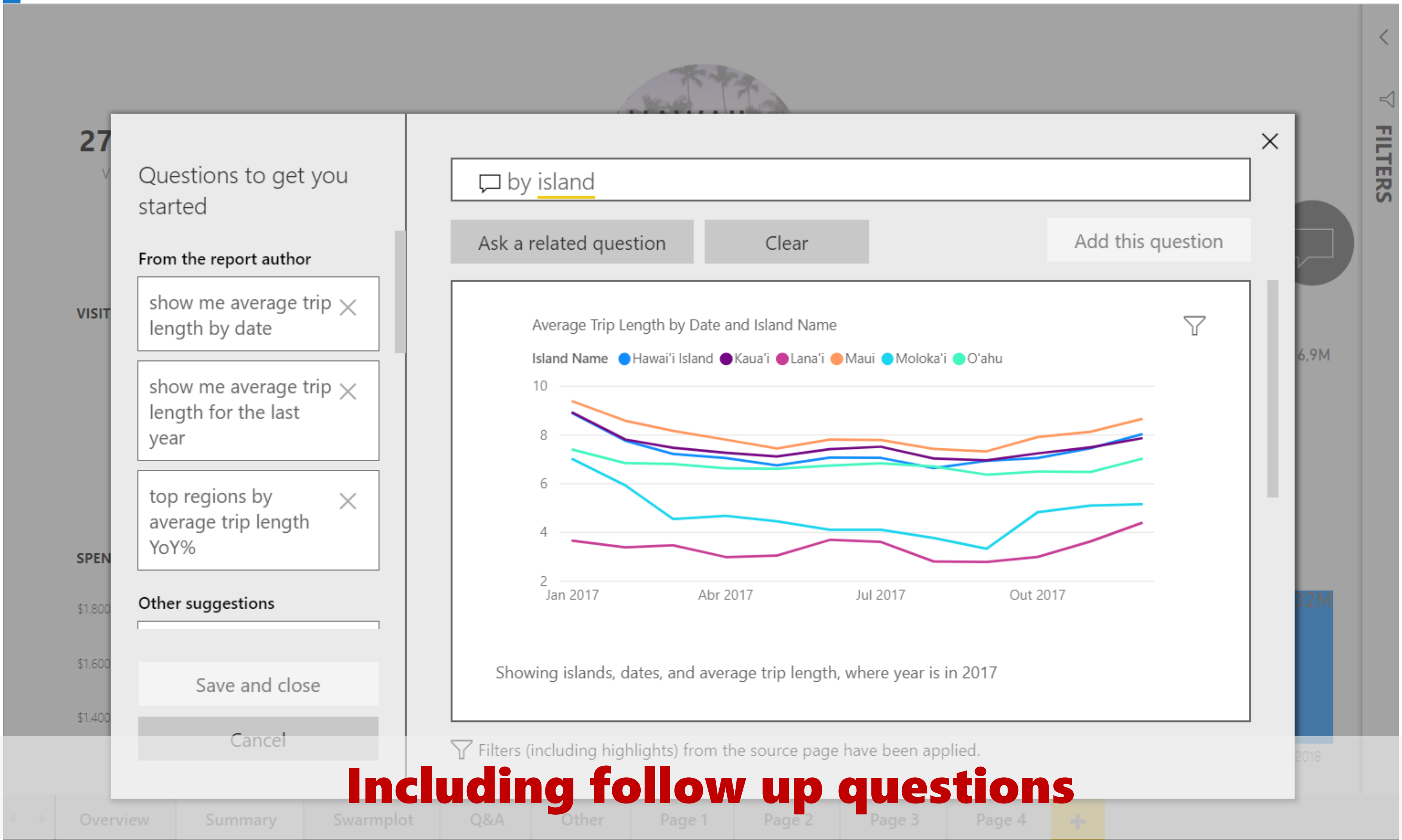
Advanced features for EDA



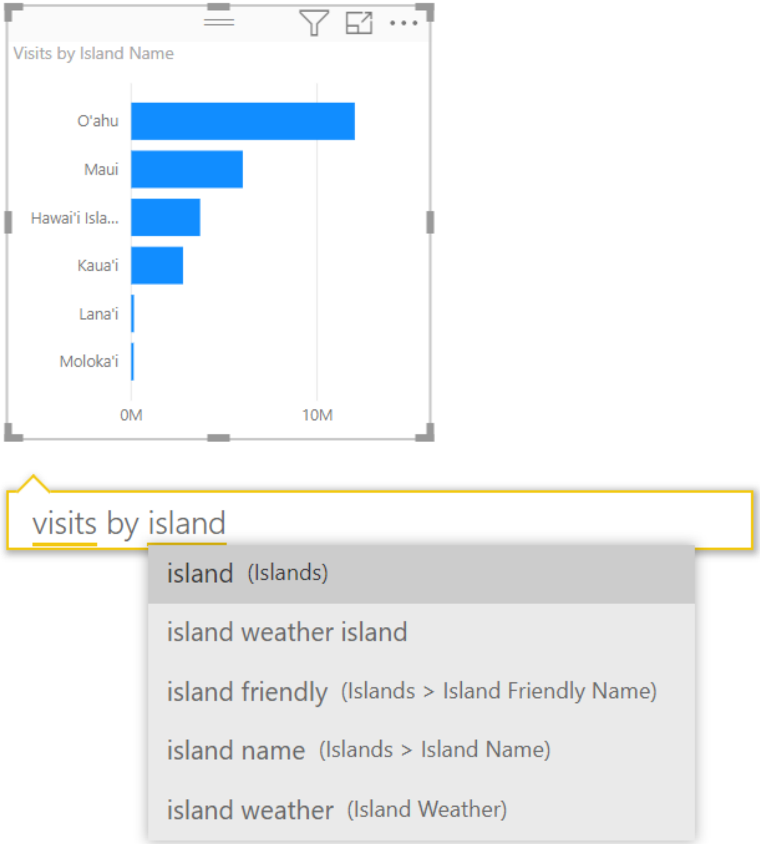
Custom R and Python interactive EDA



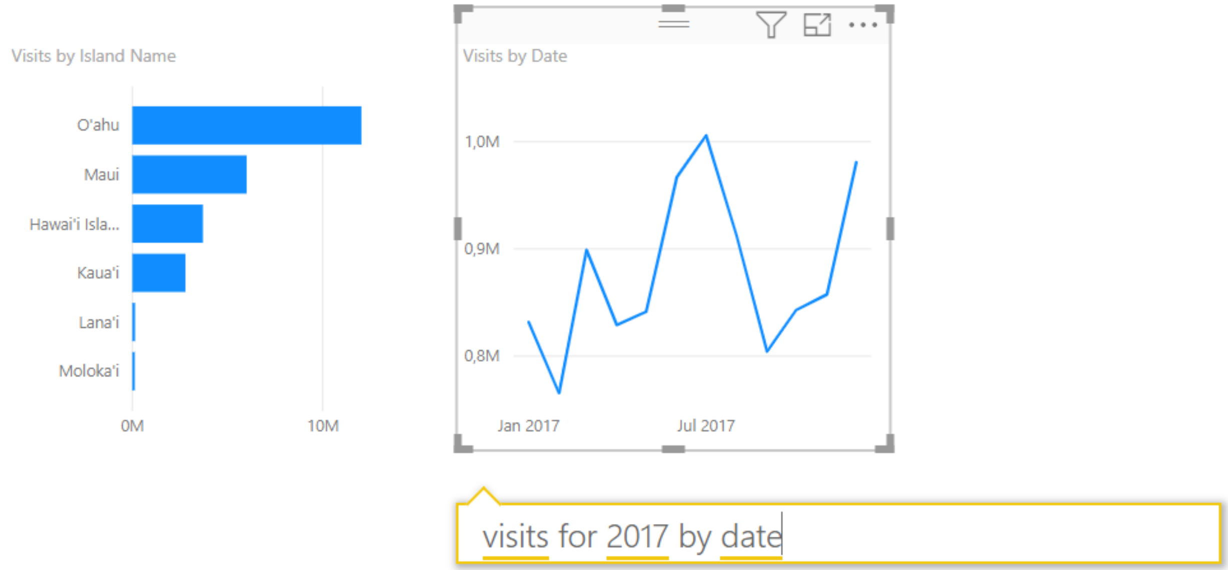
Use natural language for quick questions & visuals

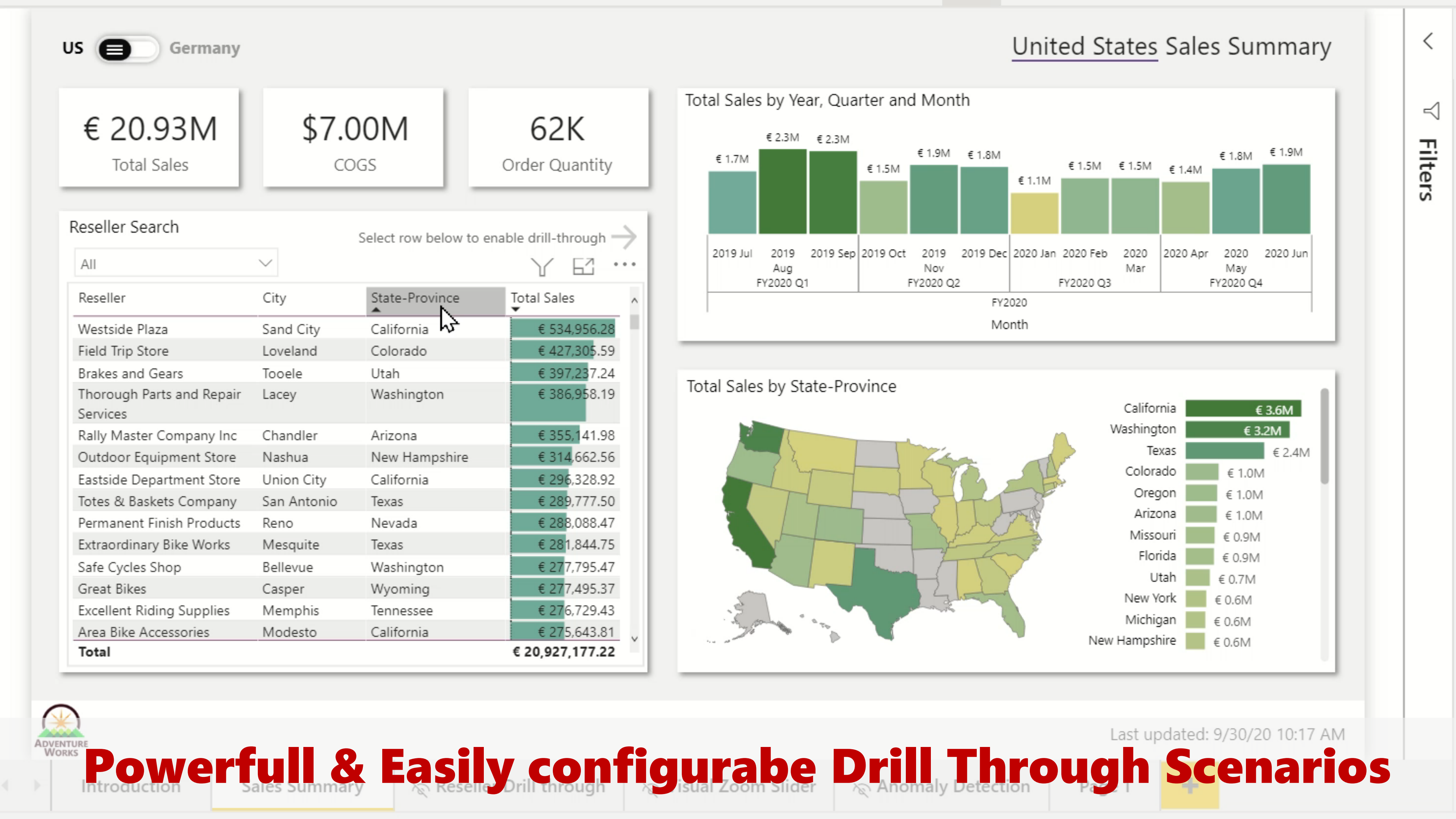


Including follow up questions

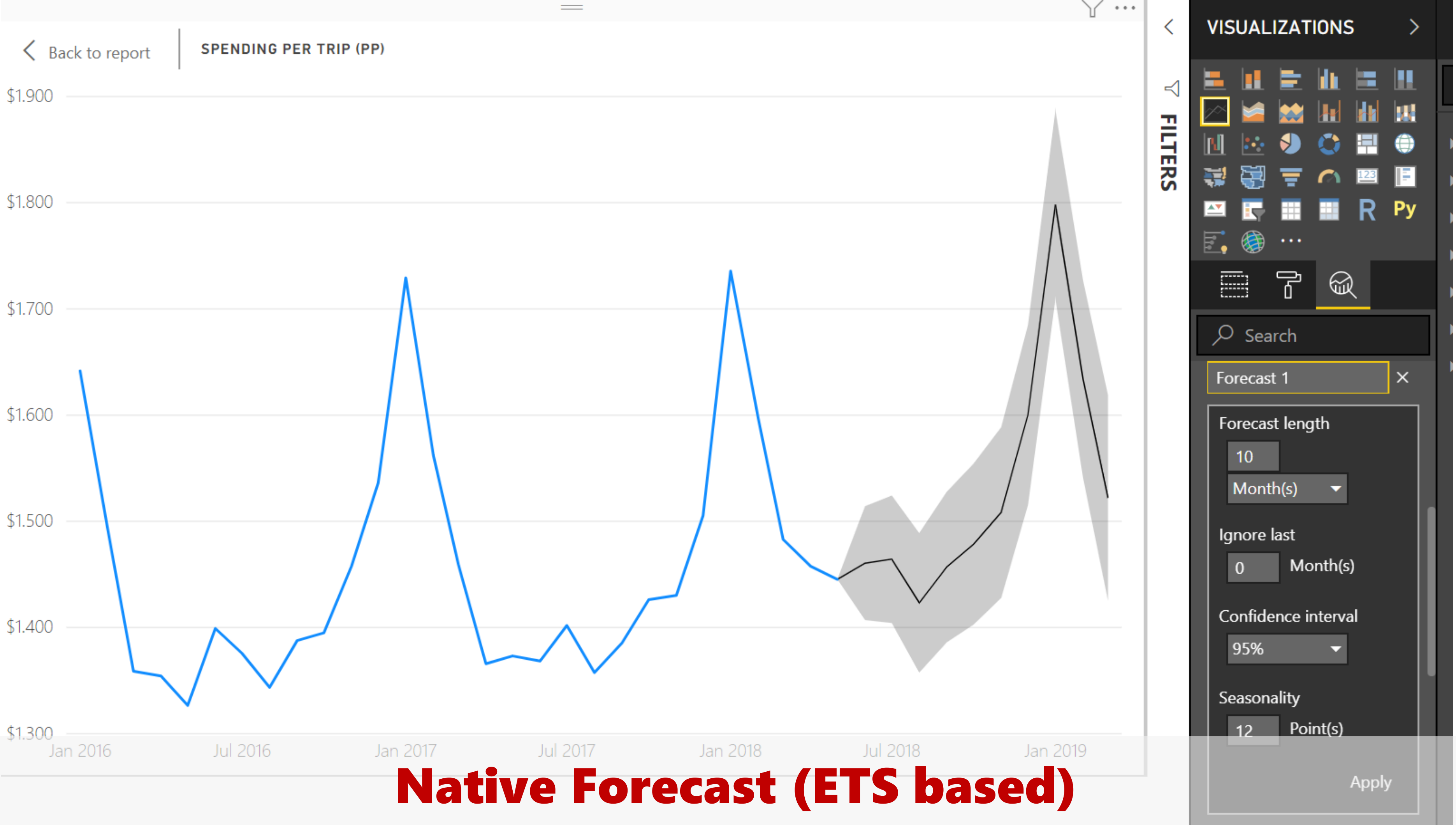


Visual creation using Q&A feature

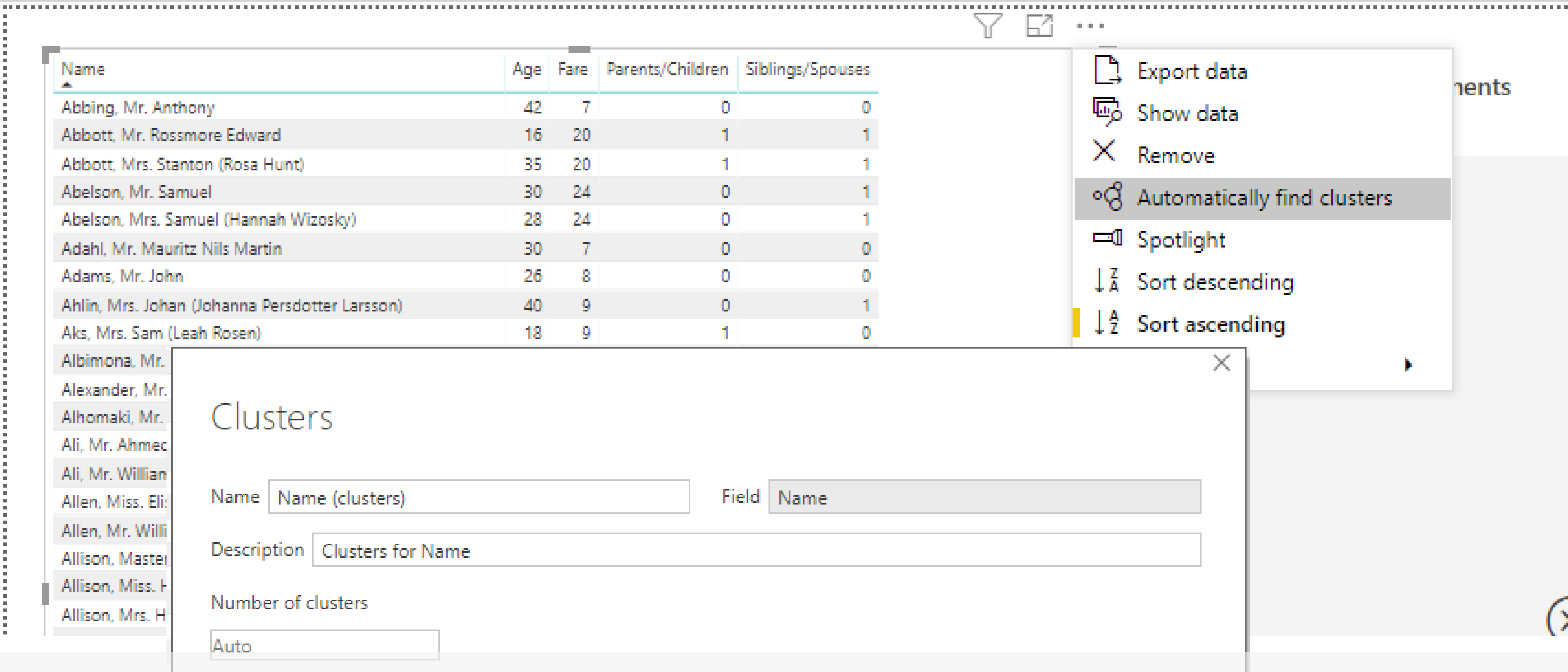

Visits by Island Name
O'ahu
Maui
Hawai'i Isla...
Kaua'i
Lana'i
Moloka'i
0M
10M
Visits by Date
1,0M
0,9M
0,8M
Jan 2017
Jul 2017
visits for 2017 by date



