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

esent the available datasets and typical values

AirREGI Reservations

Contains information of reservations done

in the Air system

Store ID: Identification of the restaurant air 6b15edd1b4fbb96a 2016-01-02 17:00:00 Visit Date: The date for the reservation Reservation Date: The date the reservation was done 2016-01-01 22:00:00 Visitors: The amount of spots reserved

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

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 15:00:00

hpg_33ec1499d6b13141 2016-01-01 17:00:00

2016-01-01 Friday

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

AirREGI Visitors Information

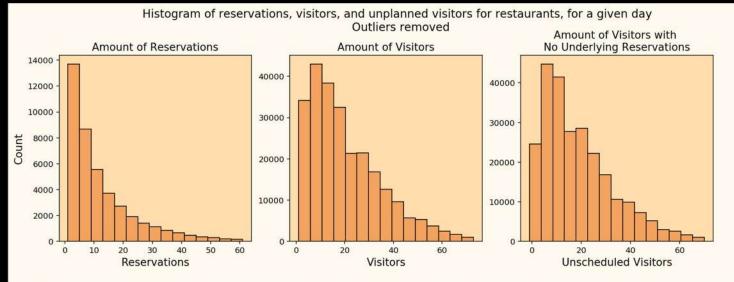
- Contains information of the visitors at restaurants for different dates

Store ID: Identification of the restaurant Visit Date: A date the restaurant is open Visitors: The amount of visitors for a date air 0f0cdeee6c9bf3d7 Italian/French Hyogo-ken Kobe-shi Kumoidori

34 6951242 135.19785249999998

air ba937bf13d40fb24 2016-01-13

- 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



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

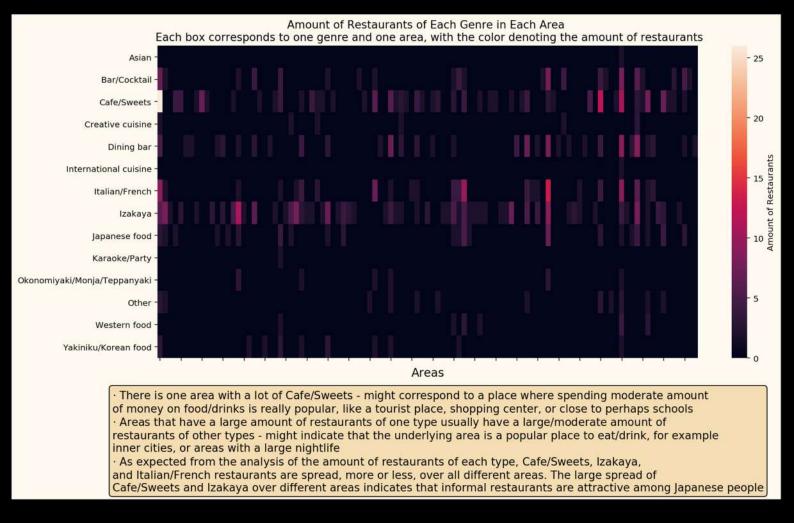
a restaurant may receive visitors without a single reservation, for a particular day - which might corresponds to weekdays or other low-traffic inducing days

Days with high amount of visitors most likely correspond to weekends or holidays, which might explain

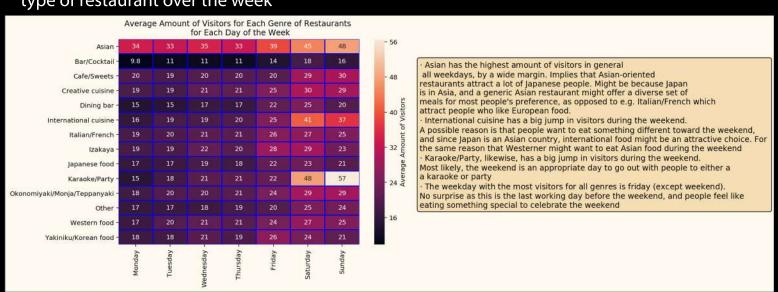
why these cases occur much less than days with low amount of visitors (which probably, in turn, corresponds to weekdays)

