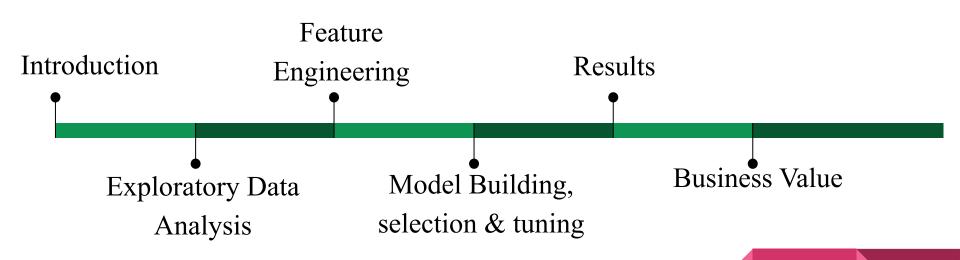


AGENDA



INITIAL DATA DICTIONARY

WEEKLY DEMAND DATA

Variable	Definition
id	Unique ID
week	Week No
center_id	Unique ID for fulfillment center
meal_id	Unique ID for Meal
checkout_price	Final price including discount, taxes & delivery charges
base_price	Base price of the meal
emailer_for_promotion	Emailer sent for promotion of meal
homepage_featured	Meal featured at homepage
num_orders	(Target) Orders Count

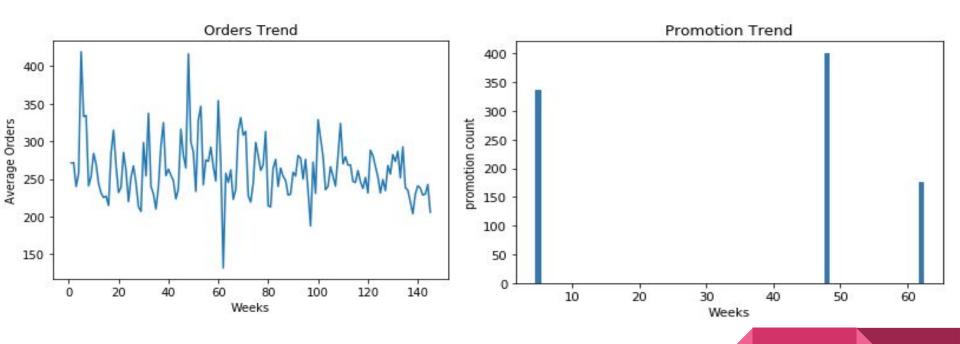
FULFILMENT CENTER INFO

Variable	Definition		
center_id	Unique ID for fulfillment center		
city_code	Unique code for city		
region_code	Unique code for region		
center_type	Anonymized center typ		
op_area	Area of operation (in km^2)		

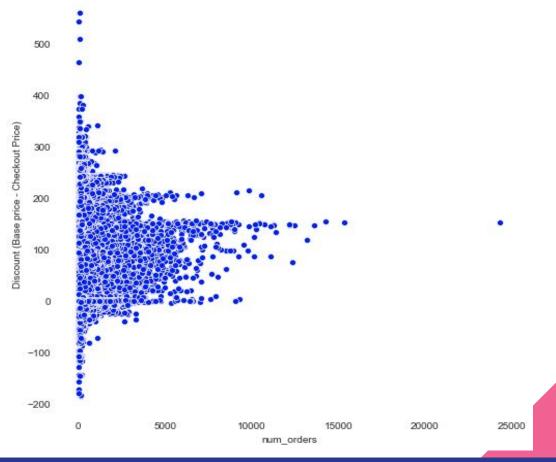
MEAL INFO

meal_id	Unique ID for the meal
category	Type of meal (soups/snacks)
cuisine	Meal cuisine (Indian/Italian/)

