# TIME SERIES ANALYSIS ON SOCIAL MEDIA POSTS: A STUDY ON TS RESTAURANTS IN HAWAII

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## ABSTRACT

The effect of the social media on different aspects is wide. Use of social media seems obvious to manage continuous customer support, quick response, understanding the seasonality, get feedbacks from customers on the businesses and also see the effect of the promotional events and activities. Finding the significance of long-term effect of several events comes with challenges because of some factors such as seasonality, time trend and availability of customers' timely response which hides the true signals about the effect of the event. In the present study, the objective is to explore the impact of the musical band and analyzing the seasonality trends of the customers against promotional events. In order to explore the capability for understanding the effect of promotional events, social media response of the customers on the musical band events organized by a restaurant chain (TS restaurants) is analyzed by applying different time series tools. Only SARIMAX model is found useful to get the association of such event on customers response using social media because along with seasonality it also takes exogenous factor into account. Facebook, Twitter and Yelp are used as social media platforms to collect the time series data of Restaurants' (TS restaurants and other restaurant in the similar location). After the analysis, the significant effect of the promotional event (musical band) is found on the overall Yelp ratings of TS restaurants. The forecast is also provided for this restaurant chain with exogeneous factor which shows the seasonality with upwards trend. Although the model is built using data for TS restaurants, the method is generic and therefore applicable to any restaurant's forecasting using exogenous event.

**Keywords**: SARIMAX, Seasonal decompose, Impact of Musical Band, Twitter, Yelp, Facebook, Social Media Analysis, Time Series Analysis, Seasonality

## 1. INTRODUCTION:

Social media is a revolutionary change in modern world history and its impact is powerful and fast. This is not only novel, but different and free approach. As restaurants want to increase their profits, but neither they want to affect the quality nor do they want to increase the price. For better growth, most businesses are using these free platforms to flourish themselves. The restaurant

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industry, mainly needs a good platform to interact their existing and new customers where they can advertise their events, take complements along with comments and concerns. In this research, the impact of such events was examined. TS restaurants (Kimo's and Leilani's) have been organizing a musical band on Fridays and Saturdays and the effect of its impact on their business been crucial to understand. By using Twitter and Facebook, many business reports showed that restaurant entrepreneurs can draw business and increase sales [1, 2, 3].

In the present study, the effect of the social media was studied when time is taken into the consideration. Social media platforms used in the study are Twitter, Facebook and Yelp. To understand it better, real time data of TS restaurants and its competitor was explored, and time series analysis was performed. The time series forecasting models use the past movements of variables to forecast. When a time series has a seasonal variation generally seasonal autoregressive integrated moving average (SARIMA) models are applied but this model is not sufficient to forecast when there is any influence of external factor. For this purpose, seasonal autoregressive integrated moving average with exogenous regressors (SARIMAX) model is used.

The structure of this study is as follows: Section 2 presents a literature survey. Section 3 presents methodology of the classical decompose method and SARIMAX model. Section 4 presents the information about the datasets used in the analysis. Section 5 describes the results and discussion of the SARIMAX model. Section 6 presents conclusion.

## 2. LITERATURE SURVEY:

In earlier studies, the company culture and its impacts on consumer behavior was studied by Gilkey in 2018 in which he explored the time impact on consumer sentiments. Precisely, he used the social media data on a chain of restaurants to see the trend of sentiment score categories over time [4]. Qureshi et. al., in 2014 also studied the impact of the social media marketing on the consumer preferences in the restaurant industry [5].

However, the comprehensive time series model like SARIMAX to forecast the demand in food retail industry were applied in very few studies. ARIMA model which is nested in SARIMAX model but does not have seasonality and exogenous factor is applied often. Shukla & Jharkharia in 2013, applied ARIMA models to investigate the applicability in wholesale vegetable market [6]. Da Veiga et al., in 2014, applied ARIMA and Holt-Winters (HW) models to forecast a time series of a group of perishable dairy products [7]. The seasonality component with ARIMA known as

SARIMA has been applied in a few studies. Aburto & Weber in 2003 presented an additive hybrid SARIMA and neural network to forecast demand in a Chilean supermarket [8]. Arunraj et. al. in 2016, applied the SARIMAX model to forecast daily sales of perishable food in retail industry [9]. In another study, Hultkrantz in 1995 applied the SARIMAX to model dynamic price response of inbound tourism guest-nights in Sweden [10].

Apart from forecasting the food industry, the SARIMAX models were also used as forecasting tools in diverse fields of application, like traffic data has been studied by Cools et. al [11]. They used ARIMAX and SARIMAX models to forecast daily traffic counts. They also investigated the consideration of weekly seasonality and holidays as external variables at different site locations [11].

Kim et. al., in 2016 determined the impact of social media reviews on restaurant performance [12]. He mentioned that for a restaurant with an excellence certificate, a larger number of reviews or a better overall rating promotes net sales, guest counts, and average check to a larger degree compared to a restaurant without an excellence certificate [12].

To understand the seasonality and trend, seasonal decomposition is being a widely used analysis. Velkoski in 2015, in his study about restaurant consumption as an economic indicator used the seasonal decomposition to isolate the smoothed trend cycle component [13]. Jayraman et. al., in 2010 used the seasonal decomposition method to describe the pattern of the monthly international tourist arrivals for 2002 to 2009 and to identify the peak and lean periods of visitors for East Malaysia [14].

During literature survey, no study has yet been found in which comprehensive time series model like SARIMAX is applied on social networking data of the restaurant.

## 3. METHODOLOGY:

### 3.1 Seasonal Decomposition

A wide variety of patterns can be exhibited by time series data. It is often found useful to split it into several components. The time series pattern has only three components trend, seasonality, and cycles. When a time series is decomposed, one gets trend-cycle component (commonly called trend) and seasonal component with a remainder component which contains the random error component.

Assuming additive decomposition, the time series data can be written as:

$$y_t = S_t + T_t + R_t$$

Where $S_t$ is seasonal component, $T_t$ is trend cycle component and $R_t$ is the random component or random error at given time t. Additive decomposition is the most appropriate if the magnitude of the seasonal variation around the trend cycle does not vary with time. In the present study, additive seasonal decomposition was used.

### 3.2 SARIMAX Model

The SARIMAX model was developed using Box and Jenkins (1976) [15], seasonal auto-regressive integrated moving average (ARIMA) with regressors factor 1, factor 2 and factor 3.

Precisely, the SARIMAX model is best explained in the following equation:

$$Y_t = \phi_t Y_{t-1} + .. + \phi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + .. + \theta_q \epsilon_{t-q} + \beta_{1t} X_{1t} + .. + \beta_{1t-n} X_{1t-n} + ..$$

$$+ \beta_{wt} X_{wt} + .. + \beta_{\mathrm{wt-m}} X_{wt-m} + \epsilon_t \qquad (1)$$

Where,

$Y_t$ is the difference in levels of data at t;

$\phi_t$ is the autoregressive coefficient for order j, with i=1,..p;

$\theta j$ is the term for moving average for order j, with j=1,…q;

$X_{kt}$ is the exogenous variable k at time t, with k=1,..w;

$\beta_{kt}$ is the parameter associated with exogenous variable k at time t, with k=1, …,w;

$\epsilon_t$ is the error term of the model.

p is the order of autoregressive part,

d is the order of the differencing.

q is the order of the moving-average process.

In simple language, SARIMAX is most comprehensive model for the time series analysis which consider seasonality, autoregression integrated with moving average and effect of exogenous factors.

## 4. DATASET:

The dataset has been extracted from three different social media websites i.e., Twitter, Facebook, and Yelp of the TS restaurants (Kimo's and Leilani's) and a restaurant of its competitor's chain.

### 4.1 Facebook Dataset

The dataset of Kimo's restaurant is from January 2010 to October 2017. This dataset contains 3302 instances. The dataset of Leilani's restaurant is from October 2011 to September 2017. This dataset contains 765 instances. The dataset of the restaurant of its competitor's chain is from November 2009 to September 2017. The dataset contains 1987 instances. All these datasets have 16 features namely, Status id, status message, link name, status type, status link, status publish, comment, share and number of reactions as: like, love, wow, hahas, sad, angry, and special.

### 4.2 Twitter Dataset

The dataset of Kimo's restaurant is from September 2011 to September 2017. This dataset contains 3199 instances. The dataset of Leilani's restaurant is from October 2011 to August 2017. This dataset contains 1416 instances. The dataset of restaurant of its competitor's chain is from April 2009 to September 2017. The dataset contains 2934 instances. All these datasets have 14 features namely, Username, UserId, Location, Total Tweets, Total Followers, Total Following, user verified, user description, tweetid and tweettime.

### 4.3 Yelp Dataset

The dataset of Kimo's restaurant is from August 2005 to September 2017. This dataset contains 2080 instances. The dataset of Leilani's restaurant is from January 2006 to September 2017. This dataset contains 1624 instances. The dataset of restaurant of its competitor's chain is from March 2015 to September 2017. The dataset contains 76 instances. All these datasets have 6 features namely, Date, Rating, Review, Username, UserLocation and AVGRating (Average Rating).