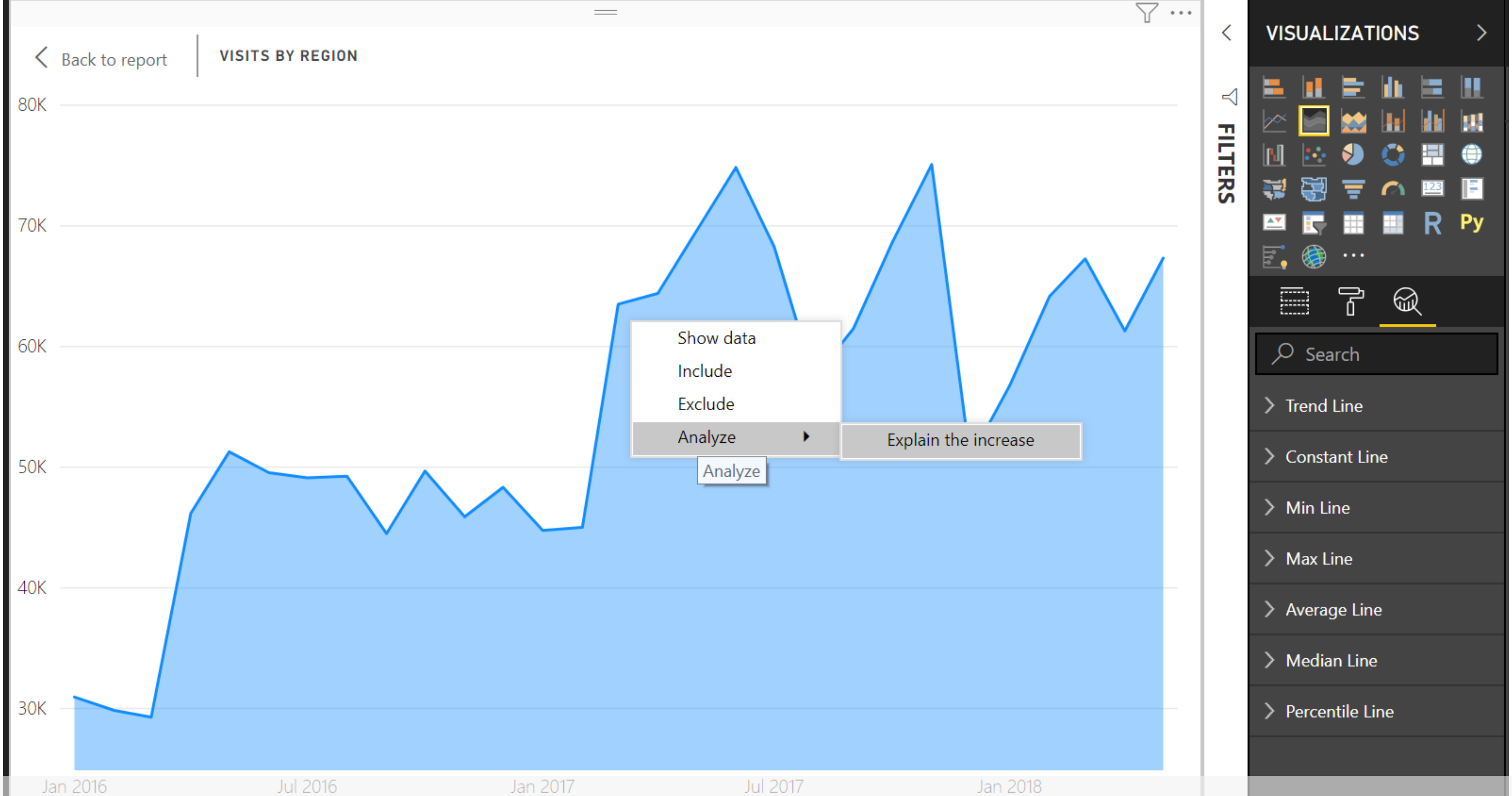
Powerfull & Easily configurabe Drill Through Scenarios



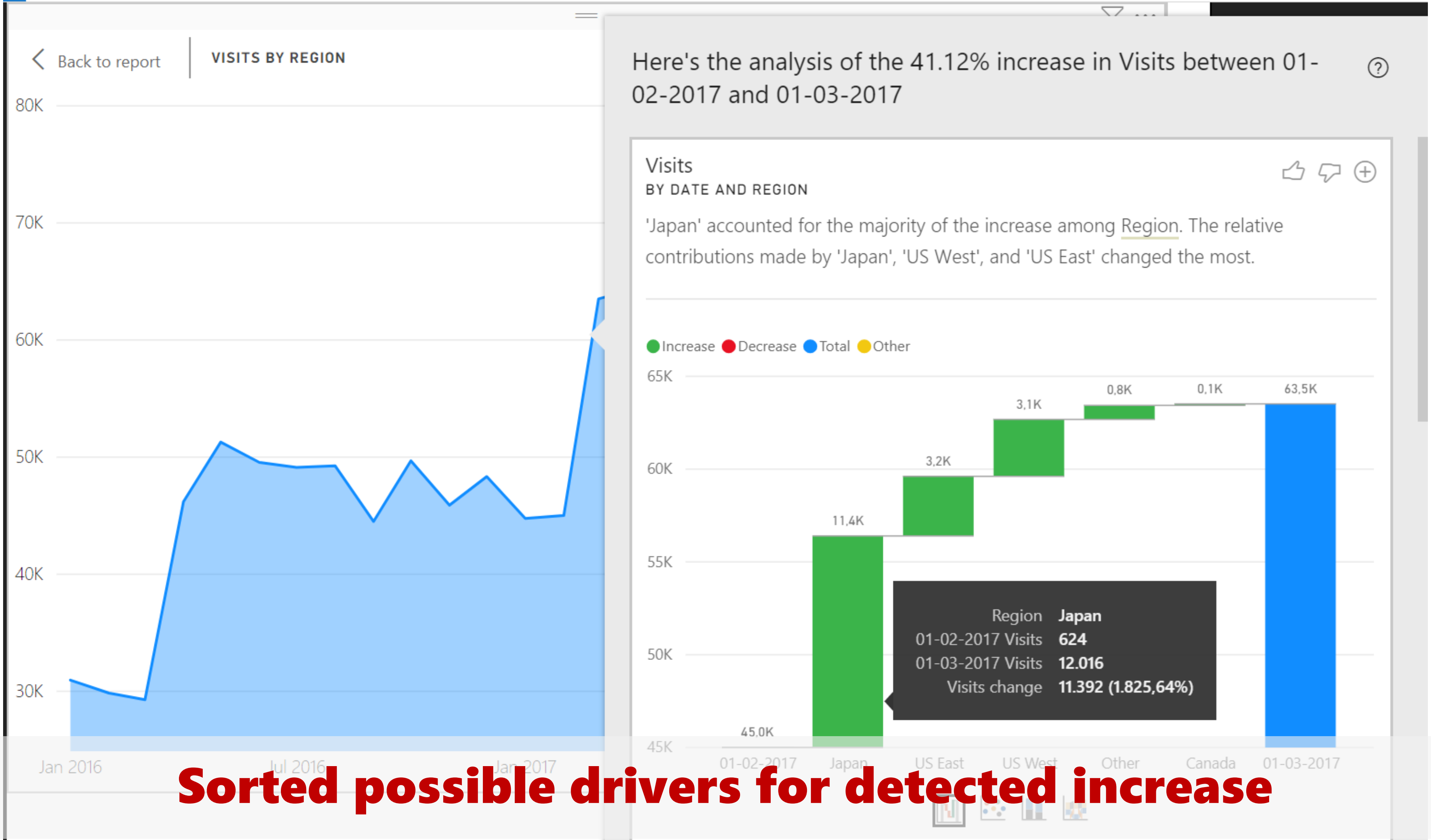
Native Forecast (ETS based)



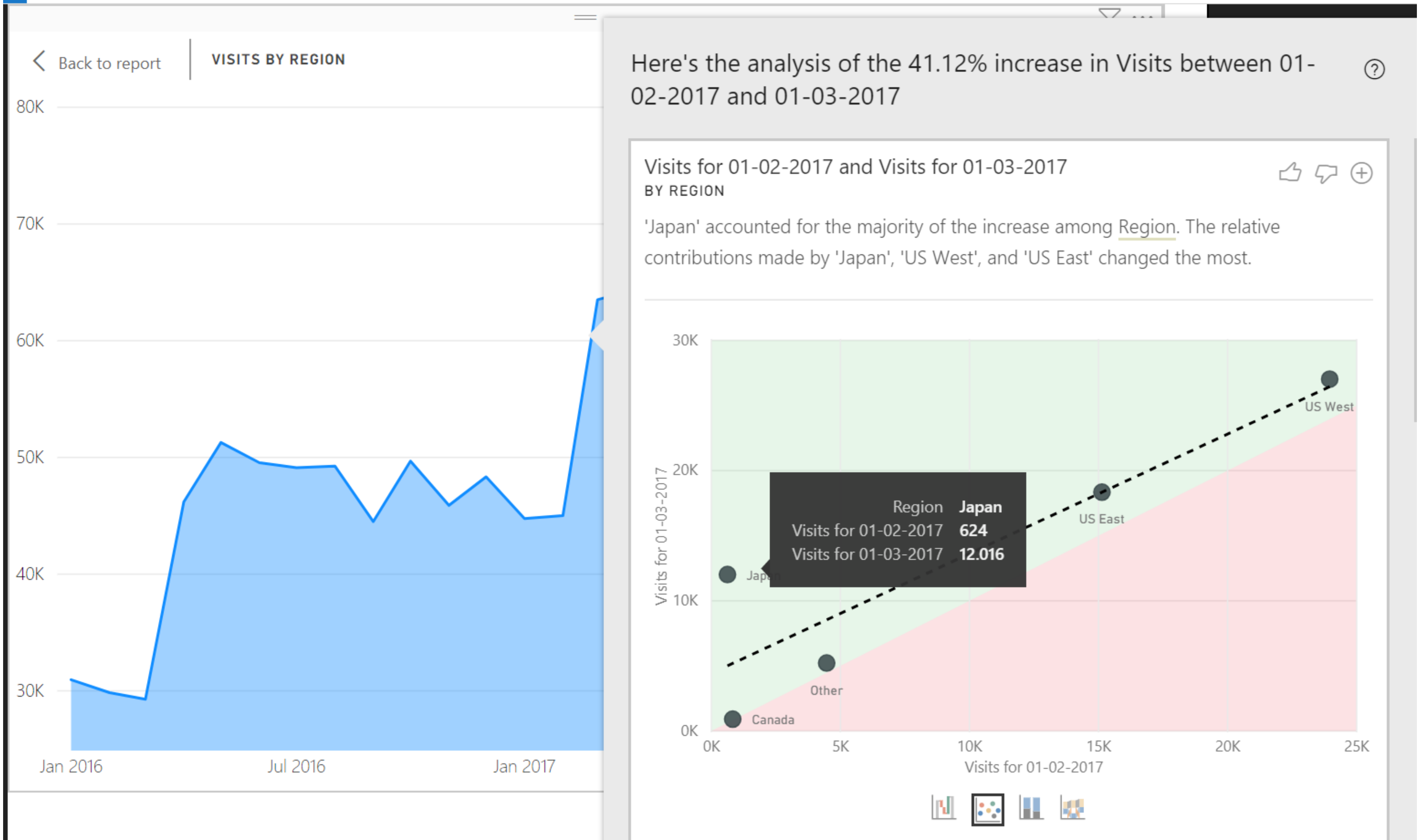
Built-in Clustering Support

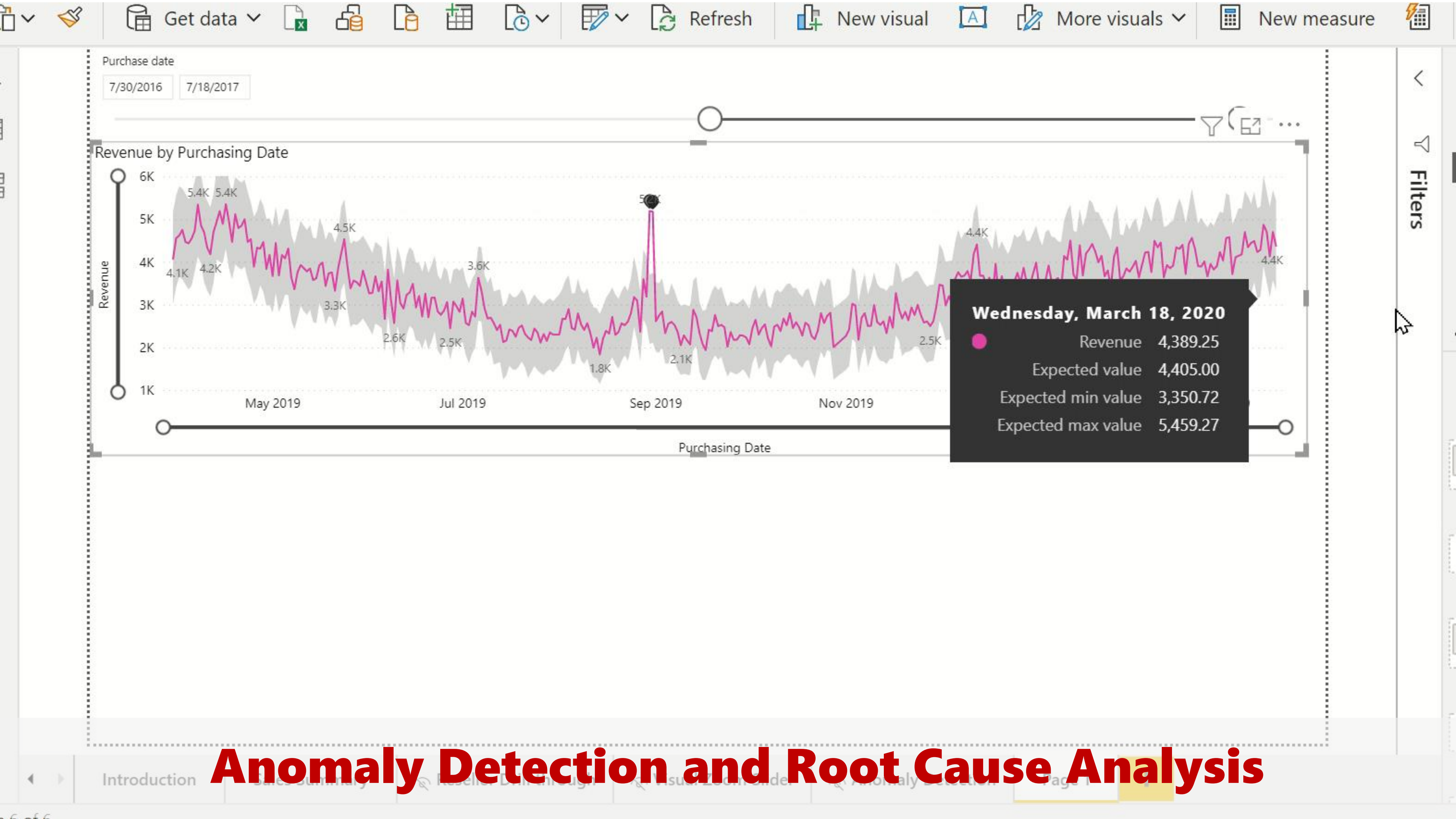


Root causes (explain the increase/decrease)

