Tracking service quality improvement through online review using SPC & ABSA

2022-25172 LEE SOO IN

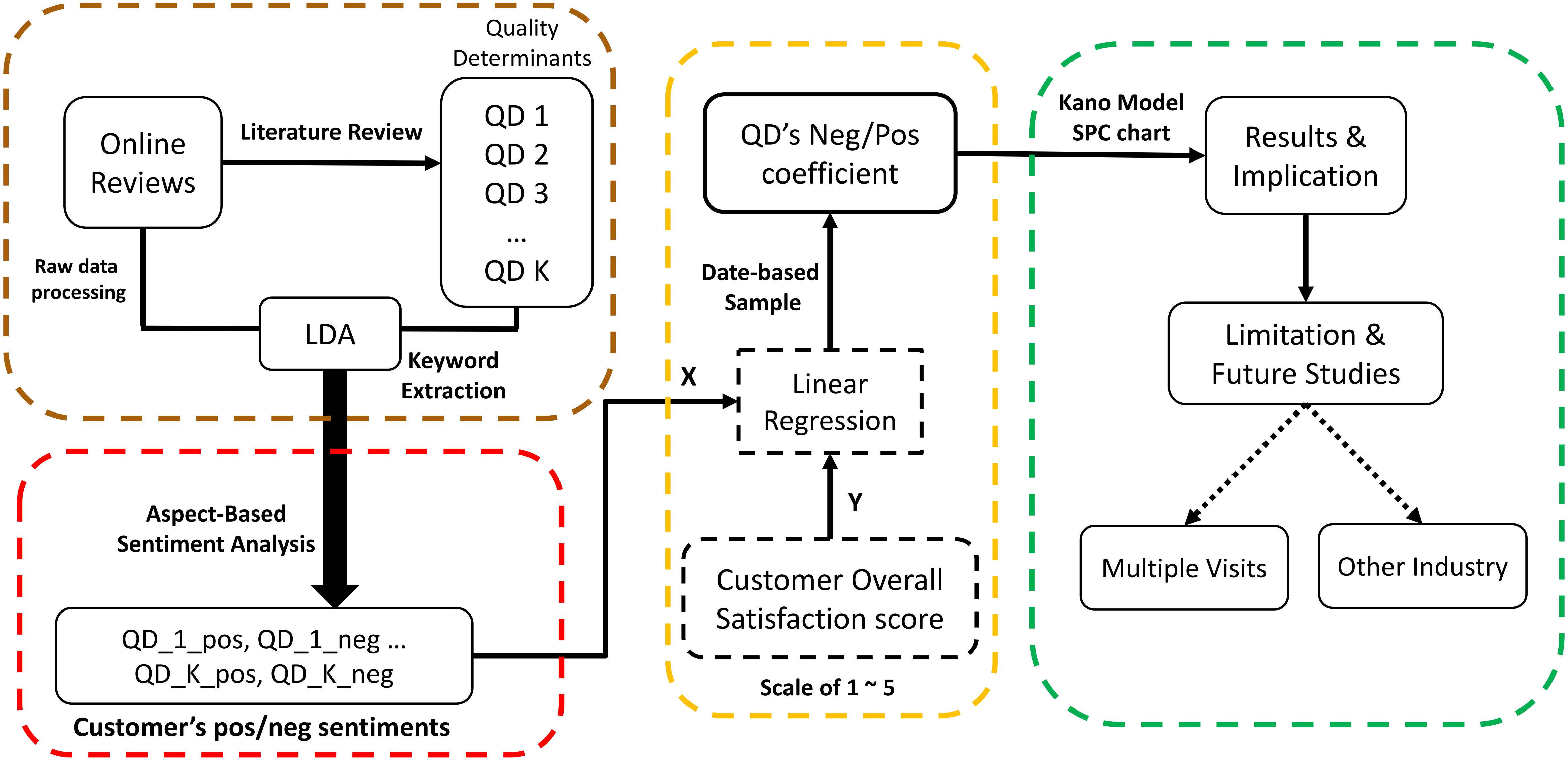
Introduction

- Needs of understanding customer's review
  - One-star increase in Yelp rating leads to a 5-9 percent increase in revenue (Luca, 2017)
  - Identifying each Quality determinants to different categories provide **managerial implication** to service provider
    - Customer's review sentiments provide customer's perception on each determinants
    - Customer's sentiment for each components can be **varied by word** he uses
- Needs of Quality tracking & Limitation with current approaches
  - Companies generally adopt quality tracking techniques to monitor the quality of service after its provision
  - Traditional service quality tracking are usually done by surveying or customer monitoring
    - Expensive & Limited number of customers for representation
  - Under Quality 4.0 paradigm, online customer review can work as service quality tracking
    - User-generated contents accumulated during long time can be used as **monitoring service quality**
- Needs of better detection (representation)
  - Detection on customer's valuation on each Quality determinants **improves** service provider's weakness
  - Trend Analysis on customer's perception can modify service provider's **next strategies**

Research Goal

1. Accurately measure customer sentiment on each Quality Determinants using **DL approach**
2. Identifying customer's QD into different categories through **time-varying review data**
3. Understanding the **relationship** between each QD's sentiment and customer's satisfaction
4. **Tracking** customer's QD coefficients changes through sliding time windows
5. Providing managerial insights to service provider using **SPC-chart** on QD coefficient changes

Experiments Overview & Contents



Literature Review

- Restaurant’s Service Quality Determinants
  - Service quality, customer satisfaction, and behavioral intentions in fast-food restaurants (Hong Qin, 2009)
    - Provided direct and positive relationship between food quality and customer satisfaction using SERVQUAL
  - Revisiting customer’s perception of service quality in the fast food restaurants (Aidin Namin, 2017)
    - Founded evidence that customer satisfaction can be improved through service, quality, food quality and price value
  - **Determinants of customer-perceived service quality in fast-food restaurants and their relationship to customer satisfaction and behavioral intentions (G Qin, 2008)**
    - Modified SERVPERF instrument to find service quality in fast-food restaurant
- Usage of Customer’s review and its satisfaction for evaluation
  - **Modelling customer satisfaction from online reviews using ensemble neural network and effect-based kano model (Jian-Wu Bi, 2019)**
    - First extracted customer satisfaction dimension from online reviews based on latent Dirichlet allocation (LDA)
    - Categorized each CSD (Customer Satisfaction Dimension) using effect-based Kano Model (EKM)