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

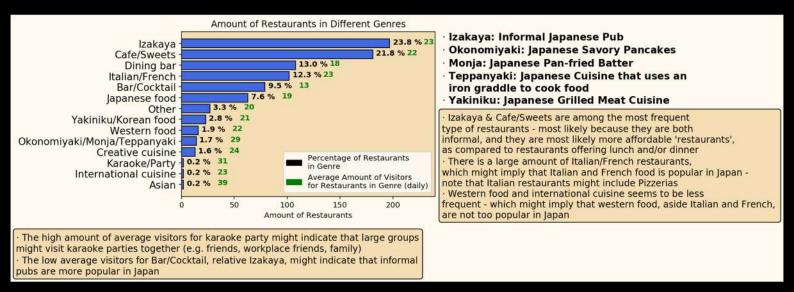


- Intuitively, the traffic to restaurants should change over the week, with perhaps an uptick of visitors during the weekend. This can be considered by the average amount of visitors for each type of restaurant over the week



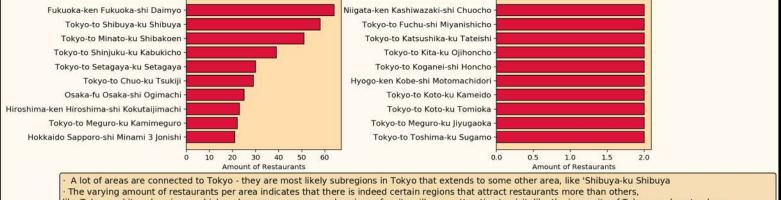
Recruit Restaurants - Forecasting - Data Analysis - Type of restaurants in Japan, amount of restaurants in areas

- 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

Top 10 Areas by Amount of Restaurants in Area



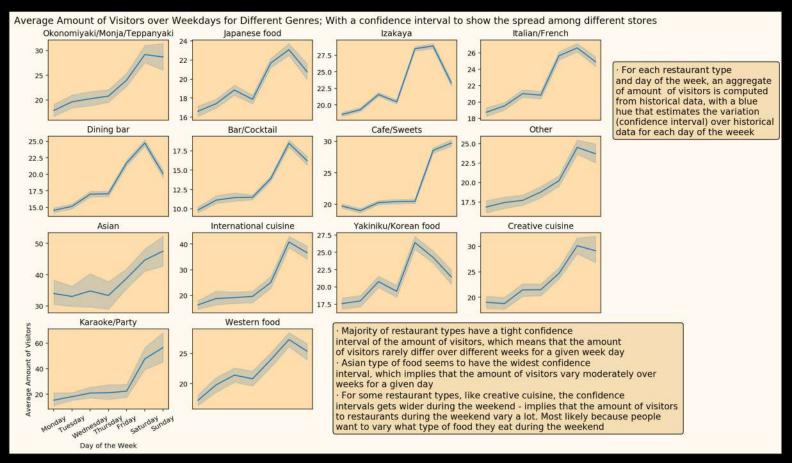
like Tokyo and its subregions - which makes sense, as some subregions of a city will more attractive to visit, like the inner city of Tokyo, or close to places where people work

The bottom implies that some areas have almost no restaurants, but also imply that each area have at least two restaurants - note that low amount of restaurants will also imply that some areas won't have at least one restaurant of each genre

