

Power BI for Data Science and Machine Learning

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What's Power BI anyway?

(Very Successful & Powerful ☺)

*Low/no-code platform
for
Data & Business Understanding*



Pages

Cover Layout

Sales Overview

Company Performance

Purchases

Customer Analysis

Price Analysis

Movements

FAQ

Sales Overview



\$22.63M



-9.40%



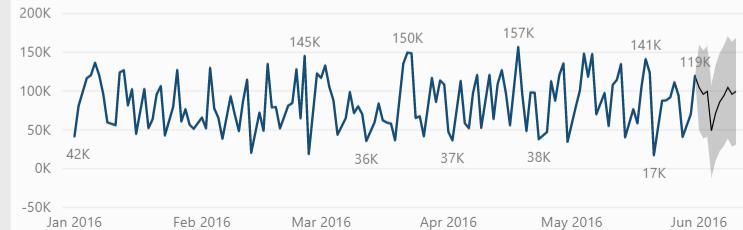
-0.20%

Sales Amount vs LY and Sales Profit by Month

Sales Amount (ly) Sales Amount Sales Profit Purchase Amount



Sales Profit Forecast



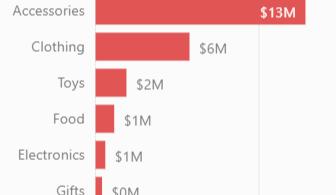
Date

1/1/2016

12/31/2016



Sales Amount by Category



Invoice Status by Customer

Invoice St... Not Paid Paid



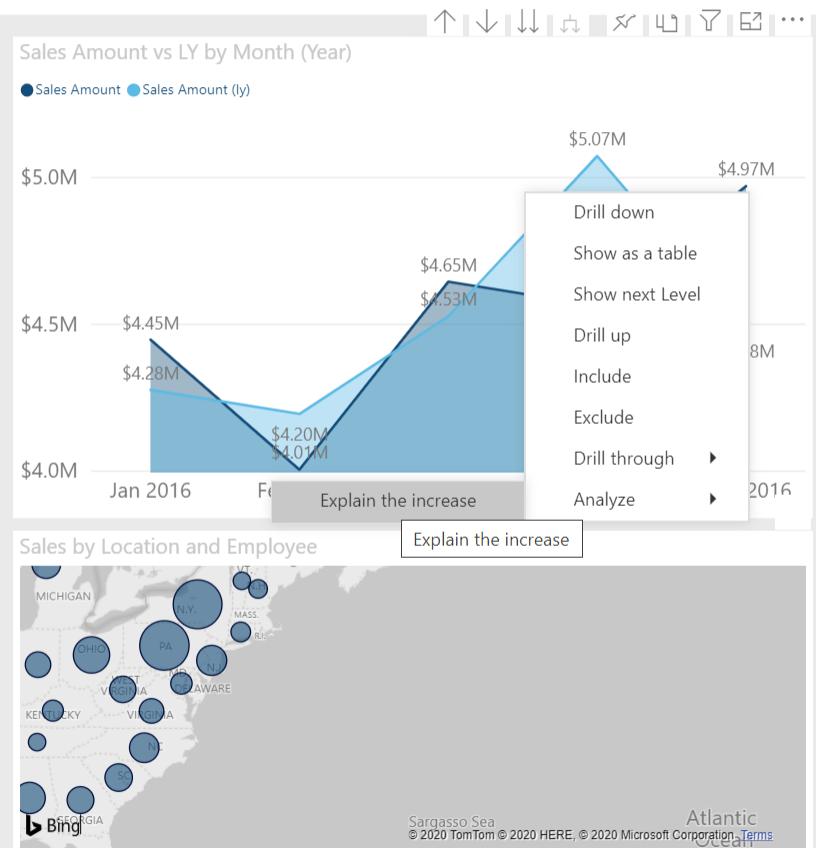
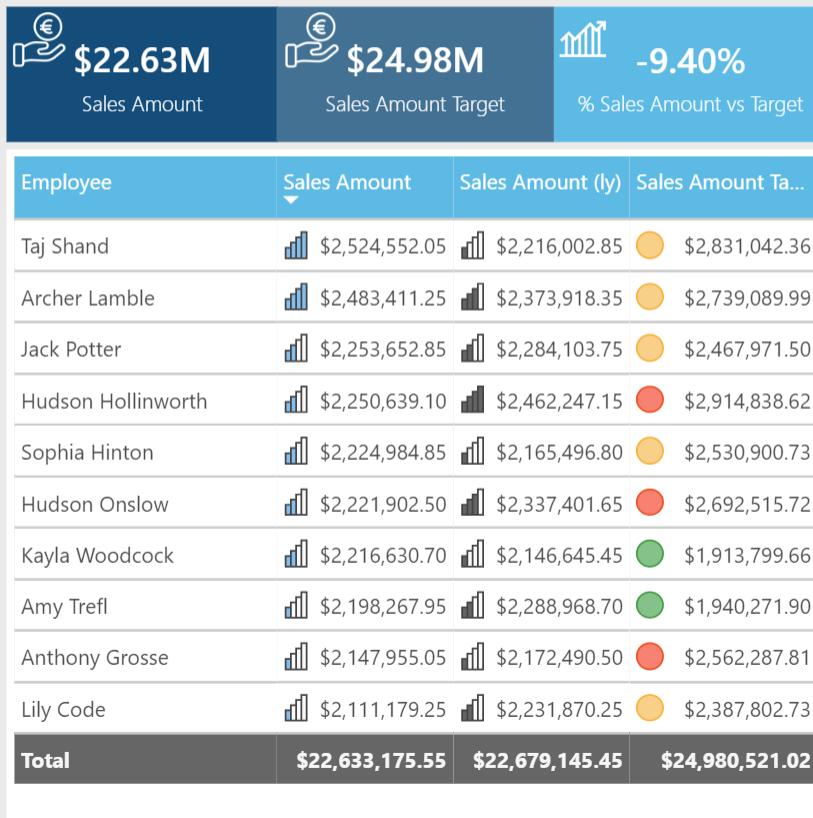
Sales Amount by Country, State Province and Category

Category N/A Novelty Shop





Company Performance





Análise Mensal do Balanço Social

Trabalhadores por Grupo Profissional

Trabalhadores
122K

Total Trabalhadores por Grupo Profissional	
Enfermeiros	39.217
Assistente...	24.610
Médicos ...	17.096
Assistente...	15.933
Médicos ...	9.408
Técnicos d...	7.702
Outros	6.671
Técnicos ...	1.632

Trabalhadores (homól.)
119K

Variação Mensal de Trabalhadores em Valor Absoluto



Trabalhadores (var. homól.)
3K

Nacional

Trabalhadores (var. homól. em perc)
0.00K%



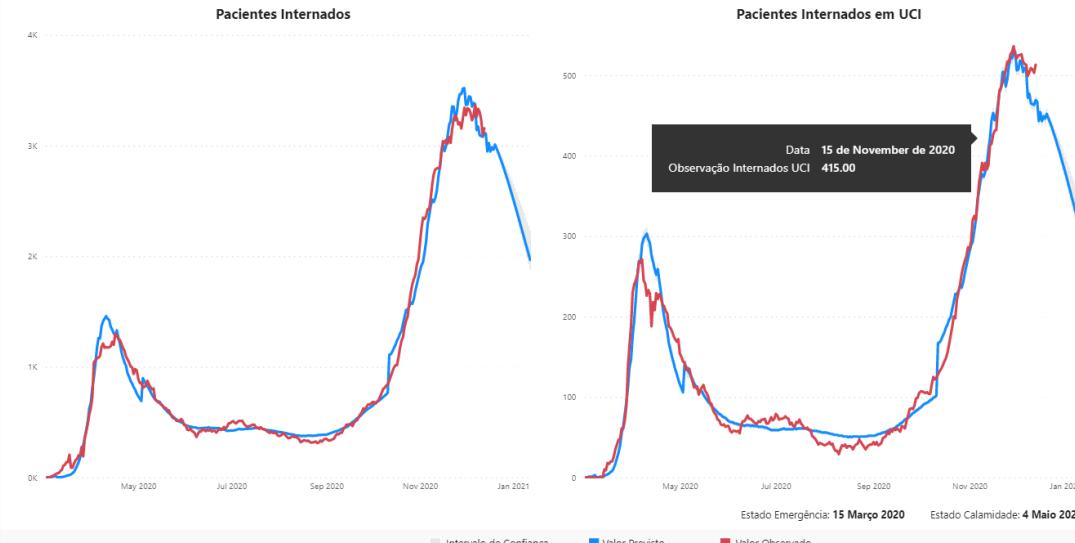
Total Trabalhadores por Região, Instituição





Modelos Epidemiológicos

Modelo Epidemiológico de Evolução dos Pacientes Internados em Portugal



Microsoft Power BI

4 of 6 >



Why so Powerful?

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 Choose Columns Remove Columns Manage Columns Keep Rows Remove Rows Sort Split Column Group By Data Type: Binary Merge Queries Use First Row as Headers Append Queries Combine Files Combine Text Analytics Vision Azure Machine Learning Replace Values Combine AI Insights

Close New Query Data Sources Parameters Query Manage Columns Reduce Rows Sort Transform

Queries [14]

- Config [3]
 - DATA_PATH (C:\Users\rquintin...)
 - 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	Data
		3 distinct, 3 unique	1 distinct, 0 unique	3 distinct, 3 unique	3 distinct
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

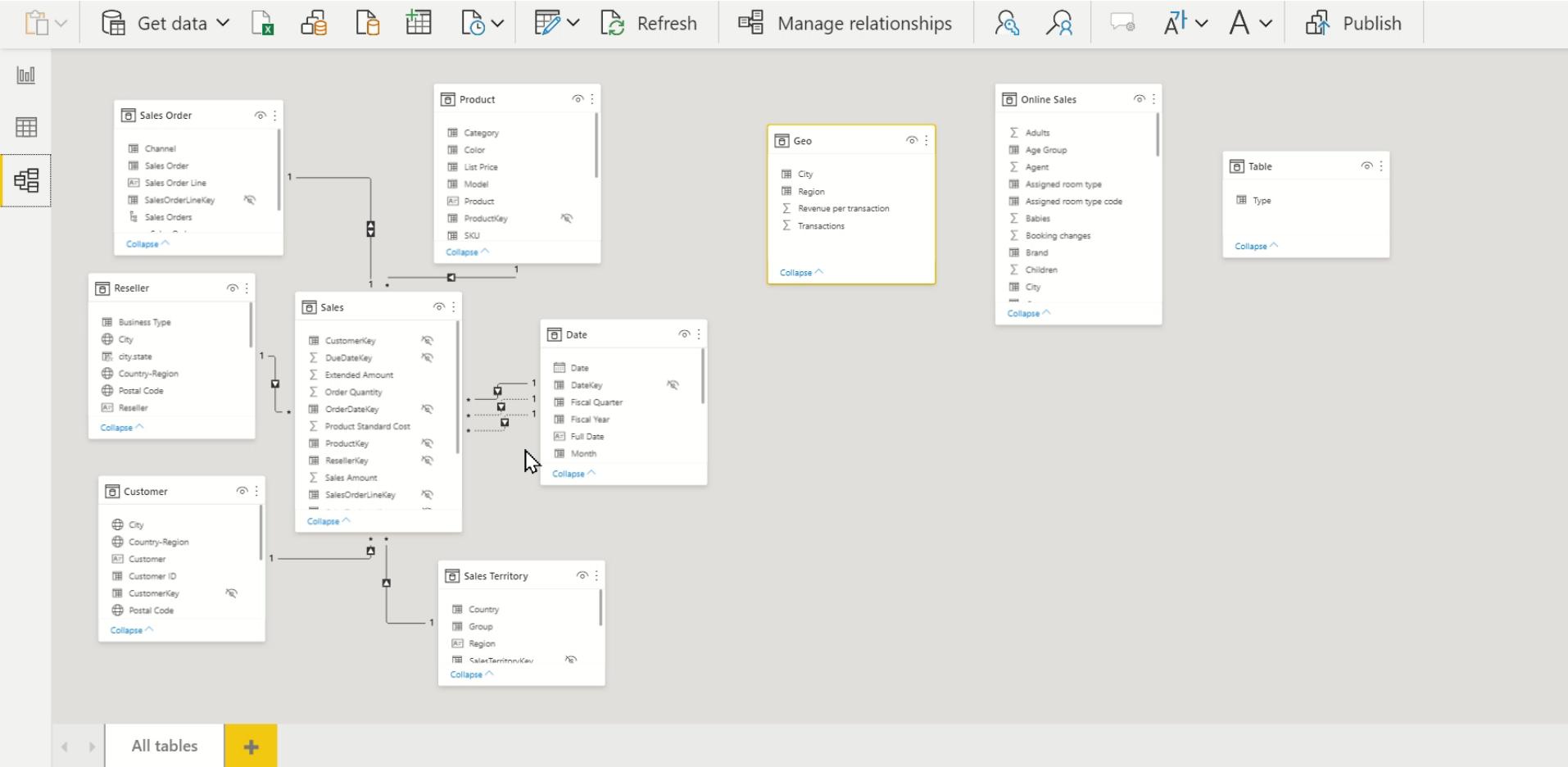
Name: Submissions

All Properties

APPLIED STEPS

Source	Filter
Filtered Hidden Files1	Enabled
Invoke Custom Function1	Enabled
Renamed Columns1	Enabled
Removed Other Columns1	Enabled
Expanded Table Column1	Enabled
Changed Type	Enabled
Renamed Columns	Enabled

Visual & Code Data Prep / Intellisense / Profiling / ...



