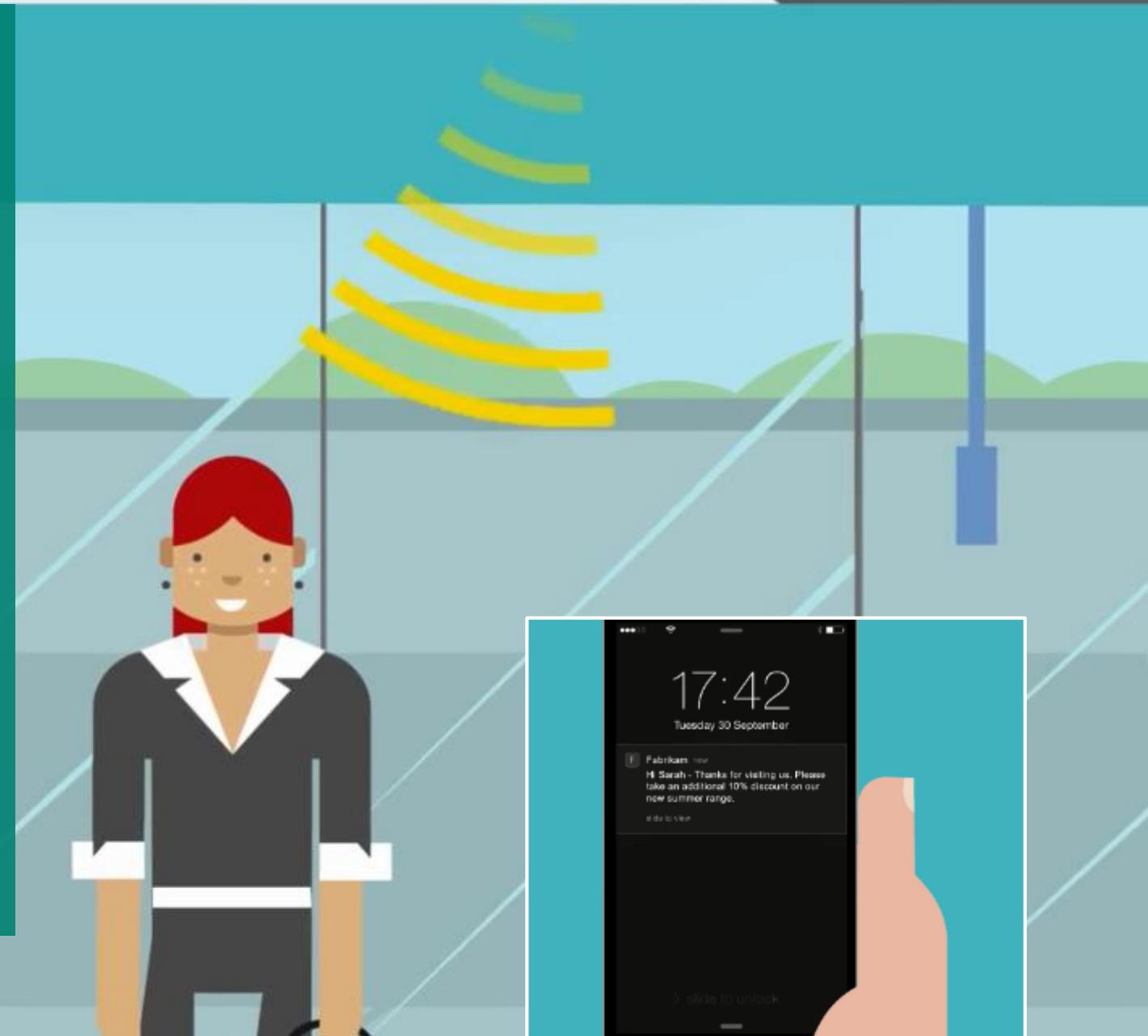


Intelligent Retail with Machine Learning approach

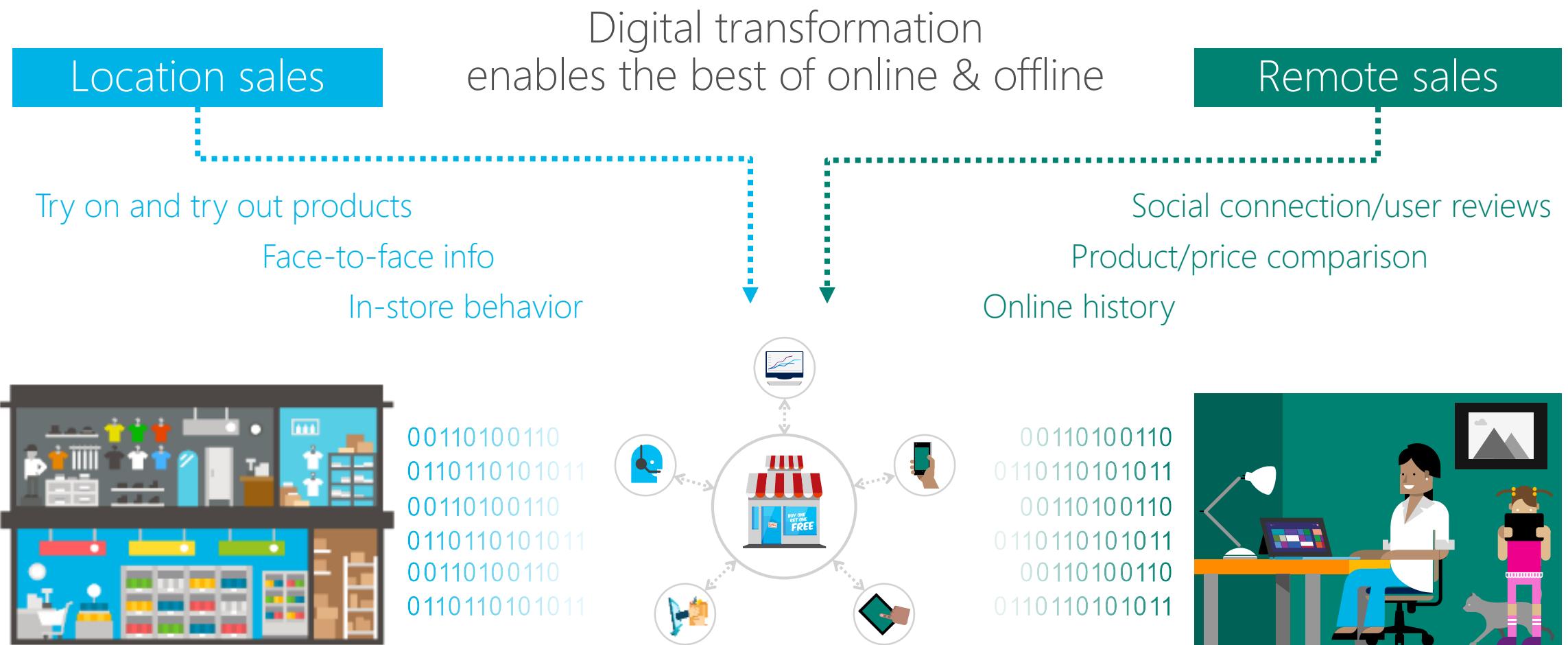
Dmitriy Solopov



TRANSFORM with DATA



Modern retail is data driven



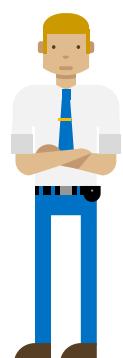
Success hinges on insights and optimization

Technology provides solutions to existing and emerging problems

I need to be able to meet demand anywhere, on any channel, but I'm hindered by disconnected processes

Providing more personalized, relevant offers would require analytic tools and know-how that I don't have

Keeping up with rapidly changing customer preferences feels out of reach with my current forecast methods



Merchandising Director

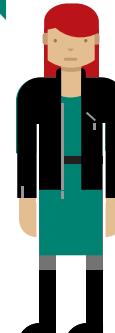


COO

I want my employees to delight customers, but they lack up-to-date customer info and the latest digital tools



VP of Stores



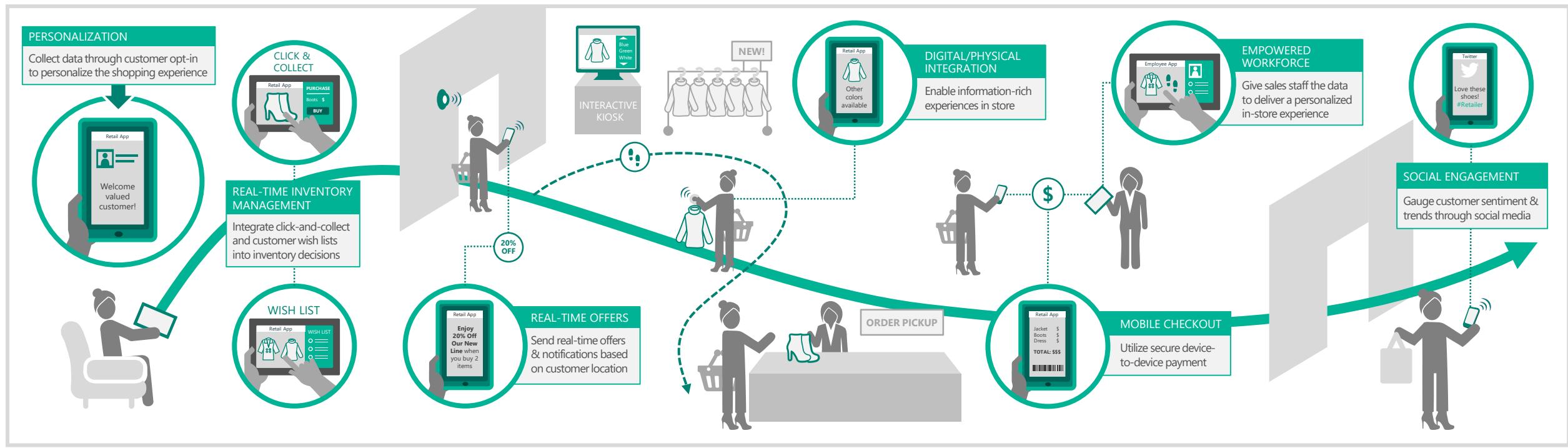
CMO

I want technology to be a growth engine for the business, but legacy systems hold me back



CIO

The modern retail environment



Optimize your forecasting and react faster



Merchandising Director



COO



Optimize your forecasting and react faster



Increase loyalty and share of wallet through hyper-local assortments and inventory

with scalable cloud solutions that take advantage of data, such as social and weather, to complement existing demand signals

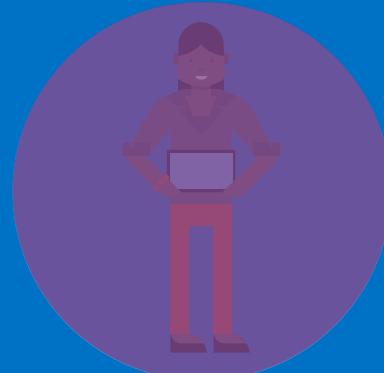
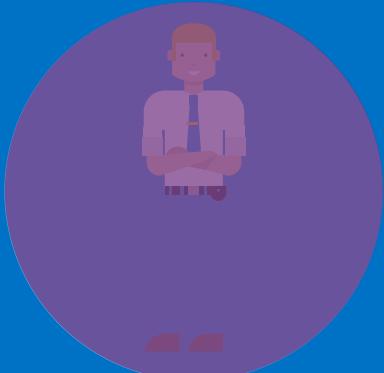
Improve management of merchandise allocation across channels

with data-driven understanding of what will sell, when, where, and to whom

Enable forward-thinking, agile pricing and promotions

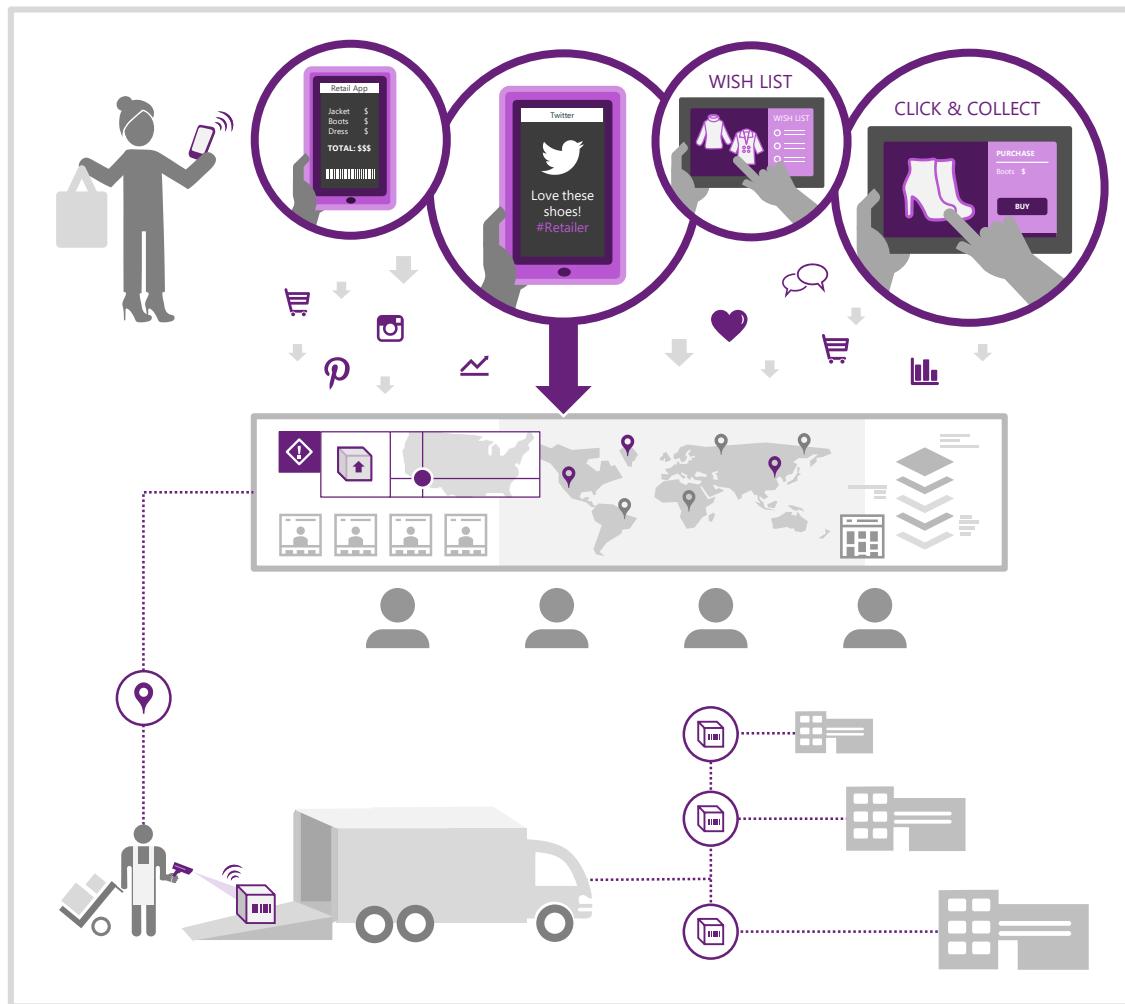
with analytics capabilities to predict optimum pricing and quickly make changes as needed

Modernize your supply chain with analytics-driven operations



coo

Modernize your supply chain with analytics-driven operations



Reduce time to market for new products and services

using actionable insights provided by market trend analysis and customer feedback

