Final Project

Group 3. Presentation for the board of directors.



Data for the next generation store

How to bring value to the Company through Data Science.



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Business insights and self-service dashboard.



Clustering for understanding product cycles.



Predictions for sales.



Replenishment model. ML Ops Roll out plan, Deployment Strategy.

Introduction Data source and information available. Objectives of the project.

Available information



Sales, calendar and prices for years 2011 to 2016.



Information from 10 stores across 3 regions: New York, Boston and Philadelphia.

Objectives



Go from global trends to understand the angles of the business.

2

Achieve a deeper understanding on how our sales behave. 3

Understand the products similarities, cycles and tendencies.

4

Build an accessible data repository with meaningful insights available for all our stack holders



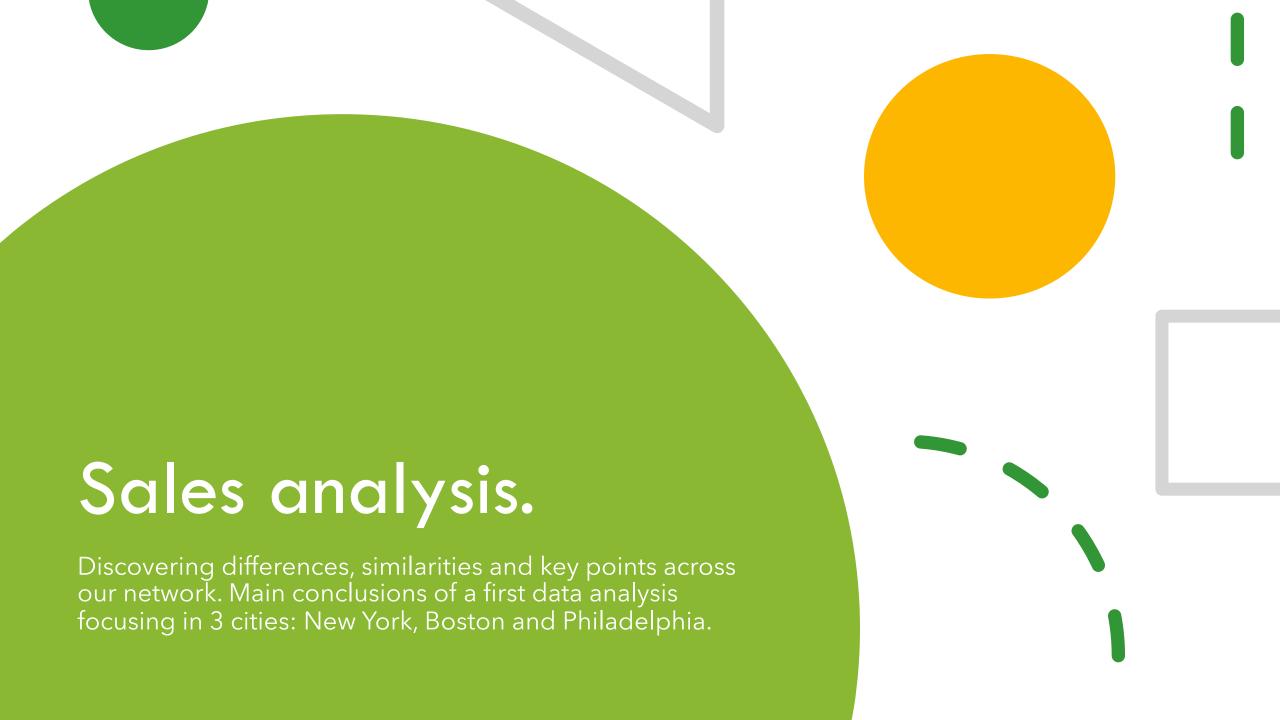
Use our past data to predict future sales.



Propose a data-based Machine learning project implantation to optimize shop replenishment.

This is just the starting point of a journey to discover how data science can help us improving and optimizing our results.





Business insights – first level.

A separate presentation has been prepared for showing the results of the first data analysis in a very detailed way, and was already discussed in a previous meeting.

In any case, here we are just summarizing the key aspects of this first approach as a starting point of the rest of the project.



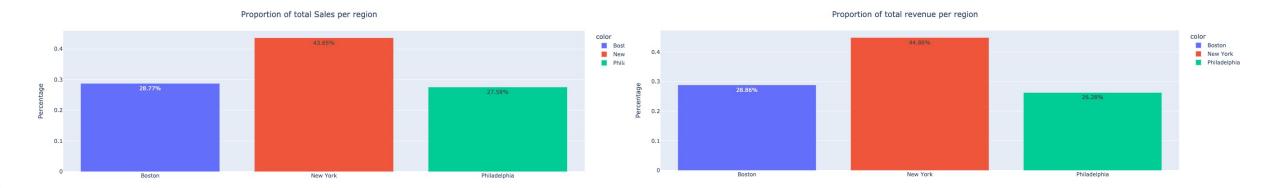


Regions and shops

Units sold and revenue per region (%)

Distribution of sales (units) per region

Distribution of revenue (\$) per region



We checked that the proportion of total sales and items sold are aligned, meaning that the revenue of the business is stable across regions. We also saw a slightly difference in the New York and Philadelphia percentages, meaning that same number of sales in NY and PH have a slightly higher revenue in NY.