### 4.4 Outlier Detection and Data Preprocessing:

There were no null values in the datasets. During exploration of Twitter data of Kimo's, boxplot was used for detecting outliers and encountered some unrealistic observation e.g., at tweettime 3/3/2014 4:09, 3431547 of retweets were found i.e., unrealistic and has error point and removed this data point.

## 5. RESULTS:

**5.1 Seasonal Decompose:** The seasonal decomposition method is applied to the datasets obtained from different social platforms i.e., Facebook, Twitter and Yelp to understand the seasonality and trend. The detailed description for each of the data is given below:

### *5.1.1 Facebook Data*

While analyzing the Facebook dataset, time series of number of reactions is considered. After applying seasonal decomposition using the seasonal decompose method, provided by the Python statsmodels library [16], Kimo's is showing the increasing trend for number of reactions from the beginning (fig1 a) whereas Leilani's showed the increasing trend from mid 2015 (fig1 b). The seasonal decomposition on dataset of competitor's restaurant related with number of reactions had also been performed and the trend and seasonality were factored out. The similar trend to Leilani's is observed (fig1 c).

Looking at the seasonality of these restaurants for each month taking the lag 12, a meaningful seasonal pattern is observed. Precisely looking at the output data set, the following months were observed:

- Seasonality with high number of reactions,
  - for Kimo's on months January and August.
  - for Leilani's on months June and July.
  - for competitor's restaurant on months January and March.
- Seasonality with low number of reactions,
  - for Kimo's on month November.
  - for Leilani's on month November.
  - for competitor's restaurant on months November.