Fast (column store) Semantic Models

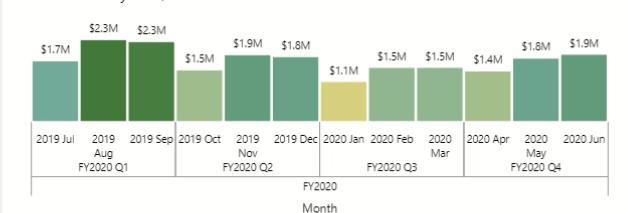
Name Cancellations  Online Sales \$% Format Whole number  \$ % , .00  0  Uncategorized  ...X  1 Cancellations = CALCULATE(COUNT('Online Sales'), 'Online Sales'[Status] = "Cancelled")
us  Germany\$20.93M
Sales Amount\$7.00M
COGS62K
Order Quantity

Reseller Search

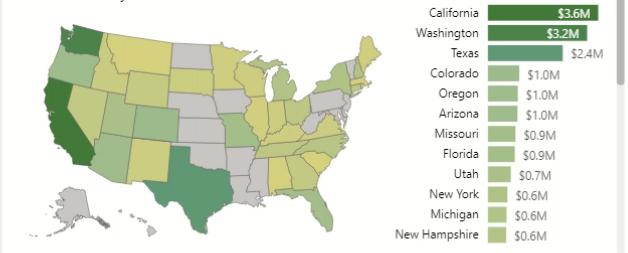
Select row below to enable drill-through →

Reseller	City	State-Province	Sales Amount
Westside Plaza	Sand City	California	\$534,956.28
Field Trip Store	Loveland	Colorado	\$427,305.59
Brakes and Gears	Tooele	Utah	\$397,237.24
Thorough Parts and Repair Services	Lacey	Washington	\$386,958.19
Rally Master Company Inc	Chandler	Arizona	\$355,141.98
Outdoor Equipment Store	Nashua	New Hampshire	\$314,662.56
Eastside Department Store	Union City	California	\$295,328.92
Totes & Baskets Company	San Antonio	Texas	\$289,777.50
Permanent Finish Products	Reno	Nevada	\$288,088.47
Extraordinary Bike Works	Mesquite	Texas	\$281,844.75
Safe Cycles Shop	Bellevue	Washington	\$277,795.47
Great Bikes	Casper	Wyoming	\$277,495.37
Excellent Riding Supplies	Memphis	Tennessee	\$276,729.43
Area Bike Accessories	Modesto	California	\$275,643.81
Total			\$20,927,177.22

Sales Amount by Year, Quarter and Month



Sales Amount by State-Province



Last updated: 9/30/20 10:17 AM



ADVENTURE WORKS

Introduction

Sales Summary

Reseller Drill through

Visual Zoom Slider

Anomaly Detection

Page 1



Powerful Analytical Engine for Metric Modelling

Visualizations >



Filters



Values

Add data fields here

Drill through

Cross-report



Keep all filters



Add drill-through fields here

Fields

Search

Customer

Date

Geo

Online Sales

- Σ Adults
- Age Group
- Agent
- Assigned ro...
- Assigned ro...
- Σ Babies
- Booking ch...
- Brand
- Cancellations
- Children
- City
- Company
- Country
- Customer

\$20.93M

Sales Amount

\$7.00M

COGS

62K

Order Quantity

Reseller Search

Select row below to enable drill-through →

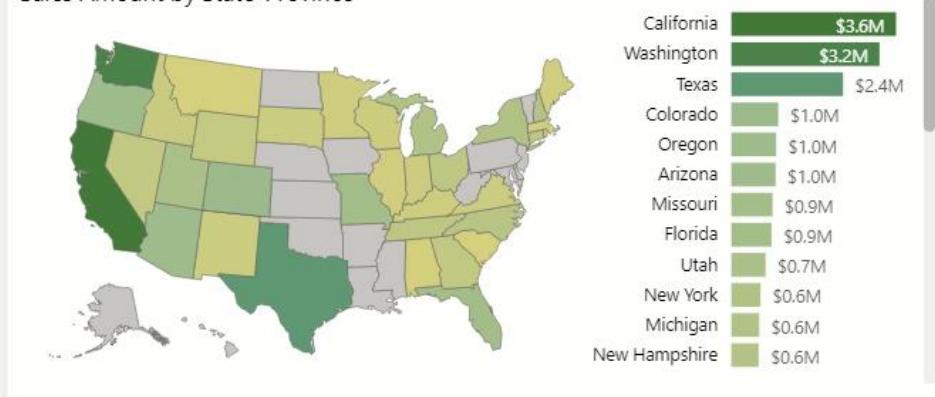
All

Reseller	City	State-Province	Sales Amount
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Brakes and Gears	Tooele	Utah	\$397,237.24
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Sales Amount by Year, Quarter and Month



Sales Amount by State-Province



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

Sales & Returns Sample v201912 - Power BI Desktop

Sign in

File Home Insert Modeling View Help External Tools Format Data / Drill

Get data Refresh New visual More visuals New measure Publish

Microsoft | Skateboard Store Last Refresh: Jun 30th, 2019 / Chicago, IL, USA

Key Influencers Analyzes your data, ranks the factors that matter, and displays them as key influencers.

Decomposition Tree Enables users to drill into any dimension to understand what is driving a key metric.

Category Breakdown

Product	Net Sales
Power BI	\$52K
Word	\$36K
OneNote	\$31K
PowerPoint	\$30K
XBOX	\$27K
PowerApps	\$23K
Excel	\$21K
Skype	\$20K
Publisher	\$19K
XBOX ONE	\$18K
\$0K	\$50K

Store Breakdown

Store	Net Sales
Fama	\$40K
Contoso	\$39K
VanArdsel	\$34K
Aliqui	\$34K
Abbas	\$32K
Barba	\$30K
Leo	\$30K
Pomum	\$30K
Salvus	\$27K
Natura	\$26K
\$0K	\$50K

Net Sales vs net sales PM by date as stacked column chart

Net Sales and Net Sales PM

May 05 Jun 02 Jun 30

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Legal Intro Net Sales Returns Return Rate Market Basket Analysis Net Sales Tooltip Returns To

Visuals Fields

Analysis DAX Design DAX % Return Rate Age Associated Product Association Calendar Customer Issues and Promo... Product Sales STable Store Tooltip Info Tooltip Info2

Net Sales

First Tip...

Search...



Welcome

Data Sources

Goal

Robot

Configure

Skills/Plugins

Results

Models

Export

Publish

About Mineshaft AI

Start ML Robot

Select Model

Show 5 entries

Search:

runId	runDesc	score	cols	alg	gridModels	timeTrain
1	#1 >masterTable	62.37	15	glmnet	31	3.4
2	#1 >features_masterTable_with_Lookup	67.48	23	glmnet	31	4.3
3	#1 >features_TemporalCount	67.14	24	glmnet	31	4
4	#1 >features_Drug_Specialty	67.07	40	glmnet	31	6.4
5	#1 >features_ProcedureGroupgrouping	67.03	33	glmnet	31	5.7

Showing 1 to 5 of 6 entries

Previous 1 2 Next

Summary Data Insights Reports Test/Predict

Show 5 entries

Search:

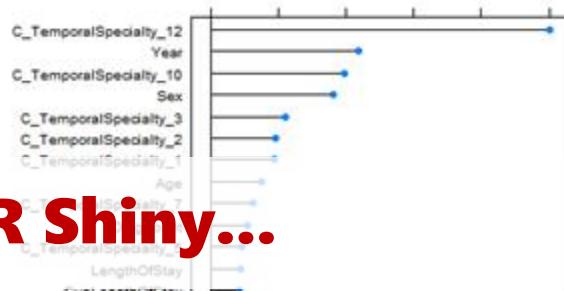
Overall

C_TemporalSpecialty_12 100

Year 43.5540129144048

C_TemporalSpecialty_10 39.395567340402

Sex 35.9933749126642



Disclaimer: Know a bit of R Shiny...

SHAP Dash! Explanations on Dash - DevScope AI Lab

	Age	Workclass	Final Weig	Education	Education-
<input type="checkbox"/>	43	Private	175133	Some-col	10
<input type="checkbox"/>	43	Private	157473	HS-grad	9
<input type="checkbox"/>	21	?	197583	Some-col	10
<input type="checkbox"/>	35	Federal-g	403489	HS-grad	9
<input type="checkbox"/>	57	Self-emp	256630	Bachelor	13
<input type="checkbox"/>	25	Private	150312	HS-grad	9
<input type="checkbox"/>	43	Private	72338	Masters	14
<input type="checkbox"/>	25	Private	108838	Bachelor	13
<input type="checkbox"/>	53	Private	185283	HS-grad	9
<input type="checkbox"/>	36	Private	116358	Masters	14
<input type="checkbox"/>	36	Private	65382	HS-grad	9

And Python Plotly Dash...

Choose Season:

2020_2021

Choose League:

Bundesliga

Choose Matchday:

1

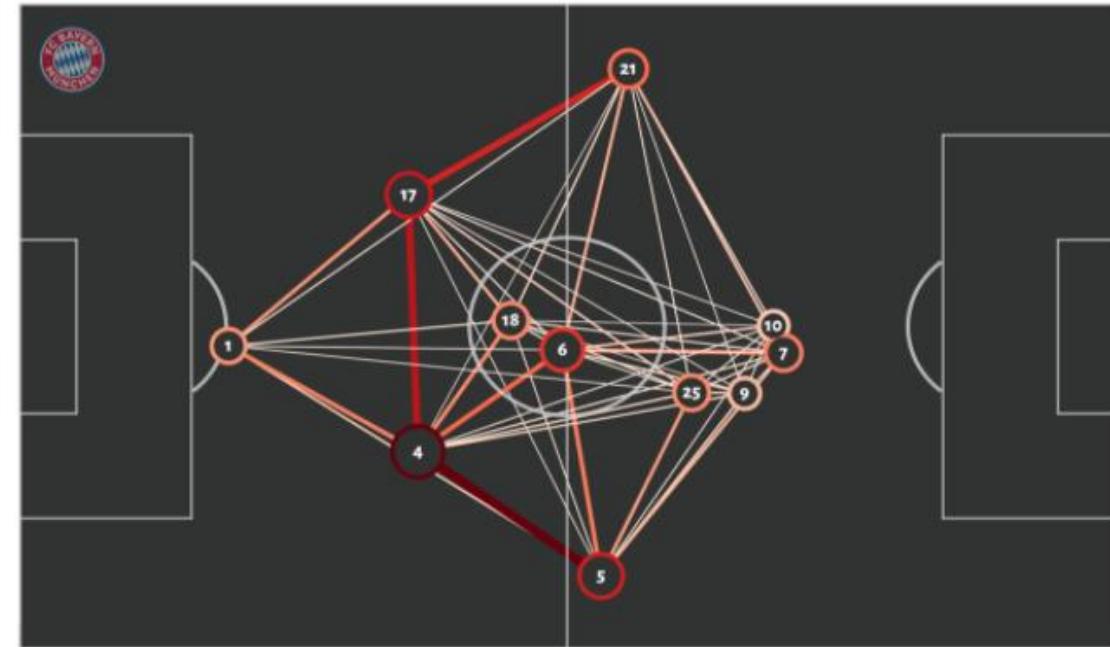
Choose Match:

Bayern_Schalke_Bundesliga_20...

Pick Home Team Color



Pick Away Team Color



No	Player	Centrality	No	Player	Centrality
4	Niklas Süle	0.257	4	Ozan Kabak	0.232
17	Jérôme Boateng	0.194	10	Nabil Bentaleb	0.216
6	David Alaba	0.193	13	Sebastian Rudy	0.159
8	Joshua Kimmich	0.178	15	Leon Goretzka	0.158
1	Manuel Neuer	0.156	25	Andreas Christensen	0.155
18	Thiago Alcantara	0.153	20	Joshua Zirkzee	0.152
19	Joshua Kimmich	0.149	21	Robert Lewandowski	0.148
2	Edin Džeko	0.147	22	Mark Uth	0.146
16	Joshua Kimmich	0.145	23	Sebastian Rudy	0.144
11	Thiago Alcantara	0.143	24	Joshua Kimmich	0.142
12	Edin Džeko	0.141	26	Joshua Kimmich	0.140
14	Edin Džeko	0.139	27	Edin Džeko	0.138
16	Thiago Alcantara	0.137	28	Edin Džeko	0.136
18	Thiago Alcantara	0.135	29	Edin Džeko	0.134
20	Edin Džeko	0.133	30	Edin Džeko	0.132
21	Robert Lewandowski	0.131	31	Edin Džeko	0.130
22	Robert Lewandowski	0.129	32	Edin Džeko	0.128
23	Robert Lewandowski	0.127	33	Edin Džeko	0.126
24	Robert Lewandowski	0.125	34	Edin Džeko	0.124
25	Robert Lewandowski	0.123	35	Edin Džeko	0.122
26	Robert Lewandowski	0.121	36	Edin Džeko	0.120
27	Robert Lewandowski	0.119	37	Edin Džeko	0.118
28	Robert Lewandowski	0.117	38	Edin Džeko	0.116
29	Robert Lewandowski	0.115	39	Edin Džeko	0.114
30	Robert Lewandowski	0.113	40	Edin Džeko	0.112
31	Robert Lewandowski	0.111	41	Edin Džeko	0.110
32	Robert Lewandowski	0.109	42	Edin Džeko	0.108
33	Robert Lewandowski	0.107	43	Edin Džeko	0.106
34	Robert Lewandowski	0.105	44	Edin Džeko	0.104
35	Robert Lewandowski	0.103	45	Edin Džeko	0.102
36	Robert Lewandowski	0.101	46	Edin Džeko	0.100
37	Robert Lewandowski	0.099	47	Edin Džeko	0.098
38	Robert Lewandowski	0.097	48	Edin Džeko	0.096
39	Robert Lewandowski	0.095	49	Edin Džeko	0.094
40	Robert Lewandowski	0.093	50	Edin Džeko	0.092
41	Robert Lewandowski	0.091	51	Edin Džeko	0.090
42	Robert Lewandowski	0.089	52	Edin Džeko	0.088
43	Robert Lewandowski	0.087	53	Edin Džeko	0.086
44	Robert Lewandowski	0.085	54	Edin Džeko	0.084
45	Robert Lewandowski	0.083	55	Edin Džeko	0.082
46	Robert Lewandowski	0.081	56	Edin Džeko	0.080
47	Robert Lewandowski	0.079	57	Edin Džeko	0.078
48	Robert Lewandowski	0.077	58	Edin Džeko	0.076
49	Robert Lewandowski	0.075	59	Edin Džeko	0.074
50	Robert Lewandowski	0.073	60	Edin Džeko	0.072
51	Robert Lewandowski	0.071	61	Edin Džeko	0.070
52	Robert Lewandowski	0.069	62	Edin Džeko	0.068
53	Robert Lewandowski	0.067	63	Edin Džeko	0.066
54	Robert Lewandowski	0.065	64	Edin Džeko	0.064
55	Robert Lewandowski	0.063	65	Edin Džeko	0.062
56	Robert Lewandowski	0.061	66	Edin Džeko	0.060
57	Robert Lewandowski	0.059	67	Edin Džeko	0.058
58	Robert Lewandowski	0.057	68	Edin Džeko	0.056
59	Robert Lewandowski	0.055	69	Edin Džeko	0.054
60	Robert Lewandowski	0.053	70	Edin Džeko	0.052
61	Robert Lewandowski	0.051	71	Edin Džeko	0.050
62	Robert Lewandowski	0.049	72	Edin Džeko	0.048
63	Robert Lewandowski	0.047	73	Edin Džeko	0.046
64	Robert Lewandowski	0.045	74	Edin Džeko	0.044
65	Robert Lewandowski	0.043	75	Edin Džeko	0.042
66	Robert Lewandowski	0.041	76	Edin Džeko	0.040
67	Robert Lewandowski	0.039	77	Edin Džeko	0.038
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73	Robert Lewandowski	0.027	83	Edin Džeko	0.026
74	Robert Lewandowski	0.025	84	Edin Džeko	0.024
75	Robert Lewandowski	0.023	85	Edin Džeko	0.022
76	Robert Lewandowski	0.021	86	Edin Džeko	0.020
77	Robert Lewandowski	0.019	87	Edin Džeko	0.018
78	Robert Lewandowski	0.017	88	Edin Džeko	0.016
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81	Robert Lewandowski	0.011	91	Edin Džeko	0.010
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84	Robert Lewandowski	0.005	94	Edin Džeko	0.004
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90	Robert Lewandowski	0.000	100	Edin Džeko	0.000
91	Robert Lewandowski	0.000	101	Edin Džeko	0.000
92	Robert Lewandowski	0.000	102	Edin Džeko	0.000
93	Robert Lewandowski	0.000	103	Edin Džeko	0.000
94	Robert Lewandowski	0.000	104	Edin Džeko	0.000
95	Robert Lewandowski	0.000	105	Edin Džeko	0.000
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101	Robert Lewandowski	0.000	111	Edin Džeko	0.000
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108	Robert Lewandowski	0.000	118	Edin Džeko	0.000
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120	Robert Lewandowski	0.000	130	Edin Džeko	0.000
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122	Robert Lewandowski	0.000	132	Edin Džeko	0.000
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131	Robert Lewandowski	0.000	141	Edin Džeko	0.000
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159	Robert Lewandowski	0.000	169	Edin Džeko	0.000
160	Robert Lewandowski	0.000	170	Edin Džeko	0.000
161	Robert Lewandowski	0.000	171	Edin Džeko	0.000
162	Robert Lewandowski	0.000	172	Edin Džeko	0.000
163	Robert Lewandowski	0.000	173	Edin Džeko	0.000
164	Robert Lewandowski	0.000	174	Edin Džeko	0.000
165	Robert Lewandowski	0.000	175	Edin Džeko	0.000
166	Robert Lewandowski	0.000	176	Edin Džeko	0.000
167	Robert Lewandowski	0.000	177	Edin Džeko	0.000
168	Robert Lewandowski	0.000	178	Edin Džeko	0.000
169	Robert Lewandowski	0.000	179	Edin Džeko	0.000
170	Robert Lewandowski	0.000	180	Edin Džeko	0.000
171	Robert Lewandowski	0.000	181	Edin Džeko	0.000
172	Robert Lewandowski	0.000	182	Edin Džeko	0.000
173	Robert Lewandowski	0.000	183	Edin Džeko	0.000
174	Robert Lewandowski	0.000	184	Edin Džeko	0.000
175	Robert Lewandowski	0.000	185	Edin Džeko	0.000
176	Robert Lewandowski	0.000	186	Edin Džeko	0.000
177	Robert Lewandowski	0.000	187	Edin Džeko	0.000
178	Robert Lewandowski	0.000	188	Edin Džeko	0.000
179	Robert Lewandowski	0.000	189	Edin Džeko	0.000
180	Robert Lewandowski	0.000	190	Edin Džeko	0.000
181	Robert Lewandowski	0.000	191	Edin Džeko	0.000
182	Robert Lewandowski	0.000	192	Edin Džeko	0.000
183	Robert Lewandowski	0.000	193	Edin Džeko	0.000
184	Robert Lewandowski	0.000	194	Edin Džeko	0.000
185	Robert Lewandowski	0.000	195	Edin Džeko	0.000
186	Robert Lewandowski	0.000	196	Edin Džeko	0.000
187	Robert Lewandowski	0.000	197	Edin Džeko	0.000
188	Robert Lewandowski	0.000	198	Edin Džeko	0.000
189	Robert Lewandowski	0.000	199	Edin Džeko	0.000
190	Robert Lewandowski	0.000	200	Edin Džeko	0.000
191	Robert Lewandowski	0.000	201	Edin Džeko	0.000
192	Robert Lewandowski	0.000	202	Edin Džeko	0.000
193	Robert Lewandowski	0.000	203	Edin Džeko	0.000
194	Robert Lewandowski	0.000	204	Edin Džeko	0.000
195	Robert Lewandowski	0.000	205	Edin Džeko	0.000
196	Robert Lewandowski	0.000	206	Edin Džeko	0.000
197	Robert Lewandowski	0.000	207	Edin Džeko	0.000
198	Robert Lewandowski	0.000	208	Edin Džeko	0.000
199	Robert Lewandowski	0.000	209	Edin Džeko	0.000
200	Robert Lewandowski	0.000	210	Edin Džeko	0.000
201	Robert Lewandowski	0.000	211	Edin Džeko	0.000
202	Robert Lewandowski	0.000	212	Edin Džeko	0.000
203	Robert Lewandowski	0.000	213	Edin Džeko	0.000
204	Robert Lewandowski	0.000	214		

