A DS Market Data Science Project

Data Driven Sales forecasting and Business Insight

Proactive Inventory and cost Management

Customer Centric Resource Allocation

DS Market Data Science Project

WHO are we?

Project Team

- Nicole, Senior data scientist
- Christa Santos, Project Advisor
    - Carmen Cutillas (Project member)
    - Gloria Miori (Project member)
    - Luca Dati (Project member)
    - Paul Jumalon (Project member)

Objective

Define - Understand and engineer data that is available and should be made available

List down S.M.A.R.T. goals / Deliverables in line with all stakeholders' requirements

Define key priorities and levels of data that would both drive tactical and strategic outcomes

Present key findings to the business that would enable efficiencies in the organisation and a more customer centric approach

Measure / Analyse - Based on assumptions and analysis, create measures aligned to priorities defined and set

Provide tangible self-service dashboards for proper measurement of data

Provide key findings back to the business

Improve - Implement Product Management, AGILE approach in model deployment, iterations and development and Scrum Standard 3-5-1 Practices

Control - Adoption and Customer centric measures over set project time frame

Hypercare phase where transition over to the business of specific deployments are agreed with the business owners

Expected Outcome:

Business Insights and Self-Service dashboard

CLUSTERING model Using PyCaret

Time Series Predictions for Sales using Prophet

ML Ops Roll out plan, Deployment Strategy

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WHO are we here for?

Stakeholders:

DS Market in partnership with Nuclio :

DS Market

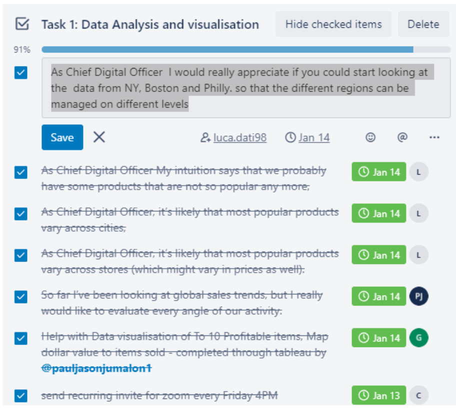
- Nicole, Senior data scientist
- Michelle, Chief Digital Officer
- Justin, HR Director
- Paul Rogers, Finance Director
- Martin, Technology Lead
- External Customers and
- Procurement department

Nuclio

- Felipe Calderero
- Miquel Larsson
- Christa Santos
- Pedro Costa

Voice of the customer (VOC)

VOCs were put together through two main approaches: from **a**. results data received and tracked and **b**. proactive discussions with stakeholders.



a. From emails and communication between stakeholder's user-stories were created and subdivided into tasks distributed across the project team. DSMarket Final Project | Trello

b. Assumptions were formulated from understanding the nature and definition of data input

DS Market Affinity Diagram.pdf

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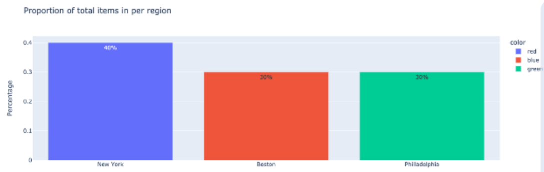
Task 1 : Business Insight – First Level

Initial look into the data covers date range year: 2011 to 2016

National View :

Findings :

the proportion of total sales and items sold are aligned, meaning that the revenue of the business is stable across regions. We can see 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.



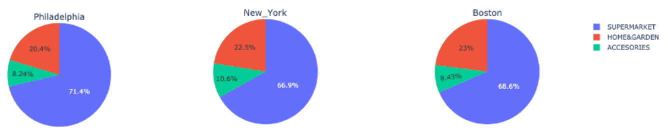
Findings :

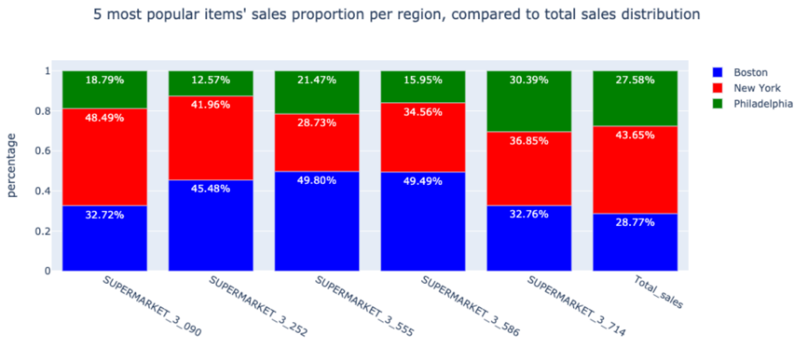
New York accounts for the 43% of the sales across this 3 regions, which lead us to consider it a **key region.**
Tribeca is pushing up the sales of the NY area, being Greenwich_Village the best 2nd shop , Harlem an average store and Brooklyn the one with the lower sales number across the three regions. We also need to consider **Tribeca as a key store**.