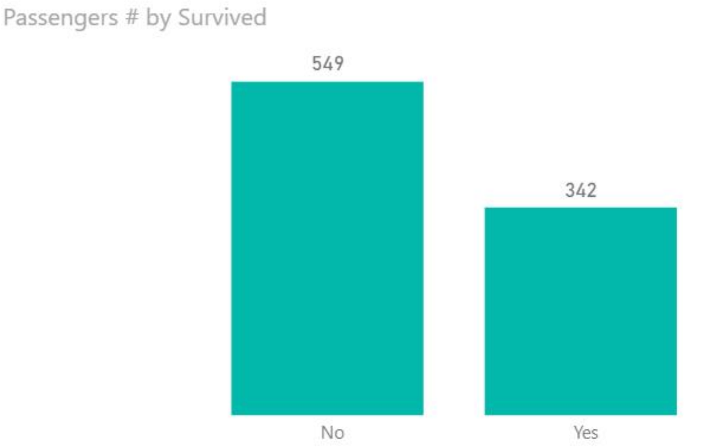


Sorted possible drivers for detected increase


Back to report
VISITS BY REGION
80K
70K
60K
50K
40K
30K
Jan 2016
Jul 2016
Jan 2017
Here's the analysis of the 41.12% increase in Visits between 01-02-2017 and 01-03-2017
Visits for 01-02-2017 and Visits for 01-03-2017
BY REGION
'Japan' accounted for the majority of the increase among Region. The relative contributions made by 'Japan', 'US West', and 'US East' changed the most.
30K
20K
10K
0K
Visits for 01-03-2017
Region Japan
Visits for 01-02-2017 624
Visits for 01-03-2017 12.016
US West
US East
Other
Canada
0K
5K
10K
15K
20K
25K
Visits for 01-02-2017



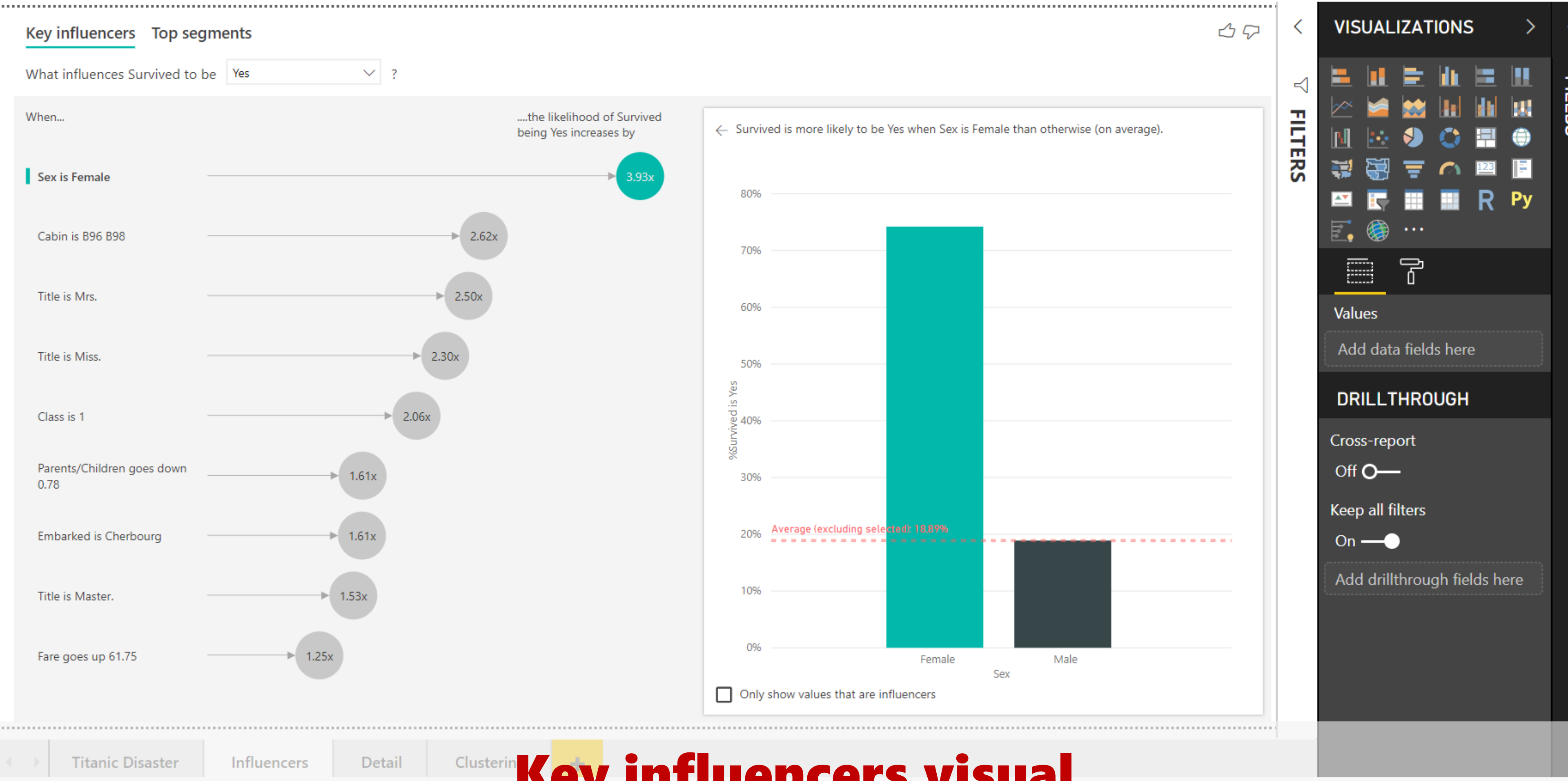
Anomaly Detection and Root Cause Analysis



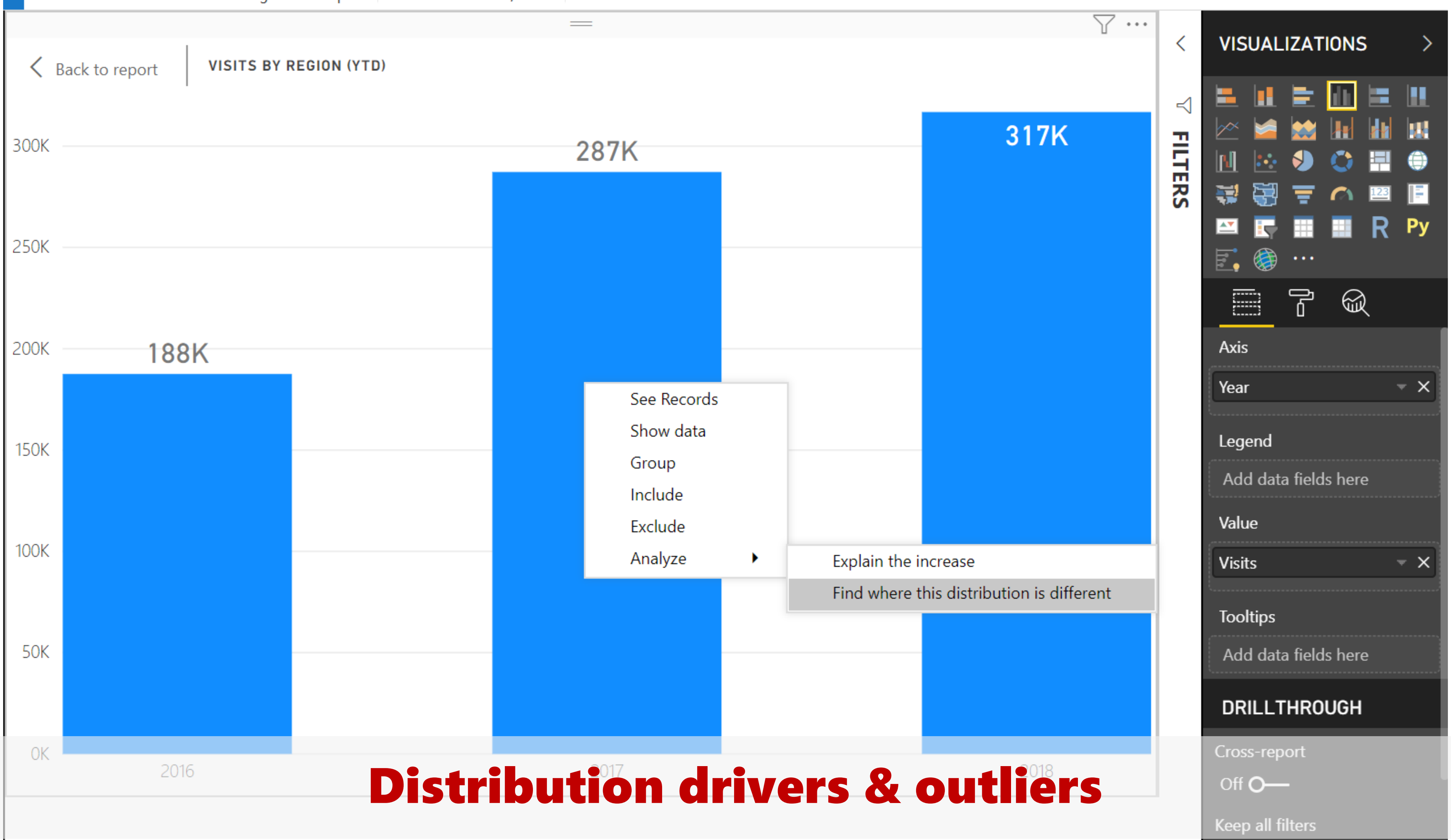
PassengerId	Name	Family	Sex	Age	Class	Fare	Parents/Children	Siblings/Spouses	Embarked	Ticket	Cabin	Title	Survived
1	Braund, Mr. Owen Harris	Braund	Male	22	3	7	0	1	Southampton	A/5 21171		Mr.	No
2	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	Cumings	Female	38	1	71	0	1	Cherbourg	PC 17599	C85	Mrs.	Yes
3	Heikkinen, Miss. Laina	Heikkinen	Female	26	3	7	0	0	Southampton	STON/O2. 3101282		Miss.	Yes
4	Futrelle, Mrs. Jacques Heath (Lily May Peel)	Futrelle	Female	35	1	53	0	1	Southampton	113803	C123	Mrs.	Yes
5	Allen, Mr. William Henry	Allen	Male	35	3	8	0	0	Southampton	373450		Mr.	No
6	Moran, Mr. James	Moran	Male		3	8	0	0	Queenstown	330877		Mr.	No
7	McCarthy, Mr. Timothy J	McCarthy	Male	54	1	51	0	0	Southampton	17463	E46	Mr.	No
8	Palsson, Master. Gosta Leonard	Palsson	Male	2	3	21	1	3	Southampton	349909		Master.	No
9	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	Johnson	Female	27	3	11	2	0	Southampton	347742		Mrs.	Yes
10	Nasser, Mrs. Nicholas (Adele Achem)	Nasser	Female	14	2	30	0	1	Cherbourg	237736		Mrs.	Yes
11	Sandstrom, Miss. Marguerite Rut	Sandstrom	Female	4	3	16	1	1	Southampton	PP 9549	G6	Miss.	Yes
12	Bonnell, Miss. Elizabeth	Bonnell	Female	58	1	26	0	0	Southampton	113783	C103	Miss.	Yes
13	Saundercock, Mr. William Henry	Saundercock	Male	20	3	8	0	0	Southampton	A/5. 2151		Mr.	No
14	Andersson, Mr. Anders Johan	Andersson	Male	39	3	31	5	1	Southampton	347082		Mr.	No
15	Vestrom, Miss. Hulda Amanda Adolfina	Vestrom	Female	14	3	7	0	0	Southampton	350406		Miss.	No
16	Hewlett, Mrs. (Mary D Kingcome)	Hewlett	Female	55	2	16	0	0	Southampton	248706		Mrs.	Yes
17	Rice, Master. Eugene	Rice	Male	2	3	29	1	4	Queenstown	382652		Master.	No
18	Williams, Mr. Charles Eugene	Williams	Male		2	13	0	0	Southampton	244373		Mr.	Yes

