Service Intelligence Week 4.

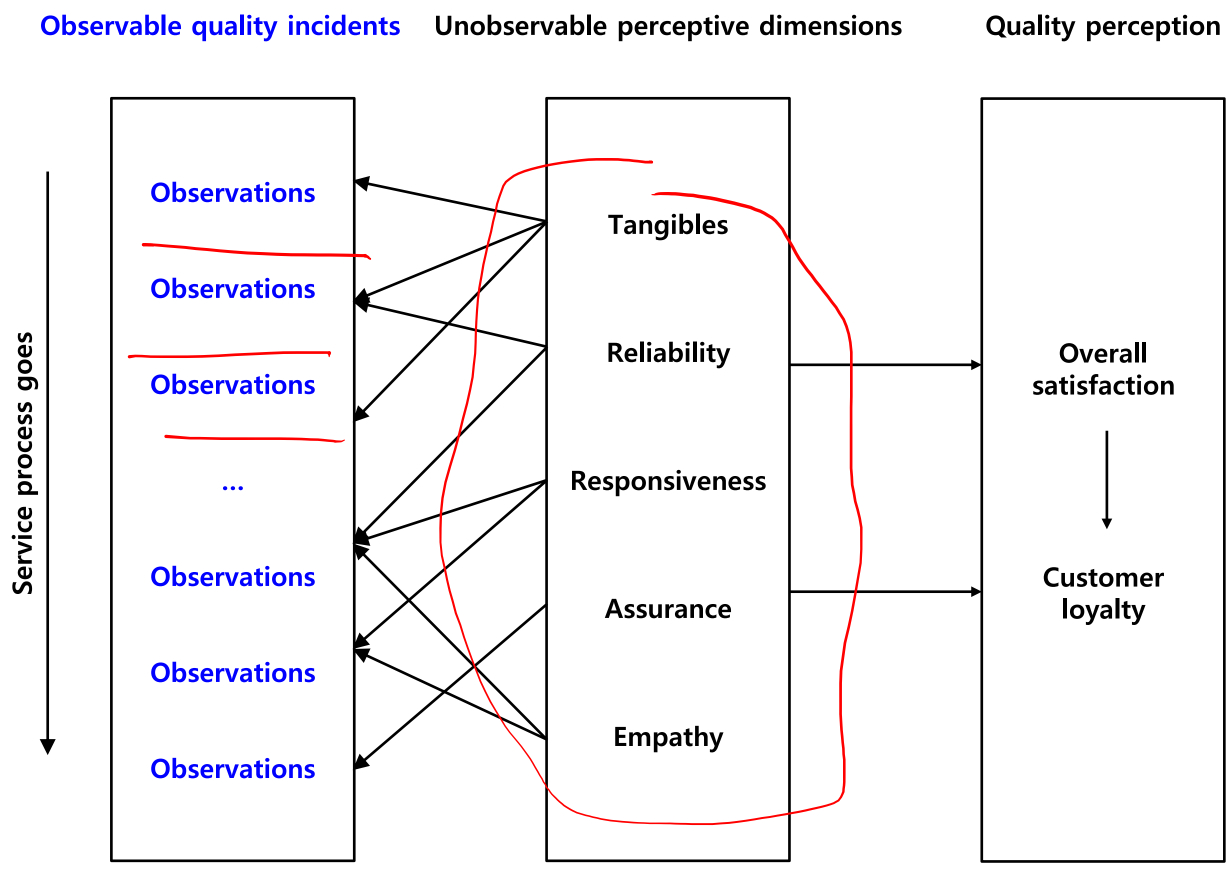
[Service Review Mining for Service Improvement]

Chiehyeon Lim

2022. 9. 21

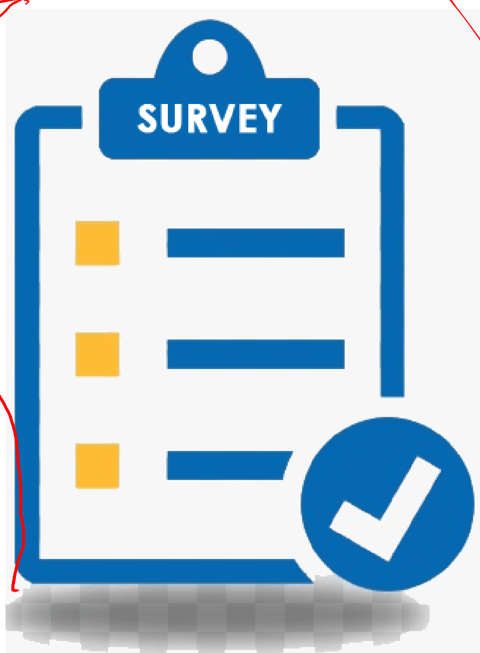
Illustration of Service Quality Evaluation

- What other observations are available these days?



Online Review Mining for Service Improvement

- What other observations are available these days?



VS

Hotels.com

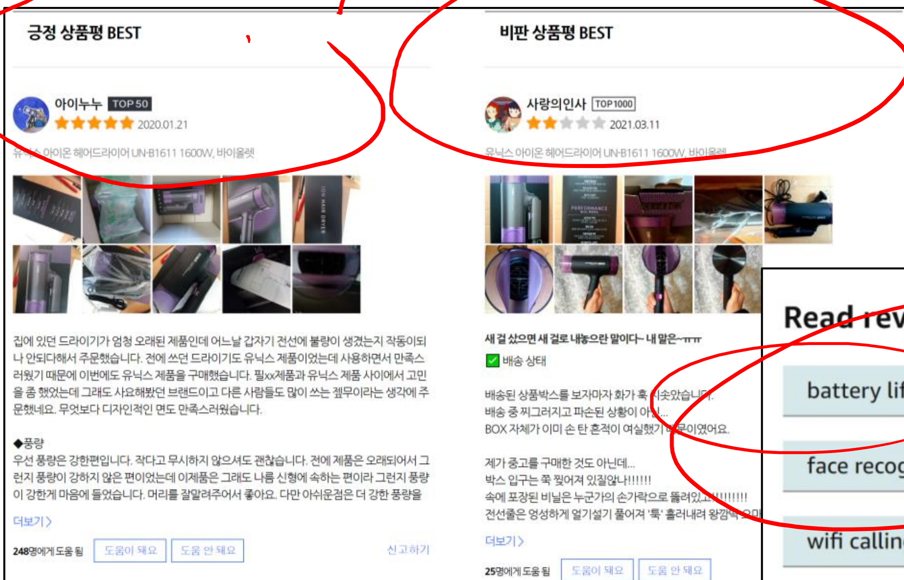
yelp

Tripadvisor

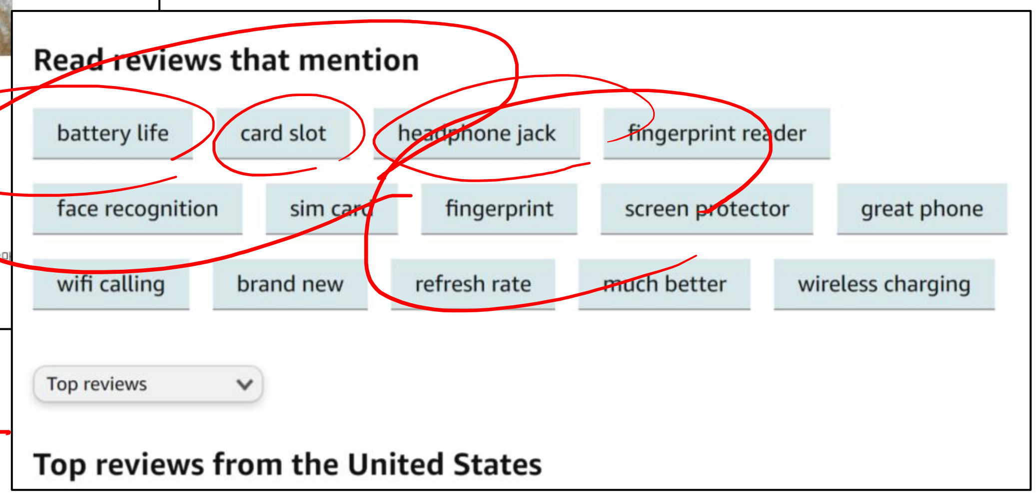
amazon

What is Online Review Mining?

- Review analysis for customers
  - Best and worst review retrieval, top keywords, and keyword-based search, etc



Best and worst reviews in Coupang



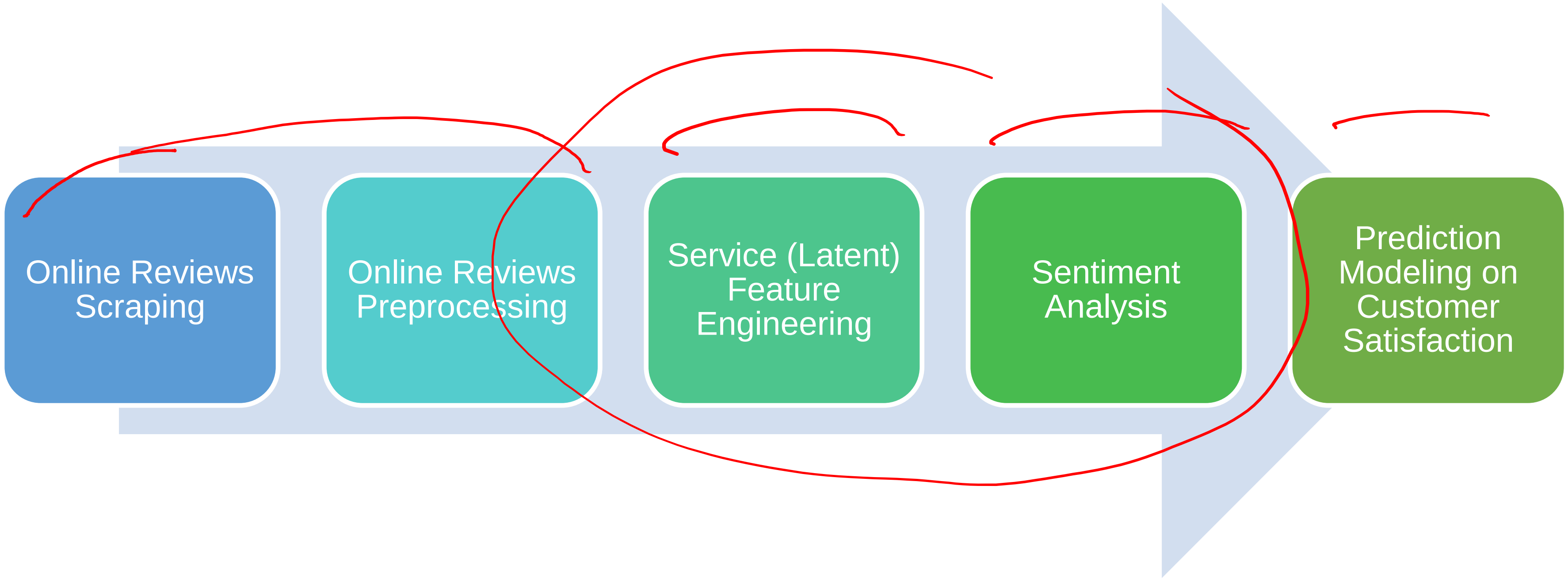
Top keywords and keyword-based search in Amazon

What is Online Review Mining?