Returns
\$52.3K

-59.8%
m/m

Units Returned
1,007

-59.8%
m/m

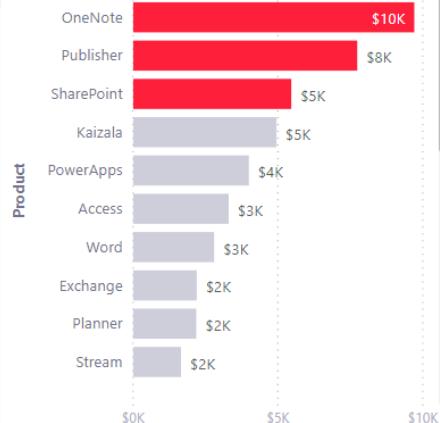
Key Influencers

Analyzes your data, ranks the factors that matter, and displays them as key influencers.

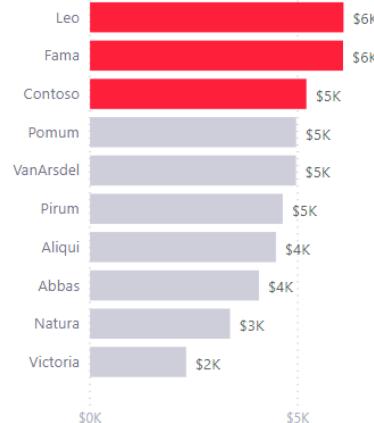
Decomposition Tree

Enables users to drill into any dimension to understand what is driving a key metric.

Category Breakdown



Store Breakdown



Show me Returns Over Time. Only Leo, Contoso, Fama, and Pomum

Store ● Contoso ● Fama ● Leo ● Pomum



Visual

Tabular

Visual

Map

Restart Q&A

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Legal

Intro

Net Sales

Returns

Return Rate

Market Basket Analysis

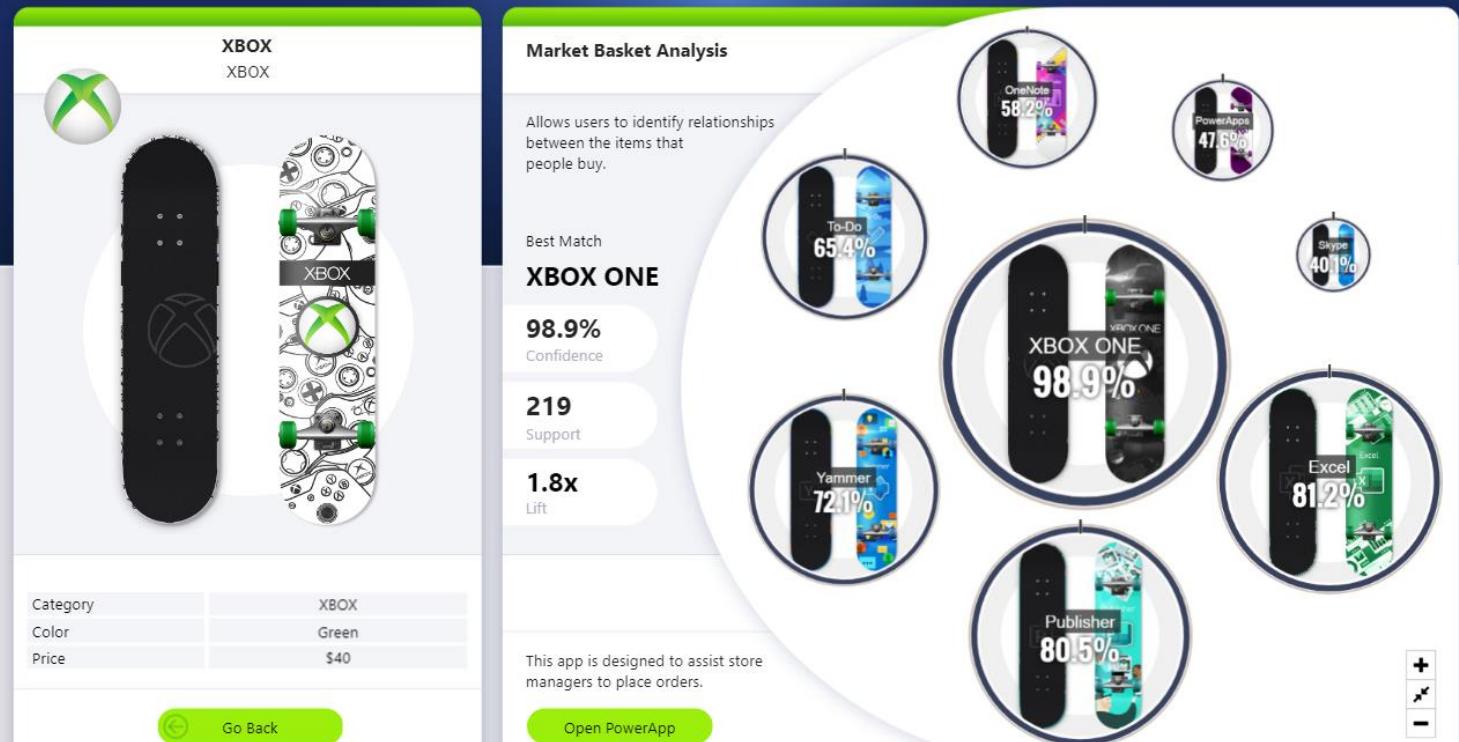
Net Sales Tooltip

Returns Tooltip

CathegoryBreakdown

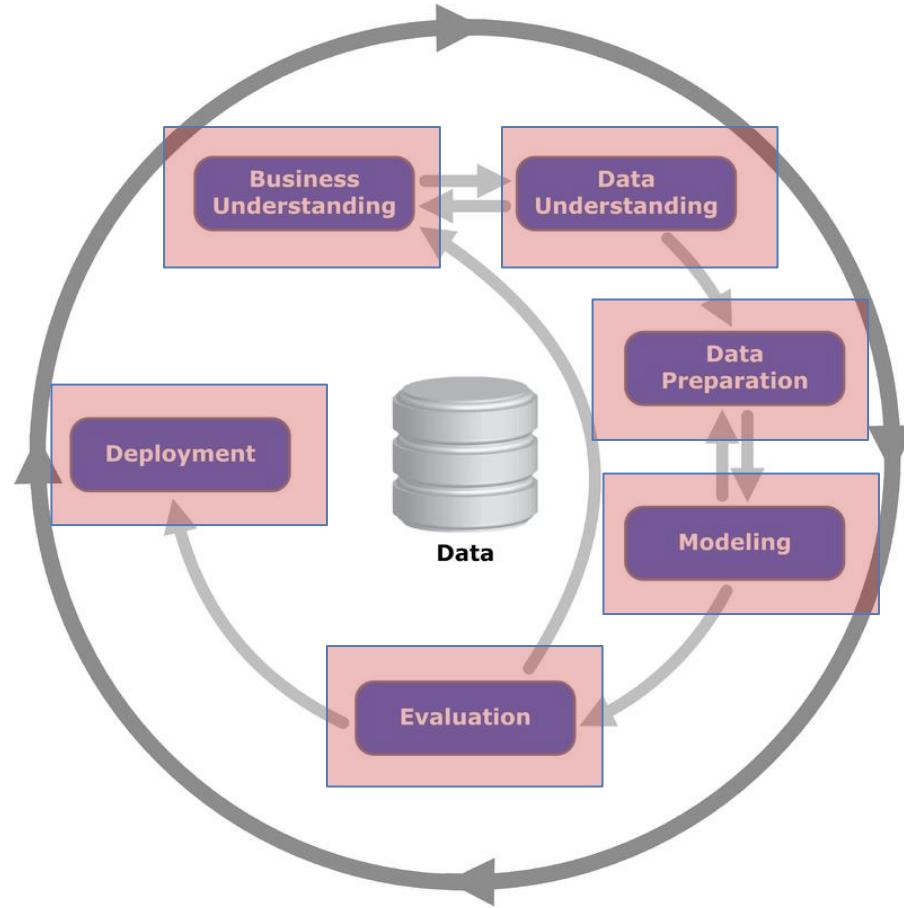
KeyInfluenc

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



Where Power BI can help?

Actually...
(with new Auto ML)

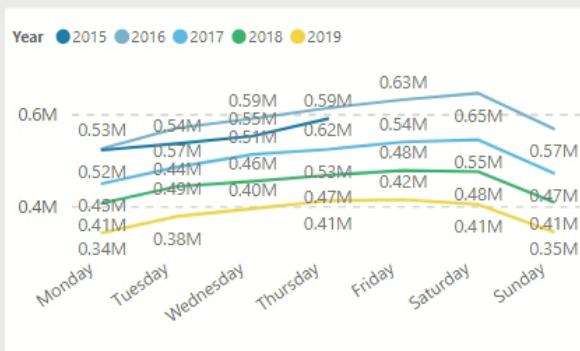


https://en.wikipedia.org/wiki/Cross-industry_standard_process_for_data_mining

Time Series

Metric

Taxi Passengers



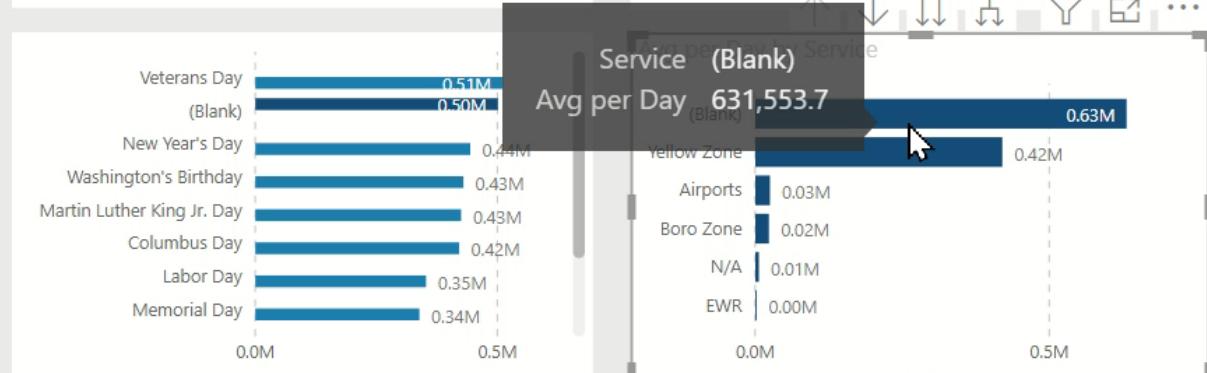
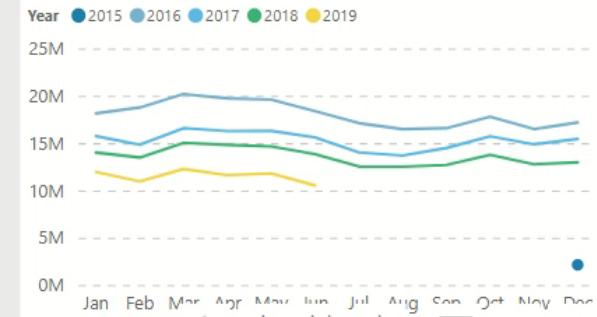
Service, Borough, Zone

