Demand Forecasting

Author Name: Arkaprova Saha

Date: 7th Jan 2023

Problem Statement

The Client is a **multi-city meal delivery** service. It has various fulfillment centers which each keep an inventory of items. The task is to design a model capable of forecasting the demand of various meals in various centers in order to keep an adequate inventory of items so as not let items go stale and keep up with the demand at the same time.

AGENDA

1. EDA
2. Time Series Models
3. Regression Models
4. More Granular Models
5. Results and Prediction
6. Further Work

Exploratory Data Analysis

Data Description

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 incl. all
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

Fulfillment Center Data

Variable	Definition
center_id	Unique ID for center
city_code	Unique code for city
region_code	Unique code for region
center_type	Anonymized center typ
op_area	Area of operation

Meal Info Data

meal_id	Unique ID for meal
Category	Type of Meal (Snack..)
Cuisine	Meal Cuisine (Indian,..)

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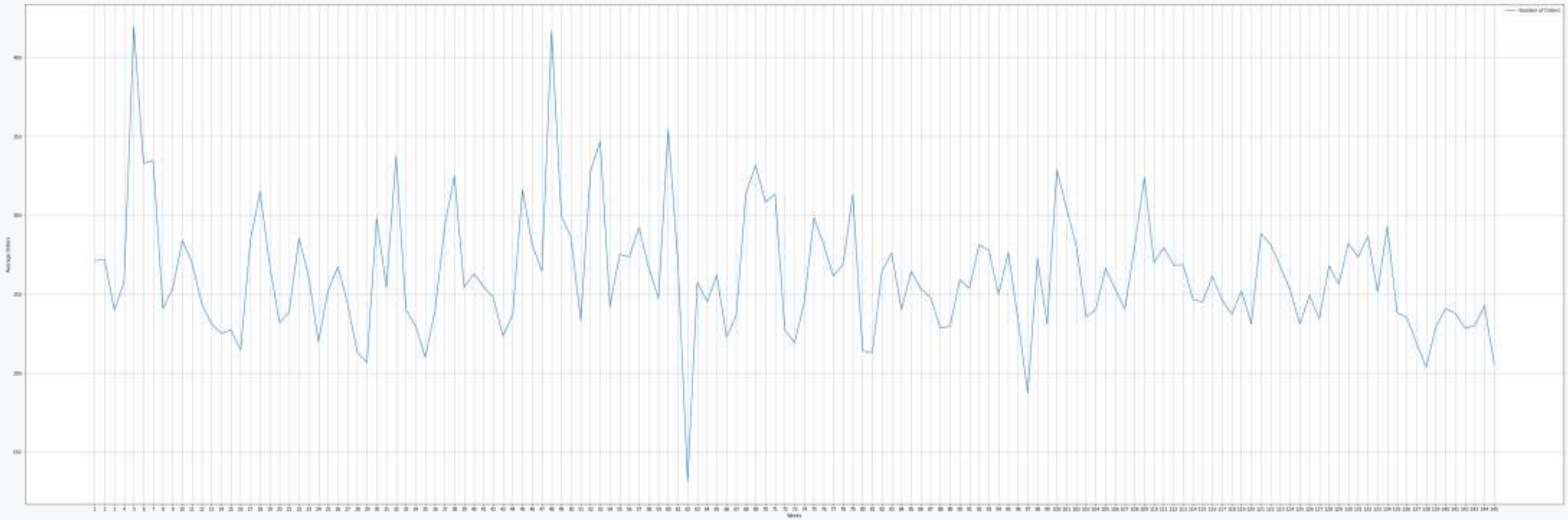
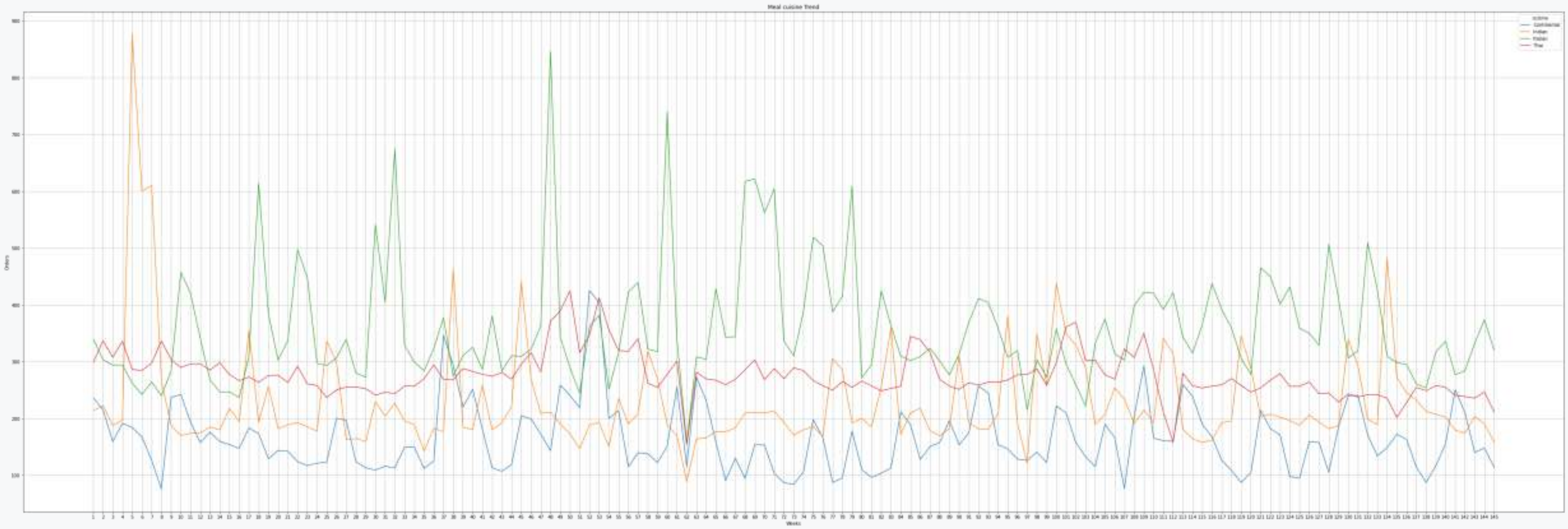
Trend average Orders per week