Findings :

We can see that "ACCESSORIES" have a higher quota in NY, while Boston has the highest percentage of "HOME&GARDEN" across the 3 areas. Philadelphia percentage of "SUPERMARKET" items sold is significantly higher when compared to NY.

Category Composition of Categories by Region





Findings :

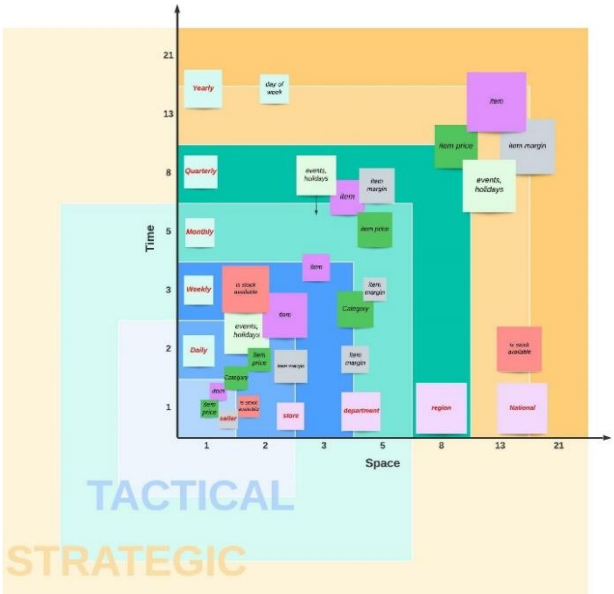
We can see that products 2 to 4 have a higher percentage of sales in Boston. It is significant that the sales of 555 are perceptually higher in Philadelphia than in NY. 714 has almost the same weight in Philadelphia than in NY.

Findings :

Top 3 products in NY are the same than the general top 10 products by units sold. The first one accounts for almost half the total of the product sales. The top 4 products are within the top 4 globally, but with a different order. The sales of 586 in Boston (the nº1 by revenue product) accounts for half of the global sales of the product. The top item in Philadelphia is not on the global Top Ten nor in any other top product classification. This is a good example of how thinking globally but acting locally can improve the results of the business.

Boston and New York regions are more alike than Philadelphia, in terms of type of products being more sold.
For less sold items we just find some common points, but establishing analogies is difficult even for Boston and NY. While Boston and NY have some Supermarket products among the less sold, the majority or less sold items in Philadelphia are in the home & garden category.

Task 1.2 : Self Service Reporting and Dashboards



Data Compositions 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

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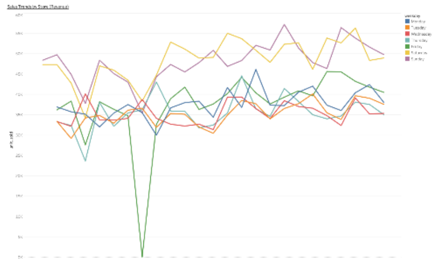
example insights :



Unit Sales Trends by Day of Week | Tableau Public Date Range : 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

SELF SERVICE DATA VISUALISATION

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. This would compute actual
Item Clusters | Tableau Public	Cluster on item segmentation	Used as input to the workstreams for deployment below.

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Task 2 : Clustering

The clustering part works on the item_sales.csv. The clustering part is aiming at identifying products that behave similarly.

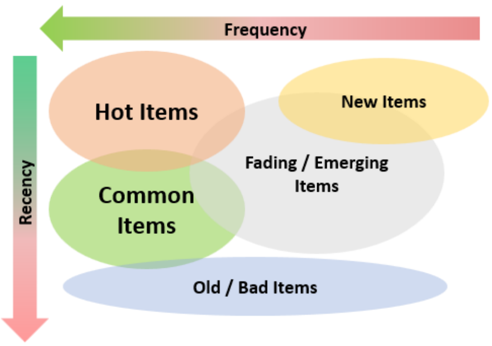
The data from the Tribeca store (most selling store) were used to create the clusters.