- Review analysis for companies
  - Topic analysis, sentiment analysis (i.e., performance analysis), and importance analysis, etc

Restaurant reviews analysis

Online Review Mining Framework for Service Improvement



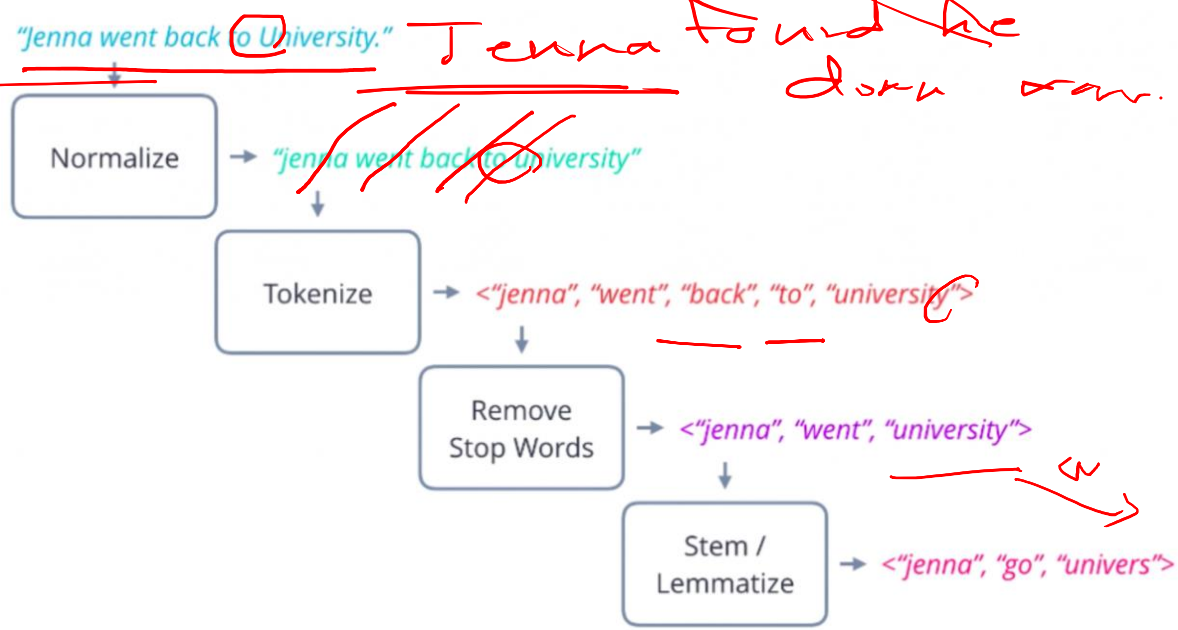
Online Reviews Scraping

- What is online reviews scraping?
  - Web scraper goes to review web platforms or websites and extracts all the data that interests you

Web scraping

Online Reviews Preprocessing

- What is text preprocessing?
  - Method to clean the text data and make it ready to feed data to the model
    - Lowercasing
    - Tokenization
    - Removal of stop words
    - Lemmatization
    - POS (Part-Of-Speech) tagging



Jenna found the
down man.

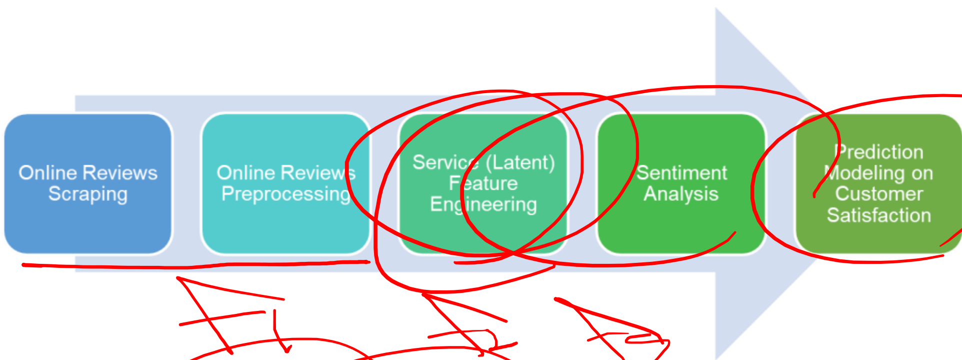
On the Customer Review – Word Feature Matrix

	Word 1	Word 2	Word 3	…	Word m-1	Word m	Rating
Review 1	1	2	0	3	4	0	5
Review 2	-	-	-	-	-	-	5
Review 3	-	-	-	-	-	-	4
…	-	-	-	-	-	-	3
…	-	-	-	-	-	-	4
…	-	-	-	-	-	-	1
…	-	-	-	-	-	-	4
…	-	-	-	-	-	-	5
…	-	-	-	-	-	-	4
…	-	-	-	-	-	-	3
Review n-1	-	-	-	-	-	-	2
Review n	-	-	-	-	-	-	4

On the Customer Review – Service Feature Matrix

	Feature 1	Feature 2	Feature 3	…	Feature k-1	Feature k	Rating
Review 1	?	?	?	?	?	?	5
Review 2	?	?	?	?	?	?	5
Review 3	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	1
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	5
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
Review n-1	?	?	?	?	?	?	2
Review n	?	?	?	?	?	?	4

Sentiment Analysis and Satisfaction Prediction Modeling



rating = $f(F_1, F_2, F_3 \rightarrow)$

$F_1 \quad F_2 \quad F_3$

	Word 1	Word 2	Word 3	…	Word m-1	Word m	Rating
Review 1	1	2	0	3	4	0	5
Review 2	-	-	-	-	-	-	5
Review 3	-	-	-	-	-	-	4
…	-	-	-	-	-	-	3
…	-	-	-	-	-	-	4
…	-	-	-	-	-	-	1
…	-	-	-	-	-	-	4
…	-	-	-	-	-	-	5
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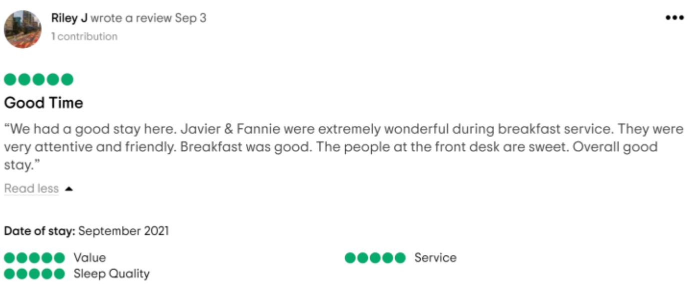
	Feature 1	Feature 2	Feature 3	…	Feature k-1	Feature k	Rating
Review 1	?	?	?	?	?	?	5
Review 2	?	?	?	?	?	?	5
Review 3	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	1
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	5
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
Review n-1	?	?	?	?	?	?	2
Review n	?	?	?	?	?	?	4

Case Study

- Hotels in Singapore
  - Hotels requiring improvement due to low customer satisfaction
  - Time: 2010.01-2019.12
  - Customer reviews in 2020 were not considered due to Covid-19

Case Study: Online Reviews Scraping and Preprocessing

- Remove duplicate reviews
- Collect reviews with the information of customer segments and hotel classes
- Selenium web crawler library of Python was used to collect customer reviews from TripAdvisor
- NLTK package of Python was used to structure each review into preprocessed word tokens

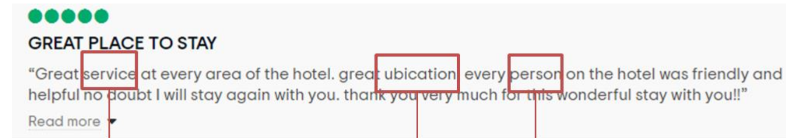


Collected data information based on customer segments

Information	All	Hotel classes			Travel types				
		Class 2	Class 3	Class 4	Solo	Couple	Friends	Family	Business
Sample	32,044	4,571	12,528	14,945	3,318	9,853	3,593	7,812	4,892
Ratio	0.56	0.51	0.54	0.60	0.59	0.56	0.58	0.60	0.50

Service Feature Engineering

- What is service feature engineering in online review mining?



hospitality, professionalism

location, accessibility, proximity

staff, personnel, manager, concierge

Review*word matrix

	$word_1$	…	$word_m$
$Review_1$	value		
…			
$Review_n$			

Dimension reduction

Review*feature matrix

	$feature_1$	…	$feature_i$
$Review_1$			
…			
$Review_n$			

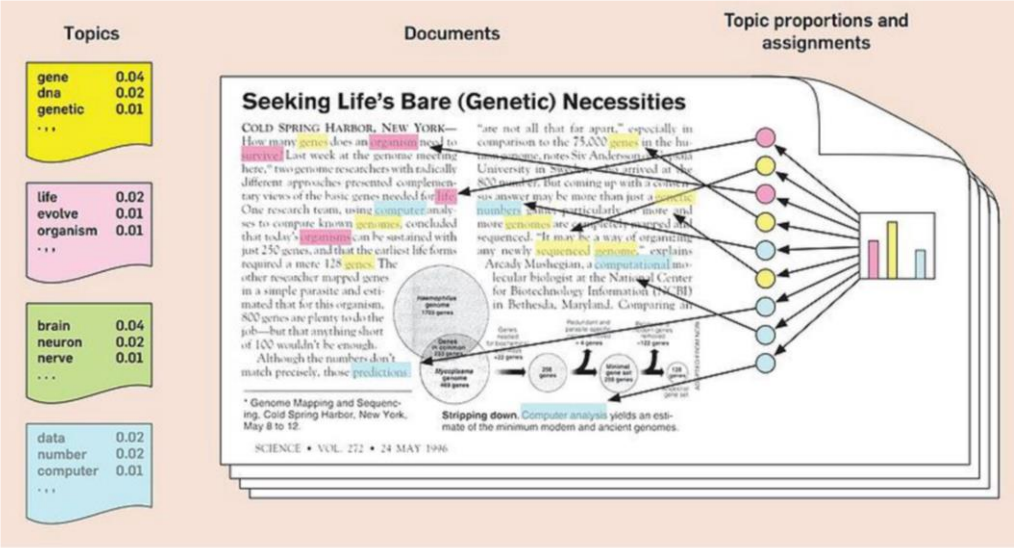
Example of hotel service features: location, breakfast, room, service, sleep quality, value, etc.

How to estimate the value?

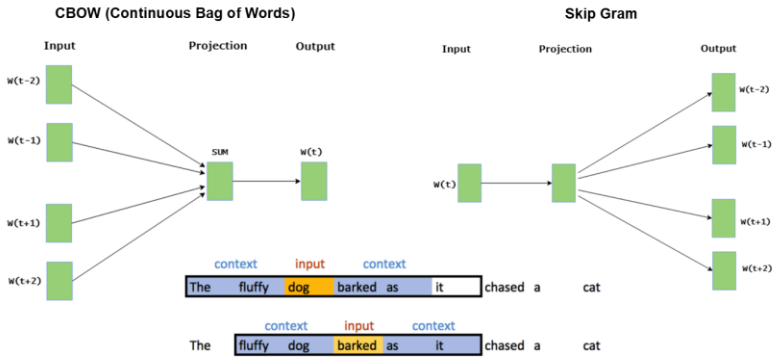
	about	bird	heard	is	the	word	you
About the bird, the bird, bird bird bird	1	5	0	0	2	0	0
You heard about the bird	1	1	1	0	1	0	1
The bird is the word	0	1	0	1	2	1	0

Service Feature Engineering

- How to perform feature engineering from online reviews?
  - Latent topic feature extraction: LDA (Latent Dirichlet Allocation), NMF (Nonnegative Matrix Factorization)
  - Word embedding (vectorization): Word2Vec, BERT (Bidirectional Encoder Representations from Transformers)



Topic analysis



word embedding

Service Feature Engineering

- NMF (Lee and Seung, 1999) and LDA (Blei et al, 2003)
  - Idea: each review can be described by a distribution of topics and each topic can be described by a distribution of words

Review*word matrix (input)

	$word_1$	$\dots$	$word_m$
$Review_1$			
$\dots$			
$Review_n$			

Review*topic matrix (output)