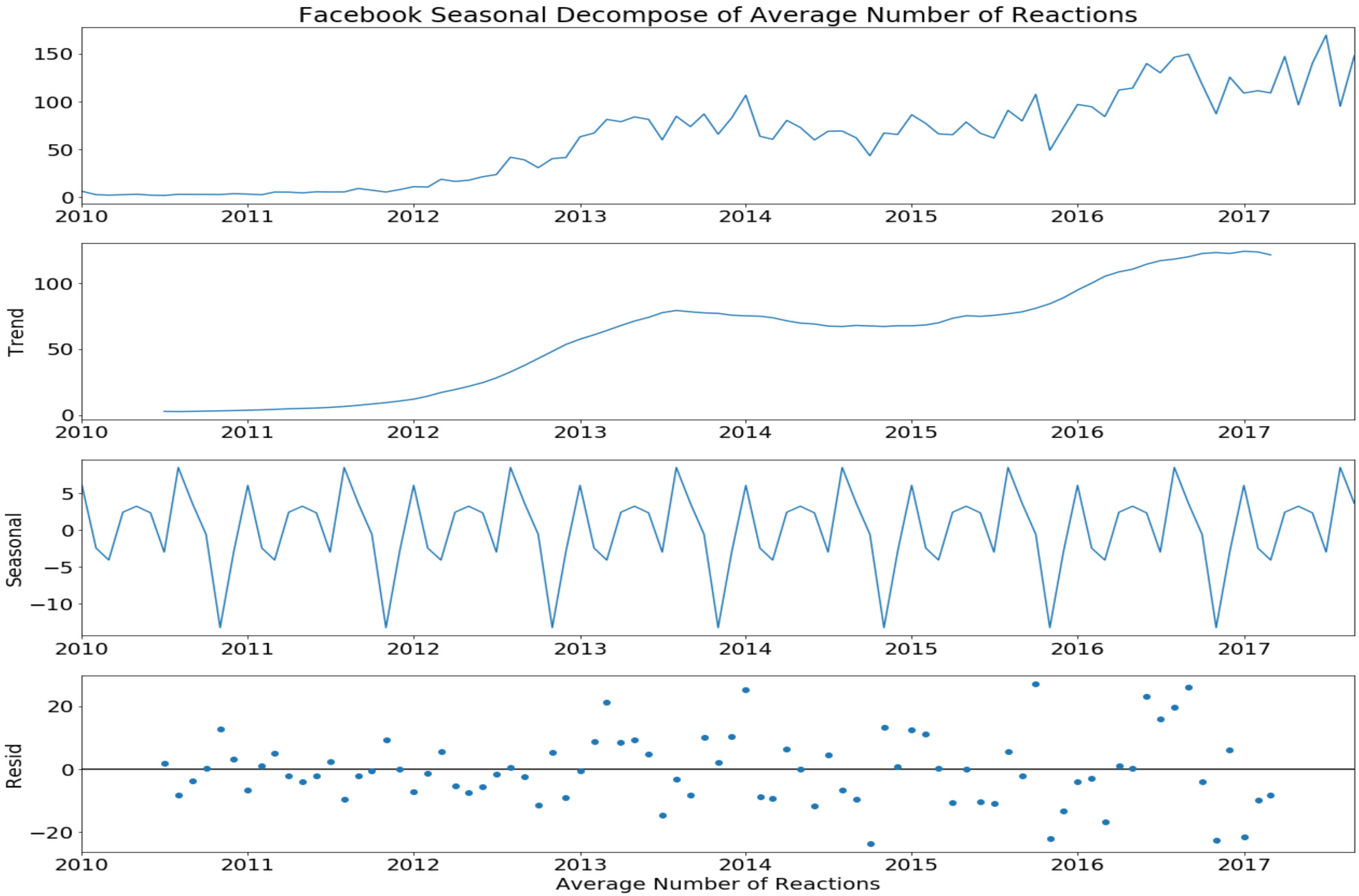


**Fig1 a. Seasonal Decompose of Average Number of Reactions of TS restaurants (Kimo's)**

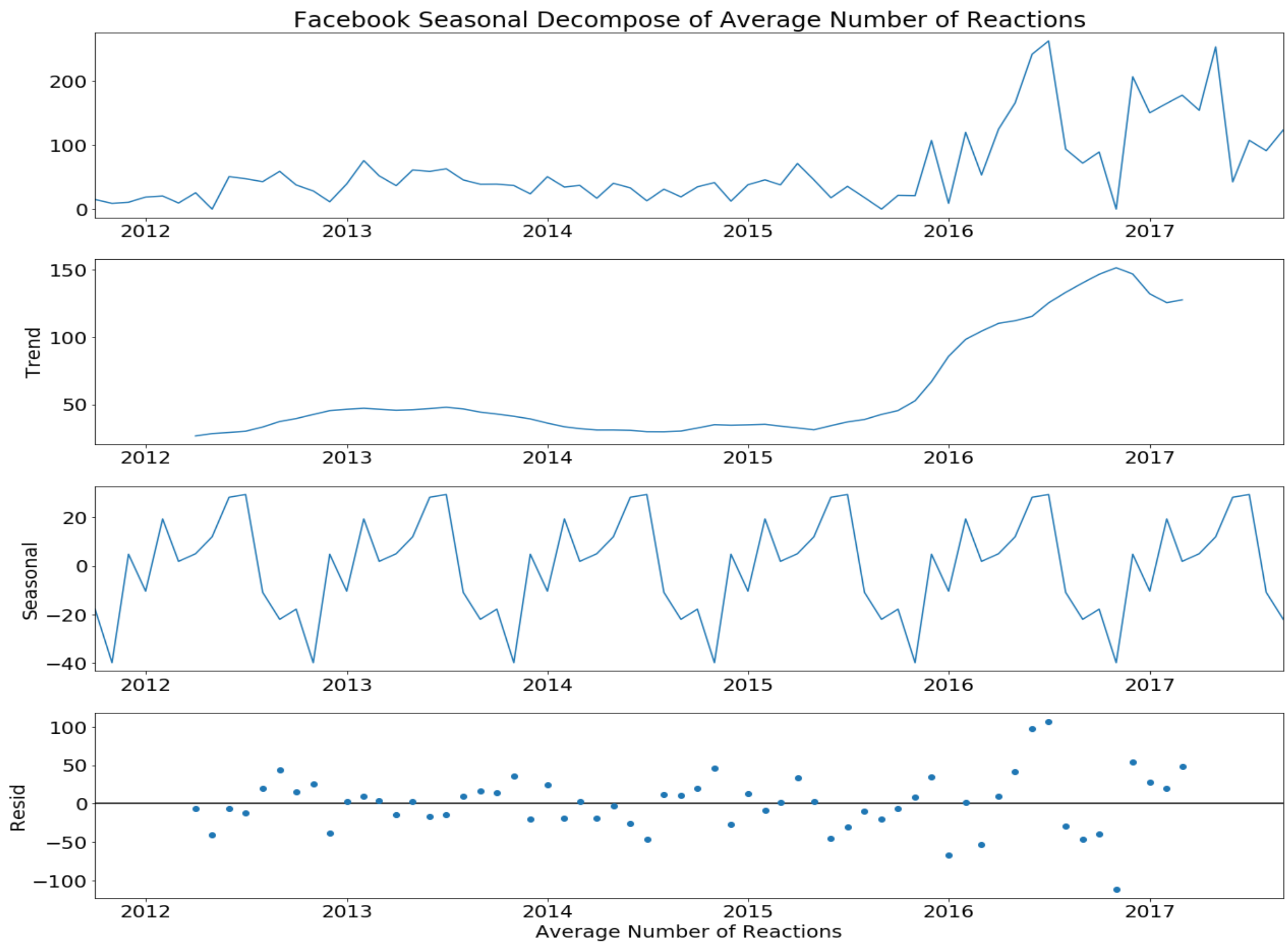


**Fig1 b. Seasonal Decompose of Average Number of Reactions of TS restaurants (Leilani's)**

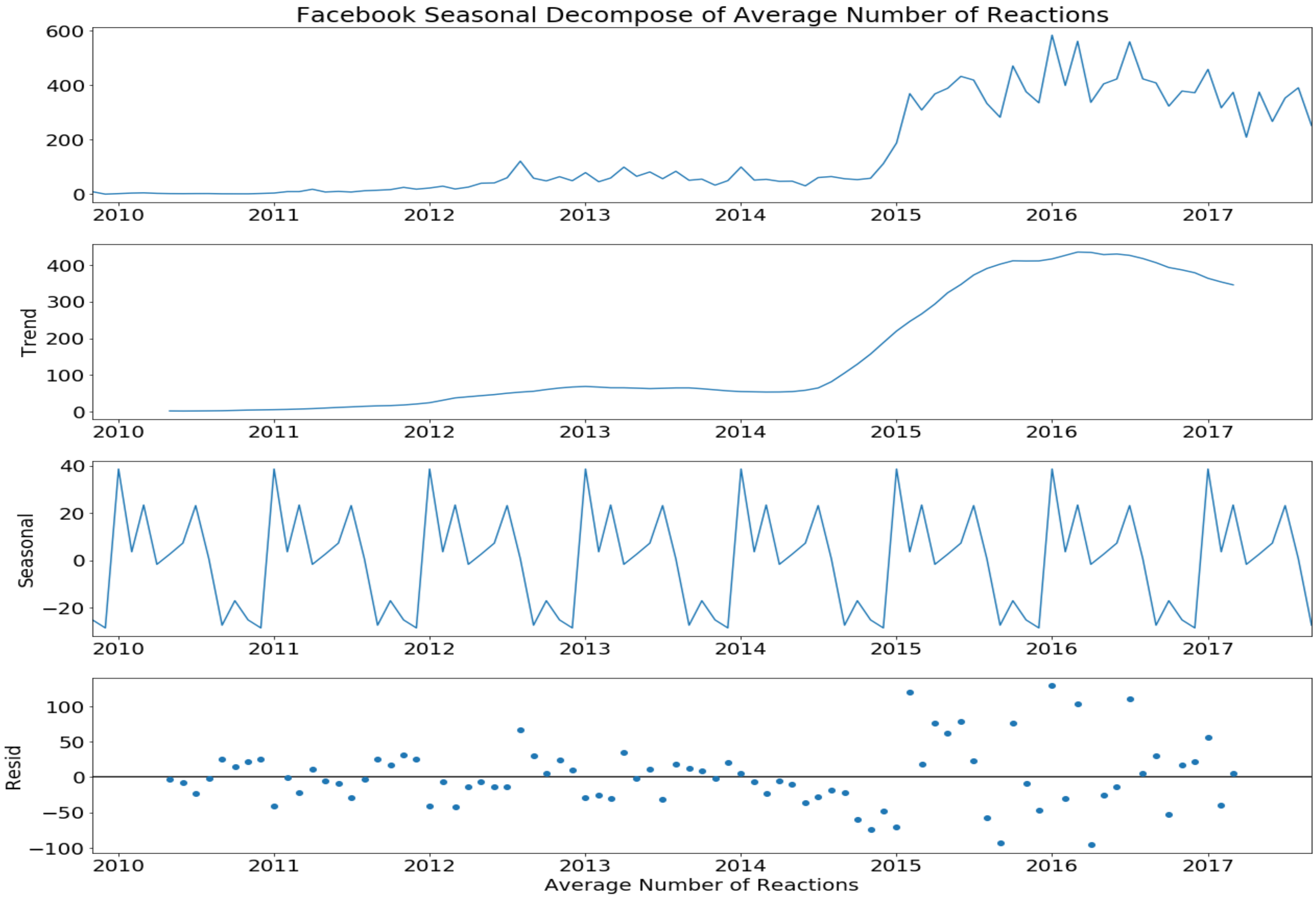


**Fig1 c.** Seasonal Decompose of Average Number of Reactions of Restaurant of Different Chain

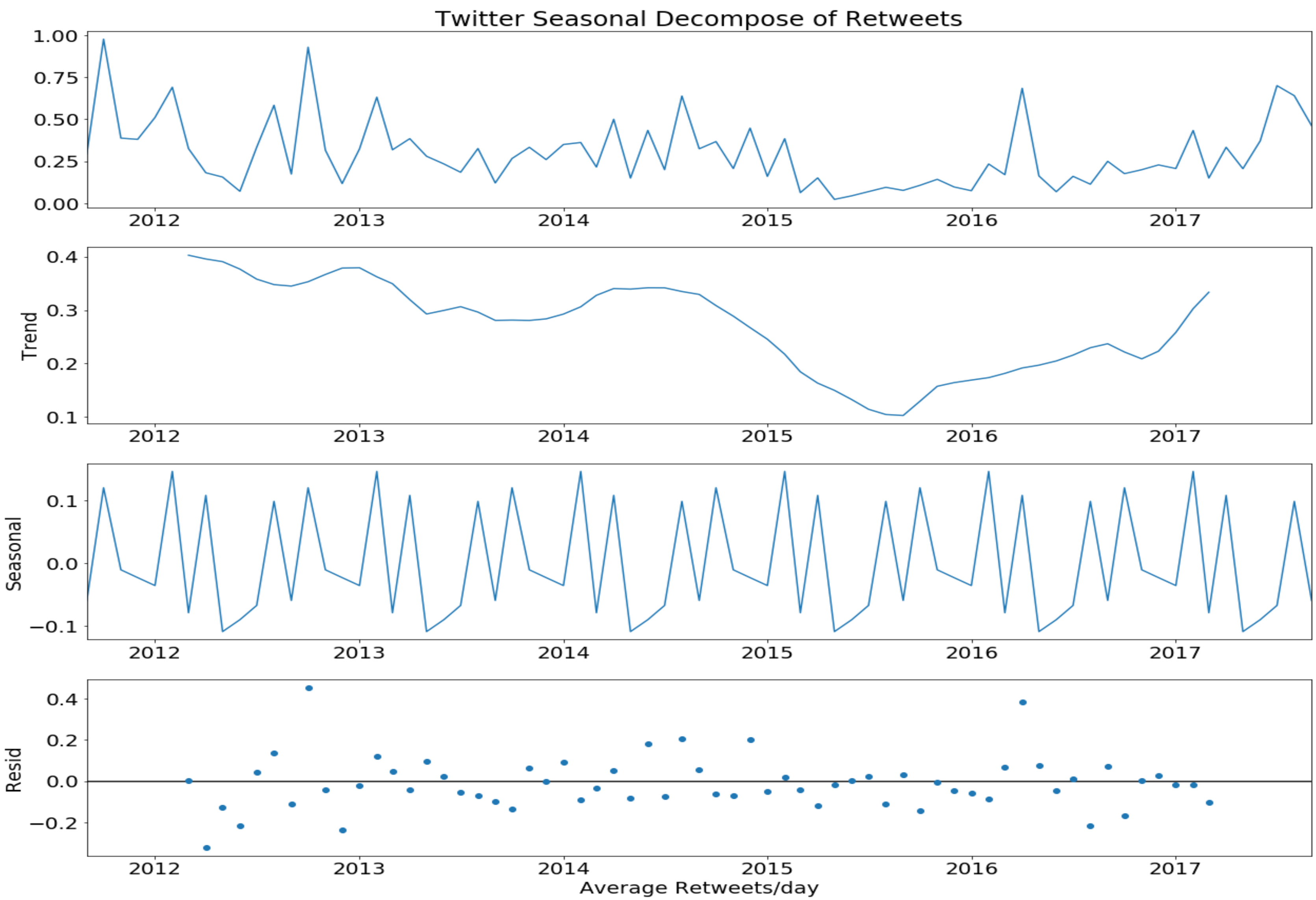


**Fig2 a. Seasonal Decompose of Average Retweets of TS restaurants (Kimo's)**

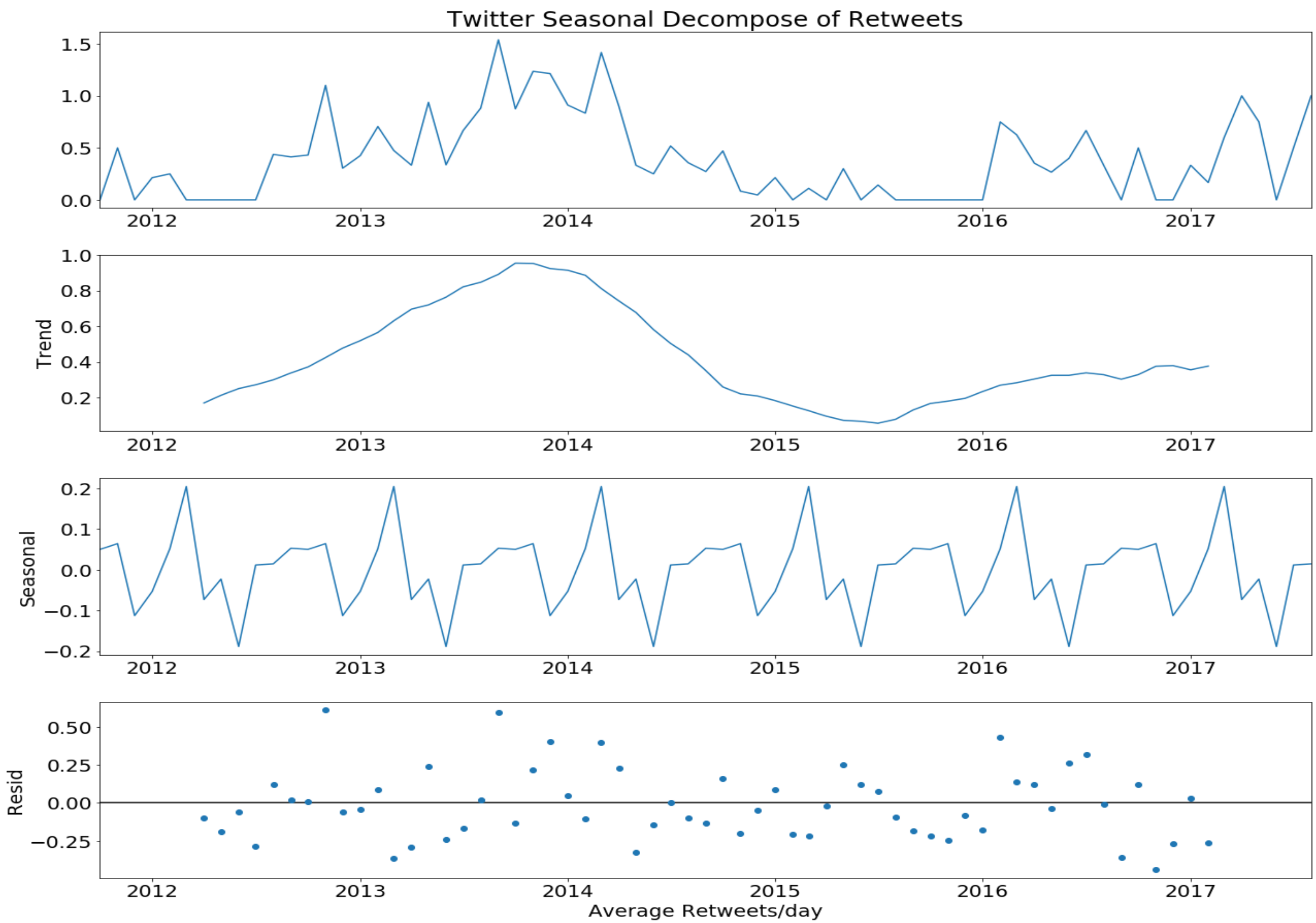


**Fig2 b. Seasonal Decompose of Average Retweets of TS restaurants (Leilani's)**

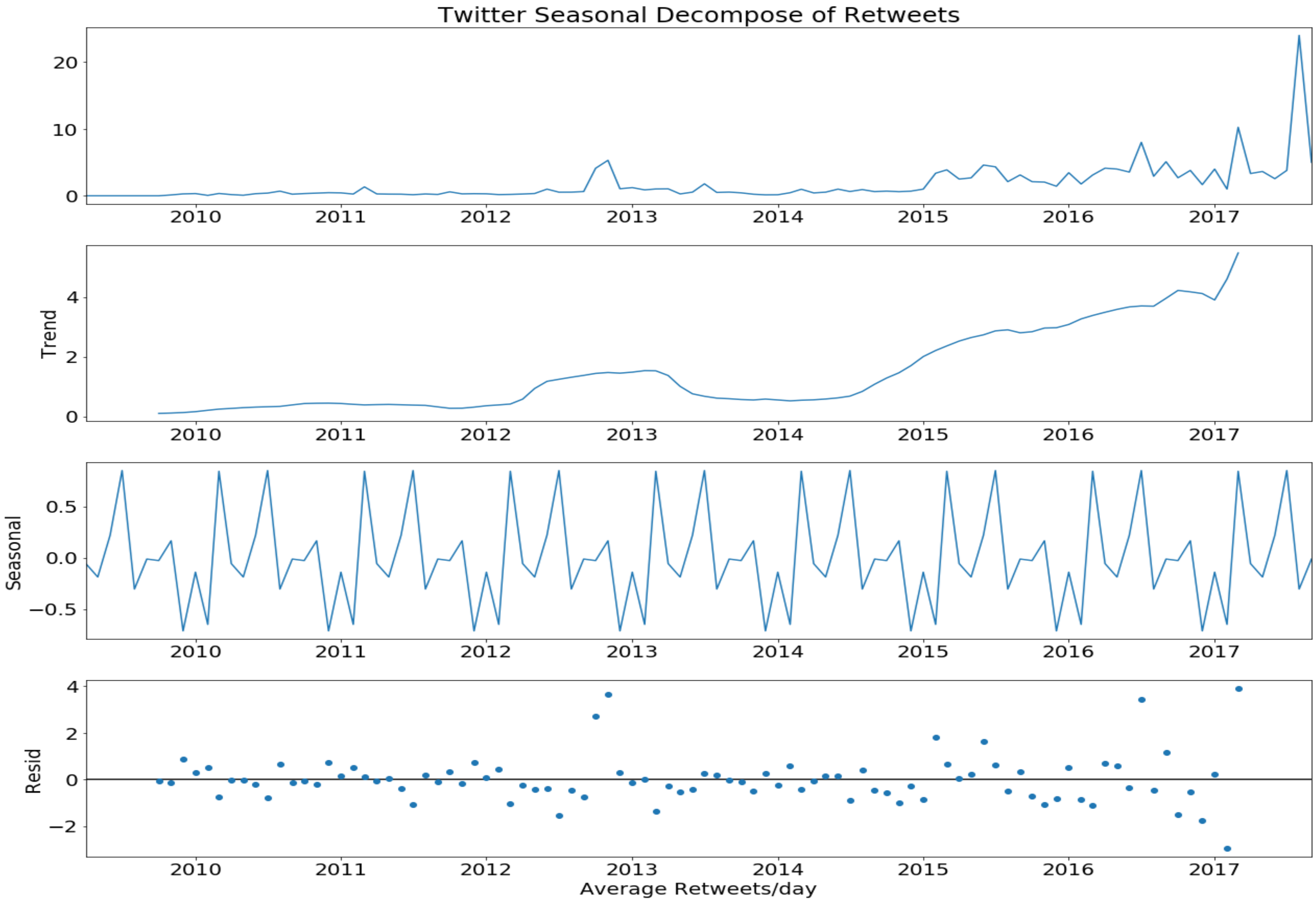


**Fig2 c. Seasonal Decompose of Average Retweets of Restaurant of Different Chain**

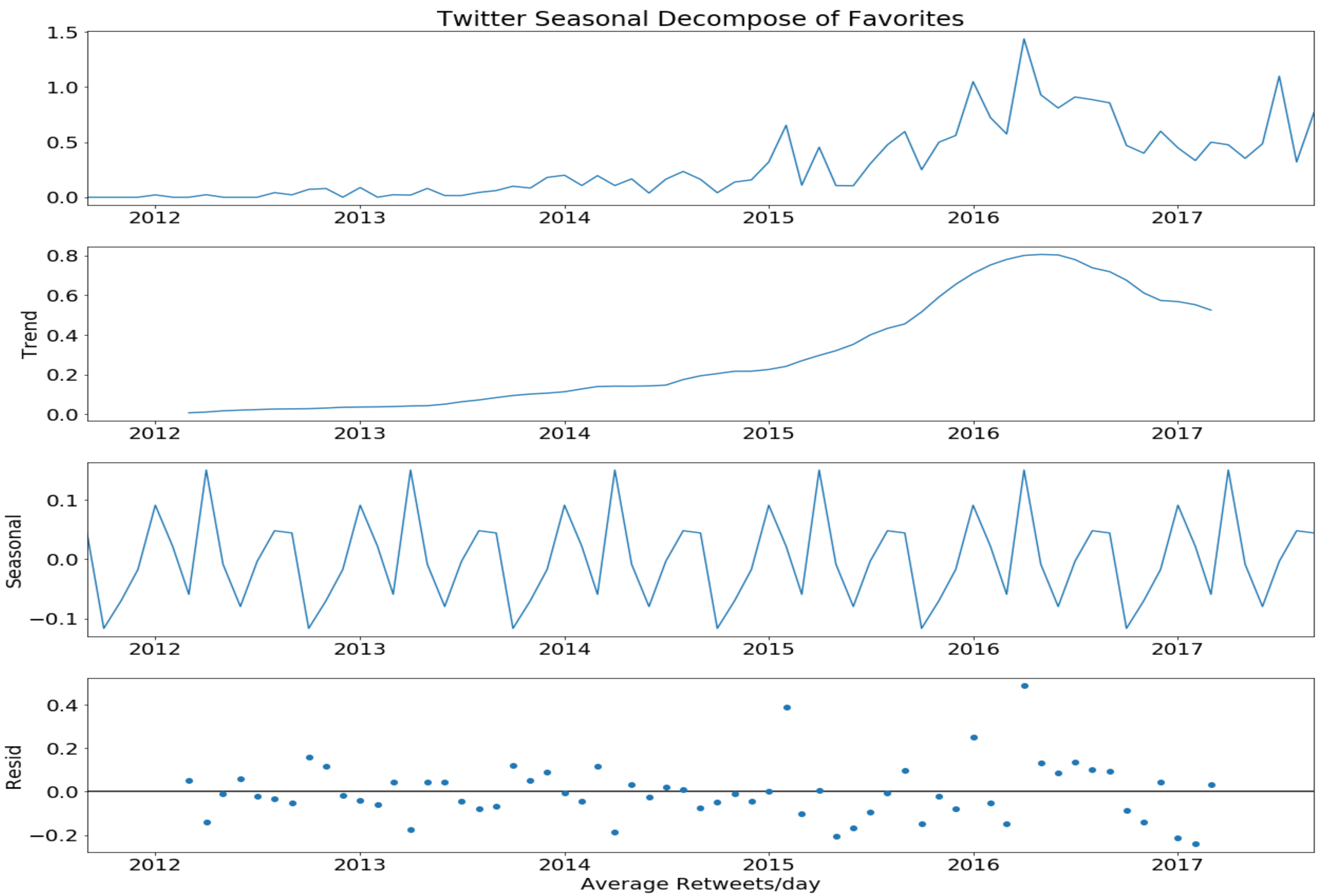


**Fig3 a. Seasonal Decompose of Average Favorites of TS restaurants (Kimo's)**

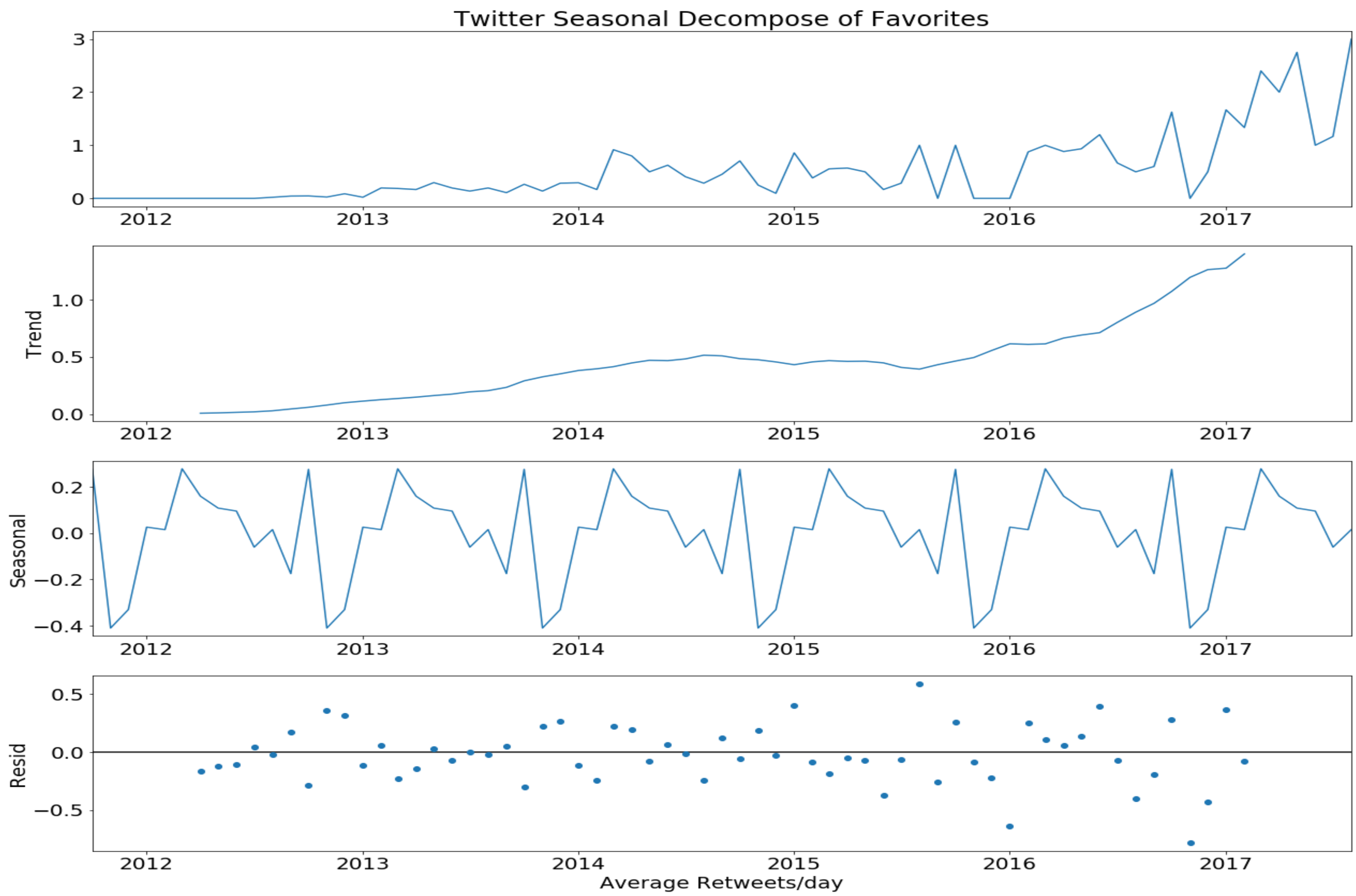


**Fig3 b. Seasonal Decompose of Average Favorites of TS restaurants (Leilani's)**

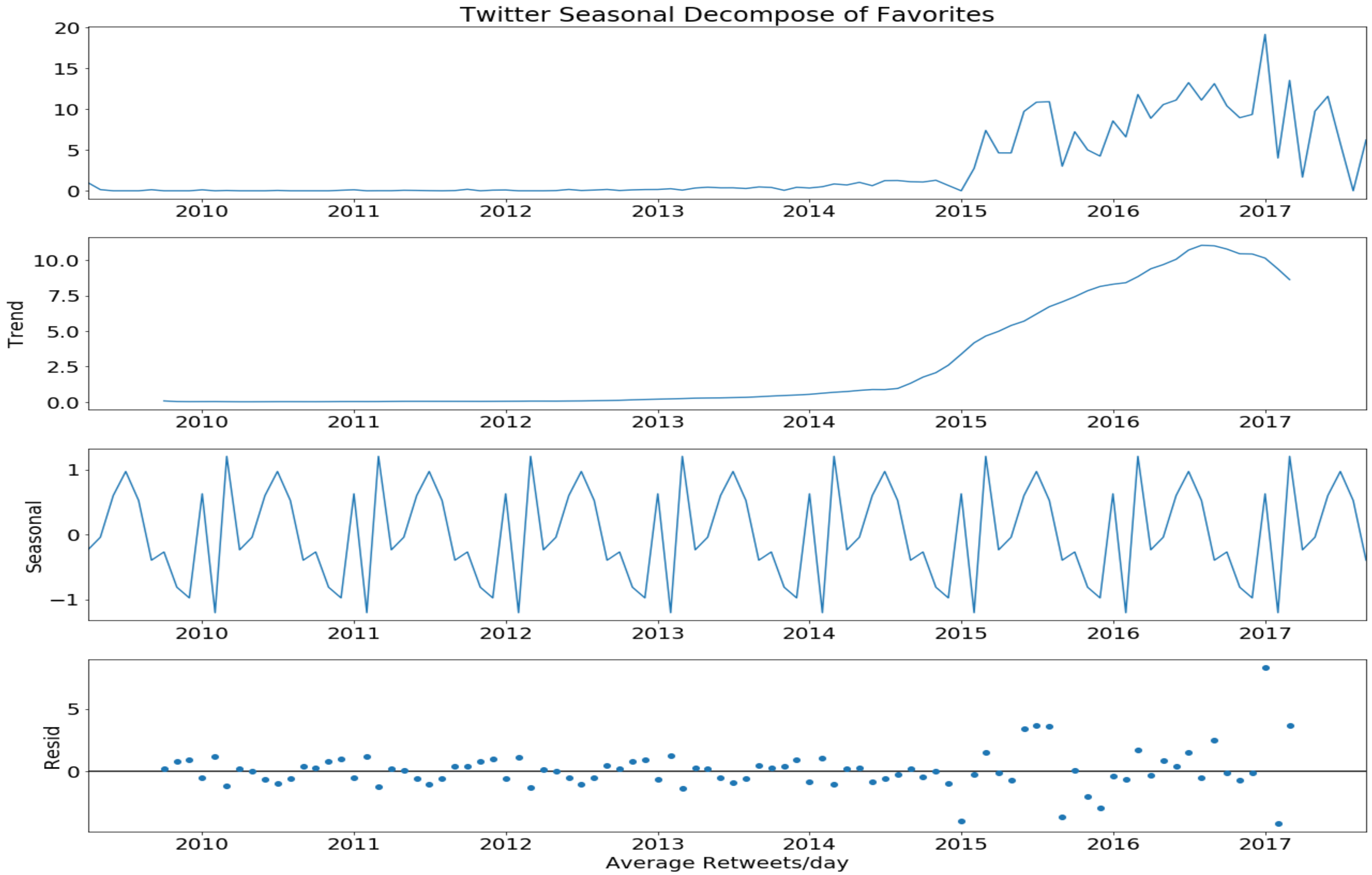