All

12/28/2015

12/31/2020

devscope



638M

Value

498.1K

Avg per Day

3.48M

Avg per Week

Reusable TimeSeries/Forecast EDA

Kaggle Days Porto 2019

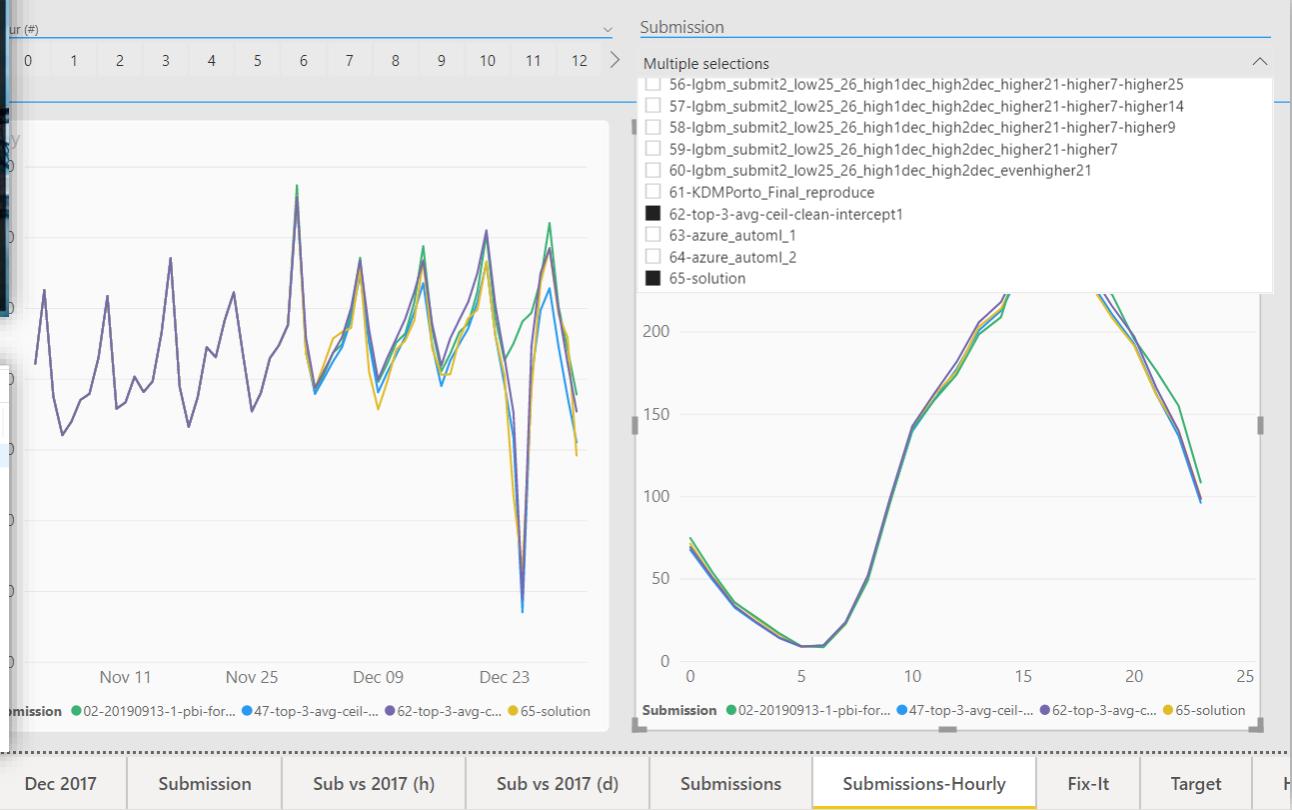
talkdesk kaggle DSPT

1 month ahead hourly Contact Center Agent Forecast

Team DevScope
Dewan Fayzur, Rui Quintino, Luís Costa, Luís Maia

data > kaggle-days-porto > submissions

Name
sample_submission.csv
20190913-1-pbi-forecast-hour.csv
20190913-2-pbi-forecast-25_26-half.csv
20190913-2-pbi-forecast-21-22-23 increase.csv
20190913-2-pbi-forecast-21-22-23 decrease.csv
lgbm_submit2.csv
lgbm_submit.csv
lgbm_submit_before_circular.csv
20190913-2-pbi-forecast-25_26-half_108.csv
lgbm_submit_custom_MaeLeadime_year_10.65_126.66_1month_v...
lgbm_submit2_low25_26.csv
lgbm_submit_TotalCall_holiday_year_15.05_120.87_1month_valida...
lgbm_submit_year_holiday_rround_2553_10.80_125.97_1month_v...

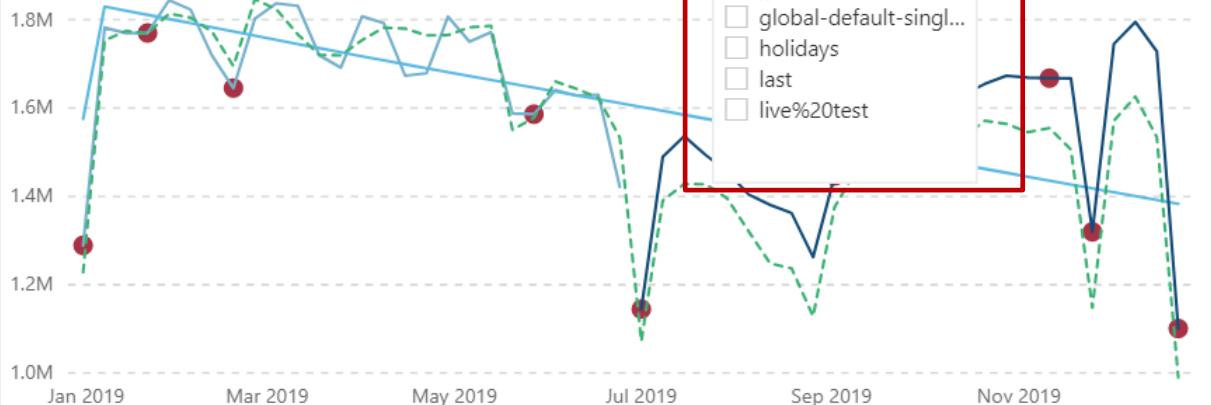


Leaderboards (ex: submission evaluation/validation)

Forecast

Metric
All Trips (With Test)

Holidays ● Trips ● Adjusted Trend ● Trend ● Forecast ● Adjusted ● Test



Forecast Version
4k_run

- 4k_run
- 8k_run_cutoff_mape
- baseline-default
- global
- global-default-singl...
- holidays
- last
- live%20test

Service, Borough, Zone
All

1/1/2019 12/29/2019

devscope

83,879,351

Year

-17.86%

% Diff (YTD)

84,437,750

Forecast (Simple)

0.67%

Abs. Perc. Error (Simple)

102,399,456

LY

-18.09%

Value % (Δ LY-YTD)

81,021,841

Forecast (Full Year)

3.41%

Abs. Perc. Error (Full Year)

-20.88%

Forecast % (Δ LY)

7.22%

Abs. Perc. Error

8.10%

MAPE (week)

39,587,847

Trips (Test)

36,730,337

Forecast (Test)

7.22%

Abs. Perc. Error

8.10%

MAPE (week)

Trend Adjustment

0.00

Eval performance & behaviors for different models

2020-09-21 10:38:38

Wind-dependent Variables: Predict Wind Speeds of Tropical Storms

HOSTED BY RADIANT EARTH FOUNDATION

Press F11 to exit full screen



Submissions

BEST

CURRENT RANK

COMPETITORS

SUBS. MADE

LEADERBOARD

8.8177

2

260

2 of 3

SUBMISSION RESTRICTIONS

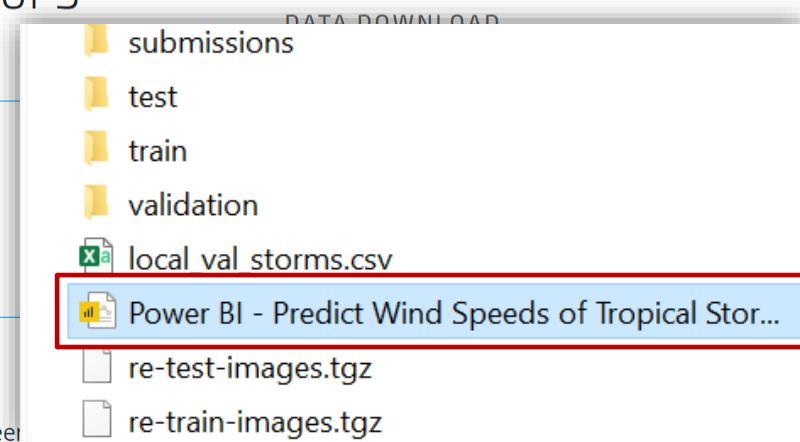
Competitors are allowed 3 submissions per 1 day.

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 between values and the actual values. The goal is to minimize RMSE.



SHARE YOUR WORK!

Facebook

Twitter

in LinkedIn

Email

ML Competitions (I kid you not! 😊)

Machine Learning model governance at scale



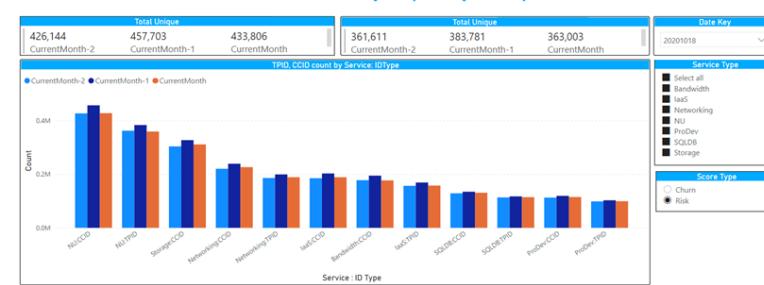
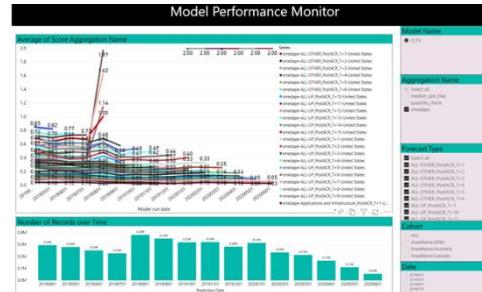
Petersaddow

Follow

Nov 13 · 13 min read

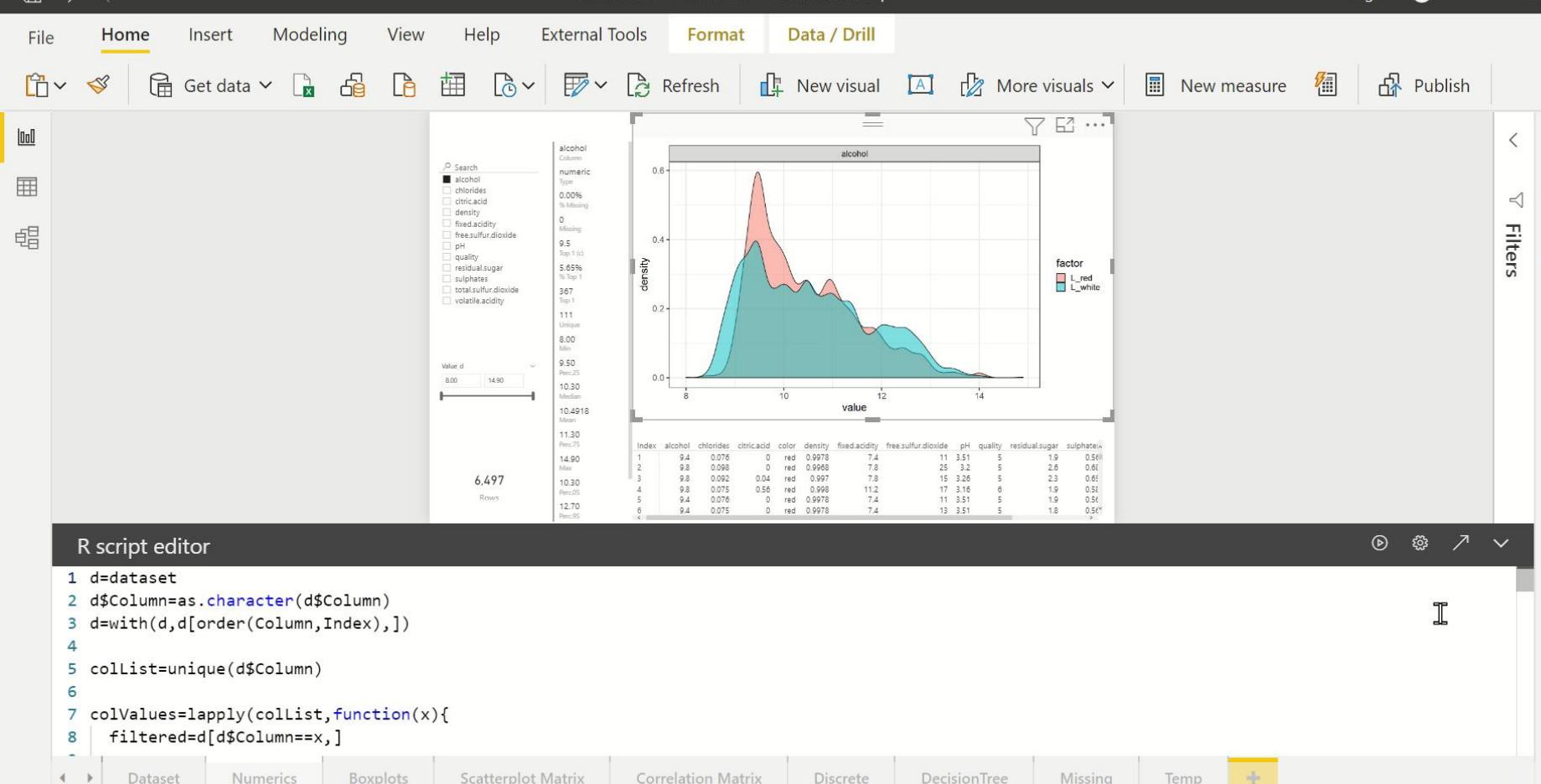


Author Peter Saddow is joined for this article by co-author Daniel Yehdego



Machine Learning Governance (msft CGA team Cloud+AI)

Advanced features for EDA



Custom R and Python interactive EDA

27

Questions to get you started

From the report author

show me average trip length by date X

show me average trip length for the last year X

top regions by average trip length YoY% X

Other suggestions

Save and close

Cancel

average trip length for 2017 by date

Ask a related question

Clear

Add this question X

Average Trip Length by Date



Showing dates and average trip length, where year is in 2017

Filters (including highlights) from the source page have been applied.

Use natural language for quick questions & visuals

27

Questions to get you started

From the report author

show me average trip length by date X

show me average trip length for the last year X

top regions by average trip length YoY% X

Other suggestions

Save and close

Cancel

by island X

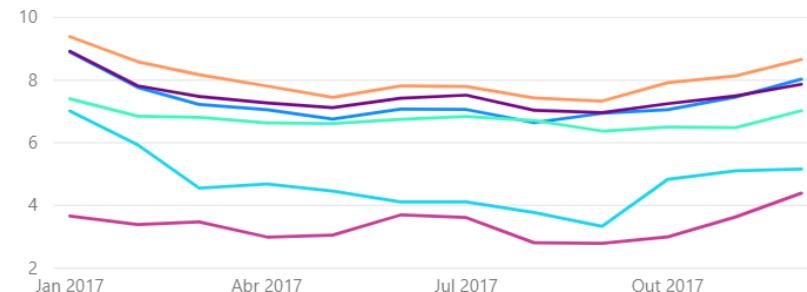
Ask a related question

Clear

Add this question

Average Trip Length by Date and Island Name

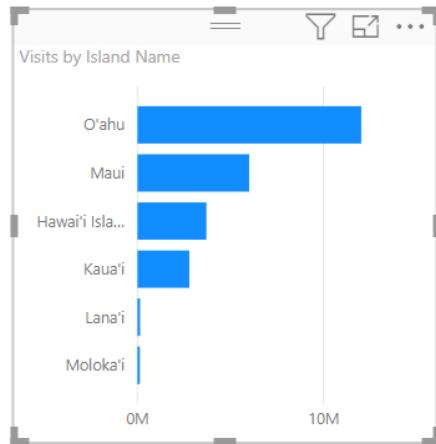
Island Name • Hawai'i Island • Kaua'i • Lana'i • Maui • Moloka'i • O'ahu



Showing islands, dates, and average trip length, where year is in 2017

X Filters (including highlights) from the source page have been applied.