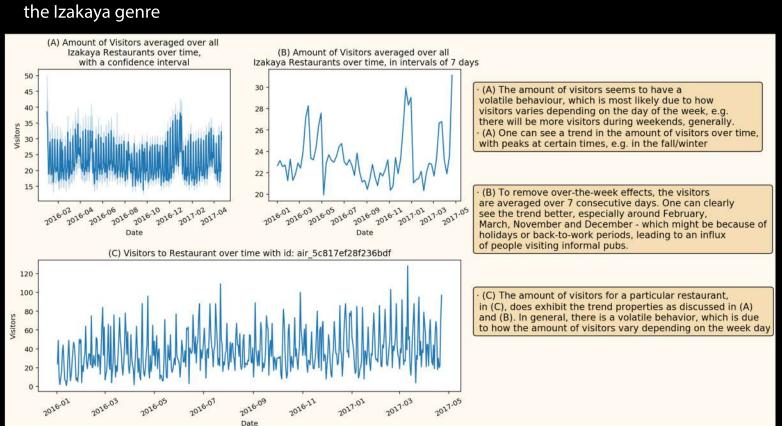
Bottom 10 Areas by Amount of Restaurants in Area

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

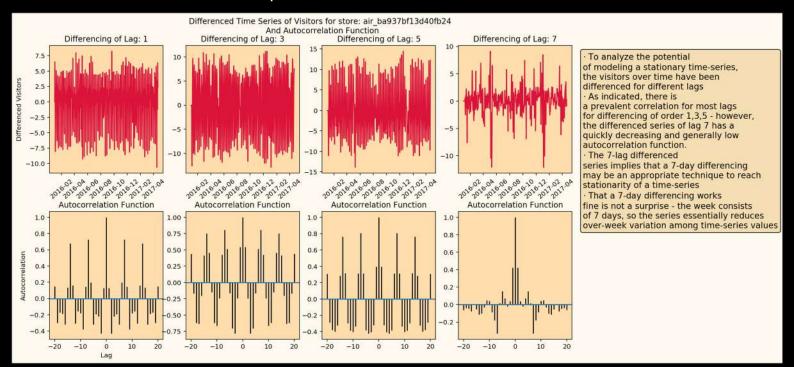


- For visitors in a particular genre, an idea is to analyze restaurants in the Izakaya genre. In particular, it is of interest to analyze the amount of visitors over time for a particular store in the Izakaya genre

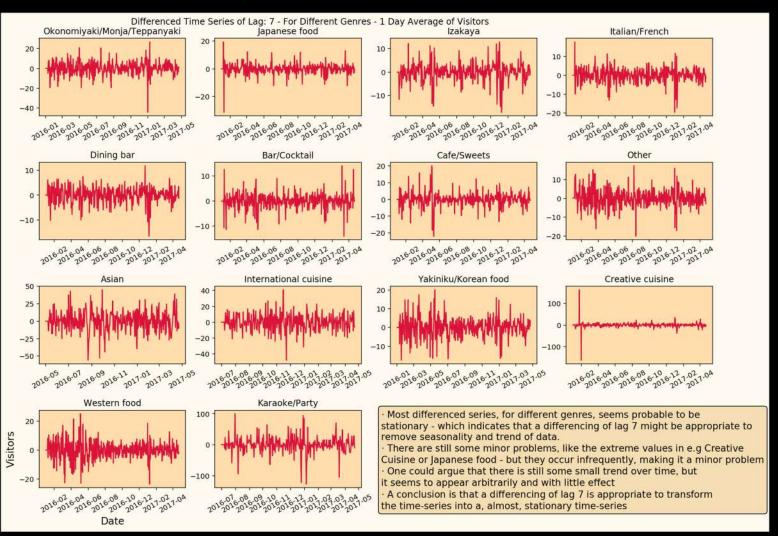


Recruit Restaurants - Forecasting - Prediction Analysis - Time series analysis

- Before applying matemathical 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 $\overline{7}$, 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

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

ARIMA(p,d,q) Model	with statsmodels	package (Python)
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Based on utilizing d=7, i.e. a differencing of lag 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

For the search of optimal p, q, all ARIMA models for p=1,2,...,7

and q=1,2,...,7 have been considered

on a training set.

Optimal Parameters for Different Genres - KMSE					
Genre Name	р	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		

Ontimal Darameters for Different Conres DMCE

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

Karaoke/Party

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

11.45

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

