

Recruit Restaurant Visitor Data Analysis and Forecasting Project



Running a thriving local restaurant isn't always as charming as first impressions appear. There are often all sorts of unexpected troubles popping up that could hurt business.

One common problem is that restaurants need to know how many customers to expect each day to effectively purchase ingredients and schedule staff members. This forecast isn't easy to make because many unpredictable factors affect restaurant attendance, like weather and local competition. It's even harder for newer restaurants with little historical data.

Recruit Holdings has unique access to key datasets that could make automated future customer prediction possible. The datasets comes from a restaurant review service (Hot Pepper Gourmet) and restaurant point of sales service (AirREGI, and reservation log management (Restaurant Board).

Recruit challenges people to use reservation and visitation data to predict the total number of visitors to a restaurant for future dates. This information will help restaurants be much more efficient and allow them to focus on creating an enjoyable experience for their customers.

In this paper, a key findings from a data analysis of the available datasets are presented, and a prediction algorithm is constructed with ARIMA for different types of restaurants.

The results indicate that there is a lot of interesting properties of the datasets, which could be used to improve processes. In addition, the prediction is shown to perform remarkably well in predicting the amount of visitors, in general, to different types of restaurants.

The original source of the problem and datasets can be found at:
<https://www.kaggle.com/c/recruit-restaurant-visitor-forecasting>

Recruit Restaurants - Forecasting - Data Analysis - Description of datasets, distribution of visitors and reservations

- For a start, all the datasets available will be presented, for an idea of what characteristics we can analyze

Description of Datasets

Want to present the available datasets and typical values

AirREGI Reservations

- Contains information of reservations done in the Air system

Store ID: Identification of the restaurant

Visit Date: The date for the reservation

Reservation Date: The date the reservation was done

Visitors: The amount of spots reserved

air_6b15edd1b4fbb96a

2016-01-02 17:00:00

2016-01-01 22:00:00

3

Hot Pepper Gourmet Reservations

- Contains information of reservations done in the HPG system

Store ID: Identification of the restaurant

Visit Date: The date for the reservation

Reservation Date: The date the reservation was done

Visitors: The amount of spots reserved

hpg_33ec1499d6b13141

2016-01-01 17:00:00

2016-01-01 15:00:00

2

Date Information

- Contains information of dates

Calendar Date: A date

Day of the Week: Which day of the week

Holiday: Whether the date is a holiday

2016-01-01

Friday

1

AirREGI Store Information

- Contains information of the stores in the air system

Store ID: Identification of the restaurant

Store Genre: The type of restaurant

Area: The area the restaurant is located at

Latitude: The latitude of the restaurant's location

Longitude: The longitude of the restaurant's location

air_0f0cdeee6c9bf3d7

Italian/French

Hyogo-ken Kobe-shi Kumoidori

34.6951242

135.19785249999998

AirREGI Visitors Information

- Contains information of the visitors at restaurants for different dates

Store ID: Identification of the restaurant

Visit Date: A date the restaurant is open

Visitors: The amount of visitors for a date

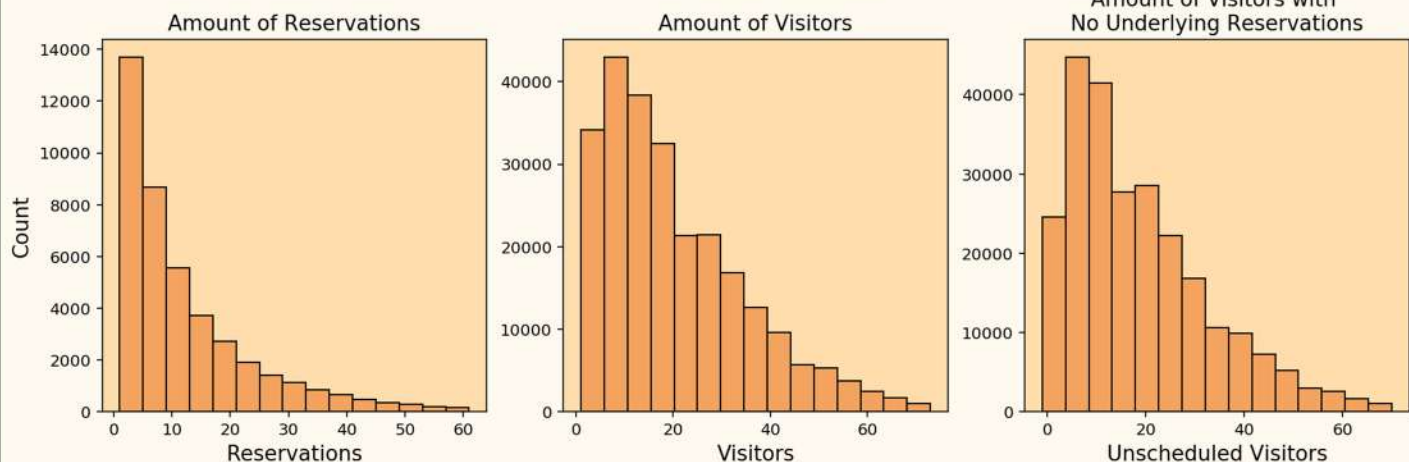
air_ba937bf13d40fb24

2016-01-13

25

- To give a rough idea of how many people people, on average, visit and book reservations for restaurants, we may consider the distribution of visitor and reservation values