Literature Review

- Quality tracking with customer's review
  - **Product quality tracking based on digital Voice-of-Customers (Federico, 2023)**
    - Showed the potential of digital Voice-of-Customers as a source of information to monitor quality over time
  - **Customer complaints monitoring with customer review data analytics : An integrated methods of sentiment and statistical process control analyses (Juram Kim, 2021)**
    - Integrated sentiment analysis (VADER) and statistical process control chart (SPC) to monitor customer complaint at acceptable time and cost

- Aspect Based Sentiment Analysis (ABSA)
  - SentiHood: Targeted Aspect Based Sentiment Analysis Dataset for Urban Neighborhoods
    - First extract fine-grained information with respect to **multiple** entities mention in user comment
  - **Modeling Aspect Sentiment Coherency via local sentiment aggregation**
    - Fine-tune the pre-trained model from **BERT** and provided better result compare to other lexicon-based approach (ABSA)
  - Restaurant survival prediction using customer-generated content: An ABSA of online reviews
    - Based on ABSA, it investigated the effect of customer review in **predicting restaurant survival**
    - Divided overall review into 5 categories, location, tastiness, price, service, atmosphere

Raw data Processing

DATA CLEANING

- Data Refinement
  - Remove non-English reviews
  - Remove duplicate reviews
- Basic cleaning
  - Removing URL
  - Remove Tags
  - Remove special characters “[^a-zA-Z0-9\s]”
  - Convert to lower case (easier for lemmatization)
- **Total refined reviews: 7646 reviews**

WORD TOKENIZATION

- Tokenization
  - Breaking down text into individual tokens
- Lemmatization
  - Reducing a word to its base or dictionary form
    - Providing -> Provide
  - Use only **noun** for conceptual analysis
- Stop words
  - Exclude non-important word for faster computation
    - Yelp dataset: “acme”, “nola”, “oyster”, “orleans”

Quality Determinants

IDENTIFICATION OF QUALITY DETERMINANTS

Your experience with this fast food restaurant						Importance f	
Very good	Good	Natural	Bad	Very bad	Questions	Very low	Low
5	4	3	2	1	Convenient parking place	1	2
5	4	3	2	1	Interior decoration and design	1	2
5	4	3	2	1	Location	1	2
5	4	3	2	1	Clean tables	1	2
5	4	3	2	1	Ease of access to the menu	1	2
5	4	3	2	1	Staff appearance	1	2
5	4	3	2	1	Staff friendliness	1	2
5	4	3	2	1	Trained and knowledgeable staff	1	2
5	4	3	2	1	Relaxing place to eat	1	2
5	4	3	2	1	Trustfulness of the staff	1	2
5	4	3	2	1	Fast service	1	2
5	4	3	2	1	Reliability of waiting time as it shows on the bill	1	2
5	4	3	2	1	Staff being professional during busy times	1	2
5	4	3	2	1	Reasonable wait time	1	2
5	4	3	2	1	Easiness of ordering and payment	1	2
5	4	3	2	1	Staff being error free when taking orders	1	2
5	4	3	2	1	Helpfulness of staff/ managers when an ordering error happens	1	2
5	4	3	2	1	Ease of access to napkin, ketchup, etc.	1	2
5	4	3	2	1	Convenience of restaurant hours based on your schedule	1	2
5	4	3	2	1	Food quality	1	2
5	4	3	2	1	Kids menu offering	1	2
5	4	3	2	1	Food being nutritious	1	2
5	4	3	2	1	Food being tasty	1	2
5	4	3	2	1	Freshness of ingredients	1	2
5	4	3	2	1	Variety of food options on the menu	1	2
5	4	3	2	1	Food price	1	2
5	4	3	2	1	Beverages price	1	2
5	4	3	2	1	Meal size	1	2

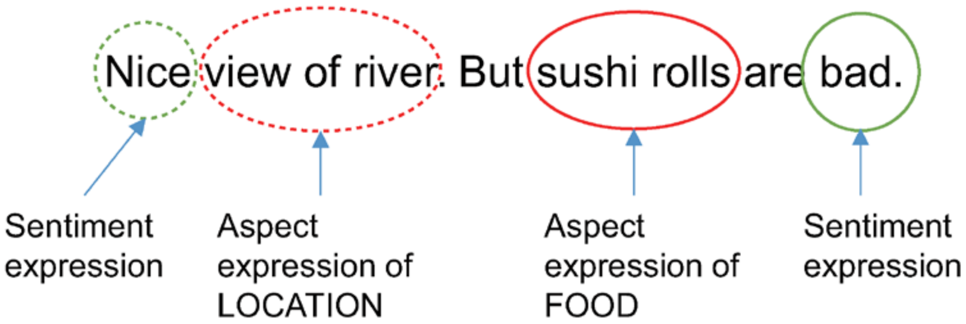
Table 1 Sources of questionnaire items.

Constructs	Item label	Item wording	Sources
Tangibles	Tang1 Tang2 Tang3 Tang4 Tang5	Appealing physical facilities Seat availability Parking availability Separation of smoking area Clean dining area	Cronin and Taylor 1992; Johns and Howard 1998; Kara et al. 1995
Employee behaviors	Empl1 Empl2 Empl3 Empl4 Empl5	Well-dressed Wearing sanitary gloves and hair net Friendly and courteous Knowledgeable Trustworthy	Cronin and Taylor 1992; Johns and Howard 1998
Reliability	Rely1 Rely2 Rely3 Rely4	Providing service as promised Sympathetic and reassuring Accurate charge On-schedule service	Cronin and Taylor 1992
Responsiveness	Prompt1 Prompt2 Prompt3	Telling exact service time Employees available to requests Prompt service	Cronin and Taylor 1992
Empathy	Empa1 Empa2 Empa3 Empa4	Individual attention Convenient operating hours Completely packaged food Availability of sauces, etc.	Cronin and Taylor 1992; Johns and Howard 1998
Food quality	Food1 Food2 Food3 Food4	Clean Healthy Fresh A variety of food and beverage	Johns and Howard 1998; Kivela et al. 1999
Price/value	PV1 PV2 PV3	Competitive price Value worthy of price Special discounts	Kim and Kim 2004; Kara et al. 1995
Customer satisfaction	CS1 CS2 CS3 CS4	Satisfaction of food quality, service quality, and price/value Overall satisfaction	Cronin and Taylor 1992
Behavioral intentions	BI1 BI2 BI3	Intention to dine here again Recommendation Saying good things about the FFR	Boulding et al. 1993; Keillor et al. 2004

Quality Determinants	Indicator (Example)
Environment	Clean dining area, Interior Design
Server	Friendly Employee, Tips
Service	Prompt Service, Reservation
Line	Line Management, Waiting time
Food	Food Quality, Variety of options
Dessert	Desserts Variety, Fitness
Pricing	Value worth of price
Parking	Parking availability, Locations
Beverage	Bar & Drink variety

Aspect based Sentiment Analysis

WHAT IS ABSA?