As we discussed, New York accounts for the 43% of the sales of the three areas.



Sales per store in each region



Sales per store in each region (units)

Considering NY as a key territory, we all agreed that it is clear how Tribeca is pushing up the sales of the NY area, being Greenwich_Village the best 2nd shop, Harlem an average store and Brooklyn the one with the lower sales number across the three regions. **Tribeca is a key store**.



Revenue per store



Sales per store (\$)

There is an interesting finding when comparing the sales per item and revenue across stores. As we have seen, some of our regions make a higher revenue with less sales (and others make a smaller revenue with more sales). We cannot affirm that the first ones are more profitable stores since we do not have enough information (purchase price, COL...)



Sales per store



Yorktown, Queen
Village and
Midtown Village
are our shops in PH.
Being Yorktown and
Queen Village the
4th and 5th stores by
items sold, these
are the 5th and 7th
by revenue.

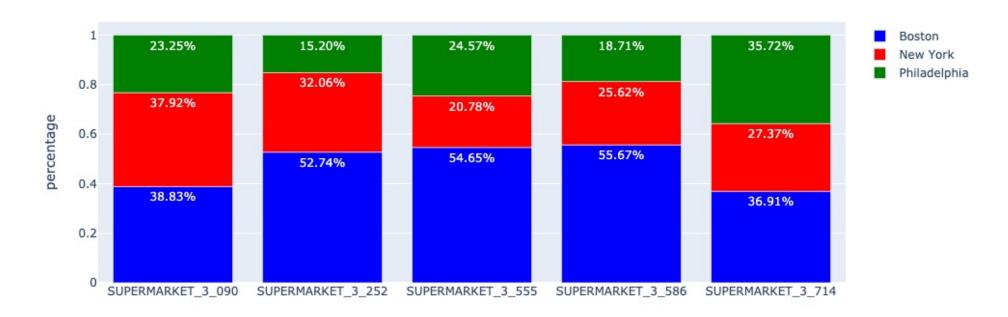
Revenue per store





Supermarket categories and products

5 most popular items' sales proportion per region, compared to total sales distribution



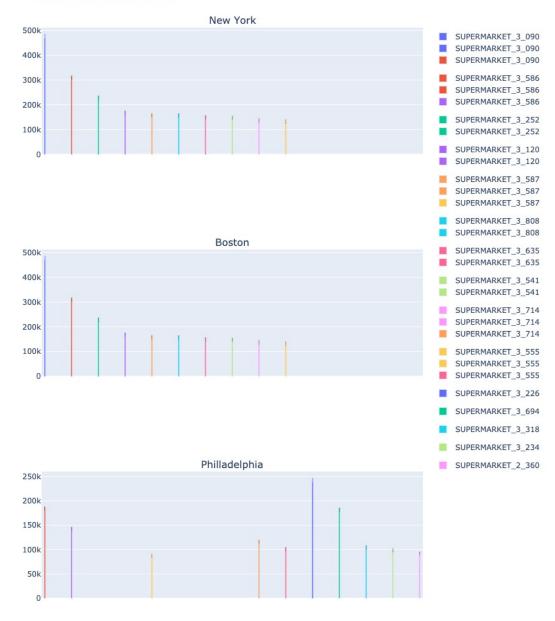
Item sales % per region

When considering the top 5 most popular products, we saw how they were not equally sold across the different regions.

Some insights: It is significant that the sales of 555 are percentually higher in Philadelphia than in NY. 714 has almost the same weight in Philadelphia than in NY.



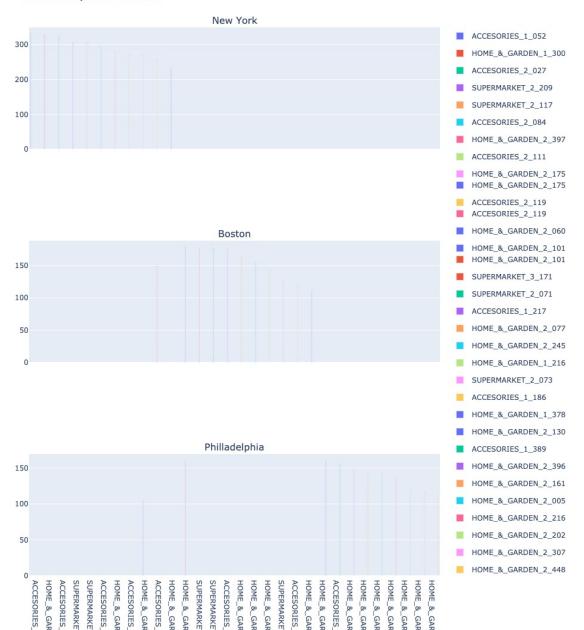
Most Popular items



Despite not being a very aesthetic graph, it allowed us to visually see how most popular items vary across regions.

We can also see how Boston and New York regions are more alike than Philadelphia, in terms of which of products are more sold.

least Popular items



This format of graph showed again in a very visual way the differences between the top 10 less sold products across regions.