	$Topic_1$	$\dots$	$Topic_k$
$Review_1$			
$\dots$			
$Review_n$			

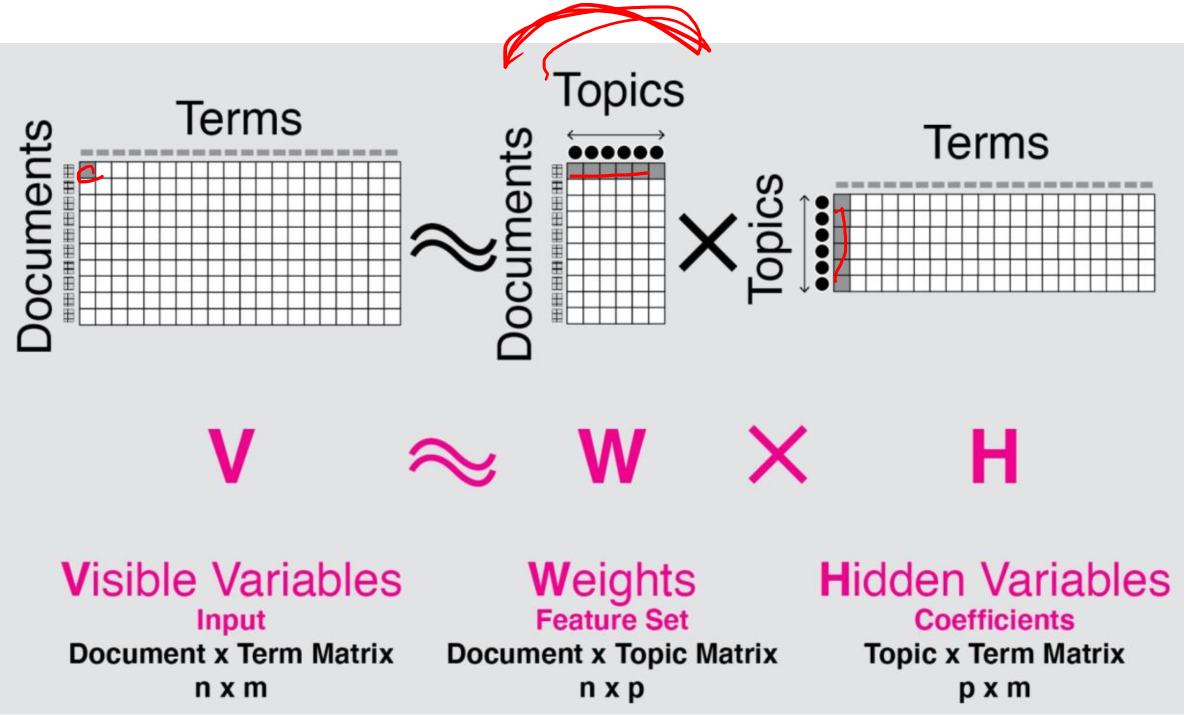
Topic*word matrix (output)

	$word_1$	$\dots$	$word_m$
$Topic_1$			
$\dots$			
$Topic_k$			

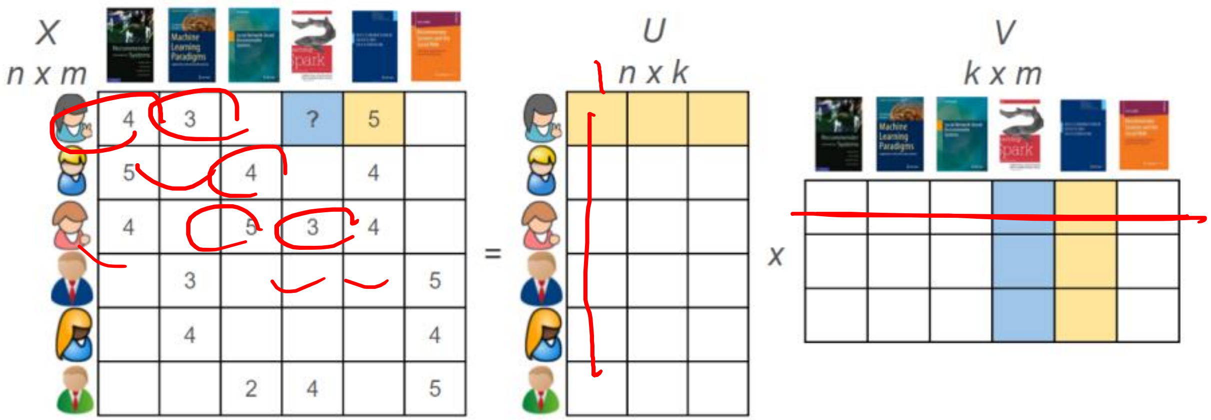
Service Feature Engineering

- NMF (Lee and Seung, 1999)
  - NMF is a linear-algeabreic model, that factors high-dimensional vector into a low-dimensionality representation similar to principal component analysis

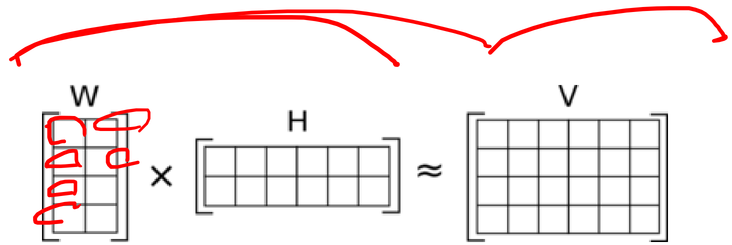
reviews

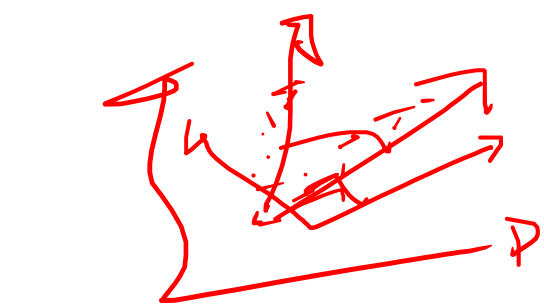


Recall the Collaborative Filtering with Matrix Factorization



$\|V - WH\|_F^2$





initialize: $\mathbf{W}$ and $\mathbf{H}$ non negative.

Then update the values in $\mathbf{W}$ and $\mathbf{H}$ by computing the following, with n as an index of the iteration.

$$\mathbf{H}^{n+1}_{[i,j]} \leftarrow \mathbf{H}^{n}_{[i,j]} \frac{((\mathbf{W}^n)^T \mathbf{V})_{[i,j]}}{((\mathbf{W}^n)^T \mathbf{W}^n \mathbf{H}^n)_{[i,j]}}$$

and

$$\mathbf{W}^{n+1}_{[i,j]} \leftarrow \mathbf{W}^{n}_{[i,j]} \frac{(\mathbf{V}(\mathbf{H}^{n+1})^T)_{[i,j]}}{(\mathbf{W}^n \mathbf{H}^{n+1} (\mathbf{H}^{n+1})^T)_{[i,j]}}$$

Until $\mathbf{W}$ and $\mathbf{H}$ are stable.

Target rating matrix *R*

user \ item	1	2	3	4	5	6
1	5	?	4	?	3	3
2	?	4	?	?	3	?
3	3	?	?	3	?	?
4	?	4	?	5	?	1

User feature matrix *P* (initial state)

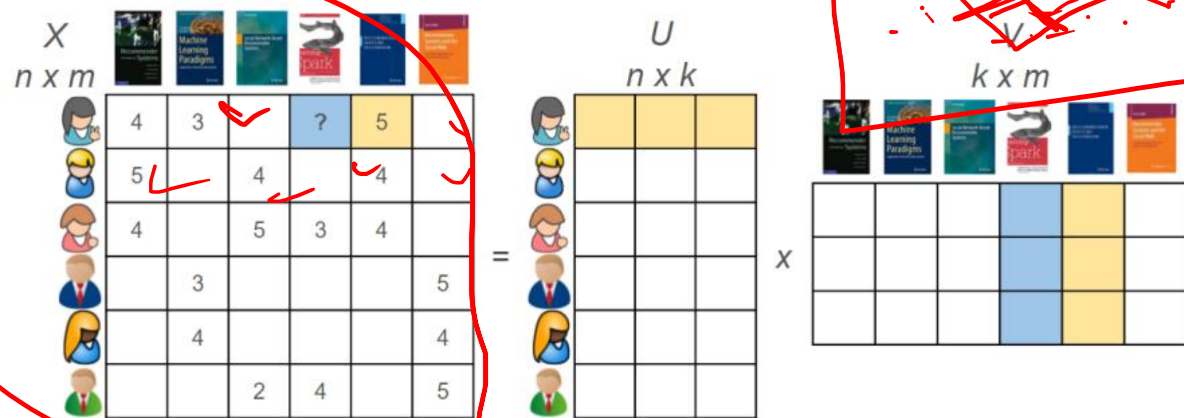
user \ dimension	1	2	3
1	0.11	0.07	0.19
2	0.09	0.16	0.19
3	0.09	0.05	0.04
4	0.03	0.13	0.18

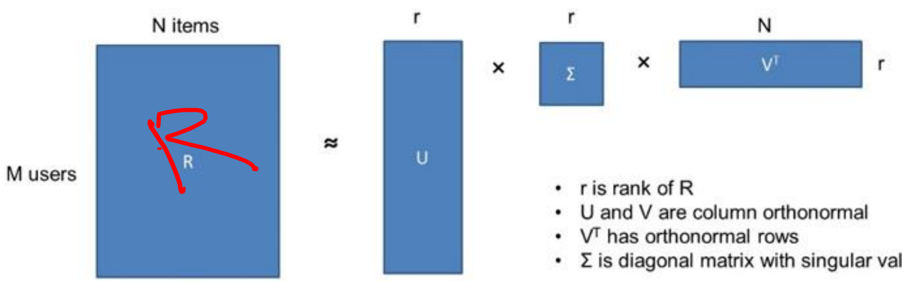
Item feature matrix *Q* (initial state)

dimension \ item	1	2	3	4	5	6
1	0.16	0.01	0.07	0.17	0.02	0.20
2	0.18	0.19	0.10	0.05	0.18	0.15
3	0.02	0.18	0.03	0.14	0.17	0.06

Image source: https://medium.com/@lineyin/the-singular-value-decomposition-and-pca-cae825ff28fc
https://www.dataminingapps.com/2020/02/singular-value-decomposition-in-recommender-systems/
https://en.wikipedia.org/wiki/Non-negative_matrix_factorization

Recall the Collaborative Filtering with Matrix Factorization



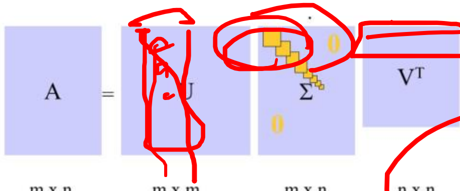


- r is rank of R
- U and V are column orthonormal
- V^T has orthonormal rows
- Σ is diagonal matrix with singular values

$R \neq U\Sigma V^T$

$(RV = U\Sigma)$

orthogonal   scaler



$R = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \cdots$

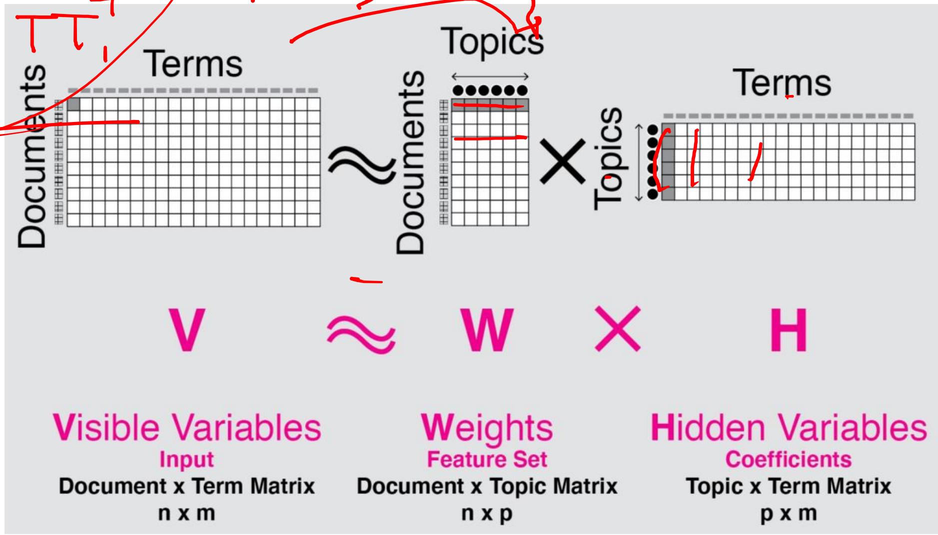
Image source: https://medium.com/@lineyin/the-singular-value-decomposition-and-pca-cae825ff28fc
https://www.dataminingapps.com/2020/02/singular-value-decomposition-in-recommender-systems/
https://en.wikipedia.org/wiki/Non-negative_matrix_factorization

Service Feature Engineering

- NMF (Lee and Seung, 1999)
  - NMF operates by starting with a guess of values for W and H, and iteratively minimizing the loss function
  - Typically it is implemented by updating one matrix (either W or H) for each iteration, and continuing to minimize the error function

$$Minimize \|V - WH\|_F^2, W, H \geq 0$$

$DT_{11} = \vec{DT_1} \cdot \vec{TT_1}^T$



Recall the Attempt to Estimate the Mechanism Behind the Simple Dot Product

- Deep-learning-based nonlinearity consideration complements the traditional approaches

Neural Collaborative Filtering*

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ABSTRACT

In recent years, deep neural networks have yielded immense success on speech recognition, computer vision and natural language processing. However, the exploration of deep neural networks on recommender systems has received relatively less scrutiny. In this work, we strive to develop techniques based on neural networks to tackle the key problem in recommendation — collaborative filtering — on the basis of implicit feedback.