- Targeted aspect-based sentiment analysis
  - Targets are identified from <u>Quality determinants</u>
- BERT
  - Bidirectional transformers to pre-train large corpus and find-tunes the pre-trained model on other task

COMPARE WITH VADER

	SA	ABSA
Task	Overall Text	Each aspect
Output	Single label	<u>Each aspect label</u>
Accuracy	Product review	Service improvement

	VADER	BERT
Speed	Faster	Slower
Model	Model-free (Lexicon)	Trained data
Accuracy	Lower	<u>Higher</u>

<u>ABSA using VADER, not works well in many contexts!</u>

Validation with ABSA

USER MANUAL & SAMPLE

- Sample 100 review for each QD
- Presenter manually tagged sentiments each QD
- Small limitation exist with small samples

QD	Accuracy (100)
Parking	95%
Employee	61%
Price	71%
Service	42%

ABSA RESULT WITH E

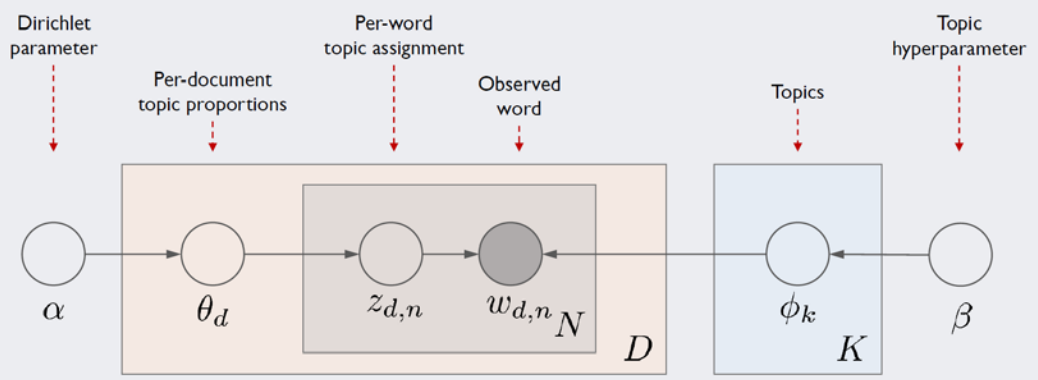
Model		Laptop14		Restaurant14		MAMS	
		Acc	F1	Acc	F1	Acc	F1
BERT-BASE	Base	80.36(0.78)	77.04(0.71)	86.34(0.18)	80.01(0.28)	82.52(1.13)	81.87(1.23)
RoBERTa-BASE	Base	82.76(0.63)	79.73(0.77)	87.77(1.61)	82.10(2.01)	83.83(0.49)	83.29(0.50)
DeBERTa-BASE	Base	82.76(0.31)	79.45(0.60)	88.66(0.35)	83.06(0.29)	83.06(1.24)	82.52(1.25)
LSA_P-BERT	LSA w/o DWA	80.67(0.47)	77.20(0.69)	86.43(0.13)	80.71(0.47)	83.58(0.56)	83.00(0.55)
LSA_T-BERT	LSA w/o DWA	80.72(0.31)	77.16(0.27)	87.53(0.58)	81.85(0.69)	83.03(0.34)	82.34(0.42)
LSA_S-BERT	LSA w/o DWA	80.62(0.55)	76.89(0.44)	86.70(0.62)	81.11(0.79)	82.41(1.35)	81.71(1.45)
LSA_P-RoBERTa	LSA w/o DWA	82.55(0.78)	79.93(0.83)	87.68(0.48)	82.46(0.65)	83.31(0.47)	82.90(0.62)
LSA_T-RoBERTa	LSA w/o DWA	82.76(0.55)	80.08(0.44)	87.59(1.03)	82.02(1.29)	83.53(0.45)	82.92(0.32)
LSA_S-RoBERTa	LSA w/o DWA	82.92(0.39)	80.10(0.57)	88.21(0.89)	82.32(0.78)	83.95(0.34)	83.30(0.54)
LSA_P-DeBERTa	LSA w/o DWA	84.27(0.47)	81.38(0.23)	89.60(0.51)	84.90(0.49)	84.06(0.08)	83.57(0.18)
LSA_T-DeBERTa	LSA w/o DWA	84.27(0.31)	81.18(0.29)	89.79(0.71)	84.88(1.13)	83.01(0.86)	82.53(0.92)
LSA_S-DeBERTa	LSA w/o DWA	83.91(0.78)	81.24(1.01)	89.73(0.46)	84.71(0.55)	83.31(0.41)	82.80(0.58)
LSA_P-BERT	LSA	81.35(0.63)	77.79(0.48)	87.23(0.22)	81.06(0.67)	83.13(0.30)	82.53(0.44)
LSA_T-BERT	LSA	81.35(0.39)	78.43(0.52)	87.32(0.22)	81.86(0.20)	83.51(0.26)	82.90(0.28)
LSA_S-BERT	LSA	81.03(0.31)	77.45(0.37)	87.41(0.40)	81.52(0.49)	83.23(0.56)	82.68(0.52)
LSA_P-RoBERTa	LSA	83.39(0.35)	80.47(0.44)	88.04(0.62)	82.96(0.48)	83.37(0.31)	83.78(0.29)
LSA_T-RoBERTa	LSA	83.44(0.56)	80.47(0.71)	88.30(0.37)	83.09(0.45)	83.31(0.41)	83.60(0.22)
LSA_S-RoBERTa	LSA	83.23(0.44)	80.30(0.68)	88.48(0.52)	83.81(0.62)	83.58(0.39)	83.78(0.24)
LSA_P-DeBERTa	LSA	84.33(0.55)	81.46(0.77)	89.91(0.09)	84.90(0.45)	83.91(0.31)	83.31(0.21)
LSA_T-DeBERTa	LSA	84.80(0.39)	82.00(0.43)	89.91(0.40)	85.05(0.85)	84.28(0.32)	83.70(0.47)
LSA_S-DeBERTa	LSA	84.17(0.08)	81.23(0.27)	89.64(0.66)	84.53(0.79)	83.61(0.30)	83.07(0.28)