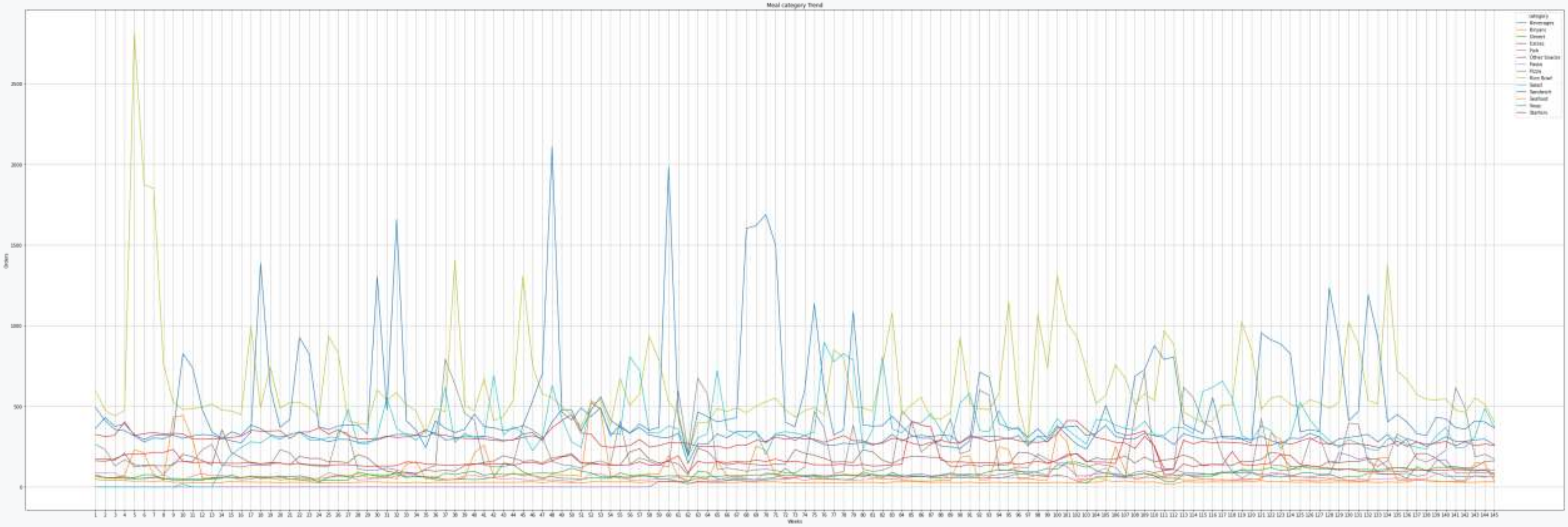


Trend according to different categories



Meal cuisine wise trend

Trend according to different categories

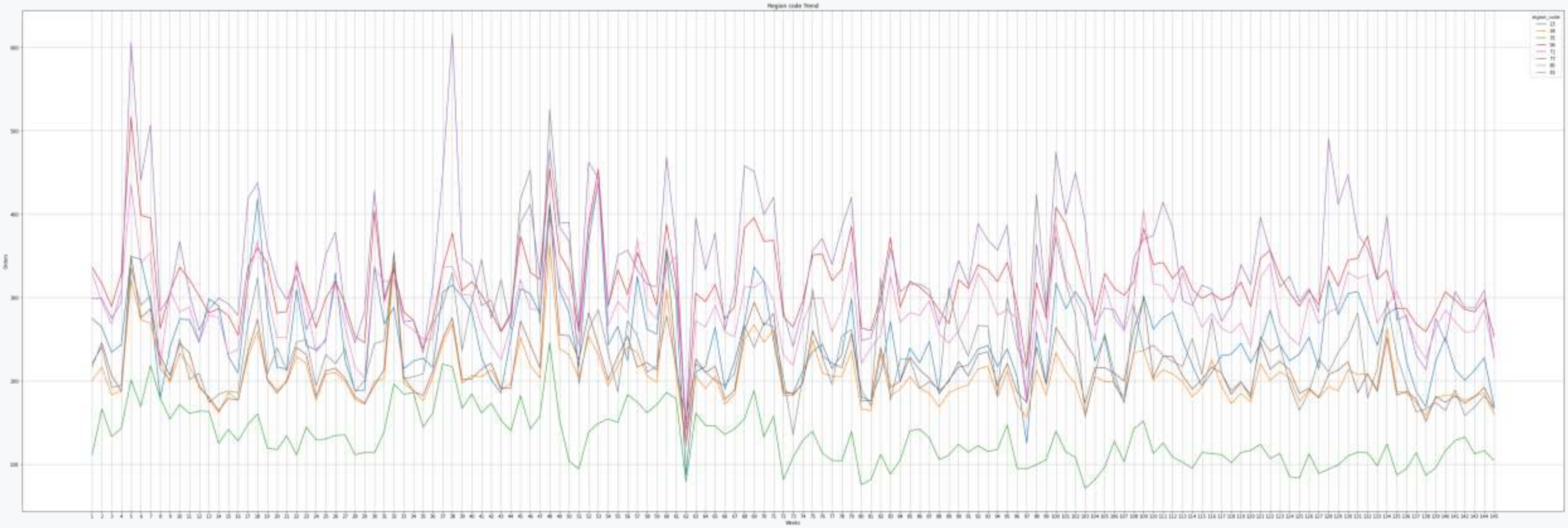


Meal Category Wise trend

Trend according to different categories