Quick glimpse/preview of Key predictors/influencers

Titanic Disaster | Influencers | Detail | Clustering



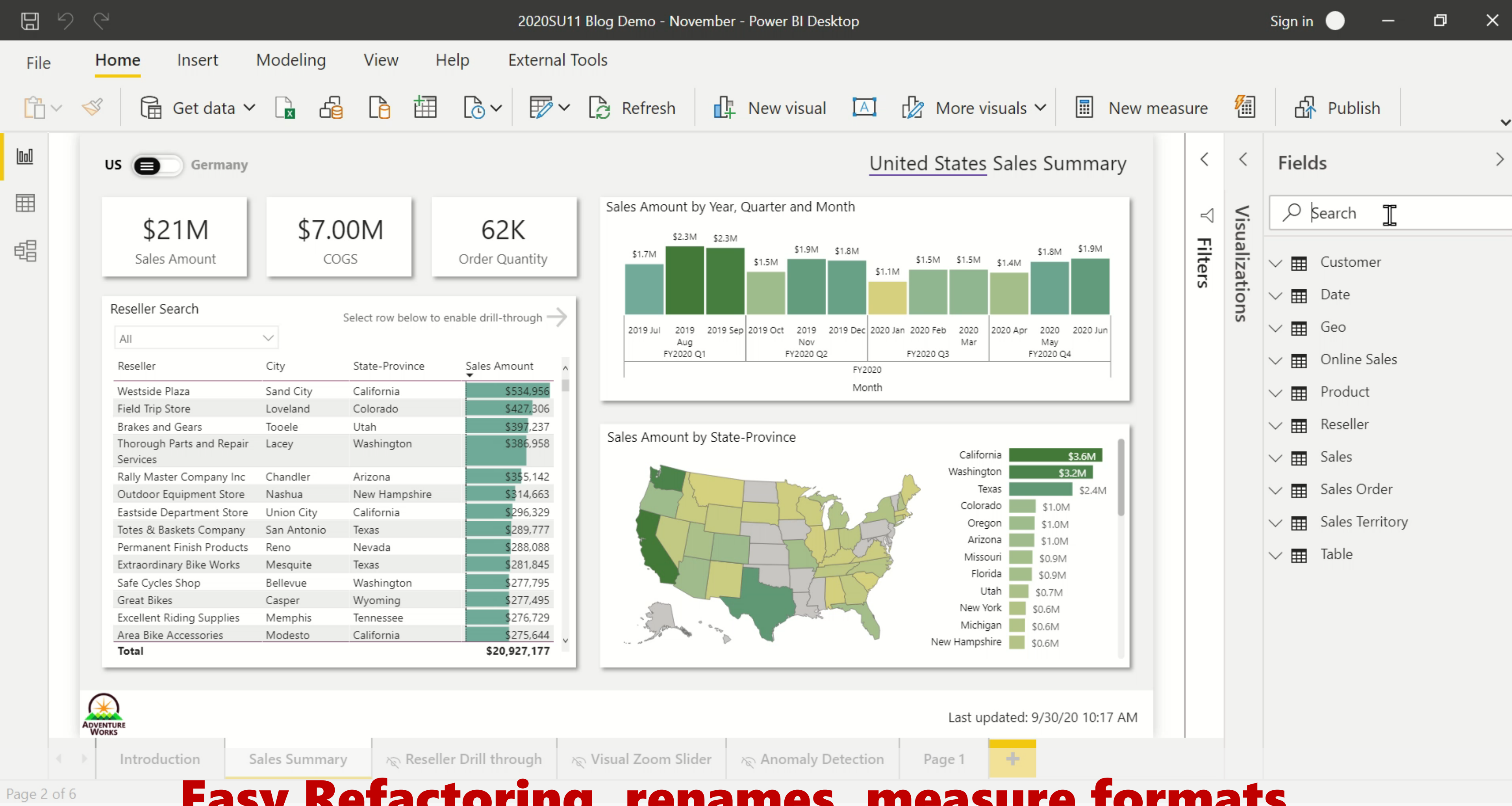
Key influencers visual



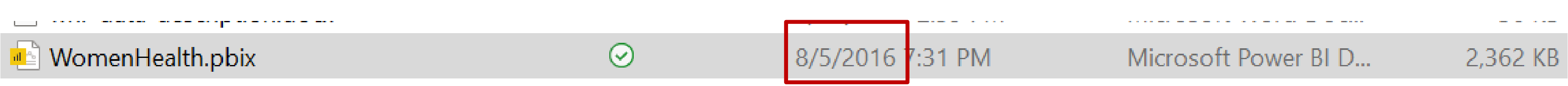
Distribution drivers & outliers

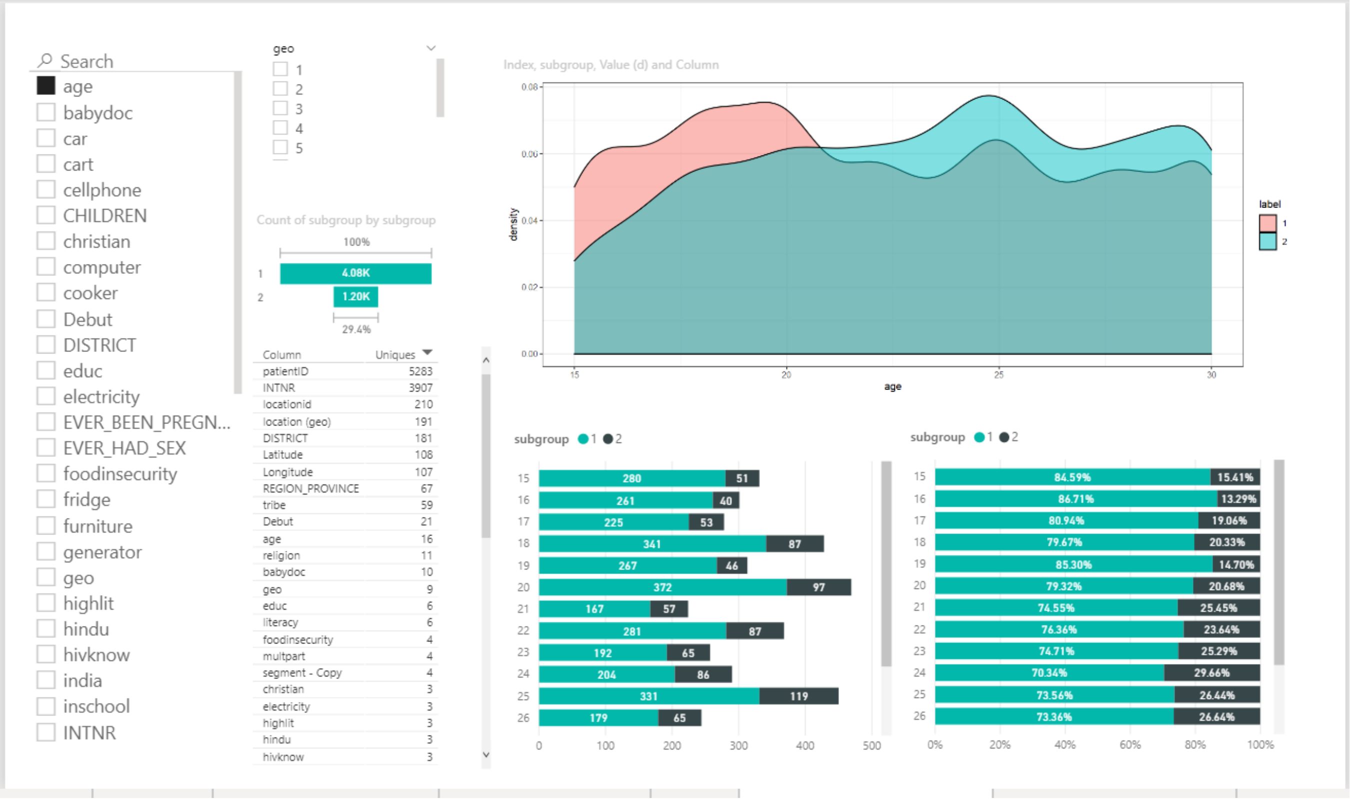

Back to report
VISITS BY REGION (YTD)
300K
250K
200K
150K
100K
50K
0K
188K
2016
Here are the filters that cause the distribution of Visits by Year to change the most
REGION
'Japan', with 20,4% of records; 'US East', with 20,4% of records; and 'Canada', with 20,4% of records, among others, most affect the distribution.
Japan
US East
Canada
Visits for Japan
Visits (Overall)
60K
40K
20K
0K
0,4M
0,3M
0,2M
0,1M
0,0M
Visits (Overall)
2016
2017
2018
Comparing proportions

Other Tips & Cool Features

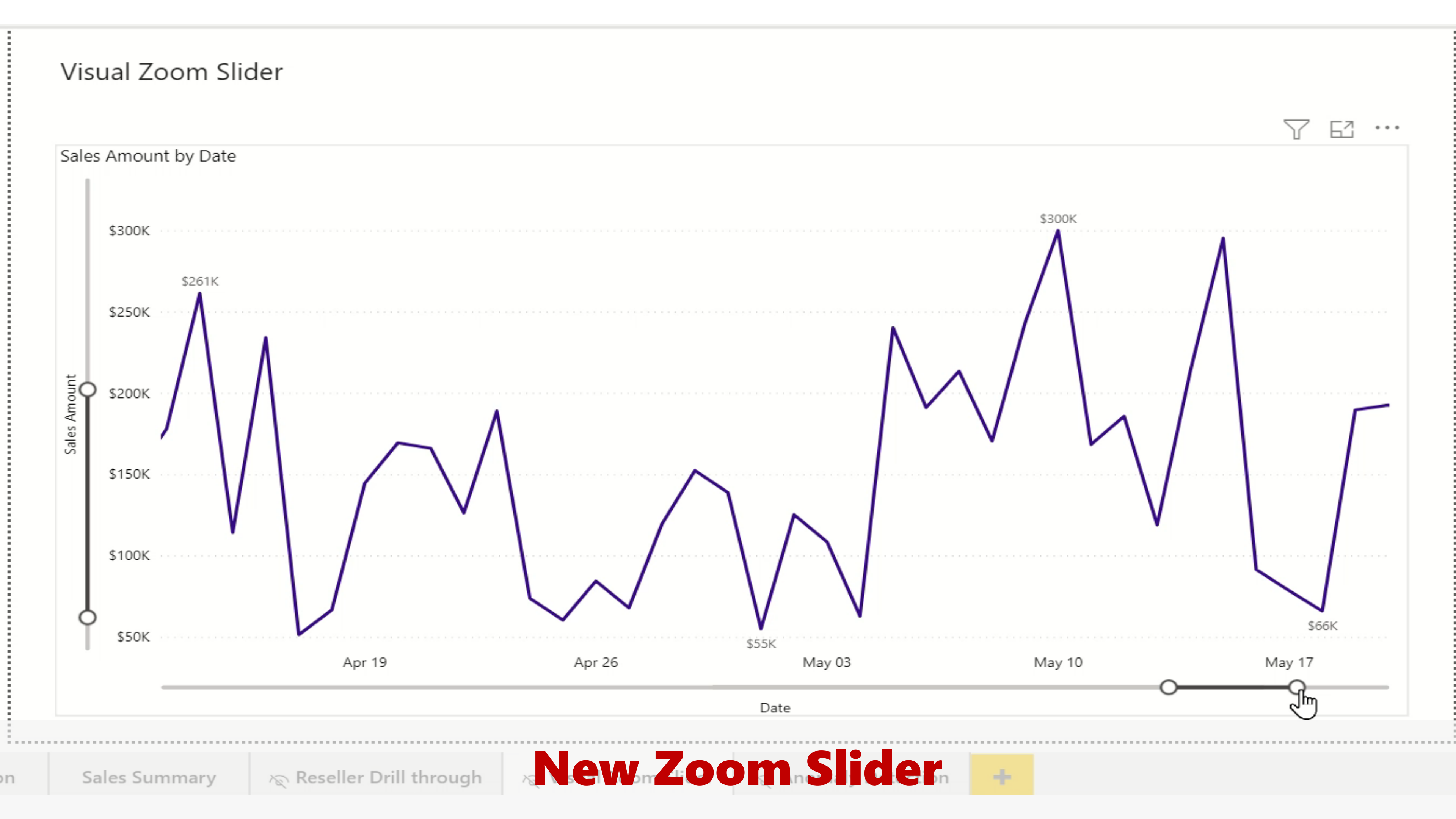


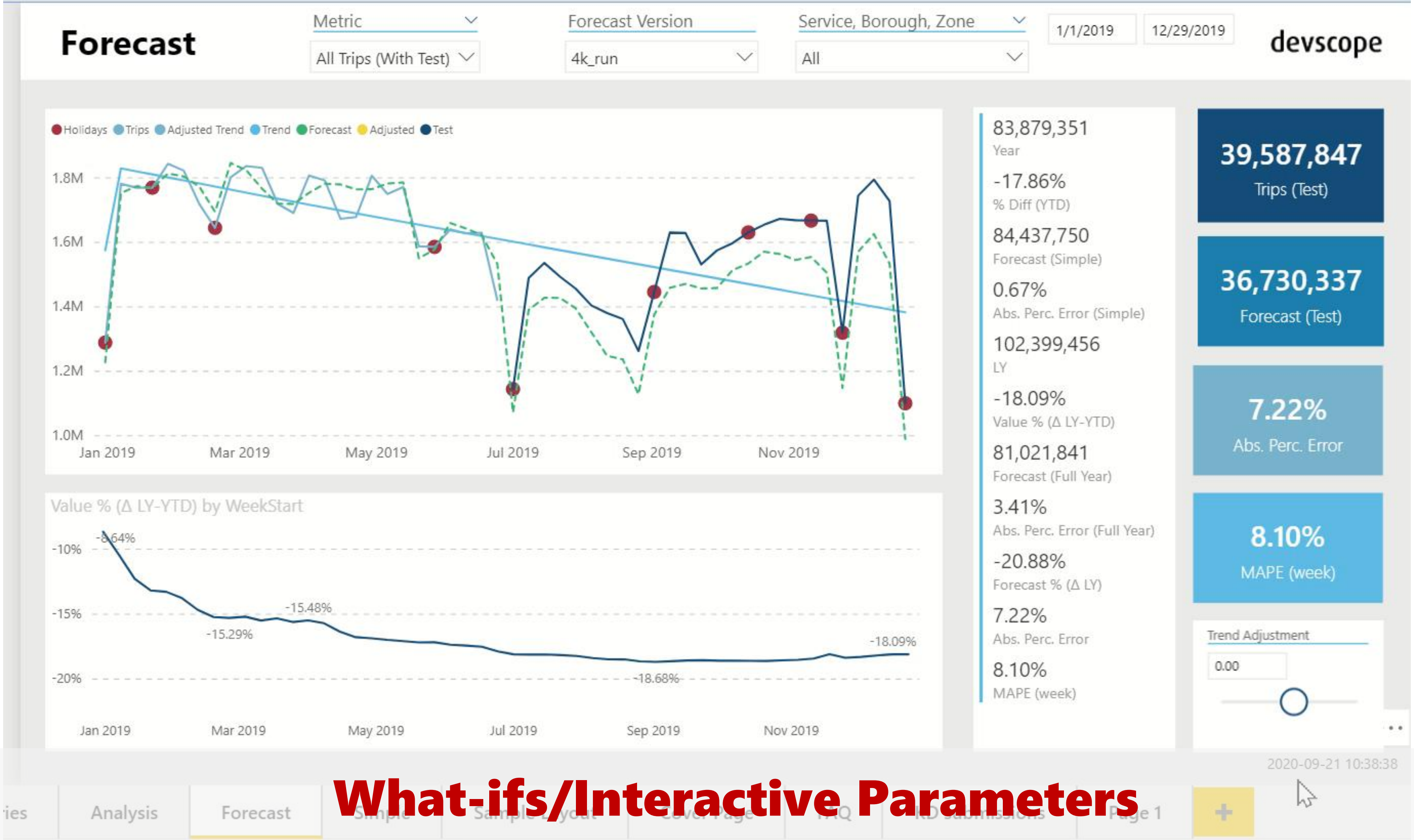
Easy Refactoring, renames, measure formats,…





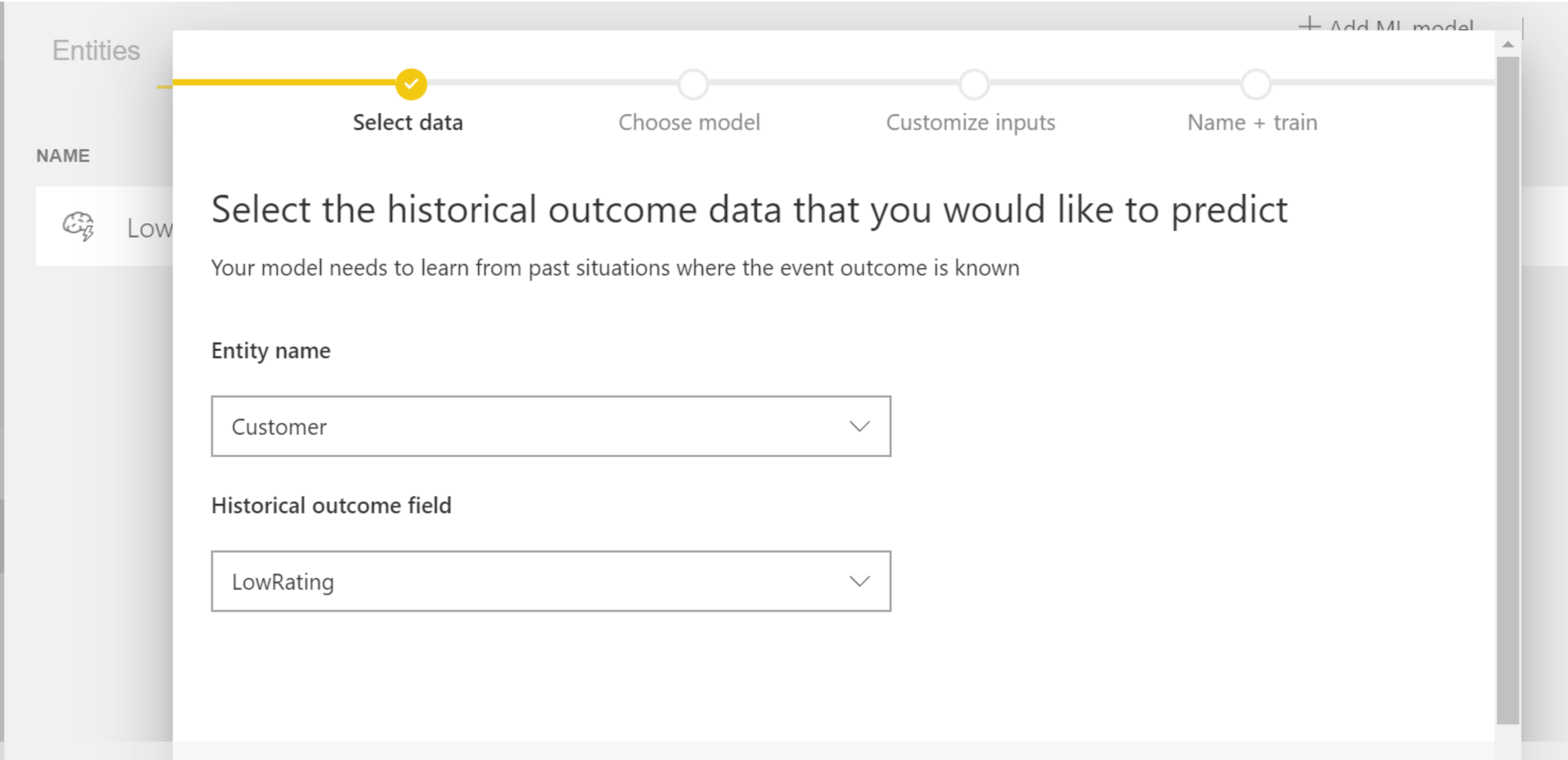
Reproducibility (just open it!)