Average around 80%, ABSA Dataset

Key word extraction

TOPIC MODELLING

- Definition
  - Process of identifying and extracting hidden themes or topics from a collection of documents
- Latent Dirichlet allocation
  - Statistical model in NLP for topic modeling
  - Estimate final topic words distribution



INTEGRATE LDA & ABSA

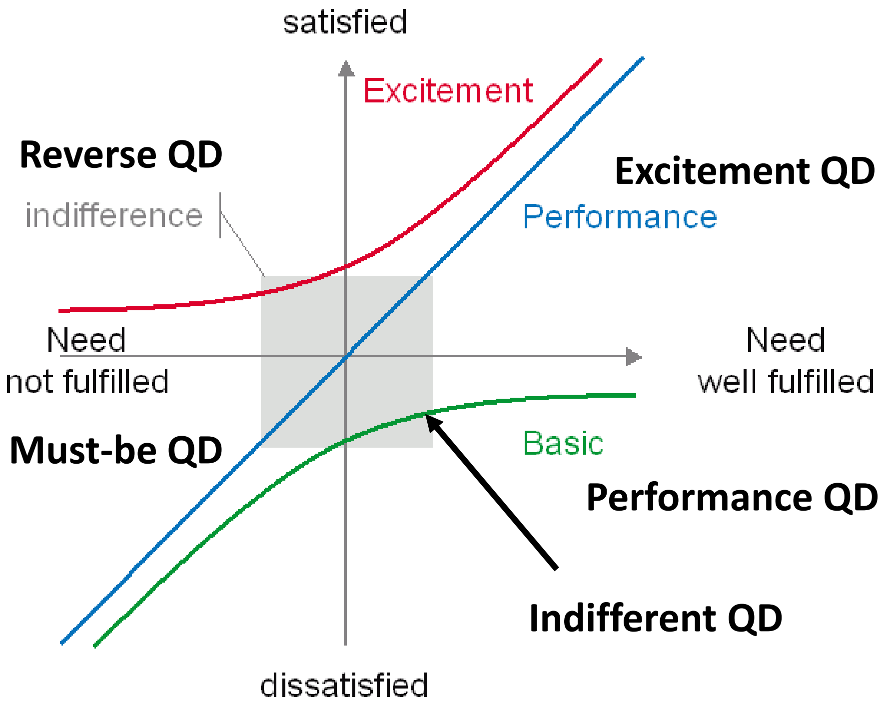
- Limitation in ABSA
  - Problems with different words with similar meaning
    - Waiter, Server, Staff – same meaning in restaurant, <u>but may signal different meaning in other text</u>
  - Specific examples should be included
    - Crab cake, etouffee – example of foods
    - Bread pudding, cheese – example of dessert
- LDA for overcoming limitations
  - Finding customer's frequent used words (Keywords)
  - Match frequent used words into Quality determinants
    - $\{Beverage, drink, beer, wine, bar, vodka\} \in \ set\{Beverage)$

KANO-model

DEFINITION

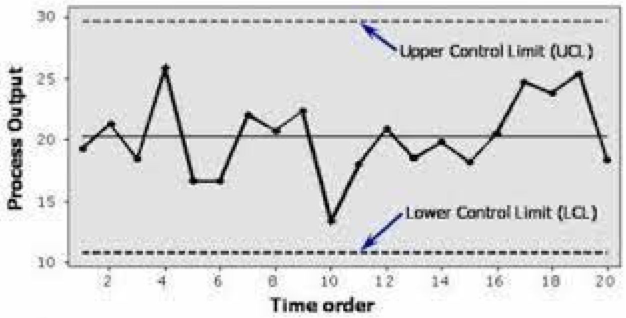
- KANO MODEL
  - Used to prioritize customer needs and determine customer satisfaction levels
  - Categorized five quality factor based on consumer's expectation and fulfillment
- Literature Review (Pipeline)
  - Modeling Customer Satisfaction from online reviews using ensemble neural network and effect-based Kano Model
    - Changed Satisfied as negative sentiment coefficient
    - Changed fulfillment as positive sentiment coefficient

EFFECT-BASED KANO MODEL



Statistical Process Control

- Graph tool to monitor and analyze the variation in a process over time
  - Helps to determine whether process is operating within acceptable limits
  - Can be used to considering in service recovery and improvement process
    - $UCL_i = \overline{\beta_i} + L * \sigma(\beta_i), i \; for \; each \; QD_{pos/neg}$
    - $LCL_i = \overline{\beta_i} - L * \sigma(\beta_i), \; i \; for \; each \; QD_{pos/neg}$



- Literature Review (Pipeline)
  - Customer complaints monitoring with customer review data analytics : An integrated methods of sentiment and statistical process control analyses (Stated L = 2)
    - Coefficient that plot outside of either control limit, interpreted as signal that service is out-of-control, investigation is needed
      - QD_pos with above UCL: Incentives needed
      - QD_neg with under LCL: Improvements needed
    - Possible to observe the variations in coefficients over different time periods – customer's satisfaction trend
      - Increasing Trend & Decreasing Trend

Case Study with Yelp Dataset

ONLINE SOURCES

- Yelp
  - Online platform providing crowed-sourced reviews and information about local business
  - Gained review data from Yelp
- Kaggle
  - Online platform providing datasets for data science
  - Used initial raw data process codes from Kaggle

ACME OYSTER HOUSE (NEW ORLEANS)

- 7673 reviews (from 2005 to 2022)
  - Highest number of reviews in restaurants section
- Customer's satisfaction scores
  - 4.0 (YELP)
  - 4.5 (Google Map)