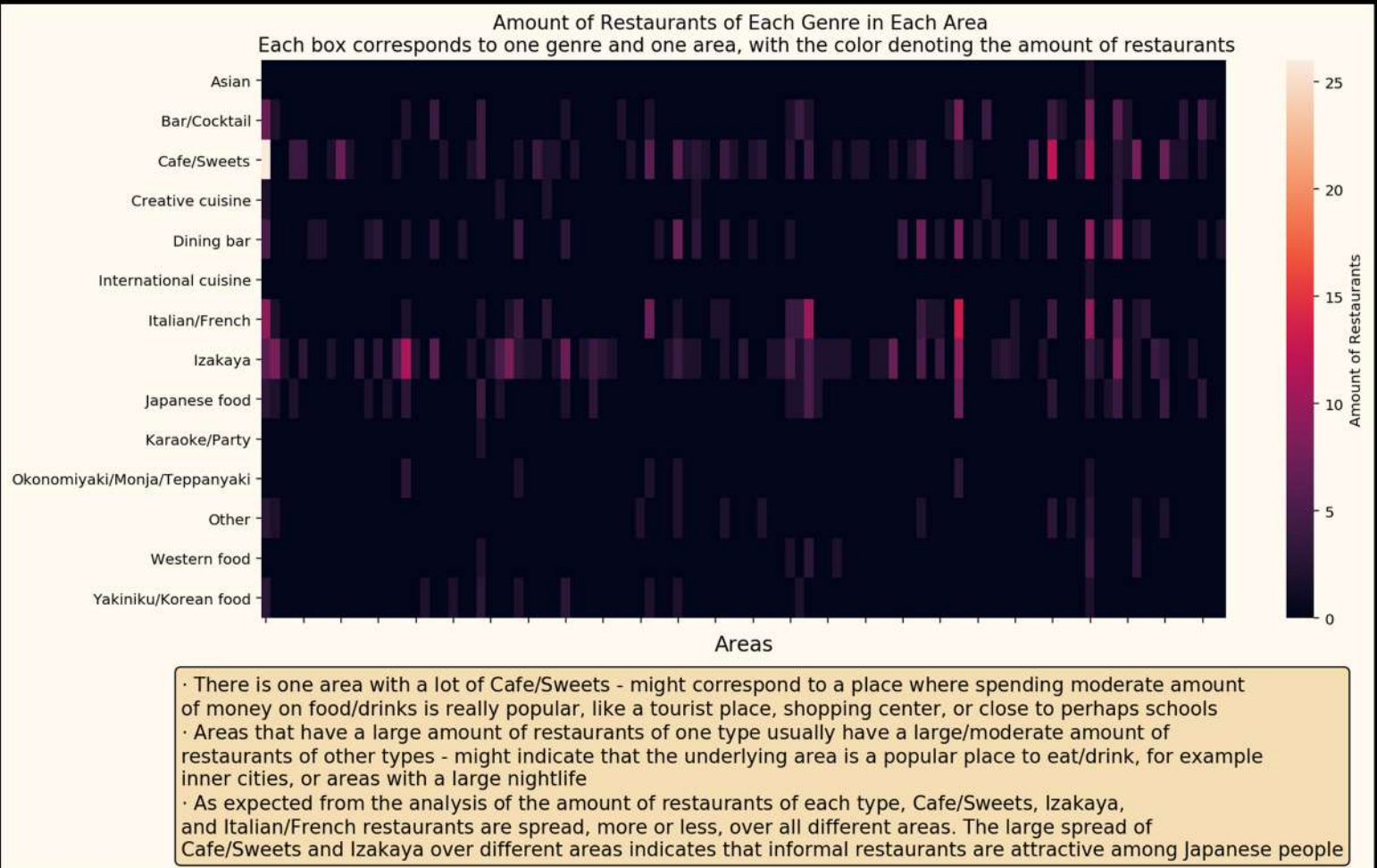
Histogram of reservations, visitors, and unplanned visitors for restaurants, for a given day
Outliers removed