Develop a more cost-effective, collaborative supply chain

through end-to-end visibility and seamless partner and supply chain communication

Optimize inventory management

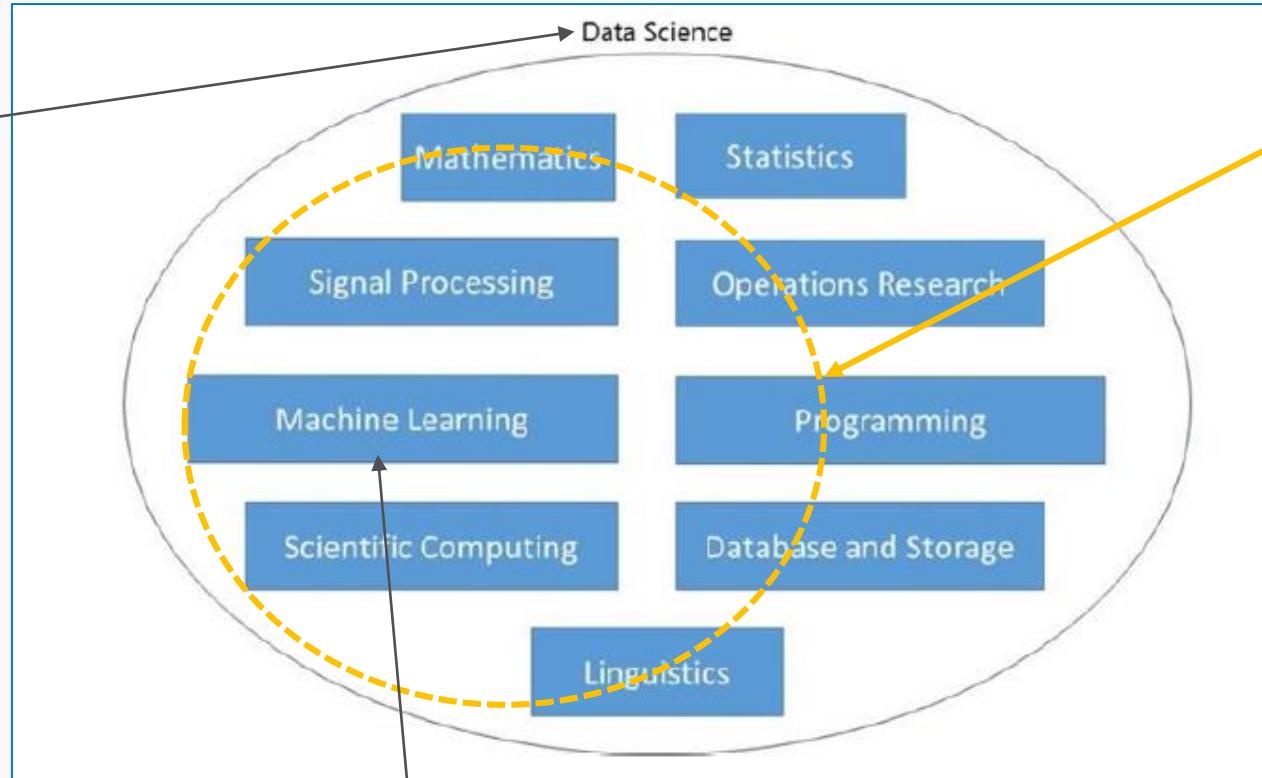
using real-time predictive analytics and mobile devices to improve inventory transparency and anticipate customer and channel demand

Machine Learning Demystified

Data Science

[Data Science]

Set of disciplines that aggregates maths, statistics, ml etc...to get useful insights from data



[Machine Learning]

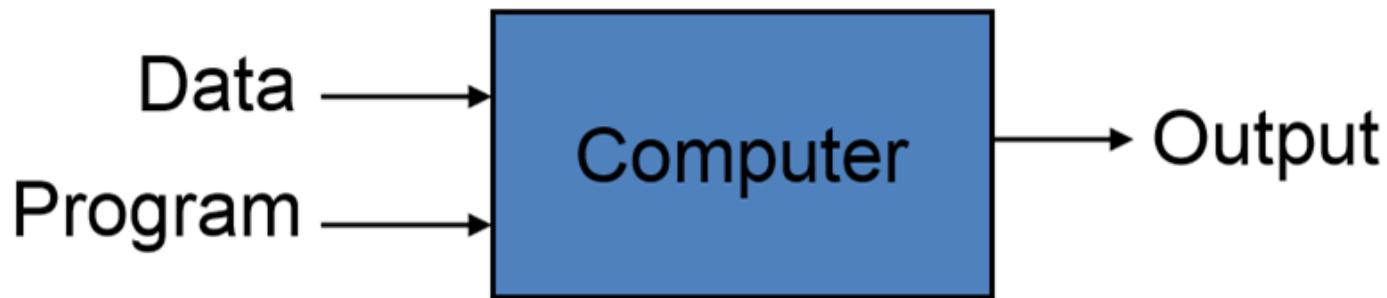
Process of automated self learning from the data

[Predictive Analytics]

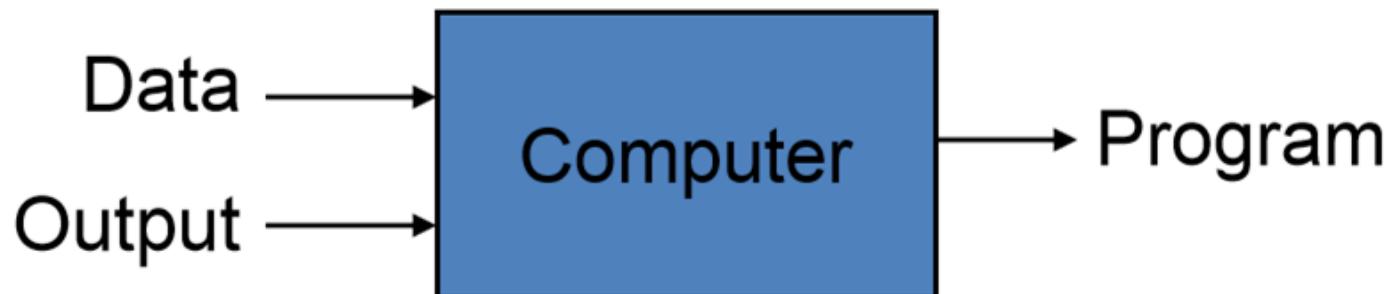
Encompasses a variety of statistical techniques from [predictive modeling](#), [machine learning](#), and [data mining](#) that analyze current and historical facts to make [predictions](#) about future or otherwise unknown events

Understanding Machine Learning

Traditional Programming



Machine Learning



The ML process



[Define business problem]



[Acquire and prepare data]



[Develop]



[Deploy]



[Monitor]

Jargon

[table] [database]

[data points] [rows][samples]

[features] [columns] [attributes] [variables]

[labels]

[algorithm]

Flu (2015)	Weight (Kgr)	Medicine (ml)	Class
Yes	10	5	M
No	17	10	F
Yes	25	15	F
Yes	12	6	M
No	37	25	F

Data should be



[Relevant]

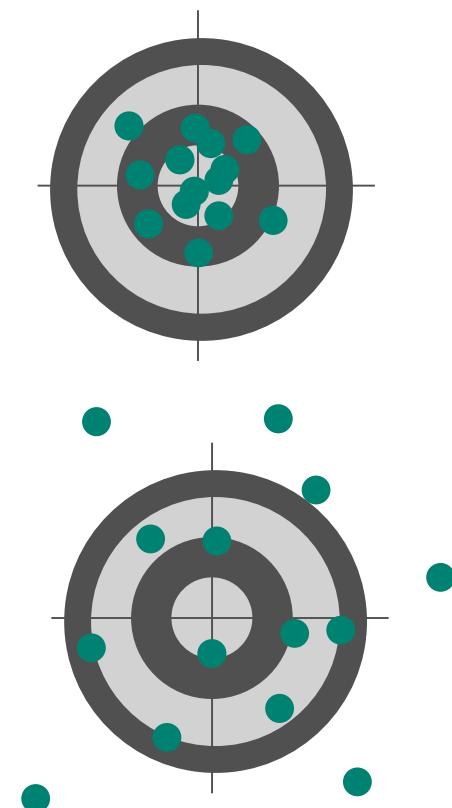
Flu (2015)	Weight (Kgr)	Medicine (ml)	Gender
Yes	10	5	M
No	17	10	F
Yes	25	15	F
Yes	12	6	M
No	37	25	F

[Connected]

Flu (2015)	Weight (Kgr)	Medicine (ml)	Gender
Yes	10	5	M
No	17	10	F
Yes	25	15	F
Yes	12	6	M
?	37	?	F

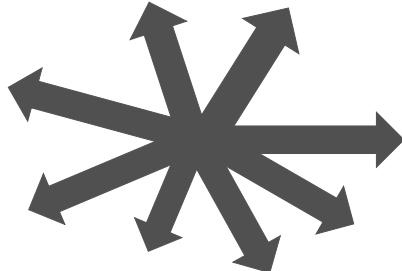
[Missing Values]

[Accurate]



Vague questions vs. Sharp questions

Data is numbers and names



Can't be answered with a name or a number

- What can my data tell me about my business?
- What should I do?
- How can I increase my profits?



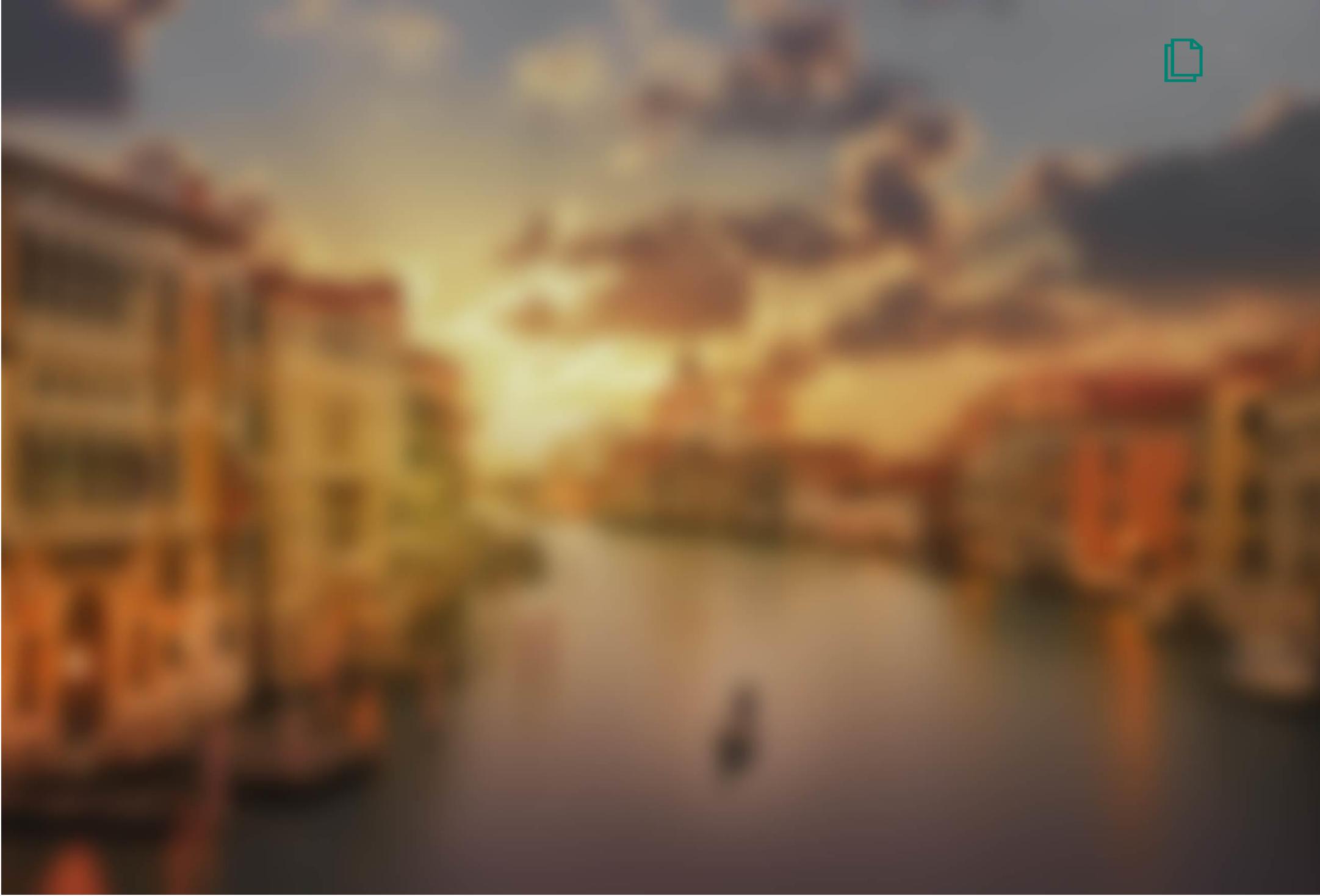
Can be answered with a name or a number.

- How many Model Q Gizmos will I sell in Montreal during the third quarter?
- Which car in my fleet is going to fail first?