Clustering features created are frequency (total number of sold products per item) and recency (days since last purchase). For the model creation the features were log transformed since their distribution was not gaussian.
95% of the Tribeca data was used to train the model, 5% for testing.
Data normalisation was performed within Pycaret with MinMax scaler.
A k-means model with number of clusters = 5 has been created. The elbow curve was used to find the best number of clusters.
The cluster model is saved as cluster_model_items.pkl The cluster model is applied to all other stores and results saved in csv files.

Cluster interpretation

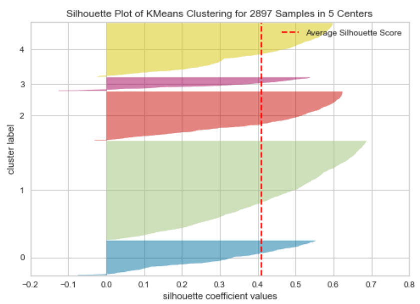
In general, the best products will present high frequency and low recency, worst products will have low frequency and high recency.

The clusters identified can be interpreted as follow:



- Cluster 0 - Transition Items - Fading or emerging products: Cluster with 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 high frequency and low recency: these are the hot/top selling products;
- 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 product (upper part of the cluster) that sold in the past but now are not selling anymore;
- Cluster 4 - New Items: Cluster with low frequency and low recency: these are new/appearing products;

Model evaluation

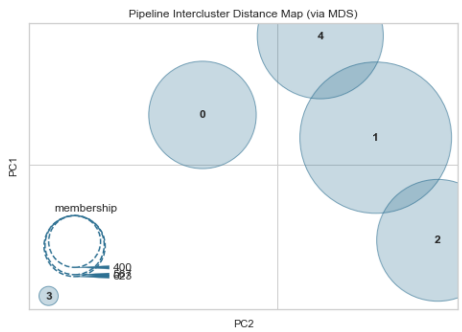


The silhouette value is 0.41:

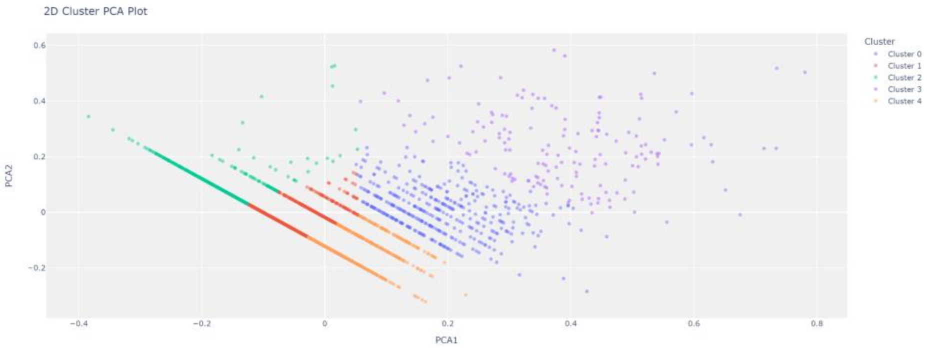
Two clusters are well apart, while three clusters are close to each other and overlap. This is expected since there can be a subtle line between hot, common, and new items.

The silhouette plot is in the picture above.

The distance between clusters is described in the picture on the right.

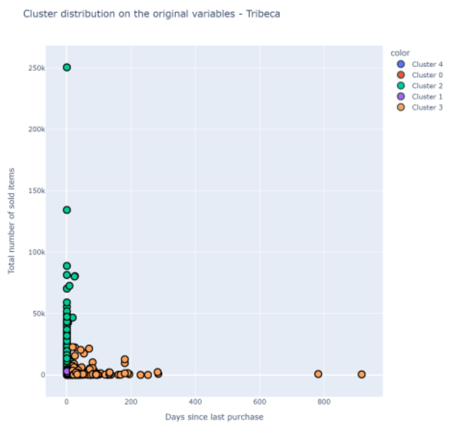


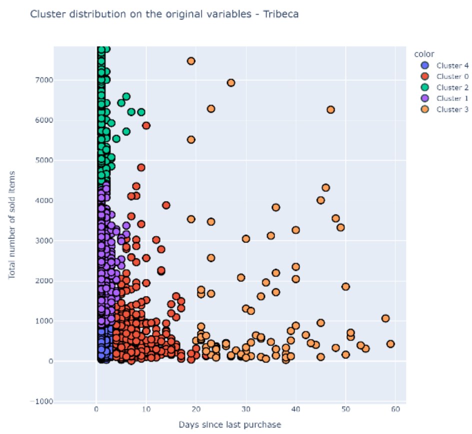
The cluster segmentation on the variable used for modelling is as in the plot below:



While on the original variables, it looks as in the plots below. The plot on the right is a zoomed area of the left plot.