Although some recent work has employed deep learning for recommendation, they primarily used it to model auxiliary information, such as textual descriptions of items and acoustic features of musics. When it comes to model the key factor in collaborative filtering — the interaction between user and item features, they still resorted to matrix factorization and applied an inner product on the latent features of users and items.

By replacing the inner product with a neural architecture that can learn an arbitrary function from data, we present a general framework named NCF, short for *Neural network-based Collaborative Filtering*. NCF is generic and can express and generalize matrix factorization under its framework. To supercharge NCF modelling with non-linearities, we propose to leverage a multi-layer perceptron to learn the user–item interaction function. Extensive experiments on two real-world datasets show significant improvements of our proposed NCF framework over the state-of-the-art methods. Empirical evidence shows that using deeper layers of neural networks offers better recommendation performance.

Keywords

Collaborative Filtering, Neural Networks, Deep Learning, Matrix Factorization, Implicit Feedback

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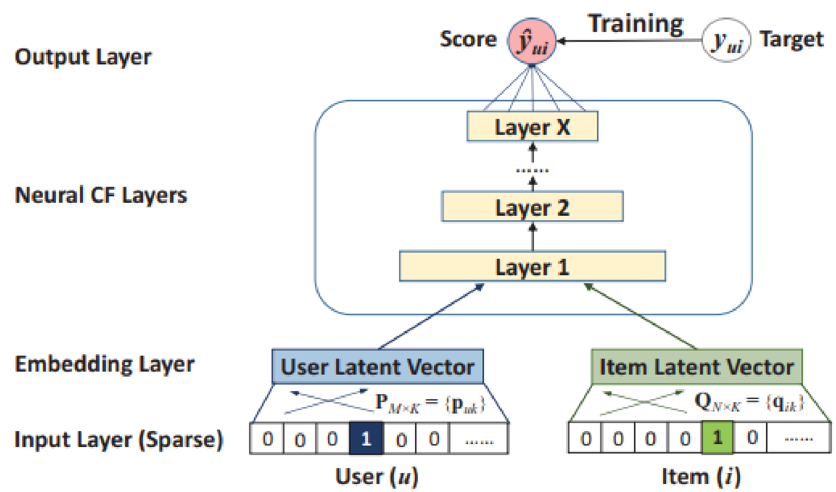
1. INTRODUCTION

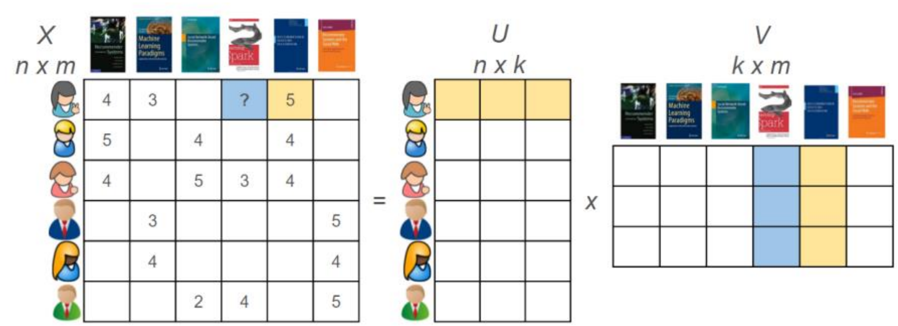
In the era of information explosion, recommender systems play a pivotal role in alleviating information overload, having been widely adopted by many online services, including E-commerce, online news and social media sites. The key to a personalized recommender system is in modelling users' preference on items based on their past interactions (*e.g.*, ratings and clicks), known as collaborative filtering [31, 46]. Among the various collaborative filtering techniques, matrix factorization (MF) [14, 21] is the most popular one, which projects users and items into a shared latent space, using a vector of latent features to represent a user or an item. Thereafter a user's interaction on an item is modelled as the inner product of their latent vectors.

Popularized by the Netflix Prize, MF has become the *de facto* approach to latent factor model-based recommendation. Much research effort has been devoted to enhancing MF, such as integrating it with neighbor-based models [21], combining it with topic models of item content [38], and extending it to factorization machines [26] for a generic modelling of features. Despite the effectiveness of MF for collaborative filtering, it is well-known that its performance can be hindered by the simple choice of the interaction function — inner product. For example, for the task of rating prediction on explicit feedback, it is well known that the performance of the MF model can be improved by incorporating user and item bias terms into the interaction function[1]. While it seems to be just a trivial tweak for the inner product operator [14], it points to the positive effect of designing a better, dedicated interaction function for modelling the latent feature interactions between users and items. The inner product, which simply combines the multiplication of latent features linearly, may not be sufficient to capture the complex structure of user interaction data.

This paper explores the use of deep neural networks for learning the interaction function from data, rather than a handcraft that has been done by many previous work [18, 21]. The neural network has been proven to be capable of approximating any continuous function [17], and more recently deep neural networks (DNNs) have been found to be effective in several domains, ranging from computer vision, speech recognition, to text processing [5, 10, 15, 47]. However, there is relatively little work on employing DNNs for recommendation in contrast to the vast amount of literature

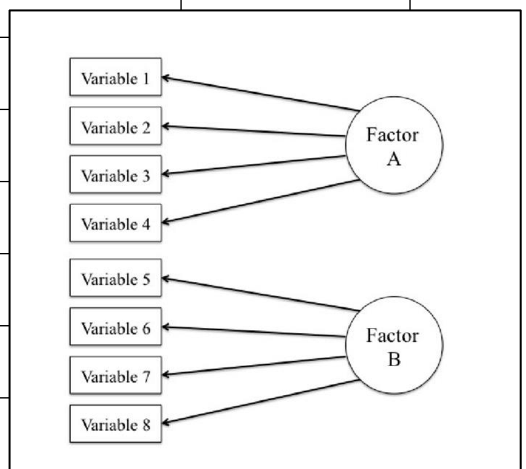
[1] http://alex.smola.org/teaching/berkeley2012/slides/8_Recommender.pdf

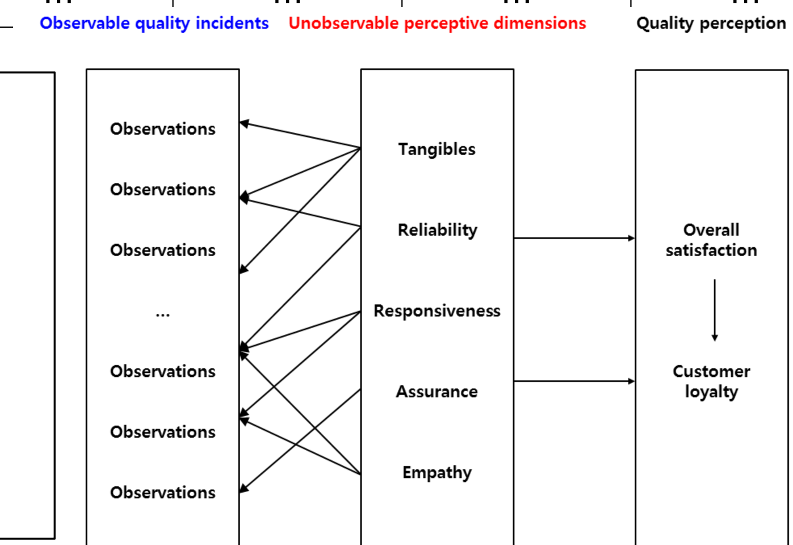




Recall the Attempt to Estimate the Latent Factors Generating the Observed Data

	metric 1	metric 2	metric 3	…	metric m-1	metric m
Customer 1	…	…	…	…	…	…
Customer 2	…	…	…	…	…	…
Customer 3						
…						
…						
…						
…						
…						
…						
…	…	…	…	…	…	…
Customer n-1	…	…	…	…	…	…
Customer n	…	…	…	…	…	…





Service Feature Engineering

- Assume that there is a certain process of generating review words with latent service features

	Word 1	Word 2	Word 3	…	Word m-1	Word m	Rating
Review 1	1	2	0	3	4	0	5
Review 2	-	-	-	-	-	-	5
Review 3	-	-	-	-	-	-	4
…	-	-	-	-	-	-	3
…	-	-	-	-	-	-	4
…	-	-	-	-	-	-	1
…	-	-	-	-	-	-	4
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Review n-1	-	-	-	-	-	-	2
Review n	-	-	-	-	-	-	4

Service Feature Engineering

- Assume that there is a certain process of generating review words with latent service features

T_1 T_2 T_3 ...

r_1

r_2

r_3

Z ordered

P_1 P_2 P_3

r_1

r_2

r_3

w_1 w_2 w_3 w_4 ...

T_1 0.01 0.02 0.05

T_2

T_3

Function of

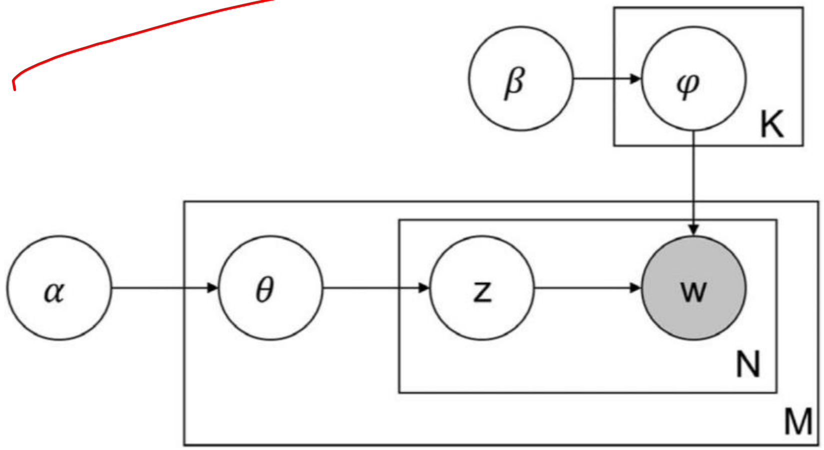
α, β, w

Service Feature Engineering

- Latent Dirichlet Allocation (LDA) (Blei et al, 2003)

Step 1: Choose $\theta_i \backsim \mathrm{Dir}(\alpha)$, where $i \in \{1, \ldots, M\}$
Step 2: Choose $\varphi_k \backsim \mathrm{Dir}(\beta)$, where $k \in \{1, \ldots, K\}$
Step 3: For each word position i, j, where $i \in \{1, \ldots, M\}$ and $j \in \{1, \ldots, N_i\}$
Choose a topic $z_{ij} \backsim \mathrm{Multinomial}\ (\theta_i)$
Choose a word $w \backsim \mathrm{Multinomial}\ (\varphi_{z_{ij}})$

P1=P(topic k / document D)
P2=P(word w / topic k)



Graphical model representation of LDA

M = number of customer reviews
N = number of words in a review
K = number of topics
α = parameter of the Dirichlet prior on the per-review topic distribution
β = parameter of the Dirichlet prior on the per-topic word distribution
θ_i = topic distribution for review i (the sum of θ_i is 1)
φ_k = word distribution for topic k
z_{ij} = topic for the j^{th} word in review i
w = specific word