Not enough data



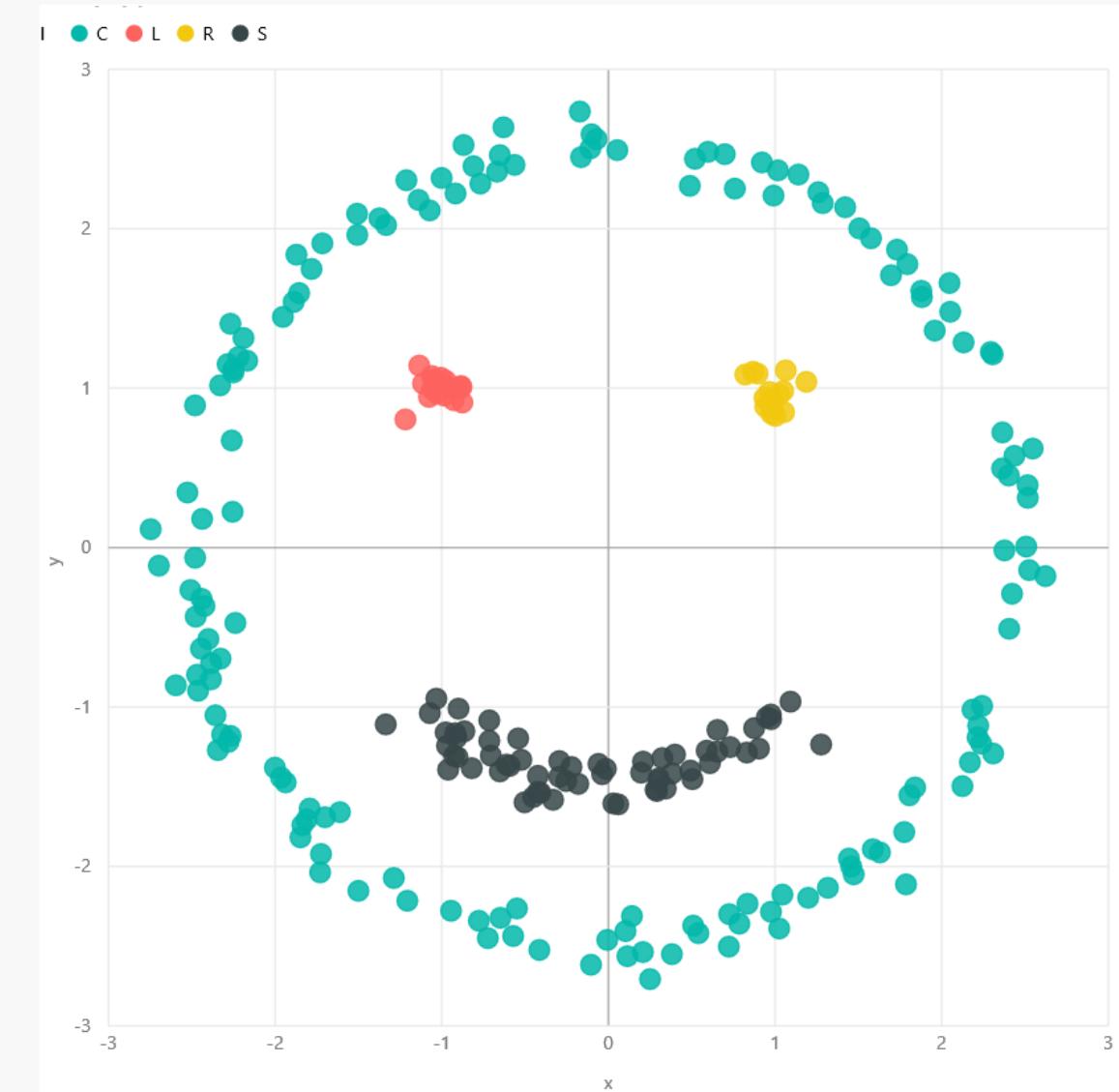
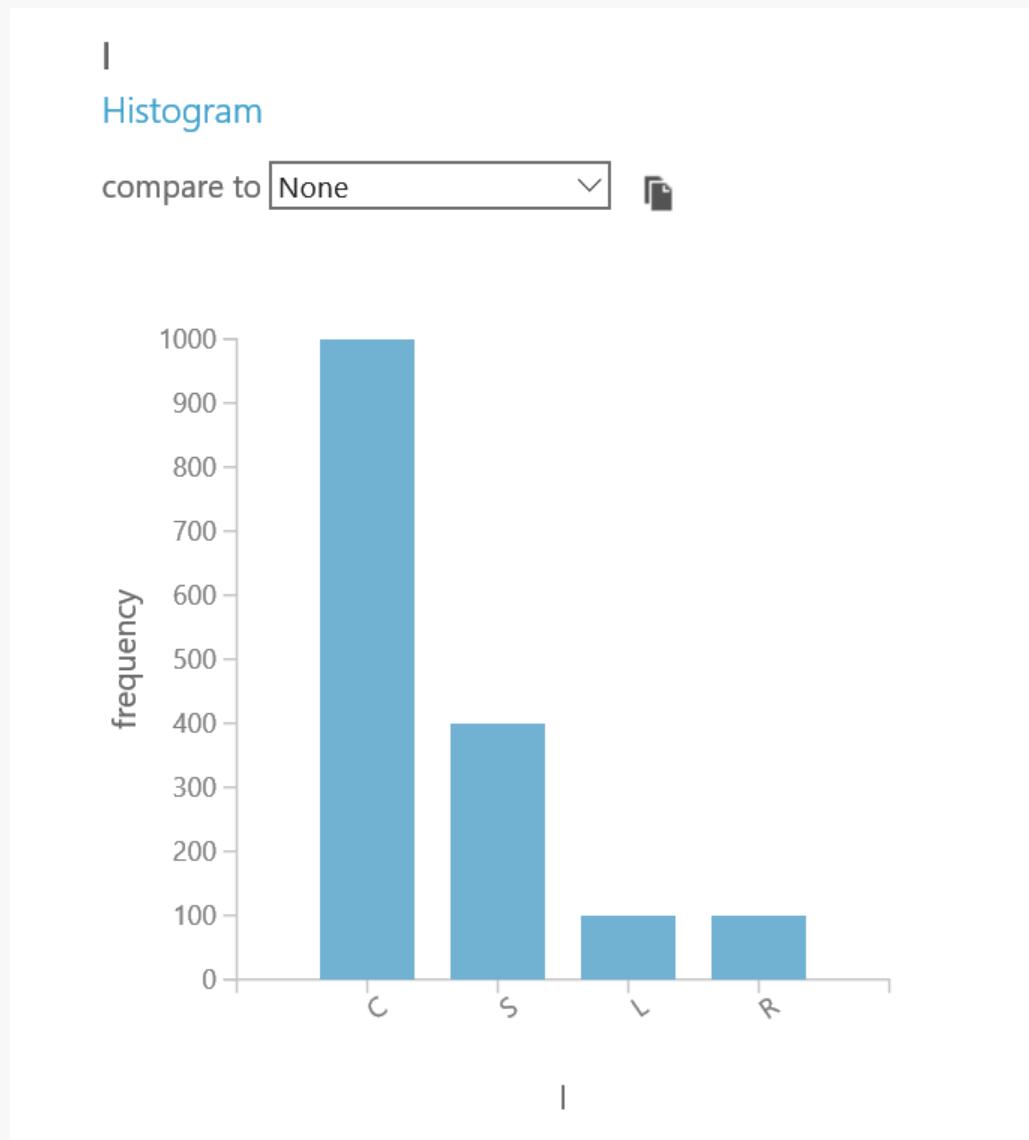
Barely enough data



Enough data



Visualize



Machine Learning alone is not Data Science

1. Data quality: Is it garbage?
2. Data exploration: What does it look like?
3. Feature Engineering: What does it mean?
4. Operationalization: How do I harvest data and deliver answers?

Machine Learning algorithms answers a question

Prediction: What value?

Classification: What class?

Clustering: Which group?

Anomaly detection: Is it weird?

Recommendation: Which option?

How much / how many?

- What will the temperature be next Tuesday?
- What will my fourth quarter sales in Portugal be?
- How many new followers will I get next week?



[regression] Example: Sales Forecast

[Browse all](#)[Experiments](#)[Machine Learning APIs](#)[Tutorials](#)[More](#) ▾**EXPERIMENT**

Retail Forecasting: Step 1 of 6, data preprocessing

Microsoft • published on March 18, 2015

Summary

Accurate and timely forecast in retail business drives success. It is an essential enabler of supply and inventory planning, product pricing, promotion, and placement. As part of Azure ML offering, Microsoft provides a template letting data scientists easily build and deploy a retail forecasting solution.

Description

Retail Forecasting Template

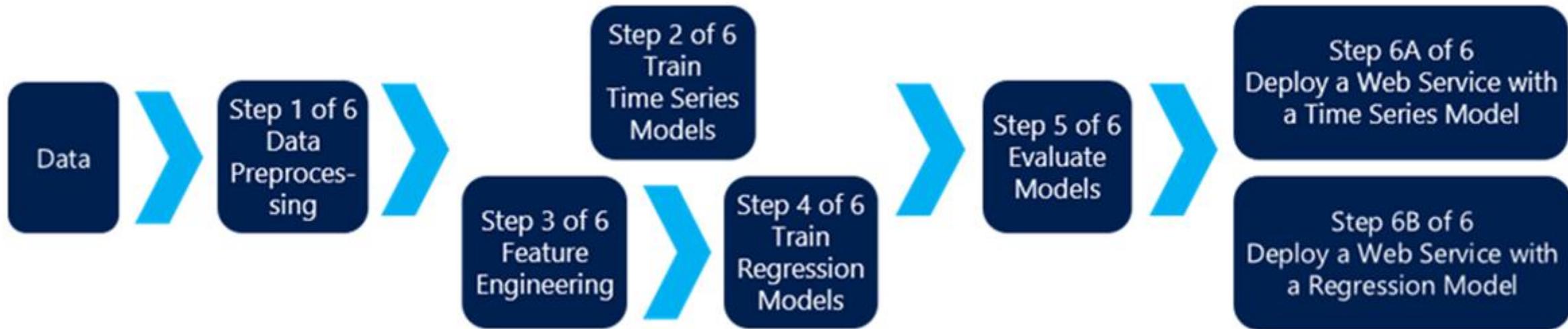
Accurate and timely forecast in retail business drives success. It is an essential enabler of supply and inventory planning, product pricing, promotion, and placement. As part of the Azure Machine Learning offering, Microsoft provides a template letting data scientists easily build and deploy a retail forecasting solution. In this document, you will

[Open in Studio](#)[+ Add to Collection](#)

4721 views

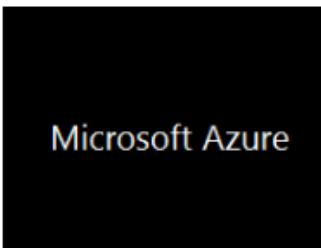
1715 downloads

Forecasting Template Workflow





Home > Data > Forecasting - AutoRegressive Integrated Moving Avera...



Forecasting - AutoRegressive Integrated Moving Average (ARIMA) API built with Azure Machine Learning

Data

Published by: Azure Machine Learning

Categories: Machine Learning

Date added: 10/9/2014

[Get support for this offering](#)

Forecasting - AutoRegressive Integrated Moving Average (ARIMA) API is an example built with Microsoft Azure Machine Learning that fits an ARIMA model to data input by the user and subsequently outputs forecasted values for future dates.

Will the demand for a specific product increase this year? Can I predict my product sales for the Christmas season, so that I can effectively plan my inventory? Forecasting models are apt to address such questions. Given the past data, these models examine hidden trends and seasonality to predict future trends.

25,000
Transactions/month

\$0.00
per month
[SIGN UP](#)

Sample Web App

A sample web app for testing the ARIMA web service.

Documentation

Documentation of creation as well as consumption of web service.

Which category?

- Which customer will churn?
- Which aircraft is causing this radar signature?
- What is the topic of this news article?

[classification algorithm]



[Browse all](#)[Solution Templates](#)[Experiments](#)[Machine Learning APIs](#)[Notebooks](#)[Competitions](#)[Tutorials](#)[Collections](#)

COLLECTION

Retail Customer Churn Prediction Template

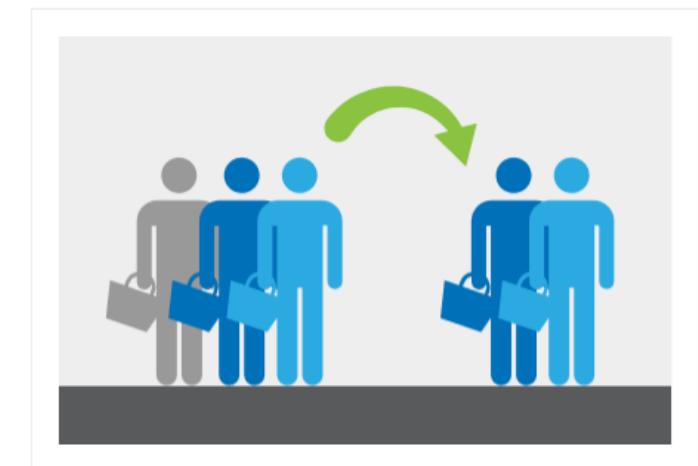
Microsoft • published on October 1, 2015

Summary

This collection of experiments demonstrates the Retail Customer Churn Template on how to build and deploy a retail churn prediction model.

Description

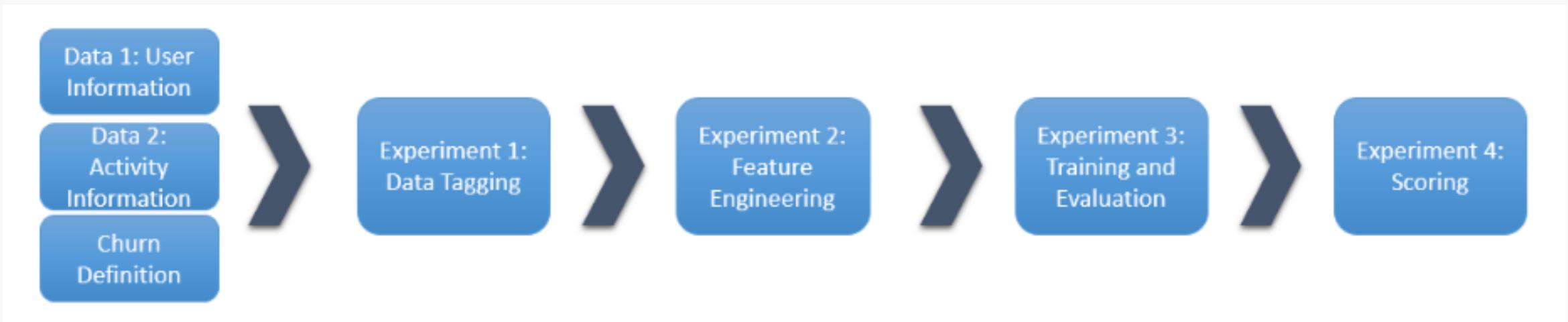
Predicting customer churn is an important problem for banking, telecommunications, retail and many others customer related industries. As part of the Azure Machine Learning offering, Microsoft is providing this template to help retail companies predict customer churns. This template provides pre-configured machine learning modules along with custom Python scripts in the **Execute Python Script** Module for solving the customer churn prediction problem for the Retail Stores. This template focuses on binary



+ Add to Collection

1652 views

Churn Template Workflow



Browse all

Solution Templates

Experiments

Machine Learning APIs

Notebooks

Competitions

Tutorials

Collections



COLLECTION

Modeling Price Elasticity - Demo Experiments in the Cortana Analytics Webinar for Retail Pricing



Xueshan Zhang • published on October 13, 2015

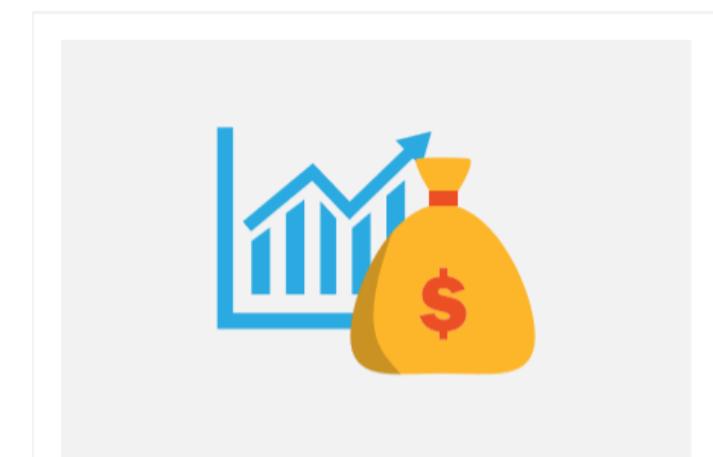
Summary

This collection includes demo experiments used in the Cortana Analytics Webinar for Retail Pricing.

Description

Price elasticity is the foundation of price optimization. Experiments in this collection use transaction data to show how to determine price elasticity. Starting from the basic example in Experiment 'Part 1' which demos a product's own price elasticity, users will learn how to add cross-item effects in Experiment 'Part 2'. They will get to know how to deal with combos and add external information including weather and holiday into the model in Experiment 'Part 3'. After finishing the series, users are equipped with the proper knowledge to deal with real-world datasets.