Including follow up questions



visits by island

island (Islands)

island weather island

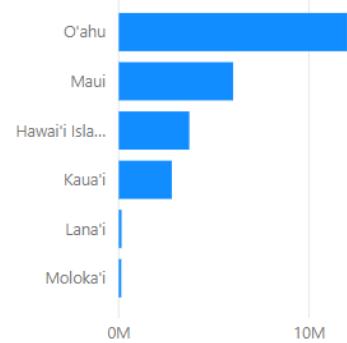
island friendly (Islands > Island Friendly Name)

island name (Islands > Island Name)

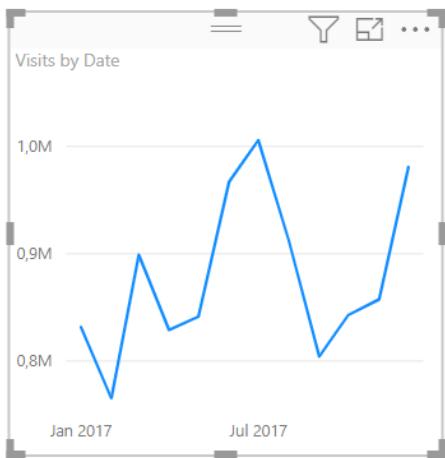
island weather (Island Weather)

Visual creation using Q&A feature

Visits by Island Name



Visits by Date



visits for 2017 by date

€ 20.93M
Total Sales

\$7.00M
COGS

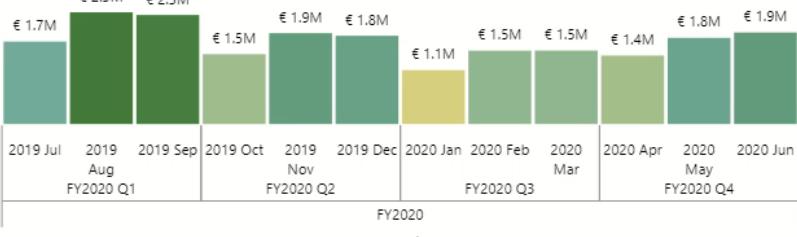
62K
Order Quantity

Reseller Search

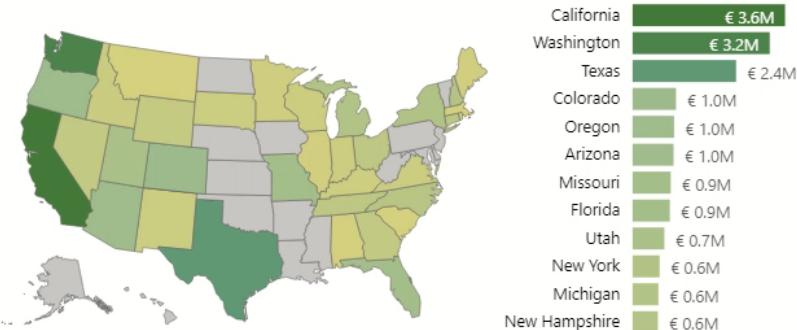
Select row below to enable drill-through →

Reseller	City	State-Province	Total Sales
Westside Plaza	Sand City	California	€ 534,956.28
Field Trip Store	Loveland	Colorado	€ 427,305.59
Brakes and Gears	Tooele	Utah	€ 397,237.24
Thorough Parts and Repair Services	Lacey	Washington	€ 386,958.19
Rally Master Company Inc	Chandler	Arizona	€ 355,141.98
Outdoor Equipment Store	Nashua	New Hampshire	€ 314,662.56
Eastside Department Store	Union City	California	€ 296,328.92
Totes & Baskets Company	San Antonio	Texas	€ 289,777.50
Permanent Finish Products	Reno	Nevada	€ 288,088.47
Extraordinary Bike Works	Mesquite	Texas	€ 281,844.75
Safe Cycles Shop	Bellevue	Washington	€ 277,795.47
Great Bikes	Casper	Wyoming	€ 277,495.37
Excellent Riding Supplies	Memphis	Tennessee	€ 276,729.43
Area Bike Accessories	Modesto	California	€ 275,643.81
Total			€ 20,927,177.22

Total Sales by Year, Quarter and Month



Total Sales by State-Province

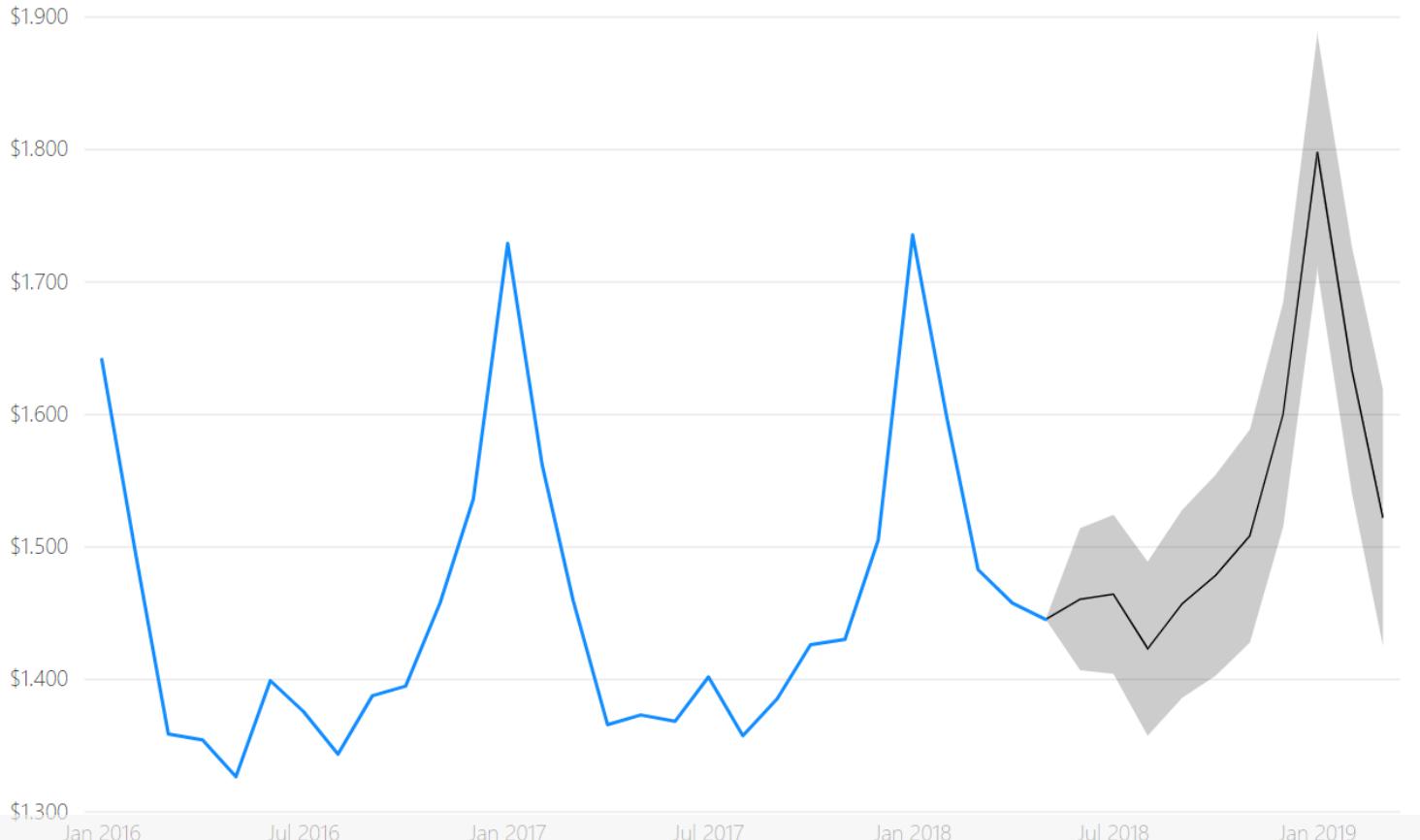


Powerfull & Easily configurable Drill Through Scenarios

Last updated: 9/30/20 10:17 AM

[Back to report](#)

SPENDING PER TRIP (PP)



Native Forecast (ETS based)

VISUALIZATIONS



FILTERS

Search: Forecast 1

Forecast length: 10 Month(s)

Ignore last: 0 Month(s)

Confidence interval: 95%

Seasonality: 12 Point(s)

Apply

Name	Age	Fare	Parents/Children	Siblings/Spouses
Abbing, Mr. Anthony	42	7	0	0
Abbott, Mr. Rossmore Edward	16	20	1	1
Abbott, Mrs. Stanton (Rosa Hunt)	35	20	1	1
Abelson, Mr. Samuel	30	24	0	1
Abelson, Mrs. Samuel (Hannah Wizosky)	28	24	0	1
Adahl, Mr. Mauritz Nils Martin	30	7	0	0
Adams, Mr. John	26	8	0	0
Ahlin, Mrs. Johan (Johanna Persdotter Larsson)	40	9	0	1
Aks, Mrs. Sam (Leah Rosen)	18	9	1	0
Albimona, Mr.				
Alexander, Mr.				
Alhomaki, Mr.				
Ali, Mr. Ahmed				
Ali, Mr. William				
Allen, Miss. Eli				
Allen, Mr. Willi				
Allison, Master				
Allison, Miss. H				
Allison, Mrs. H				

Components

Export data
Show data
Remove
Automatically find clusters
Spotlight
Sort descending
Sort ascending

Clusters

Name: Name (clusters) Field: Name

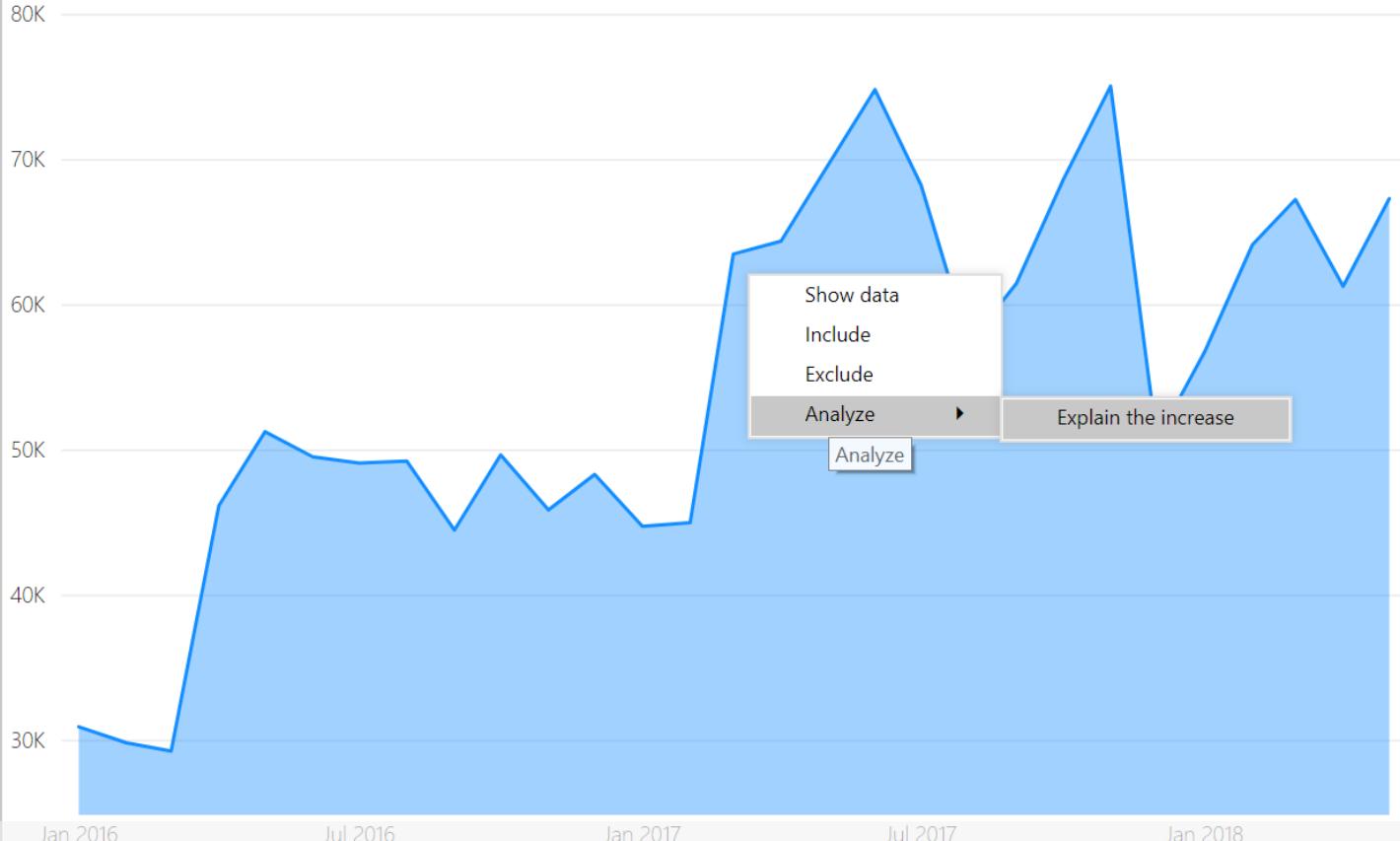
Description: Clusters for Name

Number of clusters: Auto

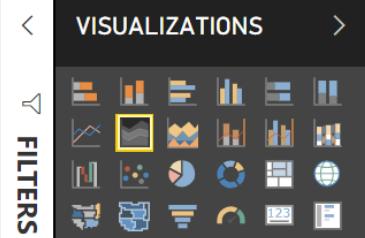
Built-in Clustering Support

< Back to report

VISITS BY REGION



Root causes (explain the increase/decrease)



[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

BY DATE AND 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.

● Increase ● Decrease ● Total ● Other

65K

60K

55K

50K

45K

45,0K

11,4K

3,2K

0,8K

0,1K

63,5K

Region Japan

01-02-2017 Visits 624

01-03-2017 Visits 12.016

Visits change 11.392 (1.825,64%)

01-02-2017

Japan

US East

US West

Other

Canada

01-03-2017

Sorted possible drivers for detected increase

[Back to report](#)

VISITS BY REGION

80K

70K

60K

50K

40K

30K

Jan 2016

Jul 2016

Jan 2017

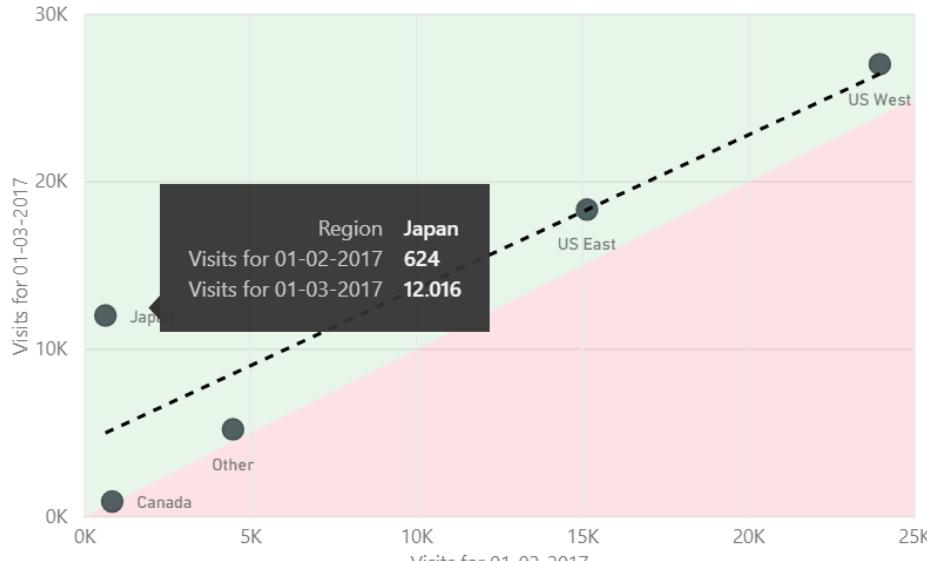
Here's the analysis of the 41.12% increase in Visits between 01-02-2017 and 01-03-2017

