SHRIRAM **HANGARGEKAR**

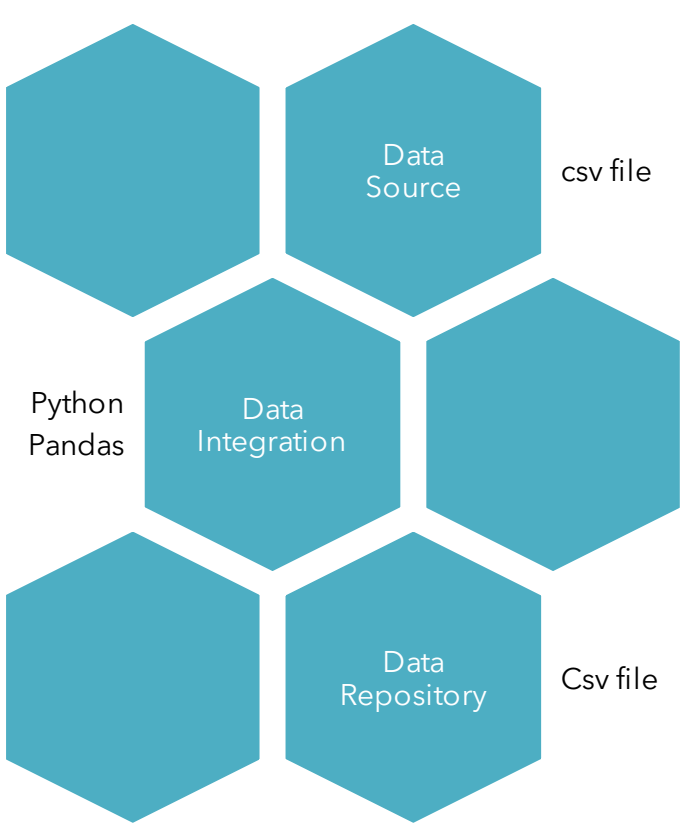
RESTAURANT VISITOR FORECASTING

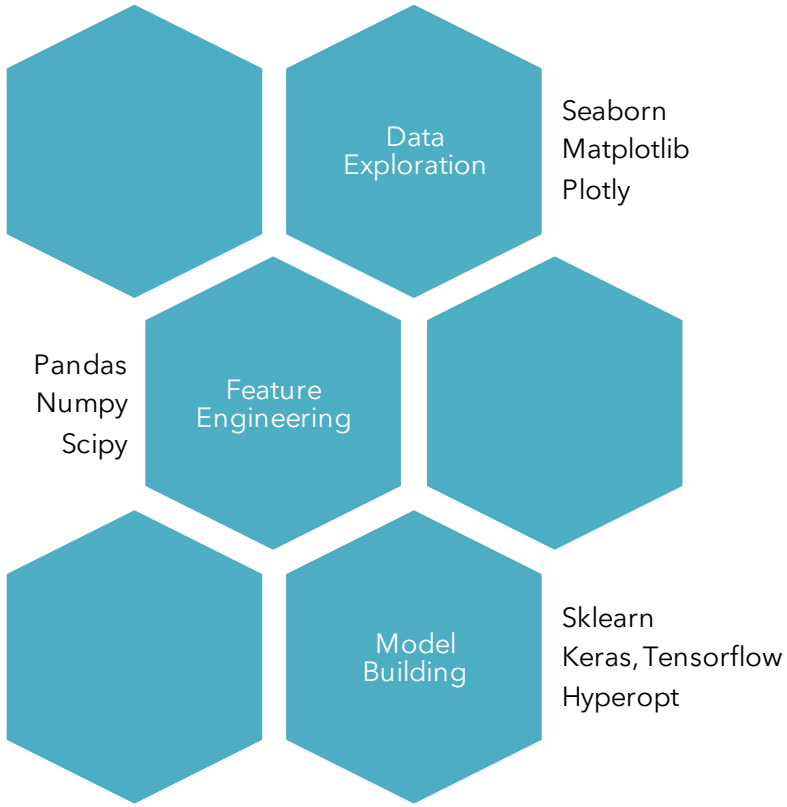
IBM ADVANCED DATA SCIENCE CAPSTONE PROJECT

VISITOR FORECASTING

- What is the problem?
- Why is it an important problem?
- So, what is the solution?
- What is needed for solution?
- How is the solution achieved?

ARCHITECTURAL DECISIONS





EXTRACT – TRANSFORM - LOAD

- Connect to Data Source
- Download csv's in file
- Load in Pandas data-frame

Transform

- Handle missing data
- Adjusting the ranges
- Matching data types

Load

- Merge all data
- Connect to server
- Store as csv

ETL - DATA SOURCE

② **AIR RESERVATION SYSTEM STORE INFO DATA**

AIR System ID	string
Genres	string
Area Location	string
Longitude	float
Latitude	float

① **AIR RESERVATION SYSTEM RESERVATION DATA**

Reservation ID	int
Reservation Date	datetime
Reservation Store	string
Visit Date	datetime
Reserved Visitors	string

④ **NATIONAL HOLIDAY DATA**

Date	datetime
Day	string
Flag	boolean

③ **HISTORIC VISITORS' DATA**

Visit Date	datetime
Reservation Store	string
Total Visitors	int

⑦ **STORE ID RELATIONSHIP**

Store ID	int
AIR System ID	string
HPG System ID	string

⑥ **HPG RESERVATION SYSTEM STORE INFO DATA**

HPG System ID	string
Genres	string
Area Location	string
Longitude	float
Latitude	float

⑤ **HPG RESERVATION SYSTEM RESERVATION DATA**

Reservation ID	int
Reservation Date	datetime
Reservation Store	string
Visit Date	datetime
Reserved Visitors	string