Related Resources: Check the video of the [Cortana Analytics Webinar for Retail Pricing](#), which is hosted



+ Add to Collection

532 views

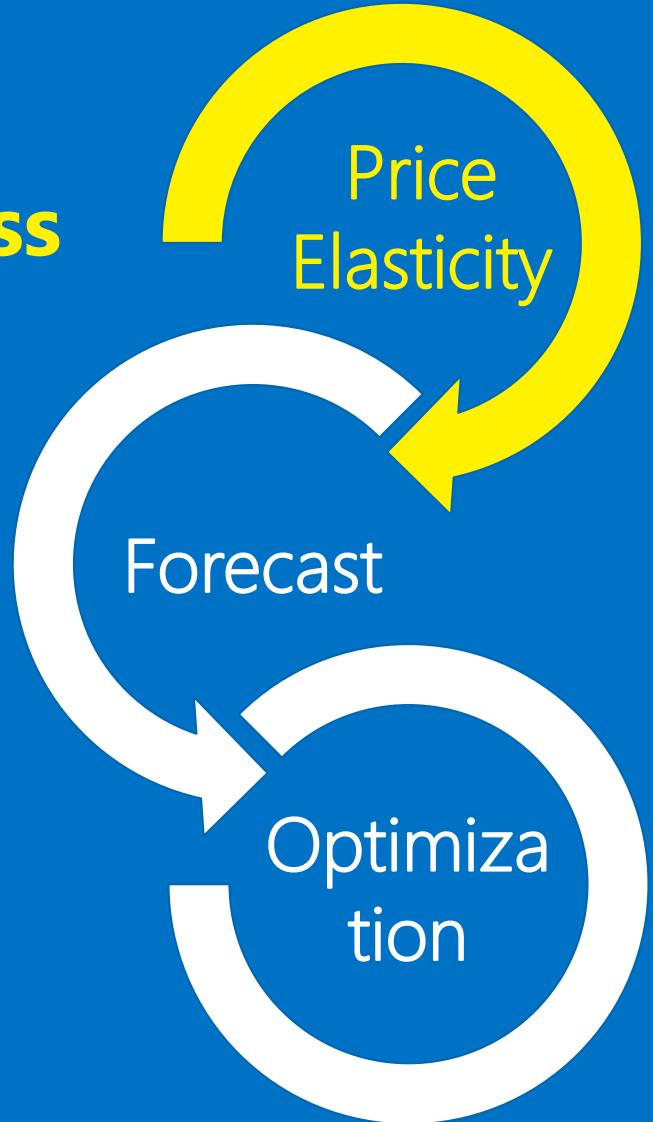
Price Elasticity - Coffee Example



$$\text{Price Elasticity} = \frac{\% \text{ Change in Demand}}{\% \text{ Change in Price}}$$

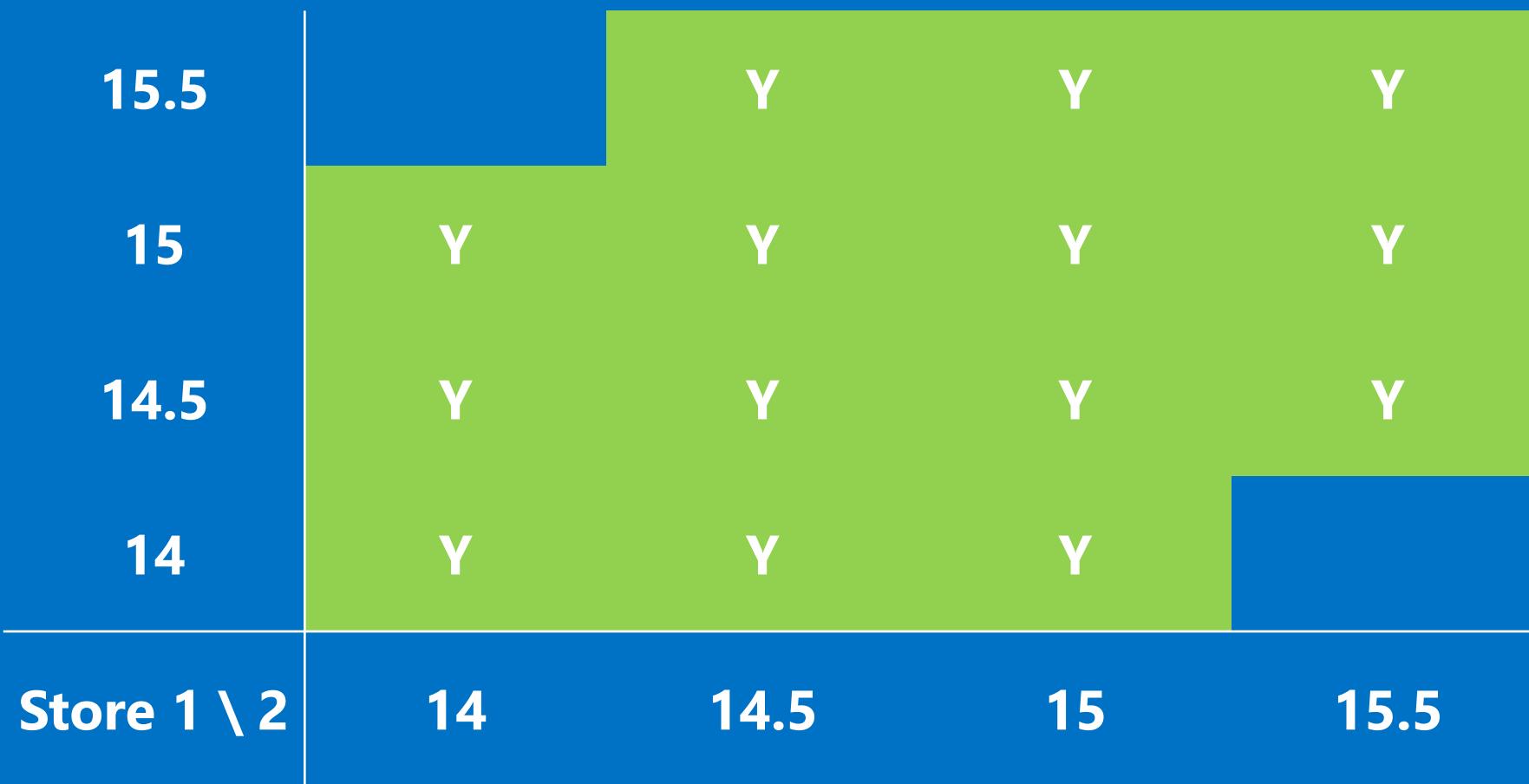
Definition

- **Estimate Price Elasticity in Business**
Identify sensitive stores and items
- Forecast Demand and Revenue
- Optimize Prices



Do I have the right price?

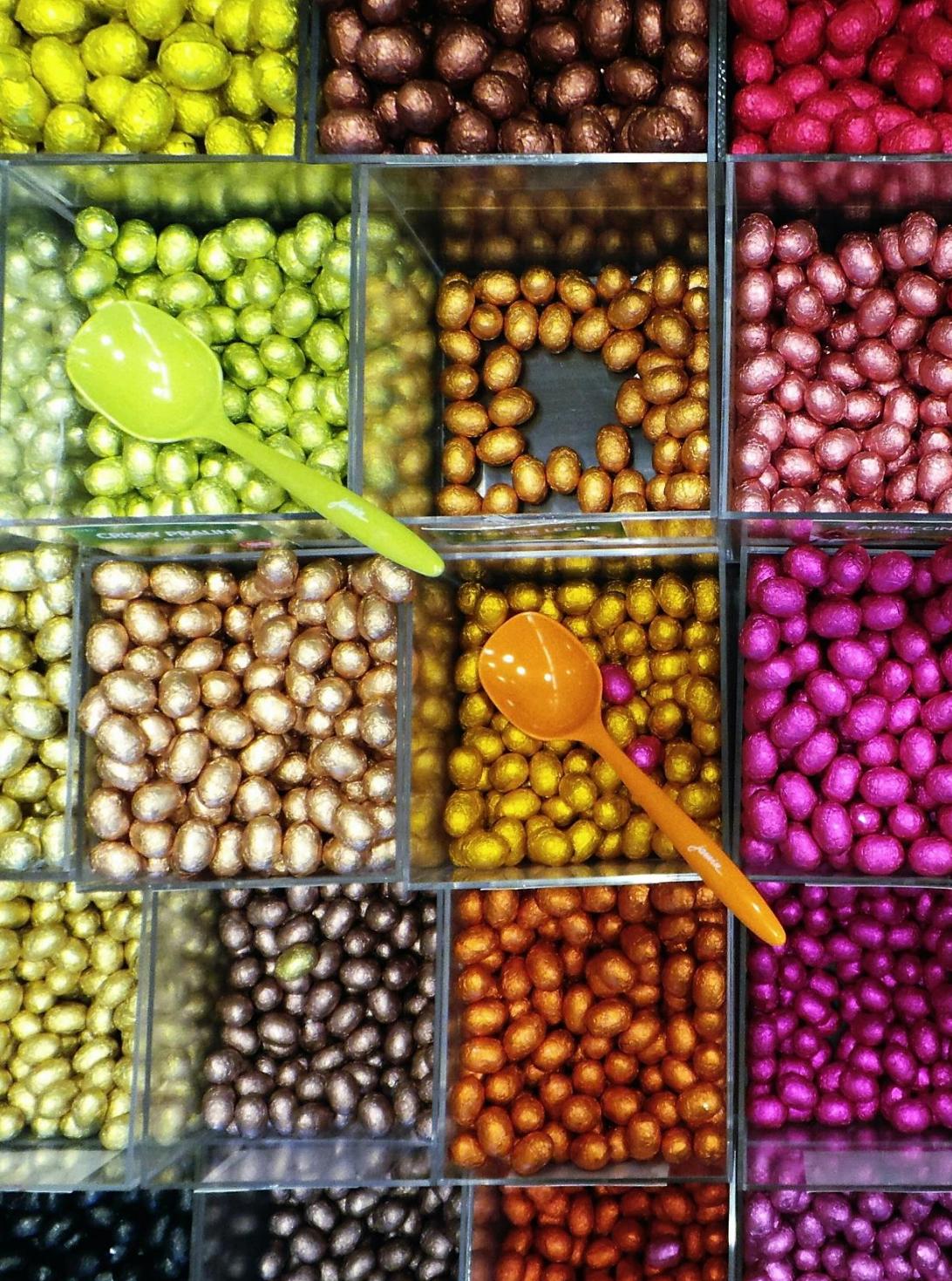
- Number of eligible price combinations is limited.



Which groups?

- What could be Cross-selled/Up-selled?
- What is frequently bought together?

[clustering] [recommendation]



[Browse all](#)[Solution Templates](#)[Experiments](#)[Machine Learning APIs](#)[Notebooks](#)[Competitions](#)[Tutorials](#)[Collections](#)

MACHINE LEARNING API

Recommendations

Microsoft • published on April 22, 2015

Description

The Recommendations API built with Microsoft Azure Machine Learning helps your customer discover items in your catalog. Customer activity in your digital store is used to recommend items and to improve conversion in your digital store.

The recommendation engine may be trained by uploading data about past customer activity or by collecting data directly from your digital store. When the customer returns to your store you will be able to feature recommended items from your catalog that may increase your conversion rate.

Microsoft Azure Machine Learning's Recommendations supports 3 common scenarios:

Frequently Bought Together (FBT) Recommendations

In this scenario the recommendations engine will recommend items that are likely to be purchased together in the same transaction with a particular item.

[Sign up ↗](#)[+ Add to Collection](#)

17234 views

[Browse all](#)[Solution Templates](#)[Experiments](#)[Machine Learning APIs](#)[Notebooks](#)[Competitions](#)[Tutorials](#)[Collections](#)**EXPERIMENT**

Frequently bought together - market basket analyses using ARULES



Martin Machac • published on December 23, 2015

Summary

Example of using Arules R library for associations mining.

This library can be used for e.g. Market Basket Analyses , Recommendations

Description

It can be used for finding Frequently bought together item-sets. This example used "single" transactions format where each data row contains TransactionID and ItemID. One transaction is on multiple records as when going through check out in a supermarket. R device port shows Item frequency plot. Data used are from publicly available data from R library (data("Groceries")). Support and confidence parameter can be entered in a Enter data manually module.

[Open in Studio](#)[+ Add to Collection](#)