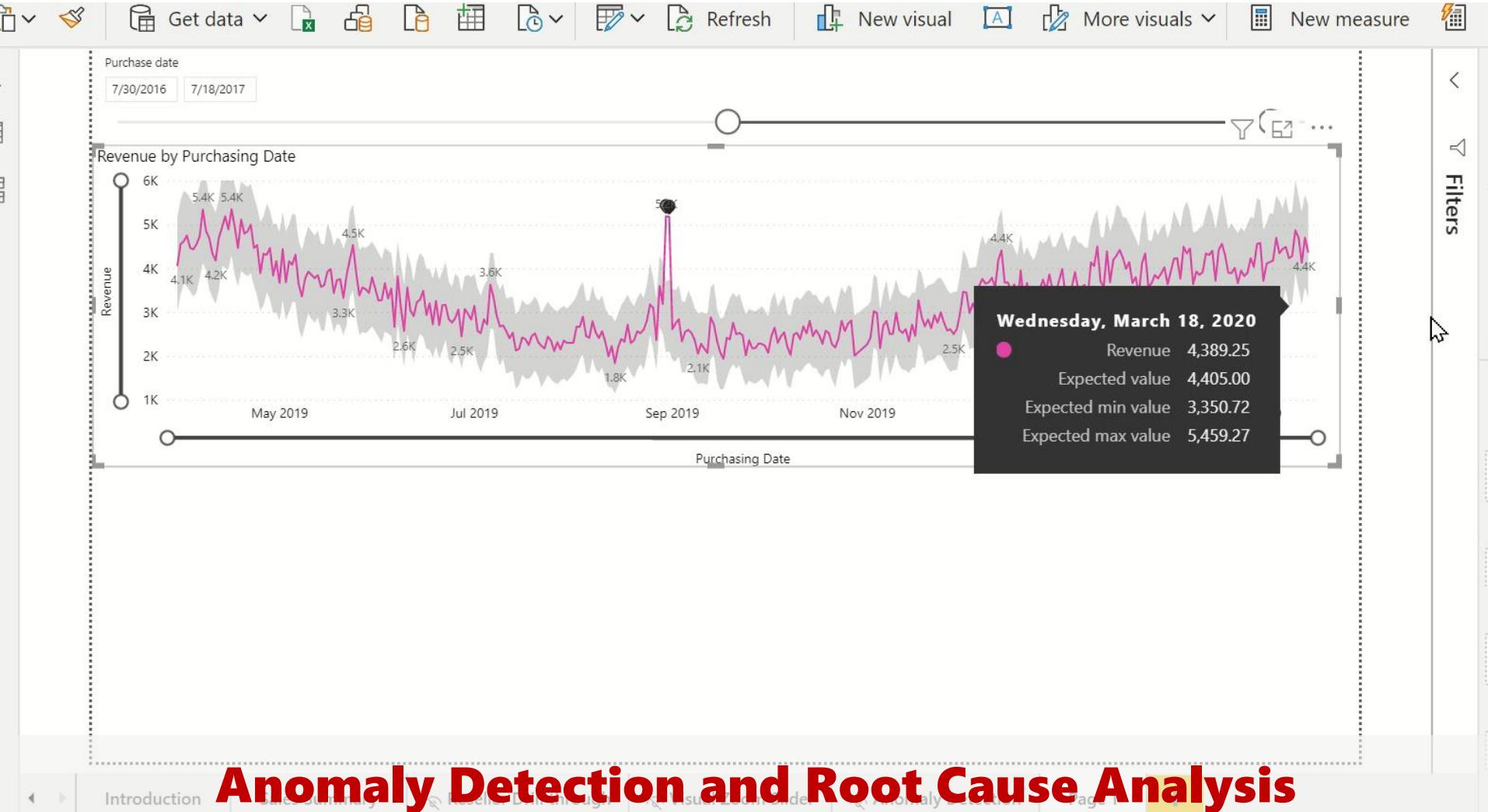


Visits for 01-02-2017 and Visits for 01-03-2017
BY REGION



'Japan' accounted for the majority of the increase among Region. The relative contributions made by 'Japan', 'US West', and 'US East' changed the most.



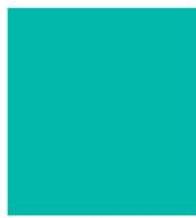


Passengers # by Survived

549



342



FILTERS

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	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	Saunderscock, Mr. William Henry	Saunderscock	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	0	Southampton	244373		Mr.	Yes

Quick glimpse/preview of Key predictors/influencers

Titanic Disaster

Influencers

Detail

Clustering



VISUALIZATIONS



FILTERS



Values

Add data fields here

DRILLTHROUGH

Cross-report



Keep all filters



Add drillthrough fields here

Key influencers Top segments



What influences Survived to be Yes ?

When...

Sex is Female

...the likelihood of Survived being Yes increases by

3.93x

Cabin is B96 B98

→

2.62x

Title is Mrs.

→

2.50x

Title is Miss.

→

2.30x

Class is 1

→

2.06x

Parents/Children goes down 0.78

→

1.61x

Embarked is Cherbourg

→

1.61x

Title is Master.

→

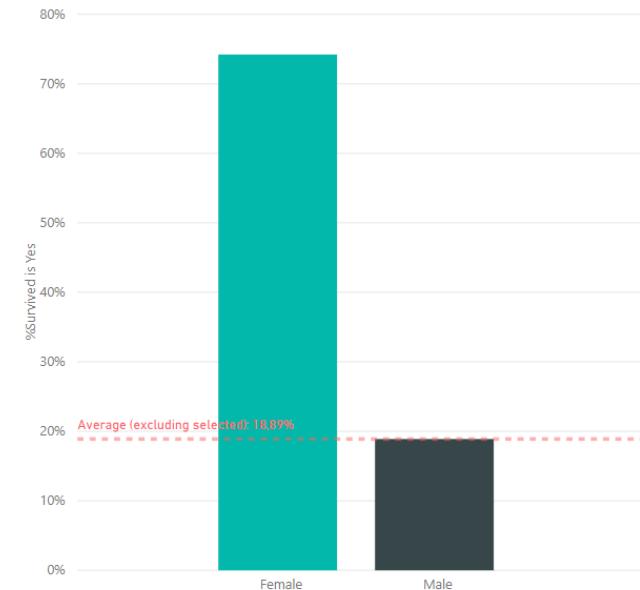
1.53x

Fare goes up 61.75

→

1.25x

← Survived is more likely to be Yes when Sex is Female than otherwise (on average).



Key influencers visual

Titanic Disaster

Influencers

Detail

Clustering

[Back to report](#)

VISITS BY REGION (YTD)

300K

287K

250K

188K

150K

- See Records
- Show data
- Group
- Include
- Exclude
- Analyze

Explain the increase

Find where this distribution is different

100K

50K

0K

2016

2017

2018

Distribution drivers & outliers

FILTERS

VISUALIZATIONS



Axis

Year

Legend

Add data fields here

Value

Visits

Tooltips

Add data fields here

DRILLTHROUGH

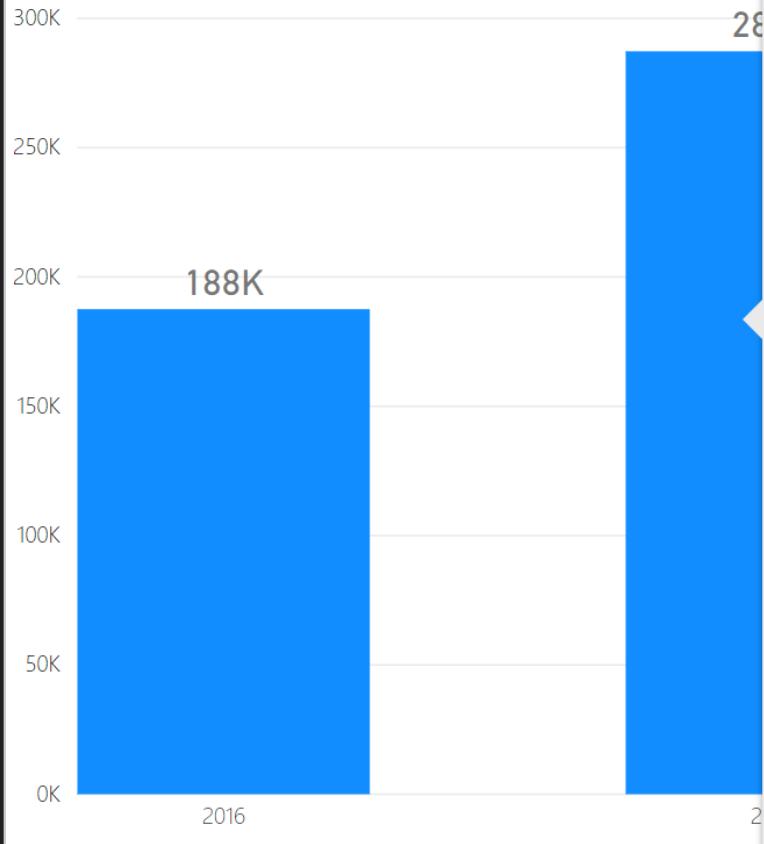
Cross-report

Off

Keep all filters

[Back to report](#)

VISITS BY REGION (YTD)



Here are the filters that cause the distribution of Visits by Year to change the most [?](#)

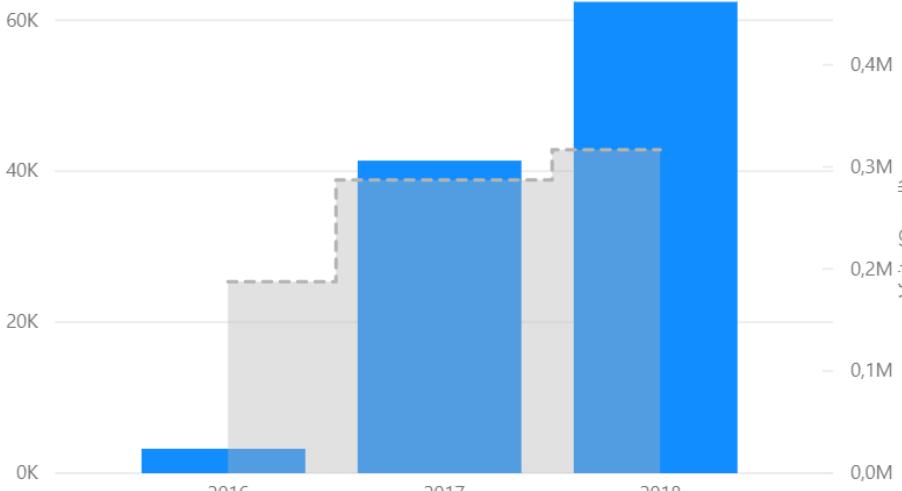
REGION



'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 \(Overall\)](#)



Comparing proportions [\(i\)](#)

Other Tips & Cool Features

United States Sales Summary

US  Germany

\$21M
Sales Amount

\$7.00M
COGS

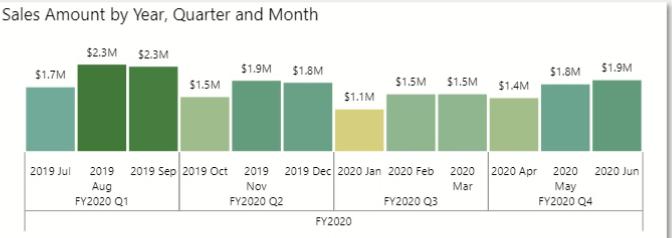
62K
Order Quantity

Reseller Search

Select row below to enable drill-through →

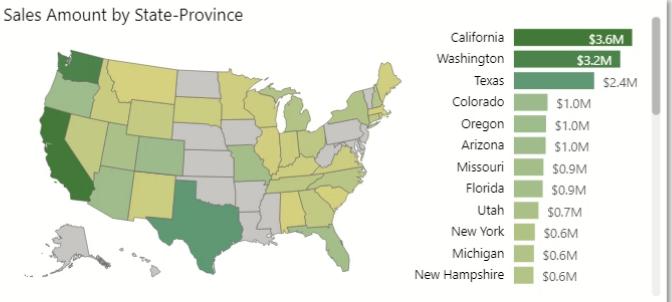
Reseller	City	State-Province	Sales Amount
Westside Plaza	Sand City	California	\$534,956
Field Trip Store	Loveland	Colorado	\$427,306
Brakes and Gears	Tooele	Utah	\$397,237
Thorough Parts and Repair Services	Lacey	Washington	\$386,958
Rally Master Company Inc	Chandler	Arizona	\$355,142
Outdoor Equipment Store	Nashua	New Hampshire	\$314,663
Eastside Department Store	Union City	California	\$296,329
Totes & Baskets Company	San Antonio	Texas	\$289,777
Permanent Finish Products	Reno	Nevada	\$288,088
Extraordinary Bike Works	Mesquite	Texas	\$281,845
Safe Cycles Shop	Bellevue	Washington	\$277,795
Great Bikes	Casper	Wyoming	\$277,495
Excellent Riding Supplies	Memphis	Tennessee	\$276,729
Area Bike Accessories	Modesto	California	\$275,644
Total			\$20,927,177

Sales Amount by Year, Quarter and Month



Period	Sales Amount (\$M)
2019 Jul	\$1.7M
2019 Aug	\$2.3M
2019 Sep	\$2.3M
2019 Oct	\$1.5M
2019 Nov	\$1.9M
2019 Dec	\$1.8M
2020 Jan	\$1.1M
2020 Feb	\$1.5M
2020 Mar	\$1.5M
2020 Apr	\$1.4M
2020 May	\$1.8M
2020 Jun	\$1.9M

Sales Amount by State-Province



State-Province	Sales Amount (\$M)
California	\$3.6M
Washington	\$3.2M
Texas	\$2.4M
Colorado	\$1.0M
Oregon	\$1.0M
Arizona	\$1.0M
Missouri	\$0.9M
Florida	\$0.9M
Utah	\$0.7M
New York	\$0.6M
Michigan	\$0.6M
New Hampshire	\$0.6M