**Fig3 c. Seasonal Decompose of Average Favorites of Restaurant of Different Chain**

### *5.1.2 Twitter Data*

While analyzing the Twitter dataset, time series of retweets and favorites is considered. After applying seasonal decomposition using the seasonal decompose method, provided by the Python statsmodels library [16], Kimo's and Leilani's both are showing the increasing trend for retweets from 2015 (fig2 a, b). The trends went down for early years till 2015 however in favorites both restaurants i.e., Kimo's and Leilani's showed increasing trend in favorites from the beginning (fig3 a, b). In Kimo's, the trend shows small decrease in year 2017 when compared with 2016. The seasonal decomposition on competitor's restaurant data related with retweets and favorites is performed and the trend and seasonality were factored out. In favorites, no trend is shown from 2009 to 2015 for almost six years (fig3c). The trend increases afterwards till 2017 and then started showing downward trend. In retweet, the similar trend is obtained, and no meaningful trend is obtained till 2014 and an upward is observed (fig 2c).

After looking at the seasonality of these restaurants for each month taking the lag 12, a meaningful seasonal pattern is observed. Looking at the output data precisely for months, the following results were found:

- ❖ Seasonality with high number of retweets,
    - for Kimo's on months February and October.
    - for Leilani's on months February, March and October with highest in March.
- ❖ Seasonality with low number of retweets,
    - for Kimo's on month May.
    - for Leilani's on month June.
- ❖ Seasonality: high number of favorites,
    - for Kimo's on months April and January.
    - for Leilani's on months March and October are highest and have almost same value.
- ❖ Seasonality: low number of favorites,
    - for Kimo's on month October.
    - for Leilani's on month November and December.

### *5.1.3 Yelp Data*

In figure 4, the decomposition of ratings and Yelp data time series is obtained using the seasonal decompose() method, provided by the Python statsmodels library [16].The seasonal decompose() method requires to specify whether the model is additive or multiplicative. The additive was chosen as the pattern was additive decomposition is the most appropriate if the magnitude of the seasonal variation around the trend cycle does not vary with time. In fig4 a and b, represents the seasonality decomposition for Kimo's and Leilani's time series data. There were a smaller number of ratings in the beginning years and increased gradually over time. The time series decomposition shows a linear trend over time increasing from 2006 to 2017. The seasonal factor remains after removing trend and error suggests some months with high number of ratings while other with a low number of ratings. The lag of 12 was taken, representing the monthly seasonal behavior. Precisely, looking at the output of the seasonal decomposition for Kimo's on