Improvement areas

- We could only access to a limited part of the data. Accessing the company's database would help us evaluate possible optimizations in the process of data cleaning and preparation and identify additional potentially useful information.
- Having additional information, like the commercial name of the items, would had helped us in our analysis. Data is powerful, but understandable human context is necessary for a complete analysis. Purchase price would had helped us studying profitability.



Self service Reporting and dashboards

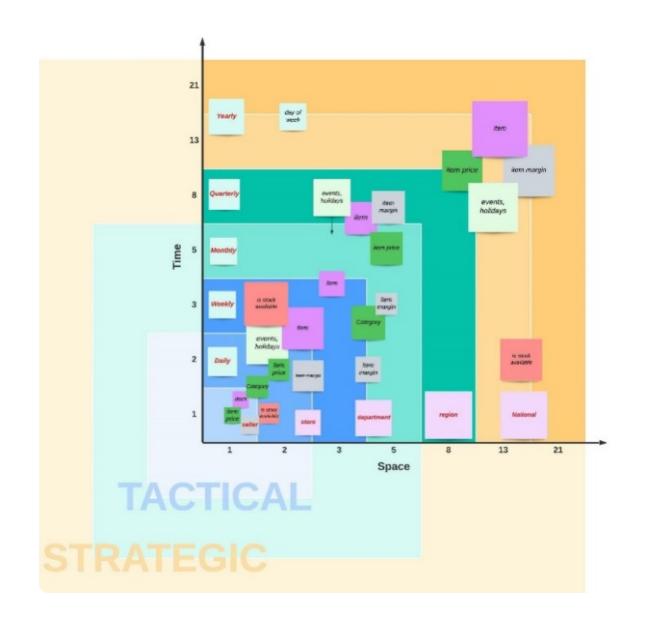
Bl solution implementation

For data analysis to be useful within an organization, it needs to be accessible to all stakeholders. The steps toward a data driven decision company must include an easy and powerful way to access the available information.

<u>Data Compositions</u> and Self Service Strategy

- Key results measures:
 - Revenue
 - Items sold
- Available Dashboards revolve around Purpose and Audience
- Relevance of data can be influenced by the combination of 3
 Main factors:
 - **Time :** Date, Week, Month, Quarter, Year
 - Space: Store, Department, Region, Country
 - Matter: stock_available, id, item, category, price

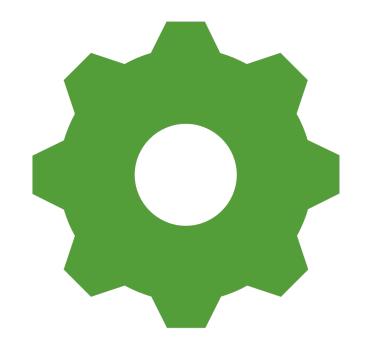




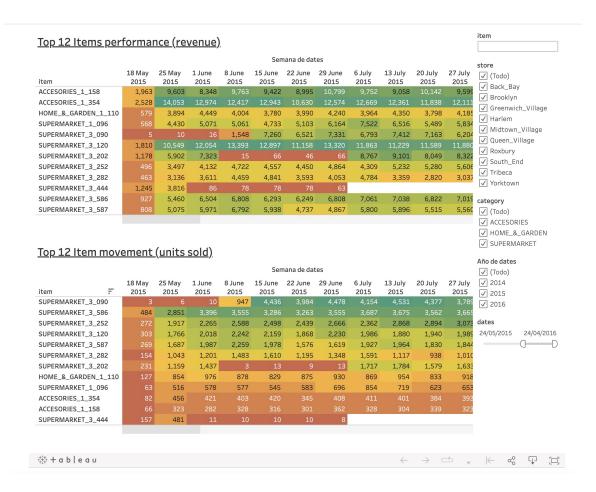
Reports matrix

In this matrix we can see how we need to go from the most **tactic shop daily** reports, to the ones used **strategically** each **year** to review margin and prices of the business.

We proposed Tableau as BI tool and shared with you its potential by creating some dashboards with the available information.







Top 12 performance

This dashboard can lead us to conclusions like:

- -Top 12 items vary over different time ranges.
- -Different stores have different top 12 items.
- -Specific products may start and stop selling at a given time.
- -There is high seasonality with some products: they may be top sellers at one point and be at the bottom at some other.
- -There are some products that were popular at a given time but are not selling any more.



region Sales Trends by Store (Revenue) ✓ Boston ✓ New York ✓ Philadelphi. ✓ (Todo) ✓ Back_Bay ✓ Brooklyn 120K ✓ Greenwich_Village ✓ Midtown_Village ✓ Queen_Village ✓ Roxbury ✓ South_End Leader Board Greenwich_Village Tribeca Back_Bay 11,760,972 Brooklyn 2,013,616 Yorktown Greenwich_Village 13,934,943 Midtown Village Roxbury 10,614,240 2.705.376 Midtown Village 10,399,570 2.862.559 Back Bay Queen_Village 2,693,424 9,088,234 Queen_Villag Roxbury South_End Tribeca 19.686.679 3,557,537 Brooklyn Yorktown 12,231,558 ✓ SUPERMARKET

Sales by store (revenue)

This dashboard:

Shows Top 12 items and how they vary over different time ranges and stores.