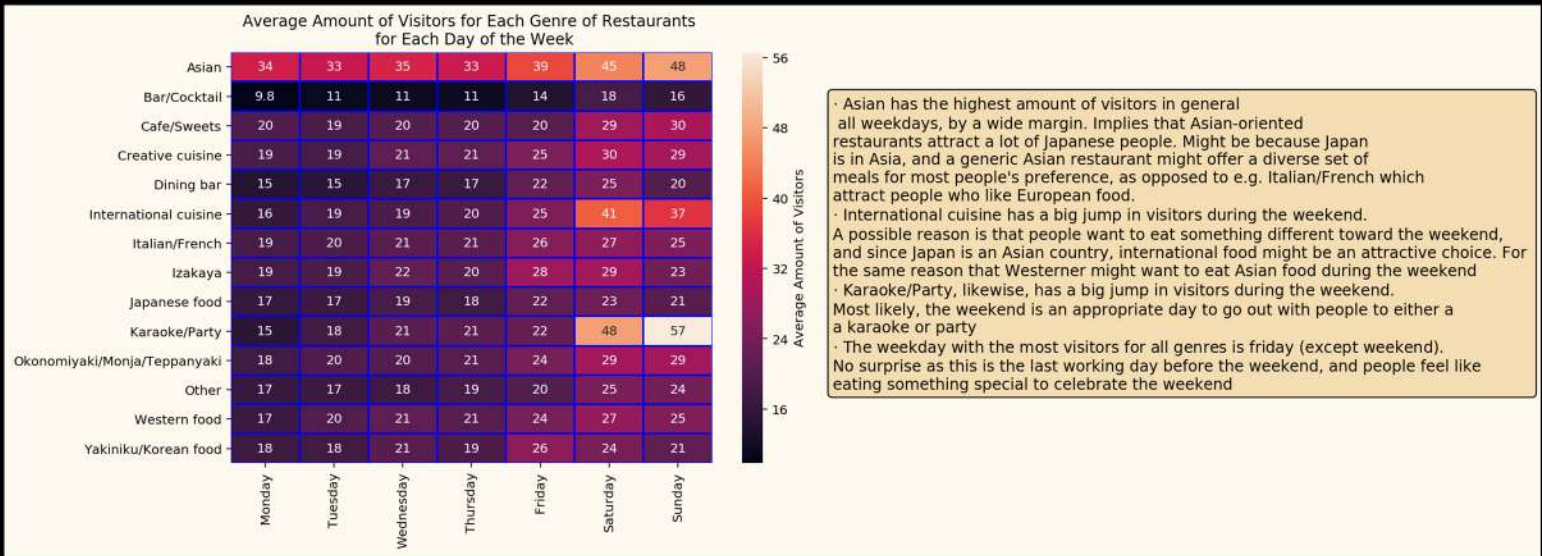
- Amount of reservations done for a restaurant, for a given day, is often smaller than 10 but there exists cases where reservations reach larger values like 10, 20, 30 - perhaps they corresponds to holiday/weekend days
- Amount of visitors, generally, exceeds the number of reservations, implying that restaurants often receive more customers than the amount of reservations - indicates consumers seldom have to worry about a restaurant running out of places
- Further illustrating the relation between reservations and visitors, the amount of visitors with no underlying reservations are mostly non-negative, implying again that restaurants tends to receive more customers than the amount of reservations they receive
- Also note that from the amount of reservations and visitors, we can see that there exists a lot of cases where a restaurant may receive visitors without a single reservation, for a particular day - which might corresponds to weekdays or other low-traffic inducing days
- Days with high amount of visitors most likely correspond to weekends or holidays, which might explain why these cases occur much less than days with low amount of visitors (which probably, in turn, corresponds to weekdays)

Recruit Restaurants - Forecasting - Data Analysis - Type of restaurants in areas, amount of visitors to every type of restaurant over the week

- As all areas are different, there is an interest in considering what type, and how many, restaurants exists in each area - perhaps there is some area with a lot of Dining Bars