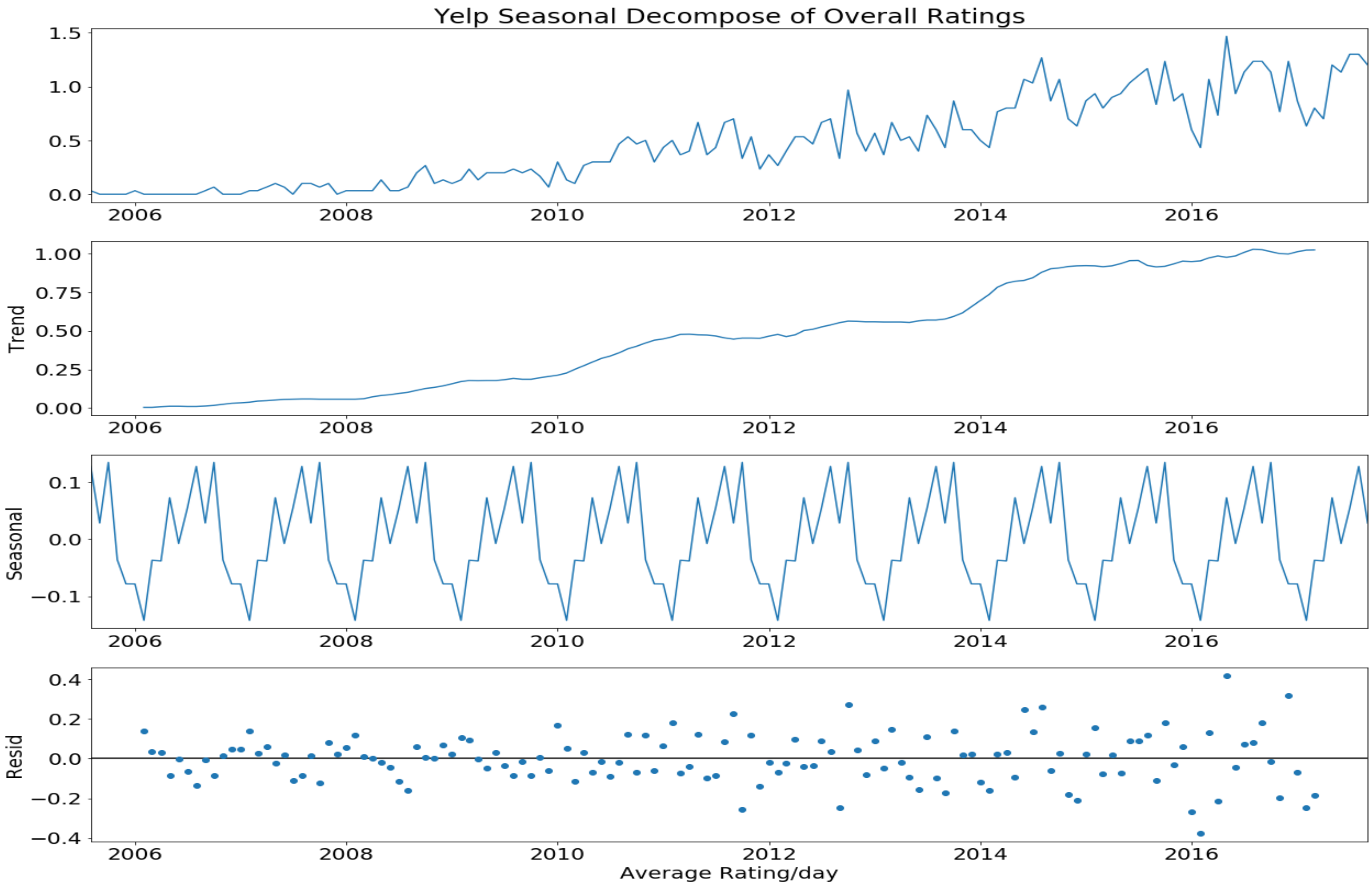


**Fig4 a. Seasonal Decompose of Yelp Overall Ratings of TS restaurants (Kimo's)**

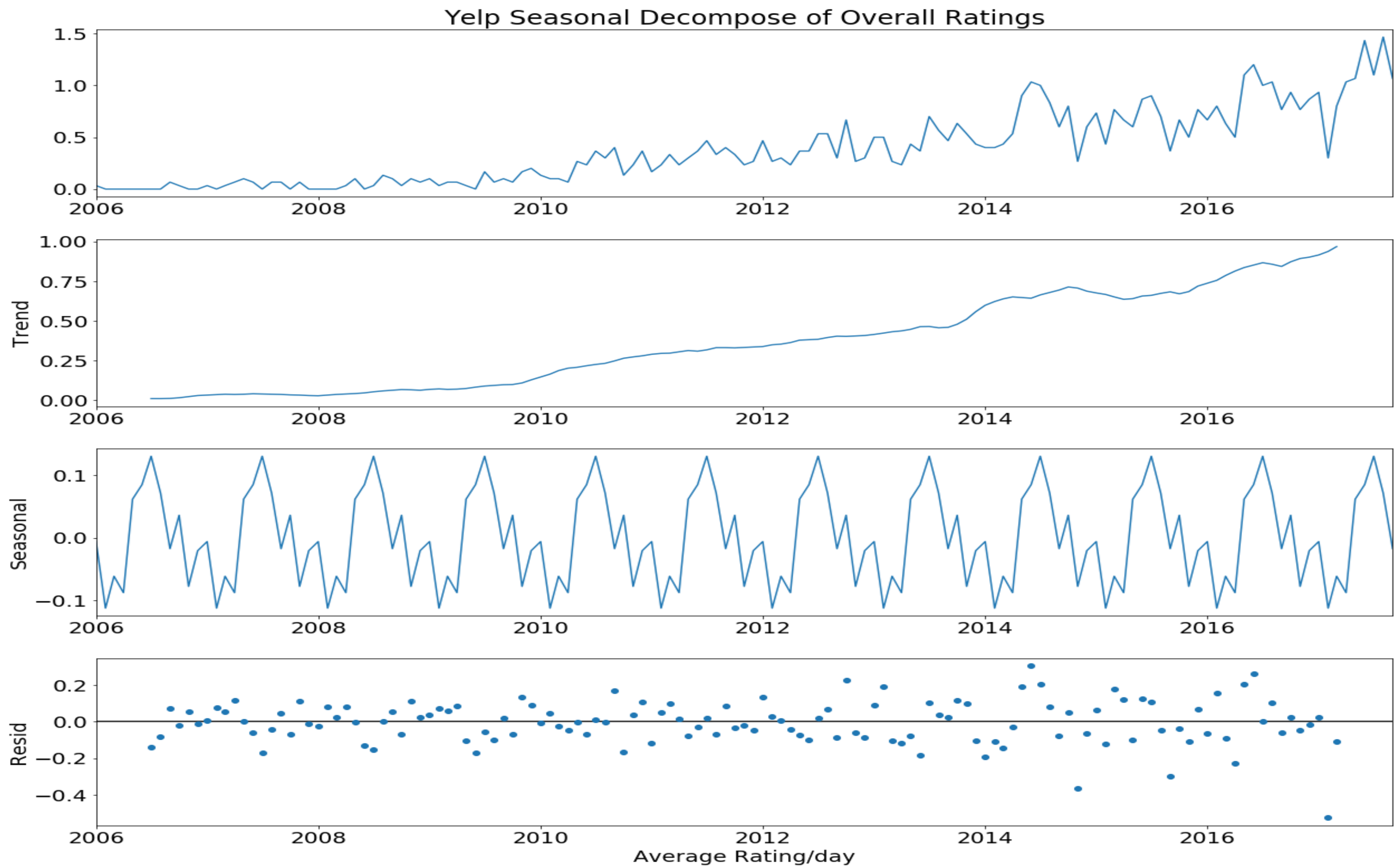


**Fig4 b. Seasonal Decompose of Yelp Overall Ratings of TS restaurants (Leilani's)**

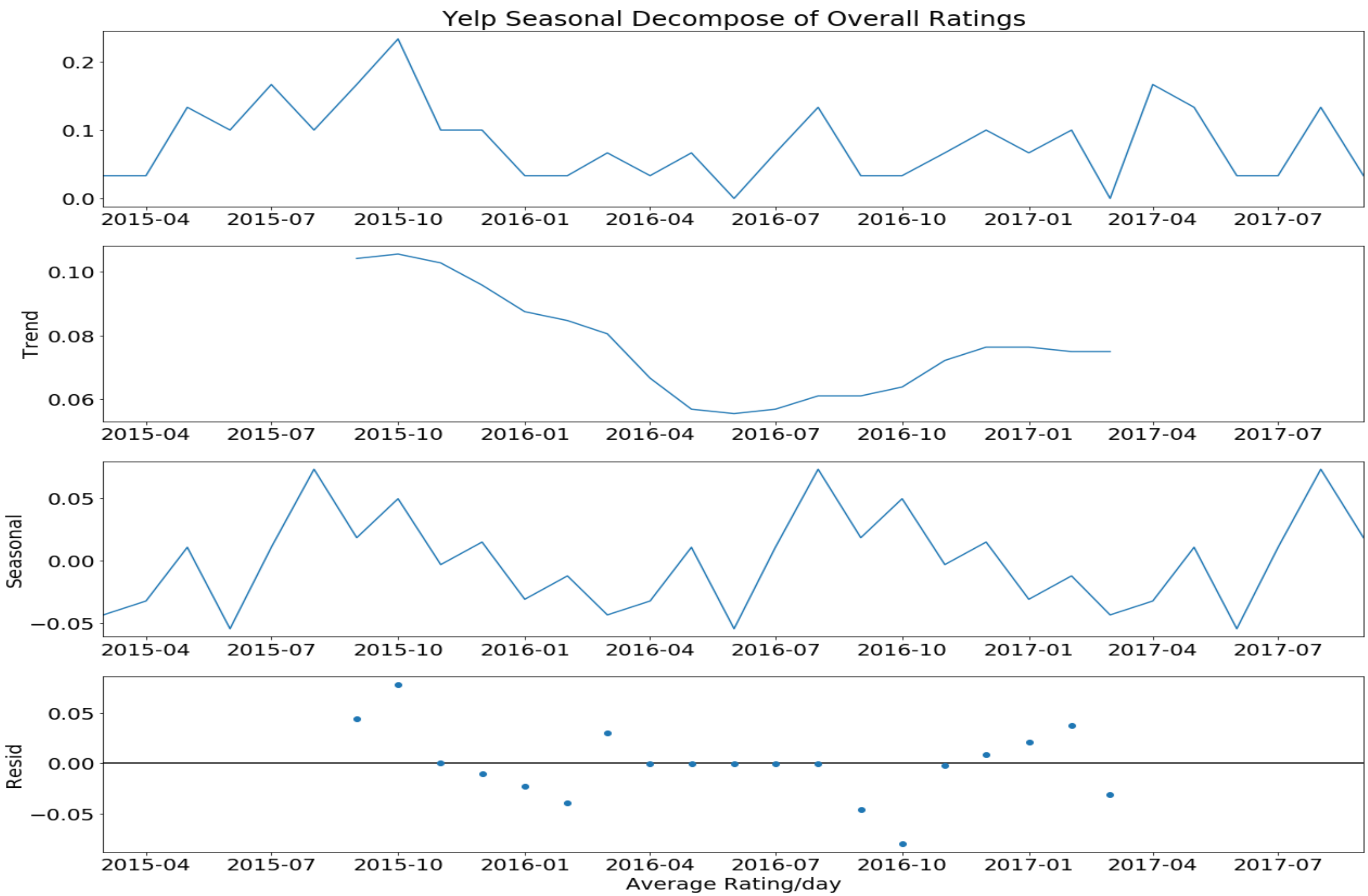


**Fig4 c. Seasonal Decompose of Yelp Overall Ratings of Restaurant of Different Chain**

month October has highest number of overall ratings, for Leilani's on months June & July has the highest number of overall ratings whereas for Kimo's on month February has the lowest number of overall ratings, for Leilani's on month February has the lowest number of overall ratings.

Exploring the competitor's restaurant, exceedingly small dataset was found in comparison to Kimo's and Lelani's with respect to the number of observations. However, in seasonal decomposition (Fig4 c), there is a decreasing trend in the beginning till year 2016 and then a small increase that remains less than the 2015. The seasonality factor does not reveal any seasonal pattern.

### 5.2 SARIMAX Model

SARIMAX model is applied to Yelp dataset using the number of ratings per day as the endogenous variable to observe the time series process for Kimo's and Leilani's restaurants. The purpose mainly was to see if the exogenous variable is significant or not along with other parameters. Only Yelp data is used as Twitter and Facebook provides information about the time of tweets and posts by restaurants. The time of consumer reactions was not collected in the dataset. Many time series models were tried for this analysis such as, autoregression, ARIMA and SARIMA, then the most comprehensive model SARIMAX i.e., seasonal auto regressive integrated moving average exogenous model is applied to find the significant parameters for seasonality, autoregression, moving average and exogenous factor. For TS restaurants, the effect of musical band events which was organized on Fridays and Saturdays was also of interest. For this, exogenous variable with value 1 on Fridays and Saturdays and 0 otherwise is used in the model. To find out the best set of parameters for the model, model selection method using minimum AIC criterion is used [17]. For Kimo's, the minimum AIC -153.57 is found for the model with the number of AR parameters, differences, and MA parameters 0, 1 and 1 respectively, and seasonal component of the model with the AR parameters, differences, MA parameters, and periodicity as 1, 0, 1 and 12 respectively. Using this model, the significant effect of the exogenous parameter ($p<0.001$) and significant estimates of the moving average ($p<0.001$) was found. Significant effect of seasonal auto regression and moving average are also found ($p<0.001$) (Table 1). After analyzing the residuals, no outliers are found and residuals are found to be normally distributed. The Ljung-Box Q test was conducted to ascertain whether the residual series were random. A p value 0.75 suggested that the residual sequence was white noise and that it does not contain any information that was not adequately extracted. Using this model, the forecast for the Kimo's restaurant till September 2021 (Fig 5) was provided. The mean squared error (MSE) obtained by the SARIMAX model is 0.014 which is small and shows that the model is a good fit.