Last updated: 9/30/20 10:17 AM

Fields

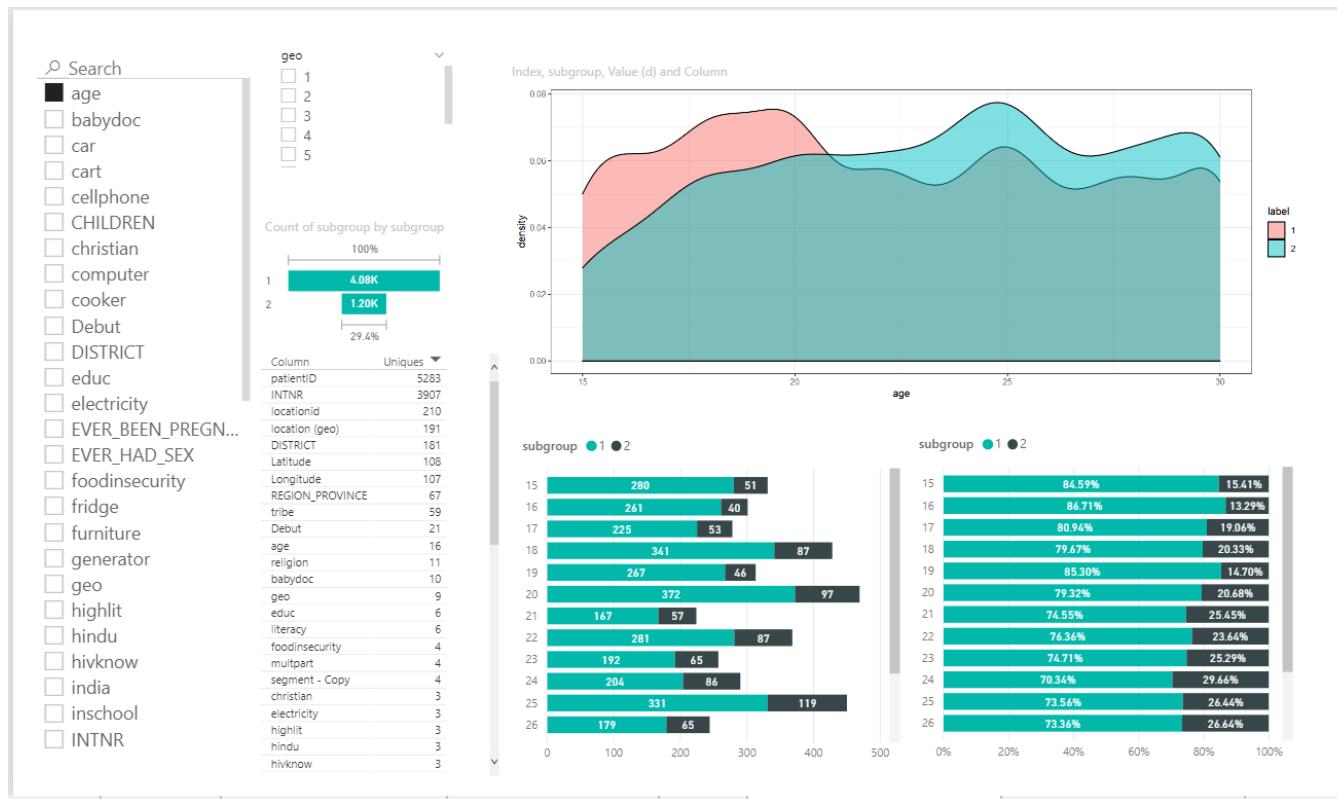
🔍 Search 

Visualizations

Filters

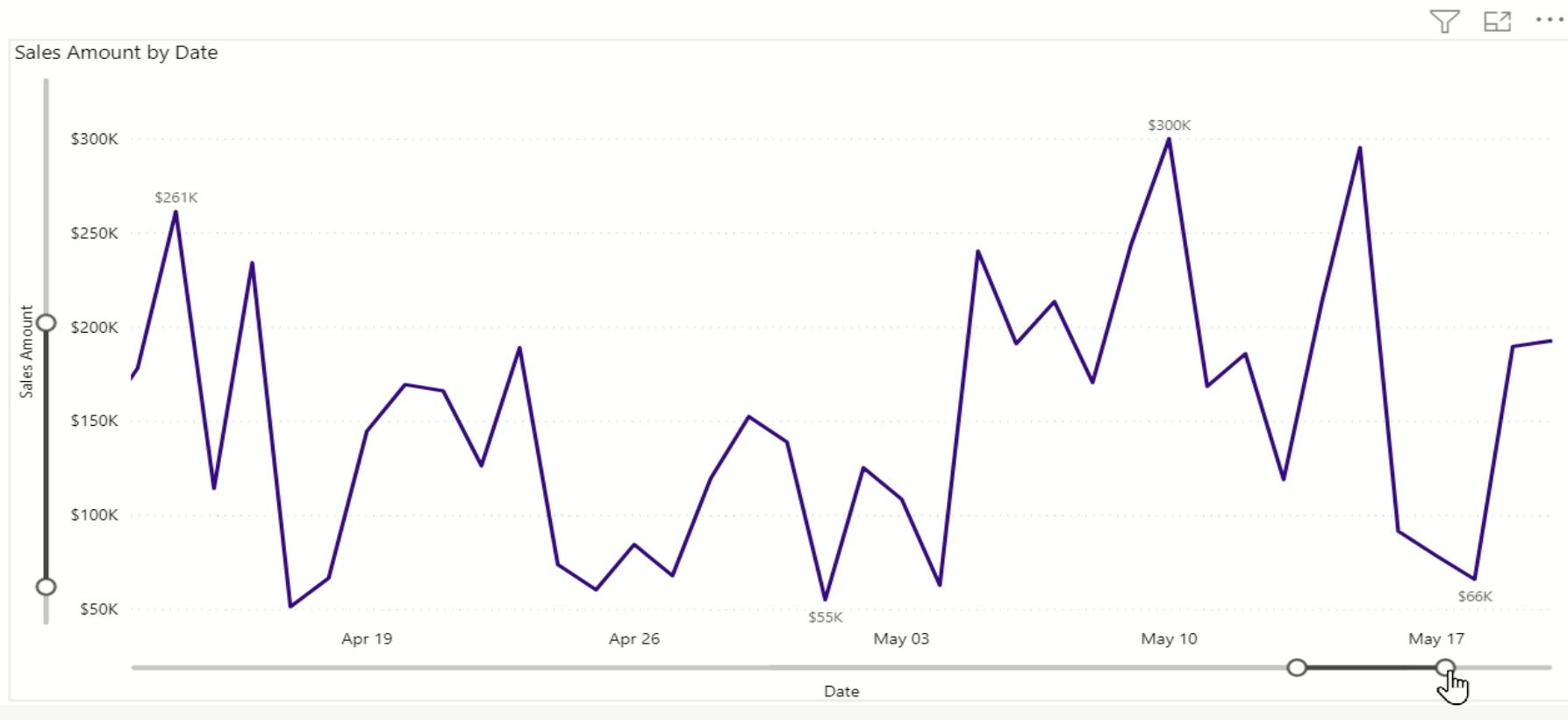
- Customer
- Date
- Geo
- Online Sales
- Product
- Reseller
- Sales
- Sales Order
- Sales Territory
- Table

Easy Refactoring, renames, measure formats,...



Reproducibility (just open it!)

Visual Zoom Slider



New Zoom Slider

on

Sales Summary

Reseller Drill through

+

Forecast

Metric

All Trips (With Test)

Forecast Version

4k_run

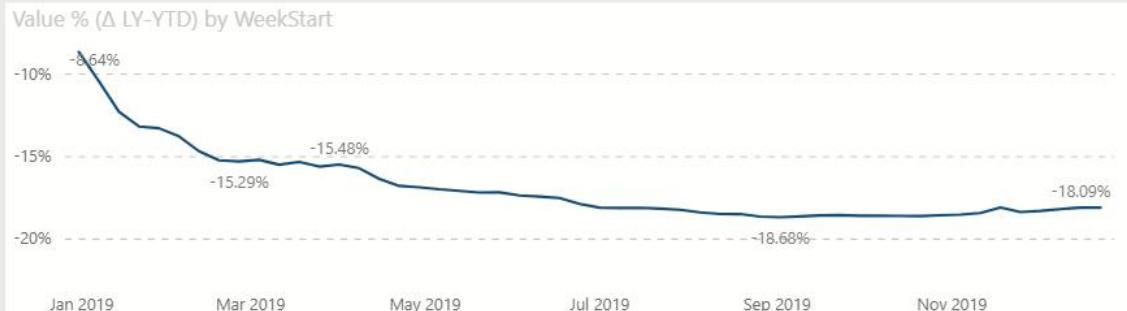
Service, Borough, Zone

All

1/1/2019

12/29/2019

devscope



83,879,351

Year

-17.86%

% Diff (YTD)

84,437,750

Forecast (Simple)

0.67%

Abs. Perc. Error (Simple)

102,399,456

LY

-18.09%

Value % (Δ LY-YTD)

81,021,841

Forecast (Full Year)

3.41%

Abs. Perc. Error (Full Year)

-20.88%

Forecast % (Δ LY)

7.22%

Abs. Perc. Error

8.10%

MAPE (week)

39,587,847

Trips (Test)

36,730,337

Forecast (Test)

7.22%

Abs. Perc. Error

8.10%

MAPE (week)

Trend Adjustment

0.00



2020-09-21 10:38:38

What-ifs/Interactive Parameters

ies

Analysis

Forecast

Simple

Sample Coverage

Coverage

N.Q.

RD Submissions

Page 1



Power BI & Auto ML

+ Add ML model

Entities



Select data



Choose model



Customize inputs



Name + train

NAME



Low

Select the historical outcome data that you would like to predict

Your model needs to learn from past situations where the event outcome is known

Entity name

Customer

Historical outcome field

LowRating

Semantic Models based Auto ML (cloud/premium feature)

Entities

Select data

Choose model

Customize inputs

Name + train

+ Add ML model

X Close

NAME



Low

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



Entities Machine learning models

Add ML model | Save Close

NAME

Low Ratings Model

LAST TRAINED

STATUS

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 nowRefresh 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	404
Total Data Provided	Total Data Sampled
304	100
Training Data	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 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.

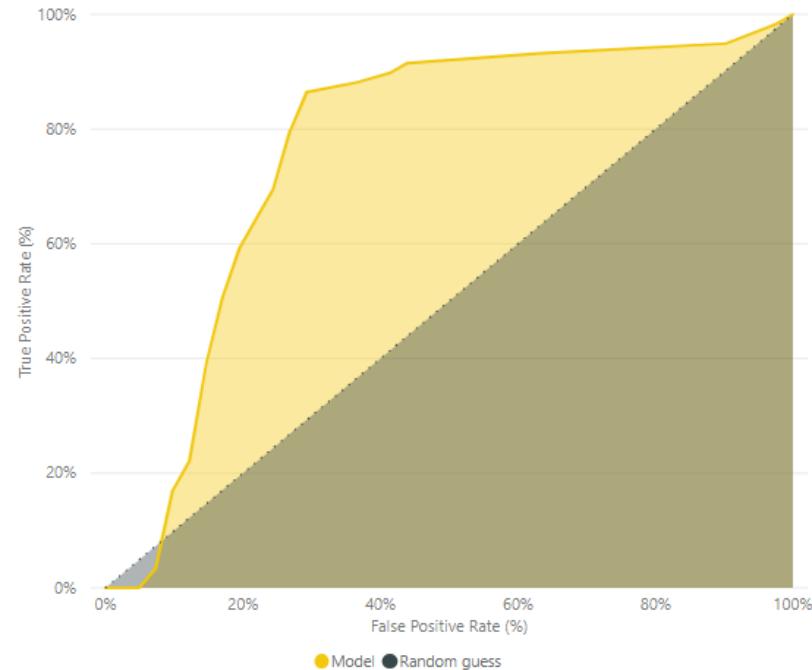
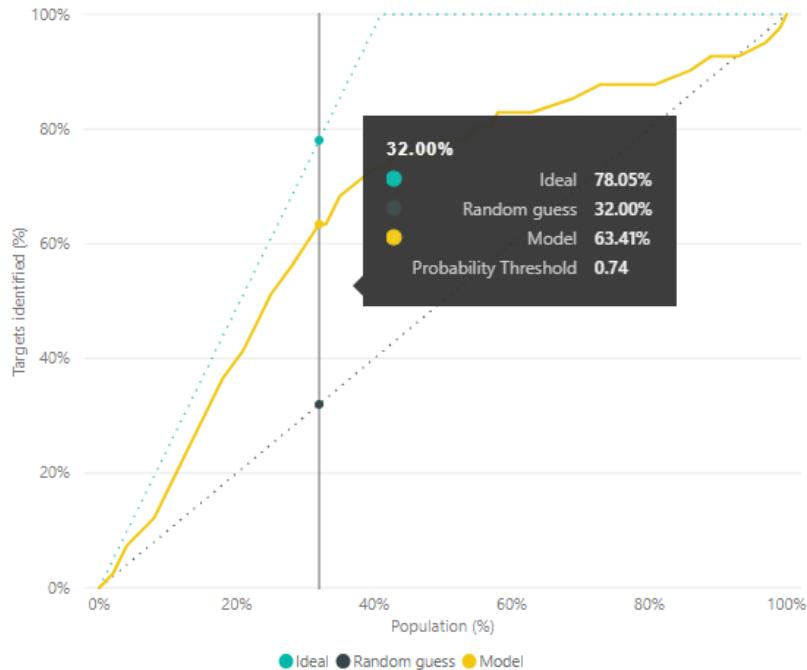
Titanic Survival model accuracy preview

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.



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

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Samples

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



Documentation

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

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About Events Members Photos Discussions More

Power BI Portugal

Lisbon, Portugal

2,184 members · Public group

Organized by Manuel D. and 7 others

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[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)

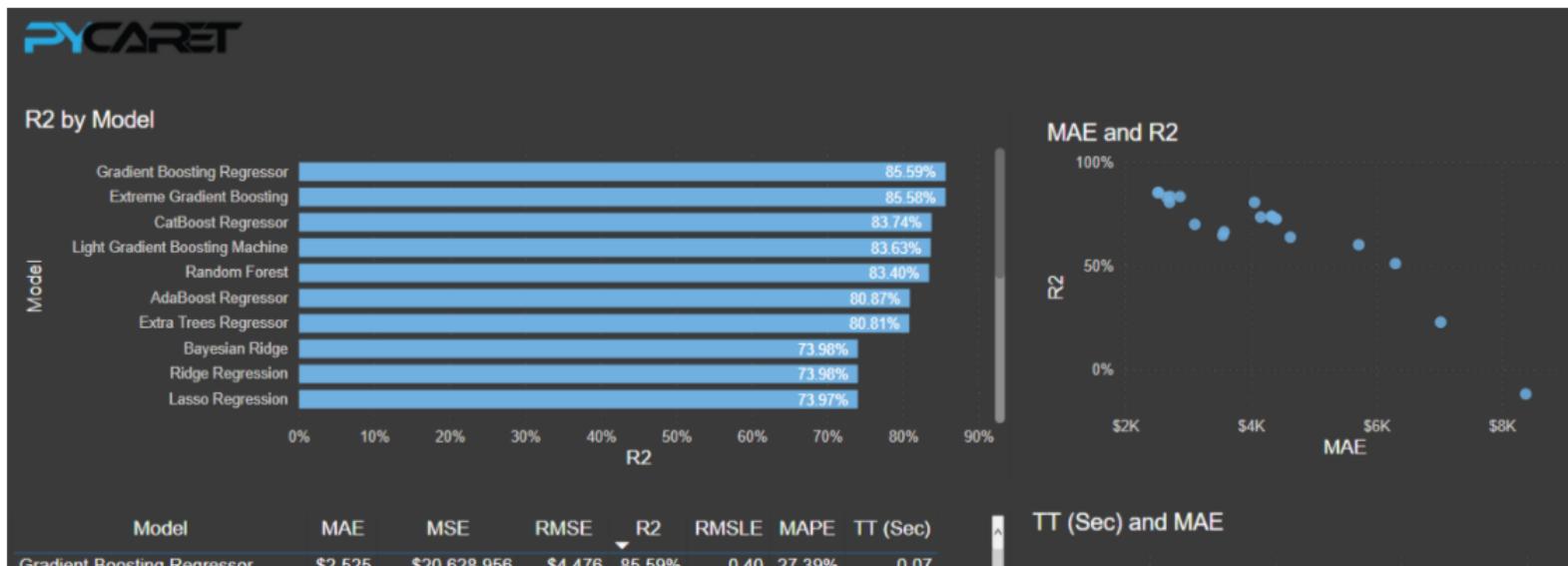
- not a true Data Science/Machine Learning workbench (sadly... 😞)
 - Ex: no native distribution plots, histograms (custom visuals available)
- Yeap, not Open Source...
- Not the best format for CI/CD (binary)
- Not scriptable/automation friendly
- Windows only
 - No Linux, No MacOs
(but note: lots of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

- Overview
 - How to create a forecast in PowerBI?

Thank you!



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[Linkedin.com/\[in/rquintino\]\(https://www.linkedin.com/in/rquintino\)](https://www.linkedin.com/in/rquintino)

[Twitter \[@rquintino\]\(https://twitter.com/@rquintino\)](https://twitter.com/@rquintino)

[Medium \[/devscope-ai\]\(https://medium.com/devscope-ai\)](https://medium.com/devscope-ai)

[Github \[/DevScope/ai-lab\]\(https://github.com/DevScope/ai-lab\)](https://github.com/DevScope/ai-lab)

\$20.93M

Sales Amount

\$7.00M

COGS

62K

Order Quantity

Reseller Search

Select row below to enable drill-through →

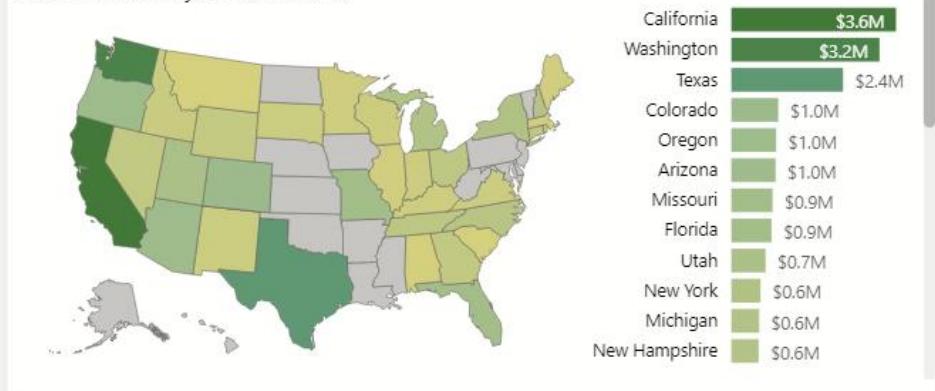
All

Reseller	City	State-Province	Sales Amount
Westside Plaza	Sand City	California	\$534,956.28
Field Trip Store	Loveland	Colorado	\$427,305.59
Brakes and Gears	Tooele	Utah	\$397,237.24
Thorough Parts and Repair Services	Lacey	Washington	\$386,958.19
Rally Master Company Inc	Chandler	Arizona	\$355,141.98
Outdoor Equipment Store	Nashua	New Hampshire	\$314,662.56
Eastside Department Store	Union City	California	\$296,328.92
Totes & Baskets Company	San Antonio	Texas	\$289,777.50
Permanent Finish Products	Reno	Nevada	\$288,088.47
Extraordinary Bike Works	Mesquite	Texas	\$281,844.75
Safe Cycles Shop	Bellevue	Washington	\$277,795.47
Great Bikes	Casper	Wyoming	\$277,495.37
Excellent Riding Supplies	Memphis	Tennessee	\$276,729.43
Area Bike Accessories	Modesto	California	\$275,643.81
Total			\$20,927,177.22

Sales Amount by Year, Quarter and Month



Sales Amount by State-Province



Questions/ Feedback ?