It allows to interpret that specific products may start and stop selling at any given time.

Also that there is high seasonality with the different products, some products may be top sellers at one point and be at the bottom at some other.



Example of dashboard insights:

<u>Unit Sales Trends by Day of Week | Tableau Public Date Range:</u>

24/05/2015 - 04-24-2016

Tops **Revenue Sales** occur from Friday to Monday.

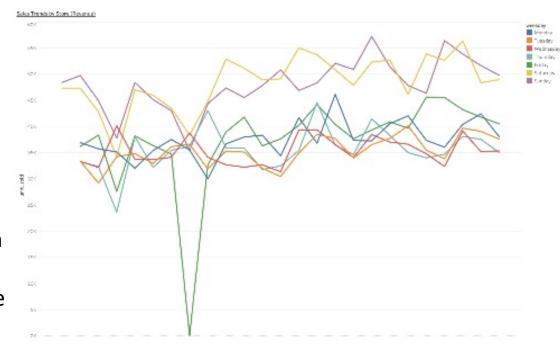
Around 650.000 USD was earned on all the Sundays versus 462.000 USD on all Wednesdays of the selected date range.

Average **revenue** across all stores on Sundays is 132 USD compared to lowest average of 97 USD on Wednesdays.

Around 147.000 **units** were sold on all the Sundays versus 100.000 **units** were sold on all Wednesdays of the selected date range.

An average of 30 units were sold on Sundays versus 21 units sold on Tuesdays and Wednesdays

Saturday is the peak day for Roxbury, Yorktown and Midtown Village Top Days over time can spike up and down, this can significantly be seen during holidays such as Thanksgiving, Christmas and New Years





Link	Description	Possible applications
Global Sales by Day of the week Tableau Public	Actual Average of Revenue sales by Day of the week compared against the forecasted average per day of week.	Weekly Tactical operational management benchmarking across stores and regions Target setting
Global Revenue and Unit Sales predictions Tableau Public	Global Revenue predictions. Global Unit Sales predictions .	Strategic Global forecasting Top-Down goal setting Global budget and stock procurement allocation
Revenue trends by Store Tableau Public	This shows store trends and comparison of store performance over selected periods of time.	Store sales performance management Trend analysis Sales step goals and kpi's
Top 12 Items Performance Tableau Public	-Top 12 items vary over different time ranges -Different stores have different top 12 items -Specific products may start and stop at any given time -There is high seasonality with the different products, some products may be top sellers at one point and be at the bottom as some	Sales bundles for items that are likely to sell together Sales campaigns for items that have high affluence to seasons or events
Top and Bottom revenue earners by Store Tableau Public	Shows total revenue and unit sold of Top 10 and Bottom 10 items by Store You can select different time periods to see change in top and bottom items and break this down by store	store product performance management operational sales / mktg management customer insights top / bottom by item
Top and Bottom Items (Revenue) by Region Tableau Public	Shows total revenue and unit sold of Top 10 and Bottom 10 items by region You can select different time periods to see change in top and bottom items and break this down by store	regional product performance management operational sales / mktg management customer insights top / bottom by item
Unit Sales Trends by Day of Week Tableau Public	Shows Trends over time of Unit Sales per day of the week	Evaluation. Model evaluation to see if day of the week campaigns are still relevant for both Stock replenishment and per store.
Global Units Sales Dashboard Tableau Public	This Dashboard shows different reports representing actual unit sales values over different time breakdowns.	Evaluation of Inventory management against unit sales.



Task 2 - Clustering

How identifying similarities and grouping products can help marketing and store management.

Clustering: grouping products by its behaviour.

- The clustering part is aiming at identifying products that behave similarly.
- The data from the **Tribeca** store (most selling store) were used to create the clusters.
- Clustering features created are **frequency** (total number of sold products per item) and **recency** (days since last purchase).
- The cluster model has been applied to the rest of the stores and their results are also available.



Cluster segmentation: Log transformed features.

2D Cluster PCA Plot

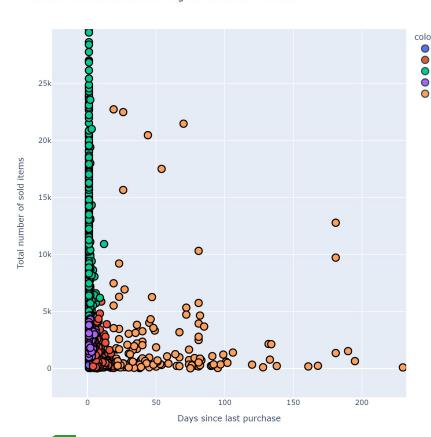
Cluster
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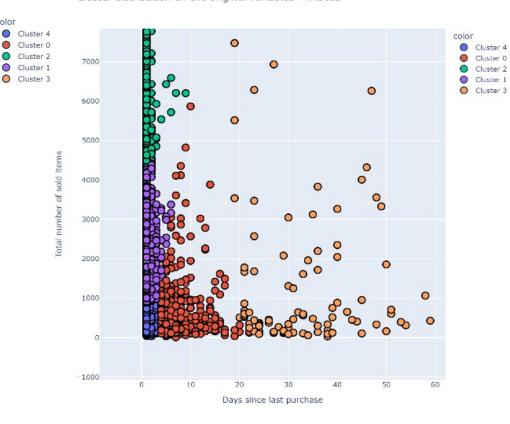