Visual Zoom Slider
Sales Amount by Date
Sales Amount
$300K
$250K
$200K
$150K
$100K
$50K
$261K
$300K
$55K
$66K
Apr 19
Apr 26
May 03
May 10
May 17
Date
Sales Summary
Reseller Drill through
New Zoom Slider

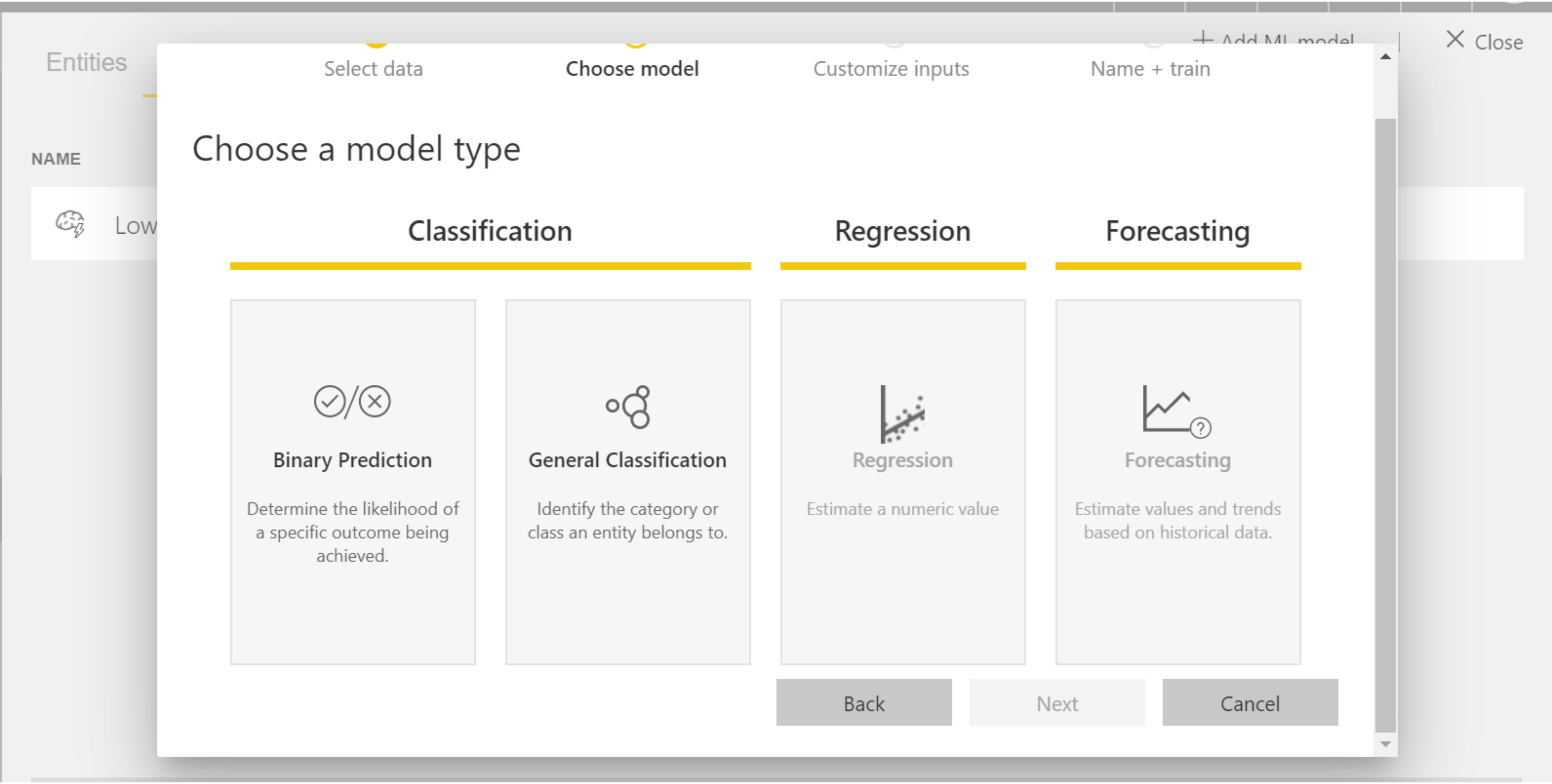


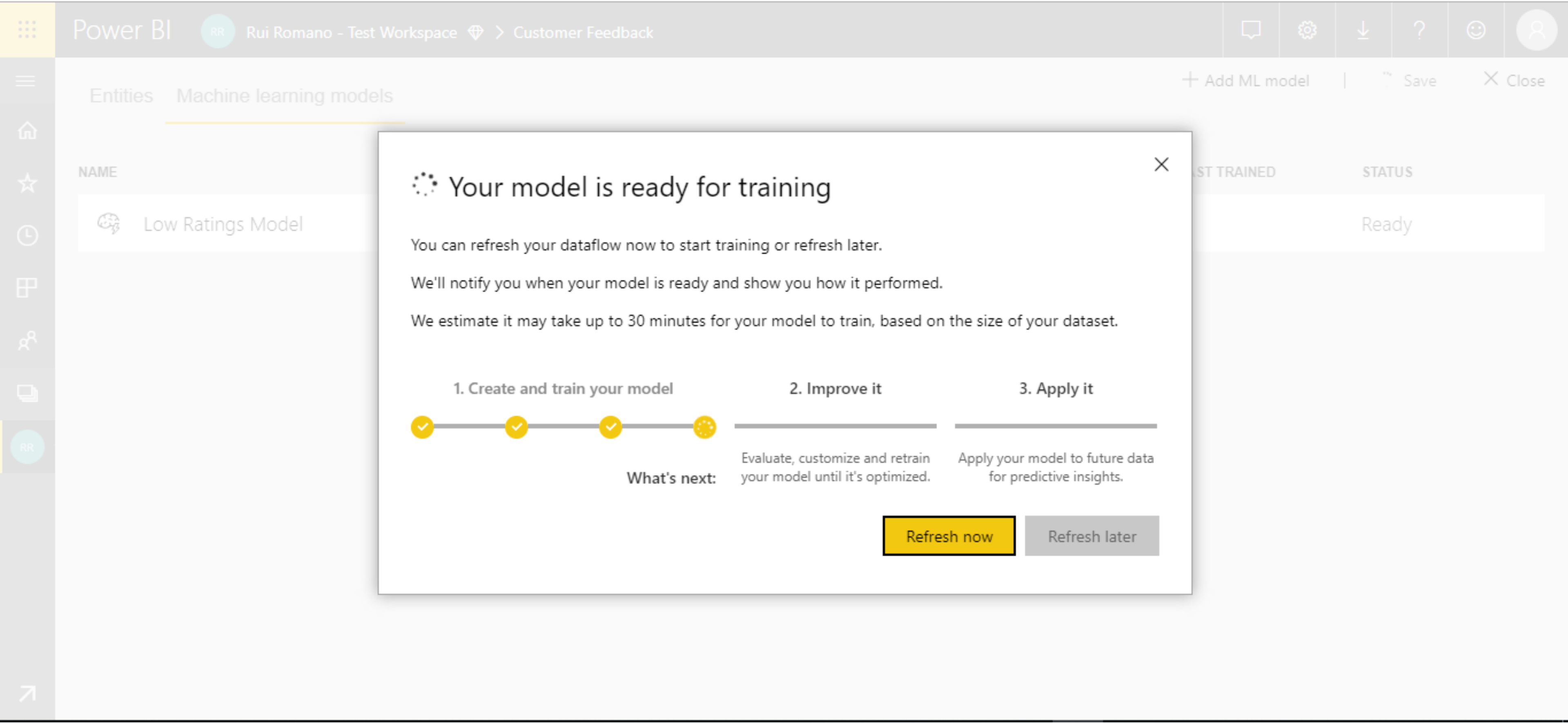
What-ifs/Interactive Parameters

Power BI & Auto ML



Semantic Models based Auto ML (cloud/premium feature)


Entities
NAME
Low
Add ML model
Close
Select data
Choose model
Customize inputs
Name + train
Choose a model type
Classification
Regression
Forecasting
Binary Prediction
Determine the likelihood of a specific outcome being achieved.
General Classification
Identify the category or class an entity belongs to.
Regression
Estimate a numeric value
Forecasting
Estimate values and trends based on historical data.
Back
Next
Cancel


Power BI
Rui Romano - Test Workspace
Customer Feedback
Add ML model
Save
Close
Entities
Machine learning models
NAME
ST TRAINED
STATUS
Low Ratings Model
Ready
Your model is ready for training
You can refresh your dataflow now to start training or refresh later.
We'll notify you when your model is ready and show you how it performed.
We estimate it may take up to 30 minutes for your model to train, based on the size of your dataset.
1. Create and train your model
2. Improve it
3. Apply it
What's next:
Evaluate, customize and retrain your model until it's optimized.
Apply your model to future data for predictive insights.
Refresh now
Refresh later

Titanic Survival model accuracy preview

This report summarizes the accuracy of the binary prediction model and enables you to find an optimal threshold for defining your business outcome.

Apply model

Edit model

Model Performance

78%

Area under ROC curve

Training summary data

304
Total Data Provided

404
Total Data Sampled

304
Training Data

100
Validation Data

How the model was tested

The model predicted Survived probabilities for a test set of 100 records and compared the predicted outcomes (based on the selected threshold) to the historical outcomes.

Inspect your model

Learn about the performance of your model by inspecting the accuracy diagrams below.

Cumulative Gains Chart

A Cumulative Gains chart shows what percentage of the positive rows can be by detected by targeting a percentage of the total rows.

This chart compares the performance of 3 approaches:
- "Model" -- your model is used to sort the rows in descending order of the predicted score indicating the target category.
- "Ideal" -- a theoretically "perfect" model, which would always rank any rows in the target category above rows that do not belong to the target category
- "Random guess" -- no model being used. The rows are assumed to be evenly distributed so, for example, 10% of the total rows are expected to contain 10% of the target category

ROC Curve

An ROC (Received Operating Characteristics) curve tells you how capable your model is to distinguish between the target category (positive) and the other rows in your data (negative).

A model will produce probability, between 0 and 1, for each row it scores. Typically, you will select a threshold (e.g. 0.5) and decide that everything above that threshold will be treated as a positive prediction and everything below will be treated as a negative prediction.

Each point on the ROC curve represents a possible value of the probability threshold. The vertical coordinate represents the rate of correct positive predictions, while the horizontal coordinate represents the rate of negatives incorrectly labeled by your model as positives.

Model Performance | Accuracy Report | Technical Details

Titanic Survival model accuracy preview

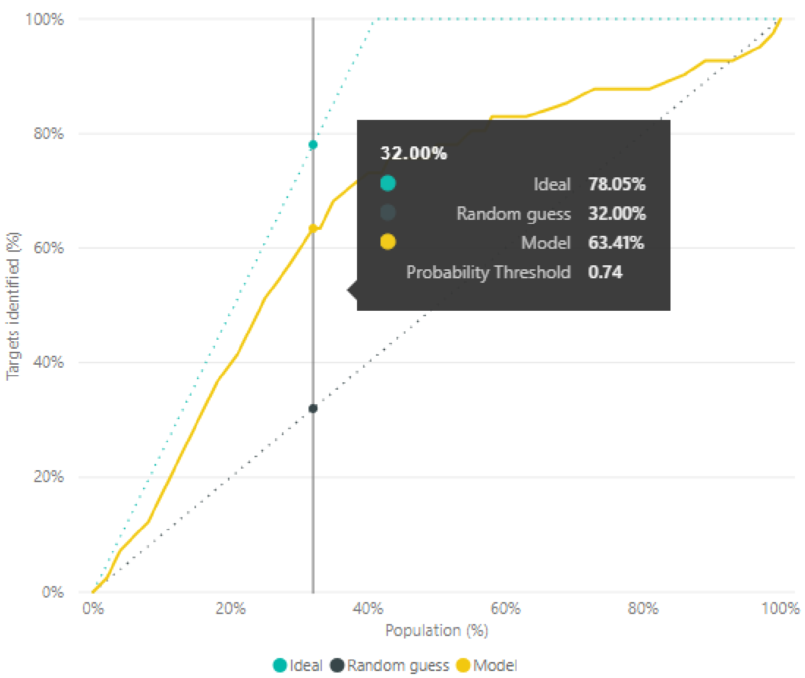
This report summarizes the accuracy of the binary prediction model and enables you to find an optimal threshold for defining your business outcome.

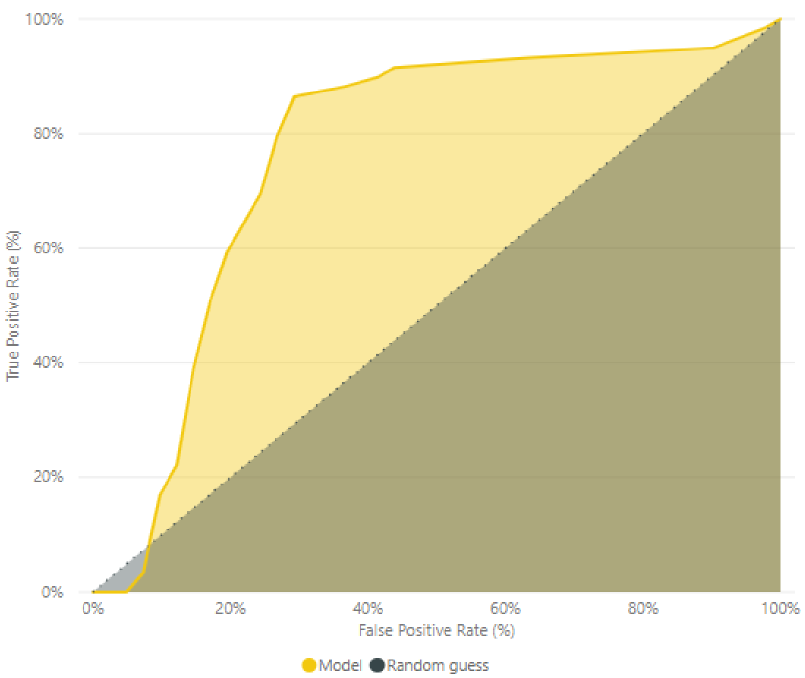
Apply model

Edit model

The performance of your model gets better as it gets close to the ideal model line.

ideal model that is achieved by your model. The higher the curve, the better your model is at predicting positives as positives and negatives as negatives.





Model Performance | Accuracy Report | Technical Details

How to Start?

Microsoft Power BI Desktop

Important! Selecting a language below will dynamically change the complete page content to that language.

Select Language: English

Download

Microsoft Power BI Desktop is built for the analyst. It combines state-of-the-art interactive visualizations, with industry-leading data query and modeling built-in. Create and publish your reports to Power BI. Power BI Desktop helps you empower others with timely critical insights, anytime, anywhere.

⊕ Details

⊕ System Requirements

⊕ Install Instructions

Press F11 to exit full screen

Learn Power BI

From creating your first graph to trying the latest advanced technique, our collected resources make it easy to learn about Power BI.

Guided learning

Follow our courses of videos and articles that walk you through how to accomplish common tasks with Power BI.

Learn more ›

Samples

Review examples of dashboards, reports, and desktop files, and see how some of our partners are putting Power BI to use.

Go to samples ›

Documentation

View in-depth articles for all of Power BI's tools and features, from getting started to advanced techniques.

Go to documentation ›

Power BI Portugal

Lisbon, Portugal
2,184 members · Public group
Organized by **Manuel D.** and **7 others**

Share:

About | Events | Members | Photos | Discussions | More

Join this group

What we're about

We are a group of Power BI users and data enthusiasts, interested on leveraging data analytics in real business scenarios. Our group will cover several areas, from Data Engineering, Data Modelling, Data Visualization, to more advanced analytics such as Machine Learning, Storytelling or Open Data, always learning from peers and industry experts.

Why Power BI? Power BI is creating a real buzz in the business analytics space, counts with more than 5 million subscribers. It allows Business users to get...

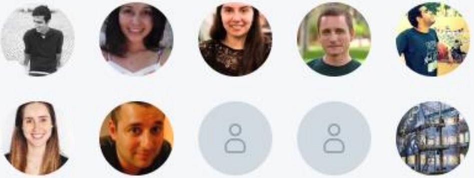
Read more

Organizers

Manuel D. and **7 others**
Message

Members (2,184)

See all



Some Limitations (Power BI Desktop)

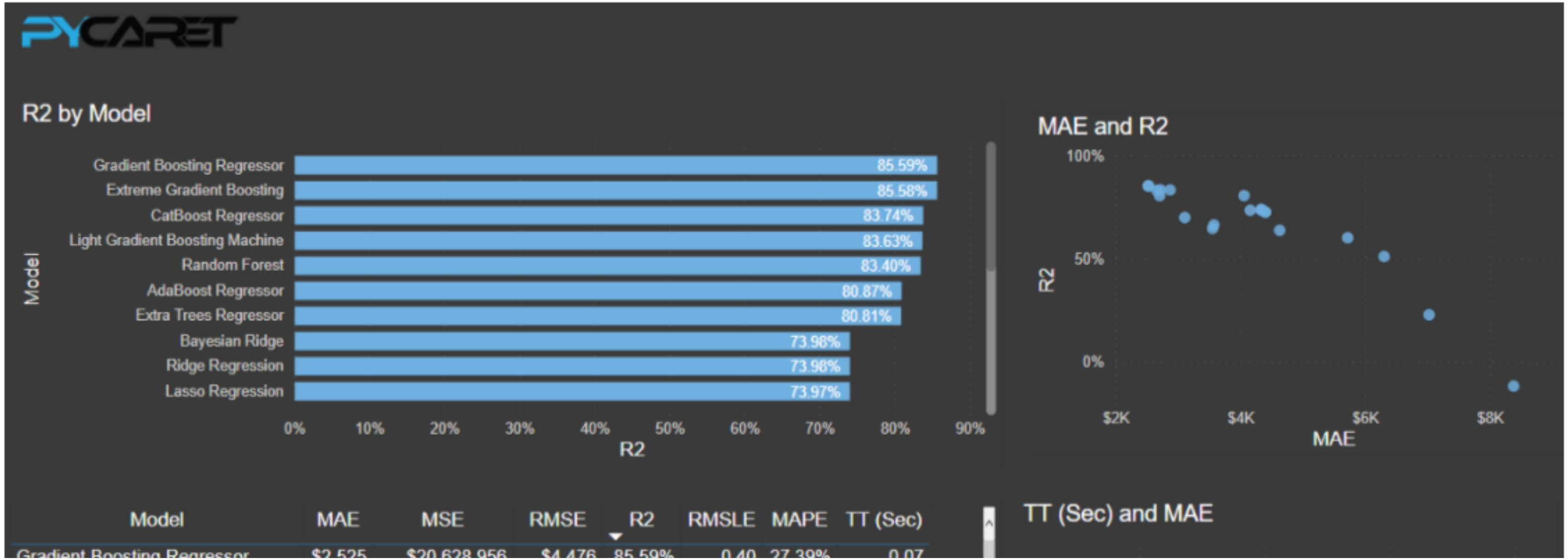
- not a true Data Science/Machine Learning workbench (sadly... ☹)
  - Ex: no native distribution plots, histograms (custom visuals available)
- Yeap, not Open Source...
- Not the best format for CI/CD (binary)
- Not scriptable/automation friendly
- Windows only
  - No Linux, No MacOs

    (but note: lots of Power BI feature available on web/cloud version)
- Not the fastest reading formats like Excel, CSV
  - Like, *damn slow*...
  - But after load... "damn fast" ☺

References & Further reading

Build your own AutoML in Power BI using PyCaret 2.0

Moez Ali Aug 5 · 8 min read



Time series Forecasting in Power BI

Time series forecasting in PowerBI. (An Almost) Comprehensive Guide

Apr 24, 2020 • 37 min read

forecasting Python powerbi forecasting_in_powerbi

View On GitHub launch binder Open in Colab

Thank you!