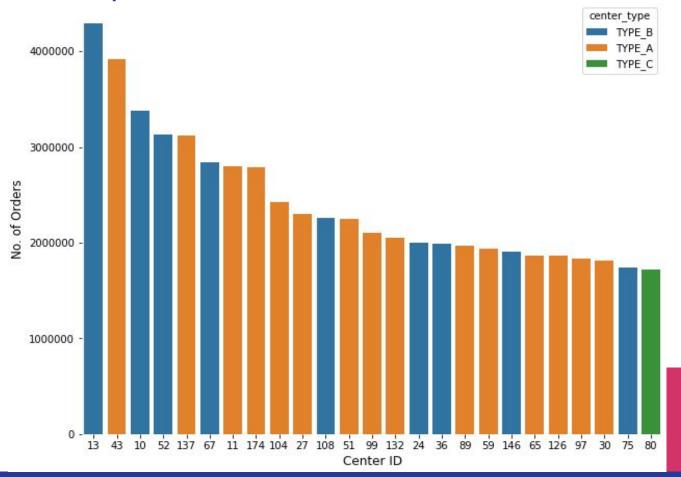
Average orders per week



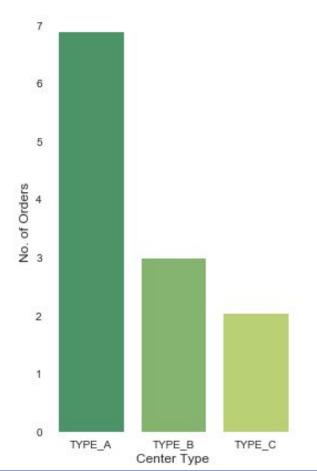
Discount v/s No. of Orders



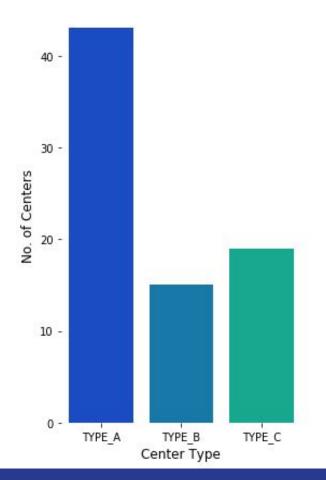
Top 25 Centers with Maximum Orders



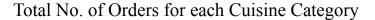
Total No. of Orders for each Center type



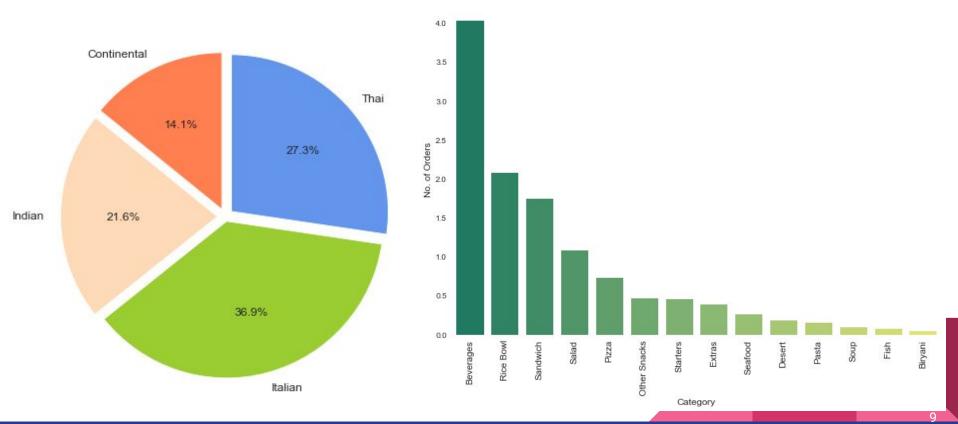
Total No. of Centers for each Center type



Meal wise Order Trend



Total No. of Orders for each Meal Category



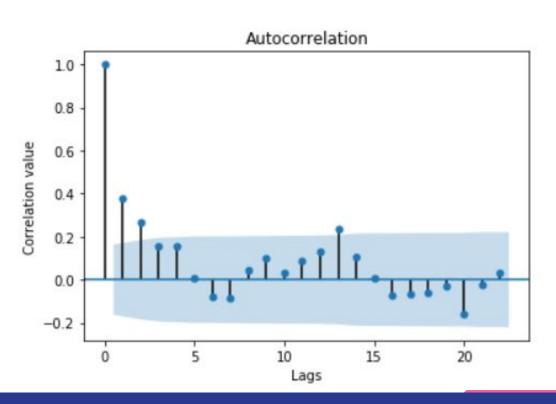
Feature Engineering 1

The table captures the weekly trend of price and demand across different categorical variables