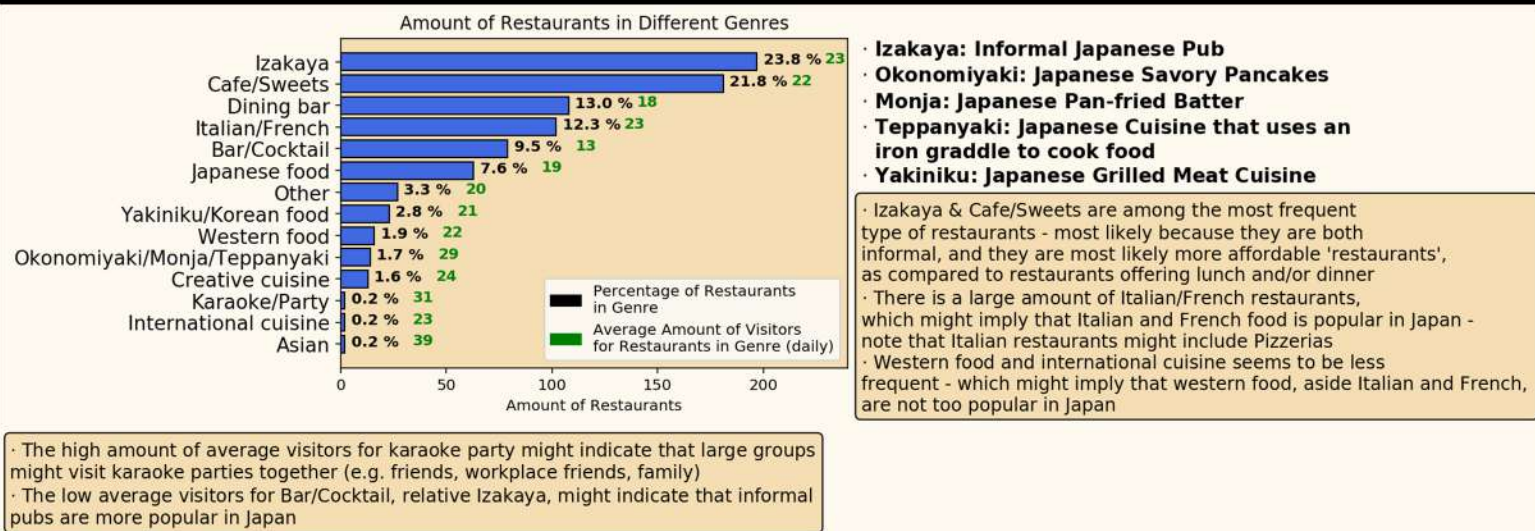


- Intuitively, the traffic to restaurants should change over the week, with perhaps an uptick of visitors during the weekend. This can be considered by the average amount of visitors for each type of restaurant over the week

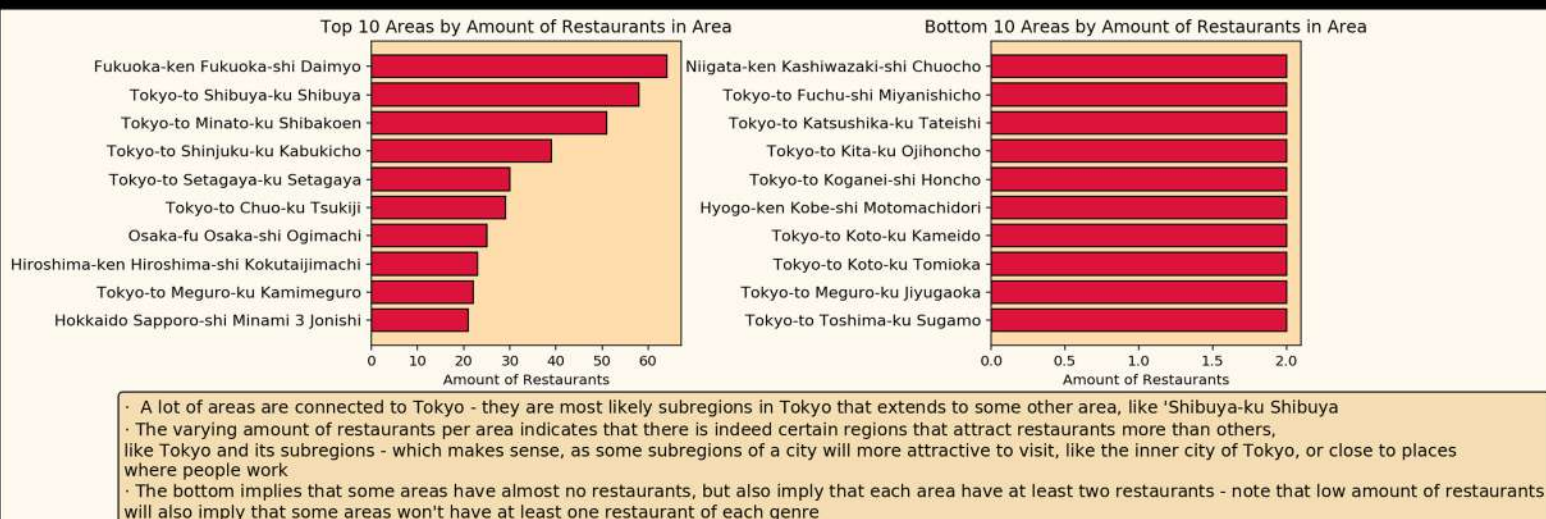


Recruit Restaurants - Forecasting - Data Analysis - Type of restaurants in Japan, amount of restaurants in areas