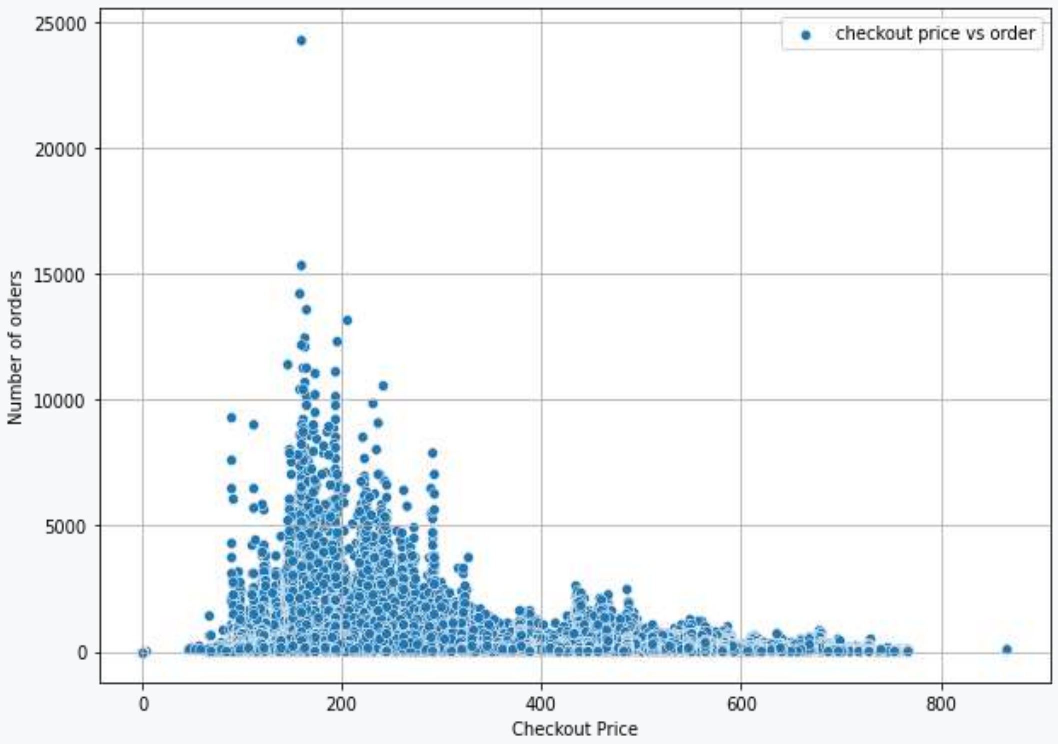
Center Wise Trend

Trend according to different categories

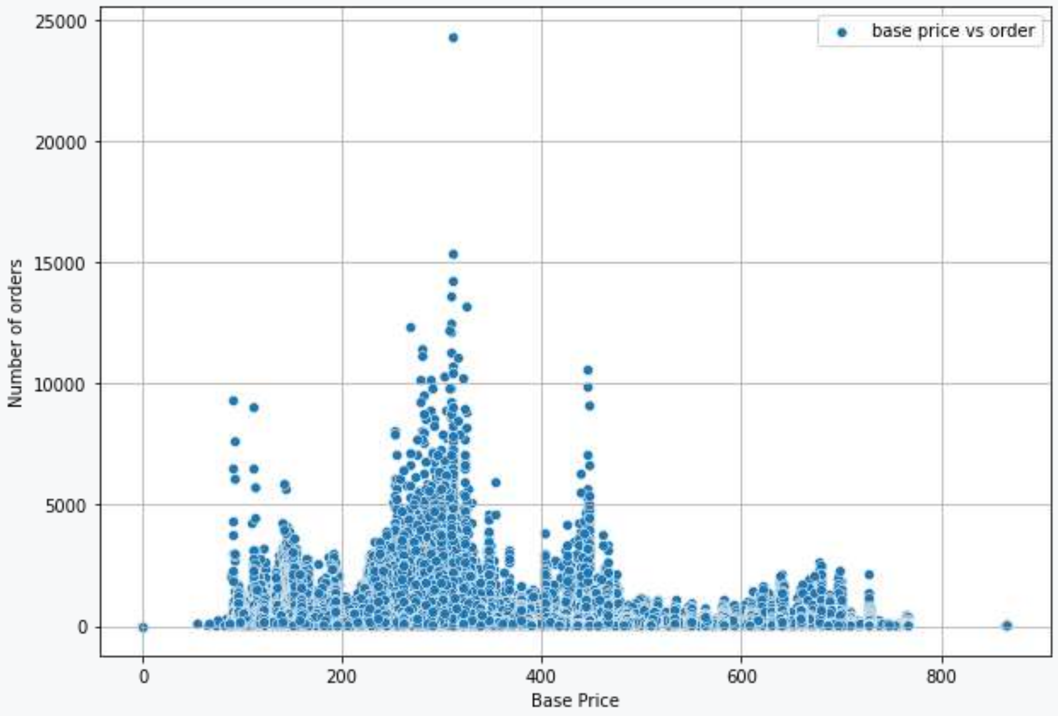


Region Wise Trend

Price v/s Number of Orders



Checkout Price vs Number of Orders