Last updated: 9/30/20 10:17 AM

Questions/Feedback ?

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 Twitter [@rquintino](https://twitter.com/@rquintino)

 Medium [/devscope-ai](https://medium.com/@devscope-ai)

 Github [/DevScope/ai-lab](https://github.com/DevScope/ai-lab)

Power BI & AI Built-in models

Edit queries

Power Query

Get data Refresh Options Manage columns Transform column Transform table Reduce rows Add column AI insights ...

Customers Customer Comments Image Classification Key Phrases

x ✓ fx = Source{[Schema = "hotel", Item = "Hotel Customer Comments"]}[Data]

	A ^B _C categories	Date	A ^B _C Guest Comment	A ^B _C Hotel Name	1 ² ₃ Index	1.2 long
1	Hotels	7/2/2014, 5:00:00 PM	First impression not great ...	Grand Kailua		93
2	Hotels	10/30/2013, 5:00:00 PM	Beautiful, clean, and conve...	Grand Kailua		58
3	Hotels	9/20/2014, 5:00:00 PM	It is hard to find the resort....	Grand Kailua		98
4	Hotels	2/9/2015, 4:00:00 PM	Close to the shopping cent...	Grand Kailua		59
5	Hotels	7/22/2016, 5:00:00 PM	Condos were okay but limi...	Grand Kailua		97
6	Hotels	3/1/2016, 4:00:00 PM	Dirt everywhere, dust on fu...	Grand Kailua		107
7	Hotels	9/29/2014, 5:00:00 PM	experience was average...a...	Grand Kailua		75
8	Hotels	5/27/2016, 5:00:00 PM	Had a room right on the w...	Grand Kailua		61
9	Hotels	12/12/2014, 4:00:00 PM	Great location and well ma...	Grand Kailua		69
10	Hotels	6/1/2016, 5:00:00 PM	Great location, within walki...	Grand Kailua		106
11	Hotels	3/1/2015, 4:00:00 PM	great stay. Very convenient...	Grand Kailua		64
12	Hotels	7/3/2016, 5:00:00 PM	Awesome stay. Was here f...	Grand Kailua		104

Name
Customer Comm
Entity type ⓘ
Custom
Applied steps
Source
x Navigation 1

Example: Natural Language Processing steps

Invoke function

- 📁 CognitiveServices [4]
 - fx CognitiveServices.TagImages
 - fx CognitiveServices.ExtractKeyPhr...
 - fx CognitiveServices.DetectLangu...
 - fx CognitiveServices.ScoreSentim...

CognitiveServices.ScoreSentiment

This function returns a numeric score between 0 and 1. Scores close to 1 indicate positive sentiment, while scores close to 0 indicate negative sentiment. A score of 0.5 indicates the lack of sentiment (e.g. a factoid statement). You can provide a language ISO code as optional parameter.

text *



Guest Comment



Show ▾

languageISOCode



en

Invoke

Cancel

Access to AI APIs (Azure Cognitive Services)

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

	1.2 longitude	1.2 latitude	A ^B C province	A ^B C Guest Comment	1.2 Sentiment Score
1	93	-155.989	19.63 HI	First impression not great ...	0.754
2	58	-155.989	19.63 HI	Beautiful, clean, and conve...	0.997
3	98	-155.989	19.63 HI	It is hard to find the resort....	0.793
4	59	-155.989	19.63 HI	Close to the shopping cent...	0.944
5	97	-155.989	19.63 HI	Condos were okay but limi...	0.031
6	107	-155.989	19.63 HI	Dirt everywhere, dust on fu...	0.06
7	75	-155.989	19.63 HI	experience was average...a...	0.945
8	61	-155.989	19.63 HI	Had a room right on the w...	0.71
9	69	-155.989	19.63 HI	Great location and well ma...	0.988
10	106	-155.989	19.63 HI	Great location, within walki...	0.877
11	64	-155.989	19.63 HI	great stay. Very convenient...	0.968
12	104	-155.989	19.63 HI	Awesome stay. Was here f...	0.781
13					

Name
Customer Comments

Entity type ⓘ
Custom

Applied steps
Source
Navigation 1
Removed columns
Reordered columns

Cancel Done

Sentiment Analysis of Guest Comments

Edit queries

Power Query

Get data Refresh Options Manage columns Transform column Transform table Reduce rows Add column AI insights ...

Customers
Customer Comments
Image Classification
Key Phrases

Name
Image Classification

Entity type ①
Custom

Applied steps

Source
Navigation 1

Index	Image	Probability	Image Tag
1	0 https://hotelpictures.blob.c...	0.995	A/C
2	1 https://hotelpictures.blob.c...	0.998	A/C
3	5 https://hotelpictures.blob.c...	0.97	Pool
4	6 https://hotelpictures.blob.c...	0.981	A/C
5	7 https://hotelpictures.blob.c...	0.994	A/C
6	8 https://hotelpictures.blob.c...	0.992	A/C
7	9 https://hotelpictures.blob.c...	0.984	Pool
8	10 https://hotelpictures.blob.c...	0.977	Beach
9	10 https://hotelpictures.blob.c...	0.916	View
10	10 https://hotelpictures.blob.c...	0.898	Water View
11	11 https://hotelpictures.blob.c...	1	Hotel Room
12	11 https://hotelpictures.blob.c...	0.996	Clean
13	11 https://hotelpictures.blob.c...	0.992	Dated/Old Hotel Room

Cancel Done

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

X ✓ fx = Source{[Schema = "hotel", Item = "Key Phrases"]}[Data]

Index	Keyphrases
1	AC unit
2	AC unit
3	accommodating
4	accommodating
5	adults
6	adults
7	adults
8	air conditioning
9	air conditioning
10	air conditioning
11	air conditioning
12	air conditioning
13	air conditioning

GUEST REVIEWS



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 disappointed 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

SENTIMENT SCORE BY HOTEL



REFERENCES AND SENTIMENT BY TOPIC



	<input type="checkbox"/> Members.Joined Group on	<input checked="" type="checkbox"/> Members.Last visited group on	<input type="checkbox"/> Members.Last Attended	Custom
1	01/02/2019	13/02/2019	06/02/2019	20190201
2	27/01/2019	27/01/2019	06/02/2019	20190127
3	06/01/2019	27/02/2019	06/02/2019	20190106
4	06/01/2019	27/02/2019	06/02/2019	20190106
5	06/01/2019	27/02/2019	06/02/2019	20190106
6	22/01/2019	04/02/2019	06/02/2019	20190122
7	26/02/2019	02/03/2019	no	20190226
8	<input type="checkbox"/> A ^B _C Members.Name	<input checked="" type="checkbox"/> A ^B _C Members.U	Custom	no
	Rodrigo Fazendeiro	Fastwheels	Fazendeiro, R.	
	Nuno Gomes	user 5182529	Gomes, N.	
	Daniel Monteiro	user 6053978	Monteiro, D.	
	A ^B _C Members.Name	<input checked="" type="checkbox"/> A ^B _C Members.U	Custom	
	Rodrigo Fazendeiro	Fastwheels	rfa zendeiro	
	Nuno Gomes	user 5182529	ngomes	
	Daniel Monteiro	user 6053978	dmonteiro	
	Daniel Monteiro	user 6053978	dmonteiro	

Prep by example

powerbi-kaggle-days-p

File Home Transform

New Recent Enter Data

Vision

Close & Apply Close New Query

Date

731 distinct, 731 unique

1 12/31
2 1/1
3 1/2
4 1/3
5 1/4
6 1/5
7 1/6
8 1/7
9 1/8
10 1/9
11 1/10
12 1/11
13 1/12
14 1/13
15 1/14
16 1/15
17 1/16
18 1/17
19 1/18
20 1/19

Tag images

Analyze images to generate tags based on what they contain.

[Learn more](#)

Image (optional)

Date

Language ISO code (optional)

Example: abc

Premium capacity used for AI Insights

Default (based on availability)

Text Analytics Vision Azure Machine Learning AI Insights

Properties

STEPS

- ertCalendarSem
- ertDayWeek
- ertDayName
- ertWeekYear
- ertMonthYear
- ertQuarterYear
- ertSemesterYear
- italized Each Word
- ative (Year)
- ative (Month)
- ative (Day)
- rgedHolidays
- andedHolidays
- ledWorkDay
- ordered Columns
- nged Type
- lumnPT

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

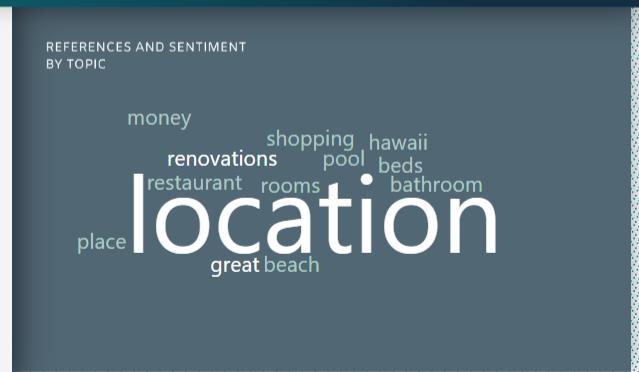
25 COLUMNS, 731 ROWS Column pr... PREVIEW DOWNLOADED AT 12:59 AM



GUEST REVIEWS



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,



- New
- Home
- Author
- Notebooks
- Automated ML
- 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

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
1.2 Example: 123

workclass
A>Bc Example: abc

fnlwgt
1.2 Example: 123

education
A>Bc Example: abc

educational_num
1.2 Example: 123

marital_status
A>Bc Example: abc

occupation
A>Bc Example: abc

... And using directly in Power BI/Power Query

File Home Transform

New Recent Enter Data

Close & Apply Close New Query

Date

731 distinct, 731 unique

1 12/31
2 1/1
3 1/2
4 1/3
5 1/4
6 1/5
7 1/6
8 1/7
9 1/8
10 1/9
11 1/10
12 1/11
13 1/12
14 1/13
15 1/14
16 1/15
17 1/16
18 1/17
19 1/18
20

Text Analytics
Vision
Azure Machine Learning
AI Insights

Properties

STEPS

CalendarQuarter
CurrentCalendarQuarter
CurrentQuarterYear
CurrentQuarterYear
CurrentMonthYear
CurrentMonthYear
CurrentYear
CurrentYear
CurrentWeekYear
CurrentWeekYear
CurrentDayWeek
CurrentDayName
CurrentDay
CurrentMonth
CurrentQuarter
CurrentSemester
Capitalized Each Word
Native (Year)
Native (Month)
Native (Day)
DashedHolidays
DashedHolidays
DashedWorkDay
DashedWorkDay
DashedType
ColumnPT

PREVIEW DOWNLOADED AT 12:59 AM

BI, Analytics
&
Data Science/Machine Learning

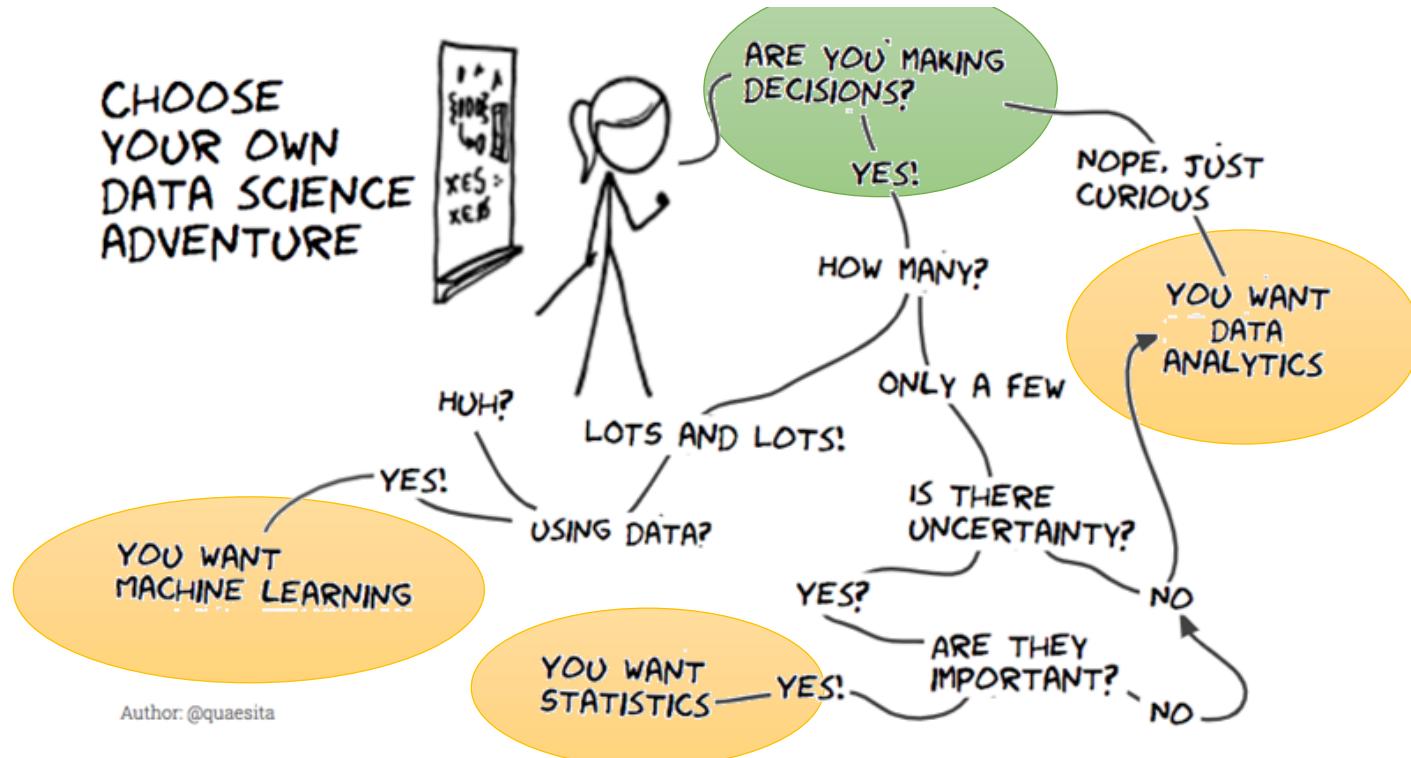
What on earth is data science?

The quest for a useful definition



Cassie Kozyrkov [Follow](#)

Aug 18, 2018 · 7 min read



Author: @quaesita

The Data Science Landscape

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



Dr. Stefan Karenfort Nov 27 · 9 min read ★

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				