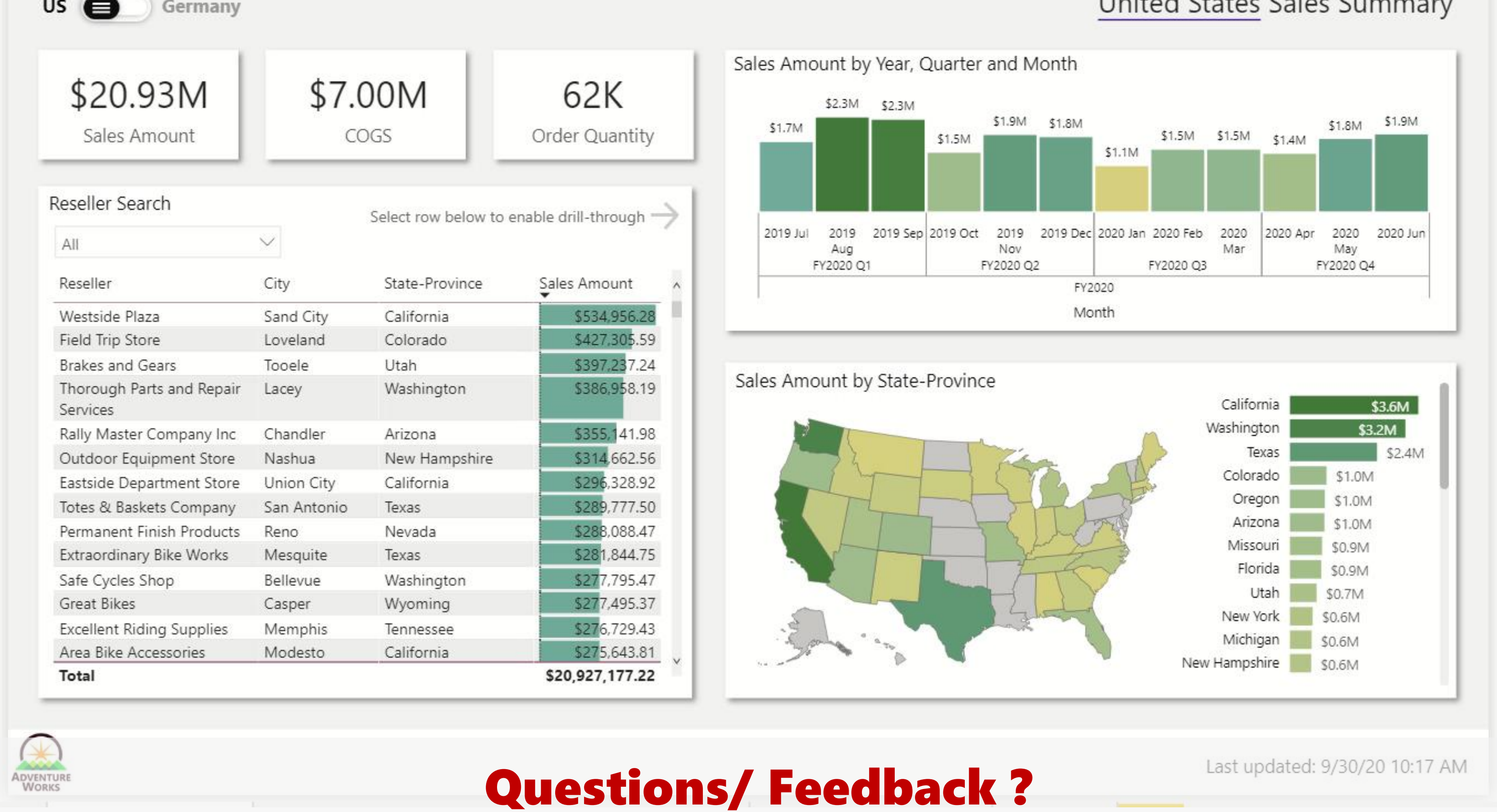
rui.quintino@devscope.net

Linkedin.com/ in/rquintino

Twitter @rquintino

Medium /devscope-ai

Github /DevScope/ai-lab



Questions/ Feedback ?

Questions/Feedback ?

rui.quintino@devscope.net

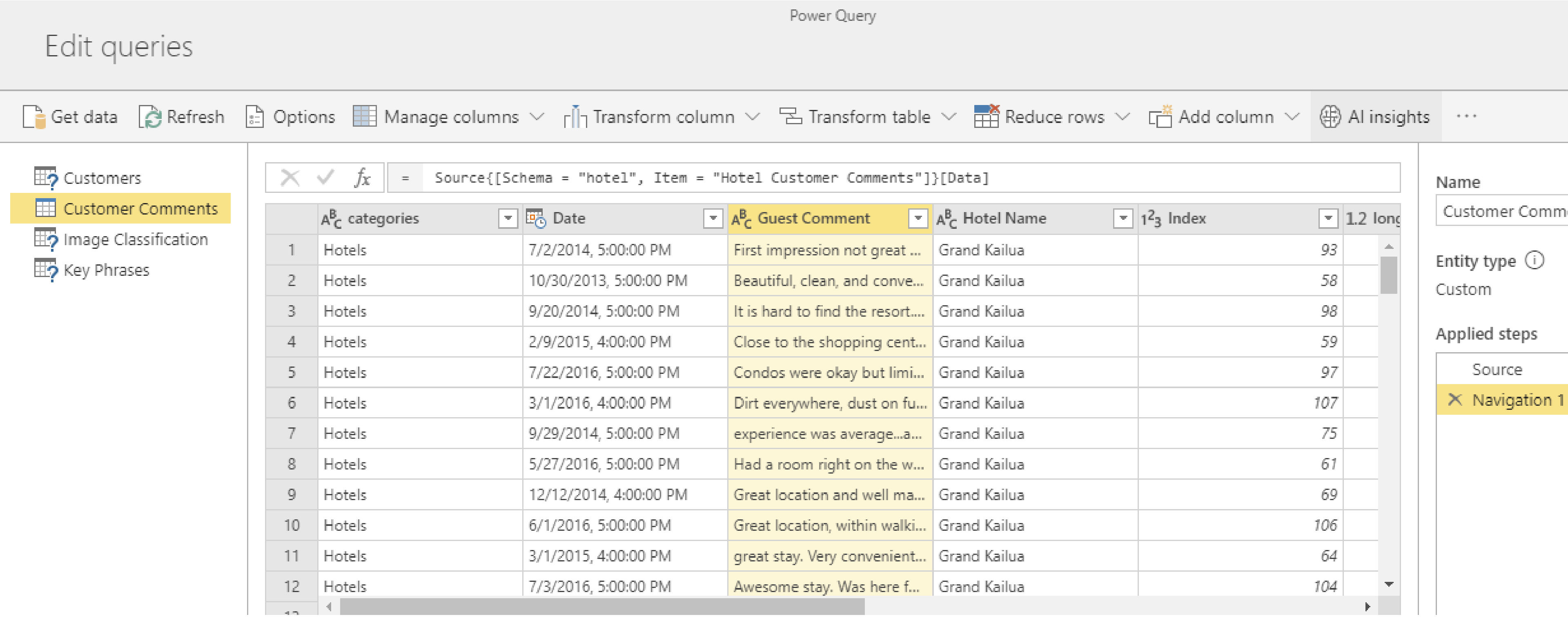
Linkedin.com/ in/rquintino

Twitter @rquintino

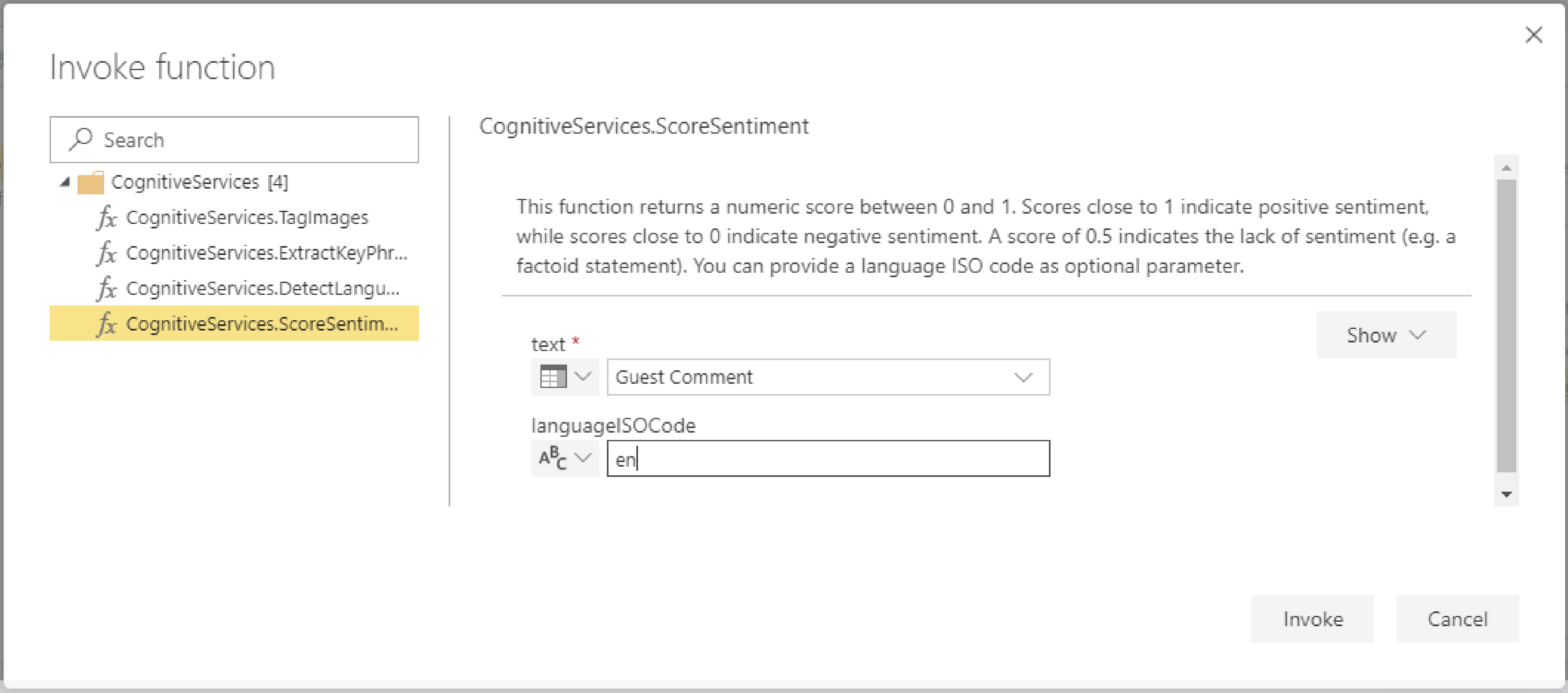
Medium /devscope-ai

Github /DevScope/ai-lab

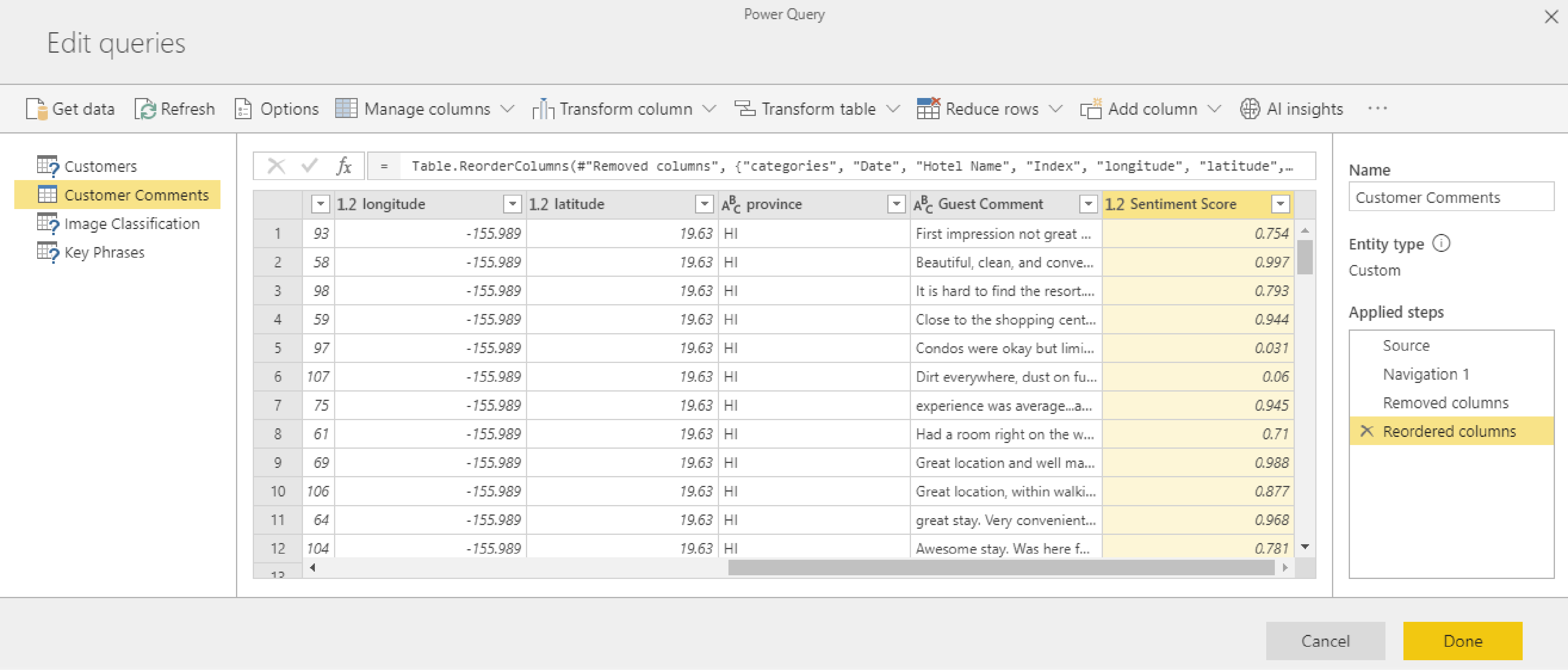
Power BI & AI Built-in models



Example: Natural Language Processing steps



Access to AI APIs (Azure Cognitive Services)