Base Price vs Number of Orders

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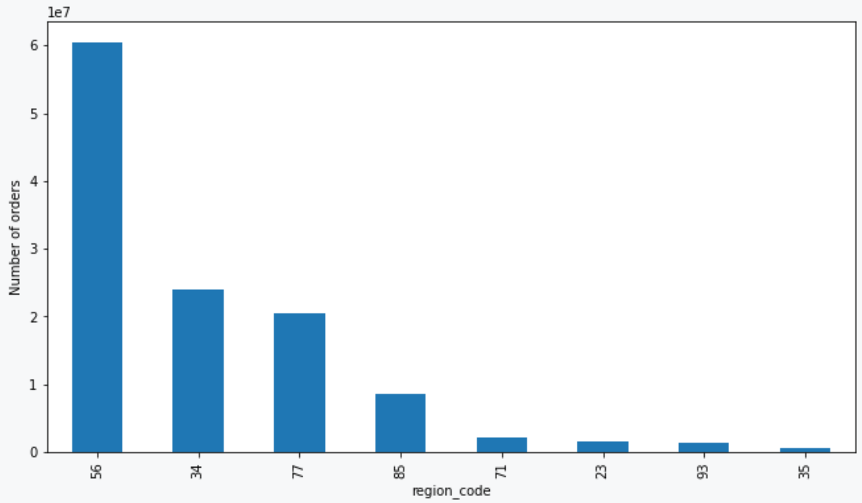
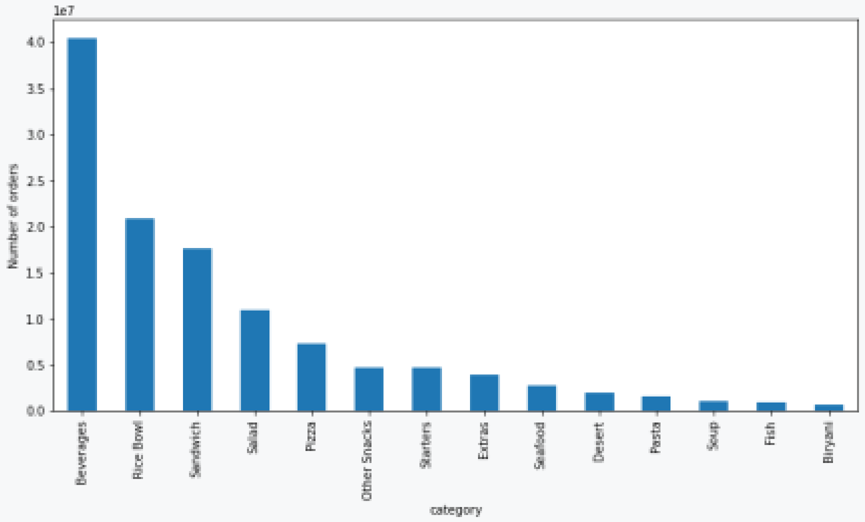
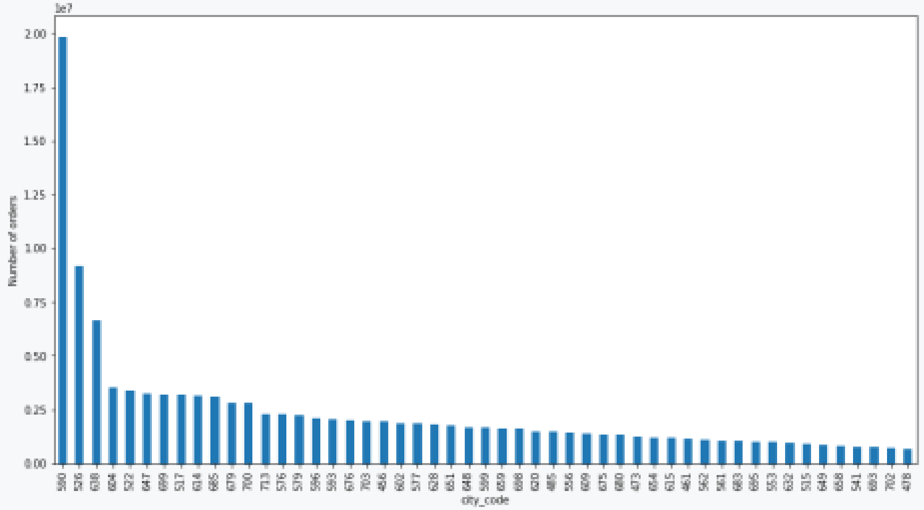
Visualization of orders, among region, meal catagory