Demand Forecasting

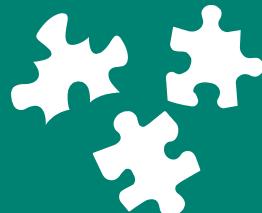


ARCACONTINENTAL



Current Situation

Current Situation



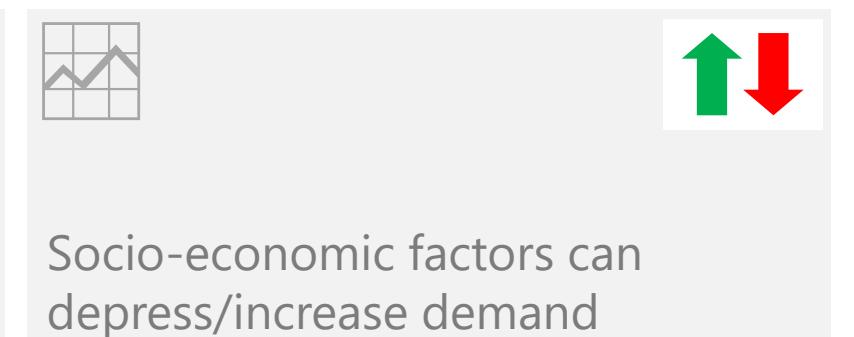
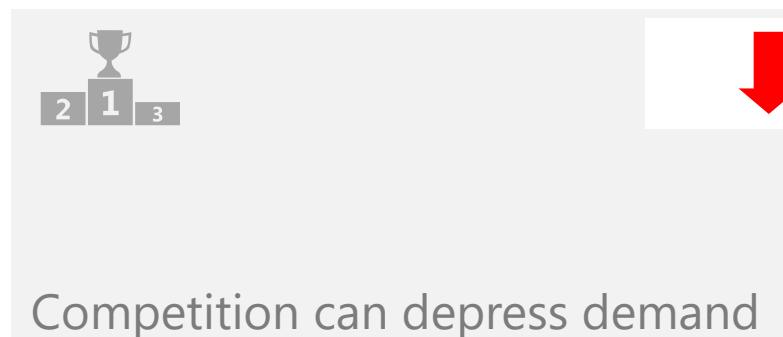
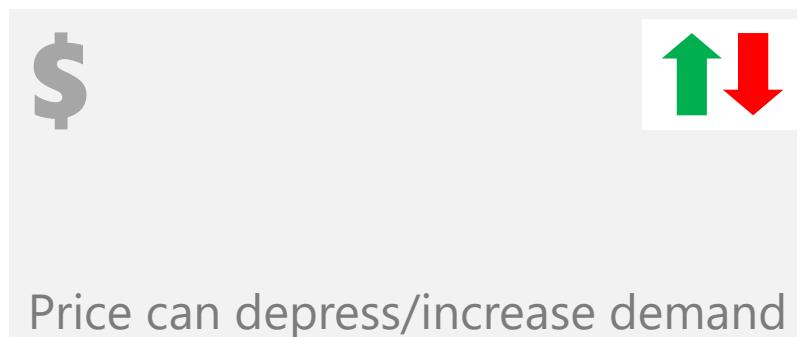
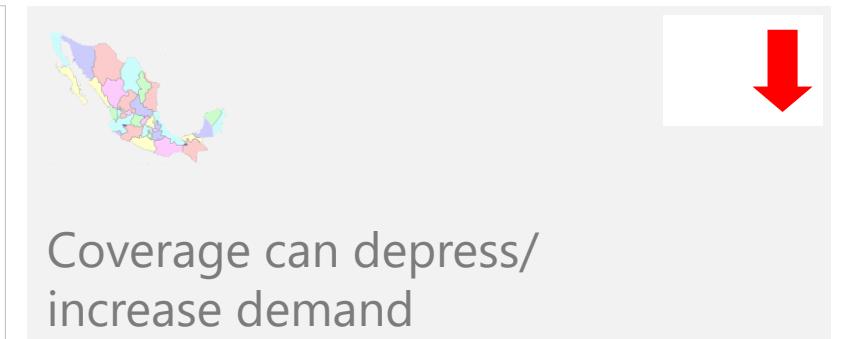
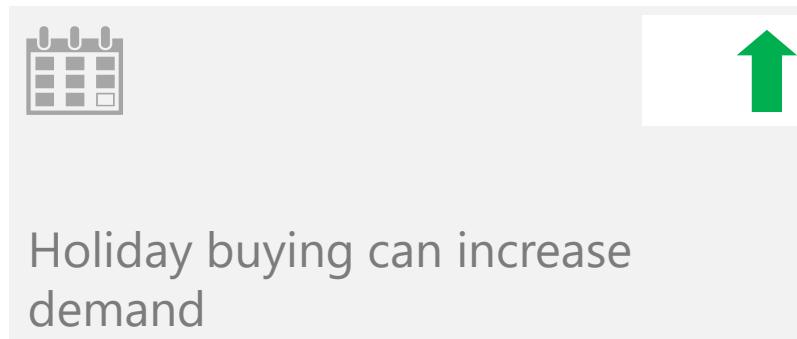
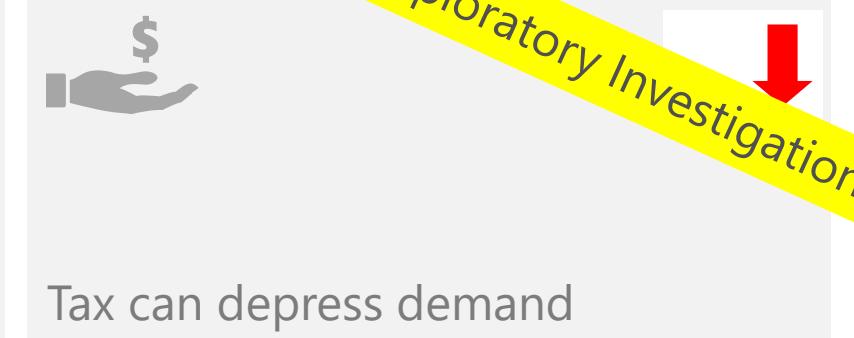
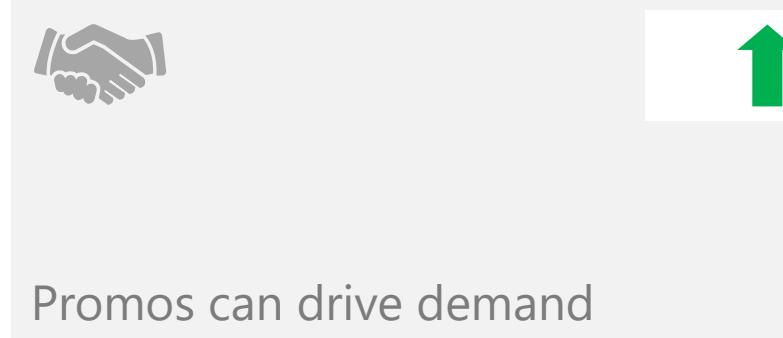
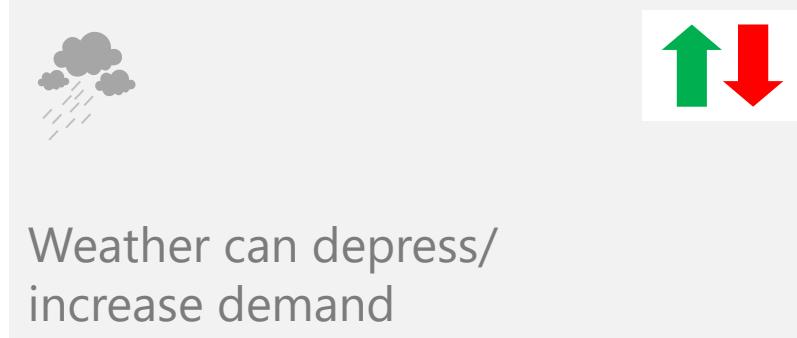
- Current demand forecasting process has limitations and lacks in its ability to explain correlations and causality
- No knowledge/capability to systematically understand business drivers and impact (e.g. promo profitability and package discounts)
- Promotions are managed in a manual fashion and with limited insight into effectiveness
- Senior leadership believes that big data and advanced analytics provide an opportunity to increase sales, grow market share and become more profitable

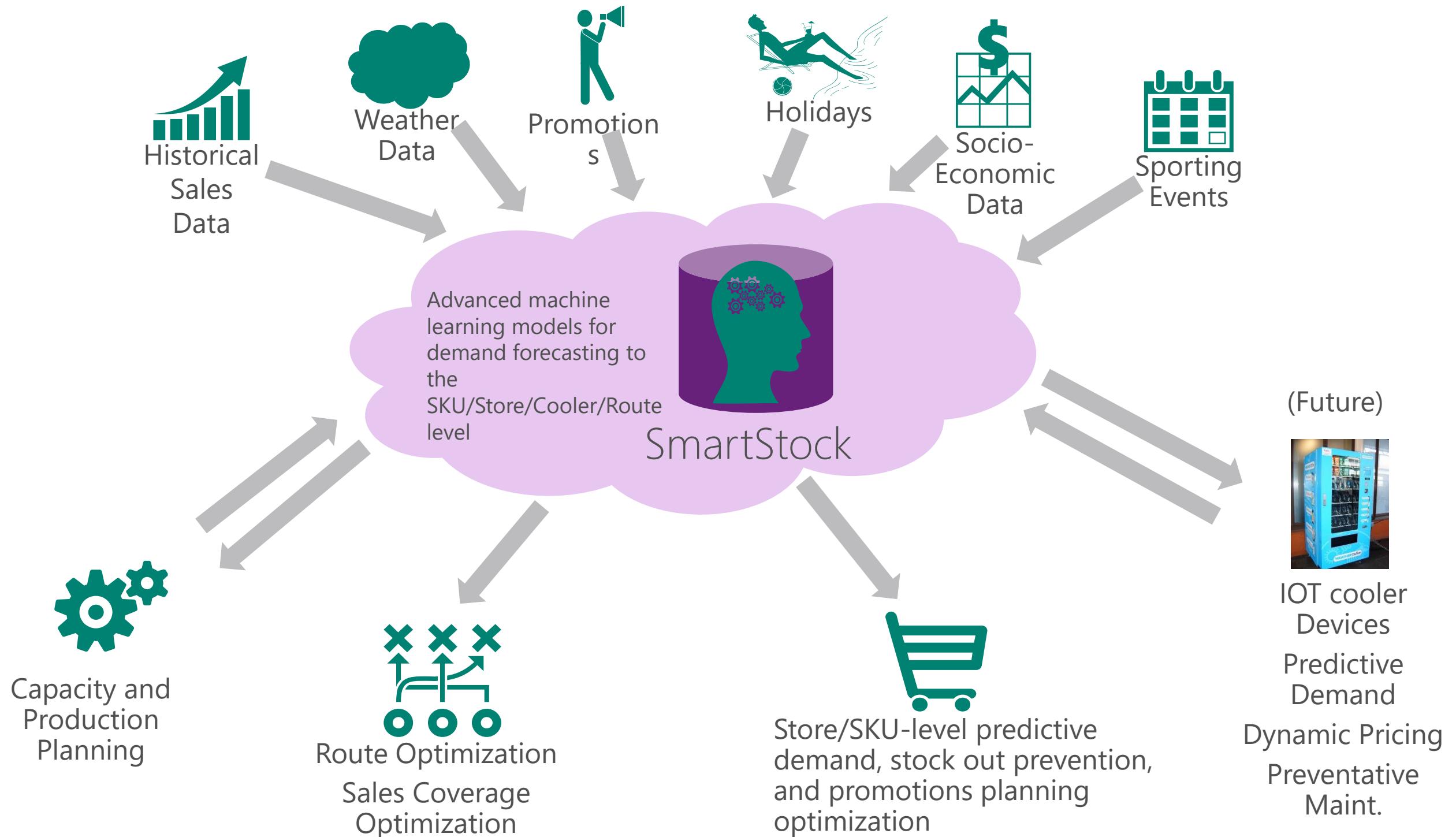
Challenges/ Risks



- Access to data outside the ERP systems
- Lack of data science resources and skill sets
- Infrastructure considerations

Typical drivers of demand for beverage sales





Regional Retail Store Beverage Sales Overview – 1

Seattle is facing sales problems

1

Sales for Northwest Territory retailer

Regional retail store beverage segment stagnating sales
management sales intuition points to higher sales but ...

Actual Sales and Delta by City

A map of the Western United States with state boundaries. Major cities are marked with colored circles: red for Seattle, teal for Portland, and blue for San Francisco. The map includes labels for British Columbia, Saskatchewan, Montana, North Dakota, South Dakota, Wyoming, Colorado, New Mexico, Arizona, Nevada, Utah, Idaho, Oregon, and California. A copyright notice at the bottom reads "© 2015 Microsoft Corporation © 2015 HERE".

Sales by City

City	Forecast Sales	Actual Sales	Delta
Boise	285.10	286.68	1.58
Las Vegas	366.10	366.30	0.20
Portland	352.60	352.96	0.36
San Francisco	512.90	514.95	2.05
Seattle	457.00	446.44	-10.56
Total	1,973.70	1,967.34	-6.36

Overall Forecast Sales and Actual Sales by Week

A line chart titled "Overall Forecast Sales and Actual Sales by Week". The y-axis ranges from 190 to 240 in increments of 10. The x-axis shows weeks from 201514 to 201522. A light blue line represents "Forecast Sales" and a dark blue line represents "Actual Sales". Both lines show a general upward trend over the period.

Juice Segment

A bar chart titled "Juice Segment" comparing "Forecast Sales" (light blue bars) and "Actual Sales" (dark blue bars) for each week from 201514 to 201522. The y-axis ranges from 0 to 100. Actual sales are consistently slightly higher than forecast sales.

Water Segment

A bar chart titled "Water Segment" comparing "Forecast Sales" (light blue bars) and "Actual Sales" (dark blue bars) for each week from 201514 to 201522. The y-axis ranges from 0 to 100. Actual sales are consistently slightly higher than forecast sales.

Soft Drinks Segment

A bar chart titled "Soft Drinks Segment" comparing "Forecast Sales" (light blue bars) and "Actual Sales" (dark blue bars) for each week from 201514 to 201522. The y-axis ranges from 0 to 80. Actual sales are consistently slightly higher than forecast sales.

Overview Sales Driver Analysis Sales Driver Impact Further Sales Improvement Conclusion +

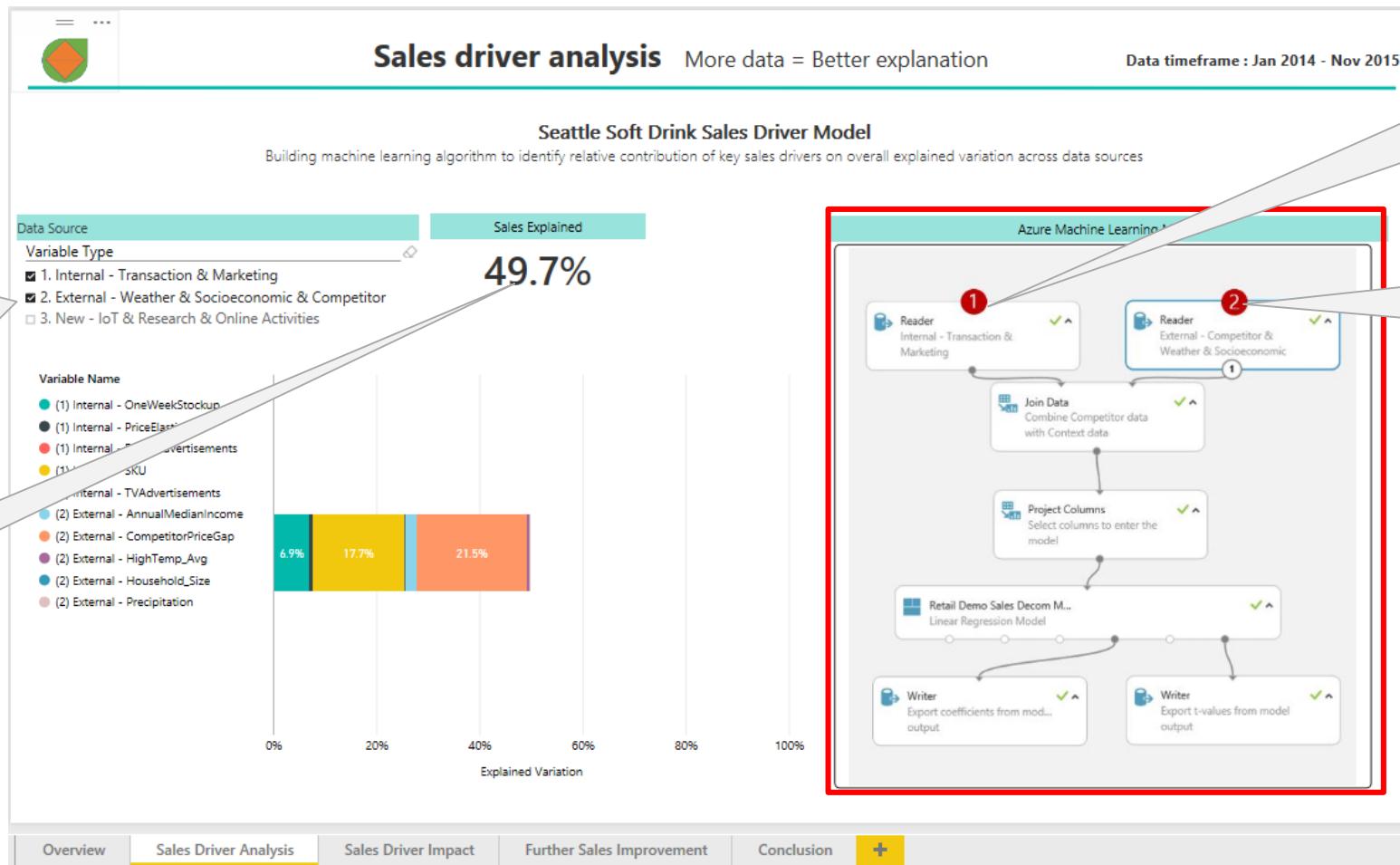
Sales Driver Analysis – 2

Add external data to and now the model accuracy is improved

3
External weather, demographic, and competitor data include variables as:

- Temperature
- Precipitation
- Household size
- Annual Income
- Competitor Price Gap

4
Variations explained improves to near 50%



1
Transaction dataset in AML experiment

2
External dataset enters the model in AML experiment

Sales Driver Analysis – 3

With IoT, research, and online activity data, we can build sales models of unprecedented power for end users

The screenshot shows the Azure Machine Learning Studio interface for the "Seattle Soft Drink Sales Driver Model". The main title is "Sales driver analysis" with the subtitle "More data = Better explanation" and the "Data timeframe : Jan 2014 - Nov 2015".