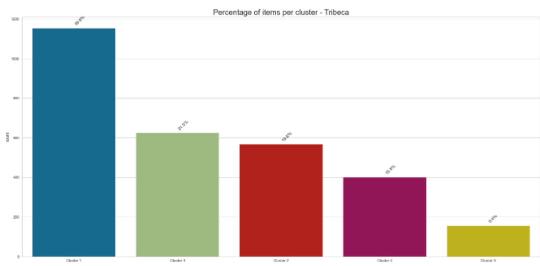
These results can be explored on the following dashboard: [Item Clusters | Tableau Public]



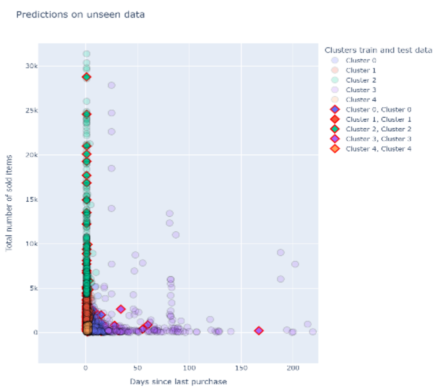


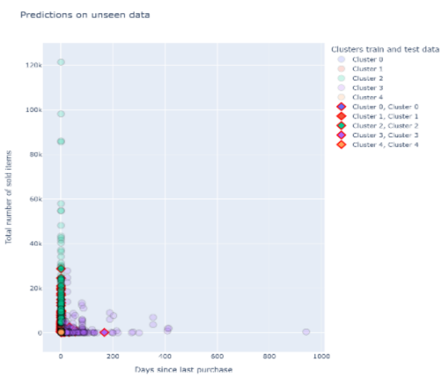
The cluster with the most product is, as expected, the Common Items cluster. The cluster with less items is again, as expected, the Old/Bad Items.

The item distribution within the clusters is described in the histogram on the right.



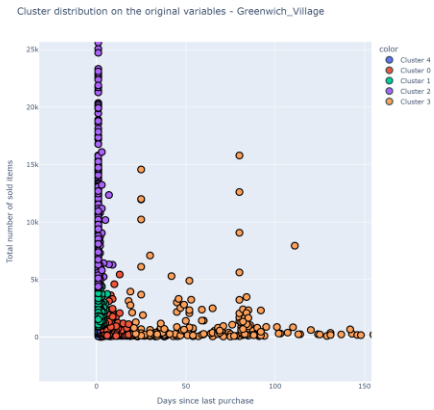
The model has been applied to the test data with the results as reported in the plots below:

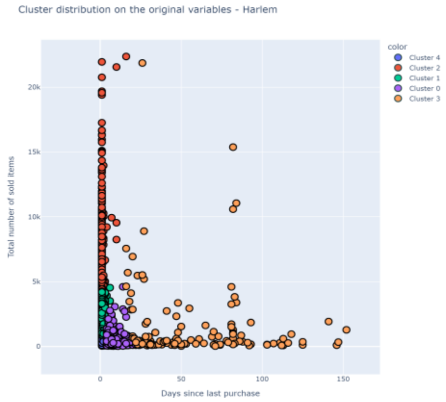


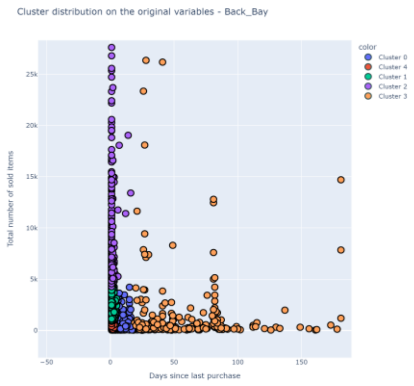


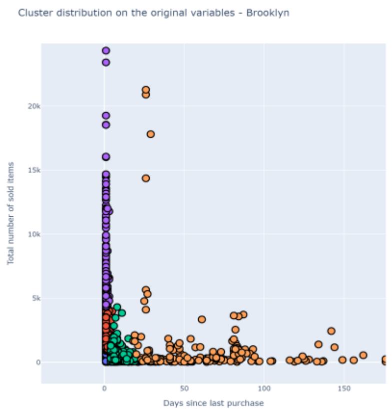
The model has been checked against the 10 most sold and less sold products in the New York area. All most sold products are in Cluster 2: Hot items. Less sold products are in Cluster 0, 3, and 4. This is expected as well since products that sold very little can be either bad/old products, new products, or transition products (emerging or fading products)