Region wise total number of orders

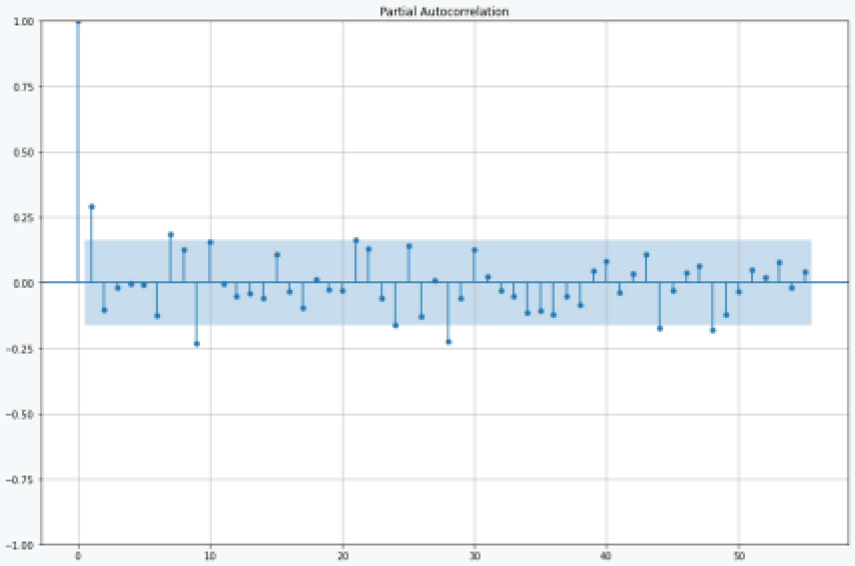


Category wise number of orders

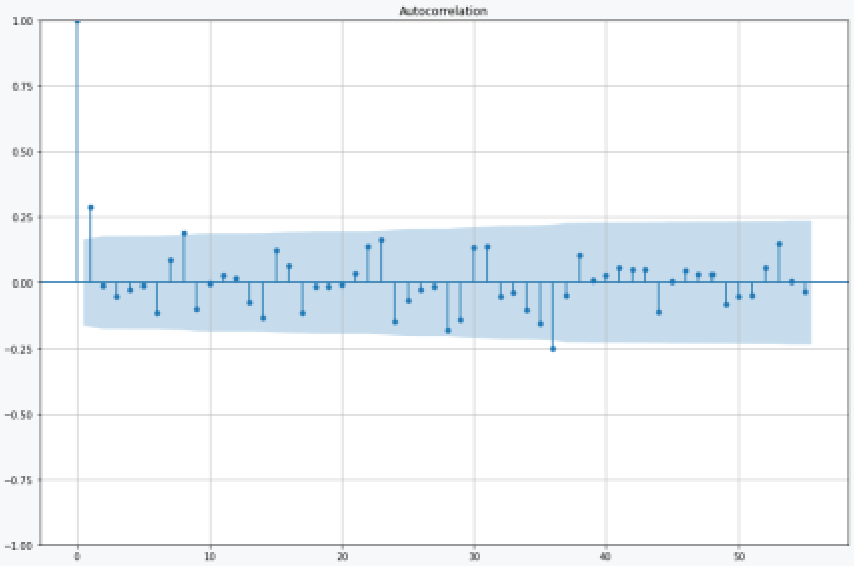


City wise total number of orders

Checking Stationarity



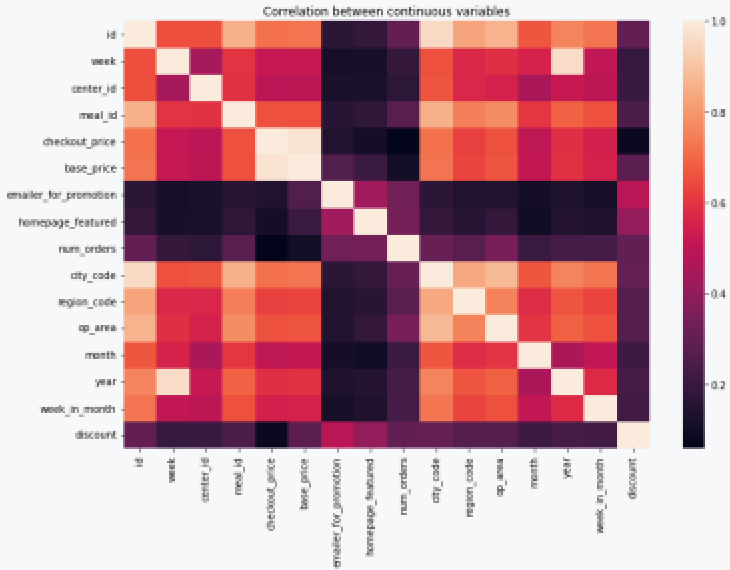
PACF Plot



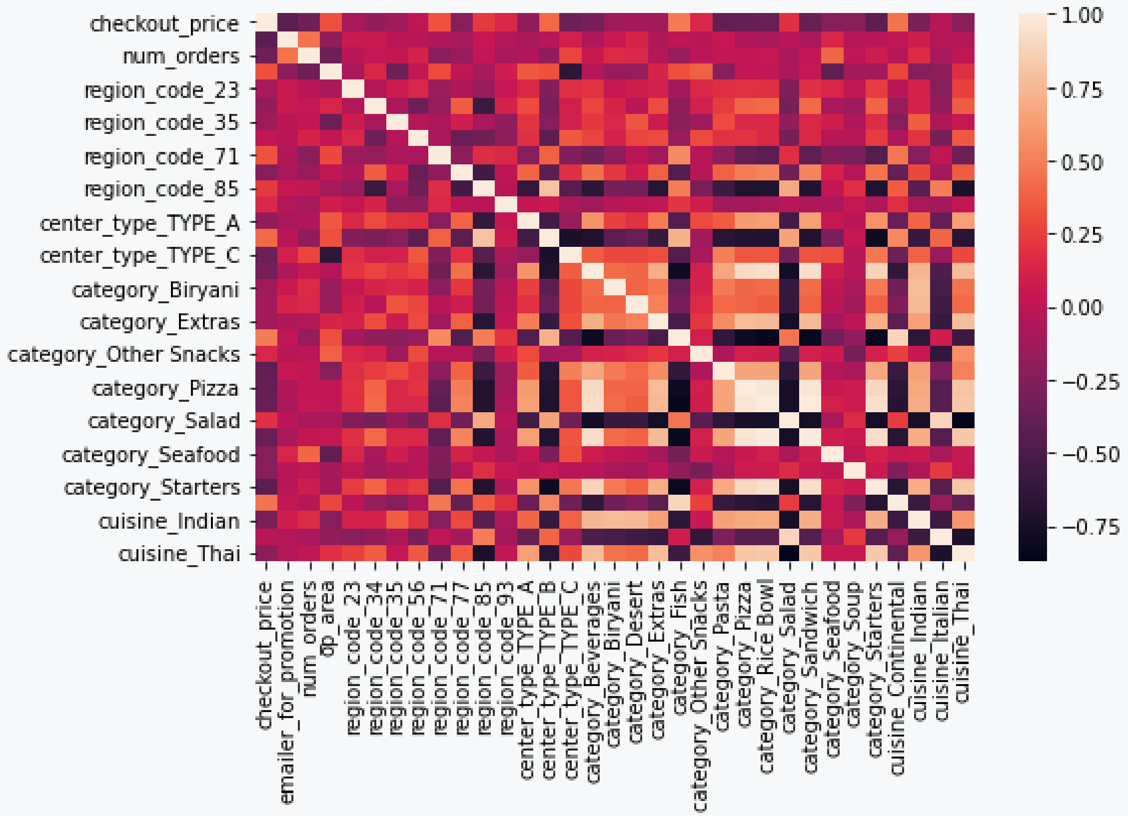
ACF Plot

- Note from the ACF and PACF plot that there are no consecutive peaks after 1, indicating there is no severe non-stationarity

Correlation b/w Regressors



Heatmap for variables



Heatmap after applying dummy variables

- Note from the ACF and PACF plot that there are no consecutive peaks after 1, indicating there is no severe non-stationarity