Usage LDA as finding similar keyword

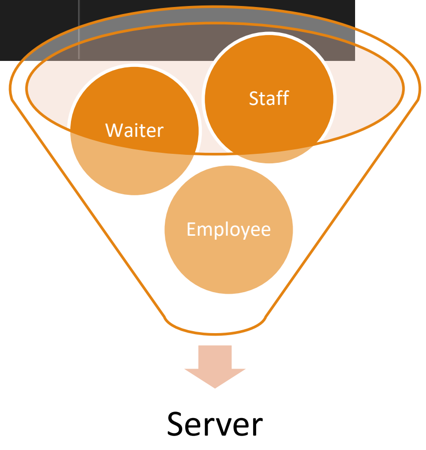
LDA RESULTS

```
[(0,
  '0.192*"etouffee" + 0.177*"atmosphere" + 0.101*"fun" + 0.077*"shooter" + '
  '0.069*"etoufee" + 0.053*"family" + 0.034*"job" + 0.027*"light" + '
  '0.024*"shuck" + 0.022*"feel"'),
 (1,
  '0.150*"line" + 0.069*"dozen" + 0.062*"bar" + 0.042*"minute" + 0.042*"table" '
  '+ 0.042*"order" + 0.035*"thing" + 0.034*"people" + 0.030*"wait" + '
  '0.029*"friend"'),
 (2,
  '0.160*"rice" + 0.111*"dinner" + 0.072*"year" + 0.069*"husband" + '
  '0.066*"sausage" + 0.042*"bean" + 0.039*"item" + 0.037*"wife" + '
  '0.035*"vodka" + 0.027*"hurricane"'),
 (3,
  '0.092*"amount" + 0.069*"soup" + 0.055*"option" + 0.052*"gravy" + '
  '0.047*"care" + 0.045*"evening" + 0.044*"choice" + 0.037*"weekend" + '
  '0.033*"salt" + 0.030*"bread_pudding"'),
 (4,
  '0.165*"horseradish" + 0.157*"bomb" + 0.090*"opinion" + 0.041*"folk" + '
  '0.037*"kick" + 0.024*"com" + 0.000*"allergy" + 0.000*"youtube" + '
  '0.000*"freaking" + 0.000*"https"'),
 (5,
  '0.175*"bread" + 0.160*"sauce" + 0.116*"cheese" + 0.097*"butter" + '
  '0.047*"buttery" + 0.033*"reason" + 0.029*"garlic" + 0.020*"wish" + '
  '0.020*"stuff" + 0.014*"type"'),
```

CONCEPT & DICTIONARY

```
concepts = {
    'environment': ['interior', 'table', 'ambient', 'atmosphere', 'washroom', 'kitchen'],
    'server': ['staff', 'employee', 'server', 'attitude','waitress', 'waiter','worker',' job' 'tip'],
    'service': ['service', 'reservation', 'order', 'time', 'schedule'],
    'line': ['wait', 'line', 'seat'],
    'food': ['menu', 'food', 'dish' 'appetizer', 'course', 'size', 'bowl', 'variety', 'choice', 'piece'],
    'dessert': ['dessert', 'cake', 'coffee'],
    'pricing': ['price','payment', 'cost', 'worth'],
    'parking': ['parking', 'car', 'location', 'space', 'place', 'spot', 'city'],
    'beverage': ['beverage', 'drink', 'beer', 'wine', 'bar', 'vodka'],
    }
```

Matched Frequent used words into QD



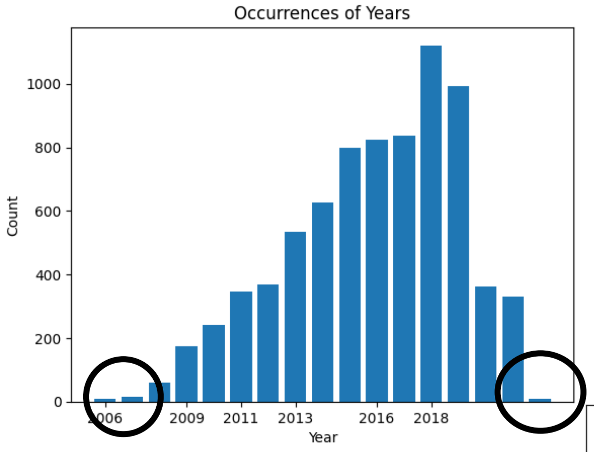
Post Sentimental Analysis

	CSDs			
Online reviews	f_1	f_2	...	f_I
r_1	Positive	Missing value	...	Missing value
r_2	Negative	Missing value	...	Positive
...	...	...	...	...
r_M	Missing value	Positive	...	

- Positive: 1
- Negative: -1
- Not mentioned: 0

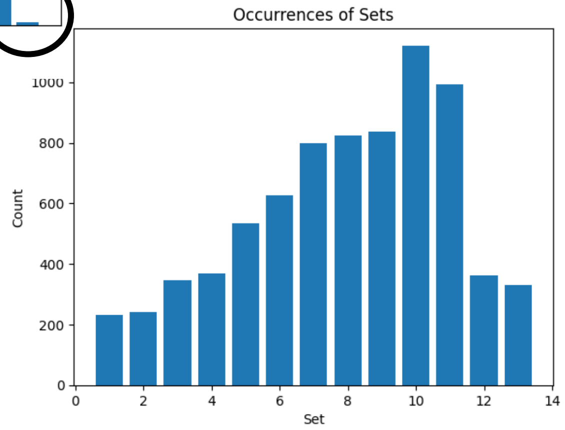
	CSDs						
	f_1		f_2		...	f_I	
Online reviews	S_1^{Pos}	S_1^{Neg}	S_2^{Pos}	S_2^{Neg}	...	S_I^{Pos}	S_I^{Neg}
r_1	1	0	0	0	...	0	0
r_2	0	1	0	0	...	1	0
...	...	...	...	...	...	...	...
r_M	0	0					

If QD value is 1, then QD_pos = 1, QD_neg = 0
Else if QD value is -1, then QD_neg = 1, QD_pos = 0
else both QD tag as 0



Too small sample,
exclude for trend analysis

Start 2008 ~ End 2021
each 2 year for 1 set
sliding 1 year each (14 set)



Data Analysis of QD sentiments

NUMBER OF POS/NEG SENTIMENTS

QD	Pos	Neg
Environment	1000	270
Server	1296	429
Service	2982	740
Line	2580	1665
Food	2706	651
Dessert	263	63
Pricing	1614	327
Parking	2589	682
Beverages	1665	498