Cluster segmentation: Original variables

Cluster distribution on the original variables - Tribeca







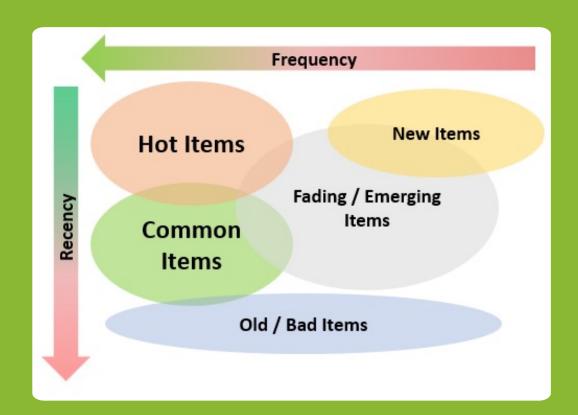
The plot on the right is a zoomed area of the left plot.

These results can be explored on the following dashboard:

<u>Item Clusters | Tableau</u> <u>Public</u>



Cluster interpretation



Cluster interpretation:

Cluster 0 - Transition Items - Fading or emerging products: Medium recency and a wide range in frequency: they could be emerging products (lower-left part of the cluster) or fading products (upper-right) part of the cluster.

Cluster 1 - Common Items: Cluster with medium frequency and low recency: these are common products, should include most of the product and as a matter of fact it is the cluster with more items.

Cluster 2 - Hot Items: Cluster with <u>high frequency</u> and <u>low recency</u>: these are the hot/top selling products.

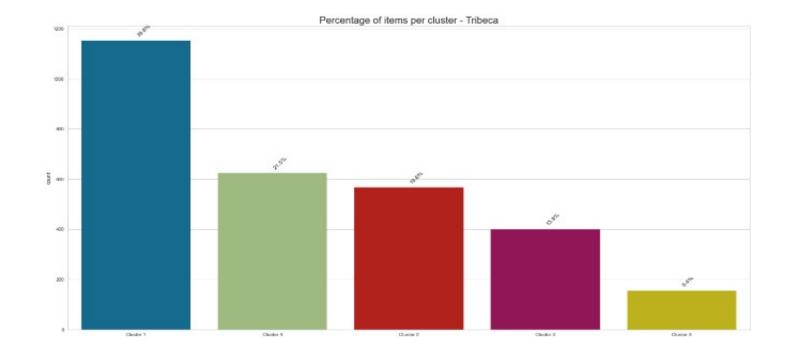


Cluster interpretation:

Cluster 3 – Old/Bad Items: Cluster with high recency and a wide range in frequency: they could be bad products, that never sold (lower part of the cluster) or old products (upper part of the cluster) that sold in the past but now are not selling anymore.

Cluster 4 - New Items: Cluster with <u>low frequency</u> and <u>low recency</u>: these are new/appearing products.





Item distribution histogram.

- The cluster with the most product is, as expected, the Common Items cluster.
- The cluster with less items is again, as expected, the Old/Bad Items

Model evaluation.

- Model checked against the 10 most sold and less sold products in the New York area.
 - All most sold products are in Cluster 2: Hot items.
 - Less sold products are in Cluster 0, 3, and 4 --> products that sold very little can be either bad/old products, new products, or transition products (emerging or fading products)
- This cluster model has been applied to data for all the other stores, with similar results. The same item can correspond to a different cluster depending on the store.



Considerations

- Products that were **hot items** but **haven't been sold recently** could be wrongly segmented as old/bad products. They would be better identified as *fading products* instead.
- The line between **Common/Hot** and **Common/New** products is a **subtle line**. It is important not to act on products that are on the border of clusters.
- **Seasonal** products could appear in **any cluster**, depending on the season when the model's data last date was, and if they are good or bad selling products.



Considerations

• Fading/emerging products will tend to move to other clusters as the time passes by.

Emerging products → Common or Hot items cluster Fading products → Old/Bad product cluster.

- New items will move to other clusters as the time passes by as well.
 Good products → Common or Hot cluster
 Bad products → Old/Bad product cluster.
- The model needs to be **re-trained regularly during different seasons** to see the evolving behaviour of the products and discover new Hot products or new Bad products to act upon. A good retraining time could be **quarterly**, to have a picture of the behaviour during all seasons.



Aplications:

Cluster segmentation can give an insight on products to act upon, e.g.:

- An insight of bad/old products could be used to evaluate if **removing** some of them from the store, or to **relocating** the stock where the product is still in a good selling cluster (to minimize stockage)
- An insight on hot products, could be used for example for developing a new **pricing strategy** for them intended increase the revenues.

Cluster segmentation can be used for modelling predictions.



Task 3 – Sales forecasting

Using past data to predict future needs.