- To get an idea of what type of restaurants exists in Japan, and in what proportions, we consider an analysis of the `air_genre_name` attribute in the datasets

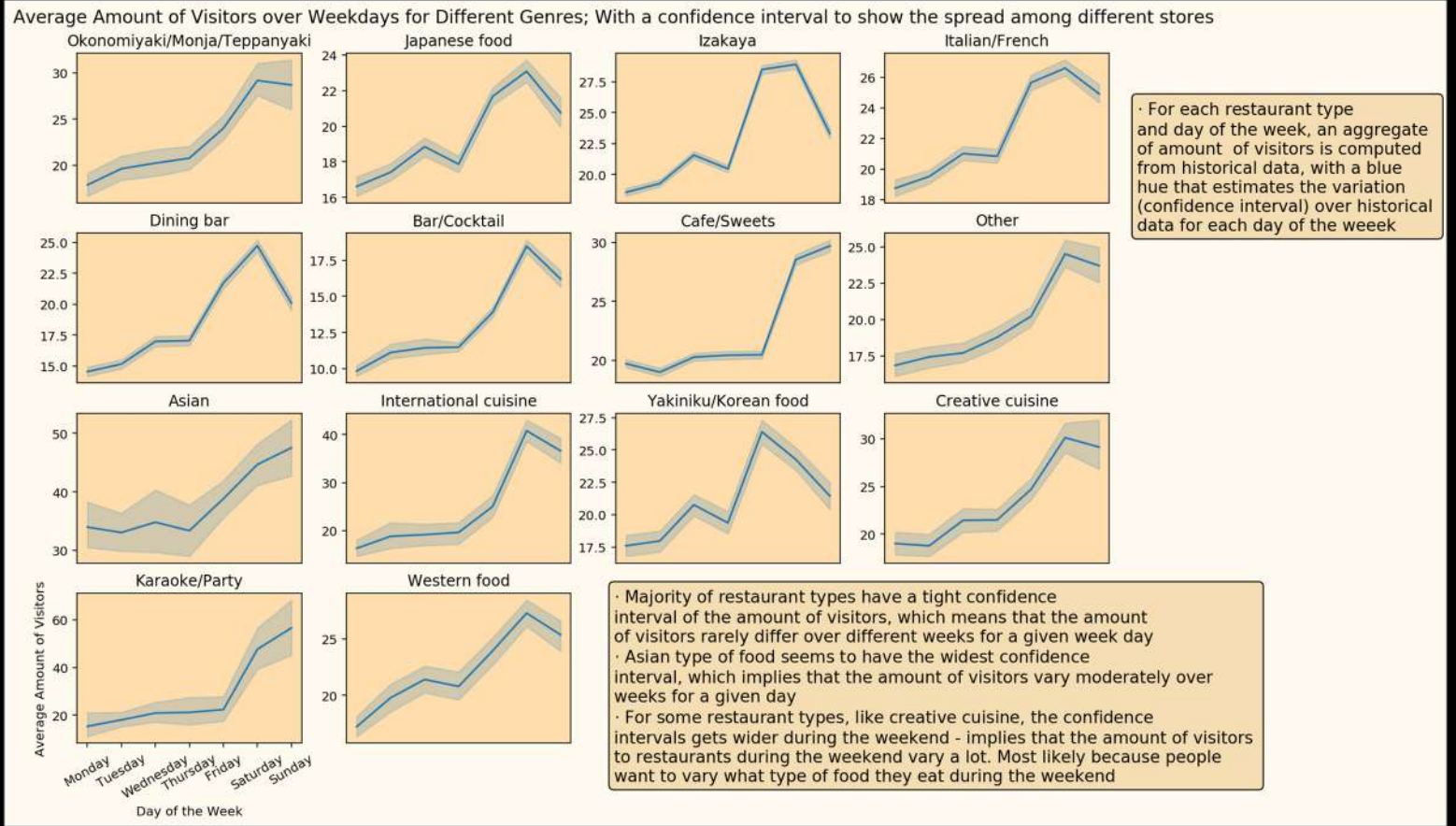


- Another interesting property is what areas of Japan exists, and how many restaurants exists in each area. Because the amount of areas exceed 100, only the top ten and top bottom areas by count are considered