TOP 5 INTER-QD CORRELATION

Inter-QD	Correlation
(service_neg, food_neg)	0.399
(line_pos, pricing_pos)	0.386
(service_neg, parking_neg)	0.371
(service_neg, beverage_neg)	0.365
(food_neg, parking_neg)	0.361

Except Intra-QD correlation, line & service

Multiple Linear Regression

- **Average Satisfaction: 4.13**
- **Adjusted-R squares: 0.71**
  - H_0: $\beta_i^{pos}, \beta_i^{neg} = 0, \forall i$
  - H_1: $Not\ all\ variables's\ coefficents\ are\ 0$
    - Enviornment_neg, Server_neg, Dessert_neg (Cannot reject H_0)

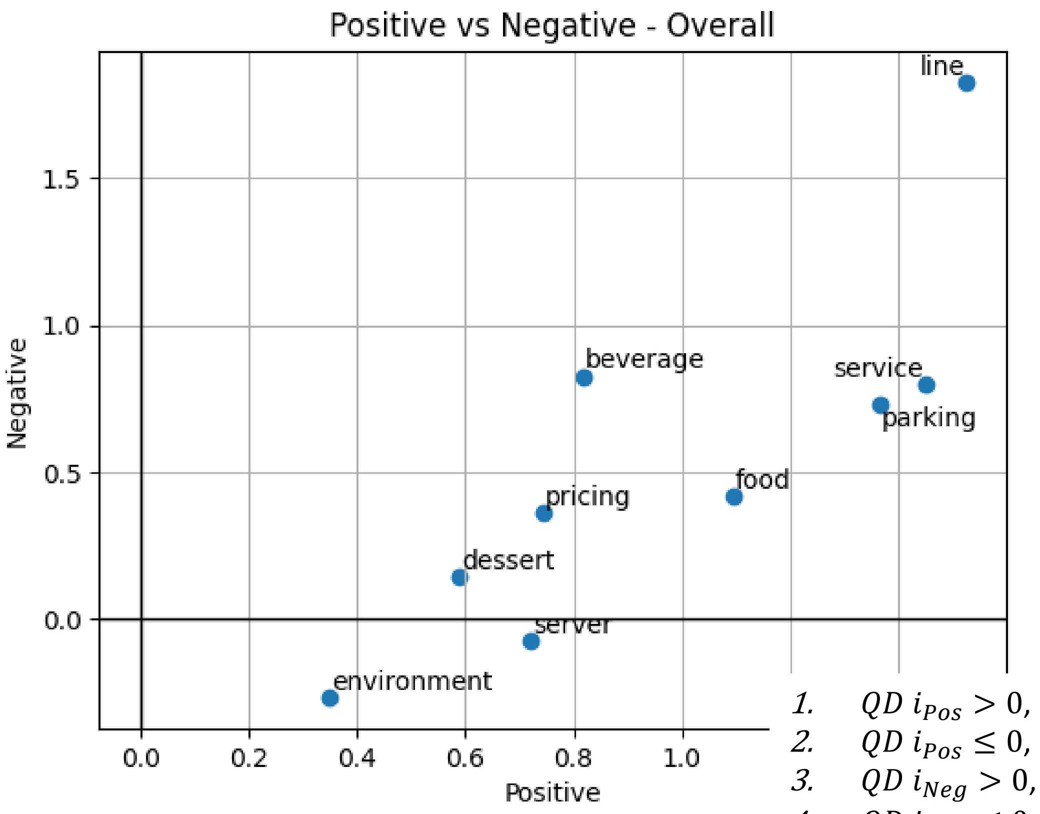
OLS Regression Results

Dep. Variable:	stars	R-squared (uncentered):	0.710
Model:	OLS	Adj. R-squared (uncentered):	0.709
Method:	Least Squares	F-statistic:	1032.
Date:	Thu, 01 Jun 2023	Prob (F-statistic):	0.00
Time:	10:16:28	Log-Likelihood:	-17130.
No. Observations:	7613	AIC:	3.430e+04
Df Residuals:	7595	BIC:	3.442e+04
Df Model:	18		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
environment_pos	0.3479	0.081	4.319	0.000	0.190	0.506
environment_neg	-0.2650	0.160	-1.661	0.097	-0.578	0.048
server_pos	0.7203	0.073	9.910	0.000	0.578	0.863
server_neg	-0.0727	0.129	-0.563	0.574	-0.326	0.181
service_pos	1.4509	0.056	25.920	0.000	1.341	1.561
service_neg	0.7998	0.109	7.356	0.000	0.587	1.013
line_pos	1.5235	0.065	23.305	0.000	1.395	1.652
line_neg	1.8254	0.071	25.614	0.000	1.686	1.965
food_pos	1.0946	0.057	19.288	0.000	0.983	1.206
food_neg	0.4190	0.110	3.804	0.000	0.203	0.635
dessert_pos	0.5886	0.145	4.051	0.000	0.304	0.873
dessert_neg	0.1456	0.295	0.494	0.622	-0.433	0.724
pricing_pos	0.7431	0.070	10.546	0.000	0.605	0.881
pricing_neg	0.3635	0.141	2.581	0.010	0.087	0.640
parking_pos	1.3658	0.057	24.089	0.000	1.255	1.477
parking_neg	0.7327	0.109	6.720	0.000	0.519	0.946
beverage_pos	0.8179	0.067	12.246	0.000	0.687	0.949
beverage_neg	0.8263	0.121	6.839	0.000	0.589	1.063

Omnibus:	148.498	Durbin-Watson:	1.553
Prob(Omnibus):	0.000	Jarque-Bera (JB):	90.722
Skew:	-0.115	Prob(JB):	2.00e-20
Kurtosis:	2.517	Cond. No.	11.7