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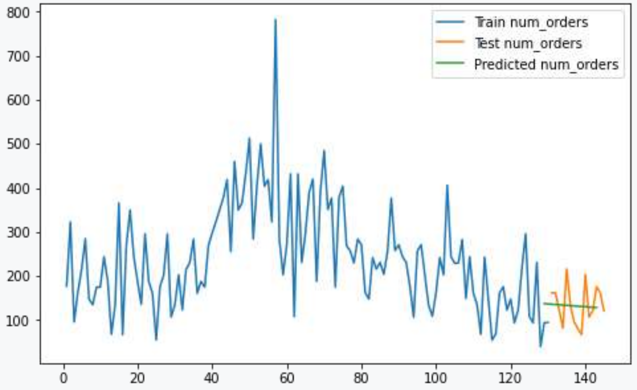
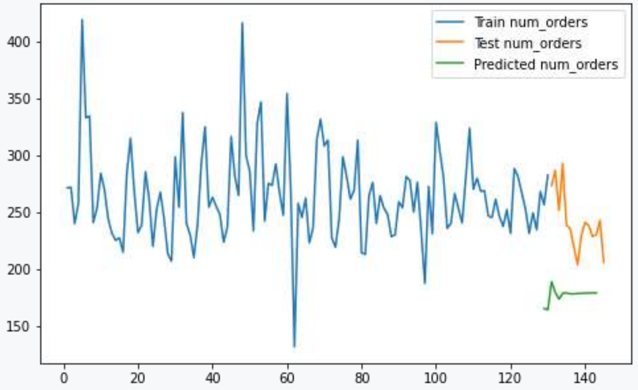
Time Series Models on weekly aggregated data

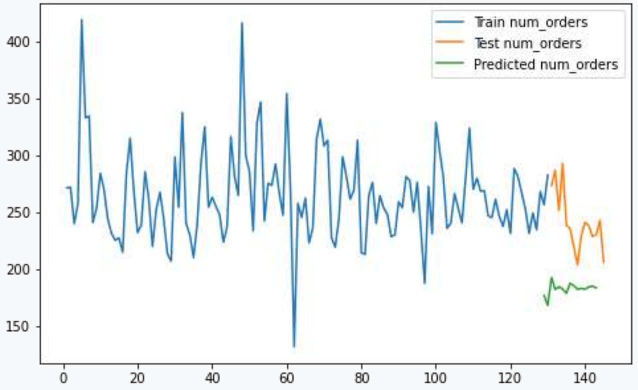
Index	TS Model	R^2	MAPE
1	Vector ARIMA	-0.001	30.99
2	VARMAX (Using Exogenous Variables)	-6.706	25.70
3	VARMAX (Using Exogenous Variables and dropping regressors with high correlation)	-5.67	23.47



Model 1



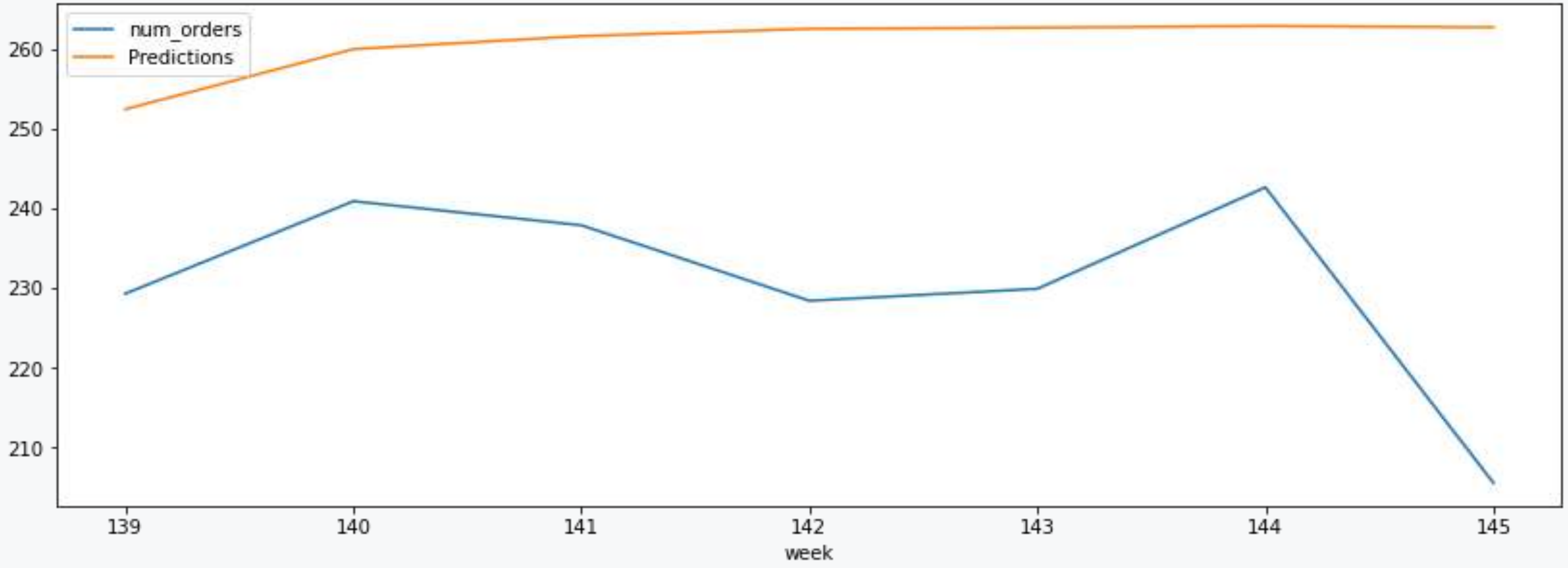
Model 2



Model 2

LSTM Model

Model	R^2	MAPE
LSTM	-6.86	13.31



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Interpretation

- Note that time series models are aggregated over weeks only, because of which they are losing lot of information, hence MAPE although is less but R2 is also very low.
- Hence these time series models aggregated over weeks are consistently giving bad predictions.
- We could try to fit the time series models without aggregating over week, that would be very time consuming, and costly to calculate.