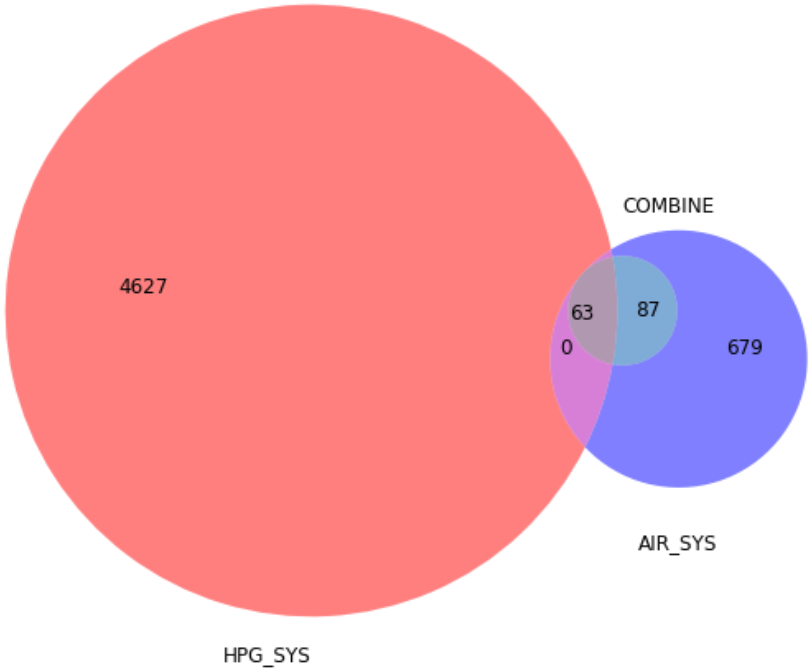
	Name	Date modified
①	air_reserve	11/21/2017 7:31 AM
②	air_store_info	11/21/2017 7:31 AM
③	air_visit_data	11/21/2017 7:32 AM
④	date_info	11/21/2017 7:32 AM
⑤	hpg_reserve	11/21/2017 7:32 AM
⑥	hpg_store_info	11/21/2017 7:31 AM
⑦	store_id_relation	11/21/2017 7:32 AM