1 Transaction dataset in AML experiment: A callout points to the "Data Source" section, which lists three types of variables: Internal - Transaction & Marketing, External - Weather & Socioeconomic & Competitor, and New - IoT & Research & Online Activities. The total "Sales Explained" is 89%.

2 External dataset enters the model in AML experiment: A callout points to the "Azure Machine Learning Model" flowchart, which shows data readers for Business Context Data, Competitor Activity Data, and Consumer Behavior Data being joined together. The flowchart is highlighted with a red border.

3 IoT dataset enters the model in AML experiment: A callout points to the "Retail Demo Sales Decom M..." step in the flowchart, which is identified as a Linear Regression Model.

4 New IoT, research and online activity data include variables as: A callout points to the "Variable Name" section, which lists various variables categorized by type and source.

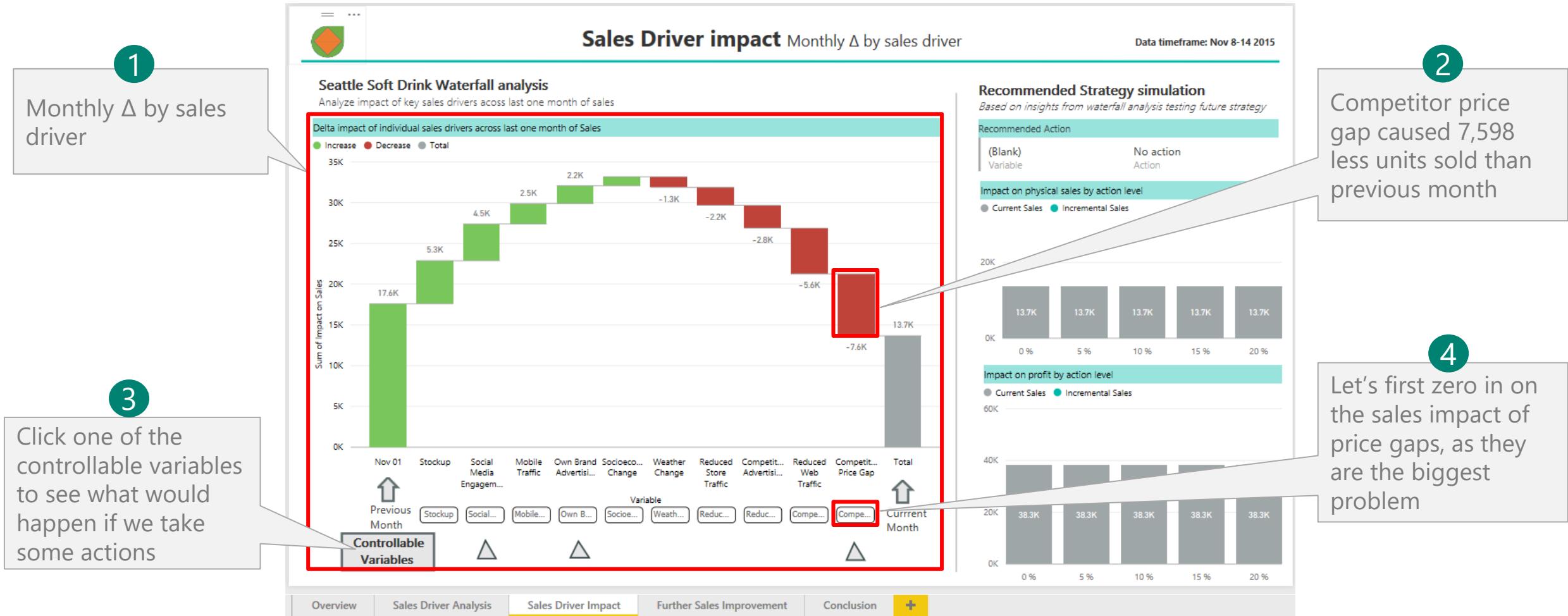
5 Variations explained improves to 89%: A callout points to the "Sales Explained" value of 89%.

Chart Data:

Variable Type	Explained Variation (%)
Internal - Transaction & Marketing	6.9%
External - Weather & Socioeconomic & Competitor	17.7%
New - IoT & Research & Online Activities	21.5%
Internal - PriceElasticity	11.0%
Internal - RadioAdvertised	15.6%
Internal - SKU	8.2%
Internal - Advertisements	0.0%
External - Household_Size	0.0%
External - Precipitation	0.0%
New - BEACON_ShelfTraffic%	0.0%
New - BEACON_StoreTraffic	0.0%
New - MobileTraffic	0.0%
New - SocialMediaTraffic	0.0%
New - SurveyResearch	0.0%
New - WebTraffic	0.0%

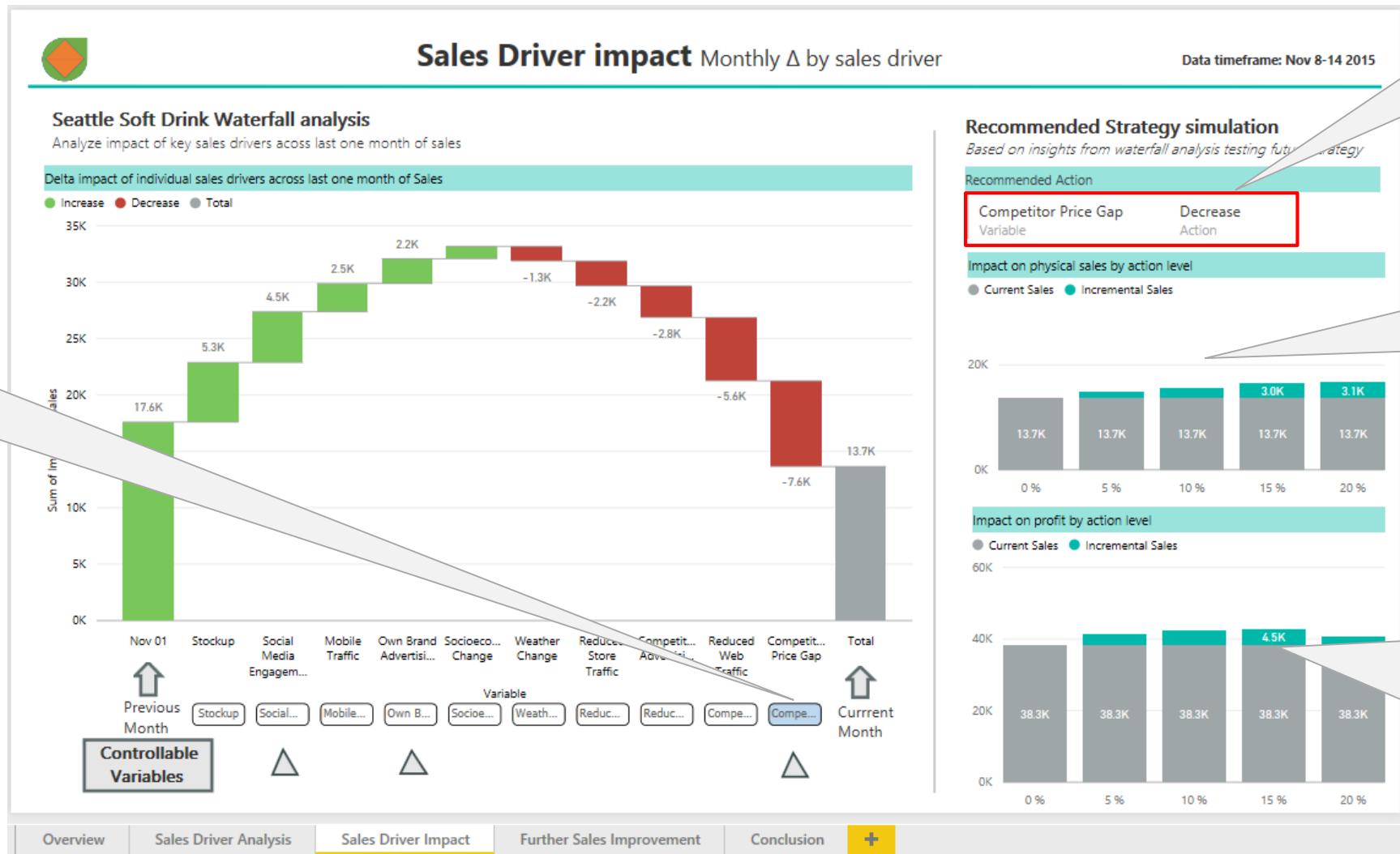
Sales Driver Impact - 1

Analyze impact of key sales drivers over the last one month



Sales Driver Impact - 2

What would be the impact on sales if I adjust my pricing?



1
Select competitor price gap as it is a controllable variable

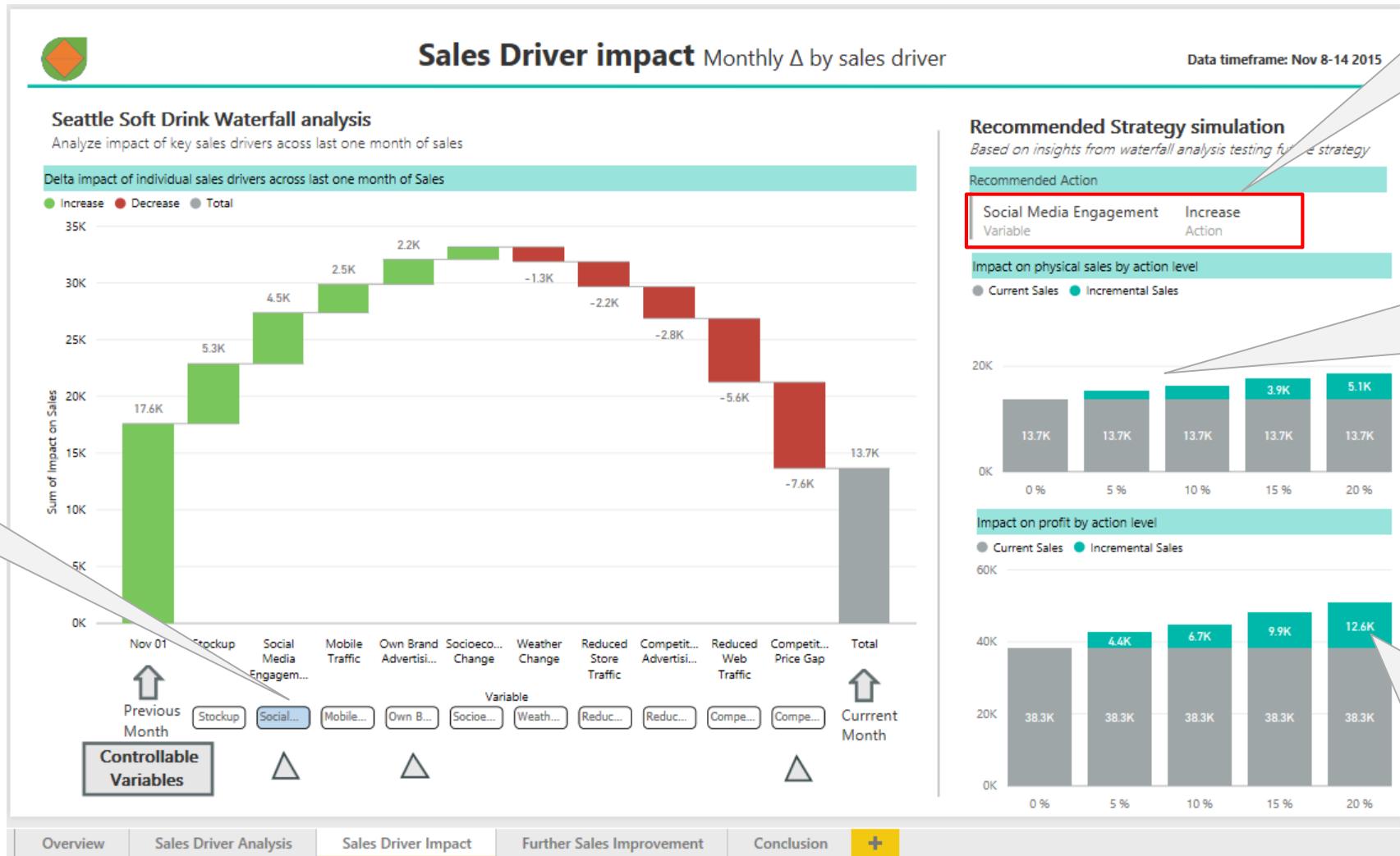
2
It would be recommended to decrease the competitor price gap

3
See the impact on physical sales if we reduce the price gap by different levels

4
See the impact on profit if we reduce the price gap by different levels. When it is reduced by 15%, we would be able to achieve 4.5K incremental profit.

Sales Driver Impact - 2

What would be the impact on sales if I adjust my pricing?



1

Select Social Media Engagement as it is a controllable variable

2

It would be recommended to increase social media engagement

3

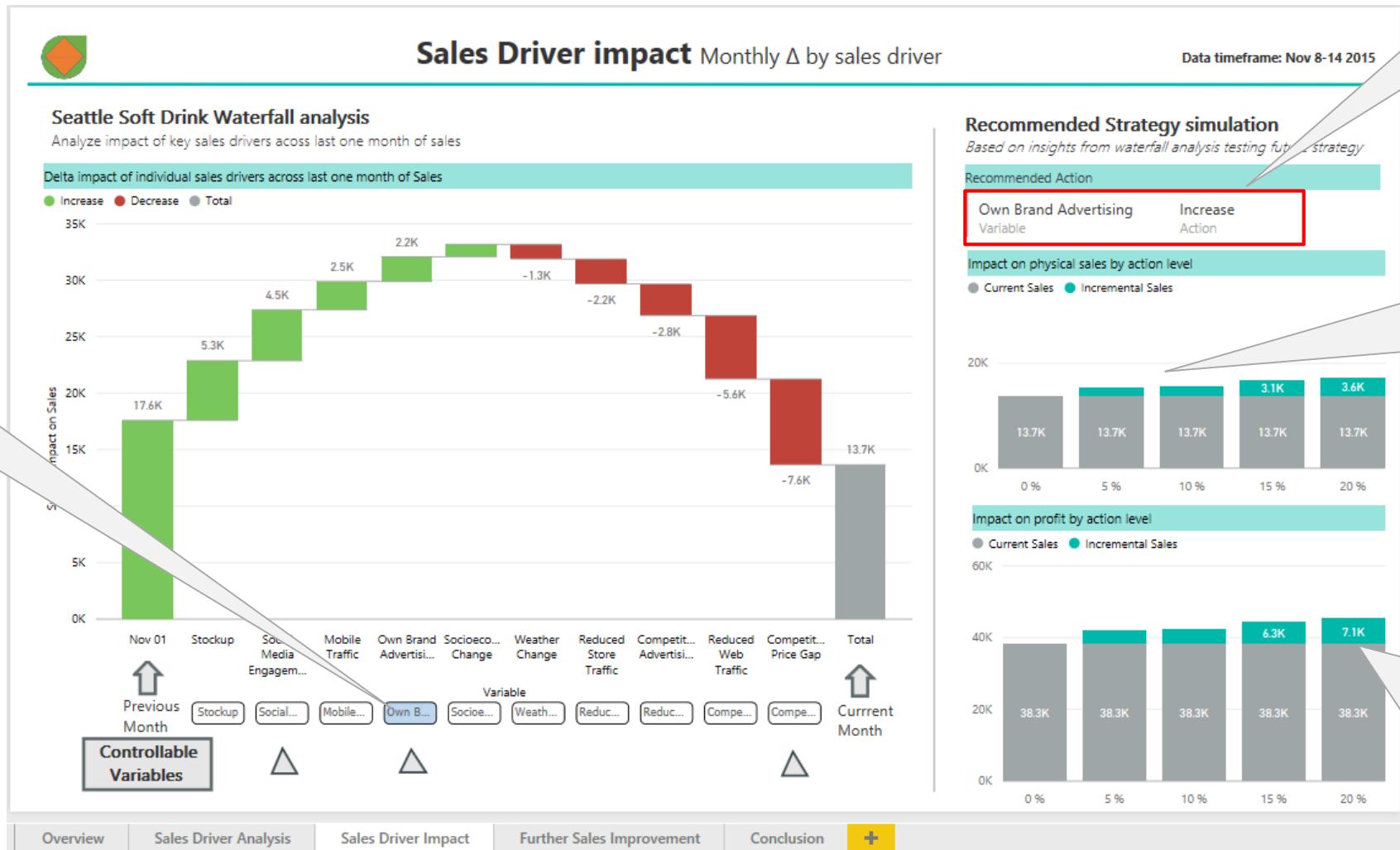
See the impact on physical sales if we increase social media engagement by different levels

4

See the impact on profit if we increase social media engagement by different levels. When it is increased by 20%, we would be able to achieve 12.6K incremental profit.