Sentiment Analysis of Guest Comments

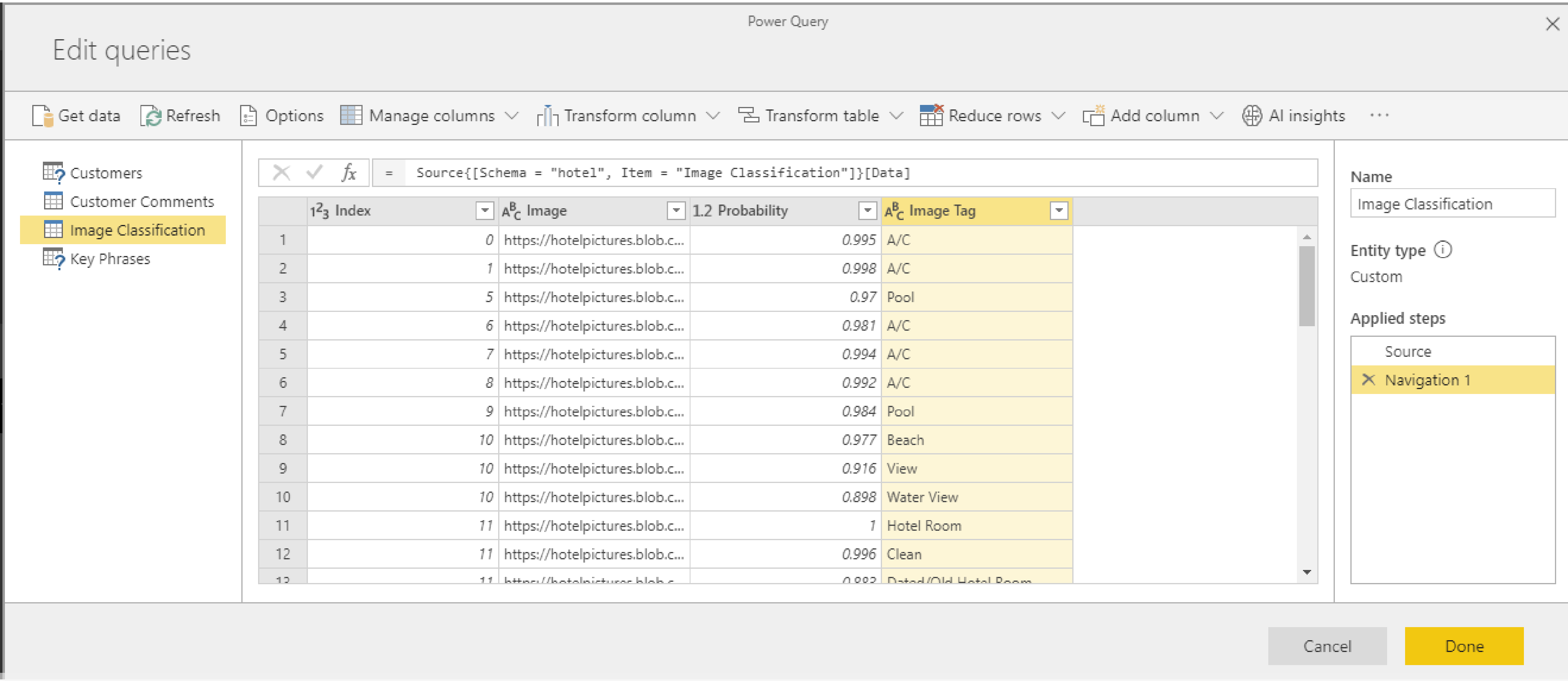
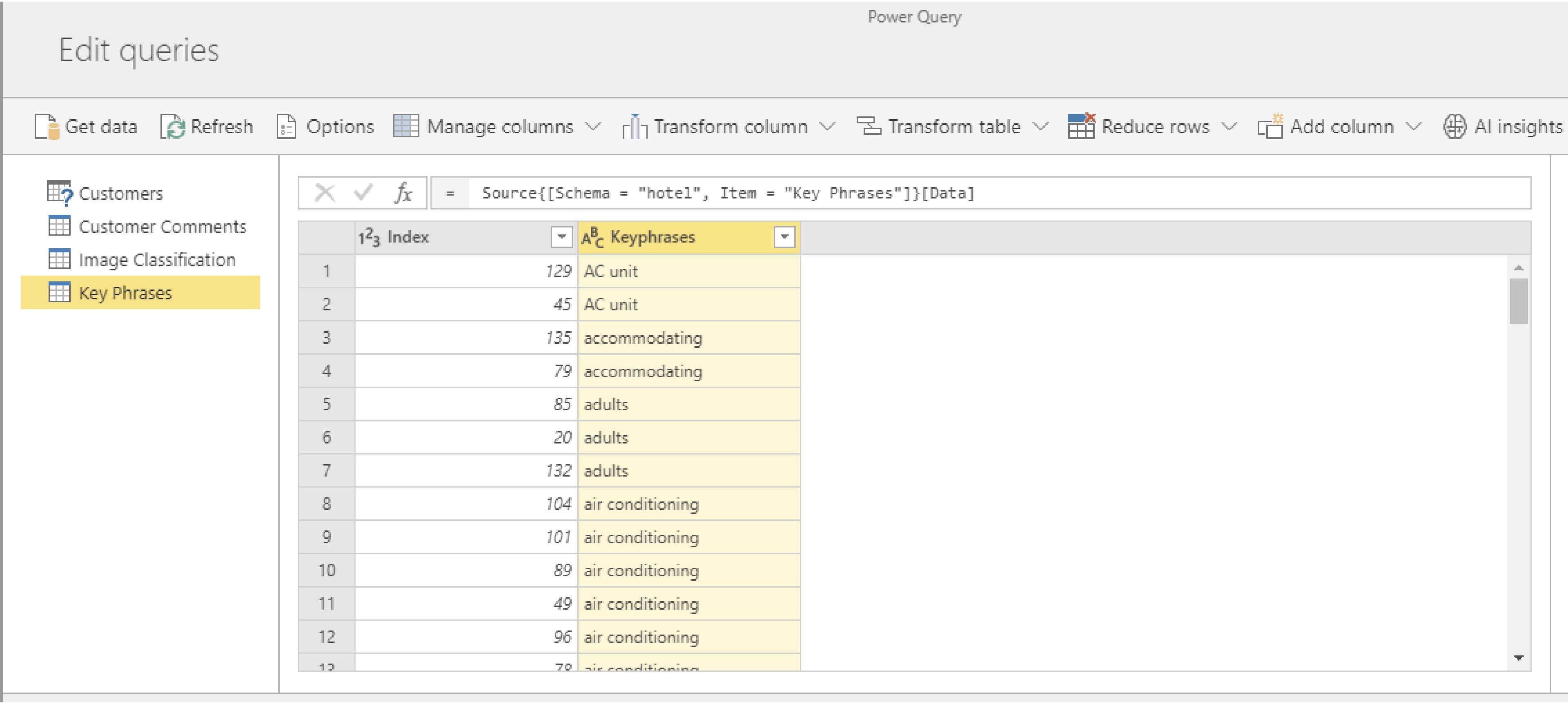
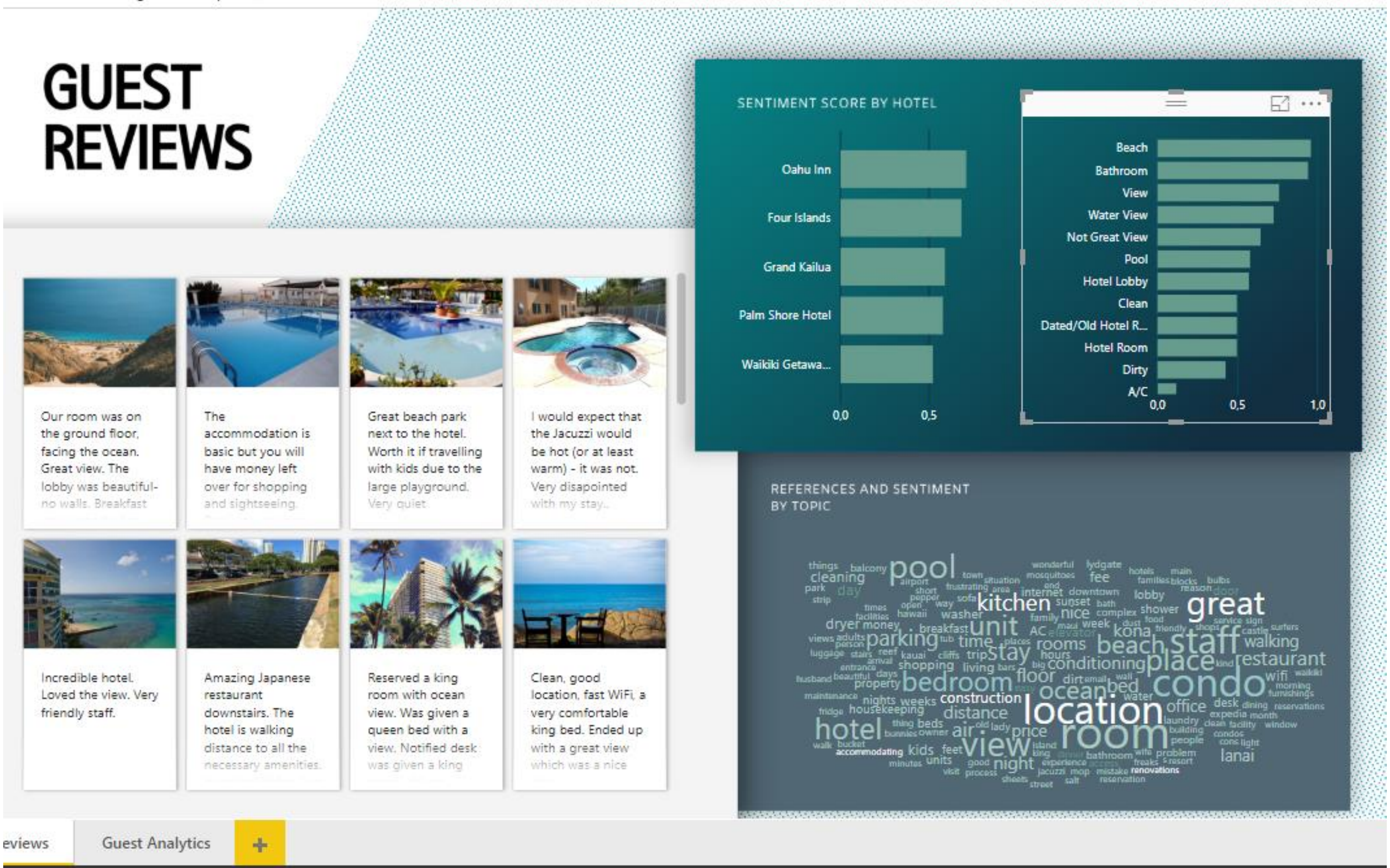


Image Tagging and Key Phrases


Power Query
Edit queries
Get data
Refresh
Options
Manage columns
Transform column
Transform table
Reduce rows
Add column
AI insights
Customers
Customer Comments
Image Classification
Key Phrases
fx
=
Source{[Schema = "hotel", Item = "Key Phrases"]}[Data]
Index
Keyphrases
1 129 AC unit
2 45 AC unit
3 135 accommodating
4 79 accommodating
5 85 adults
6 20 adults
7 132 adults
8 104 air conditioning
9 101 air conditioning
10 89 air conditioning
11 49 air conditioning
12 96 air conditioning

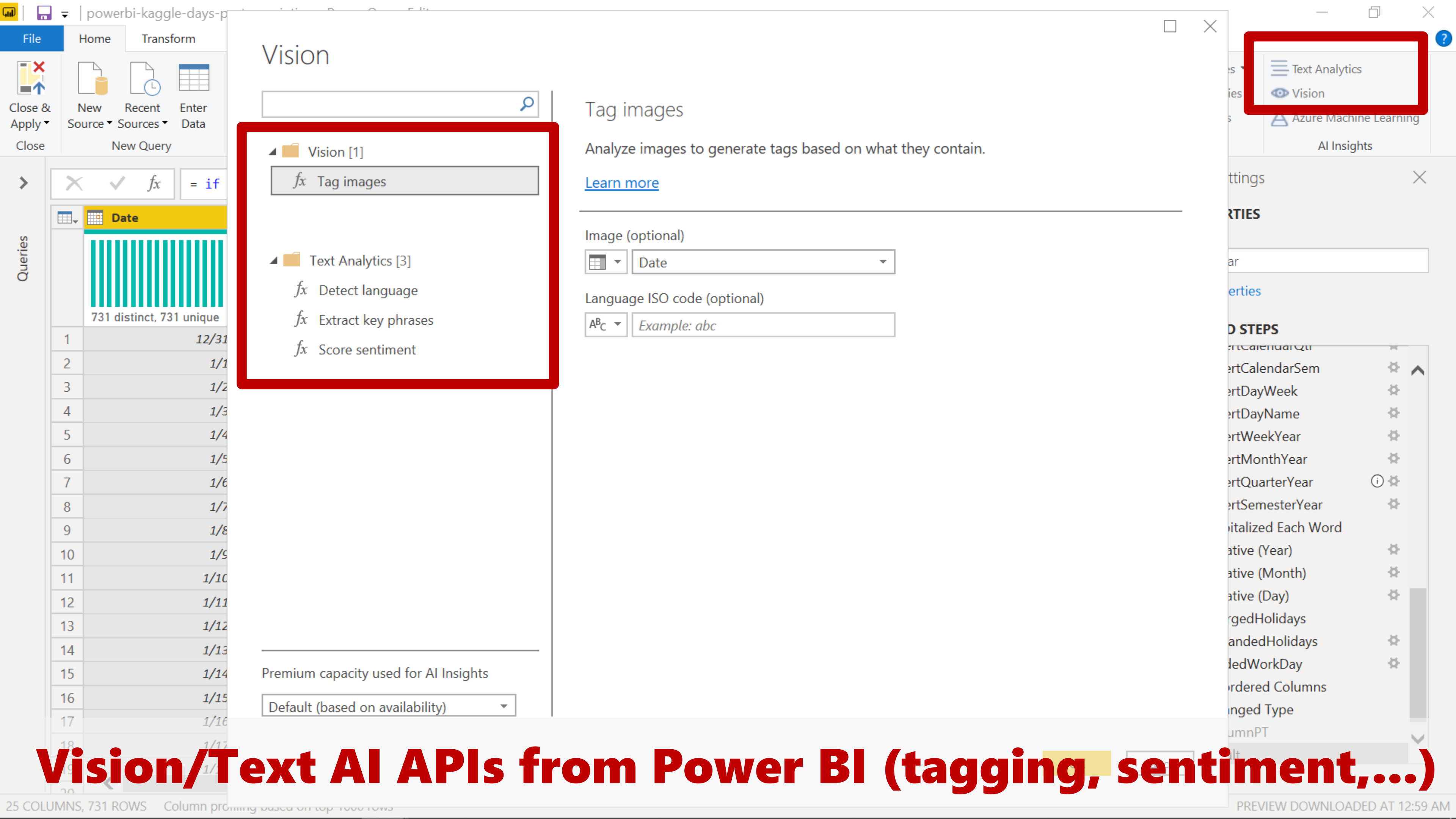

GUEST
REVIEWS
SENTIMENT SCORE BY HOTEL
Oahu Inn
Four Islands
Grand Kailua
Palm Shore Hotel
Waikiki Getawa...
0,0
0,5
Beach
Bathroom
View
Water View
Not Great View
Pool
Hotel Lobby
Clean
Dated/Old Hotel R...
Hotel Room
Dirty
A/C
0,0
0,5
1,0
Our room was on the ground floor, facing the ocean. Great view. The lobby was beautiful- no walls. Breakfast
The accommodation is basic but you will have money left over for shopping and sightseeing.
Great beach park next to the hotel. Worth it if travelling with kids due to the large playground. Very quiet
I would expect that the Jacuzzi would be hot (or at least warm) - it was not. Very disapointed with my stay...
Incredible hotel. Loved the view. Very friendly staff.
Amazing Japanese restaurant downstairs. The hotel is walking distance to all the necessary amenities.
Reserved a king room with ocean view. Was given a queen bed with a view. Notified desk was given a king
Clean, good location, fast WiFi, a very comfortable king bed. Ended up with a great view which was a nice
REFERENCES AND SENTIMENT
BY TOPIC
pool
kitchen
great
unit
parking
staff
beach
stay
place
restaurant
bedroom
condo
location
room
hotel
view
eviews
Guest Analytics
+

	Members.Joined Group on	Members.Last visited group on	Members.Last Attended	Custom
1	01/02/2019	13/02/2019	06/02/201	20190201
2	27/01/2019	27/01/2019	06/02/201	20190127
3	06/01/2019	27/02/2019	06/02/201	20190106
4	06/01/2019	27/02/2019	06/02/201	20190106
5	06/01/2019	27/02/2019	06/02/201	20190106
6	22/01/2019	04/02/2019	06/02/201	20190122
7	26/02/2019	02/03/2019	nu	20190226
8			nu	20190227

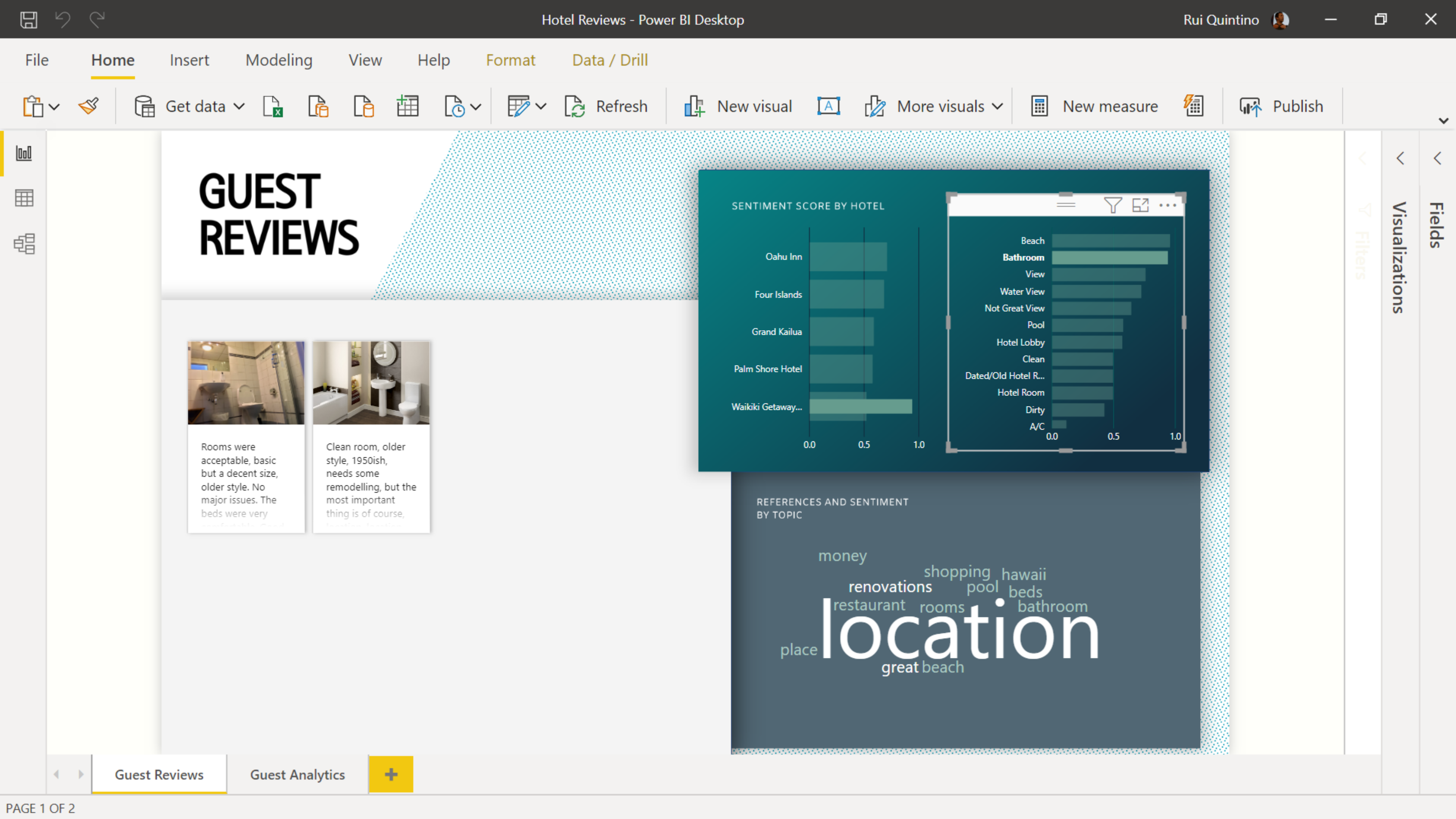
Members.Name	Members.U	Custom
Rodrigo Fazendeiro	Fastwheels	Fazendeiro, R.
Nuno Gomes	user 5182529	Gomes, N.
Daniel Monteiro	user 6053978	Monteiro, D.