Source: https://www.kaggle.com/c/recruit-restaurant-visitor-forecasting/data

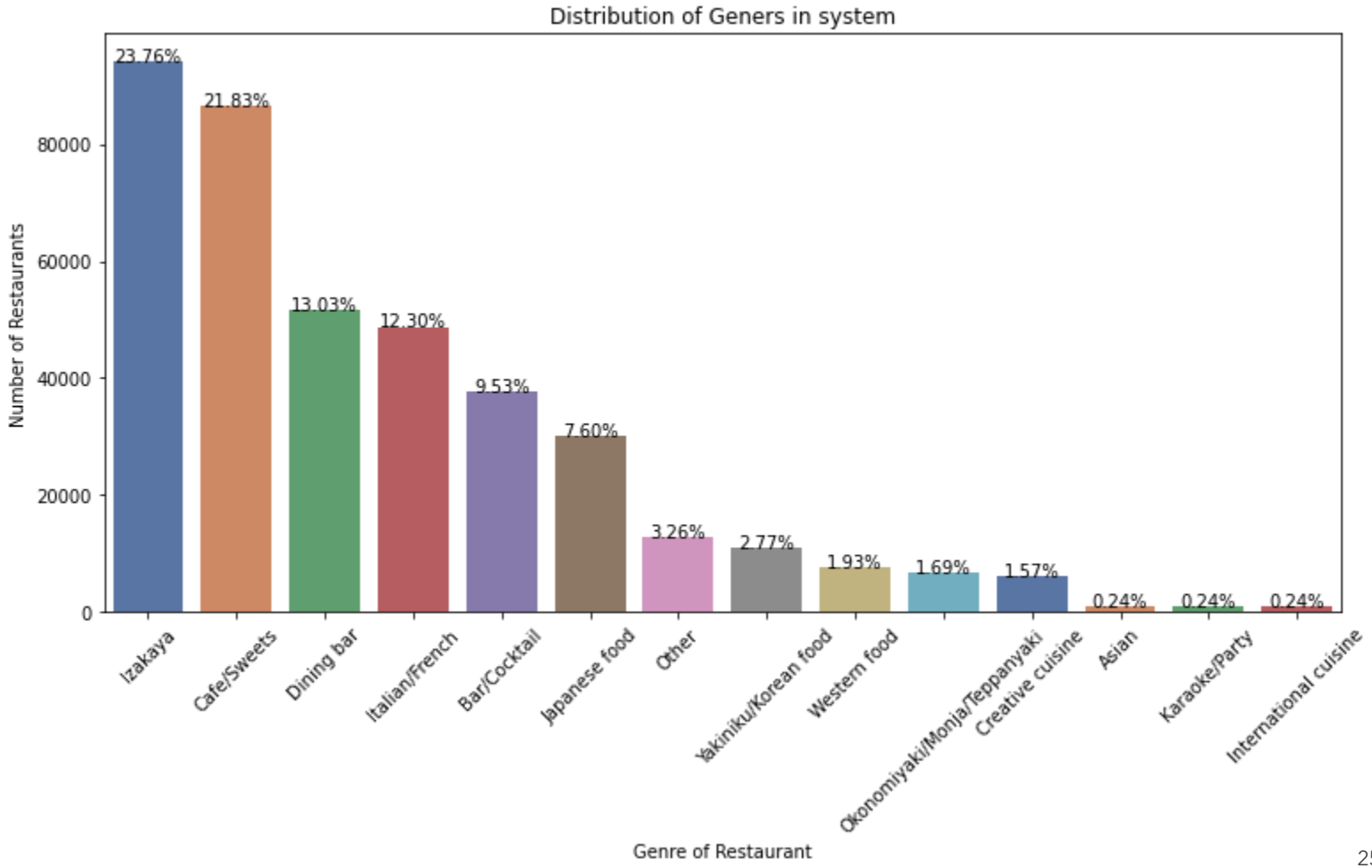
RESTAURANTS BY SYSTEMS

-	AIR_SYS	HPG_SYS
Unique	679	4627
Combine	150	63
Explicit	0	87

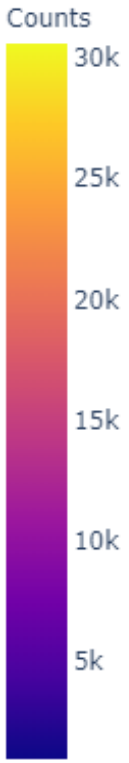
System-wise distribution of hotels



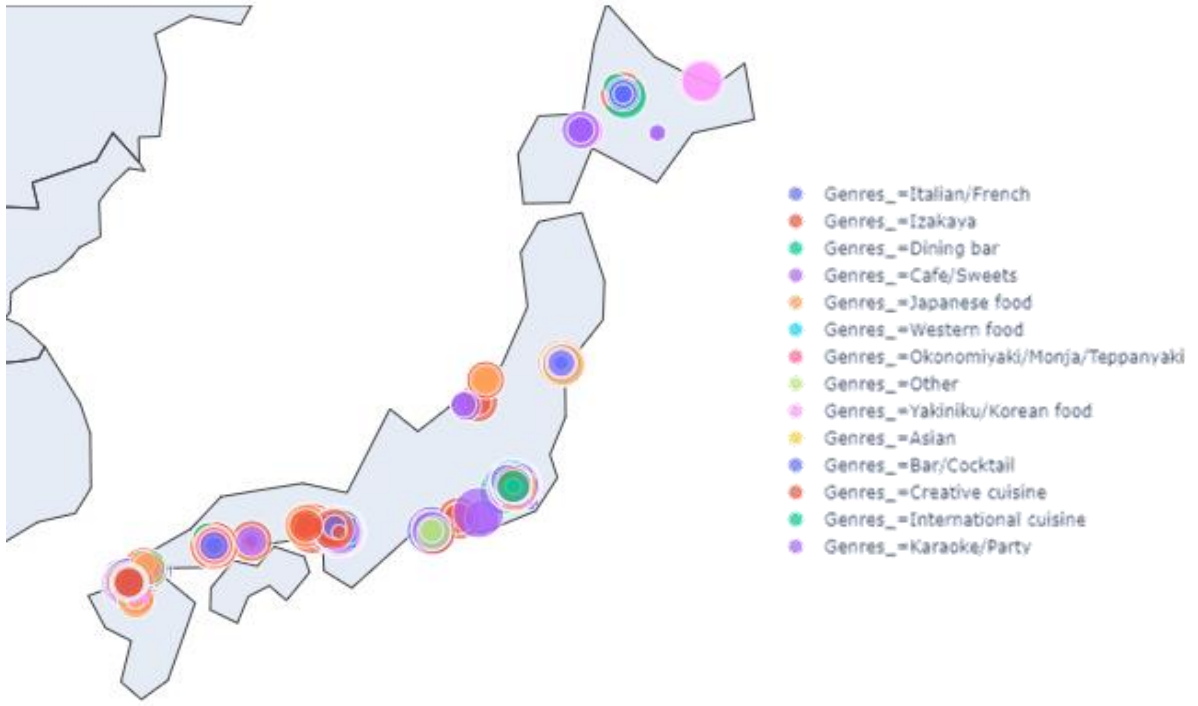
RESTAURANTS BY GENRES



RESTAURANTS AND VISITORS BY LOCATION