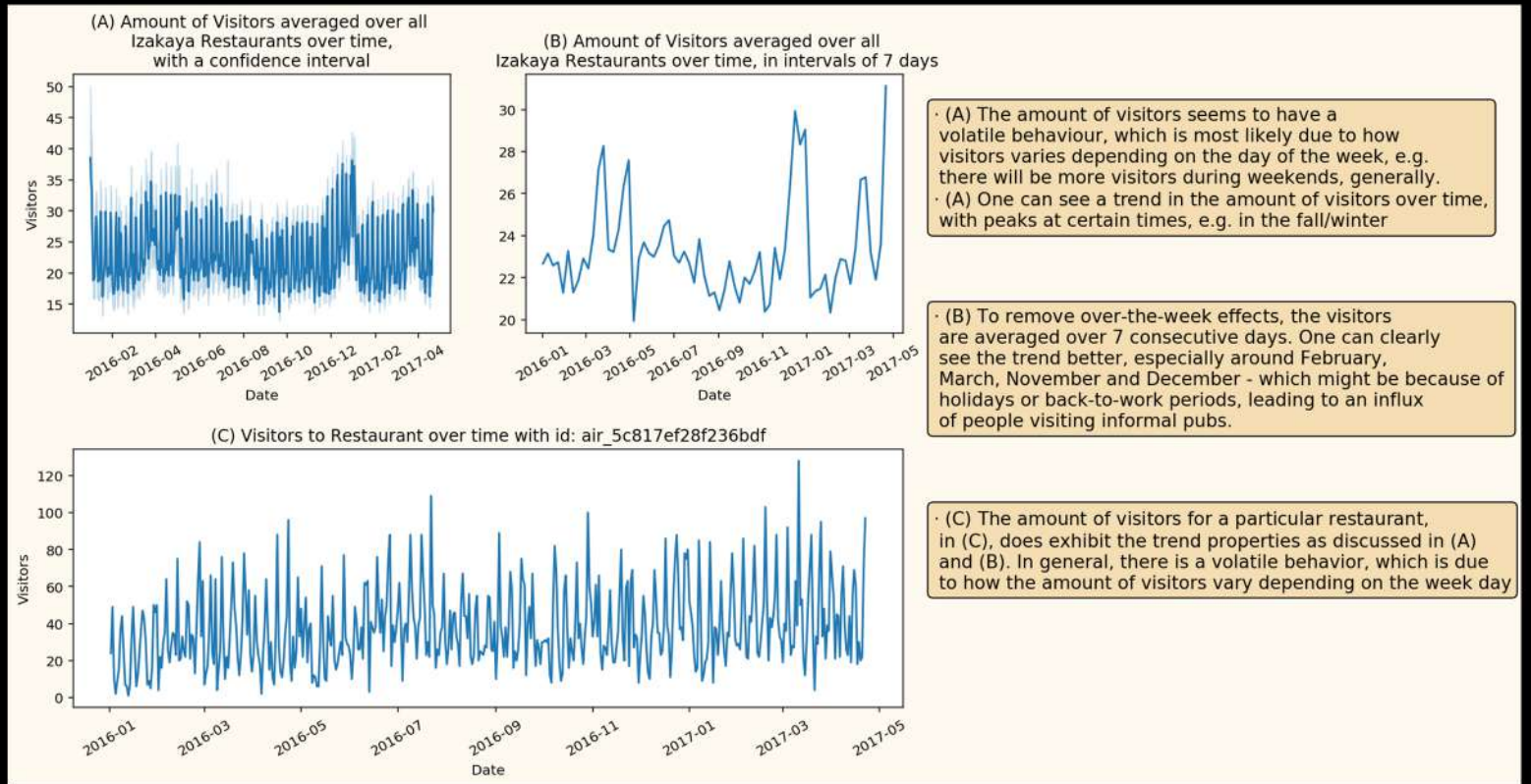


Recruit Restaurants - Forecasting - Data Analysis - Average Amount of Visitors over the week, time-series for a particular restaurant

- To analyze how the amount of visitors varies over each day of the week, the average of amount of visitors is computed for each genre over all days of the week