Initial considerations

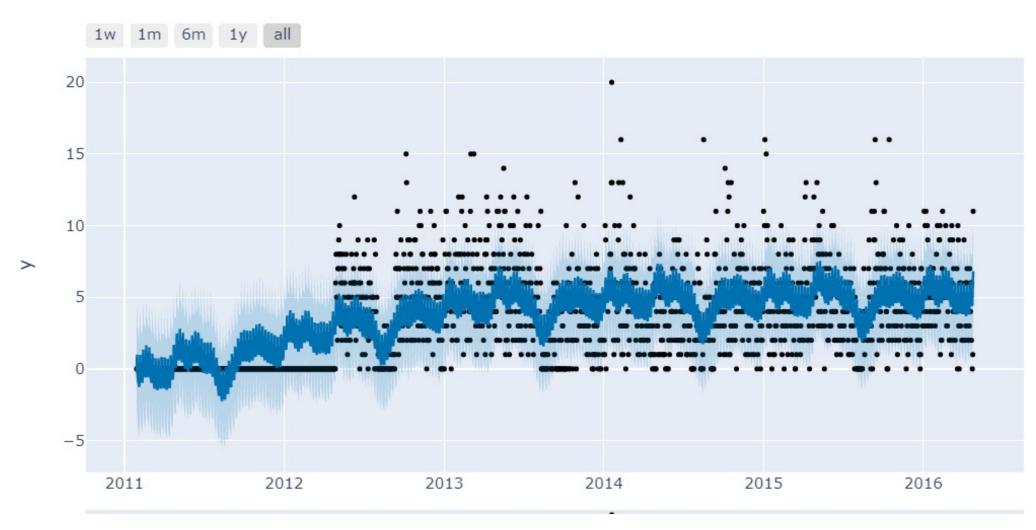
First thought: Create a model for every product in each store. Constraint: we did not have the computer power required.

Thus, we used the clusters priorly established to group the products and created a model for every cluster-

As a test set, we decided to select **Tribeca**, and within this store we have selected the **50 items with the highest unit sold in the last 30 days**. The predictions for one of these items can be found in the next slide.



Tribeca top 50 products last 30 days





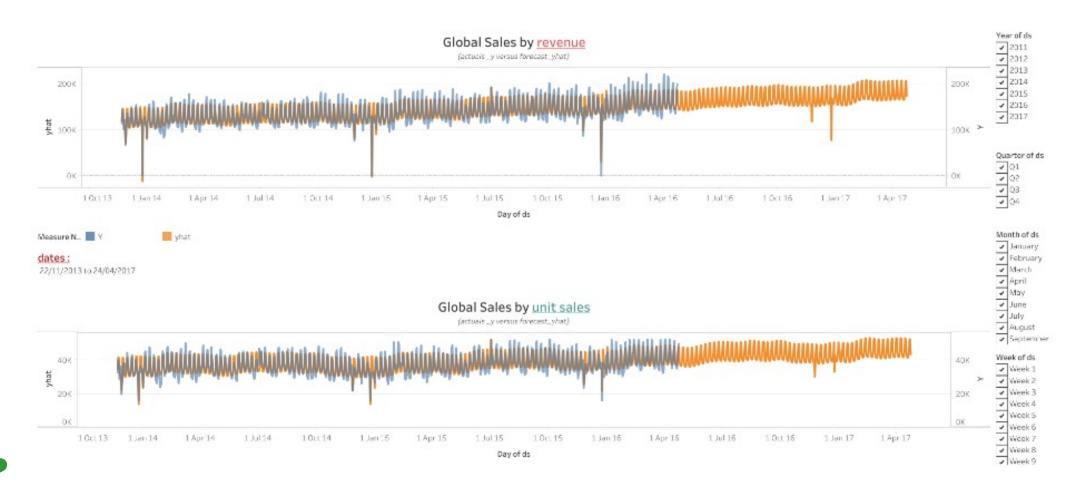
Validation considerations

The model is unable to catch all the seasonality in the data, this is because it is a generalised model on a cluster of products. Therefore, the inventory strategy that would match our model is an **average strategy**.

Once our model is validated, we can go on to **create the** models for every cluster in each store and predict the units sold for each of these products. For consolidated predictions (i.e. sales per category, department) we would simply sum the individual predictions.



Model user case value (national)





Model user case value:

Potential **1,400,000M USD** Value of Model quarterly with even with an accuracy of 70 percent.

Assuming model is run **across** all stores of the United States

Comparision to previous year's actual performance for the quarter to the same quarter predictions for Quarter4-2016 and Quarter 1-2017.