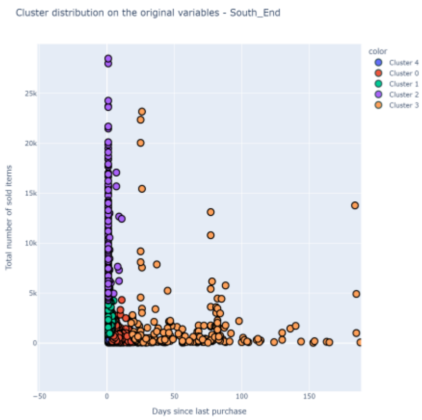
This cluster model has been applied to data for all the other stores, with similar results. The same item can correspond to a different cluster depending on the store.

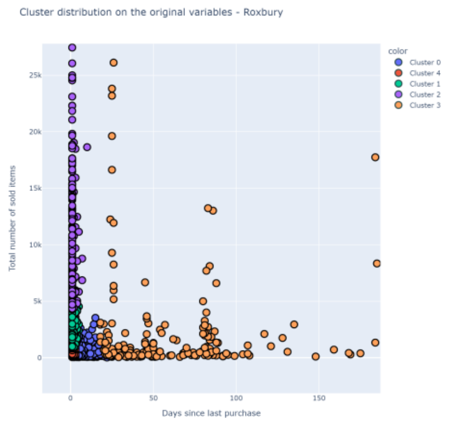


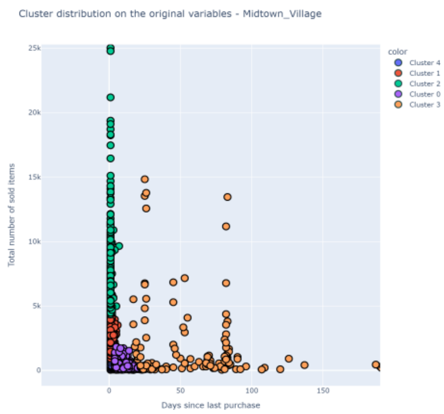


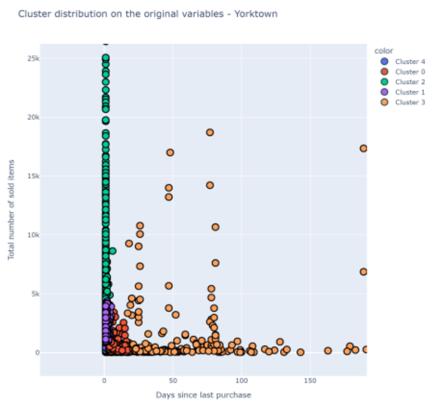


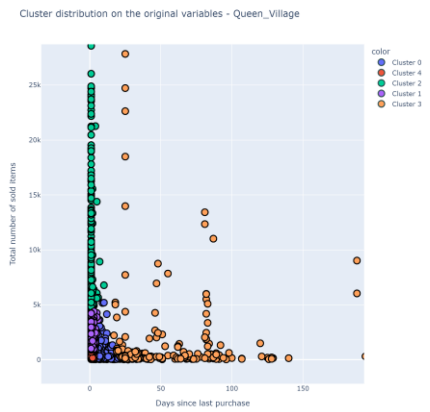












Limitations:

Products that were hot items but haven't been sold recently are 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. I.e. increasing the price of a Common product, instead of a very Hot one, could lead to a loss of selling for that product due to the price increase. It is better to act on products that are in the outer part of a cluster.

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.

Fading/emerging products will tend to move to other clusters as the time passes by. If they are emerging products they will move to the Common or Hot items cluster, if they are fading products, they will move to the Old/Bad product cluster.

New items will move to other clusters as the time passes by as well. If they are good products, they will move into the Common or Hot cluster, if bad products they will move to the 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.