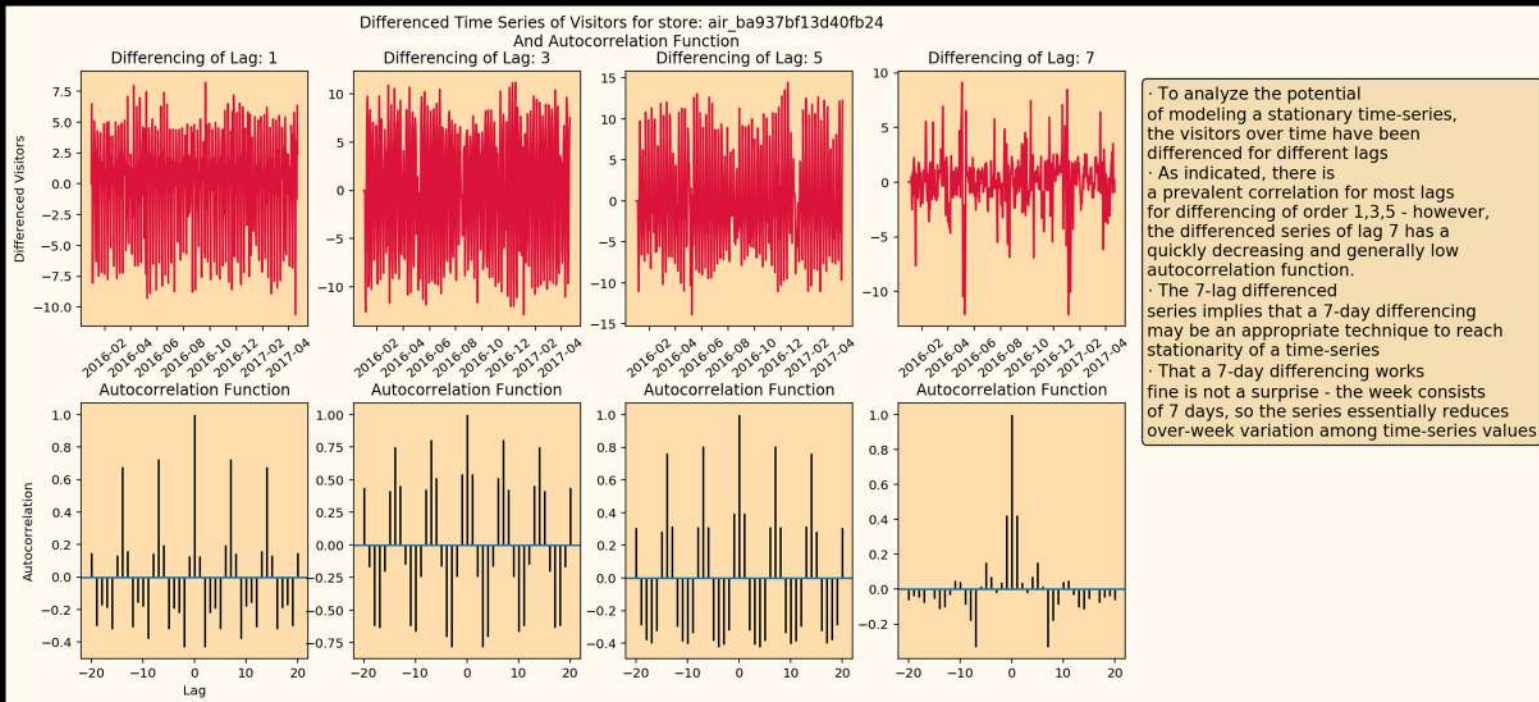


- For visitors in a particular genre, an idea is to analyze restaurants in the Izakaya genre. In particular, it is of interest to analyze the amount of visitors over time for a particular store in the Izakaya genre