On the Customer Review – Word Matrix

	Word 1	Word 2	Word 3	…	Word m-1	Word m	Rating
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…	-					-	4
…	-					-	1
…	-					-	4
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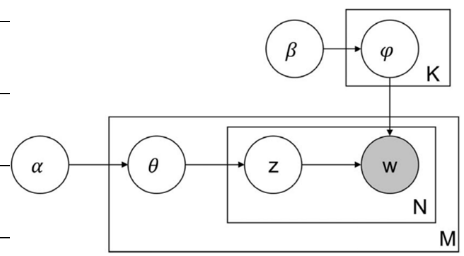

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β = parameter of the Dirichlet prior on the per-topic word distribution
θ_i = topic distribution for review i (the sum of θ_i is 1)
φ_k = word distribution for topic k
z_{ij} = topic for the j^{th} word in review i
w = specific word

Graphical model representation of LDA

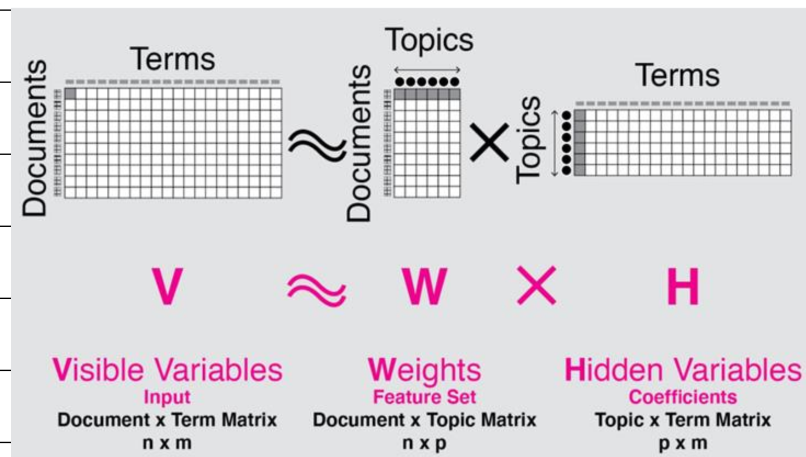
On the Customer Review – Word Matrix

$tf\text{-}idf\ value\ after\ normalization, when$

$$tf\text{-}idf(t,d) = tf(t,d) \times (\log\frac{1+n_d}{1+df(d,f)} + 1)$$

	Word 1	Word 2	Word 3	…	Word m-1	Word m	Rating
Review 1	0.04	0.18	0	0.23	0.10	0	5
Review 2	-	-	-	-	-	-	5
Review 3	-					-	4
…	-					-	3
…	-					-	4
…	-					-	1
…	-					-	4
…	-					-	5
…	-					-	4
…	-					-	3
Review n-1	-	-	-	-	-	-	2
Review n	-	-	-	-	-	-	4

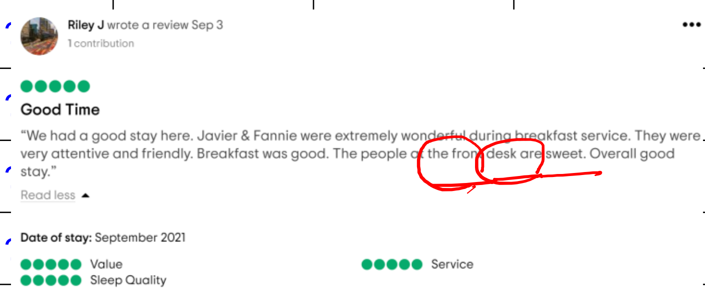
$$Minimize \ ||V - WH||, W, H \geq 0$$



On the Customer Review – Word Matrix

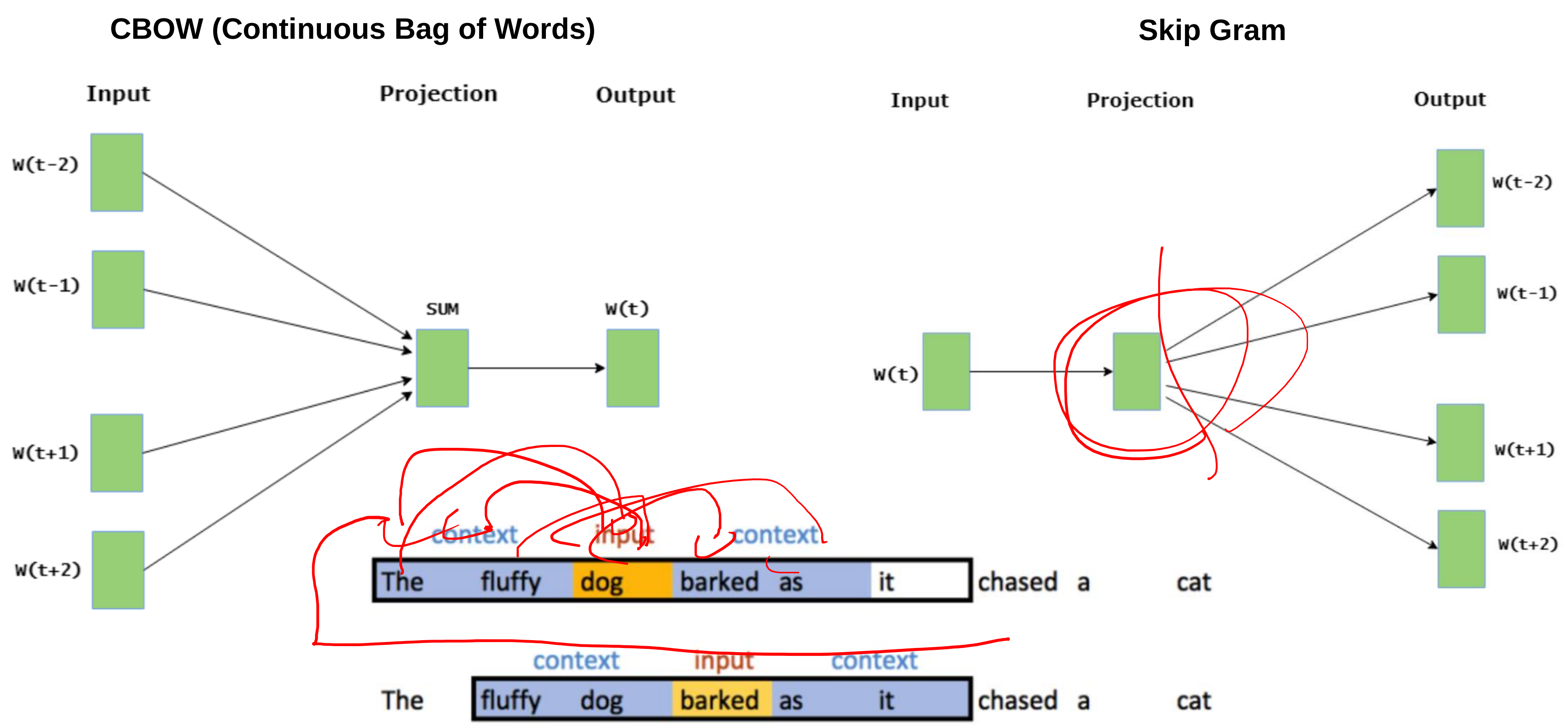
desk Front

	Word 1	Word 2	Word 3	…	Word m-1	Word m	Rating
Review 1	?	?	?	?	?	?	5
Review 2	?	?	?	?	?	?	5
Review 3	?	?	?	?	?	?	4
…	?					?	3
…	?					?	4
…	?					?	1
…	?					?	4
…	?	?	?	?	?	?	5
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
Review n-1	?	?	?	?	?	?	2
Review n	?	?	?	?	?	?	4



Word Vectorization for Service Feature Engineering

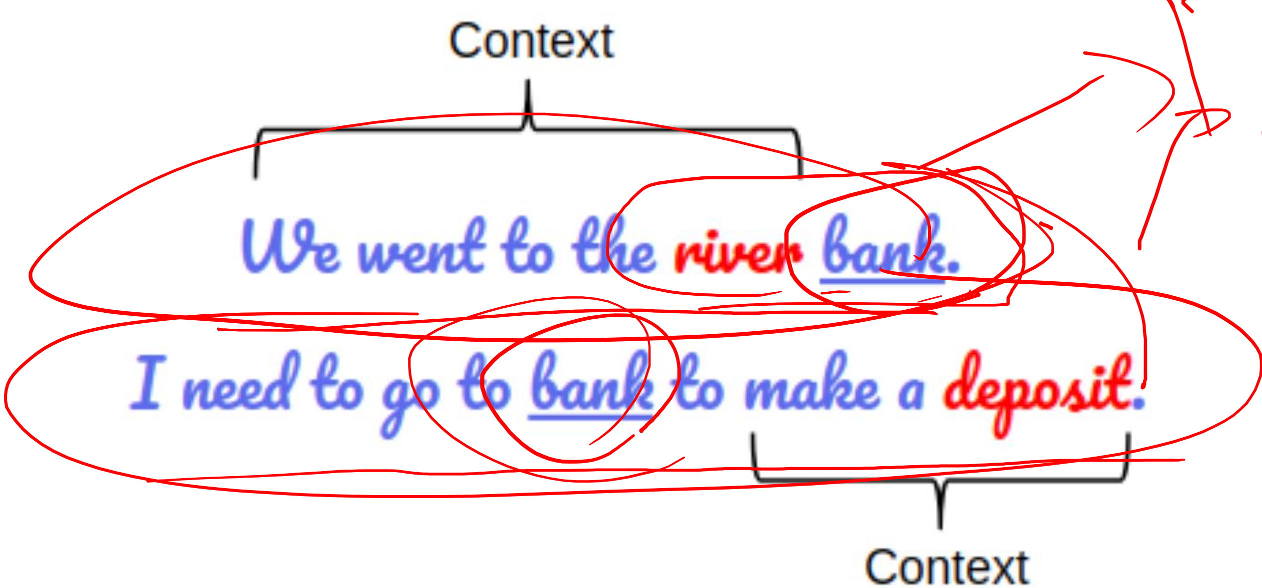
- Word2vec (Mikolov et al., 2013)
  - Word2Vec uses shallow two layer neural networks having one input layer, one hidden layer and one output layer



Window size: 5

Word Vectorization for Service Feature Engineering

- Word2vec (Mikolov et al., 2013) and BERT (Devlin et al., 2019)
  - Word2vec will generate the same single vector for the word bank for both the sentences
  - BERT will generate different vectors for the word bank being used in different contexts



Case Study: Service Feature Engineering

- Use LDA to identify latent service features and their related words
- For example, the Gensim library of Python, which applies variation expectation maximization algorithm (Blei et al. 2003) can be used to execute LDA

Hotel service features in Singapore

	Feature	Frequent word	# of words	# of reviews
f_1	Location	location, $\cdots$	63	26,700
f_2	View	view, outlook,$\cdots$	15	6,527
f_3	Breakfast	breakfast, buffet,$\cdots$	24	13,484
f_4	Sleep quality	bed, mattress,$\cdots$	20	10,707
f_5	Bathroom	bathroom, toilet,$\cdots$	24	11,466
f_6	Service	service, staff,$\cdots$	32	20,864
f_7	Check	check, checkin,$\cdots$	19	12,651
f_8	Value	value, price,$\cdots$	6	11,477
f_9	Internet	internet, wifi,$\cdots$	32	6,137

Sentiment Analysis

- What is sentiment analysis?
  - Actual performance of features can be determined from a customer perspective
  - The sentiments of the identified features are obtained at each review

●●●●●

GREAT PLACE TO STAY

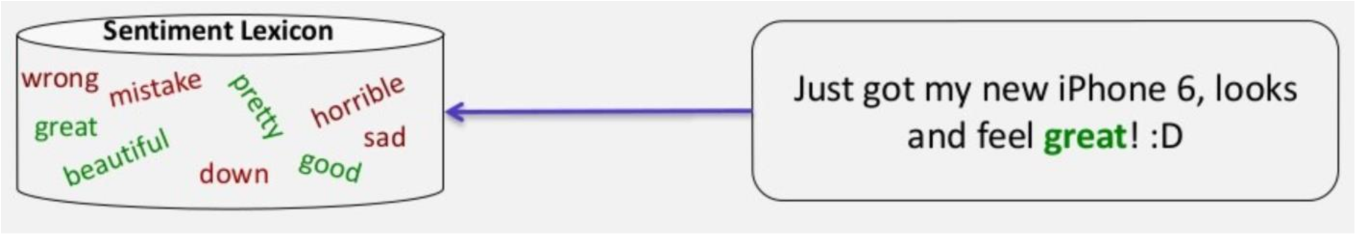
"Great service at every area of the hotel. great ubication, every person on the hotel was friendly and helpful no doubt I will stay again with you. thank you very much for this wonderful stay with you!!"