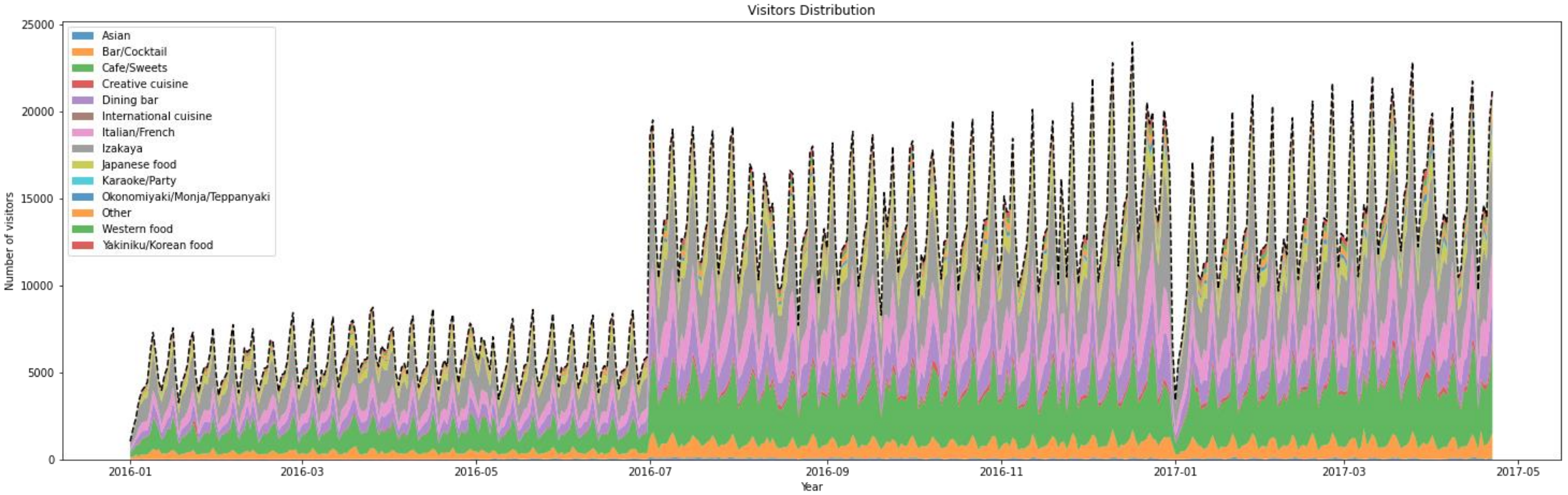


Restaurants by Area

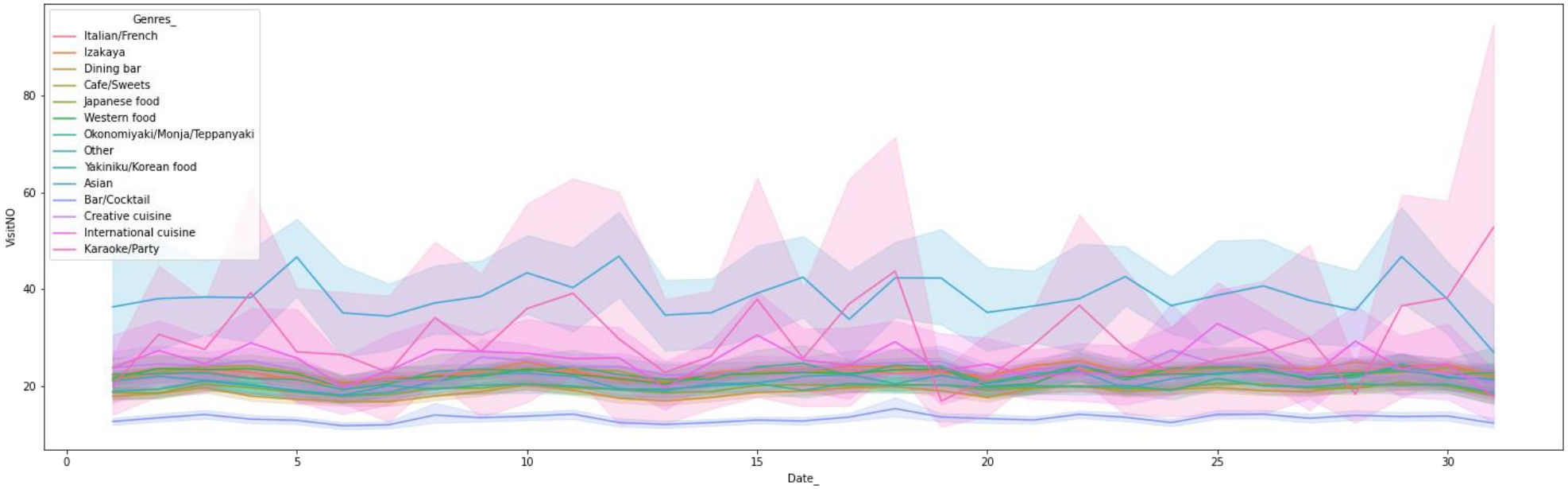


Visitors by Area

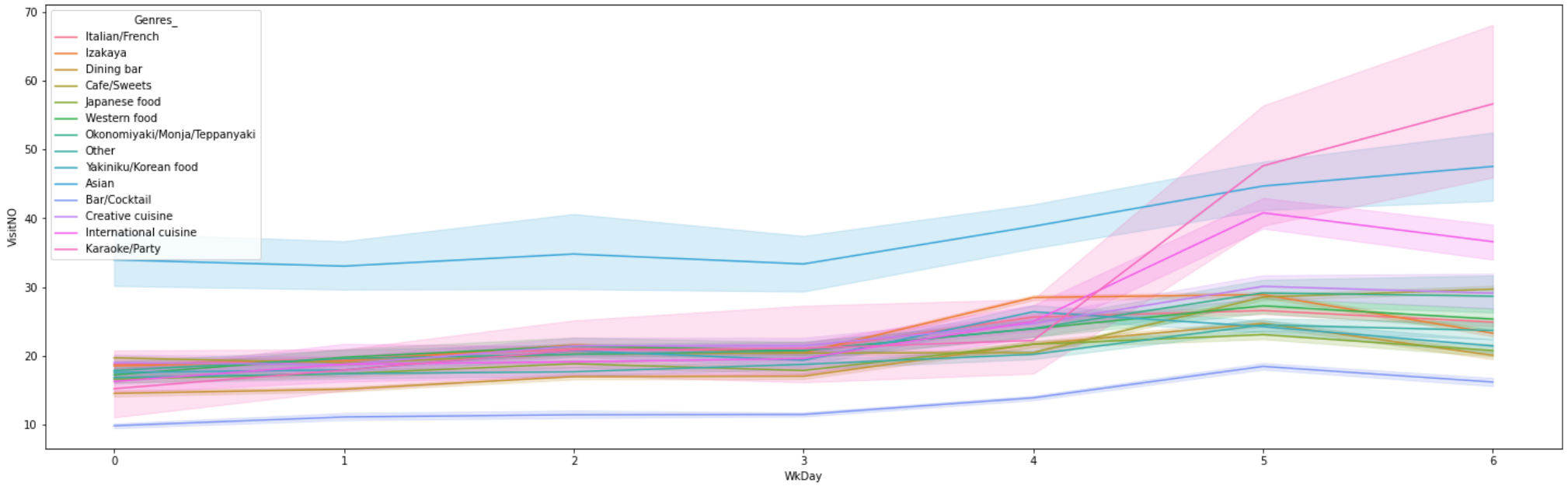
VISITORS TIMESERIES PLOT



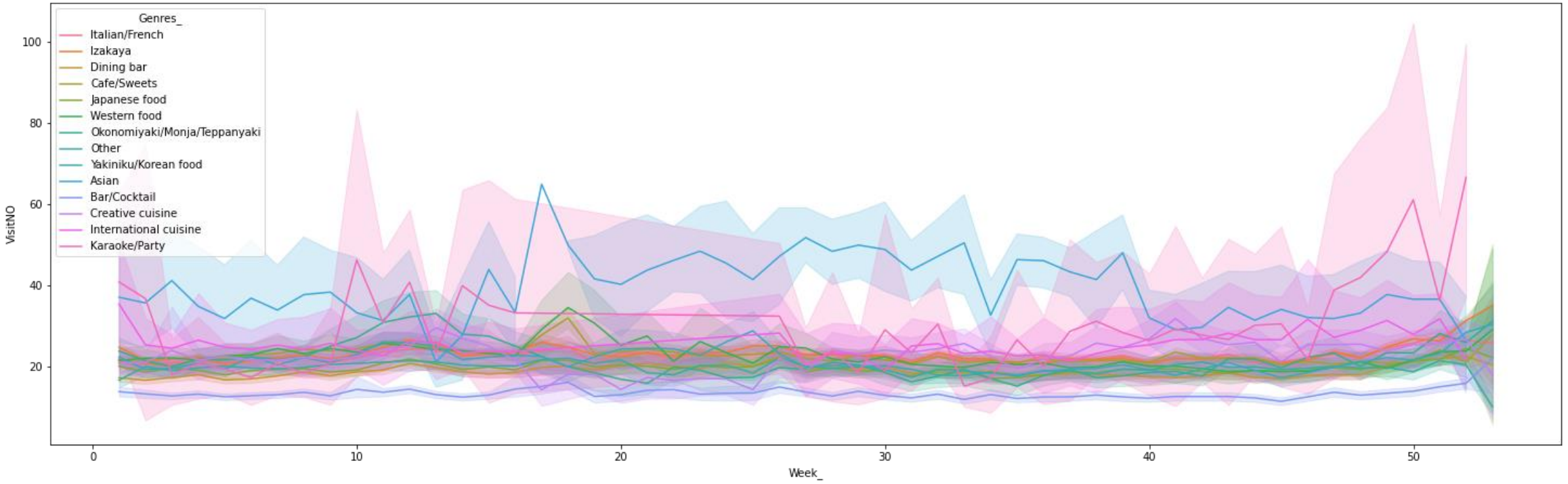
TRENDS IN VISITORS – OVER MONTH



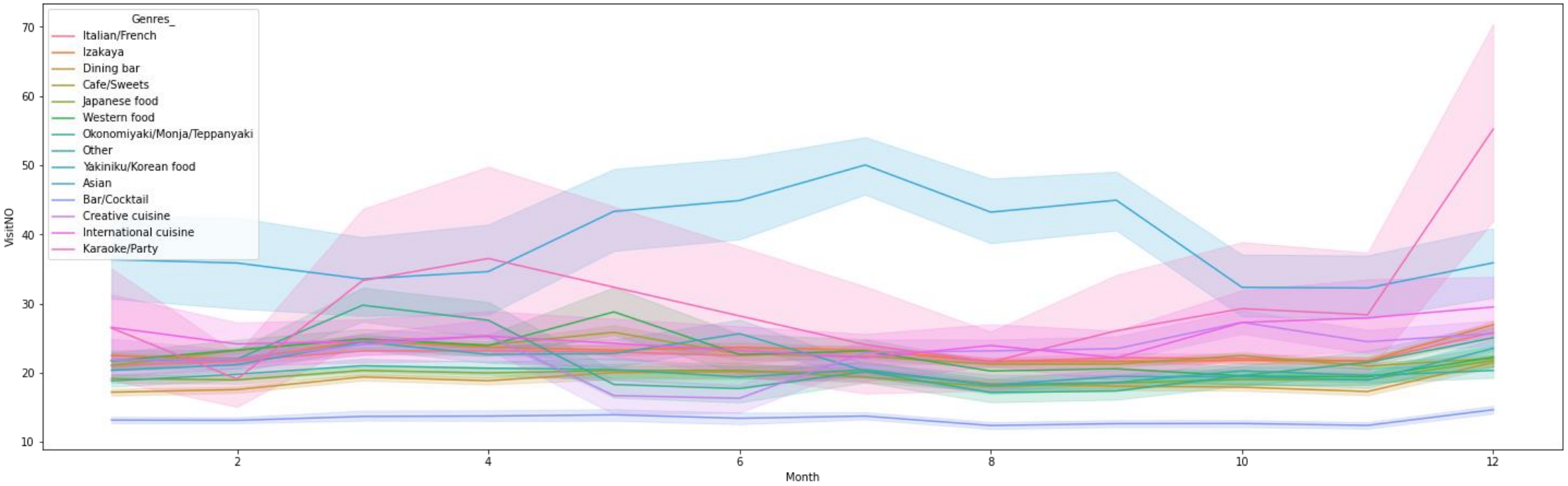
TRENDS IN VISITORS – OVER WEEK