Regression Models

Regression Models on weekly aggregated data

Regression Model	R^2	MAPE
Feature selection	-271.21	845.42
Feature selection and adding all dummy variables	-213.22	791.56

Regression Models on unaggregated data

Before fitting the below models applied feature selection by removing highly correlated regressors, and using 10 week lagged values of orders data

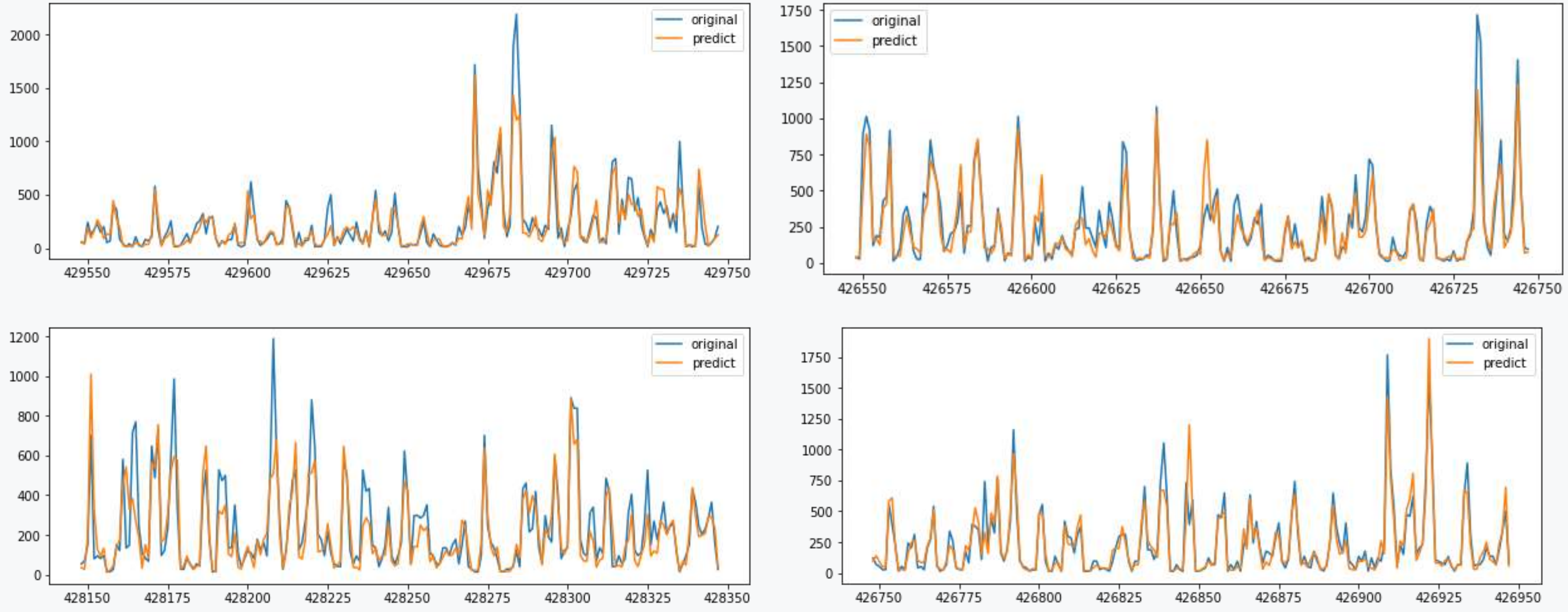
Regression Model	R^2	MAPE
Simple Linear Regression	64	1295
Ridge Regression	64	1294.1
Decision Tree Regressor	68.58	1186.341
Random Forest Regressor	72	1126.18

Regression Models on unaggregated data

The MAPE were very high even after feature selection, so taken logarithm for the orders, and prices columns

Regression Model	R^2	MAPE
XGB Regressor	82	46

	original	predict
426548	42.0	34.245853
426549	27.0	47.589993
426550	891.0	506.909760
426551	1013.0	890.895203
426552	917.0	801.760864
...	...	...
456543	68.0	39.689484
456544	42.0	26.164320
456545	501.0	251.571106
456546	729.0	333.632477
456547	162.0	182.971420



Some visualization and values for XGB Model

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More Granular Models

Granular Models

Meal and Center level Models

We fitted the XGB Model in Meal and Center level data to get better results, i.e reducing the MAPE.

	meal_id	evaluation_rmse	eval_r2	eval_mape
10	2707	32.264983	86.184055	4.383884
0	1885	33.628449	86.087928	4.381540
17	2290	29.102730	83.140702	3.507366
16	1109	32.055489	82.864772	4.275824
1	1993	33.769081	81.664403	4.385856
24	1971	42.052052	81.003201	5.863224
35	1727	34.588831	80.022605	4.846121
23	1754	36.048856	80.001197	4.707992
27	2826	37.417472	79.082064	5.184638
5	1311	41.659915	77.941385	6.410683

Meal Level Performance

	center_id	evaluation_rmse	eval_r2	eval_mape
1	13	43.790570	85.384924	6.340471
36	43	53.221096	83.380899	8.176820
58	52	49.994053	83.267980	7.796434
32	106	48.404886	83.224247	8.733789
56	10	46.750340	83.202802	7.022161
29	99	55.363618	82.762005	10.041479
0	11	53.784688	82.605869	8.971987
62	137	52.887359	82.395924	8.609536
48	65	51.000040	81.674604	8.848757
44	67	51.483439	81.484539	8.270885

Center Level Performance

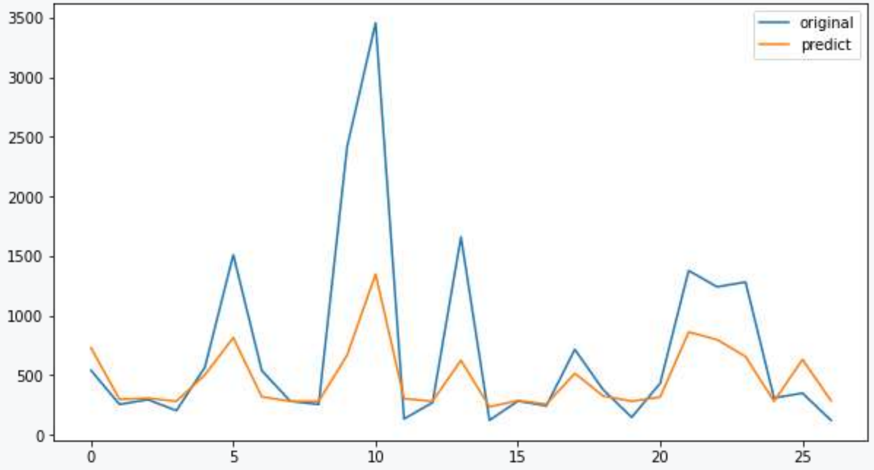
Meal cross Center Level

	meal_id	center_id	evaluation_rmse	eval_r2	eval_mape
49	1971	10	54.696932	64.363683	6.859026
45	1971	13	48.593895	59.678376	5.443007
47	1971	52	55.757960	57.014507	6.515912
52	1971	137	78.287611	56.567207	10.929453
46	1971	43	74.607814	54.328736	8.050363
8	2707	65	25.318738	50.347663	3.568447
40	1993	10	21.759717	50.219971	2.560521
50	1971	99	99.322682	49.995836	15.555788
18	2290	13	37.706170	49.310547	2.923199
51	1971	11	72.047152	48.063196	8.929475