Sales Driver Impact - 2

What would be the impact on sales if I adjust my pricing?



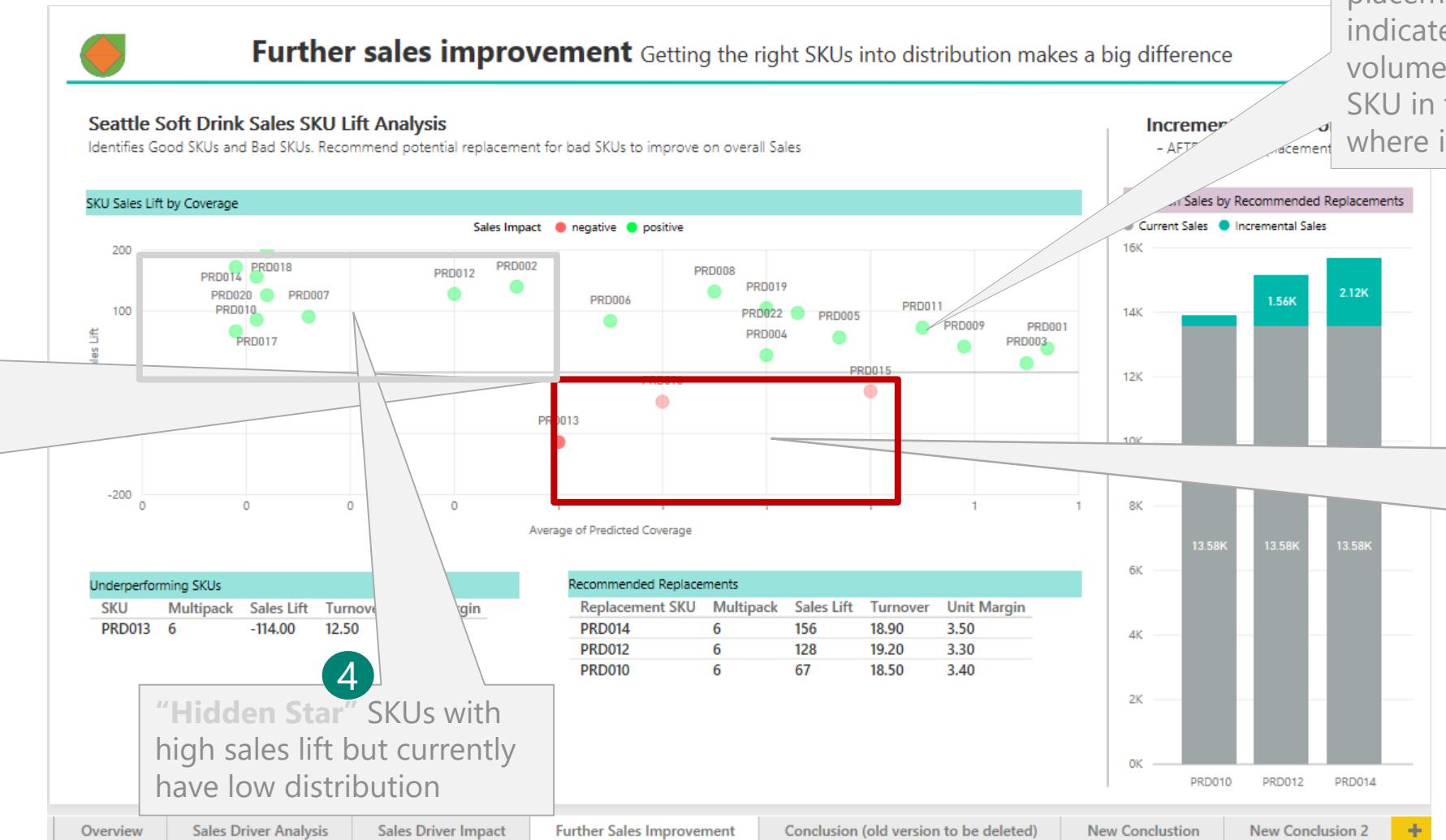
2
It would be recommended to increase our own brand advertising

3
See the impact on physical sales if we increase advertising by different levels

4
See the impact on profit if we increase advertising by different levels.
When it is increased by 20%, we would be able to achieve 7.1K incremental profit.

Further Sales Improvement - 1

Getting the right SKUs into distribution makes a big difference



1

Each dot represents a different SKU. The Y axis placement of each dot indicates the physical volume increased by each SKU in the store-weeks where it is present

2

We can use the SKU sales lift to see where we have "dog" SKUs that decrease overall sales, and where we have high potential "hidden stars" to replace them with

3

"Dog" SKUs with negative sales lifts can be replaced as they decrease total sales because of cannibalization

4

Further Sales Improvement - 2

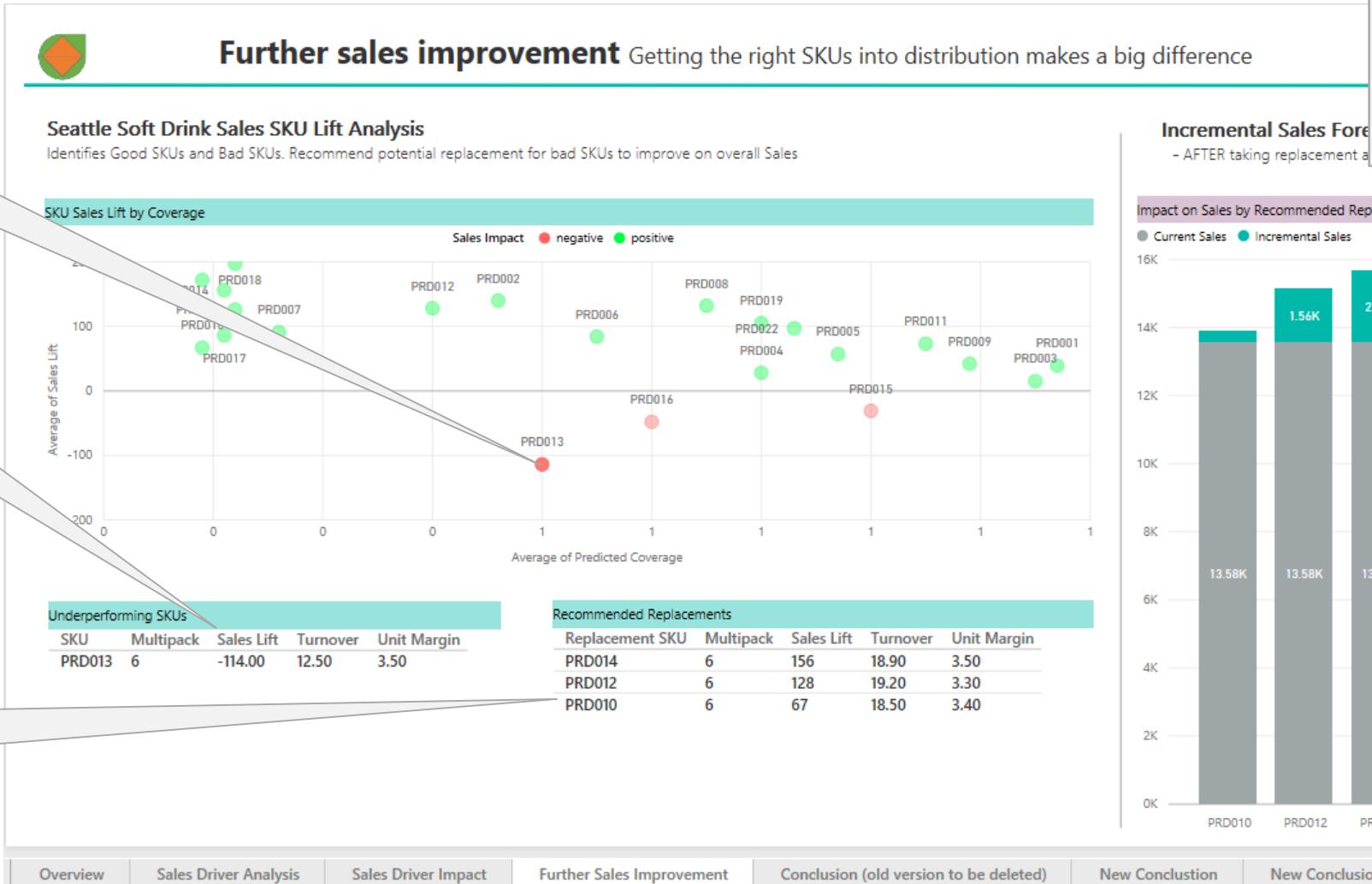
Getting the right SKUs into distribution makes a big difference

4

1
Click PRD013 as it has the lowest sales lift

2
See more details about PRD013

3
See what the recommended replacements are



We could achieve the highest incremental physical sales if replace PRD013 with PRD014

Further Sales Improvement - 2

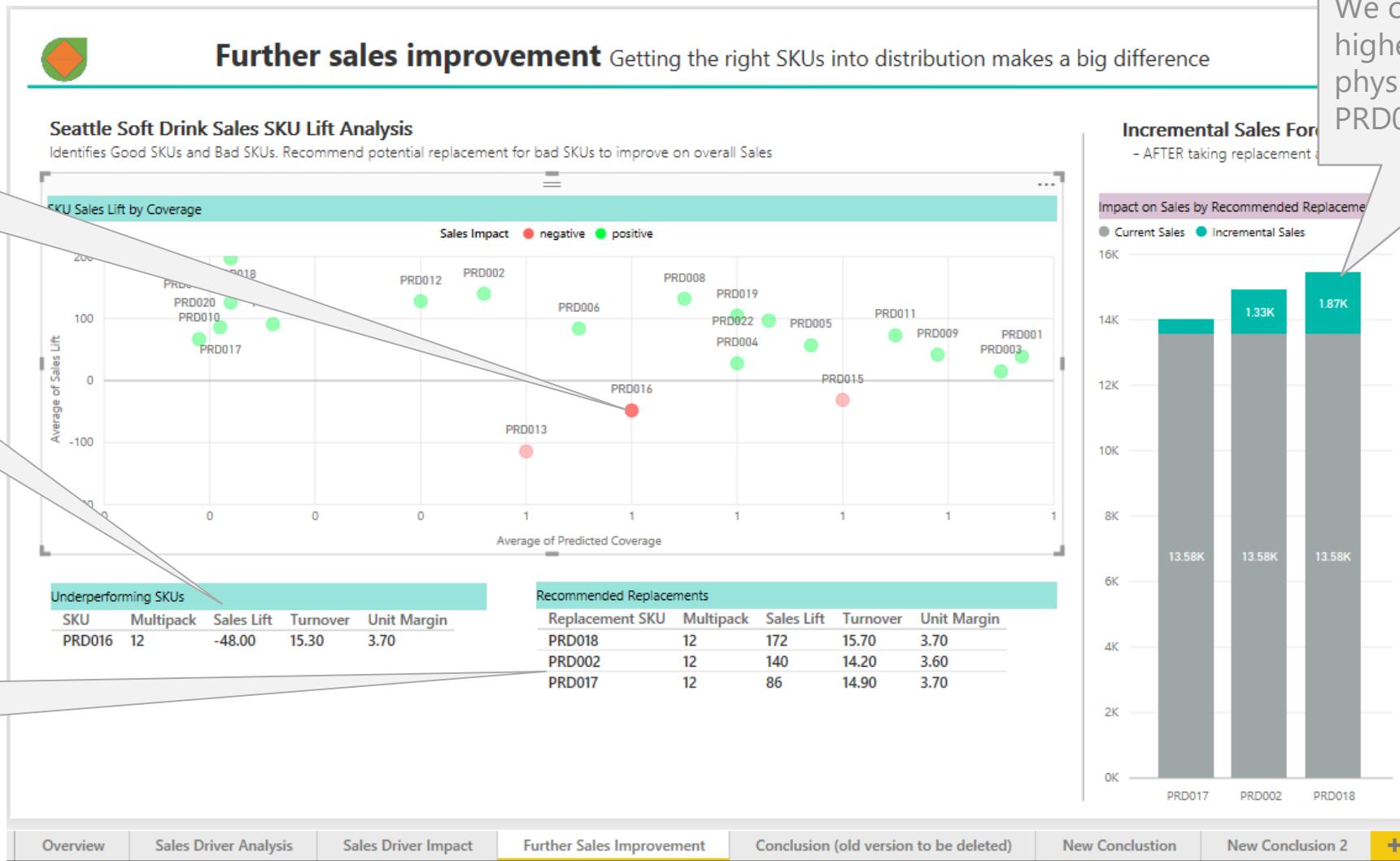
Getting the right SKUs into distribution makes a big difference

4

1
Click PRD016 as it has the second lowest sales lift

2
See more details about PRD016

3
See what the recommended replacements are



We could achieve the highest incremental physical sales if replace PRD016 with PRD018