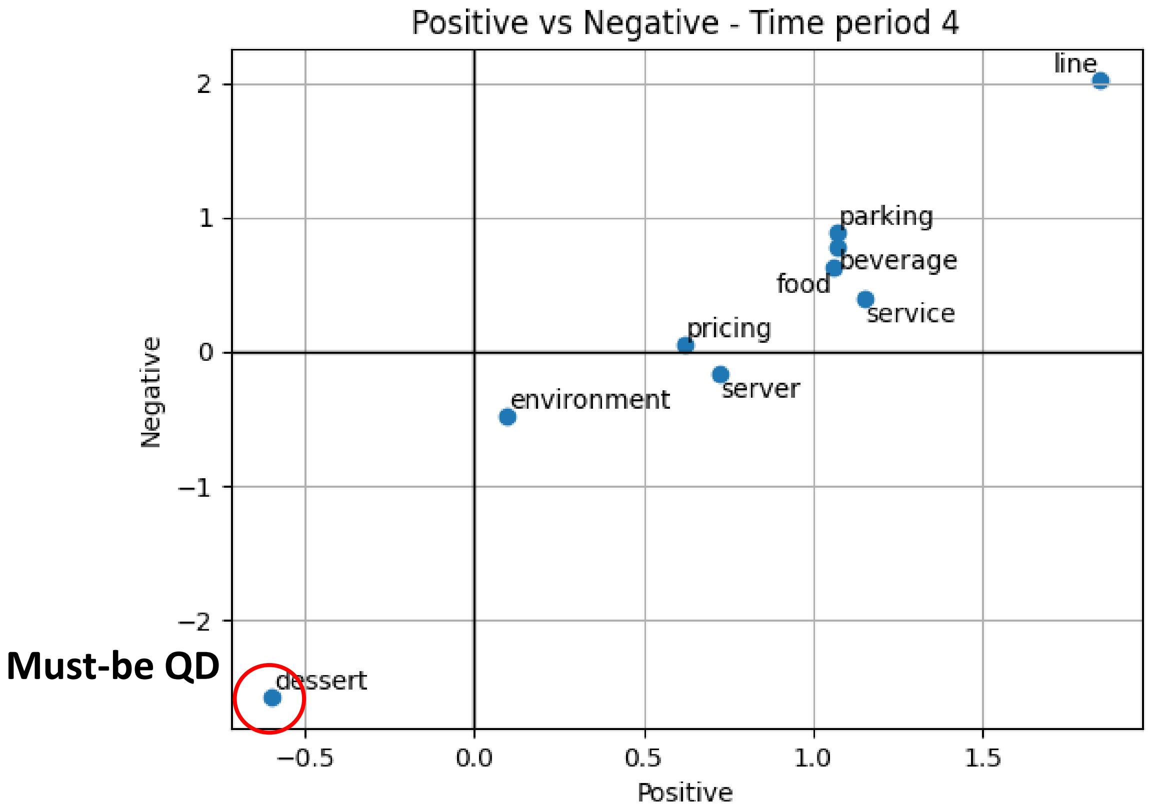
Effect-based KANO model

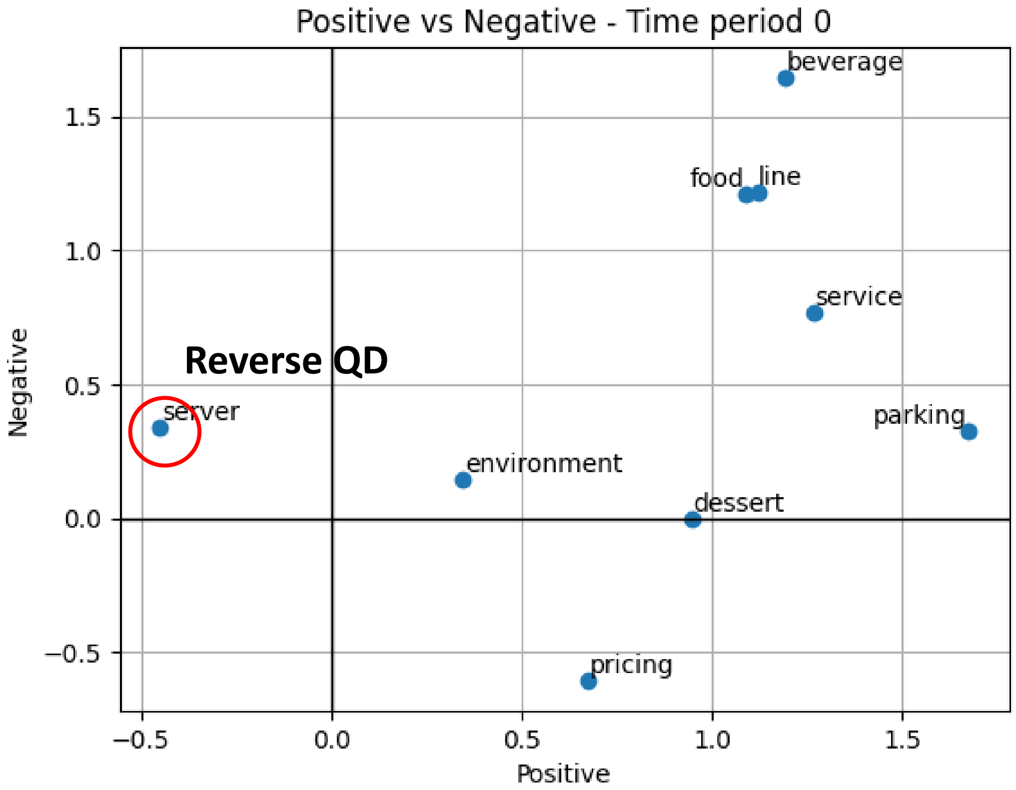


- Excitement QD
  - Line, Beverage, Service, Parking, Food, pricing
- Performance QD
  - Environment, Server
- Indifferent QD
  - Dessert
- **Each QD can be varied by each time period**

1. $QD\ i_{Pos} > 0$, customer satisfaction will increase as customer's requirement on QD is fulfilled
2. $QD\ i_{Pos} \leq 0$, customer satisfaction will not increase as customer's requirement on QD is fulfilled
3. $QD\ i_{Neg} > 0$, customer satisfaction will not decrease, as customer's requirement on QD is unfulfilled
4. $QD\ i_{Neg} \leq 0$, , customer satisfaction will decrease, as customer's requirement on QD is unfulfilled