	meal_id	center_id	category	checkout_price	num_orders	price/avg_price_week_category	Avg_orders_cat_week
week							
1	1062	10	Beverages	5.206147	6.763885	0.977655	5.147244
2	1062	10	Beverages	5.216890	6.663133	1.005516	5.431697
3	1062	10	Beverages	5.222300	6.747587	1.006351	5.240581
4	1062	10	Beverages	5.211451	7.092574	0.999393	5.264703
5	1062	10	Beverages	5.217053	6.865891	0.994085	4.962804

Picking the Number of Lags

Below we see the autocorrelation plot for demand



Feature Engineering 2

The tables below show the features which capture the previous week trend to predict next week's demand

	meal_id	center_id	num_orders	expanding_mean	weighted_average_2w	weighted_average_3w		meal_id	center_id	perc_diff	num_orders_lag_1	perc_diff_lead1	target_lead
week							week						
1	1062	10	6.763885	6.763885	NaN	NaN	1	1062	10	0.000000	NaN	0.104365	6.663133
2	1062	10	6,663133	6.713509	6.696717	NaN	2	1062	10	0.104365	6.763885	0.208166	6.747587
3	1062	10	6.747587	6.724868	6.719435	6.722152	3	1062	10	0.208166	6.663133	-0.104256	7.092574
4	1062	10	7.092574	6.816794	6.977578	6.906004	4	1062	10	-0.104256	6.747587	0.209480	6.865891
5	1062	10	6.865891	6.826614	6.941452	6.921735	5	1062	10	0.209480	7.092574	-2.357580	6.998510

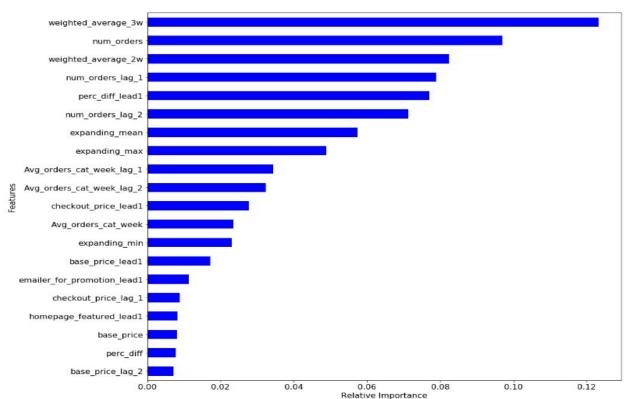
Model Selection

Split data into train, validation and test set.

Model/ Metrics	MSE	Training R-squared	Validation R-squared
Linear Regression	0.20	0.77	0.74
Lasso	0.79	0.0	-0.01
Random Forest	0.24	0.99	0.92
Gradient Boosting	0.37	0.89	0.87

Model Results

Test Set MSE: 0.31 Test Set R-Squared: 0.89



Let's get to Business!

• The cost of each order = inventory cost + overhead cost + profit

(60%) + (30%) + (10%)

Inventory cost = Loss incurred during overprediction (Inventory loss)

Profit = Loss incurred due to underprediction (Order loss)

Convention Adopted

Model Prediction	Actual demand	Prediction - sales	Type of Loss
5	6	-1 (Under Prediction)	Order loss
5	4	+1 (Over Prediction)	Inventory loss

A Quantitative measure

Baseline model (Avg sales/meal_id/c enter_id)	Actual Sales	Forecasted sales	Baseline Loss	Forecasted loss
4	7	8	- 3 = 3x order loss	+1 = 1x inventory loss

Where:

Order loss = profit per meal = 10% of checkout price of that meal. Inventory loss = cost of perishables = 60% of checkout price of the meal.

The Losses

Monetary loss Baseline prediction

\$386,015

Monetary loss Model Prediction

\$279,384

\$ Amount we save if we use the model :



\$106,631

Additional Use Case

What if we decide to increase the cost of each meal by 25%?

The overall demand decreases by: 39087 orders

What if we launch a 50% promotion?

The demand increases by: 40524 orders