Applications:

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**.

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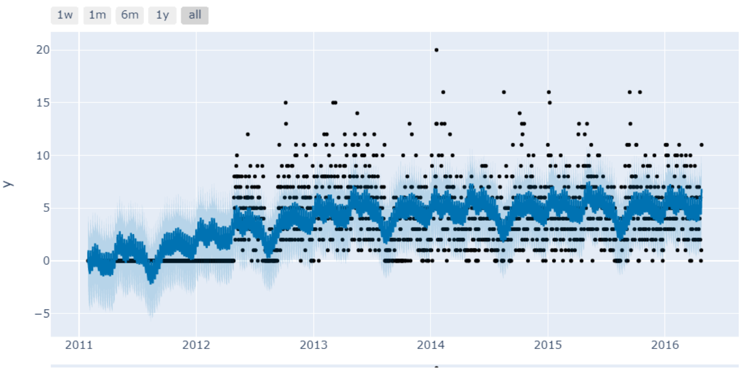
Task 3: Sales Predictions

Sales Predictions (revenue)

a. At first, we wanted to create a model for every product in each store but we quickly realised that 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

b. As a test set, we decided to select the most profitable store, 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 graph below



d. we can see that the model is unable to catch t 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.

c. 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.

Business user case Value (National) :

	Sum of yhat	Sum 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**		

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

This is in assumption that model is run **across** all stores of the United States

This is in comparison 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

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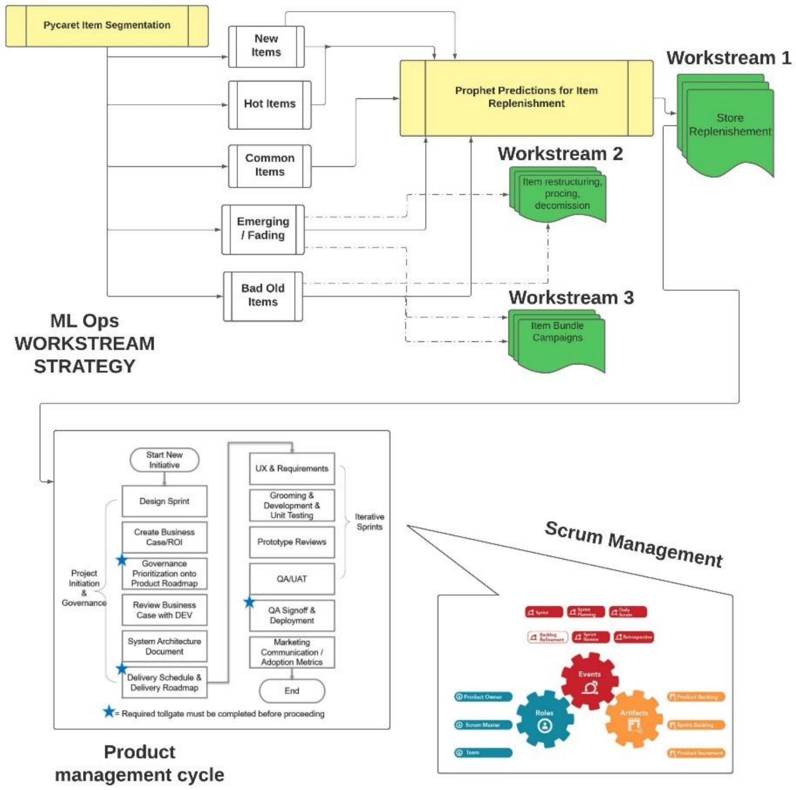
Task 4 : Store supply use case (with MLOps) (items sold)