Read more ▾

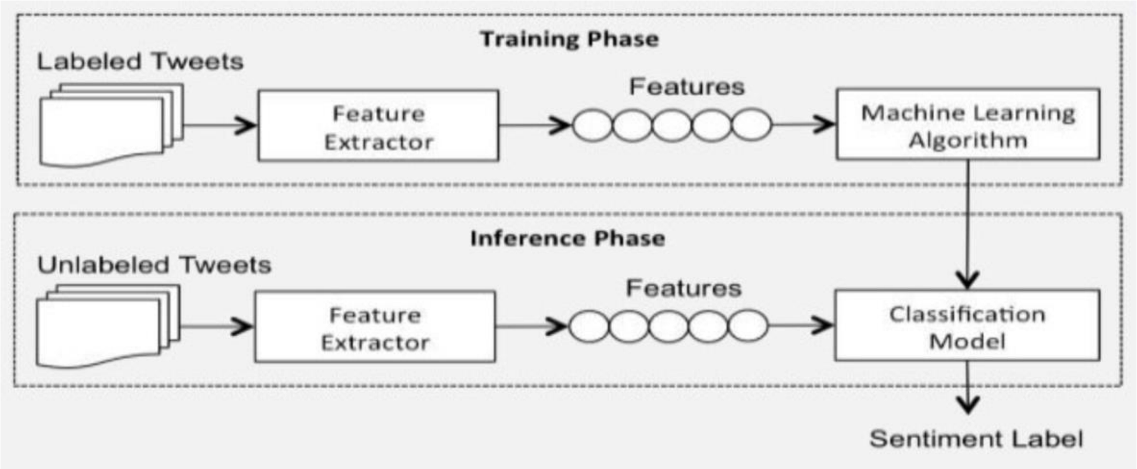
Sentiment analysis of features: Service (very positive), Location (very positive), Staff (very positive)

Sentiment Analysis

- How to perform sentiment analysis?
  - Lexicon-based approach: e.g., VADER (Valence Aware Dictionary for Sentiment Reasoning)



  - Machine learning approach



Sentiment Analysis

- VADER sentiment analysis (Gilbert et al., 2014) and SentiStrength (Thelwall et al., 2012)
  - A lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments in social media
  - Available regardless of the domain

Lexicon	Positive Words	Negative Words
Simplest (SM)	good	bad
Simple List (SL)	good, awesome, great, fantastic, wonderful	bad, terrible, worst, sucks, awful, dumb
Simple List Plus (SL+)	good, awesome, great, fantastic, wonderful, best, love, excellent	bad, terrible, worst, sucks, awful, dumb, waist, boring, worse
Past and Future (PF)	will, has, must, is	was, would, had, were
Past and Future Plus (PF+)	will, has, must, is, good, awesome, great, fantastic, wonderful, best, love, excellent	was, would, had, were, bad, terrible, worst, sucks, awful, dumb, waist, boring, worse
Bing Liu	2006 words	4783 words
AFINN-96	516 words	965 words
AFINN-111	878 words	1599 words
enchantedlearning.com	266 words	225 words
MPAA	2721 words	4915 words
NRC Emotion	2312 words	3324 words

Case Study: Sentiment Analysis

	f_1	f_2	…	f_9
1	**Location** was great	Awesome **view**	…	Terrible **internet** speed
2		City **view** was not good	…	
3			…	
…	…	…	…	…
32044			…	

Sentiment intensity score from VADER sentiment analyzer

'Location': 0.6249

'View': 0.6249, -0.3412

'Internet', -0.4767

$$S_{im} = \begin{cases} 4, & if\ 0.525 \le \text{Sentiment intensity} \le 1 \\ 3, & if\ 0.05 \le \text{Sentiment intensity} < 0.525 \\ 0, & if\ -0.05 < \text{Sentiment intensity} < 0.05 \\ 2, & if\ -0.525 < \text{Sentiment intensity} \le -0.05 \\ 1, & if\ -1 \le \text{Sentiment intensity} \le -0.525 \end{cases}$$

Encoding for input variable

	f_1	f_2	…	f_9	Star ratings
1	4	4	…	2	0
2	0	2	…	0	0
3	0	0	…	0	1
…	…	…	…	…	…
32044	0	0	…	0	1

0 → Negative label (1, 2, 3 ratings)

1 → Positive label (4, 5 ratings)

Input variables (f_1 … f_9)

Output variables (Star ratings)

Prediction Modeling on Customer Satisfaction

- What is prediction modeling on customer satisfaction?
  - Prediction modeling for identifying the effect or importance values of performance of service features on overall customer satisfaction
  - For example, linear logit classification or other models with interpretation can be applied

	f_1	f_2	…	f_i	Star ratings
1	5	5	…	2	0
2	0	2	…	0	0
3	0	0	…	0	1
…	…	…	…	…	…
M	0	0	…	0	1

Input variables: f_1 … f_i; Output variables: Star ratings

Negative label (1, 2, 3 ratings) → 0

Positive label (4, 5 ratings) → 1

Dataset for prediction modeling on customer satisfaction

Case Study: Prediction Modeling on Customer Satisfaction

- Logit model
  - $y = 0.227 \cdot location + 0.085 \cdot view + 0.095 \cdot breakfast + 0.009 \cdot sleep\ quality + 0.119 \cdot bathroom + 0.328 \cdot service + 0.01 \cdot check + 0.087 \cdot value + 0.04 \cdot internet$

$$Y_i = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \cdots \beta_i A_i$$

	f_1	f_2	…	f_9	Star ratings
1	5	5	…	2	0
2	0	2	…	0	0
3	0	0	…	0	1
…	…	…	…	…	…
32044	0	0	…	0	1

Input variables (f_1 … f_9) — Output variables (Star ratings)

Negative label (1, 2, 3 ratings)

Positive label (4, 5 ratings)

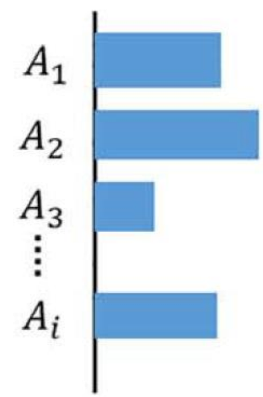
Prediction Modeling on Customer Satisfaction

$Y = f(A_1\ A_2\ A_3\ A_4\ A_5$

- **Feature ablation**
  - Technique for calculating feature importance values that works for any machine learning models
    - 1) Train the model on your train set and calculate a score on the test set
    - 2) For each of the *i* features, remove it from the training data and train the model. Then, calculate the score on the test set.
    - 3) Importance of each feature is the difference between the original score and the score by removing a feature

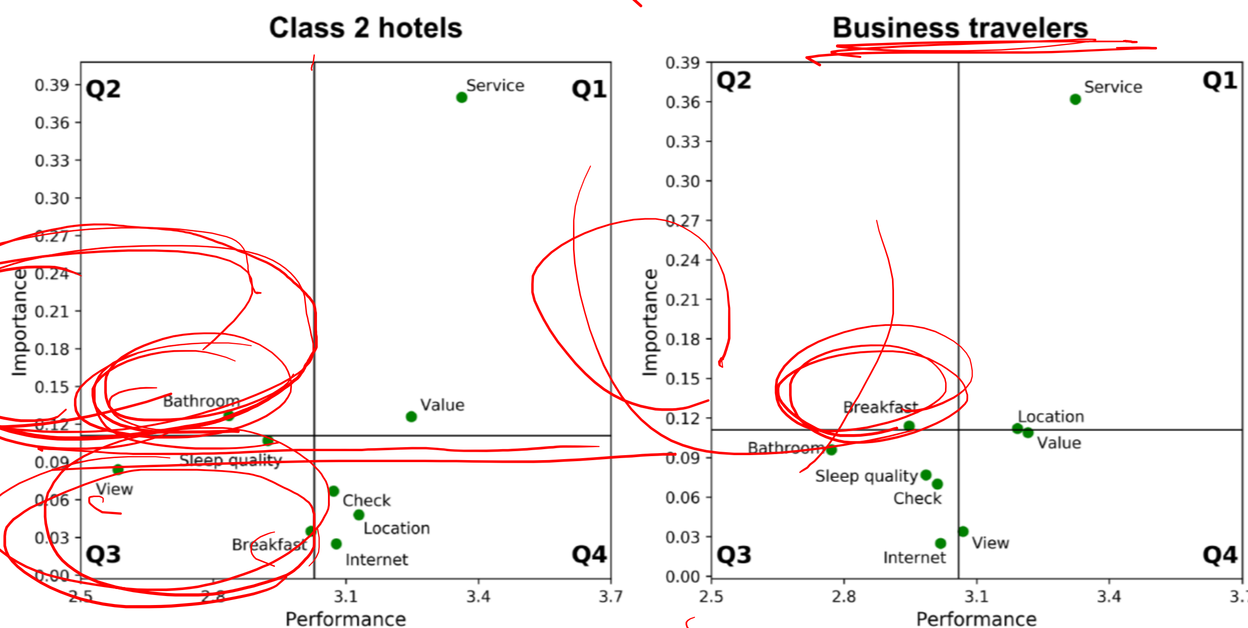
i.e., What about changes in model performance after removing each feature?

Machine learning models (ex. Neural network, random forest, naïve bayes, SVM)

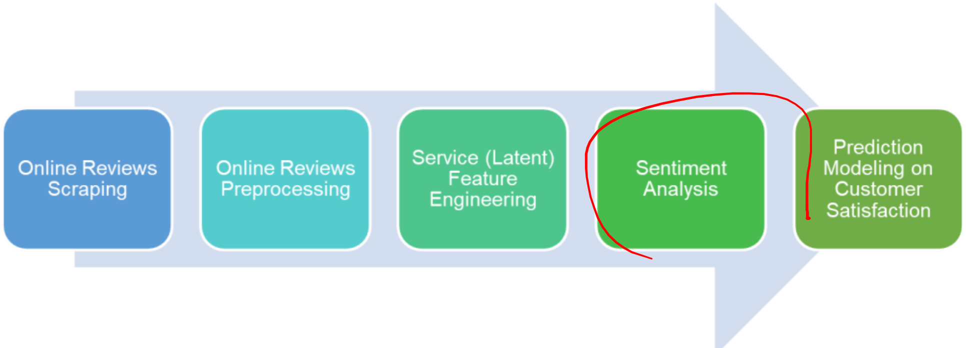


Service Improvement Implications from Online Review Mining

- Importance-Performance Analysis (IPA) for service improvement
  - Q1: “Keep up the good work” : major strengths
  - Q2: “Concentrate here” : immediate action for improvement
  - Q3: “Low priority” : minor weaknesses
  - Q4: Possible overkill” : minor strengths



Online Review Mining Framework for Service Improvement



	Word 1	Word 2	Word 3	…	Word m-1	Word m	Rating
Review 1	?	?	?	?	?	?	5
Review 2	?	?	?	?	?	?	5
Review 3	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	1
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	5
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
Review n-1	?	?	?	?	?	?	2
Review n	?	?	?	?	?	?	4

	Feature 1	Feature 2	Feature 3	…	Feature k-1	Feature k	Rating
Review 1	?	?	?	?	?	?	5
Review 2	?	?	?	?	?	?	5
Review 3	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	1
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	5
…	?	?	?	?	?	?	4
…	?	?	?	?	?	?	3
Review n-1	?	?	?	?	?	?	2
Review n	?	?	?	?	?	?	4

Assignment 4 (by 10.7 11:59 pm)

- By yourself, (1) complete the construction of the review-feature dataset on service quality of hotels in Singapore based on the practice demonstrated by the TA. Then, (2) using the review-feature matrix you constructed, develop a service quality prediction model for the hotels in Singapore (i.e., predict the customer's quality evaluation with review data). Do it all by yourself, and describe the analysis process and outcome in detail. Interpret the outcome (e.g., name the service features you identified, interpret the coefficient/importance values of service features to the quality ratings).
- (3) What other interesting machines can be developed using the review-feature matrix dataset you constructed? Describe your ideas in detail (e.g., describe the learning objective and process). Try to think your own creative, unique ideas! You have completed the basic review mining activities (tasks 1 and 2) as well as your own idea generation (task 3). Then, (4) describe how you can use your machine(s) to automate the monitoring, evaluation, and improvement of hotel service quality? Imagine you are working for a real hotel.
- Using a similar approach that you have practiced so far, (5) what other services can be improved using review mining machines or another intelligent machine that learns other types of raw data traces of service quality (e.g., customer behavior data)? Assume that you actually manage the quality of service in question. (6) How would you conduct this job in your own creative, unique way? What kinds of data and methods are you going to collect, analyze, and learn? Describe your service intelligence development plan in detail. If possible, visualize your plan clearly (e.g., draw an image, construct a mathematical model).
- Upload your code and a several paragraph essay on the tasks (1)~(6) in the Blackboard.