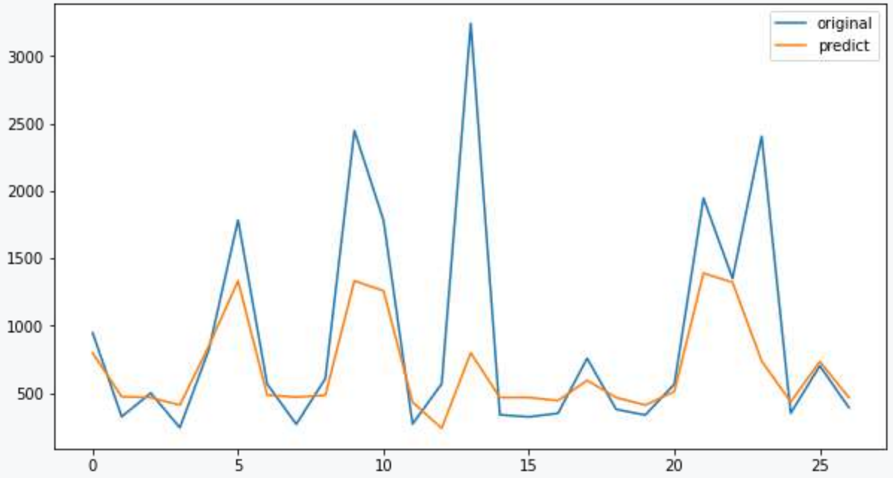
We fitted the model in 10x10 top meal and centers into total 100 data, and found out that the best meal level models or best center level models did not perform best in meal cross center level, the R^2 has reduced significantly.

Results and Prediction

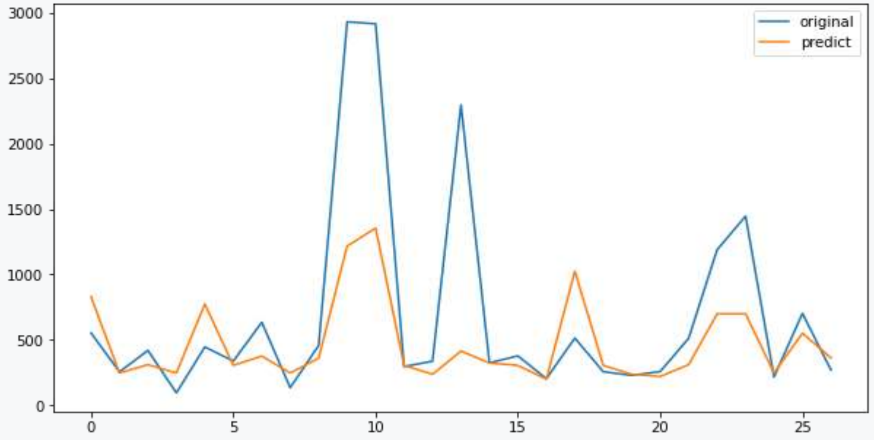
Predictions and Insights



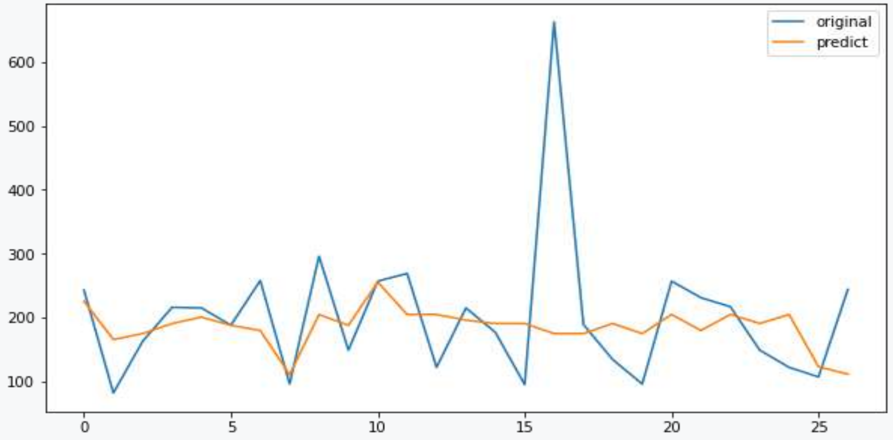
Prediction for meal_id 1970 center id 10



Prediction for meal_id 1970 center id 13



Prediction for meal_id 1970 center id 52



Prediction for meal_id 2760 center id 65

Predictions and Insights

- A good feature of these predictions can be seen, that they have predicted the peaks and dips properly
- Also, on average predictions are higher than original, but for peaks or special cases the predictions are lower than the original, this insight will help in a way by not storing excessive foods that might perish, in case of special occasions in future did not really have that high demand, thus mitigating the risks.
- For the meal cross center data which has not performed better we might have to fit other models

Future Scopes

Future Scopes

- Due to the time series models not performing well, and being costly to apply in large datasets, we had to resort to regression models.
- Which essentially converted the forecasting problem into prediction problem.
- To avoid this, we can try to apply time series model in all data of meal cross center granularity.
- Second approach, we have also seen the LSTM model performed moderately, well for a 12-week window of prediction.
- We can apply LSTM to all the required regressors to get a forecast (future values) on them.
- Then take these future values to predict demand for number of orders in future, using a good regression model, to save time and computation.
- Github Link for the project

Thank You!
For attending

Email: arkaprova@sigmoidanalytics.com

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USA: New York, San Francisco, Dallas | Peru: Lima | India: Bengaluru