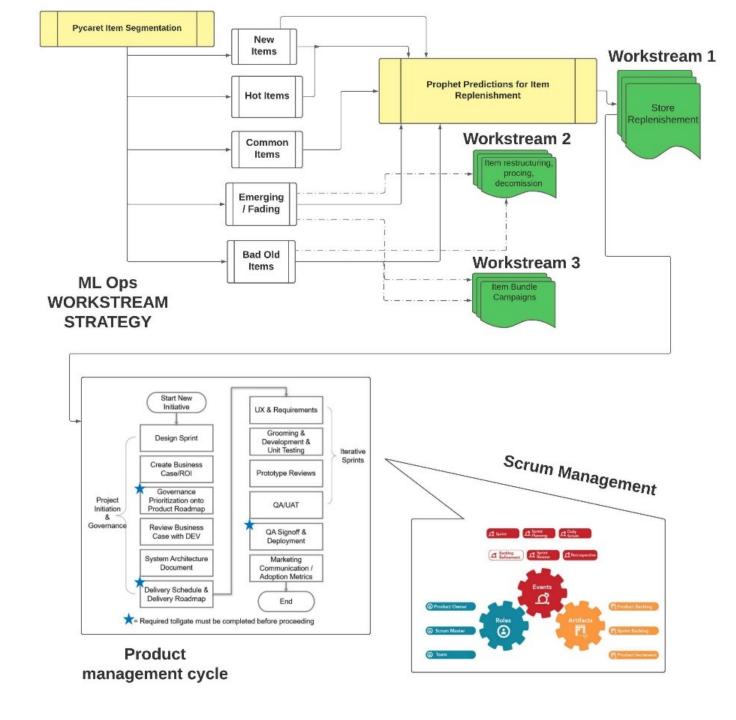
Model to be deployment assumption is computed for Quarter4-2016 and Quarter 1-2017

	Su	m of yhat	Su	m of y		
2014	\$	46 857 636,60	\$	46 685 289,36		deviation
Qtr1	\$	11 376 245,96	\$	11 151 306,90	\$ -224 939,05	-1,98%
Qtr2	\$	11 607 184,82	\$	11 642 899,54	\$ 35 714,72	0,31%
Qtr3	\$	12 080 579,50	\$	11 962 669,30	\$ -117 910,20	-0,98%
Qtr4	\$	11 793 626,32	\$	11 928 413,61	\$ 134 787,29	1,14%
2015	\$	52 117 898,86	\$	51 950 761,22	\$ -167 137,64	-0,32%
Qtr1	\$	12 276 813,18	\$	12 251 301,88	\$ -25 511,30	-0,21%
Qtr2	\$	12 787 365,55	\$	12 802 010,39	\$ 14 644,84	0,11%
Qtr3	\$	13 604 060,14	\$	13 469 445,75	\$ -134 614,39	-0,99%
Qtr4	\$	13 449 659,99	\$	13 428 003,19	\$ -21 656,80	-0,16%
2016	\$	59 642 637,00	\$	18 245 489,01	\$ -41 397 147,99	
Qtr1	\$	14 162 388,11	\$	14 195 256,65	\$ 32 868,54	0,23%
Qtr2	\$	14 655 602,24	\$	4 050 232,37	\$ -10 605 369,87	
Qtr3	\$	15 440 524,44			\$ -15 440 524,44	
Qtr4	\$	15 384 122,22			\$ -15 384 122,22	
2017	\$	20 225 488,57			\$ -20 225 488,57	
Qtr1	\$	15 844 147,59			\$ -15 844 147,59	
Qtr2	\$	4 381 340,98			\$ -4 381 340,98	
Grand Total		293660853,7		231855179,6		



Task 4 – Store supply use case (with ML Ops)

Let's put our data to work.



MLOps Project Management: Artefacts, Infrastructure, Cadence, Adoption, Evaluation

MLOps Project Management

- Models are to branch out into multiple workstreams, the main workstream is the **Store replenishment use case**.
- Standard Product management cycles will be observed through to deployment and monitoring until closure of project.
- Standard Scrum management process will be deployed within the management of sprints.
- Kanban boards will be used to manage tasks using tools such as Trello or java to manage backlog.



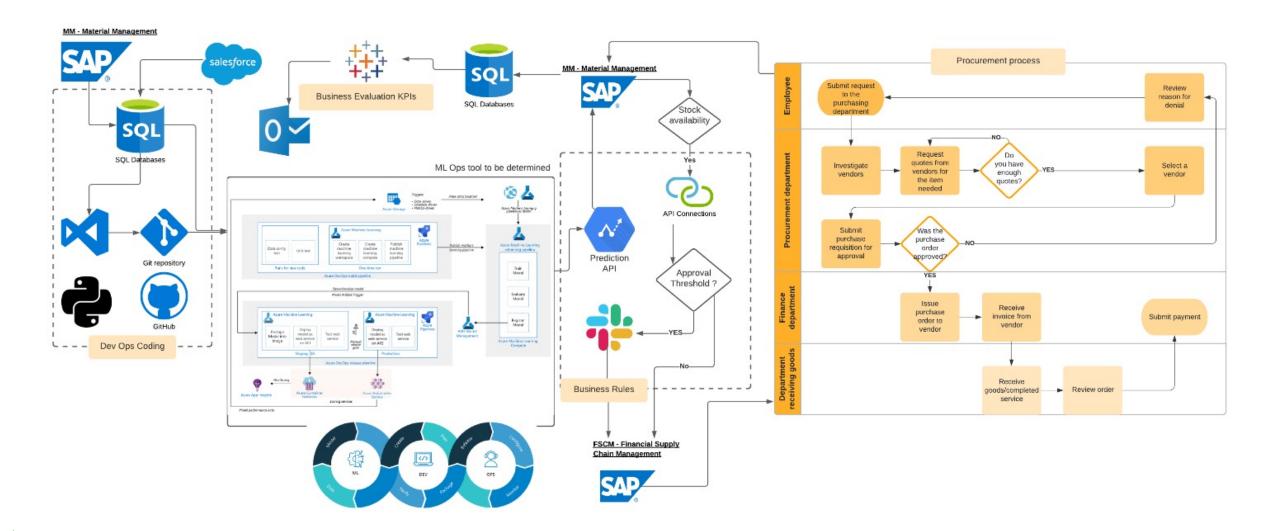
Business considerations

- New York as region comprises 43 percent of National Sales
- Tribeca is the top store nationally and in its region
- Sales occur the most on Saturdays and Sundays and the least on Tuesdays and Wednesdays