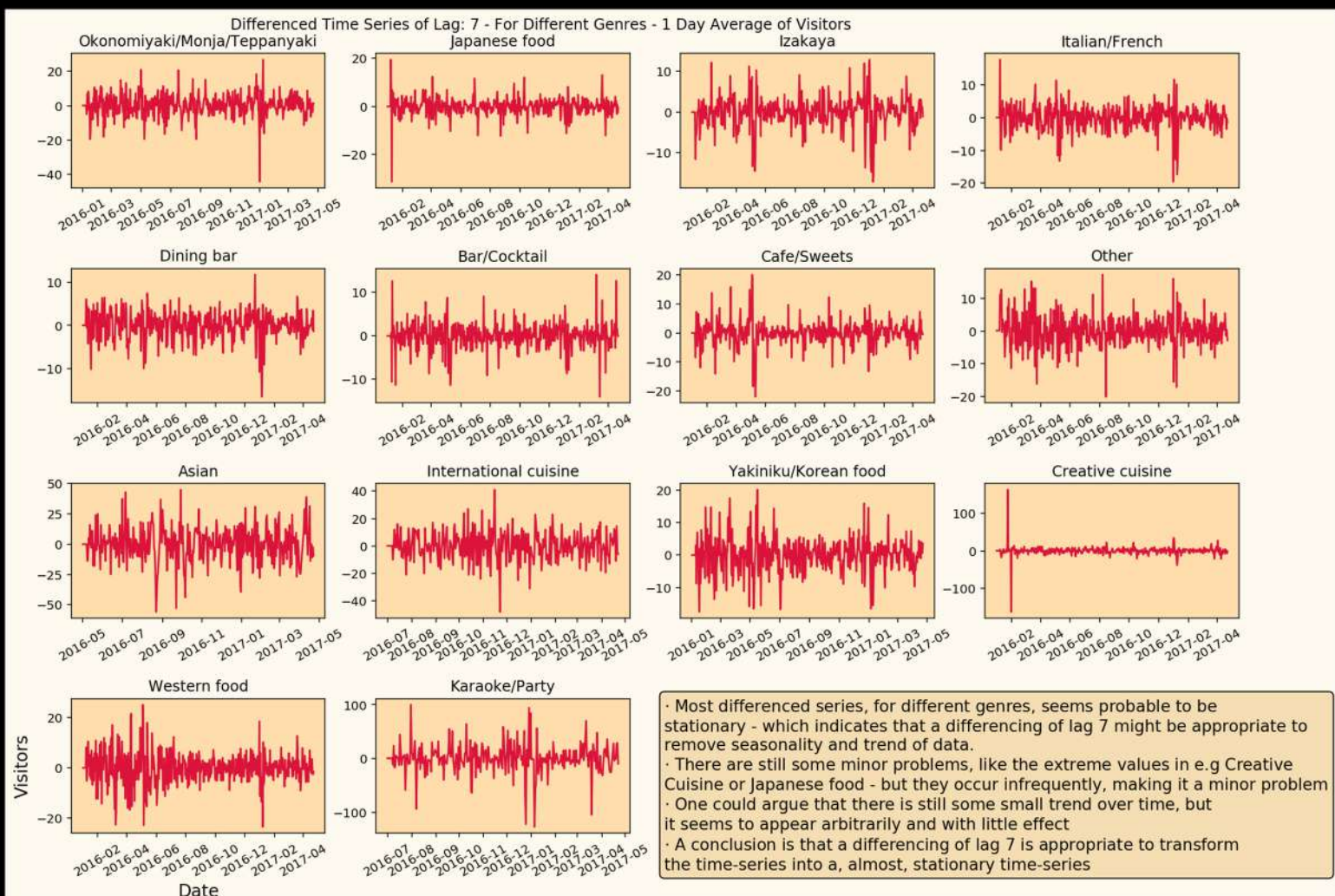


Recruit Restaurants - Forecasting - Prediction Analysis - Time series analysis

- Before applying mathematical models to our time-series data, a key idea is to analyze whether the time-series can be transformed to a stationary, or almost, time-series. One typical approach is to difference the time-series, and check for weak stationarity (constant mean over time, and time-independent autocorrelation function)



- To further illustrate the effect of differencing time-series with a lag of 7, we consider this type of transformation to the average amount of visitors (daily) for each type of restaurant, to see if the assumption of stationarity is plausible



Recruit Restaurants - Forecasting - Prediction Analysis - Optimal ARIMA models, and prediction on a week of days with optimal ARMA models

- With our 7-day differenced time-series of the daily average visitors of each genre, the next step is to fit it to optimal ARIMA models. Based on considering different AR and MA orders, and comparing the prediction performance with two metrics on a test week

Optimal Parameters for Different Genres - MAE

Genre Name	p	q	MAE
Okonomiyaki/...	5	3	2.66
Japanese food	6	3	1.37
Izakaya	5	3	1.65
Italian/French	7	3	2.58
Dining bar	6	1	0.64
Bar/Cocktail	7	1	0.96
Cafe/Sweets	4	2	1.79
Other	6	1	1.88
Asian	5	1	12.4
International cuisine	4	2	5.66
Yakiniku/Korean food	5	2	1.25
Creative cuisine	6	3	3.8
Western food	2	3	2.65
Karaoke/Party	6	3	9.86

Optimal Parameters for Different Genres - RMSE

Genre Name	p	q	RMSE
Okonomiyaki/...	7	2	3.46
Japanese food	7	3	1.91
Izakaya	6	2	2.0
Italian/French	7	3	3.0
Dining bar	6	2	0.86
Bar/Cocktail	7	3	1.2
Cafe/Sweets	7	2	2.65
Other	6	1	2.09
Asian	4	2	14.61
International cuisine	4	2	6.5
Yakiniku/Korean food	5	2	1.87
Creative cuisine	6	3	4.59
Western food	2	3	3.22
Karaoke/Party	6	3	11.45

ARIMA(p,d,q) Model - with statsmodels package (Python)

Based on utilizing $d=7$, i.e. a differencing of lag 7

To find optimal p and q, two metrics, MAE and RMSE, are evaluated on on a test set consisting of a week, given an ARIMA model trained on a training set.

For the search of optimal p, q, all ARIMA models for $p=1,2,\dots,7$ and $q=1,2,\dots,7$ have been considered

In above tables, the optimal choices of p and q for each genre is presented.

MAE is the mean of the residuals, with respect to true and predicted time series values.

RMSE is the square root of the mean of the residuals squared

- With our optimal models, based on MAE, the last step is to evaluate the models on a week of days, the validation set, to really measure the performance of our models

Optimal ARIMA Models, based on MAE, Predictions on a Single Week (Validation Dates); For Different Genres, 1 Day Average of Visitors