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



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 3years

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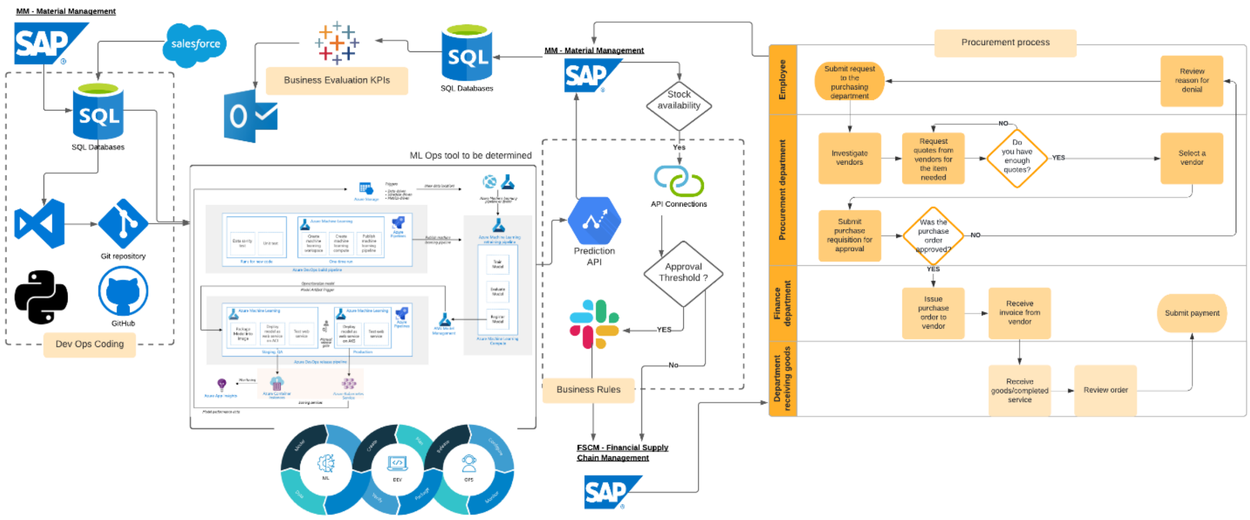
Infrastructure: Workstream. Store Supply Use Case



[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.

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

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

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ML Ops Project Deployment plan

Project Management Deployment.pdf

	Data Science PM	Stage Gates	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15	W16	W17	W18	W19	W20	W21	W22	W23	W24	W25	W26	W27	W28	W29	W30
Pilot Phase	Business Understanding	Initiate																														
	Preprocessing and Modelling	Plan and Develop																														
	Productivitization and Scaling	Deploy																														
	Monitoring and Maintenance	Closure																														
Phase 2		Initiate																														
		Plan and Develop																														
		Deploy																														
		Closure																														

Evaluation

Accuracy metrics will be added to the dashboard comparing projected with actuals.

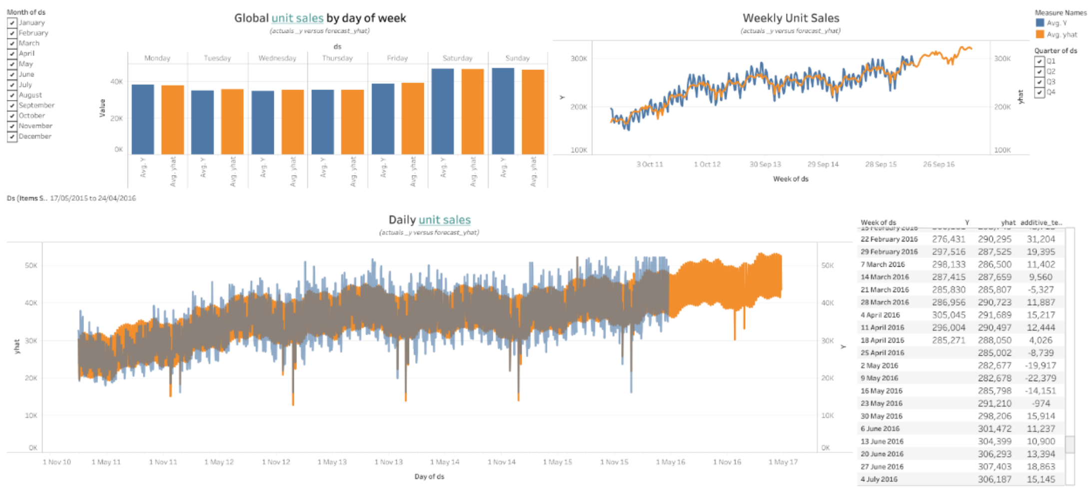
-

Relevancy metrics so 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]



Business Continuity / Governance

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

1. Remaining stock for an item below sales predicted for the item in next X days == trigger reorder.
2. 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.
    a. ==trigger email to Purchases, Ops and Marketing for business and Marketing actions.
3. 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.
4. Out of stock == trigger reorder
    i. == trigger email to Purchases and Ops.
5. Total sales go +20% above predictions for X days == trigger email to Purchases with items with risk of out of stock and suggested reorder.
6. Total sales go -20% under predictions for X days == trigger email with with next order quantities proposal for over-stocked products.