Notice on the Survey This Class

- This course is operated under the “AI-adopted course development project” of UNIST. Thus, the UNIST Education center would like to support the operations of this course.
  - The “AI-adopted course” is a type of interdisciplinary course where the students learn AI-related knowledge and problem-solving skills on the topics of the major (i.e., industrial engineering) through practice-oriented learning and group-project-based learning. This way, the students can integrate the traditional topics of the major with the modern AI knowledge and skills, so that they can broaden and deepen their perspectives of the major.
  - As such, in this class, please participate in the survey to identify the needs of students taking the AI-adopted courses in UNIST, so that the lecturer and Education center ensure the courses operate well throughout this semester.
- Link: https://docs.google.com/forms/d/e/1FAIpQLSendUKPN3aqhPvaomcTg0r9LYeC15UAur5_F2s8NzJLz1Lw0g/viewform

SCAN ME

Term Project Announcement:

“Develop Your Own Service Intelligence”

Topics of the Service Intelligence Course

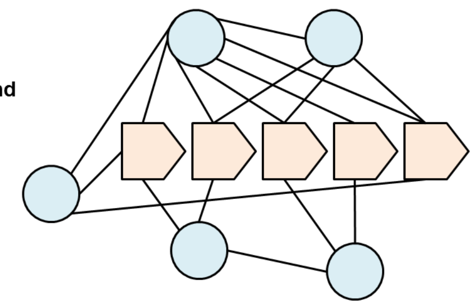
Service Review Mining

Behavioral Data Mining

Recommender Systems Development

Service Quality Evaluation and Improvement

All Weeks



Customer Segmentation and Service Customization

Special Lectures on Service Intelligence

Service Process Assessment and Improvement

Service Optimization

Industrial Service Intelligence

Previous Term Project Topics

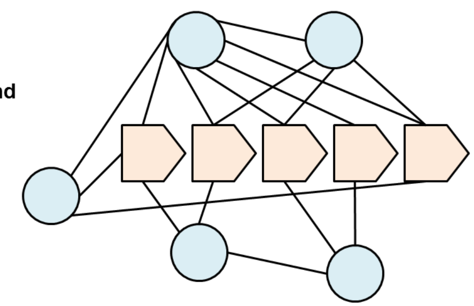
Review-based food recommendation

Behavior-and-symptom -based health diagnosis

Animation recommender system
Book recommender system

Metainfo-and-review-based restaurant recommendation

All Projects



Customized service design for air conditioning machine users and clients

Allergy-free diet planning for children

Optimal routing for COVID-19 vaccine distribution

Industrial service solution development for shale gas productivity prediction and investment

Assignments, Grading, and Policies

- Assignments
  - You need to complete an assignment as you follow along with the required class
  - Each assignment will require you to answer questions, solve problems, and/or write a report
  - Assignments must be done in the MS Word format and submitted with the filename “Assignment#_ID_Name.docx” (e.g., Assignment1_20201200_ChiehyeonLim.docx)
- Grading

Item	Portion	Criteria
Class Participation	10%	Attendance and In-Class-Presentation for Discussion
Assignments	40%	Comprehension, Completeness, and Creativity
Term Project	50%	Completeness, Adherence to the Course Material, and Creativity

- Other policies: Late work with penalty and NO cheating

Service Review Mining Practice

Demonstrated by TA Shin

Customer Complaints Monitoring with ML

Shouldn't We Consider the Service Quality Dynamics in Time?

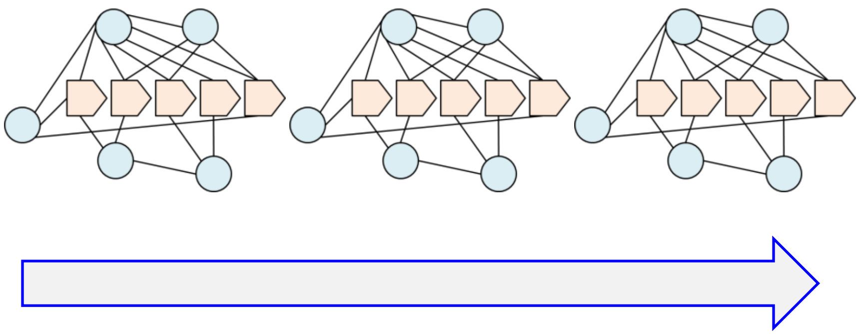
consumer behaviors
(user behaviors)

service delivery
and experience

quality

value cocreation

technology and
self-service



relationship

innovation

design and
development

productivity

knowledge and
employee
management

cost and pricing

service operations
and supply chain
management

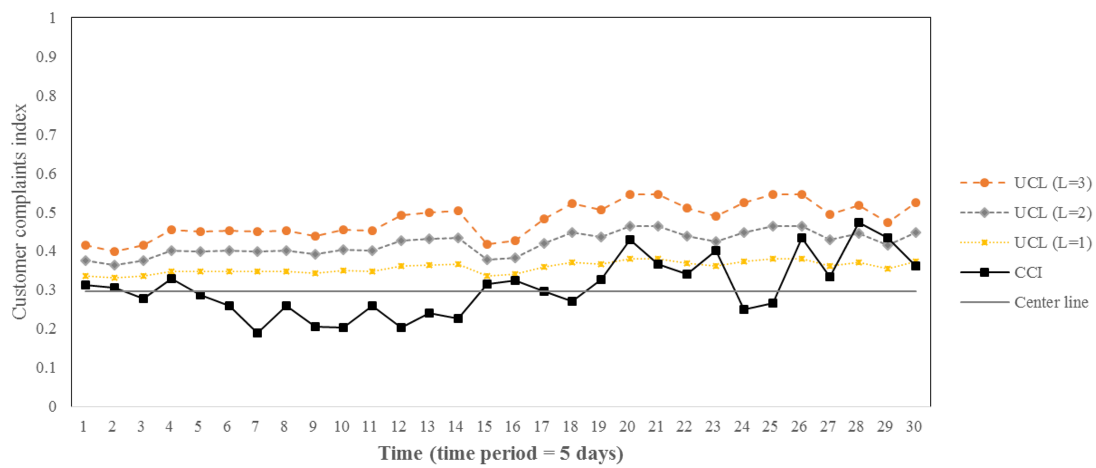
On the Time Dynamics of Customer Review – Service Feature

	Feature 1	Feature 2	Feature 3	…	Feature m-1	Feature m	Rating
Review 1	…	…	…	…	…	…	5
Review 2	…	…	…	…	…	…	5
Review 3	…	…	…	…	…	…	4
…	…	…	…	…	…	…	3
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	1
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	5
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	3
Review n-1	…	…	…	…	…	…	2
Review n	…	…	…	…	…	…	4

	Feature 1	Feature 2	Feature 3	…	Feature m-1	Feature m	Rating
Review 1	…	…	…	…	…	…	5
Review 2	…	…	…	…	…	…	5
Review 3	…	…	…	…	…	…	4
…	…	…	…	…	…	…	3
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	1
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	5
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	3
Review n-1	…	…	…	…	…	…	2
Review n	…	…	…	…	…	…	4

	Feature 1	Feature 2	Feature 3	…	Feature m-1	Feature m	Rating
Review 1	…	…	…	…	…	…	5
Review 2	…	…	…	…	…	…	5
Review 3	…	…	…	…	…	…	4
…	…	…	…	…	…	…	3
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	1
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	5
…	…	…	…	…	…	…	4
…	…	…	…	…	…	…	3
Review n-1	…	…	…	…	…	…	2
Review n	…	…	…	…	…	…	4

Time



Case Study on the Mobile Game Service Quality Monitoring

- Case study of mobile game service
  - Representing 58% of all downloads in the mobile markets
  - One of the fastest-changing areas with fierce competition
  - Need to manage service quality and update their game services by adding new attributes or fixing bugs

- Data summary
  - Database: Apple app store
  - Application: Angry bird 2
  - Data variables: Date, reviewer ID, rating, title, review content, version
    - Pre-processing the review contents via NLTK in python
  - Period: 2017-07-31 ~ 2017-12-25
  - Country: United States
  - Total number of reviews: 2,010

Case Study on the Mobile Game Service Quality Monitoring

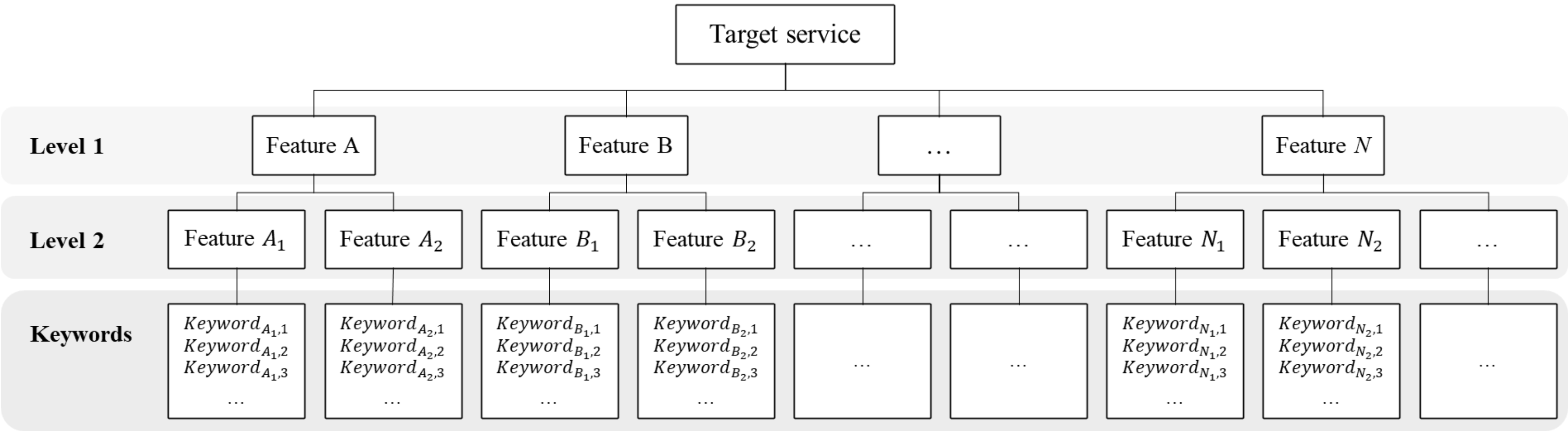
- Step 1: Data collection and pre-processing
  - Collecting the review date and review content
  - Pre-processing the review content via tokenization, stop-words removal, POS tagging, and lemmatization
  - Part of the customer review database

No.	Date	Reviewer ID	Rate	Title	Review content (raw data)	Review content (after pre-processing)	Version
1	2017-07-31	CPJ***	3	A good pastime	It's Angry Birds, but on steroids. The graphics and sound effect make it fun to pass the time playing.	[(angry, JJ), (bird, NN), (steroid, JJ), (graphic, JJ), (sound, NN), effect, NN), (make, VBP), (fun, NN), (pas, NN), (time, NN), (play, NN)]	2.14.0
…	…	…	…	…	…	…	…
2010	2017-12-25	Frogit to***	5	Frogit	It's addictive I can't stop playing I have so much fun great game!	[(addictive, JJ), (cant, NN), (stop, VB), (play, NN), (much, JJ), (fun, NN), (great, JJ), (game, NN)]	2.17.2