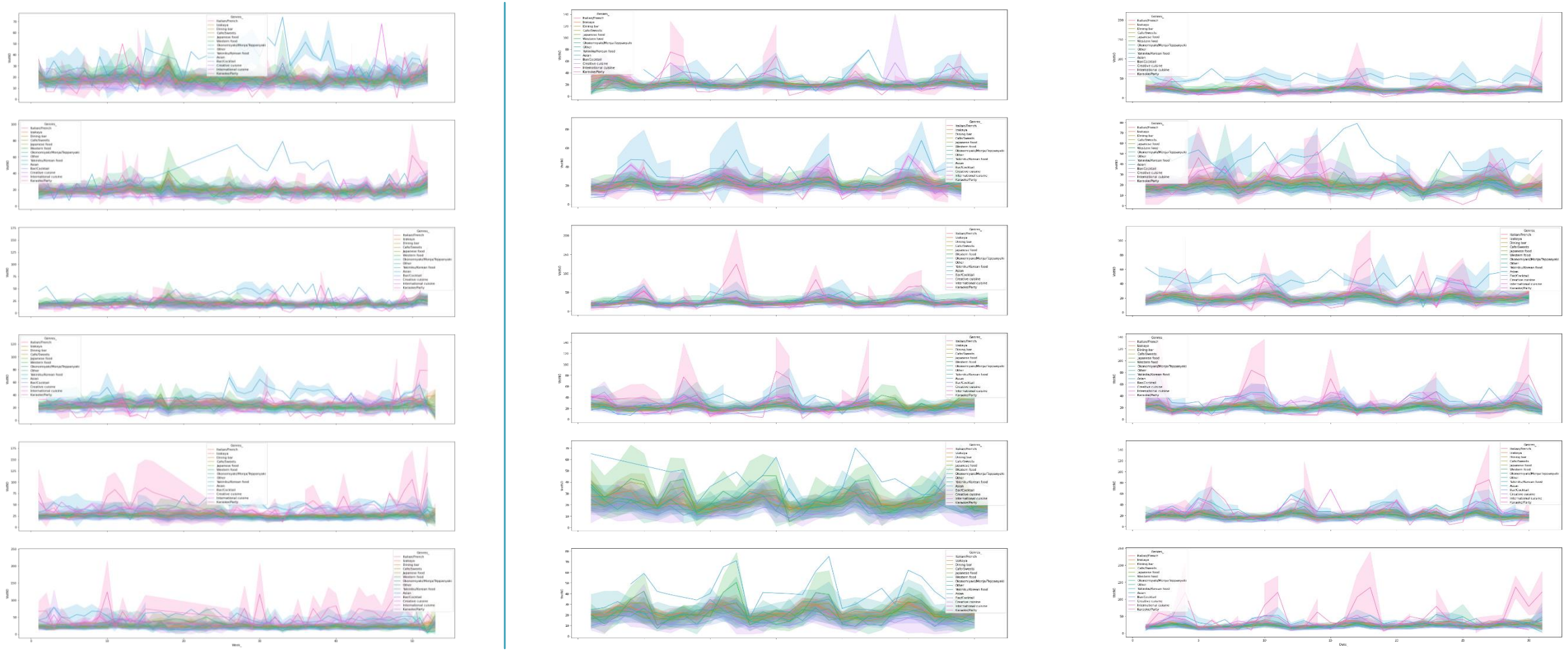
TRENDS IN VISITORS – OVER YEAR



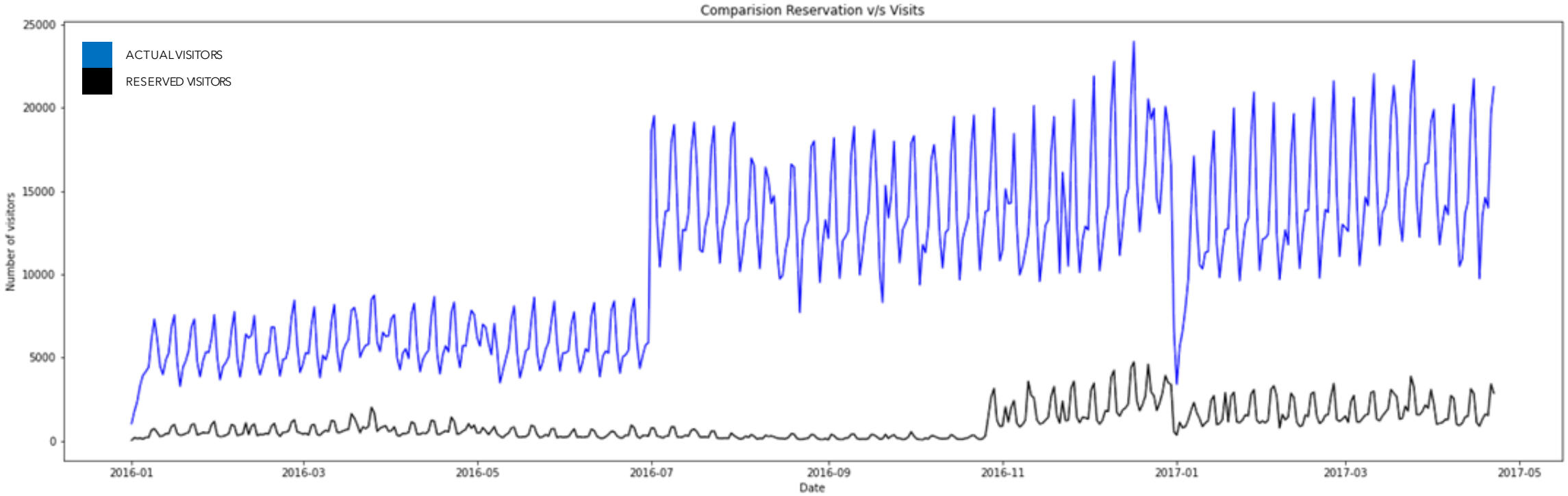
TRENDS IN VISITORS – OVER YEAR



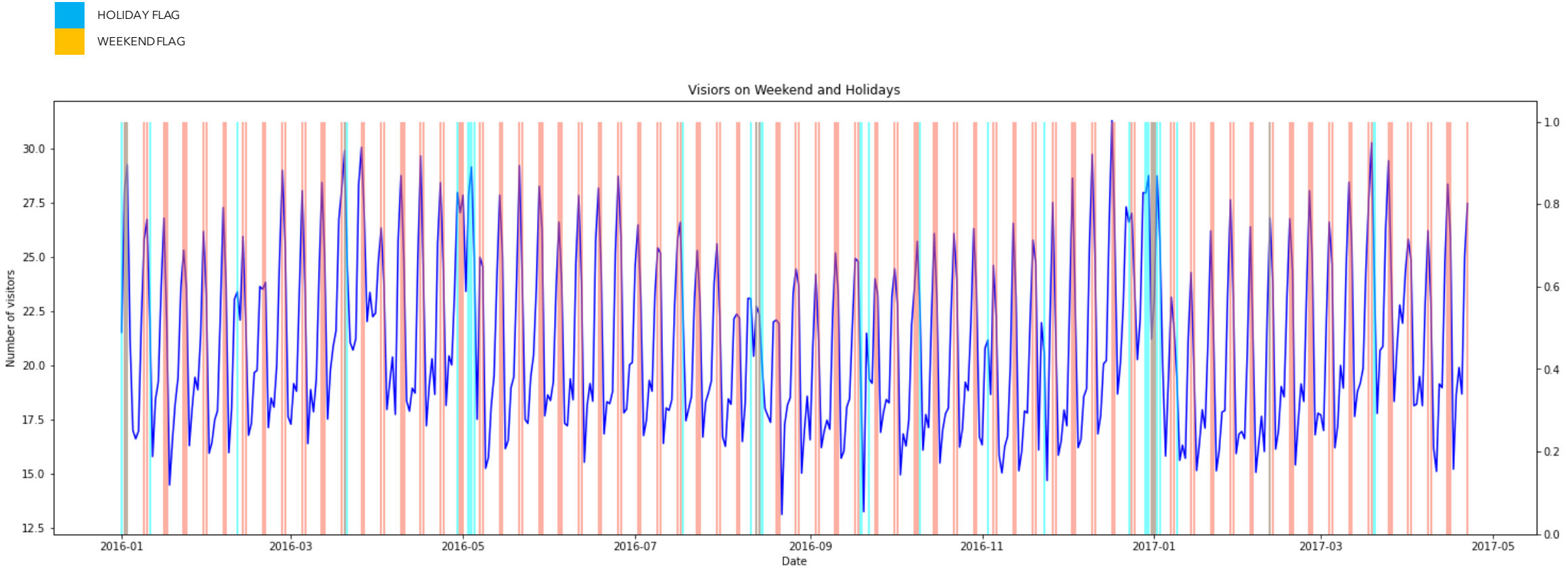
VISITORS VISITING PATTERN ACROSS YEAR



VISITORS – ACTUAL V/S RESERVED

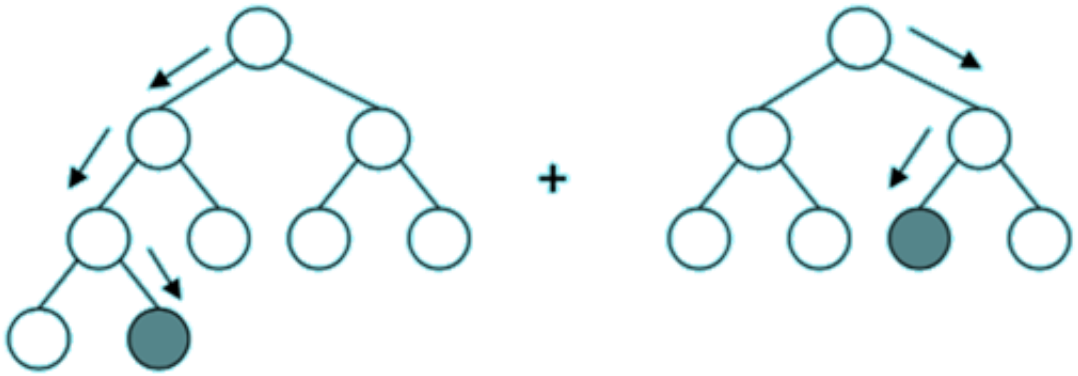


VISITORS – ON HOLIDAYS & WEEKENDS

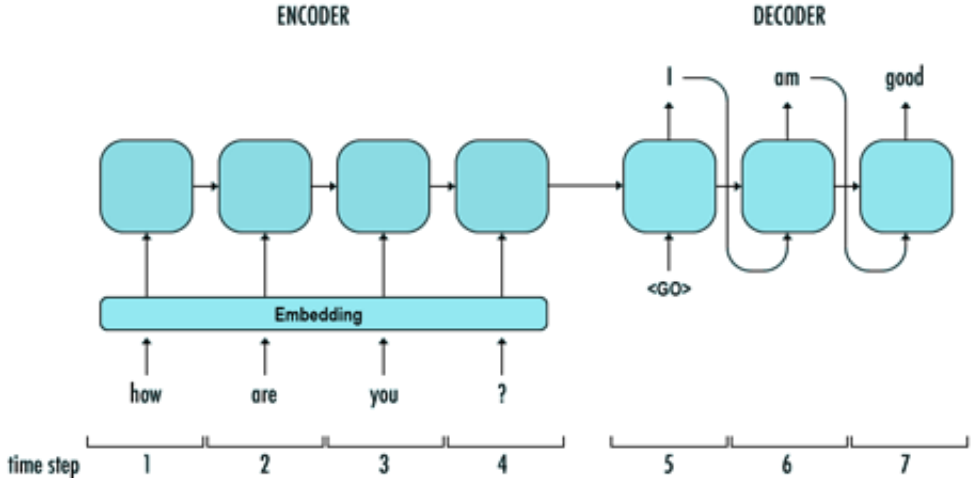


MODEL DEFINITION