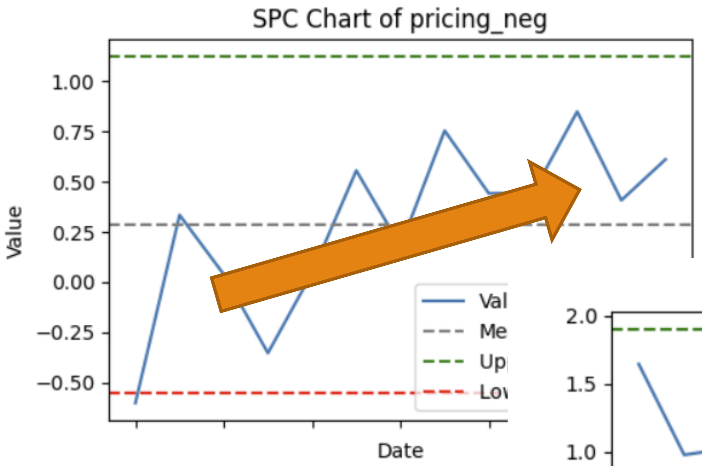
KANO model under different Time period



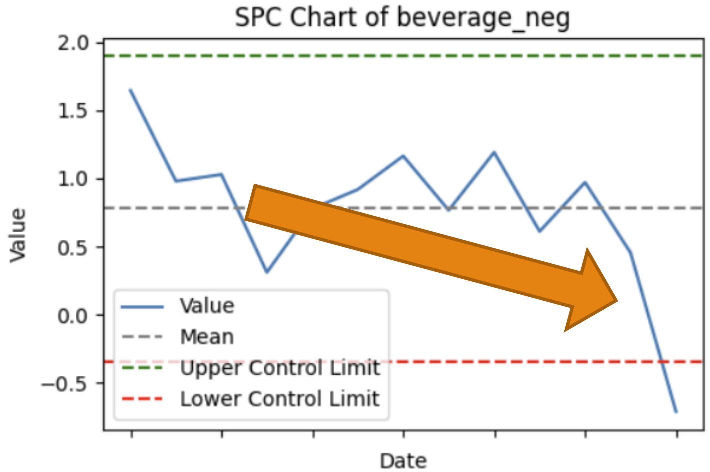


SPC & Implication

TREND ANALYSIS (L=2)

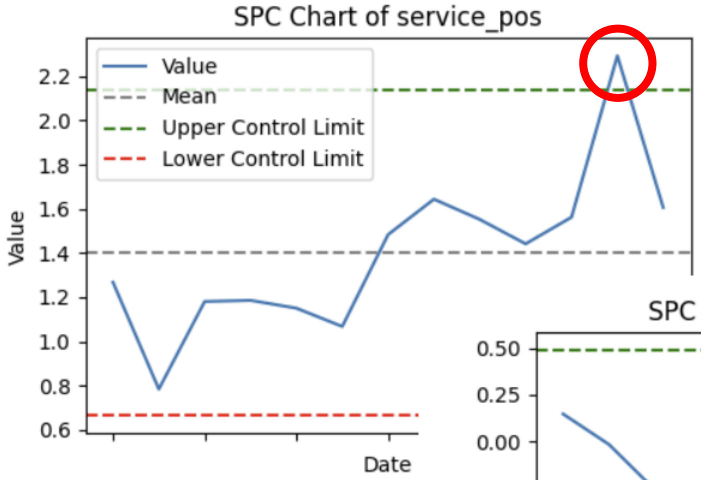


Increasing Trend

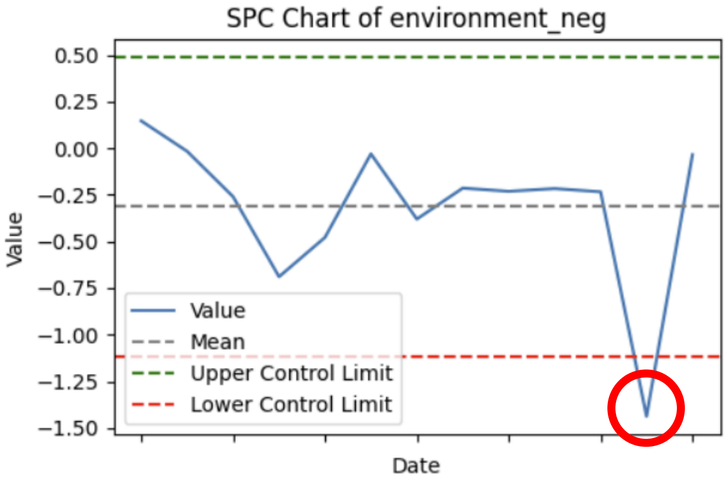


Decreasing Trend

OUTLIER DETECTION (L=2)



Incentives needed



Improvements needed

Limitation

REGRESSION METHOD

- Linear regression best way?
  - Assume changes with same weight
    - Is score 1 to score 2 and score 4 and score 5 same?
    - Limited categorical range vs. Continuous predicted y
- Logistic regression
  - Hard to interpret for each coefficient
    - Each score 1 to 5 scale has own coefficients
    - Maximum 5 * 18 = 90 coefficients
- Suggestion (Machine learning approach)
  - <u>**Gradient Boosting Method with Shapley value**</u>
    - Can understand features with positive or negative impact
    - How different features influenced that specific prediction

VALIDATION OF REVIEW AND SCORE

- Limitation with current NLP sentiment analysis
  - 5-star rating: 3634
    - 22 reviews: More than 5 negative sentiment of QD
  - 1-star rating: 215
    - 42 reviews: No negative sentiment to any QD
- Is five-star matters?
  - People no longer believe 5 stars as extraordinary
  - Score less than 5 star is rather flaws in restaurants

“△△식당, 가성비·친절·재방문 의사”…리뷰, 어디까지 믿을까

신소윤 기자 +구독

October 14, 2021

Is A 4.5-Star Rating Better Than 5 Stars?

Future Studies

COMPARE WITHIN MULTIPLE VISITS

- Multiple Visits with different sentiment
  - 89 customer: visited more than twice
  - 69 customer: different QD's sentiment for second visit
  - **29 customer: Changed stars for second visit**
- Tables with different sentiments for second visit
  - Finding the correlation between coefficient changes

QD	Pos	Neg
Environment	10	7
Server	9	9
Service	25	13
Line	25	19
Food	18	7

QD	Pos	Neg
Dessert	2	0
Pricing	16	7
Parking	23	6
Beverages	22	7

APPLICATION WITH DIFFERENT INDUSTRY

- Electronics
  - Study on the change of improved products and **various product groups** according to consumer reviews
    - Samsung Galaxy Series & Apple iPhone series
- Automobiles
  - Gain insights into strategies for addressing customer concerns, **improving product quality**, and enhancing customer satisfaction
    - KIA K series & BMW product Segmentation

Questions & Answer

RELATED CODES WILL BE UPLOADED AT GITHUB

See you at https://github.com/bizsooin