** Part of speech tags and descriptions: CD=cardinal number, DT=determiner, JJ=adjective, NN=noun (singular), PRP=personal pronoun, RB=adverb, RBR=adverb (comparative), VB=verb (base form), VBD=verb (past tense), VBP=verb (non-3rd person singular present), VBZ=verb (3rd person singular present), WRB=wh-adverb

Case Study on the Mobile Game Service Quality Monitoring

- Step 2: Construction of a service feature hierarchy with keyword dictionary
  - Service feature hierarchy



Case Study on the Mobile Game Service Quality Monitoring

- Step 2: Construction of a service feature hierarchy with keyword dictionary

  - Service feature hierarchy employed in this study

Service feature (level 1)	Description	Service feature (level 2)	Description	Ciurumelea et al. (2017)	McIlroy et al. (2016)	Khalid et al. (2015)	Maalej and Nabil (2015)	Fu et al. (2013)
Compatibility	Issues related to version of the OS or the specific phone device	Version	Issues related to update or mobile app version	✓	✓	✓		
		Hardware	Issues related to a specific mobile phone device of OS	✓	✓	✓		✓
Usage	Reports the things that are uncomfortable to use and things that user want to improve	Attribute requests	Issues related to additional attribute(s) or modification	✓	✓	✓	✓	
		Bug reporting	Issues related to unexpected bug		✓	✓	✓	
		Difficulty of game	Issues related to difficulty of mobile game	Added by the authors				
		Spam	Issues related to advertisement					✓
Resources	Mentions the memory or battery usage	Battery	Issues related to battery usage	✓	✓	✓		
		Memory	Issues related to memory usage	✓	✓	✓		
Pricing	Refers the licensing model, price of the app, or in-app purchase issues	Price	Issues related to the licensing model, price of the app, or in-app purchase	✓	✓	✓		✓
Protection	States the security issues or user privacy	Security	Issues related to security or lack of it	✓				
		Privacy	Issues related to permissions and privacy	✓	✓	✓		

Case Study on the Mobile Game Service Quality Monitoring

- Step 3: Identification of customer complaints
  - Part of the results of sentiment analysis

Review contents	Positive	Neutral	Negative	Compound	Classification
It's Angry Birds, but on steroids. The graphics and sound effect make it fun to pass the time playing.	0.268	0.645	0.087	**0.671**	Positive
Amazing and fun game I love it	0.79	0.21	0.0	**0.906**	Positive
I love playing the game it is so much fun and it is challenging it make your mind work thank you so much	0.446	0.554	0.	**0.913**	Positive
It's cute and the upgrades are nice	0.537	0.463	0.0	**0.7**	Positive
The graphics on this latest version are amazing! Even on my iPad 2.	0.254	0.746	0.0	**0.624**	Positive
…	…	…	…	**…**	…
App keeps freezing when you are playing, do you lose your archived levels. Very frustrating!	0.088	0.54	0.372	**-0.699**	Negative
Too hard to reach boss - run out of birds before getting to final room!	0.074	0.811	0.114	**-0.151**	Negative
Game has started freezing in the middle of the game. Is there a bug?	0.0	0.896	0.104	**-0.103**	Negative

- Out of 2,010 customer reviews, a total of 640 customer reviews identified as customer complaints

Case Study on the Mobile Game Service Quality Monitoring

- Step 4: Development of a customer complaints chart via SPC
  - Three issues for developing the customer complaints chart using SPC
    - In terms of the use of statistic
      - Interpreting each customer complaint as non-conformity
      - Defining customer complaints index (CCI) by modifying the index used for measuring service performance (Chen and Yang, 2000; Rasouli and Zarei, 2016; Yang and Chen, 2000)

$$CCI_{i,t} = \frac{\text{The number of negative customer reviews}_{i,t}}{\text{The total number of customer reviews}_{i,t}} = \frac{N(NCR_{i,t})}{N(CR_{i,t})}$$

where $NCR_{i,t}$ represents the number of negative customer reviews for the *i* th service feature at the time period *t*

- Defining the center line(CL) and upper control limit (UCL) as:

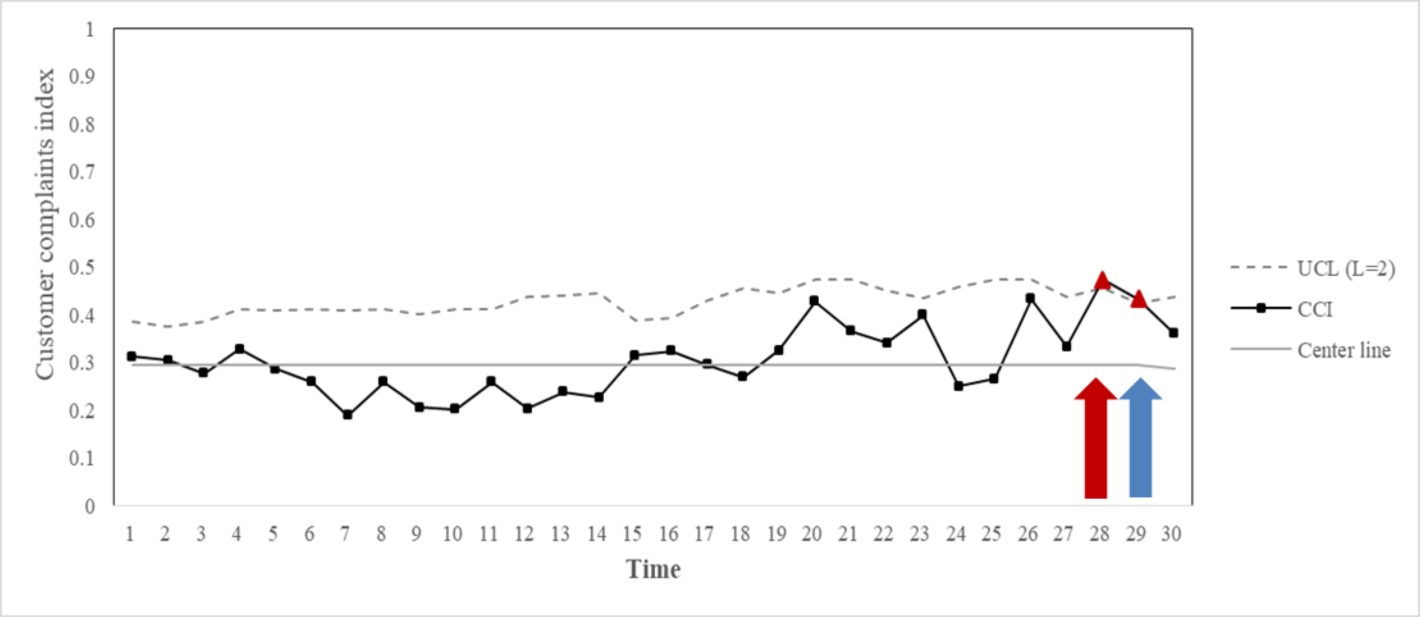
$$CL_i = \frac{\sum_{t=1}^{T} NCR_{i,t}}{\sum_{t=1}^{T} CR_{i,t}} \qquad UCL_{i,t} = CL_i + L\sqrt{\frac{CL_i(1 - CL_i)}{CR_{i,t}}}$$

where *T* and *L* denote the number of time periods and sensitivity parameter, respectively

Case Study on the Mobile Game Service Quality Monitoring

- Step 4: Development of a customer complaints chart via SPC
  - Customer complaints chart for the overall status

    (time period=5days, L=2)



Scheduled update to add a new attribute on December 11th, which caused the compatibility issue

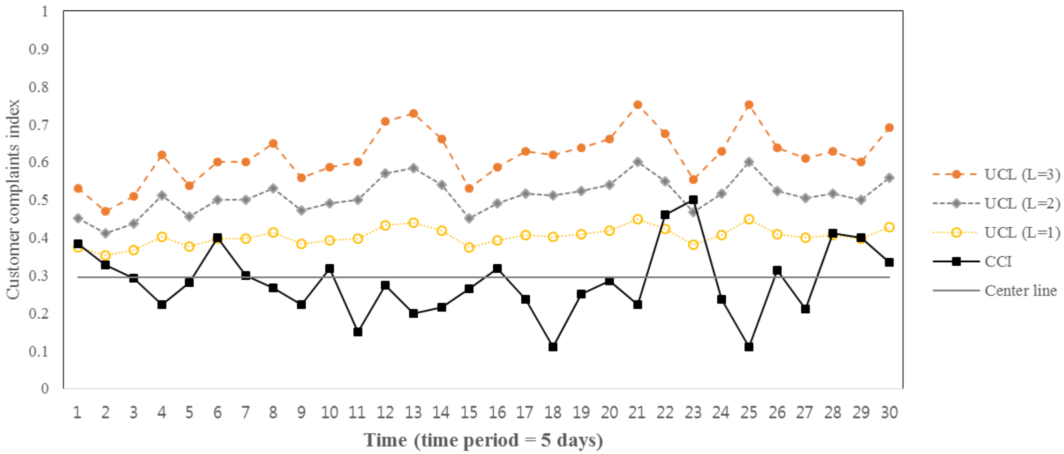
Out-of-control signals on December 13th-17th

Minor update to solve the compatibility problem on December 20th

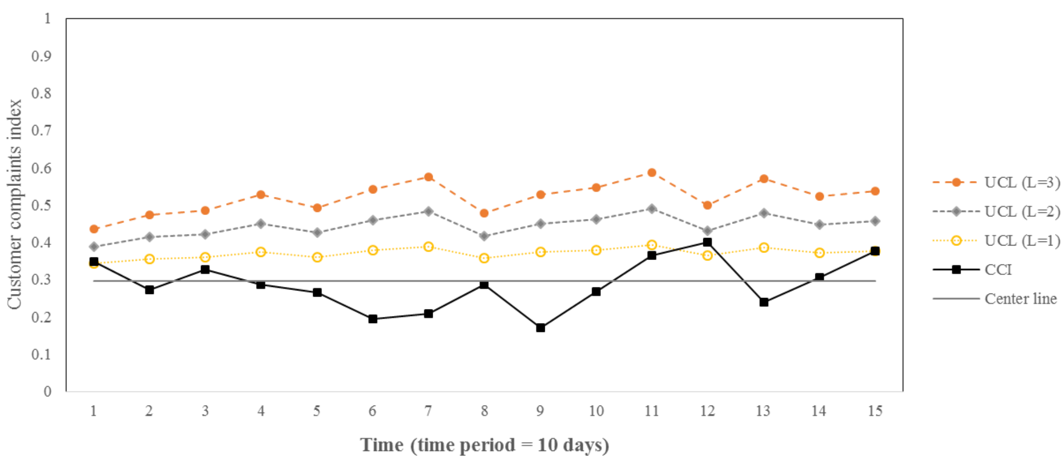
Case Study on the Mobile Game Service Quality Monitoring

- Customer complaints chart for the attribute request feature with different value of control parameters

(a)



(b)



Service feature (level 1)	Description	Service feature (level 2)
Compatibility	Issues related to version of the OS or the specific phone device	Version Hardware
Usage	**Reports the things that are uncomfortable to use and things that user want to improve**	**Attribute requests** Bug reporting Difficulty of game Spam
Resources	Mentions the memory or battery usage	Battery Memory
Pricing	Refers the licensing model, price of the app, or in-app purchase issues	Price
Protection	States the security issues or user privacy	Security Privacy

Further Readings Recommended

- Shin, J., Joung, J., and Lim, C., "Online Review Mining Meets Interpretable Machine Learning for Customer-oriented Service Quality Management," 2022. Article 6
- Kim, J. and Lim, C., "Customer Complaints Monitoring with Customer Review Data Analytics: An Integrated Method of Sentiment And Statistical Process Control Analyses," Advanced Engineering Informatics, Vol. 49, 101304, 2021. Article 7