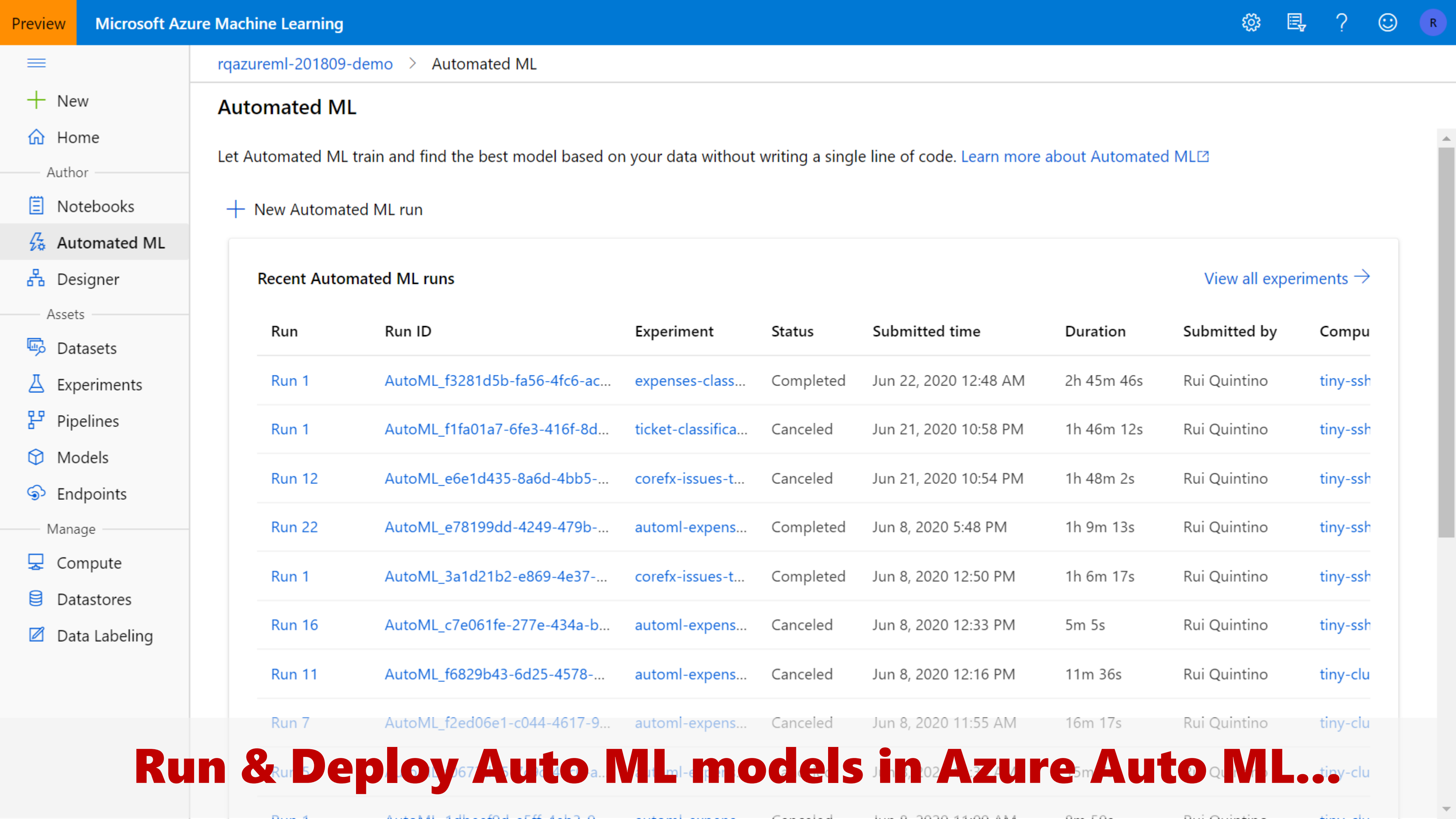
Members.Name	Members.U	Custom
Rodrigo Fazendeiro	Fastwheels	rfazendeiro
Nuno Gomes	user 5182529	ngomes
Daniel Monteiro	user 6053978	dmonteiro
Daniel Monteiro	user 6053978	dmonteiro

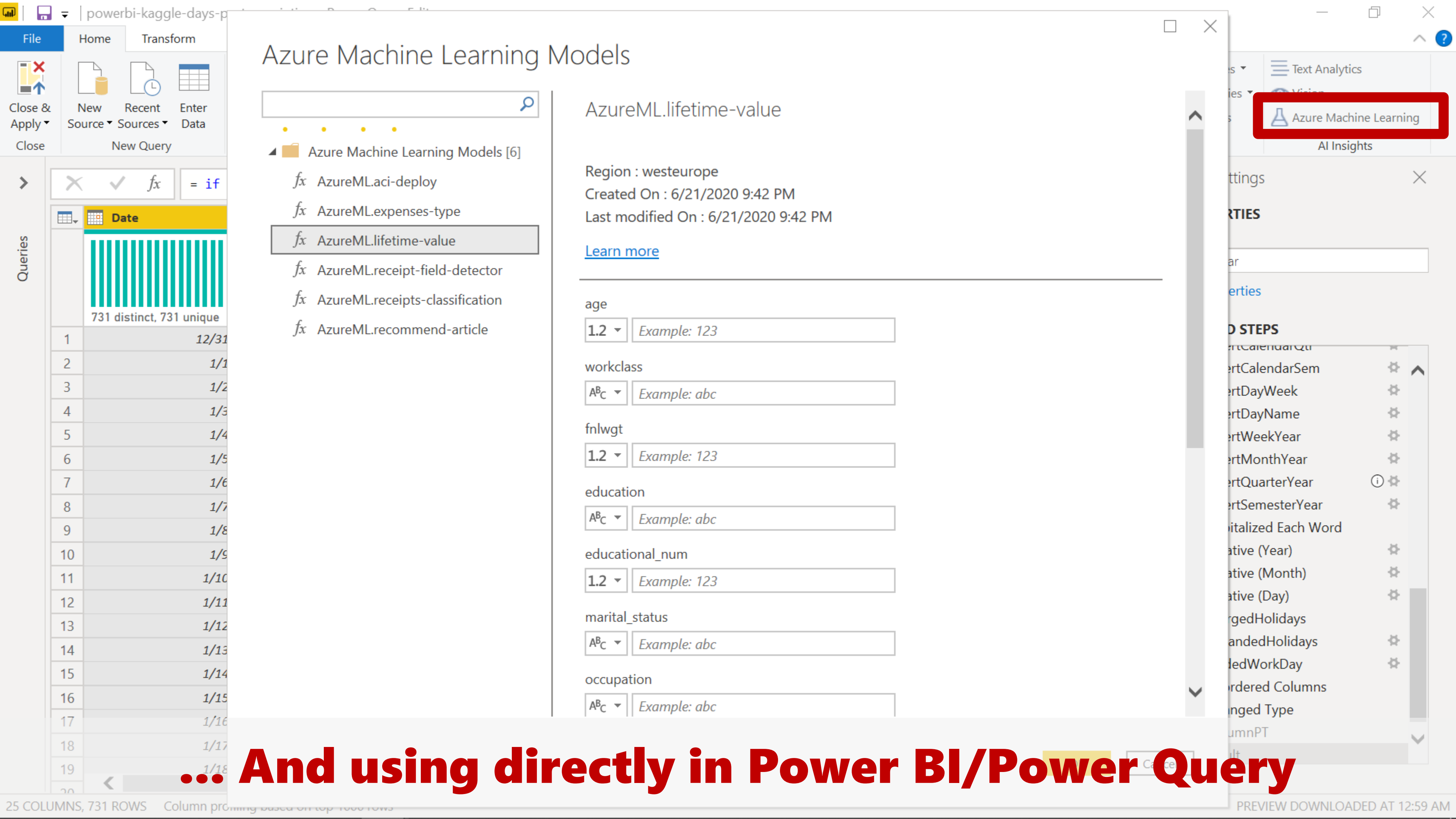
Prep by example



Vision/Text AI APIs from Power BI (tagging, sentiment,...)


Hotel Reviews - Power BI Desktop
Rui Quintino
File
Home
Insert
Modeling
View
Help
Format
Data / Drill
Get data
Refresh
New visual
More visuals
New measure
Publish
GUEST REVIEWS
SENTIMENT SCORE BY HOTEL
Oahu Inn
Four Islands
Grand Kailua
Palm Shore Hotel
Waikiki Getaway...
0.0
0.5
1.0
Beach
Bathroom
View
Water View
Not Great View
Pool
Hotel Lobby
Clean
Dated/Old Hotel R...
Hotel Room
Dirty
A/C
0.0
0.5
1.0
Rooms were acceptable, basic but a decent size, older style. No major issues. The beds were very
Clean room, older style, 1950ish, needs some remodelling, but the most important thing is of course,
REFERENCES AND SENTIMENT BY TOPIC
money
shopping
hawaii
renovations
pool
beds
restaurant
rooms
bathroom
place
location
great
beach
Guest Reviews
Guest Analytics
Visualizations
Fields
PAGE 1 OF 2


Preview
Microsoft Azure Machine Learning
R
rqazureml-201809-demo
Automated ML
New
Home
Author
Notebooks
Automated ML
Designer
Assets
Datasets
Experiments
Pipelines
Models
Endpoints
Manage
Compute
Datastores
Data Labeling
Automated ML
Let Automated ML train and find the best model based on your data without writing a single line of code. Learn more about Automated ML
New Automated ML run
Recent Automated ML runs
View all experiments
Run | Run ID | Experiment | Status | Submitted time | Duration | Submitted by | Compu
Run 1 | AutoML_f3281d5b-fa56-4fc6-ac... | expenses-class... | Completed | Jun 22, 2020 12:48 AM | 2h 45m 46s | Rui Quintino | tiny-ssh
Run 1 | AutoML_f1fa01a7-6fe3-416f-8d... | ticket-classifica... | Canceled | Jun 21, 2020 10:58 PM | 1h 46m 12s | Rui Quintino | tiny-ssh
Run 12 | AutoML_e6e1d435-8a6d-4bb5-... | corefx-issues-t... | Canceled | Jun 21, 2020 10:54 PM | 1h 48m 2s | Rui Quintino | tiny-ssh
Run 22 | AutoML_e78199dd-4249-479b-... | automl-expens... | Completed | Jun 8, 2020 5:48 PM | 1h 9m 13s | Rui Quintino | tiny-ssh
Run 1 | AutoML_3a1d21b2-e869-4e37-... | corefx-issues-t... | Completed | Jun 8, 2020 12:50 PM | 1h 6m 17s | Rui Quintino | tiny-ssh
Run 16 | AutoML_c7e061fe-277e-434a-b... | automl-expens... | Canceled | Jun 8, 2020 12:33 PM | 5m 5s | Rui Quintino | tiny-ssh
Run 11 | AutoML_f6829b43-6d25-4578-... | automl-expens... | Canceled | Jun 8, 2020 12:16 PM | 11m 36s | Rui Quintino | tiny-clu
Run 7 | AutoML_f2ed06e1-c044-4617-9... | automl-expens... | Canceled | Jun 8, 2020 11:55 AM | 16m 17s | Rui Quintino | tiny-clu
Run & Deploy Auto ML models in Azure Auto ML...


Azure Machine Learning Models
Azure Machine Learning Models [6]
AzureML.aci-deploy
AzureML.expenses-type
AzureML.lifetime-value
AzureML.receipt-field-detector
AzureML.receipts-classification
AzureML.recommend-article
AzureML.lifetime-value
Region : westeurope
Created On : 6/21/2020 9:42 PM
Last modified On : 6/21/2020 9:42 PM
Learn more
age
workclass
fnlwgt
education
educational_num
marital_status
occupation
Azure Machine Learning
AI Insights
Text Analytics
731 distinct, 731 unique
25 COLUMNS, 731 ROWS
PREVIEW DOWNLOADED AT 12:59 AM
... And using directly in Power BI/Power Query

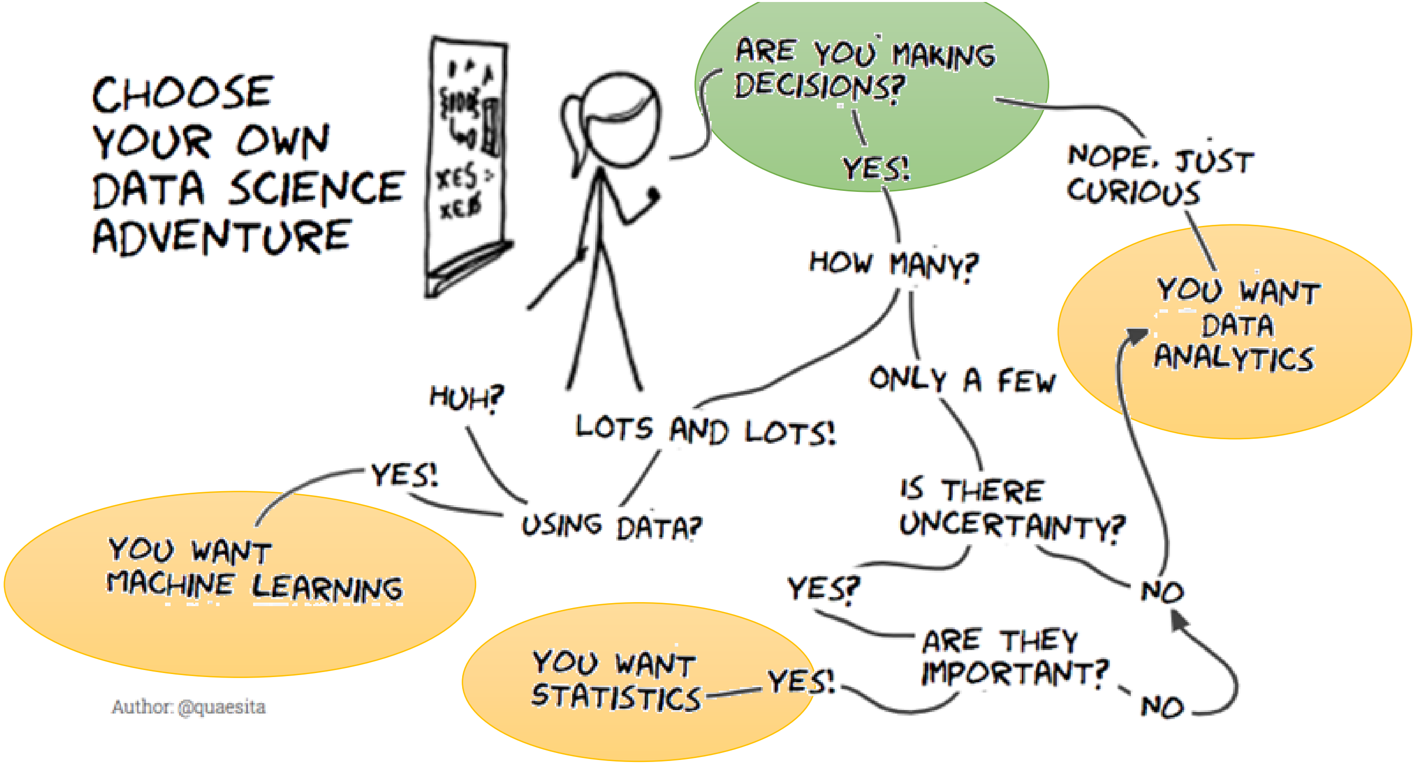
BI, Analytics
&
Data Science/Machine Learning

What on earth is data science?

The quest for a useful definition

Cassie Kozyrkov Follow

Aug 18, 2018 · 7 min read



The Data Science Landscape

An attempt to provide structure and reference points in a complex field

Dr. Stefan Karenfort Nov 27 · 9 min read ★

	Data Science					
Discipline	Analytics		Statistics		Machine Learning	
Focus	"Ask better questions"		"Give better answers"		"Decision making at scale"	
Sub-Discipline	Business Analysis	Exploratory Data Analytics	Descriptive Statistics	Inferential Statistics	Supervised Machine Learning	Unsupervised Machine Learning
Tools	Spreadsheets, Visualization Tools		Statistical Packages		Programming Languages	
Process	Business Understanding > Data Collection > Data Preparation > Model Building > Evaluation > Deployment					

https://towardsdatascience.com/the-data-science-landscape-f6f7842c9865