- CLASSICAL ML MODEL
- Gradient Booster Regressor



- DEEP LEARNING MODEL
- Seq2Seq LSTM Encode-Decoder



FEATURE ENGINEERING

- Features Derived:
  - From visit date: year, month, date, day, weekend, holiday
  - From area: City, ward, Street
  - From reservation: reservation days, visitors reserved
  - From visitors: statistical features – min, max. mean, median, std
- Features Transformed:
  - Categorical : Label encoder
  - Numeric: Min Max Scaler
- Previous 7 days visitors (only for LSTM)

MODEL EVALUATION

- Data split 80:10:10 train-test-validation split
- Root mean squared logarithmic error as metric

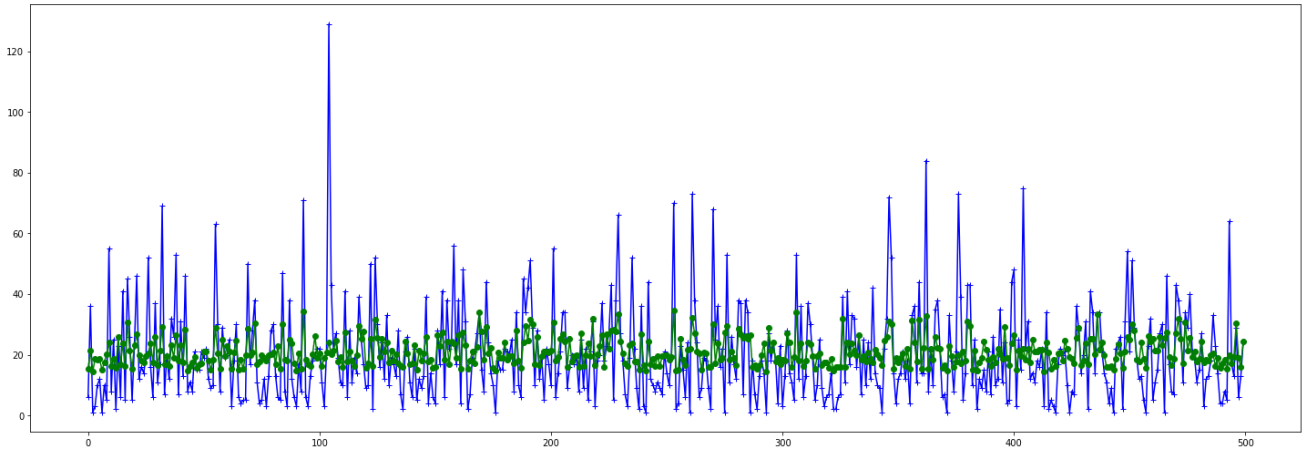
$$RMSLE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\log(1+p) - \log(1+a))^2}$$