Further Sales Improvement - 2

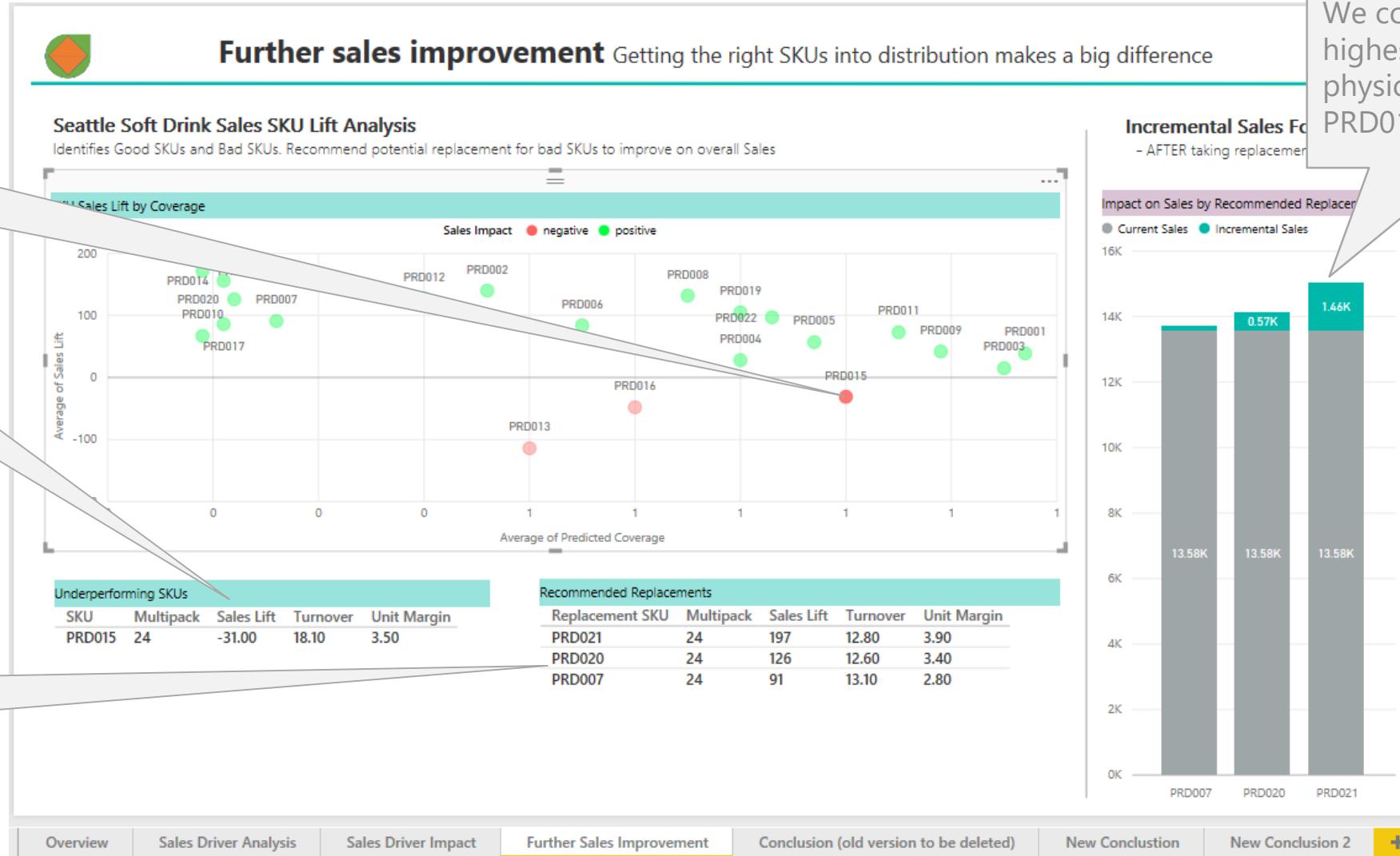
Getting the right SKUs into distribution makes a big difference

4

1
Click PRD015 as it is another "dog" SKU

2
See more details about PRD015

3
See what the recommended replacements are



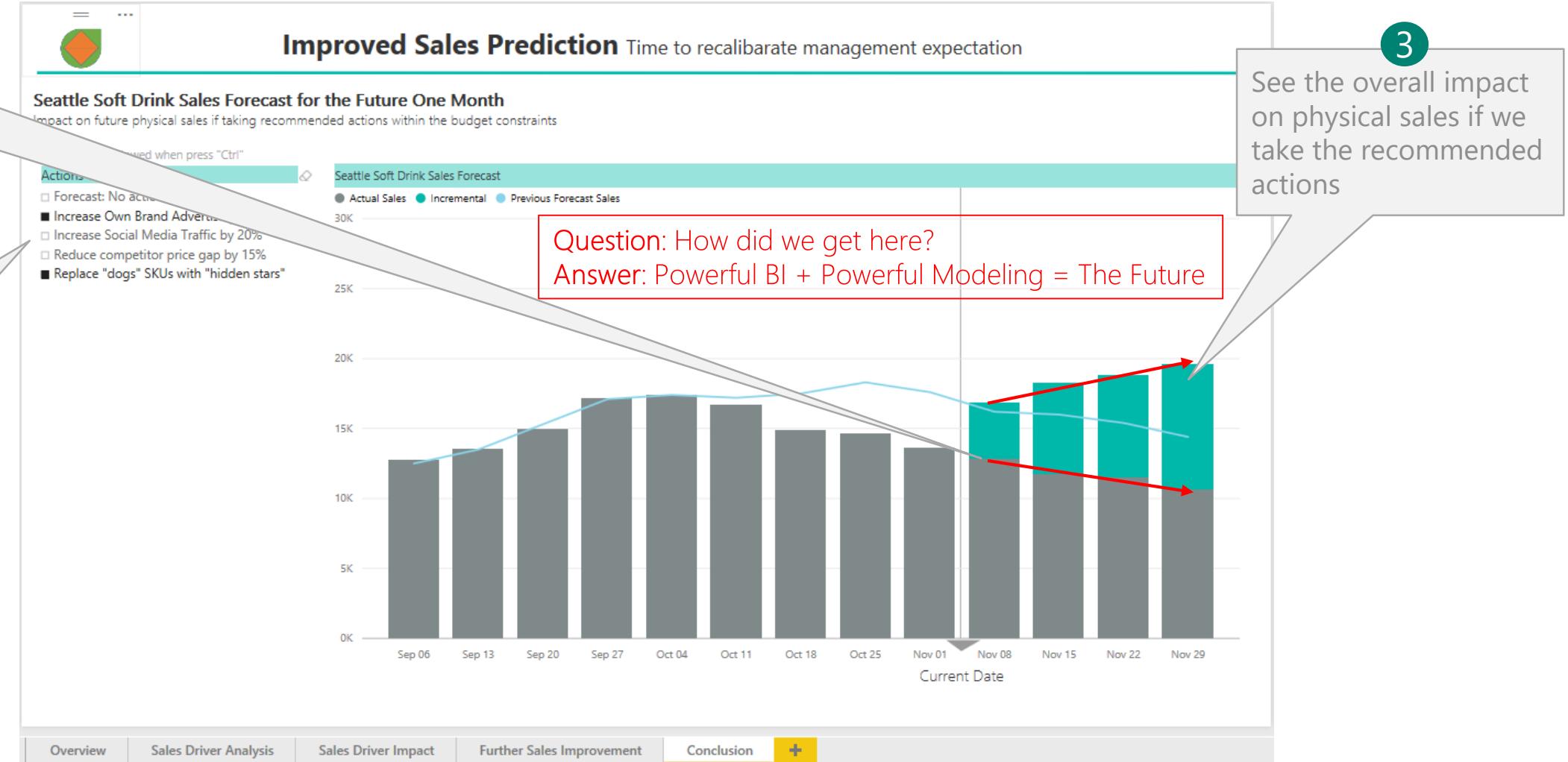
We could achieve the highest incremental physical sales if replace PRD015 with PRD021

Conclusion

Sales improved and it is time to recalibrate management expectation

1
The sales will continue sliding down if no actions are taken

2
Within the budget constraints, select the recommended actions



Delight your customers with personalized shopping experiences



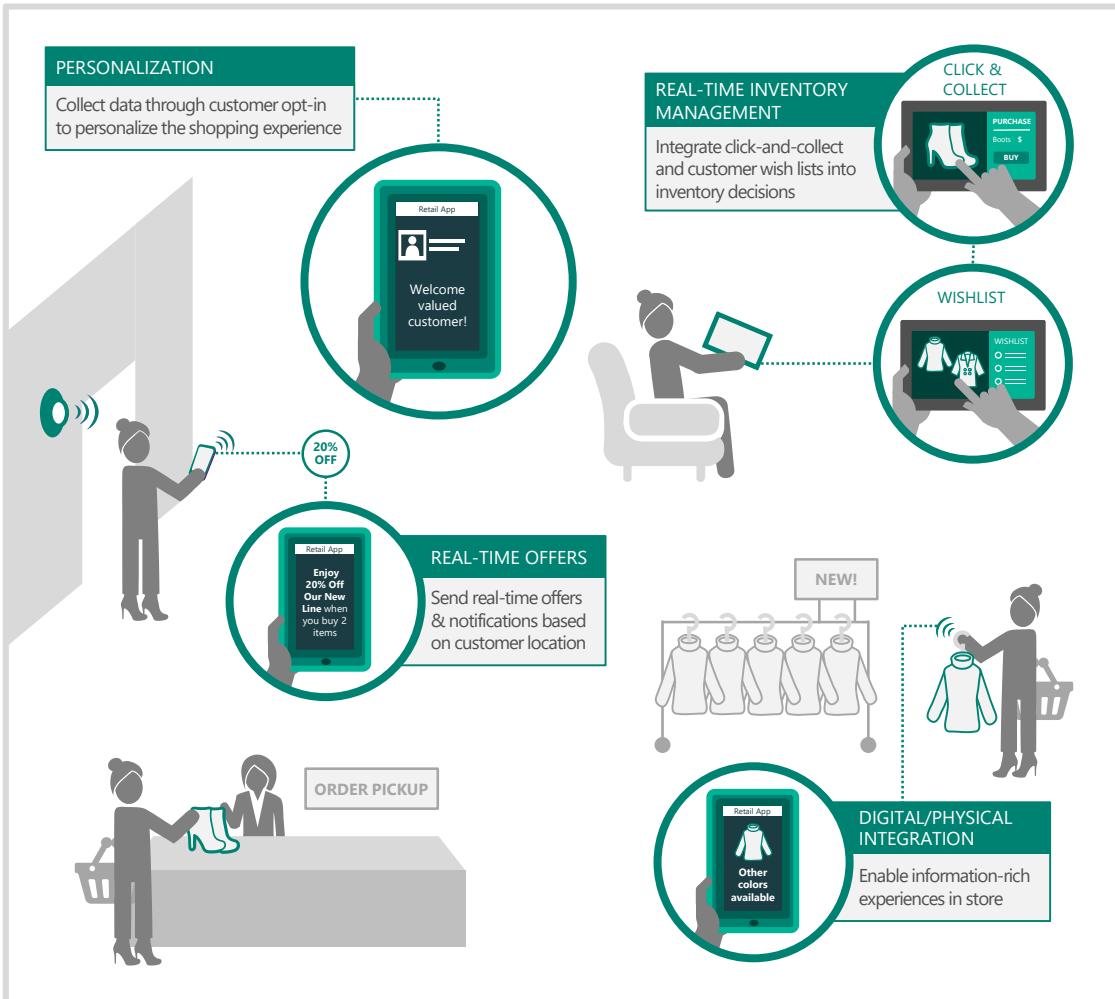
VP of Stores



CMO



Delight your customers with personalized shopping experiences



Connect with customers at the right time, right place with the right offers

by gathering data from various points of customer contact to understand customer behaviors and respond with relevant offers

Predict what customers want before they tell you

using predictive analytics solutions to create relevant cross-sell and upsell opportunities throughout the customer journey

Deliver engaging in-store experiences

by combining technologies that give customers rich information when they shop online with the in-store experiences of trying out products and engaging with informed sales associates

Harness the power of your data to gain a competitive edge



Merchandising Director



COO



VP of Stores



CMO

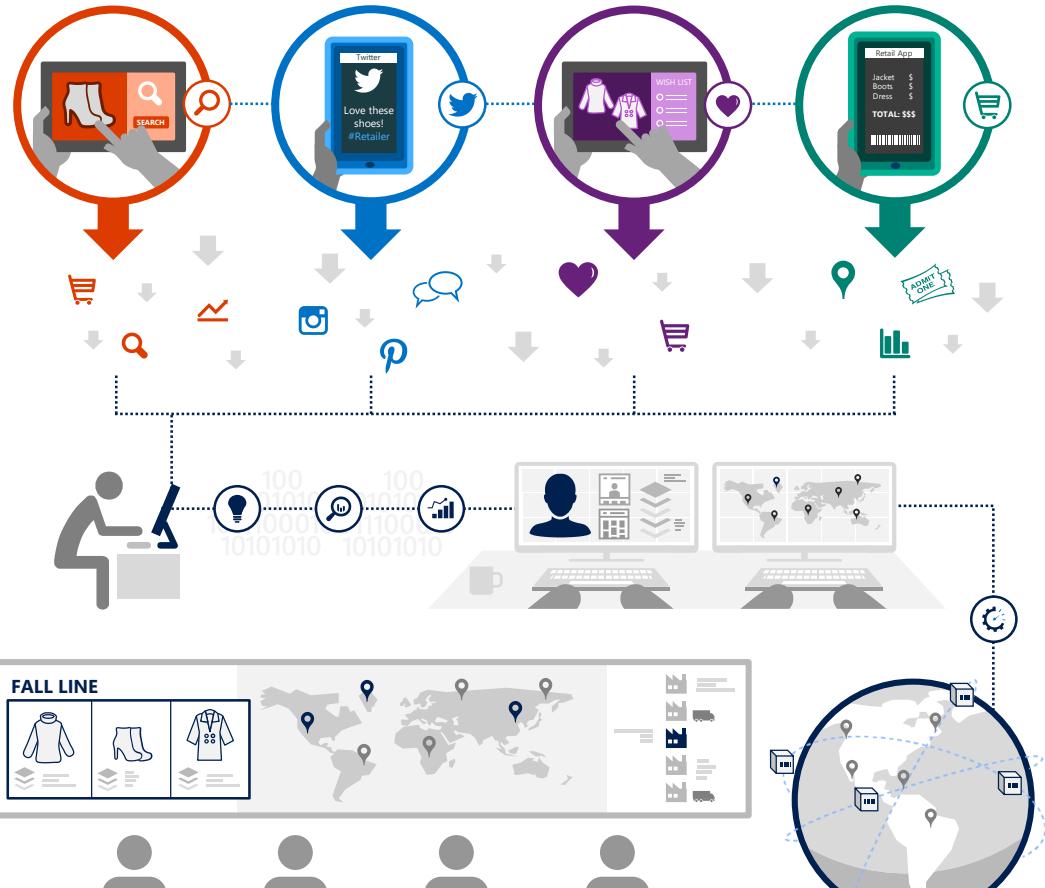


CIO

Harness the power of your data to gain a competitive edge



\$94B data opportunity for retail¹



Become an insight-driven organization
to differentiate from the competition

by learning from the valuable data you already have—every device, sensor, upload, tweet, purchase, shipment and keystroke

Evolve from reactive to proactive to help
build, monitor and improve your brand

through advanced visibility into what your customers are saying
and the ability to offer innovative customer experiences

Keep pace with rapid change and innovate
to give customers what they want

by leveraging advanced analytics to transform your data
into intelligent action

Enjoy data-driven retail with Microsoft



00110100110
0110110101011
00110100110
0110110101011
00110100110
0110110101011



00110100110
0110110101011
00110100110
0110110101011
00110100110
0110110101011



Optimize your forecasting and react faster

Modernize your supply chain with analytics-driven operations

Empower your workforce to provide a differentiated customer experience

Delight your customers with personalized shopping experiences

Harness the power of your data to gain a competitive edge



© 2013 Microsoft Corporation. All rights reserved. Microsoft, Windows, Windows Vista and other product names are or may be registered trademarks and/or trademarks in the U.S. and/or other countries.
The information herein is for informational purposes only and represents the current view of Microsoft Corporation as of the date of this presentation. Because Microsoft must respond to changing market conditions, it should not be interpreted to be a commitment on the part of Microsoft, and Microsoft cannot guarantee the accuracy of any information provided after the date of this presentation. MICROSOFT MAKES NO WARRANTIES, EXPRESS, IMPLIED OR STATUTORY, AS TO THE INFORMATION IN THIS PRESENTATION.