For Leilani's, the minimum AIC -163.81 is found for the model with the number of AR parameters, differences, and MA parameters 1, 1 and 1 respectively and seasonal component of the model with the AR parameters, differences, MA parameters, and periodicity as 1, 0, 1 and 12 respectively. Using this model, the significant effect of the exogenous parameter ($p<0.001$), significant estimates for the seasonal auto regression and moving average ($p<0.001$) were found (Table 2). Residual analysis shows no outliers and residuals are normally distributed. The Ljung-Box Q test was conducted to ascertain whether the residual series were random. A p value greater than 0.05 suggested that the residual sequence was white noise and that it does not contain any information that was not adequately extracted. Using this model, the forecast for the Kimo's restaurant till September 2021 (Fig 6) was provided. The mean squared error (MSE) obtained by the SARIMAX model is 0.012 which is small and shows that the model is a good fit. From the forecast, upward trends for Kimo's as well as Leilani's were found along with seasonality patterns.

**Table 1. Description of SARIMAX model of Kimo's Restaurant**

| Parameter | Coefficient | Standard Error | z | P | 95% CI |
|---|---|---|---|---|---|
| Exogenous | 1.14 | 0.15 | 7.46 | <0.001* | (0.84, 1.44) |
| MA1 | -0.89 | 0.04 | -20.40 | <0.001* | (-0.98, -0.81) |
| SAR12 | 0.93 | 0.10 | 9.01 | <0.001* | (0.73, 1.14) |
| SMA12 | -0.69 | 0.18 | -3.78 | <0.001* | (-1.05, -0.33) |
| AIC | -153.57 | | | | |
| Log Likelihood | 81.78 | | | | |

| | |
|---|---|
| Ljung-Box (Q) | 38.68 (P=0.75) |
| MSE | 0.014 |

*Significant based on 5% type I error rate.

MSE is Mean Squared Error. AIC is Akaike Information Criterion.

**Table 2. Description of SARIMAX model of Leilani's Restaurant**

| Parameter | Coefficient | Standard Error | z | P | 95% CI |
|---|---|---|---|---|---|
| Exogenous | 1.09 | 0.13 | 8.35 | <0.001* | (0.83, 1.34) |
| AR1 | 0.05 | 0.07 | 0.73 | 0.467 | (-0.09, 0.19) |
| MA1 | -1.00 | 61.54 | -0.02 | 0.987 | (-121.61, 119.61) |
| SAR12 | 1.11 | 0.03 | 39.22 | <0.001* | (1.05, 1.16) |
| SMA12 | -0.74 | 0.10 | -7.20 | <0.001* | (-0.94, -0.54) |
| AIC | -163.81 | | | | |
| Log Likelihood | 87.907 | | | | |
| Ljung-Box (Q) | 54.63 (P=0.06) | | | | |
| MSE | 0.012 | | | | |

*Significant based on 5% type I error rate.

MSE is Mean Squared Error. AIC is Akaike Information Criterion.

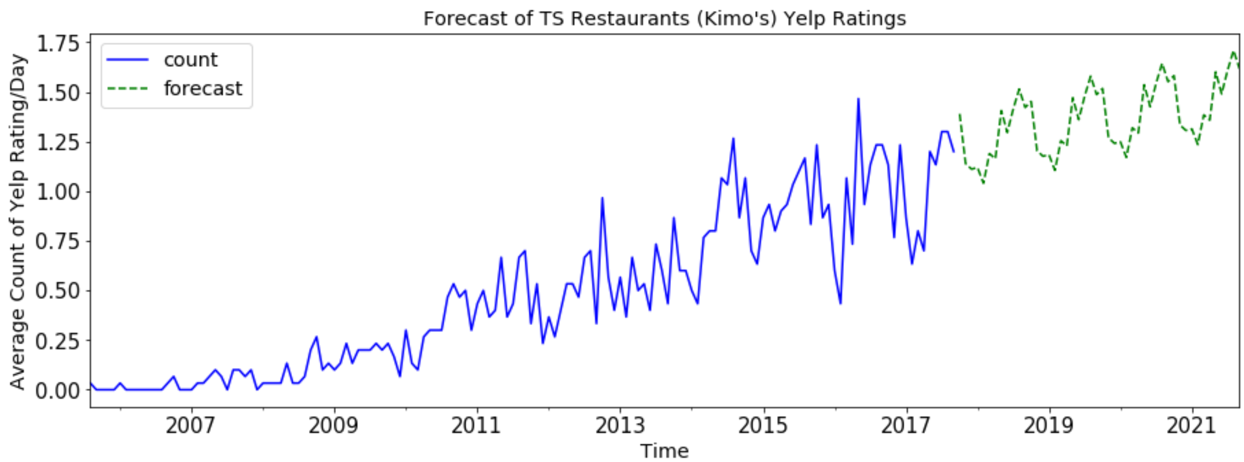


Fig 5. Forecast of TS Restaurant (Kimo's) by SARIMAX Model

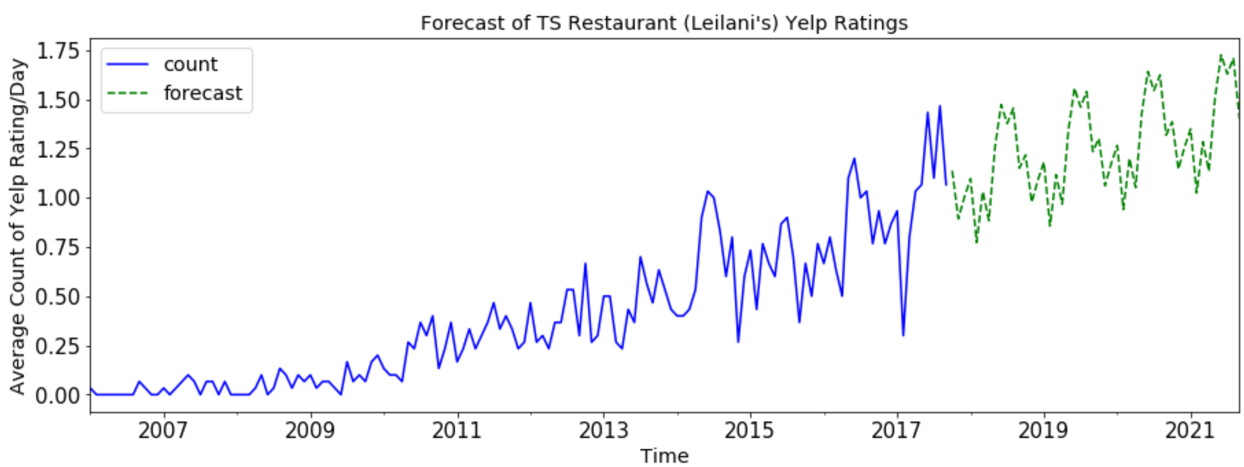


Fig 6. Forecast of TS Restaurant (Leilani's) by SARIMAX Model

# 6. CONCLUSION:

The effect of social media is used to improve the business by organizing events and understanding their effect. In the present study, the objective was to understand the effect of the musical band event, however, finding such effects come with many challenges and proper selection of model plays a crucial role. Firstly, seasonal decomposition is used, in the seasonal decomposition, the seasonality and cyclic effect are factored out to see the signals of trends. The seasonality factor using each platform provided conclusion about the peak and low of the seasons with some differences. More details about seasonality and trend of each platform are provided in section 5.1. For seasonality factor, the results should be interpreted cautiously as the twitter retweets and favorites have differences in their underlying definitions. Similar differences can be implied to

Facebook number of reactions and Yelp ratings. The seasonality is always been an interest of a business to prepare for the best and worst season, using seasonal decompose, months for restaurants in which they attract the customers more/less is found. In such case, the business can implement new strategies during the time when seasonality is low so the profit can be maximized.

Using Yelp data of TS restaurants, the trend can be easily seen (fig 4a, b), however finding the effect of the musical band event remained a challenge. SARIMAX model allows to see the effect of exogenous factor is used for this purpose. Finally, the parameter of exogenous variable has found statistically significant (Table 1) which confirms the effect of musical band event on the business which is not easy to see by any other analysis.

Many social platforms provide the different structure of the dataset and provides less and more flexibility to use them in the analysis. In this study, three social media platforms Yelp, Facebook, and Twitter were analyzed, each of them has different pros and cons. For Facebook and Twitter dataset, the lack of the information about the timestamp of the customers' response was found, but the number of responses, retweets and favorites were useful for analyzing trend and seasonality about the businesses. However, the dataset obtained from Yelp had the timestamp for customers' ratings, which were used to understand the impact of events in the business and therefore used for SARIMAX model. All the three datasets helped in drawing useful conclusions. In the conclusion, significant effect of the musical band was found and used as exogenous parameter in the SARIMAX model to provide the forecast till September 2021 for the TS restaurants (fig 5 and 6).

During the research, need of the different experiments using the social events is realized such as organizing the events other than the weekend can be useful to differentiate the effect of weekends and the events on the business clearly. Further research can be done to precisely understand the effect of these social media platforms on the business events by collecting the data about the flux of the customers by the restaurants and combining the data with the social media platforms. Further research is needed to come up with the methodology for improving different modelling and machine learning techniques to incorporate the effect of exogeneous factor after adjusting for other covariates.

## 7. ACKNOWLEDGEMENT:

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