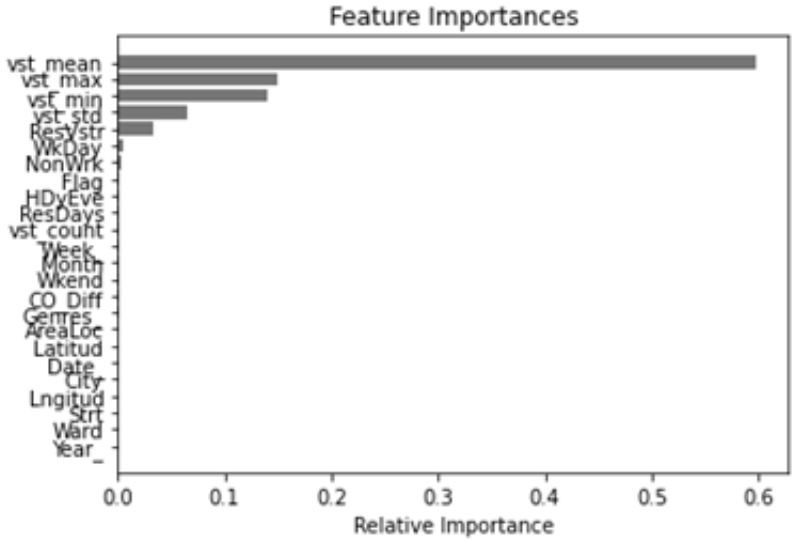
n is the total number of observations | p_i is your prediction of target | a_i is the actual target for i.

  - Robustness to the effect of the outliers
  - Measurement of relative error
  - Biased penalty for overestimation

GRADIENT BOOST MODEL

- K-fold cross-validation and training
- Prediction is averaged over 5 folds
- Hyper Parameter tuning performed



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Performance of base model:
0.71
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Performance of fine model:
0.72
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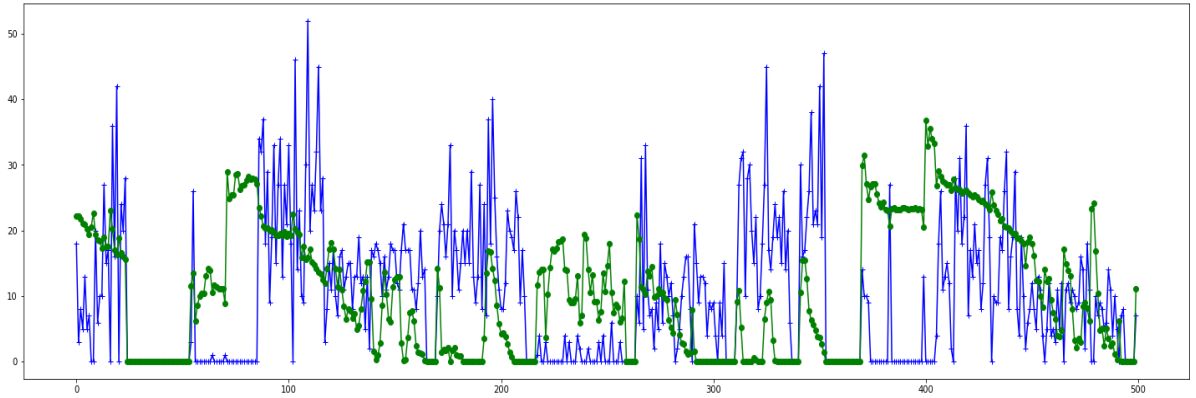
LSTM ENCODE-DECODER

- One layer of encoder
- Two layers of decoder units
- Two iterations with different features

Layer (type)	Output Shape	Param #	Connected to
input_5 (InputLayer)	[(None, None, 32)]	0	[]
input_6 (InputLayer)	[(None, None, 32)]	0	[]
lstm_3 (LSTM)	[(None, 64), (None, 64), (None, 64)]	24832	['input_5[0][0]']
lstm_4 (LSTM)	(None, None, 64)	24832	['input_6[0][0]', 'lstm_3[0][1]', 'lstm_3[0][2]']
lstm_5 (LSTM)	[(None, None, 64), (None, 64), (None, 64)]	33024	['lstm_4[0][0]']
time_distributed_1 (TimeDistributed)	(None, None, 1)	65	['lstm_5[0][0]']

Total params: 82,753
Trainable params: 82,753
Non-trainable params: 0

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Performance of first model:
1.61
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Performance of second model:
2.09
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SUMMARY

- GBM works better
- Further tasks: Tuning LSTM for better performance
  - Activation Function
  - Number of layers
  - Number of hidden units in each layer
  - Optimizer
- Links below:
  - Architectural decision document :

Recruite_Restaurants_Visitors_Forecasting_ADD_Document.pdf

  - Entity relationship diagram:

Database Documentation.pdf

  - Jupyter Notebook:

IBM_Capstone.ipynb

Algorithm	Variation	RSMLE	Visual
Gradient Boost	Before tuning	0.7174	--
	After tuning	**0.7204**	**OK**
Encoder-Decoder	With 3 prev days	1.6358	---
	With 7 prev days	2.0922	---