Top 12 Items Performance | Tableau Public_Top 10 of the products only comprise of around 3 percent of items sold 950,000 items sold over 3 years



Infrastructure: Workstream. Store Supply Use Case



Infrastructure: Workstream. Store Supply Use Case

List of Top MLOps Tools 2022 (trustradius.com)

Data sources input from SAP and Salesforce relating to sales, events and prices.

Data engineering and coding will be occurring through VS Studio

Git being the repository and collaboration venue

ML Ops is to be determined- in diagram; we are looking at azure.

Api to connect prediction models to SAP Material Management system to trigger workflows and business rules that would initiate automation.



Infrastructure: Workstream. Store Supply Use Case

Slack will be used as an approval workflow tool and a communication chanel

SAP FSCM Module will once again be consulted to trigger automated Purchase orders and payment approvals

This would lead back to **SAP material Management** to update stock

Tableau will be used as dashboards to measure business evaluation KPIs

Automated reports will be made available through **Outlook.** Governance triggers will be also sent through Outlook and Slack.

Tabpy will be used to link VS Studio and Python if MLOps tool has limitations on Business reporting data



Project timeline proposal

	Data Science PM	Stage Gates	W1	W2	W3	W4	W5	W6	W7 N	N8 V	v9 W	V10	W11	W12	W13	W14	W15	W16	W17	W18	W19	W20	W21	W22	W23	W24	W25	W26	W27	W28	W29	W30
	Business Understanding	Initiate																														
Pilot Phase	Preprocessing and																															
	Modelling	Plan and Develop	7,									- 9		,					37 - 28		× 25	37 39	x 8				× 19	y 19	x 8	x 2	S 12	S 10
	Productivitization and																															
	Scaling	Deploy																														
	Monitoring and																					8						8	· · · · · ·		1	× ×
	Maintenance	Closure																														
		Initiate						, 9																				5	3 9			
	Phase 2	Plan and Develop																														
		Deploy																														
		Closure																														



Evaluation Metrics to keep our model accurate and relevant.

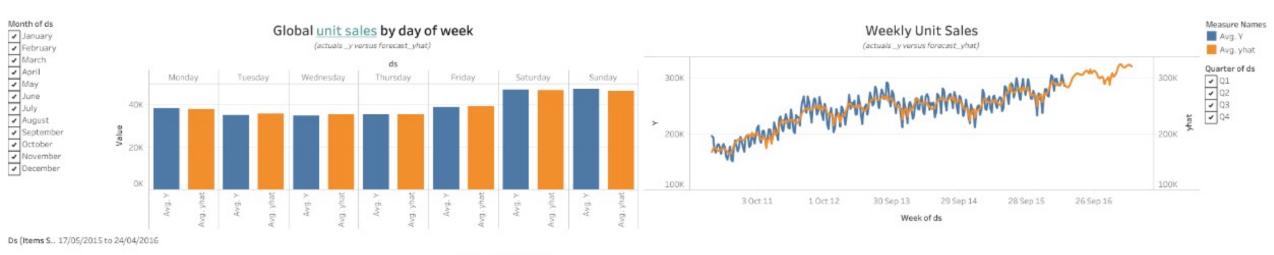
Model evaluation

- Accuracy metrics will be added to the dashboard comparing projected with actuals.
- Relevancy metrics will be used to check if assumptions are still accurate and current.

Global Units Sales Dashboard | Tableau Public
Global Revenue and Unit Sales predictions | Tableau Public
Global Sales by Day of the week | Tableau Public



Dashboards for model evaluation





Business Continuity - Governance

Accuracy measures

 Swapping models and running models in parallel to swap with better accuracy

 Retraining notifications when decrease in accuracy by 5percent.



Business rules... keeping us humble

Remaining stock for an item below sales predicted for the item in next X days == trigger reorder.

Sales of an item go +20% above predictions for X days == trigger email with suggested new reorder quantity for the product and get approval through slack for redefinition and reorder. ==trigger email to Purchases, Ops and Marketing for business and Marketing actions.

Sales of an item go -20% below predictions for X days == trigger email (to Purchases, Ops and Marketing) and hold reorders until approval process through slack.



Business rules... keeping us humble

- Out of stock == trigger reorder
 - == trigger email to Purchases and Ops.
- Total sales go +20% above predictions for X days == trigger email to Purchases with items with risk of out of stock and suggested reorder.
- Total sales go -20% under predictions for X days == trigger email with next order quantities proposal for over-stocked products.





Questions?

